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Course of Econometric Theory

The impact of oil and gas price shocks on Italian GDP and IPI: an SVAR and SVEC approach

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1 Introduction

Since the oil embargo proclaimed by the Organization of Petroleum Exporting Countries (OPEC) in 1973, the rapid and unexpected increases in oil prices have been the subject of great interest for economists. Given the enormous scale of the national recessions that occurred in the seventies, the controversy about the macroeconomic determinants of oil shocks could arouse amazement: why should we doubt the capacity of oil shocks to determine significant variations in Gross Domestic Product (GDP) observed in so many countries? Arguably, the primary basis of this debate lies in the minimal impact on GDP that oil and its close substitutes covered in most cases before 1973. Moreover, what happened in 1973 could not be considered a pure case study due to the concomitant emergence of a plurality of other relevant factors. To mention a few, at the time of 1973, the world economy had just abandoned the fixed exchange rate sanctioned by the Bretton Woods agreements, and some countries were on the verge of recession. Thus, separating these effects to determine the weight of oil shocks on changes in GDP, the unemployment rate, and other recession indicators after 1973 has been technically complex and led to the broad economic literature that will be intensely debated in the next section of this thesis.

The scepticism regarding the relation between macroeconomic output deterioration and oil price shocks was enhanced in Bohi (1989). From his study, no link emerged between the changes in oil prices and employment in the productive sectors considered at a three-digit breakdown level of the Standard Industrial Classification (SIC) system. Bohi's work, together with the identification of asymmetrical macroeconomic effects to oil price variations highlighted in Mork (1989), moved the researchers to focus on the transmission mechanism through which oil shocks cause, or contribute to, macroeconomic recessions.

Different transmission mechanisms have been identified and studied as (a) the labour market, (b) the use of capital goods, (c) changes in interest rates, (d) investment freeze, and (e) sectoral shocks. More precisely, the analysis of labour market mechanisms has used the concept of aggregated and allocative channels. The former concern the traditional macroeconomic mechanisms of potential effects on output, income transfers and wages' rigidity, while the latter are related to the correspondence between the level of use of inputs desired by the enterprises and the one used. In this regard, Keane and Prasad (1996) found out that in the United States oil price increases have reduced the real wages of all workers, but they have increased the relative salaries of qualified ones. Moreover, they have shown that changes in the price of oil do not induce a shift of workers towards the sectors that recorded the relative wage increase. This result can be partially explained by considering that oil shocks may change the optimal technologies employed in industries in a way that destroys some of the workers' minor tangible skills, causing them to seek employment in industries that require skills below the apparent level of human capital.

Several studies have shown that interest rates react to oil price increases. For instance, Balke (2002) has identified asymmetric reactions of interest rates in the short and long term to distinguish positive and negative oil shocks. The evidence exposed in Balke's study signal the existence of a preference in the interest differential between the commercial papers from four to six months and Treasury Bills at six months. This relation may suggest the presence of a desire for security if increases in oil prices raise uncertainty in the economy.

Last, the sectoral shock hypothesis (Lilien, 1982; Hamilton, 1988), also known as the hypothesis of employment dispersion, supposes that one shock with differentiated effects on different sectors has a more significant impact on aggregate unemployment. The dispersion increase of sectoral shocks implies a higher labour reallocation resulting in a broader overall unemployment rate. The reallocation effects of any price shock, positive or negative, can cause increases in the creation or destruction of jobs. Thus, the time needed for resources to be reabsorbed elsewhere leads to decreased aggregate employment.

The purpose of this thesis is to analyse and understand the dynamic effects of shocks in Crude oil Brent (COB) and Natural gas Dutch TTF (TTF) prices on Italian Gross Domestic Product and Industrial Production Index (IPI) through the last two decades. The first two variables are acquired from the public database of the World Bank, and their values are expressed in dollars and nominal terms. At the same time, the last two measures are obtained directly from the National Statistical Institute of Italy (ISTAT). To capture the impact of the two energy commodities price shocks on our macroeconomic variables, we include some control variables such as the World Trade Volume (WTV), the Euro-Dollar Exchange Rate (EXCH), the 3-moth Euribor interest rate (ERB), and the Italian inflation level (INF). Two different econometric models generate the results obtained from our study. The first part of the analysis employs a Structural vector autoregression (SVAR) approach, while the second part examinates the variables' relationship through a vector error correction (VEC) model. We consider this second type of econometric model due to cointegration among our variables. Indeed, VEC models, differently from VARs, can capture variables' long-run relationships that are possibly lost in VAR analyses. Both models are estimated on quarterly data over a sample period from 2000 Q1 to 2021 Q4. The identification issue is solved through the Cholesky decomposition of the variance-covariance matrix of VAR and VEC residuals, ordering first, in the Cholesky factor, the energy commodity price, the control variables in the order they have been presented above, and last the output variables (alternatively GDP or IPI). The principal outcomes of our analysis are the impulse responses of the output variables to a two standard deviation shock in the two energy commodities prices. Then, we disclose some variance error decomposition analysis to illustrate how much information each variable in the system contributes helps to explain the output variables' total variance.

Our findings on the IRFs analysis exhibit, in general, a clear relationship between the variables of interest. They present positive Crude oil Brent or Natural gas Dutch TTF price shocks as harming the Italian Gross Domestic Product and Industrial Production Index. However, the impulse response functions of our two models capture the relationships at different levels. The impact of COB price shocks on our macroeconomic variables is more tenuous in IRFs estimated using a SVAR than a SVEC approach. Moreover, the former shows a negative effect that does not remain statistically significant for a lasting period. On the contrary, the IRFs obtained from the SVEC analysis report a more persistent and intense negative effect due to a COB price increase. The variation between the two models' IRFs continues if we consider the impact analysis of Dutch TTF price shock on our output variables. Here, the diversity between the two models' results is evident, especially considering the IRFs of GDP to TTF. In summary, with a two standard deviation shock in COB price, the Industrial Production Index registers a more significant negative impact following VAR and VEC IRFs. The former estimates a negative impact from lag 3 to 10, with the highest record of -0,7% in lag 5, while the latter returns a more severe effect. Regarding the IRFs of GDP to COB price shocks, we observe a convincing similarity among the SVAR and SVEC results showing a resemblant path in the first five lags. Thus, the latter persists on its negative path leading to a significant and delayed impact on GDP, oscillating between -0,62% and -0,92% from lag 6 to 12. For what concerns the analysis of the effect of Dutch TTF price shocks on our macroeconomic variables, we observe a similar trend on both VAR and VEC IRFs in the case of IPI. Indeed, both show a rapid decrease after initial positive effects, bringing a negative impact since lag 3 and 4, respectively. Then, while the VAR response turns gradually back to zero, the VEC IRF endures manifesting a relevant long-run negative effect of TTF price shocks on the Industrial Production Index with a maximum negative impact of -0,74% in lag 7. Finally, we observe a feebler correspondence between the models' IRFs in our last case, with the VAR results indicating a scarce negative effect on GDP in contrast with VEC ones. Last, our variance decomposition results align with what was presented until now. We found that both Crude oil Brent and Dutch TTF variances explain a significant portion of the total variance of our macroeconomic variables. More precisely, our VAR results show that COB's variance can explain, on average, the 22,9% and 15,1% of IPI and GDP total variance, respectively. Remaining on our VAR variance decomposition results, we observe that TTF's variance also presents an informative power. Indeed, the IPI and GDP total variances are explained by the gas price variance of 9,80% and 8,64% over 12 quarters. The VEC equivalent analyses do not show remarkable variations from these results, remaining close to these average values.

The remainder of this thesis is structured as follows; Section 2 presents a literature review on the topic of the two energy commodities considered and their economy price shock implications. Section 3 describes the VAR and VEC models employed in the analysis. In Section 4, we present the data used in the study, while in Section 5, the empirical analysis and results are shown and described. Finally, Section 6 concludes and offers some reflections about directions for further research.

2 Literature review

In both empirical and theoretical literature, it has been copiously debated that energy source shocks, especially the ones referring to oil, exhibit an adverse impact on multiple macroeconomic activities (Aguriar-Conraria and Soares, 2011; Iwayemi and Fowowe, 2011, Milani, 2009, Holmes and Wang, 2003). For example, Reyenolds and Kolodziej (2008) show that the fall in the Gross Domestic Product of the former Soviet Union was Granger-caused by the downturn in oil production. This phenomenon can be partially explained by observing the production and operation costs co-movements with energy prices. These costs are strongly related to the price of energy since it is an irreplaceable intermediate good to produce electricity.

Harmful economic effects may arise from significant energy price changes, increasing or decreasing. For example, price volatility might induce business investment procrastination by strengthening uncertainty or inducing costly sectoral resource reallocation. Bernanke (1983) grants a theoretical illustration of the uncertainty channel. The economist pointed out that when projects are irreversible, agents must make investment timing decisions that trade off the extra returns from early commitment against the benefits of increased information gained by waiting. Indeed, the uncertainty on the energy sources price may be followed by an increase in the option value for the investment delay, which shrinks the incentive to invest. For instance, firms commonly face this critical decision when choosing whether to implement an energy-efficient or inefficient capital. However, such disruption does not only affect firms' decisions. Uncertainty about future energy prices also shortens consumers' spending on cars, housing, and investment goods (Hamilton, 2003). The costly sectoral resources reallocation channel has been examined by Ferderer (1996), showing that oil price volatility, measured by monthly standard deviations of daily oil prices, helps to forecast aggregate output movement in the U.S.

The real economy suffers from changes in oil prices from both the supply and demand side (Jimenez-Rodriguez and Sanchez, 2005). As stated before, it is observable a consistent reflection of the increase in oil price into higher production cost. From the supply side, the investment demand is negatively affected by the increasing uncertainty related to the oil price movements and the decreasing rate of return on investment eroded by the new cost level. Simultaneously with the supply, the consumption demand shrinks due to the impact of higher production costs on the final product price. The robust transmission mechanism of oil price shock to the inflation path does not leave the other economic variables unaltered. Inflationary pressure may cause a drop in demand and this, in turn, results in a production fall, which can create unemployment (Loungani, 1986). Moreover, such a relationship between oil price and employment does not hold only for industrial production but can also be enlarged to the agricultural one (Uri, 1995).

Two consecutive oil shocks in the early 1970s brought some economists to examine the impact of shocks to oil price levels on economic activities. Hamilton (1983) can be seen as a pioneer study to understand such relationships better. His study examines the behaviour of oil prices and the output of the U.S. economy over 1948-1981. The analysis concludes that every U.S. recession between World War II and 1973 (except the 1960-1961 recession) has been preceded by a drastic increase in the price of crude petroleum. Hamilton (1988) has observed the costly sectoral resource allocation impediment through a multi-sector analysis. The principal cost source that emerged from the study involves the strong aversion of workers of the adversely affected sectors to search for new job positions. It was shown that relative price shocks could reduce aggregate employment leading the affected workers to remain unemployed while waiting for an optimal condition to be restored in their sector. Friedman (1977) expresses similar beliefs on the relationship between the natural rate of unemployment and inflation level uncertainty. The economist opined that the latter could increment the former through a decreased allocative efficiency and, hence, a decline in output. From Friedman's belief, it is possible to draw a relevant consequential conclusion. If the uncertainty about inflation can be considered responsible for the decreasing production, then similar effects may be induced on output by the uncertainty of the oil price level.

Energy shocks have also posed policymakers with the difficult challenge of balancing the trade-off between high inflation and higher unemployment. Killian (2009) proposes a structural VAR model for the global crude oil market and its interaction with global demand for industrial commodities. Three different shocks to the global crude oil market have been identified in his study: a crude oil supply shock, a shock to the global demand for all industrial commodities, and a demand shock that is specific to all industrial commodities. Analysing the impact of oil price shock on the U.S. stock market, he found that the implications of higher oil prices for U.S. real GDP and Consumer Price Index (CPI) inflation depend on the cause of oil price increase. Killian (2009) found that an increases in the precautionary demand for crude oil causes an immediate, persistent, and significant increase in the actual price of crude oil; an increase in the aggregate demand for industrial commodities causes a delayed but sustained rise in the actual price of oil; and that crude oil production disruption causes a slight and transitory increase in the actual price of oil with in the first year.

However, recent years have shown how the use of natural gas as an alternative energy source from oil is spreading. A partial justification for this trend can be found in the constant increase of energy consumption in the world and the necessity to control for two significant threats of environmental pollution: the climate change phenomenon and accelerated consumption growth of non-renewable energy sources (Energy Balance, 2008). In addition, Natural gas has been chosen more frequently for industrial and electricity generation thanks to its relative fuel efficiency, low emissions, quick construction timelines, and capital costs. Since this trend seems to continue until 2035 (EIA, 2010), it is significant to investigate the empirical relationship between Natural gas prices and economic growth. To the best of our knowledge, there appears to be far less research on the connection between Natural gas prices and macroeconomic activity. However, it could be realistic to assume that rising Natural gas prices will likely have less of an overall impact than growing oil prices because the total amount of natural gas consumed in the economy is around half that of petroleum. Early work in this field was published in a special issue of Contemporary Policy Issues in October 1982. Three studies investigated the impact of removing Natural gas price regulations on (i) regional economic activity (Leone, 1982), (ii) income distribution between households and providers (Stockfisch, 1982), and (iii) inflation (Ott and Tatom, 1982a). The studies' overall conclusion was that the projected impacts of Natural gas deregulation (higher prices, greater inflation, and declining real incomes) were not likely to be substantial. The Energy Modelling Forum (1987) discovered that a 10% rise in natural gas prices had nearly the same effect on real U.S. GDP growth (two years after the shock) as a 20% increase in oil prices. According to the median outcome of 11 models implemented, a 50% oil shock lowered real GDP by around 1.5% after one year and by slightly less than 3% by the end of two years.

Finally, Cullen, Friedberg, and Wolfram (2005) investigated the impact of anticipated and unexpected shocks to household disposable income resulting from increasing energy expenditures on household consumption at the disaggregated level. Energy price rises, they discovered, reduce consumption among lower-income households, but only when the increase is unexpected. To conclude, Arman and Zare (2005) implemented a vector error correction model, finding a unidirectional causality from economic growth to Natural gas consumption for 1967-2002. Nevertheless, several studies focused on investigating the relationship between the real GDP and Natural gas consumption, founding a bidirectional causality using a VEC model and a comparable time window (Zemani, 2007; Asgharpour et al. 2009).

3 VAR and VEC models

Fundamentally, a VAR model is a multivariate time series model composed of a system of linear equations that represents the relationships between multiple variables. The model is defined to allow the variable's current observations to be related to its and other variables' past values in the system. Introduced in the seminal work "*Macroeconomics and Reality*" of Sims (1980), the VAR methodology is traditionally used in finance and econometrics to perform fundamental modelling goals such as forecasting, structural inference, and policy analysis. A relevant advantage of VAR models against univariate autoregressive models lies in the former's possibility to allow feedback between the variables in the model. A specific type of VAR model is the structural one (SVAR). Its peculiarity consists of restrictions that allow the identification of causal relationships that can be used to model and forecast the impacts of individual shocks. However, VARs were thought for stationary variables only. Therefore, differencing the series to make them stationary is one solution, but at the cost of ignoring possibly relevant "long-run" relationships between the levels. A further step in this direction was accomplished by Davidson, Hendry, Srba Yeo (1978), Hendry von Ungern-Sternberg (1981), and Salmon (1982). They extensively discussed a slightly different type of econometric model known as the error correction model in which the changes in a variable depend on the deviations from some equilibrium relation. This type of model shows a strict relation to the concept of cointegration explored by Granger (1981), Engel and Granger (1987), and Johansen (1995). If cointegration between variables is found, then a VEC model should be considered since it allows to combine levels and differences.

3.1 Introduction to VAR models

Predictions of economic variables constitute a key aspect for policymakers in the selection process between alternative courses of action. To acquire critical information about the future development of a variable, it is often useful to analyse its and other past variables' values contained in their corresponding time series. Embracing what has been accurately explained by Lutkepohl (2005), it is plausible to express this forecasting approach as follows. Let us focus for a moment on the value of the variable of interest y_t, with $t = 1, ..., T$. Then, a forecast for period $T + h$ may have the form

$$\hat{y}_{T+h} = f\,(y_T,\ y_{T-1}, ...), \tag{1}$$

where $f(.)$ stands for some appropriate function, frequently linear, of the past observations $y_T, y_{T-1}....$ Given the smooth application of linear functions and the simpleness of dealing with them, it may be helpful to begin with a forecast that is linear functions of past observations. Suppose that to predict the value of y_{T+1}, hence $h = 1$, only a finite number of p past y values is used. Then the prediction formula would appear as follow

$$\hat{y}_{T+1} = v + \alpha_1 y_T + \alpha_2 y_{T-1} + \ldots + \alpha_p y_{T-p+1}. \tag{2}$$

Since the computation of the predicted value, $\hat{y}_{T+1}$ may not return the true value, y_{T+1}, it is essential to define a forecast error $u_{T+1} := y_{T+1} = \hat{y}_{T+1}$ and to include it in the prediction formula so that (2) becomes

$$y_{T+1} = \hat{y}_{T+1} + u_{T+1} = \ v + \alpha_1 y_T + \alpha_2 y_{T-1} + \ldots + \ \alpha_p y_{T-p+1} + \ u_{T+1}. \tag{3}$$

The last step required to move ahead from the prediction formula above to an autoregressive process consists of assuming that our numbers are realisations of random variables with the same data generation law prevailing in each period T. This would allow us to reformulate the (3) as follow

$$y_t = v + \ \alpha_1 y_{t-1} + \ldots + \ \alpha_p y_{t-p} + \ u_t, \tag{4}$$

where the quantities $y_t, y_{t-1}, ..., y_{t-p}$ and u_t are now random variables and where we assume that the forecast errors u_t for different periods are uncorrelated.

Despite this, it is regularly noticed that the value of one variable is not independent from the present and past values of other variables since they may possess additional explanatory power. Then, considering them would imply the equation (1) to assume a more general form

$$\hat{y}_{k,T+h} = f_k\left(y_{1,T}, \ldots, y_{K,T}, y_{1,T-1}, \ldots, y_{K,\ T-1}, \ldots\right), \tag{5}$$

where y_{kt} is a set of time series, with $k = 1, ..., K$ and $t = 1, ..., T$, called a multiple time series. Following the exact reasoning used for the single variable case, (2) can be augmented to consider a multiple time series

$$\begin{aligned}\hat{y}_{k,T+1} = v + \alpha_{k1,1} y_{1,T} + \alpha_{k2,1} y_{2,T} + \ldots + \alpha_{kK,1} y_{K,\ T} + \ldots + \alpha_{k1,p} y_{1,T-p+1} \\ + \ldots + \alpha_{kK,p} y_{K,T-p+1}, \qquad k = 1,\ \ldots, K.\end{aligned}$$

It may be convenient to simplify the notation above using a more compact formula with the help of matrices and vectors.

$$\hat{y}_{T+1} = v + A_1 y_T + \ldots + A_p y_{T-p+1},$$

where $y_t := (y_{1t}, ..., y_{Kt})', \hat{y}_t := (\hat{y}_{1t}, ..., \hat{y}_{Kt})', v := (v_1, ..., v_K)'$ and $A_i := \begin{bmatrix} \alpha_{11,i} & \cdots & \alpha_{1K,i} \\ \vdots & \ddots & \vdots \\ \alpha_{K1,i} & \cdots & \alpha_{KK,i} \end{bmatrix}$.

Then if the y_ts are regarded as random vectors, this predictor is just the optimal forecast obtained from a vector autoregressive model of the form

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \tag{6}$$

where the $u_t = (u_{1t}, ..., \ u_{Kt})'$ is a K-dimensional *white noise* or *innovation process*, that is $E\,(u_t) = 0$, $E(u_t u_t') =$ and $E(u_t u'_s) = 0$ for $s \neq t$.

3.2 Properties of VAR processes

3.2.1 Stability

Considering a VAR(p) model (VAR model of order p), a bunch of properties and assumptions must be respected to proceed with the analysis. To visualise a VAR(p) it is sufficient to contemplate the equation (6). The main property needed to be checked in a VAR(p) analysis refers to its stability. However, to investigate this implication, it may be helpful to start from a VAR(1) model of the form

$$y_t = v + A_1 y_{t-1} + u_t. \tag{7}$$

It is reasonable to assume that this generation mechanism starts at some time t = 1, say, we get

$$y_1 = v + A_1 y_0 + u_1$$

$$y_2 = v + A_1 y_1 + u_2 = v + A_1(v + A_1 y_0 + u_1) + u_2 = (I_K + A_1)v + A_1^2 y_0 + A_1 y_0 + A_1 u_1 + u_2$$

$$\vdots$$

$$y_t = (I_K + A_1 + ... + A_1^{t-1})v + A_1^{t-1} y_0 + \sum_{i=0}^{t-1} A_1^i u_{t-i}. \tag{8}$$

From the equations above, it is notable that the vectors $y_1, ..., y_t$ and their joint distributions are determined only by $y_0, u_1, ..., u_t$. Hence, it may look reasonable to derive the following VAR(1) model from (8)

$$y_t = v + A_1 y_{t-1} + u_t = (I_K + A_1 + ... + A_1^j)v + A_1^{j+1} y_{t-j-1} + \sum_{i=0}^{j} A_1^i u_{t-i}. \tag{9}$$

Since A_t^{j+1} converges to zero as $j \to \infty$, we can ignore the term $A_t^{j-1} y_{t-j-1}$ in the limit. Moreover,

$$(I_K + A_1 + A_1^j)v \to j \to \infty (I_K - A_1)^{-1} v := \mu.$$

Hence, if all eigenvalues of A_1 have modulus less than 1, by saying that y_t is the VAR(1) process in equation (7), we mean that y_t is the well-defined stochastic process

$$y_t = \mu + \sum_{i=0}^{\infty} A_1^i u_{t-i} \qquad t = 0, \pm 1, \pm 2. \tag{10}$$

The eigenvalues condition imposed above makes the VAR(1) a stable process. This rule can be expressed equivalently as

$$\det(I_K - \ A_1 z) \ \neq \ 0 \qquad for \ |z| \ \leq \ 1.$$

What has been said above can be extended smoothly to VAR(p) processes, with $p > 1$, since any VAR(p) process can be expressed in VAR(1) form. The corresponding Kp-dimensional VAR(1) of a general VAR(p), as the one in (7), would appear as follow

$$Y_t = v + A Y_{t-1} + U_t, \tag{11}$$

where

$$Y_t = \begin{bmatrix} y_t \\ y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix},$$

$$v = \begin{bmatrix} v \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

$$A = \nu + \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_K & 0 & \cdots & 0 & 0 \\ 0 & I_K & \vdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_K & 0 \end{bmatrix},$$

$$u_t = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

The stability condition for the process specified above recalls the one already defined for the VAR(1) process. Actually, Y_t is stable if

$$\det(I_K - Az) \neq 0 \quad \text{for} |z| \leq \ 1.$$

3.2.2 Stationarity

As the VAR(1) considered until now, a stochastic process is stationary if its first and second moments are time-invariant. More precisely, a stochastic process can be stationary in two different strength levels. Weak stationarity is verified if and only if all the couple of random variables $W_t^2 = (y_t, y_{t+1})$ present first and second moment constant in time. In other words, we could have said that a stochastic process y_t is weakly stationary if

$$E(y_t) = \mu \quad \text{for all } t$$

and

$$E[(y_t - \mu)(y_{t-h} - \mu)'] = \Gamma y(h) = \Gamma y(-h)' \quad \text{for all } t \text{ and } h = 0, 1, 2, ...$$

Instead, a stochastic process must satisfy stricter requirements to be depicted as strongly stationary. Let us consider a process's window with an extent equal to k. Then, we get a random variable with k dimensions $W_t^k = (y_t, ..., y_{t+k-1})$. Its density function may depend on t. However, if it is not verified, the W_k distribution will be equal to the one of W_{t+1}^k, W_{t+2}^k.... In that case, a stochastic process is considered strongly stationary if what just said remains valid for all values of k. In other words, a stochastic process is strongly stationary if the distributional characteristics of all the marginals remain constant in time.

It is pertinent to stress a fundamental relationship between the two properties. Indeed, to verify the stationarity of a stochastic process, it is sufficient to prove its stability. However, such a relationship does not hold conversely. In other words, a stable VAR(p) is stationary, while an unstable process is not necessarily nonstationary.

3.3 Structural VAR analysis

Structural vector autoregressive models were introduced by Sims (1980). Although VAR models constitute an advantageous approach to modelling multivariate time series, they present a critical drawback in their standard form, missing the possibility to describe the contemporaneous relationship between the analysed variables. This concern appears crucial especially in the impulse response analysis derived from such models. The critical issue with simple VAR models lies in the impossibility of disentangling what impact a change in one variable will have on the others in the model. Indeed, a simple VAR model explains each variable as a function of its own and other variables' past observations without admitting structural restrictions. On top of that, the SVAR methodology has been widely used in applied time series research since it allows, among other possible applications, to examine the causal relationships between variables and the impact that individual shocks will have on other variables.

To get into the SVAR model mechanism, let us start from the following bivariate model with two endogenous variables, y_1 and y_2.

$$\begin{aligned} y_{1,t} &= \varphi_{11} y_{1,t-1} + \varphi_{12} y_{2,t-1} + b_{11}\varepsilon_{1,t} + b_{12}\varepsilon_{2,t} \\ y_{2,t} &= \varphi_{21} y_{1,t-1} + \varphi_{22} y_{2,t-1} + b_{21}\varepsilon_{1,t} + b_{22}\varepsilon_{2,t} \end{aligned} \tag{12}$$

where $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are separate contemporaneous shocks to each variable. These shocks are zero-mean white noise processes. Thus, the structural impacts of the shocks on the endogenous variable in question should be captured by the matrix

$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}.$$

Unfortunately, we cannot estimate B since $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are unobserved. Then, the first step required to solve this issue is to combine the shock components of the bivariate model (12)

$$\begin{aligned} u_{1,t} &= b_{11}\varepsilon_{1,t} + b_{12}\varepsilon_{2,t} \\ u_{2,t} &= b_{21}\varepsilon_{1,t} + b_{22}\varepsilon_{2,t} \end{aligned} \tag{13}$$

so that we can rewrite the two-equation system on its reduced VAR form

$$\begin{aligned} y_{1,t} &= \varphi_{11} y_{1,t-1} + \varphi_{12} y_{2,t-1} + u_{1,t} \\ y_{2,t} &= \varphi_{21} y_{1,t-1} + \varphi_{22} y_{2,t-1} + u_{2,t} \end{aligned} \tag{14}$$

The unknown parameters can be estimated through *OLS*, but the residuals from these estimates will still not return the impacts of the shocks $\varepsilon_{1,\ t}$ and $\varepsilon_{2,\ t}$ on y_1 and y_2. That is because the SVAR model presents an identification problem that requires restrictions to be solved. To see the issue, let us begin from the matrix representation of (13)

$$U_t = B\varepsilon_t.$$

We can procure the identity

$$\Sigma_u = BB',$$

where σ_u represents the covariance matrix of the reduced form residuals

$$\Sigma_u = E[u_t u't] = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix}.$$

That implies $\Sigma_u = BB\prime$ is equivalent to

$$\begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

or

$$\begin{aligned} \sigma_{11}^2 &= b_{11}^2 + b_{12}^2 \\ \sigma_{12}^2 &= b_{11}b_{21} + b_{12}b_{22} \\ \sigma_{21}^2 &= b_{11}b_{21} + b_{12}b_{22} \\ \sigma_{22}^2 &= b_{21}^2 + b_{22}^2 \end{aligned}$$

Now it should be clear that our model is under-identified since $\sigma_{12}^2 = \sigma_{21}^2$, and we remain with only three unique equations but four unknown terms. More equations are required to solve this problem, resulting in restrictions. Cholesky identification may be considered the most used restriction. This identification scheme assumes that some shocks have no contemporaneous effect on one or more of the endogenous variables. For example, assuming shock to y_2 has no contemporaneous impact on y_1, this would imply that $b_{12} = 0$. In matrix form, this assumption would appear as follow

$$B = \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix}.$$

Since it is possible to order the variables such that the B matrix is lower triangular, we can use the Cholesky decomposition of Σ_u for estimation.

Now that SVAR models have been introduced, we can proceed to the analysis of the different techniques disposable to interpret the results returned by the model and capture all the information available among the set of variables.

3.3.1 Impulse response analysis

One of the most required final analysis results is the response of one variable to an impulse in another variable in a system that involves several different variables. Also known as multiplier analysis, impulse response analysis means to trace out the effect of an exogenous shock or innovation in one of the variables on some or all the other variables.

To approach this type of analysis, it may be reasonable to consider a simplified example with only three variables y_1, y_2, and y_3. To isolate the effect of a one-unit innovation in y_1 on the other two variables, suppose that all of them hit their mean value prior to time $t = 0$, $y_t = \mu$ for $t < 0$. Then, if the shock occurs in period $t = 0$, that is $u_{1,0} = 1$, it is possible to trace out what happens to the system during periods $t = 1, 2, ...$ if no other shocks take place.

Supposing the mean value to be equal to 0 in $t = 0$, the VAR(1) would appear as follow

$$y_t = A_1 y_{t-1} + u_t.$$

Then, tracing a unit shock in the first variable in period $t = 0$, it turns out that the unit innovation effect $y_i = (y_{1,i}, y_{2,i}, y_{3,i})'$ is just the first column of A_1^i. Equivalently, the matrix A_1 can estimate the unit shock effect in y_2 (y_3) at $t = 0$ on the other variables after i periods. In this case, it would be necessary to concentrate on the second (third) column of A_1^i. It may be more evident now that the elements of A_1^i represent the effects of unit shocks system's variables after i periods. Therefore, they are called *impulse responses* or *dynamic multipliers.*

The result above holds more generally for higher-order VAR(p) processes. Referring to the VAR(1) form for a generic VAR(p), (11), with the only exception on v fixed equal to 0, the results follow immediately. The matrix's columns do not anymore represent the impulse response elements, but they are represented by the elements of the upper left-hand $(K \times K)$ block of A^i, named Φ_i. More precisely, the $jk-th$ element of this block represents the reaction of the $j - th$ variable of the system to a unit shock in variable k, i periods ago, provided that the effect is not contaminated by other shocks in the system.

Sometimes it might be of interest not only to investigate the single-period effects of a shock but its accumulated effect over several periods. For instance, the $k - th$ column of $\Psi_n := \sum_{i=0}^{n} \Phi_i$ contains the accumulated responses over n periods to a unit shock in the $k - th$ variable of the system in $t = 0$. Extending the sum to infinity, we get the matrix of *long-run effects* or *total multipliers.*

3.3.2 Forecast error variance decomposition

Forecast error variance decomposition (FEVD) is a statistical method used in multivariate analysis to interpret the relations between variables described by VAR and VEC models. The variance decomposition helps to identify the amount of information each variable contributes to the others in the model. In other words, it decomposes the variance of the forecast error into the contributions from the exogenous shocks in the system. It effectively demonstrates how vital a shock is in explaining the variations of the variables in the model and how the relevance of this shock is persistent in time. Indeed, some shocks may not be responsible for variations in the short run but may cause longer-term fluctuations.

From equation (6), with $v = 0$ for simplifying the matter, the h steps ahead forecast at origin t can be obtained recursively for $h = 1, 2, ...,$ as

$$y_{t+h|t} = A_1 y_{t+h-1|t} + ... + A_p y_{t+h-p|t}.$$

Thus, the forecast error turns out to be

$$y_{t+h} - y_{t+h|t} = u_{t+h} + \sum_{i=1}^{h-1} \phi_i u_{t+h-i} \sim \left(0,\ \Sigma_h = \Sigma_u + \sum_{i=1}^{h-1} \phi_i \Sigma_u \phi_i'\right),$$

where the ϕ_is are the coefficient matrices of the power series expansion $(I_K - A_1 z - ... - A_p z^p)^{-1} = I_K + \sum_{i=1}^{\infty} \phi_i z^i$. Supposing that the vector u_t can be decomposed in instantaneously uncorrelated innovations with economically meaningful interpretation, say $u_t = B\varepsilon_t$ with $\varepsilon_t \sim (0, I_K)$. Then, $\Sigma_u = BB'$ and the forecast error variance can be written as $\Sigma_h = \sum_{i=0}^{h-1} \Theta_i \Theta_i'$. Thus, naming the $(n, m)th$ element of Θ_j by $\theta_{nm,j}$, the forecast error variance of the $k - th$ element of the forecast error vector is seen to be

$$\sigma_k^2(h) = \sum_{j=0}^{h-1} \left(\theta_{k1,j}^2 + ... + \theta_{kK,j}^2\right) = \sum_{j=1}^{K} \left(\theta_{kj,0}^2 + ... + \theta_{kj,h-1}^2\right).$$

Finally, the term $\left(\theta_{kj,0}^2 + ... + \theta_{kj,h-1}^2\right)$ may be interpreted as the contribution of the jth innovation to the h-step forecast error variance of variable k. In addition, dividing the term by $\sigma_k^2(h)$ we obtain the percentage contribution of innovation j to the h-step forecast error variance of variable k (Lutkepohl, 2005).

3.4 Integrated and cointegrated processes

Despite the frequent use by econometricians of VAR processes, the stationarity property does not always allow a process to capture some main features of many economic time series. Thus, if we are principally interested in analysing the original variables (or their logarithms) rather than the rates of change, it is essential to work with models that accommodate the nonstationary features of the data. It is possible to achieve these results by relaxing the stationarity property of VAR processes. However, a VAR process can generate stochastic and deterministic trends if the determinantal polynomial of the VAR operator has roots on the unit circle. Before introducing a model that offers a convenient way to parameterise and specify the variables, inspecting the concept of the integrated and cointegrated processes may be helpful.

Starting from the former, assuming that all economic time series can be modelled through stationary stochastic processes is incorrect. Indeed, the majority present an undeniable trend in time, implying the unfeasibility to model them with the just cited vector autoregressive processes. Then, it is possible to observe the series from a different perspective. Supposing that the trend is growing linearly in time, it is plausible to represent the series through their first difference, y_t. Since the growth essay should reasonably fluctuate within a band, one can imagine representing the series y_t by means of a stationarity process with a perhaps nonzero mean. Thus, if Δy_t is stationary, it admits a Wold representation of the type:

$$\Delta y_t = \mu + C(L)u_t,$$

where μ is the average growth rate. It is possible to read this expression as the description of y_t as an ARMA process, where $A(L) = 1 - L$. Hence, the value of z for which $A(z) = 0$ is 1. Processes with unit roots are not stationary; therefore, y_t is not stationary, but it may be that its first difference is. In this case, y_t is said to be difference-stationarity (DS). Another frequently used expression is that y_t is an $I(1)$ process, which reads "*integrated of order one*", to say that y_t must be differentiated once to be stationary.

Moving to cointegration, it appears evident how many economic variables are affected by equilibrium relationships. Assume to collect the variables of interest in the vector $y_t = (y_{1t}, ..., y_{Kt})'$ and their long-run equilibrium relation as $y_t = \beta_1 y_{1t} + ... + \beta_K y_{Kt} = 0$, where $\beta = (\beta_1, ..., \beta_K)'$. Then, such a relationship may not be exactly satisfied. Indeed, we may have that $\beta' y_t = z_t$, where z_t is a stochastic variable representing the deviations from the equilibrium in any period. The fact that there is an equilibrium among y_ts does not exclude the possibility that they wander extensively as a group. Thus, they may be driven by a common stochastic trend.

To clarify matters, it may be helpful to follow the definition of cointegration introduced by Granger (1981) and Engle Granger (1987). The variable of our K-dimensional process y_t are called cointegrated of order $I(d, b)$, briefly, $y_t - CI(d, b)$, if all components of y_t are $I(d)$ and there exists a liner combination $z_t := y_t$ with $\beta = (\beta_1, ..., \beta_K)' \neq 0$ such that z_t is $I(d - b)$. Finally, A process consisting of cointegrated variables is called a cointegrated process, while the vector β is called a cointegration vector.

3.5 Introduction to VEC models

The concept of cointegration is strongly linked to error correction models that have been extensively discussed in the econometrics literature (see, e.g., Davidson, Hendry, Srba Yeo (1978), Hendry Von Ungern-Sternberg (1981), Salmon (1982)). Their main characteristics include the changes in a variable depending on the deviations from some equilibrium relation. Suppose, for example, to work with two variables that have an equilibrium relation of the form $y_{1t} = \beta_1 y_{2t}$ and that the changes in y_{1t} depend on the deviations from this equilibrium in period $t-1$,

$$\Delta y_{1t} = \alpha_1(y_{1,t-1} - \beta_1 y_{2,t-1}) + u_{1t}.$$

More general, an error correction model may foresee that y_{it} depends on previous changes in both variables. Thus, if a similar relationship may hold for y_{2t}, that would lead to the following model

$$\begin{aligned} \Delta y_{1t} &= \alpha_1(y_{1,t-1} - \beta_1 y_{2,t-1}) + \gamma_{11,1}\Delta y_{1,t-1} + \gamma_{12,1}\Delta y_{2,t-1} + u_{1t} \\ \Delta y_{2t} &= \alpha_2(y_{1,t-1} - \beta_1 y_{2,t-1}) + \gamma_{21,1}\Delta y_{1,t-1} + \gamma_{22,1}\Delta y_{2,t-1} + u_{2t}. \end{aligned} \tag{15}$$

Understanding the close relationship between the error correction models and the concept of cointegration may be simplified by assuming that y_{1t} and y_{2t} are both $I(1)$ variables. That would imply all terms in (15) involving Δy_{it} are stable. Moreover, u_{1t} and u_{2t} are also stable since they are white noise errors. In this way, with a simple rearrangement of the equation above, we obtain the following

$$\alpha_i(y_{1,t-1} - \beta_1 y_{2,t-1}) = \Delta y_{it} - \gamma_{i1,1}\Delta y_{1,t-1} - \gamma_{i2,1}\Delta y_{2,t-1} + u_{it}.$$

Because an unstable term cannot equal a stable process, it must be that the left-hand side of the equation is stable too. Hence, if $\alpha_1 \neq 0$ or $\alpha_2 \neq 0$, $y_{1t} = \beta_1 y_{2t}$ is stable and represents a cointegration relation.

The matrix notation of the model (15) can be written as

$$\Delta y_t = \alpha\beta' yt - 1 +_1 \Delta y_{t-1} + u_t$$

or

$$y_t - y_{t-1} = \alpha\beta' y_{t-1} - \mathbf{\Gamma_1}(y_{t-1} - y_{t-2}) + u_t, \tag{16}$$

where $y_t = (y_{1t}, y_{2t})', u_t = (u_{1t}, u_{2t})'$,

$$\alpha :== \begin{bmatrix} \alpha 1 \\ \alpha 2 \end{bmatrix}, \ \beta' := (1 -_1), \Gamma_1 := \begin{bmatrix} \gamma 11,1 & \gamma 12,1 \\ \gamma 21,1 & \gamma 22,1 \end{bmatrix}.$$

From (16) we can obtain a VAR(2) representation

$$y_t = (I_K + \Gamma_1 + \alpha\beta')y_{t-1} - \Gamma_1 y_{t-2} + u_t.$$

More generally, it is possible to see how cointegration can arise in K-dimensional VAR models. Consider the specific case in which all individual variables of the K-dimensional VAR(p) process

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \tag{17}$$

are $I(1)$ or $I(0)$ with $y_t = (y_{1t}, ..., y_{Kt})'$. This process is called *cointegrated of rank* r if

$$\Pi := -(I_K - A_1 - ... - A_p)$$

has rank r. Furthermore, Π can be written as a matrix product $\alpha\beta'$ with α and β being of dimension $(K \times r)$ and rank r. The matrix β is called the *cointegration matrix*, and α is sometimes called the *loading* *matrix.* If $r = 0$, Δy_t has a stable VAR(p 1) representation and, for $r = K$, $|I_K - A_1 - ... - A_p| = |-\Pi| \neq 0$; hence, the VAR operator has no unit roots, so y_t is a stable VAR(p) process.

Now it is possible to rewrite the (17) on its vector error correction model representation

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + ... + \Gamma_{p-1} \Delta y_{t-p+1} + u_t = \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + ... + \Gamma_{p-1} \Delta y_{t-p+1} + u_t,$$

where

$$\Gamma_i \coloneqq -(A_{i+1} + ... + A_p), \quad i \ = \ 1, ..., \ p-1.$$

4 Data

To capture the impact of oil and gas price shock on the Italian economy, the data employed are multiple quarterly time series over a time window of more than 20 years, from 2000 Q1 to 2021 Q4. The exogenous variables adopted to represent the price level trend of oil and gas are Crude oil Brent (COB) and Natural gas Dutch TTF (TTF), respectively. Then, the impact of a shock on those is observed in two output variables: Gross Domestic Product (GDP) and Industrial Production Index (IPI) for the Italian economy. To capture the proper relationship between COB and TTF price shocks and our output variables, the analysis entails four control variables: the World Trade Volume (WTV), the Euro-Dollar exchange rate (EXCH), the 3-month Euribor interest rate (ERB), and the Italian price level (INF). Therefore, we first inspect the two exogenous price variables to then move through the output and control variables of the analysis.

4.1 Energy commodities price

4.1.1 Crude oil Brent

The Brent field is an oil and gas field discovered in 1971 and located in the East Shetland Basin of the North Sea. It is owned by Shell Exploration & Production, who started the production on site in 1976. However, it began its climb only in 1979 when Brent Pipeline System, the biggest at the time, was concluded. The strategic proximity to Europe and its peculiar mix are the main characteristics of crude oil Brent, which has gradually become the dominant price reference in the oil market. Brent oil prices are quoted daily on the London Stock Exchange market and the ICE or Intercontinental Exchange market. Thus, its price depends on the purchases and sales of investors and, therefore, on speculation worldwide.

According to the World Bank's time series, COB prices have fluctuated dramatically over the last decade. There are mostly seven lengthy periods. The first, which lasted from 2006 to 2008, allowed Brent to achieve an all-time high of roughly 133,87$ per barrel. The economic crisis that followed in 2008 caused the price to plummet to 41,58$ in January 2009. Then, until May 2011, an immediate upward rebound occurred, reaching a high of approximately 120$ and lasting until 2014. COB fell precipitously in 2015, with a minimum peak of 30,80$. The price level then shows a slight rebound from 2016 to 2019, with a relative maximum of 80,47$. Finally, the COVID-19 pandemic in 2019-2020 abruptly ended this fifth phase, forcing the cessation of most economic activities. The pandemic shock caused a significant price drop, with a minimum peak of 23,34$. Finally, the economic recovery in 2021 caused Brent prices to return to pre-pandemic levels.

Figure 1: Time Series of Crude oil Brent ($ per Barrel)

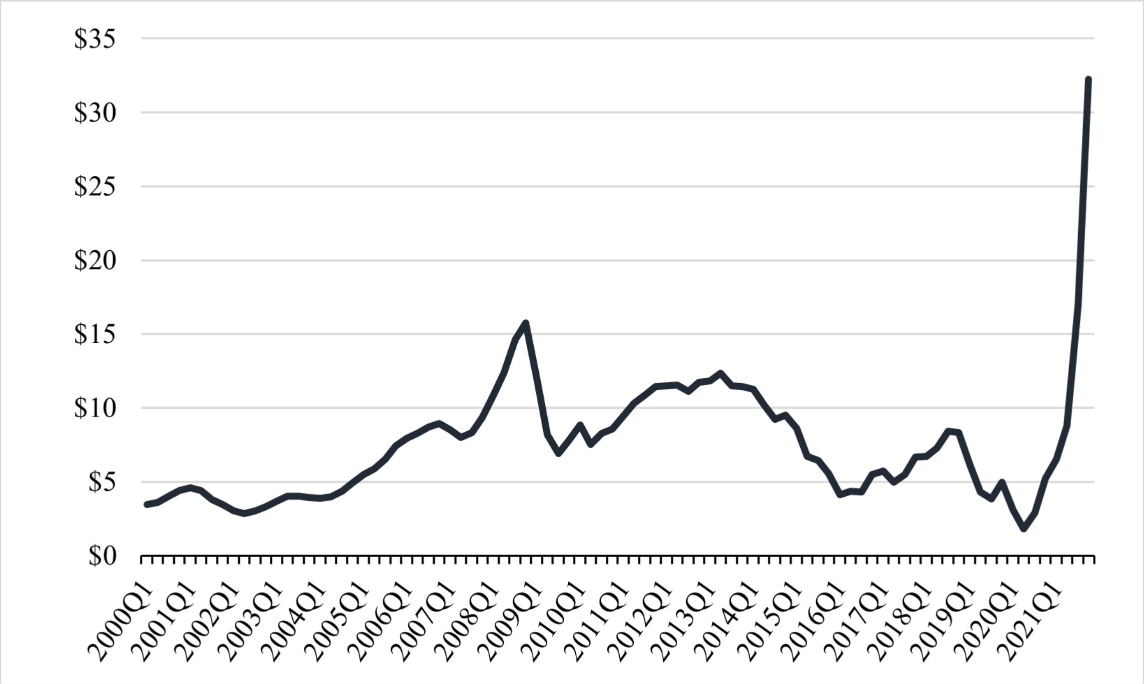
4.1.2 Natural gas Dutch TTF

Methane is the main component of natural gas, one of the most widely utilized energy sources. The largest known gas fields are in Qatar and Iran. However, these are not the countries having the most Natural gas reserves. Indeed, most of these reserves are in Russia, where the second and third largest gas fields in the world, Urengoy and Yamburg, are located.

Natural gas is traded on the world's major stock exchanges, with quotes on venues such as the New York Mercantile Exchange (NYMEX), the New York Mercantile Exchange (ICE), and the Title Transfer Facility (TTF). The latter is situated in the Netherlands and is regarded as the most liquid market by volume. As a result, it is used as a pricing reference at the European level. Every day, inside the TTF, Natural gas purchase and sale rates for various maturities are negotiated, which are subsequently reflected in the tariffs applied by the providers. The gas supplier will base its offer to the ultimate consumer on the pricing agreed in these marketplaces.

Four distinct eras may be seen when looking at the World Bank's TTF natural gas time series. The first period spans 2006 to 2008, when the price of TTF hit its historic high of over 15.50$. Then, as in the COB series, following the 2008 financial crisis, we saw a quick drop that ended in the first half of 2009 at 6,67$. The series is then distinguished by a lengthy period of low price volatility from 2009 to 2018, except for a decline in gas prices with a minimum peak of 3.91$ in March 2016. Finally, the last stage encompasses the COVID-19 pandemic years from 2019 to 2021. In these three years, we see a significant price reduction in 2020, with the lowest peak in May 2020 at 1,57$. However, the epidemic not only saw the lowest gas price level since 2000 but also the highest in its history, with a maximum value of 38,03$ in December 2021.

Figure 2: Time Series of Dutch TTF ($ per kWh)



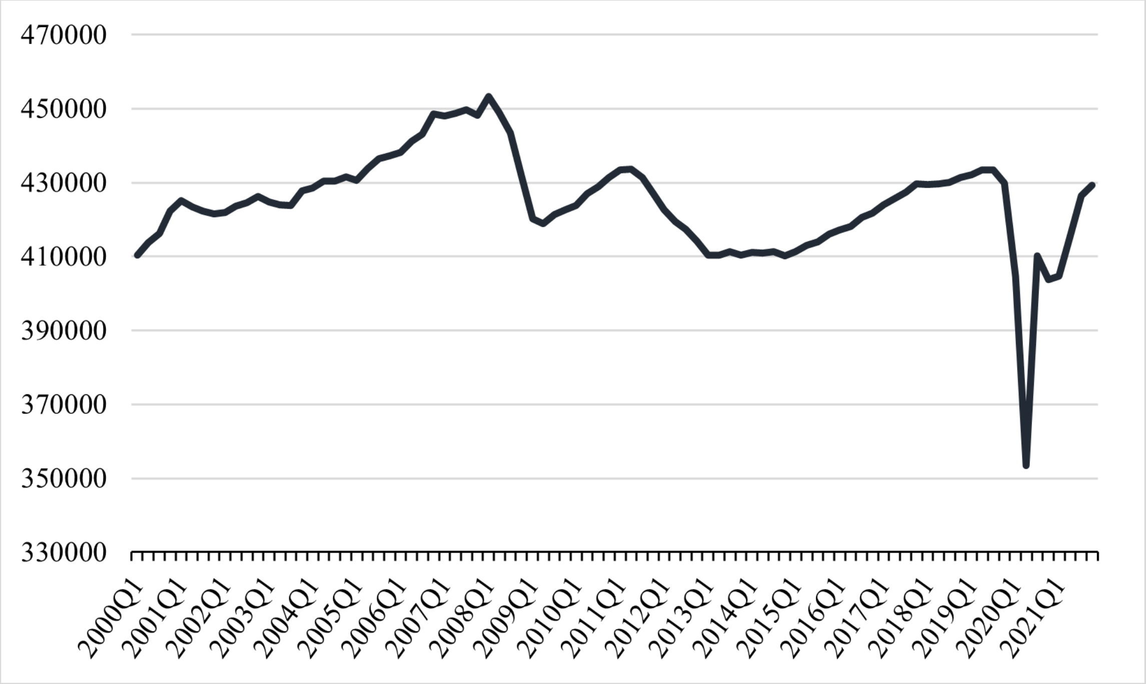
4.2 Output variables

The National Statistics Institute of Italy's database (ISTAT) was utilized to obtain information on the output variables. It is a public research body that deals with general censuses of population, services and industry, agriculture, sample surveys on families and general economic surveys at a national level. The ISTAT Gross Domestic Product at market prices represents the result of the production activity of resident-producing units. The Industrial Production Index refers exclusively to three NACE 2007 activity sectors: a) mining and quarrying, b) manufacturing, and c) electricity, gas, steam, and air conditioning supply. It describes the trend of Italian production by detecting production volumes. The survey of industrial production is performed monthly and carried out directly through a longitudinal panel of enterprises, generally with more than 20 employees, who report the monthly production volumes relating to a basket of elementary products.

The time series of the two variables are shown in Figures 3 and 4. Both variables had a limited decline beginning with the terrorist assault in 2001, which produced instability in financial markets and concern that may extend from the United States to all other markets and economies. However, rapid economic policy responses and collaboration among major countries and monetary authorities prevented a severe worldwide crisis from starting. The same cannot be said analysing the impact of the 2008 financial crisis, where the failure of Lehman Brothers overwhelmed the international economy. The most challenging year for Italy was 2009, when the GDP marked a contraction of 5%, and the IPI decreased by almost 31 points. The years following the 2008 financial crisis show a consistent pattern for the two variables. In 2012, international speculators attacked Italy's sovereign bonds, indicating a considerable and persistent decline in both macroeconomic variables until 2015. Finally, the time series shows the severe economic impact of the COVID-19 epidemic on the Italian economy. The repercussions are principally visible in 2020, with the GDP contracting by 8.9% and the IPI falling by 25,4 points in only two quarters.

Figure 3: Time Series of the Industrial Production Index (with 2010=100)

Figure 4: Time Series of the Gross Domestic Product (Mln of euro)

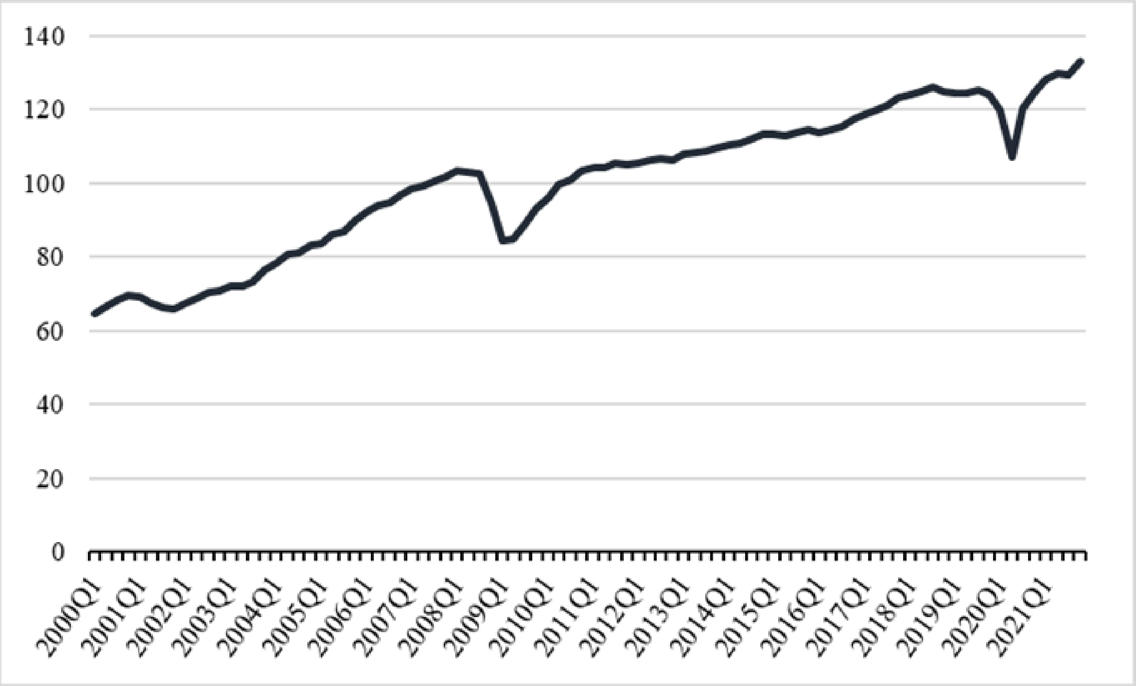


4.3 Control variables

As previously stated, the study considers a set of four control variables. Their time series demonstrate a wide range of responses to the shocks that characterized the time window used in the analysis.

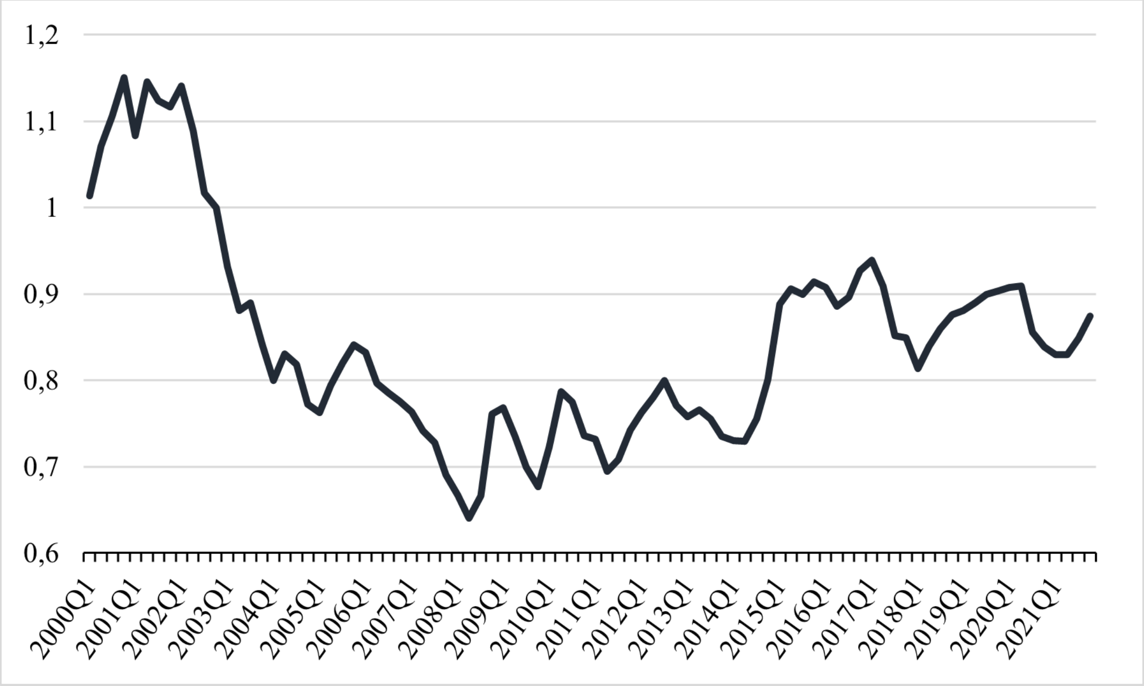
The CPB World Trade Monitor database, which gathers, combines, and summarizes international trade and industrial output changes, is used to collect statistics on World Trade Volume. The trade monitor includes 81 nations, accounting for about 99% of global trade volumes. Therefore, the WTV denotes merchandise trade or commodity trade as the average of the export and import indices. Figure 5 depicts its time series from the first quarter of 2000 to the fourth quarter of 2021. It may be regarded as a distinct growing pattern with just three breaks. A first brief downward trend is observable in 2001 as response to international arising uncertainty after the collapse of the Twin Towers. Then, the variable exhibits a persistent increasing path that is interrupted by the blow-up of the US subprime mortgages babble. Then, the series saw a substantial decrease during the 2008 financial crisis, losing 18,5 points. Furthermore, the years after the restart of the crisis show a weaker growing tendency than the years preceding it. Finally, the COVID-19 pandemic's adverse effects are observable, especially during 2019 and 2020. The highly integration and connection among the production networks play a critical role as the nature of the great trade and production collapse in both crises. However, while the 2008 crisis represents a drop in imports and exports, the latter appears similar in magnitude but does not represent a general drop in trade and production. Indeed, trade and production increased in several products (e.g. pharmaceutical products, food, electronics and telecommunication technology products) while decreasing in others such as fuels, aircraft, cars, mechanical machinery, and steel.

Figure 5: Time Series of the World Trade Volume



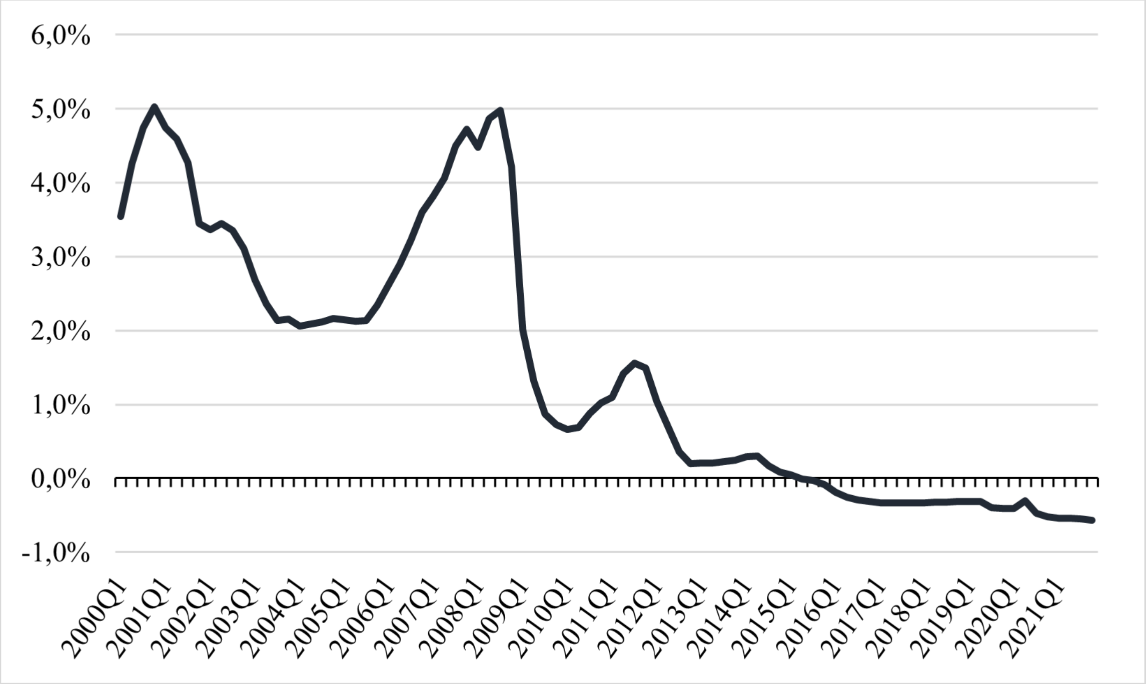
The analysis incorporates the time series of Euro-Dollar Exchange rates to adjust for potential reactions of our output variables to changes in the national currency. Data on this control variable are acquired from the Bank of Italy database, indicating how many Euros are required to get one Dollar during the given time window. In Figure 6, the period from 2000 Q1 to 2021 Q4 shows that the average ratio between the two currencies is 0.85, with most of the observations below such value lying approximately between 2005 and 2015.

Figure 6: Time Series of the Euro-Dollar Exchange Rate



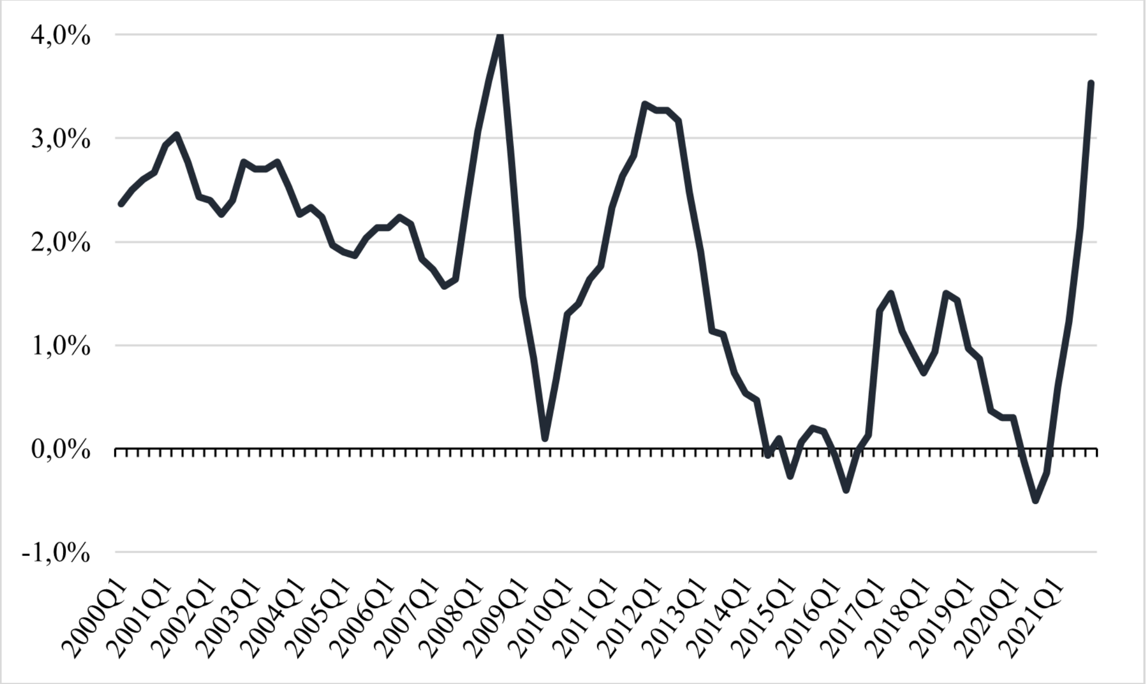
The Bank of Italy database is used to obtain the 3-month Euribor time series. Figure 7 shows a clear four-period distinction for the variable under consideration. This time series, like earlier ones, indicates an initial reaction to the horrific terroristic incident of 2001, with the interest rate hitting over 5%. The second spike of our variable derives from the shock induced by the 2008 financial crisis, with a magnitude comparable to the one experienced in 2001. Then, from 2011 to 2012, interest rates rose because of the European sovereign debt crisis, which saw the collapse of banking institutions, massive government debt, and fast expanding bond yield spreads in government assets in various European nations.

Figure 7: Time Series of the 3-month Euribor



Last, in Figure 8 we present the trend of the Italian price level. Three spikes are recognisable in the price level discontinuous trend. The highest value is observed in 2008 Q3 at 4.0%, followed by a rapid fall ceased at 0.1% in 2009 Q3. However, this low-price level showed to be not persistent in time. Indeed, the second spike is registered at 3.3% in 2011 Q4 as the result of a sharp increase began after the minimum value occurred in 2009 Q3. Then, a final robust growth is observed during the recovery period following the COVID crisis, with a maximum peak at 3.5% at 2021 Q4.

Figure 8: Time Series of the Italian inflation



4.4 Variables stationarity and unit root tests

In this section, we aim to introduce and analyse the principal methodologies to test stationarity and whether our variables of interest are stationary or not. It is observable that nonstationary behaviour is often the most dominant characteristic for economic time series. For example, most of the time series representing aggregate economic behaviour like the Gross Domestic Product and Industrial Production show growth characteristics over long periods while other time series appear to wander around as if they have no fixed population mean. To explain or forecast series of this type, it is necessary to employ a mechanism to capture their nonstationary elements or transform them to achieve stationarity. Several tests are available to verify the stationarity properties in the time series data. For example, in ARMA and ARCH/GARCH framework, the autocorrelation function (ACF) and correlogram analysis is generally adopted to verify such properties. Indeed, observing a correlogram diminishing trend with lang length increase, we can assert the stationarity for the variable while the opposite can be said in case the autocorrelations remain in place. However, the low reliability of these methods suggests embracing more precise techniques, which are under the name of unit root tests.

The Dickey-Fuller, or DF, test is a prominent approach for testing the unit root hypothesis (Dickey and Fuller, 1981). The null hypothesis of the DF test is that an autoregressive time series model has a unit root, implying that the data series is not stationary. Thus, the alternative hypothesis is usually stationarity or trend stationarity; however, it varies based on the test version. To understand the DF test mechanism, we can consider a simple first-order AR process, AR(1) hereafter, of the form:

$$x_t = \rho x_{t-1} + u_t. \tag{18}$$

The equation above implies that the value of x depends on its past value only. Therefore, attention must be placed on the value of p since it is the coefficient of interest for determining unit root or stationarity.

$$\begin{cases} \rho < 1 & \text{The series is stationary} \\ \rho = 1 & \text{The series is nonstationary} \end{cases}.$$

If the value of ρ is less than one, we expect that shocks in x will vanish in time, letting the series converge to its unconditional mean. Alternatively, if the value of ρ is equal to one, we foresee that shocks in the data series will be permanent in time, and the series is characterised as unit root. Finally, the extreme case in which ρ is greater than one implies that the series will explode. Nevertheless, since the upfront assumption on the equation (18) is the presence of stationarity and not the uncertainty that it is a unit root, we need to rewrite the model by the first difference to include the latter. Thus, the model appears as follows

$$\Delta x_t = (\rho - 1)x_{t-1} + u_t = \delta x_{t-1} + u_t. \tag{19}$$

Hence, the reasoning for ρ can now be extended to the new coefficient of interest for determining unit root or stationarity, δ. The null and alternative hypotheses for the test remain invariant, but they refer to 0 instead of 1. Moreover, we can implement equation (19) to consider possible drift and trend

$$\Delta x_t = \alpha_0 + \delta x_{t-1} + u_t, \qquad \text{(with drift) or}$$

$$\Delta x_t = \alpha_0 + \alpha_1 t + \delta x_{t-1} + u_t. \quad \text{(with drift and trend)}$$

Beyond its simplicity, the DF test is considered one of the weakest tests for the presence of unit root incorporating only AR(1) data-generating processes for the series. The usual series' long-term association with its historical events makes such an assumption demanding and stringent. Therefore, some parametric and nonparametric alternative approaches have been introduced to handle autocorrelation. The most affirmed ones are the Augmented Dickey-Fuller (ADF) test for the parametric solution and the Philip and Perron (1998) test for the nonparametric one. The former can be seen as an extension of the previous DF test. Indeed, the ADF test presents a similar equation with higher-order lags to capture the higher-order autocorrelation as follows

$$\Delta x_t = \alpha_0 + \alpha_1 t + \delta x_{t-1} + \beta_1 \Delta x_{t-1} + \beta_2 x_{t-2} + ... + \beta_p \Delta x_{t-p} + u_t,$$

where the inclusion of several lags on the right-hand side of the equation should be sufficient to remove autocorrelation in the residuals. However, the ADF test does not comprise the structural shift in the data.

To address the issue that the process generating data x_t may have a higher order of autocorrelation than is admitted in the test equation (18), Philips and Perron (1998) propose estimating the initial DF equation to test the unit root and then modifying the inferences of the coefficient to correct the impacts of autocorrelations. Philips-Perron test performs a nonparametric correction of the t-test statistic providing more robust results concerning unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation.

To proceed with our analysis, inspecting our variables' stationarity is necessary. As seen from the figures in the previous sections, it would be highly daring to conclude whether our series are stationary or not only by looking at their graphic representations. Then, we perform unit root tests to ensure our variables' correct characterisation. We implement the last two methods to verify whether a given time series may be stationary with the ADF and PP test reporting consistent results. The p-values of the tests for both our exogenous and output variables are higher than the significance level 0,05; hence, we must accept the null hypothesis of a unit root. Similar results can be obtained for data on the control variables except for the inflation time series. Indeed, tests' results suggest that its path is stationary over time.

5 Empirical analysis and results

This Section focuses on whether the price of our energy commodities affects the macroeconomic variables of interest. The analysis aims to inspect their magnitude and persistence over time. First, Section 5.1 discusses and analyses the two models' methodology used to study the variables' relationships. Then, the following sections give brief and accurate summaries of the outcomes. Finally, Section 5.3 discusses our model robustness results.

5.1 Empirical methodology

5.1.1 VAR methodology

We executed multiple analyses using VAR and VEC models to measure the effects of oil and gas price shocks on the Italian Gross Domestic Product and the Industrial Production Index. The first slot of results is obtained from a SVAR analysis of our variables. Hence, a separate model is computed for every couple of exogenous and output variables. Then, four impulse response functions present the impacts of an energy commodity price shock on GDP and IPI separately. Finally, we provide a variance decomposition analysis to show how much our energy commodities price variance contributes to the total variance of our output variables.

We start by fitting a VAR to quarterly data from 2000Q1 to 2021Q4. The reduced-form finite-order VAR representation, estimated by OLS, reads:

$$Y_t = \sum_{j=1}^{p} A_j Y_{t-j} + u_t,$$

where

$$u_t \sim N(0, \Sigma_u),$$

and

$$Y_t = \begin{bmatrix} \Delta log(Brent\ price)_t \\ \Delta(International\ Trade\ Volume)_t \\ \Delta(Exchange\ rate)_t \\ \Delta(Euribor)_t \\ Inflation_t \\ \Delta log(Output\ variables)_t \end{bmatrix},$$

or

$$Y_t = \begin{bmatrix} \Delta log(Dutch\ TTF\ price)_t \\ \Delta(International\ Trade\ Volume)_t \\ \Delta(Exchange\ rate)_t \\ \Delta(Euribor)_t \\ (Inflation)_t \\ \Delta log(Output\ variables)_t \end{bmatrix}.$$

A_j are the matrices of coefficients, u_t is the vector of residuals whose variance-covariance matrix is Σ_u. As observable from the vectors $(5 \times 1) Y_t$, we consider the variables in their differences, except for inflation kept at the level. This decision derives from stationarity test results from which inflation time series appear already stationary without the need to be differenced. The model specification contemplates a further exogenous variable, *covidratio*, necessary to stabilise the model due to the COVID-19 pandemic shock. It is obtained through the daily ratio between Italian and World COVID-19 positive tests. Thus, the variable is transformed into quarters to be compatible with the model frequency. The vector autoregression models with COB display $p = 3$ lags for both output variables cases, while $p = 2$ lags for models using TTF as exogenous variable. To choose the number of lags, we rely on the information obtained by the most famous lag length criteria (AIC, BIC, SC, H.Q, LR, FPE). Then, the accuracy of our choice and autocorrelation among the error terms are verified with the Lagrange Multiplier (LM) test. The null hypothesis of serial correlation is rejected with the mentioned number of lags; thus, the model well fit the data generating process. The variables' order on matrix Y_t follows the fundamental assumption that oil and gas price shocks affect the control and output variables contemporaneously. However, since oil and gas are located on the top of the matrix, they are not influenced by other variables' shocks but only by their ones.

On top of that, to correctly identify the model, we adopt the Cholesky decomposition of the variance-covariance matrix of structural innovations, $\Sigma_u = BB'$, where B is the unique lower-triangular Cholesky factor with non-negative diagonal elements. The Cholesky decomposition specifies the VAR through the following order: the delta log of energy commodity prices (alternatively the COB and TTF), the delta of World Trade Volume, the delta of the Euro-Dollar exchange rate, the delta of 3-months Euribor interest rate, the inflation level, and the delta log of the output variable (either GDP or IPI). The Cholesky decomposition appears as follows:

$$R = \begin{bmatrix} R_{11} & 0 & 0 & 0 & 0 & 0 \\ R_{21} & R_{22} & 0 & 0 & 0 & 0 \\ R_{31} & R_{32} & R_{33} & 0 & 0 & 0 \\ R_{41} & R_{42} & R_{43} & R_{44} & 0 & 0 \\ R_{51} & R_{52} & 6_{53} & R_{54} & R_{55} & 0 \\ R_{61} & R_{62} & R_{63} & R_{64} & R_{65} & R_{66} \end{bmatrix}.$$

As anticipated, the list of zeros in the first row represents the assumption that oil and gas prices are not affected by other variables shocks. Instead, the distribution of contemporaneous impact between variables is shown by the matrix columns. Ordering our exogenous variables first, we allow their shocks to affect all the other variables contemporaneously, implying an immediate impact on the real economy. Following the same reasoning, the last column refers to the output variables exhibiting they do not present contemporaneous effects on other variables.

5.1.2 VEC methodology

Together with vector autoregressive models, econometricians point out a different method to establish the relational model among economic variables. As already said in Sections 3.4 and 3.5, there is a strong connection between the concepts of cointegration and VEC models. If the variables have a cointegration relationship, an autoregressive distributed lag model may be used to develop an error correction model. Because each equation in a VAR may be thought of as an autoregressive distributed lag model, the VECM can be seen as a VAR model with cointegration restrictions. Thus, when an extensive range of short-term dynamic fluctuation is in place, VEC expressions can restrict the long-term behaviour of the endogenous variables and be convergent to their cointegration relation.

It is possible to define the VEC methodology implemented in our analysis through 4 main steps. The first passage foresees implementing a stationarity test for the variables considered in the system. The objective here is to verify if the variables considered are $I(0)$, $I(1)$, or, at most, $I(2)$ to proceed with the analysis. The results are obtained from the commonly accepted ADF unit root test shown in Section 4.4. Then, we proceed with the estimation of a VAR model. In this case, we perform the VAR estimations using variables at their levels, while a classical VAR analysis demands all the variables considered to be stationary, hence, to differentiate them if they are not. Therefore, our VAR model is estimated to determine optimal lag intervals for the variables in the system. The method adopted to determine the optimal lag periods is the Schwartz criterion, and the results obtained are used to define the (p-1) lags that will be adopted to execute the VEC analysis. Thus, the vector error correction models display $(p-1)=2$ lags in all output variables cases. The third passage involves a cointegration test. The key to the cointegration test lies in selecting the proper form and lag order. To test for cointegration between variables, we use the Johansen (1988) method that leaves space to a total of 5 possible deterministic trend assumptions of the test. However, to simply matter, they can be summarized in these three more general cases:

1. Assume no deterministic trend in data
2. Allow for a linear deterministic trend in data
3. Allow for a deterministic quadratic trend in data

with our tests mostly indicating the first case. Johansen cointegration tests on our variables show that results are to reject the null hypothesis of none cointegrated equations under the 5% level. Thus, we conclude that there are stable and long-term equilibrium relationships among our variables. Therefore, on the premise of the existence of cointegration relationships, VEC modelling can be further conducted.

Table 1: Johansen cointegration test with COB and IPI

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0,5808	142,8392	83,9371	0,0000
At most 1*	0,3169	68,9459	60,0614	0,0074
At most 2	0,1708	36,5506	40,1749	0,1106
At most 3	0,1238	20,6264	24,2760	0,1348
At most 4	0,0913	9,3935	12,3209	0,1474
At most 5	0,0146	1,2536	4,1299	0,3069

Table 2: Johansen cointegration test with COB and GDP

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0,4776	128,2242	95,7537	0,0001
At most 1*	0,2446	73,8481	69,8189	0,0230
At most 2*	0,2081	50,2850	47,8561	0,0290
At most 3*	0,1863	30,6858	29,7971	0,0394
At most 4	0,1308	13,3661	15,4947	0,1020
At most 5	0,0188	1,5954	3,84115	0,2066

Table 3: Johansen cointegration test with TTF and IPI

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0,5709	146,4739	83,9371	0,0000
At most 1*	0,3347	74,5486	60,0614	0,0019
At most 2	0,1955	39,9048	40,1749	0,0532
At most 3	0,1508	21,4104	24,2760	0,1101
At most 4	0,0736	75,1801	12,3209	0,2765
At most 5	0,0119	1,0160	4,1299	0,3639

Table 4: Johansen cointegration test with TTF and GDP

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0,3668	106,3002	83,9371	0,0005
At most 1*	0,3162	67,4575	60,0614	0,0104
At most 2	0,1957	35,1546	40,1749	0,1463
At most 3	0,1143	16,6451	24,2760	0,3346
At most 4	0,0555	6,3308	12,3209	0,3968
At most 5	0,0173	1,4812	4,1299	0,2621

Our VEC models can be presented in the following form:

$$\Delta X_t = v + \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i X_{t-i} + u_t,$$

where p is the lag of the respective VAR model in levels, $\Pi = \sum_{j=1}^{p} A_j - I_k, \Gamma_i = \sum_{j=i+1}^{p} A_j$, and

$$X_t = \begin{bmatrix} log(Brent\ price)_t \\ (International\ Trade\ Volume)_t \\ (Exchange\ rate)_t \\ (Euribor)_t \\ Inflation_t \\ log(Output\ Variables)_t \end{bmatrix},$$

or

$$X_t = \begin{bmatrix} log(Dutch\ TTF)_t \\ (International\ Trade\ Volume)_t \\ (Exchange\ rate)_t \\ (Euribor)_t \\ (Inflation)_t \\ log(Output\ Variables)_t \end{bmatrix}.$$

Finally, in the following tables we report the coefficients of the cointegration vectors observing an overall coherent result with the economic theory.

Table 5: β CEs from VEC with COB and IPI

	COB(-1)	wtv(-1)	exch(-1)	euribor(-1)	inflation(-1)	IPI(-1)
CE 1	1,00000	0.000000	2015,07400	95,02133	-311,18970	-17,26132
			(385,920)	(35,5118)	(64,4410)	(3,38941)
			[5.22148]	[2.67577]	[-4.82906]	[-5.09272]
CE 2	0.000000	1,00000	502,32400	36,70444	-63,36373	-5,50966
			(93,7007)	(8,62221)	(15,6462)	(0.82294)
			[5.36094]	[4.25696]	[-4.04979]	[-6.69507]

Table 6: β CEs from VEC with COB and GDP

	COB(-1)	wtv(-1)	exch(-1)	euribor(-1)	inflation(-1)	GDP(-1)
CE 1	1,00000	0,00000	0,00000	0,00000	-3,56039	0,00119
					(8,49203)	(0,00071)
					[-0,41926]	[1,66258]
CE 2	0,00000	1,00000	0,00000	0,00000	-16,86424	0,00195
					(9,28015)	(0,00078)
					[-1,81724]	[2,49391]
CE 3	0,00000	0,00000	1,00000	0,00000	0,78417	-0,00002
					(0,17475)	(0,00002)
					[4,48739]	[-1,21943]
CE 4	0,00000	0,00000	0,00000	1,00000	-1,69639	-0,00012
					(0,33530)	(2,8E-05)
					[-5,05927]	[-4,19546]

Table 7: β CEs from VEC with TTF and IPI

	TTF(-1)	wtv(-1)	exch(-1)	euribor(-1)	inflation(-1)	IPI(-1)
CE 1	1,000000	0,178795	112,056700	8,744971	-14,500300	-1,247556
		(0.20516)	(22,1689)	(3,5602)	(3,68779)	(0.36388)
		[0.87150]	[5.05468]	[2.45631]	[-3.93197]	[-3.42852]

Table 8: β CEs from VEC with TTF and GDP

	TTF(-1)	wtv(-1)	exch(-1)	euribor(-1)	inflation(-1)	GDP(-1)
CE 1	1,000000	0,000000	-56,978120	-12,604130	37,021340	0,000046
			(41,6078)	(4,63332)	(8,27247)	(0,000088)
			[-1,36941]	[-2,72033]	[4,47524]	[0,52408]
CE 2	0.000000	1,000000	176,993600	45,332040	-91,190140	-0.000583
			(113,374)	(12,625)	(22,5411)	(0.00024)
			[1.56114]	[3.59065]	[-4.04550]	[-2.42468]

The results of our SVEC analysis are obtained using the Cholesky decomposition explained in section 5.1.1

5.1.3 Lags choice and model checking

Describing a general K-dimensional multiple time series $y_1, ..., y_T$ with $y_t = (y_{1t}, ..., y_{Kt})$', which is known to be generated by a VAR(p) process,

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t,$$

it rarely happens that the VAR order p is known. In Section 3, we have not assumed that all the estimated A_i are nonzero. Indeed, it may be the case that A_p is zero. Thus, we should look at p only as an upper bound for the VAR order. The correct choice of p plays a critical role in any VAR analysis since an unnecessarily large value will reduce the forecast precision of the corresponding model. Furthermore, it may invalidate the precision estimates of the impulse responses since they strongly depend on the accuracy of the parameters' estimates. Therefore, it is essential to dispose of procedures or criteria for choosing an adequate VAR order which provides the best trade-off between model fit and parsimony. The most famous and used lag length criteria or information criteria are Akaike (AIC), Schwartz (SC) criteria, and Hannan and Quinn (HQ) criteria . The information criteria general form is

$$IC(p) = ln(\Sigma) + f(p),$$

where $f(p)$ is an increasing function of the number of lags p whose functional form varies depending on the specific criterion. The two right terms of the above equation show an inverse relation to p. The former presents a negative correlation, meaning that the fit grows as p rises. On the other hand, the number of parameters to be estimated would be higher, making things more sophisticated. To choose the optimal p is then necessary to select the one that conveys the smallest IC(p). Since the criteria to which we refer the most in our analysis is the Schwartz, it may be relevant to have a closer look at it. From a VAR(p) process, the SC criterion is defined as

$$SC(p) = ln|\widetilde{\Sigma_u}(p)| + \frac{ln(T)}{T}\, pK^2,$$

where pK^2 are the number of freely estimated parameters excluding the constant terms in the VAR model. The estimate $\hat{p}(SC)$ for p is chosen to minimise the criterion above, and it should reasonably be an integer value.

To run a correct analysis is of our interest to choose a VAR order obtained by a criterion that has desirable sampling properties. In this regard, one the most desirable asymptotic property of an estimator is its consistency. Then, let y_t be a K-dimensional stationary, stable VAR(p) process with standard white noise. Suppose the maximum order $M \neq p$ and $\hat{p}$ is chosen as to minimize a criterion

$$Cr\left(m\right) = ln\left|\widetilde{\sum_{u}}\left(m\right)\right| + mc_T T,$$

over $m = 0, 1, ..., M$. Here, c_T is a nondecreasing sequence of real numbers that depends on the sample size T. Then, $\hat{p}$ is consistent if and only if

$$c_T \to \infty \text{ and } c_T T \to \infty \text{ as } T \to \infty \tag{20}$$

and strongly consistent if and only if (22) holds and

$$c_T 2lnT > 1$$

eventually, as $T \to \infty$.

Therefore, since Schwartz criterion presents $c_T = K^2 ln(T)$, it satisfies the requirements to be strongly consistent for any dimension of K. However, this result does not necessarily imply that AIC or HQ are inferior to SC. Indeed, AIC is inferior to HQ and SC if only this characteristic is considered. Nevertheless, we have ignored the small sample properties of the estimator. In small samples, AIC may have better properties than HQ and SC. Indeed, the former criteria is designed for minimising the forecast error variance. Thus, models based on AIC may produce superior forecasts in a small sample, although they may not estimate the correct orders. In this regard, Shibita (1980) showed that, under suitable conditions, AIC minimise the 1-step ahead forecast MSE asymptotically.

To grasp a small sample comparison of AIC, HQ, and SC, let $y_{-M+1}, ..., y_0, y_1, ..., y_T$ be any K-dimensional multiple time series and suppose that VAR(m) models, $m = 0, 1, ..., M$, are fitted to $y_1, ..., y_T$. Then the following relations hold:

$$\hat{p}(SC) \leq \ \hat{p}(AIC) \qquad if\, T \geq 8$$

$$\hat{p}(SC)(HQ) \qquad for\ al\ T$$

$$\hat{p}(HQ) \leq \hat{p}(AIC) \qquad if\, T \geq 16$$

The relations above suggest that there exists the following order across the three criteria for $T \geq 16$:

$$\hat{p}(SC) \leq \hat{p}(HQ) \leq \hat{p}(AIC),$$

meaning that AIC always suggests the largest p, SC is the most parsimonious, and HQ is between the two.

Then, we dispose of several procedures to check the adequacy of the lags chosen for the models. For instance, the overall significance of the residual autocorrelations up to lag p can be estimated through a Lagrange Multiplier (LM) or Portmanteau test. Since the tests present many similarities, it is sufficient to show only one of them. Focusing on the former, assume a VAR model for the error vector $u_t =$

$D_1 u_{t-1} + \ + D_h u_{t-h} + v_t$, where v_t is white noise. It should be equal to u_t if there is no residual autocorrelation. Therefore, the following pair of hypotheses are tested

$$H_0 : D_1 = ... = D_h = 0 \qquad \text{against} \qquad H_1 : D_j \neq 0 \text{ for at least one } j \in \{1, ..., \ h\}.$$

The null hypothesis represents the situation in which all residual autocorrelations are 0, while the alternative hypothesis represents the one in which at least one autocorrelation is not 0.

Finally, Non-normality tests are employed to verify whether the residuals' third and fourth moments align with those of the normal distribution. Non-normal residuals indicate that the model is not a good representation of the data generation process.

5.2 Empirical results

5.2.1 VAR model IRFs

In this Section we observe the results of the multivariate VAR models. The following IRFs' x-axes range from Q1 through Q4 of the subsequent quarters relative to the initial shock. At the same time, the y-axes quantify the percentage change in the variables concerning two standard deviation shocks of the energy commodity prices considered (COB, TTF). We report the results considering a 95 per cent confidence ban, highlighting that the drops and rebounds reported are statistically significant at the 5% level. The IRFs of the multivariate models that we will observe are basically exposed to demonstrate the effect of our exogenous variables' shocks on the Italian Gross Domestic Product and its Industrial Production Index. The results are obtained by adding other macroeconomic variables shocks to the system, mainly the one induced by our control variables.

Figure 9: IRF of GDP to COB

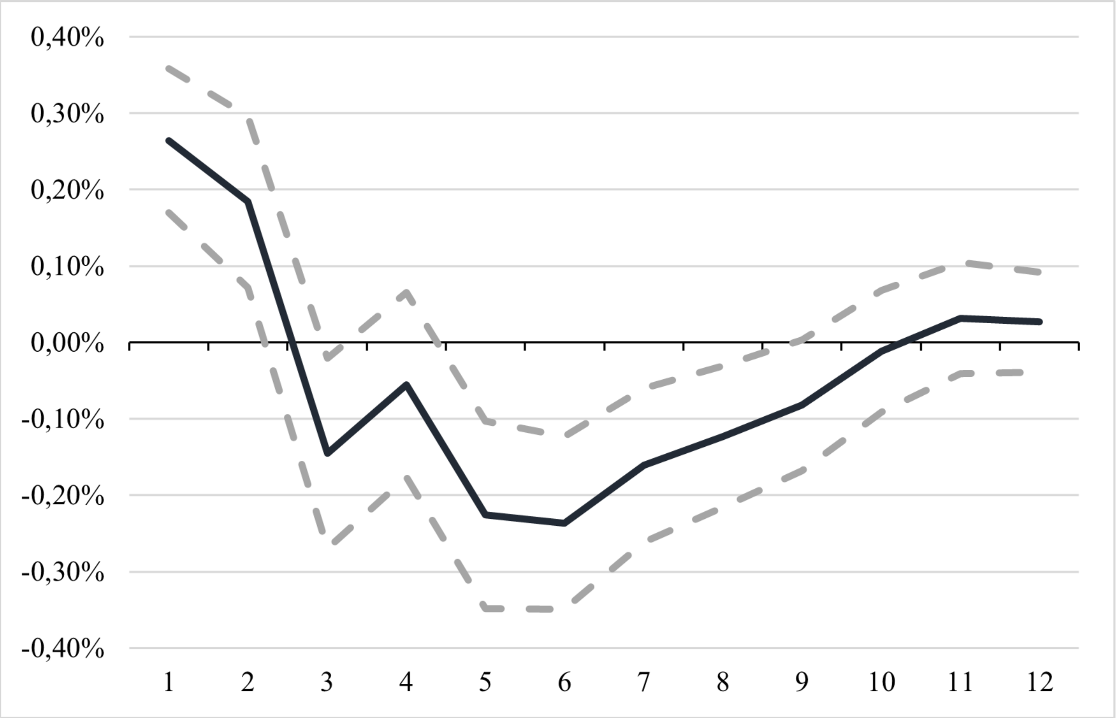
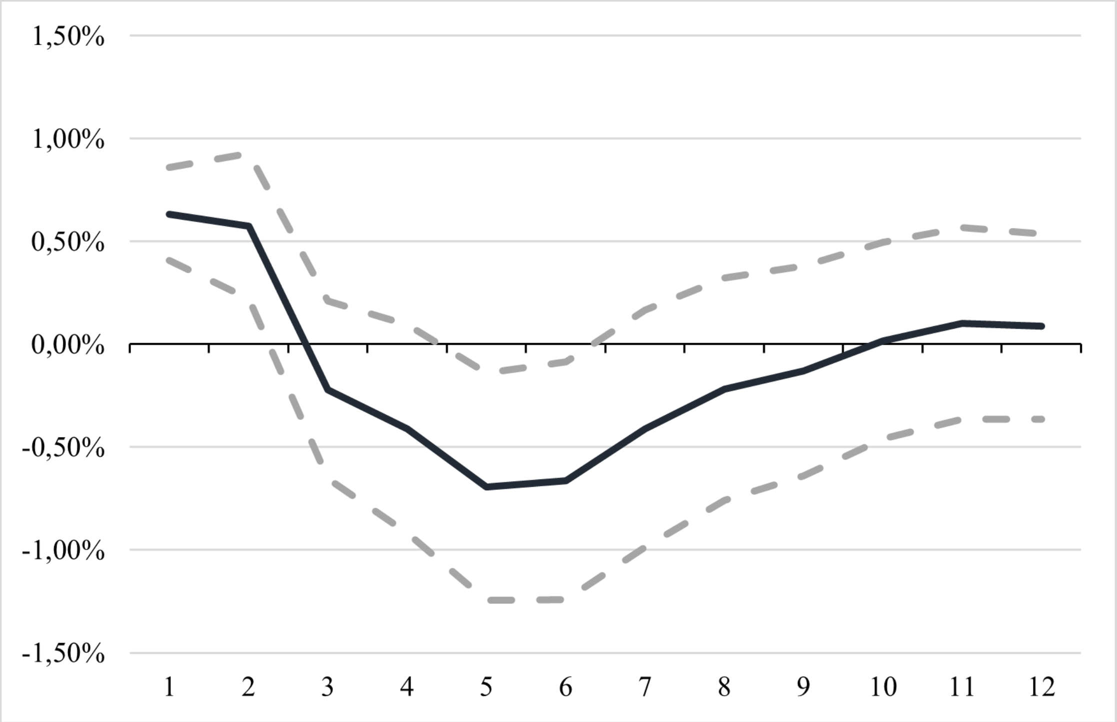


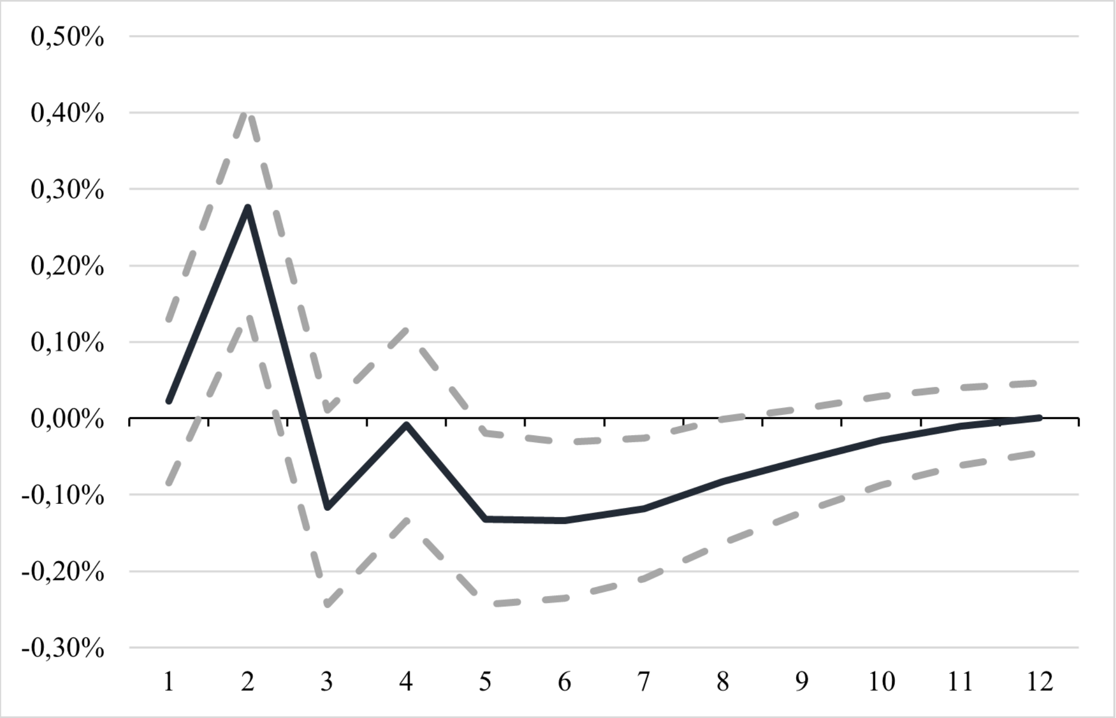
Figure 10: IRF of IPI to COB



Figures 9 and 10 show the IRF of Gross Domestic Product and the Industrial Production Index to a two-standard deviation shock in the COB price, respectively. Hence, we can observe that an unanticipated increase in Brent prices positively impacts our macroeconomic variables in the first lags. This trend appears in all the impulse response functions reported in this thesis, and its origin may lie in an indirect effect induced by the oil or gas prices increase. Indeed, it might be the case where net exporting countries of our energy commodities benefit from such positive price shocks and transfer part of their strengthened purchasing power on the Italian exported products. However, the significance level of such impact drops rapidly. Analysing the IPI's IRF, the starting positive impact on this variable is not statistically significant after the second lag, as for PIL's IRF. Subsequentially, the two IRFs show a similar pattern. Following the order above, we observe that the shock leads to a negative peak of about -0,7% in the Industrial Production Index and -0,24% in Gross Domestic Product, registered five and six quarters after the shock. In general, we observe an insistent detrimental effect from lag 2 to 10. Thus, we conclude that the GDP and IPI IRFs show negative responses that are statistically significant and moderate in size. The results seem consistent with most academic studies that signal an asymmetric relation between oil prices and macroeconomic output (see Mory, 1993; Rotemberg and Woodford, 1996; Hooker, 1996). The industrial production processes and daily life use of oil's derivatives, or pure oil directly, has, as a first consequence, the immediate community awareness of oil price shocks. The increase in common and essential products' prices directly affects investment and consumption. While firms face higher production costs, families see their disposable income eroded by higher inflationary levels causing the analysed IRFs responses.

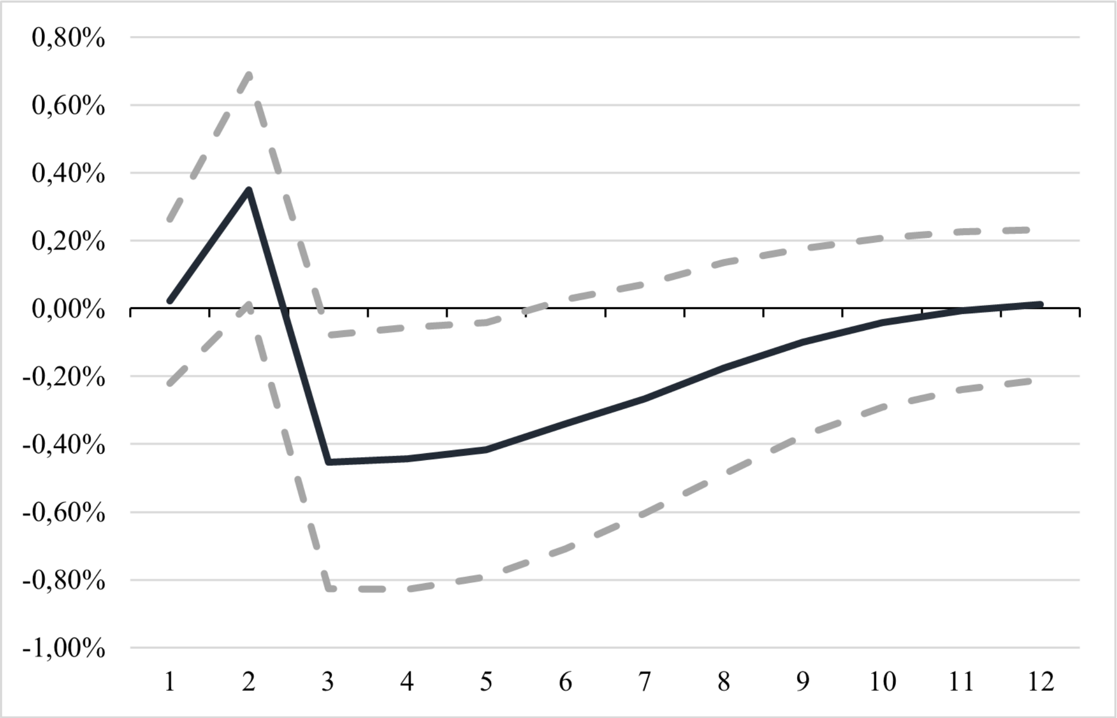
The focus now moves to the impulse response analysis of gas price shocks on our output variables. In Figures 11 and 12 we present the IRFs of Italian GDP and IPI to a shock in TTF. The former may appear

Figure 11: IRF of GDP to TTF



not very helpful in understanding the effect of the gas price shocks on the Gross Domestic Product, while the IPI's IRF seems to signal clearer its relations with such price movements. The first difference emerging from comparing the two IRFs is in lag 2. As seen before in the COB related IRFs, we observe a similar behaviour looking at the response of GDP to gas price shocks where a slightly positive reaction is in place in lag 2. However, the expected negative relationship between the two variables arises from lag 3 and turns statistically significant in lags 5 and 6, moving slowly to zero afterwards. The IPI impulse response function to TTF price shocks allows for a cleaner description. While the GDP IRF does not produce very interesting findings in the first four lags, here we observe a resolute negative effect since lag 3. Furthermore, the harmful effect of a TTF price increase on IPI remains and is statistically significant until lag 6. Finally, the cumulative effect from lag 3 to 6 is -1,65%.

Figure 12: IRF of IPI to TTF



5.2.2 VEC model IRFs

The specific requirement of stationarity for time series that characterise a VAR model brings chances of losing information about the relationship among variables' time series. Differencing the series to make them stationary may be possible to work with integrated series. Nevertheless, this approach may implicate the critical cost of ignoring potentially meaningful long-run relationships between the variables' levels. In this Section, we aim to expose the IRFs resulting from vector error correction models, which combine levels and differences, and see if they present discrepancies from what has been shown in Section 5.2.1.

Figure 13: VAR and VEC IRFs of IPI to COB

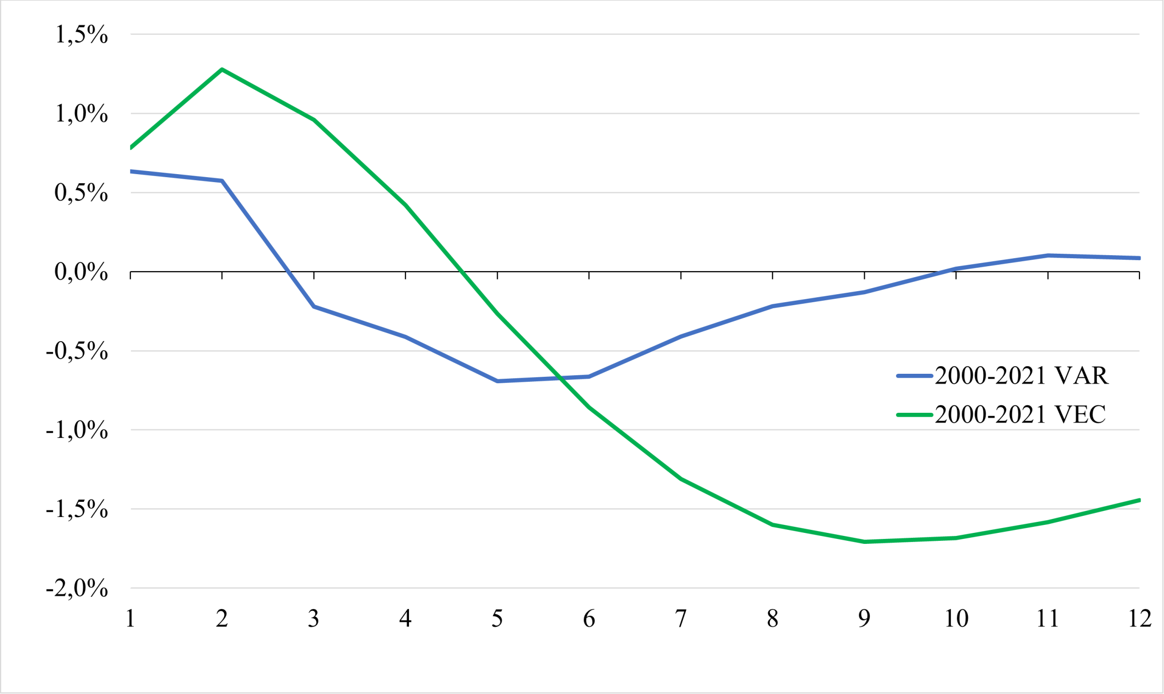
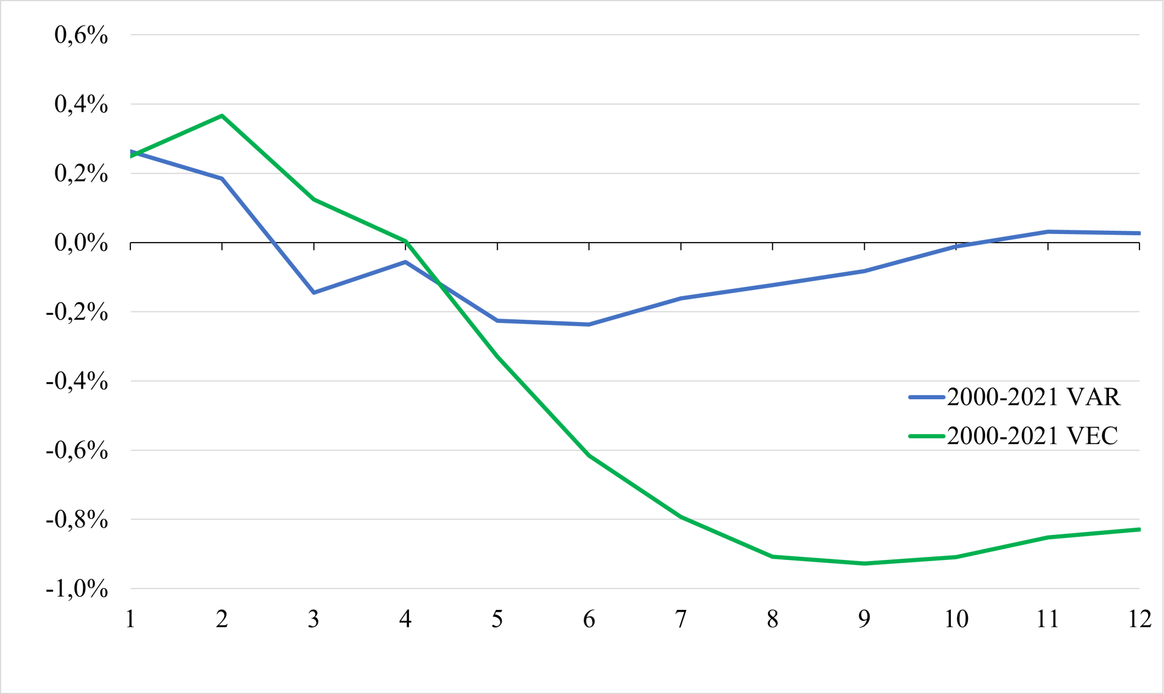


Figure 14: VAR and VEC IRFs of GDP to COB



Figures 13 and 14 compare the COB-related impulse response functions obtained from the two models. The VEC IRFs of IPI and GDP to a two s.d. shock in Brent price appear similar in shape, but they are significantly different in magnitude. Indeed, the former suggests that the Industrial Production Index is more affected by the shock analysed. Moreover, they both differ from their reciprocal VAR IRFs. After a more intense initial impact of COB price shocks on our macroeconomic variables, we observe that durable negative responses are in place. The VEC IRFs assume negative values from lag 5 and 4, respectively.

Thus, the responses of IPI and GDP exhibit a stronger negative impact persistency, not returning to zero in the last lags but showing a smooth recover. However, it seems that the paths defined by the VEC IRFs do not compromise the result obtained on the related VAR analyses. Actually, the main difference between the two models' outcomes seems to lie in the long-run information relationships lost in the latter.

Figure 15: VAR and VEC IRFs of IPI to TTF

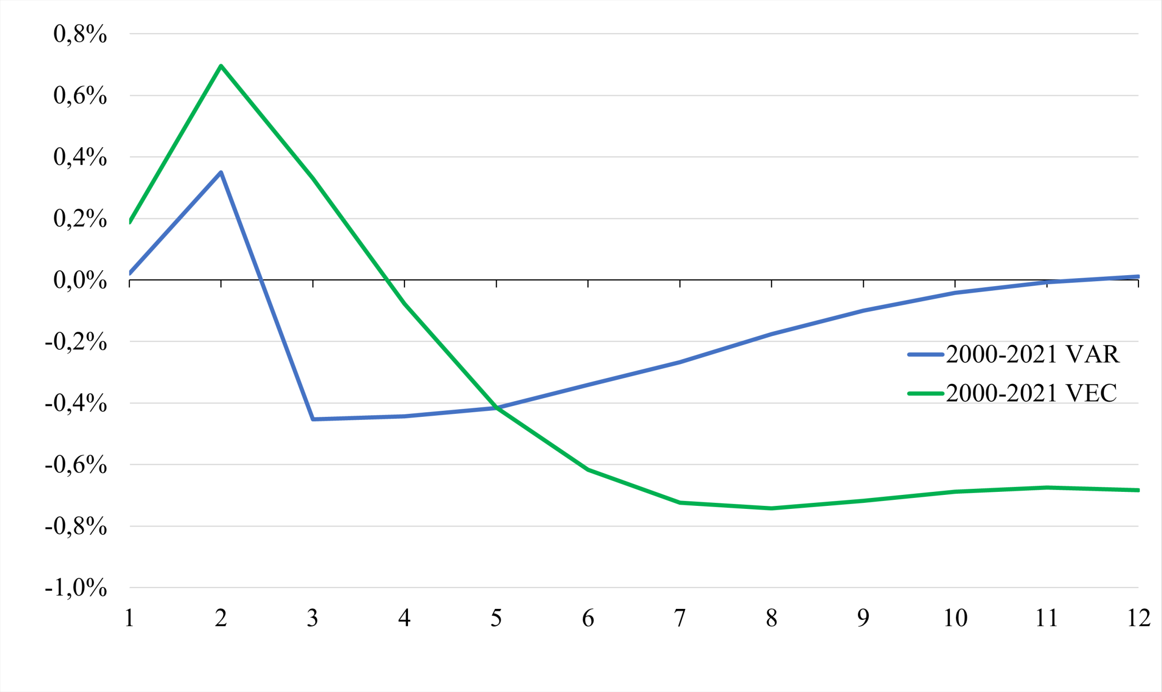
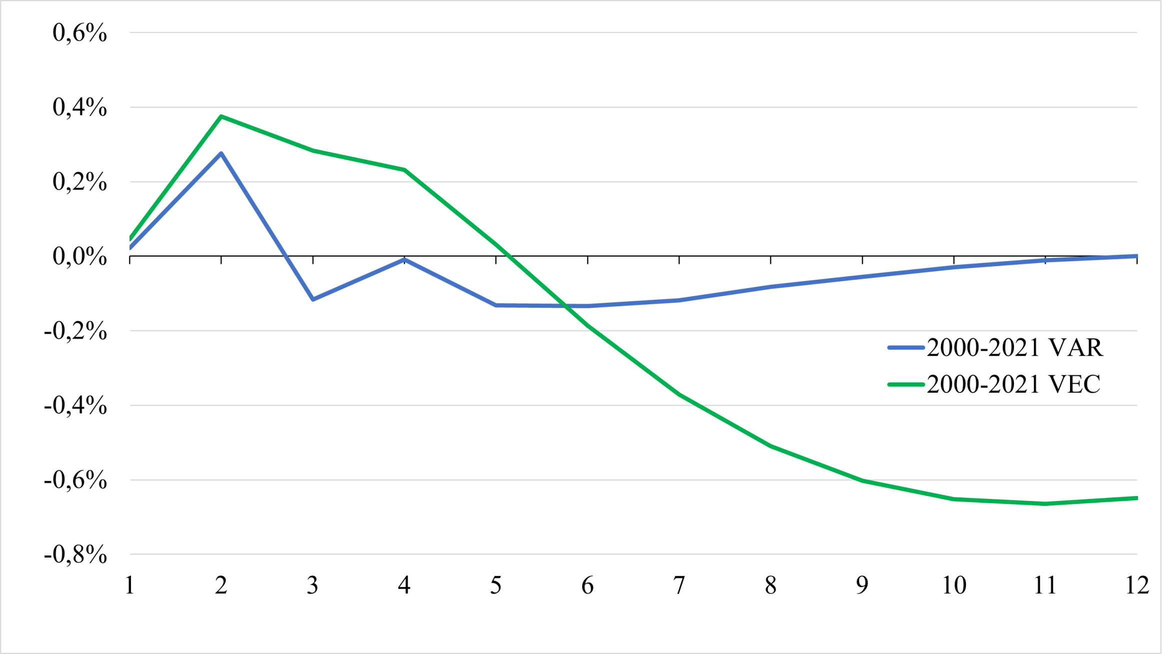


Figure 16: VAR and VEC IRFs of GDP to TTF



Then, we present VEC IRFs for the TTF cases as well. Figure 15 proposes the VAR and VEC IRFs of the Industrial Production Index to a two s.d. shock in TTF price. The closeness between the two models' outcomes is particularly evident as they show resemblant responses. Furthermore, the negative impact registered in the VEC IRF is not excessively more severe, with its peak at -0,74% in lag 8. However, the effect of TTF price shocks on IPI estimated by the vector error correction model exhibits stronger durability.

Finally, Figure 16 shows the VAR and VEC IRFs of the Gross Domestic Product to a two s.d. shock in TTF price. Conversely, from the other couple of IRFs combinations, these last two responses appear rather dissimilar. However, the former was not very informative about the impact of natural gas price shock on the Italian GDP. Thus, looking at the overall results we have obtained since now, we believe that the latter may be more reliable to observe such an impact. It appears almost identical in terms of magnitude to the one seen for IPI, but its timing does not match rigorously. Indeed, the negative impact is slightly delayed.

5.2.3 Emprical variance decomposition

This section illustrates the results of our variance decomposition analysis performed in both VAR and VEC models. Through these analyses, we aim to illustrate how much the amount of information each variable in the system contributes helps to explain the other variables' variance. As observable in the tables below, the results are reported until lag 12. From what has been seen through the examination of impulse response functions, we do expect that our energy commodity variables' fluctuations originate part of the total variance in our macroeconomic variables (GDP, IPI).

Table 9: Variance Decomposition VAR with COB and GDP

Period	Δlog(COB)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(GDP)
1	7,001342	35,01112	1,035017	3,903223	0,061269	52,98803
2	9,488669	33,88104	2,834572	5,301133	0,176077	48,31851
3	10,21864	31,43178	2,828114	6,926354	4,343928	44,25118
4	10,21572	31,65343	3,208026	6,775482	4,949832	43,19751
5	13,57534	30,07986	3,119406	6,525783	5,504422	41,19519
6	16,89625	28,92555	3,008535	6,192503	5,897985	39,07918
7	18,20441	28,41936	3,351803	6,140346	5,958003	37,92608
8	19,02283	28,11903	3,428246	6,109604	5,883458	37,43684
9	19,36598	28,02132	3,407855	6,08728	5,85295	37,26462
10	19,33881	27,98259	3,464171	6,127817	5,864757	37,22185
11	19,38091	27,94522	3,468735	6,130244	5,894906	37,17999
12	19,41458	27,92769	3,470006	6,127508	5,892474	37,16774

Notes: The table reports the variance decomposition of Δlog(GDP) with respect to the other variables in the VAR system with COB as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Gross Domestic Product's total variance in each quarter from the initial shock. The numbers in the table are percentages.

Table 10: Variance Decomposition VAR with COB and IPI

Period	Δlog(COB)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(IPI)
1	10,02432	56,25351	0,814425	0,109792	0,090903	32,70705
2	14,81196	47,32242	4,263035	1,353229	0,541977	31,70738
3	14,56004	43,95712	6,730739	1,308405	3,952625	29,49107
4	16,15311	40,13788	7,85996	1,326697	6,855955	27,6664
5	22,13786	36,55508	7,489044	1,213549	7,395774	25,20869
6	26,69577	34,14405	6,945687	1,122756	7,743046	23,34869
7	28,18111	33,31836	6,953353	1,330741	7,605578	22,61086
8	28,52115	33,0805	6,966668	1,505553	7,545933	22,3802
9	28,61541	32,98788	6,944165	1,548224	7,551759	22,35256
10	28,57896	32,94084	6,964434	1,581284	7,611197	22,32328
11	28,65382	32,8673	6,954539	1,607721	7,645343	22,27128
12	28,72397	32,83425	6,948489	1,606203	7,637426	22,24973

Notes: The table reports the variance decomposition of Δlog(IPI) with respect to the other variables in the VAR system with COB as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Industrial Production Index's total variance in each quarter from the initial shock. The numbers in the table are percentages.

The first tables of our variance decomposition analysis are extrapolated from two of our VARs, keeping the Crude oil Brent price in both cases and alternatively our output variables. Although the overall results seem similar, a separate description will be delivered to assist the tables reading. In Table 9, we observe that the fluctuations in Italian Gross Domestic Product for the first half of the period are primarily due to its fluctuations, accounting, on average, for 45% of its total variance. Columns 1 and 2 of the same table report respectively the percentage contribution of Crude oil Brent and World Trade Volume to the GDP's total variance. As expected, column 2 presents relative high values that can be explained by the strong interconnection between the prosperity of national economies and the flourishness of international trade. However, we are mainly interested in column 1 outcome for our analysis. Variations in the Crude oil Brent price explain GDP's total variance through an increasing sequence starting around 7% and, since lag 9, stabilising approximately at 19%. This result suggests and signals that the effects of oil price shocks cannot be ignored in GDP forecasting attempts.

Regarding columns 3, 4, and 5, they show feeble contributions to the total variance of Italian GDP since their cumulative sum does not go beyond 15%, with their maximum values of 3.47%, 6.93%, and 7.65%, respectively. Furthermore, they continue to present an equivalent contribution level if we turn to Table 10. Conversely, some differences are observable from the second table's first two and the last columns. Indeed, COB and WTV fluctuations appear more considerable than before in explaining the total variance of IPI during the entire period. Meticulously, the former shows more remarkable improvement, with COB's fluctuations explaining almost 29% of IPI's total variance.

Table 11: Variance Decomposition VAR with TTF and GDP

Period	Δlog(TTF)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(GDP)
1	0,051932	41,47028	0,519039	0,570268	0,000248	57,38824
2	6,902304	37,13455	2,200525	3,259487	0,000453	50,50268
3	7,698481	36,2296	2,28296	4,363072	0,654472	48,77141
4	7,514925	35,52613	2,250453	4,347678	2,746267	47,61455
5	8,541293	34,91014	2,207922	4,474047	4,488565	45,37803
6	9,459214	34,68703	2,457975	4,440715	5,878227	43,07684
7	10,17109	34,36007	2,818794	4,368248	6,621607	41,66019
8	10,50838	34,21772	3,029106	4,306215	6,896731	41,04185
9	10,6721	34,13053	3,130606	4,285381	6,954837	40,82655
10	10,7192	34,09578	3,164554	4,288691	6,955789	40,77599
11	10,72453	34,088	3,170535	4,296898	6,954641	40,76539
12	10,72213	34,08922	3,169934	4,302069	6,960256	40,75639

Notes: The table reports the variance decomposition of Δlog(GDP) with respect to the other variables in the VAR system with TTF as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Gross Domestic Product's total variance in each quarter from the initial shock. The numbers in the table are percentages.

Table 12: Variance Decomposition VAR with TTF and IPI

Period	Δlog(TTF)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(IPI)
1	0,010622	63,86945	0,731859	0,219673	0,619897	34,54849
2	2,562647	58,178	2,818123	0,677789	0,961658	34,80109
3	6,345346	54,21444	3,236065	0,69643	3,081563	32,42616
4	9,069548	50,44226	3,12866	1,643379	6,618406	29,09775
5	10,86591	47,88594	3,776356	2,195989	9,079064	6,19673
6	11,87912	46,62513	4,431502	2,227488	10,29147	24,5453
7	12,51349	45,93879	4,84818	2,172208	10,74993	23,77741
8	12,8018	45,63491	5,062732	2,149251	10,85098	23,50033
9	12,89904	45,52343	5,143129	2,158876	10,84702	23,42851
10	12,91505	45,4935	5,160045	2,17806	10,84004	23,4133
11	12,91036	45,4882	5,15893	2,191661	10,84687	23,40397
12	12,9063	45,48678	5,157367	2,197463	10,85827	23,39382

Notes: The table reports the variance decomposition of Δlog(IPI) with respect to the other variables in the VAR system with TTF as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Industrial Production Index's total variance in each quarter from the initial shock. The numbers in the table are percentages.

Tables 11 and 12 replicate a variance decomposition of the total variance, respectively, for the Italian Gross Domestic Product and Industrial Production Index. In these cases, we present the percentage contribution of Natural gas price Dutch TTF, instead of Crude oil Brent, to our output variables' total variance. While the last four columns of both tables appear similar to the ones presented in Tables 1 and

2, the percentage contribution of the other two variables is distributed slightly differently.

Commenting on Table 11 first, we observe that the World Trade Volume fluctuations acquired a more substantial contribution power to the GDP total variance than before, with a maximum delta increase of approximately 6%, while the other control variables' values do not present considerable changes. From column 1 of Table 3, we can finally observe the percentage contribution of Natural gas to the GDP's total variance. Dissimilarly to the values mentioned for COB, TTF fluctuations supply less information about our macroeconomic variable's total variance. More precisely, the former explains at most 11% of the latter. Nevertheless, such a contribution loss should not lead to conclude that Natural gas price fluctuations are irrelevant. On the contrary, it remains the second higher contribution value, and it should undoubtedly be taken as significant. Comparable results are obtained in Table 12, where the Industrial Production Index replaces the Gross Domestic Product. In this case, it is worth pointing out a growth in the maximum value for Natural gas of almost 3%, while the other variables remain quite unalerted.

Table 13: Variance Decomposition VEC with COB and IPI

Period	log(COB)	wtv	exch	euribor	inflation	log(IPI)
1	16,64352	52,68419	0,041381	0,433859	1,111122	29,08593
2	27,73078	50,59685	1,434716	1,658879	0,629516	17,94926
3	26,40836	47,55035	4,29347	2,470151	2,599176	16,67849
4	21,45272	45,08239	5,431249	2,697809	9,266639	16,0692
5	17,64091	41,12794	5,37303	2,840764	18,16031	14,85705
6	17,00725	34,9548	4,462866	2,763479	27,75515	13,05644
7	18,92639	28,60894	3,516373	2,653888	35,16525	11,12916
8	21,70142	23,4243	2,925315	2,585538	39,91764	9,445783
9	24,03598	19,68302	2,671381	2,639937	42,77121	8,198477
10	25,57472	17,12156	2,6154	2,80878	44,5452	7,334337
11	26,40944	15,40687	2,634207	3,067111	45,73066	6,751713
12	26,70617	14,27487	2,66235	3,387817	46,60759	6,361199

Notes: The table reports the variance decomposition of log(IPI) with respect to the other variables in the VEC system with COB as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Industrial Production Index's total variance in each quarter from the initial shock. The numbers in the table are percentages.

Table 14: Variance Decomposition VEC with COB and GDP

Period	log(COB)	wtv	exch	euribor	inflation	log(GDP)
1	6,605851	38,46614	0,123853	2,28627	0,24923	52,26865
2	11,24179	32,22284	0,569144	1,240048	0,994907	53,73127
3	8,361034	35,60144	0,89223	2,087625	4,070211	48,98746
4	6,140696	40,36789	0,655301	2,31183	6,564913	43,95937
5	7,040464	41,03856	0,500673	2,291631	9,943155	39,18551
6	11,98736	36,97494	0,416274	2,380936	12,22172	36,01877
7	18,18941	31,7833	0,349091	2,310635	14,0494	33,31817
8	24,14036	27,3289	0,329293	2,232317	14,55549	31,41364
9	28,5584	23,86283	0,331416	2,216192	14,76931	30,26185
10	31,63402	21,25222	0,377866	2,16933	15,04208	29,52448
11	33,61781	19,38694	0,440889	2,15105	15,36916	29,03415
12	35,09455	17,91661	0,486518	2,125149	15,84938	28,52779

Notes: The table reports the variance decomposition of log(GDP) with respect to the other variables in the VEC system with COB as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Gross Domestic Product's total variance in each quarter from the initial shock. The numbers in the table are percentages.

The variance decomposition analysis now moves to the second model considered. Tables 13 and 14 present how much each variable's variance impacts IPI and GDP total variance if we perform a vector error correction model. We observe from both tables that the COB variance preserves its explanatory power on our output variables' variance, showing a higher contribution for the one of GDP. The contribution of COB's variance differs barely concerning the values shown in Table 1, while a more relevant variation is observable to the ones shown in Table 2. The difference at lag 12 is almost +15.69% and -1,92%, respectively, for Tables 13 and 14. The other variables' variance impact on GDP and IPI total variance does not present significant change, except for inflation. It succeeds in contributing almost 47% and 16% to IPI and GDP total variance, respectively. Last, low variance information levels of our output variables' total variance can be found in columns related to the Exchange Rate and Euribor.

Table 15: Variance Decomposition VEC with TTF and IPI

Period	log(TTF)	wtv	exch	euribor	inflation	log(IPI)
1	0,322594	70,28008	0,003212	0,997066	1,42209	26,97496
2	0,832409	75,86714	1,464152	2,328979	0,728344	18,77898
3	0,873719	74,24249	2,581992	3,150696	2,021534	17,12957
4	2,925091	65,10786	2,389299	2,654589	8,817391	18,10577
5	4,804139	53,39063	1,938064	2,289601	20,01527	17,56229
6	5,797499	42,68188	1,931322	2,511004	31,36947	15,70883
7	6,327864	34,39548	2,313048	2,982069	40,33691	13,64462
8	6,589885	28,6222	2,908878	3,438432	46,57177	11,86884
9	6,66778	24,67875	3,575356	3,75929	50,78877	10,53005
10	6,647403	21,86004	4,208715	3,925002	53,76225	9,596587
11	6,594563	19,72676	4,75867	3,960645	55,99589	8,963471
12	6,542089	18,03352	5,217411	3,903534	57,77045	8,533432

Notes: The table reports the variance decomposition of log(IPI) with respect to the other variables in the VEC system with TTF as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Industrial Production Index's total variance in each quarter from the initial shock. The numbers in the table are percentages.

Table 16: Variance Decomposition VEC with TTF and GDP

Period	log(TTF)	wtv	exch	euribor	inflation	log(GDP)
1	1,055599	37,72876	0,103588	0,722465	1,005002	59,38458
2	14,83112	28,69751	0,61155	1,15681	1,717669	52,98534
3	18,01292	26,7603	0,418534	0,813257	5,144872	48,85012
4	17,66979	23,20337	0,327652	0,619045	9,76391	48,41623
5	14,5558	18,79206	0,459827	0,522793	17,11496	48,55457
6	11,61842	14,91155	0,979278	0,557957	24,87276	47,06004
7	10,24287	11,95004	1,72704	0,686225	31,2426	44,15122
8	10,36538	9,857578	2,45615	0,827706	35,63236	40,86083
9	11,37491	8,39667	3,050577	0,958176	38,3555	37,86416
10	12,69765	7,349202	3,484668	1,07102	39,94184	35,45562
11	13,98945	6,567891	3,775984	1,167985	40,83621	33,66248
12	15,09467	5,964201	3,955225	1,252275	41,33409	32,39954

Notes: The table reports the variance decomposition of log(GDP) with respect to the other variables in the VEC system with TTF as energy commodity price for 12 quarters. These results explain how much each variable's variance impacts on Gross Domestic Product's total variance in each quarter from the initial shock. The numbers in the table are percentages.

The final two tables we present consist of the outcome of our VEC variance decomposition analysis in the cases in which the TTF price is considered. Uniformly to what we have seen in each table, the IPI and GDP variance decomposition analyses presented here do not show significant differences. In Tables 15 and 16, the contribution of TTF's variance differs barely concerning the values shown in their corresponding

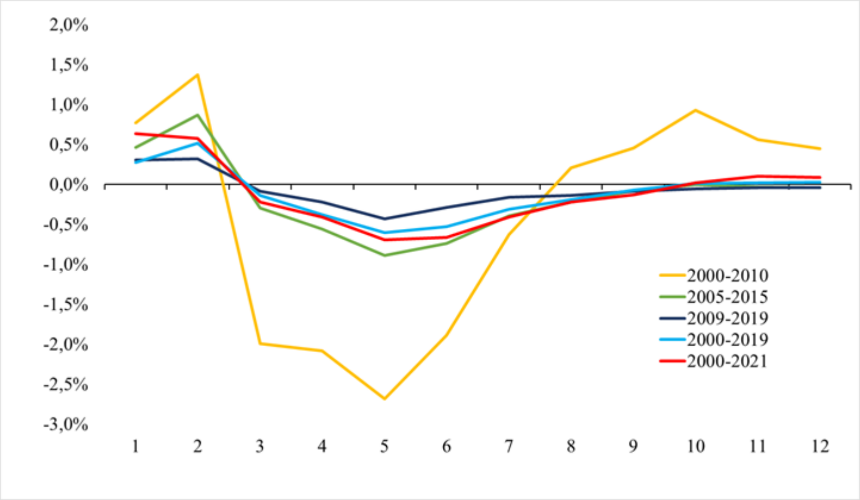
VAR analyses. The difference at lag 12 is almost -6,36% and +4.37%, respectively, for Tables 15 and 16. Finally, we observe a determined increase in the inflation's variance information level in both Tables.

5.3 Robustness checks

In this Section, we verify the robustness of our results. We have observed that shocks in COB and TTF prices affect the Italian Gross Domestic Product and Industrial Production Index. However, for the completeness of our analysis, we implement a robustness analysis to verify if our estimates are accurate and do not depend on the specification or the sample utilized. Therefore, we first consider an alternative specification for all our models. More precisely, we make some changes in the adopted control variables, leaving the others unaltered. We substitute the Euro-Dollar Exchange Rate and the 3-month Euribor interest rate for the Italian nominal effective exchange rate (NER) and the Euro OverNight Index Average (EONIA) interest rate, respectively. NER is obtained, as its precursor, from the Bank of Italy database. In general, the effective exchange rate, or multilateral exchange rate, is an index of the price competitiveness of an economic area relative to a distinct group of competing economic areas. In our specific case, a weighted average of the exchange rates between the local currency and the currencies used in the competing area is utilized to generate the nominal effective exchange rate. The second variable used to respecify our models is instead obtained from Bloomberg. The transformed VARs are based on the same sample of the original ones, 2000 Q1 to 2021Q4, and maintain quarterly observations. Then, we validate our results showing our VAR and VEC analyses through four different sample periods. First, considering an eleven-year sample, we show the results from 2000 Q1 to 2010 Q4, then from 2005Q1 to 2015 Q4, and finally from 2009 Q1 to 2019 Q4. It is observable that we exclude the last two years, 2020 and 2021, from the above samples. This choice is motivated by the fact that the last two years' extreme events have led to extreme disruptions in the variables that our model cannot adequately analyse within a lower number of observations. However, we present a backwards reduced full sample model from 2000 Q1 to 2019 Q4, excluding only these two years, to show the robustness of our results. We conclude that we can observe different robustness levels in our models. Sample sizing and new model specification checks in our VARs reveal that the results are more robust when considering Brent price shocks instead of TTF price shocks. This trend is present also in the last four sample sizing checks for the robustness of our VEC models. That can be due to the used specification arising principally from reasoning based on the available knowledge on the transmission mechanisms of oil price shocks to the real economy.

Figure 17: Robustness checks in VAR with COB and IPI

(a) Different sample periods of VAR with COB and IPI



(b) Different specifications of VAR with COB and IPI

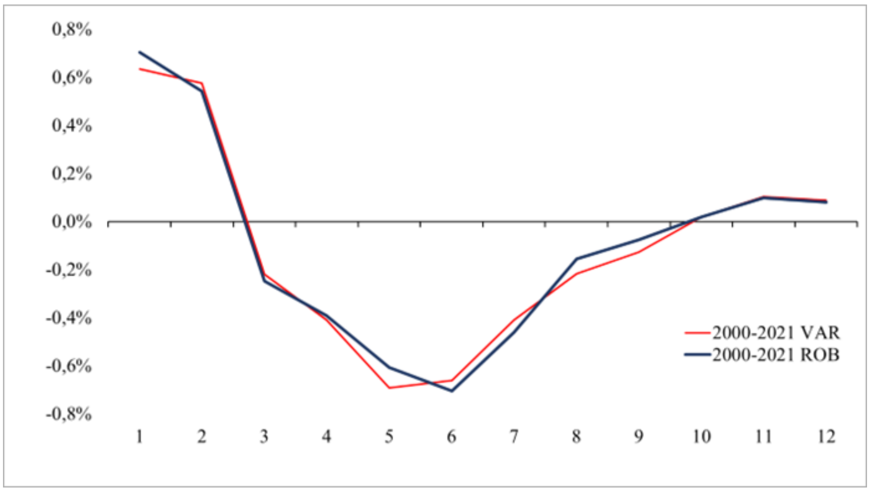
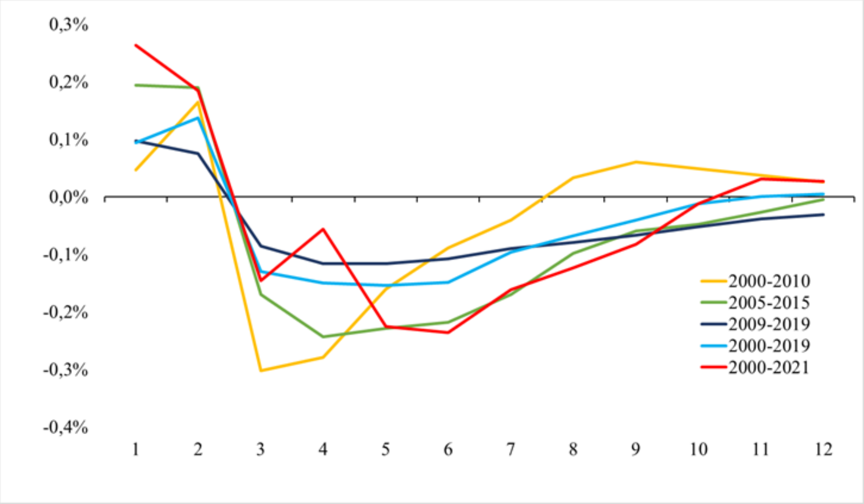


Figure 18: Robustness checks in VAR with COB and GDP

(a) Different sample periods of VAR with COB and GDP



(b) Different specifications of VAR with COB and GDP

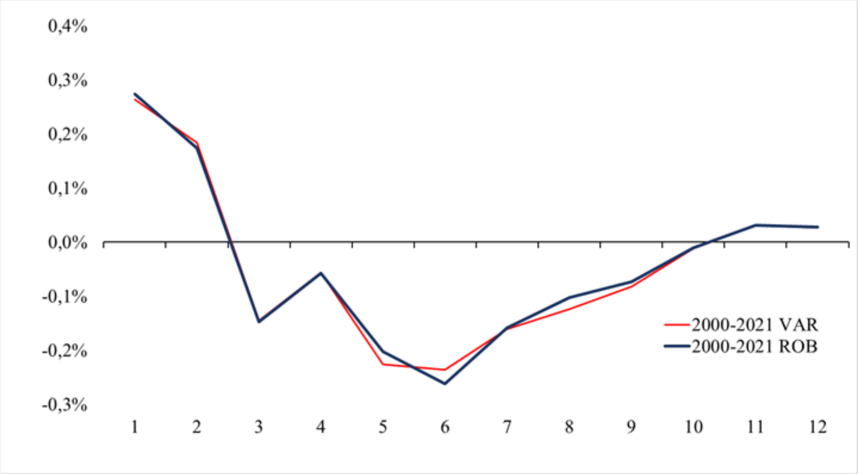
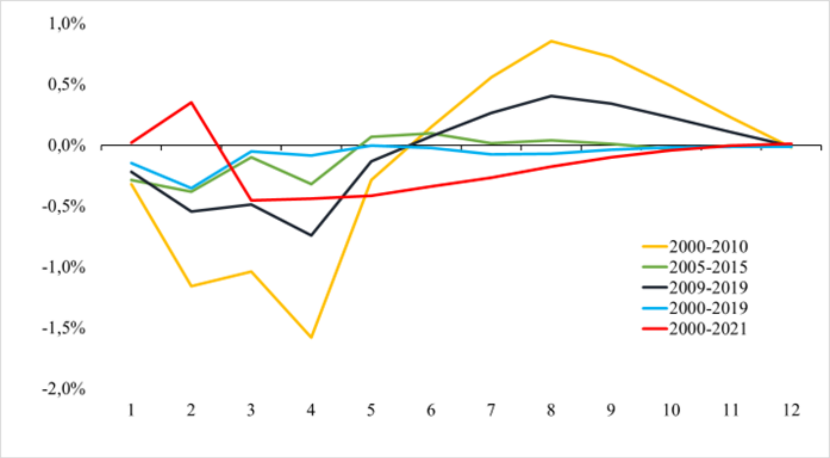


Figure 19: Robustness checks in VAR with TTF and IPI

(a) Different sample periods of VAR with TTF and IPI



(b) Different specifications of VAR with TTF and IPI

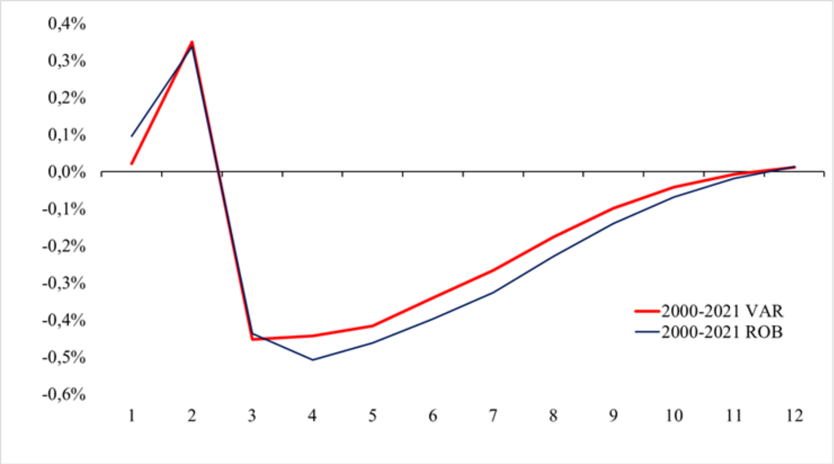
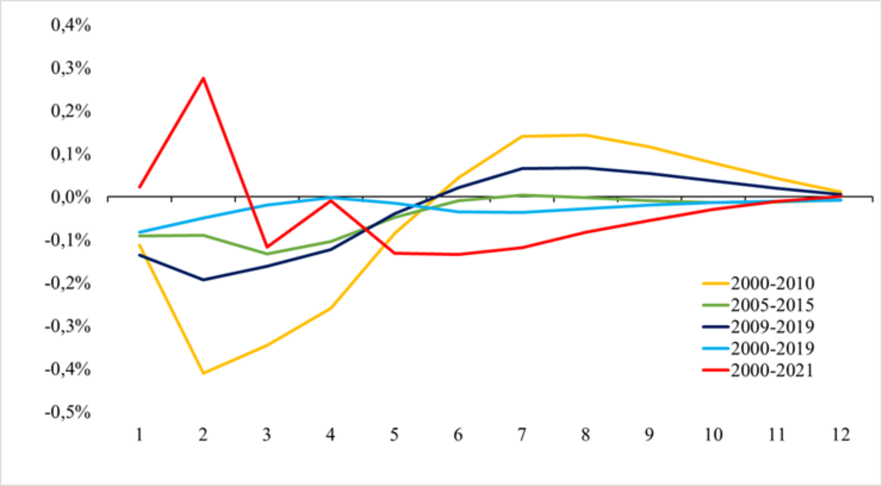


Figure 20: Robustness checks in VAR with TTF and GDP

(a) Different sample periods of VAR with TTF and GDP



(b) Different specifications of VAR with TTF and GDP

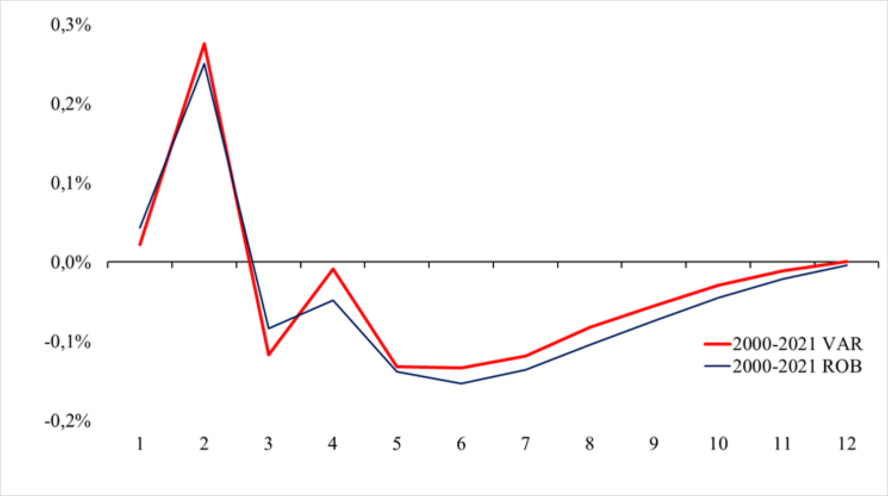


Figure 21: Robustness checks of VEC with COB and IPI

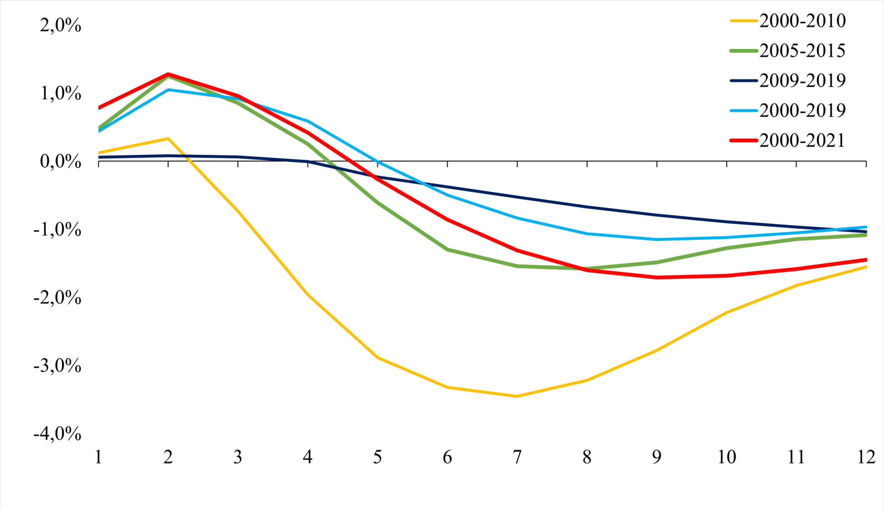


Figure 22: Robustness checks of VEC with COB and GDP

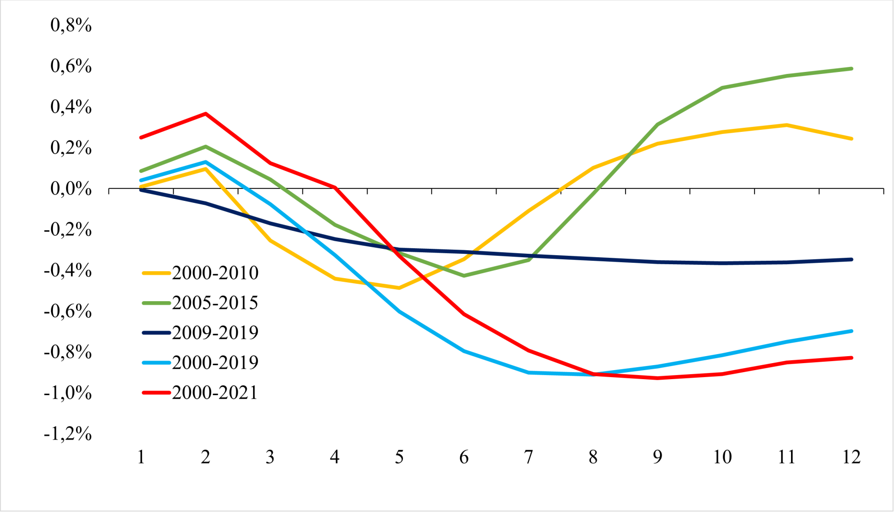


Figure 23: Robustness checks of VEC with TTF and IPI

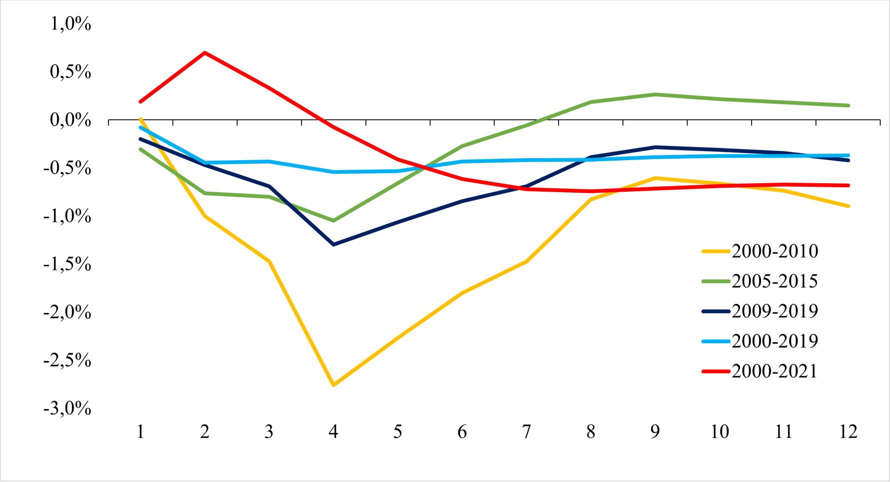
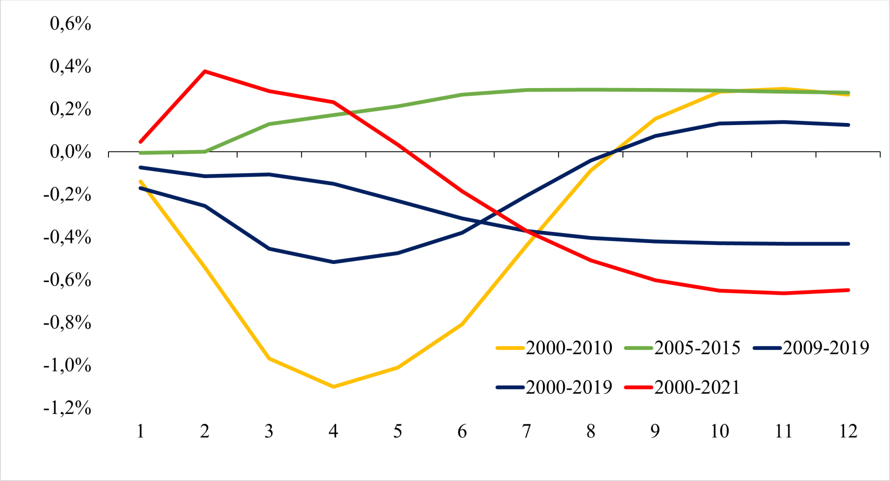


Figure 24: Robustness checks of VEC with TTF and GDP



6 Conclusion

This thesis studies the effect of Crude oil Brent and Natural gas Dutch TTF price shocks on the Italian real economy activity. We focus on the relationships between oil and gas prices with GDP and IPI, which are analysed in terms of vector autoregression and vector error correction by using a specification composed by four control variables to capture the price shocks transmission mechanisms. We implement our analysis on a quarterly data over a period of 22 years.

As a first step, we perform unit root test to verify the stability of the variables utilized in our analysis and proceed to differentiate the ones that are not. Thus, we conduct vector autoregressions considering the Cholesky decomposition to control for contemporaneous effects among the variables. The result we obtain from vector autoregressions are broadly consistent with the expectation that the GDP and IPI of an oil importing economy, as Italy, suffers increases in oil prices. Similar consideration can be derived observing the impulse response functions of vector autoregression when we substitute the oil with the gas price. Here is observable how, especially for the Industrial Production Index, a two positive standard deviation on the Dutch TFF induces a statistically significant negative effect on our macroeconomic variables. After a SVAR analysis we investigate the possibility of cointegrated relationships between our variables. Thus, performing the Johansen test, we observe that our systems of variables concern at least one or more cointegrated equations. To account for this result, we reiterate the analysis in terms of vector error correction to observe eventually changes in the impulse response functions and variance decomposition tables.

The impacts of Crude oil Brent and Dutch TTF price shocks on our macroeconomic variables are less certain in IRFs calculated using a SVAR technique than in IRFs estimated using a SVEC approach. Furthermore, the former has a detrimental impact that is not statistically significant over time. The IRFs produced from the SVEC study, on the other hand, show a more lasting and strong negative effect because of price increase. Following VAR and VEC IRFs, the Industrial Production Index has a more severe negative impact with a two-standard deviation shock in Brent price. The former predicts a negative impact from lag 3 to 10, with a maximum negative estimate of -0,7% in lag 5, whereas the latter denotes a more severe effect. In terms of the IRFs of GDP to COB price shocks, we find a strong resemblance between the SVAR and SVEC findings, with a comparable course in the first five lags. As a result, the latter continues its downward trend, resulting in a significant and delayed impact on GDP, ranging between -0.62% and -0.92% from lag 6 to 12. Regarding the impact of Dutch TTF price shocks on our macroeconomic variables, we see a similar pattern on both VAR and VEC IRFs in the case of IPI. Indeed, both exhibit a quick decline following early favourable effects, resulting in a negative influence since lags 3 and 4, respectively. Then, while the VAR reaction progressively returns to zero, the VEC IRF persists, demonstrating a significant long-run negative influence of TTF price shocks on the Industrial Production Index, with a maximum negative impact of -0.74% in lag 7.

Our variance decomposition results are consistent with what has been stated thus far. We discovered that the variances of Crude Oil Brent and Dutch TTF explain a considerable fraction of the overall variance of our macroeconomic variables. More specifically, our VAR results suggest that Brent variance may explain 22,9% and 15,1% of total IPI and GDP variance, respectively. Continuing with our VAR variance decomposition results, we see that TTF's variance has an informative power. Indeed, the IPI and GDP total variances over 12 quarters are explained by the TTF price variances for 9,80% and 8,64%, respectively. The VEC equivalent analyses indicate no significant differences from these results, maintaining close to these average values.

Finally, while the literature on the impacts of oil price movements on the real economy is extensive, many available paths can help investigate the effects of a gas price shock. First, further consideration regarding the control variables used may assist in getting closer to those that better capture its transmission mechanisms. Then, augmenting the analysis to the differences in the economic effects of gas price shocks for net gas importing and exporting countries may allow interesting comparative results.

References

[1] Aguiar-Conraria, L., Soares, M.J. (2011). "Oil and the macroeconomy: using wavelets to analyze old issues". *Empirical Economics,* 40, 645–655.

[2] Arman, S., Zare, R. (2005). "An Investigation of Granger – Causal Relationship between Energy Consumption Economic Growth in Iran (1967-2002)". *Iranian Journal of Economic Research,* (24), 117-143.

[3] Asgharpour, H., Behdubi, D. Qazyinnian, M.H. (2009). "Structural break: the case of gas consumption and economic growth in Iran". *Quarterly Energy Economics Review,* 19, 105-122.

[4] Balke, N. S., Brown, S. P. A., Yücel, M. K. (2002). "Oil Price Shocks and the U.S. Economy: Where Does the Asymmetry Originate?". *The Energy Journal*, 23(3), 27–52.

[5] Ben S. Bernanke, (1983). "Irreversibility, Uncertainty, and Cyclical Investment". *The Quarterly Journal of Economics,* Volume 98, Issue 1, Pages 85–106

[6] Cullen, J. B, Friedberg, L., Wolfram, C. (2005). "Do Households Smooth Small Consumption Shocks? Evidence from Anticipated and Unanticipated Variation in Home Energy Costs". *UC Berkeley: Center for the Study of Energy Markets.*

[7] Douglas B. Reynolds, Kolodziej M. (2008). "Former Soviet Union oil production and GDP decline: Granger causality and the multi-cycle Hubbert curve". *Energy Economics,* Vol. 30, Issue 2, Pages 271-289.

[8] Dickey, D. A., Fuller, W. A. (1981). "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root". *Econometrica,* 49(4), 1057–1072.

[9] Energy Balance, (2004) Ministry of Energy (MOE), Deputy for Power Energy Affairs-Power Energy Planning Department, Iran

[10] Engle, R. F., Granger, C. W. J. (1987). "Co-Integration and Error Correction: Representation, Estimation, and Testing". *Econometrica,* 55(2), 251–276

[11] Ferderer, J. (1996). "Oil price volatility and the macroeconomy". *Journal of Macroeconomics,* Vol. 18, Issue 1, Pages 1-26

[12] Friedman, J. W. (1977). "Uligopoly and the theory of games". *Amsterdam: North-Holland.*

[13] Granger, C. W. J. (1969). "Investigating Causal Relations by Econometric Models and Cross-spectral Methods". *Econometrica,* 37(3), 424–438.

[14] Granger, C. W. J. (1981). "Some Properties of Time Series Data and Their Use in Econometric Model Specification". *Journal of Econometrics,* 16, 121-130.

[15] Hamilton, J. D. (1983). "Oil and the Macroeconomy since World War II". *Journal of Political Economy,* 91(2), 228–248.

[16] Hamilton, J. D. (1988). "A Neoclassical Model of Unemployment and the Business Cycle". *Journal of Political Economy,* 96(3), 593–617

[17] Hendry, David F., and Thomas von Ungern-Sternberg (1980). "Liquidity and Inflation Effects on Consumers' Expenditure. In A. Deaton (Author), Essays in the Theory and Measurement of Consumer Behaviour: In Honour of Sir Richard Stone (pp. 237-260)." *Cambridge University Press.*

[18] Holmes M., Wang P. (2019). "Oil Price Shocks and the Asymmetric Adjustment of UK Output: A Markov-switching approach". *International Review of Applied Economics,* T17:2, 181-192.

[19] Iwayemi, A., Fowowe, B. (2011). "Impact of oil price shocks on selected macroeconomic variables in Nigeria". *Energy Policy,* Vol. 31, Issue 2, Pages 603-612

[20] James E. H. Davidson, Hendry, D. F., Srba, F., Yeo, S. (1978). "Econometric Modelling of the Aggregate Time-Series Relationship Between Consumers' Expenditure and Income in the United Kingdom". *The Economic Journal,* 88(352), 661–692.

[21] James D. Hamilton (2003). "What is an oil shock?". *Journal of Econometrics,* Vol.113, Issue 2, Pages 363-398.

[22] Jimenez-Rodriguez, R., Sanchez, M. (2005). "Oil price shocks and real GDP growth: empirical evidence for some OECD countries". *Applied Economics,* Vol. 37, Issue 2, Pages 201-228.

[23] Johansen S. (1995). "Identifying restrictions of linear equations with applications to simultaneous equations and cointegration". *Journal of Econometrics,* Vol. 69, Issue 1, Pages 111-132.

[24] Johansen S. (2014). "Statistical analysis of cointegration vectors". *Journal of Econometric Dynamic and Control,* Vol. 12, Issue 2-3, Pages 231-254.

[25] Joskow, P. L., Bohi, D. R., Gollop, F. M. (1989). "Regulatory Failure, Regulatory Reform, and Structural Change in the Electrical Power Industry". *Brookings Papers on Economic Activity. Microeconomics,* 125–208.

[26] Keane, M. P., Prasad, E. S. (1989). "The Employment and Wage Effects of Oil Price Changes: A Sectoral Analysis". *The Review of Economics and Statistics,* 8(3), 389–400

[27] Kilian, L., Park, C. (2009). "The Impact of Oil Price Shocks on the U.S. Stock Market". *International Economic Review,* 50(4), 1267–1287.

[28] Kilian, L. (2009). "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market". *The American Economic Review,* 99(3), 1053–1069.

[29] Leone, R. (1982). "Impact of Higher Natural Gas prices on the northeast regional economy". *Contemporary Economic Policy,* Vol. 1, Issue 1, Pages 1-8.

[30] Lilien, D. M. (1982). "Sectoral Shifts and Cyclical Unemployment". *Journal of Political Economy,* 90(4), 777–793.

[31] Loungani, P. (1986). "Oil Price Shocks and the Dispersion Hypothesis". *The Review of Economics and Statistics,* 68(3), 536–539.

[32] Lüktepohl, H., (2005). "New Introduction to Multiple Time Series Analysis". *Springer.*

[33] Mark A. Hooker (1996). "What happened to the oil price-macroeconomy relationship?". *Journal of Monetary Economics,* Vol. 38, Issue 2, Pages 195-213.

[34] 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.

[35] Mory, J.F. (1993). "Oil Prices and Economic Activity: Is the Relationship Symmetric?". *The Energy Journal,* 14, 151-161.

[36] Milani, F. (2009). "Expectations, learning, and the changing relationship between oil prices and the macroeconomy". *Energy Economics,* Vol. 31, Issue 6, Pages 827-837.

[37] Ott, M. and Tatom, J.A. (2009). "Are there adverse inflation effects associated with natural gas decontrol?". *Contemporary economic policy,* Vol.1, Issue 1, Pages 27-46.

[38] Peter C. B. Phillips, Perron, P. (1988). "Testing for a Unit Root in Time Series Regression". *Biometrika,* 75(2), 335–346.

[39] Rotemberg J., Woodford M. (1996). "Imperfect Competition and the Effects of Energy Price Increases on Economic Activity". *Journal of Money, Credit, and Banking,* Vol. 28, No 4, Part 1.

[40] Salmon, M. (1982). "Error Correction Mechanisms". *The Economic Journal,* 92(367),615–629.

[41] Shibata, R. (1980). "Asymptotically Efficient Selection of the Order of the Model for Estimating Parameters of a Linear Process". *The Annals of Statistics,* 8(1), 147–164.

[42] Sims, C. A. (1980). "Macroeconomics and Reality". *Econometrica,* 48(1), 1–48.

[43] Stockfisch, J.A. (1982). "The income distribution effects of a natural gas price increase". *Contemporary economic policy,* Vol. 1, Issue 1, Pages 9-26.

[44] Uri, N. D. (1996). "The Impact of Crude Oil Price Volatility on Agricultural Employment in the United States". *Energy Environment,* 7(1), 57–74.

[45] Zamani, M. (2007). "Energy consumption and economic activities in Iran". *Energy Economics,* Vol. 29, Issue 6, Pages 1135-1140.

[46] U.S. Energy Information Administration, International Energy Outlook 2010, This document is available at `http://www.eia.gov/oiaf/ieo/index.html`

Summary

Since the oil embargo proclaimed by the Organization of Petroleum Exporting Countries (OPEC) in 1973, the rapid and unexpected increases in oil prices have been the subject of great interest for economists. Given the enormous scale of the national recessions that occurred in the seventies, the controversy about the macroeconomic determinants of oil shocks could arouse amazement: why should we doubt the capacity of oil shocks to determine significant variations in Gross Domestic Product (GDP) observed in so many countries? Arguably, the primary basis of this debate lies in the minimal impact on GDP that oil and its close substitutes covered in most cases before 1973. Moreover, what happened in 1973 could not be considered a pure case study due to the concomitant emergence of a plurality of other relevant factors. To mention a few, at the time of 1973, the world economy had just abandoned the fixed exchange rate sanctioned by the Bretton Woods agreements, and some countries were on the verge of recession. Thus, separating these effects to determine the weight of oil shocks on changes in GDP, the unemployment rate, and other recession indicators after 1973 has been technically complex and led to the broad economic literature that will be intensely debated in the next section of this summary.

The scepticism regarding the relation between macroeconomic output deterioration and oil price shocks was enhanced in Bohi (1989). From his study, no link emerged between the changes in oil prices and employment in the productive sectors considered at a three-digit breakdown level of the Standard Industrial Classification (SIC) system. Bohi's work, together with the identification of asymmetrical macroeconomic effects to oil price variations highlighted in Mork (1989), moved the researchers to focus on the transmission mechanism through which oil shocks cause, or contribute to, macroeconomic recessions.

Different transmission mechanisms have been identified and studied as (a) the labour market, (b) the use of capital goods, (c) changes in interest rates, (d) investment freeze, and (e) sectoral shocks. More precisely, the analysis of labour market mechanisms has used the concept of aggregated and allocative channels. The former concern the traditional macroeconomic mechanisms of potential effects on output, income transfers and wages' rigidity, while the latter are related to the correspondence between the level of use of inputs desired by the enterprises and the one used. In this regard, Keane and Prasad (1996) found out that in the United States oil price increases have reduced the real wages of all workers, but they have increased the relative salaries of qualified ones. Moreover, they have shown that changes in the price of oil do not induce a shift of workers towards the sectors that recorded the relative wage increase. This result can be partially explained by considering that oil shocks may change the optimal technologies employed in industries in a way that destroys some of the workers' minor tangible skills, causing them to seek employment in industries that require skills below the apparent level of human capital.

Several studies have shown that interest rates react to oil price increases. For instance, Balke (2002) has identified asymmetric reactions of interest rates in the short and long term to distinguish positive and negative oil shocks. The evidence exposed in Balke's study signal the existence of a preference in the interest differential between the commercial papers from four to six months and Treasury Bills at six months. This relation may suggest the presence of a desire for security if increases in oil prices raise uncertainty in the economy.

Last, the sectoral shock hypothesis (Lilien, 1982; Hamilton, 1988), also known as the hypothesis of employment dispersion, supposes that one shock with differentiated effects on different sectors has a more significant impact on aggregate unemployment. The dispersion increase of sectoral shocks implies a higher labour reallocation resulting in a broader overall unemployment rate. The reallocation effects of any price shock, positive or negative, can cause increases in the creation or destruction of jobs. Thus, the time needed for resources to be reabsorbed elsewhere leads to decreased aggregate employment.

The purpose of this thesis is to analyse and understand the dynamic effects of shocks in Crude oil Brent (COB) and Natural gas Dutch TTF (TTF) prices on Italian Gross Domestic Product and Industrial Production Index (IPI) through the last two decades. The first two variables are acquired from the public database of the World Bank, and their values are expressed in dollars and nominal terms. At the same time, the last two measures are obtained directly from the National Statistical Institute of Italy (ISTAT). To capture the impact of the two energy commodities price shocks on our macroeconomic variables, we include some control variables such as the World Trade Volume (WTV), the Euro-Dollar Exchange Rate (EXCH), the 3-moth Euribor interest rate (ERB), and the Italian inflation level (INF). Two different econometric models generate the results obtained from our study. The first part of the analysis employs a Structural vector autoregression (SVAR) approach, while the second part examinates the variables' relationship through a vector error correction (VEC) model. We consider this second type of econometric model due to cointegration among our variables. Indeed, VEC models, differently from VARs, can capture variables' long-run relationships that are possibly lost in VAR analyses. Both models are estimated on quarterly data over a sample period from 2000 Q1 to 2021 Q4. The identification issue is solved through the Cholesky decomposition of the variance-covariance matrix of VAR and VEC residuals, ordering first, in the Cholesky factor, the energy commodity price, the control variables in the order they have been presented above, and last the output variables (alternatively GDP or IPI). The principal outcomes of our analysis are the impulse responses of the output variables to a two standard deviation shock in the two energy commodities prices. Then, we disclose some variance error decomposition analysis to illustrate how much information each variable in the system contributes helps to explain the output variables' total variance.

Our findings on the IRFs analysis exhibit, in general, a clear relationship between the variables of interest. They present positive Crude oil Brent or Natural gas Dutch TTF price shocks as harming the Italian Gross Domestic Product and Industrial Production Index. However, the impulse response functions of our two models capture the relationships at different levels. The impact of COB price shocks on our macroeconomic variables is more tenuous in IRFs estimated using a SVAR than a SVEC approach. Moreover, the former shows a negative effect that does not remain statistically significant for a lasting period. On the contrary, the IRFs obtained from the SVEC analysis report a more persistent and intense negative effect due to a COB price increase. The variation between the two models' IRFs continues if we consider the impact analysis of Dutch TTF price shocks on our output variables. Here, the diversity between the two models' results is evident, especially considering the IRFs of GDP to TTF. In summary, with a two standard deviation shock in COB price, the Industrial Production Index registers a more significant negative impact following VAR and VEC IRFs. The former estimates a negative impact from lag 3 to 10, with the highest record of -0,7% in lag 5, while the latter returns a more severe effect. Regarding the IRFs of GDP to COB price shocks, we observe a convincing similarity among the SVAR and SVEC results showing a resemblant path in the first five lags. Thus, the latter persists on its negative path leading to a significant and delayed impact on GDP, oscillating between -0,62% and -0,92% from lag 6 to 12. For what concerns the analysis of the effect of Dutch TTF price shocks on our macroeconomic variables, we observe a similar trend on both VAR and VEC IRFs in the case of IPI. Indeed, both show a rapid decrease after initial positive effects, bringing a negative impact since lag 3 and 4, respectively. Then, while the VAR response turns gradually back to zero, the VEC IRF endures manifesting a relevant long-run negative effect of TTF price shocks on the Industrial Production Index with a maximum negative impact of -0,74% in lag 7. Finally, we observe a feebler correspondence between the models' IRFs in our last case, with the VAR results indicating a scarce negative effect on GDP in contrast with VEC ones. Last, our variance decomposition results align with what was presented until now. We found that both Crude oil Brent and Dutch TTF variances explain a significant portion of the total variance of our macroeconomic variables. More precisely, our VAR results show that COB's variance can explain, on average, the 22,9% and 15,1% of IPI and GDP total variance, respectively. Remaining on our VAR variance decomposition results, we observe that TTF's variance also presents an informative power. Indeed, the IPI and GDP total variances are explained by the gas price variance of 9,80% and 8,64% over 12 quarters. The VEC equivalent analyses do not show remarkable variations from these results, remaining close to these average values.

Literature review

In both empirical and theoretical literature, it has been copiously debated that energy source shocks, especially the ones referring to oil, exhibit an adverse impact on multiple macroeconomic activities (Aguriar-Conraria and Soares, 2011; Iwayemi and Fowowe, 2011, Milani, 2009, Holmes and Wang, 2003). For example, Reyenolds and Kolodziej (2008) show that the fall in the Gross Domestic Product of the former Soviet Union was Granger-caused by the downturn in oil production. This phenomenon can be partially explained by observing the production and operation costs co-movements with energy prices. Indeed, these costs are strongly related to the price of energy since it is an irreplaceable intermediate good to produce electricity.

Harmful economic effects may arise from significant energy price changes, increasing or decreasing. For example, price volatility might induce business investment procrastination by strengthening uncertainty or inducing costly sectoral resource reallocation. Bernanke (1983) grants a theoretical illustration of the uncertainty channel. The economist pointed out that when projects are irreversible, agents must make investment timing decisions that trade off the extra returns from early commitment against the benefits of increased information gained by waiting. Indeed, the uncertainty on the energy sources price may be followed by an increase in the option value for the investment delay, which shrinks the incentive to invest. For instance, firms commonly face this critical decision when choosing whether to implement an energy-efficient or inefficient capital. However, such disruption does not only affect firms' decisions. Uncertainty about future energy prices also shortens consumers' spending on cars, housing, and investment goods (Hamilton, 2003). The costly sectoral resources reallocation channel has been examined by Ferderer (1996), showing that oil price volatility, measured by monthly standard deviations of daily oil prices, helps to forecast aggregate output movement in the U.S. The real economy suffers from changes in oil prices from both the supply and demand side (Jimenez-Rodriguez and Sanchez, 2005). As stated before, it is observable a consistent reflection of the increase in oil price into higher production cost. From the supply side, the investment demand is negatively affected by the increasing uncertainty related to the oil price movements and the decreasing rate of return on investment eroded by the new cost level. Simultaneously with the supply, the consumption demand shrinks due to the impact of higher production costs on the final product price. The robust transmission mechanism of oil price shock to the inflation path does not leave the other economic variables unaltered. Inflationary pressure may cause a drop in demand and this, in turn, results in a production fall, which can create unemployment (Loungani, 1986). Moreover, such a relationship between oil price and employment does not hold only for industrial production but can also be enlarged to the agricultural one (Uri, 1995).

Two consecutive oil shocks in the early 1970s brought some economists to examine the impact of shocks to oil price levels on economic activities. Hamilton (1983) can be seen as a pioneer study to understand such relationships better. His study examines the behaviour of oil prices and the output of the U.S. economy over 1948-1981. The analysis concludes that every U.S. recession between World War II and 1973 (except the 1960-1961 recession) has been preceded by a drastic increase in the price of crude petroleum. Hamilton (1988) has observed the costly sectoral resource allocation impediment through a multi-sector analysis. The principal cost source that emerged from the study involves the strong aversion of workers of the adversely affected sectors to search for new job positions. It was shown that relative price shocks could reduce aggregate employment leading the affected workers to remain unemployed while waiting for an optimal condition to be restored in their sector. Friedman (1977) expresses similar beliefs on the relationship between the natural rate of unemployment and inflation level uncertainty. The economist opined that the latter could increment the former through a decreased allocative efficiency and, hence, a decline in output. From Friedman's belief, it is possible to draw a relevant consequential conclusion. If the uncertainty about inflation can be considered responsible for the decreasing production, then similar effects may be induced on output by the uncertainty of the oil price level.

Energy shocks have also posed policymakers with the difficult challenge of balancing the trade-off between high inflation and higher unemployment. Killian (2009) proposes a structural VAR model for the global crude oil market and its interaction with global demand for industrial commodities. Three different shocks to the global crude oil market have been identified in his study: a crude oil supply shock, a shock to the global demand for all industrial commodities, and a demand shock that is specific to all industrial commodities. Analysing the impact of oil price shock on the U.S. stock market, he found that the implications of higher oil prices for U.S. real GDP and Consumer Price Index (CPI) inflation depend on the cause of oil price increase. Killian (2009) found that an increases in the precautionary demand for crude oil causes an immediate, persistent, and significant increase in the actual price of crude oil; an increase in the aggregate demand for industrial commodities causes a delayed but sustained rise in the actual price of oil; and that crude oil production disruption causes a slight and transitory increase in the actual price of oil with in the first year.

However, recent years have shown how the use of Natural gas as an alternative energy source from oil is spreading. A partial justification for this trend can be found in the constant increase of energy consumption in the world and the necessity to control for two significant threats of environmental pollution: the climate change phenomenon and accelerated consumption growth of non-renewable energy sources (Energy Balance, 2008). In addition, Natural gas has been chosen more frequently for industrial and electricity generation thanks to its relative fuel efficiency, low emissions, quick construction timelines, and capital costs. Since this trend seems to continue until 2035 (EIA, 2010), it is significant to investigate the empirical relationship between Natural gas prices and economic growth. To the best of our knowledge, there appears to be far less research on the connection between Natural gas prices and macroeconomic activity. However, it could be realistic to assume that rising Natural gas prices will likely have less of an overall impact than growing oil prices because the total amount of Natural gas consumed in the economy is around half that of petroleum. Early work in this field was published in a special issue of Contemporary Policy Issues in October 1982. Three studies investigated the impact of removing Natural gas price regulations on (i) regional economic activity (Leone, 1982), (ii) income distribution between households and providers (Stockfisch, 1982), and (iii) inflation (Ott and Tatom, 1982a). The studies' overall conclusion was that the projected impacts of Natural gas deregulation (higher prices, greater inflation, and declining real incomes) were not likely to be substantial. The Energy Modelling Forum (1987) discovered that a 10% rise in natural gas prices had nearly the same effect on real U.S. GDP growth (two years after the shock) as a 20% increase in oil prices. According to the median outcome of their 11 models implemented, a 50% oil shock lowered real GDP by around 1.5% after one year and by slightly less than 3% by the end of two years.

Finally, Cullen, Friedberg, and Wolfram (2005) investigated the impact of anticipated and unexpected shocks to household disposable income resulting from increasing energy expenditures on household consumption at the disaggregated level. Energy price rises, they discovered, reduce consumption among lower-income households, but only when the increase is unexpected. To conclude, Arman and Zare (2005) implemented a vector error correction model, finding a unidirectional causality from economic growth to Natural gas consumption for 1967-2002. Nevertheless, several studies focused on investigating the relationship between the real GDP and Natural gas consumption, founding a bidirectional causality using a VEC model and a comparable time window (Zemani, 2007; Asgharpour et al. 2009).

Empirical results

VAR model IRFs

In this Section we observe the results of the multivariate VAR models. The following IRFs' x-axes range from Q1 through Q4 of the subsequent quarters relative to the initial shock. At the same time, the y-axes quantify the percentage change in the variables concerning two standard deviation shocks of the energy commodity prices considered (COB, TTF). We report the results considering a 95 per cent confidence ban, highlighting that the drops and rebounds reported are statistically significant at the 5% level. The IRFs of the multivariate models that we will observe are basically exposed to demonstrate the effect of our exogenous variables' shocks on the Italian Gross Domestic Product and its Industrial Production Index. The results are obtained by adding other macroeconomic variables shocks to the system, mainly the one induced by our control variables.

Figure 25: IRF of GDP to COB

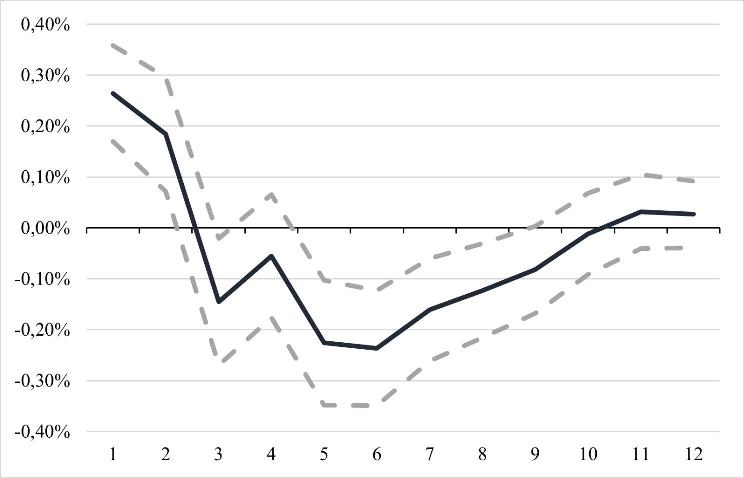
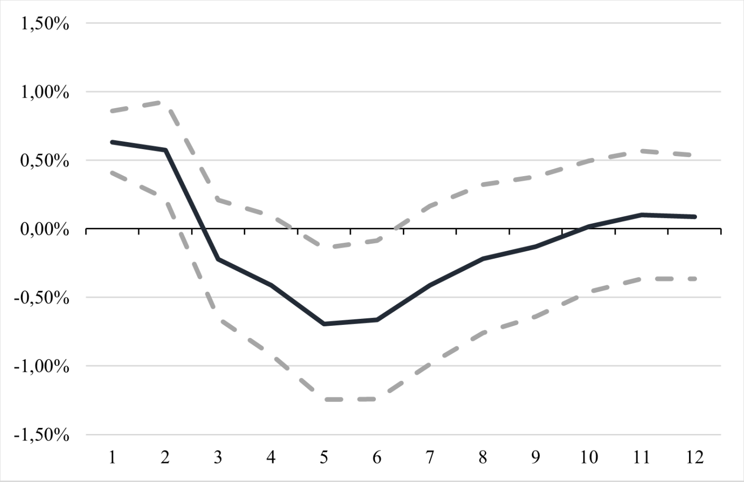


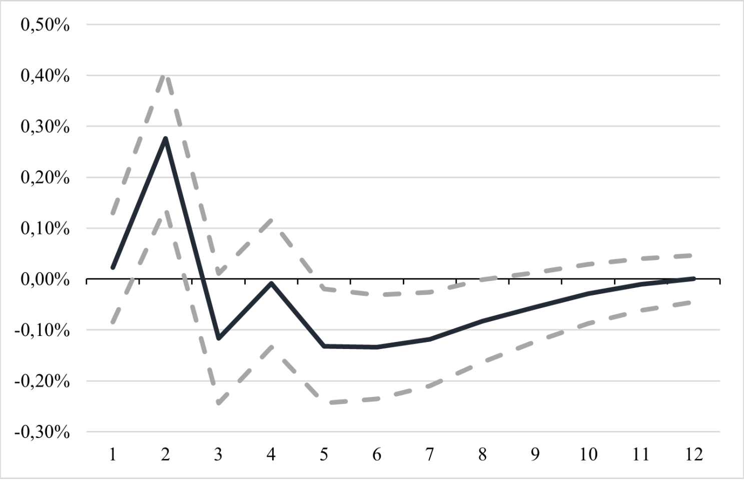
Figure 26: IRF of IPI to COB



Figures 25 and 26 show the IRF of Gross Domestic Product and the Industrial Production Index to a two-standard deviation shock in the COB price, respectively. Hence, we can observe that an unanticipated increase in Brent prices positively impacts our macroeconomic variables in the first lags. This trend appears in all the impulse response functions reported in our study, and its origin may lie in an indirect effect induced by the oil or gas prices increase. Indeed, it might be the case where net exporting countries of our energy commodities benefit from such positive price shocks and transfer part of their strengthened purchasing power on the Italian exported products. However, the significance level of such impact drops rapidly. Analysing the IPI's IRF, the starting positive impact on this variable is not statistically significant after the second lag, as for PIL's IRF. Subsequentially, the two IRFs show a similar pattern. Following the order above, we observe that the shock leads to a negative peak of about -0,7% in the Industrial Production Index and -0,24% in Gross Domestic Product, registered five and six quarters after the shock. In general, we observe an insistent detrimental effect from lag 2 to 10. Thus, we conclude that the GDP and IPI IRFs show negative responses that are statistically significant and moderate in size. The results seem consistent with most academic studies that signal an asymmetric relation between oil prices and macroeconomic output (see Mory, 1993; Rotemberg and Woodford, 1996; Hooker, 1996). The industrial production processes and daily life use of oil's derivatives, or pure oil directly, has, as a first consequence, the immediate community awareness of oil price shocks. The increase in common and essential products' prices directly affects investment and consumption. While firms face higher production costs, families see their disposable income eroded by higher inflationary levels causing the analysed IRFs responses.

The focus now moves to the impulse response analysis of gas price shocks on our output variables. In Figures 27 and 28 we present the IRFs of Italian GDP and IPI to a shock in TTF price. The former may appear not very helpful in understanding the effect of the gas price shocks on the Gross Domestic Product, while the IPI's IRF seems to signal clearer its relations with such price movements. The first difference emerging from comparing the two IRFs is in lag 2. As seen before in the COB related IRFs, we observe a similar behaviour looking at the response of GDP to gas price shocks where a slightly positive reaction is in place in lag 2. However, the expected negative relationship between the two variables arises from lag 3 and turns statistically significant in lags 5 and 6, moving slowly to zero afterwards.

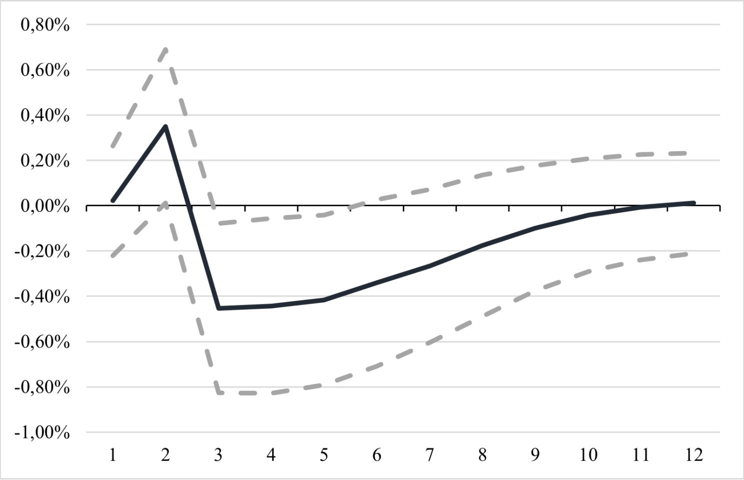
Figure 27: IRF of GDP to TTF



The IPI impulse response function to TTF price shocks allows for a cleaner description. While the

GDP IRF does not produce very interesting findings in the first four lags, here we observe a resolute negative effect since lag 3. Furthermore, the harmful effect of a TTF price increase on IPI remains and is statistically significant until lag 6. Finally, the cumulative effect from lag 3 to 6 is -1,65%.

Figure 28: IRF of IPI to TTF



VEC model IRFs

The specific requirement of stationarity for time series that characterise a VAR model brings chances of losing information about the relationship among variables' time series. Differencing the series to make them stationary may be possible to work with integrated series. Nevertheless, this approach may implicate the critical cost of ignoring potentially meaningful long-run relationships between the variables' levels. In this Section, we aim to expose the IRFs resulting from vector error correction models, which combine levels and differences, and see if they present discrepancies from what has been shown in the previous Section.

Figure 29: VAR and VEC IRFs of IPI to COB

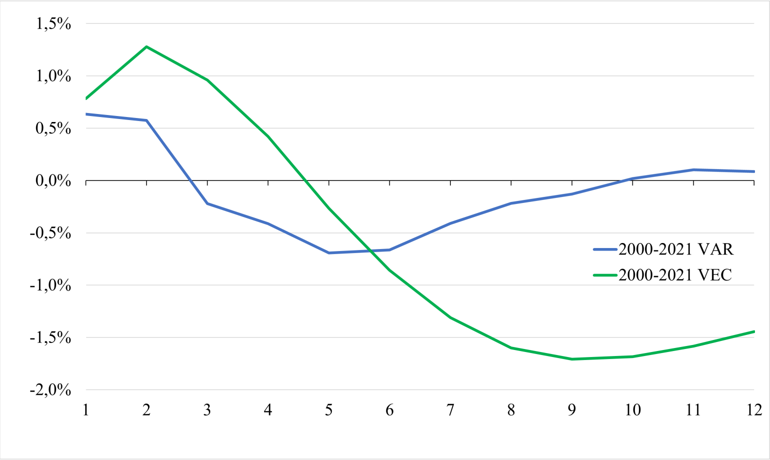
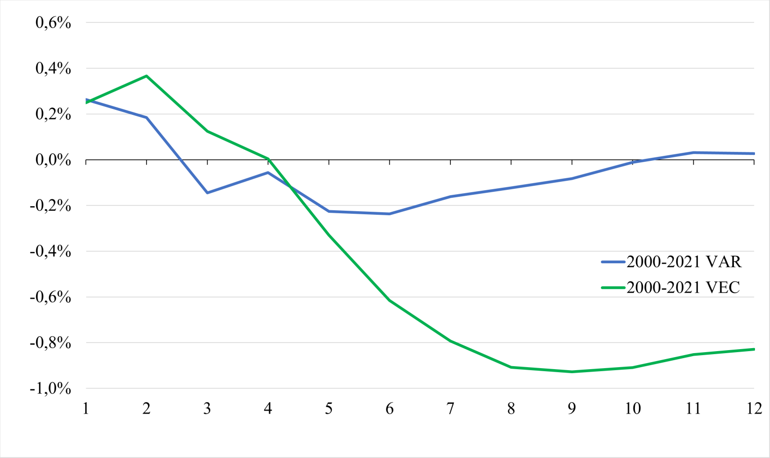


Figure 30: VAR and VEC IRFs of GDP to COB



Figures 29 and 30 compare the COB-related impulse response functions obtained from the two models. The VEC IRFs of IPI and GDP to a two s.d. shock in Brent price appear similar in shape, but they are significantly different in magnitude. Indeed, the former suggests that the Industrial Production Index is more affected by the shock analysed. Moreover, they both differ from their reciprocal VAR IRFs. After a more intense initial impact of COB price shocks on our macroeconomic variables, we observe that durable negative responses are in place. The VEC IRFs assume negative values from lag 5 and 4, respectively. Thus, the responses of IPI and GDP exhibit a stronger negative impact persistency, not returning to zero in the last lags but showing a smooth recover. However, it seems that the paths defined by the VEC IRFs do not compromise the result obtained on the related VAR analyses. Actually, the main difference between the two models' outcomes seems to lie in the long-run information relationships lost in the latter.

Figure 31: VAR and VEC IRFs of IPI to TTF

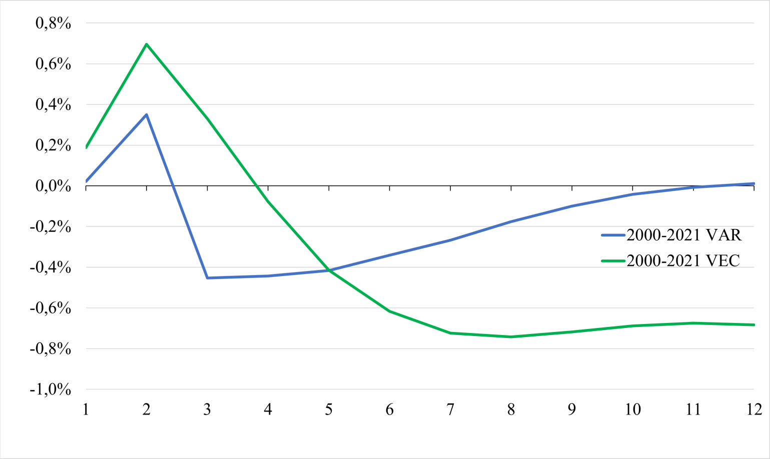
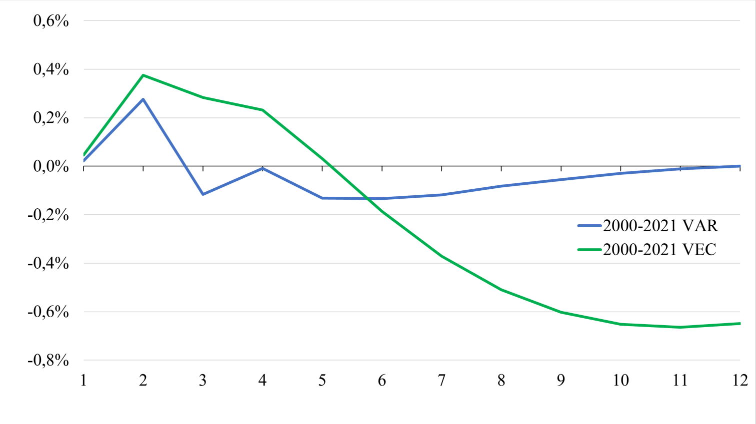


Figure 32: VAR and VEC IRFs of GDP to TTF



Then, we present VEC IRFs for the TTF cases as well. Figure 31 proposes the VAR and VEC IRFs of the Industrial Production Index to a two s.d. shock in TTF price. The closeness between the two models' outcomes is particularly evident as they show resemblant responses. Furthermore, the negative impact registered in the VEC IRF is not excessively more severe, with its peak at -0,74% in lag 8. However, the effect of TTF price shocks on IPI estimated by the vector error correction model exhibits stronger durability.

Finally, Figure 32 shows the VAR and VEC IRFs of the Gross Domestic Product to a two s.d. shock in TTF price. Conversely, from the other couple of IRFs combinations, these last two responses appear rather dissimilar. However, the former was not very informative about the impact of natural gas price shock on the Italian GDP. Thus, looking at the overall results we have obtained since now, we believe that the latter may be more reliable to observe such an impact. It appears almost identical in terms of magnitude to the one seen for IPI, but its timing does not match rigorously. Indeed, the negative impact is slightly delayed.

Emprical variance decomposition

This section illustrates the results of our variance decomposition analysis performed in both VAR and VEC models. Through these analyses, we aim to illustrate how much the amount of information each variable in the system contributes helps to explain the other variables' variance. As observable in the tables below, the results are reported until lag 12. From what has been seen through the examination of impulse response functions, we do expect that our energy commodity variables' fluctuations originate part of the total variance in our macroeconomic variables (GDP, IPI).

Table 17: Variance Decomposition VAR with COB and GDP

Period	Δlog(COB)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(GDP)
1	7,001342	35,01112	1,035017	3,903223	0,061269	52,98803
2	9,488669	33,88104	2,834572	5,301133	0,176077	48,31851
3	10,21864	31,43178	2,828114	6,926354	4,343928	44,25118
4	10,21572	31,65343	3,208026	6,775482	4,949832	43,19751
5	13,57534	30,07986	3,119406	6,525783	5,504422	41,19519
6	16,89625	28,92555	3,008535	6,192503	5,897985	39,07918
7	18,20441	28,41936	3,351803	6,140346	5,958003	37,92608
8	19,02283	28,11903	3,428246	6,109604	5,883458	37,43684
9	19,36598	28,02132	3,407855	6,08728	5,85295	37,26462
10	19,33881	27,98259	3,464171	6,127817	5,864757	37,22185
11	19,38091	27,94522	3,468735	6,130244	5,894906	37,17999
12	19,41458	27,92769	3,470006	6,127508	5,892474	37,16774

Table 18: Variance Decomposition VAR with COB and IPI

Period	Δlog(COB)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(IPI)
1	10,02432	56,25351	0,814425	0,109792	0,090903	32,70705
2	14,81196	47,32242	4,263035	1,353229	0,541977	31,70738
3	14,56004	43,95712	6,730739	1,308405	3,952625	29,49107
4	16,15311	40,13788	7,85996	1,326697	6,855955	27,6664
5	22,13786	36,55508	7,489044	1,213549	7,395774	25,20869
6	26,69577	34,14405	6,945687	1,122756	7,743046	23,34869
7	28,18111	33,31836	6,953353	1,330741	7,605578	22,61086
8	28,52115	33,0805	6,966668	1,505553	7,545933	22,3802
9	28,61541	32,98788	6,944165	1,548224	7,551759	22,35256
10	28,57896	32,94084	6,964434	1,581284	7,611197	22,32328
11	28,65382	32,8673	6,954539	1,607721	7,645343	22,27128
12	28,72397	32,83425	6,948489	1,606203	7,637426	22,24973

The first tables of our variance decomposition analysis are extrapolated from two of our VARs, keeping the Crude oil Brent price in both cases and alternatively our output variables. Although the overall results seem similar, a separate description will be delivered to assist the tables reading. In Table 17, we observe that the fluctuations in Italian Gross Domestic Product for the first half of the period are primarily due to its fluctuations, accounting, on average, for 45% of its total variance. Columns 1 and 2 of the same table report respectively the percentage contribution of Crude oil Brent and World Trade Volume to the GDP's total variance. As expected, column 2 presents relative high values that can be explained by the strong interconnection between the prosperity of national economies and the flourishness of international trade. However, we are mainly interested in column 1 outcome for our analysis. Variations in the Crude oil Brent price explain GDP's total variance through an increasing sequence starting around 7% and, since lag 9, stabilising approximately at 19%. This result suggests and signals that the effects of oil price shocks cannot be ignored in GDP forecasting attempts.

Table 19: Variance Decomposition VAR with TTF and GDP

Period	Δlog(TTF)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(GDP)
1	0,051932	41,47028	0,519039	0,570268	0,000248	57,38824
2	6,902304	37,13455	2,200525	3,259487	0,000453	50,50268
3	7,698481	36,2296	2,28296	4,363072	0,654472	48,77141
4	7,514925	35,52613	2,250453	4,347678	2,746267	47,61455
5	8,541293	34,91014	2,207922	4,474047	4,488565	45,37803
6	9,459214	34,68703	2,457975	4,440715	5,878227	43,07684
7	10,17109	34,36007	2,818794	4,368248	6,621607	41,66019
8	10,50838	34,21772	3,029106	4,306215	6,896731	41,04185
9	10,6721	34,13053	3,130606	4,285381	6,954837	40,82655
10	10,7192	34,09578	3,164554	4,288691	6,955789	40,77599
11	10,72453	34,088	3,170535	4,296898	6,954641	40,76539
12	10,72213	34,08922	3,169934	4,302069	6,960256	40,75639

Table 20: Variance Decomposition VAR with TTF and IPI

Period	Δlog(TTF)	Δ(wtv)	Δ(exch)	Δ(euribor)	inflation	Δlog(IPI)
1	0,010622	63,86945	0,731859	0,219673	0,619897	34,54849
2	2,562647	58,178	2,818123	0,677789	0,961658	34,80109
3	6,345346	54,21444	3,236065	0,69643	3,081563	32,42616
4	9,069548	50,44226	3,12866	1,643379	6,618406	29,09775
5	10,86591	47,88594	3,776356	2,195989	9,079064	6,19673
6	11,87912	46,62513	4,431502	2,227488	10,29147	24,5453
7	12,51349	45,93879	4,84818	2,172208	10,74993	23,77741
8	12,8018	45,63491	5,062732	2,149251	10,85098	23,50033
9	12,89904	45,52343	5,143129	2,158876	10,84702	23,42851
10	12,91505	45,4935	5,160045	2,17806	10,84004	23,4133
11	12,91036	45,4882	5,15893	2,191661	10,84687	23,40397
12	12,9063	45,48678	5,157367	2,197463	10,85827	23,39382

Regarding columns 3, 4, and 5, they show feeble contributions to the total variance of Italian GDP since their cumulative sum does not go beyond 15%, with their maximum values of 3.47%, 6.93%, and 7.65%, respectively. Furthermore, they continue to present an equivalent contribution level if we turn to Table 18. Conversely, some differences are observable from the second table's first two and the last columns. Indeed, COB and WTV fluctuations appear more considerable than before in explaining the total variance of IPI during the entire period. Meticulously, the former shows more remarkable improvement, with COB's fluctuations explaining almost 29% of IPI's total variance.

Tables 19 and 20 replicate a variance decomposition of the total variance, respectively, for the Italian Gross Domestic Product and Industrial Production Index. In these cases, we present the percentage contribution of Natural gas price Dutch TTF, instead of Crude oil Brent, to our output variables' total variance. While the last four columns of both tables appear similar to the ones presented in Tables 17 and 18, the percentage contribution of the other two variables is distributed slightly differently.

Table 21: Variance Decomposition VEC with COB and IPI

Period	log(COB)	wtv	exch	euribor	inflation	log(IPI)
1	16,64352	52,68419	0,041381	0,433859	1,111122	29,08593
2	27,73078	50,59685	1,434716	1,658879	0,629516	17,94926
3	26,40836	47,55035	4,29347	2,470151	2,599176	16,67849
4	21,45272	45,08239	5,431249	2,697809	9,266639	16,0692
5	17,64091	41,12794	5,37303	2,840764	18,16031	14,85705
6	17,00725	34,9548	4,462866	2,763479	27,75515	13,05644
7	18,92639	28,60894	3,516373	2,653888	35,16525	11,12916
8	21,70142	23,4243	2,925315	2,585538	39,91764	9,445783
9	24,03598	19,68302	2,671381	2,639937	42,77121	8,198477
10	25,57472	17,12156	2,6154	2,80878	44,5452	7,334337
11	26,40944	15,40687	2,634207	3,067111	45,73066	6,751713
12	26,70617	14,27487	2,66235	3,387817	46,60759	6,361199

Table 22: Variance Decomposition VEC with COB and GDP

Period	log(COB)	wtv	exch	euribor	inflation	log(GDP)
1	6,605851	38,46614	0,123853	2,28627	0,24923	52,26865
2	11,24179	32,22284	0,569144	1,240048	0,994907	53,73127
3	8,361034	35,60144	0,89223	2,087625	4,070211	48,98746
4	6,140696	40,36789	0,655301	2,31183	6,564913	43,95937
5	7,040464	41,03856	0,500673	2,291631	9,943155	39,18551
6	11,98736	36,97494	0,416274	2,380936	12,22172	36,01877
7	18,18941	31,7833	0,349091	2,310635	14,0494	33,31817
8	24,14036	27,3289	0,329293	2,232317	14,55549	31,41364
9	28,5584	23,86283	0,331416	2,216192	14,76931	30,26185
10	31,63402	21,25222	0,377866	2,16933	15,04208	29,52448
11	33,61781	19,38694	0,440889	2,15105	15,36916	29,03415
12	35,09455	17,91661	0,486518	2,125149	15,84938	28,52779

Commenting on Table 19 first, we observe that the World Trade Volume fluctuations acquired a more substantial contribution power to the GDP total variance than before, with a maximum delta increase of approximately 6%, while the other control variables' values do not present considerable changes. From column 1 of Table 19, we can finally observe the percentage contribution of Natural gas to the GDP's total variance. Dissimilarly to the values mentioned for COB, TTF fluctuations supply less information about our macroeconomic variable's total variance. More precisely, the former explains at most 11% of the latter. Nevertheless, such a contribution loss should not lead to conclude that Natural gas price fluctuations are irrelevant. On the contrary, it remains the second higher contribution value, and it should undoubtedly be taken as significant. Comparable results are obtained in Table 20, where the Industrial Production Index replaces the Gross Domestic Product. In this case, it is worth pointing out a growth in the maximum value for Natural gas of almost 3%, while the other variables remain quite unalerted.

The variance decomposition analysis now moves to the second model considered. Tables 21 and 22 present

Table 23: Variance Decomposition VEC with TTF and IPI

Period	log(TTF)	wtv	exch	euribor	inflation	log(IPI)
1	0,322594	70,28008	0,003212	0,997066	1,42209	26,97496
2	0,832409	75,86714	1,464152	2,328979	0,728344	18,77898
3	0,873719	74,24249	2,581992	3,150696	2,021534	17,12957
4	2,925091	65,10786	2,389299	2,654589	8,817391	18,10577
5	4,804139	53,39063	1,938064	2,289601	20,01527	17,56229
6	5,797499	42,68188	1,931322	2,511004	31,36947	15,70883
7	6,327864	34,39548	2,313048	2,982069	40,33691	13,64462
8	6,589885	28,6222	2,908878	3,438432	46,57177	11,86884
9	6,66778	24,67875	3,575356	3,75929	50,78877	10,53005
10	6,647403	21,86004	4,208715	3,925002	53,76225	9,596587
11	6,594563	19,72676	4,75867	3,960645	55,99589	8,963471
12	6,542089	18,03352	5,217411	3,903534	57,77045	8,533432

how much each variable's variance impacts IPI and GDP total variance if we perform a vector error correction model. We observe from both tables that the COB variance preserves its explanatory power on our output variables' variance, showing a higher contribution for the one of GDP. The contribution of COB's variance differs barely concerning the values shown in Table 17, while a more relevant variation is observable to the ones shown in Table 18. The difference at lag 12 is almost +15.69% and -1,92%, respectively, for Tables 21 and 22. The other variables' variance contribution on GDP and IPI total variance does not present significant change, except for inflation. It succeeds in contributing almost 47% and 16% to IPI and GDP total variance, respectively. Last, low variance information levels of our output variables' total variance can be found in columns related to the Exchange Rate and Euribor.

Table 24: Variance Decomposition VEC with TTF and GDP

Period	log(TTF)	wtv	exch	euribor	inflation	log(GDP)
1	1,055599	37,72876	0,103588	0,722465	1,005002	59,38458
2	14,83112	28,69751	0,61155	1,15681	1,717669	52,98534
3	18,01292	26,7603	0,418534	0,813257	5,144872	48,85012
4	17,66979	23,20337	0,327652	0,619045	9,76391	48,41623
5	14,5558	18,79206	0,459827	0,522793	17,11496	48,55457
6	11,61842	14,91155	0,979278	0,557957	24,87276	47,06004
7	10,24287	11,95004	1,72704	0,686225	31,2426	44,15122
8	10,36538	9,857578	2,45615	0,827706	35,63236	40,86083
9	11,37491	8,39667	3,050577	0,958176	38,3555	37,86416
10	12,69765	7,349202	3,484668	1,07102	39,94184	35,45562
11	13,98945	6,567891	3,775984	1,167985	40,83621	33,66248
12	15,09467	5,964201	3,955225	1,252275	41,33409	32,39954

The final two tables we present consist of the outcome of our VEC variance decomposition analysis in the cases in which the TTF price is considered. Uniformly to what we have seen in each table, the IPI and GDP variance decomposition analyses presented here do not show significant differences. In Tables 23 and 24, the contribution of TTF's variance differs barely concerning the values shown in their corresponding

VAR analyses. The difference at lag 12 is almost -6,36% and +4.37%, respectively, for Tables 23 and 24. Finally, we observe a determined increase in the inflation's variance information level in both Tables.

Conclusion

This thesis studies the effect of Crude oil Brent and Natural gas Dutch TTF price shocks on the Italian real economy activity. We focus on the relationships between oil and gas prices with GDP and IPI, which are analysed in terms of vector autoregression and vector error correction by using a specification composed by four control variables to capture the price shocks transmission mechanisms. We implement our analysis on a quarterly data over a period of 22 years.

The impacts of Crude oil Brent and Dutch TTF price shocks on our macroeconomic variables are less certain in IRFs calculated using a SVAR technique than in IRFs estimated using a SVEC approach. Furthermore, the former has a detrimental impact that is not statistically significant over time. The IRFs produced from the SVEC study, on the other hand, show a more lasting and strong negative effect because of price increase. Following VAR and VEC IRFs, the Industrial Production Index suffers a more severe negative impact with a two-standard deviation shock in Brent price. The former predicts a negative impact from lag 3 to 10, with a maximum negative estimate of -0,7% in lag 5, whereas the latter denotes a more severe effect. In terms of the IRFs of GDP to COB price shocks, we find a strong resemblance between the SVAR and SVEC findings, with a comparable course in the first five lags. As a result, the latter continues its downward trend, resulting in a significant and delayed impact on GDP, ranging between -0.62% and -0.92% from lag 6 to 12. Regarding the impact of Dutch TTF price shocks on our macroeconomic variables, we see a similar pattern on both VAR and VEC IRFs in the case of IPI. Indeed, both exhibit a quick decline following early favourable effects, resulting in a negative influence since lags 3 and 4, respectively. Then, while the VAR reaction progressively returns to zero, the VEC IRF persists, demonstrating a significant long-run negative influence of TTF price shocks on the Industrial Production Index, with a maximum negative impact of -0.74% in lag 7. Our variance decomposition results are consistent with what has been stated thus far. We discovered that the variances of Crude Oil Brent and Dutch TTF explain a considerable fraction of the overall variance of our macroeconomic variables. More specifically, our VAR results suggest that Brent variance may explain 22,9% and 15,1% of total IPI and GDP variance, respectively. Continuing with our VAR variance decomposition results, we see that TTF's variance has an informative power. Indeed, the IPI and GDP total variances over 12 quarters are explained by the TTF price variances for 9,80% and 8,64%, respectively. The VEC equivalent analyses indicate no significant differences from these results, maintaining close to these average values.

Finally, while the literature on the impacts of oil price movements on the real economy is extensive, many available paths can help investigate the effects of a gas price shock. First, further consideration regarding the control variables used may assist in getting closer to those that better capture its transmission mechanisms. Then, augmenting the analysis to the differences in the economic effects of gas price shocks for net gas importing and exporting countries may allow interesting comparative results.