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Investigating the Effect of Green Finance Initiatives on Renewable Energy Penetration in Europe

Tibor Szendrei[1], Andrea Eross[1], Mustapha Mohammed[2], and Erkal Ersoy[1]

[1]Accountancy, Economics & Finance, Heriot-Watt University, UK
[2]King's College London, UK

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Abstract

As climate change becomes an ever-present problem, efforts have been made to make energy generation greener. One key tool to encourage renewable energy generation are feed-in-tariff policies, which have been employed in various countries across Europe. Using quarterly data, this study investigates the impact these policies had on the greening of the economy, on carbon emissions and on macroeconomic factors in European countries for the period 2011-2021. To achieve this, an energy augmented production function is postulated and estimated using a Bayesian Global VAR framework. We find a large degree of heterogeneity in the impact of feed-in-tariffs have on renewable energy penetration across the countries. Furthermore, negative externalities of simultaneous employment of green finance is found, highlighting that some coordination might be necessary to maximise the impact of such policies in achieving the goal of a greener energy profile.

Keywords: Bayesian Global VAR, Energy policy, Feed-in-tariff, GIRF, renewable energy, spillover effects.

1 Introduction

Climate change and its severe impact have been well documented in the literature, and there have been continual calls to increase renewable energy production in the energy generation profile of countries. One policy to encourage renewable energy generation is the feed-in-tariff framework, which has been widely adopted in European countries. The aim of these policies is to spur private-sectors' investment in renewable projects and speed up the "greening" of the economy. Supported by the European Green Deal (EGD), the European Commission aims to make Europe the first sustainable and energy independent continent by 2050. However, the green investment policies yielded ambiguous responses; both positive and negative impact on innovation, improvements in productivity and greening of the economy were recorded, as markets react to policy shocks asymmetrically (Böhringer et al., 2017). So far, the literature has been primarily concerned with the evaluation of negative externalities caused by the life cycle of Green House Gas (GHGs) emissions of renewable energies, which is well known to be difficult to quantify. However, while using renewable energy does not produce GHGs, there is a cost component of producing, transporting and storing renewable energy, thus generating a significant amount of GHGs.[1] Therefore, as renewable energy production and consumption increase, inadvertently so do greenhouse gas emissions increase. As per the EGD, to achieve carbon neutrality, a country should produce at least 45% of its total energy with renewable energy. The EU as a whole has achieved its 20% renewable energy production target by 2020, however it pledges to produce 42.5% by 2030.

All European countries support a green agenda, as it improves their energy security, creates jobs, and stabilises prices. The adoption of renewable energy presumably drives down the prices of fossil fuels, however it is disputed whether this is the case in the long-run. The literature does not establish whether subsidising renewable initiatives creates green jobs. However, harnessing green energy is more labour intensive compared to producing brown energy. Moreover, investment in renewable energy is slow due to the fact that these are initiated by governments, while the private sector is sluggish at recognising green investment opportunities (Borenstein, 2012). On the other hand, green investment generates network and learning externalities, as well as spillover effects that are more significant intra-nationally rather than inter-nationally (Moretti, 2012).

[1] Amponsah et al. (2014) provide an excellent overview of the literature pertaining to the GHGs emissions' life cycle, specifically assessing the environmental impacts renewable energy has on sustainable development.

Besides, energy generated from renewable sources, and technology innovation in general, has its hidden costs. The market value of renewable energy generated is time and location dependent, and as such, the correct price level at which green energy is priced is a function of its policy instrument (such as price paid and/or quantity) and the level of real interest rate. However, at the moment, Europe imports more renewable energy than it exports[2], despite the fact that the UK is the leading wind turbine energy exporter in the world.

Alas, energy trade linkages within Europe are scarce due to the fact that new renewable electricity transmission projects are not being developed. As such, some countries - in particular those with access to natural resources, namely wind and solar energy - that have a well developed green energy harvesting infrastructure, have excess renewable electricity unable to trade more widely but with their direct neighbouring countries. This in turn creates spillover effects. Due to this shortcoming, the EU has now prioritised the development of further electricity transmission interconnection projects (via mountains and submarine), imposing that at least 10% of renewable electricity to be traded within Europe.

Considering the above issues, the primary objective of this study is to evaluate the effectiveness of feed-in-tariff policies in achieving carbon neutrality, while simultaneously achieving macroeconomic policy objectives. Therefore, to quantify the impact of feed-in-tarrif policy implementation in Europe, we set the following arguments. In order to attain sustainable green economic growth in the long-run, the GDP growth per capita of an economy should increase, whereas the rate of unemployment, carbon emissions, interest rates and inflation should decrease, while at the same time energy prices should be less volatile. Reliance on intermittent energy sources such as wind and solar inevitably diminishes the penetration of renewable energy and sustainable green economic growth. We therefore assess the channel through which these variables' aggregate demand and supply shocks transmit spillover effects and externalities, and whether there are significant cross-country differences on the impact the shocks have on the greening of the economy.

To achieve the above objectives, the model first postulates an energy-augmented production function to infer which key economic variables to include in the model. We expect that the resulting energy-augmented economic model can successfully reveal several spillover effects: 1) there is technology spillover as outlined by Ertur and Koch (2007), 2) there is energy spillover

[2]More information on Europe's energy trade can be found here: `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=International_trade_in_products_related_to_green_energy#Overall.2C_the_EU_imports_more_green_energy_products_than_it_exports`

on account of energy trade, and 3) there is carbon price spillover on account of brown energy generation. Therefore, relying on methodologies that take the various spillovers into account is critical when studying the impact of feed-in-tariffs on energy generation. Using different sets of spatial weights, we are able to assess the spatial propagation and time dynamics of shocks. Moreover, in an effort to address heterogeneity observed between 29 European countries that can be solved using flexible prior distributions, this study uses the Bayesian Global VAR (BGVAR) methodology of Cuaresma et al. (2016) and Feldkircher and Huber (2016).

After estimating the GVAR model, we look at the posterior inclusion probabilities for the different equations. Doing so reveals very large degree of heterogeneity across countries for several of the estimated equations. In particular, the equation describing green finance[3] portrays the largest degree of heterogeneity with different variables being important for the different countries. Using the inclusion probabilities also reveals that the fossil fuel price dynamics enter each others equations, which highlights that it is not enough to include multiple global variables, but one also needs to model them jointly in a dominant unit.

The GVAR framework also allows us to create country specific and global shocks to the green finance variables, and study the impacts of it on various variables. Using the generalised impulse responses reveals that, for a select of countries, feed-in-tariff policies increase renewable energy production and decrease GDP growth — results that are in line with the literature. As for the effect of green financing on GHGs emissions, interest rate and inflation, the responses are mixed; some countries respond positively whereas others respond negatively. Unemployment increases for all identified countries when green financing policies are adopted. Global shocks reveal significant spillover effects through the real and energy sectors, in particular when GDP, unemployment and interest rate effects are considered.

The rest of this study is structured as follows. Section 2.1 introduces our methodology in detail, while section 3 discusses the characteristics of our dataset. Section 4 outlines our findings as well as our interpretations thereof, and section 5 concludes.

[3]In the context of this study, we refer to green finance as financial incentives to transition to sustainable energy production, and not as green finance which "represents the global financial community's first structured attempt to join financial performance and positive environmental impact" as defined by Berrou et al. (2019, p. 4).

2 Model and Methodology

2.1 Production function with Energy as input

To frame the analysis, we first postulate an economic model with energy as an explicit input. The role of energy in production has been studied extensively (Bercegol and Benisty (2022) among others), and Keen et al. (2019) proposed several versions of energy-augmented Cobb Douglas production functions. The authors found that energy as an input for labour and/or capital yields more intuitive properties for production profiles than simply including it as an extra factor of production. We will use this insight and propose to augment capital with energy. This results in the following production function:

$$Y_{i,t} = [A_{i,t}L_{i,t}]^{\alpha}[K(E_{i,t})]^{\beta} \tag{1}$$

where we hold $\alpha + \beta = 1$ for constant returns to scale. A represents total factor productivity and L is labour, $K(E)$ is capital as a function of energy, and Y is output of the economy (commonly measured with GDP). All measures are indexed with i for country, and t for time. Following Keen et al. (2019), we define capital, $K(E_{i,t})$, as:

$$K(E_{i,t}) = K_{i,t} \cdot E^{K}_{i,t} \cdot \xi^{K}_{i,t} \tag{2}$$

where $K_{i,t}$ is the capital stock, $E^{K}_{i,t}$ is energy consumed by capital and $\xi^{K}_{i,t}$ is a measure of efficiency of converting energy into output. Taking measurements of each component individually is a daunting task. Furthermore, there is even a debate in the literature about how to define the non-energy related variable $K_{i,t}$ (Sraffa, 1960; Pasinetti et al., 2003; Samuelson, 1966), which implies that the energy measures relating to capital are just as tenuous to capture. Nevertheless, $K_{i,t} \cdot E^{K}_{i,t}$ simply measures the sum of energy consumed in an industry (Keen et al., 2019). We will focus on the sum of energy consumption over all industries, denoted by $E^{\Sigma K}_{i,t}$. In essence, this measure is the amount of energy consumed in economy i at time t. As such, the last term that needs to be defined more explicitly is a measure of energy efficiency, $\xi^{K}_{i,t}$. We make the common simplifying assumption that any change in this term is captured by technology growth and is absorbed by A.[4]

[4]Due to the small sample size, it may be reasonable to go a step further and assume that $\xi^{K}_{i,t}$ is constant. However, because we have technology spillovers in our model, we feel that making the constant $\xi^{K}_{i,t}$ assumption would be less likely to hold.

With the above simplifications we can recast our production function as:

$$Y_{i,t} = [A_{i,t}L_{i,t}]^{1-\beta}[E_{i,t}^{\Sigma K}]^{\beta} \tag{3}$$

Dividing by $L_{i,t}$ and taking logs of the above equation yields an easily estimable function:

$$ln\Big(\frac{Y_{i,t}}{L_{i,t}}\Big) = (1-\beta)ln(A_{i,t}) + \beta ln\Big(\frac{E_{i,t}^{\Sigma K}}{L_{i,t}}\Big) \tag{4}$$

Estimation of functions of similar forms have been performed by Bercegol and Benisty (2022). In this paper we nest Energy production into the economic model, and as such we simplify the equation further. For the sake of notation convenience we write $y_{i,t} = Y_{i,t}/L_{i,t}$ and $e_{i,t}^{\Sigma K} = E_{i,t}/L_{i,t}$.

Equation (4) pins down the production function with energy as an explicit input. Nevertheless, it does not inform us about how Energy is obtained. Our next step is to formulate energy production as a function of several inputs. Note that in the above formulation, capital is simply a means to turning energy into useful output. As such, no additional market clearing conditions are needed as the price of energy is absorbed by the return to capital. Note, how in the above formulation, we have not allowed for energy storage, which implies that energy consumption will equal energy production. As such, we refer to $E_{i,t}^{\Sigma K}$ as energy production hereinafter.[5] We postulate a very simple energy production equation where there are two technologies available, one utilising Fossil Fuels (denoted as $E_{i,t}^{F}$) and one utilising Green Energy (denoted as $E_{i,t}^{G}$), as well as having energy imports from neighbouring countries.

$$e_{i,t}^{\Sigma K} = e_{i,t}^{F}(ln(y_{i,t-1}), P_t^F, \xi_{i,t}^F) + e_{i,t}^{G}(ln(y_{i,t-1}), \xi_{i,t}^G, GFin_{i,t}) + \sum_{j\neq i}^{N} e_{j,t}^{\Sigma K} \tag{5}$$

As in Equation (2), the ξ terms refer to the efficiency of technology. We assume that any changes in these terms are absorbed by A. This will simplify the above equation drastically at the cost of making advancements in technology to be shared among all the factors of the production. As such, this model should be interpreted as an exogenous energy augmented growth model. We leave for future research the possibility to allow for different rates of technological growth for the different types of technology.

Green Energy as a function of output and Green Finance ($GFin$) are motivated by the Environmental Kuznets Curve (EKC) of Grossman and Krueger (1991), who find an inverted

[5]We make this assumption on account of energy production data being more readily available for a large set of countries.

U-shape for pollution as a function of GDP per capita. The presence of the EKC was verified by Apergis and Payne (2009) for the USA, Jalil and Mahmud (2009) for China, and Pata (2018) for Turkey. In essence, high levels of output entail more tendency to invest in green energy. The inclusion of a Green Finance indicator is motivated by Zhou et al. (2020), who find evidence of green finance having an impact on environmental quality, which is measured by greenhouse gases. While it is reasonable to assume that the channel through which output and Green Finance influence renewable energy penetration is common, including both variables in the function can help partial out the impacts. Importantly, when output increases, the demand for more energy generation increases in tandem (as highlighted by the inclusion of $ln(y_{i,t-1})$ in the brown energy generation function in Equation (5)).[6] Inclusion of these variables can help identify the magnitude of a Green Finance shock that impacts energy generation.

For simplicity we will assume that the functions of brown and green energy production are linear. Given that the EKC is a non-linear relationship between pollution and GDP per capita, it can be argued that green energy generation might have non-linearities. Nevertheless, due to the small time-frame used in the analysis, it is unlikely that the countries would move much along a non-linear production curve. To this end, any non-linearities in the function can be approximated by a locally linear function. Note, that while countries do not portray non-linearities across time, non-linearities in the energy generation might still be an issue across countries. As such, estimating country specific parameters can alleviate concerns about potential mis-specifications. The need for country specific parameters motivates the usage of a GVAR framework in the EU setting.

In the above model we include both fossil fuels and foreign energy generation. The distinction between importing fossil fuels and energy is made for the simple reason, that (with current technology) it is not cost effective to import energy over large distances. As such, energy trade will only occur with neighbouring countries, while trade in fossil fuels does not have such a limit.

Note, that without making Green Energy a function of these variables, the only reason to invest in green energy would be to insure the economy against Fossil Fuel price shocks. This naturally means that there is also an indirect effect of Fossil Fuel prices on Green Energy generation.

[6]Equation (5) highlights how the factors of energy production showcase a large degree of endogeneity. Given the endogeneity present in the production functions, utilising a Vector Autoregressive (VAR) framework is advisable.

The final term remaining to estimate in Equation (4) is the Total Factor Productivity (TFP) term A. To account for technology spillovers, we opt to follow Ertur and Koch (2007)'s idea for spatial spillovers in technology:

$$A_{i,t} = \Omega_t(\mu)(e^{\Sigma K}_{i,t})^{\phi} \prod_{j \neq i}^{N} A_{j,t}^{\gamma w_{i,j}} \tag{6}$$

This function describes the level of technology of country i at time t using three terms: (1) a shared exogenous level of technology Ω_t, which grows at an exogenous rate μ; (2) a technology term that increases with energy production, which follows the logic of Arrow (1962) in the sense that as more energy is produced, there is an increased knowledge spillover within the economy governed by the parameter ϕ; and finally (3) a cross-border technology spillover $A_{j,t}^{\gamma w_{i,j}}$, where $w_{i,j}$ is the i, j element of the spatial weight matrix. It is important to note that there is a parameter γ that regulates the level of international spillovers which is assumed to be shared among the countries.

Taking logs of Equation (6) leads to:

$$ln(A_{i,t}) = ln(\Omega_t) + \phi ln(e^{\Sigma K}_{i,t}) + \sum_{j \neq i}^{N} \gamma w_{i,j} ln(A_{j,t}) \tag{7}$$

Ertur and Koch (2007) show how the above equation can be implemented in an econometric model. In particular, they note that with the inclusion of spatial variables, one is capable of capturing the impact of γ and ϕ. This motivates the usage of a GVAR model rather than a Panel VAR model, as using the spatial weights are a simple and elegant way to incorporate the parameters that account for the spillover effects.

In summary, our energy augmented production model is described by Equations (4), (5) and (7). Looking at these equations, a couple of things emerge as guidance for the estimation strategy. First, it is clear that one has to introduce spatial econometrics to incorporate the technology spillovers, as well as energy trade. Second, it is difficult to ascertain exogeneity of the parameters (e.g. production as well as green energy generation is influenced indirectly by the price of Fossil Fuels), which leads us to only consider estimators with which we can tackle endogeneity. Finally, global prices of Fossil Fuels are also important as it has an influence on output through energy production. On account of these considerations the Global VAR framework popularised by Pesaran et al. (2004) is an alluring candidate for estimation, nevertheless the limited sample size makes its application difficult. Consequently, we opt to utilise the Bayesian Global VAR (BGVAR) methodology popularised by Cuaresma et al. (2016) and

Feldkircher and Huber (2016).[7]

2.2 Estimation Framework

The starting point of a GVAR is the VARX. As above, the subscript i represents countries and t refers to time. We can represent country i using a VARX(p_i,q_i), where p refers to domestic variables' lags, and q refers to foreign variables' lags. Note, that the lag orders do not have to be shared across the countries. One can represent the VARX concisely as follows:

$$\begin{aligned} x_{i,t} &= c_i + \sum_{p=1}^{p_i} \Phi_{i,p} x_{i,t-p} + \sum_{q=0}^{q_i} (\Lambda_{i,q} x^*_{i,t-q} + \Psi_{i,q} \omega_{t-q}) + u_{i,t} \\ x^*_{i,t} &= \sum_{j=0}^{N} w_{i,j} x_{j,t}, \;\; w_{i,i} = 0 \end{aligned} \tag{8}$$

where c_i is a constant, w is a spatial weight used to construct the foreign variables x^*, and ω_t is a dominant unit as defined by Chudik and Pesaran (2013). It is important to note that $\sum_{j=0}^{N} w_{i,j} = 1$ (i.e. the spatial weight matrix is row normalised (Anselin, 2013)[8]), and that we consider contemporaneous effects of foreign variables in Equation (8) too. With the above specification it can be shown that $\bar{u}_{i,t} = \sum_{j=0}^{N} w_{i,j} u_{j,t} \xrightarrow{p} 0$ as $N \to \infty$, i.e. that the residuals of our system of equations are cross-sectionally weakly correlated.

To estimate the model described in Section 2.1, our $x_{i,t}$ includes the following variables: the log of Real GDP per capita (with year 2010 as a base in EUR), Primary Electricity Production per Capita, Ratio of Green Energy in primary electricity production (referred to as Ren), and a proxy for Green Finance using Feed-in-Tariff data. We also include the inflation rate, unemployment rate and the 10-year bond rate to allow for the impact of monetary policy to be studied. Total GHGs emissions are also included to measure the impact of green initiatives on pollution. The price of fossil fuels (oil and gas) are included in the model as global variables. The demand for clean energy has been growing, which has led to more supply of capital related to green energy, such as investment in photovoltaic panels. This naturally leads to lower costs related to installation of such projects. To ensure that these (global) supply changes

[7]For further details on the specifics of estimating the BGVAR, please see Boeck et al. (2022).

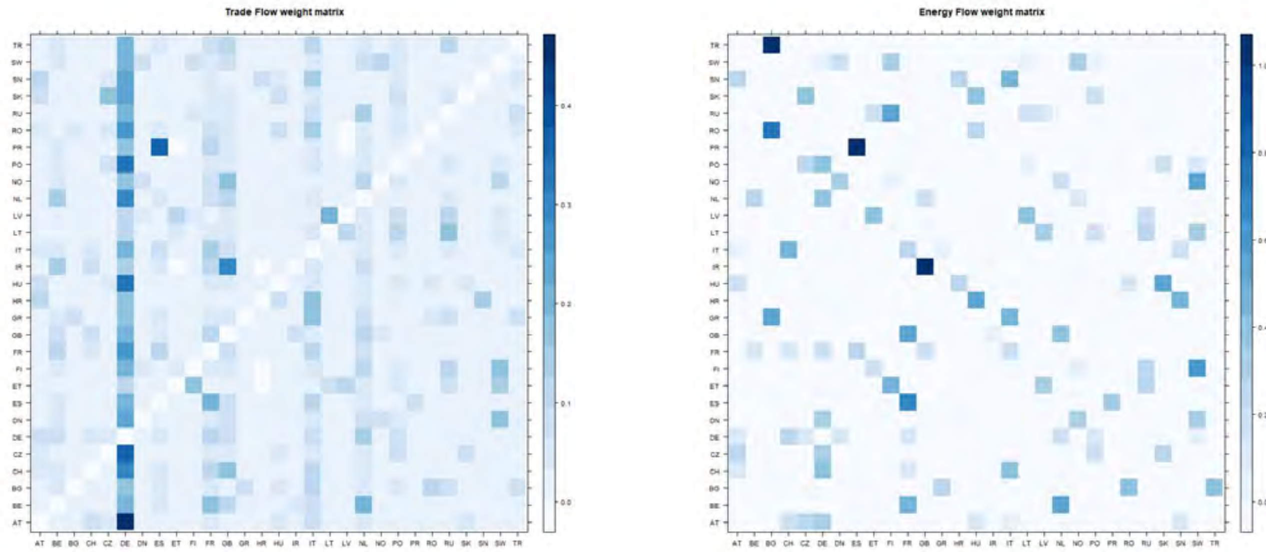
[8]Row normalisation of spatial weight matrices is essential for several reasons: 1) It ensures comparability across units by standardising the influence that each spatial unit exerts on another, making the total influence of neighbours consistent across units, and 2) It also maintains the integrity of the model by avoiding the artificial inflation of influence from densely connected regions over those with fewer connections.

are accounted for, we include the S&P Clean Energy Index as an additional variable in the dominant unit. We discuss our data in detail in Section 3.

From Equation (8) it is clear that the weights play a key role in ensuring an econometrically valid system of equations. To this end, we use two types of weights for the different variables. The first type of weight is constructed using bilateral trade flows data from 2016. Specifically, we take the average of Free On Board (FOB) exports and Cost, Insurance, and Freight (CIF) imports. This weight is applied to construct the foreign real and financial variables. However, as alluded to in Section 2.1, energy cannot be traded as easily, which necessitates a different weight matrix for the foreign Electricity Generation variable. An obvious candidate is to use a weight matrix that identifies the neighbours of each country, as electricity trade can only occur among direct neighbours. Nevertheless, this would not factor in that electricity trade is limited by cross-border electricity infrastructures in place. In an effort to create a better foreign energy variable, we utilise the entso-e Transparency Platform[9] to obtain cross border energy flows for the year 2016. As with trade flow data, we take the average of the import and export values of all goods over the whole year to get a single entry for each $w_{i,j}$. The differences in the two weight matrices are presented in the heatmaps shown in Figure 1. It is clear that the two weights are different, which potentially will lead to richer and more realistic spill-over profiles. In part (a) one can see that Germany is the main trading partner and acts as a hub, in particular for neighbouring countries. As for the Energy flow trade matrix shown in part (b), one can see that trade occurs exclusively with neighbours, but not equally with all neighbours. For instance, Turkey trades energy heavily with Bulgaria, but not with Greece, despite having borders with both; Romania trades more with Bulgaria than Hungary. Using the cross-border flows of electricity yields a more nuanced picture of electricity trade in Europe. This will be leveraged to capture energy spillovers better.

As mentioned above, the price of fossil fuels as well as the Clean Energy Index enter our country specific VARX models as common variables. These common variables are grouped together in a dominant unit and capture global variation akin to a dynamic factor (Chudik and Pesaran, 2013; Smith and Yamagata, 2011). In essence, the inclusion of these common variables in the country specific models forms connections between the country models and the dominant units model. Importantly, the dominant unit needs to be treated like the foreign variables, meaning that the contemporaneous as well as the lagged values enter the equations for the country VARs. Note that the proposed dominant unit in our benchmark framework

[9] More information can be found here: `https://transparency.entsoe.eu/dashboard/show`.



(a) Trade Flow (Row norm.: $\sum_{j=0}^{N} w_{i,j} = 1$) (b) Energy Flow (Row norm.: $\sum_{j=0}^{N} w_{i,j} = 1$)

Figure 1: Trade and Energy Flow Weight matrices

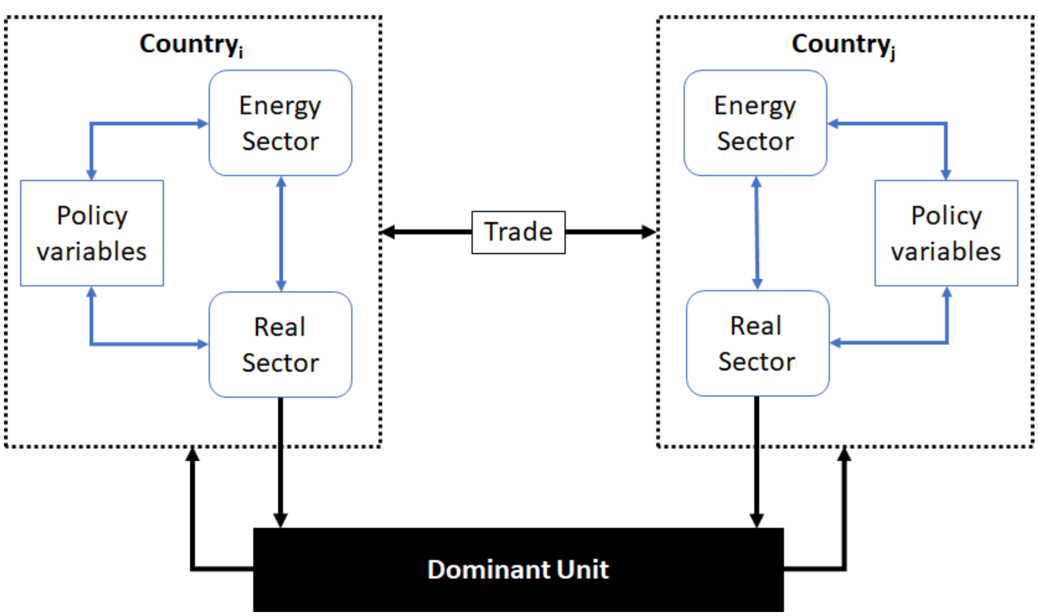


Figure 2: Schematic representation of the GVAR model

is a multivariate model. As such, we construct a multivariate model of oil prices, natural gas prices, and Clean Energy index as:

$$\omega_t = \mu + \sum_{i=1}^{p_\omega} \Phi_i \omega_{t-i} + \sum_{j=1}^{q_\omega} \tilde{x}_{t-j} + \eta_t \tag{9}$$

In the above specification, we allow for feedback effects from the countries to the dominant unit via $\tilde{x}_t$. This variable is constructed as $\tilde{x}_t = \tilde{W} x_t$. To keep the model parsimonious, we allow feedback effects only through output (GDP growth). This entails that the dominant units' equation will include the global variables, and the weighted GDP growth. The feedback effects also require a specific weight matrix. This weight matrix is constructed by taking a proportion of GDP per capita in 2016.[10] In essence, we assume that large economies have larger feedback effects on the dominant unit model. Note, that since the dominant unit model is also a VAR, the common variables in the dominant unit model can only enter with a lag to ensure exogeneity.

We present a schematic form of our GVAR in Figure 2. In each country, the Energy Sector, Real Sector and Policy variables (such as $GFin$) are determined endogenously. Through trade, other countries' energy and real sectors have an influence on each other, and this will be a primary channel through which spillovers occur. However, the dominant unit will also exercise an impact on countries through the price of Fossil Fuels (and Clean Energy Index). Finally, the Real Sector will have an impact on the dominant unit model through $\tilde{x}_t$. Comparing this figure to Equation (5), highlights how the GVAR framework is capable of recreating the key elements of the proposed energy production function: it allows for country specific coefficients, the different sectors are jointly determined, trade in electricity is captured, and finally price shocks of fossil fuels in brown electricity generation is captured through the dominant unit.

The Bayesian Global VAR (BGVAR) model can be estimated using the assumption of homoskedasticity or heteroskedasticity. Due to the fact that homoskedastic models are nested within heteroskedastic ones, we opt to estimate the model utilising stochastic volatility by implementing the method of Kastner (2019).

2.3 Prior choice

The model description revealed that there are many different lag orders that have to be selected: N lag parameters for domestic variables, N lag parameters for foreign variables, and 2 lag

[10] We opt to look at 2016 proportion of GDP per capita since all other weight matrices are based on 2016.

parameters for the dominant units model. This problem can be tackled in the Bayesian realm via priors that shrink unnecessary variables in each equation. In the VAR literature a very popular choice for shrinking away unnecessary variables is the Minnesota prior (Litterman, 1986; Koop et al., 2010). The key idea of the prior is that for each equation in the VAR, one can tune the importance of own lags, lags of other variables, and exogenous variables. While this seems reasonable for most VAR applications, GVAR allows for very complex univariate dynamics, and it might thus not be necessary to increase the lag length as much as one would in a standard VAR (Burriel and Galesi, 2018). Furthermore, there are two types of exogenous variables in the model (foreign variables, and dominant unit variables), while the Minnesota prior has one hyperparameter to fine-tune the shrinkage profile. On account of these reasons, we opt to utilise the Stochastic Search Variable Selection (SSVS) prior of George et al. (2008).

The key to the SSVS prior is that it imposes a mixture of normal distributions on the coefficients of the VARX models, formally specified as:

$$\Psi_{i,j}|\delta_{i,j} \sim (1-\delta_{i,j})\mathcal{N}(0,\tau_{0,j}^2) + \delta_{i,j}\mathcal{N}(0,\tau_{i,j}^2) \tag{10}$$

where $\delta_{i,j}$ is a binary random variable specific to coefficient j of country i. In essence, this variable regulates whether a variable is included in the equation or not. If the variable is not included in the equation (i.e. $\delta_{i,j} = 0$), then the prior on the coefficient is $\mathcal{N}(0,\tau_{0,j}^2)$, where $\tau_{0,j}^2$ is set to a small positive number. This will pull the coefficient's value towards 0. If, on the other hand $\delta_{i,j} = 1$ and the variable is included in the equation, then the prior on the coefficient is $\mathcal{N}(0,\tau_{i,j}^2)$, where $\tau_{i,j}^2$ is some large positive number. Making $\tau_{i,j}^2$ a large number means that when the variable is included in the equation, we have an uninformative prior on the coefficient, which allows the variable to have any value. Note, that it is possible to set the mean value of $\mathcal{N}(0,\tau_{i,j}^2)$ to be something other than 0 if we have prior information on the given coefficient.

An alluring feature of the SSVS is that by averaging the draws of $\delta_{i,j}$ leads to Posterior Inclusion Probabilities (PIP) for every coefficient. Note, that the PIP is going to be coefficient and country specific, allowing us to explore the drivers of renewable energy penetration in our production function framework.

3 Data

Our data contains quarterly observations for the period 2011Q1-2021Q4. For country selection, we focus on the European energy market with an aim to include as many countries as possible.

We consider 29 countries in our estimation (the full list of countries is provided in Table 5 in the Appendix), including Turkey, Norway, Switzerland, and Russia in addition to the majority of the EU countries. Our sample consists of both developed and emerging European economies, as well as the most important renewable energy producers. Some countries in the Balkan region were not included due to the unavailability of data pertaining to green electricity generation. Although these countries differ due to their specific monetary and fiscal policy, use of common currency and free capital flows and labour markets, they are also highly integrated via trade links. Due to the fact that energy is traded primarily via onshore neighbouring country networks, we exclude island countries such as Cyprus, Iceland and Malta from our estimation. There is however a well developed energy transition and interconnection between the UK and the Republic of Ireland via the Single Electricity Market using the offshore grid infrastructure. For the purpose of this study, we focus on the most prevalent renewable energy sources in the region, namely wind and solar generation. We present the list of variables employed in our analysis in Table 4, which is found in the Appendix.

Subsidising green initiatives was non-existent before the year 2000. The only initiative related to renewable energy incentive was the "Stromeinspeisungsgesetz" law adopted in 1991 in Germany, which was later replaced by the "Energiewende" initiative written in law in 2010. Since then, however, Germany has moved away from feed-in-tariffs to energy auctions, which led to the polarisation of the renewable energy transformation scene (Leiren and Reimer, 2018). Similar initiatives that have been implemented in Denmark and Spain started to penetrate the energy market in the early 2000s, with schemes that are now called feed-in-tariff. Besides, renewable energy policy instruments come in two major forms: price initiatives, such as feed-in-tariffs and quantity initiatives. Under these schemes, major energy providers offer long-term contracts to small renewable energy producers at a fixed above-market price, providing certainty for renewable energy investments. Many EU countries have adopted this "price-based" framework over the past 20 years, however few countries, such as Ireland, Norway, Romania, Sweden and the UK have also adopted "quantity" based green certificate schemes. Because of this wide and sequential adoption of the framework, we are going to use the feed-in-tariff rates as a proxy for our Green Finance ($GFin$) variable for the European energy market as follows:

$$Gfin_{t,j} = \sum_{s=1}^{2} Feed\ in\ Tariff_{t,j,s} \times Energy\ Produced_{t,j,s} \tag{11}$$

where s is the type of energy generation: wind or solar. Feed-in-tariff rates, which are sourced from the OECD, are a form of monetary incentive paid for surplus energy produced by accredited installation of renewable technologies. As mentioned earlier, this variable is a proxy of total green financing. Nevertheless, we argue that the above proxy is a sufficient measure to track green finance incentives. Norway, Romania and Poland does not have feed-in-tariff data.[11]

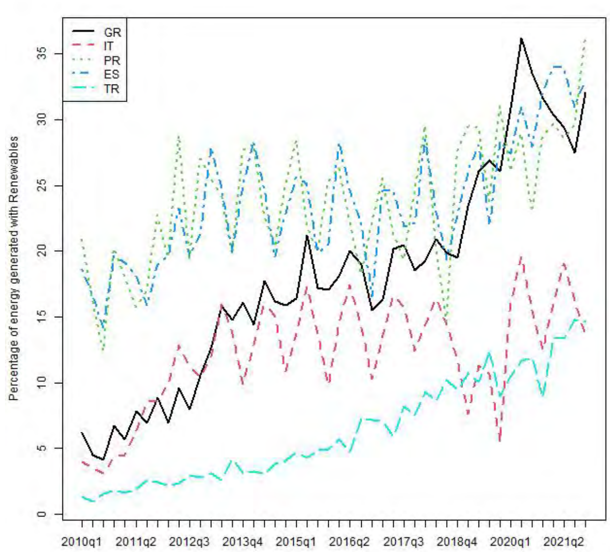
To gauge the proliferation of renewable electricity in electricity production, we opt to construct the following measure:

$$Ren_{t,j} = \frac{Total\ Renewable\ Electricity\ Generation_{t,j}}{Net\ Electricity\ Generation_{t,j}} \tag{12}$$

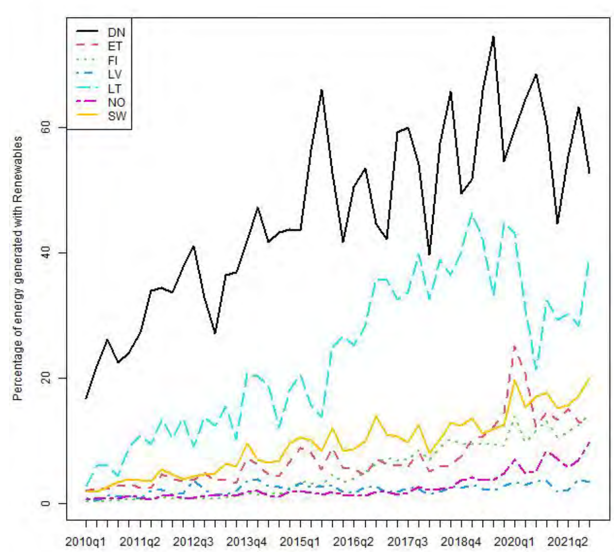
Makieła et al. (2022) use a similar measure to gauge the greenness of an economy and call it the "going green indicator". Such a measure is preferred to simply looking at total renewable electricity generation, since our measure of choice tracks whether renewable electricity is displacing old electricity generation — a critical distinction for our purposes. Net Electricity Generation accounts for the total primary electricity supply (adjusted for exports, imports and stock changes) of wind and solar energy only, and is the equivalent of heat produced of one ton of crude oil). The data was sourced from the International Energy Agency (IEA) (IEA, 2022). As shown in panels (a) to (d) of Figure 3, the countries with the largest proportion of renewable energy in energy generation in Europe are Denmark, Lithuania, Germany and Ireland. Note that the trajectories are also vastly different for the various countries, with Greece, Romania, Hungary, Croatia, and the Netherlands showing larger green energy penetration than average at different periods. We also see from the figures that there is a large degree of seasonality in the country profiles, which has to be dealt with. We note, that feed-in-tariffs have been used extensively to spur investment in wind and solar energy generation, while it has been less extensively used for hydroelectricity. Due to this reason our results will be in relation to the feed-in-tariff policies effectiveness in increasing the share of wind and solar electricity in total electricity generation. Given how hydroelectricity generation is largely geography dependent, and that there has been no big changes in hydroelecticity per capita generation in the sample period, we do not expect that the exclusion of this source to impact our overall results. Be-

[11] Green loans have become more prevalent in some countries since 2016, which might further spur renewable energy generation, but is not captured in our Green Finance variable. Nevertheless, the green loan and green bond market has been in its infancy between 2016 and 2022, if at all available in the countries considered. We leave for future research to re-examine the impact of these new financial tools once they have proliferated more countries' credit markets.

sides, of all renewable energies, the production of offshore wind energy has the least burden on emissions.



(a)



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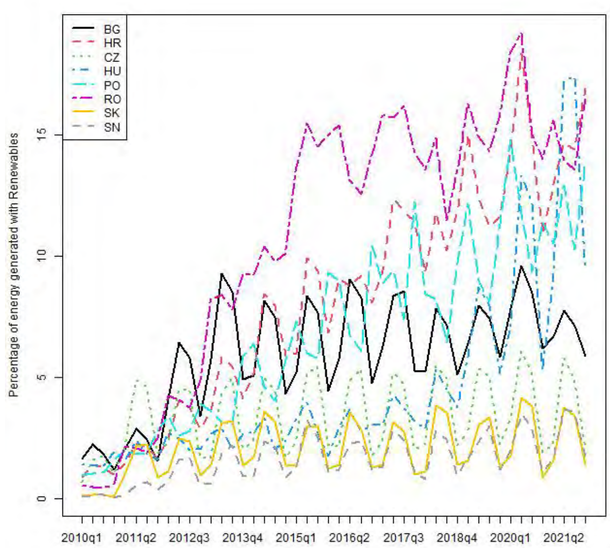
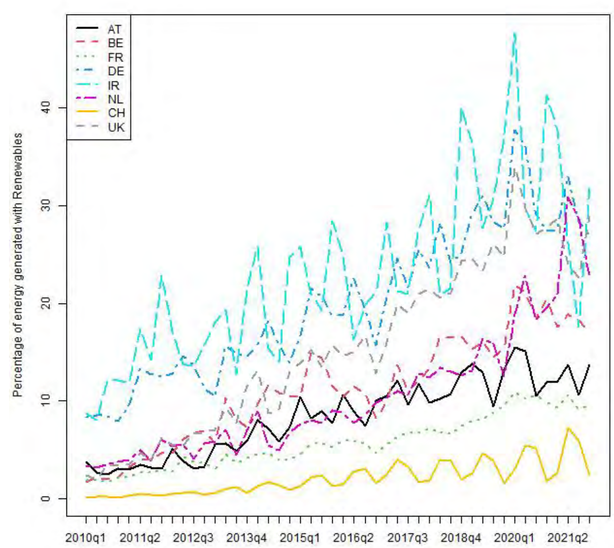


(c)



(d)

Figure 3: Percentage of energy production generated with Solar and Wind Energy. We separate the countries into four sub-figures to be able to show the difference in magnitudes.

To calculate quarterly GDP per capita growth, we take quarterly chain linked volumes (2010) of GDP from Eurostat where available[12]. This is then divided by the linearly interpolated annual population figures obtained from the BP Statistical Review of World Energy (BP, 2022).

Primary electricity per capita (denoted by E) accounts for the net production of electricity generated using both fossil fuels and renewable energy in a country, divided by the total number of the population. The data, which includes fossil fuels plus renewable generation, is independent of the use of energy, and is taken from the monthly IEA database. To create quarterly electricity supply values, we take the sum of the three months of the corresponding quarter. The same is done to calculate quarterly values of wind and solar electricity generation per capita.

For the electricity variable, Bulgaria, Croatia, and Romania did not have monthly data available before 2015. To tackle this, yearly growth rates were used to extrapolate the data from 2015 back to 2010. The yearly growth rates were taken from the BP Statistical Review. For Russia, the whole electricity series is linearly interpolated on account of only having access to annual data from the BP Statistical Review.[13]

We collect monthly data, which we transform to quarterly frequency, for the S&P Global Clean Energy Index from Bloomberg (denoted by P_{clean}). This index is aimed at gauging the performance of global clean energy-related companies that make up the 100 constituent list. However, for Europe, companies from Denmark, Portugal, Germany, Switzerland, Spain, Italy, Austria, Norway, Turkey, France and Greece contribute to the index weight (Table 3 in the Appendix shows the index weight for each country). The clean energy industry has facilitated the spillover of risk to other markets; when clean energy prices fluctuate (either rise or fall), funding in the like of subsidies - such as feed-in-tariffs - will have an impact on energy firms, and ultimately on the economy (Liu et al., 2021). On the other hand, an increase in oil prices and economic activity leads to an increase in green energy production (Bloch et al., 2015).

Our analysis focuses on the impact of green finance on European economies. However, the EU had an economically tumultuous time during the sample period. In particular, the European sovereign debt crisis has led to a long period of low interest rates. While green policies such as "feed-in-tariffs" focus on reducing the uncertainty of the revenues earned in green projects, building green infrastructure is capital intensive. As such, we also include the long-term interest rate as a variable.[14] This is done to ensure that the the responses to the shock

[12]Russia's quarterly real GDP is taken from the FRED database.

[13]Due to this data limitation we do not construct the renewable energy variable for Russia.

[14]We opt to use long term interest rates rather than short term ones for the following reasons: 1) they

of Green Finance variable is not influenced by the monetary policy shocks. Other monetary variables, namely inflation rate and unemployment, are also included on account of interest rates being endogenously determined in monetary policy models.

It is well documented in the literature that in the long-run, shock driven changing inflation and interest rate expectations destabilise sustainable economic growth. Producing renewable energy demands high capital expenditures, and increasing market uncertainty has a direct effect on investment and ultimately consumption. If the cost of financial funds increases, above equilibrium level interest rates potentially inhibit renewable energy manufacturers as well as consumers from accessing the essential amount of capital for renewable energy demand, while increasing inflation rates discourage investment in green initiatives (Akan, 2023). We therefore include inflation calculated from the Headline Consumer Price Index (denoted by $Infl$), which is sourced from the World Bank, and the 10-year government bond rate (denoted by Int), which is sourced from the FRED database, in our model.

Some evidence highlights that it is difficult to reduce GHGs while at the same time attaining sustainable growth and reducing unemployment. Ng et al. (2022) argue that an increase in the unemployment rate leads to the reduction of the carbon footprint, which is in sharp contrast with the argument of Naqvi et al. (2022) who argue that producing renewable energy reduces unemployment rates. We therefore include unemployment (denoted as $Unemp$) as a variable in our model to clear up ambiguity. The majority of unemployment data is sourced from the World Bank, whereas unemployment data for Denmark, Greece, Italy, Netherlands and Latvia are sourced from the FRED database, which is based on OECD data.

Quarterly green house gas emission data (denoted by $GHGs$), which comprises of carbon dioxide, methane, nitrious oxide and fluorinated gases is measured by the International System of Environmental-Economic Accounting. It accounts for gases emitted into the atmosphere owing to economic activities of households and businesses.

The dominant unit's variables' data for P_{oil} and P_{gas} are taken from Refinitiv. P_{oil} is the Brent Crude Oil FOB price for a barrel of crude oil, while the P_{gas} variable is Natural Gas import prices at German border. The S&P Clean Energy Index, which measures the performance of companies in global clean energy-related businesses, is also taken from Refinitiv.

We difference all variables for all countries to ensure stationarity. For GDP, Total Energy production, Price of oil, Price of Gas, and Clean Energy index we take year-on-year percentage

also encompass country specific risks; 2) they are not shared among the Eurozone countries; and 3) Green infrastructure projects are inherently long term projects.

changes. For the interest rate, inflation, renewable energy penetration, and unemployment rate we take the raw difference from the previous year such that these variables track percentage point changes from the previous year, rather than the percentage change. This transformation was chosen on account of the variables already being in percentage terms, and thus making it easier to interpret changes in percentage points, rather than percent changes of percentages. Finally we also utilise raw differences for the feed-in-tariff variable. This was done on account of the feed-in-tariff policy being introduced during the sample period for many countries, and consequently this variable has many zero entries. As such, the unit of this variable will be euros per capita spent via feed-in-tariffs. Naturally, since we still use raw changes from the previous year, interpretation will be changes in the amount dedicated to green energy production through the feed-in-tariff scheme.

It is not realistic to assume that all variables will have foreign counterparts. As such, $GFin$, GHG and Ren will not have a foreign counterpart. The first is constructed based on feed-in-tariffs, and there is no reason to assume a direct cross-country relationship in this dimension. The latter variable lacks a foreign counterpart because, to our knowledge, energy trade does not depend on the source of energy production. In other words, we believe trading partners are not concerned about where the electrons they are importing have come from, partly because it is physically infeasible to trace this to its source. We note that lagging behind other countries in terms of green energy penetration can lead to political pressure, but identifying political channels through which green energy production is achieved is beyond the scope of our study. Finally, GHG of a specific country is unlikely to be influenced directly by trade partners, and instead is impacted indirectly through production.

4 Results

In order to filter out the global green energy effects from feed-in-tariff effects, we propose the following three models.

In **Model 1** we include the Clean Energy index (P_{clean}) along with the oil and gas prices (P_{oil} and P_{gas}) as global weakly exogenous variables into the dominant unit. We call this the base (or benchmark) model and assume that feed-in-tariff policies were introduced in all of the countries of interest, and these trade with each other via the two trade matrices W_{Trade} and W_{Energy}. Due to the fact that we have a system of equations in the GVAR, we have equations for all our country specific variables. However, we demonstrate our reasoning using only the output ($y_{i,t}$ representing GDP/capita growth) and dominant unit equations, as shown in Equation (13).

$$
\begin{aligned}
y_{i,t} &= y_{i,t-1} + X_{i,t-1} + P_{oil,t} + P_{gas,t} + P_{clean,t} + W_{trade} Z_{R,-i,t-1} + W_{energy} Z_{E_s,-i,t-1} \\
P_{p,t} &= W_{DU} y_{i,t-1} + P_{oil,t-1} + P_{gas,t-1} + P_{clean,t-1}
\end{aligned}
\tag{13}
$$

where $X_{i,t-1}$ is a vector of domestic variables consisting of total energy per capita, renewable energy penetration, GHGs, unemployment, inflation and interest rate variables. W_{trade} and W_{energy} represent the trade and energy flow matrices. The vector $Z_{s,-i,t-1}$ is a subset of $X_{i,t-1}$ and it specifies the variables of every country except i for time t and sector s. The sectors are given in Figure 2 and correspond to the real sector (denoted by R), containing y (as GDP/capita growth), unemployment, inflation and interest rate; and the energy sector (denoted by E), which contains the energy variable E. Note, that $GHGs$, $Ren_{t,j}$, and $GFin$ are not part of either sector, and instead are in their own block termed Policy variables, that are domestic only. The dominant unit will have three equations specified by the subscript p (for P_{oil}, P_{gas} and P_{clean}) based on Equation (9).

Due to the fact that the Clean Energy index (P_{clean}) is a global measure, and 24% of the weight is based on European countries' green energy input (see Table 3 in the Appendix), one could argue that this index is not exogenous. To ensure that our results are not driven by an endogenous common variable, we re-estimate the model without the Clean Energy index. Therefore, in **Model 2**, the dominant unit consists only of the oil price (P_{oil}) and gas price (P_{gas}. This model's equations are take the following form:

$$
\begin{aligned}
y_{i,t} &= y_{i,t-1} + X_{i,t-1} + P_{oil,t} + P_{gas,t} + W_{trade} Z_{R,-i,t-1} + W_{energy} Z_{E,-i,t-1} \\
P_{p,t} &= W_{DU} y_{i,t-1} + P_{oil,t-1} + P_{gas,t-1}
\end{aligned}
\tag{14}
$$

In **Model 3**, we set Russia to be the dominant unit, and the price variables become country specific for Russia. Considering that for the time frame we investigate the majority of oil and gas imports to Europe are from Russia, this specification is set up to ensure that our results are not driven by mis-specifying the underlying network structure.[15] One might argue that this entails an underlying network structure where Russia is the dominant unit. As such, the

[15]We are aware that since the start of the Russia-Ukraine war, the value of fossil fuel exports from Russia to Europe has decreased significantly due to imposed sanctions (McWilliams et al., 2023). However, we do not include this time frame into our investigation.

results of Model 3 allows us to verify a different underlying network structure for the common variables. Formally, Model 3 is as follows:

$$
\begin{aligned}
y_{i,t} &= y_{i,t-1} + X_{i,t-1} + P_{oil,t:t-1} + P_{gas,t:t-1} + W_{trade}Z_{R,-i,t-1} + W_{energy}Z_{E,-i,t-1} \\
P_{p,t} &= y_{RU,t-1} + X_{RU,t-1} + P_{oil,t-1} + P_{gas,t-1} + W_{trade}Z_{R,-RU,t-1} + W_{energy}Z_{E,-RU,t-1}
\end{aligned} \tag{15}
$$

Note, that this output (GDP/capita growth) equation slightly changes for Russia considering the price variables are endogenous. On account of this, the Price explanatory variables for Russia are included with a lag.

The GVAR model was ran with a burn-in of 50,000 draws. 25,000 draws were saved with a thinning of 5 (i.e. every 5^{th} draw was saved). Explosive draws (i.e. draws with an eigenvalue of above 1) are discarded to ensure only stationary draws are considered when making inference about the models. The lag order of the GVAR is set to one.[16]

Table 1 shows the first order serial correlation of cross-unit residuals. This table summarises the share of p-values that fall into different significance categories. Importantly, since the null hypothesis is that there remains no serial correlation in the residuals, we ideally have a large share of p-values when the probability is larger than 0.1: 148 p-values for Model 1 (67.89% of the total of p-values), 143 for Model 2 and 145 for Model 3. The table verifies the findings of Burriel and Galesi (2018), that in a GVAR even low lag orders result in models with modest serial correlation in the residuals.

To assess whether the estimation algorithm has converged, Geweke's statistic is used. This diagnostic is based on testing the equality of the means of the first 10% and the last 50% of the saved draws. If the samples are drawn from a stationary distribution, then the two means should be equal. Importantly, this test statistic is asymptotically standard normally distributed. Inspecting the chains of Model 1, 9.39% of the variables' z-values exceed the threshold of 1.96, which is indicative of model convergence. For Model 2 and 3, Geweke's statistics are 9.14% and 8.95%, respectively. These values show that only a small fraction of all coefficients did not convergence, inciting confidence in our models' performance.

[16]The small lag number is not an issue, as the serial correlation of the residuals is negligible.

	Model 1		Model 2		Model 3	
Prob	# of p-values	as %	# of p-values	as %	# of p-values	as %
>0.1	148	67.89%	143	65.9%	145	66.82%
0.05-0.1	9	4.13%	9	4.15%	8	3.69%
0.01-0.05	18	8.26%	20	9.22%	20	9.22%
<0.01	43	19.72%	45	20.74%	44	20.28%

Table 1: F-tests of first order serial autocorrelation of cross-unit residuals for Models 1, 2 and 3

Finally, Table 2 presents the cross-unit correlation of the residuals. The key assumption of the GVAR model is that there is almost no cross-unit correlation in the residuals. The importance of this assumption is highlighted in Dees et al. (2007), who stress that evidence of violation of said assumption would make structural and spillover analysis impossible. The results reveal that there is limited cross unit correlation, as for all three models, the probability of less than 0.1% cross-unit correlation in the residuals - as expected - are significantly high for most variables (with values above 78%). $GFin$ and Ren have more equations with larger cross-correlation in the residuals, which is likely on account of these variables not having a foreign counterpart in the specification. As such, we can be reasonably confident that the foreign variables absorb any cross-country correlation in the residuals.

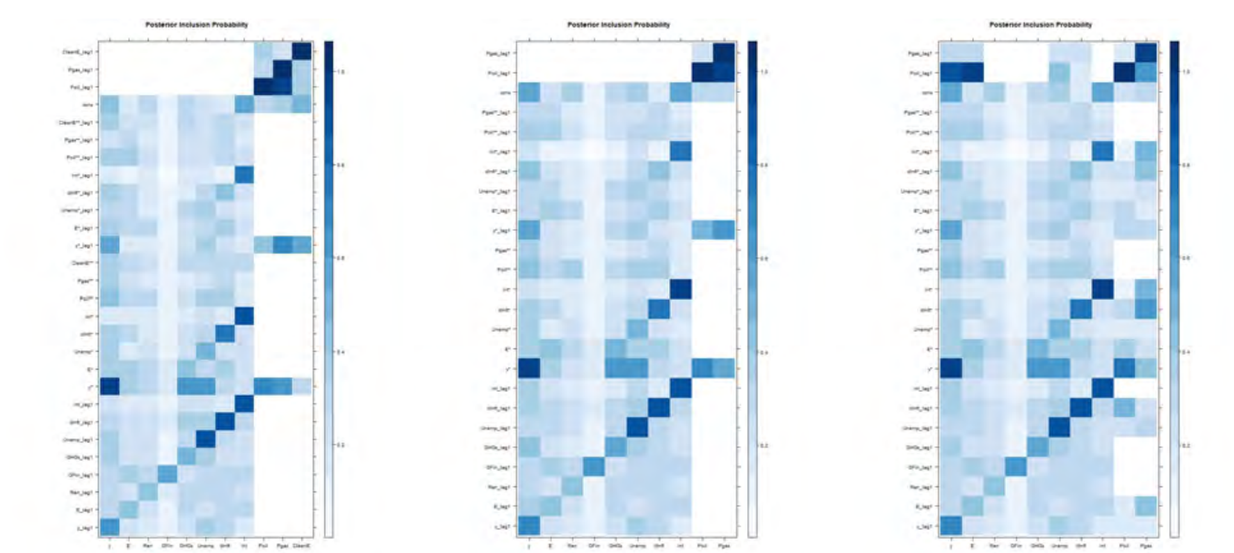
4.1 Inclusion Probabilities

The average posterior inclusion probabilities (PIP) for the countries is shown in Figure 4. Looking at the dominant unit, which are given in the rightmost three columns in each model's panel, we see that demand side effects are important as both the contemporaneous and lagged growth in output per capita enter the equations of the fossil fuel prices. Importantly, demand feedback effect enters all price equations as well as the Clean Energy Index equation signifying the importance of including such feedback effects when modelling fossil fuel prices. The PIP results for the dominant unit also reveal that fossil fuel prices have an impact on each other. This highlights that it is critical to model fossil fuel prices jointly when studying energy markets.

While Figure 4 is adequate to analyse which variables enter the different equations on average, there is a possibility that there will be heterogeneity across countries for the different equations. To this end, Figures 5, 6, and 7 look at PIP of several equations for each country

Prob	y (GDP)	E	Ren	$GFin$	$GHGs$	$Unemp$	$Infl$	Int
Model 1								
<0.1	23 (79.31%)	30 (100%)	7 (25%)	20 (86.96%)	6 (25%)	29 (100%)	26 (89.66%)	22 (91.67%)
0.1-0.2	6 (20.69%)	0 (6.67%)	10 (35.71%)	3 (13.04%)	8 (33.33%)	0 (0.00%)	3 (10.34%)	2 (8.33%)
0.2-0.5	0 (0.00%)	0 (0.00%)	11 (39.29%)	0 (0.00%)	10 (41.67%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
>0.5	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
Model 2								
Prob	y (GDP)	E	Ren	$GFin$	$GHGs$	$Unemp$	$Infl$	Int
<0.1	26 (89.66%)	26 (89.66%)	5 (17.86%)	18 (78.26%)	7 (29.17%)	29 (100%)	25 (86.21%)	23 (95.83%)
0.1-0.2	3 (10.34%)	3 (10.34%)	12 (42.86%)	5 (21.74%)	9 (37.5%)	0 (0.00%)	4 (13.79%)	1 (4.17%)
0.2-0.5	0 (0.00%)	0 (0.00%)	11 (39.29%)	0 (0.00%)	8 (33.33%)	0 (0.00%)	0 (0.00%)	10 (41.67%)
>0.5	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
Model 3								
Prob	y (GDP)	E	Ren	$GFin$	$GHGs$	$Unemp$	$Infl$	Int
<0.1	25 (86.21%)	26 (89.66%)	5 (17.86%)	18 (78.26%)	7 (29.17%)	29 (100%)	25 (86.21%)	23 (95.83%)
0.1-0.2	4 (13.79%)	3 (10.34%)	12 (42.86%)	5 (21.74%)	8 (33.33%)	0 (0.00%)	4 (13.79%)	1 (4.17%)
0.2-0.5	0 (0.00%)	0 (0.00%)	11 (39.29%)	0 (0.00%)	9 (37.5%)	0 (0.00%)	0 (0.00%)	10 (41.67%)
>0.5	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)

Table 2: Average pairwise cross-unit correlation of residuals. Occurrences are shown in parentheses.



(a) M1 Average PIP (b) M2 Average PIP (c) M3 Average PIP

Figure 4: Average Posterior Inclusion Probabilities for all models

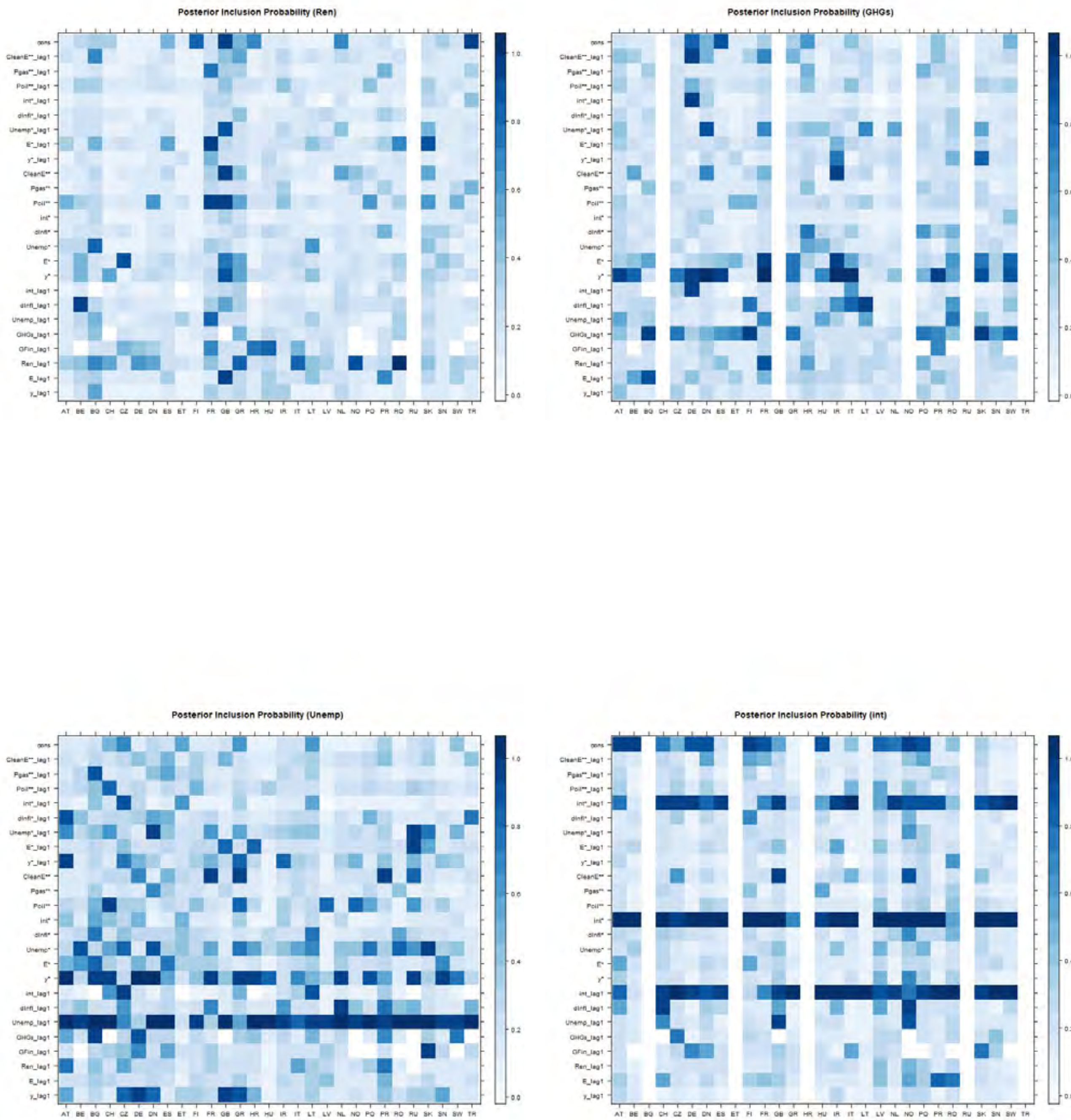


Figure 5: M1 Country specific Posterior Inclusion Probabilities for select equations

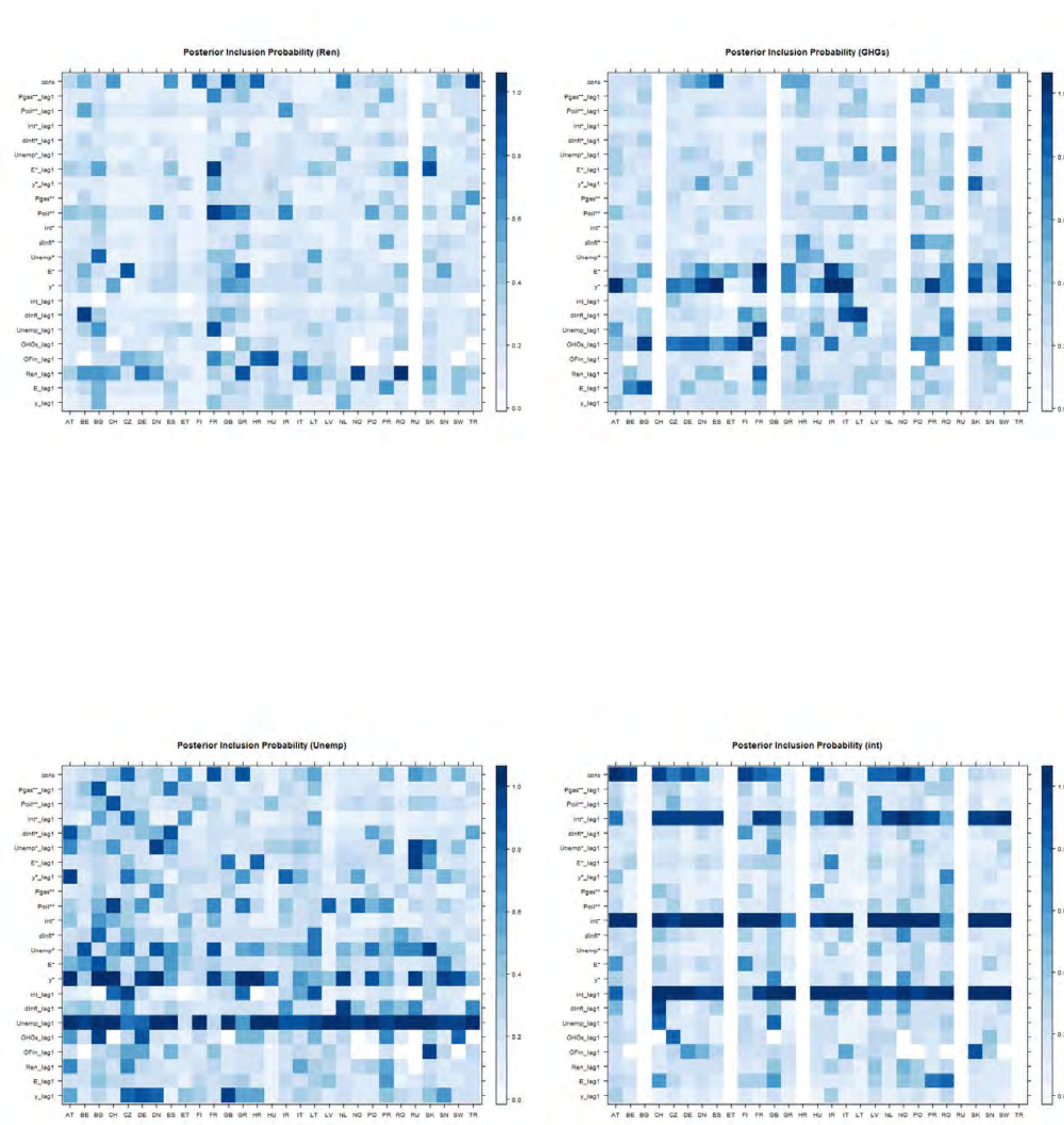


Figure 6: M2 Country specific Posterior Inclusion Probabilities for select equations

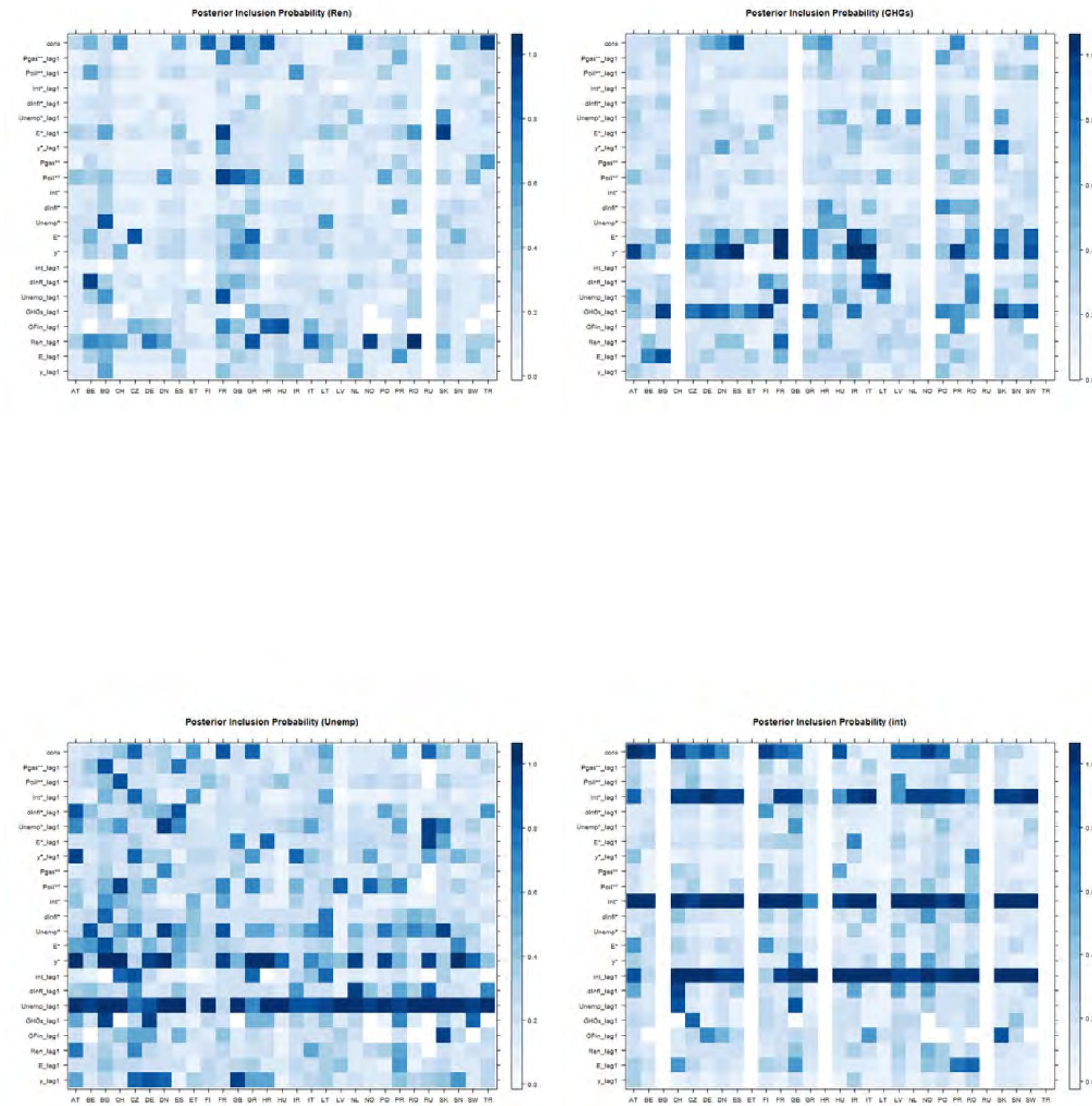


Figure 7: M3 Country specific Posterior Inclusion Probabilities for select equations

individually. Importantly, this figure reveals that there exists large heterogeneity across the countries in which variables enter the equations. Focusing on the *Ren* equation, we can see that $GFin$ is important for Czech Republic, Germany, France, Croatia, Hungary, and Italy for all three models. Interestingly, the price of oil P_{oil} also enters the equation for some countries, highlighting that insuring against fossil fuel fluctuations is a potential driver for expanding renewable energy generation. Foreign energy per capita growth also seems to be important for some countries, such as the Czech Republic, the UK, and Greece. This variable is important for the aforementioned countries for all three model specifications. This is likely driven by the fact that the more neighbouring countries one can trade energy with, the more likely it is that one can transition to green energy without it leading to periods of blackout in that country. Note how this reasoning also entails that there is a possibility of negative externalities in transitioning to green energy: if all countries do so simultaneously, this insurance net cannot be relied on at the early stages of the transition.

Looking at GHG equations, we see that there is less heterogeneity than in the *Ren* equation. Broadly, foreign output per capita and the own lag of GHG are two variables that are often selected, with some degree of heterogeneity for other variables. Furthermore, as with the *Ren* equation, there are several countries where no variable is particularly important. This is true for all three model specifications.

Turning to *Unemp* equations, we note that noticeably less heterogeneity across countries. In particular, unemployment rate seems to be dominated by its own lag and foreign output. However, other variables frequently enter the equation for some countries, such as the lag of domestic output for Germany, Denmark, Czech Republic, and the UK. In stark contrast with GHG and *Ren*, there is no country where no variable is important. This is true for all the models we consider.

Finally, of the equations presented, *int* portrays the least amount of heterogeneity across countries. In particular, interest rates seems to be dominated by their own lag, as well as the lag and contemporaneous effect of the foreign interest rate.

4.2 Generalised Impulse Response analysis

When conducting impulse response analyses, shocks are often orthogonalised for identification purposes, and Cholesky decomposition is frequently utilised in this context. While this approach works well for a small system of equations, such as traditional VARs, it is less clear how to employ it in a GVAR setting (Pesaran et al., 2004). In particular, when using Cholesky decomposition, we assume that shocks propagate through our estimated model sequentially. Proposing such orderings for small VARs is feasible, but is far more cumbersome for large GVARs with hundreds of equations. Exact identification in a GVAR would require large amounts of restrictions. Furthermore, while the shock of interest is orthogonal within the country model, correlation across the country models means that the responses to the shock cannot be interpreted structurally (Eickmeier and Ng, 2015). An alternative approach is to use the generalised IRF (GIRF) of Koop et al. (1996), in which ordering of the variables does not matter. As such, in this paper we will opt to use GIRFs.

First, we assess the country specific responses to a shock in Green Finance for all three models before moving on to assessing global responses to the same shock. A country-specific shock to $GFin$ is equivalent to asking the question "how would a variable in a specific country respond if only this country would increase $GFin$ by one standard deviation?." Note here that a key advantage of a GVAR over running country-specific VARs is that in the former, spillovers are accounted for and indirect feedback leads to different IRFs, whereas this dynamic is unavailable in the latter by individually shocking a country's VAR. Second, we save the one standard deviation shock value for each individual country and use these values to create a global shock, which captures the impact of a situation where $GFin$ is increased in all countries simultaneously. In essence, for the global shock scenario, we ask the question "how would a variable in a specific country respond if all countries would increase $GFin$ by one (country specific) standard deviation?." This global shock allows us to test whether there are externalities associated with a simultaneous implementation of feed-in-tariffs across the board.

In this section, we focus on shocking $GFin$, and seeing how the Ren, y (as GDP growth), GHG, $Unemp$, int and $dinfl$ respond to country, and global shocks. We only present the countries that had statistically significant impulse responses at the 68% level.[17] Figures' horizon line display quarterly intervals. As expected, outcomes will vary significantly, considering that economic output and financial endowment are unique to the countries under scrutiny. In all figures the solid black line shows the median response, while the grey area shows the region between the 16th and 84th percentiles respectively.

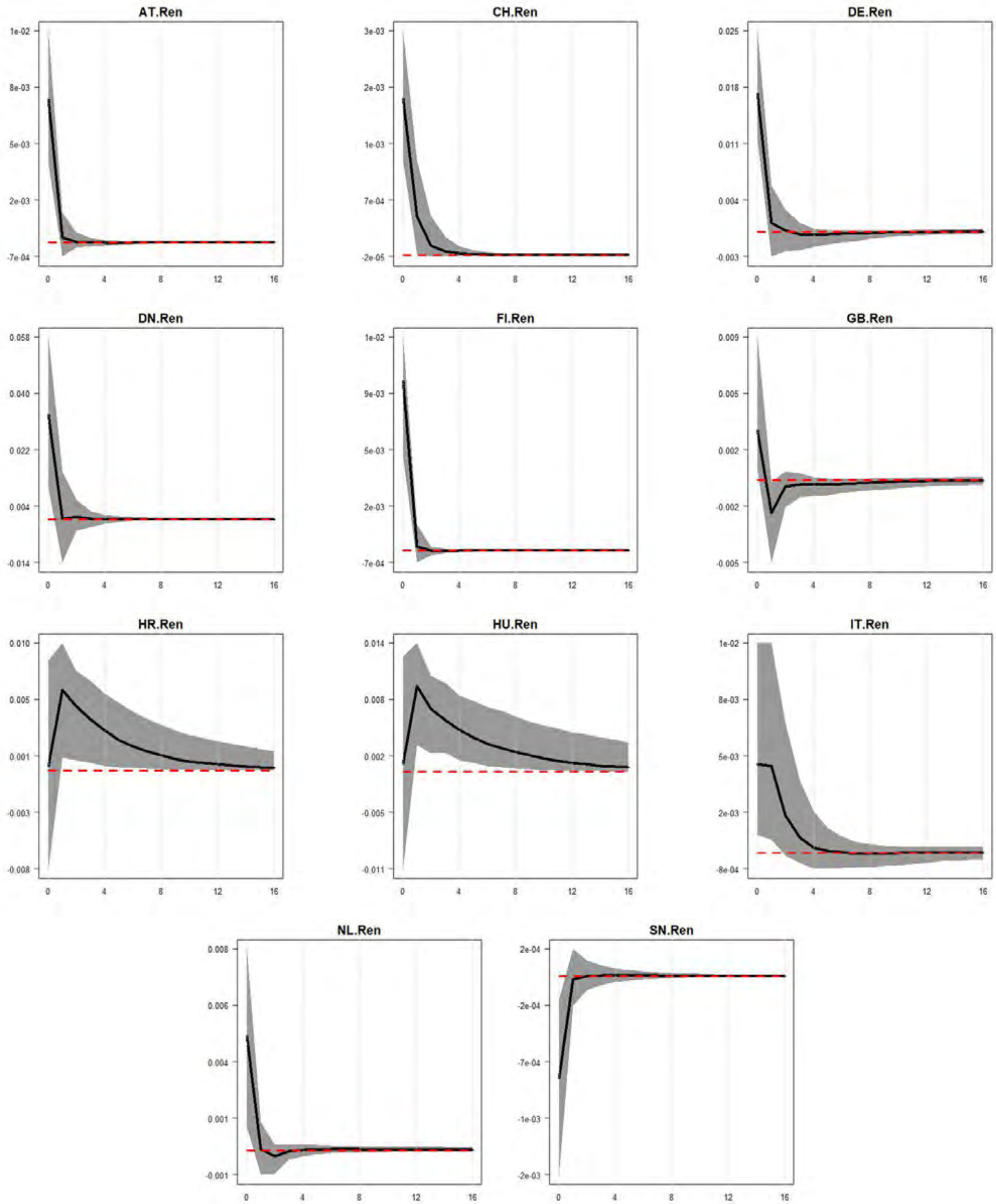


Figure 8: M1 Country specific Response of Renewable Energy to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

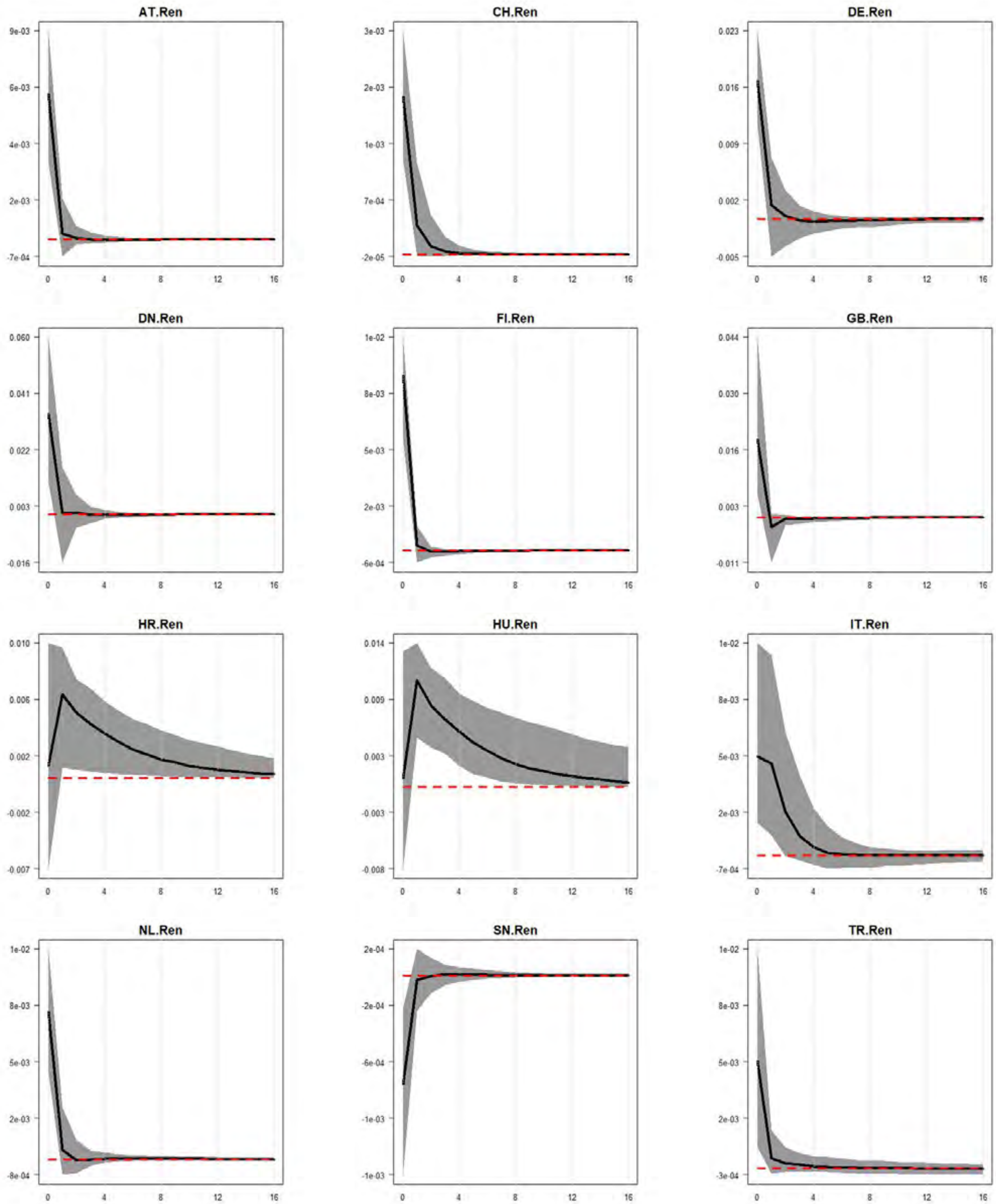


Figure 9: M2 Country specific Response of Renewable Energy to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

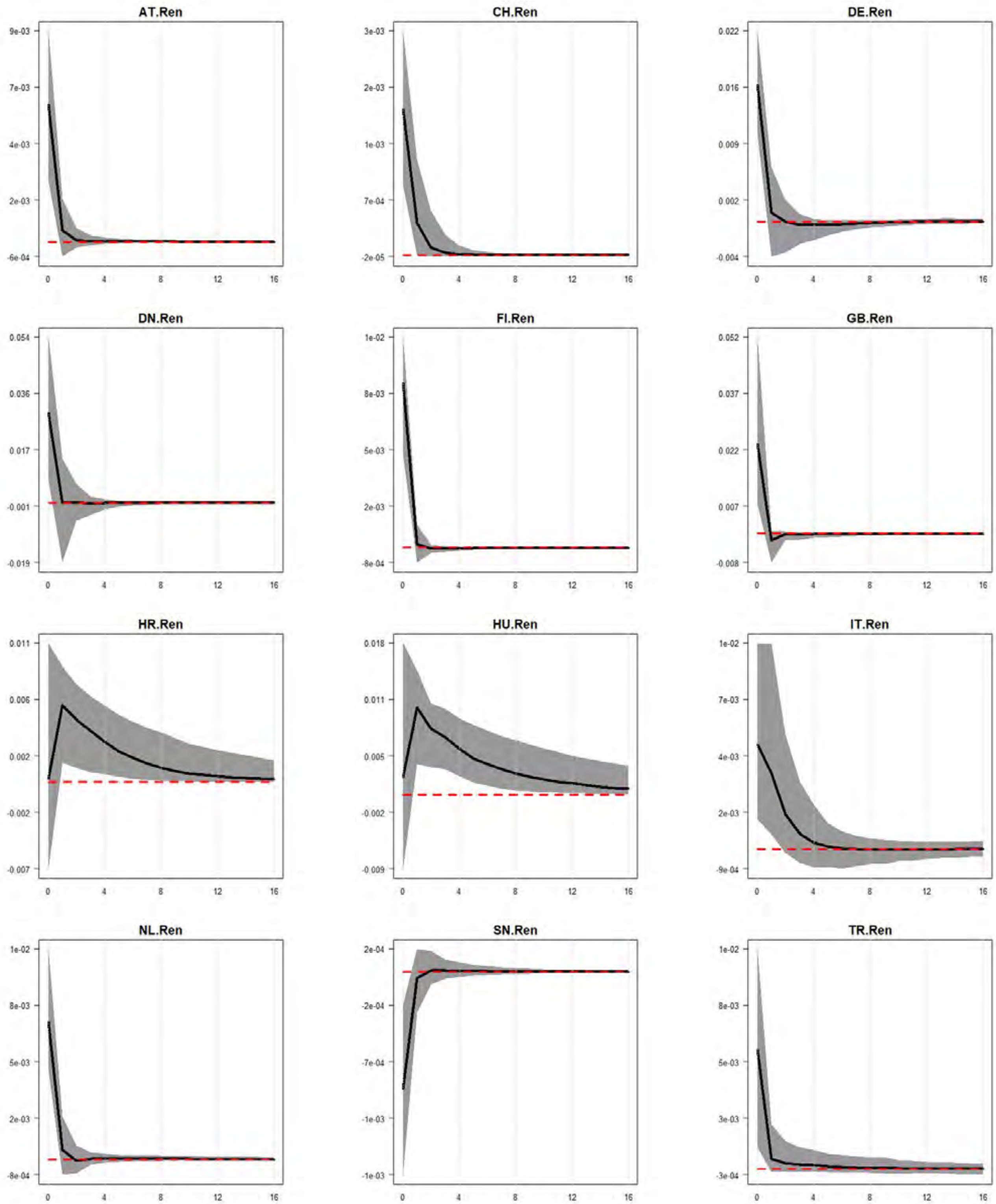


Figure 10: M3 - Country specific Response of Renewable Energy to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

4.2.1 Response of Renewable Energy to a shock in Green Finance

Figures 8, 9 and 10, show the response of *Ren* to a country-specific shock to $GFin$ for models 1, 2, and 3, respectively. For all three models, Austria, the Czech Republic, Germany, Denmark, Finland, the UK, Croatia, Hungary, Italy, and the Netherlands are identified as responding with an increase in renewable energy generation in response to feed-in-tariff policy implementation, whereas Turkey only responds with an increase of renewable energy generation in Model 2 and 3. Apart from Croatia and Hungary, for which the shock lasts longer, the disturbances are transitory, as shocks' effect disappear after 2-3 quarters. Note that these responses are all in relation to the change in renewable energy penetration. As such, these IRFs should not be interpreted as transitory changes in renewable energy penetration, but instead as transitory changes in the *growth* of renewable energy penetration. As such these changes are likely to lead to long term increases in renewable energy penetration. To this end, it seems that feed-in-tariff policy implementation does help in spurring investment in renewable energy generation for a select of countries.

Although the magnitude of shocks is generally small, we see the highest shock for Denmark: a one standard deviation increase in green finance investment leads to over 0.50% increase in *Ren*. This tells us that feed-in-tariffs have been hugely impactful in starting up renewable energy generation in Denmark. This is corroborated by the fact that, out of all countries that make up the S&P Global Clean Energy Index constituents, Denmark contributes with 9.6% to the index's weight (see Table 3 in the Appendix). Figure 3 also further corroborates this fact as discussed in section 3 above.

On the other hand, for Slovenia we observe that an increase in green finance investment leads to a temporary decrease in renewable energy penetration. This decline could be due to the fact that Slovenia experienced stagnation for in 2010 followed by negative output growth between 2011-2013.[18]

Relying on the fact that all three models yield similar results in terms of countries affected, magnitude and length of shock, we conclude that our results are robust to different specifications, and the identified countries are the ones that have a significant response in their renewable energy penetration to a shock in feed-in-tariff.

[17] We follow Sims and Zha (1999) in reporting the 68% error bands rather than the 95% one.

[18] Information on Slovenia's sustainable climate plan can be found here: `https://energy.ec.europa.eu/system/files/2020-06/si_final_necp_main_en_0.pdf`.

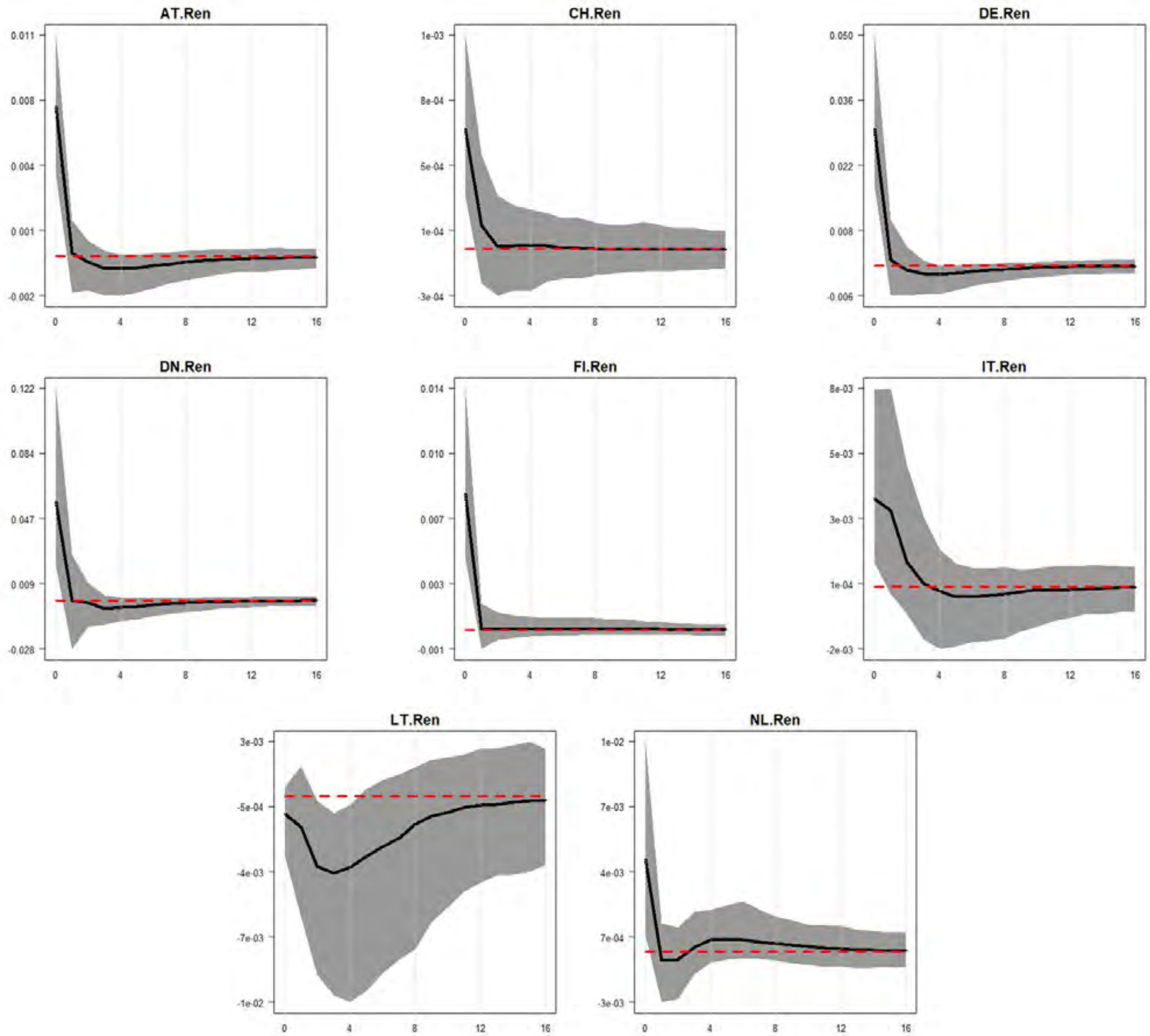


Figure 11: M1 - Global Response of Renewable Energy to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

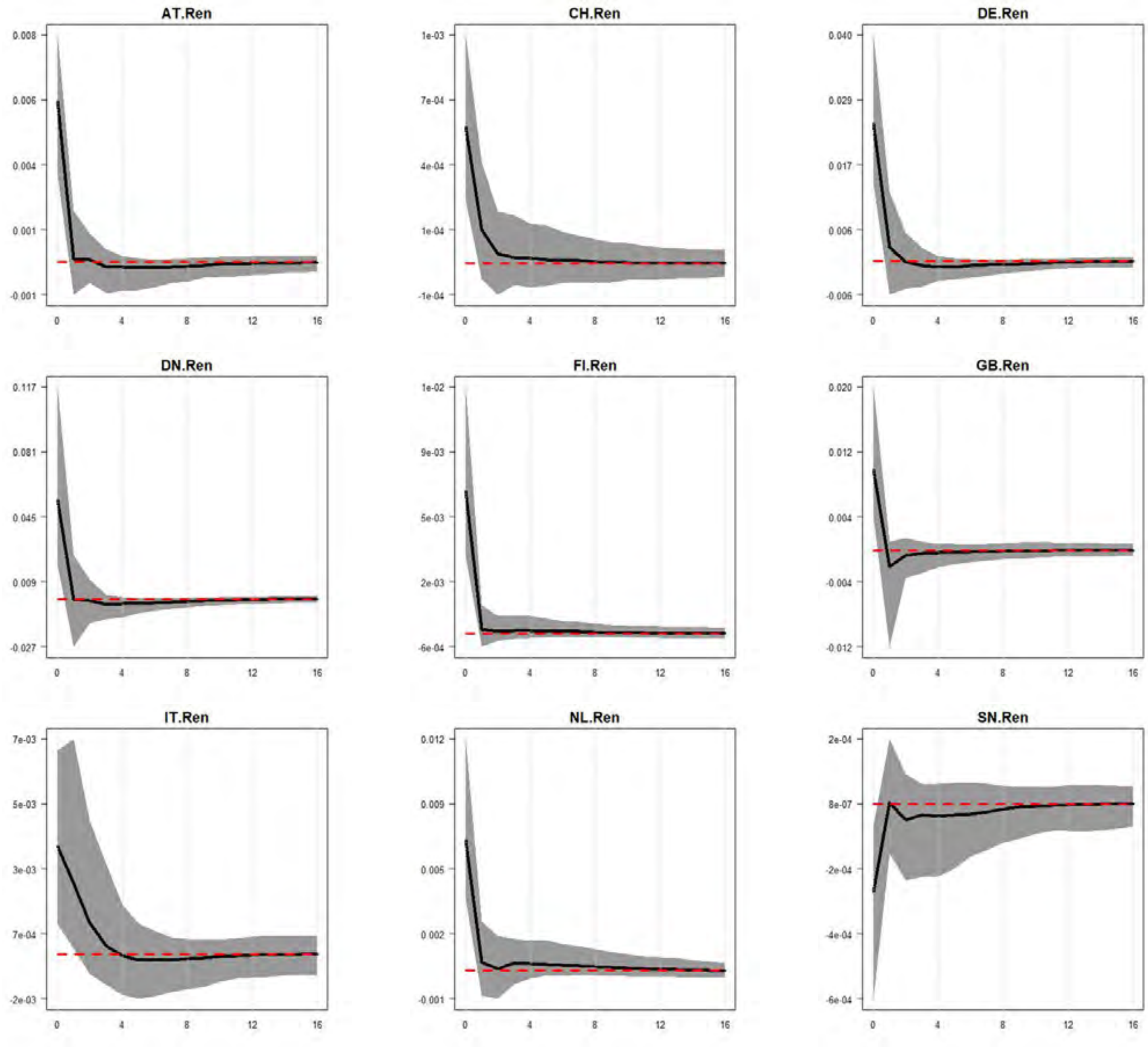


Figure 12: M2 Global Response of Renewable Energy to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

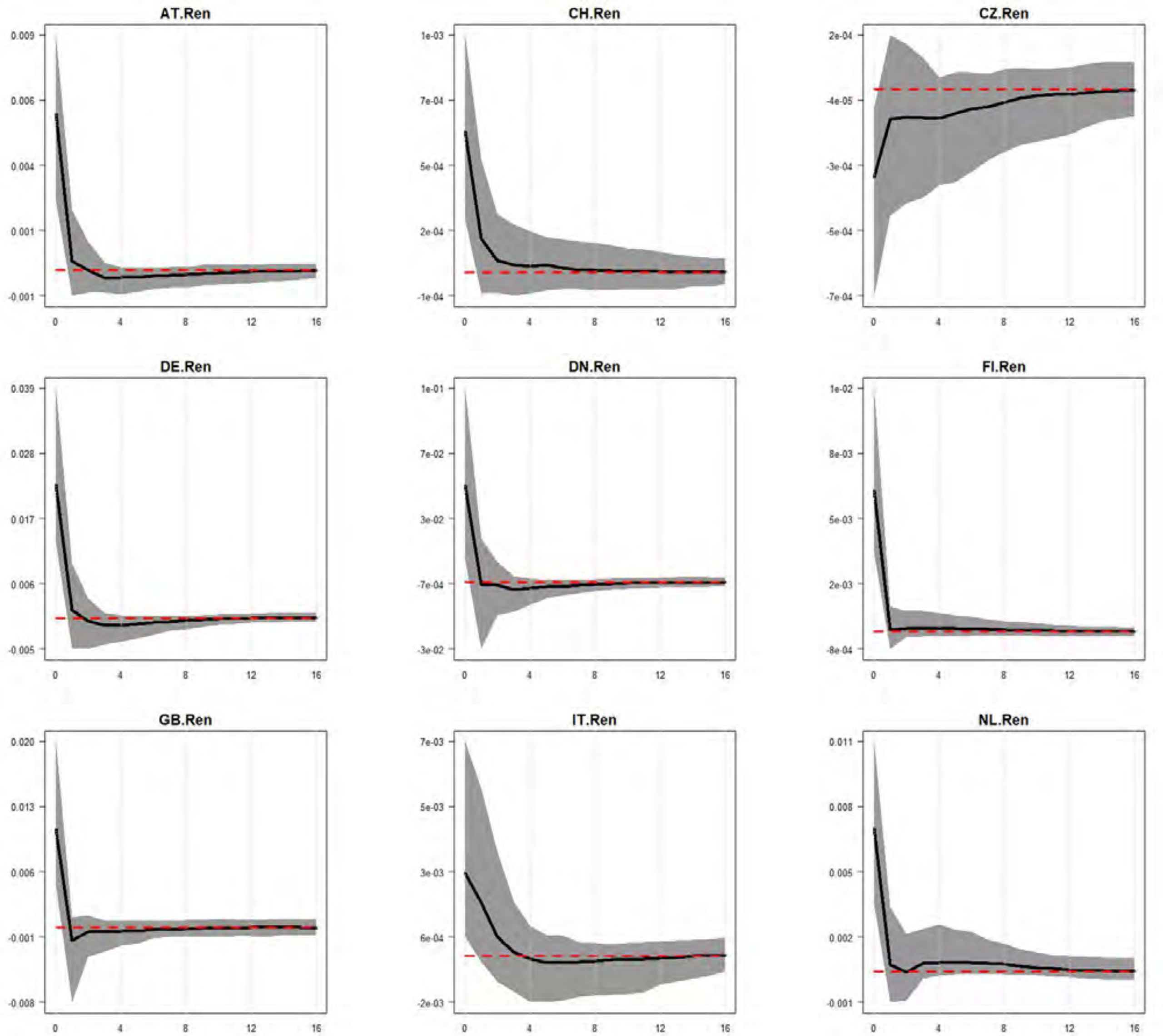


Figure 13: M3 Global Response of Renewable Energy to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Assessing the global shock to Green Finance in Figures 11, 12 and 13, we see that there are less countries identified. For all three models, the countries with a significant impact are Austria, Switzerland, Germany, Denmark, Finland, Italy, and the Netherlands, while Lithuania is significant for Model 1 only, Slovenia is significant for Model 2 only, the Czech Republic is significant for Model 3 only, and the UK is significant solely for Model 2 and 3. All, bar the Czech Republic, Lithuania and Slovenia, display a positive response, albeit short-lived. Noteworthy is Lithuania's case, despite responding negatively with a small magnitude, the shock lasts the longest, i.e. for four quarters in all three models. The fact that less countries portray significant responses, and a small proportion of significant responses are negative, entails that the simultaneous implementation of feed-in-tariffs across Europe has negative externalities. In particular, the western European economies are likely to retain the positive impact of feed-in-tariffs at the expense of the smaller and less developed eastern European counterparts. As such, we argue that feed-in-tariff policies, while effective in kick starting renewable energy generation in the region, were unfortunately effected by negative externalities likely on account of competition for scarce resources used to develop the green projects in these countries.

4.2.2 Response of GDP growth to a shock in Green Finance

The country specific results of the dynamic impact of a one standard deviation shock of Green Finance on GDP growth are presented in Figures 14, 15 and 16. For Model 1, Austria, Denmark, the UK, the Netherlands and Turkey respond with a decrease in output growth when green financing increases with one standard deviation. Switzerland responds initially with an increase in growth output in the first quarter, however the shock's effect becomes negative from the second quarter. All countries' shock effect dies out quite rapidly—typically after 2-4 quarters. For Model 2, Austria, Finland, the UK, Croatia and Turkey respond with a decrease in output growth when green financing increases with one standard deviation. This might mean that initially, other necessary resources (such as know-how, natural resources, skilled labour and technology) needed for sustainable growth are not in place, and/or the existing resources are not efficiently used and allocated. Moreover, it is imperative to understand that decoupling GDP growth from resource use and carbon emissions is not something achievable in the short-run. Also, the yearly real GDP growth rate of developed countries is usually very low for the period 2010-2020, in most cases at levels around 1% - with Austria achieving a surprising -6.5% GDP growth rate in 2020, Finland a rate of -2.4%, the UK a rate of 1.6% rate, Croatia a rate of -8.5% and Turkey a rate of 1.9%.[19] High growth assumes an increased energy demand, which in turn makes transition to a zero net emission economy challenging. Besides, if resources are used productively, it is not unreasonable to argue that green growth (which is independent of GDP growth) could be realised at low or even negative output growth levels (Hickel and Kallis, 2020).

On the other hand, the response in Switzerland is an increase in output growth when

[19] Real GDP growth rates for selected countries can be found here: `https://www.imf.org/external/datamapper/NGDP_RPCH@WEO/EU/EURO/EUQ/NMQ`.

green financing increases with one standard deviation, meaning that green investment creates the necessary conditions for output growth. Denmark initially experiences a negative shock that lasts a quarter, after which the shock's effect on output growth becomes positive. For Switzerland, Denmark and the UK, the shock's effect lasts for about 2-4 quarters, whereas for the remaining countries the effect lasts for about eight quarters. Overall, the results mean that the implementation of green policies might make a difference, however in the short term the effect on output growth is transitory. For Model 3, when Russia is considered to provide most of the energy and it is assumed that there are no feed-in-tariff policies, Austria, Denmark, Finland, the UK, and Turkey respond with a decrease in output growth when green financing increases with one standard deviation. Switzerland initially responds with an increase in output growth when green financing increases. Apart for Switzerland, Denmark and the UK, the shock lasts for about eight quarters. Yet again, this means that in the absence of feed-in-tariff policies, output growth changes only effects a handful of countries in the short run.

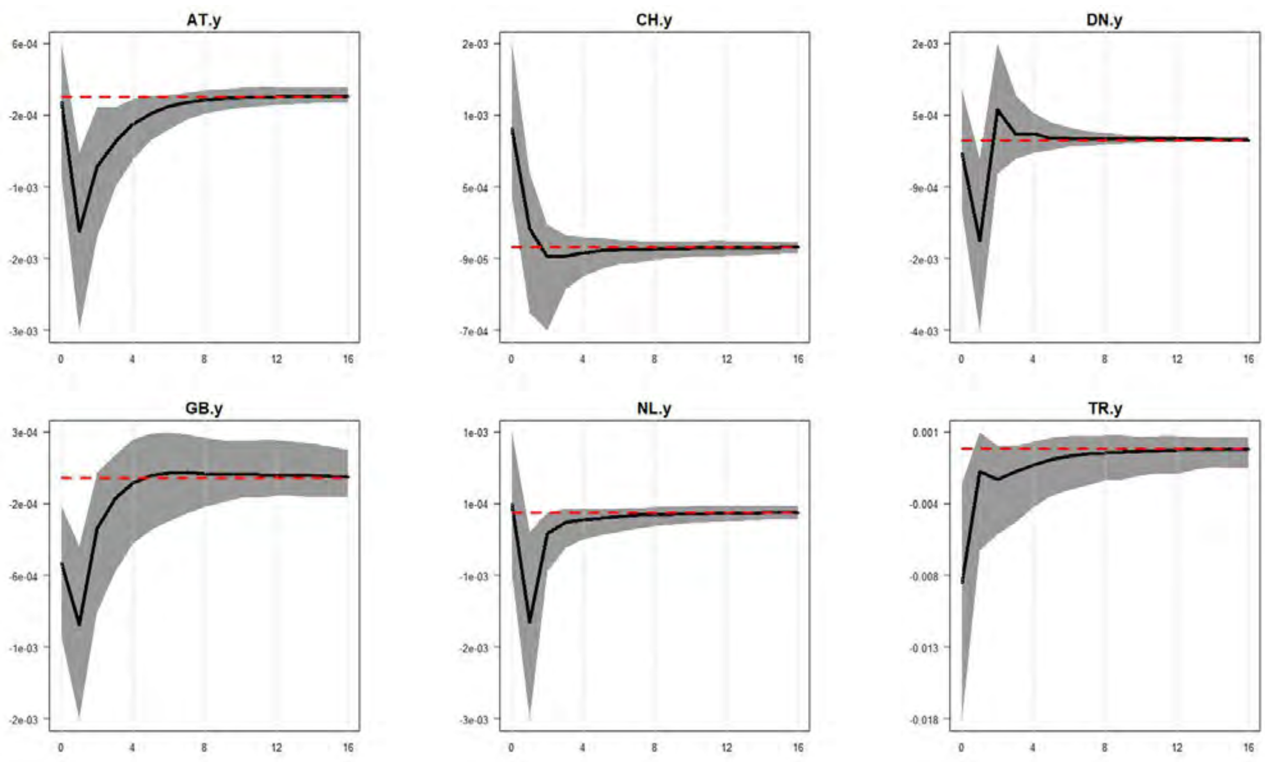


Figure 14: M1 Country specific Response of GDP growth to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

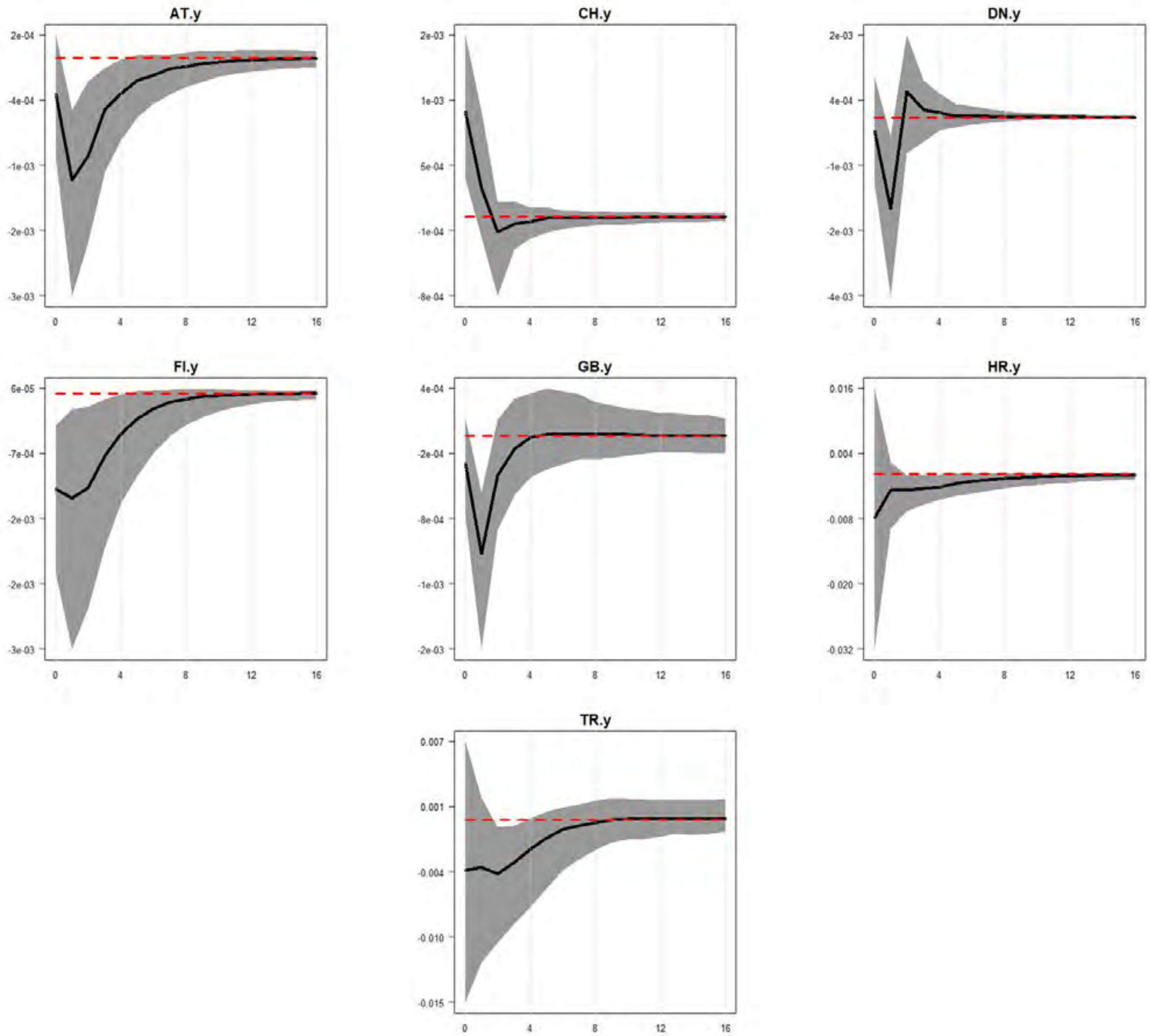


Figure 15: M2 Country specific Response of GDP growth to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

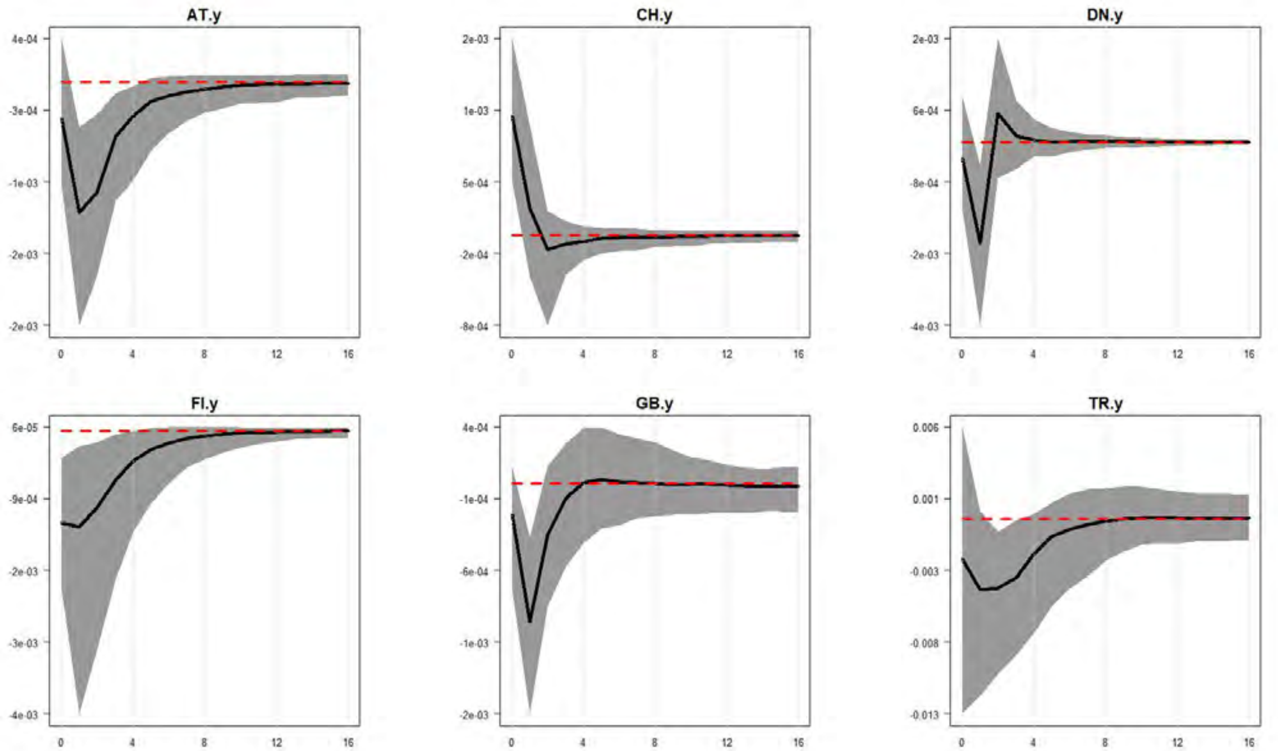


Figure 16: M3 Country specific Response of GDP growth to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

The global results of one standard deviation shock of green financing on output growth are presented in Figures 17, 18 and 19. Significant negative spillover effects are identified for Model 1 when a notable part of Europe responds; Austria, the Czech Republic, Germany, France, the UK, Croatia, Hungary, Lithuania, Latvia, the Netherlands, Portugal, Sweden and Turkey respond with a drop in output growth when all 29 countries increase simultaneously their green financing with one standard deviation. The most pronounced effect is observed for Lithuania when output growth decreases by 0.001 percent. This might be due to the fact that, being part of the Nord Pool (a power exchange network between some Nordic countries), it is cheaper for Lithuania to import energy rather than produce it, which in turn means that green financing is not of high importance and did not contribute to an increase in output. The effect of the shock on Croatia, Estonia, Italy and Turkey is initially negative, but becomes positive after one quarter. In Model 2, the spillover effects are not so pronounced. Only Austria and Turkey experience a decline in output growth for 4-8 quarters, while Denmark and Finland experience a decrease of output growth for one quarter, after which the shock's effect becomes positive.

Model 3 yields similar results to Model 2, however when all 29 countries increase simultaneously their green financing with one standard deviation, negative spillover effects are experienced by Austria and initially by Denmark and Finland, however for the latter two the shock's effect turns positive after 2-4 quarters.

Based on results from all three of our models, we conclude that a simultaneous increase in green financing across Europe would lead to a decrease in output growth in the key countries in our dataset.

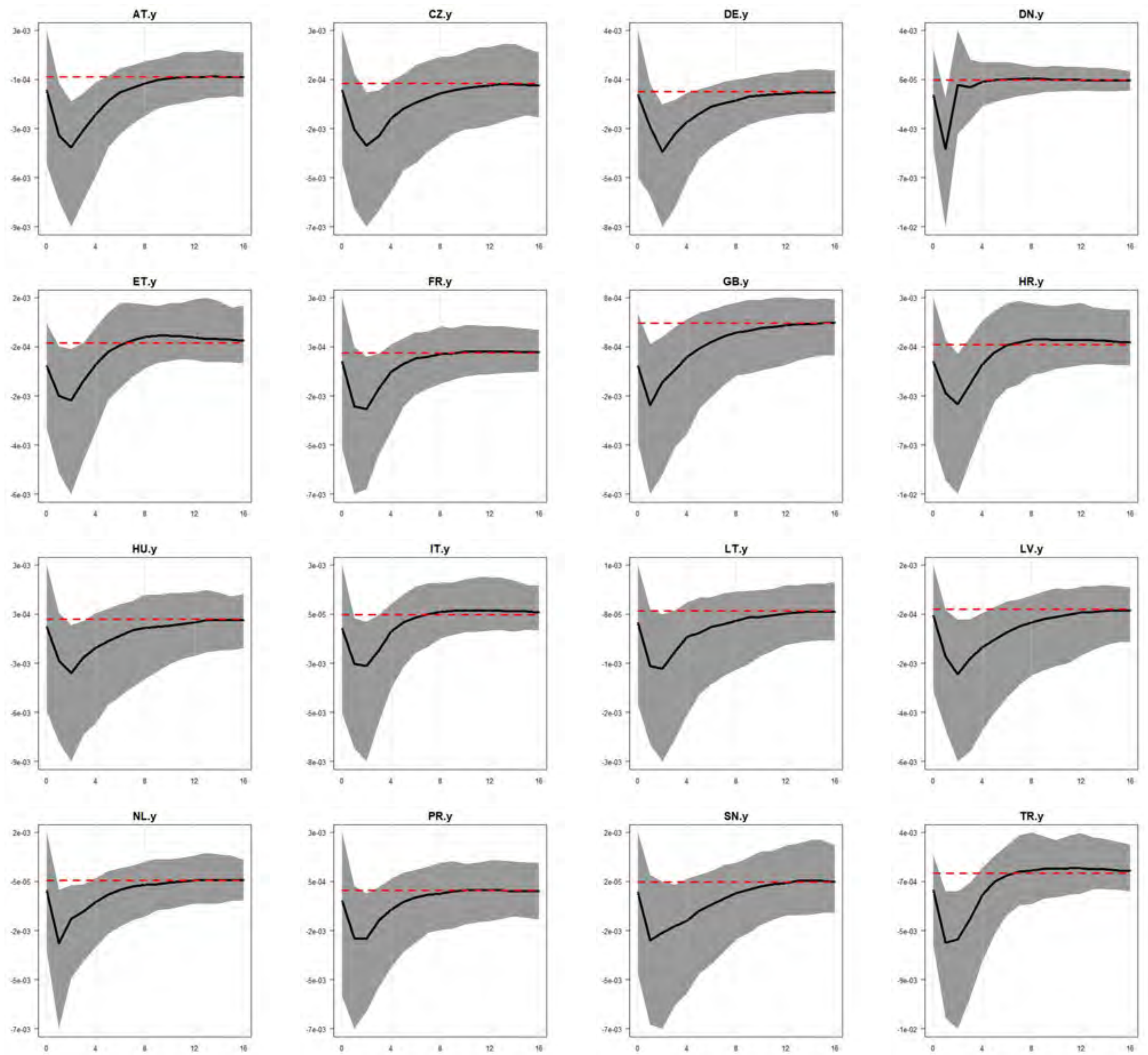


Figure 17: M1 Global Response of GDP growth to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

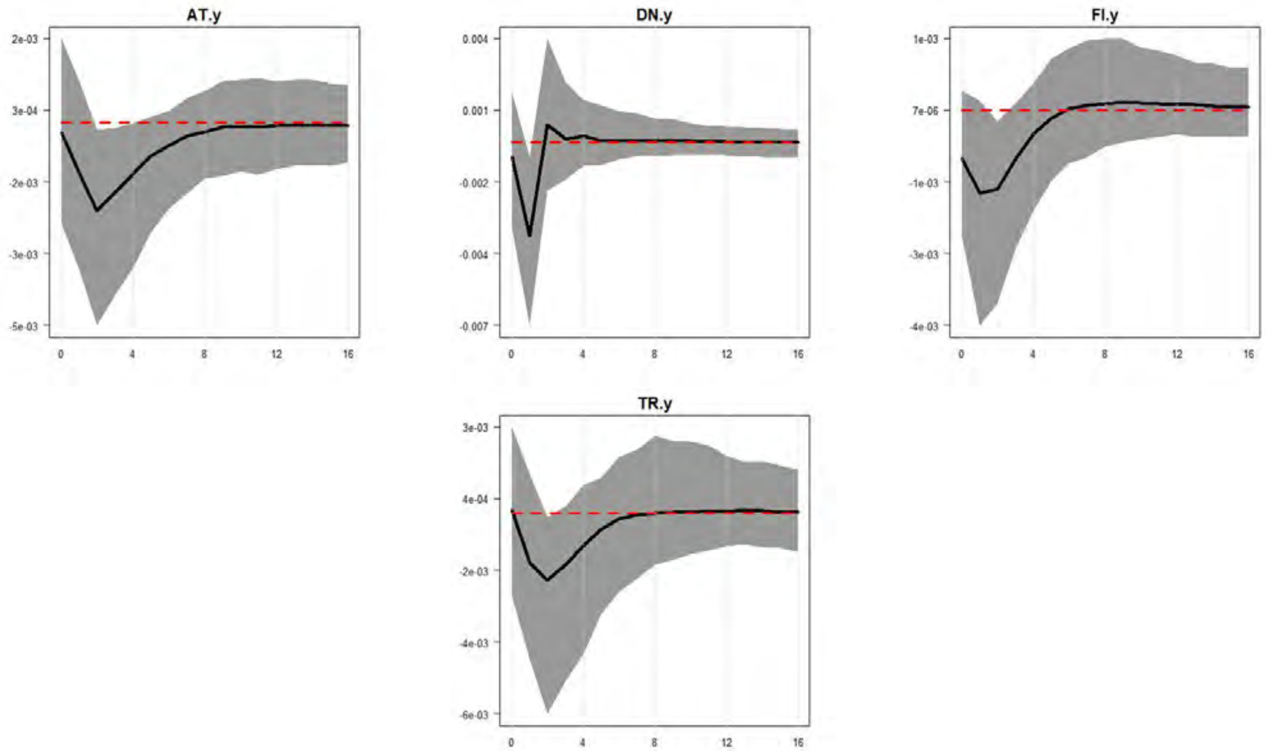


Figure 18: M2 Global Response of GDP growth to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

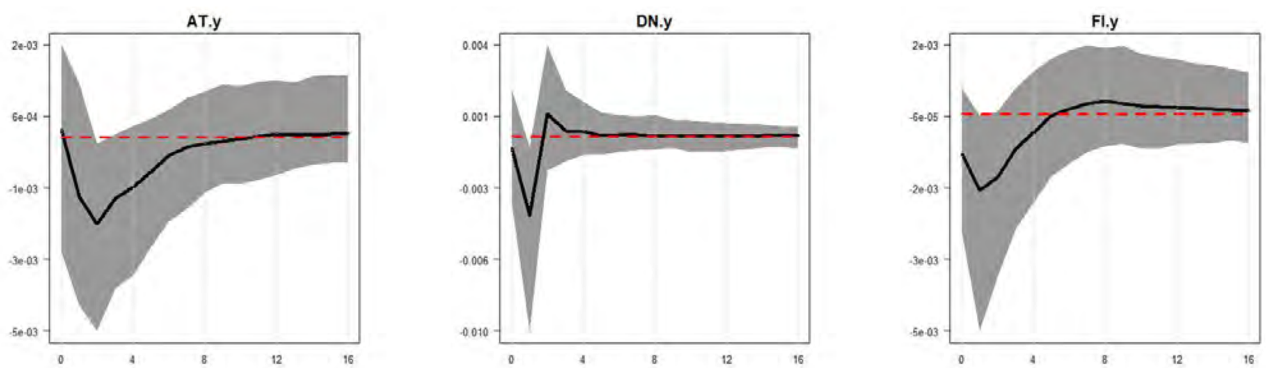


Figure 19: M3 Global Response of GDP growth to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

4.2.3 Response of GHGs to a shock in Green Finance

If we look at the country level shock effects for Model 1 in Figure 20, a one standard deviation shock to green financing leads to 0.3 percent increase in GHGs emission growth for Bulgaria. This could be due to the fact that Bulgaria's GHGs intensity of GDP is more than three times that of the European Union, while the funds originating from national co-financing policies to spur the greening of the economy are one fifth of that originating from EU funds[20]. The shock's effect peaks at three quarters and lasts for over 12 quarters. Note that the GHGs variable is first differenced, so these effects are not transitory, given that there is no reversal in the sign. This finding is not at odds with the findings of the literature: Liu et al. (2022) shows that after green projects are started, GHGs increase initially, and only decrease later as the industry matures. In stark contrast, Germany responds with a 0.02 percent decrease in GHGs emissions. Given the findings of Liu et al. (2022), this is likely due to the fact that Germany's renewable energy generation industry has been present (and growing) for about a decade prior the considered sample.

Models 2 and 3 identify Austria, Denmark and Estonia as responding to shocks, as shown in Figures 21 and 22. While the magnitude of shocks is small and the shocks' effect disappear after four quarters, only Denmark's and Austria's (albeit the effect is positive for two quarters, then it switches sign) GHGs emissions decrease when green financing increases. This again corroborates the fact that Denmark has been at the forefront of the greening of the economy out of all European countries. Estonia's GHGs increases, and this might be due to the fact that Estonia primarily uses shale oil as the main source of generating energy, and its carbon intensity is known to be one of the highest among the OECD countries; moreover, green initiatives and R&D investments are limited, and carbon taxes are low compared to the rest of European countries (Tatomir, 2022).

Looking at the global shock of GHGs to Green Finance in Figures 23, 24 and 25, there seems to be less variation compared to the respective models country specific shock. This entails that there is less externality present for $GHGs$. For all three models Estonia responds to a shock in Green Finance, whereas Spain responds to shocks in Model 1 only, and Denmark responds to a shock in Models 2 and 3. The magnitude of the shock is greatest for Estonia, when one standard deviation increase in green financing leads to around 0.2 percent increase in GHGs emissions

[20]More on Bulgaria's climate action progress can be found here: `https://climate.ec.europa.eu/system/files/2023-04/bg_2022_factsheet_en.pdf`.

in the medium term. This might suggest that there might be a period of time for Estonia for which adjustment to renewable technology is needed. As expected, for Denmark, while the magnitude is low, an increase in green financing leads to a decrease in GHGs emissions. This highlights, that unlike the case of the *Ren* variable and output growth, simultaneous increases in feed-in-tariffs across Europe is less likely to lead to externalities. Nevertheless, this is also explained by the fact that far less countries portray significant impacts on GHGs for country specific green finance shocks. Given the findings of Liu et al. (2022), the same models will need to be evaluated when the Renewable energy generation industries become more mature for more European economies.

Figure 20: M1 Country specific Response of GHGs to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

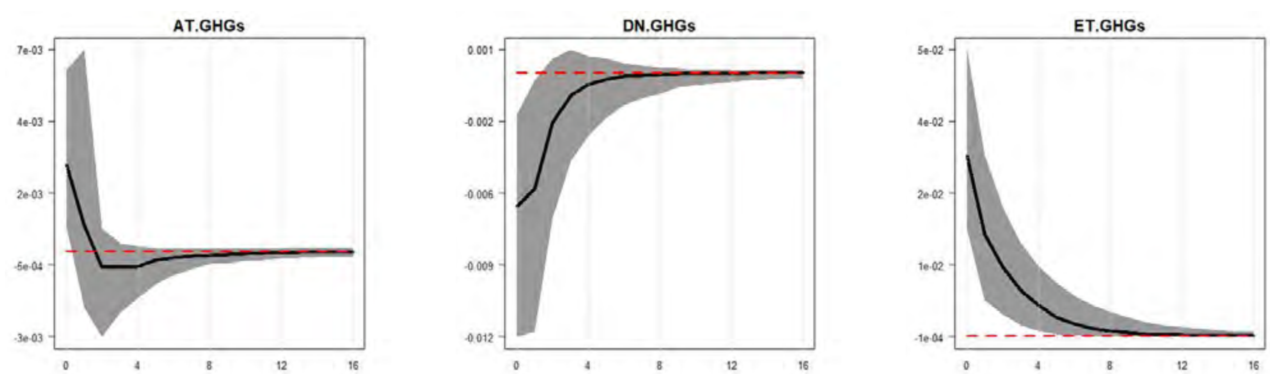


Figure 21: M2 Country specific Response of GHGs to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

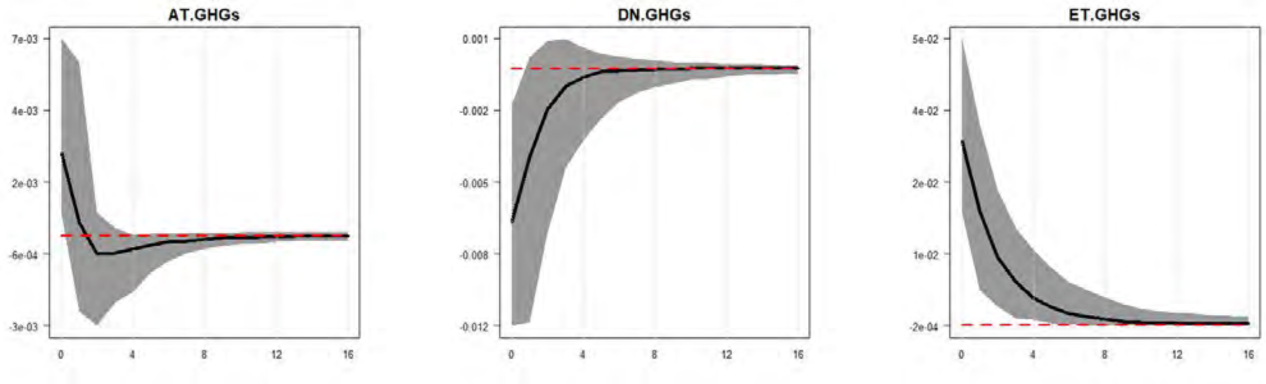


Figure 22: M3 Country specific Response of GHGs to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Figure 23: M1 Global Response of GHGs to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Figure 24: M2 Global Response of GHGs to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Figure 25: M3 Global Response of GHGs to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

4.2.4 Response of unemployment to a shock in Green Finance

Country specific responses of unemployment to a one standard deviation Green Finance shock are positive for Austria, Germany and Slovakia, as shown in Figures 26, 27 and 28. For all three models, one standard deviation increase in green financing leads to above 0.75 percent increase in unemployment growth for Austria, and the effects last for approximately eight quarters, which is the strongest response of all countries. Slovakia responds with an increase in unemployment with around 0.2 percent lasting approximately for eight quarters. For Germany, the shock's response is the smallest, and initially unemployment decreases in Model 1. This could be translated as there being a temporary shift to green jobs, such as waste management. Therefore, when interpreting these results, one must account for the issues that structural unemployment poses, i.e. the mismatch between the skills the labour force has (mainly those needed for brown jobs) and what employers need when recruiting for jobs in renewable industries. On the other hand, the majority of policy reports (European Commission, 2019; Asikainen et al., 2021) argue that the greening of the economy led to a decrease in unemployment, however this is highly unlikely to be accurate considering green initiatives' effect has not been fully felt yet, as unemployment is a lagging indicator of economic activity.

While our research does not account for green, white and brown unemployment separately, according to IMF (2022), it is expected that brown unemployment (representing those who are unskilled and work in the coal/mining industry and account for around 5% of the European labour force) would rise (Marin and Vona, 2019), whereas green aggregate employment (a small percentage, and which requires specialised labour force) would also rise when moving to a circular economy. Undoubtedly, the reallocation of jobs depends significantly on country specifics such as labour subsidies and not least on re-training the brown labour force, among others. The sectors that produce the highest amount of GHGs account only for 25% of employment in EU (Vandeplas et al., 2022), and the majority of the labour force works in the white industries that generate approximately 12% of GHGs - this might explain why the greening of the economy does not significantly effect the aggregate employment of European countries in the short and medium term. Unemployment will decrease if newly created green jobs are not in geographically and demographically distinct areas, and labour force can easily reallocate. Green jobs are expected to grow in the field of energy efficiency makeovers and/or R&D for green innovations, however changes will unequally affect regions and population groups within Europe. Disregarding how vulnerable, dangerous, expensive and slow to harness nuclear energy is - while considering it being the cleanest energy source - European economies have moved towards (re)opening plants, which might effect aggregate demand in the long-run. To sum up, there seems to be a limited effect of Green Finance on aggregate employment.

Global responses of unemployment to a Green Finance shock are shown in Figures 29, 30 and 31 and display the typical hump shape for all three models. For Model 1, when all European countries introduce green finance initiatives at the same time, Austria, the Czech Republic, Switzerland, Estonia, Croatia, Ireland and Slovakia respond with an increase in unemployment to the shock. Germany initially responds with an insignificant negative shock, which then turns positive after one quarter. We note that for all countries the shock leads to an increase in unemployment with a lag: for the majority of the countries, there is a significant positive effect from the second quarter to around the sixth quarter. We note that the different models identify different countries as having a significant response in unemployment. In particular, Model 1 identifies that unemployment increases for a wide variety of countries when green finance initiatives are jointly introduced across Europe, while Model 2 and 3 only show significant changes for Austria. Apart from Austria's response, the shock lasts for about 12 quarters, which is expected as unemployment responds slowly to technology shocks.

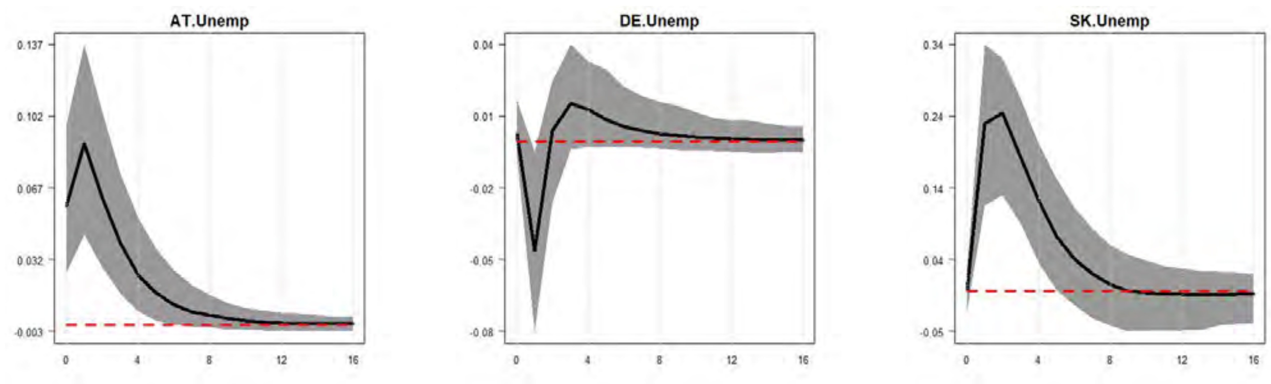


Figure 26: M1 Country specific Response of Unemployment to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Figure 27: M2 Country specific Response of Unemployment to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Figure 28: M3 Country specific Response of Unemployment to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

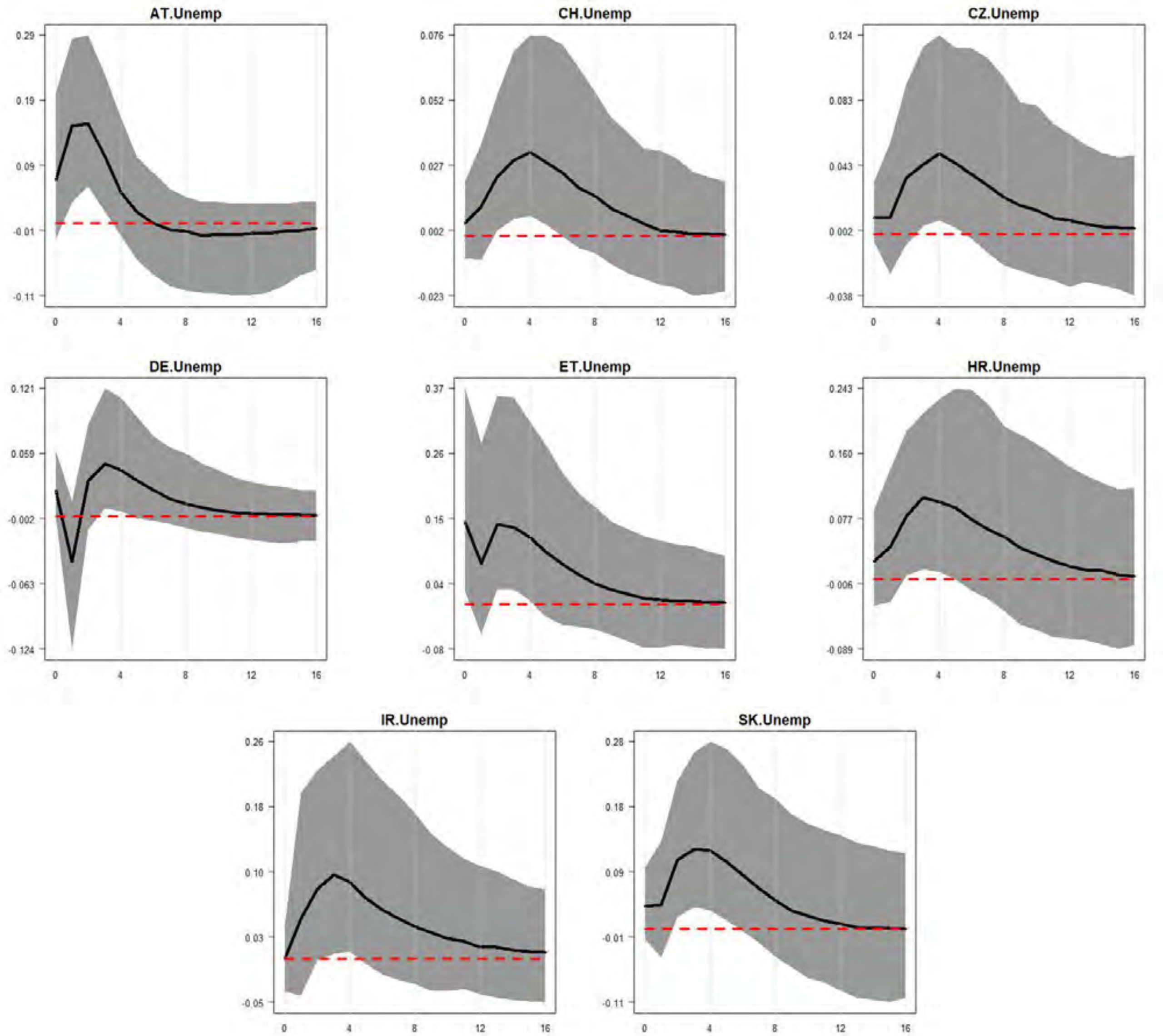


Figure 29: M1 Global Response of Unemployment to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

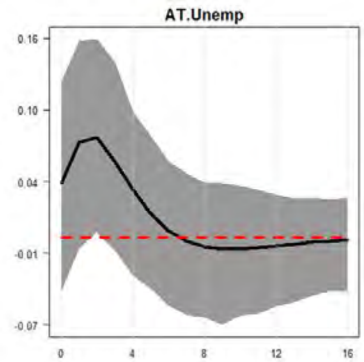


Figure 30: M2 Global Response of Unemployment to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

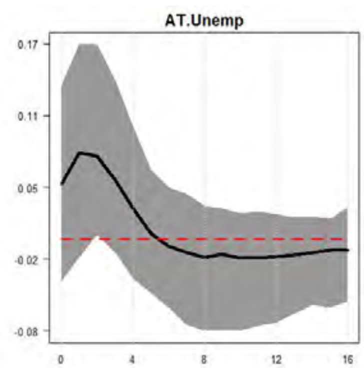


Figure 31: M3 Global Response of Unemployment to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

4.2.5 Response of Interest Rate to a shock in Green Finance

Country specific responses of interest rate to green financing are shown in Figures (32), (33) and (34). Germany responds in all three models with a similar inverted hump shape and magnitude. If green financing goes up with one standard deviation, interest rate decreases with 0.07 percent, lasting for approximately four quarters. This would suggest that long term interest rates drop which can encourage further green investment. On the other hand, high interest rates hinder transition to a green economy due to high capital expenditure requirement of renewable technologies and infrastructure. Besides, the development of renewable technologies in Germany are primarily carried out using project finance, which usually carries low interest charges. This response is also in line with the theory that price and return are inversely related, in the sense that setting up renewable technologies (which are known to be capital intensive) requires high upfront costs, and consequently interest rates would go down. Egli et al. (2018) do find that for Germany, the cost of capital in particular for wind energy projects is lower. However, considering that the interest rate is a lagging macroeconomic indicator, if output increases due to increase in green technology innovation - while at the same time unemployment decreases - interest rates could increase due to inflationary pressures. This is true for Denmark; for Model 1 and 2, if green financing increases with one standard deviation, interest rates go up by approximately 0.030 percent, however this only lasts for 2 quarters. Slovakia responds in a similar fashion, and the response is the most striking; moreover, the effect lasts much longer (over 16 quarters), with the interest rate increasing by approximately 0.22 percent if green financing increases by one standard deviation.

Figure 32: M1 Country specific Response of Interest Rate to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

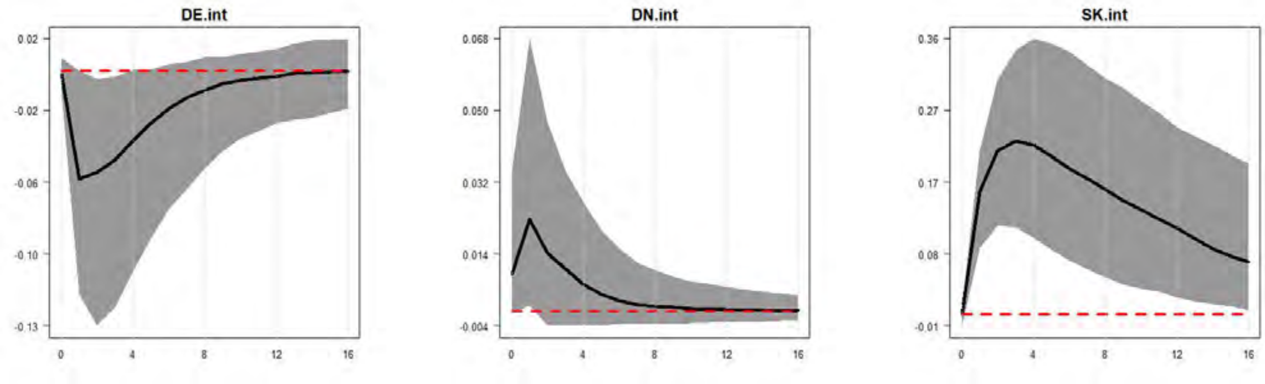


Figure 33: M2 Country specific Response of Interest Rate to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Figure 34: M3 Country specific Response of Interest Rate to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Global responses of interest rate to green finance shocks clearly show the presence of externalities in the region. As shown in Figures (35), (36) and (37), all three models identify spillover effects in Austria, the Czech Republic, Switzerland, Germany, Spain, Finland, France, the UK, Hungary, Ireland, Italy, Latvia, the Netherlands, Slovakia and Slovenia. In particular, all these countries respond with a decrease in interest rates if green financing increases by one standard deviation. Portugal also responds with a decrease in interest rates for Model 2. Interestingly, the magnitude of responses is similar (between 0.10-0.22 percent change for one standard deviation increase in green financing) and is deemed a high change for all countries, while all displaying an inverted hump shaped response. For all three models the effect of the shock dies away after around 4-6 quarters. Given that the majority of the countries are Eurozone countries and interest rates are set by the European Central Bank, the response in interest rates being similar among many countries is not too surprising. Slovenia responds the most; one standard deviation increase in green financing induces a decrease in the long-term interest rate of 0.22 percent in Model 1. These results highlight that simultaneously implementing increases in feed-in-tariff policies can have an influence on monetary policy tools.

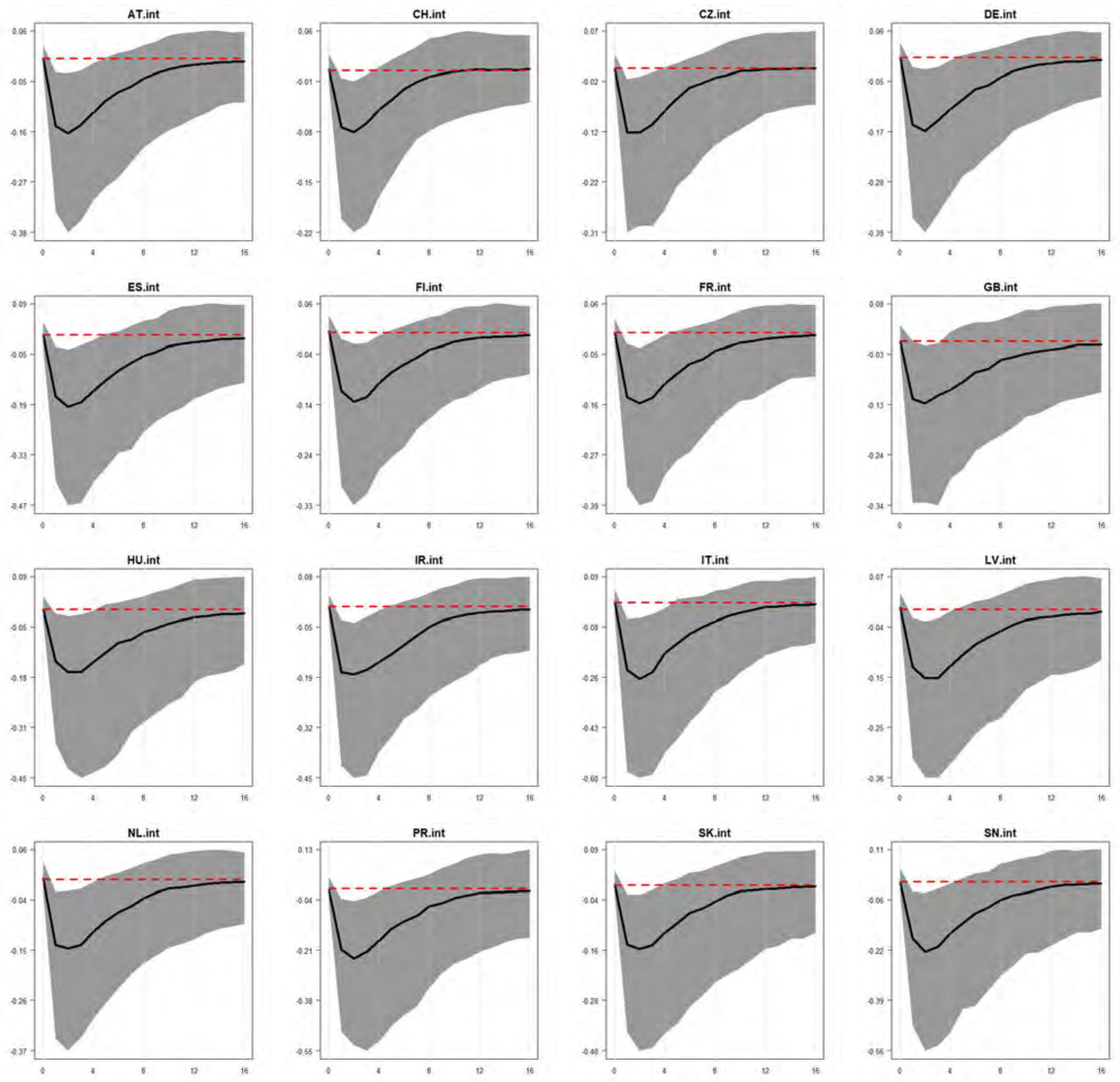


Figure 35: M1 Global Response of Interest Rate to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

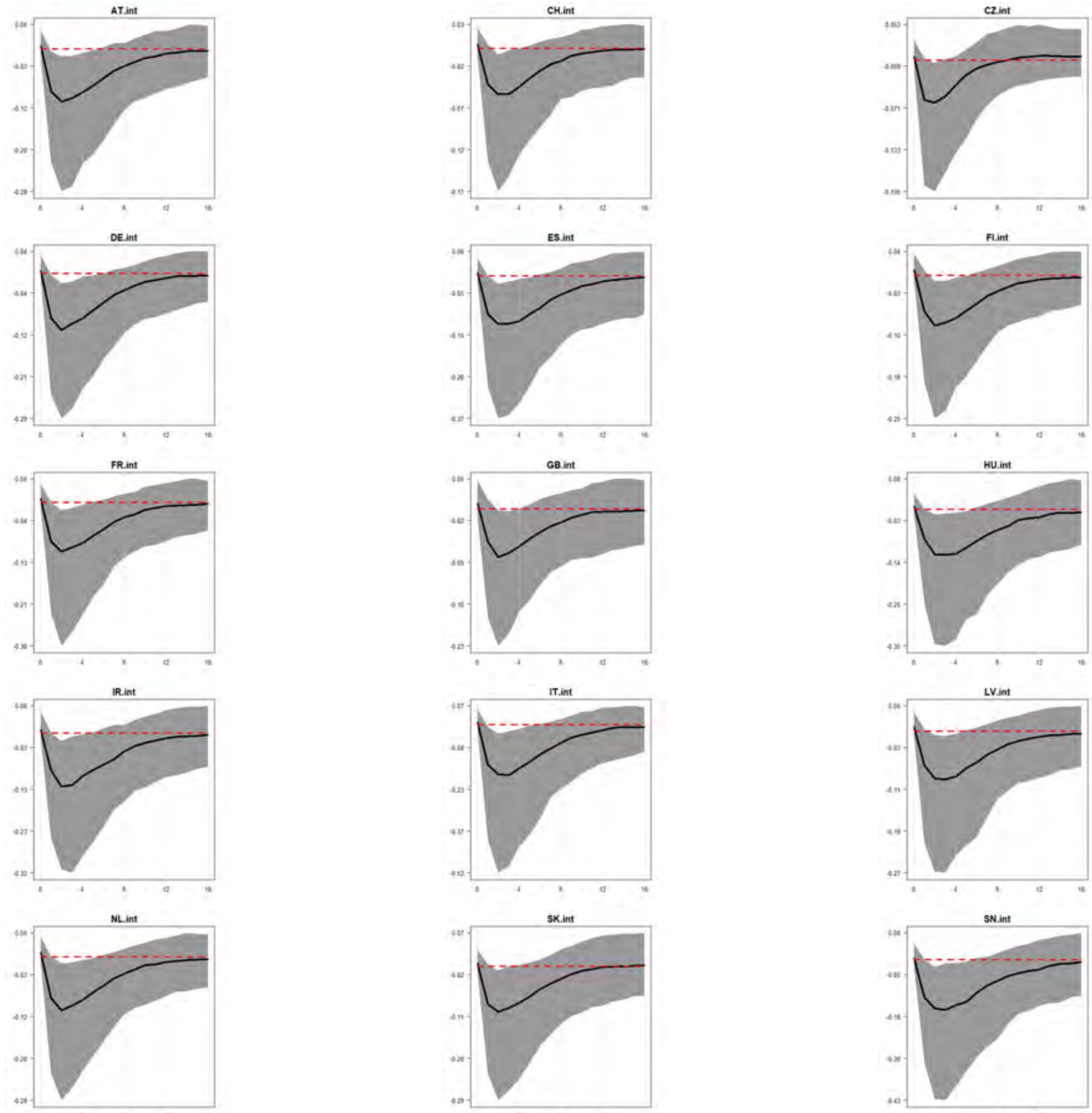


Figure 36: M2 Global Response of Interest Rate to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

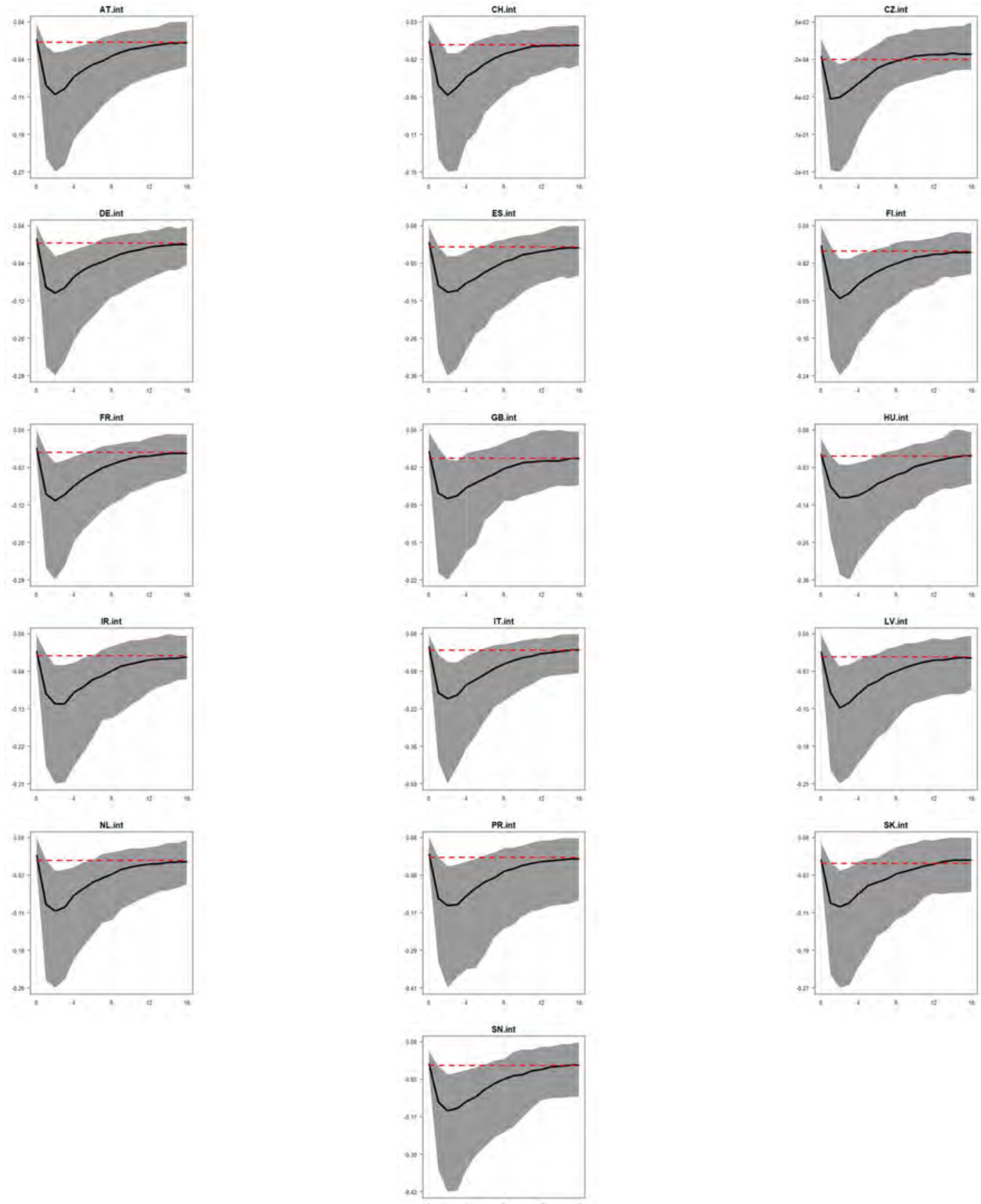


Figure 37: M3 Global Response of Interest Rate to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

4.2.6 Response of Inflation to a shock in Green Finance

Country specific responses are presented in Figures 38, 39 and 40. To the best of our knowledge, this is the first study that examines the effect of a green investment shock on inflation. A low level of inflation is a prerequisite for achieving green growth, considering that green investment and capital is inefficiently allocated in an inflationary environment. Slovakia and Turkey respond with an increase in inflation to a Green Finance shock for all three models. The Netherlands responds with a decrease in inflation in all three models, however the effect of the shocks are transitory as they disappears after four quarters. The most pronounced response is for Turkey; one standard deviation increase in green financing induces a 0.0085 percent increase in inflation. Slovenia responds with an increase in inflation in Model 1 only.

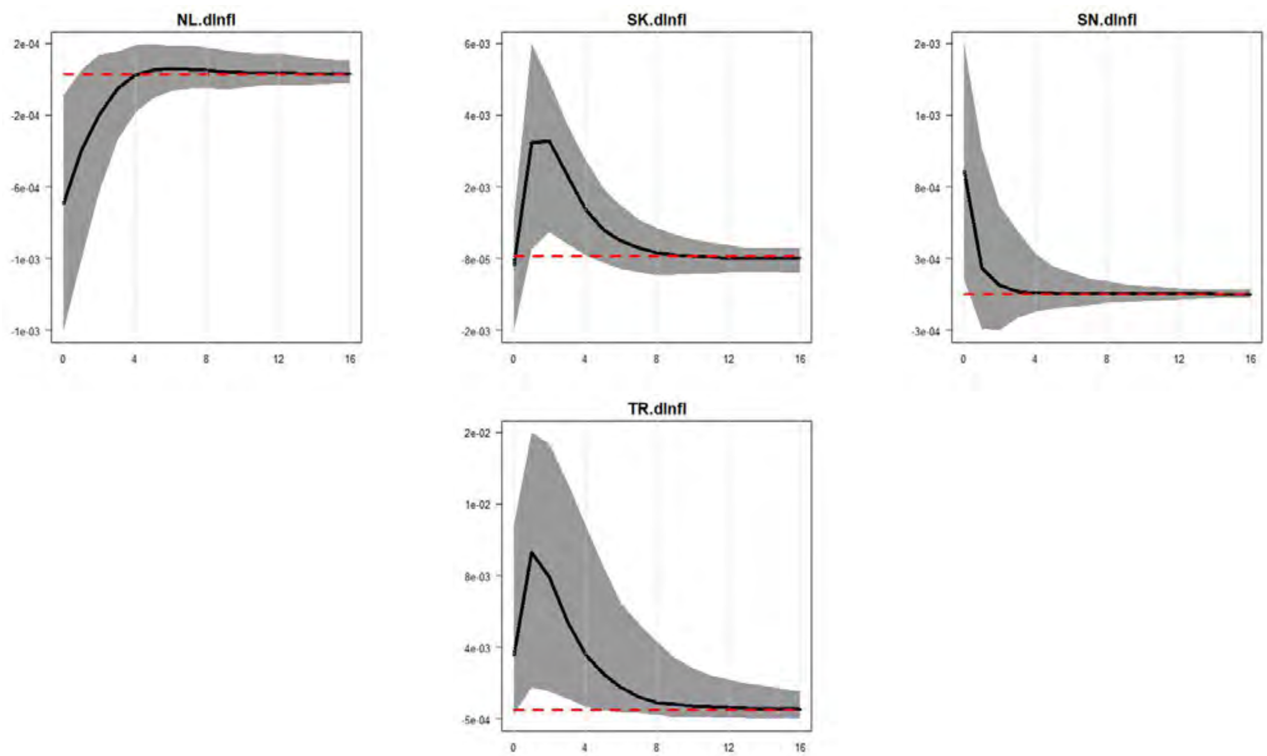


Figure 38: M1 Country specific Response of Inflation to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

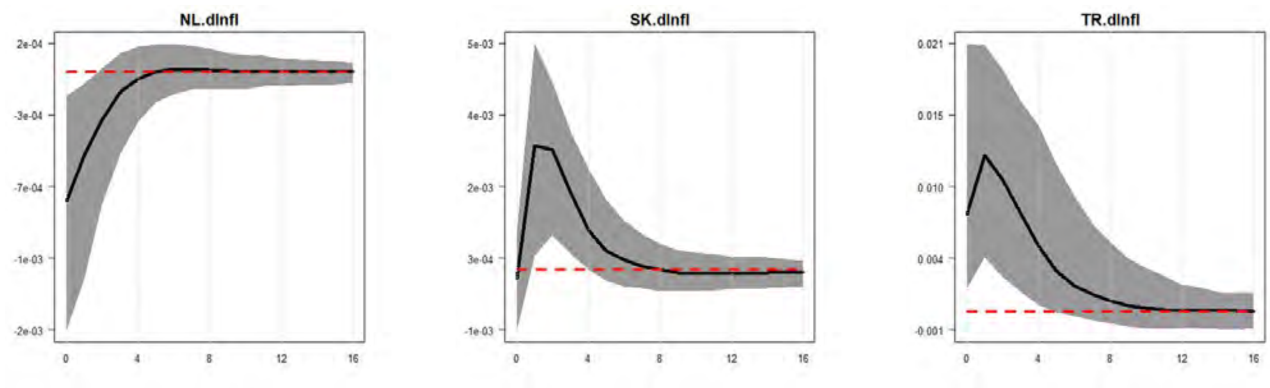


Figure 39: M2 Country specific Response of Inflation to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

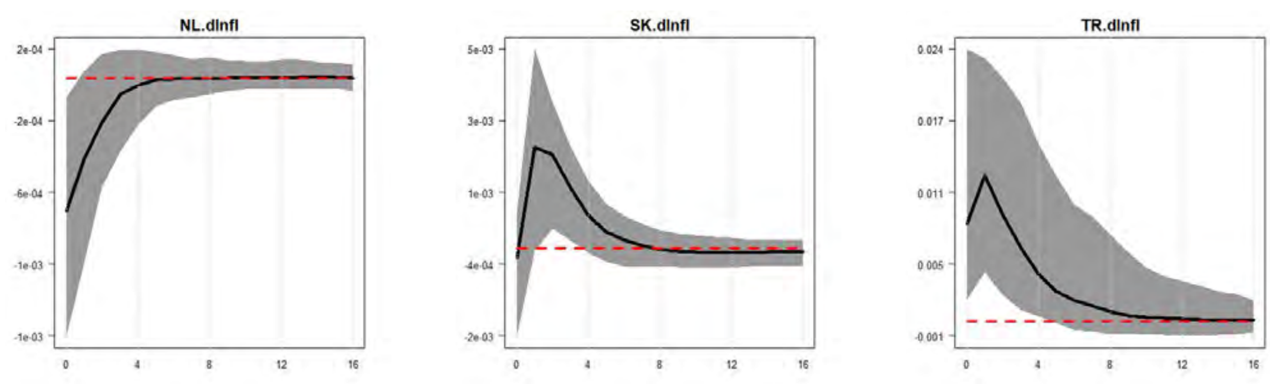


Figure 40: M3 Country specific Response of Inflation to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Global responses are presented in Figures 41 and 42.[21] When all countries jointly implement feed-in-tariff policies, the UK and the Netherlands respond initially with a slight drop in inflation when green investment increases by one standard deviation in Model 1, however this effect is short lived and the shock's effect disappears after around one quarter. On the other hand, Turkey responds with an increase in inflation in Model 2; one standard deviation increase in green investment increases inflation by 0.0009 percent, however this effect lasts for approximately 2 quarters.

[21]When Russia is the dominant unit (Model 3), no counties have a global response to Green Finance shocks.

Figure 41: M1 Global Response of Inflation to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

Figure (42)

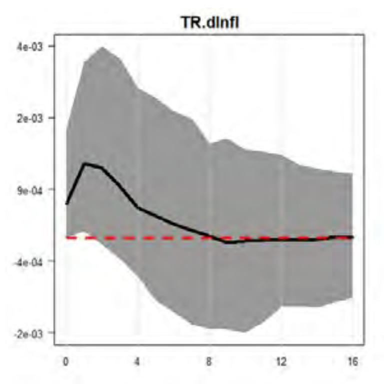


Figure 42: M2 Global Response of Inflation to Green Finance shocks

Note: Figure displays median impulse responses to a one standard deviation increase in green financing. The shock's effect is in percentage points and the horizon is quarterly.

5 Conclusion

In this study we assess cross-country dynamics by examining spatio-temporal shocks in a multi-country framework using a Bayesian Global VAR model. To the best of our knowledge, this is the first study that examines how green finance shocks affect 29 European countries' renewable generation adoption, GHGs emissions, GDP growth, unemployment rate, interest rate, and inflation rate.

Implementing an energy-augmented production function, which can be used for the study of the economic impacts of energy generation, allows us to link energy generation by fuel type with the overall economy. Furthermore, our approach uncovers various spillover types, underscoring the necessity for diverse spatial weight matrices.

We identify several significant short-run spillover effects. First, feed-in-tariff policies stimulate renewable energy penetration in approximately a third of the European countries of interest. Second, green initiatives do not yield in output growth, and only a handful of countries are affected by the shocks. Third, green investment does not seem to greatly effect GHGs emissions, considering that only two and respectively three countries are identified in all three models. Fourth, unemployment increases when renewable energy projects are subsidised. Fifth, interestingly, green finance shocks spread predominantly via interest rates (via the finance channel) as a large number of countries are identified; interest rates decrease when feed-in-tariff policies are implemented. Finally, inflation increases when green investment is increased.

In summary, we can conclude that feed-in-tariff policies have been successful in making green energy penetrate the energy generation of some of the countries in Europe. Nevertheless, the results also reveal that the impact of green finance might have been negatively impacted by too many countries introducing green finance policies simultaneously. This has possibly led to competition for resources, which has limited the overall positive effect of these policies. As such, our results suggest that some coordination is required to achieve the greatest impact of introducing wind and solar farms across the EU energy grid in the most cost effective way. Moreover, we find evidence that knowledge and technology should be shared across European countries. We conjecture that since the majority of the countries we study are in the EU, such a coordination should be feasible.

From a policy advice perspective, our results indicate that governments should be watchful of monetary policy tools they implement, as these affect the rate and level at which the greening of the economy occurs. In light of the high interest rates and inflation following the onset of the Russian-Ukrainian conflict, we expect the elevated cost of capital to negatively impact green investment. In this context, governments may wish to consider moving away from laissez-faire neoliberal green finance and monetary policy tools, whose main concerns are often price stability, inflation targeting, and quantitative easing applications. Neither green investment assets, such as green bonds, nor practices, such as Corporate Social Responsibility, have been proven to support a harmonised sustainable development. Promoting green financial funding and green assets using public money seem to boil down to investment practices to primarily attract new investors, and not necessarily to promote long-term sustainability (Dziwok and Jäger, 2021).

Albeit late, green monetary policy has been considered by the European Central Bank (ECB, 2021). A sustainable green transition does not rest on a "one-size-fits-all" approach, but in progressive monetary policies that advance solutions to environmental issues that are grounded on climate-related risk approaches embedded in the risk assessment of the whole financial sector of individual countries, taxing activities that cause climate change and foster global unity when tackling environmental problems. Developing a green infrastructure and supporting public projects should come first before financing private green projects, and fortunately the Green Deal of the European Commission partly supports this.

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Country	Number of company constituents	Index weight
Denmark	2	9.6%
Portugal	3	4.9%
Germany	4	2.4%
Switzerland	2	1.8%
Spain	2	1.7%
Italy	1	1.1%
Austria	1	0.9%
Norway	1	0.5%
Turkey	2	0.4%
France	1	0.4%
Greece	1	0.3%
EU Total	20	24%

Table 3: S&P Global Clean Energy Index country breakdown

Variable name	Code	Dominant Unit	Description	Source
Renewable Energy	$Ren_{t,j}$	No	Measure of renewable electricity proliferation in a country	International Energy Agency
Green Finance	$Gfin_{t,j}$	Yes	Measure of total green financing based on feed-in-tariff rates	OECD
Real GDP	GDP	No	Yearly real GDP per capita using 2017 PPP exchange rates	World Bank
Primary Energy per capita	E	No	Net production of electricity generated using both fossil and renewable energy, divided by the total number of the population	International Energy Agency
Green House Gas Emmissions	GHGs	No	Measure emissions of carbon dioxide, methane, nitrious oxide and fluorinated gases in a country	EUROSTAT
Headline Consumer Price Index	Inf	No	Inflation rate in a country	World Bank
Unemployment	Unemp	No	Unemployment rate in a country	World Bank and FRED
10-year Bond rate	Int	No	Long-term interest rate in a country	FRED
S&P Clean Energy Index	P_{clean}	Model 1	Measure of clean energy production company performance	Refinitiv
Non-renewable and clean-energy energy prices	P_{oil} and P_{gas}	Models 1, 2 and 3	Oil and Gas Prices	Refinitiv

Table 4: List of variables

Country name	ISO country code
Austria	AT
Belgium	BE
Bulgaria	BG
Croatia	HR
Czech Republic	CZ
Germany	DE
Denmark	DN
Estonia	ET
Finland	FI
France	FR
Great Britain	GB
Greece	GR
Hungary	HU
Ireland	IR
Italy	IT
Latvia	LV
Lithuania	LT
Netherlands	NL
Norway	NO
Poland	PO
Portugal	PR
Romania	RO
Russian Federation	RU
Slovak Republic	SK
Slovenia	SN
Spain	ES
Sweden	SW
Switzerland	CH
Turkey	TR

Table 5: List of countries and their ISO code.