How do oil prices impact macroeconomic variables and consumer confidence across European countries? An analysis of the energy crisis on households' consumer confidence.

Author: Mohammed Gibraan MUHAJIZ

Student number: 663911

Supervisor: Dr. Felix Ward

Second Assessor: Dr. Lorenzo Pozzi

Date: 17th October 2023.

Erasmus School of Economics

Preface and Acknowledgment.

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, the Erasmus School of Economics or the Erasmus University of Rotterdam.

I would like to thank my supervisor, Dr. Felix Ward, for guiding me through the process and reciprocating the same enthusiasm I had for this research topic. I am grateful for his help and the valuable insights and feedback he has given me.

Abstract

In this paper, I examine the effects of the 2022-2023 oil price shock on the economy in France, Germany, Italy, and Spain, paying particular attention to the effect of an oil price shock on the Consumer Confidence Index (henceforth, CCI), and attempt to understand how this crisis differs from previous shocks to the price of oil. For this purpose, a SVAR model was used using five variables, namely, oil price statistics, CCI, long-term government bond yield, HICP, and industrial production index. The origin of the shock was mostly based on supply-side effects, but movements in the demand for oil have also been seen. The results indicate asymmetric responses; there are some similarities in the response of the variables to the shock but also some differences that I attempt to explain using the literature and differences in national circumstances. Nevertheless, the shock to oil prices does not seem to be persistent as energy prices are returning to "normal" levels and the (energy component of) HICP is decreasing. I then submit several policy recommendations that aim to improve the conduct of future research, fight the inflationary pressures facing the EU, help poor households who suffered a lot, and reduce the dependence on oil. Concerning energy dependence, the EU needs to find alternative sources of energy to avoid similar situations in the future. Investments in renewables need to be increased, not just for environmental purposes, but as the crisis has shown us, oil can be used as a political and economic weapon. Policies should try to anticipate movements in oil supply, oil demand, prices, and inflation expectations to achieve better results since late responses to a crisis can have long-lasting consequences. Finally, I outline the limitations of this study and propose relevant domains for future research.

Table of Contents

1/ Introduction

On the eve of World War One, Winston Churchill (1913) declared in front of parliament that "safety and certainty in oil, lie in variety and variety alone". The strategic decision to move away from coal into oil came with a price, the reliance on foreign suppliers for their energy needs. This 'black gold' is used for transport, heating, electricity, and as a raw material for producing other products thus becoming a staple in the global economy.

In February 2022, Russia initiated an invasion campaign against Ukraine. The invasion sparked an uprising from the European Union (EU) which decided to take a stand against its neighbor in the east. Follows a set of diplomatic and economic sanctions from both sides as the EU condemned the war and Russia suspended gas and oil deliveries to the West. Russia being the world's second-largest oil exporter in the world and the third-largest oil producer, this incident has already generated long-lasting consequences for both European and Russian consumers.

In this paper, I will assess how fluctuations in oil prices have impacted macroeconomic aggregates and consumer confidence in four European countries, namely France, Germany, Italy, and Spain. I use a structural vector autoregression model (SVAR) and report my findings through Granger-causality tables, impulse response functions (IRFs), and forecast error variance decomposition (FEVD) tables. The countries chosen for this analysis are not random, they represent the four largest economies in the EU, which makes them high-energy consumers, and share a relative geographical proximity. They are also amongst the oldest members of the EU and the euro area while being very reliant on Russian oil imports. The model specification includes a combination of macroeconomic variables such as oil prices, industrial production, a measure of inflation (viz. HICP), a measure of interest rate (viz. long-term government bond yields), and a measure of consumer confidence. In doing so, our model looks at the potential channels of an oil price shock on households whereas most papers focus on the pass-through effect on other macroeconomic variables.

This paper aims to study the impact of the Ukraine war on macroeconomic aggregates and a consumer confidence index. The paper will contribute to the large body of literature on the topic of oil price shocks and their impact on macroeconomic aggregates. It will also attempt to clarify how the latest oil crisis differs from previous shocks. This is relevant for many reasons. Firstly, the war in Ukraine is a relatively recent event, yet to be over. The outcome of the war is still uncertain and there is no clear contingency plan on what to do after it has ended. Secondly, oil is a staple in the production functions of our economies, and fluctuations in this market often lead to complicated outcomes; it is therefore closely monitored by economists, investors, industries, and the government. The literature on oil price fluctuations tells us that there are many factors to consider when assessing the impact of a shock in a particular economy and understanding its cause. Thirdly, the paper contributes to another interesting body of literature, consumer confidence. The literature suggests that consumer confidence can be used as a suitable indicator of economic activity and a potential predictor of recession or economic downturns. The relationship between consumer confidence and oil prices is not as elaborately developed. This paper is a useful contribution to the relationship between both variables. Fourthly, by choosing different European countries, I expect our findings to show that an oil shock will have varying effects in Europe because of the heterogeneity in the macroeconomic conditions of our sample. Put simply, I expect that consumer confidence will react differently to oil price fluctuations based on factors such as the size of each economy, energy dependence levels, and the inflation rate in that country.

The paper is organised as follows. Section 2 will provide important background knowledge on the current events that prompted the writing of this paper. It also explains the sanctions imposed by the EU and how each country in the sample prepared for the cuts in imports. In section 3, I will summarize the literature review on oil prices, inflation, and the consumer confidence index (CCI) with an attempt to connect the different elements. Exploring those facets will allow the reader to understand the historical relationships and contemplate their changing nature. Section 4 will exhibit our empirical strategy, list the tests to verify common assumptions in SVAR models, and describe the findings. This includes a description of the criteria for the sample selection, transformations of the data, and various balancing tests. In section 5, I will explain how the empirical analysis fits and point out other aspects that are relevant to the issue but were not included in this paper. This involves the structure of the domestic oil markets and the current measures taken by each to protect households against spiralling oil prices as well as limitations to my findings. Finally, I will give concluding remarks in section 6 of this paper and reveal proposed domains for future research.

2/ Basic Facts

Studies on oil price shocks are not original. Several papers documented the adverse effect of the 1973 embargo led by the Organization of Arab Petroleum Exporting Countries (OPEC) against the US and its allies in response to their support of Israel. The incident showed how much power is retained by key players in the energy market, and, to a certain extent, shaped the diplomatic and geopolitical policies in Western countries. Unilateral decisions from this *cartel* have affected the global price of oil in the past. Some commentators blamed the embargo for the stagflation in the 1970s. Section 3 will explore these claims more closely.

The formation of crude oil is a natural process where organic materials are transformed through high pressure and high temperature occurring over millions of years. The distribution of this resource is unevenly distributed across the globe. Unfortunately, oil production in Europe has always been low, with Italy being the biggest producer but at a production capacity much lower than major exporters in the Middle East, America, or Russia. The demand on the other hand remains high with Germany being the highest consumer. The subsequent loss of oil imports comes at a great economic price for European governments who are pushed to look for alternative suppliers. However, the increased demand from Asian countries like China and India is putting European efforts for diversification at risk, driving other supplies down and prices up.

The EU has already sanctioned 1800 individuals and entities (European Council, 2023). Among those sanctions, an oil ban has been implemented by the EU. It is therefore illegal to "purchase, import or transfer [of] seaborne crude oil and certain petroleum products from Russia to the EU" since December 2022 for crude oil and February 2023 for refined petroleum products, however, the Council has allowed for exception in the importation of crude oil by pipeline for heavily dependent countries. Those measures, while unprecedented, demonstrate the fragile bargaining power of the EU as provisions to protect dependent countries were necessary to pass the ban. To a certain extent, this shows that national interests still prevail over a joint action. Roberts (2007) mentions divergence in national policies within the EU well before the war; for instance, France prefers to protect its domestic energy firms whereas Germany is more inclined to negotiate bilateral agreements. Figure 1 also plots the Italian reaction to the war. Total oil imports from Russia soared in the immediate aftermath of the Russian invasion, even after agreeing to the oil embargo on Russia, the imports remained high until December 2022. The explanation for this behaviour can be attributed to the particular refinery in Sicily owned by the Russian oil company Lukoil. Section 5 will elaborate more on this. The EU hoped that these sanctions would seriously weaken the Russian economy and its military budget, which it has, but they might have underestimated the Russians' persistence. Increased exports to China and India, also members of the BRICS, have compensated part of the loss incurred by European sanctions. Moreover, a recent article in The Economist (2023) has pointed out that European sanctions have just generated new trade routes using "laundromat" countries such as China, India, Singapore, Turkey, and the United Arab Emirates.

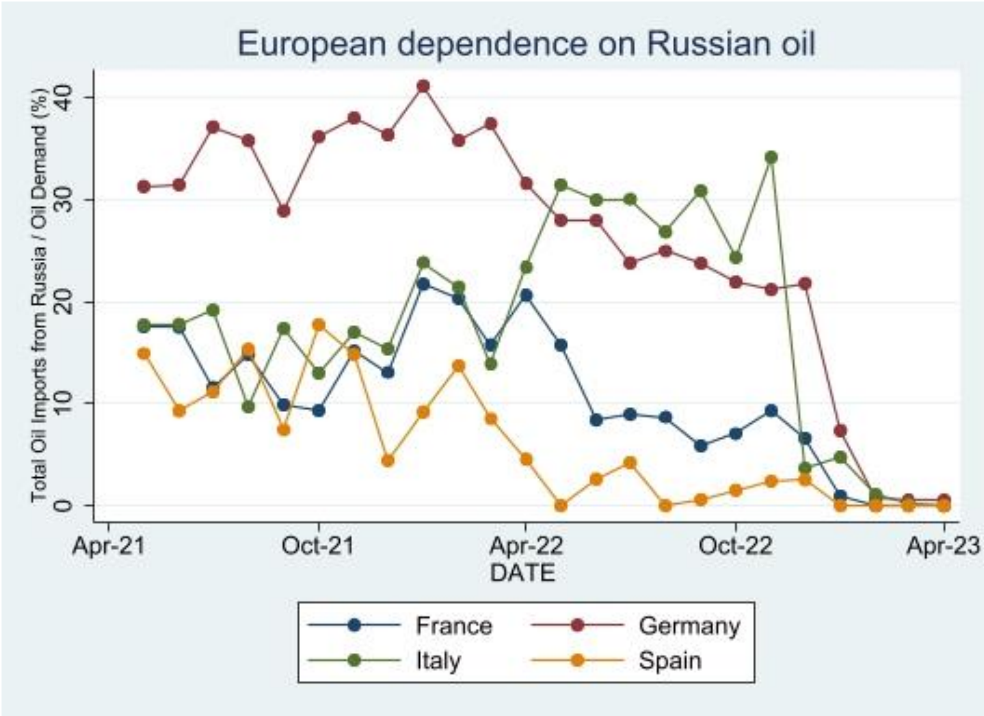

Figure 1. The European dependence on Russian oil. Source: IEA (2023) Monthly Reliance on Russian Oil for OECD Countries

Figure 1 shows how France, Germany, Italy, and Spain are dependent on Russian imports to satisfy their domestic oil demand. Germany was the most dependent country in the sample before the war erupted.

Robert (2007) identified the root of the problem. The EU and Russia have a special relationship; they are unequal trading partners because there exist large economic asymmetries between the two. The Europeans are energy-poor but have a comparative advantage in technology and capital investments whereas Russia has a rich source of energy but low levels of capital investments. She also identifies the inefficient energy usage of the Russian economy, in particular the lack of capital to meet demand. Previous attempts to structure and deregulate the energy trade were made by the EU but Russia denied this. In retrospect, this was an early signal of Putin's intentions to exploit the asymmetries in trade for his political battles.

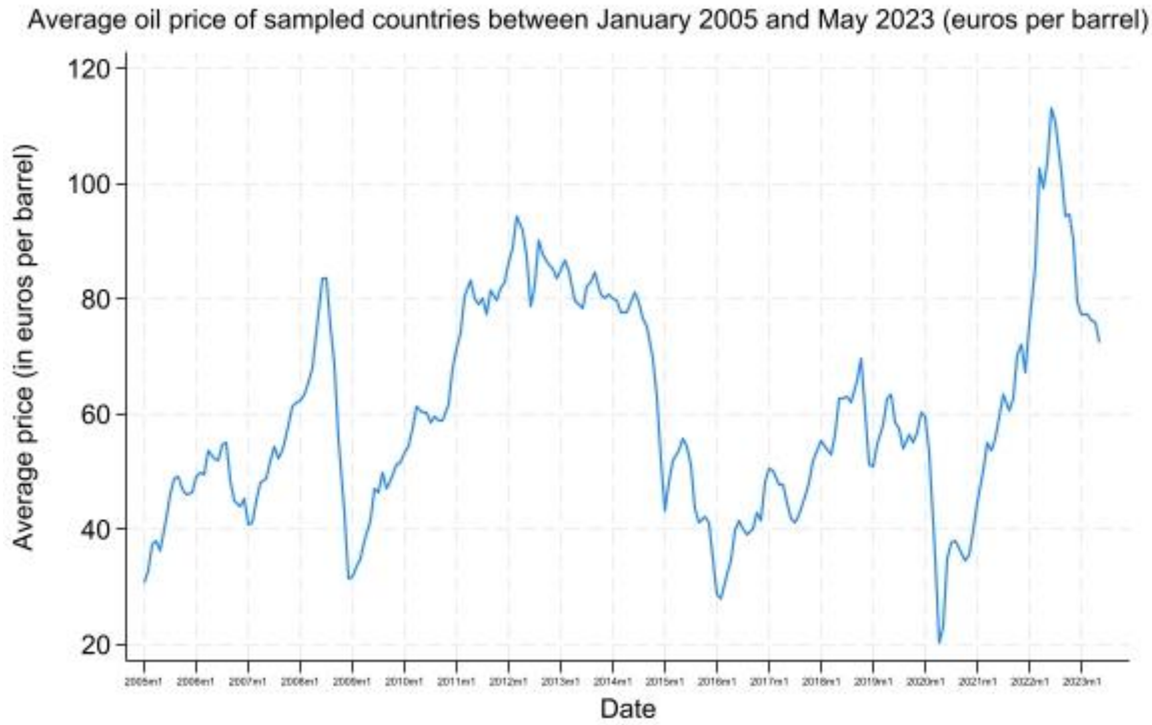

Figure 2. Evolution in the price of crude oil. Source: data collected from Eurostat's (2023) Crude oil imports by field of production – monthly data. Note: Price is converted into euros and then a new average data is generated using the price levels in all 4 countries.

While the beginning of the war has indeed led to a sharp escalation in prices, it had already begun before the invasion of Ukraine. Prices have since then decreased after a peak in July 2022. Nevertheless, the possibility of a future hike in the price is a source of concern for policymakers. Saudi Arabia and Russia have already announced cuts in the production and export of oil citing uncertainty in the demand for oil as a justification (McCormick, 2023) raising uncertainty in an already tense market.

3/ Literature review

a. Oil prices

In this subsection, I will explain how oil prices are determined, describe the different players involved in the supply chain and the evolution of their market power, and show the effects of an oil price increase in the macroeconomy.

i. Determinants of the oil prices

The supply and demand for oil determine the price of a commodity. The oil market is not immune to this reality and is therefore subject to both types of shocks. This is consistent with the high price volatility observed. Shifts in demand can be a consequence of income effects, changes in population growth, etc (Smith, 2009). It concerns households and firms. Supply shocks are mostly exogenous and can be caused by intentional production cuts by suppliers, changes in extraction technology, availability of oil, or other factors. The supply-side channel describes the positive relationship between the price of inputs and the production cost. An increase in the price of a commodity like oil will lead to an increase in production costs, and thus a decrease in capital utilisation and total output (Finn, 2000). It is important to note that positive technological shocks and improvements in the efficiency of oil can counteract the negative effects. It is possible to estimate the actual shifts in supply and demand by calculations of their respective elasticities. Those elasticities differ according to the location, time of measurement, and method of estimation. In general, the elasticity of demand is negative whereas the supply elasticity is positive but quite inelastic (Smith, 2009). These estimates are consistent with consumer response to an oil price shock and suppliers' behaviour. Smith observes that global demand since 1975 has increased at a much higher rate than supply.

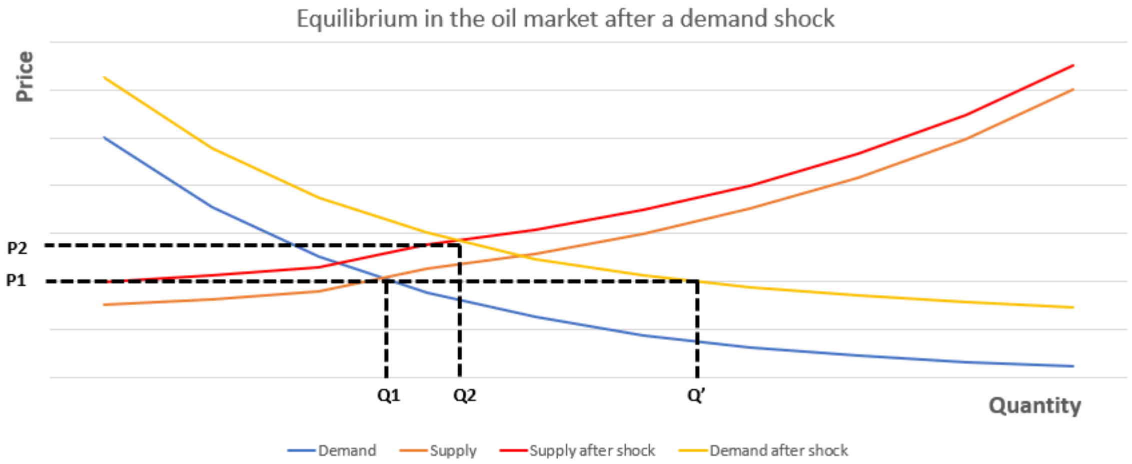

Figure 3. The impact of a positive demand shock on the oil market equilibrium. Source: Smith (2009).

The origin of the shock can lead to two different equilibria in the market. An oil price increase can be the result of a negative supply shock or a positive demand shock. In the case of a positive demand shock, the demand curve shifts to the right/top. With a demand shock, both the price and quantities increase. In the case of a negative supply shock, prices are raised but the quantity of oil supplied has declined.

Coady et al. (2015) establish three components for an efficient consumer price for energy products. Prices should capture the opportunity cost of supplying oil to the consumer, a Pigouvian tax to account for the negative externalities, and a consumption tax. The opportunity cost of supply reflects a cost to the country importing oil; the country has little influence over this cost because it is determined by international prices, and transport and distribution costs. The Pigouvian tax is ideally equal to the external cost generated by additional consumption. Since the external cost is hard to estimate, the value of this tax depends on the government's assessment of the environmental and health costs of consumption. The final consumers fully bear the cost of the last component, the consumption cost, which is tax collected to generate extra revenue for the government. The authors also evaluate the trend in energy subsidies. Subsidies lower consumer prices to a rate below the efficient level but since the supply (opportunity) cost is outside the government's influence, they are introduced at the expense of the Pigouvian tax or consumption tax. They estimate oil subsidies to be at $ 1.6 trillion in 2013, this is especially important for advanced economies given that they are more reliant on oil than emerging countries. Subsidies come at a great fiscal cost to the government; thus, they recommend removing post-tax energy subsidies which will also cut deaths from local air pollution by more than half. The paper nonetheless recognises that removing subsidies is difficult when prices are high as it will be faced with public opposition.

The energy intensity of production in Europe is on average lower than in Japan and the US (LeBlanc and Chinn, 2004). However, institutional arrangements and regulations in the European retail energy market lead to higher prices. The authors suggest that more powerful labour unions and a less competitive product market explain how inflation in Europe is more responsive to changes in oil prices.

The model set by Arezki et al. (2017) describes another aspect of the dynamic oil market. They assume that the short-run supply is dependent on the available extraction technology. The equilibrium between supply and demand is achieved, in which oil supply is mainly a function of the cumulative production of oil and the real price of oil. Their oil demand equation is a function of global GDP growth (demand for oil and the global GDP growth are procyclical), the short-run price elasticity of demand, and the long-run elasticity of demand which includes a ten-year lag. The analysis also elaborates on the effects of permanent and transitory disruption in oil supply. On the one hand, a transitory one-standard-deviation reduction in oil supply entails a decline in oil production and is followed by oil prices increasing by more than 10% as demand is slow to respond to higher prices. In this scenario, output will also experience a minor decline for about two years. A permanent one-standard-deviation adverse shock to oil supply would permanently lower oil production and global output while raising prices. The authors thereby confirm that the prolongation of the war will likely lead to irreversible changes in the global economy as the sanctions against Russia are unlikely to be dropped by the EU. On the other hand, they estimate that a one-standard-deviation shock to oil demand leads to a permanent increase in the demand levels. Supply will catch up to the demand shock with time as investment in new extraction technology increases, but prices will rise contemporaneously.

ii. Oil suppliers and their market power

The oil market structure went through a shift. It was initially dominated by large multinationals who produced 89% of the world's oil but a series of nationalisations in and outside OPEC countries led to a change in market players. It is now state-owned companies that account for the majority of exports and control a large number of reserves. Känzig (2021) shows that negative news about the oil supply from OPEC countries has a significant negative and immediate effect on the US economy. Oil supply news shocks lead to increases in oil prices, a decrease in production, and a strengthening of reserves. Barsky and Killian (2001) argue that a sustained oil price increase is only possible when there is an excess demand in the oil market. This is why OPEC was successful in raising oil prices in the 70s and not so much in later periods. Kohl (2002) examines the behaviour of OPEC during the late 1990s and early 2000s. He observes that the market power of the organisation does indeed allow them to manipulate prices to a certain extent. However, he states that the OPEC miscalculated certain aspects of their actions which served against their interest and the global interest. Furthermore, the author describes the limitations of the organisation, namely, their inability to predict shifts in oil demand (due to weak data), the access to only one instrument to manipulate prices, the exposure to a depreciation of currencies, and fuel taxes which influence demand. Another concern for the organisation is linked to the (speculative) oil futures market which can affect the volatility of prices and has (partly) forced a decline in oil prices. The influence of OPEC on those speculators is weak. According to Beidas-Strom and Pescatori (2014), speculation accounts for 3 to 22% of short-term volatility in the price of oil. Another study by Quint and Venditti (2020) shows that the increase in oil prices during a temporary coalition between the OPEC countries and Russia between 2017 and the beginning of 2020 is not owed to their effort to tighten the market. They estimate that this particular coalition only explained a 4 USD increase in price (for reference the oil price rose by 50 USD over their period of analysis). The paper once again mentions the inability of major exporters to follow a common strategy. An increase in oil production from new participants also diminishes the market power of existing countries or coalitions; Russia threatened the ability of OPEC to influence price (Dees et al., 2004), and the emergence of the US as a major producer and exporter seems to be changing the paradigm (Quint and Venditti, 2020). Barsky and Kilian (2004) explain that shifts in the expectations of oil supply induce a precautionary demand for the commodity. This idea was later expanded by Kilian and Lee (2013) who posited that shifts in the oil market expectations, such as the one that followed the Libyan crisis in 2011 and tensions in Iran in 2012, can lead to increases in prices through positive demand-side effects. Concerns about the supply of oil from the Middle East lead to speculative demand shifts, i.e. participants in the physical market store oil in anticipation of rising prices in the future, which in turn drive contributes to the surge in the demand for oil and its price. The result of this precautionary demand is high real prices which is unlikely to disappear without a decline in global growth.

At the firm level, Nerlinger and Utz (2022) assessed the performance of energy companies following the Ukraine war by looking at their stock returns. They found that energy firms became more profitable as they consistently outperformed the stock market. The authors also found that the location of a firm influences its return, noticing higher returns in American firms compared to European and Asian energy companies. Nonetheless, they conjecture that local European firms have still benefited from higher selling prices as they saw a surge in their profitability. This can have important policy implications.

iii. Oil prices and the macroeconomy

Early studies on the impact of oil showed a negative relationship between the price of the commodity and the real economy (Jiménez-Rodríguez and Sánchez, 2005). Similarly, several studies demonstrated a link between oil price hikes and the probability of entering a recession (Hamilton, 1983, Finn, 2000). However, this relationship broke down in the 1980s. Hamilton (1983) demonstrates that exogenous shocks to oil prices affect economic activity using a linear VAR model but not in the same context as before. He finds evidence of a structural break in this relationship between 1972-Q4 and 1973-Q1. Mork (1989) discovers an asymmetric impact on output; oil price increases have a significant negative impact whereas declines do not affect output levels as opposed to the previous paradigm under which increases, and price declines have a symmetric effect. Hooker (1996) and Hamilton (2003) come to a slightly different conclusion as they find that decreases in the price of oil are small and have a smaller effect than increases, but they remain present.

The propagation and magnitude of the shock depend on its origin. Cashin et al. (2012) explain that supply-driven increases in prices lead to a significant and lasting decrease in economic activity and higher inflationary pressure whereas demand-driven surges in price lead to a short-run increase in output. Regarding the Ukraine war, the disruption contains both characteristics of a change in the supply and a change in the demand. The price increase was initially driven by supply-side factors as sanctions on Russian oil lowered the availability of oil. However, Suzan and Bounfour (2023) estimate that oil consumption increased by 2% between February 2022 and February 2023. Supply chains in the European oil market went through an important restructuring. According to their study, other oil-exporting countries either increased their production and/or diverted part of their export towards the European market, thereby offsetting the negative effects of the Russian cuts. Section 2 mentioned how the Italian government increased oil imports from Russia in preparation for the sanctions.

An adverse shock to oil prices creates short-run effects on economic activity and are dissipated in the long-run (Cuñado and Pérez de Gracia, 2003). Blanchard and Gali (2007) introduce a New-Keynesian model to explain why the economic effect of the 2000s' shock in oil price did not have the same amplitude as the one in the 1970s. Following New-Keynesian traditions, the model assumes agents are forward-looking and use rational expectations to optimise consumption (found with an intertemporal equation for determining the optimal consumption using interest rates and CPI inflation). Nevertheless, the standard New-Keynesian model is modified by introducing oil as an input in both consumption and production and allowing for real wage rigidities. They rationalise the decreasing effects of an adverse oil price shock by providing three plausible explanations: firstly, the decrease in real wage rigidity affects the reaction to monetary policy. Policies to contain inflation in the 2000s are now also stabilising GDP because there is no trade-off between the two. This entails a positive correlation between GDP and CPI denoting to a demand-driven shock. In a historical context, this makes sense since the 1997 oil shock originated from the Asian Financial shock, shifting global oil demand whereas the 1973 shock was supply-driven. Secondly, they observed that monetary policy has become more responsive to oil price shocks and has taken more aggressive stances against inflation. This improved the credibility of monetary authorities which explains part of the decline in the volatility of macroeconomic variables. Thirdly, they suggest that oil represents a smaller share in consumption and production, and this explains part of the decline in the volatility. The sum of these effects is consistent with the observed, decreasing volatility in macroeconomic aggregates. On the other hand, De Gregorio et al. (2007) believe that the reduction in the oil intensity of economies is the most important factor explaining the weakened pass-through between oil prices and inflation. This is followed by a reduction in the exchange rate pass-through, a more favourable inflation environment, and the fact that oil price increases at the time were mostly due to an increase in demand. Having considered all this, the current inflationary levels appear puzzling. This will be explored below.

The real wage has declined again in Europe since 2019. Fairless (2023) partially blames an ageing population and the decreasing labour supply for the loss in purchasing power while the pandemic and the war exacerbated the effects. A combination of high inflation and decreasing real wage can lead to an erosion in the trust towards monetary policy and a fall in the CCI as households can observe their dwindling purchasing power and reflect this on the economic performance of the current administrations (De Boef and Kellstedt, 2004). A ceteris paribus growth in inflation rates and oil prices causes a reduction in disposable and discretionary income. Because of those additional costs, households have an incentive to consume less and save more.

Chen (2009) follows the findings of Blanchard and Gali. He finds evidence for a gradual change in the pass-through between oil prices and inflation using a rolling regression on his panel data and discovers multiple window periods under which changes in the pass-through have occurred. This eliminates the possibility of a one-time break in the transmission of oil prices to inflation. Concerning current events, it is feasible that successive effects of the pandemic, the war, and other domestic events have gradually changed the pass-through. He lists five (potential) explanations for the decline in the pass-through and concludes that the role of the exchange rate (i.e. the appreciation of the domestic currency), a more efficient and active monetary policy, and an increase in trade are the most probable and causal explanations for this decline in pass-through.

Cuñado and Pérez de Gracia (2003) evaluate the effects of oil prices on inflation and the industrial production index (IPI) across several European countries. Their results verify the hypothesis of country-specific effect and find that using national oil prices measured in national currency yields a stronger impact which they credit to the role of exchange rates on macroeconomic aggregates. Their analysis also rejects the hypothesis of a cointegrating long-run relationship between oil prices and economic activity in all European economies and can only verify the existence of a cointegrating long-run relationship between oil prices and inflation in the UK and Ireland. A potential explanation is that countries have different fiscal responses to a crisis. This could be due to different preferences for macroprudential and microprudential policies. The effects of COVID-19 in Europe have been severe. Governments had to expand their fiscal expenditure to protect households and firms against COVID-19 and renew this commitment after the war. It was an abrupt shock to the economy and led to austerity and an increase in government deficit.

Choi et al. (2017) establish a relationship between the level of energy subsidy in a country and inflationary pressure. In other words, when the country has high levels of energy subsidies, the impact of an oil price shock on inflation is reduced because it distorts price signals from the shock and diverts the traditional passthrough into headline inflation. This observation contradicts the recommendation of Coady et al. (2015), or at least puts them into perspective.

Hunt et al. (2001) warn of the dangers of delayed policy. They advocate for a rapid policy intervention to a persistent price increase as delaying the response to such a shock can erode the credibility of monetary policy, to the point that under high uncertainties, an early aggressive policy is still preferred over a delayed response.

It is important to remind the reader that the effects described above concern the influence of an exogenous shock on net importers of oil. The impact of an oil shock on oil exporters can be very different but since the countries considered in this model are all oil importers themselves, I did not dwell on the literature on oil price shocks for exporting countries.

b. Inflation and interest rates

The higher credibility of monetary policy is cited as (one of) the main explanations for the reduction in the pass-through from an oil price shock to the macroeconomy. How did central banks achieve this? Central banks use monetary policy to achieve the objectives set by governments. The main mandate of the European Central Bank (ECB) is price stability, viz. maintaining an acceptable level of inflation. They use interest rates to control inflation to influence the amount of borrowing in the economy, which in turn, reduces output and ultimately reaches inflation. An inflation target of 2% was implicitly, and then explicitly set. The European monetary union comes at a cost for national governments who had to sacrifice the power to set their interest rate. Consequently, national governments resort to fiscal policies to complement the ECB's monetary policy but even then, they have to respect certain fiscal rules. These rules aim to improve budgetary discipline among Member States and while progress in this aspect is observed, countries with high government debt levels tend to struggle with their medium-term budgetary objectives (Leiner-Kellinger and Nerlich, 2019).

The most volatile component of inflation, measured by the HICP, is energy. The movement of the energy component generally follows the movement in oil prices. During COVID and up until the beginning of 2021, the energy component of HICP was at its lowest level since 2015 (Eurostat, 2023). It then increased rapidly directly after the war. Following this trend, the all-item HICP measure started rising too, but the response was not immediate. The energy component has declined since then and the ECB is now seeing encouraging signs in the movement of all-item HICP.

Pertaining to our analysis, Mishkin (2007) demonstrates that inflation persistence has declined over the years, and inflation has become less sensitive to exogenous shocks. He attributes these changes in inflation dynamics to a change in inflation expectations. Due to the sustained levels of high inflation rates and the tenth consecutive interest rate hike within the euro area, worries about a de-anchoring of inflation expectations have been raised. Adrian (2022) said that long-run inflation expectations are still relevant to central bankers because they provide a statement about their credibility and are useful in reviewing short-term inflation dynamics. Several measures of inflation expectations exist based on different dimensions (e.g. differences in the time horizon, differences in the target population, that is, households or firms). A short-run time horizon is used for actual inflation whereas long-run expectations reflect the credibility of monetary policy. Roberts (1998) examined the rationality level of inflation expectations. He uses survey measures of inflation expectations and finds that inflation expectations are neither perfectly rational nor very irrational. Meeks and Monti (2022) observe that heterogeneous beliefs are significant determinants of inflation, especially during disruptions. Moreover, expectations are one element in the computation of consumer confidence.

A study by Bătrâncea (2020) analysed the early effects of inflation and economic activity (estimated with GDP growth) on confidence indicators across 27 European countries during the COVID pandemic. She used a Panel Least Square regression to test the relationships and concluded that GDP growth did not impact consumer confidence while the higher rates of inflation changed the confidence indicator.

Borio and Filardo (2007) show that models of inflation are generally "country-specific" which tend to omit important global factors (arising from globalisation). Moreover, central banks adopted inflation-targeting in the 90s which coincides with the increase in globalisation. The interconnectedness is particularly high inside the EU and the countries included in this paper are amongst the biggest economies in the region and some share borders with each other. The globe-centric approach has important features, such as the impact of global excess demand on domestic inflation. As a consequence, the authors state that a country-centric approach provides an incomplete picture of the inflation process. An important distinction between the country-centric approach and the globe-centric approach is that factors that affect national macroeconomic aggregates are treated as exogenous under the country-centric approach whereas they are seen as endogenous in the globe-centric approach. The importance of global factors for the determination of domestic inflation implies that policymakers should pay attention to external developments, thus policies should anticipate changes in those factors rather than just react to them.

Sek et al. (2015) showed that the transmission mechanism of an oil price shock onto domestic inflation is relative to the country's oil dependency. When dependency is high, the impact of an oil price shock is indirect but for low dependency countries, the effects are direct. Spain and Italy are amongst the high dependency group in their analysis. France and Germany are not included in their sample but given Figure 1, it is fair to suppose that they would have also been highly dependent countries. For highly dependent countries, a shock in the price of oil has an indirect effect on domestic prices. Their theory suggests that the exchange rate and the exporter's production cost account for the main determinants of domestic inflation in the long-run. In other words, the exporter's production cost is a bigger determinant than the domestic output level.

Bodenstein et al. (2010) investigate how the zero lower bound (ZLB) has influenced the propagation of oil price shocks. Their model describes a two-country setting with nominal rigidities in price and wages. The oil market clears when the sum of domestic and foreign oil production equals the sum of consumption. With a supply shock, the effect on activity is cushioned in a liquidity trap because output and inflation move in opposite directions. As real interest rates and inflation rates move in opposite directions (keeping nominal interest rates constant), an increase in inflation stimulates certain sectors of the economy which reduces the magnitude of the contraction. Nevertheless, there are still gaps in our understanding of inflation dynamics. Coibion et al. (2020) describe a veil of inattention amongst households and firms who lost interest in central banks' communication strategies. This suggests that such unconventional monetary policy might no longer be efficient, posing a challenge to policymakers in the future.

c. Consumer confidence

The CCI is a useful measure to assess how households perceive the economy and collect information on savings and spending patterns for consumers in a given country, at a given point in time. Howrey (2001) demonstrates the ability of the Michigan sentiment index to evaluate the probability of entering a recession by looking at whether it can predict the future growth of real GDP. A more interesting relationship is perhaps based on the correlation between CCIs and spending. The idea that consumer sentiment indicators can explain changes in household spending has been empirically supported. The findings presented by Carroll et al. (1994) show that lagged consumer sentiment explains movements in household spending. To determine the cause of this explanatory power, they test several simple models which they reject, but propose an alternative solution, a model based on habit formation and precautionary savings which is consistent with their data. It was previously established that an oil price shock might manifest as a decline in purchasing power, which could result in precautionary savings.

If the relationship between the CCI and consumption patterns holds, policymakers are right to monitor movements in CCI since consumption is a major component of the GDP aggregate. The ratio of household expenditure to GDP inside the EU ranges from 23.3% (of GDP) to 71.5%. In France, Germany, Italy, and Spain, the values are close to 50% (Eurostat, 2023). This shifts aggregate demand to the right which increases aggregate supply and production. The movements in the CCI mirror the income effect. The CCI can also be viewed as a bottom-up approach to analyse the correlation between micro-level data and macro-level data. Several factors influence confidence indicators; (too much) inflation, unemployment, and even falling housing prices can negatively impact households' perceptions of the economy.

The study of CCIs is also pertinent to political economics. De Boef and Kellstedt (2004) describe CCI as a process of *internalising information and perception of the objective economy* and *transforming it into a subjective economic viewpoint*. This process is in turn used by the electorate to make political decisions. They maintain that the influence of politics on confidence indicators is often downplayed in the literature. Day-to-day politics affect CCI through the media. Fiscal policies are shown to impact confidence as through their effect on money circulation and consumption. They also discuss the existence of an equilibrium between consumer confidence and political performance, i.e. the equilibrium will shift downwards if the recent (perceived) performance of an administration or politician is weak. Given that individuals require (objective) information about the general economy to form their expectations and assessments, the media plays a crucial role in the formation of the CCI. There are two channels through which the media affects individual perceptions. The first one is the transmission of information to the public, the second is the interpretation of this information. Most news agency are inclined to make a political judgment on the information they relay which expose individuals to potential bias.

The literature on consumer confidence is a study of psychological factors that influence household perception and decision-making choices. Casey and Owen (2013) put into perspective the previous reports of negativity bias in CCI. This bias implies that households are more susceptible to bad news than good news. Although they observe the existence of this negative effect on households, they put the relative importance of this negativity bias into perspective and state that positive asymmetries are also common. An example used by the authors is the sudden and sharp increase in CCI in October 2001 following the shock of the September 11 attacks. Rising patriotism or relief after the initial shock is said to be responsible for this increase in confidence. This example verifies the existence of positive and negative externalities. They explain that the actual movement of CCI is relative to a reference point and expectations. Dées and Brinca (2011) also find evidence of asymmetries and note that the predictive power of CCI on consumption is particularly strong when the index faces large fluctuations.

Golinelli and Parigi (2004) find that consumer sentiment indices are not correlated to a fixed, single determinant. The indices are country-specific and time-specific. Spillovers are possible, especially in a highly integrated world economy. Dées and Brinca (2011) evaluated the link between consumer sentiments and consumption expenditure using a cross-country analysis involving the US and the euro area. They find evidence of a confidence channel in the international transmission of shocks running from the US to the euro area.

Nonetheless, it is necessary to address the potential flaws of the CCI. A recurrent critique of confidence statistics is related to their measurements. Early concerns about the measurement of consumer attitude indices (including the product of a study conducted by a Federal Reserve Committee) have been dismissed as very few changes were introduced in the way the main indices are aggregated. This is also relayed by Dominitz and Manski (2004). The authors explored three dimensions through which these measures can be improved. Firstly, remove questions about the business condition in household surveys as respondents do not have the expertise to accurately forecast future conditions. The surveys should instead focus on relevant matters to the average respondent. Secondly, they want to include more probabilistic questions that are proven to improve the information on consumer beliefs. Thirdly, institutions that calculate the indices should report their findings for separate questions and different subgroups of the population. Furthermore, theories about the movement of the CCI often involve a natural level (De Boef and Kellstedt, 2004) or 'reference point' (Casey and Owen, 2013). Under these hypotheses, what matters is the ordinal effect on CCI rather than the cardinal values themselves.

Al-Eyd et al. (2009) question the predictive role of CCI using data from 1973 to 2005 in five OECD countries, including three of the countries in our model. According to them, there is only a weak effect that confidence indicators influence consumption. The link between the two variables has declined over the years. Therefore, their policy recommendations show a preference for models using relationships between consumption, income, and wealth to forecast short-term movements in consumption. While Jonsson and Lindén (2009) present a generally positive opinion on the confidence indicator, they recognise the possibility of omitted variable bias which would compromise the predictive power of the CCIs on spending since OVB cannot never entirely be avoided.

Criticisms over the effectiveness of confidence indicators have been expressed elsewhere. The Economist (2023) recently published an article suggesting investors, policymakers and economists pay too much attention to consumers. The article points out that consumer spending has been relatively resilient despite having the lowest levels in the Michigan Consumer Sentiment Index. Consumers spend too much emphasis on inflation which is reflected in gloomy responses to the survey questions. This is perhaps an irrational response as they do not consider other factors such as the accumulation of savings in response to COVID. The paper highlights how such indicators have entertained a growing market for sentiment indices despite doubts about their trustworthiness. Going back to De Boef and Kellstedt (2004), the individual perception of the economy can lead to an irrational assessment of the objective country-wide economy. Considering that the average respondent does not understand the impact of budget deficit on monetary policy, the authors imply that CCIs might capture a naïve and/or false picture of the economic situation.

Jonsson and Lindén (2009) use the 11 questions included in the EU harmonised consumer questionnaire to construct 2047 confidence indicators and test their correlation with private consumption growth. The ideal questionnaire should resort to both micro and macro questions, but they still prefer micro questions for their superior predictive power of private consumption growth. A criticism of the CCI used by the European Commission is shared by the authors but they recognise the need for further investigations since the choice of the optimal indicator may vary with time. Thus, a frequent update of the questionnaire could help in obtaining more significant indices. Their paper runs a cross-country analysis of the European CCI and concludes that variations across countries are significant and can be resolved using the global indicators they constructed. This global indicator is the second-best choice and an alternative to a multitude of country-specific indicators. The indicator is built on three questions about: a) the general economic situation over the past 12 months, b) whether it is the right moment to make major purchases given the general economic situation, c) their prediction of future consumption expectations on major purchase compared to the past 12 months.

In sum, the literature on CCI, oil prices, and monetary policy hints at evolving relationships between the variables. Nonlinear specifications of oil prices are now required to evaluate the impact of an oil price shock on the economy. The same thing can be said about the variables that are related to monetary policy. The introduction of unconventional monetary policy (i.e. improvement in credibility levels or the ZLB) has generated changes in the channels and magnitude of pass-through.

4/ Empirical analysis

In this section, I will describe the data used and the transformations needed to run a SVAR analysis. The results from the Granger-causality tests, the impulse response functions, and the forecast error variance decomposition (FEVD) tables will be presented.

a. Data

For the purpose of this analysis, data has been collected from various sources. Data on the oil price import is obtained from the statistical office of the European Union, Eurostat. The data is a collection of monthly (total) crude oil imports between January 2005 and May 2023. This is the national value of oil prices so variations across the countries are present. The variations can be due to differences in transportation and distribution costs, differences in the VAT, and differences in the valuation of externalities. A monthly time frequency allows us to increase the number of observations in the analysis and lets us observe the impromptu effects of the war. It is measured in US dollars (USD) per barrel so a conversion into euros per barrel is done to assess the true cost to the households. This is particularly important given the sharp depreciation of the euro against the USD at the end of 2022. It means that the real price in Europe has increased so the effects on inflation should consequently be more pronounced (LeBlanc and Chinn, 2004; Cuñado and Pérez de Gracia, 2003). The change in the relationship between oil prices and the macroeconomy (Hooker, 1996; Hamilton, 1996) demands a transformation of the data to obtain causality. I follow a method suggested by Hooker (2002) which resorts to the maximum of Mork's (1989) oil price change and zero. The coefficient on oil price decrease is assigned a value of 0 because of the asymmetric responses to oil price shocks, i.e. Mork finds a strong negative correlation between an oil price increase and the GNP growth but an oil price decrease has no correlation with the GNP growth. Thus, let us call this new variable, "POS_Oil_Price_m"[1]. It is computed by first calculating the changes in oil prices using the formula below:

[1] In the section where I report the Granger-causality results and the IRFs, I will refer to the variables by a simplified version of their real interpretation such as "oil price" instead of "changes in the oil price" for

$Change\ in\ Oil\ price = \frac{Oil\ price_t}{Oil\ price_{t-3}}$ -1

Then, POS_Oil_Price $\begin{cases} Change\ in\ Oil\ price\ if\ Change\ in\ Oil\ price\ > 0 \\ or\ else\ 0 \end{cases}$

In the original suggestion, the author used quarterly data. To obtain a variable closer to this, I divide the "Oil price at time t" by the "Oil price at time t-3".[2]

The data on consumer confidence comes from the OECD database. This is a monthly composite of several survey questions. It is transformed into an index; values below 100 indicate that households hold a pessimistic view of the future economic situation, and consequently, tend to save more; values above 100 indicate an optimistic perception of future economic performance, which makes them more inclined to spend. As mentioned in Section 3, doubts about the usefulness of CCIs have been raised. In this paper, I assume that the CCI is correlated with consumption. For this data, the OECD follows the definition given by the EC Joint Harmonized EU Programme of Business and Consumer Surveys to compute an arithmetic average net balance of four questions:

1. Financial situation over the past 12 months
2. Expected financial situation for the next 12 months
3. Expected generic economic situation for the next 12 months
4. Expected major purchases for the next 12 months

The respondents can choose between five answers with a larger weight assigned to the extreme responses:

1. A lot better; to which the OECD assigns a weight of 1
2. A little better; to which the OECD assigns a weight of 0.5
3. The same; to which the OECD assigns a weight of 0.5
4. A little worse; to which the OECD assigns a weight of 0.5
5. A lot worse; to which the OECD assigns a weight of 1

The CCI is then calculated with the following formula:

$$CCI_t = \frac{1}{4}\sum_{i=1}^{4} X_{i,t}$$

where $X_{i,t}$ is the net balance of the four questions and the indicator is normalised by subtracting from CCI_t its mean, then divided by its standard deviation, and then rescaled by adding a value of 100.

---

simplicity. Similarly, "log_CCI" shall be referred to as "CCI", "log_ind_prod" is "industrial production", "FDlog_HICP" will be "HICP", and "FDlog_Int_rate" will be "interest rate".

[2] This choice also avoids issues with the stability tests I ran using Oil price at time t-1.

The data then needs to be log-transformed. A closer look at the questions reveals that the survey questionnaire contains both forward-looking and backward-looking components. The first question asks the respondent to evaluate past situations whereas the other three are trying to gauge his or her predictions for the year to come. An important distinction is made by looking at the target population of the questions, namely, Question 1, Question 2, and Question 4 are more individual-specific whereas Question 3 is about the broader economic situation which does not necessarily coincide. Question 4 evaluates the respondents' propensity to spend as the buffer stock model tells us that savings rates increase during recessions and periods of uncertainty (Mody et al. 2012). If respondents see no significant purchases in the future, it suggests that they intend to accumulate a safe level of wealth that can be used in a recession.

Since there is no monthly data on GDP, I looked at other proxy variables for economic activity. Industrial production seemed like an interesting alternative. Fueki et al. (2018) used a similar data set to run a SVAR model. Other variables might have been considered, like retail sales or even satellite night data. Furthermore, as mentioned in the literature, oil is an input in the production function of firms (Blanchard and Gali, 2007). A rise in the price transmits into higher production costs which can theoretically lead to a contraction of output if the shock is supply-driven.

The Harmonized Index of Consumer Prices (HICP) of all items is used as a measure of inflation obtained from Eurostat. The HICP eases the cross-country comparison since it is constructed with a harmonized approach and a commonly accepted definition. The indicator describes the "change over time of the prices of consumer goods and services acquired by households". To obtain results, it is necessary to take the log of this variable, and then take its first derivative. This transformation means that the new variable, "FDlog_HICP" now reflects the percentage change in the HICP.

Finally, the interest rate is obtained from Eurostat. I have chosen long-term government bond yields as a measure of interest rate because it allows for diverging rates within the sample[3]. This indicator follows the Maastricht criterion. It calculates the return to an investor from the bond. This measure of interest rate can also create implications about the risk in a market as interest rates tend to be high when uncertainty is also high, thus, there is an additional benefit to using long-term government bond yield; they are (imperfect) proxies of inflation expectations since they relate to future uncertainties (Adrian, 2022). Given the existence of certain negative values in France and Germany's long-term government bond yields, I eliminate negative observations from the sample by finding the minimum value in the sample and adding that number to each observation in the variable, and then normalised to 1. This allows me to get a new variable for interest rate that I can log-transform.

[3] Moreover, using the 3-month interest rate has failed the stability test required to perform the SVAR for the Italian model.

New interest rate= interest rate – "min" +1

This process is repeated for each country in the analysis to allow for a more accurate comparison.

b. Methodology

i. Description and theoretical considerations

A structural autoregression (SVAR) is a type of time series model used to analyse the dynamic effects of selected economic variables. It provides the advantage of observing contemporaneous effects in the model.

The theoretical representation of a SVAR of order P resembles the following equation:

$$\beta_0 y_t = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \epsilon_t$$

where:

- y_t represents the endogenous variable.
- β_0 represents a vector describing contemporaneous effects.
- α represents the intercept vector in the model.
- y_{t-i} represents the autoregressive coefficients.
- β_i represents the matrix of autoregressive coefficients.
- ϵ_t represents the structural error term (with a mean of 0).

The structural error term can be decomposed in terms of a combination of error term such as $e_t = \beta_0^{-1}\epsilon_t$. Further restrictions are imposed by the following Cholesky decomposition (reflected by the zeroes in the matrix below):

$$e_t \equiv \begin{pmatrix} e_t^{Ind\ prod} \\ e_t^{Oil\ price} \\ e_t^{HICP} \\ e_t^{interest\ rate} \\ e_t^{CCI} \end{pmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{bmatrix} \begin{pmatrix} \epsilon_t \\ \epsilon_t \\ \epsilon_t \\ \epsilon_t \\ \epsilon_t \end{pmatrix}$$

According to this specification, industrial production (as the proxy for GDP) is considered a contemporaneously exogenous variable since oil price, HICP, interest rate, and the CCI only influence output in the future. This restriction is derived from the work of Jiménez-Rodríguez and Sánchez (2005). Oil price is contemporaneously affected by industrial production alone. Our measure for inflation, the HICP, is assumed to be contemporaneously affected by industrial production and oil prices. I assume that the interest rate is contemporaneously affected by the industrial production variable, the oil price variable, and the HICP. Finally, the CCI is contemporaneously affected by every variable.

This concludes the section on the identification strategy of this analysis.

ii. Preliminary tests

I will now describe the aim and results of several preliminary tests. The corresponding tables can be found in Appendices A, B, C, and D. [4]

I run several Augmented Dickey-Fuller tests to detect the presence of a unit root, i.e. whether a time series variable is non-stationary. In a SVAR, all series must be stationary, viz. certain attributes of the variable do not change over time. A p-value for Z(t) below 0.05 ensures that the series is stationary. This is the case for our 5 variables in all four countries.

The choice of lags is determined by conducting different tests, namely the Likelihood Ratio (LR) test, the Final Prediction Error (FPE) test, the Akaike Information Criterion test, the Hannan-Quinn (HQIC) test, and the Schwartz (SBIC) test. The tests have different preferences for the optimal number of lags in all of the countries, so I follow the LR criterion which seems to be the preferred choice in the literature when the tests do not agree with each other (Kumar, 2005; Jiménez-Rodríguez and Sánchez, 2005).

In addition, I ran an eigenvalue stability condition which is a prerequisite for a proper interpretation of VAR and SVAR models. All the values have a modulus of less than 1 and are inside the unit circle so the SVAR satisfies the stability condition.

Finally, I tested for autocorrelation in the residuals of the SVAR with a Lagrange multiplier (LM) test in each country. The results indicate no autocorrelation at the selected lag order (12).

iii. Findings

Having performed the preliminary tests, it is now possible to analyse the causality and movements of the CCI and other macroeconomic aggregates following a shock in oil price. I ran Granger causality Weld tests to determine if variables in the system can predict each other. The results are presented below.

A. __France__

Equation	Excluded	chi2	df	Prob>Chi2
POS_Oil_ Price_m	log_ind_pr od	8.898	12	0.712

[4] For convenience to the readers, I have organised appendices by country.

POS_Oil_Price_m	FDlog_HICP	46.363	12	0.000
POS_Oil_Price_m	FDlog_int_rate	30.481	12	0.002
POS_Oil_Price_m	log_CCI	56.895	12	0.000
POS_Oil_Price_m	ALL	163.100	48	0.000
log_ind_prod	POS_Oil_Price_m	7.214	12	0.843
log_ind_prod	FDlog_HICP	16.075	12	0.188
log_ind_prod	FDlog_int_rate	21.513	12	0.043
log_ind_prod	log_CCI	10.029	12	0.613
log_ind_prod	ALL	56.530	48	0.186
FDlog_HICP	POS_Oil_Price_m	23.436	12	0.024
FDlog_HICP	log_ind_prod	12.570	12	0.401
FDlog_HICP	FDlog_int_rate	48.074	12	0.000
FDlog_HICP	log_CCI	8.962	12	0.706
FDlog_HICP	ALL	120.080	48	0.000
FDlog_int_rate	POS_Oil_Price_m	27.285	12	0.007
FDlog_int_rate	log_ind_prod	30.878	12	0.002
FDlog_int	FDlog_HI	31.677	12	0.002

_rate	CP			
FDlog_int_rate	log_CCI	39.040	12	0.000
FDlog_int_rate	ALL	149.310	48	0.000
log_CCI	POS_Oil_Price_m	23.912	12	0.021
log_CCI	log_ind_prod	10.788	12	0.547
log_CCI	FDlog_HICP	12.370	12	0.416
log_CCI	FDlog_int_rate	20.362	12	0.061
log_CCI	ALL	68.313	48	0.029

Table 1. Granger-causality results for France. Note: Granger-causality is inferred at the 5% significance level when the p-value < 0.05.

The interpretation of the Granger-causality table is as follows. If the p-value is smaller than 0.05, variable X Granger-causes variable Y at the 5% significance level. Positive results are highlighted. In the French SVAR model, the log of the CCI is Granger-caused by the variable for the change in oil price. This means that an oil price shock helps in the prediction of future movements of consumer confidence. The null hypothesis is rejected for all other variables which means that no variable in our specification can predict changes in CCI. On the other hand, the model finds other interesting evidence: every variable in our specification model Granger-cause the interest rates, so they also explain percentage changes in interest rates. Long-term government bond yields are sometimes used as proxies for inflation expectations, therefore, our results signal that policymakers should be more worried about the long-term impact of the war. Only the oil price variable and the interest seem to Granger-cause the percentage change in HICP, this is reassuring news as it seems like raising the interest rate remains an effective way of containing inflation. Industrial production in France seems to respond only to percentage changes in the interest rate, this verifies the relationship between monetary policy and output, and if we suppose that industrial production can be used as a proxy for economic activity, there is a causation between both interest rate and economic activity. Finally, percentage changes in the interest rate, percentage change in the HICP, and the log of CCI Granger-cause changes in the oil price.

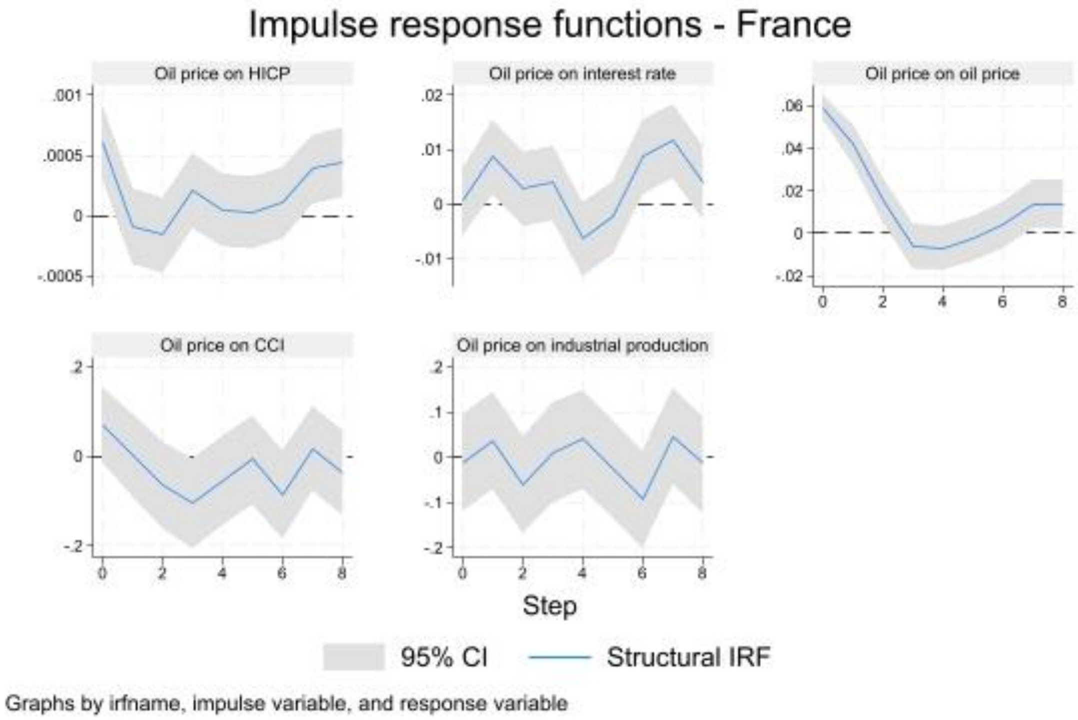

Figure 4: Graphs of the impulse response function to a shock in the oil price variable in France.

The impulse response functions map the evolution of each variable to a shock in the oil price. In this paper, I compute the IRFs with 8 forecast periods. The top left graph plots the response of the HICP to a shock in oil price, the graph on its right plots the response of interest rate, and the top right graph shows the persistence of an exogenous oil price shock. The bottom left graph depicts the response of CCI to an exogenous shock, and the bottom right graph shows the response of our variable for economic activity. Figure 4 shows the impulse response graphs in France. A one standard deviation shock to oil causes a decrease in CCI in the overall 8 periods. The grey bands however indicate the confidence interval which seems to be high for the CCI. The movement of industrial production is hard to characterize but given that it is the only variable not Granger-caused by oil price in France and the confidence interval is also high. Finally, the shock is not very persistent the effects reach near zero levels within 3 months.

Step	(1) sfevd	(2) sfevd	(3) sfevd	(4) sfevd	(5) sfevd
0	0	0	0	0	0
1	1	.000196	.073033	.000158	.013573
2	.9643	.002422	.071548	.02997	.011148
3	.893854	.008003	.073934	.032143	.017209
4	.881673	.007582	.080091	.036158	.034839
5	.858178	.009391	.080196	.050565	.037927
6	.805168	.010184	.078554	.051552	.037097
7	.744537	.020785	.078278	.070684	.047278
8	.660331	.022264	.099543	.106292	.046864

(1) irfname = order1, impulse = POS_Oil_Price_m, and response = POS_Oil_Price_m.
(2) irfname = order1, impulse = POS_Oil_Price_m, and response = log_ind_prod.
(3) irfname = order1, impulse = POS_Oil_Price_m, and response = FDlog_HICP.
(4) irfname = order1, impulse = POS_Oil_Price_m, and response = FDlog_int_rate.
(5) irfname = order1, impulse = POS_Oil_Price_m, and response = log_CCI.

Table 2. Structural Forecasting Error Variance Decomposition in France. Note: Each column describes the response of a different variable to a shock in the oil price variable.

The FEVD examines how much of the variability in X is explained by a shock on Y. In other words, Column (1) describes the changes in oil prices due to a shock in oil prices. Column (2) describes the changes in industrial production arising from a shock in oil prices. Column (3) shows the change in HICP, Column (4) represents the interest rate, and finally, Column (5) is for the CCI. After 8 months, 4.69% of the variation in the CCI can be explained by the oil price shock and 10.63% of the variation in interest rate. The oil price shock explains about 9.95% of the variation in HICP but only 2.23% of the changes in economic activity (assuming that industrial production is a sufficient proxy for GDP).

B. Germany

Equation	Excluded	chi2	df	Prob>Chi2
POS_Oil_Price_m	log_ind_prod	16.795	12	0.157
POS_Oil_Price_m	FDlog_HICP	20.777	12	0.054
POS_Oil_Price_m	FDlog_Int_rate	30.591	12	0.002
POS_Oil_Price_m	log_CCI	12.046	12	0.442
POS_Oil_Price_m	ALL	98.621	48	0.000

log_ind_prod	POS_Oil_Price_m	13.393	12	0.341
log_ind_prod	FDlog_HICP	24.837	12	0.016
log_ind_prod	FDlog_Int_rate	15.111	12	0.235
log_ind_prod	log_CCI	16.155	12	0.184
log_ind_prod	ALL	59.286	48	0.127
FDlog_HICP	POS_Oil_Price_m	33.750	12	0.001
FDlog_HICP	log_ind_prod	8.737	12	0.725
FDlog_HICP	FDlog_Int_rate	27.051	12	0.008
FDlog_HICP	log_CCI	25.568	12	0.012
FDlog_HICP	ALL	115.890	48	0.000
FDlog_Int_rate	POS_Oil_Price_m	23.512	12	0.024
FDlog_Int_rate	log_ind_prod	15.494	12	0.216
FDlog_Int_rate	FDlog_HICP	22.795	12	0.030
FDlog_Int_rate	log_CCI	18.274	12	0.108
FDlog_Int_rate	ALL	92.332	48	0.000
log_CCI	POS_Oil_Price_m	48.313	12	0.000
log_CCI	log_ind_pr	17.429	12	0.134

	od			
log_CCI	FDlog_HICP	21.593	12	0.042
log_CCI	FDlog_Int_rate	27.621	12	0.006
log_CCI	ALL	114.140	48	0.000

Table 3: Granger-causality results for Germany. Note: Granger-causality is inferred at the 5% significance level when the p-value < 0.05.

In Germany, there is evidence of Granger-causality from a change in oil price, the HICP, and the interest rate to the CCI. In other words, an oil price shock can help predict changes in consumer confidence. The percentage change in interest rate is Granger-caused by the percentage change in HICP and our variable for oil price changes, which implies that household expectations may be sensitive to changes in HICP and oil prices. Apart from the industrial production variable, all other variables Granger-cause HICP. Finally, the percentage change in HICP Granger-cause the log of industrial production and oil price is sensitive to the interest rate variable. However, like in the case of France, oil prices do not help in the forecast of industrial production. A potential explanation for this is rooted in Bodenstein et al. (2010) observation about the ability of the ZLB to mitigate a fall in output.

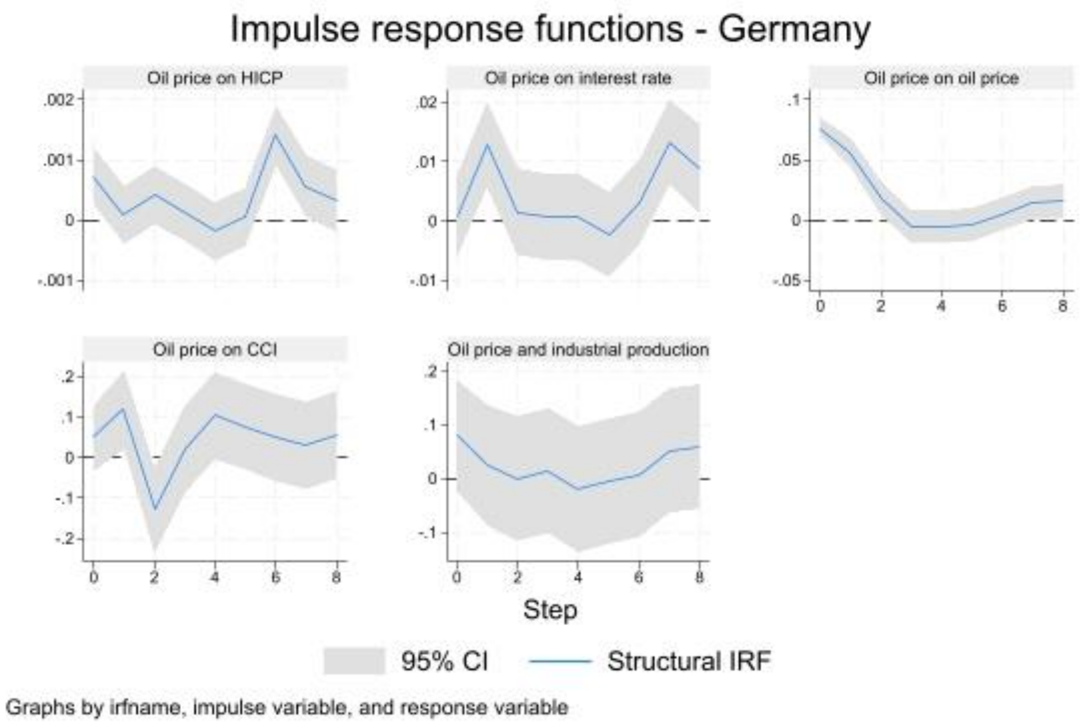

Figure 5: Graphs of the impulse response function to a shock in the oil price variable in Germany.

A one-standard-deviation shock in the oil price variable induces an initial increase in consumer confidence followed by a steep decline in the second period. However, the CCI is quick to recover and return to normal levels. Thus, the effect of an exogenous shock in oil price only produces short-term changes in the CCI and is different from the one observed in France. The oil price shock is not persistent as there seems to be no effect after 3 months. The response of the HICP manifests itself in the 6th period which also coincides with a (second) peak in the interest rate variable. The high confidence interval for industrial production points to an unstable response.

Step	(1) sfevd	(2) sfevd	(3) sfevd	(4) sfevd	(5) sfevd
0	0	0	0	0	0
1	1	.011089	.044059	.000259	.006783
2	.947839	.010299	.043729	.058185	.032475
3	.90381	.009324	.055873	.057839	.054767
4	.886403	.009356	.055952	.057195	.052115
5	.86823	.009613	.056494	.056086	.065777
6	.85501	.009193	.055471	.056236	.072397
7	.839529	.009068	.17049	.058239	.072106
8	.8102	.012148	.183076	.106235	.071629

(1) irfname = order2, impulse = POS_Oil_Price_m, and response = POS_Oil_Price_m.
(2) irfname = order2, impulse = POS_Oil_Price_m, and response = log_ind_prod.
(3) irfname = order2, impulse = POS_Oil_Price_m, and response = FDlog_HICP.
(4) irfname = order2, impulse = POS_Oil_Price_m, and response = FDlog_Int_rate.
(5) irfname = order2, impulse = POS_Oil_Price_m, and response = log_CCI.

Table 4. Structural Forecasting Error Variance Decomposition in Germany. Note: Each column describes the response of a different variable to a shock in the oil price variable.

The FEVD reveals that the oil price shock explains 7.16% of the variations in CCI after 8 months. It represents 10.62% of the variations in the interest rate, 18.31% of the variations in HICP, and 1.21% of the variations in the economic activity.

C. ***Italy***

Equation	Excluded	chi2	df	Prob>Chi2
POS_Oil_ Price_m	log_ind_pr od	7.072	12	0.853
POS_Oil_ Price_m	FDlog_HI CP	30.285	12	0.003
POS_Oil_ Price_m	FDlog_Int _rate	29.090	12	0.004
POS_Oil_ Price_m	log_CCI	21.046	12	0.050
POS_Oil_	ALL	88.155	48	0.000

Price_m				
log_ind_prod	POS_Oil_Price_m	29.347	12	0.003
log_ind_prod	FDlog_HICP	25.758	12	0.012
log_ind_prod	FDlog_Int_rate	22.690	12	0.030
log_ind_prod	log_CCI	8.857	12	0.715
log_ind_prod	ALL	83.386	48	0.001
FDlog_HICP	POS_Oil_Price_m	58.060	12	0.000
FDlog_HICP	log_ind_prod	8.626	12	0.735
FDlog_HICP	FDlog_Int_rate	41.860	12	0.000
FDlog_HICP	log_CCI	20.279	12	0.062
FDlog_HICP	ALL	123.280	48	0.000
FDlog_Int_rate	POS_Oil_Price_m	19.511	12	0.077
FDlog_Int_rate	log_ind_prod	5.830	12	0.924
FDlog_Int_rate	FDlog_HICP	20.841	12	0.053
FDlog_Int_rate	log_CCI	21.329	12	0.046
FDlog_Int_rate	ALL	71.636	48	0.015

log_CCI	POS_Oil_Price_m	25.165	12	0.014
log_CCI	log_ind_prod	7.343	12	0.834
log_CCI	FDlog_HICP	12.401	12	0.414
log_CCI	FDlog_Int_rate	12.446	12	0.411
log_CCI	ALL	75.790	48	0.006

Table 5: Granger-causality results for Italy. Note: Granger-causality is inferred at the 5% significance level when the p-value < 0.05.

Exogenous shocks in oil prices seem to have a direct effect on consumer confidence as oil price changes Granger-causes consumer confidence. No other variable seems to affect consumer confidence in Italy, on the other hand, consumer confidence seems to influence long-term government bond yield. The HICP is responsive to changes in oil price and the interest rate, whereas most variables in this model (except for consumer confidence) affect the Italian economic activity (proxied by industrial production). Industrial production is Granger-caused by oil prices. Finally, changes in oil prices are Granger-caused by percentage change in the HICP and the interest rate.

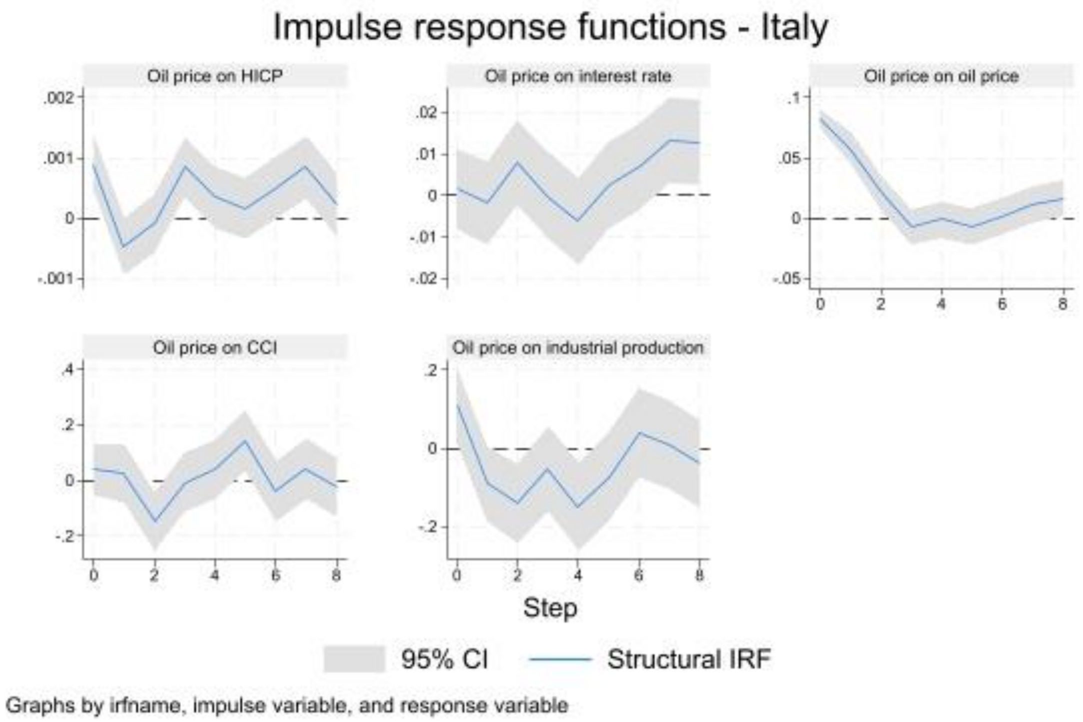

Figure 6: Graphs of the impulse response function to a shock in the oil price variable in Italy.

A one-standard-deviation shock to oil prices is associated with a positive shock in the interest rate. The effect of the shock on the CCI leads to an initial decline, then there is a peak reached around the fifth month and a smaller decline afterward. The effects of an oil price shock are not very persistent, reaching once again near zero levels within 3 months. As for industrial production, the shock is associated with an overall decline at the end of the forecasting period. This is in line with the predicted effects of a supply shock, but given the limited amount of forecast, we do not know whether the drop is persistent or not.

Step	(1) sfevd	(2) sfevd	(3) sfevd	(4) sfevd	(5) sfevd
0	0	0	0	0	0
1	1	.024842	.07421	.000454	.003124
2	.953856	.040795	.086948	.001021	.003604
3	.944563	.070328	.084599	.011738	.039519
4	.936121	.066273	.132911	.011599	.038884
5	.887643	.093686	.131479	.017576	.040309
6	.866793	.098033	.130591	.018285	.069023
7	.83068	.096975	.137896	.025167	.07039
8	.802401	.096546	.17403	.050903	.070607

(1) irfname = order3, impulse = POS_Oil_Price_m, and response = POS_Oil_Price_m.
(2) irfname = order3, impulse = POS_Oil_Price_m, and response = log_ind_prod.
(3) irfname = order3, impulse = POS_Oil_Price_m, and response = FDlog_HICP.
(4) irfname = order3, impulse = POS_Oil_Price_m, and response = FDlog_Int_rate.
(5) irfname = order3, impulse = POS_Oil_Price_m, and response = log_CCI.

Table 6. Structural Forecasting Error Variance Decomposition in Italy. Note: Each column describes the response of a different variable to a shock in the oil price variable.

The FEVD table in Italy suggests that the shock in the oil price explains 7.06% of the changes in the CCI after 8 months, 5.09% of the changes in interest rates, 17.40% of the changes in HICP, and 9.65% of the changes in economic activity. The oil price explains a significant share of the change in HICP like it did in Germany.

D. Spain

Equation	Excluded	chi2	df	Prob>Chi2
POS_Oil_Price_m	log_ind_prod	15.559	12	0.212
POS_Oil_Price_m	FDlog_HICP	37.109	12	0.000
POS_Oil_Price_m	FDlog_Int_rate	27.098	12	0.007

POS_Oil_Price_m	log_CCI	14.904	12	0.247
POS_Oil_Price_m	ALL	107.400	48	0.000
log_ind_prod	POS_Oil_Price_m	45.410	12	0.000
log_ind_prod	FDlog_HICP	32.058	12	0.001
log_ind_prod	FDlog_Int_rate	25.411	12	0.013
log_ind_prod	log_CCI	3.176	12	0.994
log_ind_prod	ALL	116.120	48	0.000
FDlog_HICP	POS_Oil_Price_m	20.414	12	0.060
FDlog_HICP	log_ind_prod	14.809	12	0.252
FDlog_HICP	FDlog_Int_rate	24.907	12	0.015
FDlog_HICP	log_CCI	13.381	12	0.342
FDlog_HICP	ALL	96.927	48	0.000
FDlog_Int_rate	POS_Oil_Price_m	17.233	12	0.141
FDlog_Int_rate	log_ind_prod	10.901	12	0.537
FDlog_Int_rate	FDlog_HICP	36.267	12	0.000
FDlog_Int_rate	log_CCI	16.799	12	0.157
FDlog_Int	ALL	117.330	48	0.000

	_rate			
log_CCI	POS_Oil_Price_m	19.749	12	0.072
log_CCI	log_ind_prod	16.090	12	0.187
log_CCI	FDlog_HICP	3.172	12	0.994
log_CCI	FDlog_Int_rate	11.061	12	0.524
log_CCI	ALL	49.472	48	0.414

Table 7: Granger-causality results for Spain. Note: Granger-causality is inferred at the 5% significance level when the p-value < 0.05.

In Spain, no variable Granger-causes the CCI. The variables for the percentage change in the interest rate and the percentage change in HICP Granger-cause each other. No other variable is Granger-causing these two macroeconomic indicators. Industrial production on the other hand is Granger-caused by oil price changes, percentage changes in the interest rates, and the HICP. Similar to our results in the Italian SVAR, this is in line with Cuñado and Pérez de Gracia (2003). A possible explanation for why a change in oil price Granger-caused industrial production in Spain when it did not in France and Germany (which are arguably considered to be bigger industrial powerhouse relative to Spain) is that oil refineries in Spain are more important there and makes peninsula a net-exporter of oil products.

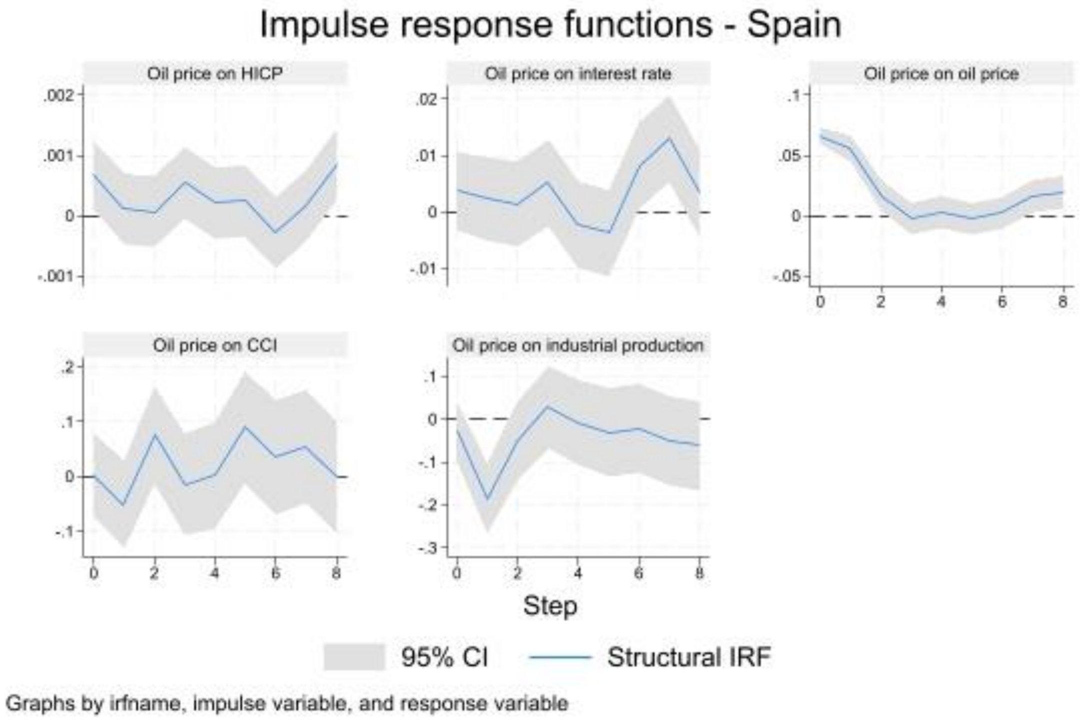

Figure 7: Graphs of the impulse response function to a shock in the oil price variable in Spain.

The shock is associated with an immediate negative change to industrial production, but it gradually recovers after it reaches its minimum in period 1. This response is a bit more consistent with the perceived behaviour of economic activity following an oil-supply shock (Cashin et al., 2012)[5]. The responses of other variables are difficult to characterize. The HICP hits its lowest level in the 6th period but seems to be increasing fast towards the end. The response of CCI is irregular and subject to a large confidence interval. The graphs are consistent with the Granger-causality findings. The most noticeable response is the effect on industrial production.

[5] Although the recovery of industrial production is still too fast and too high. The IRFs plotted by Cashin et al. (2012) show a very small and gradual increase in the GDP indicator after the 4th period.

Step	(1) sfevd	(2) sfevd	(3) sfevd	(4) sfevd	(5) sfevd
0	0	0	0	0	0
1	1	.00325	.025985	.005278	8.6e-06
2	.963386	.094156	.025425	.006412	.007443
3	.908694	.083852	.024948	.006797	.019391
4	.867334	.079024	.039416	.014777	.018238
5	.813869	.074312	.040434	.016153	.016776
6	.801457	.06829	.042731	.019884	.029892
7	.768351	.065996	.043675	.037156	.030033
8	.717975	.067335	.04404	.079527	.03426

(1) irfname = order4, impulse = POS_Oil_Price_m, and response = POS_Oil_Price_m.
(2) irfname = order4, impulse = POS_Oil_Price_m, and response = log_ind_prod.
(3) irfname = order4, impulse = POS_Oil_Price_m, and response = FDlog_HICP.
(4) irfname = order4, impulse = POS_Oil_Price_m, and response = FDlog_Int_rate.
(5) irfname = order4, impulse = POS_Oil_Price_m, and response = log_CCI.

Table 8. Structural Forecasting Error Variance Decomposition in Spain. Note: Each column describes the response of a different variable to a shock in the oil price variable.

Finally, the FEVD results for Spain show that 3.43% of the changes in the CCI can be explained by the oil price shock after 8 months. This becomes 7.95% for the interest rate and 4.40% for the inflation measure. The effects of the oil price shock on Spanish HICP are considerably lower relative to the other three countries. This points to asymmetries in the pass-through across the sample. Finally, the oil price shock explains 6.73% of the changes in the variable for economic activity.

We cannot make conclusive statements about the origin of this asymmetry since our data contains values that are also prior to this conflict. Factors driving confidence indicators are country-specific. The results presented here concur with the observation made in the literature review. While oil price shocks seem to be a relevant factor for the forecast of CCI in France, Germany, and Italy, this evidence suggests that oil prices are not relevant in forecasting consumer confidence in Spain. My analysis does not explain the reason for this divergence, and as seen in Section 3 there could be a variety of factors influencing the CCI. However, I was unable to identify the convergence in the factors affecting consumer confidence relayed by Golinelli and Parigi (2004). In this model, more variables are Granger-causing CCI in Germany than they are in France. A potential explanation for this can be the difference in Germany's reliance on oil (as shown in Figure 1). Germany was the biggest importer of Russian oil in our sample. Nevertheless, the results verify Bodenstein et al. (2010) observation about the impact of a supply shock on GDP in the presence of the ZLB; there is no Granger-causality running from changes in oil price to industrial production, the confidence intervals are sufficiently high to reject a meaningful relation, and the FEVDs estimate that a shock in oil price explains a very small percentage of the change in industrial production (2.23% in France and 1.21% in Germany).

While Granger-causality is a useful test for evaluating the potential effects of an oil price shock on the economy, it is not a test to demonstrate true causation. This test confirms whether X helps in the forecast of Y, demonstrating interesting, short-term predictive powers. Nevertheless, the results convey large disparities in the importance and effect of oil price shocks on the macroeconomy. Looking at the IRFs of "oil price on oil price" and the first columns of the FEVD tables, it is possible to draw a conclusion on the persistence of an oil price shock. The forecasts displayed in the IRFs show dissipating effects after only 3 months. The FEVDs confirm this. The fifth column of each table displays the effect of a shock in oil price on the CCI. In all four cases, the variability in CCI increases with the number of steps and usually peaks around the 7th or 8th step. This is true with most variables, except for oil prices where the variability decreased.

At first glance, the response of HICP to a shock in oil prices is inconsistent with most predictions made in the literature. Both supply- and demand-driven shocks to oil prices entail an *immediate* increase in inflation; this is not what we observe in the IRFs. However, the situation can be explained by Choi et al.'s (2017) observation about the mitigating effects of energy subsidies. The EU quickly responded to spiralling prices by increasing subsidies to the public. Nevertheless, the effects of subsidies are short-lived as HICP will eventually climb.

5/ Discussion and policy recommendations

a. Domestic oil markets and emergency responses

As members of the International Energy Agency (IEA) and the EU, each country in our sample must respect the safety requirement set by Article 2 of the International Energy Programme (IEP) and the 2009 Directive 2009/119/EC (under EU legislation). These legal foundations ensure that each member state maintains a minimum volume of oil stocks, equal to 90 days of net oil imports, that are to be released in case of a disruption in oil supplies.

As most oil imports in France are supplied by the sea, the distribution of storage capacity across the country is uneven. The regions of Normandy and Provence account for almost half of the national storage capacity which is no coincidence since the two biggest ports for petroleum products are in those regions. Nevertheless, the extensive pipeline network a priori compensates for this disparity in storage and even provides supplies to Switzerland. The CPSSP is in charge of holding French oil stocks, operated by market operators but with close governmental monitoring. The German storage agency is known as the National Petroleum Stockpiling Agency (EBV) which can delegate part of its responsibilities but is required to hold at least 90% of its stipulated duties. However, in the case of crude oil, stocks should be available for release within 150 days of the Federal Government's decision. In Italy, the refineries play a crucial role in the economy, they make the country a net exporter of oil production, but the refining industry has started to contract since the late 2000s. Furthermore, the government is expecting a reduction in oil demand in the medium- to long-term. The public agency in charge of stockholding duties (the Organismo Centrale di Stoccaggio Italiano, or OCSIT) was meant to maintain stockholding levels equal to 30 days of net imports (which represent a third of the obligation set by the IEP), but the process got postponed because of the tightening in the market and the subsequent release of stocks. The rest of the stockholding duty is reserved for private companies. Currently, there is no plan to increase oil storage capacity. Furthermore, the IEA recognises that the current process of stock release by the OCSIT (and, all most other stockholding agencies) is lengthy as the organisation does not own any storage capacity and does not plan to do so in the future. Furthermore, a provision allows obligated industry stocks to be held outside the country. Spanish consumption of crude oil between 2000 and 2020 has also decreased and is expected to fall due to environmental policies that aim to modify transport patterns. Oil security is very important to the Spanish government and is integrated into the National Security System. Similar to the French, the Spanish distribution of stocks is unevenly distributed but once again, the comprehensive network of pipelines is mostly capable of compensating for this. The pipelines are owned and operated by a private firm, the Compañía Logística de Hidrocarburos (CLH Group).

The majority of all crude oil imports in the four countries are used for transportation needs. Each country has a legislative and regulatory framework to, in theory, overcome an unpredictable oil supply disruption with the assistance of their respective agencies. The IEA monitors the activity of these agencies in place to protect the oil supply.

There are short-term measures used to reduce oil demand in a crisis. The IEA lists some of these measures in their “10-Point Plan to cut oil use” (IEA, 2022) and estimates that their suggestions can reduce oil demand by 2.7 million barrels a day in the next 4 months. The most effective measures according to their calculations involve reducing speed limits on highways by at least 10 km/h and allowing workers to work from home whenever it is feasible (these would respectively save around 430 kb/d and 500 kb/d). The effects of these actions seem plausible since they directly target transportation. In the medium- to long-term, they would also help advanced economies with their energy transition by reducing their reliance and demand on oil. However, those measures can have a pronounced effect on households with limited mobility capacity and living in rural areas who are often the poorest members of society. This further accentuates the regional disparities within a country and inside the EU. Concerning the possibility of remote working, a study exploited the remote working possibility during COVID to analyse the demography of workers in the US and found that higher-wage occupations tend to have a better chance of working from home (Maria del Rio-Chanona et al., 2020). Moreover, further research needs to be done on the impact of these measures on economic activity, specifically on how it will impact productivity and output in the economy. This would help governments assess the trade-offs.

The IEA report suggests that the burden on the poorest members of the population can be eased by temporarily reducing taxes on energy products. They do not specify which component of the consumer price should be reduced: the Pigouvian tax or the consumption tax. If the policy aims to alleviate the disposable income of households (and households alone), then they should reduce the consumption tax because it is borne by consumers. If the wish of the government is to also assist firms, then reducing the Pigouvian tax should be considered. However, governments are faced with a trade-off; assisting households leads to higher equity but it introduces the risk of higher externalities and reduces the fiscal budget (which is important for countries facing high levels of government debt). In sum, the report is a useful assessment of measures to stabilise the oil market, however, it does not provide any guidance on how to implement such measures and potential externalities to consider.

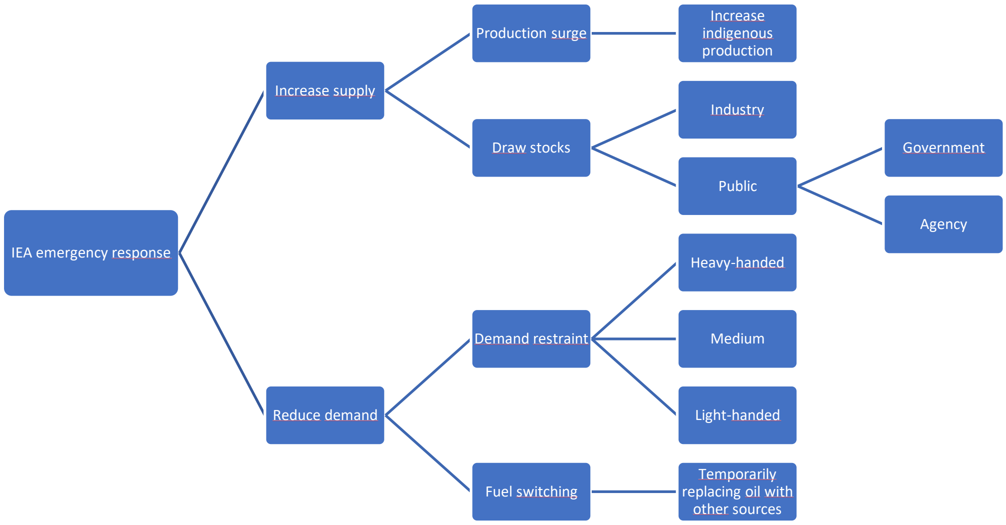

Figure 8: Emergency response system to a tightening of the oil market. Source: IEA (2022), "A 10-Point Plan to Cut Oil Use"

In France, demand restraint measures are only used in exceptional circumstances. They are complements to draw stock measures. The IEA compiled 89 demand restraint measures. In Germany, demand restraint restricts the disposal, acquisition, and utilization of oil. The provisions also limit the use of motorized vehicles based on location, time, distance, etc. However, the German government tends to favour measures that would increase the supply of oil. Demand restraint measures are also permitted under Italian and Spanish legislation.

There are three categories of measures:

- Light-handed measures: includes information campaigns to promote savings and reduction in consumption.
- Medium-handed measures: generally target transportation and include measures such as driving restrictions and speed limit reduction.
- Heavy-handed measures: usually more assertive measures such as the rationing of fuels, electricity, and compulsory restrictions on energy and motor vehicle use.

The final tool at the disposal of a country's oil dependency is the release of oil stocks into the economy. Companies that trade oil within the border have stockholding duties as well (or they must pay a monthly dividend to public institutions), but only the national agencies have the power to release the reserves to the public. Figure 8 summarises the emergency responses available for the regulation of the oil market. It shows how exposed Europeans are in this crisis, as the availability of measures is restricted. Temporarily replacing oil with other energy sources is a long-term solution that does not meet the short-term needs of households. They most likely require further investment which makes it costly. Increasing indigenous production is also constrained by the availability of the resource. In March and April 2022, the EU and the IEA coordinated a release of oil stocks to stabilize a volatile oil market. Despite this, oil reserves in Germany remained high according to the IEA data (2023), in fact, the reserves in Germany kept growing until the oil embargo in December 2022 and then started shrinking, like in every other country in the sample. The German anticipation is in line with Känzig's (2021) observation about negative news on oil supply. His predictions match Germany's behaviour as prices and inventories increased in the immediate aftermath of the war. On the other hand, reserves in France, Italy, and Spain were immediately down after the coordinated releases in March and April 2022. Furthermore, Table 4 and Table 6 show that the pass-through effect of an oil price shock into the HICP is higher in Germany and Italy. It is feasible that the precautionary responses of these countries (Germany increasing its stocks, and Italy increasing its imports) have led to this higher pass-through.

Increasing the supply and reducing the demand have very different effects on the real economy. By increasing the supply, the government can maintain the existing level of output. Reducing the demand for oil may induce economic slack.

Country	Total IEA stock levels in days of previous year's net imports	Industry (portion of Total IEA stock levels covered by industry stocks)	Public (portion of Total IEA stock levels covered by government-owned and agency-owned stocks + held abroad)
France	113	31	82
Germany	127	32	95
Italy	122	106	16
Spain	107	64	43

Table 9: Summary table of oil stocks held in June 2023. Source: IEA (2023), *Oil Stocks of IEA countries.*

The table above points to several things, firstly, as of June 2023, all four countries in our sample have met their obligations set by the IEA and Article 2 of the IEP; secondly, there is a difference in the strategy used within the EU, while France and Germany mostly rely on publicly owned emergency stocks, Italy and Spain seem to prefer deferring their responsibilities to the industry. This is especially true for Italy and could become problematic under certain circumstances. For instance, Lukoil, the second largest company in Russia, controlled an important refinery in Sicily which might explain the initial increase in oil imports from Russia and imports remained abnormally high until the embargo became effective. The control over stockholding requirements can be strategic because in often cases public oil stocks and industry-held oil stocks are co-mingled.

Divergence in the domestic oil market and the emergency response system can complicate coordinated EU-level responses as interests are not aligned. Nonetheless, given the low persistence of the oil price shock and the relative success of stabilising prices when they first started climbing after the war, there is hope that the current infrastructure is well-equipped to respond to new shocks.

b. Policy recommendations

The changing nature of the relationships described in the literature and the empirical analysis highlight the importance of frequent and periodic research. This is in line with Lucas' critique (1976) which states that policies should not be assessed based on non-structural statistical relationships described by historical data. Under these circumstances, Parag et al. (2023) provide useful guidance on how to improve research during crises. They insist on the need to conduct quick research. Researchers must have access to flexible funding opportunities by removing administrative obstacles, should identify the need for better platforms for collaborative work and exchange of data, and set criteria and guidebooks for prioritising certain research approaches.

The story of inflation expectations tells us why public trust matters. This is related to the credibility of monetary policy. In recent years, the usage of unconventional monetary policy such as forward guidance was preferred over the conventional manipulation of nominal interest rates. While the interest rate hikes served us well in this crisis by limiting the effects of HICP, worries about its effect on expectations are understandable. Adrian (2022) said that long-run inflation expectations are still relevant to central bankers because they provide a statement about their credibility and are useful in reviewing short-term inflation dynamics, but he does not reject the possibility that short-term household expectations can complicate the return of inflation to its target level of 2% even though long-term inflation expectations seem to have re-anchored. In this case, we are (potentially) experiencing a new structural break in the relationship between inflation expectations and inflation. Inflation expectations have fluctuated over the years and its effects were seen with the Phillips curve. While the ZLB has mitigated part of the negative effects on output in previous oil crises, it might have generated a veil of inattention which reduces agents' incentives to track inflation. In the long-term, this will negatively impact the credibility of the central bank, and by extension, the effectiveness of monetary policies. Nevertheless, the Granger-causality results in all four countries indicate the usefulness of interest rates in forecasting future values of HICP for the time being. Given the high level of inflation across the EU, it also implies that policymakers still have room for further increases in the interest rate.

Bielecki (2002) notes that even if there is no serious threat to the supply of oil, public concerns are often justified by supply bottlenecks and the limited number of suppliers in the global oil market with unbalanced market shares. Given that oil prices Granger-cause CCI in three countries, the government should aim to diversify oil supplies in the face of reductions in OPEC production and the increasing demands in Asia. There are political and economic gains from doing this. Extending the security framework to include emerging countries and other sources is also cited as a priority. Arezki et al. (2017) mention investments in the exploration of unconventional oil production such as shale oil, ultra-deep water oil, and oil sands for diversification. The data they present confirms this since unconventional oil production has increased with investment in that particular technology. They also relay that the ratio of oil consumption to GDP has been decreasing since 1971. A possible explanation put forward by the authors is the improvement in fuel efficiency, especially in advanced economies. On the other hand, the increased demand for transport vehicles in emerging economies can potentially offset the fuel efficiency. The literature on exogenous oil price shocks suggests that the price of oil might not return to its pre-war levels. Given that oil prices respond to global demand and supply is exhaustible, future increases in prices cannot be excluded unless we diversify our energy needs with alternative sources. All in all, the EU must solve its dependency issue and invest in alternative sources of energy. Replacing oil with renewable alternatives was always praised by environmentalists. The over-reliance on oil should now be cited as a justification for investing in renewables. This is featured in the IEA's (2022) report under the fuel switching measure (cf. Figure 8). The tenth point in their plan suggests that by promoting the use of electric and more efficient vehicles, an estimated 100 kb/d can be saved. It is worth noting that this is one of the least effective measures advanced in the paper but has the added benefit of creating some positive externalities. Germany is already among one of the biggest exporters of electric vehicles and the energy crisis might incentivise governments to invest in this growing market. A structural change in the energy requirement of a country seems like a daunting task, but to a certain extent, it is not unprecedented. The German government closed its nuclear facility and replaced it with coal to produce electricity. The aim is to, once again, gradually switch towards renewable sources. Furthermore, as signatories of several environmental agreements, France, Germany, Italy, and Spain have already committed to decrease their greenhouse gas emissions. However, focusing on renewable resources does not avoid the possibility of future supply shock; most of the materials, minerals, and components needed to produce renewable energy come from outside of Europe. Nevertheless, the current crisis should be considered as a wake-up call to respect their previous engagement.

Finally, Nicolay et al. (2023) recommend the use of windfall profit taxes for members of the EU. They estimate that a revenue cap on inframarginal technologies and a solidarity contribution for the fossil fuel sector would ultimately support households and other firms. The data revealed that the effect of the shock on industrial production was mild, but it does not reveal the disparities between the sectors. As observed by Nerlinger and Utz (2022) energy firms are the winners of this crisis. Theoretically, the proposed tax would not create any distortions since the tax is on economic rent and would therefore not reduce investment by those firms (Auerbach et al., 2007). The excess profit for these firms was irregular and unexpected and the introduction of a stricter revenue cap in 2022 could have raised 106 billion euros. However, they recognise that these taxes may have undesirable consequences. Firstly, the solidarity contribution and revenue cap require a system of double taxation which in turn would increase the asymmetric taxation of profits and loss and could negatively impact investment and innovation incentives. Secondly, a windfall tax at the EU-level enables firms to anticipate the introduction of these taxes and results in tax avoidance by shifting activities to countries with lower rates. Nonetheless, coordination within the EU would optimise the effectiveness of this policy and reduce tax arbitrage. Thirdly, windfall profit taxes can deter the entry of new players into the market. Nevertheless, I believe that maintaining this tax and redistributing the generated tax revenue to the poorest households can be beneficial as they help mitigate the risk on CCI and avoid structural changes in consumption patterns. Considering the decline in real wages, this should be an effective measure for restoring the purchasing power of households. Most countries have increased their budget on energy subsidies to reduce the pass-through effect (Choi et al., 2017). This should however only be a temporary solution as Coady et al. (2015) have demonstrated that it can have negative repercussions on health and is too costly in the long-run.

The EU should decide how it wishes to position itself in the war. Despite the sanctions imposed, Russian oil has found its way to the European market through “laundromat” countries. The bloc must explore solutions to this problem and attempt to negotiate with those countries. Furthermore, certain actions (such as the exceptions to the sanctions or Italy’s decision to pile up on Russian oil before the sanctions) indicate that the EU actions were not as firm as they might imply. Uncertainties in the market explain the reticence towards more irreversible measures but given the detrimental effects of a persistent shock in prices, a proactive response to a price shock is preferable to a delayed response (Hunt et al., 2001).

c. Limitations

The choice of variables reflects the study’s intention to analyse specific aspects of this oil price shock, but the availability of data constrained the econometric analysis. One might question the validity of the variable, especially since the effects of CCI on spending are not always approved by the literature but are assumed to be relevant in this paper. The literature on consumer confidence indices reveals that it is an aggregate measure of individual, financial situation, and a personal assessment of the overall economy. This prevents us from understanding what specific component of the CCI was the most affected by the shock. Other variables not included in the specification should also be considered, like a different proxy for economic activity such as retail sales. Furthermore, standard econometric theory tells us that it is impossible to dismiss entirely the possibility of an OVB. For instance, the war also influenced the global food market as grain exports from Ukraine were destroyed which in turn led to a global food crisis that could also explain the rise in HICP. The Granger-causality tests, the IRFs, and the FEVD provide some interesting findings in the short-run. However, our model specification does not allow for an analysis of the long-term effects. With more data and an increase in the forecasting period, it is possible to look at the long-term implications of this disruption. In light of Lucas' critique (1976) the validity of these results can quickly cease to exist. Moreover, limitations on the interpretation of Granger-causality do not allow for the verification of true causal relationships.

5/ Conclusion

In this paper, I examine the effects of the 2022-2023 oil price shock on the four largest EU economies, paying particular attention to the effect of the shock on the CCI. For this purpose, a SVAR model was used using five variables; namely, oil price statistics, CCI, long-term government bond yield, HICP, and industrial production index. In addition to data on oil prices and the CCI, common macroeconomic aggregates such as long-term government bond yields, the HICP, and industrial production were collected. Section 3 summarised the relevant literature on consumer confidence, oil prices, and variables related to monetary policy. It helps us understand the channels and transmission mechanisms through which an oil price shock may affect the wider economy and influence household consumption. The 2022-2023 oil crisis is mostly driven by supply-side changes, but we have seen throughout the papers that some of the implied effects were asymmetric and mitigated by country-specific conditions, such as oil dependency, domestic oil market structure, and pre-emptive measures taken by individual Member States. Oil price shocks seem to be a relevant factor for the forecasting of CCI in France, Germany, and Italy, but there is no evidence of Granger-causality in Spain. This is not an alarming outcome and could be explained by the fact that the impact of an oil price shock is country-specific and time-varying. However, it is difficult to pinpoint the underlying cause for this effect as confidence indicators can be influenced by an array of psychological, political, and economic factors. Differences in the demand for oil across Europe can further influence the exogenous variable in this model. Nevertheless, given the (potential) benefits of confidence indicators in forecasting consumer spending habits, policymakers should monitor oil price movements, especially in countries where Granger-causality is running from oil prices to CCI. A positive sign of the behaviour of the oil price shock is found in the data. The results of the IRFs graphs and FEVD tables allow us to say that a shock to oil price does not seem to have be persistent effect. Energy prices are returning to "normal" levels and the energy component of HICP is decreasing. However, inflation in the sampled countries is still above the 2% target. To maintain (relatively) low prices, the government should explore the demand restraint measures presented by the IEA with an appropriate plan of action based on national circumstances (structure of the oil market, effect on the public, costs) and be prepared for future hikes in the price of oil as production cuts can be expected.

Given the reduced pass-through between oil prices and inflation suggested in the literature, I sought to explain the current puzzle of high inflationary pressure after decades of (rather) stable rates. This can be explained by a potential shift in expectations and a precautionary increase in oil demand (observed in Germany and Italy where the pass-through was the most significant). Therefore, I recommend periodic and frequent analyses of potential changes in global and domestic factors are necessary, especially if the war is prolonged and the existing relationship between the variables is changing since the changes in the relationship between these variables are to be expected.

Future research should look at the effects of the oil crisis in other EU countries, particularly in Eastern parts of the continent closer to the conflict. Additionally, oil is not the only supply disruption that resulted as a consequence of the war. Within the energy market, gas also plays a significant role for the EU economies, and the global food crisis documented by economists last year has also been reported to influence inflationary pressure. We can extend the model by adding additional variables that are often mentioned in the literature. Employment and real wages would be interesting additions to the model as they can influence both the oil demand (Blanchard and Gali, 2007) and are also an important aspect of the New-Keynesian framework. The importance of the real exchange rate channel should also be considered. Furthermore, this paper uses one method of non-linear transformation, but other alternatives should be examined and could lead to different results. Finally, a different measure of confidence should be examined, particularly indices that look at the business conditions. The effects of the sanctions on Russia are also an interesting topic of research, especially since it pertains to the discussion on the persistence of the shock, although the availability of Russian data is an issue.

6/ References

- Adrian, T. (2023). T*he Role of Inflation Expectations in Monetary Policy*. IMF. https://www.imf.org/en/News/Articles/2023/05/15/sp-role-inflation-expectations-monetary-policy-tobias-adrian.
- Al-Eyd, A.; Barrell, R.; Davis, P. E. (2009). Consumer Confidence Indices and Short-term Forecasting of Consumption, *Manchester School*, 77(1), 96-111.
- Auerbach, A. J.; Devereux, M. P.; Simpson, H. (2007). Taxing Corporate Income. *CESIFO Working Paper*, No. 2139
- Arezki, R; Jakab, Z.; Laxton, D.; Matsumoto, A; Nurbekyan, A.; Wang, H; and Yao, J. (2017). Oil Prices and the Global Economy. *IMF Working Paper*, WP/17/15.
- Barsky, R. B.; and Kilian, L. (2002) Do we really know that oil caused the Great Stagflation? A monetary alternative, *NBER Macroeconomics Annual 2001, Volume 16*.
- Barsky, R. B.; and Kilian, L (2004). Oil and the Macroeconomy Since the 1970s. *Journal of Economic Perspectives*, 18(4), 115-134.
- Beidas-Strom, S.; and Pescatori, A. (2014). Oil Price Volatility and the Role of Speculation, *IMF Working Paper*, WP/14/218.
- Bătrâncea, L. (2020). Does Economic Growth and Inflation Impact Consumer Confidence during a Pandemic? An Empirical Analysis in EU Countries. *MID Journal*, 3(1), 5-13.
- Bielecki, J. (2002). Energy security: is the wolf at the door*? The Quarterly Review Economics and Finance*, 42(2002), 235-250.
- Blanchard, O. and Galí, J. (2007) The Macroeconomic Effects of Oil Price Shocks: Why are the 2000S so different from the 1970s? *NBER Working Paper Series.*
- Bodenstein, M.; Guerrieri L.; Gust, C. (2010) Oil Shocks and the Zero Bound on Nominal Interest Rates. *Board of Governors of the Federal Reserve System International Finance Discussion Papers Number 1009*.
- Borio, C. V; and Filardo, A. (2007). Globalisation and Inflation: New-Cross Country Evidence on the Global Determinants of Domestic Inflation.
- Casey and Owen (2013). Good News, Bad News, and Consumer Confidence. *Social Science Quarterly*, 94(1), 292-315.
- Carroll, C. D.; Fuhrer, J. C.; Wilcox, D. W. (1994) Does Consumer Sentiment Forecast Household Spending? If Son Why? *The American Economic Review*, 84(5), 1397-1408.
- Cashin, P.; Mohaddes, K.; Raissi, M.; and Raissi, M. (2012). The Differential Effect of Oil Demand and Supply Shocks on the Global Economy, *IMF Working Paper*, WP/12/253.
- Chen, S. (2009). Oil Price pass-through into inflation. *Energy Economics*, 31(2009), 126-133.
- Choi, S.; Furceri, D.; Loungani, P.; Mishra, S.; and Poplawski-Ribeiro, M. (2017). Oil Prices and Inflation Dynamics: Evidence from Advanced and Developing Economies. *IMF Working Paper*, WP/17/196.

- Churchill, W. (1913). “Safety and certainty in oil, lie in variety and variety alone”. Great Britain Parliament, London, United Kingdom.
- Coady, D.; Parry, I.; Sears, L; and Shang, B. (2015). How Large Are Global Energy Subsidies? IMF Working Paper, WP/15/105.
- Coibion, O.; Gorodnichenko, Y.; Kumar, S.; and Pedemonte, M. (2020). Inflation expectations as a policy tool? Journal of International Economics, 124(2020).
- Cuñado, J. ; and Pérez de Gracia, F. (2003). Do oil price shocks matter? Evidence for some European countries. Energy Economics, 25(2023).
- De Boef and Kellstedt (2004). The Political (and Economic) Origins of Consumer Confidence, *American Journal of Political Science*, 48(4), 633-649.
- De Gregorio, J.; Landerretche, O. ; Neilson, C. (2007). Another Pass-Through Bites the Dust? Oil Prices and Inflation, *Central Bank of Chile Working papers*.
- Dees, S.; Karadeloglou, P.; Kaufmann, R. K.; and Sánchez, M. (2004). Does OPEC Matter? An Econometric Analysis of Oil Prices. *The Energy Journal*, 25(4).
- Dées, S. and Brinca, P. S. (2011). Consumer confidence as a predictor of consumption spending. Evidence for the United States and the Euro Area. European Central Bank Working Paper Series, No 1349/June 2011.
- Dominitz, J., and Manski, C. F. (2004). How Should We measure Consumer Confidence? *Journal of Economic Perspectives*, 18(2), 51-66.
- European Council – Council of the European Union (2023) EU sanctions against Russia explained. Available at: https://www.consilium.europa.eu/en/policies/sanctions/restrictive-measures-against-russia-over-ukraine/sanctions-against-russia-explained/
- Eurostat (2023), HICP – monthly data (index). Available at: https://ec.europa.eu/eurostat/databrowser/view/PRC_HICP_MIDX__custom_7512921/default/table?lang=en (Accessed on 22 September 2023)
- Eurostat (2023), Interest rates – monthly data. Available at: https://ec.europa.eu/eurostat/databrowser/view/EI_MFIR_M__custom_7517657/default/table?lang=en (Accessed on 22 September 2023)
- Eurostat (2023), Crude oil imports by field of production – monthly data. Available at: https://ec.europa.eu/eurostat/databrowser/view/NRG_TI_COIFPM__custom_7549541/default/table?lang=en (Accessed on 22 September 2023)
- Eurostat (2023), “Household consumption by purpose”. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Household_consumption_by_purpose#Analysis_of_EU_aggregates
- Eurostat (2023), Inflation in the euro area. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Inflation_in_the_euro_area

- Fairless, T. (2023) Europeans are becoming poorer. 'Yes, we're all worse off'. The Wall Street Journal. Available at: https://www.wsj.com/articles/europeans-poorer-inflation-economy-255eb629.
- Finn, G. (2000). Perfect Competition and the Effects of Energy Price Increases on Economic Activity. *Journal of Money, Credit and Banking*, 32(3), pp. 400-416.
- Fueki, T.; Higashi, H. ; Higashio, N. ; Nakajima, J. ; Ohyama, S.; and Tamanyu, Y. (2018). Identifying oil price shocks and their consequences: the role of expectations in the crude oil market, *Bank for International Settlement Working Paper*, Working Paper 725.
- Golinelli, R., and Parigi, G. (2004). Consumer Sentiment and Economic Activity: A Cross Country Comparison, *Journal of Business Cycle Measurement and Analysis*, 1(2), 147-170.
- Hamilton, J. D. (1983). 'Oil and the Macroeconomy since World War II'. *Journal of Political Economy*, 91(2), 228-248
- Hamilton, J. D., (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics* 38, 215–220
- Hamilton, J. D., (2003). What Is an Oil Shock? *Journal of Econometrics*, 363-398
- Hooker, M. A., (1996) What happened to the oil price-macroeconomy relationship? *Journal of Monetary Economics*, 38(1996), 195-213.
- Hooker, M. A., (2002) Are Oil Shocks Inflationary? Asymmetric and Nonlinear Specifications versus Changes in Regime. *Journal of Money, Credit and Banking*, 3'(2), 540-561.
- Howrey, P. E. (2001) The Predictive Power of the Consumer Index of Consumer Sentiment. *Brookings Papers on Economic Activity*, 32(1), 175-216.
- Hunt, B.; Isard, P.; Laxton, D. (2001) The Macroeconomic Effects of Higher Oil Prices. *IMF Working Paper*, WP/01/14.
- IEA (2022). A 10-Point Plan to Cut Oil Use.
- IEA (2023) Monthly Reliance on Russian Oil for OECD countries. Available at : https://www.iea.org/data-and-statistics/data-product/monthly-reliance-on-russian-oil-for-oecd-countries
- IEA (2023), Oil Stocks of IEA Countries, IEA, Paris https://www.iea.org/data-and-statistics/data-tools/oil-stocks-of-iea-countries
- Jiménez-Rodríguez, R., & Sánchez, M. (2005). Oil price shocks and real GDP growth: empirical evidence for some OECD countries. *Applied economics*, 37(2), 201-228
- Jonsson, A.; and Lindén, S. (2009). The quest for the best consumer confidence indicator, *European Economy - Economic Papers 2008 - 2015*.
- Känzig, D. R. (*2021)*. The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements. *American Economic Review*, 111 (4), 1092-1125.
- Kilian, L.; and Lee., T. K. (2013). Quantifying the Speculative Component in the Real Price of Oil: The Role of Global Oil Inventories. *Journal of International Money and Finance*, 42(C), 71-87.
- Kohl, W. L. (2002) OPEC behavior, 1998-2001. *The Quarterly Review of Economics and Finance*, 42(2002), 209-233.

- Kumar, S. (2005). The macroeconomic effects of oil price shocks: Empirical evidence for India. Available at SSRN 900285.
- LeBlanc, M.; and Chinn, M. K. (2004). Do High Oil Price Presage Inflation? The Evidence from G-5 Countries. *SSRN Electronic Journal*, 34(28346).
- Leiner-Killinger, N.; and Nerlich, C. (2019). Fiscal Rules in the euro area and lessons from other monetary unions. *ECB Economic Bulletin*, Issue 3/2019.
- Lucas, R. E. (1976). Econometric policy evaluation: A critique. Carnegie-Rochester Conference Series on Public Policy. Volume 1. 19-46. https://doi.org/10.1016/S0167-2231(76)80003-6.
- McCormick. (2023) Saudi Arabia's energy minister says oil cuts not about 'jacking up prices', Financial Times. Available at: https://on.ft.com/3PIIcs0
- Maria del Rio-Chanona, R.; Mealy, P.; Pichler, A.; Lafond, F.; and Farmer, D. J. (2020). Supply and demand shocks in the COVID-19 pandemic: an industry and occupation perspective, *Oxford Review of Economic Policy*, 36(1), 94-137.
- Meeks, R.; and Monti, F. (2022). Heterogenous Beliefs and the Phillips Curve. *Centre for Applied Macroeconomic Analysis Working Paper 51/2022.*
- Mishkin, F. S., (2007) Inflation Dynamics, *International Finance*, 10(3), 317-334.
- Mody, A.; Ohnsorge, F.; and Sandri, D. (2012). Precautionary Savings in the Great Recession. *IMF Working Paper*, WP/12/42. https://doi.org/10.1111/j.1468-2362.2007.00205.x
- Mork, K. A. (1989). Oil and the Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results. *Journal of Political Economy*, 97(3), 740-744.
- Nerlinger, M.; Utz, S. (2022) The impact of the Russia-Ukraine conflict on energy firms: A capital market perspective. *Finance Research Letter*, 50(2022).
- Nicolay, K.; Steinbrenner, D.; Woelfing, N.; Spix J. (2023) The effectiveness and distributional consequences of excess profit taxes or windfall taxes in light of the Commission's recommendation to Member States, publication for the Subcommittee on tax matters, *Publication for the Subcommittee on tax matters, Policy Department for Economic, Scientific and Quality of Life Policies, European Parliament.*
- OECD (2023), Consumer confidence index (CCI) (indicator). doi: 10.1787/46434d78-en (Accessed on 21 September 2023)
- OECD (2023), Industrial production (indicator). doi: 10.1787/39121c55-en (Accessed on 22 September 2023)
- Parag, Y; Fawcett, T.; Hampton, S. ; Eyre, N. (2023) Energy saving in a hurry: A research agenda and guidelines to study European responses to the 2022-2023 energy crisis. *Energy Research & Social Science*, 97(2023).
- Quint, D.; Venditti, F. (2020). The influence of OPEC+ on oil prices: a quantitative assessment. *ECB Working Paper Series No 2467 / September 2020.*

- Roberts, C. A. (2007). Russia and the European Union: The Sources and Limits of "Special Relationship". *USAWC Press.*
- Roberts, J. M. (1998) Inflation Expectations and the Transmission of Monetary Policy. *Finance and Economics Discussion Series from Board of Governors of the Federal Reserve System (U.S.),* No 1998-43.
- Sek, S. K., Teo, X. Q., Wong, Y. N. (2015). A Comparative Study on the Effects of Oil Price Changes on Inflation. *Procedia Economics and Finance*, 26(2015), 630-636.
- Smith, J., L. (2009). World Oil: Market or Mayhem? *Journal of Economic Perspectives*, 23(3), 145-164.
- Suzan, S.; and Bounfour, A. (2023). New Oil Map. Impact of Russia's War on Ukraine on Supply and Demand. *Transport & Environment.*
- The Economist (2023). Buyers of Russian crude are exporting refined oil to the West. Available at: https://www.economist.com/graphic-detail/2023/06/20/buyers-of-russian-crude-are-exporting-refined-oil-to-the-west?utm_medium=cpc.adword.pd&utm_source=google&utm_campaign=a.io_apac_freetrial&utm_content=conversion.non-brand.anonymous.apac_sg_en_free-trial_na_non-brand_google_subs_pmax_other_na_na&gclid=CjwKCAjw9-6oBhBaEiwAHv1QvEDN-6rr6qin4kkgjU4VYJEhray8FHt8DcmuB_LuyJl9fkjG2irTkhoCaGEQAvD_BwE.
- The Economist (2023). Economists and investors should pay less attention to consumers. Available at: https://www.economist.com/finance-and-economics/2023/04/27/economists-and-investors-should-pay-less-attention-to-consumers.

Appendix A – France

1. Augmented Dickey-Fuller tests

```
Dickey–Fuller test for unit root          Number of obs  = 220
Variable: POS_Oil_Price_m                 Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test          ──────── critical value ─────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────
 Z(t)            -7.112        -3.470       -2.882       -2.572
──────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Dickey–Fuller test for unit root          Number of obs  = 220
Variable: log_CCI                         Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test          ──────── critical value ─────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────
 Z(t)            -7.710        -3.470       -2.882       -2.572
──────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Dickey–Fuller test for unit root          Number of obs  = 220
Variable: log_ind_prod                    Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test          ──────── critical value ─────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────
 Z(t)           -11.364        -3.470       -2.882       -2.572
──────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Dickey–Fuller test for unit root          Number of obs  = 219
Variable: FDlog_HICP                      Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test          ──────── critical value ─────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────
 Z(t)           -14.559        -3.470       -2.882       -2.572
──────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Dickey–Fuller test for unit root          Number of obs  = 219
Variable: FDlog_int_rate                  Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test      ──────── critical value ─────────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)           -10.424       -3.470       -2.882       -2.572
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

2. Lag-order selection tests

Lag-order selection criteria

Sample: 2006m2 thru 2023m5 Number of obs = 208

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	721.634				7.0e-10	-6.89071	-6.85827	-6.81048
1	858.553	273.84	25	0.000	2.4e-10	-7.96686	-7.77221*	-7.48548*
2	891.319	65.532	25	0.000	2.2e-10	-8.04153	-7.68469	-7.15901
3	908.556	34.474	25	0.098	2.4e-10	-7.96689	-7.44784	-6.68322
4	929.148	41.184	25	0.022	2.5e-10	-7.9245	-7.24325	-6.23969
5	954.366	50.435	25	0.002	2.5e-10	-7.92659	-7.08314	-5.84063
6	993.892	79.053	25	0.000	2.2e-10	-8.06627	-7.06061	-5.57917
7	1016.11	44.428	25	0.010	2.3e-10	-8.03948	-6.87162	-5.15123
8	1032.67	33.132	25	0.128	2.5e-10	-7.95839	-6.62832	-4.66899
9	1058.18	51.006	25	0.002	2.5e-10	-7.96322	-6.47096	-4.27268
10	1076.54	36.732	25	0.061	2.7e-10	-7.89944	-6.24497	-3.80774
11	1100.54	47.994	25	0.004	2.8e-10	-7.88979	-6.07312	-3.39695
12	1187.18	173.28*	25	0.000	1.6e-10*	-8.48249*	-6.50362	-3.58851

* optimal lag
Endogenous: POS_Oil_Price_m log_ind_prod FDlog_HICP FDlog_int_rate log_CCI
Exogenous: _cons

3. Stability condition test

```
. asdoc varstable
```

Eigenvalue stability condition

Eigenvalue	Modulus
-.9908977	.990898
.9845412 + .07530108i	.987417
.9845412 - .07530108i	.987417
-.4883635 + .8511456i	.981299
-.4883635 - .8511456i	.981299
-.03143641 + .9802525i	.980756
-.03143641 - .9802525i	.980756
-.8445516 + .4955923i	.979224
-.8445516 - .4955923i	.979224
.495303 + .8376701i	.973148
.495303 - .8376701i	.973148
.840665 + .4708805i	.963559
.840665 - .4708805i	.963559
.92018 + .1996097i	.941581
.92018 - .1996097i	.941581
-.09477507 + .936563i	.941346
-.09477507 - .936563i	.941346
-.6056605 + .7201818i	.941003
-.6056605 - .7201818i	.941003
.8728332 + .3278192i	.932364
.8728332 - .3278192i	.932364
.5737122 + .7075385i	.91091
.5737122 - .7075385i	.91091
.4219294 + .806358i	.910076
.4219294 - .806358i	.910076
.05899509 + .9058103i	.907729
.05899509 - .9058103i	.907729
-.6961238 + .5728878i	.901548
-.6961238 - .5728878i	.901548
.7183724 + .532842i	.894416
.7183724 - .532842i	.894416
-.8604823 + .2381165i	.892821
-.8604823 - .2381165i	.892821
.2512435 + .8554278i	.89156
.2512435 - .8554278i	.89156
-.1647154 + .8735218i	.888916
-.1647154 - .8735218i	.888916
.8864902	.88649
-.3139342 + .8269954i	.884577
-.3139342 - .8269954i	.884577
.512773 + .7103039i	.876052
.512773 - .7103039i	.876052
-.8387164 + .1389906i	.850155
-.8387164 - .1389906i	.850155
-.836039	.836039
-.6197106 + .5455476i	.825629
-.6197106 - .5455476i	.825629
-.774616 + .2059087i	.801516
-.774616 - .2059087i	.801516
.593155 + .5155191i	.785871
.593155 - .5155191i	.785871
-.2563653 + .6830655i	.72959
-.2563653 - .6830655i	.72959
-.4796745 + .505669i	.696986
-.4796745 - .505669i	.696986
.6409475 + .2630179i	.692815
.6409475 - .2630179i	.692815
.6127854	.612785
.1446828 + .4728696i	.494509
.1446828 - .4728696i	.494509

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

4. Lagrange multiplier test for autocorrelation

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	21.5183	25	0.66338
2	17.4166	25	0.86613
3	27.3791	25	0.33722
4	31.5216	25	0.17233
5	26.7302	25	0.36950
6	43.0997	25	0.01365
7	26.4730	25	0.38271
8	33.3869	25	0.12168
9	39.4609	25	0.03310
10	16.8039	25	0.88878
11	28.5597	25	0.28274
12	29.9805	25	0.22502

H0: no autocorrelation at lag order

Appendix B – Germany

1. Augmented Dickey-Fuller tests

```
Dickey-Fuller test for unit root          Number of obs  = 220
Variable: POS_Oil_Price_m                 Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test       ──────── critical value ─────────
              statistic            1%           5%          10%
───────────────────────────────────────────────────────────────
 Z(t)            -7.766        -3.470       -2.882       -2.572
───────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.


Dickey-Fuller test for unit root          Number of obs  = 220
Variable: log_CCI                         Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test       ──────── critical value ─────────
              statistic            1%           5%          10%
───────────────────────────────────────────────────────────────
 Z(t)            -7.555        -3.470       -2.882       -2.572
───────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.


Dickey-Fuller test for unit root          Number of obs  = 220
Variable: log_ind_prod                    Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test       ──────── critical value ─────────
              statistic            1%           5%          10%
───────────────────────────────────────────────────────────────
 Z(t)            -8.519        -3.470       -2.882       -2.572
───────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.

Dickey-Fuller test for unit root          Number of obs  = 219
Variable: FDlog_HICP                      Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test       ──────── critical value ─────────
              statistic            1%           5%          10%
───────────────────────────────────────────────────────────────
 Z(t)           -15.479        -3.470       -2.882       -2.572
───────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Dickey–Fuller test for unit root          Number of obs  = 219
Variable: FDlog_ind_prod                  Number of lags =   0

H0: Random walk without drift, d = 0
```

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-21.608	-3.470	-2.882	-2.572

MacKinnon approximate *p*-value for Z(t) = 0.0000.

2. Lag-order selection tests

Lag-order selection criteria

Sample: 2006m2 thru 2023m5 Number of obs = 208

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	637.724				1.6e-09	-6.08389	-6.05145	-6.00366
1	770.474	265.5	25	0.000	5.6e-10	-7.11994	-6.9253*	-6.63857*
2	797.832	54.715	25	0.001	5.4e-10	-7.14261	-6.78577	-6.26009
3	823.382	51.1	25	0.002	5.4e-10*	-7.1479*	-6.62885	-5.86423
4	835.204	23.644	25	0.540	6.2e-10	-7.02119	-6.33994	-5.33637
5	864.933	59.459	25	0.000	5.9e-10	-7.06666	-6.22321	-4.9807
6	888.945	48.024	25	0.004	6.0e-10	-7.05716	-6.05151	-4.57006
7	916.66	55.43	25	0.000	5.9e-10	-7.08327	-5.91541	-4.19502
8	936.813	40.305	25	0.027	6.2e-10	-7.03666	-5.7066	-3.74726
9	952.722	31.819	25	0.163	6.9e-10	-6.94925	-5.45699	-3.25871
10	969.134	32.824	25	0.136	7.5e-10	-6.86667	-5.2122	-2.77498
11	985.061	31.854	25	0.162	8.4e-10	-6.77943	-4.96276	-2.28659
12	1037.5	104.88*	25	0.000	6.6e-10	-7.04327	-5.06439	-2.14928

* optimal lag
Endogenous: POS_Oil_Price_m log_ind_prod FDlog_HICP FDlog_Int_rate log_CCI
Exogenous: _cons

3. Stability condition test

Eigenvalue stability condition

Eigenvalue	Modulus
-.9727546	.972755
.8339152 + .4923736*i*	.968425
.8339152 - .4923736*i*	.968425
-.8427796 + .4764494*i*	.968133
-.8427796 - .4764494*i*	.968133
-.4647898 + .8324718*i*	.953435
-.4647898 - .8324718*i*	.953435
.9496157 + .06426594*i*	.951788
.9496157 - .06426594*i*	.951788
.4637905 + .8285761*i*	.949547
.4637905 - .8285761*i*	.949547
-.00920964 + .9460767*i*	.946121
-.00920964 - .9460767*i*	.946121
.703969 + .6126267*i*	.933212
.703969 - .6126267*i*	.933212
.9300222	.930022
-.05093805 + .9283984*i*	.929795
-.05093805 - .9283984*i*	.929795
.7649348 + .5165164*i*	.922992
.7649348 - .5165164*i*	.922992
.4572835 + .8009041*i*	.922256
.4572835 - .8009041*i*	.922256
.3081901 + .8604815*i*	.914007
.3081901 - .8604815*i*	.914007
-.5714673 + .7118912*i*	.912888
-.5714673 - .7118912*i*	.912888
-.7807485 + .4646396*i*	.908547
-.7807485 - .4646396*i*	.908547
.8938343 + .1486239*i*	.906106
.8938343 - .1486239*i*	.906106
-.8554937 + .2653891*i*	.895713
-.8554937 - .2653891*i*	.895713
.8225946 + .3016832*i*	.87617
.8225946 - .3016832*i*	.87617
-.271718 + .8214276*i*	.865202
-.271718 - .8214276*i*	.865202
-.8413222 + .1877662*i*	.86202
-.8413222 - .1877662*i*	.86202
.5322664 + .6716606*i*	.856992
.5322664 - .6716606*i*	.856992
-.6544215 + .5429301*i*	.850318
-.6544215 - .5429301*i*	.850318
.7304185 + .4056722*i*	.835512
.7304185 - .4056722*i*	.835512
-.04901604 + .8246174*i*	.826073
-.04901604 - .8246174*i*	.826073
-.5302391 + .6176323*i*	.814017
-.5302391 - .6176323*i*	.814017
.1094646 + .7950914*i*	.802591
.1094646 - .7950914*i*	.802591
.3451205 + .7075566*i*	.787239
.3451205 - .7075566*i*	.787239
-.7761636	.776164
-.2282561 + .7334766*i*	.768172
-.2282561 - .7334766*i*	.768172
-.4319674 + .3780949*i*	.574066
-.4319674 - .3780949*i*	.574066
-.5483545	.548354
.4558381	.455838
.1010422	.101042

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

4. Lagrange multiplier test for autocorrelation

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	13.3963	25	0.97126
2	22.1739	25	0.62568
3	29.1237	25	0.25878
4	20.1078	25	0.74115
5	17.8070	25	0.85047
6	30.8737	25	0.19323
7	25.2669	25	0.44750
8	36.0082	25	0.07148
9	26.7659	25	0.36768
10	11.5947	25	0.98954
11	27.7308	25	0.32039
12	19.9850	25	0.74761

H0: no autocorrelation at lag order

Appendix C – Italy

1. Augmented Dickey-Fuller tests

Dickey–Fuller test for unit root Number of obs = 220
Variable: POS_Oil_Price_m Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-7.893	-3.470	-2.882	-2.572

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Dickey–Fuller test for unit root Number of obs = 220
Variable: log_CCI Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-8.777	-3.470	-2.882	-2.572

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Dickey–Fuller test for unit root   Number of obs = 220
Variable: log_ind_prod   Number of lags =   0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-10.149	-3.470	-2.882	-2.572

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Dickey–Fuller test for unit root   Number of obs = 219
Variable: FDlog_HICP   Number of lags =   0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-13.041	-3.470	-2.882	-2.572

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Dickey–Fuller test for unit root   Number of obs = 219
Variable: FDlog_Int_rate   Number of lags =   0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-10.850	-3.470	-2.882	-2.572

MacKinnon approximate *p*-value for Z(t) = 0.0000.

2. Lag-order selection test

Lag-order selection criteria

Sample: 2006m2 thru 2023m5 Number of obs = 208

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	445.694				9.9e-09	-4.23744	-4.205	-4.15721
1	551.182	210.98	25	0.000	4.6e-09	-5.01136	-4.81672	-4.52999*
2	603.677	104.99	25	0.000	3.5e-09	-5.27574	-4.91889	-4.39322
3	626.604	45.854	25	0.007	3.6e-09	-5.2558	-4.73675	-3.97214
4	708.208	163.21	25	0.000	2.1e-09	-5.80007	-5.11882	-4.11526
5	734.575	52.735	25	0.001	2.1e-09	-5.81323	-4.96977	-3.72726
6	824.383	179.62	25	0.000	1.1e-09	-6.43638	-5.43072*	-3.94927
7	851.197	53.627	25	0.001	1.1e-09*	-6.45381*	-5.28595	-3.56556
8	866.477	30.56	25	0.204	1.2e-09	-6.36035	-5.03029	-3.07095
9	883.008	33.063	25	0.129	1.3e-09	-6.27893	-4.78666	-2.58838
10	894.509	23.001	25	0.578	1.5e-09	-6.14912	-4.49465	-2.05743
11	905.416	21.814	25	0.646	1.8e-09	-6.01361	-4.19694	-1.52077
12	954.111	97.391*	25	0.000	1.5e-09	-6.24146	-4.26258	-1.34747

* optimal lag
Endogenous: log_CCI POS_Oil_Price_m log_ind_prod FDlog_HICP FDlog_Int_rate
Exogenous: _cons

3. Stability condition test

Eigenvalue stability condition

Eigenvalue	Modulus
.5008982 + .8654042*i*	.999912
.5008982 - .8654042*i*	.999912
-.4973958 + .8637292*i*	.99671
-.4973958 - .8637292*i*	.99671
-.9836148	.983615
.9620436 + .06633051*i*	.964328
.9620436 - .06633051*i*	.964328
.8066771 + .4878382*i*	.942716
.8066771 - .4878382*i*	.942716
-.04869016 + .9357454*i*	.937011
-.04869016 - .9357454*i*	.937011
-.806369 + .4461998*i*	.921588
-.806369 - .4461998*i*	.921588
.7631359 + .5055256*i*	.915386
.7631359 - .5055256*i*	.915386
-.9096764	.909676
.1402958 + .8983831*i*	.909272
.1402958 - .8983831*i*	.909272
-.7269372 + .5392243*i*	.905097
-.7269372 - .5392243*i*	.905097
.8813405 + .1785505*i*	.899245
.8813405 - .1785505*i*	.899245
.8505333 + .2669415*i*	.89144
.8505333 - .2669415*i*	.89144
.5988323 + .6582138*i*	.889857
.5988323 - .6582138*i*	.889857
-.09715314 + .8696789*i*	.875089
-.09715314 - .8696789*i*	.875089
-.814935 + .3063444*i*	.870612
-.814935 - .3063444*i*	.870612
.2052048 + .8441867*i*	.868769
.2052048 - .8441867*i*	.868769
.4369764 + .7426646*i*	.861684
.4369764 - .7426646*i*	.861684
.7707396 + .3726777*i*	.856112
.7707396 - .3726777*i*	.856112
-.3760521 + .7612552*i*	.849073
-.3760521 - .7612552*i*	.849073
-.4845498 + .6859331*i*	.839817
-.4845498 - .6859331*i*	.839817
-.612608 + .5698707*i*	.836685
-.612608 - .5698707*i*	.836685
-.01276463 + .8364305*i*	.836528
-.01276463 - .8364305*i*	.836528
.433663 + .69388876*i*	.818256
.433663 - .69388876*i*	.818256
-.2981044 + .7557269*i*	.812397
-.2981044 - .7557269*i*	.812397
-.6587811 + .4663361*i*	.807132
-.6587811 - .4663361*i*	.807132
.5391536 + .5710979*i*	.785391
.5391536 - .5710979*i*	.785391
-.7798584 + .033328479*i*	.780568
-.7798584 - .033328479*i*	.780568
.05270592 + .7659526*i*	.767764
.05270592 - .7659526*i*	.767764
.7673055	.767306
-.7318189 + .08169411*i*	.736365
-.7318189 - .08169411*i*	.736365
.7350955	.735095

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

4. Lagrange multiplier test for autocorrelation

Lagrange-multiplier test

lag	chi2	df	Prob>Chi2
1	20.543	25	0.718
2	18.028	25	0.841
3	26.277	25	0.393

4	36.161	25	0.069
5	39.284	25	0.035
6	16.412	25	0.902
7	26.047	25	0.405
8	10.143	25	0.996
9	14.415	25	0.954
10	31.366	25	0.177
11	24.352	25	0.499
12	27.337	25	0.339

H0: no autocorrelation at lag order

Appendix D – Spain

1. Augmented Dickey-Fuller tests

```
Dickey–Fuller test for unit root          Number of obs  = 221
Variable: POS_Oil_Price_m                 Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test        ──────── critical value ────────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -7.052       -3.470       -2.882       -2.572
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Dickey–Fuller test for unit root          Number of obs  = 221
Variable: log_CCI                         Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test        ──────── critical value ────────
              statistic           1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)            -6.182       -3.470       -2.882       -2.572
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Dickey–Fuller test for unit root          Number of obs  = 221
Variable: log_ind_prod                    Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test       ───────── critical value ─────────
              statistic           1%           5%          10%
────────────────────────────────────────────────────────────────
 Z(t)            -5.720       -3.470       -2.882       -2.572
────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.


Dickey–Fuller test for unit root          Number of obs  = 220
Variable: FDlog_HICP                      Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test       ───────── critical value ─────────
              statistic           1%           5%          10%
────────────────────────────────────────────────────────────────
 Z(t)           -12.425       -3.470       -2.882       -2.572
────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.


Dickey–Fuller test for unit root          Number of obs  = 220
Variable: FDlog_Int_rate                  Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey–Fuller
                   Test       ───────── critical value ─────────
              statistic           1%           5%          10%
────────────────────────────────────────────────────────────────
 Z(t)           -10.427       -3.470       -2.882       -2.572
────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

2. Lag-order selection tests

Lag-order selection criteria

Sample: 2006m2 thru 2023m6   Number of obs = 209

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	546.359				3.9e-09	-5.18047	-5.14814	-5.10051
1	770.566	448.42	25	0.000	5.8e-10	-7.08676	-6.89279	-6.607
2	852.835	164.54	25	0.000	3.3e-10	-7.63479	-7.27918*	-6.75523*
3	875.132	44.594	25	0.009	3.4e-10	-7.60892	-7.09167	-6.32956
4	913.892	77.52	25	0.000	3.0e-10	-7.7406	-7.0617	-6.06143
5	939.677	51.569	25	0.001	3.0e-10	-7.7481	-6.90757	-5.66914
6	1005.39	131.43	25	0.000	2.0e-10*	-8.13773*	-7.13556	-5.65897
7	1024.42	38.046	25	0.046	2.2e-10	-8.08054	-6.91672	-5.20197
8	1033.1	17.372	25	0.868	2.6e-10	-7.92443	-6.59896	-4.64606
9	1057.26	48.324	25	0.003	2.6e-10	-7.91641	-6.42931	-4.23824
10	1074.02	33.511	25	0.119	2.9e-10	-7.83752	-6.18877	-3.75955
11	1099.7	51.353	25	0.001	2.9e-10	-7.84399	-6.0336	-3.36622
12	1128.14	56.884*	25	0.000	2.8e-10	-7.87693	-5.9049	-2.99936

3. Stability condition test

Eigenvalue stability condition

Eigenvalue	Modulus
.4946596 + .8601385*i*	.992233
.4946596 - .8601385*i*	.992233
-.4929523 + .8552096*i*	.98711
-.4929523 - .8552096*i*	.98711
-.9603716	.960372
.9530422 + .09135333*i*	.95741
.9530422 - .09135333*i*	.95741
.8191965 + .47251142*i*	.945702
.8191965 - .47251142*i*	.945702
.01079171 + .94389322*i*	.943955
.01079171 - .94389322*i*	.943955
.4679428 + .8154327*i*	.94016
.4679428 - .8154327*i*	.94016
-.8032668 + .4440354*i*	.917826
-.8032668 - .4440354*i*	.917826
.8144485 + .381743*i*	.899474
.8144485 - .381743*i*	.899474
-.05525622 + .8950566*i*	.896761
-.05525622 - .8950566*i*	.896761
.8933403 + .01545539*i*	.893474
.8933403 - .01545539*i*	.893474
.7855278 + .4120414*i*	.887036
.7855278 - .4120414*i*	.887036
.561213 + .68591433*i*	.88625
.561213 - .68591433*i*	.88625
-.879168 + .1030286*i*	.885184
-.879168 - .1030286*i*	.885184
.2593115 + .83845233*i*	.877636
.2593115 - .83845233*i*	.877636
.8327994 + .2631802*i*	.873395
.8327994 - .2631802*i*	.873395
-.5274988 + .69346556*i*	.871292
-.5274988 - .69346556*i*	.871292
.6137986 + .5885004*i*	.850342
.6137986 - .5885004*i*	.850342
-.3661216 + .7598784*i*	.843481
-.3661216 - .7598784*i*	.843481
-.1496883 + .8266237*i*	.840067
-.1496883 - .8266237*i*	.840067
-.6527417 + .517286*i*	.83286
-.6527417 - .517286*i*	.83286
.07778165 + .81918849*i*	.822869
.07778165 - .81918849*i*	.822869
-.7686419 + .2811759*i*	.818456
-.7686419 - .2811759*i*	.818456
-.2706591 + .77087033*i*	.817005
-.2706591 - .77087033*i*	.817005
-.665967 + .4459625*i*	.801495
-.665967 - .4459625*i*	.801495
-.7624419 + .086992173*i*	.767389
-.7624419 - .086992173*i*	.767389
-.6041553 + .4719052*i*	.766615
-.6041553 - .4719052*i*	.766615
.7145148	.714515
.245324 + .62848223*i*	.674666
.245324 - .62848223*i*	.674666
.2372283 + .3921062*i*	.458284
.2372283 - .3921062*i*	.458284
.3645412	.364541
-.2915118	.291512

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

4. Lagrange multiplier test for autocorrelation

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	26.0350	25	0.40573
2	17.6617	25	0.85641
3	30.8704	25	0.19334
4	28.6127	25	0.28043
5	41.7563	25	0.01909
6	51.9338	25	0.00122
7	16.2873	25	0.90600
8	17.6844	25	0.85549
9	33.9053	25	0.10995
10	25.8316	25	0.41663
11	46.6265	25	0.00542
12	36.3289	25	0.06676

H0: no autocorrelation at lag order