The macroeconomic impact of shocks in energy commodity prices: a cross-country analysis

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Abstract

This thesis studies the impact of shocks in energy-commodities markets on the global real economic activity. Indeed, the last years have witnessed an increased demand of these assets that has made them key drivers of global economic growth. After creating a global panel of energy-commodities data, we analyse the impact of energy shocks on the French, German, Indian, Chinese, Japanese, Russian and US economy. The analysis reveals differences in the response to these shocks between energy-exporting and energy-importing countries: the former are less exposed to turmoil in energy markets than the latter. This heterogeneity becomes sharper when we move from a short-run to a long-run analysis. The analysis relies on the Factor-Augmented Vector Autoregressive model (FAVAR) introduced by Bernanke et al. (2005). Under this approach, standard Vector Autoregressive models can be used to investigate panel data with a substantial cross-section dimension.

Keywords: FAVAR, PCA, SVAR, Impulse response function, AIC, BIC, Industrial Production, Consumer Price Index, Energy commodities, Energy production, Energy consumption.

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1 Introduction

Global primary energy demand has been constantly increasing in the last decades. Thus, energy commodity prices are increasingly influencing the economies of countries worldwide. Energy commodities stand at the beginning of every industrial process, affecting the prices of every good produced. Whenever there is a shock in these prices, the economies respond differently to take advantage and avoid losses. Therefore, some researchers studied the relationship and the effective influence of energy commodities on the countries. Sims (1992) studied how some macroeconomic variables reacted when one was shocked, also reporting the influence of energy commodity prices on Industrial Production and the Consumer Price Index. The countries analysed were France, Germany, Japan, the United Kingdom, and the United States from 1961 to 1982. Fukunaga et al. (2010) studied the effects of only oil price changes on Industry-level production and prices in the United States and Japan. Regarding the topic of the relationship between energy commodity prices and macroeconomic variables, the majority of the studies focus on the effects of monetary policies on prices. Bernanke and Mihov (1998) compared and discussed different VAR models to analyse the macroeconomic effect of monetary policy shocks. Leeper et al. (1996) tried to expand their VAR model to thirteen variables; they understood that it was necessary to include a greater number of variables to analyse macroeconomic effects. Yin and Han (2016) measured the impacts of the US and China monetary policies on commodity prices.

This thesis studies the impact of shocks in energy-commodities markets on the global real economic activity. Indeed, the last years have witnessed an increased demand of these assets that has made them key drivers of global economic growth. That is why, the research question of this paper is how much commodities' shocks influence the behavior of Industrial Production and the Consumer Price Index of different countries. The analysis reveals differences in the response to these shocks between energy-exporting and energy-importing countries: the former are less exposed to turmoil in energy markets than the latter. This heterogeneity becomes sharper when we move from a short-run to a long-run analysis; the results show how importer countries' industries anticipate the price increase with changing the production level, while CPI responds gradually to the shock. For the study, we use a model presented by Bernanke et al. (2005), the FAVAR model. Many different researchers used this model to analyse the response of macroeconomic variables to shocks related to prices, indexes, interest rates (Moench (2008), Ludvigson and Ng (2009), Gupta et al. (2010), Gupta and Kabundi (2010), Zagaglia (2010), Chevallier (2011), Lombardi et al. (2012),Byrne et al. (2013), Vasishtha and Maier (2013)). Under this approach, standard Vector Autoregressive models can be used to investigate panel data with a substantial cross-section dimension. It consists of a first step in extracting the leading factors from a large data matrix with the PCA method. In the second step, a multivariate vector model regresses the factors extracted with the variables considered observable, in our case, Industrial Production and Consumer Price Index. In the first application, we use differentiated time series to observe the effects in the short run. In the second application, we use time series in absolute variables for the study of the effects in the long run.

All the time series of energy commodity prices in the panel data are provided by Bloomberg. The goal of the gathering is to give the most possible extensive view of the worldwide area. However, at the same time, we consider only those countries for which we finish with a consistent number of different time series found. For every country, we search for prices related to that country of Coal, Coke, Crude Oil, Heating Oil, Petrol, Gasoline, Diesel, Natural Gas, Methane, Electricity, Uranium, Nickel, Cobalt, Manganese, Lithium, Germanium, Gallium, Ethanol, Iron, Silicon. The result is the creation of seven different datasets relative to France, Germany, India, China, Japan, Russia, and the USA. Ultimately, the macroeconomic variables (IP, CPI) are provided by FRED (Federal Reserve Economic Data) because it gives those time series in absolute values, which we need in our study.

The rest of the paper is organized as follows: Section 3 presents all the methodology applied in the study. The theory of Bernanke's model is reported in Section 3.1, while Section 3.2 introduces the importance of identification. Section 3.3 presents the application of Bernanke's model for our study: we start by reporting all the adjustments made on the time series before running the model in Section 3.3.1. Subsequently, Section 3.3.2 reports the extraction with PCA in the first step of the estimation. In Section 3.3.3 we present the regression of the factor and the observable variables in a Trivariate-VAR and Section 3.3.4 describes the data used in the model and their collection process. Section 4 discusses the study's empirical results, starting from the analysis for each country from Section 4.1 to 4.7 and then giving general considerations on the general behavior in Section 5. Finally, Section 5.3 suggests some ideas for the extension of the study.

2 Energy commodities in the world

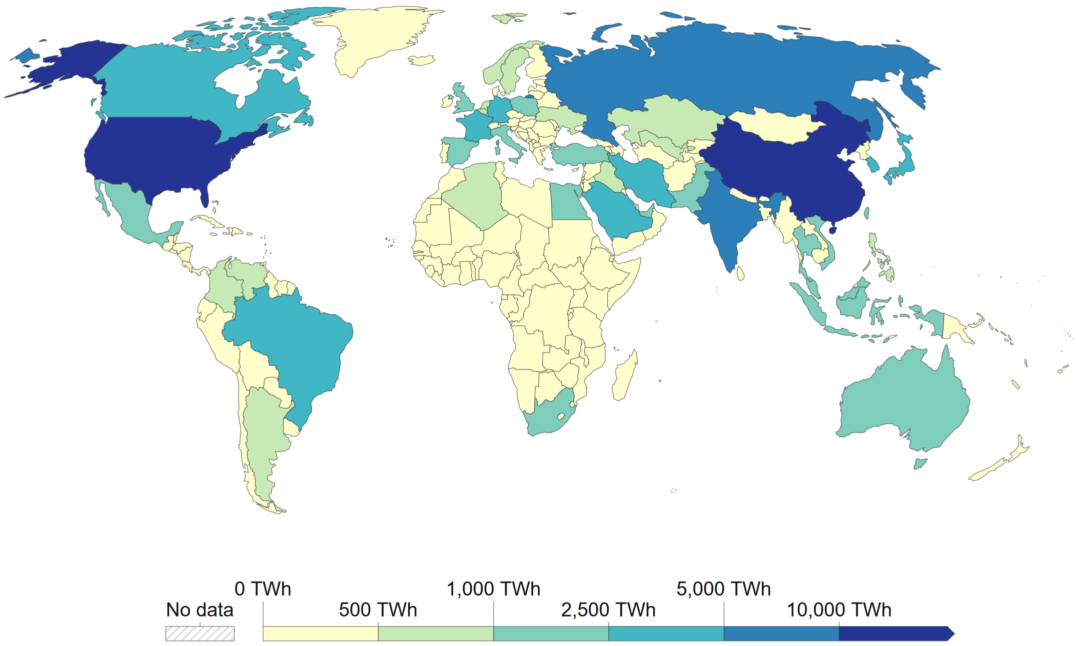


Figure 1: *Ritchie et al. (2022a): Primary energy consumption in the world by country in 2021, measured in terawatt-hours per year.*

An energy commodity is any raw material, semi-product, or finite product used in energy production, used by the cities for heating and cooling as well as energetic and not energetic firms. From this definition, it is clear that energy commodities play an essential role in the economy of many countries or because they represent an important reason for expenditure or because they are a resource for the country. That is why the paper analyses how shocks of these energy commodity prices influence the economic outlook of such countries and how it relates to their energy consumption and production, if they are affected, how they are affected, and which differences there are with those that consume less energy. In particular, we want to understand how differently the Industrial production (IP) and Consumer Price Index (CPI) of a net energy exporter country and a net energy importer react to this shock in the short and long run.

In Figure 1 it is possible to notice how energy consumption is distributed in the world: the highest energy consumption is nowadays in USA and China, then India, Russia, and all the others[1]. The energy consumption level in a country is due to many factors, such as the size of the national population, the availability of primary energy sources and the typology of national industries, and the efficiency of their processes. Chemical, Coal and Petroleum extraction, and Primary Metals are all sectors with energetic intensive industries. At the same time, the production of food, textiles, construction, and mining are light industry sectors. China, India, and the United States are the world's most populated countries.

[1]C gives a more detailed description of every country's energy consumption levels and trends.

Moreover, their economies are in the first top five economies in terms of PIL. Of course, with these notable sizes, their energy consumption is higher than the others. But, as we will see in Section 4, this does not mean that shocks in energy commodity prices have a more significant impact than in other countries.

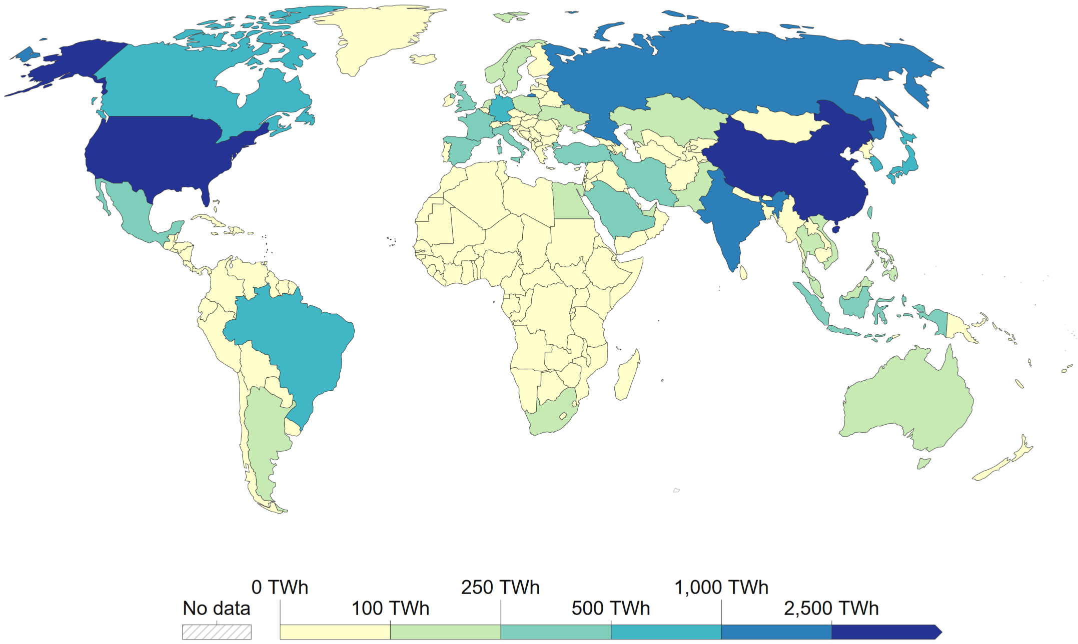


Figure 2: *Ritchie et al. (2022a): Electricity generation in the world by country in 2022, measured in terawatt-hours per year.*

Energy consumption is not the only variable that connects a country to energy prices. Even its energy production has a considerable impact on its economy. Estimating the energy production of a country is challenging because together with primary energy, even semi-products or finite energy products are produced; therefore, electricity generation is a good indicator of energy production. Figure 2 gives a map of how electricity production is spread worldwide, and this helps in understanding the energy balances of the countries[2]. Comparing Figure 1 and Figure 2, it is easy to see that they appear very similar; this means a strict balance between energy production and the top five energy-producing nations. As a result, the effects of the costs and benefits of energy consumption and production add up to a singular one, which is the one we observe in our study.

Not all energy commodities impact in the same way. Their incidence depends on how much national industries request commodities, their availability in the country, and the price volatility if imported. Today Global primary energy consumption is dominated by fossil fuels like Oil (33.1%), Coal (27%), and Gas (24.3%). Renewable sources are still a small percentage (11%)[3]. Concerning Crude oil, the United States is the greater producer (16.7% of world total), then Russia (12.6% of world total) and China (4.3% of world total).

[2]C gives a more detailed description of every country's electricity generation levels and trends.
[3]Ritchie et al. (2022b)

As far as Coal is concerned, China is the first producer (46.6% of world total), then there is India (9.7% of world total) and the United States (8.1%). Natural Gas is mainly produced in the United States (23.4% of world total), followed by Russia (18.3% of world total) and China (4.4% of world total). France, Germany, and Japan are those in which the production of fossil fuels is minimal. Germany has the only considerable share of Coal production, but it is only 1.4% of the world total production. Moreover, Germany is the one that has the most invested in renewable sources like wind and solar energy, which impacts the country's curves. France has an important nuclear energy production (15.2% of world total), while Japan seems to have the worst energy situation of all the seven countries analysed.

3 Methodology

The model used in this study is the model presented by Bernanke et al. (2005). We use this model with two different sequences of data: the firsts were time series that we turn into stationary ones with the use of logarithms and differentiation for the study of the short run; the seconds are non-differentiated time series because, having high persistence, they let us analyse the effects in the long run. In this section, the standard model introduced by Bernanke et al. (2005) is presented, together with the econometric framework of the study and the relative data collection.

3.1 FAVAR model

The FAVAR model was introduced by Bernanke et al. (2005) before that Bernanke and Blinder (1992) and Sims (1992) developed VAR methods to attempt to identify and measure the effects of monetary policy innovations on macroeconomic variables. After that, the FAVAR model has been widely used to analyse the impacts of macroeconomic innovations (Moench (2008), Ludvigson and Ng (2009), Gupta et al. (2010), Gupta and Kabundi (2010), Zagaglia (2010), Chevallier (2011), Lombardi et al. (2012),Byrne et al. (2013), Vasishtha and Maier (2013)).

FAVAR stands for Factor-Augmented Vector Autoregressive model, and it is a method that allows us to analyse a more significant number of variables than we can do with a standard Vector Autoregression (VAR) model. The reason is that when the aim is to identify a macroeconomic trend, the econometrician tends to put the greatest possible number of variables. However, standard VAR models require the estimation of $p \times N^2$ parameters every time, where p is the number of lags considered in the model and N is the number of variables. The larger N, the greater the number of parameters we have to estimate and the less accurate their estimation[4], whereas the FAVAR model can handle larger datasets by extracting hidden factor structures, which are the variables of a standard vector autoregression. In this way, the implemented VAR is more parsimonious and more precise in the estimation of parameters. As we will see later, the method used to extract the factors is Principal Component Analysis (PCA) made on all the variables collected to catch the macroeconomic dynamics.

The general form of the FAVAR model is:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t \,, \tag{1}$$

where F_t is a $K \times 1$ vector of unobserved variables, while Y_t is a $M \times 1$ vector of observable economic variables, $\Phi(L)$ is a matrix of lag polynomials of order p and $e_t \sim N(0, \Sigma)$ is a

[4]Leeper et al. (1996): to conserve degrees of freedom, standard VARs rarely employ more than six to eight variables.

normally distributed $(N+K) \times 1$ vector of shocks. Without knowing F_t, it is impossible to estimate Equation(1) because when you deal with macroeconomic dynamics, there is an observability problem. The econometrician can only sometimes observe these dynamics, maybe because they are reserved information of central banks or maybe because they are not observable at all, and neither can they observe them. Using particular indicators that can capture most macro dynamics may be tempting. However, this would be misleading because there may be better choices for capturing the particular macrodynamic in question, or other, less apparent variables may influence it. That is why we should extract the unobservable, latent factor by a larger dataset containing all the observable, explanatory variables, called data matrix X, in which X_t is the $N \times 1$ vector that includes an informational time series (in our case time series belonging to energy commodity prices).

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + v_t \,, \tag{2}$$

where Λ^f is an $N \times K$ matrix of factor loadings, Λ^y is $N \times M$, and the $N \times 1$ vector of error terms v_t are mean zero but not fully uncorrelated because principal component estimations allows for some cross-correlation that must vanish as $N \to \infty$[5]. In our study X_t has the form:

$$X_t = \Lambda^f F_t + v_t \,, \tag{3}$$

so the assumption is that it is composed only of the factors and not Y_t[6]. It is possible to choose many methods to extract the unobserved factors F_t from the data matrix X; here, we go for a two-step estimation procedure, which uses asymptotic principal component methods to find the factors before running the entire factor-augmented VAR. Bernanke et al. (2005), in the first step, estimates the space spanned by the factors using the first $K+M$ principal components of X_t, defined as the $K \times 1$ dimensional vector $\hat{C}_t(F_t, Y_t)$,

$$\hat{C}_t = \beta_{F^s} \hat{F}_t^S + \beta_Y Y_t + \epsilon_t \,. \tag{4}$$

Following our assumption made in Equation(3), it is clear that even the principal components depend only from F_t and not from Y_t, therefore the formula becomes:

$$\hat{C}_t = \beta_{F^s} \hat{F}_t^S + \epsilon_t \,. \tag{5}$$

Now that F_t is known, it is possible to go for the second step and estimate Equation(18), whose reduced-form VAR has the the following structural form:

[5] Stock and Watson (2002)

[6] This assumption will be explained in Section 3.3

$$\Gamma(L)\begin{bmatrix}\hat{F}_t\\ Y_t\end{bmatrix} = e_t\,, \tag{6}$$

where $\Gamma(L)$ is a lag polynomial of finite order p. Finally, impulse response functions (IRFs) of $\hat{F}_t$ and Y_t are computed as follows:

$$\begin{bmatrix}\hat{F}_t\\ Y_t\end{bmatrix} = \Psi(L)u_t\,, \tag{7}$$

where $\Psi(L)$ is a lag polynomial of order h and $\Psi(L) = \Gamma(L)^{-1}B$, B is a Cholesky factor that will be defined later with u_t, a vector of structural innovations uncorrelated in the cross-section, but not observable. IRFs are the most crucial instrument for the dynamic analysis of a VAR. In a generic stationary VAR defined as:

$$\Gamma(L)y_t = e_t\,, \tag{8}$$

the impulse response functions are all contained in H, an $N \times N \times n$ three-dimensional array, where N is the number of variables in the VAR and n is the length of the responses. Therefore a single impulse response function is defined as:

$$H(i,j,n) = (C_n)_{ij} = \frac{\partial y_t}{\partial e_{jt-n}}\,, \tag{9}$$

that means the answer of the i^{th} variable to the j^{th} shock after n periods. e_t is also called the prevision error between y_t and its expected value. In a multivariate regression, we have N prevision errors, one for each variable, related to an unexpected event that is impossible to predict. In this way, e_t of a single variable is the result of the sum of all the errors in the model, each impacting differently because the variance-covariance matrix has off-diagonal elements that are not zero. Indeed, there is a contemporaneous correlation between the variables in the VAR model, so it does not represent the exact impact of the shock of a single variable on all the others[7]. In this case we say that e_t are correlated shocks and they are not what we are looking for; we want to work with uncorrelated shocks, called structural shocks[8] and they are defined as:

$$e_t = Bu_t\,, \tag{10}$$

where e_t is observable, while u_t and B are not. B is a lower triangular matrix with positve diagonal elements, which is obtained by a Cholesky decomposition, and if we put together

[7] Pesaran and Shin (1997), Koop et al. (1996)

[8] Kilian (2009)

Equations (8) and (10) we obtain

$$\Gamma(L)y_t = Bu_t\,, \tag{11}$$

therefore,

$$H(i,j,n) = \frac{\partial y_t}{\partial u_{ij-n}} = (C_n \cdot B)_{ij}\,, \tag{12}$$

where, in our case $y_t \equiv \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix}$. In this way, we obtain the impulse response to the structural shock, which means obtaining how the variables respond to a shock that directly impacts them in the time. It is important to understand how we can obtain matrix B from the empirically estimable matrix Σ, which is the variance-covariance matrix of e_t. Giving a look at Equation (10) we can deduce that

$$\Sigma = BB'\,. \tag{13}$$

Equation (13) has infinitely many solutions; the only way to obtain a unique matrix $\hat{B}$ is to use Cholesky decomposition. This method says that any symmetric and positive definite matrix, in our case Σ, can be decomposed as the product of a lower triangular matrix which is unique, in our case B, and its transposed. Indeed equation (10) will become:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{nt} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & \cdots & 0 \\ b_{21} & b_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \\ \vdots \\ u_{nt} \end{bmatrix} = \begin{bmatrix} b_{11}u_{1t} \\ b_{21}u_{1t} + b_{22}u_{2t} \\ \vdots \\ b_{n1}u_{1t} + b_{n2}u_{2t} + \cdots + b_{nn}u_{nt} \end{bmatrix}. \tag{14}$$

As it is possible to understand from Equation (14), every error is generally $e_{it} = \sum_{j=1}^{i} b_{ij}u_{ij}$ and it is easy to understand that the order of the variables is determinant for the resulting IRFs. Here we follow Bernanke's criterion to put first the endogenous factor and then Y_t. As explained later, the fact that, inside Y_t, IP is put before CPI is not determinant for the shape of the impulse response functions; indeed if we compute them by switching the order of the observable variables, we obtain the same results.

3.2 Identification

In order to run the correct form of the model, we need to impose some restrictions on the system. From Equation(3), we get that Λ^f and $\hat{F}_t$ are the solutions of the estimation problem, but we can define $\tilde{\Lambda}^f = \Lambda^f H$ and $\tilde{F}_t = H^{-1}\hat{F}_t$, where H is a $K \times K$ nonsingular matrix, which would also satisfy Equation (3). Observing X_t cannot help distinguish between these two solutions; therefore, we must impose a normalization.

In our case, we use the standard normalization implicit in PCA, imposing $C'C/T = I$, where C are the common components extracted. Following PCA method, C are estimated as $\hat{C} = \sqrt{T}\hat{Z}$, where $\hat{Z}$ are the eigenvectors corresponding to the K largest eigenvalues of the variance-covariance matrix XX', sorted in descending order. Then $\hat{F}_t$ is obtained as:

$$\hat{F}_t = \sqrt{T} X' \hat{Z} \, . \tag{15}$$

3.3 Econometric framework of the thesis

For our study, we use the same model and follow the same steps for both specifications. The difference is that in the first one, we work with differentiated time series to obtain stationarity and analyse the effects in the short run. In the second specification, instead, we work with non-differentiated time series so that we can keep their persistence and analyse the effects in the long run.

3.3.1 Preliminary tests and preprocessing

After creating a global panel of energy-commodities data, we adjust the time series collected for both model applications. In the first case, we work with stationary time series. Therefore all of them are analysed running the Augmented Dickey–Fuller test[9] (ADF), turned into stationary ones if needed with the help of logarithms and 1^{st} differences. We implement all the procedures in MATLAB using the function *adftest*. With all stationary time series, the only step left is to rescale the data from the original range so that all values are within the range of 0 and 1 (mean zero and unit variance)[10]. After normalization, it is possible to work with PCA and extract the leading principal factor. In the second case, we work to obtain datasets with non-differentiated time series, so we still run the ADF test, but this time we make the opposite. Indeed, we make a cumulative sum of all the time series representing monthly variations, obtaining all the time series as the behavior of the overall values. Same as for the first specification of the model, we work with PCA to extract the factor after normalization. Another solution can be using the correlation matrix, but the built-in MATLAB function *pca* computes individually the variance-covariance matrix associated with the starting one.

[9]Dickey and Fuller (1979)

[10]PCA is a variance-maximizing method that projects the original data in directions that maximize the variance. Therefore if they are on a different scale, it will project onto the directions of those with bigger variances only because they are on a bigger scale; indeed, the results would be wrong.

3.3.2 First step

As said, from PCA, we extract the eigenvectors corresponding to the K largest eigenvalues (in our case only the largest) of the variance-covariance matrix. In our study it was extract only one factor three different reasons:

- *statistical*: the first component is the one that better explains the dataset's variance because it represents a single direction of all the variables in the dataset. Indeed it preserves the maximum amount of information. The more factors we extract, the more directions we add, and the less variance we explain every time. By extracting only one factor, we have the certainty that we lose the minimum amount of information in the extraction.

- *macroeconomic*: As said, the first component represents a single direction, and this helps us interpret the economic meaning. In this way, we have a factor representing the movement of all commodity prices in the same direction[11] (all increasing or all decreasing), which is easier to interpret and explain. If we extract more factors, they would represent prices moving in different directions (some increasing and some decreasing), and it would be more difficult, if not impossible, to motivate the influence and the correlation of those effects with our observable variables economically.

- *economical*: another critical issue to consider is the parsimony of the model. If we add more factors in the multivariate regression, we have to estimate more parameters, with the risk of less precise estimation. At the same time, if we put only one factor, we have fewer parameters and a more precise estimation.

Keep in mind that in our case, we are extracting a commodity prices factor, so the data matrix X does not contain IP and CPI, while in Bernanke et al. (2005), they were searching for a macroeconomic factor, and therefore even IP and CPI were included in the data matrix. For the same reason, we do not need a clearing regression of the factors extracted, as Bernanke did, because they do not have any influence from the observable variables IP and CPI.

3.3.3 Second step

Second step consists in creating a VAR model where the endogenous variable and the two observable ones are regressed in order to compute impulse response functions; in this case, the built-in MATLAB function *varm* is used to create a Trivariate-VAR(L) model, together with *estimation* function to fit the data into the model created, where $(F_t \quad Y_t)' = (\hat{F}_t \quad IP_t \quad CPI_t)'$:

[11] Pearson (1901)

$$\begin{bmatrix} F_t \\ IP_t \\ CPI_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ IP_{t-1} \\ CPI_{t-1} \end{bmatrix} + v_t \,, \tag{16}$$

and,

$$\Phi(L) = \Phi \equiv \begin{bmatrix} \alpha_1 & 0 & 0 \\ \beta_1 & \beta_2 & \beta_3 \\ \gamma_1 & \gamma_2 & \gamma_3 \end{bmatrix} . \tag{17}$$

As it is possible to see from Equation (17), the lag matrix $\Phi(L)$ has some constrains, $\alpha_2, \alpha_3 = 0$, because we do not want the factor to depend on past values of IP and CPI but only on their current one and, of course, on past energy commodity prices. We follow this criterion because it is the same that Bernanke et al. (2005) used for his first two factors; in their case, they had four unobserved variables in the VAR model[12]. This makes our VAR model constrained, indeed a Structural VAR (SVAR). A critical issue to discuss is the number of lags to insert in the model; we take into consideration a range of 1-6 lags, and the best option seems to be the choice of one lag when we use stationary time series and two lags when we work with non-differentiated times series. In both cases, the best options are $L = 1$ or $L = 2$ because they have similar information criteria scores. For the case with stationary time series, we prefer to go for one lag because, in most countries, it is the best option and because it means fewer parameters to estimate, indeed a more precise estimation. For the second, the choice is to go for two lags because we work with far more persistence time series; therefore, we go for a model with more memory even if sometimes information criteria suggest going for one. We use both the Akaike Information Criterion (AIC) introduced by Akaike (1974) and the Bayesian Information Criterion (BIC) introduced by Schwarz (1978): while the BIC suggests one (two) lag for the first (second) study, the AIC indicates a larger number of lags. This due to the fact that including more lags yields minimal likelihood improvements after a certain point[13]. The following figures report the results [14].

[12] Bernanke et al. (2005), *Section II.B.*, pages 393-397

[13] The formulas used are:

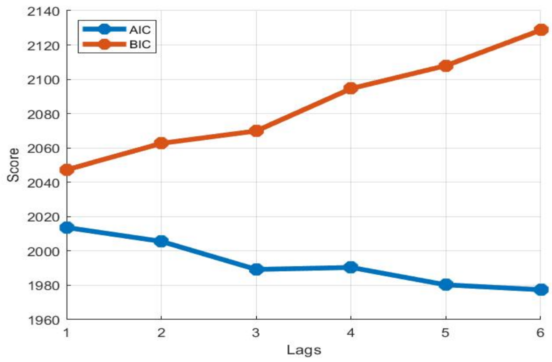
$$AIC = 2(p) - 2\mathcal{L},$$
$$BIC = p \cdot \ln(T) - 2\mathcal{L},$$

where $\mathcal{L}$ is the log-likelihood of the model, T is the sample size and p is the number of parameters estimated by the model.
Suppose p becomes p' with the increase of one lag ($p' > p$), $T = 100$ stays constant, $\mathcal{L}$ becomes $\mathcal{L}'$ such that $\mathcal{L}' - \mathcal{L} = 5$, we get:

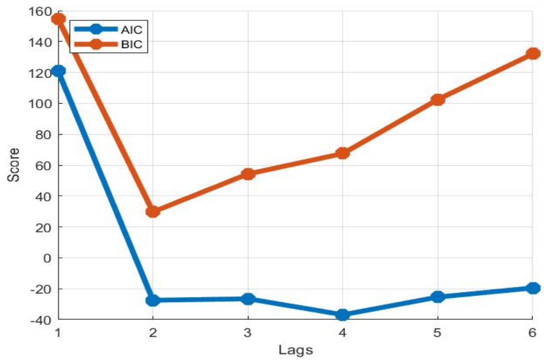
$$p\ln(T) - 2\mathcal{L} > p'\ln(T) - 2\mathcal{L}', \text{ rearranging } (p' - p) > \frac{2(\mathcal{L}' - \mathcal{L})}{\ln(T)} \text{ for BIC,}$$
$$2(p) - 2\mathcal{L} > 2(p') - 2\mathcal{L}', \text{ rearranging } (p' - p) > 2(\mathcal{L}' - \mathcal{L}) \text{ for AIC.}$$

Indeed, to have an increase in AIC, we need $(p' - p) > 10$; while to have an increase in BIC, we need $(p' - p) > \frac{10}{4.6} = 2.17$.

[14] Other analysis and backtesting are reported in Appendix B.2.



(a) Japan results, 1^{st} model specification



(b) Japan results, 2^{nd} model specification

Figure 3: *AIC and BIC values for Japan for both model specifications. Blue line represents AIC, while red one represents BIC. For the results of the other countries see Appendix A.*

Therefore the model implemented is a Trivariate-VAR(1) in which we put in order the unobservable variable F_t as the first variable and then the observable ones, respectively IP and CPI. As explained later, the Impulse Response Functions (IRF) are computed using Cholesky decomposition, where the order of variables is important because it determines the way they impact each other; that is why we impose some restrictions on coefficients. Indeed, all the coefficients of the influence of previous values of IP and CPI on the Factor are put equal to zero because this one is not influenced by them, at least at the beginning. Instead, the fact that IP stands before CPI is irrelevant, and if we switch the order of these two variables, their IRF to the factor shock are the same, confirming that their order does not change the results. However, IP is put before CPI even because IP is an actual quantity, while CPI is almost an average value, so IP is more exogenous[15]. At the end of the study is interesting to analyse the different Impulse Response Functions (IRF) of the observable variables to a 1% shock in the commodity prices factor. These curves come from MATLAB's built-in function *irf*, which by default computes them by using orthogonalized shocks (structural shocks) and not the generalized ones; in this way, our VAR becomes a SVAR (structural VAR). In the last case shocks are defined as $\epsilon_t = Bu_t$, where the vector ϵ_t is observable, while B and u_t are not. However, if we can estimate $Bu_t = B^{-1}\epsilon_t$, the matrix B is estimated using the variance-covariance matrix $E = BB'$ that has infinite solutions, that means a problem of under-identification. If we use Cholesky decomposition, we get B as the Cholesky factor, a unique lower triangular matrix. Knowing their difference is fundamental because IRF to generalized shocks represents the response to a prevision error. In contrast, IRF to structural shocks let us understand how variables respond to an effective shock of the other variables and their impact on the behavioral relationship between them.

Our model analyses the behavior of the observable variables to the Factor and this for each country. After obtaining the results of the impulse curves, it is evident that the first specification of the model catches only the effects in the first 6-8 months, a short period

[15]Appendix B.1

considered the time of adaptation of the industrial processes, while the second cathces the effects for many years. The idea is to compare the effects in the short run with the ones in the long run. All the plots are done considering a confidence interval of 68%, as common in the macroeconomic literature, see Jurado et al. (2015) among the others. These confidence bands are asymmetric because of the use of quantiles in the computation done by MATLAB's function.

3.3.4 Data

The initial purpose was to deal with GDP and Inflation, but the problem is that these indicators are quarterly time series, while all the others for commodity prices are monthly time series; that is why IP is used as a substitute for GDP and CPI, computed month over month, for Inflation. The choice of countries is made trying to find the best compromise between selecting them from every continent of the world and taking care of their importance, their role in the world of energy production and consumption, and most importantly, the availability of data. Following these selection criteria, the selected countries are China, France, Germany, India, Japan, Russia, and the USA.

The first step of all the work is collecting all the time series related to the commodities from the early 2000s' until today, all using the Bloomberg research portal and FRED (Federal Reserve Economic Data) for the macroeconomic variables. Lengths of datasets are different because of availability of data changes country by country, and it is preferred to analyse the greatest number of countries instead of analysing a limited number with larger datasets (the goal is having the most extensive view of the world, a wide cross-country analysis). So the smaller length of some datasets is not for the absence of interest for that country but for lack of data availability in the last 20 years because most of the time series found start around 2010. Datasets contain a wide range of future prices, spot prices, rates, and indexes for coal, coke, crude oil, heating oil, natural gas, methane, electricity, uranium, petrol, gasoline, diesel, ethanol, copper, lithium, cobalt, manganese, nickel, iron, silicon, germanium, gallium.

Once the gathering is done, we review each dataset, deleting the incorrect ones. More specifically, after choosing the option of monthly time series, the program gives as output even quarterly and yearly time series just repeating the value of the index in the interval month by month, that means for quarterly time series it gives the same value for three months and for yearly time series Bloomberg provides 12 times the same value. It is easy to understand that it is necessary to delete those time series; otherwise, it would be a misspecified starting point for the study.

Regarding macroeconomic variables (IP and CPI), initially, the choice was to go for a seasonally adjusted Bloomberg time series representing the percentage change computed month over month. However, in this way, it is possible only to work with the standardized time series. Therefore we would not be able to observe the effects in the long run. Working with differentiated time series makes one lose the persistence needed to work for scenarios in the long run. So we go for FRED because this source offers the pattern of the overall value of IP and CPI month by month. In this way, it is easy to have both the amount produced and the change month over month.

	First obs.	Last obs.	Observations	Number of time series
France	30/04/2002	30/11/2022	248	17
Germany	31/08/2004	31/01/2023	222	12
India	30/04/2004	31/12/2022	225	9
China	31/03/2005	31/07/2020	185	8
Japan	31/07/2004	30/04/2022	214	15
Russia	31/01/2004	31/09/2021	213	9
United States	31/05/2001	31/12/2022	260	22

Table 1: *This table resumes the data collection for the study. For each country it is reported the date of the first and of the last observation, the number of total observations and the number of different time series collected.*

4 Empirical results

The purpose of this section is to introduce and discuss the empirical findings obtained from the model. Firstly, we provide an overview of the energy situation in each country. Subsequently, we analyse the Impulse Response Functions (IRFs) of the Industrial Production (IP) and Consumer Price Index (CPI) in response to a positive shock of 1% in energy commodity prices. These analyses are performed for both model specifications.

4.1 France

Since 2000, France has not been increasing its energy production while its electricity consumption has continuously been increasing[16]. Regarding coal and oil, France is a net importer of coal and crude oil and has a small export of oil products. The share of renewable energy in the whole energy consumption has increased from 9.3% in 2000 to 15.5% in 2019; other countries have made more. There is a significant nuclear component in France, but it is valid only in electricity production, which accounts only for 20% of total energy consumption. The fossil fuel component accounts for 50% of energy consumption. Nowadays, French energy independence is about 54.3%[17]. So, the situation in France in the last 20 years is a situation of a country that has kept its energy supply and consumption the same, with a high dependence on fossil fuels and with not an increasing share of renewables. Moreover, the constant increase in electricity consumption is also a sign that industrial processes are not turning into more efficient ones, as is happening in Germany where the whole electricity consumption is decreasing together with energy consumption.

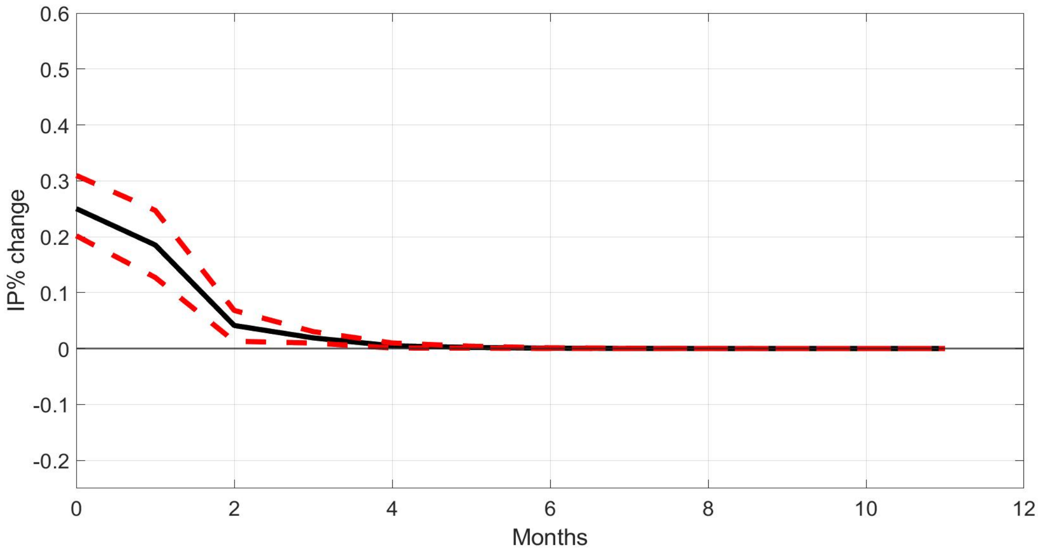


Figure 4: *Impulse response functions of French IP to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

[16]See Appendix C
[17]Ritchie et al. (2022c)

Due to the French energy situation, in the short run, we have that after 1% positive shock of energy commodity prices, the impulse response of IP is increasing by about 0.25%.

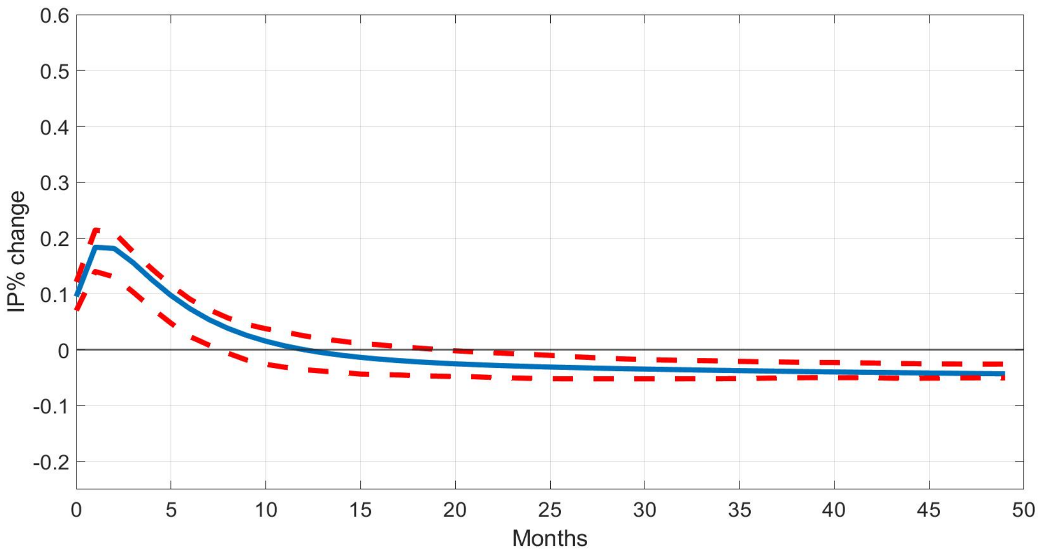


Figure 5: *Impulse response functions of French IP to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

The increase in IP may be because, having fixed price contracts, firms try to increase their production to create some stocks and take advantage of the higher costs in the future when they have to decrease their IP. Indeed, in the second application of the model, where the effects have a greater persistence, France shows a production increase in the first year, but after 12 months, the level starts to decrease constantly. The reason is that costs are not affordable if the production level is constant, so firms choose to produce less.

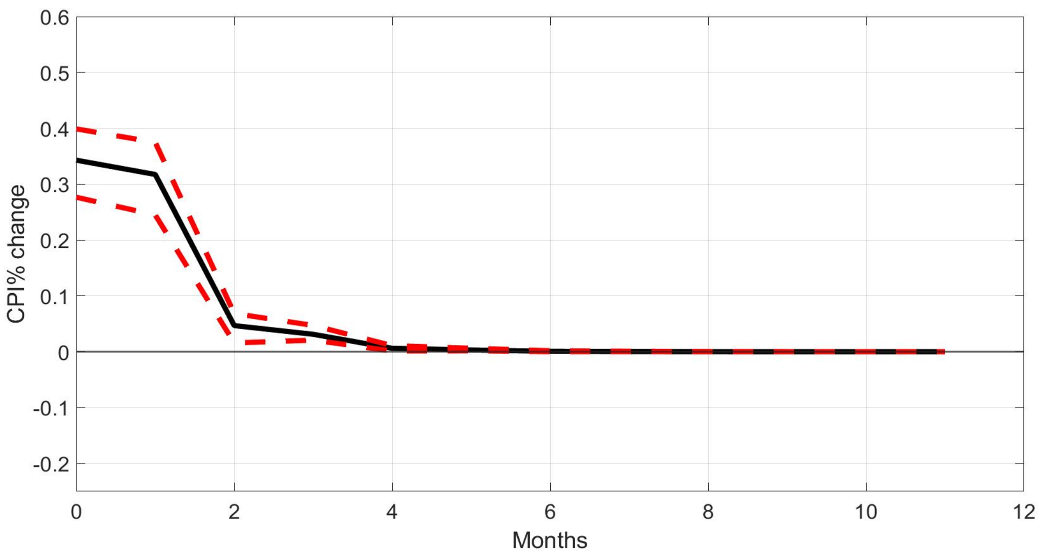


Figure 6: *Impulse response functions of French CPI to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

Similarly to IP in the short run, even the overall price level (CPI) increases by 0.35% after the energy commodity prices shock and then it vanishes after 4 months. In the long run, the results show how the positive shock of energy commodity prices brings a constant increase of CPI during the years of approximately 0.1%.

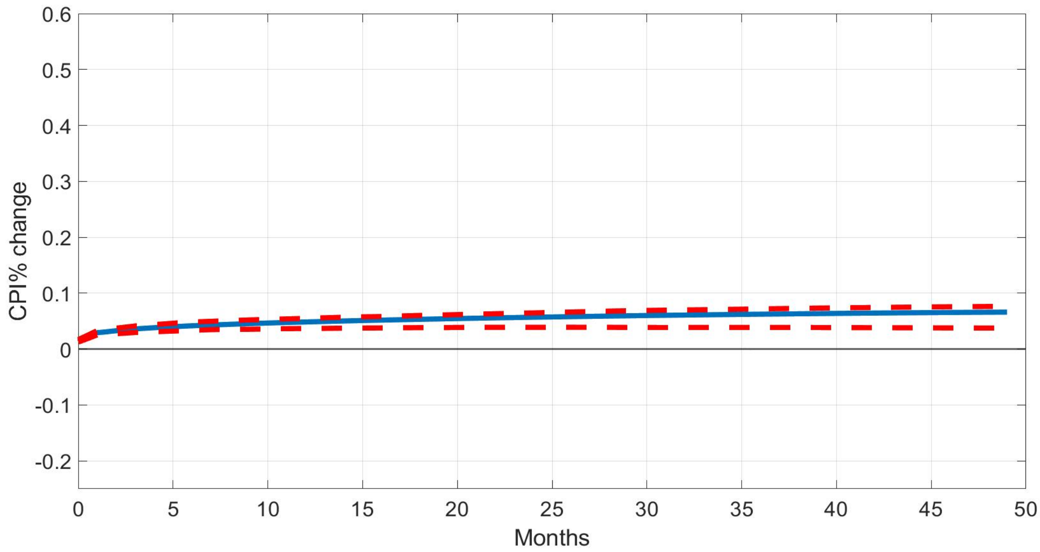


Figure 7: *Impulse response functions of French CPI to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

This correlation can be explained by the fact that France is not in an easy energy situation because, following the zero-emission target of the EU, they closed almost all the coal electricity plants and half of their nuclear ones. In addition, the Russia-Ukraine war and the following problems between Russia and Europe meant increased import prices for France, which probably impacted consumer prices.

4.2 Germany

Germany is an example of an energy importer country that managed to find an alternative solution to its lack of sources; at least, this is what the results tell us. In the last 20 years, Germany has been decreasing its energy production. However, at the same time, differently from France, it has decreased its final electricity consumption from 2000 up to today[18]. This is a sign that Germany is becoming a more efficient country, and it is easy to think that even industries are. Germany is a net importer of coal and crude oil with a considerable export of oil products. The share of renewable energy in the final energy consumption has increased from 3.7% in 2000 to 17.2% in 2019, a signal that this country is strongly investing in a more efficient carbon-independent energy national system. Concerning the final energy consumption in the last 20 years, Germany has been decreasing its dependence on oil products from around 40/45% to a share of 30/35%. What Germany has done differently from France is that it has been changing the composition of its final energy consumption through a less carbon-independent one, which is a benefit for the industry, mainly in terms of reduced costs, as it is possible to see from the German IRF of IP.

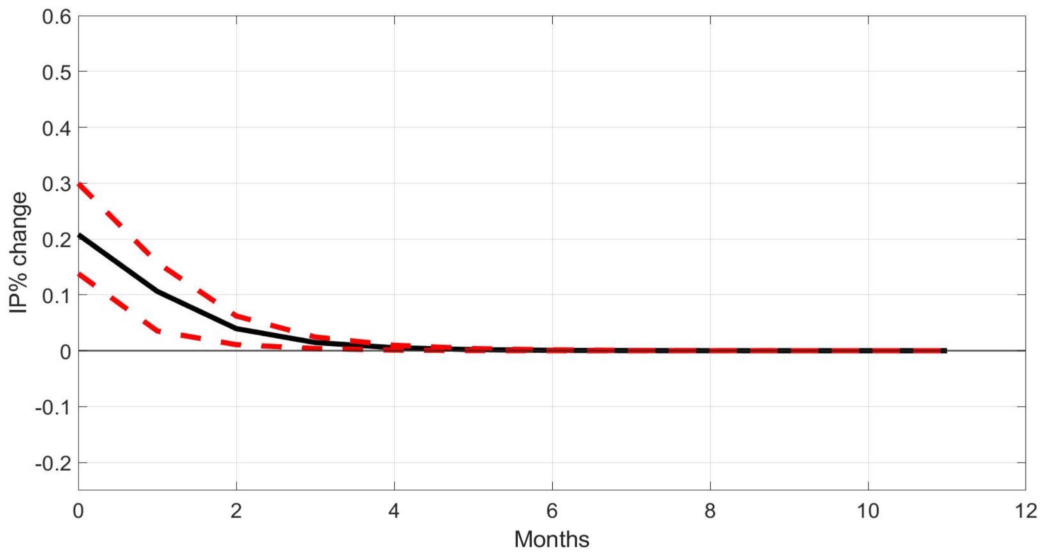


Figure 8: *Impulse response functions of German IP to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

In the short run, Germany's IP responds positively to a shock in energy commodity prices but with a smaller size than France (0.2%). Following the idea of France's explanation, that means German industries have to anticipate less the new future prices, so they will have to create fewer stocks in the months after the price increase.

[18]See Appendix C

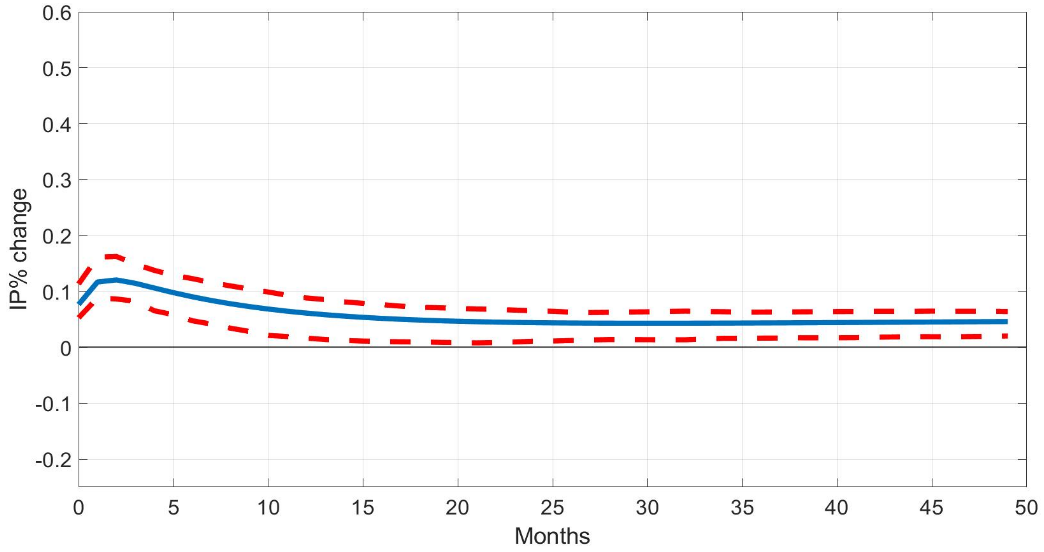


Figure 9: *Impulse response functions of German IP to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

In the long run, with non-differentiated time series, what happens is that after the increase suddenly after the shock, there is not a decrease of the curve below the zero level. However, it stabilizes in a position above and next to the zero level, which means Germany, in these years, has been preparing so that its industries can benefit if energy prices increase. Because thanks to an improving energy situation, they are more competitive than other countries, especially Europe. Talking then about CPI, it is possible to say that the impact of the shock on it has a similar effect as the one for France, which can also be reliable given that both countries belong to European Union. So monetary policies are taken by this one with effect on every country.

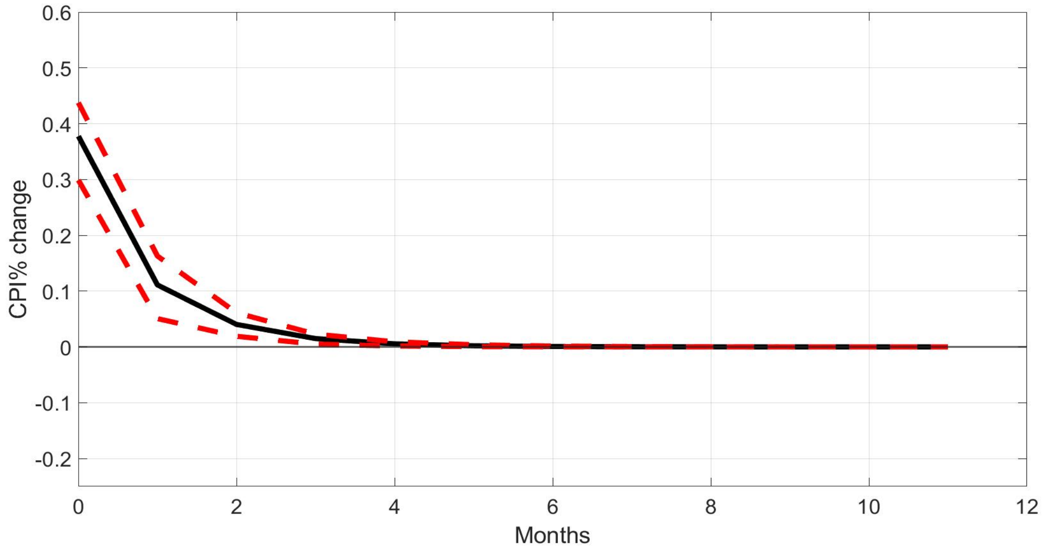


Figure 10: *Impulse response functions of German CPI to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

In the short run, what happens is an immediate increase in CPI of about 0.4%; this effect vanishes after 4-6 months. In the long run, the increase stabilizes on a positive level below 0.1%, meaning that the effect continues and brings higher prices even in the future. This behavior is easily explainable because Germany has a robust automotive industry that suffers from higher energy prices, so transmission to the customers is the easiest solution.

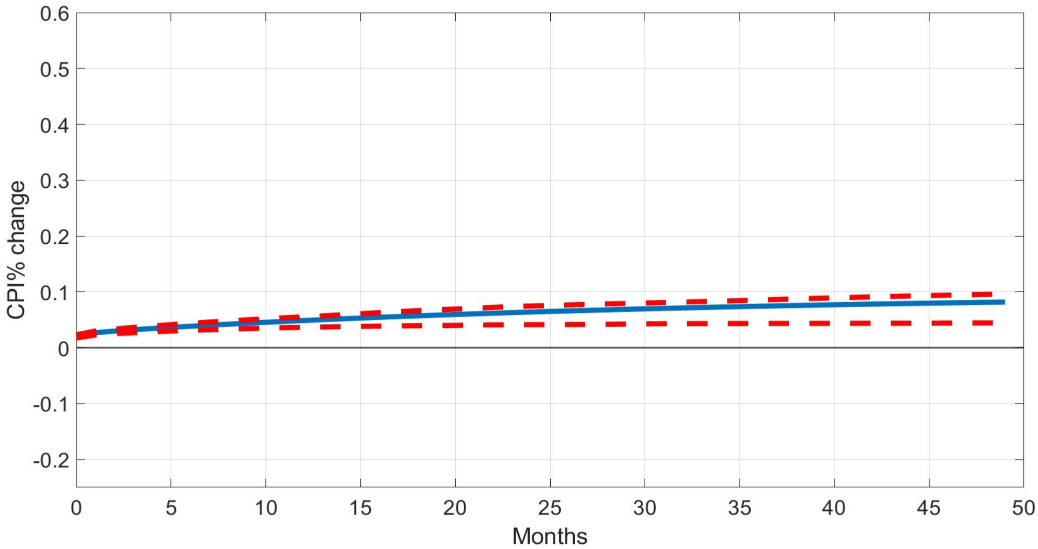


Figure 11: *Impulse response functions of German CPI to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

4.3 India

India's energy trends from 2000 to 2020 show that this country has constantly been increasing its energy production and consumption levels[19]. India is a net energy importer, so it might seem strange that from the results, India has a benefit in IP with no impact on CPI. The fact is that in the last ten years, India has been increasing its production and the export of electricity using coal; indeed, in India, there are 7% of the whole coal reserves of the world. Even with this great availability of coal, India cannot satisfy the country's needs of the country so it has been obliged to make deals with other countries to import gas (Russia) and crude oil (Iran, Iraq, Kuwait, Saudi Arabia, USA). India has so many deals with different countries because, over the years, it wanted to diversify most of its energy imports because of the risk of too elevated prices. Moreover, India is a great refiner of oil bought from the cheaper Russian oil and then sold to Europe and the USA, which is why India's oil export has increased during the last 20 years.

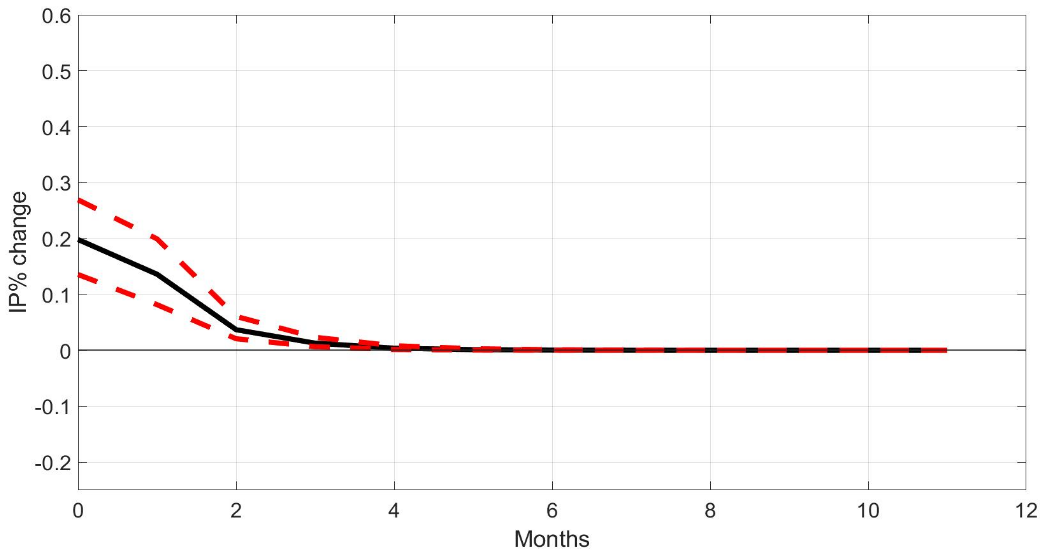


Figure 12: *Impulse response functions of Indian IP to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

As known, our model catches only the last 20 years, so creating a positive shock on energy prices, the model told us that the answer of the Indian IP is an immediate increase of 0.2% that vanishes after four months. According to what was said before, the increase is smaller than in France and Germany because India needs less to create stocks for future higher energy prices. However, it can increase oil refining to sell it to other countries at higher prices. In the long run, the IRF shows that India has an increase of 0.1% in the first six months, and then the level is stabilized at a positive level very close to zero. That is a sign that India does not need to increase its IP in the future, maybe because it has reached a good equilibrium.

[19] See Appendix C

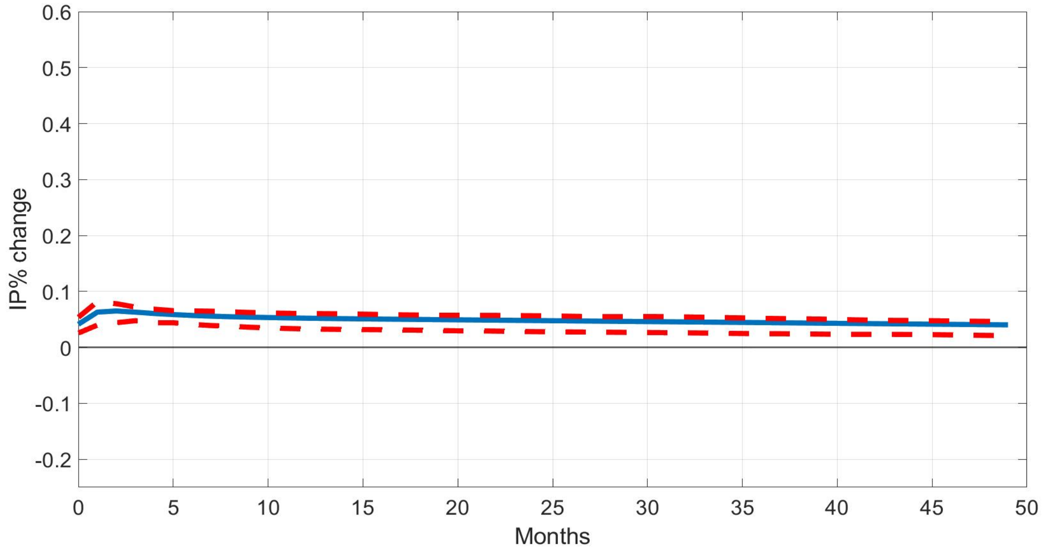


Figure 13: *Impulse response functions of Indian IP to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

As far as Indian CPI is concerned, there is a response of the index to a shock in energy commodity prices of about 0.2% in the general price level that lasts for four months. While in the long run, there are no significant effects observed because, in recent years, the inflation level of India has been growing considerably, so it may be not so much influenced by energy prices but more by the globalization of the country, unlike Europe or the USA, where energy price increases may have a more significant effect because the inflation has been more constant.

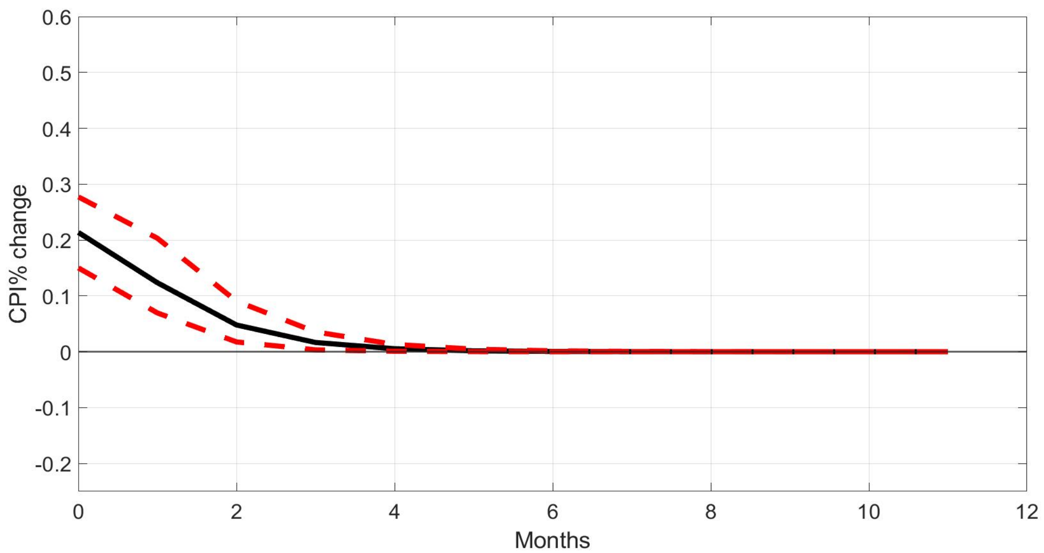


Figure 14: *Impulse response functions of Indian CPI to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

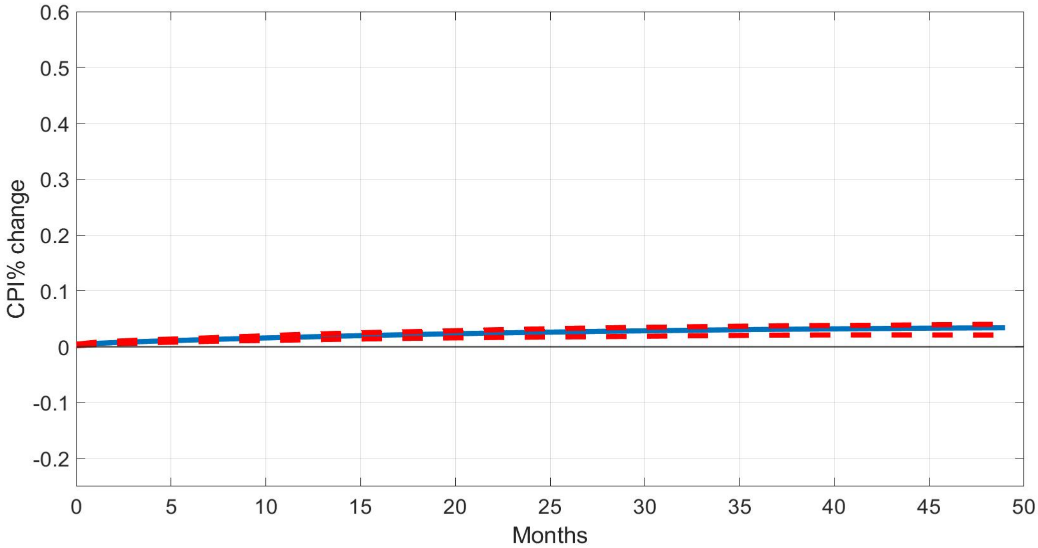


Figure 15: *Impulse response functions of Indian CPI to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

4.4 China

China's IP and CPI are not so affected by commodity prices, even if China is one of the most importers and exporters, producers, and consumers of energy in the world, considering the sizes of industries and population. In the last 20 years, total primary supply and electricity consumption have been strongly increasing[20]. This means the country is developing and becoming a bigger system without exposing more to energy supply from foreign countries. Coal accounts for 60% of China's energy supply, and the most is imported from Indonesia (58%) and Russia (23%). Then China has Oil accounting for 20%, and lately, it has been increasing the supply of natural gas (5%) and nuclear energy (5%). So this country is still strongly bonded to carbon fossil energies, but there are small signals that it is slowly becoming a more sustainable energy system. In the last years, the share of renewables in the share of total final consumption went from 2.6% in 2000 to 10.6% in 2020.

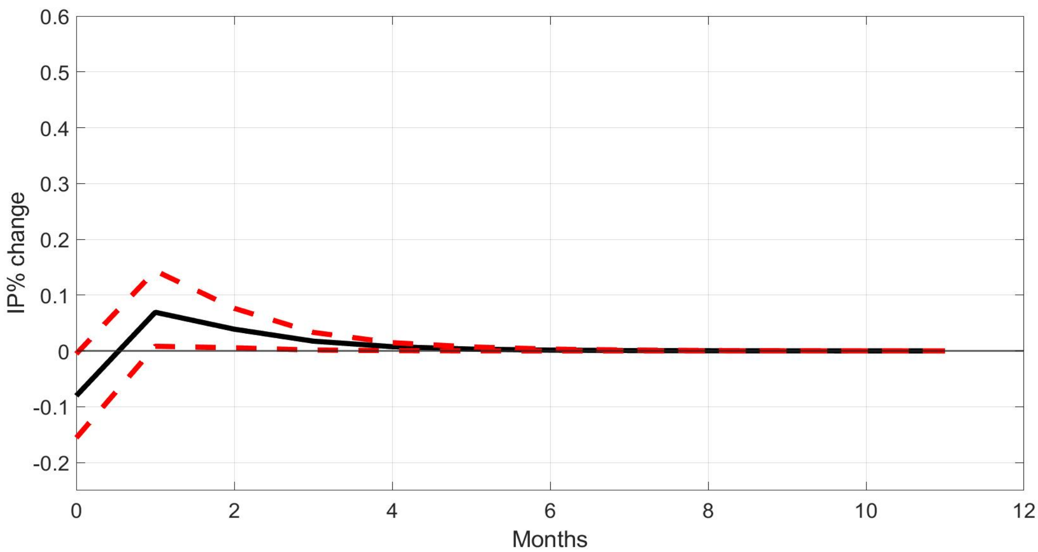


Figure 16: *Impulse response functions of Chinese IP to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

In the short run, Chinese IP is the only one in all the countries we analysed that shows a minimal immediate decrease followed by an increase of the same size the month after, then the effect vanishes suddenly. That means that IP is not significantly affected by an increase in energy commodity prices and that Chinese industries do not see the shock as a reason to create stocks for the future. The same happens for IP in the long run, as it is possible to see the IRF is flat in the long run; precisely, it stabilizes above the zero level but is very close to it. This lower impact can also be thanks to the big availability of labor force and low salaries, as China has one of the greatest populations in the world, so maybe industries exploit the labor force to manage the increase in energy costs. Therefore they do not need to change their production level.

[20]See Appendix C

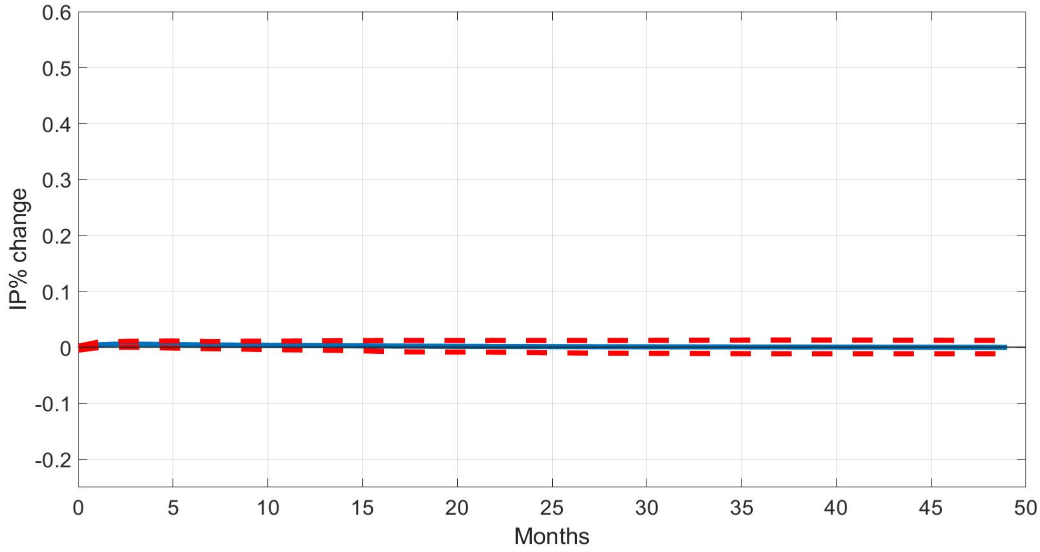


Figure 17: *Impulse response functions of Chinese IP to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

CPI behaves differently in the short run; indeed, the answer to the general price level is an immediate increase of about 0.35%, that gradually vanishes after six months. China is one of the biggest economies together with the USA. It has many exchanges with the world, which can explain why the Chinese general price level moves together with energy prices.

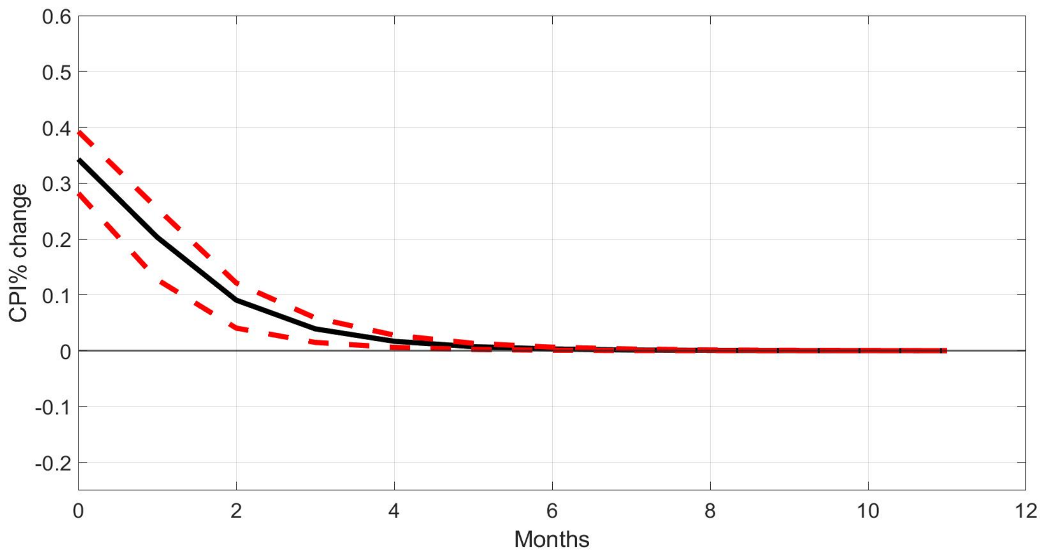


Figure 18: *Impulse response functions of Chinese CPI to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

In the long run, instead, CPI seems not affected by the shock, and the curve of the response stabilizes above the zero level. Like India and Russia, Chinese inflation has been strongly growing in the last 20 years, and maybe energy commodity prices have not been so influencing in the constant increase.

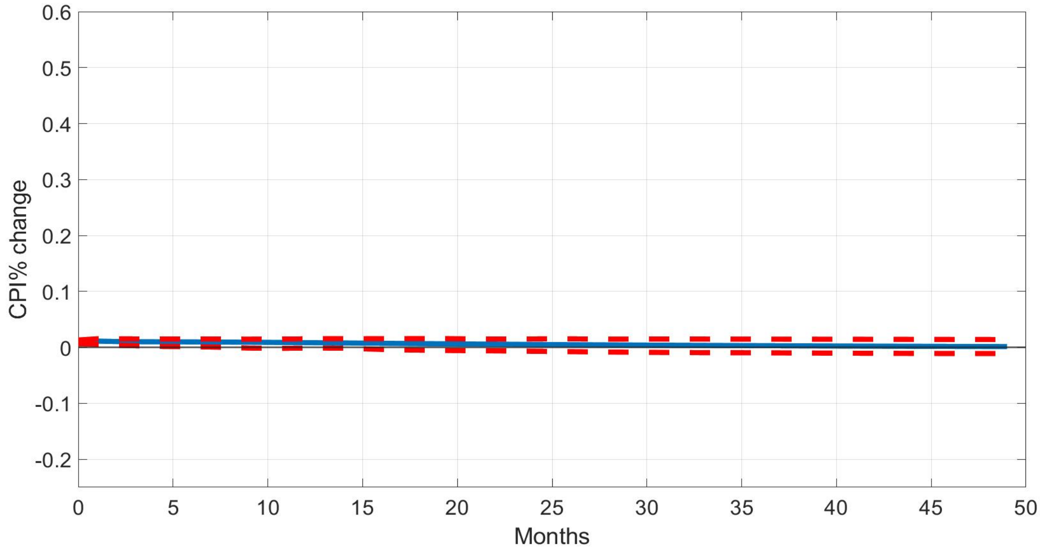


Figure 19: *Impulse response functions of Chinese CPI to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

4.5 Japan

Japan is an energy net importer country, since 2000, it has decreased its energy production with a small change of direction in the last ten years. Its total primary energy supply has been decreasing[21]. However, its final electricity consumption has been increasing, which is a sign that Japan has been increasing its exposure to energy prices worldwide. The composition of the primary energy supply in Japan is covered by around 40% from oil, around 25% from coal, the rest from natural gas, and a small percentage of renewable energy. Remember that before, a share of 10/15% was covered by nuclear production, that was reduced to an insignificant share from 2011 after Fukushima. The share of renewable energy sources in the final consumption is lower than the other countries analysed, around 7.7%; this can be another explanation for why Japan suffers from an energy price increase in the long run. Japan is still strongly dependent on carbon fossil sources, which may be why in the short run, the country behaves similarly to France or Germany and suffers as the first in the long run.

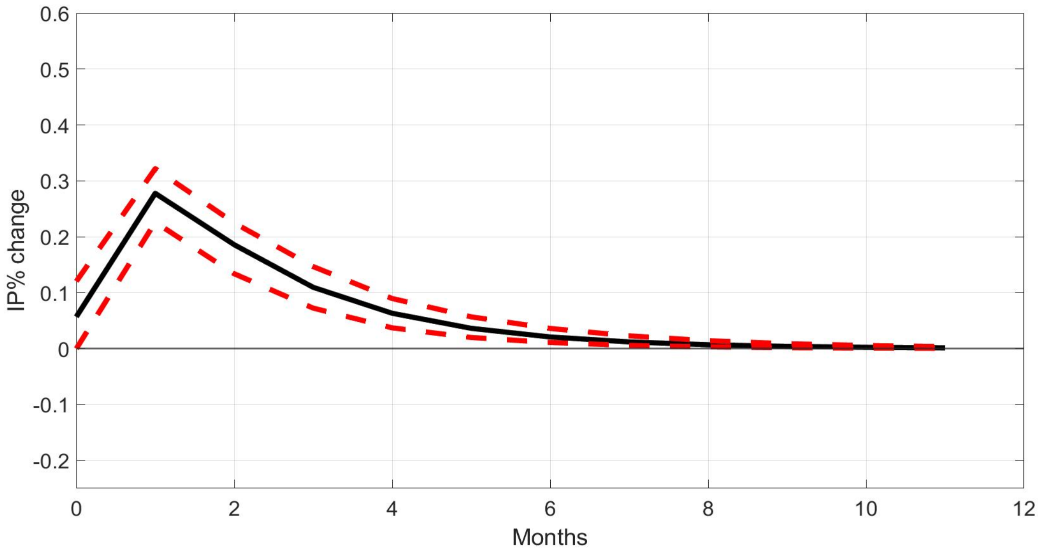


Figure 20: *Impulse response functions of Japanese IP to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

IRF shows that in the short run, there is an increase of IP that reaches its maximum in the second month, then the effect vanishes after 8-10 months lasting more than countries with similar behavior like France or Germany. One reason can be the Japanese energy situation; firms would need to increase their production to create some stocks to face higher prices in the future. Moreover, the Japanese energy supply is still strongly dependent on imports of carbon fossil sources. We have seen that countries with more significant imports tend to take advantage of IP more than countries with fewer imports or greater amounts of carbon sources or refined product exports (India, China). In this country, there is a

[21] See Appendix C

big industry component that makes products and works in support of the industries of energy countries. That is why the energy sector is determinant in changing industrial production levels. Indeed, it is possible that when commodity prices increase, Japan's industries accelerate their production to take advantage of the higher prices or because factories have to face a higher demand from other countries for energy products.

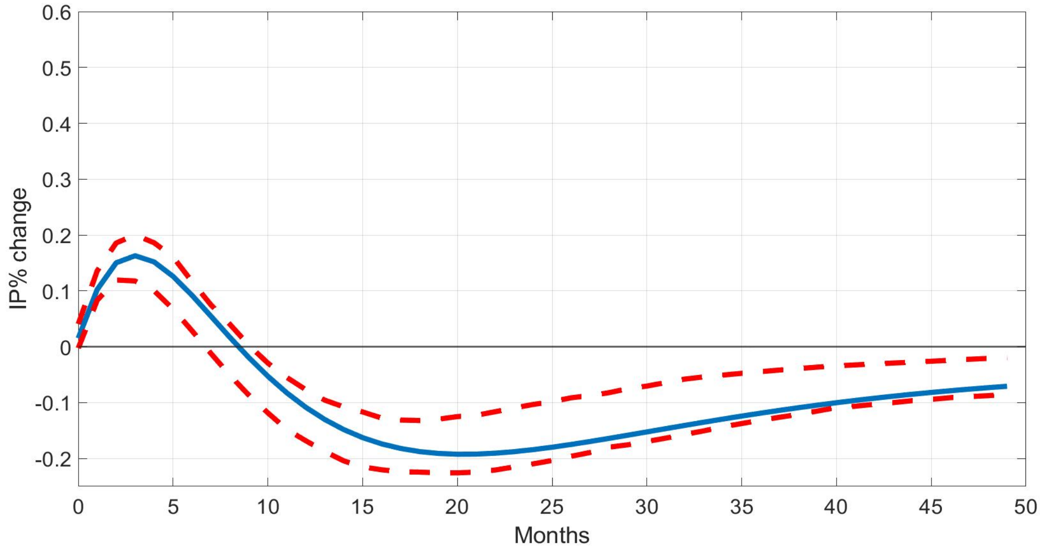


Figure 21: *Impulse response functions of Japanese IP to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

In the long run, Japanese IP behaves similarly to French one but with amplified effects. Indeed, it shows an increase in production level in the first 12 months of about 0.2%; then, when costs are unaffordable, it starts to decrease constantly in the following years.

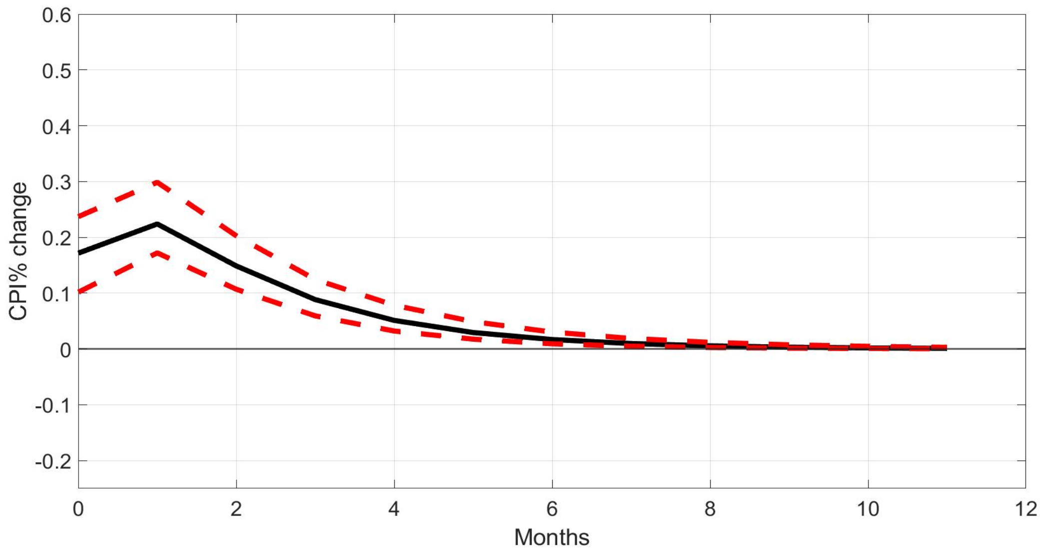


Figure 22: *Impulse response functions of Japanese CPI to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

Regarding the Consumer Price Index, it is evident how a positive shock in commodity prices is followed by an overall and durable increase of level prices in Japan for almost ten months. This increase is considerable because it shows us how the country depends on energy and how this dependence is reflected in consumer prices. In the long run, CPI increases constantly month by month at 0.1%. Japanese result confirms that countries with a difficult energy situation show increasing responses in the short run (around 0.3/0.4% both in IP and CPI) and increasing responses for the first one or two years and then a decreasing behavior for IP and constantly increasing CPI index for the following years (of about 0.1% every period). The findings from Japan confirm that countries facing a difficult energy situation exhibit initial positive responses in the short term, with both IP and CPI increasing by approximately 0.3% to 0.4% for about five months. Additionally, in the long run, the IP response is positive in the year after, while in the following years, it constantly declines. Meanwhile, the CPI index consistently increases at about 0.1% every month in subsequent years.

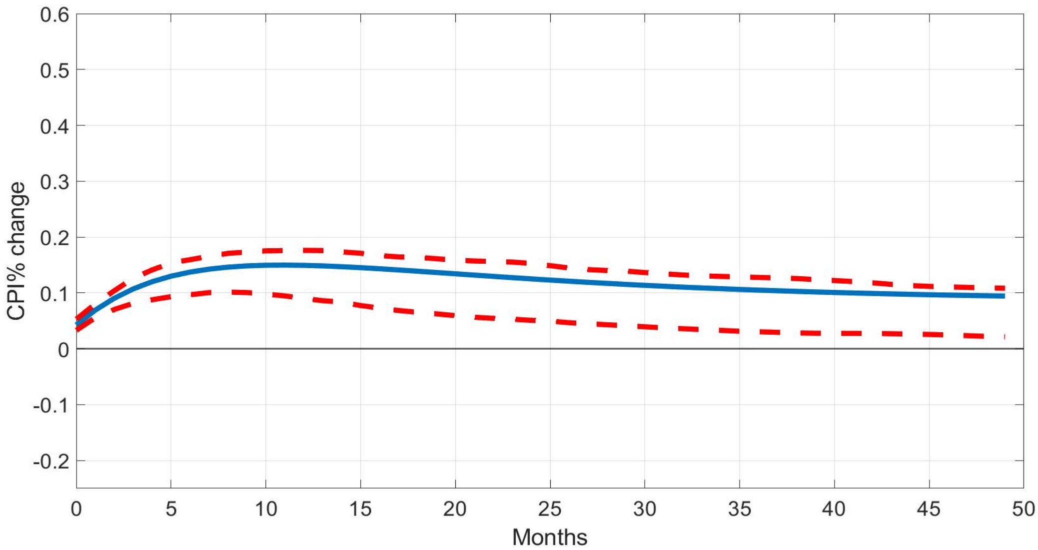


Figure 23: *Impulse response functions of Japanese CPI to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

4.6 Russia

In the last 20 years, Russia has been increasing its natural gas production, oil production, and net energy exports while electricity consumption has stayed more or less the same[22]. That means that, like India and China, Russia, more than any country, has been improving its energy situation, which was already good. Russia is known as one of the countries that produce and export more energy in the world, and what is noticed from the results is that an increase in energy commodity prices has a limited impact on Russian IP and CPI. Russia's energy situation is one of the best in the world, and it is the second gas exporter after the USA and a great exporter of Coal, oil products, and Crude Oil. That makes Russia a net exporter of energy and electricity worldwide. Natural gas accounts for about 50% of the total energy supply, then Oil for about 20%, Coal for more than 15%, Nuclear, and a small percentage of renewables. The latter has a small development in Russia. Indeed they only account for the 3.2% in the final energy consumption; a tiny percentage if we think about the 17.2% of Germany.

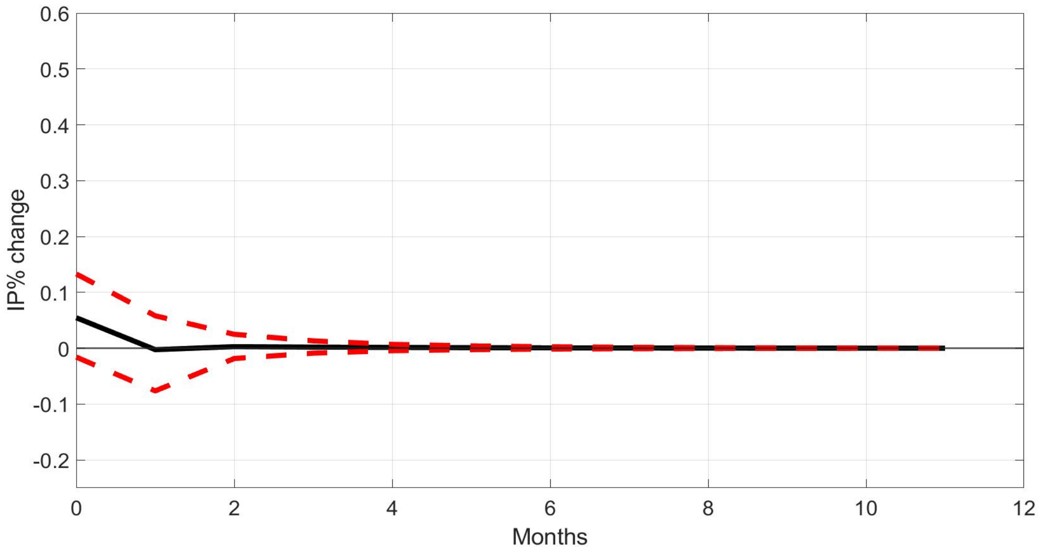


Figure 24: *Impulse response functions of Russian IP to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

In the short run Russian IP shows a positive response with a minimal size that vanishes after one month, and that might be because Russian industries do not need to take advantage of higher energy prices. After all, Russia's plentiful supply favors industries supply, and the higher prices affect foreign countries, not Russian. Therefore there is no need to increase product prices in the system.

[22]See Appendix C

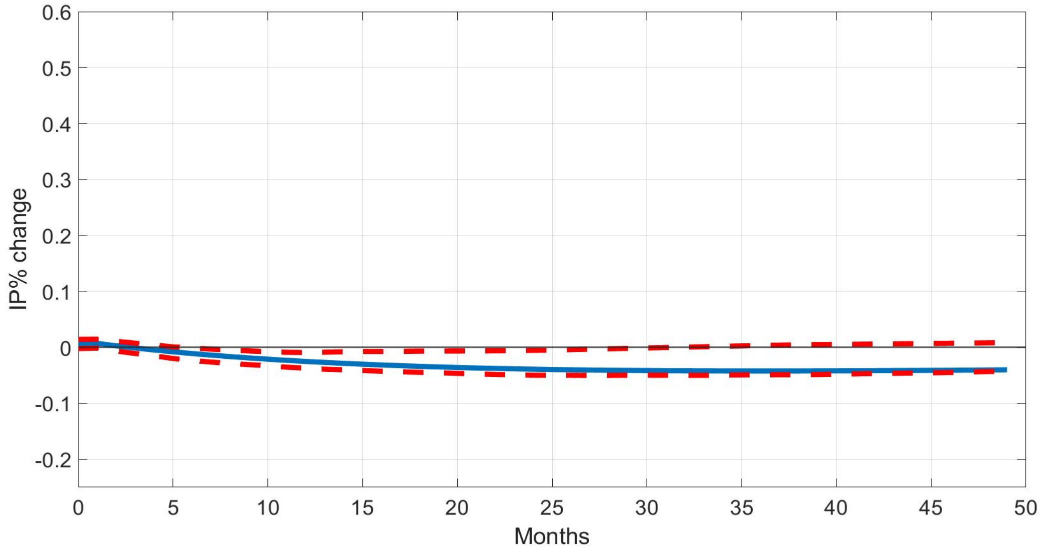


Figure 25: *Impulse response functions of Russian IP to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

In the long run, Russian IP is not too much affected by a change in energy commodity prices. Indeed the IRFs curves are almost flat. As said before, even in the long run, there is no need for Russian energy industries to increase production. It decreases a bit because of a backward effect of higher energy prices that led to a lower world energy demand. Energy is more expensive for foreign buyers, so they will find cheaper solutions or more efficient processes to increase the country's energy independence.

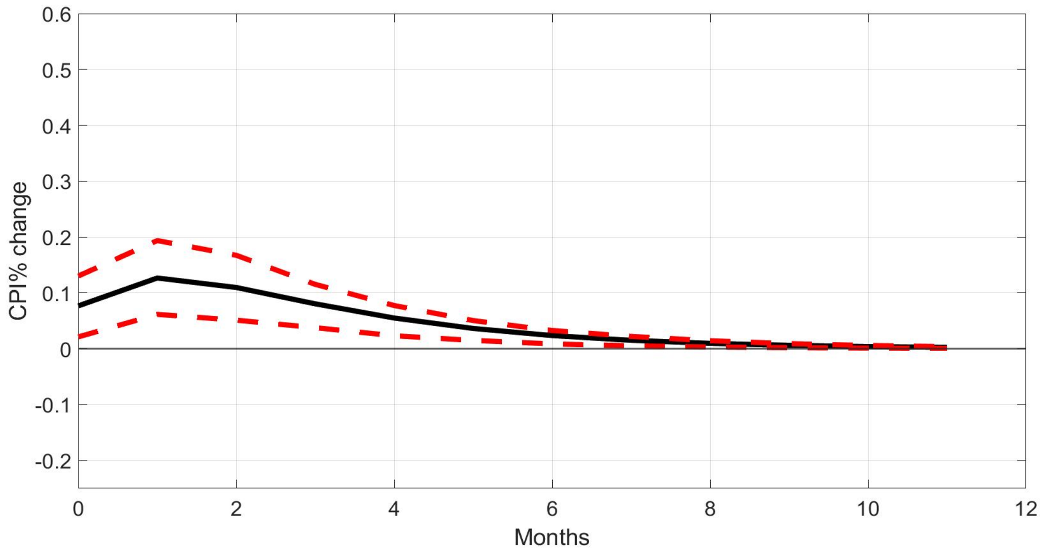


Figure 26: *Impulse response functions of Russian CPI to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

Even for CPI, the impact of commodity prices is very limited both in the short and the long run, which means it is not significantly affected by a change in energy commodity prices. Same as IP, the reason is that Russia has an excellent energy situation, so an increase in commodity prices is a benefit and not a burden. Nevertheless, like India, Russian inflation has grown significantly during the last 20 years. Another reason may be that CPI has been growing a lot independently from energy prices, so the effects of an increase in energy prices have not affected that constant increase. Undoubtedly, an increase in energy price level is a positive thing for the Russian economy.

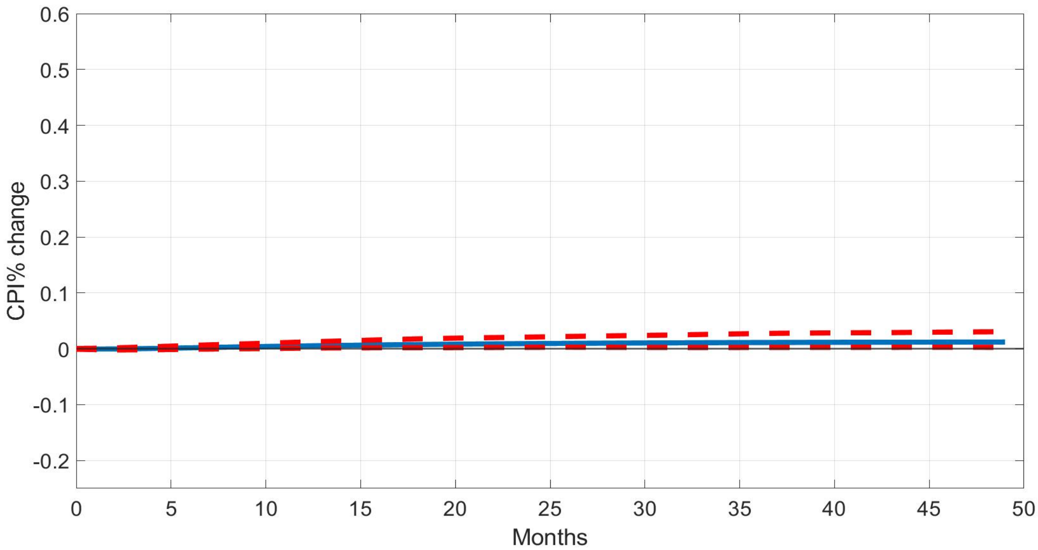


Figure 27: *Impulse response functions of Russian CPI to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

4.7 United States

In the last 10/15 years, the USA has been known for its energy policy to become more independent from the world and to try to use internal resources. Today, its independence is almost complete; of course, it has exchanges with other countries, but the USA could be energetically independent if needed. However, unlike Russia and other countries in a good energy situation, the USA shows the most considerable effects of all the seven analysed. Keep in mind that the USA is the only country that has changed its net energy position in the last 20 years, passing from being an important net energy importer to being a net exporter in 2020[23]. Both model specifications catch this trend; indeed, IP is continually increasing in the short and long run, but in a different way from the others.

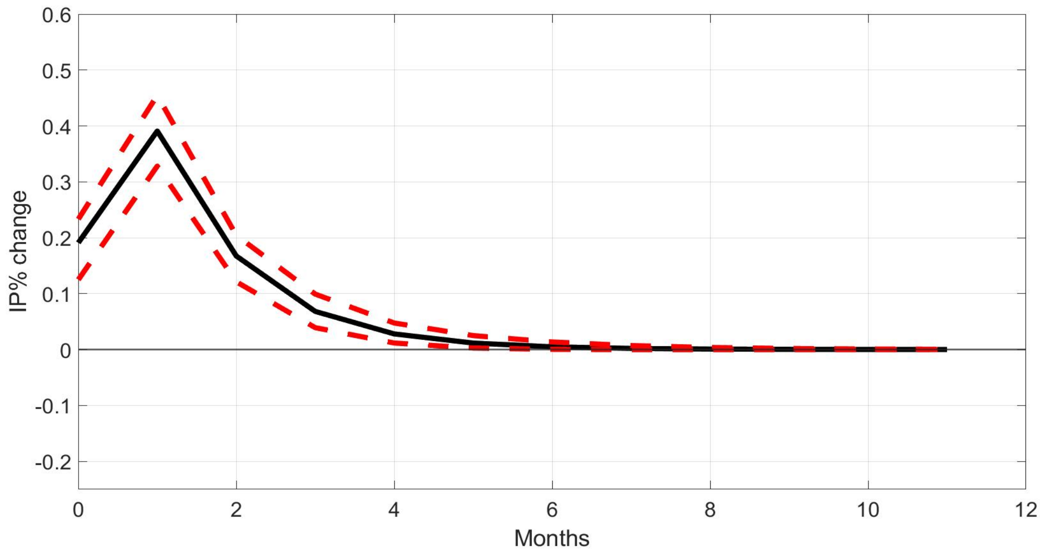


Figure 28: *Impulse response functions of US IP to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

In the short run, after a price shock of energy commodity prices, USA industrial production responds with a considerable increase (almost 0.4%), and the effect vanishes after six months without having a subsequent decrease. Therefore, the behavior of this country in the short run is like an energy importer one. The benefits of the energy balance swap that this country has had in the last decade are caught by the second model specification. In the long run, after a peak of 0.2% in the first year, the increase slowly converges to zero in almost 48 months.If things remain unchanged, the USA is improving yearly because higher prices mean only higher profits for this country so firms will increase Industrial Production.

[23]See Appendix C

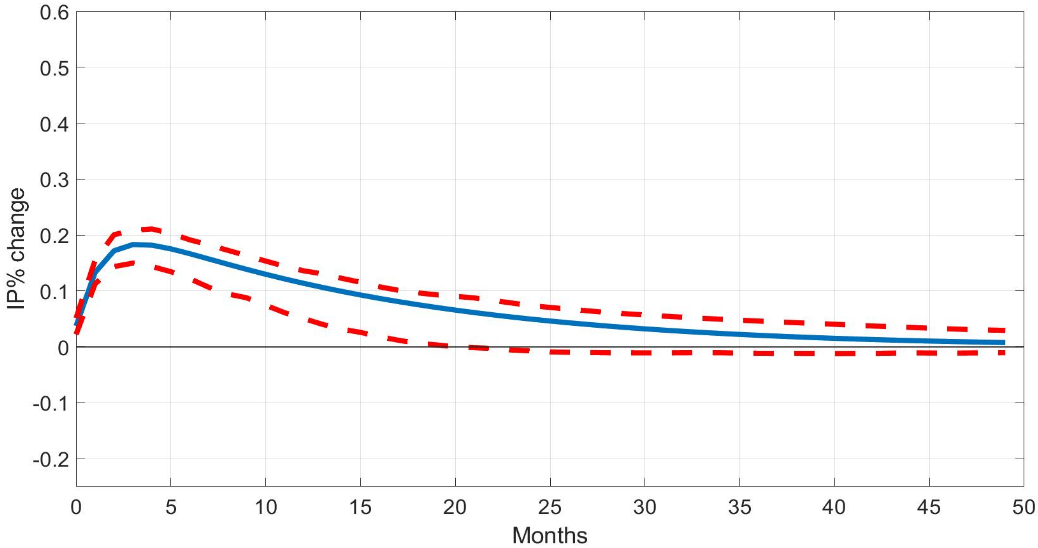


Figure 29: *Impulse response functions of US IP to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

Regarding CPI in the short run, the first specification of the model catches a constant increase in the price level of about 0.5%, the greatest in all the analysed countries. The reason is because the USA has always been a big importer of finite products from all over the world, and if energy prices rise, that means a higher cost for foreign factories which will raise their product prices. In the long run, the increase of CPI is constantly around 0.1% with a slowly convergence to zero in approximately 48 months. Nevertheless, as already said, that is not a problem because when GDP and inflation grow, the country is in a period of economic growth, and so is the USA, which seems to have one of the best situation to face the increase in the price level of commodities.

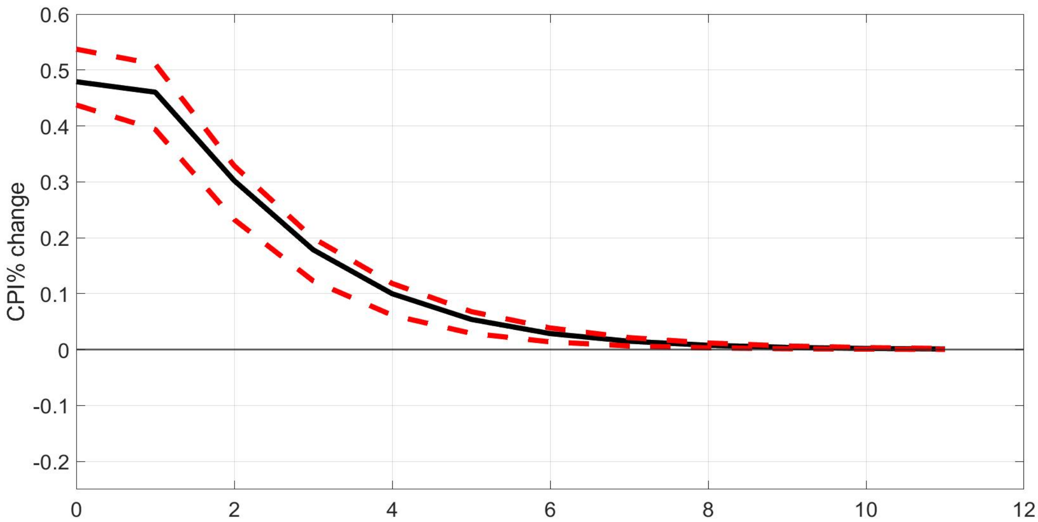


Figure 30: *Impulse response functions of US CPI to a positive shock of 1% in energy commodity prices in the short run; dotted lines represent a 68% confidence interval.*

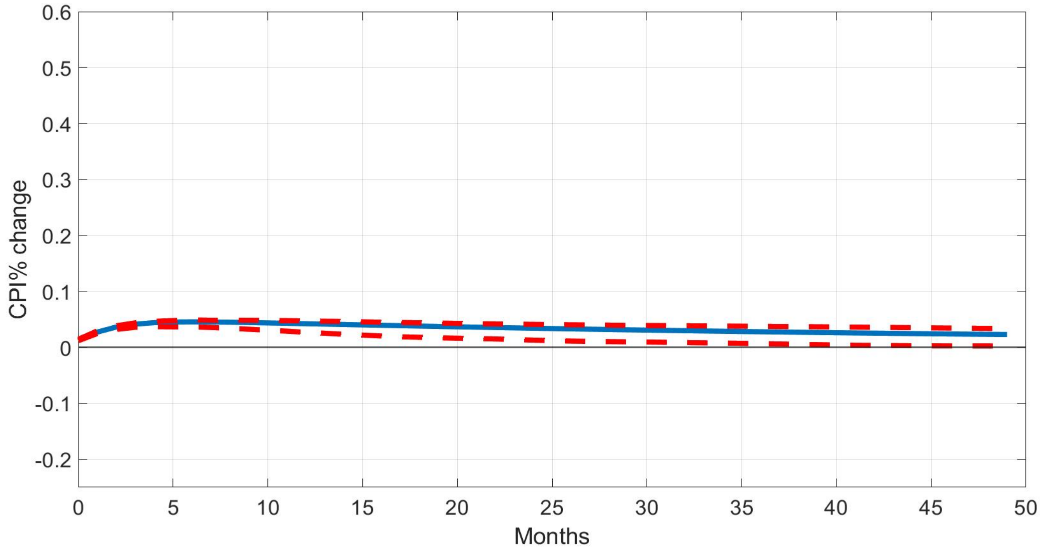


Figure 31: *Impulse response functions of US CPI to a positive shock of 1% in energy commodity prices in the long run; dotted lines represent a 68% confidence interval.*

5 General considerations

5.1 Industrial production

The influence of energy commodity prices on the industrial production of a country passes through a different number of factors, so it is not easy to catch the direct effect. Looking at macroeconomic theory, we know that in a closed economy with a given budget constraint, output decreases if costs increase. Thus, what is expected is that with higher energy prices, industrial production should decrease in the long run. From the analysis, we find out that with the first specification of the model (Trivariate-VAR(1)), we were able to catch the short-run effects on the seven countries we have analysed, while with the second model specification (Trivariate-VAR(2), with non differentaited time series), we were able to catch also the long-run ones.

- **Short run**: the results found with the standardized VAR are surprising because they show how the positive shock in energy commodity prices is followed by an increase of the IP of the country, with different sizes of the impact. We notice that the more the country has been increasing its primary energy production in the last 20 years (Russia, India, China), the less a positive shock impacts the IP of that country. Vice versa, if the energy production of that country has been decreasing, IP has a stronger positive response to a shock in energy commodity prices (France, Japan with the only exception of Germany).

  The question is why an increase in energy prices is positive for the IP of a country that is slowing its energy production in the first months. We have to keep in mind that the first specification of the model catches only the effects in the first months. Secondly, firms usually sign long term fixed-price energy contracts to ensure from price volatility, which means that they will increase production in the first months to create some stocks. In this way they produce more when the prices are still lower and they slow down the production when the energy contract is updated with the new price. In most cases, production processes and machinery are exploited at their maximum capacity, so the only way to decrease unit costs is to increase the production level before the contract expires.

- **Long run**: with the second specification we observe that after 12/24 months, the negative effects of a higher cost in energy commodity prices are reflected in the IP of those countries that are neither energy-independent nor exporters of energy semi-products. For them, the impulse curve looks to increase in the first year, with a peak after 6/8 months. Then it decreases until it stabilizes below the zero level representing a constant decrease in the overall IP. This is possible because we are working with high autocorrelated time series; therefore, they have a strong persistence, and the effect of a single shock is not reabsorbed after a few times like before, but it has an effect for a long time. For countries that are net energy importers persistently higher energy prices are unsustainable in the long run; indeed, IP is decreased. Conversely, for the countries that are net energy exporters or have a good level of semi-product export like India, the curve underlines a behavior that stabilizes positively in the long run. That means a smaller positive peak compared to countries before that stabilizes at a positive level, representing a constant little increase in the long run. Russia and China are the only two countries in the seven analysed that do not seem significantly influenced by an increase in energy commodity prices. The analysis for the first one is easy, while for China, we give an explanation in Section 4.4. A good example of a new direction is Germany, which has invested a lot in renewable energies, and the long-run IRF suggests that its IP increases even if the energy prices are greater. In addition, German industrial processes are becoming more efficient, so energy has less impact on final costs.

What emerges from the analysis of the energy situations of the countries is that coal and oil prices still have the most weight on industrial production; therefore, the things that are a benefit for the industrial sector of a country are:

1. Availability of coal and oil raw materials in the country.

2. An increasing level of energy production from their country.

3. How much the country has invested in renewable sources of energy (fossil fuels independence).

5.2 Consumer Price Index

CPI impulse responses behave differently in the short run and the long run more than IP ones. As happens for IP, the effect of the shock of energy commodity prices in CPI is slowly re-absorbed by the environment in the long run. The shock always has an increasing effect on this index; what changes is the size of the impact. CPI impulse response functions in the short run can be a good indicator of the energy situation of a country because, differently from the IP that was influenced by other factors that make China and Russia IP behave in the same way, here all net energy importers countries show a more significant impact of the energy commodity prices shock than the net energy exporters. The only exception is the United States, that have the greatest impact of all the countries we analysed in the short run, even if it has become a net energy exporter in the last few years.It may happen because the USA is one of the biggest importers of consumer products worldwide, so many world economies influence its economy. Moreover, this country became a net energy exporter only after 2018, and remember that our study is done on the last 20 years when the USA was a net energy importer. The best example to justify the fact that CPI index impulse response functions are a good indicator of a country's energy independence is China. This country is a net energy importer, and while its IP impulse response hides the Chinese energy situation making it behave like net energy importers countries like Russia, CPI's IRF in the short run clearly shows a considerable reaction (about 0.3%), underlining Chinese weakness in the energy balance. However, in the long run, these effect has no impact because the Chinese economy is strongly developing, and maybe these effects are absorbed by the strong growth of the country. That is why CPI's IRFs, in the short run, are good indicators for a country's energy independence. In general, all net energy importer countries show a more significant impact of the energy commodity prices shock in CPI than the net energy exporters. The only factor that can disturb the results is the globalization of the country intended as the grade of openness to the world's markets and the size of its economy (United States case).

- **Short run**: there are a lot of different responses of CPI indexes to the energy commodity shock of 1%, and their sizes move between a range that goes from 0.1% to more than 0.6% depending on the country's energy situation. As for IP, the most responsive countries are the ones that have the worst energy situation and that are net importers, while the size reduces for those who are net exporters. From the graphs, what is possible to see is that countries like France, Germany, Japan, and China have similar IRFs that respond immediately with an increase in level prices of about 0.4%. This effect slowly vanishes after six months. These countries are considered net energy importers, so they need to integrate their primary energy supply with external sources from other countries. India and Russia, net energy exporter countries, have relatively minor impacts with peaks that do not overcome the 0.2%; the USA should behave like them, but its grade of openness to the world, and the late net energy exporter balance, make it the most responsive in CPI to energy prices.

- **Long run**: in the long run, the consideration is different. Strong economies show impulse responses near the zero impact in level prices. Here Chinese CPI behaves as a strong energy country like Russia and India; for them, the effect of a shock in energy commodity prices is approximately zero in the long run. This might be thanks to solid monetary policies and an increasing trend in GDP that less absorb the effects on the energetic world. France, Germany, Japan, and the USA are the countries that show a constant increase in CPI after the shock. Their impulse responses of CPI stabilize in a few months around the 0.1% without being re-absorbed in the future. This behavior means how worrying can be an increase of 50% in energy commodity prices and which consequences can bring to the general level of prices in those countries.

5.3 Extensions

If there is a desire to go deeper in the study of each country, it is possible to first look at the composition of the country's industrial production to understand which sectors have the biggest share. It would be interesting to study and analyse the IRF of IP for energy-intensive firms and the results for industries with the lowest energy use, like the textile sector. We should expect that the more energy-intensive sectors should have a greater impact on an energy commodity prices shock, while we should have flat curves for the sectors that use less energy. It would also be helpful to quantify the loss in percentage and absolute terms since we have IP time series expressed in overall values and not in monthly percentage changes. Another interesting thing to do is to see which kind of energy contracts the firms of a specific country have, which is the duration of these contracts, and how their prices are determined. As said before, firms usually have fixed prices contracts for long periods, different from the inhabitants of a country that instead have variable prices month by month.

Finally, a possible extension is to use mixed frequency data, which means using GDP and Inflation, usually given in quarterly data, together with monthly or even daily data for energy commodity prices. We are talking about creating a FAVAR model using a MIDAS approach and seeing which are the direct impacts on GDP instead of Industrial production and on Inflation instead of the Consumer Price Index.

Summary

Energy commodities stand at the beginning of every industrial process, affecting the prices of every good produced. Whenever there is a shock in these prices, the countries and their industries respond differently to take advantage and avoid losses. An energy commodity is any raw material, semi-product, or finite product used in energy production, used by the cities for heating and cooling as well as energetic and not energetic firms. In this paper, we want to answer how much these commodities' shocks influence the behavior of the economies of the countries worldwide, in particular looking at two macroeconomic variables as Industrial Production and Consumer Price Index. We want to observe the differences and similarities between the behavior of energy exporter and energy importer countries. The literature gap of this study is that we give a wide analysis of the effective impact of energy commodity prices shocks in the short and in the long run, underlining the differences between energy importers and exporters, and the difference between American, European and Asian countries. We use Bloomberg for the collection of time series of energy commodity prices. The goal of the collection is to give the most possible extensive view of the worldwide area. However, at the same time, we consider only those countries for which we finish with a consistent number of different time series found. For every country, we search for prices related to that country of Coal, Coke, Crude Oil, Heating Oil, Petrol, Gasoline, Diesel, Natural Gas, Methane, Electricity, Uranium, Nickel, Cobalt, Manganese, Lithium, Germanium, Gallium, Ethanol, Iron, Silicon. The result is the creation of seven different data matrices relative to France, Germany, India, China, Japan, Russia, and the USA. Ultimately, we use FRED (Federal Reserve Economic Data) for the macroeconomic variables (IP, CPI) because it gives those time series in absolute values, which we need in our study.

For the study, we use a model presented in Bernanke et al. (2005), the FAVAR model. FAVAR stands for Factor-Augmented Vector Autoregressive model, and it is a method that allows us to analyse a more significant number of variables than we can do with a standard Vector Autoregression (VAR) model. The FAVAR model consists of a first step in extracting the leading factors from a large data matrix with the PCA method. In the second step, a multivariate vector model regresses the factors extracted with the variables considered observable, in our case, Industrial Production and Consumer Price Index. We use this model with two different sequences of data: the firsts are time series that we turn into stationary ones with the use of logarithms and differentiation for the study of the short run; the seconds are made of non-differentiated time series because, having high persistence, they let us analyse the effects in the long run.

The general form of the FAVAR model is:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t, \tag{18}$$

where F_t is a $K \times 1$ vector of unobserved variables, while Y_t is a $M \times 1$ vector of observable economic variables, $\Phi(L)$ is a matrix of lag polynomials of order p and $e_t \sim N(0, \Sigma)$ is a normally distributed $(N + K) \times 1$ vector of shocks.

$$X_t = \Lambda^f F_t + v_t, \tag{19}$$

where Λ^f is an $N \times K$ matrix of factor loadings, and the $N \times 1$ vector of error terms v_t are mean zero but not fully uncorrelated because principal component estimations allows for some cross-correlation that must vanish as $N \to \infty$. It is possible to choose many methods to extract the unobserved factors F_t from the data matrix X; here, we go for a two-step estimation procedure, which uses asymptotic principal component methods to find the factors before running the entire factor-augmented VAR. Therefore, in the first step we apply PCA to the data matrix and we extract the eigenvectors corresponding to the K largest eigenvalues of the variance-covariance matrix. In our case we extract only one factor representing the behaviour of all the commodity prices of the country we are testing.

In the second step we run our implementation of the VAR model for the study, where $(F_t \quad Y_t)' = (\hat{F}_t \quad IP_t \quad CPI_t)'$:

$$\begin{bmatrix} F_t \\ IP_t \\ CPI_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ IP_{t-1} \\ CPI_{t-1} \end{bmatrix} + v_t \, , \tag{20}$$

and,

$$\Phi(L) = \Phi \equiv \begin{bmatrix} \alpha_1 & 0 & 0 \\ \beta_1 & \beta_2 & \beta_3 \\ \gamma_1 & \gamma_2 & \gamma_3 \end{bmatrix} . \tag{21}$$

As it is possible to see from Equation (21), the lag matrix $\Phi(L)$ has some constrains, $\alpha_2, \alpha_3 = 0$, because we do not want the factor to depend on past values of IP and CPI but only on their current one and, of course, on past energy commodity prices. This makes our VAR model constrained, indeed a Structural VAR (SVAR). A critical issue to discuss is the number of lags to insert in the model; we take into consideration a range of 1-6 lags, and the best option seems to be the choice of one lag when we use stationary time series and two lags when we work with non-differentiated times series. With the first specification of the model (Trivariate-VAR(1)), we are able to catch the short-run effects on the seven countries we analyse, while with the second model specification (Trivariate-VAR(2), with non differentaited time series), we are able to catch also the long-run ones. At the end we analyse the different Impulse Response Functions (IRF) of the observable variables to a

1% shock in the commodity prices factor. In this way, we obtain the impulse response to the structural shock, which means obtaining how the variables respond to a shock that directly impacts them in the time (orthogonalized shocks), which are different from the generalized shocks. Knowing their difference is fundamental because IRF to generalized shocks represents the response to a prevision error. In contrast, IRF to structural shocks let us understand how variables respond to an effective shock of the other variables and their impact on the behavioral relationship between them.

Analysing the results, we observe that the seven countries can be divided into two groups: countries that behave like net energy importers (France, Germany, Japan) and those which behave like net energy exporters (China, India, Russia). The US is the only country that behaves differently for IP and CPI and even for short and long run. The results we find with the standardized VAR are surprising because, following macroeconomic theory, what is expected is a decrease in IP because in a closed economy with a given budget constraint, output decreases if costs increase. However, from the results, it is evident that a positive shock in energy commodity prices is followed by an increase of the IP of the country; what changes between them is the size of the impact. We notice that the more the country has been increasing its primary energy production in the last 20 years (Russia, India, China), the less a positive shock impacts the IP of that country. Vice versa, if the energy production of that country has been decreasing, IP has a stronger positive response to a shock in energy commodity prices (France, Japan with the only exception of Germany that is strongly investing in renewable energies). Firms usually have long term fixed price energy contracts, so, they will increase production in the short run to create some stocks. In most cases, production processes and machinery are exploited at their maximum capacity, so the only way to decrease unit costs is to increase the production level before the contract expires. In the long run importer countries suffer the increase of prices and that is why they show a decrease in IP after one or two years. Exporter countries instead show a small increase because for them higher prices mean higher profits. What emerge from the analysis of the energy situations of the countries is that coal and oil prices still have the most weight on industrial production; therefore, the things that are a benefit for the industrial sector of a country are:

1. Availability of coal and oil raw materials in the country.

2. How much the country has invested in renewable sources of energy (fossil fuels independence).

3. An increasing level of energy production from their country.

CPI impulse responses behave differently, the shock always has an increasing effect on this index; what changes is the size of the impact. CPI index impulse response functions in the short run can be a good indicator of the energy situation of a country because, all net energy importer countries show a more significant impact of the energy commodity prices shock than the net energy exporters because they have a worst energy situation. Net importer countries have limited postive effects in the short run. In the long run, the consideration is different because the increase is never greater than a 0.2%. Strong economies show impulse responses near the zero impact in level prices. This might be thanks to solid monetary policies and an increasing trend in GDP that let CPI absorb the effects on the energetic world. The others, net energy importers, show a constant increase in CPI after the shock, that slowly converges to zero. Their impulse responses of CPI stabilize in a few months around the 0.1% without being re-absorbed in the future. This behavior means how worrying can be an increase of 50% in energy commodity prices and which consequences can bring to the general level of prices in those countries.

References

Akaike, H. (1974) A new look at the statistical model identification. *IEEE transactions on automatic control*, *19*(6), 716–723.

Bernanke, B. S., and Blinder, A. S. (1992) The federal funds rate and the channels of monetary transmission. *The American Economic Review , Sep., 1992, Vol. 82, No. 4, pp. 901-921.*

Bernanke, B. S., Boivin, J., and Eliasz, P. (2005) Measuring the effects of monetary policy: A factor-augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics.*

Bernanke, B. S., and Mihov, I. (1998) Measuring monetary policy. *The Quarterly Journal of Economics , Aug., 1998, Vol. 113, No. 3 (Aug., 1998), pp. 869-902.*

Byrne, J., Fazio, G., and Fiess, N. (2013) Primary commodity prices: Co-movements, common factors and fundamentals. *J. Dev. Econ., 101, 16–26.*

Chevallier, J. (2011) Macroeconomics, finance, commodities: Interactions with carbon markets in a data-rich model. *Econ. Model, 28, 557-567.*

Dickey, D. A., and Fuller, W. A. (1979) Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427–431.

Fukunaga, I., Hirakata, N., and Sudo, N. (2010) The effects of oil price changes on the industry-level production and prices in u.s. and japan. *NBER Working Paper No. 15791.*

Gupta, R., Jurgilas, M., and Kabundi, A. (2010) The effect of monetary policy on real house price growth in south africa: A factor-augmented vector autoregression (favar) approach. *Econ. Model., 2010, 27, 315–323.*

Gupta, R., and Kabundi, A. (2010) The effect of monetary policy on house price inflation. *J. Econ. Stud., 37(6), 616–626.*

IEA. (2020) Key world energy statistics 2020. https://www.iea.org/reports/key-world-energy-statistics-2020

IEA. (2022a) *Key energy statistics 2020, china.* https://www.iea.org/countries/china

IEA. (2022b) *Key energy statistics 2020, france.* https://www.iea.org/countries/france

IEA. (2022c) *Key energy statistics 2020, germany.* https://www.iea.org/countries/germany

IEA. (2022d) *Key energy statistics 2020, india.* https://www.iea.org/countries/india

IEA. (2022e) *Key energy statistics 2020, japan.* https://www.iea.org/countries/japan

IEA. (2022f) *Key energy statistics 2020, united states.* https://www.iea.org/countries/united-states

Jurado, K., Ludvigson, S. C., and Ng, S. (2015) Measuring uncertainty. *American Economic Review 2015, 105(3): 1177–1216.* http://dx.doi.org/10.1257/aer.20131193

Kilian, L. (2009) Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *The American Economic Review , Jun., 2009, Vol. 99, No. 3 (Jun., 2009), pp. 1053-1069.*

Koop, G., Pesaran, M. H., and Potter, S. M. (1996) Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, Volume 74, Issue 1, September 1996, Pages 119-147.*

Leeper, E. M., Sims, C. A., Zha, T., Hall, R. E., and Bernanke, B. S. (1996) What does monetary policy do? *Brookings Papers on Economic Activity , 1996, Vol. 1996, No. 2 (1996), pp. 1-78.*

Lombardi, M., Osbat, C., and Schnatz, B. (2012) Global commodity cycles and linkages: A favar approach. *Empirical Econ., 43(2), 651–670.*

Ludvigson, S. C., and Ng, S. (2009) Macro factors in bond risk premia. *Rev. Financ. Stud., 22(12), 5027-5067.*

Moench, E. (2008) Forecasting the yield curve in a data-rich environment: A no-arbitrage factor-augmented var approach. *J. Econometrics, 146(1), 26–43.*

Pearson, K. (1901) Liii. on lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, *2*(11), 559–572.

Pesaran, M. H., and Shin, Y. (1997) Generalized impulse response analysis in linear multivariate models. *Economics Letters 58 (1998) 17–29.*

Ritchie, H., Roser, M., and Rosado, P. (2022a) Energy. *Our World in Data.* https://ourworldindata.org/energy-production-consumption

Ritchie, H., Roser, M., and Rosado, P. (2022b) Energy. *Our World in Data.* https://ourworldindata.org/energy-mix

Ritchie, H., Roser, M., and Rosado, P. (2022c) Energy. *Our World in Data.* https://ourworldindata.org/energy/country/france

Schwarz, G. (1978) Estimating the dimension of a model. *The annals of statistics*, 461–464.

Sims, C. A. (1992) Interpreting the macroeconomic time series facts: The effects of monetary policy. *European Economic Review 36, pp. 975-1011.*

Stock, J. H., and Watson, M. W. (2002) Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association , Dec., 2002, Vol. 97, No. 460, pp. 1167-1179.*

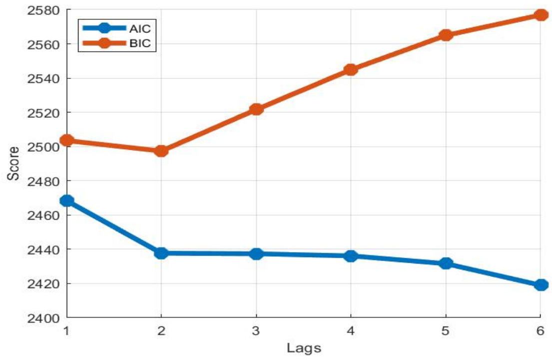
Vasishtha, G., and Maier, P. (2013) The impact of the global business cycle on small open economies: A favar approach for canada. *N. Am. J. Econ. Financ., 24, 191–207.*

Yin, L., and Han, L. (2016) Macroeconomic impacts on commodity prices: China vs. the united states. *Quantitative Finance*, *16*(3), 489–500.

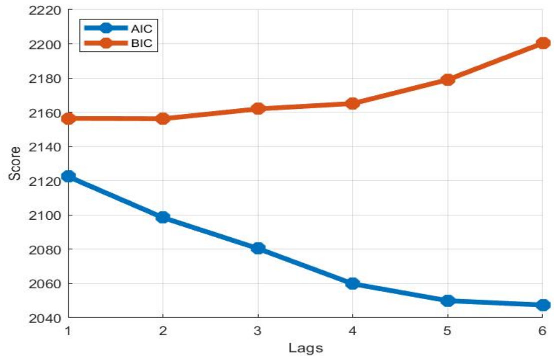
Zagaglia, P. (2010) Macroeconomic factors and oil futures prices: A data-rich model. *Energy Econ., 32, 409-417.*

Appendices

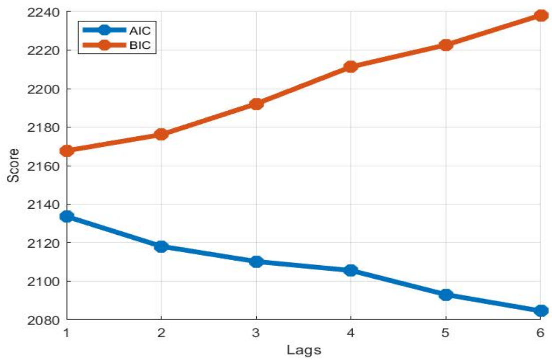
A Number of lags



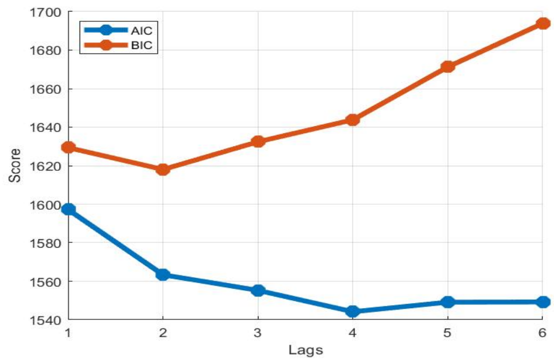
(a) France



(b) Germany



(c) India



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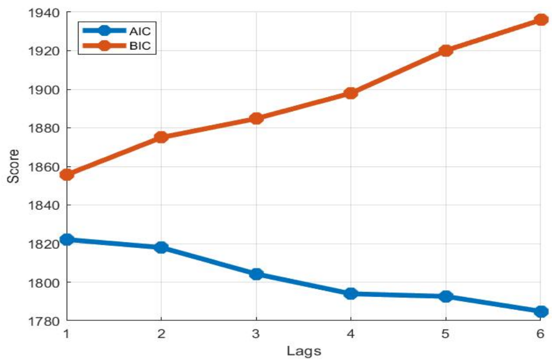
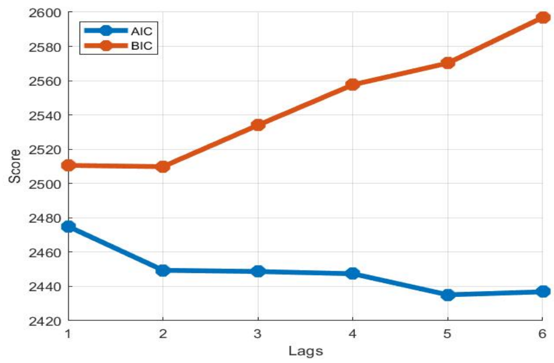
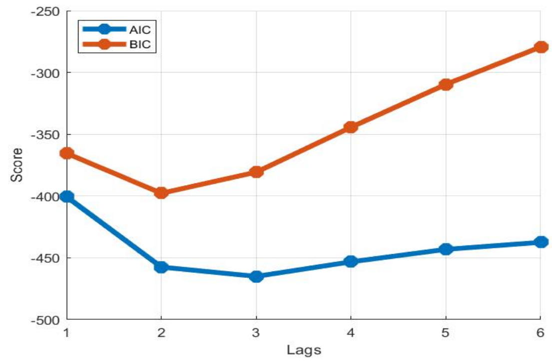


(e) Russia

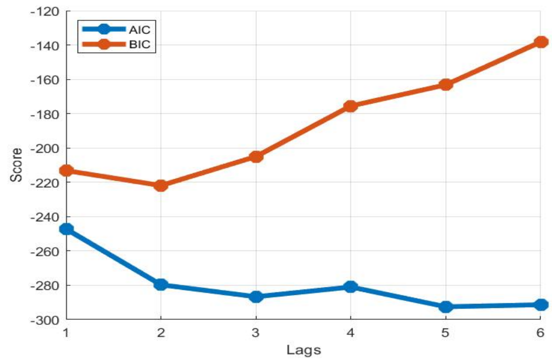


(f) United States

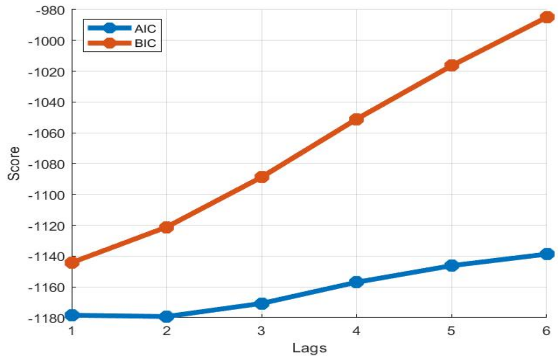
Figure 32: *AIC and BIC values for each country when stationary time series are used in the model,* 1^{st} *model specification. Blue line represents AIC, while red one represents BIC.*



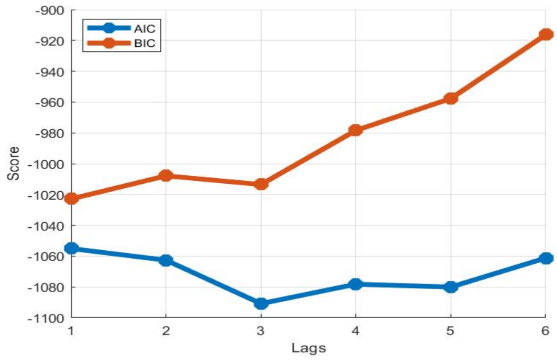
(a) France



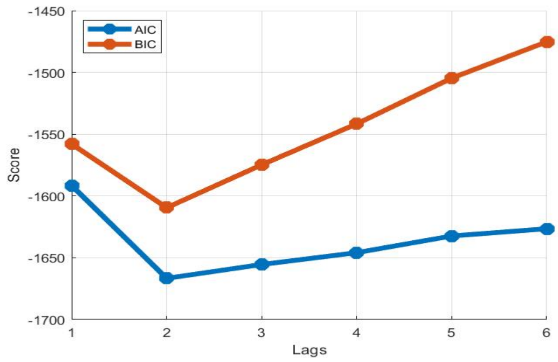
(b) Germany



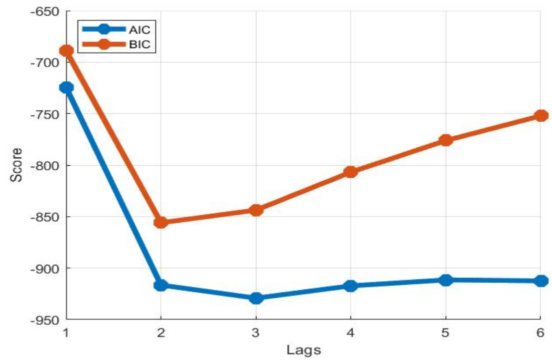
(c) India



(d) China



(e) Russia



(f) United States

Figure 33: *AIC and BIC values for each country when non-differentiated time series are used in the model,* 2^{nd} *model specification. Blue line represents AIC, while red one represents BIC.*

B Robustness checks

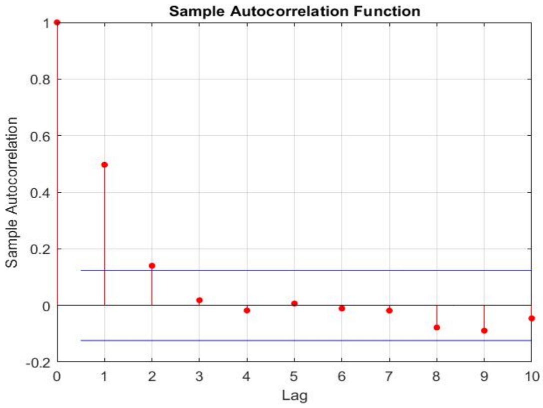
B.1 Variables order

We started checking the robustness of our results by starting from the order of the variables in the Trivariate-VAR. As said in paragraph x, we use Cholesky decomposition to find the matrix B; therefore, the order of the observable variables affects the results. However, in our case, we obtained the same results for the two model specifications by putting IP before CPI or vice versa. Indeed, their order does not influence the results.

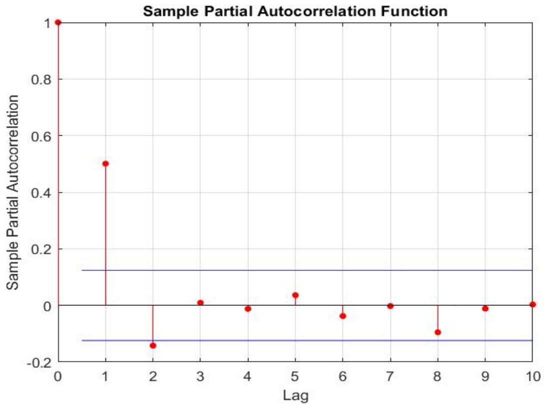
Concerning the use of different types of time series in both model specifications, in the first specification, we used the first difference to obtain stationary time series and look at the short-term effects. In the second, we did not use first differences but worked with levels time series to look at the long-term effects. In both cases, even if they are different, IRFs are qualitatively similar.

B.2 Autocorrelation and Partial-autocorrelation

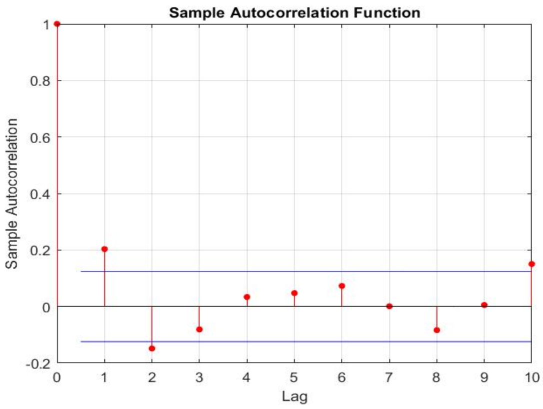
To verify the right choice in the first application of the model, the one with differentiated time series, we also looked at ACF and PACF. The graphs in the following figure show a considerable correlation of the time series at the second lag. Indeed, the choice of a Trivariate-VAR(1) looks appropriate.



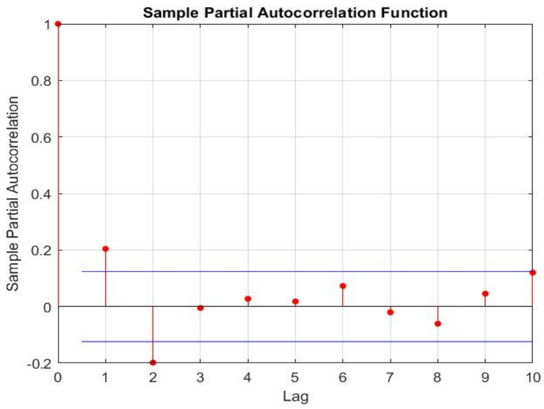
(a) ACF of the factor



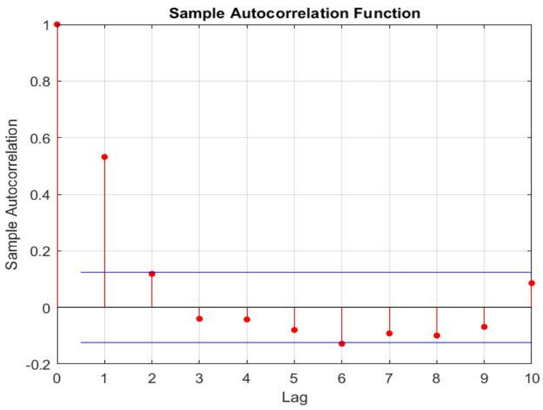
(b) PACF of the factor



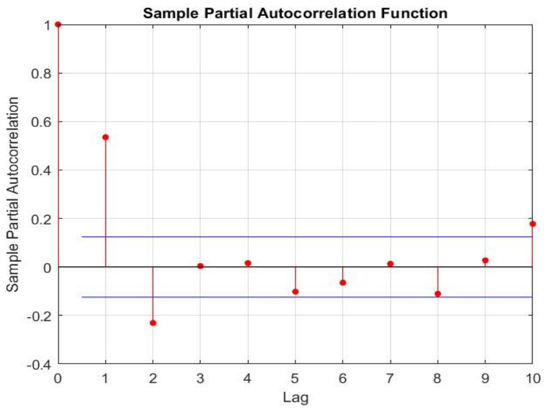
(c) ACF of IP



(d) PACF of IP



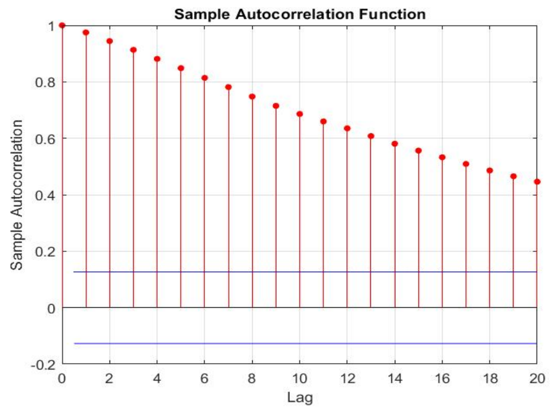
(e) ACF of CPI



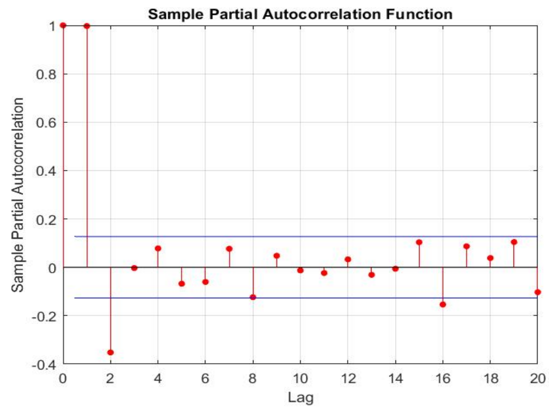
(f) PACF of CPI

Figure 34: 1^{st} *model specification: Autocorrelation functions and Partial Autocorrelation function of the three variables regressed in the second step; respectively the Factor, IP and CPI related to France country; others follow similar behaviors*

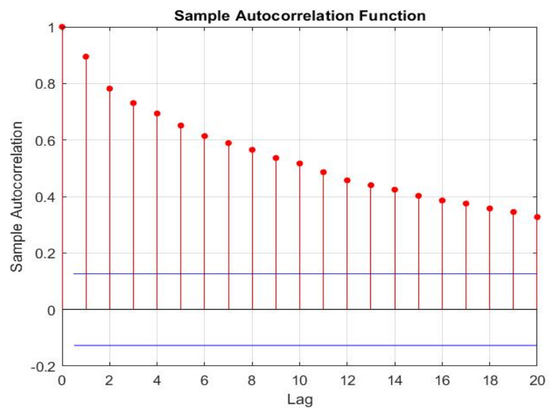
Regarding the choice in the second model specification, it was impossible to look at the autocorrelation functions because we worked with non-differentiated time series with strong persistence. Partial autocorrelation functions supported the choice of two lags, as the Information Criteria suggested. Indeed, the choice was a Trivariate-VAR(2).



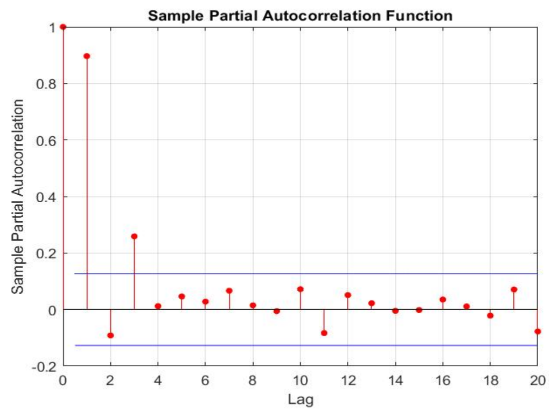
(a) ACF of the factor



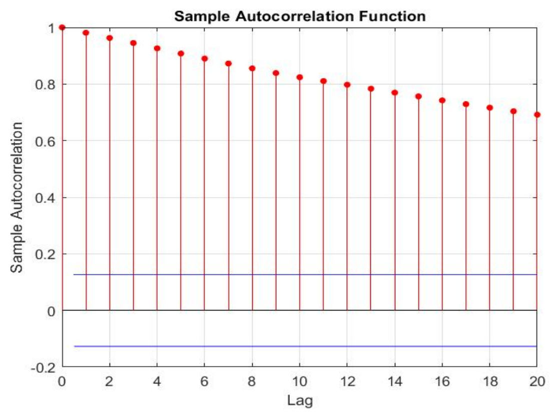
(b) PACF of the factor



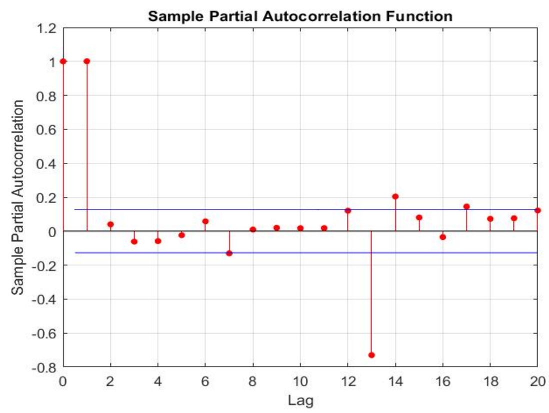
(c) ACF of IP



(d) PACF of IP



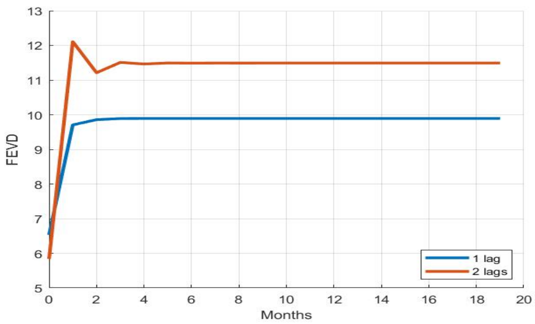
(e) ACF of CPI



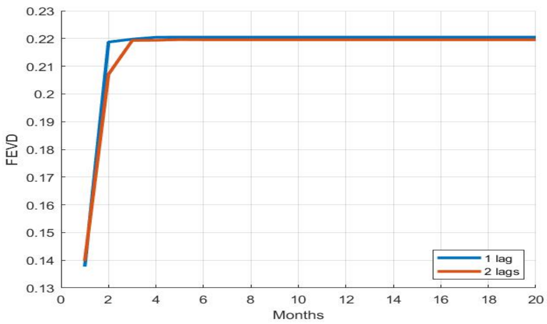
(f) PACF of CPI

Figure 35: 2^{nd} *model specification: Autocorrelation functions and Partial Autocorrelation function of the three variables regressed in the second step; respectively the Factor, IP and CPI related to France country; others follow similar behaviors*

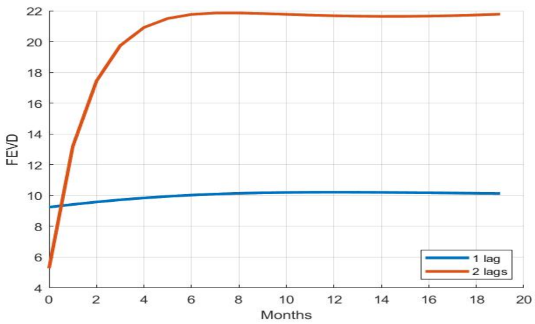
Even looking at FEVD (Forecast Error Variance Decomposition), it is clear that for the first application of the model, the choice of one lag or two lags is almost indifferent, which is why our choice is to follow the Principle of Parsimony and so to go for one lag and better parameter estimation. While for the second application, the difference is more relevant; for example, France's industrial production goes from 10% to 22%, which is why we used two lags. The graph represents all FEVD for both models for France; other countries follow similar curves.



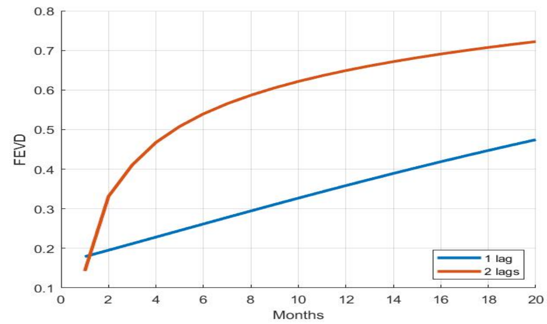
(a) FEVD for differentiated IP



(b) FEVD for differentiated CPI



(c) FEVD for non-differentiated IP

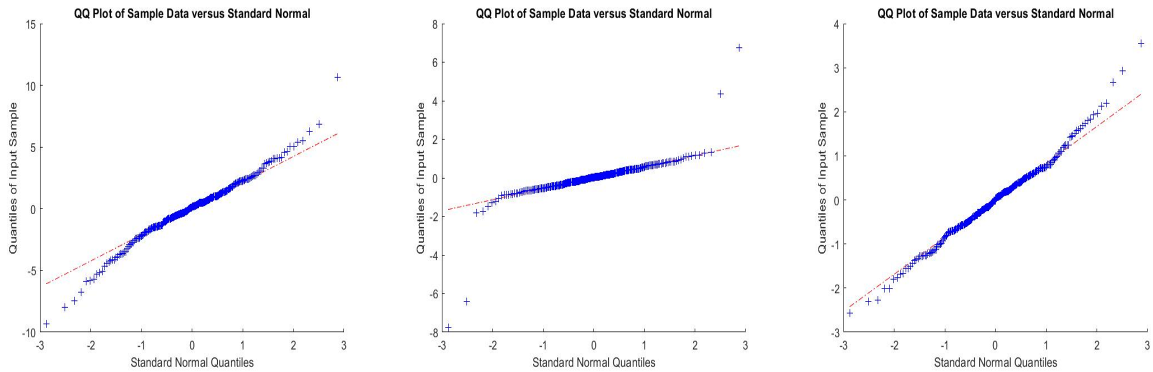


(d) FEVD for non-differentiated CPI

Figure 36: *Forecast Error Variance Decomposition of IP and CPI, for the differentiated and non-differentiated time series, for 1 and 2 lags. Graphs are related to France country; others follow similar behaviors*

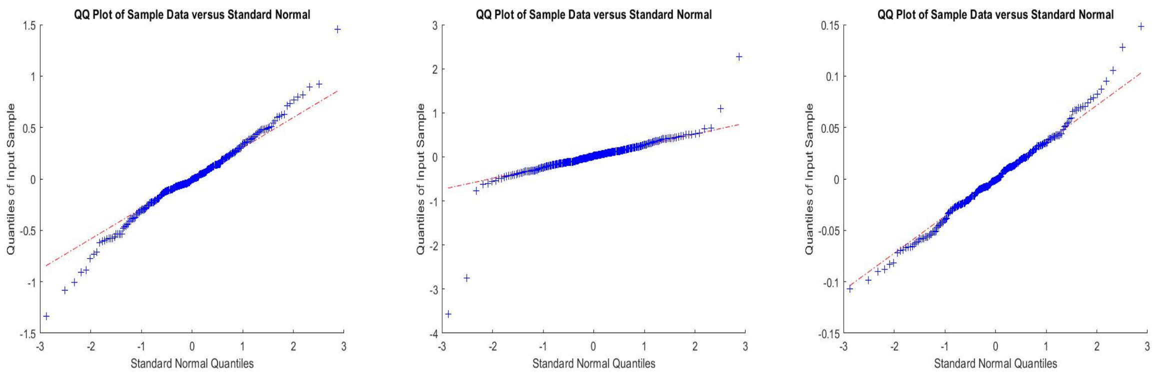
B.3 Residuals diagnostics

After the estimation, we tested the nature of the residuals, comparing them with the Standard Normal distribution. Both model specifications QQ plots appear very similar, showing fat tails of the factor distribution, meaning a bit of kurtosis. Concerning IP and CPI, tails are thinner, meaning they follow a distribution closer to a Standard Normal.



(a) Factor residuals (b) IP residuals (c) CPI residuals

Figure 37: *QQ plots of* 1^{st} *model specification residuals distributions vs Standard Normal distribution(*$\mathcal{N}$*). Residuals come from France country estimation, other countries residuals follow similar behaviour*



(a) Factor residuals (b) IP residuals (c) CPI residuals

Figure 38: *QQ plots of* 2^{nd} *model specification residuals distributions vs Standard Normal distribution(*$\mathcal{N}$*). Residuals come from France country estimation, other countries residuals follow similar behaviour*

C Countries energy statistics

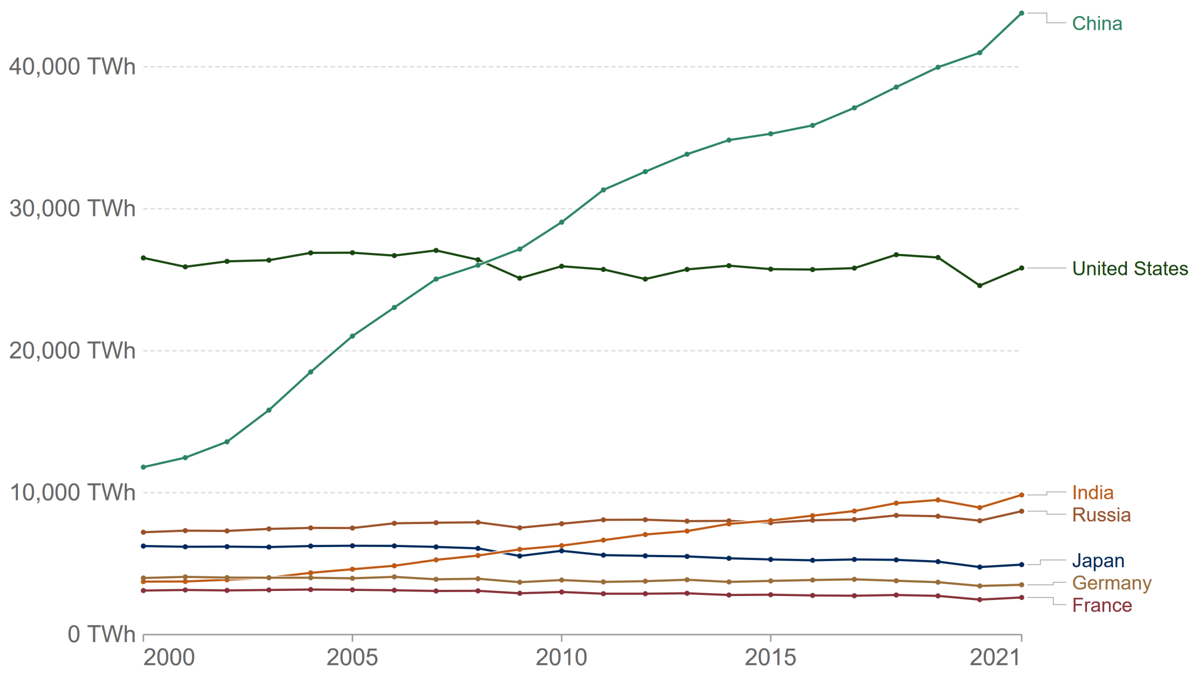


Figure 39: *Ritchie et al. (2022a), Primary energy consumption of all countries from 2000 to 2021, measured in Terawatt-Hour(TWh)*

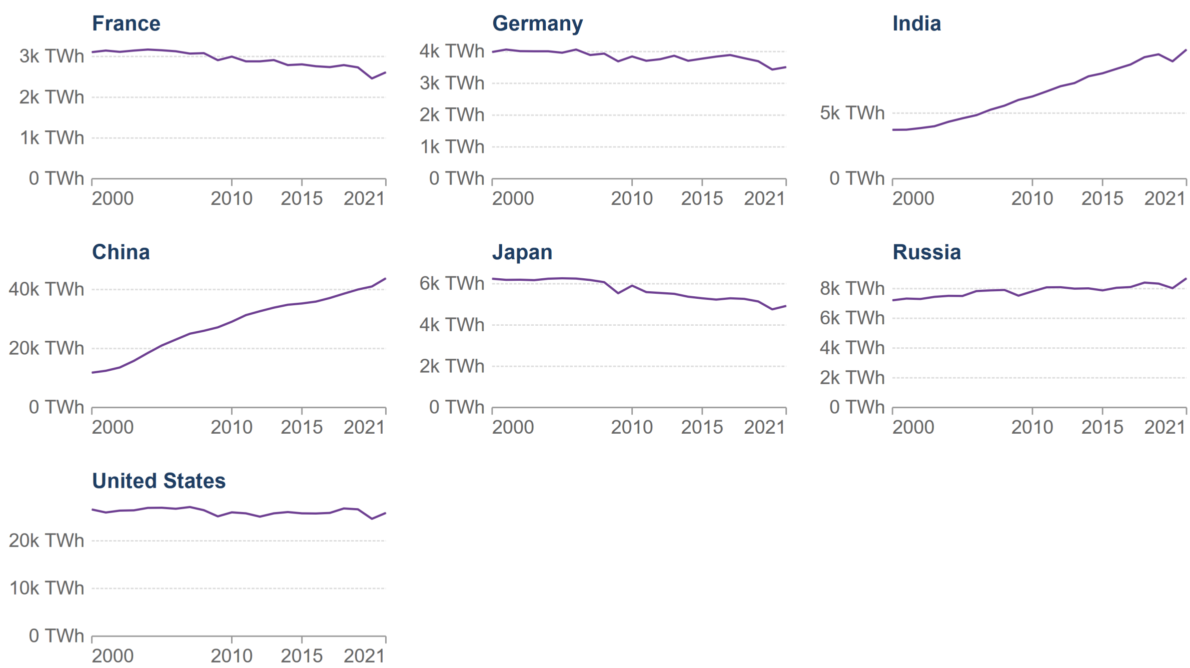


Figure 40: *Ritchie et al. (2022a), Energy consumption split by country with not aligned axis scales from 2000 to 2021, measured in Terawatt-Hour(TWh)*

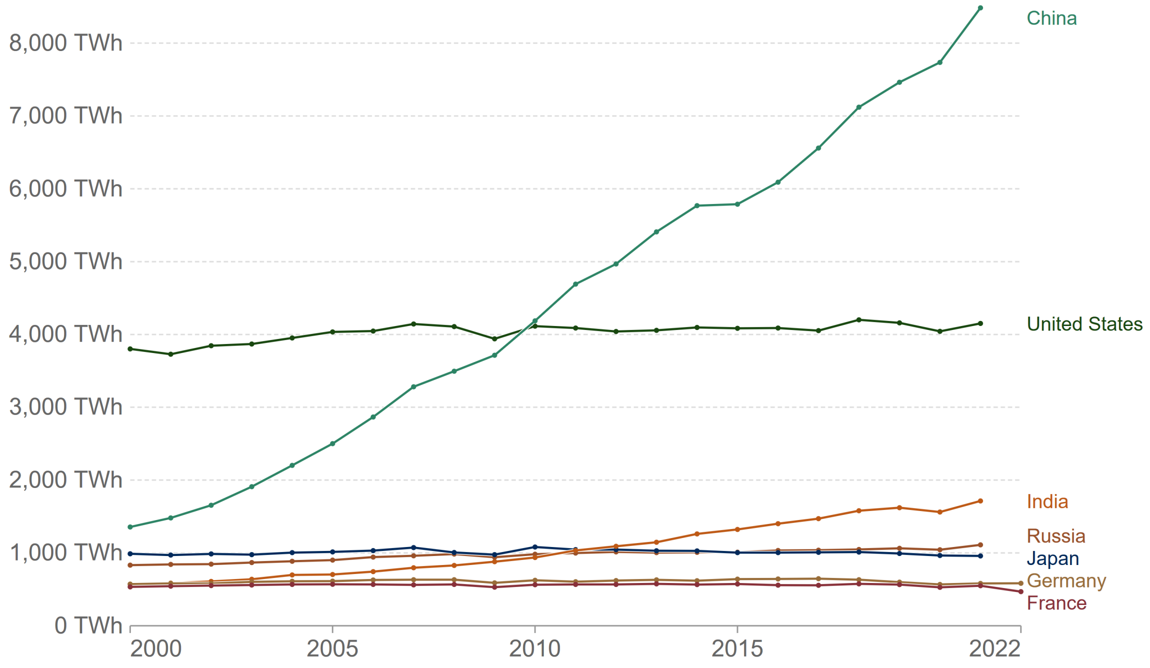


Figure 41: *Ritchie et al. (2022a), Electricity generation of all countries from 2000 to 2021, measured in Terawatt-Hour(TWh)*

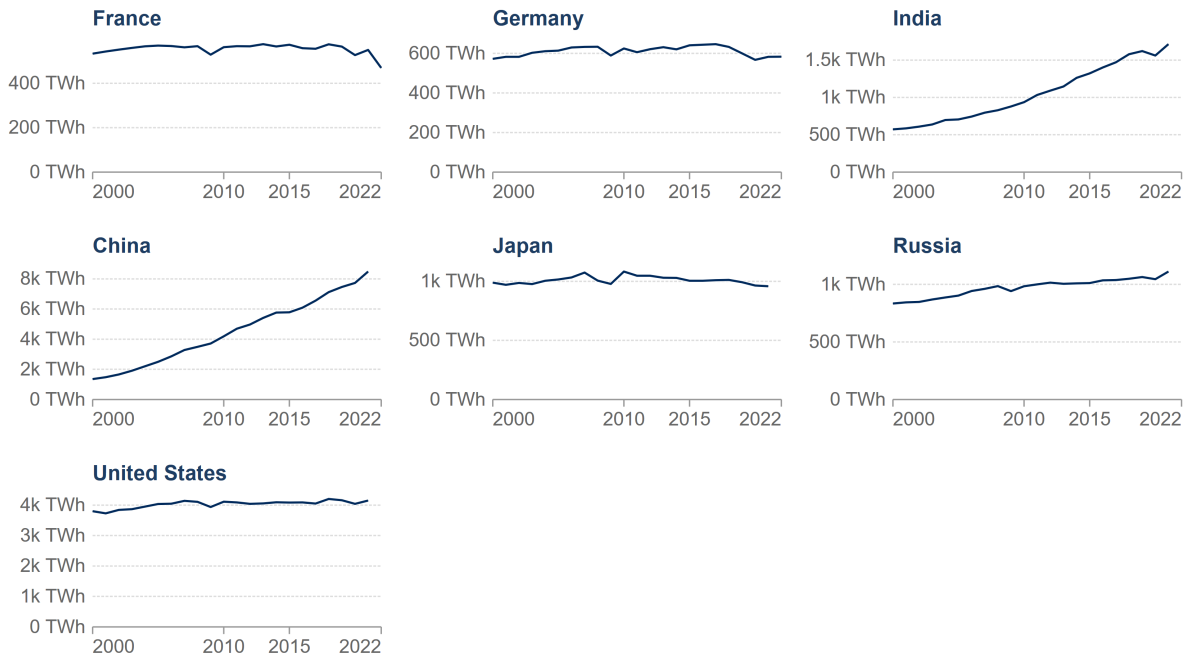


Figure 42: *Ritchie et al. (2022a), Electricity generation split by country with not aligned axis scales from 2000 to 2021, measured in Terawatt-Hour(TWh)*

Another important study we considered to comment on the IRFs of the countries is the one presented by IEA (2020), where a measure of energy production is given for every country from 1990 to 2020. As said before, electricity generation is a good indicator of the energy production of a country, but sometimes its behavior is different. A study on energy production can help us understand the dynamics of the countries. The only problem is that it does not give any analysis of Russia.

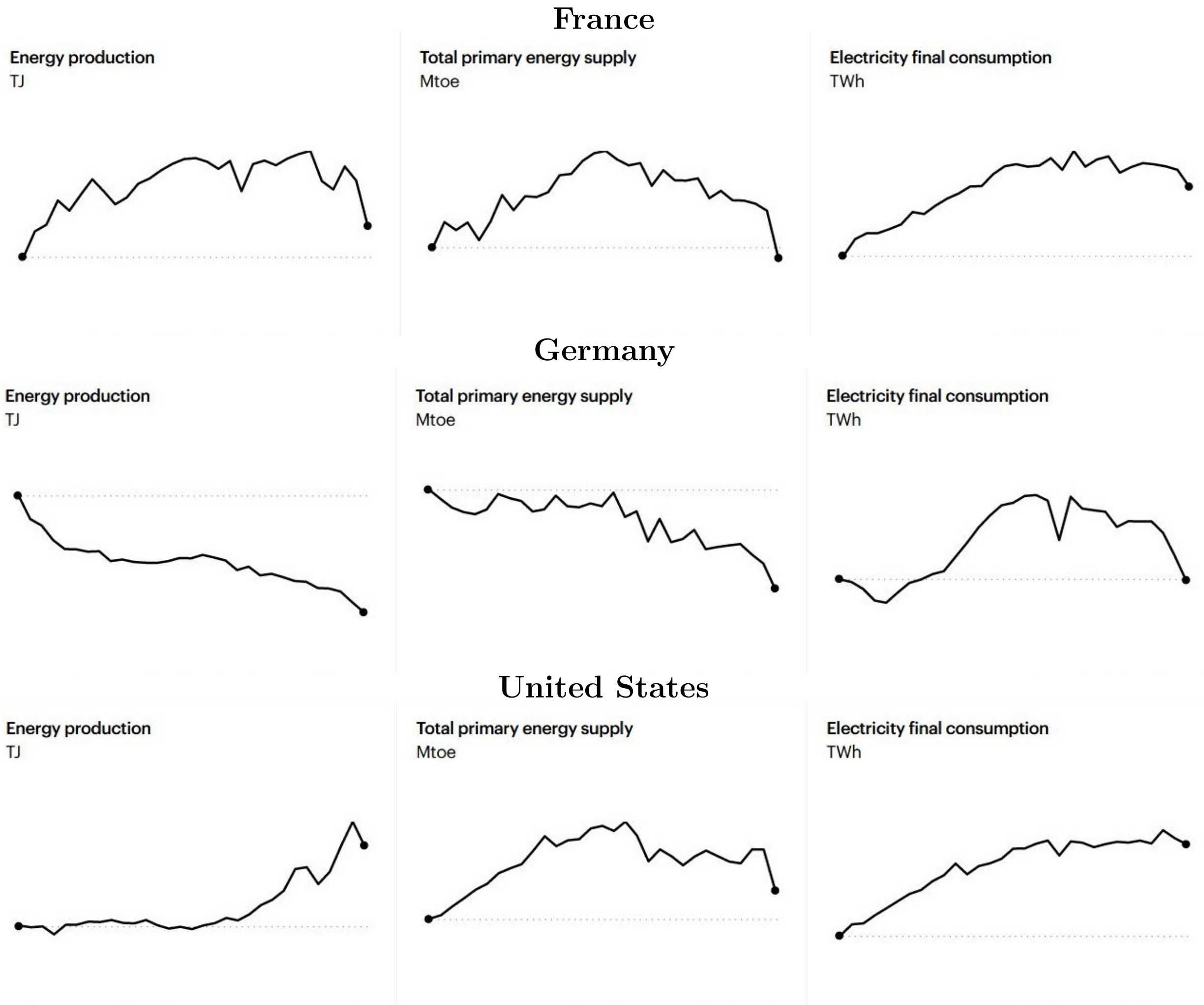


Figure 43: *Key energy statistics trends from 1990 to 2020 of OECD countries from our study. Energy production (measured in TeraJoule), Total primary energy supply (measured in MegaTonnes), and Electricity final consumption (measured in TeraWatt-hour), IEA (2022b), IEA (2022c), IEA (2022f)*

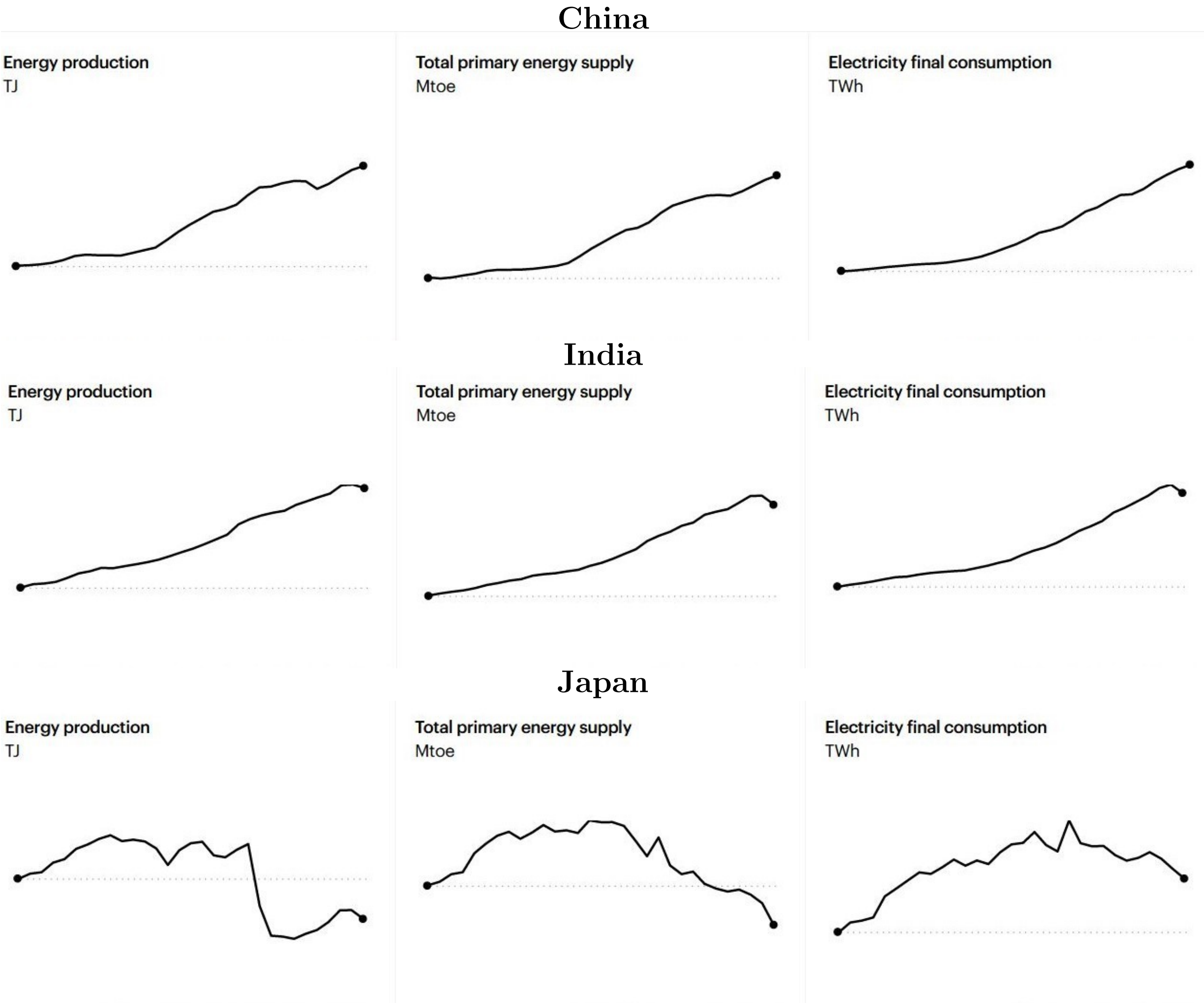


Figure 44: *Key energy statistics trends from 1990 to 2020 of Asian countries from our study. Energy production (measured in TeraJoule), Total primary energy supply (measured in MegaTonnes), and Electricity final consumption (measured in TeraWatt-hour), IEA (2022a), IEA (2022d), IEA (2022e)*

The values of these statistics in 2020 were:

- France:
  - Energy production = 5019.14 TeraJoule (+7.14% from 1990)
  - Total primary energy supply = 218.28 MegaTonnes (-2.48% from 1990)
  - Electricity final consumption = 450.83 TeraWatt-hour (+29.69% from 1990)
- Germany:
  - Energy production = 4045.70 TeraJoule (-48.09% from 1990)
  - Total primary energy supply = 278.36 MegaTonnes (-20.75% from 1990)
  - Electricity final consumption = 526.70 TeraWatt-hour (-0.13% from 1990)
- United States:

  - Energy production = 90436.97 TeraJoule (+30.75% from 1990)
  - Total primary energy supply = 2037.92 MegaTonnes (+6.45% from 1990)
  - Electricity final consumption = 4109.39 TeraWatt-hour (+40.54% from 1990)

- China:
  - Energy production = 117060.83 TeraJoule (+217.40% from 1990)
  - Total primary energy supply = 3499.48 MegaTonnes (+300.56% from 1990)
  - Electricity final consumption = 7424.99 TeraWatt-hour (+1180.94% from 1990)

- India:
  - Energy production = 23780.61 TeraJoule (+122.77% from 1990)
  - Total primary energy supply = 872.26 MegaTonnes (+211.27% from 1990)
  - Electricity final consumption = 446.54 TeraWatt-hour (+446.54% from 1990)

- Japan:
  - Energy production = 1815.82 TeraJoule (-41.54% from 1990)
  - Total primary energy supply = 384.75 MegaTonnes (-11.94% from 1990)
  - Electricity final consumption = 971.51 TeraWatt-hour (+17.06% from 1990)