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Keywords: Bayesian time series, Forecasted error variance decomposition, Gas price cap, Impulse response function, Mixture representation

JEL Classification: C11, C32, Q41, Q43

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Is the price cap for Gas useful? Evidence from European countries *

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October 30, 2023

Abstract

Since Russia's invasion of Ukraine, many countries have pledged to end or restrict their oil and gas imports to curtail Moscow's revenues and hinder its war effort. Thus, the European ministers agreed to trigger a cap on the gas price. To detect the importance of the price cap for gas, we provide a mixture representation for the gas price to detect the presence of outliers made by a truncated normal distribution and a uniform one. We focus our analysis on Germany and Italy, which are major Russian gas importers by exploiting the response of the different commodities to a gas shock through a Bayesian vector autoregressive (VAR) model. As a result, including a lower gas price cap smooths the impact of a gas shock on electricity prices, while not considering a price cap will increase exponentially this impact.

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1 Introduction

On 24 February 2022, Russia invaded Ukraine in an escalation of the Russo-Ukrainian War that began in 2014 and this invasion will continue in 2023. The conflict raises different concerns worldwide and provides evidence of a conflict between Russia, the United States and European countries. Since the European countries are not actively involved in the conflicts, they pledge to end or restrict their oil and gas imports to curtail Moscow's revenues and hinder its war effort. In particular, the Russian economy is highly dependent on its energy and oil sector, while Europe is a major importer of Russian energy, making cutting back difficult. In detail, Germany and Italy are two of the biggest European importers of Russia's gas with 56.2 billion cubic metres imported from Russia for Germany and 29.2 for Italy, respectively, as stated by the International Energy Agency for 2021.

The main question that the European Commission and its members raised was how to restrict the import of gas and how to reduce Europe's dependence on Russia's gas. Since the start of the invasion, Russia used the gas export as blackmail to the European countries to reduce their help to Ukraine. The strong increase in the gas price with peaks around 300 Euros per megawatt hour touches the households and the European industries and thus the European Commission started figuring out how to deal with the increasing gas price.

During the end of 2022 and the beginning of 2023, there were hundreds of meetings between the European ministers to discuss the possible imposition of a broad price cap on all the gas imports entering the bloc to bring soaring energy bills under control. The price cap is one measure that is supposed to help every member state mitigate the inflationary pressure, manage expectations provide a framework in case of potential supply disruptions, and limit the extra profits in the sector. Moreover, the European countries split into two different groups against or in favour of the price cap. The Nordic countries led by Germany, the Netherlands and Hungary were against the creation of a price cap, while the Southern countries led by Italy, France, Spain and Greece were in favour of a price cap. After months of huge debates in the European Parliament and among European ministers, on February 15 2023, Ministers agreed to trigger a cap if prices exceed 180 Euros per megawatt hour for three days on the Dutch Title Transfer Facility (TTF) gas hub's front-month contract.

As shown in Figure 1, gas and electricity prices are strongly correlated from 2020 to 2023 for both Germany and Italy. In particular, when the gas prices (black line) reach is peak around the half of 2022, electricity prices (red line) show a peak of around 700 Euros. This connection is also confirmed by the recent commodities literature and in detail Chuliá et al. (2019) investigate the extent and evolution of the links between energy markets such as electricity, natural gas, coal, oil and carbon. The strong connection between natural gas and electricity has been studied through factors (Hirth, 2018) or the spark spread risk management using electricity and natural gas futures (Martínez and Torró, 2018). However, these contributions focus on average periods and do not concentrate on periods of crisis and stress such as the 2020–2023 period.

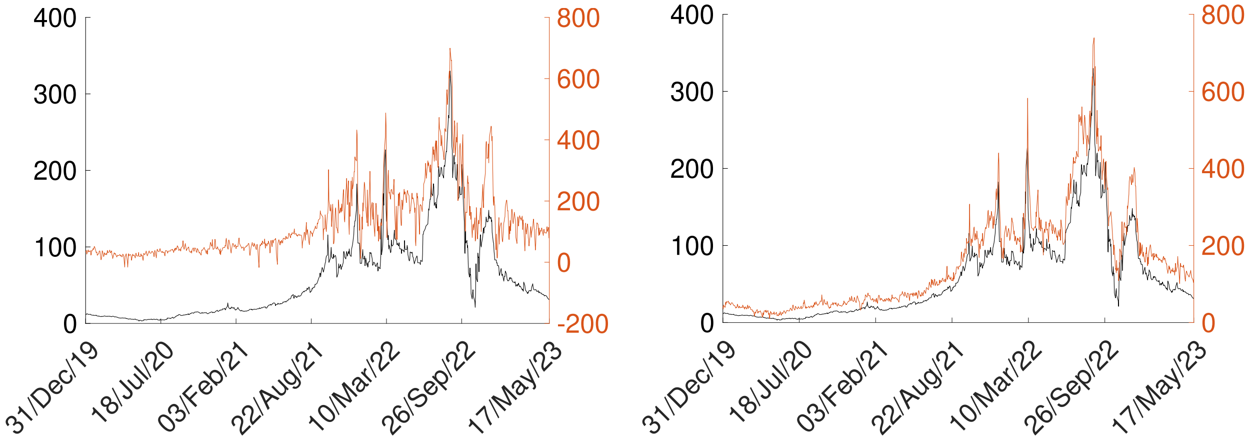


Figure 1: Gas price (black) and electricity prices (red) from January 2020 to February for Germany (left) and for Italy (right).

In particular, natural gas could be considered as a primary driver of electricity prices in the period of crisis and their relationship is complex since they are both substitutes and complements. Hence, natural gas and electricity are substitutes in all-day life (such as household heating or commercial facilities). Moreover, when electricity and gas prices reach their maximum level, they are positively linked and even significantly stronger during crisis periods (see, Uribe et al., 2018; Kyritsis and Andersson, 2019; Scarcioffolo and Etienne, 2021, for the US). For the European markets, Uribe et al. (2022) investigate the vulnerability of the electricity markets to natural gas price variations based on a quantile regression. Recently, the connection between natural gas and electricity has become crucial for the European energy transition policy to reduce the impact of other commodities, such as Brent or coal, on a green economy (see European Commission (2022) for a recent statement on European Energy Strategy and United Nations (2022) for the documentation produced after the Climate Change Conference (COP26) in Glasgow on November 2021).

The current literature on natural gas has opened debates among researchers and policymakers on the importance of reducing the impact that failure events in the natural gas network impose on the electricity market operation. Diagoupis et al. (2016) propose an efficient computational methodology based on the Monte Carlo sequential simulation approach to realistically simulate the annual operation of the natural gas network and deduce the failure events at the connection nodes of the NG-fired power plants. Another contribution by Amirnekooei et al. (2017) analyze the optimal locational marginal prices for natural gas and electricity in an integrated natural gas and electric power network. A different strand of the literature focuses on Granger causality and connectedness among natural gas and different commodities or energy sources in particular on the US market (see, Woo et al., 2006; Nakajima and Hamori, 2013; Ohler et al., 2020; Mills et al., 2021, among others).

All these contributions do not consider the current European situation and do not focus on the possible impact of a gas shock on different commodities, such as electricity prices, coal, Brent and CO_2 when a price cap is considered or not. Up to our knowledge, we introduce for the first time a methodological issue to model the gas price when a price cap is included and then we analyse different scenarios. In the price cap literature, Roeger and Welfens (2022) study the impact of a gas price cap on electricity production and consequently advocate a combination of gas price subsidies only in the electricity market and targeted transfers to households to meet both efficiency and distributional targets. On the other hand, Ehrart and Schlecht (2022) analyse the strategic implication and feasibility of imposing a price cap through a game-theoretical approach. In a different article, Ehrhart et al. (2023) compare import tariffs and price caps as policy measures to regulate a foreign monopolist and provide that for any positive import tariff, there exists a set of price caps each of which Pareto-dominates the tariff.

As shown in Figure 1 before the introduction of the price cap for natural gas, we were in the presence of different outlier values. To detect their presence, we provide a mixture representation of the gas price made by a uniform distribution to detect outliers and a truncated normal distribution for calm periods. This mixture representation allows us to detect the outliers and subsequently run a vector autoregressive (VAR) model. We use a Bayesian VAR model with different lags to extract the generalized impulse response function and to capture the impact of a gas shock on different commodities when a price cap of 180 Euros or a lower price cap of 120 is considered. As a further result, we use a forecast variance decomposition to understand how the shock is transmitted across the commodities and during different periods. We run multiple robustness checks when lower or null price caps are considered for the period between 2007 and 2023; the one between 2020 and 2023 (COVID-19 and Ukrainian war); between 2021 and 2023 and 2020 and 2022.

For the different scenarios, our results show that including a price cap smooths the impact of a gas shock on electricity prices, while not considering a price cap will increase exponentially the impact. However, the two countries behave differently across the choice of a price cap. For Germany, it seems that a price cap equal to 120 provides even better reductions in the impulse function of the different commodities, while for Italy, the imposition of a lower price cap does not yield improvements in the response to a gas shock. Moreover, we notice that gas shocks are solid drivers of electricity and coal dynamics by explaining huge fluctuations when a price cap is not considered, while it lowers closely to zero when a price cap is included.

The remainder of this article is organized as follows: Section 2 presents the novel mixture representation for the gas price outliers and their implementation. In Section 3, an analysis of the importance of imposing a price cap on the gas and the consequent impact of a gas shock on the different commodities for Germany and Italy has been proposed. Section 4 studies the importance of a gas shock to the other commodities through forecast error variable decomposition. Finally, Section 5 concludes.

2 Modelling framework

2.1 Vector autoregressive model

Before analyzing the influence of the gas price cap on other commodities, we define the n-dimensional vector of response variables $\mathbf{Y}_t$. In our scenario, we include as response variables, the daily Gas price, Brent, Coal, CO_2 and electricity prices. Thus the dimensionality of $\mathbf{Y}_t$ is a 5-dimensional vector of response variables and the vector autoregressive (VAR) model of lag p is of the form

$$\mathbf{Y}_t = \mathbf{c} + A_1\mathbf{Y}_{t-1} + \ldots + A_p\mathbf{Y}_{t-p} + \mathbf{E}_t,$$

where $\mathbf{c}$ is an $(n \times 1)$ vector of intercepts, A_i are $(n \times n)$ matrices of lagged terms for each $i = 1, \ldots, p$ and $\mathbf{E}_t$ is the error term, which is normally distributed with zero mean and Σ an $(n \times n)$ symmetric, semi-positive definite covariance matrix.

Let us define $\mathbf{B} = [\mathbf{c}, A_1, \ldots, A_p]$ the coefficient matrix such as the dimensionality is $(1 + np) \cdot n$ and $\mathbf{X}_t = [\mathbf{1}, \mathbf{Y}_{t-1}, \ldots, \mathbf{Y}_{t-p}]$ the data matrix including the lagged response variable, thus we can simplify the VAR model as a seemingly unrelated regressions (SUR) model of the form

$$\begin{aligned} \mathbf{y} &= \text{vec}(\mathbf{Y}) = (\mathbf{I} \otimes \mathbf{X})\text{vec}(B) + \text{vec}(\mathbf{E}) \\ &= \mathbf{Z}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \end{aligned} \tag{1}$$

where $\text{vec}(\cdot)$ is the operator that stacks the columns of a matrix into a single-column vector. Moreover, $\mathbf{Y} = [\mathbf{Y}_1', \ldots, \mathbf{Y}_T']'$ is the $T \times n$ data matrix and $\mathbf{y}$ is $Tn \times 1$ vectorized version of the observations, where the first T represent the gas price, the last T the electricity prices. Furthermore, $\mathbf{Z} = (\mathbf{I} \otimes \mathbf{X})$ is a block-diagonal matrix with the $T \times (1 + np)$ matrix $\mathbf{X}$ repeating on its diagonal n times, and $\boldsymbol{\beta}$ is the vectorized VAR parameters and thus has dimensionality $(1 + np) \cdot n \times 1$.

2.2 Mixture representation for gas price

Given the recent turmoil in gas prices due to the Russian invasion of Ukraine, the European Union has decided to impose a price cap on the gas price. In particular, after long discussions across the European countries, the price cap was fixed at 180 Euros. In this paper, we are interested in dealing with the usefulness of the proposed price cap and in particular we propose a mixture model for the gas price that takes care of the price cap mechanism.

The gas price values recorded during the Russian invasion of Ukraine can be considered outliers in the model and there is little information regarding these outliers or the mechanisms that gave rise to them. Moreover, these values are assumed to arise at random and thus we decide to assume a Uniform distribution where the lower and the upper bound are functions of the proposed price cap.

The mixture model for the gas price can be formulated as

$$y^{\star}_{\text{Gas},t} = \pi_{\text{Gas}} \cdot \mathcal{TN}_{(-\infty, \text{pc}-U_{min}(\text{pc})]} \left(y_{\text{Gas},t-1}, \sigma^2_{\text{Gas}}\right) + (1 - \pi_{\text{Gas}}) \cdot \mathcal{U}nif \left(\text{pc} - U_{min}(\text{pc}), \text{pc}\right), \tag{2}$$

where $\pi_{\text{Gas}} \in (0, 1)$ is the proportion of non-outliers values, pc is the price cap fixed by the researchers or the policymakers and $U_{min}(\text{pc})$ is how much variation is present in the price cap and can be fixed equal to $5\%, 10\%$ or even 20%.

In Eq (2), the first part of the mixture refers to a truncated Normal distribution $(\mathcal{TN}(\cdot, \cdot))$ with an upper bound equal to the difference between the price cap and its variation. This Normal distribution is centred on the previous value of the gas price and has variance σ^2_{Gas}, which needs to be estimated. The second part of the mixture, which refers to the outlier values of the gas price, is only based on the price cap and its difference with the variation.

Remind that the proposed mixture representation is due only for the gas price variable and thus the model implementation in the following section will start with the estimation of the parameters of Eq. (2) and continue with the usual steps done for a VAR model. Thus, in detail, we will estimate the proportion of non-outliers values, π_{Gas} and the variance σ^2_{Gas}; once obtained these values, we can derive the proposed value of the Gas price that take care of the price cap decided by the policymakers.

2.3 Model implementation

As stated at the end of the previous section, the model implementation can be split into two parts: the first is related to the new gas price influenced by the price cap and the second is related to the usual VAR representation.

Before dealing with the two-step model implementation, we can define the prior distributions for each parameter of the model. Remind that for the first step, we need to estimate π_{Gas} and σ^2_{Gas}, while for the second step of the model we need to estimate the VAR parameters, defined as $\boldsymbol{\beta}$ and Σ.

Starting from the mixture representation, for the proportion of non-outliers values we assume that a priori it follows

$$\pi_{\text{Gas}} \sim \mathcal{B}eta(\alpha_\pi, \beta_\pi).$$

The conditional variance σ^2_{Gas} is assumed a priori to follow

$$\sigma^2_{\text{Gas}} \sim \mathcal{I}Gamma(\alpha_\sigma, \beta_\sigma),$$

where $\mathcal{I}Gamma(\cdot, \cdot)$ is the inverse Gamma distribution such that we enable conditional conjugacy of σ^2_{Gas} with the likelihood.[1]

On the other hand, we can assume different prior representations for the vectorized matrix of coefficients or the VAR parameters values, but since the dimensionality of the response variable, n, is equal to 5, we prefer to work with a Normal prior distribution with diffuse prior mean and prior variances.[2] For the variance-covariance matrix, the prior follows the standard representation used when constant volatility is assumed and thus a Wishart prior distribution.

Outlier detection

When dealing with a mixture representation as outlined in Eq. (2), we need to define a latent random variable $z^*_{\text{Gas},t}$, which representation allows us to state when an outlier value (i.e. the gas price exceeds the proposed price cap) is present. This latent random variable can be represented as a Bernoulli random variable, where $z^*_{\text{Gas},t} = 0$ denotes the presence of an outlier, while when it is equal to 1, a normal value. Thus the mixture

[1] We set the hyperparameters for π_{Gas} and σ^2_{Gas} equal to 1, thus $\alpha_\pi = \beta_\pi = \alpha_\sigma = \beta_\sigma = 1$.

[2] We have run several experiments by assuming an Horseshoe or a Normal-Gamma prior and the results are available upon request to the authors.

representation in Eq. (2) can be expressed conditionally on $z^*_{\text{Gas},t}$ so that

$$\begin{aligned} y^*_{\text{Gas},t}|z^*_{\text{Gas},t} = 0 &\sim \mathcal{U}nif\left(\text{pc} - U_{min}(\text{pc}), \text{pc}\right) \\ y^*_{\text{Gas},t}|z^*_{\text{Gas},t} = 1 &\sim \mathcal{TN}_{(-\infty,\text{pc}-U_{min}(\text{pc})]}\left(y_{\text{Gas},t-1}, \sigma^2_{\text{Gas}}\right), \end{aligned}$$

then we draw $z^*_{\text{Gas},t} \sim \mathcal{B}ern(\pi)$. In details, the full conditional distributions for $z^*_{\text{Gas},t}$ are represented as

$$\begin{aligned} p(z^*_{\text{Gas},t} = 0|\pi_{\text{Gas}}, \sigma^2_{\text{Gas}}) &\propto \frac{1 - \pi_{\text{Gas}}}{U_{min}} \\ p(z^*_{\text{Gas},t} = 1|\pi_{\text{Gas}}, \sigma^2_{\text{Gas}}) &\propto \frac{\frac{\pi_{\text{Gas}}}{\sqrt{2\pi}\sigma_{\text{Gas}}} \exp\left\{-\frac{1}{2\sigma^2_{\text{Gas}}}\left(y^*_{\text{Gas},t} - y_{\text{Gas},t-1}\right)^2\right\}}{\Phi\left(\frac{\text{pc}-y_{\text{Gas},t-1}}{\sigma_{\text{Gas}}}\right) - \Phi\left(\frac{\text{pc}-U_{min}(\text{pc})-y_{\text{Gas},t-1}}{\sigma_{\text{Gas}}}\right)}, \end{aligned}$$

where the second equation is true if $y^*_{\text{Gas},t} \in [\text{pc} - U_{min}(\text{pc}), \text{pc}]$, otherwise is 0, and $\Phi(\xi)$ is the cumulative distribution function of a standard normal distribution and it is equal to $\Phi(\xi) = \frac{1}{2}\left(1 + \text{erf}\left(\frac{\xi}{\sqrt{2}}\right)\right)$. Moreover, proportionality is reconciled by dividing both the full conditionals by their sum.

A second parameter of interest when dealing with the mixture model representation is the outlier proportion, π_{Gas}, which provides the proportion of non-outlier values. Given the sample of the latent random variable $z^*_{\text{Gas},t}$, the non-outlier proportion, π_{Gas} can be sampled from a full conditional distribution as

$$\pi_{\text{Gas}}|z^*_{\text{Gas},t} \sim \mathcal{B}eta\left(\alpha_\pi + \sum_{t=1}^{T} z^*_{\text{Gas},t}, \beta_\pi + T - \sum_{t=1}^{T} z^*_{\text{Gas},t}\right),$$

due to the conjugacy between the Beta and the Binomial distribution where T is the total number of time observations.

The last term of interest for the mixture representation is the conditional variance σ^2_{Gas} which is drawn conditioning on samples of $z^*_{\text{Gas},t}$. Moreover, the mixture representation allows to work only in the scenario where $z^*_{\text{Gas},t} = 1$, thus no outliers are detected. Given $z^*_{\text{Gas},t}$, the conditional variance σ^2_{Gas} can be sampled from their full conditional viz:

$$\sigma^2_{\text{Gas}}|z^*_{\text{Gas},t}, y^*_{\text{Gas},t} \sim \mathcal{IG}amma\left(\alpha_\sigma + \frac{T_1}{2}, \beta_\sigma + \sum_{\substack{t=1 \\ z^*_{\text{Gas},t}=1}}^{T} \frac{\left(y^*_{\text{Gas},t} - y_{\text{Gas},t-1}\right)^2}{2}\right),$$

where the sum excludes any data points flagged as outliers by $z^*_{\text{Gas},t}$ and T_1 refers to

$\sum_{t=1}^{T} z^*_{\text{Gas},t}$ alias the observations that are not outliers.

2.3.1 VAR coefficients

Once the outlier detection has been done, we can define a novel vector of observation, where the first component that refers to the Gas variable is $y^*_{\text{Gas},t}$, which is drawn from the previous sampling representation. In details, $\boldsymbol{Y}_t = [y_{\text{Gas},t}, y_{\text{Brent},t}, \ldots, y_{\text{Electricity},t}]'$ becomes $\boldsymbol{Y}_t = [y^*_{\text{Gas},t}, y_{\text{Brent},t}, \ldots, y_{\text{Electricity},t}]'$. Based on the prior representation of the VAR coefficients and covariance matrix, we are able to provide closed-form posterior distributions for these parameters as stated in the Bayesian literature (Carriero et al., 2022).

As stated in Korobilis and Shimizu (2022), when sampling from a posterior normal distribution, one should work with the precision matrix Q. Rue (2001) provides a precision-based sampler to obtain samples from a Normal distribution and takes the following form:

1. compute the lower Cholesky factorization $Q = L \cdot L'$;
2. generate $Z \sim \mathcal{N}(0, I)$;
3. set $\mathbf{v} = L^{-1}(\mathbf{Z}'\mathbf{y})$ and $\boldsymbol{\mu} = L^{'-1}\mathbf{v}$;
4. set $\mathbf{u} = L^{'-1}\mathbf{Z}$ and $\boldsymbol{\beta} = \boldsymbol{\mu} + \mathbf{u}$.

The main advantage of this algorithm is that it requires inverting the Cholesky factor of Q instead of inverting Q itself, the Gibbs sampling can be written for the gas price variable as

a) update $z^*_{\text{Gas},t}$ given π_{Gas} and σ^2_{Gas};
b) update π_{Gas} given $z^*_{\text{Gas},t}$;
c) update σ^2_{Gas} given $z^*_{\text{Gas},t}$;
d) update $y^*_{\text{Gas},t}$.

Once the Gas price variable has been updated, we can define the last two steps of the Gibbs sampler

e) update $\boldsymbol{\beta}$ given Σ by using the precision sampler algorithm of Rue (2001);
f) update Σ given $\boldsymbol{\beta}$.

As shown in the previous subsection the Gibbs sampler is in closed form for all these steps relying on a computational fast approach.

2.4 Shock identification

Once the Gibbs sampler is defined, we can detect and identify the shocks. The literature on shock identifications for different macroeconomic and commodities variables has increased in recent years, but it is mainly focused on a few commodities variables. Baumeister and Hamilton (2019) is the state-of-the-art framework for estimating Structural VAR models with the Bayesian methods to identify different demand and supply shocks. For oil prices, Aastveit et al. (2023) show that inflation expectations and the associated pass-through of oil price shocks depend on demand and supply conditions underlying the global oil market. This result was achieved based on a structural VAR model of the global oil market that jointly identifies transmissions of oil demand and supply shocks through real oil prices to both expected and actual inflation. On the other hand, Kilian and Zhou (2022) use a dynamic structural model to quantify the cumulative effect of gasoline price shocks on household inflation expectations at each point in time.

Moving to other commodities, Fezzi and Bunn (2010) specified for the first time a structural asymmetric vector error-correction model to identify and estimate the demand and supply functions in hourly day-ahead wholesale electricity markets. Recently, Baumeister et al. (2022) focused on energy demand and created a new index of global economic conditions for assessing future tightness of energy demand and expected oil price pressures. Moving to more general commodities, Bjørnland and Thorsrud (2019) develop a time-varying dynamic factor model, to detect different shocks for commodity prices in resource-rich countries. Recently, Bjørnland et al. (2023) studied the joint identification of simultaneous demand and supply shocks underlying the European carbon market.

We rely on the literature on the structural VAR model and its reduction to a simple VAR model to identify the different shocks. In particular, we do not apply any sign restrictions on the shock representation as done in Bjørnland et al. (2023), but we are interested in understanding the reaction of our commodities prices (such as electricity prices) to a shock in gas prices. To identify the shock, we rely on the impulse response function and in particular, on its generalized version (GIRF) as proposed by Koop et al. (1996). Indeed, generalized impulse responses do not require that we identify any structural shocks and they provide a tool for describing the dynamics in a time series model by mapping out the reaction in commodities prices to a one standard deviation of a gas shock. As a final step, we also compute the forecast variance error decomposition to detect the importance of a gas shock to the other commodities.

3 Is the price cap for Gas useful?

This section is devoted to studying the influence of the price cap on gas on the other commodity variables. In particular, the analysis is made on two different European countries, Germany and Italy, the main importers of Russia's gas.

3.1 Data description and design of the exercise

As stated in Section 2, we use a five-dimensional vector of observation made by gas price, Brent, coal, CO_2 and electricity prices and are related to the European markets. All the variables are daily and range from January 2007 to May 2023. The natural gas price (Dutch TTF) represents a pure hub benchmark and can be used for all the EU markets, while ICE Brent represents the future oil price traded in Dollars. Coal (LMCYSPT) is settled based upon the price of coal delivered into the Amsterdam, Rotterdam region in the Netherlands, and Antwerp region in Belgium and it is traded in dollars, and CO_2 represents carbon emissions for the Euro area (EEXEUAS). The electricity prices (euros per megawatt) are day-ahead prices obtained from the corresponding power exchanges: the German auction prices of the power spot market from the European Energy Exchange (EEX), and the Italian single national prices (prezzo unico nazionale, PUN) from the Italian system operator Gestore dei Mercati Energetici (GME). In addition, we converted into euros the Coal, Brent and EU natural gas with the use of the USEURSP rates from US dollars to euros (WMR&DS).

Since we are interested in detecting the outliers in the gas price, we decided to work with levels for all the variables and we split the dataset into four different scenarios. The first scenario takes care of the entire length of the data thus starting from 2007 and ending in 2023. However, as shown in Figure 2, this scenario does not completely handle the price cap for gas, since from 2007 until 2020 the gas price does not show strong peaks. The second scenario deals with the period from 2020 to 2023 thus the COVID-19 pandemic period, where the electricity price and the gas price start to increase. The coming years with the Russian invasion of Ukraine provide strong shreds of evidence in favour of a price cap for the gas price and thus we analyse the period ranging from 2021 to 2023. As a further step, we analyse the sample from 2020 to 2022, thus excluding the Russian invasion of Ukraine but focusing on the COVID-19 pandemic.

Figure 2 provides two panels representing the gas price for the whole sample (left panel) and the period from 2020 to 2023 (right panel). As expected, the Russian invasion of Ukraine and the consequent high number of sanctions against different Russian goods have increased the gas price, asking for different sources of gas, for example from African countries (such as Algeria) or Qatar. As known in the literature, the European gas price is strongly dependent on Russian gas in particular through the Nord Stream and the Ukrainian pipelines. The Russian invasion of the Ukrainian territory provided strong debates in the European community related to the dependence of the European countries on Russia. This situation had different meetings across the European prime minister ending up with the definition of a universal price cap for the gas price of around 180 Euros and with the research of the European countries of different sources of gas supply.

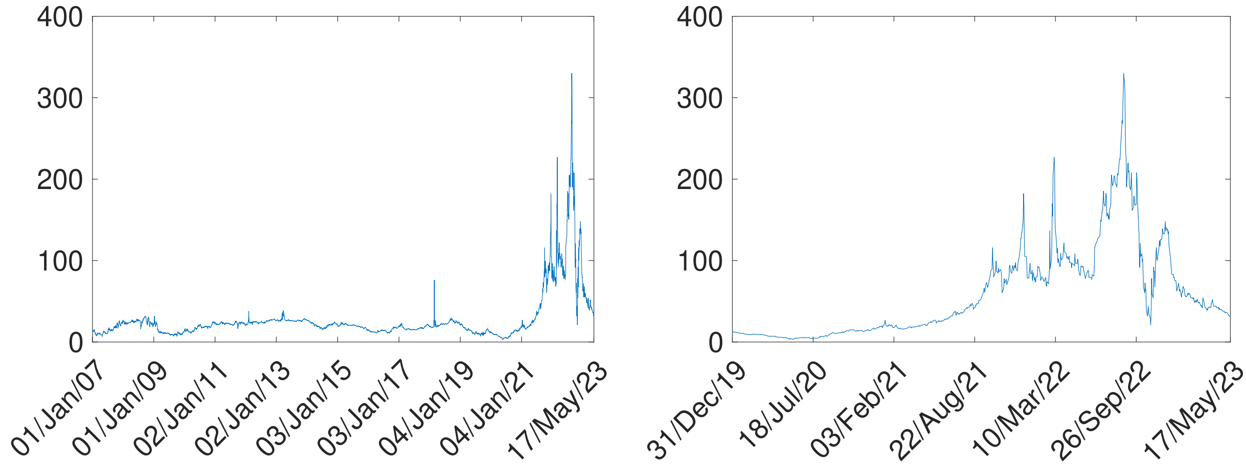


Figure 2: Gas price from January 2007 to February 2023 (left panel) and from January 2020 to February 2023 (right panel).

In Appendix A, we provide the graphical representation of the other commodities prices and in particular, we show that Coal (transformed in euro, see Figure A.1) and electricity prices (see Figure A.3) have the same patterns of the gas price with strong peaks in the last three years (from 2020 to 2023). These results are not present for the Brent price (transformed in Euro), which has the usual representation across all sample sizes (see Figure A.2).

As stated in Section 2, we focus on five different commodities variables and we use a VAR model with lags p. To decide the optimal number of lags p, we compare the models with different lags starting from 1 to 12 using the Deviance Information criterion (DIC). In particular, the optimal lag is the one that has a small DIC among the lags. Another parameter that needs to be defined is how much variation is present in the price cap, alias $U_{\min}(pc)$.

Table 1 provides the representation of the optimal lag when the price cap is equal to 180, the variation is equal to 15% times the price cap and we use length. The top panel of the table refers to Germany and the bottom refers to Italy, where the only variable that changes is the daily electricity prices. The optimal lag is provided in boldface and it refers to 12 lags for all the variables.

As provided in Appendix B, we run the VAR model with different specifications of

Table 1: DIC representation for Germany (top) and Italy (bottom) when the price cap is equal to 180, the variation, $U_{\min}(\text{pc})$, is 15% and the lag ranges from 1 to 12.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
Germany	125278.32	124537.72	124123.45	123910.57	123813.33	123720.94	123649.59	123577.98	123549.61	123485.32	123464.17	**123313.94**
Italy	121070.74	120279.51	119921.19	119705.29	119576.04	119491.07	119444.06	119395.78	119386.57	119299.12	119245.04	**119171.80**

the variation, ranging from 5% to 20% times the price cap, which is defined as equal to 180. The results in Table B.1 show that the best model is the one with 12 lags and variation equal to 15% times the price cap. Moreover, a comparison of the lags for different periods has been provided in Appendix B, where we analyse the evolution of the lags when the sample starts in 2020 and ends in 2023 (see Table B.2), or starts in 2021 and ends in 2023 (see Table B.3) and from 2020 to 2022 (see Table B.4). The results change when defining the variation equal to 20%. Moving to the optimal lags, the results are in line with the ones provided for the full sample. However, when the dataset is restricted to the period from 2020 to 2022 (see Table B.4), the best model does not change related to the variation in the price cap but in the optimal lags. Hence the best model becomes a VAR(2) for Germany and a VAR(3) for Italy.

Thus in conclusion, we analyse four different scenarios: full sample, 2020–2023, 2021–2023 and 2020–2022, where we set the number of lags equal to 12 and the variation equal to 15% times the price cap for the full sample and equal to 20% times the price cap for the other scenarios. For each scenario, we provide generalized impulse response functions (GIRF) with 68th posterior probability region of the estimated impulse responses.

3.2 Structural analysis for electricity prices

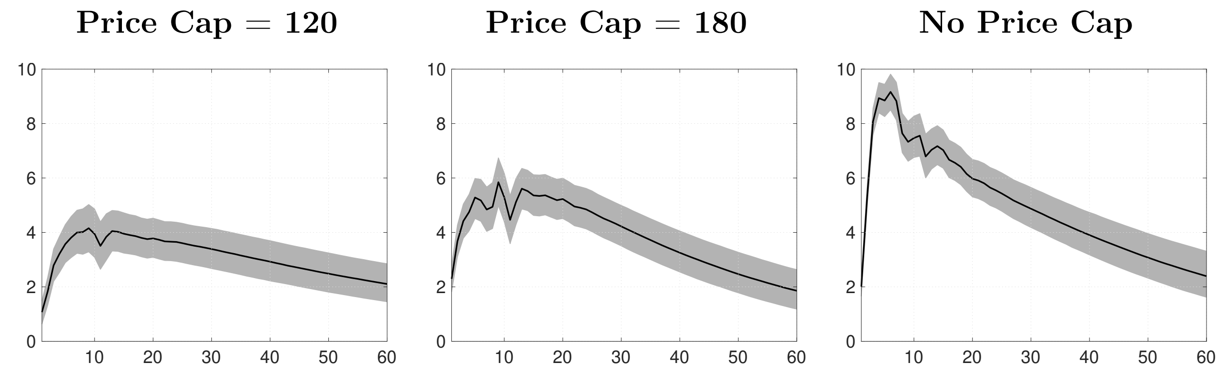
Germany

This section is devoted to the response of different commodity variables to a gas-positive shock in different periods and when a price cap has been included. In particular, we introduce a price cap equal to 180 as stated by the European Commission and then we decide to decrease it to 120 to see possible reactions of the commodity variables. We analyse the response of the commodity variables to a gas shock when no price cap has been considered and thus the model does not consider in the estimation the outlier detection.

Figure 3 provides the response in the German electricity prices to a gas shock during the whole dataset for a VAR(12) model with intercept and variation equal to 15% times the price cap. The first visual inspection provides evidence that the effect of the gas shocks is significant across the horizons and the different definitions of the price cap.

Secondly, we see that not including a price cap in the analysis provides strong jumps concerning including a price cap. Looking at the right panel of Figure 3, when a price cap is not considered, a gas-positive shock increases the electricity prices in the first 6 horizons. However after one week (alias 5 horizons), the reaction of electricity prices started to decrease substantially moving from 8.82 at horizon 7 to 4.87 at horizon 30, which means one month and a half later. As stated in Uribe et al. (2018) and Uribe et al. (2022), natural gas and electricity are both substitutes and complements. In particular, natural gas is an input for electricity generation through combined-cycle power plants, whereas electricity and natural gas are substitutes for household heating and commercial facilities. Moreover, we confirm that the influence between these two commodity prices is particularly evident and strongest when they reach maximum price levels and in the short term.

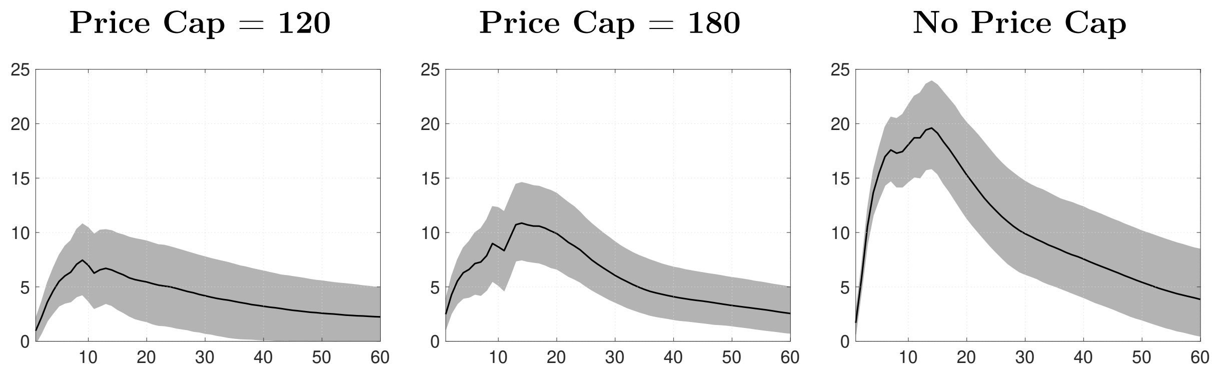
Figure 3: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2007 - 23 for VAR(12) with intercept and $U_{\min}(\mathrm{pc}) = 15\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



On the other hand, if we consider a price cap as settled by the European Commission (see center panel of Figure 3), the gas shock smoothly increases the electricity prices. The peak of the GIRF is around 9 step ahead (i.e. 2 weeks ahead), and it reaches the value of 5.84, which is far away from the maximum value obtained when the price cap was not considered. Moreover, the decrease pattern of the GIRF is less evident in the long run since the impact of a gas shock on electricity prices decreases from around 6 at horizon 9 to 4.2 at horizon 30. We decided to settle a strong price cap of around 120 as requested by some Mediterranean countries (Italy, France and Spain). The left panel of Figure 3 provides evidence of a flat impulse response function such that the impact of a gas shock on electricity prices is smooth in the short and the long run.

Comparing the results in Figure 3 with Figure 4 related to the 2020–2023 period, the GIRFs have a huge increase in the y-axis and secondly the confidence bands are bigger for all the three scenarios. Remind that for the period 2020–2023, we consider a variation in the price cap equal to 20%. In particular, when fixing a price cap of around 120, the effect of a gas shock on electricity prices becomes not significant from horizon 40 ongoing. Looking at the right panel of Figure 4, we see that not applying a price cap leads to a huge peak in the GIRF at horizon 5 at 15 and the biggest one at horizon 14 around 20.

Figure 4: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2020 - 23 for VAR(12) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



These peaks are in contrast with the different situations when a price cap of around 180 Euro is considered (center panel). In this scenario, the peak at the fifth horizon is reduced to 6.60 and at the fourteen horizon to 10.1. Thus, we can conclude that providing a price cap as decided by the European Commission reduce drastically the impact of gas positive shock on electricity prices in Germany at different horizons. This result is even more evident if we set a lower price cap (at 120 as in the right panel), in this scenario the GIRF values at the fifth and fourteen horizons are 5.50 and 6.50, respectively. As expected, the difference between a crisis and a calm period is reflected in the magnitude of the y-axis.

If Figure 4 considers both the COVID-19 pandemic and the current war, Figure 5 focuses on the current war situation. However, looking closer at the results, the dynamic response of electricity prices to a gas-positive shock behaves similarly to the 2020–2023 period. The only differences are in the magnitude of the shocks with peaks at and in the non-significance at lower horizons for the price cap equal to 120. Figure 6 focuses on the 2020–2022 period, thus the COVID-19 pandemic and the beginning of the war. As stated in Table B.4, the optimal lag selection is equal to 2 and thus in Figure 6 we explain the behaviour of the GIRF when a VAR(2) model (top) and a VAR(12) model (bottom) are considered.

As take-home results from the 2020–2022 period, we can see that the magnitude of the response reduces hugely concerning the other periods considered and equally

Figure 5: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2021 - 23 for VAR(12) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.

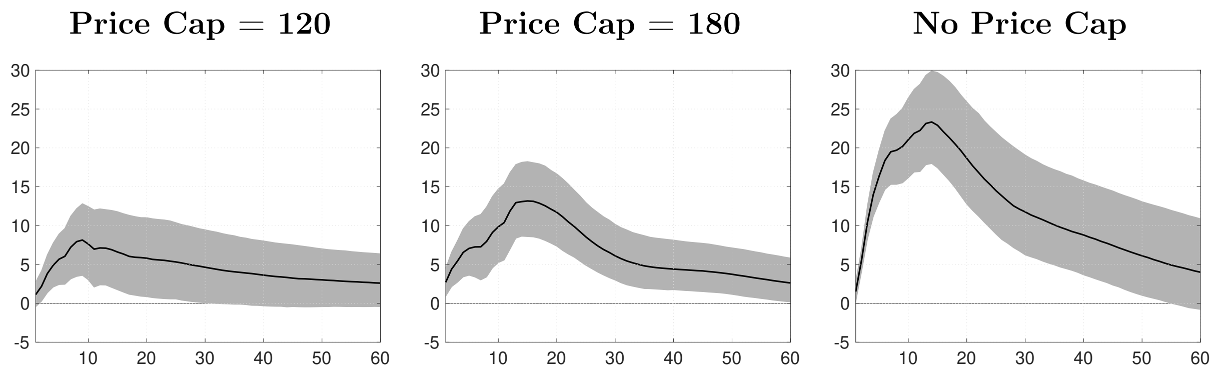
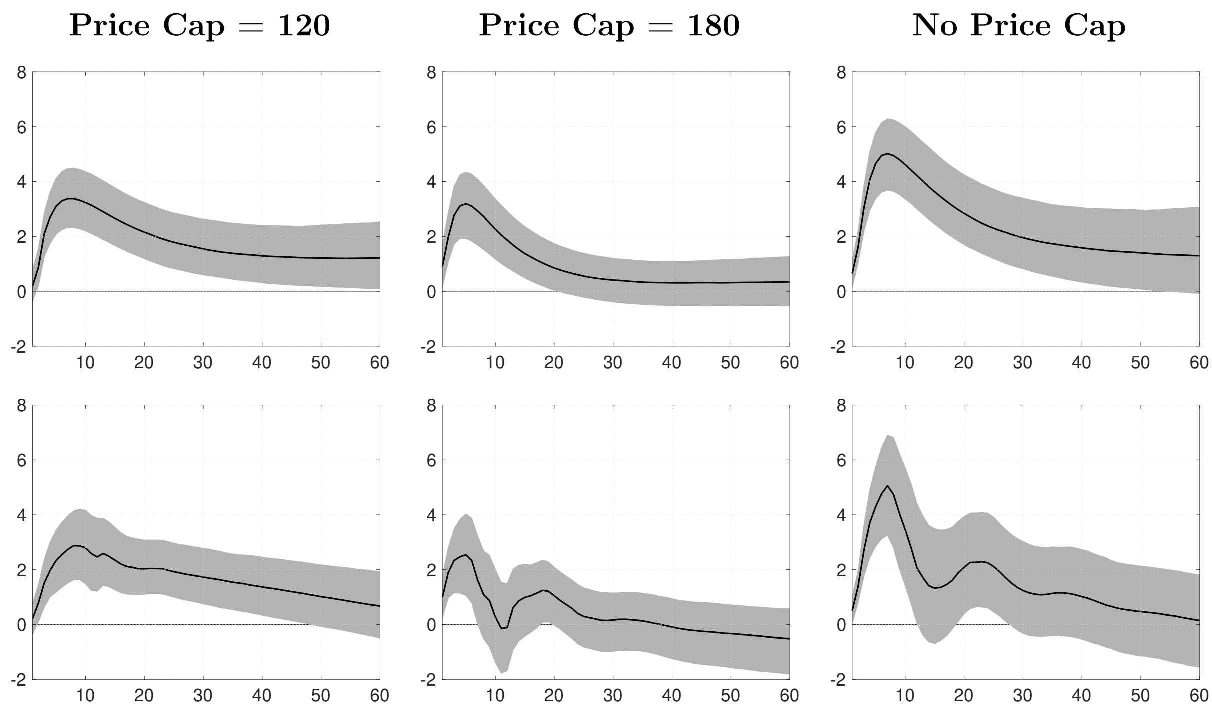


Figure 6: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2020 - 22 for VAR(2) (top) and VAR(12) (bottom) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



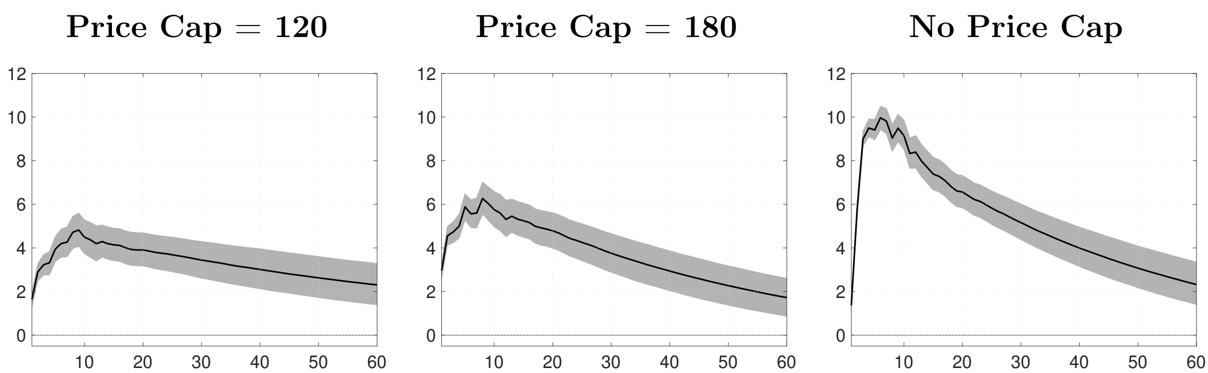
across the three scenarios analysed. Moreover, if a price cap is not considered with a VAR(2) model, the GIRF follows the same behaviour seen before, however, the GIRF changes completely if a VAR(12) is considered. Indeed, the response of electricity prices is moving after an initial peak and seems to be non-stationary after the tenth horizon. These flows are confirmed for the case of a price cap fixed at 180, where for a VAR(2) the response becomes non-stationary after horizon 20. An interesting finding from Figure 6 is that for a VAR(2) model imposing a price cap at 120 or 180 Euros does not influence the response of electricity price to a gas-positive shock. This pattern is not confirmed for a VAR(12) model where the price cap fixed at 120 Euros shows a decreasing flow and not a wavy one.

Italy

Once the analysis for Germany has been completed, we move to the second major gas importer from Russia, Italy. In particular, we follow the same analysis done previously and thus we focus on four different periods and mainly on the response of electricity prices to a gas-positive shock.

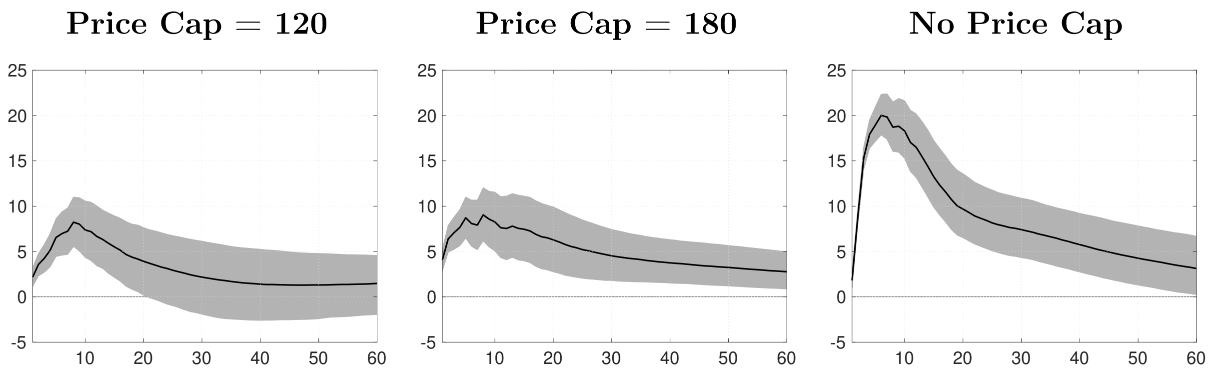
Differently from Germany, Italian electricity prices seem to be influenced less by the imposition of a smaller price cap when the full sample size is analysed. The left panel of Figure 7 shows the response over different horizons of electricity prices to a positive shock in gas price when a price cap is fixed at 120. Surprisingly, lowering the price cap does not provide a strong response with respect to fixing it at 180 (center panel), indeed they behave in the same way and the peak at horizon 10 (i.e. 2 weeks ahead) differentiates a one percentage point. The main issue is that including a price cap reduces dramatically the response of electricity to a price cap from around 10 to around 6.

Figure 7: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2007 - 23 for VAR(12) with intercept and $U_{\min}(\mathrm{pc}) = 15\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



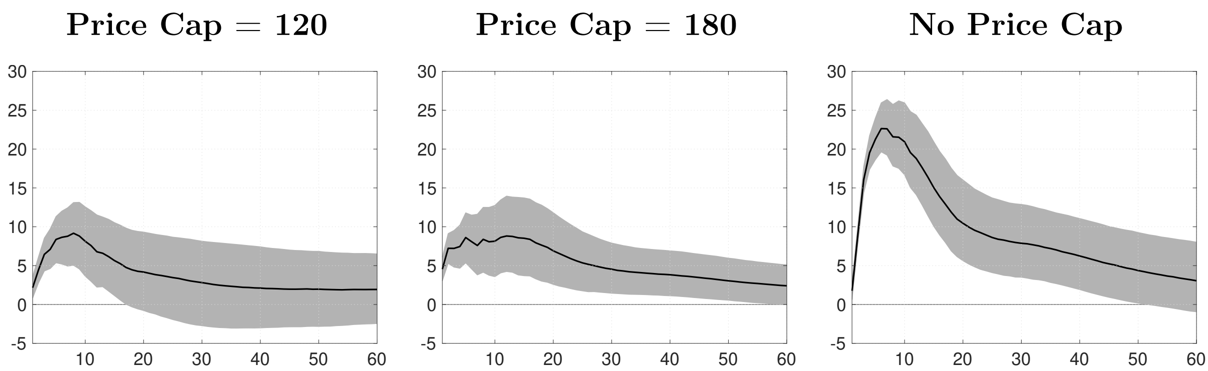
However, this analysis can be influenced by the big sample size since we are working with the period from 2007 to 2023 and thus the last period may be mitigated by the first 12 years of calm in the Italian electricity prices and the gas price. Thus, we decided to focus on three different scenarios and we started our analysis with the period from 2020 to 2023, thus analysing both the COVID-19 pandemic and the current European crisis. In Figure 8, we can confirm what was found for the full sample size.

Figure 8: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2020 - 23 for VAR(12) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



In detail, including a price cap provides strong improvements in the response of electricity prices to positive gas shocks. If a policymaker does not include a price cap in the analysis (right panel), the response of electricity prices faces huge peaks near horizon 6 of around 20 and then slowly decreases. However, if a price cap of 180 is used (center panel), the response of electricity prices to a gas shock smoothly immediately after a small jump at horizon 5 and at horizon 8 of 8.71 and 9, respectively. This behaviour is less evident if a price cap is fixed at around 120 (left panel), where the electricity prices do not significantly after the first 20 horizons (around 3 weeks) ahead. Moreover, the peaks between the two price caps are almost the same and it seems reasonable and surprising for Italy that a price cap around 180 is a better choice. When dealing with the period that includes the current war in Ukraine and when the price cap was originally proposed, we discover that the response of Italian electricity prices behaves similarly in the period from 2020 to 2023.

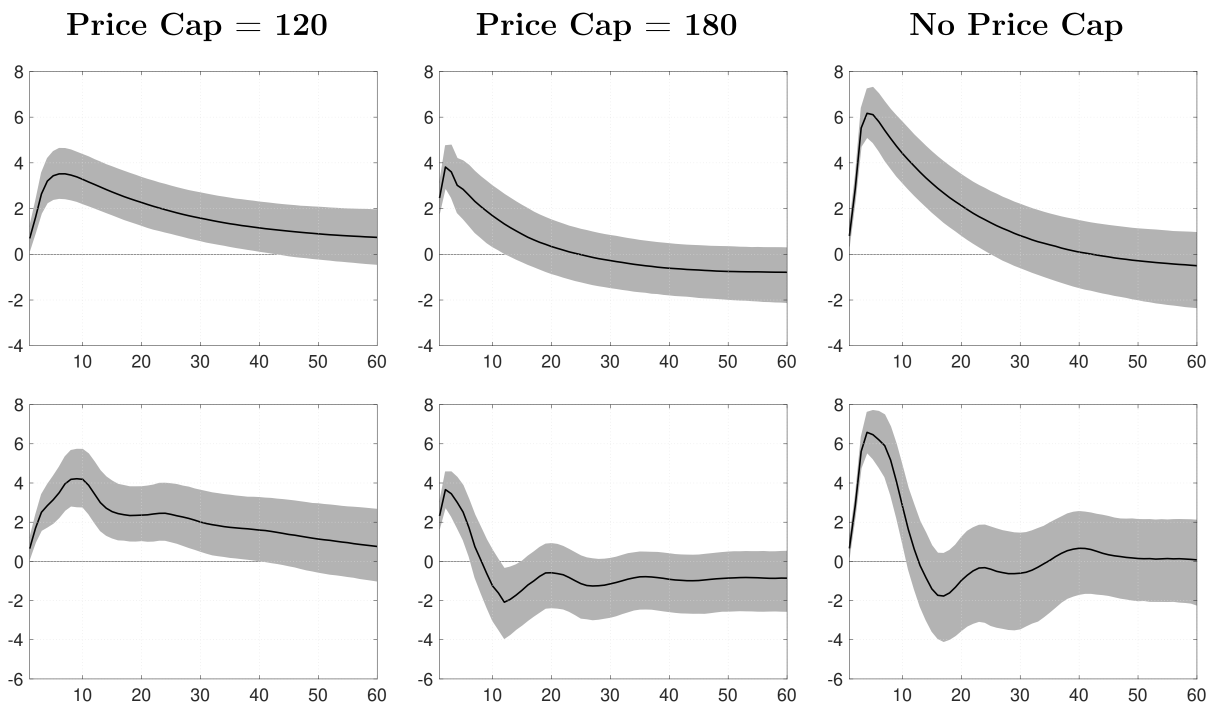
Figure 9: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2021 - 23 for VAR(12) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



Hence, Figure 9 provides evidence in favour of a price cap since its inclusion smooths the response of the prices across the horizons. Looking at the right panel, we see that the peak is even stronger at horizon 6 around 22.6 and slowly decreases, thus a gas shock strongly impacts the electricity prices. However, if a price cap is fixed at 180 (center panel), the GIRF seems to be flat with small peaks in the first horizons. The left panel shows instead the behaviour of the response of electricity prices when a price cap is fixed at 120 Euros and provides evidence of the biggest peaks with respect to the original price cap and a non-significant GIRF after horizon 20.

As a last step in the analysis, we focus on the COVID-19 period, alias from 2020 to 2022. Figure 10 represents the GIRF for a VAR(3) (top) and a VAR(12) (bottom) model with a price variation of 20% as chosen in Table B.4.

Figure 10: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2020 - 22 for VAR(3) (top) and VAR(12) (bottom) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



From the top panel of Figure 10, we confirm the results previously found for the other scenarios. However, we notice that fixing a price cap of 180 lets a peak in the response of the electricity prices to a gas shock at the first horizon and after horizon 15 it turns out to be non-significant. These movements are confirmed for the other two cases, but for a small price cap (right panel), it seems that the GIRF turns non-significant after horizon 45 and the response is always positive, while for the price cap at 180, it turns negative after horizon 30. The bottom panel supports these findings and shows even strong negative peaks for the price cap fixed at 180 after horizon 10. In conclusion, not considering a price cap provides huge peaks in the response of the electricity prices to a gas-positive shock in both models.

3.3 Structural analysis for other commodities

In the previous subsection, we focus on the response of electricity prices to a positive gas shock, but in the VAR model, we deal with different commodities prices and thus in this section, we will go through their response to a gas shock. In particular, we work with Brent and coal prices, which are strongly correlated with the gas price, and we focus on the four scenarios previously described at four different horizons: $1, 5, 10$ and 20 (1 day, 1 week, 2 weeks and one month ahead).

Table 2 and 3 provide the GIRF values for Germany and Italy jointly with the 68th posterior credible intervals, respectively. When a grey cell appears, it means that zeros belong to the 68th posterior credible intervals and thus it is not statistically significant.

In Table 2, the response of Brent to a positive gas shock is not significant across the periods and the horizons. Moreover, in the full sample (top left panel), when a price cap of 120 is fixed, the response is almost null, while when a price cap of 180 is fixed, it seems that from horizon 5 (1 week) the response of Brent price is strongly negative and even bigger than when price cap is not considered. In the period from 2020 to 2023 (top right), we have a reverse situation if a price cap is considered or not. Indeed, at horizon 5 the Brent response is positive when a price cap is not considered and negative when a price is fixed, while at horizon 20 vice-versa. In the period 2021–2023 (bottom left), the Brent price reacts negatively at the first 10 horizons if a price cap is fixed at 180, while it reacts positively when a price cap is not considered for the first 5 horizon. The bottom right part of Table 2 provides the results for a VAR(2) model for the period 2020–2022 and it shows the same situation for different price caps, thus a negative reaction of Brent to a positive gas shock across the horizons.

When moving to the coal prices, the situation changes completely, since the GIRF values are statistically significant across the scenarios and the price caps except for the period 2020–2022. Looking closer at the different periods, we notice that for the full sample, the response of coal to a shock in gas is strongly positive across the horizons, with a peak at horizon 10 and a decrease at horizon 20. Again as for the electricity prices, also for coal prices not including a price cap provides strong responses across horizons, while a price cap fixed at 180 seems to behave similarly to the price cap at 120. For the period 2020-2023, the results do not change even though at horizon 1, not considering a price cap provides a coal response of almost 3 concerning 1.1 and 0.6 when a price cap is fixed at 180 and 120.

Table 2: Impulse response to a one-standard-deviation gas positive shock in Germany.

	Horizon	*Period 2007 – 2023* Price Cap = 120	Price Cap = 180	No Price Cap	*Period 2020 – 2023* Price Cap = 120	Price Cap = 180	No Price Cap
Brent	1	0.026	-0.003	0.084	0.050	0.068	0.230
		(-0.057, 0.109)	(-0.085, 0.077)	(0.018, 0.155)	(-0.124, 0.236)	(-0.118, 0.255)	(0.076, 0.394)
	5	-0.030	-0.115	0.081	-0.180	-0.156	0.095
		(-0.190, 0.135)	(-0.277, 0.052)	(-0.069, 0.240)	(-0.550, 0.192)	(-0.542, 0.222)	(-0.263, 0.483)
	10	-0.068	-0.256	-0.174	0.010	-0.291	-0.326
		(-0.291, 0.158)	(-0.481, -0.027)	(-0.391, 0.045)	(-0.463, 0.484)	(-0.760, 0.171)	(-0.833, 0.181)
	20	-0.051	-0.130	-0.112	0.127	0.149	-0.114
		(-0.327, 0.212)	(-0.403, 0.159)	(-0.385, 0.149)	(-0.414, 0.692)	(-0.387, 0.683)	(-0.734, 0.483)
Coal	1	0.473	0.533	1.646	0.606	1.128	2.999
		(0.295, 0.655)	(0.341, 0.722)	(1.503, 1.797)	(-0.083, 1.317)	(0.376, 1.902)	(2.401, 3.572)
	5	1.609	1.830	3.029	3.166	3.561	6.237
		(1.234, 1.968)	(1.449, 2.205)	(2.675, 3.371)	(1.659, 4.717)	(1.938, 5.178)	(4.734, 7.717)
	10	2.647	2.363	3.126	5.846	4.664	8.049
		(2.142, 3.155)	(1.855, 2.876)	(2.650, 3.635)	(3.796, 8.093)	(2.455, 6.933)	(5.707, 10.496)
	20	2.241	1.892	2.465	4.252	3.866	6.860
		(1.667, 2.834)	(1.325, 2.531)	(1.924, 3.039)	(1.802, 6.792)	(1.510, 6.382)	(4.274, 10.074)
		Period 2021 – 2023			*Period 2020 – 2022*		
Brent	1	0.171	-0.051	0.273	-0.033	-0.098	0.112
		(-0.067, 0.405)	(-0.308, 0.195)	(0.063, 0.490)	(-0.193, 0.133)	(-0.272, 0.077)	(-0.038, 0.256)
	5	-0.175	-0.284	0.113	-0.146	-0.108	0.026
		(-0.621, 0.292)	(-0.747, 0.178)	(-0.337, 0.600)	(-0.418, 0.108)	(-0.390, 0.177)	(-0.271, 0.327)
	10	0.056	-0.464	-0.392	-0.222	-0.115	0.013
		(-0.500, 0.607)	(-0.979, 0.098)	(-0.999, 0.253)	(-0.575, 0.126)	(-0.474, 0.221)	(-0.418, 0.442)
	20	0.286	0.044	-0.075	-0.243	-0.114	-0.000
		(-0.285, 0.854)	(-0.492, 0.597)	(-0.753, 0.621)	(-0.699, 0.177)	(-0.504, 0.253)	(-0.554, 0.534)
Coal	1	0.802	1.103	3.177	0.839	0.259	0.814
		(-0.185, 1.799)	(0.079, 2.168)	(2.330, 3.980)	(0.382, 1.302)	(-0.240, 0.777)	(0.436, 1.208)
	5	3.958	3.318	6.894	0.310	-0.266	0.785
		(1.812, 6.127)	(1.132, 5.649)	(4.748, 9.005)	(-0.459, 1.076)	(-1.142, 0.610)	(-0.105, 1.674)
	10	7.075	4.426	9.509	-0.133	-0.613	0.580
		(4.078, 10.309)	(1.419, 7.464)	(6.092, 13.046)	(-1.226, 0.949)	(-1.760, 0.483)	(-0.780, 1.894)
	20	3.963	3.947	8.614	-0.338	-0.668	0.473
		(0.712, 7.673)	(0.714, 7.221)	(4.775, 13.444)	(-1.746, 0.989)	(-1.929, 0.454)	(-1.203, 2.065)

Notes:
[1] We run a VAR(12) with $U_{\min}(\text{pc}) = 15\% \cdot \text{pc}$ for 2007-2023 and with $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$ for 2020-2023 and 2021-2023, while for 2020-2022, we run a VAR(2) for Germany and a VAR(3) for Italy with $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$
[2] The values in parenthesis represent 68th posterior credible intervals.
[3] Grey cells indicate that zeros belong to the 68th posterior credible intervals.

Moving to the current war situation (bottom left), we notice that including a price cap of 180 provides the lowest values concerning fixing the smallest cap in particular at 2 weeks ahead (horizon 10). In the case presented until now, we notice a positive response of coal to a positive shock in the gas price, however, when dealing with the COVID-19 period (bottom right), a price cap yields a negative response of coal at longer horizons (2 weeks and 1 month) with respect to not fixing a price cap, where the response continue to be positive but not as strong as in the other scenarios.

In Table 3 we focus on the reaction of Brent and coal prices to a gas-positive shock in Italy through the same scenarios with the only difference in the model used for the period 2020–2022, where we estimate a VAR(3) instead of a VAR(2) model.

Table 3: Impulse response to a one-standard-deviation gas positive shock in Italy.

		Period 2007 – 2023			*Period 2020 – 2023*		
	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap	Price Cap = 120	Price Cap = 180	No Price Cap
Brent	1	0.035	0.006	0.092	0.067	0.085	0.283
		(-0.045, 0.117)	(-0.075, 0.088)	(0.025, 0.161)	(-0.119, 0.253)	(-0.098, 0.270)	(0.128, 0.447)
	5	0.015	-0.074	0.106	-0.026	0.043	0.226
		(-0.146, 0.179)	(-0.241, 0.090)	(-0.041, 0.263)	(-0.401, 0.336)	(-0.322, 0.418)	(-0.144, 0.597)
	10	-0.047	-0.272	-0.187	0.067	-0.127	-0.180
		(-0.278, 0.177)	(-0.489, -0.046)	(-0.399, 0.028)	(-0.390, 0.561)	(-0.581, 0.333)	(-0.656, 0.314)
	20	-0.035	-0.167	-0.140	0.205	0.362	-0.001
		(-0.314, 0.225)	(-0.434, 0.108)	(-0.398, 0.123)	(-0.336, 0.729)	(-0.157, 0.907)	(-0.527, 0.525)
Coal	1	0.410	0.471	1.760	0.539	1.136	3.361
		(0.237, 0.588)	(0.282, 0.656)	(1.614, 1.906)	(-0.149, 1.226)	(0.386, 1.889)	(2.734, 3.933)
	5	1.509	1.639	3.029	2.891	3.074	6.197
		(1.147, 1.879)	(1.262, 2.008)	(2.679, 3.378)	(1.388, 4.469)	(1.506, 4.759)	(4.716, 7.685)
	10	2.502	2.068	3.006	5.452	4.098	7.313
		(1.983, 3.000)	(1.565, 2.584)	(2.510, 3.514)	(3.435, 7.601)	(1.921, 6.308)	(5.133, 9.674)
	20	2.073	1.443	2.270	3.597	3.035	5.491
		(1.507, 2.655)	(0.857, 2.038)	(1.727, 2.821)	(1.299, 6.190)	(0.637, 5.506)	(3.249, 8.165)
		Period 2021 – 2023			*Period 2020 – 2022*		
Brent	1	0.067	0.085	0.283	-0.061	-0.118	0.111
		(-0.119, 0.253)	(-0.098, 0.270)	(0.128, 0.447)	(-0.231, 0.101)	(-0.293, 0.053)	(-0.033, 0.256)
	5	-0.026	0.043	0.226	-0.285	-0.047	0.036
		(-0.401, 0.336)	(-0.322, 0.418)	(-0.144, 0.597)	(-0.585, 0.007)	(-0.387, 0.293)	(-0.326, 0.409)
	10	0.067	-0.127	-0.180	-0.323	-0.036	0.029
		(-0.390, 0.561)	(-0.581, 0.333)	(-0.656, 0.314)	(-0.677, 0.034)	(-0.441, 0.372)	(-0.440, 0.498)
	20	0.205	0.362	-0.001	-0.335	-0.110	-0.097
		(-0.336, 0.729)	(-0.157, 0.907)	(-0.527, 0.525)	(-0.718, 0.049)	(-0.521, 0.321)	(-0.619, 0.423)
Coal	1	0.539	1.136	3.361	0.965	0.437	0.955
		(-0.149, 1.226)	(0.386, 1.889)	(2.734, 3.933)	(0.516, 1.407)	(-0.059, 0.938)	(0.591, 1.347)
	5	2.891	3.074	6.197	0.881	0.462	2.008
		(1.388, 4.469)	(1.506, 4.759)	(4.716, 7.685)	(0.037, 1.664)	(-0.510,1.398)	(1.034, 3.005)
	10	5.452	4.098	7.313	0.491	-0.058	1.264
		(3.435, 7.601)	(1.921, 6.308)	(5.133, 9.674)	(-0.533, 1.428)	(-1.247, 1.067)	(0.028, 2.555)
	20	3.597	3.035	5.491	0.007	-0.592	0.248
		(1.299, 6.190)	(0.637, 5.506)	(3.249, 8.165)	(-1.152, 1.075)	(-1.851, 0.549)	(-1.187, 1.641)

Notes: Please see the notes to Table 2.

As for Germany, also for Italy the GIRF of Brent prices to a shock in gas leads to non-significant values across all the scenarios and almost all the horizons. For the full sample period, a price cap at 180 provides a strong negative Brent response at longer horizons with respect to a small price cap and in line with not fixing a price cap. This result is not confirmed by the analyses during the crisis (2020–2023), where fixing a price cap provided a strong positive response to Brent 1 month ahead. Nice findings for Brent are available for the period 2021–2023 and 2020–2022, where fixing a price cap in the first horizons (1 day and 1 week) shows null responses in Brent to a gas shock, while not fixing it provides strong positive responses. This situation is clearer at 1 month ahead where a price cap of 120 or 180 yields strong positive responses in the Brent to a positive gas shock, while it avoids when a price cap is not considered. For Brent, the period 2020–2022 yields a strong negative response of Brent when a price cap at 120

Euros is considered, while not considering or considering 180 Euros shows null responses except for 1 day ahead.

For Coal prices, except for the 2020–2022 period, we notice a positive response of coal across horizons and in particular a peak across price caps at the 10 horizon. Indeed, 1 day ahead fixing a price cap at 120 yields the lowest positive response of coal to a shock, while at longer horizons, a price cap at 180 holds the lowest positive value. These results are not confirmed during the 2020–2022 period, where the GIRF values are not significant except for 1 day and 1 week ahead for the price cap equal to 120 and not included. Hence, the price cap at 180 shows a small positive response at 1 day and 1 week, while it becomes a negative response at longer horizons. This is in contrast with the results of a 120 price cap and a price cap not considered, where the first horizons yield strong positive responses, which are confirmed at longer horizons in particular 2 weeks ahead.

In Appendix C, we provide the impulse response function of the other commodities for a positive gas shock. Moreover, we run a robustness check when the price cap is fixed at a higher value, equal to 220. The results in this case are similar to the case equal to 180 and thus are not reported in the main paper.

4 How important is a gas shock to the other commodities?

This section is devoted to studying the importance of a gas shock to the other commodities. In particular, we report the contribution of the gas shock to the forecast error variance of electricity prices and coal prices at four different horizons. The variance decompositions are based on the median draw at each horizon ($1, 5, 10$ and 20). As for the generalized impulse response function, we rely on the generalized version of the error decomposition for the four different scenarios used and when a price cap is fixed or not.

In Table 4, we analyse the results for Germany. In detail, for the full sample (top left), we see that at small horizons the gas shock is mainly explained by its shocks. Once we move to one week ahead (horizon equal to 5), we notice that including a price cap or not including provides different results. Hence gas shocks explain around 22% of the variability in electricity prices and around 9% of the variability in coal prices. The reserve happens when a price cap is considered, where the gas shocks are not important for both the electricity and the coal prices. Gas shocks matter more in the long run where they are important for explaining 37% and 12% of the variability of electricity prices when a price cap is not considered and is fixed at 180, respectively. This importance is reduced to only 6% for a 120 price cap and it is always negligible for the coal prices when a price cap is included. Moving to one month ahead (horizon equal to 20), electricity price variability is explained for the 48% by the gas shocks when a price cap is not considered and the coal variability only by the 16%. As a take-home result, if a price cap is included, gas shocks do not explain the variability in electricity and coal prices.

Table 4: Median Forecast Error Variance Decomposition in Germany.

	Horizon	*Period 2007 – 2023* Price Cap = 120	Price Cap = 180	No Price Cap	*Period 2020 – 2023* Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	0.002	0.009	0.008	0.000	0.002	0.001
	5	0.025	0.065	0.226	0.012	0.024	0.126
	10	0.058	0.121	0.371	0.036	0.059	0.325
	20	0.106	0.214	0.480	0.065	0.151	0.495
Coal	1	0.004	0.006	0.054	0.002	0.006	0.043
	5	0.023	0.033	0.088	0.022	0.036	0.089
	10	0.067	0.065	0.134	0.079	0.065	0.182
	20	0.100	0.088	0.159	0.127	0.109	0.268
		Period 2021 – 2023			*Period 2020 – 2022*		
Electricity Prices	1	0.001	0.002	0.001	0.000	0.001	0.086
	5	0.009	0.018	0.091	0.010	0.015	0.356
	10	0.030	0.046	0.279	0.031	0.027	0.414
	20	0.054	0.146	0.468	0.053	0.032	0.418
Coal	1	0.003	0.004	0.033	0.009	0.002	0.040
	5	0.026	0.022	0.076	0.007	0.005	0.061
	10	0.088	0.042	0.171	0.008	0.007	0.054
	20	0.119	0.080	0.275	0.011	0.011	0.045

Notes: Please see the notes to Table 2.

The findings for the full sample are even more evident for the other periods. For the 2020-2023 period (top right), in the long run, gas shocks are the main drivers for electricity and coal prices when a price cap is not included. However, reducing the price cap leads to more volatility in the coal prices than in the electricity prices. In the 2020–2022 period, the inclusion of a price cap leads to almost null importance in explaining the variations of coal and electricity prices at all levels. This result is not confirmed when a price is not fixed, where the gas shocks explain around 40% of the variability of electricity prices in the medium and long run.

The previous analysis was done for Germany, while for Italy, Table 5 provides evidence of the results for different horizons. The situation in Italy is even stronger when a price cap is not analysed in almost all scenarios and at almost all horizons. In particular, for the full sample, gas shocks are solid drivers of electricity and coal dynamics by explaining on average almost 60% and 13% of fluctuations when a price cap is not considered. Indeed, it reduces drastically for coal when a price cap is considered and it moves to 26% and 15% for electricity when a price cap at 180 and 120 is considered.

These findings are confirmed for the period between 2020 and 2023 and 2021 and 2023, while for the period between COVID-19 and the beginning of the war, we notice that gas shocks were no longer solid drivers across horizons of electricity and coal dynamics. Moreover, when a price cap is not implemented lowers the coal dynamics around 7% with respect to 20% in the other scenarios, while this result is not evident for the electricity variability.

Table 5: Median Forecast Error Variance Decomposition in Italy.

		Period 2007 – 2023			*Period 2020 – 2023*		
	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	0.012	0.039	0.011	0.006	0.020	0.005
	5	0.063	0.148	0.486	0.035	0.081	0.475
	10	0.111	0.214	0.637	0.074	0.111	0.648
	20	0.153	0.268	0.672	0.089	0.140	0.643
Coal	1	0.003	0.004	0.062	0.002	0.006	0.055
	5	0.020	0.027	0.092	0.018	0.029	0.096
	10	0.061	0.051	0.132	0.068	0.050	0.177
	20	0.089	0.064	0.149	0.107	0.080	0.248
		Period 2021 – 2023			*Period 2020 – 2022*		
Electricity Prices	1	0.004	0.017	0.003	0.002	0.023	0.070
	5	0.044	0.058	0.403	0.036	0.054	0.604
	10	0.076	0.078	0.599	0.073	0.051	0.612
	20	0.082	0.114	0.600	0.099	0.045	0.565
Coal	1	0.002	0.003	0.042	0.012	0.003	0.065
	5	0.021	0.016	0.080	0.016	0.009	0.124
	10	0.079	0.028	0.165	0.015	0.011	0.100
	20	0.105	0.056	0.255	0.014	0.013	0.070

Notes: Please see the notes to Table 3.

5 Conclusion

We provide a mixture representation of the gas price to detect the presence of outliers and to study the importance of the gas price cap. We focus our analysis on Germany and Italy, two of the major Russian gas exporters, by exploiting the response of the different commodities to gas shocks through different time scenarios and price cap definitions.

Our results show that including a price cap smooths the impact of a gas shock on electricity prices, while not considering a price cap will increase exponentially the impact. However, the two countries behave differently across the choice of a price cap. For Germany, it seems that a price cap equal to 120 provides even better reductions in the impulse function of the different commodities, while for Italy, the imposition of a lower price cap does not yield improvements in the response to a gas shock. Moreover, we notice that gas shocks are solid drivers of electricity and coal dynamics by explaining huge fluctuations when a price cap is not considered, while it lowers closely to zero when a price cap is included.

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A Data representation

In this appendix, we provide the graphical representation of the other four commodities across the full sample size (left panel) and zoomed to the period from 2020 to 2023 (right panel). Figure A.1 shows the coal price and provides evidence of strong peaks in the last part of the sample around 2022 as for the gas price. Moreover, the coal price as a peak at the beginning of the sample around June/July 2008 due to international markets where U.S. coal was in demand. Another factor that affected coal prices was the escalating delivery costs for users due to the growing fuel surcharges added by transportation companies in response to the unprecedented rise in oil prices experienced during the first half of the year.

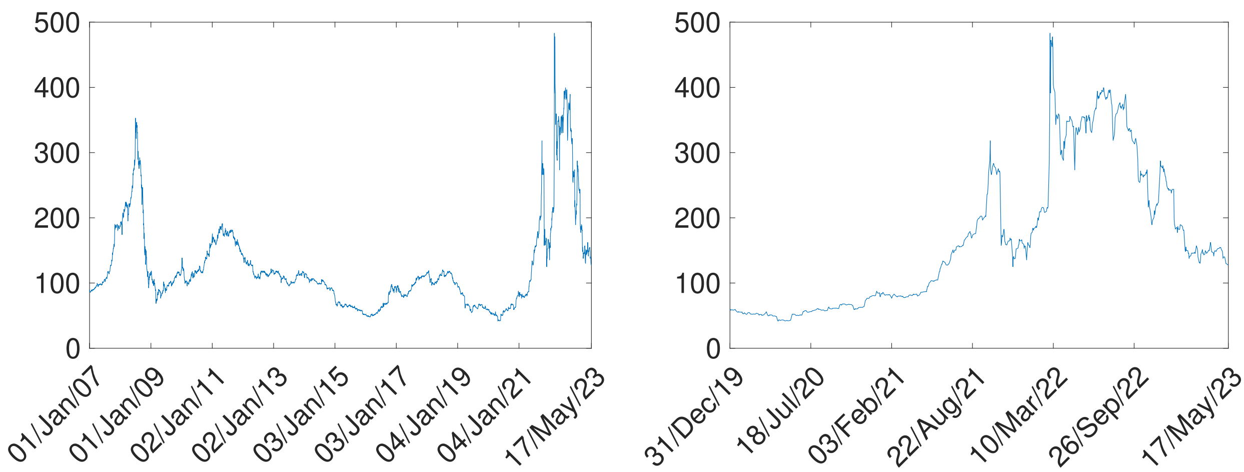


Figure A.1: Coal price in Euro from January 2007 to May 2023 (left panel) and from January 2020 to May 2023 (right panel).

On the other hand, Figure A.2 shows the behaviour of Brent price during the same period. Differently from Gas and Coal, the Brent price does not provide evidence of strong peaks in the last period with respect to the starting period of the sample. Thus it seems that Brent is not strongly influenced by natural gas and other commodities.

In Figure A.3, we represent the German (top) and the Italian electricity prices across different time periods. As shown in the literature, the German electricity prices as negative values, while the Italian one has a zero-lower bound. A second interesting effect is that the price seems to be stationary across the sample until half of 2021 when the prices exploded and followed the same behaviour as the gas price.

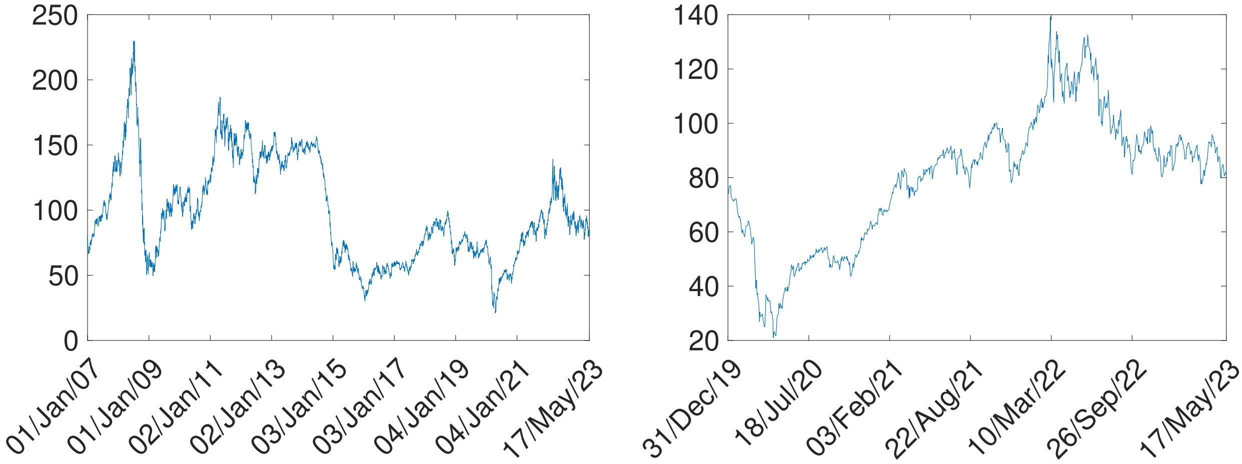


Figure A.2: Brent price in Euro from January 2007 to May 2023 (left panel) and from January 2020 to May 2023 (right panel).

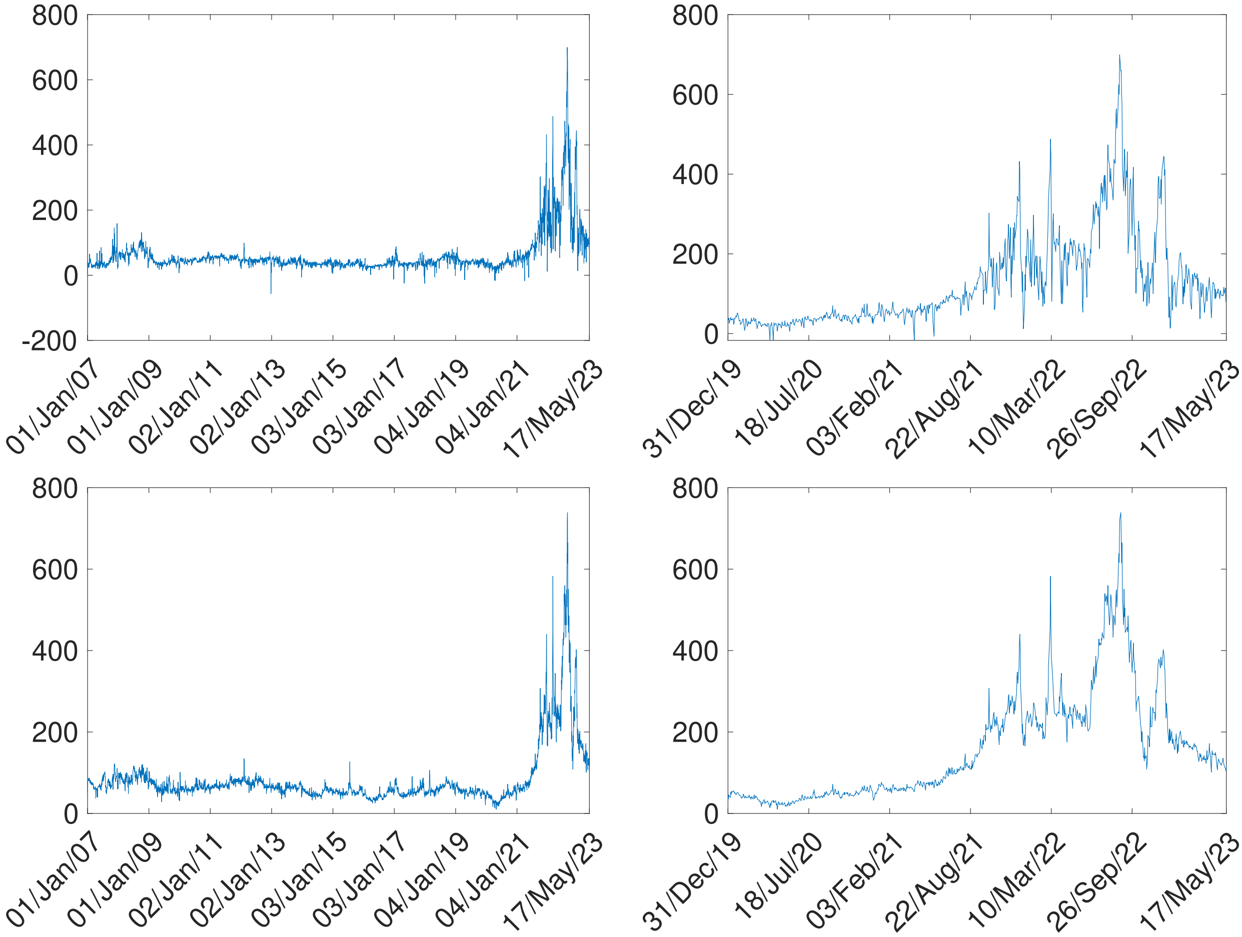


Figure A.3: German (top) and Italian (bottom) Electricity price from January 2007 to May 2023 (left panel) and from January 2020 to May 2023 (right panel).

B Optimal lag selection

This section is devoted to the robustness check related to the optimal lag selection. In particular, Table B.1 shows the DIC representation for Germany and Italy during the period from 2007 to 2023 with different lags (ranging from 1 to 12 and price cap variation from 5% to 20%. The smallest value, thus the optimal lag selection is represented in bold and for both countries it is 12 lags and variation equal to 15% of the price cap.

Table B.1: DIC representation for Germany and Italy when the price cap is equal to 180. The variation is $5\%, 10\%, 15\%$ and 20% and the lag ranges from 1 to 12 for 2007–2023.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
Germany												
$U_{\min}(pc) = 5\%$	125566.46	124816.76	124493.37	124290.05	124203.41	124107.41	124028.73	123969.59	123949.39	123897.15	123863.60	123706.79
$U_{\min}(pc) = 10\%$	125224.38	124512.05	124110.12	123899.00	123803.42	123717.34	123646.64	123581.84	123555.32	123497.17	123469.94	123323.98
$U_{\min}(pc) = 15\%$	125278.32	124537.72	124123.45	123910.57	123813.33	123720.94	123649.59	123577.98	123549.61	123485.32	123464.17	**123313.94**
$U_{\min}(pc) = 20\%$	125379.46	124617.93	124196.43	123975.03	123865.59	123772.96	123697.32	123628.22	123604.14	123534.53	123503.88	123361.90
Italy												
$U_{\min}(pc) = 5\%$	121329.37	120560.90	120276.83	120072.22	119983.65	119893.19	119848.83	119794.70	119795.01	119718.45	119666.08	119590.05
$U_{\min}(pc) = 10\%$	121007.19	120244.91	119888.32	119683.42	119563.17	119478.10	119435.67	119393.17	119381.02	119294.00	119243.23	119173.76
$U_{\min}(pc) = 15\%$	121070.74	120279.51	119921.19	119705.29	119576.04	119491.07	119444.06	119395.78	119386.57	119299.12	119245.04	**119171.80**
$U_{\min}(pc) = 20\%$	121171.61	120377.15	120006.96	119762.10	119630.04	119539.83	119490.82	119438.36	119426.53	119341.32	119284.06	119205.91

Table B.2 shows the DIC representation for Germany and Italy during the period from 2020 to 2023. The smallest value is represented in bold and for both countries it is 12 lags and variation equal to 20% of the price cap.

Table B.2: DIC representation for Germany and Italy when the price cap is equal to 180. The variation is $5\%, 10\%, 15\%$ and 20% and the lag ranges from 1 to 12 for 2020–2023.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
Germany												
$U_{\min}(pc) = 5\%$	31059.84	30963.80	30897.76	30867.22	30841.53	30803.31	30770.59	30756.63	30750.49	30730.36	30726.01	30684.54
$U_{\min}(pc) = 10\%$	31024.58	30908.80	30838.79	30802.67	30772.09	30740.10	30712.22	30694.92	30690.10	30672.56	30663.83	30620.05
$U_{\min}(pc) = 15\%$	31027.22	30910.35	30838.32	30798.45	30768.93	30734.91	30704.37	30688.41	30682.76	30663.14	30656.44	30612.49
$U_{\min}(pc) = 20\%$	30970.34	30855.80	30783.80	30737.47	30706.98	30676.84	30650.28	30636.29	30631.60	30616.37	30609.16	**30564.83**
Italy												
$U_{\min}(pc) = 5\%$	29998.52	29904.79	29858.20	29826.13	29797.35	29768.67	29743.08	29728.87	29729.62	29716.58	29698.35	29679.96
$U_{\min}(pc) = 10\%$	29984.89	29871.03	29815.13	29775.20	29748.05	29721.07	29696.01	29683.63	29682.01	29665.26	29650.99	29634.73
$U_{\min}(pc) = 15\%$	29993.52	29879.65	29828.28	29785.88	29753.73	29726.03	29705.74	29694.95	29689.45	29667.12	29657.86	29635.35
$U_{\min}(pc) = 20\%$	29943.48	29836.30	29785.80	29742.43	29707.97	29682.57	29664.06	29650.40	29650.49	29631.38	29623.80	**29604.32**

Table B.3 shows the DIC representation for Germany and Italy during the period from 2021 to 2023. The smallest value is represented in bold and for both countries it is 12 lags and variation equal to 20% of the price cap.

Table B.3: DIC representation for Germany and Italy when the price cap is equal to 180. The variation is $5\%, 10\%, 15\%$ and 20% and the lag ranges from 1 to 12 for 2021–2023.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
Germany												
$U_{\min}(pc) = 5\%$	22790.62	22725.45	22680.74	22656.44	22632.76	22605.11	22580.31	22567.97	22564.75	22547.64	22543.63	22505.76
$U_{\min}(pc) = 10\%$	22772.09	22708.38	22654.61	22629.16	22610.21	22580.67	22559.12	22541.70	22537.67	22524.00	22519.05	22483.75
$U_{\min}(pc) = 15\%$	22777.70	22703.43	22654.77	22627.26	22606.48	22578.86	22555.14	22542.87	22536.84	22522.49	22516.78	22486.57
$U_{\min}(pc) = 20\%$	22777.49	22695.01	22644.39	22612.98	22590.09	22561.00	22536.51	22526.06	22518.67	22506.05	22498.51	**22467.36**
Italy												
$U_{\min}(pc) = 5\%$	22046.17	21986.87	21954.74	21930.36	21909.65	21883.84	21866.73	21856.33	21853.11	21838.74	21833.63	21813.01
$U_{\min}(pc) = 10\%$	22030.75	21969.16	21930.98	21903.65	21885.57	21860.29	21839.02	21830.69	21827.79	21815.40	21804.65	21788.55
$U_{\min}(pc) = 15\%$	22043.77	21972.76	21936.66	21906.86	21883.01	21858.18	21838.58	21828.11	21826.78	21812.98	21802.37	21787.34
$U_{\min}(pc) = 20\%$	22048.43	21971.40	21933.78	21902.10	21876.61	21852.24	21835.97	21827.71	21821.05	21804.81	21797.58	**21782.31**

Table B.4 shows the DIC representation for Germany and Italy during the period from 2020 to 2022. The smallest value is represented in bold. For Germany, the best value is 2 lags and variation equal to 20% of the price cap, while for Italy is 3 lags and variation equal to 20% of the price cap

Table B.4: DIC representation for Germany and Italy when the price cap is equal to 180. The variation is $5\%, 10\%, 15\%$ and 20% and the lag ranges from 1 to 12 for 2020–2022.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
Germany												
$U_{\min}(pc) = 5\%$	15958.91	15928.63	15930.92	15935.91	15946.71	15954.53	15971.30	15988.05	15985.88	16024.56	16037.13	16055.93
$U_{\min}(pc) = 10\%$	15958.91	15928.63	15930.92	15935.88	15946.73	15954.59	15971.30	15988.08	15985.88	16025.30	16037.12	16055.91
$U_{\min}(pc) = 15\%$	15959.20	15929.15	15931.16	15935.86	15946.75	15954.62	15971.50	15988.05	15985.88	16024.56	16037.11	16055.95
$U_{\min}(pc) = 20\%$	15941.58	**15899.33**	15903.63	15914.04	15926.79	15936.81	15952.44	15972.96	15965.96	16001.93	16015.39	16036.31
Italy												
$U_{\min}(pc) = 5\%$	15202.05	15183.34	15175.98	15196.56	15195.94	15214.44	15255.41	15268.76	15289.51	15303.05	15311.59	15321.20
$U_{\min}(pc) = 10\%$	15202.05	15183.34	15175.98	15196.56	15195.94	15214.44	15255.41	15268.76	15289.51	15303.05	15311.59	15321.20
$U_{\min}(pc) = 15\%$	15202.00	15183.23	15176.09	15196.47	15195.89	15214.50	15255.27	15268.83	15289.63	15302.83	15311.53	15321.12
$U_{\min}(pc) = 20\%$	15194.70	15168.99	**15163.17**	15191.88	15187.66	15205.81	15245.59	15260.17	15275.59	15285.15	15297.41	15307.05

C Other Results to a gas shock

In Section C.1, GIRFs of a gas shock to the other commodities are shown when a price cap equal to 120; to 180 and no price cap are considered. In Section C.2, a robustness check when the price cap is fixed equal to 220 is provided as a graphical representation only for the electricity prices responses.

C.1 Impulse Response function

Germany

Table C.1 explains the response of the different commodities to a gas-positive shock across horizons and for the full sample. The only non-significant values are for the Brent responses across horizons and price caps, while the CO_2 has not significant values only for the horizon 10 and 20 for price cap 180 and horizon 1 for no price cap included.

Table C.1: Impulse response to a one-standard-deviation gas positive shock for 2007 - 23 in Germany.

	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	1.071	2.294	2.012
		(0.632, 1.487)	(1.815, 2.789)	(1.654, 2.365)
	5	3.573	5.283	8.845
		(2.889, 4.288)	(4.510, 5.982)	(8.255, 9.443)
	10	3.946	5.291	7.468
		(3.087, 4.863)	(4.388, 6.178)	(6.754, 8.272)
	20	3.780	5.228	5.975
		(3.086, 4.523)	(4.509, 5.991)	(5.305, 6.681)
Brent	1	0.026	-0.003	0.084
		(-0.057, 0.109)	(-0.085, 0.077)	(0.018, 0.155)
	5	-0.030	-0.115	0.081
		(-0.190, 0.135)	(-0.277, 0.052)	(-0.069, 0.240)
	10	-0.068	-0.256	-0.174
		(-0.291, 0.158)	(-0.481, -0.027)	(-0.391, 0.045)
	20	-0.051	-0.130	-0.112
		(-0.327, 0.212)	(-0.403, 0.159)	(-0.385, 0.149)
Coal	1	0.473	0.533	1.646
		(0.295, 0.655)	(0.341, 0.722)	(1.503, 1.797)
	5	1.609	1.830	3.029
		(1.234, 1.968)	(1.449, 2.205)	(2.675, 3.371)
	10	2.647	2.363	3.126
		(2.142, 3.155)	(1.855, 2.876)	(2.650, 3.635)
	20	2.241	1.892	2.465
		(1.667, 2.834)	(1.325, 2.531)	(1.924, 3.039)
CO_2	1	-0.072	-0.057	0.024
		(-0.106, -0.039)	(-0.088, -0.024)	(-0.004, 0.051)
	5	-0.246	-0.172	-0.186
		(-0.312, -0.182)	(-0.236, -0.108)	(-0.247, -0.124)
	10	-0.085	-0.057	-0.187
		(-0.171, -0.003)	(-0.141, 0.029)	(-0.271, -0.107)
	20	0.019	0.031	-0.211
		(-0.079, 0.116)	(-0.069, 0.133)	(-0.307, -0.116)

Notes:
[1] All the results are provided for a VAR(12) with intercept and with $U_{\min}(\text{pc}) = 15\% \cdot \text{pc}$.
[2] The values in parenthesis represent 68th posterior credible intervals.
[3] Grey cells indicate that zeros belong to the 68th posterior credible intervals.

In Table C.2, for the period 2020–2023, CO_2 responses are not significant across horizons except for 1 month ahead for price cap equal to 180 and for the 1 and 2 weeks ahead when no price cap is allowed.

Table C.2: Impulse response to a one-standard-deviation gas positive shock for 2020 - 23 in Germany.

	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	0.965	2.484	1.693
		(-0.234, 2.092)	(1.078, 3.857)	(0.626, 2.686)
	5	5.503	6.605	15.488
		(3.239, 7.919)	(4.041, 9.193)	(13.042, 17.840)
	10	6.992	8.683	18.076
		(3.704, 10.444)	(5.140, 12.299)	(14.658, 21.734)
	20	5.454	9.908	15.282
		(1.794, 9.229)	(6.630, 13.605)	(11.298, 20.091)
Brent	1	0.050	0.068	0.230
		(-0.124, 0.236)	(-0.118, 0.255)	(0.076, 0.394)
	5	-0.180	-0.156	0.095
		(-0.550, 0.192)	(-0.542, 0.222)	(-0.263, 0.483)
	10	0.010	-0.291	-0.326
		(-0.463, 0.484)	(-0.760, 0.171)	(-0.833, 0.181)
	20	0.127	0.149	-0.114
		(-0.414, 0.692)	(-0.387, 0.683)	(-0.734, 0.483)
Coal	1	0.606	1.128	2.999
		(-0.083, 1.317)	(0.376, 1.902)	(2.401, 3.572)
	5	3.166	3.561	6.237
		(1.659, 4.717)	(1.938, 5.178)	(4.734, 7.717)
	10	5.846	4.664	8.049
		(3.796, 8.093)	(2.455, 6.933)	(5.707, 10.496)
	20	4.252	3.866	6.860
		(1.802, 6.792)	(1.510, 6.382)	(4.274, 10.074)
CO_2	1	-0.056	-0.094	0.049
		(-0.205, 0.085)	(-0.241, 0.055)	(-0.086, 0.177)
	5	-0.398	-0.173	-0.398
		(-0.694, -0.101)	(-0.478, 0.125)	(-0.705, -0.076)
	10	-0.059	0.128	-0.513
		(-0.461, 0.325)	(-0.246, 0.511)	(-0.949, -0.078)
	20	0.397	0.507	-0.295
		(-0.069, 0.866)	(0.074, 0.998)	(-0.842, 0.232)

Notes:
[1] All the results are provided for a VAR(12) with intercept and with $U_{\min}(\mathrm{pc}) = 20\% \cdot \mathrm{pc}$.
[2] The values in parenthesis represent 68th posterior credible intervals.
[3] Grey cells indicate that zeros belong to the 68th posterior credible intervals.

For Table C.3, the same situation as shown in the previous tables is presented. In particular, for the period 2021–2023, we notice that the CO_2 is always not significant except for the price cap at 1 month ahead and for no price cap at 2 weeks ahead. Moreover, we can see that the response of CO_2 to a gas shock behaves differently across the horizons. Indeed, we notice a strong positive response at longer horizons when a price cap is considered, while when it is not included the response is negative.

Table C.3: Impulse response to a one-standard-deviation gas positive shock for 2021 - 23 in Germany.

	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	1.124	2.707	1.508
		(-0.446, 2.757)	(0.908, 4.504)	(0.200, 2.776)
	5	5.678	7.070	16.362
		(2.414, 8.925)	(3.611, 10.534)	(13.003, 19.698)
	10	7.630	9.838	21.054
		(3.027, 12.448)	(5.232, 14.710)	(16.148, 26.447)
	20	5.807	11.719	18.658
		(0.855, 11.022)	(7.355, 16.665)	(12.772, 25.926)
Brent	1	0.171	-0.051	0.273
		(-0.067, 0.405)	(-0.308, 0.195)	(0.063, 0.490)
	5	-0.175	-0.284	0.113
		(-0.621, 0.292)	(-0.747, 0.178)	(-0.337, 0.600)
	10	0.056	-0.464	-0.392
		(-0.500, 0.607)	(-0.979, 0.098)	(-0.999, 0.253)
	20	0.286	0.044	-0.075
		(-0.285, 0.854)	(-0.492, 0.597)	(-0.753, 0.621)
Coal	1	0.802	1.103	3.177
		(-0.185, 1.799)	(0.079, 2.168)	(2.330, 3.980)
	5	3.958	3.318	6.894
		(1.812, 6.127)	(1.132, 5.649)	(4.748, 9.005)
	10	7.075	4.426	9.509
		(4.078, 10.309)	(1.419, 7.464)	(6.092, 13.046)
	20	3.963	3.947	8.614
		(0.712, 7.673)	(0.714, 7.221)	(4.775, 13.444)
CO_2	1	-0.113	-0.174	0.053
		(-0.323, 0.099)	(-0.395, 0.033)	(-0.146, 0.241)
	5	-0.746	-0.019	-0.456
		(-1.157, -0.337)	(-0.439, 0.408)	(-0.887, 0.007)
	10	-0.299	0.361	-0.664
		(-0.853, 0.230)	(-0.178, 0.896)	(-1.310, -0.025)
	20	0.411	0.712	-0.312
		(-0.199, 1.029)	(0.080, 1.352)	(-1.102, 0.455)

Notes: Please see the notes to Table C.2.

For Table C.4, we compare a VAR(12) with a VAR(2) model for the period 2020–2022 due to the results obtained in Appendix B. In particular, if a VAR(12) is considered, the non-significant of CO_2 is more evident across the horizons and the cases, while it is not present for a VAR(2) model for the price cap equal to 120 and for no price cap. Moreover, we notice that for CO_2 and Coal the sign changes if we consider a VAR(2) or a VAR(12) model at longer horizons moving from a negative to a positive and vice-versa.

Table C.4: Impulse response to a one-standard-deviation gas positive shock for 2020 - 22 in Germany.

	Horizon	VAR(12) Price Cap = 120	VAR(12) Price Cap = 180	VAR(12) No Price Cap	VAR(2) Price Cap = 120	VAR(2) Price Cap = 180	VAR(2) No Price Cap
Electricity Prices	1	0.200	0.986	0.508	0.186	0.898	0.648
		(-0.358, 0.761)	(0.241, 1.752)	(0.037, 1.010)	(-0.381, 0.764)	(0.150, 1.667)	(0.141, 1.135)
	5	2.330	2.542	4.306	3.099	3.193	4.666
		(1.176, 3.439)	(1.059, 4.032)	(2.857, 5.769)	(2.081, 4.113)	(1.928, 4.348)	(3.387, 5.807)
	10	2.795	0.278	3.458	3.237	2.262	4.621
		(1.482, 4.166)	(-1.385, 2.007)	(1.415, 5.714)	(2.199, 4.363)	(1.174, 3.363)	(3.362, 5.997)
	20	2.029	1.050	2.085	2.155	0.850	2.842
		(1.103, 3.080)	(-0.027, 2.089)	(0.393, 3.934)	(1.192, 3.239)	(0.044, 1.742)	(1.702, 4.249)
Brent	1	-0.045	-0.099	0.136	-0.033	-0.098	0.112
		(-0.227, 0.140)	(-0.286, 0.089)	(-0.029, 0.295)	(-0.193, 0.133)	(-0.272, 0.077)	(-0.038, 0.256)
	5	-0.106	0.055	0.056	-0.146	-0.108	0.026
		(-0.502, 0.288)	(-0.344, 0.482)	(-0.387, 0.505)	(-0.418, 0.108)	(-0.390, 0.177)	(-0.271, 0.327)
	10	-0.446	-0.103	0.090	-0.222	-0.115	0.013
		(-1.014, 0.096)	(-0.691, 0.475)	(-0.670, 0.898)	(-0.575, 0.126)	(-0.474, 0.221)	(-0.418, 0.442)
	20	-0.401	-0.193	-0.108	-0.243	-0.114	-0.000
		(-1.011, 0.131)	(-0.743, 0.378)	(-0.894, 0.719)	(-0.699, 0.177)	(-0.504, 0.253)	(-0.554, 0.534)
Coal	1	0.956	0.536	0.934	0.839	0.259	0.814
		(0.485, 1.429)	(0.034, 1.038)	(0.554, 1.326)	(0.382, 1.302)	(-0.240, 0.777)	(0.436, 1.208)
	5	1.398	0.941	2.386	0.310	-0.266	0.785
		(0.494, 2.398)	(-0.157, 2.109)	(1.276, 3.538)	(-0.459, 1.076)	(-1.142, 0.610)	(-0.105, 1.674)
	10	1.466	-0.386	1.553	-0.133	-0.613	0.580
		(0.122, 2.831)	(-1.897, 1.181)	(-0.357, 3.606)	(-1.226, 0.949)	(-1.760, 0.483)	(-0.780, 1.894)
	20	0.466	-1.379	-0.260	-0.338	-0.668	0.473
		(-0.905, 1.959)	(-2.904, 0.063)	(-2.233, 1.870)	(-1.746, 0.989)	(-1.929, 0.454)	(-1.203, 2.065)
CO_2	1	0.076	-0.041	0.584	0.195	0.008	0.553
		(-0.068, 0.216)	(-0.181, 0.097)	(0.469, 0.691)	(0.039, 0.350)	(-0.119, 0.143)	(0.449, 0.659)
	5	0.123	-0.105	-0.042	0.333	0.095	0.425
		(-0.113, 0.370)	(-0.366, 0.148)	(-0.310, 0.228)	(0.150, 0.525)	(-0.098, 0.283)	(0.225, 0.635)
	10	0.209	-0.099	0.128	0.432	0.151	0.470
		(-0.123, 0.545)	(-0.466, 0.252)	(-0.336, 0.608)	(0.187, 0.688)	(-0.091, 0.390)	(0.167, 0.781)
	20	0.065	-0.137	0.068	0.523	0.196	0.490
		(-0.302, 0.416)	(-0.505, 0.200)	(-0.412, 0.561)	(0.191, 0.873)	(-0.101, 0.492)	(0.067, 0.946)

Notes:
[1] All the results are provided for a VAR with intercept and with $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$.
[2] The values in parenthesis represent 68th posterior credible intervals.
[3] Grey cells indicate that zeros belong to the 68th posterior credible intervals.

Italy

In this subsection, we analyse the results for Italy. In Table C.5, we focus on the full sample period and it yields not-significant results for Brent at all horizons and for CO_2 at 2 weeks and 1 month ahead for the price cap scenario and at 1 day ahead when a price cap is not considered. Moreover, we notice that the response in CO_2 is almost null at longer horizons when a price cap is considered in the analysis.

Table C.5: Impulse response to a one-standard-deviation gas positive shock for 2007 - 23 in Italy.

	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	1.641	2.959	1.367
		(1.300, 1.974)	(2.603, 3.321)	(1.115, 1.614)
	5	3.949	5.885	9.411
		(3.380, 4.526)	(5.279, 6.487)	(8.952, 9.885)
	10	4.488	5.757	9.144
		(3.734, 5.277)	(4.964, 6.582)	(8.509, 9.858)
	20	3.907	4.784	6.561
		(3.171, 4.692)	(3.988, 5.607)	(5.842, 7.325)
Brent	1	0.035	0.006	0.092
		(-0.045, 0.117)	(-0.075, 0.088)	(0.025, 0.161)
	5	0.015	-0.074	0.106
		(-0.146, 0.179)	(-0.241, 0.090)	(-0.041, 0.263)
	10	-0.047	-0.272	-0.187
		(-0.278, 0.177)	(-0.489, -0.046)	(-0.399, 0.028)
	20	-0.035	-0.167	-0.140
		(-0.314, 0.225)	(-0.434, 0.108)	(-0.398, 0.123)
Coal	1	0.410	0.471	1.760
		(0.237, 0.588)	(0.282, 0.656)	(1.614, 1.906)
	5	1.509	1.639	3.029
		(1.147, 1.879)	(1.262, 2.008)	(2.679, 3.378)
	10	2.502	2.068	3.006
		(1.983, 3.000)	(1.565, 2.584)	(2.510, 3.514)
	20	2.073	1.443	2.270
		(1.507, 2.655)	(0.857, 2.038)	(1.727, 2.821)
CO_2	1	-0.074	-0.051	0.021
		(-0.106, -0.040)	(-0.082, -0.019)	(-0.006, 0.049)
	5	-0.231	-0.143	-0.171
		(-0.295, -0.166)	(-0.207, -0.078)	(-0.232, -0.109)
	10	-0.065	-0.006	-0.143
		(-0.152, 0.022)	(-0.092, 0.075)	(-0.224, -0.061)
	20	0.046	0.063	-0.166
		(-0.047, 0.141)	(-0.039, 0.163)	(-0.261, -0.073)

Notes: Please see the notes to Table C.1.

For the period 2020–2023, in Table C.6 we have the strong positive response of CO_2 to a gas shock at longer horizons when a price cap equal to 180 is considered. While if no price cap is fixed, we have strong negative responses at 1 week, 2 weeks and 1 month ahead.

Table C.6: Impulse response to a one-standard-deviation gas positive shock for 2020 - 23 in Italy.

	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	2.175	4.067	1.814
		(1.151, 3.189)	(2.860, 5.226)	(0.928, 2.633)
	5	6.547	8.717	18.954
		(4.455, 8.612)	(6.476, 11.001)	(17.150, 20.959)
	10	7.372	8.262	18.306
		(4.352, 10.569)	(5.063, 11.547)	(15.272, 21.638)
	20	3.916	6.284	9.685
		(0.169, 7.640)	(2.755, 9.909)	(6.520, 13.582)
Brent	1	0.067	0.085	0.283
		(-0.119, 0.253)	(-0.098, 0.270)	(0.128, 0.447)
	5	-0.026	0.043	0.226
		(-0.401, 0.336)	(-0.322, 0.418)	(-0.144, 0.597)
	10	0.067	-0.127	-0.180
		(-0.390, 0.561)	(-0.581, 0.333)	(-0.656, 0.314)
	20	0.205	0.362	-0.001
		(-0.336, 0.729)	(-0.157, 0.907)	(-0.527, 0.525)
Coal	1	0.539	1.136	3.361
		(-0.149, 1.226)	(0.386, 1.889)	(2.734, 3.933)
	5	2.891	3.074	6.197
		(1.388, 4.469)	(1.506, 4.759)	(4.716, 7.685)
	10	5.452	4.098	7.313
		(3.435, 7.601)	(1.921, 6.308)	(5.133, 9.674)
	20	3.597	3.035	5.491
		(1.299, 6.190)	(0.637, 5.506)	(3.249, 8.165)
CO_2	1	-0.063	-0.063	0.024
		(-0.211, 0.089)	(-0.214, 0.081)	(-0.115, 0.156)
	5	-0.354	-0.079	-0.450
		(-0.657, -0.044)	(-0.390, 0.212)	(-0.755, -0.149)
	10	-0.014	0.307	-0.629
		(-0.408, 0.369)	(-0.083, 0.670)	(-1.034, -0.227)
	20	0.402	0.544	-0.531
		(-0.049, 0.858)	(0.105, 1.038)	(-1.040, -0.075)

Notes: Please see the notes to Table C.2.

Looking at the period 2021-2023, Table C.7 yields the same results as in the other periods, with significant values except for Brent and some horizons of coal and CO_2. However, CO_2 response are quite not significant for the 180 price cap and almost positive at longer horizons, while a 120 price cap or null price cap shows negative responses at longer horizons too.

Table C.7: Impulse response to a one-standard-deviation gas positive shock for 2021 - 23 in Italy.

	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	2.162	4.549	1.763
		(0.828, 3.606)	(3.040, 6.093)	(0.617, 2.881)
	5	8.371	8.618	21.255
		(5.369, 11.320)	(5.356, 11.797)	(18.623, 24.007)
	10	8.135	8.145	20.936
		(3.641, 12.570)	(3.578, 12.752)	(16.690, 25.955)
	20	4.177	6.904	10.456
		(-0.776, 9.321)	(2.584, 11.816)	(5.630, 16.027)
Brent	1	0.189	-0.041	0.328
		(-0.050, 0.429)	(-0.284, 0.205)	(0.118, 0.546)
	5	-0.012	-0.158	0.193
		(-0.473, 0.430)	(-0.615, 0.305)	(-0.276, 0.678)
	10	0.136	-0.323	-0.241
		(-0.396, 0.684)	(-0.847, 0.206)	(-0.840, 0.385)
	20	0.299	0.143	-0.002
		(-0.234, 0.876)	(-0.365, 0.695)	(-0.607, 0.593)
Coal	1	0.716	0.968	3.553
		(-0.309, 1.661)	(-0.069, 1.998)	(2.705, 4.352)
	5	3.536	2.752	6.756
		(1.388, 5.821)	(0.533, 5.004)	(4.619, 8.939)
	10	6.725	3.589	8.587
		(3.701, 9.736)	(0.646, 6.719)	(5.486, 12.017)
	20	3.400	2.866	6.661
		(0.197, 6.780)	(-0.166, 6.033)	(3.355, 10.511)
CO_2	1	-0.124	-0.150	0.012
		(-0.339, 0.093)	(-0.362, 0.061)	(-0.188, 0.203)
	5	-0.689	0.085	-0.588
		(-1.116, -0.257)	(-0.357, 0.512)	(-1.025, -0.124)
	10	-0.178	0.485	-0.956
		(-0.766, 0.342)	(-0.047, 1.038)	(-1.551, -0.355)
	20	0.402	0.592	-0.769
		(-0.220, 1.004)	(-0.013, 1.246)	(-1.507, -0.084)

Notes: Please see the notes to Table C.2.

Table C.8 compares the results for a VAR(12) and a VAR(3) model for the period 2020–2022. One of the findings is that a CO_2 is not significant when a VAR(12) is considered, while it becomes significant for a VAR(3) and for the price cap equal to 180. However, what we notice is that CO_2 has a negative response to gas shocks during this period if a 180 price cap or noone price cap is considered, while the sign is reverted when a price cap equal to 120 is used.

Table C.8: Impulse response to a one-standard-deviation gas positive shock for 2020 - 22 in Italy.

		VAR(12)			VAR(3)		
	Horizon	Price Cap = 120	Price Cap = 180	No Price Cap	Price Cap = 120	Price Cap = 180	No Price Cap
Electricity Prices	1	0.651	2.321	0.662	0.694	2.462	0.803
		(0.113, 1.187)	(1.662, 3.019)	(0.203, 1.125)	(0.144, 1.214)	(1.786, 3.132)	(0.339, 1.257)
	5	3.144	2.515	6.465	3.436	2.842	6.109
		(1.939, 4.360)	(1.090, 3.887)	(5.230, 7.707)	(2.395, 4.501)	(1.549, 4.094)	(4.882, 7.308)
	10	4.187	-1.253	2.832	3.279	1.686	4.413
		(2.770, 5.722)	(-3.028, 0.578)	(0.928, 4.879)	(2.210, 4.369)	(0.327, 2.996)	(3.129, 5.788)
	20	2.360	-0.580	-0.977	2.267	0.340	2.133
		(1.053, 3.816)	(-2.371, 0.914)	(-3.539, 1.228)	(1.261, 3.367)	(-0.847, 1.510)	(0.828, 3.494)
Brent	1	-0.024	-0.118	0.123	-0.061	-0.118	0.111
		(-0.213, 0.149)	(-0.295, 0.070)	(-0.039, 0.284)	(-0.231, 0.101)	(-0.293, 0.053)	(-0.033, 0.256)
	5	-0.085	-0.026	-0.024	-0.285	-0.047	0.036
		(-0.500, 0.324)	(-0.445, 0.421)	(-0.498, 0.442)	(-0.585, 0.007)	(-0.387, 0.293)	(-0.326, 0.409)
	10	-0.325	-0.008	0.119	-0.323	-0.036	0.029
		(-0.912, 0.242)	(-0.601, 0.589)	(-0.651, 0.913)	(-0.677, 0.034)	(-0.441, 0.372)	(-0.440, 0.498)
	20	-0.200	0.137	0.264	-0.335	-0.110	-0.097
		(-0.840, 0.422)	(-0.498, 0.779)	(-0.646, 1.225)	(-0.718, 0.049)	(-0.521, 0.321)	(-0.619, 0.423)
Coal	1	0.886	0.409	0.877	0.965	0.437	0.955
		(0.415, 1.352)	(-0.083, 0.915)	(0.505, 1.265)	(0.516, 1.407)	(-0.059, 0.938)	(0.591, 1.347)
	5	1.600	0.614	1.802	0.881	0.462	2.008
		(0.619, 2.573)	(-0.477, 1.696)	(0.716, 2.908)	(0.037, 1.664)	(-0.510,1.398)	(1.034, 3.005)
	10	2.216	0.679	1.784	0.491	-0.058	1.264
		(0.821, 3.600)	(-0.861, 2.209)	(-0.140, 3.705)	(-0.533, 1.428)	(-1.247, 1.067)	(0.028, 2.555)
	20	0.611	-0.373	-0.002	0.007	-0.592	0.248
		(-0.965, 2.343)	(-2.156, 1.376)	(-2.306, 2.594)	(-1.152, 1.075)	(-1.851, 0.549)	(-1.187, 1.641)
CO_2	1	0.031	-0.066	0.495	0.113	-0.078	0.447
		(-0.110, 0.176)	(-0.202, 0.074)	(0.385, 0.602)	(-0.026, 0.260)	(-0.205, 0.049)	(0.341, 0.554)
	5	0.046	-0.308	-0.339	0.010	-0.345	-0.264
		(-0.198, 0.302)	(-0.566, -0.045)	(-0.614, -0.070)	(-0.172, 0.188)	(-0.556, -0.159)	(-0.490, -0.050)
	10	0.044	-0.154	-0.146	0.037	-0.339	-0.317
		(-0.295, 0.392)	(-0.525, 0.201)	(-0.620, 0.319)	(-0.180, 0.246)	(-0.596, -0.112)	(-0.628, -0.044)
	20	-0.048	-0.218	0.054	0.084	-0.284	-0.277
		(-0.467, 0.345)	(-0.628, 0.183)	(-0.542, 0.630)	(-0.173, 0.332)	(-0.585, -0.031)	(-0.675, 0.052)

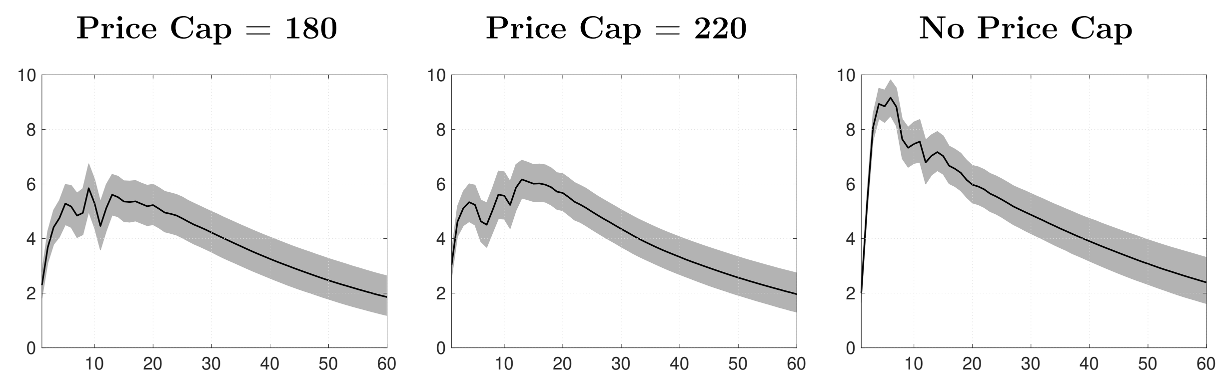
Notes: Please see the notes to Table C.4.

C.2 Robustness check

Germany

Figure C.1 shows the response of electricity prices to a gas shock in the period from 2007 to 2023 for a price cap of 180 (left), of 220 (center) and for no price cap (right). Fixing a higher price cap yields almost the same results as fixing a price cap at 180, while it provides small responses with respect to not fixing a price cap.

Figure C.1: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2007 - 23 for VAR(12) with intercept and $U_{\min}(\mathrm{pc}) = 15\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



In Figure C.2, fixing a higher price cap yields almost the same results as fixing a price cap at 180 for the 2020–2023 period.

Figure C.2: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2020 - 23 for VAR(12) with intercept and $U_{\min}(\mathrm{pc}) = 20\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.

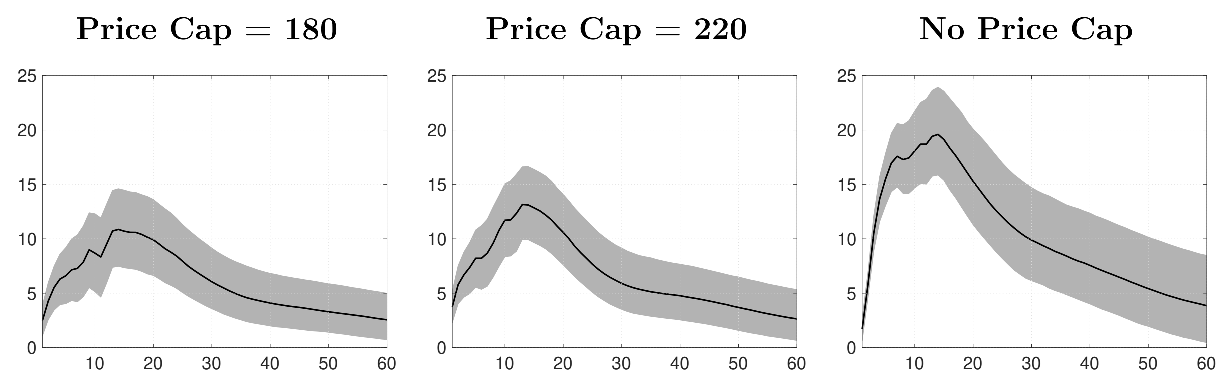
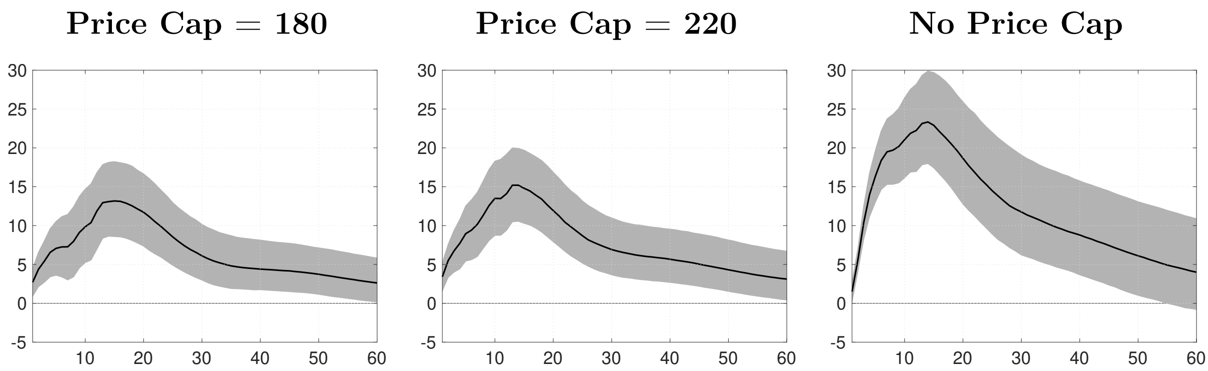


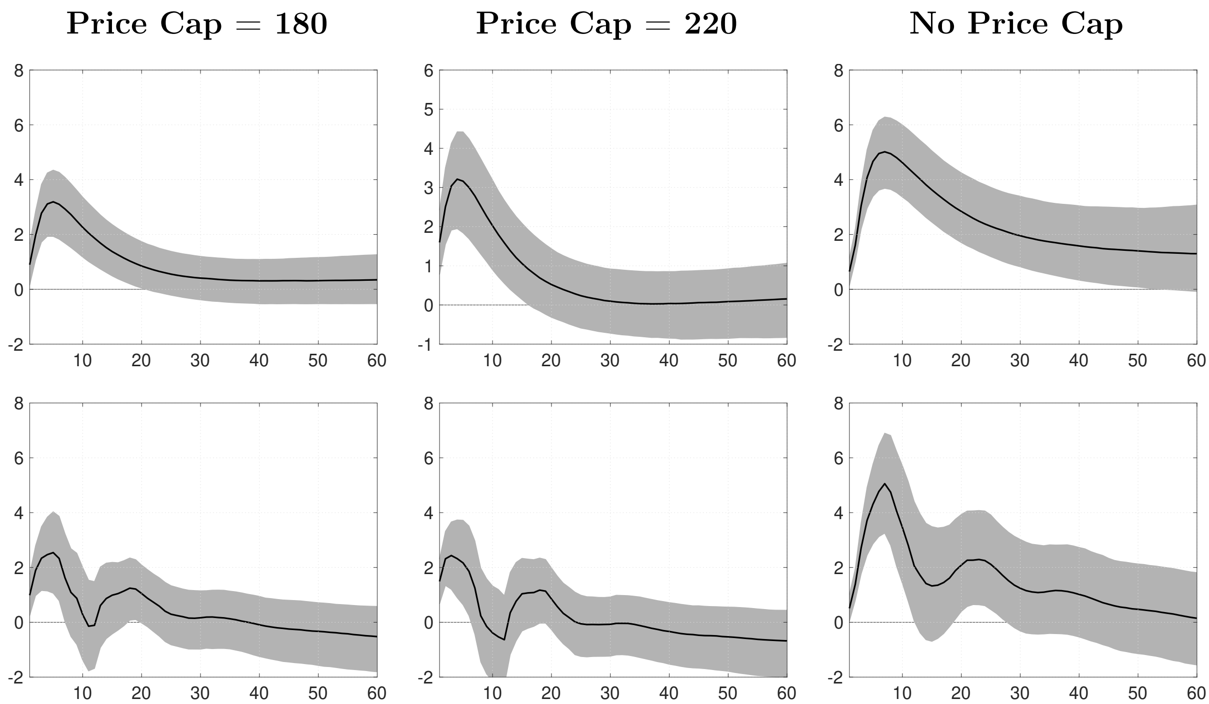
Figure C.3 shows the results for the period 2021–2023 and it holds the same conclusions seen above.

Figure C.3: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2021 - 23 for VAR(12) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



In Figure C.4 a comparison between a VAR(2) and a VAR(12) model for the period 2020-2022 is provided. If a VAR(2) model is considered, a higher price cap yields higher responses in the first horizons, while for a VAR(12) the situation is the same as in other periods.

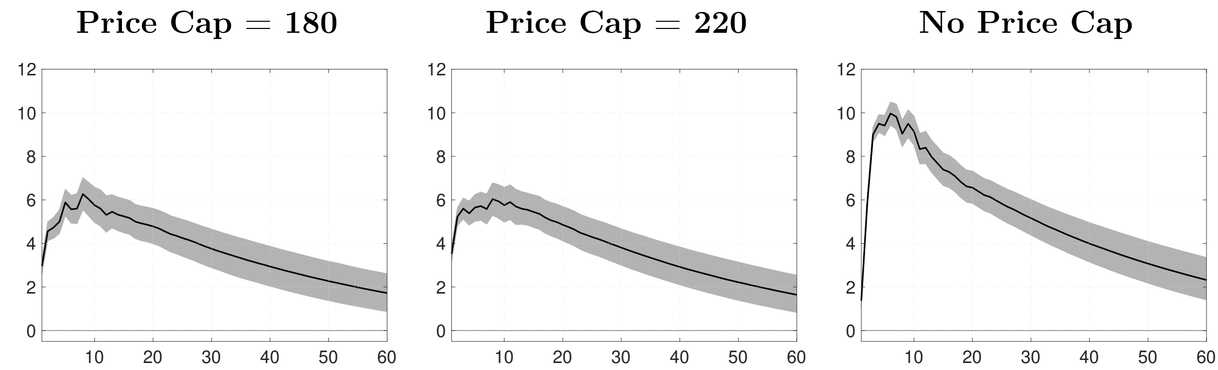
Figure C.4: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Germany for period 2020 - 22 for VAR(2) (top) and VAR(12) (bottom) with intercept and $U_{\min}(\text{pc}) = 20\% \cdot \text{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



Italy

Figure C.5 shows the response of electricity prices to a gas shock in the period from 2007 to 2023 for a price cap of 180 (left), of 220 (center) and for no price cap (right). Fixing a higher price cap yields almost the same results as fixing a price cap at 180, while it provides small responses with respect to not fixing a price cap.

Figure C.5: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2007 - 23 for VAR(12) with intercept and $U_{\min}(\mathrm{pc}) = 15\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



In Figure C.6, fixing a higher price cap yields almost the same results as fixing a price cap at 180 for the 2020–2023 period. Not fixing a price cap provides huge jumps.

Figure C.6: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2020 - 23 for VAR(12) with intercept and $U_{\min}(\mathrm{pc}) = 20\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.

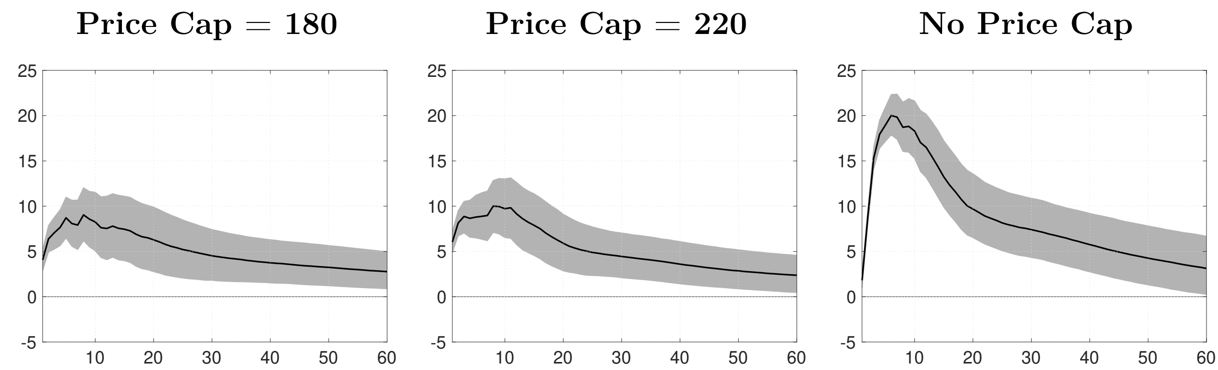
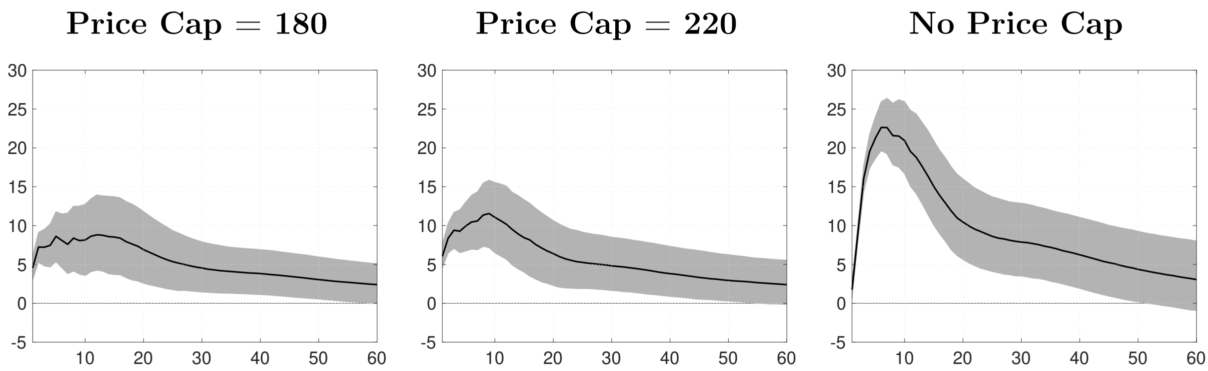


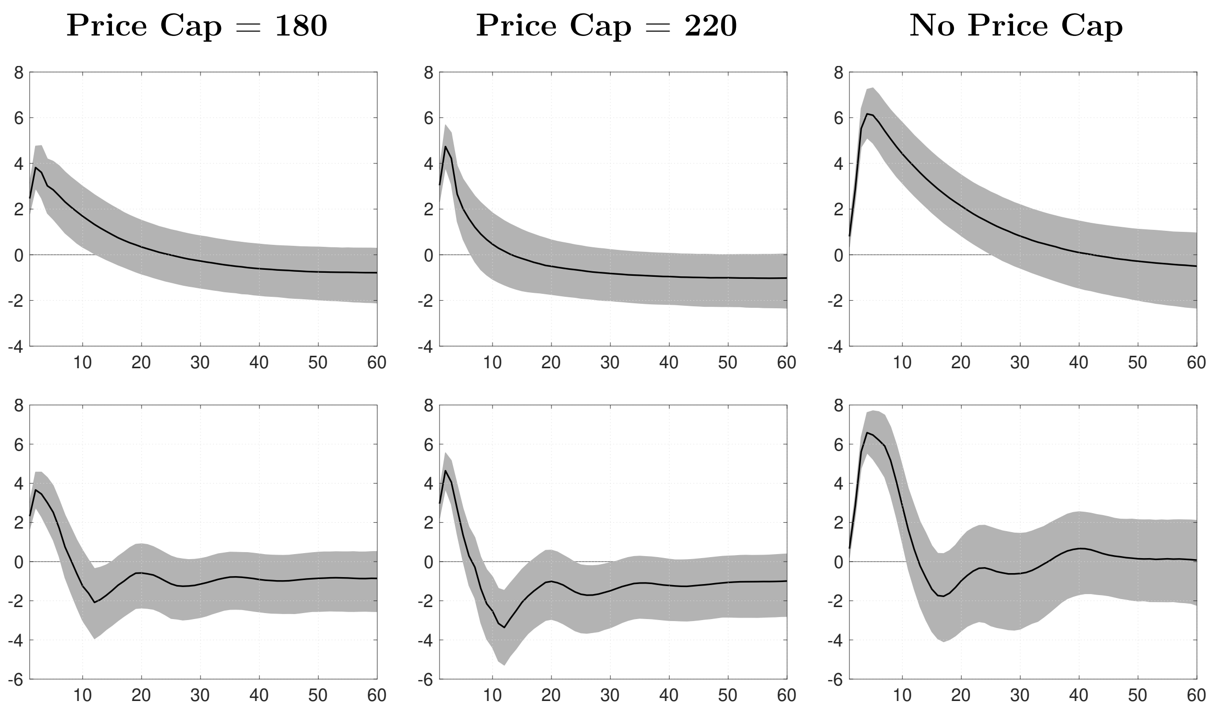
Figure C.7 shows the results for the period 2021–2023 and it holds the same conclusions seen above.

Figure C.7: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2021 - 23 for VAR(12) with intercept and $U_{\min}(\mathrm{pc}) = 20\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



In Figure C.8 a comparison between a VAR(3) and a VAR(12) model for the period 2020-2022 is provided. If a VAR(3) model is considered, a higher price cap yields higher responses in the first horizons, while for a VAR(12) the situation is the same as in other periods.

Figure C.8: Dynamic response of Electricity prices to a one-standard-deviation gas positive shock in Italy for period 2020 - 22 for VAR(3) (top) and VAR(12) (bottom) with intercept and $U_{\min}(\mathrm{pc}) = 20\% \cdot \mathrm{pc}$. The shaded area represents (16th, 84th) posterior credible intervals.



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