The Macroeconomic Effects of High-Frequency Energy Supply Shocks and their Propagation in Spatial Networks

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Abstract

I study how energy shocks are transmitted and amplified in a spatial network, and how they affect real activity and inflation differentials within a currency union. I construct a novel high-frequency measure of energy supply shocks for European countries, which improves on existing supply shocks measures commonly adopted in the literature along several dimensions. First, it is directly estimated as physical reduction in energy generation capacity and not inferred from prices or expectations. Secondly, it is at high-frequency (daily) and country-level for 30 countries. Thirdly, I can match the physical outages to plant metadata so that I can attribute the supply shock to different generation technology (e.g. fossil, nuclear, renewable). Empirically, these shocks raise wholesale electricity prices, reduce domestic generation, shift production toward fossil sources, and increase net imports. Aggregated to the monthly frequency, electricity supply shocks increase headline and core inflation, raise producer prices, tighten financial conditions, and generate a persistent decline in industrial production. To rationalise these estimates and interpret the network transmission and amplification of these supply shocks, I develop a spatial general equilibrium model in which transmission constraints generate endogenous congestion and location-specific energy prices that act as cost-push shocks. Through cross-border energy trade, localized supply disruptions propagate across countries and affect union-wide inflation and real activity. Quantitatively, network constraints substantially amplify the macroeconomic impact of energy supply shocks. That is, even the impact of an own-country supply shock is larger than its analogue in a close economy setting, as it is amplified by the spatial network. An expansion of the model is in progress, to include tradable goods as well as energy intensive technology (e.g. data centres), to develop normative predictions and counterfactuals on Euro Area inflation, trade and productivity growth.

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1 Introduction

Energy prices played a central role in the recent surge in European inflation, highlighting the importance of cost-push shocks in integrated economies. However, empirically identifying energy supply shocks is challenging, as energy prices and quantities adjust simultaneously in equilibrium. Furthermore, especially in the Euro Area, no country is an island. That is, each country is connected to the European grid, which effectively creates a network to smooth or propagate supply shocks. The response of inflation and real activity in such a network might be significantly different to a standard closed economy setting.

In this paper, I address both challenges. Firstly, I introduce a novel approach to identifying energy supply shocks that exploits high-frequency, physical disruptions to electricity generation capacity. I construct daily, country-level measures of unexpected energy supply shocks for European countries, disaggregated by generation technology, including fossil, variable renewable (wind,solar), disposable renewable (hydro, biomass), storage and nuclear power. I then develop a spatial general equilibrium model of energy transmission across countries, with congestion on the transmission links. I show that the responses of energy prices, inflation and industrial production after a simulated energy supply shocks in the model match those identified by the new empirical measure. The framework also allows for expansions of the model to include locally produced tradables, in order to run counterfactual experiments on optimal fiscal policy in a currency union in the presence of network-transmitted supply shocks. It also allows for energy intensive technology (e.g. data centres) to generate predictions and counterfactuals on union-wide productivity growth.

In the model, countries are locations on a graph. In each node energy is consumed, both by households and industrial sector, and generated. Not all nodes are connected to each other via the grid, but those that are can fix imbalances between local demand and supply by importing/exporting energy. Crucially, energy transmission incurs in infrastructure limits and congestion. This congestion means that the response across the network to an energy supply shock will not be perfectly absorbed and will have non straightforward consequences depending on the network centrality of the country affected, and on the matrix of parameters governing congestion on network edges. Calibrating these objects is therefore crucial, and is made possible by the supply shock measure. Instead of having to look at physical capacities for each interconnection, a log-linear congestion specification allows me to estimate the congestion parameters directly from energy data on prices and flows. Once the model is calibrated, simulating supply shocks yields predictions for energy prices, inflation and industrial production in each node. A supply shock in a country j pushes up energy prices and inflation, and depresses industrial production in the country itself, but less so the more central the node. Level shifts in energy generation in a country have the same qualitative effect regardless of the country, increasing prices everywhere else. When shocks are modelled as marginal cost of generation shocks instead, they might increase or decrease prices in the other countries depending on their location and on the second-round freeing of congestion.

Identifying these mechanisms in the data requires a measure of exogenous supply shocks. The existing literature has developed several approaches to identifying supply shocks, most prominently in the context of global oil markets. Seminal contributions such as Kilian (2009) use structural VARs to disentangle oil supply disturbances from demand-driven movements, while more recent

work by Känzig (2021) exploits high-frequency financial market reactions to OPEC announcements to identify oil supply news shocks that operate through expectations. These approaches have yielded important insights but are inherently global in scope, operate at monthly or quarterly frequencies, and infer supply shocks indirectly from equilibrium price responses. More recently, Patzelt (2025) studies country-level wind generation shocks. Its analysis is conducted at the monthly frequency and is confined to a single generation technology. In this paper I develop a measure that improves on these contributions along three margins: it is at daily frequency, it is at country-level and it can be disaggregated by type of energy (fossil, nuclear, renewable).

To identify supply shocks, I exploit an institutional feature of European electricity markets. Under EU Regulation 543/2013, operators are required to report unplanned generation outages of 100 MW or more within one hour of their occurrence. These reports provide high-frequency, unit-level information on unexpected reductions in available generation capacity. I collect the universe of the outage logs and match them with generation site metadata. After cleaning duplicate and spurious outage logs, I only keep those labelled "unexpected/unplanned". I can then observe the nominal capacity of the affected plant, as well as the available capacity during the outage episode. By looking at the difference between the two, I can identify the episode-level supply shock (at the plant-hour level of granularity, measured in MW). All these episodes are then aggregated to the country-day level, and also disaggregated by different generation technologies (fossil, renewable, nuclear) based on the type of plant. Together with the shocks, I also collect hourly data on electricity generation, load, price, inflows and outflows from the ENTSOE transparency platform (more information on this in the data section). This data is crucial to calibrate the model, and to test the empirical performance of the shock measure when looking at energy markets. With the shocks at hand, I then verify whether their empirical estimated causal effect on energy and macroeconomic variables matches the testable predictions of the model.

As a first validation, I look at energy markets and I show that the identified shocks behave as adverse energy supply disturbances: they raise wholesale electricity prices, reduce domestic generation, induce substitution across production technologies, and increase net imports of electricity. These responses are robust across countries and specifications.

Aggregating the high-frequency shocks to the monthly level, I then study their macroeconomic effects. I find that adverse electricity supply shocks significantly increase headline and core inflation, raise producer prices, tighten financial conditions, and lead to a gradual decline in industrial production. These effects are economically meaningful and persistent, highlighting electricity supply as an important source of cost-push inflation and real activity fluctuations. I show that this is robust across generation technology, that is fossil and renewable shocks behave very similarly.

Section 2 describes European energy markets, and Section 3 details the construction of the shock measures and their diagnostics. Section 4 presents the spatial general equilibrium model of the energy grid and outlines its testable predictions. Section 5 brings them to the data and estimates the impact of energy supply shocks first on energy market then on consumer prices and real activity. Section 6 concludes.

2 High-resolution European Electricity Market Data

The European electricity market is organized as an integrated set of bidding zones broadly corresponding to national borders, with exceptions (e.g. Germany-Luxemburg forming a joint bidding zone, or Italy as well as Scandinavian countries being divided in sub-national bidding zones). Core energy trade occurs in a day-ahead auction, cleared jointly across zones by the EUPHEMIA((Pan-European Hybrid Electricity Market Integration) algorithm. Market participants submit hourly supply and demand bids for next-day delivery; the algorithm maximizes total surplus subject to transmission constraints, yielding a zonal market-clearing price for each hour and a set of scheduled commercial exchanges (net flows) on each interconnector. Real-time operations remain with national Transmission System Operators (TSOs), who provide the cross-border capacity inputs to the auction and balance the system via intraday and balancing markets.

Transparency in European power markets increased markedly over the past decade, culminating in Regulation (EU) No 543/2013 (14 June 2013) on the submission and publication of data in electricity markets. The regulation obliges data providers and asset owners in EU Member States to report fundamental information on generation, load, transmission, and balancing, which the association of European TSOs (ENTSO-E) publishes on the ENTSO-E Transparency Platform in a harmonized, time-stamped format. From this source, I assemble an hourly constantly updating dataset at the bidding-zone level comprising:

i Actual Total Load (realized demand), measured in MW;

ii Actual Generation, total and by Production Type (i.e. nuclear, fossil, hydro, wind etc.), measured in MW;

iii Day-Ahead Prices (zonal clearing prices from the coupled auction), measured in Euro/MW;

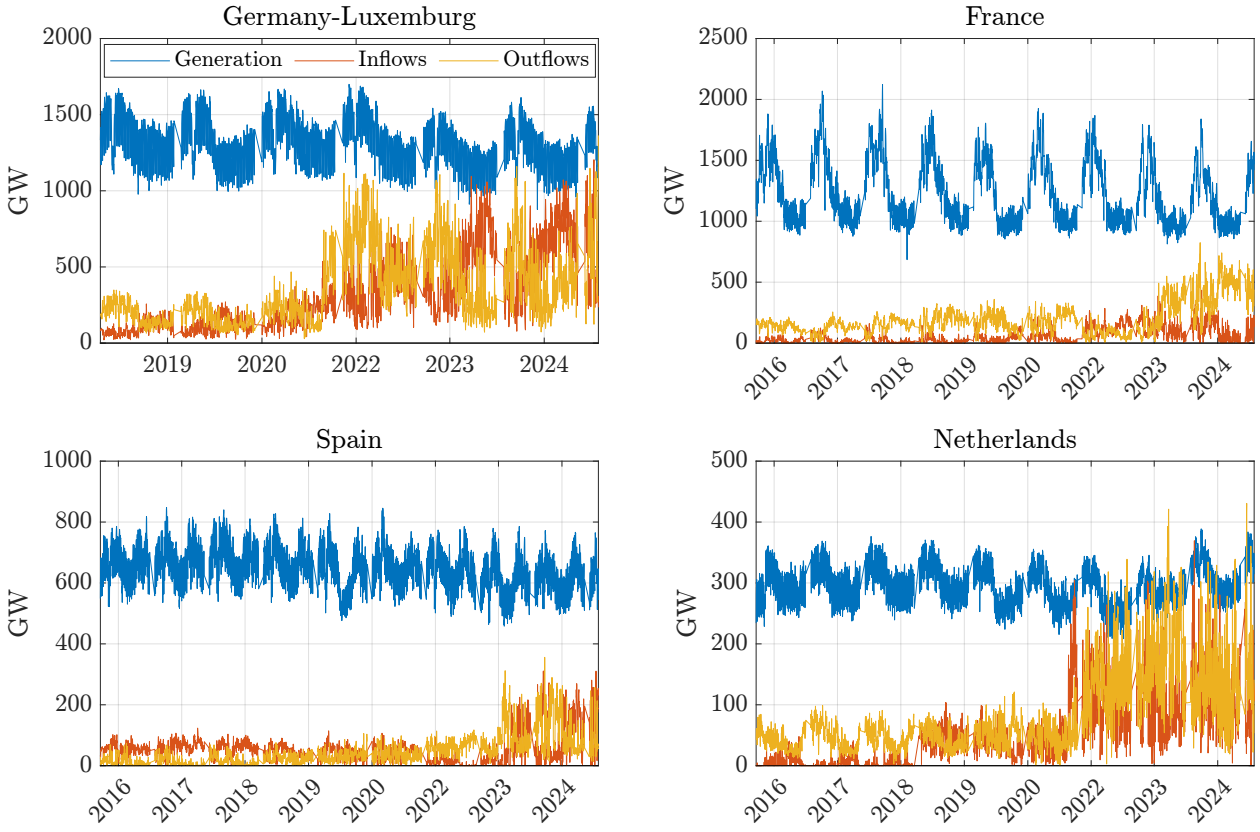
iv Cross-Border Flows: the scheduled commercial exchanges implied by the day-ahead clearing, measured in MW.

Timestamps are aligned to Europe/Brussels (CET/CEST). The data covers 30 bidding zones, hourly from January 2015 to the present (with some exceptions for bidding zones who changed or entered later in the sample). The richness of the data allows me to identify high-frequency outcomes as in the next section. This can be useful in studying the interaction of energy variables and e.g. asset prices and other high-frequency outcomes. On the other hand, they can also be used to analyse medium run trends. For example, looking at the development of European energy markets over the course of the last 10 years. The four panels of Figure 1 shows the evolution of daily generation, inflows and outflows for a selected sample of four countries: Germany (Luxemburg), France, Spain and the Netherlands.

3 Construction of a novel measure of energy supply shock

Crucially, EU regulation also mandates agents to report outages that affect generation and production facilities. That is, any time a reduction in availability of 100 MW or more in a generation

Figure 1: Electricity Market Data for Selected Bidding Zones



Note. The figure plots daily electricity generation, cross-border inflows, and outflows for four major bidding zones—Germany-Luxemburg, France, Spain, and the Netherlands. The series are constructed from ENTSO-E Transparency Platform data.

facility occurs, this has to be reported and becomes available within 1 hour on the ENTSOE transparency platform. More precisely, the Commission Regulation (EU) No 543/2013 of 14 June 2013 reads at its articles 15.1.b, 15.2 and 15.3 [1]

> *"Changes of 100 MW or more in actual availability of a generation unit, expected to last for at least one market time unit, specifying:*
>
> - *the name of the production unit;*
> - *the name of the generation unit;*
> - *location;*
> - *bidding zone;*
> - *installed Net generation capacity;*
> - *the production type;*
> - *available capacity during the event;*

[1] Link to the documentation here: ENTSOE website and EUR-Lex.

- *reason for the unavailability of the generation asset*
- *start and estimated end date (day, hour) of the change in availability.*

The information shall be published as soon as possible but no later than one hour after the change in actual availability"

To construct a time series of outages supply shock for each bidding zone, I proceed as follows. I collect the universe of outage logs from ENTSOE transaparency for the avaiable period 2015-present (the shock series are live and daily updating). For each event identifier, I retain the latest revision, drop cancellations, and exclude planned maintenance to isolate *forced/unplanned* outages. Timestamps are handled in UTC, expanded to an hourly panel over each event's active interval $[t^{\text{start}}, t^{\text{end}})$, then converted to Europe/Brussels. The energy supply measure is then computed as follows. Let u index a generating unit, $c(u)$ its bidding zone, and $p(u)$ its technology (e.g. nuclear, hydro, fossil). Denote nominal capacity by K_u and reported available capacity in hour t by $\tilde{K}_{u,t}$. Define the forced-outage shortfall:

$$O_{u,t} = K_u - \tilde{K}_{u,t}. \tag{1}$$

If multiple logs overlap within the same unit–hour, I use the highest-revision value for $K_{u,t}$ to avoid double counting. I then aggregate the plant-level $O_{u,t}$ within bidding zone-technology-hour:

$$z_{c,p,t} = \sum_{u:\, c(u)=c,\; p(u)=p} O_{u,t} \tag{2}$$

where $z_{c,p,t}$ is measured in MW and captures the energy supply reduction for country c (e.g. France) from prouction type p (e.g. nuclear). We can sum across production types and aggregate to daily to obtain $Z_{c,d}$

$$Z_{c,d} = \sum_{u:\, c(u)=c} O_{u,d} \tag{3}$$

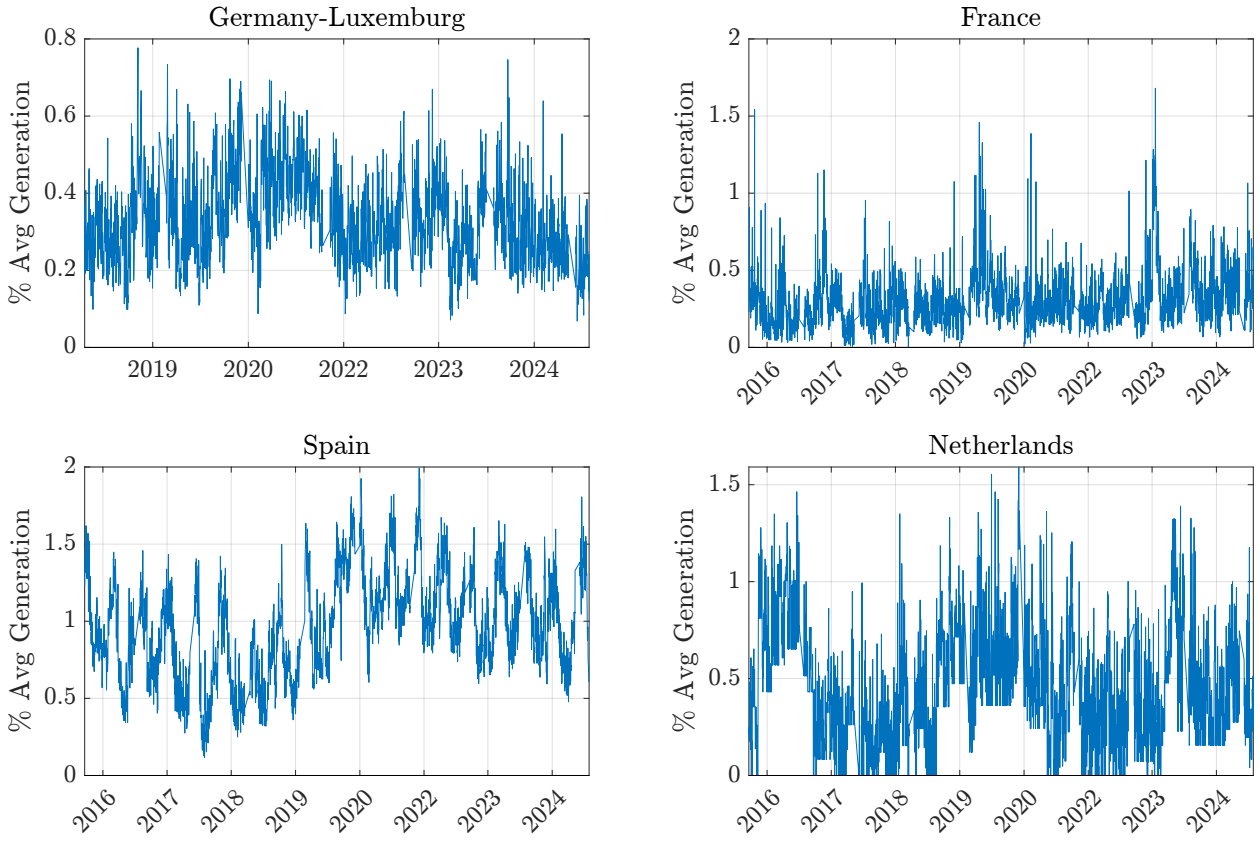
This is the daily country-level energy supply shock. Larger values of $Z_{c,d}$ indicate tighter effective supply in country c from in day d. It can be expressed in MW, in percent of total generation capacity, or normalised.

3.1 Diagnostics

The daily series of energy supply shocks is shown in Figure 2 for four sample countries. All other bidding zones are available in Appendix C. In what follows, I perform a series of tests of the validity of the series.

Serial correlation. The presence of multi-day outage spells introduces serial correlation in the shock measures. This is indeed shown in Figure B1. This can be due to multi-day outages as well as to the effect of congestion: a supply outage at one point of the network might require further effort from the other generation units, making outages more likely in turn. The autocorrelation behaviour of the shock might therefore be interesting in its own right. However, in order to make sure this

Figure 2: Daily country-level energy supply shocks

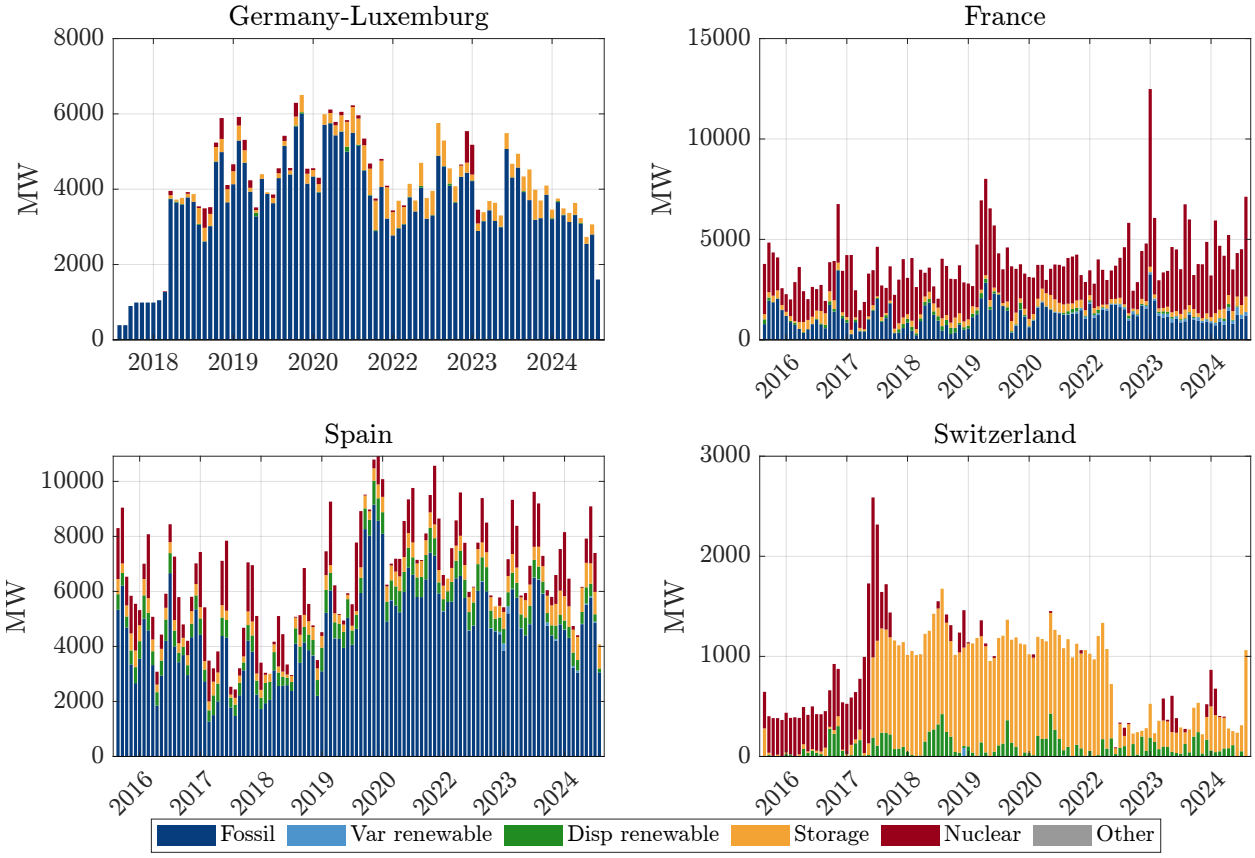


Note. The figure plots the daily series of unexpected electricity supply shocks for four selected countries, expressed as a percentage of average generation. The shocks are constructed from plant-level unplanned outages reported under EU Regulation 543/2013 and capture high-frequency, physical reductions in available generation capacity. Larger values correspond to tighter effective energy supply. Germany-Luxemburg are presented together because they form a unique bidding zone in the electricity market.

is not biasing my estimates, I always control for 30 lags and 30 leads of the shock in the baseline specifications. I also purge the shock of autocorrelation before aggregating it to monthly frequency.

Endogeneity and seasonality. Figure 2 shows that the shocks are subject to seasonal fluctutatuons. In all specifications in which time fixed effects are not included I therefore always include seasonal dummies, and when aggregating to monthly level I residualise on seasonal patterns first. Furthermore, one might fear that outage shocks are not fully exogenous to energy markets variable. For example, a period of high prices in neighbouring countries or of high domestic demand might cause an overload of the system, which might make outages more likely. I therefore test whether energy prices, load and in/outflows in the previous 30 days can predict the shock. The results are in the four panels of Figure B2. The results indicate that the energy supply shock series is not mistakenly picking up system overheating, price, import or export pressure in energy markets. Furthermore, I will show in the next section that while the shock is not predicted by energy market variables, its own impact on these variables in turn is what we would expect from an energy supply tightening. Taken together, the diagnostics support the validity of the energy supply shock series.

Figure 3: Energy supply shocks by generation technology



Note. The figure decomposes country-level energy supply shocks into contributions from different generation technologies, including fossil, variable renewable, dispatchable renewable, nuclear, storage, and other sources. This decomposition highlights the heterogeneity of supply disruptions across countries.

3.1.1 Shock decomposition by generation type

A key advantage of my novel shock series is that it allows disaggregation by generation technology. Figure 3 shows this for a sample of four countries, selected because of their diversity in energy mix. The shock series for Germany reflects its reliance on fossil, while the time series for France is predictably dominated by nuclear shocks. The picture for Spain is more diverse, with renewables and storage playing a role. Switzerland stands out as hydropumped storage shocks play a large role. This level of granularity allows me to test whether the macroeconomic impact of the shocks differs across the energy mix.

To provide a structural framework that disciplines the interpretation of the novel outage-based shocks and yields testable implications, the next section develops a spatial general equilibrium model of energy transmission across countries.

4 A Spatial General Equilibrium Model of Energy Trade

In this paper, I develop a spatial general equilibrium model of the European electricity network building on the framework of Fajgelbaum and Schaal (2020).

4.1 Environment

Preferences. The model encompasses a discrete set of locations $\mathcal{J} = \{1, \cdots, J\}$. Each location is endowed with L_j inhabitants, who work and consume according to preferences

$$u(e_j, g_j) = \eta \log(c_j) + (1 - \eta) \log(e_j^c) \tag{4}$$

where $c_j = C_j/L_j$ is per capita consumption of the locally produced non-tradable good and $e_j^c = E_j^c/L_j$ is per capita direct consumption of energy by the household.

Production. Every location j produces a a non-tradable good using labour and energy inputs

$$Y_j = A_j m_j^{\alpha_j} L_j^{1-\alpha_j} \tag{5}$$

where A_j is country-specific productivity and α captures energy intensity of production in country j. The profit maximisation of the firm determines optimal industrial energy demand m_j

$$m_j = L_j \left(\frac{\alpha_j^2 \eta_j A_j}{P_j^2} \right)^{\frac{1}{2-\alpha_j}} \tag{6}$$

Energy Generation. In each location there is a representative energy sector, producing energy to maximise profit according to

$$\max_{Gj>0} \pi(P_j, c_j(g_j)) = P_j G_j - c_j(g_j) \tag{7}$$

where $c_j(G_j)$ is a country-specific convex cost of producing energy, which depends on energy mix, availability of natural resources etc. Specifically, I assume that $c_j(G_j) = a_j + \frac{b_j}{2} G_j^2$ such that optimal generation is each country j is

$$G_j^* = \max \left\{ \frac{P_j - a_j}{b_j}, 0 \right\} \tag{8}$$

Network Topography. The locations $\mathcal{J}$ represent nodes on an undirected graph $(\mathcal{J}, \mathcal{E})$ where $\mathcal{E}$ are edges connecting the nodes. Not all nodes are directly connected to all other nodes. Specifically each location j is connected via the grid to a set of neighbours $N(j)$. This is captured by an adjacency matrix applied to $\mathcal{J}$. Energy can travel directly to/from any $i \in N(j)$ but for any $i \notin N(j)$ they must travel through a series of intermediate neighbours along the grid.

Transmission Technology. Transmitting energy from node j to i incurs in infrastructure limits and congestion. Let us define the flow of energy between directly connected nodes i and j as $Q_{j,i}$. I follow Fajgelbaum and Schaal (2020) in modelling transmission costs as

$$\tau_{j,i} = \delta^{\tau}_{j,i} \frac{Q^{\beta}_{j,i}}{I^{\gamma}_{i,j}} \quad \text{with} \quad \beta \geq 0 \quad \gamma \geq 0 \tag{9}$$

where $I_{j,i}$ is the level of grid infrastructure between i and j: a higher level of infrastructure decrease the cost of energy flowing between them. The transmission cost also depends on the size of the flows $Q_{j,i}$. That is, large flows cause congestion on the line, a *congestion externality*. $\delta^{\tau}_{j,i}$ is a scaling parameter that helps calibrating the transmission cost to time invariant characteristics of the link between i and j, say geographical barriers to grid infrstructure.

Flow Constraint. In every node, there is energy being generated, consumed, as well as going in and out. The balance of energy flows requires that for all locations $j = 1 \cdots, \mathcal{J}$, the following constraint is satisfied

$$\underbrace{L_j e_j + L_j m_j + \sum_{k \in N(j)} (1 + \tau_{jk}(Q_{jk}))Q_{jk}}_{\text{Household + Industrial Energy Consumption + Outflows}} \leq \underbrace{G_j + \sum_{i \in N(j)} Q_{ij}}_{\text{Generation+Inflows}} . \tag{10}$$

The left hand side of this inequality is country j's energy consumption, determined by direct household demand e_j and industrial optimal demand of energy input m_j, plus exports of energy to neighbours via the grid, accounting for the grid congestion cost. As consumption and indsutrial demand are in per capita terms, they are , which is bounded by the generation of the country G_j and its inflows from neighbours Q_{ij}.

4.2 Planner's problem and equilibrium

The planner takes into account the topography of the network, population and technology and solves for optimal allocations and flows, energy prices, consumption and production in each of the nodes. Formally,

$$\max_{c_j, e^c_j, m_j, G_j, \{Q_{ij}\}_{i \in N(j)}} \sum_j \omega_j L_j u(e^c_j, c_j) \tag{11}$$

$$- \sum_j C_j(G_j) \qquad \text{(Generation)}$$

$$- \sum_{(i,j) \,|\, i \in N(j)} \tau_{ij}(Q_{ij}) \qquad \text{(Congestion)}$$

subject to

$$L_j c_j \leq Y_j(m_j, L, j) \qquad \text{(Nontradable production)}$$

$$L_j e_j + L_j m_j + \sum_{k \in N(j)} Q_{jk} \leq G_j + \sum_{i \in N(j)} Q_{ij} \qquad \text{(Flow Constraint)}$$

$$c_j, e_j^c, m_j, G_j \geq 0 \qquad \text{(Non-negativity)}$$

In solving the planner's optimal allocation problem given a network, I follow Fajgelbaum and Schaal (2020) (2020) in solving the problem by duality. That is, instead of solving individually for the large set of flows on every edge and allocations on every node, we can recast the problem in its dual form. The objective is concave and all the constraints are convex. Congestion makes the flow constraint convex. We can use the first order conditions to express all choice variables as a function of the Lagrange multiplier on the balanced flow constraint, that is the vector of energy prices across all nodes $\mathbf{P_j}$. Then, the planner problem becomes

$$\min_{P_j \geq 0} \mathcal{L}(\mathbf{X}(\mathbf{P_J}), \mathbf{P_J}) \tag{12}$$

where $\mathbf{X}(\mathbf{P_J})$ denotes the choice variables as a function of the vector of Lagrange multipliers $\mathbf{P_j}$, that

Therefore, in its dual representation the problem boils down to adjusting prices until every goods-balance constraint holds exactly. Then, from $\mathbf{X}(\mathbf{P_J})$ one can recover the optimal allocation.

4.3 Network Calibration

Underlying graph. I use ENTSOE data on flows and interconnectors, together with GEOJSON files from the natural earth database to convert the European grid to a graph $(\mathcal{J}, \mathcal{E})$. For every centroid, I construct an adjacency matrix depending on whether there exist an interconnection to a neighbouring bidding zone.

Congestion. A crucial quantitative element disciplining the model are the parameters governing congestion on the network edges. The high-frequency dataset constructed in the previous section provides the ideal empirical setting to discipline β and $\kappa_{j,k} = \frac{\delta^{\tau}_{j,k}}{I^{\gamma}_{j,k}}$. We observe hourly prices and flows across all bidding zones, and from the model's first order conditions we know that:

$$Q_{j,k} = \left[\frac{1}{1+\beta} \kappa_{j,k} \max\left\{ \frac{P_k}{P_j} - 1, 0 \right\} \right]^{1/\beta} \tag{13}$$

conditioning on positive price differentials and flows, we can take logs of the first order condition to obtain an estimating specification

$$\log Q_{jk,t} = \alpha_t + \gamma_{j,k} + \delta \log(P_{k,t} - P_{j,t}) + u_{j,k,t} \tag{14}$$

Table 1: Calibrating congestion on the network

	Energy flow on jk Edge: $\log Q_{jk,t}$	
	(1) OLS	(2) IV
Price wedge: $\log(P_{k,t} - P_{j,t})$	0.130***	0.734***
	(0.002)	(0.134)
Observations	95,778	76,992
R-squared	0.487	
Cragg-Donald F		37.73
Kleibergen–Paap F		47.19
Network Edge FE	Yes	Yes
Time FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

where we can recover β as $\beta = 1/\hat{\delta}$ and κ_{jk} as $\kappa_{jk} = \hat{\gamma}/\hat{\delta}$. Evidently, a panel regression of flows on price differential would be likely be biased, because of the simultaneous determination of prices and flows. I need an instrument to obtain an unbiased estimate of β. This is where my novel supply shock measure comes in handy: by instrumenting prices by exogenous supply shocks, I can recover $\hat{\delta}$ and consequently both β and κ_{jk}. The first stage is

$$\log(P_{k,t} - P_{j,t}) = \pi z_{j,t} + \Gamma_{jk} + \nu_t \epsilon_{jk,t} \tag{15}$$

where $z_{j,t}$ is a generation shock in the origin country of the flow (as I condition on positive flows and price differences). We can then use the fitted price difference from the first stage in the second stage to retrieve unbiased estimates. The results of the estimation are presented in Table 1.

The difference between the OLS and IV results shows that instrumenting for supply shocks overcomes the attenuation bias of the OLS estimate and gives a precisely estimated value of 0.734. The vector of $\kappa_{j,k}$ is recovered by combining this $\hat{\beta}$ and the estimated fixed effects $\hat{\gamma}_{jk}$

Cost of generation. A similar procedure can be adopted to recover the vectors of generation technology parameters a_j and b_j. Once calibrated, supply shocks in the model will be introduced as either reductions in a_j or increase in b_j.

Macro parameters. To calibrate η_j, the importance of direct energy use in households' consumption baskets, I used country-level HICP weights from EUROSTAT. For α_j I match the energy intensity data from EUROSTAT and for A_j I follow the data from EUROSTAT on output per worker and per hour for European countries. I supplement these data from national statistical agencies when they might not be available on EUROSTAT, e.g. UK or Switzerland.

4.4 Model predictions for supply shocks and their propagation

After solving the calibrated model, we obtain equilibrium flows, prices and real activity. I can now run two experiments that I later bring to the data, in order to have testable prediction from the theory on the qualitative and quantitative behaviour of energy prices, inflation, energy inflows, energy outflows and industrial production after generation shocks. Specifically, I run two experiments (i.) I simulate the effect of a generation shock in country i and I look at the behavior of country i variables $\forall i$, for both shocks to a_j and b_j, then (ii.) I look at generation shocks in three countries: France, Germany and Portugal , and look at how they propagate to prices, flows and real activity across all other nodes of the network.

Country-by-Country response Figure 4 shows the response of all countries in the model to an own supply shock (assuming no simultaneous supply shock in other countries). The supply shock is calibrated as a reduction of 10% in a_j. The shock is assumed permanent, but as the model is static for the moment, there is no interesting endogenous dynamic propagation. Energy prices increase and so does inflation while inflows and outflows move to balance the system. Finally, the increase in energy prices causes an increase in marginal costs and so decreases industrial production. In the next section, I will show that my novel supply shock measure empirically matches these predictions.

Energy Supply Shock Transmission in the Network Figure 5 illustrates the model-implied spatial response to an energy supply shock originating in France. Nodes represent bidding zones and are positioned according to geographic coordinates, while the vertical axis reports equilibrium electricity prices. Colored links denote cross-border electricity flows, with intensity measured by the magnitude of net flows. The shock raises prices most strongly in France and nearby markets, with transmission across the European grid reflecting network connectivity and congestion.

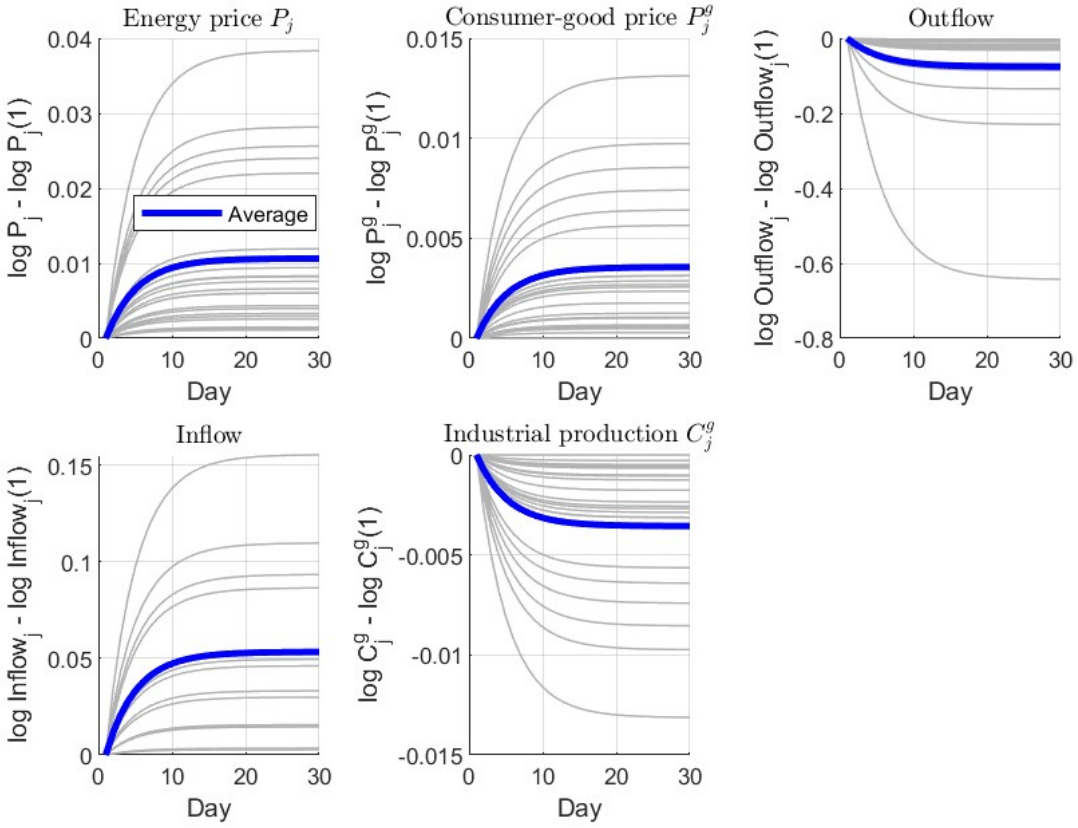
5 Causal effects of energy supply shocks

I now study the causal effects of the identified energy supply shocks on electricity markets first and then on macroeconomic outcomes. We start from the country/day shock series $Z_{c,d}$ constructed in Section 2, and first verify that it behaves as an adverse energy supply disturbance: it should reduce domestic generation, raise the zonal day-ahead price, shift the generation mix , and increase net imports of energy. The richness of the outage data allows us to estimate these effects both country by country and in a panel.

We show that results are robust to these different modelling choices. Taken together, they show that a negative supply shock, i.e. a higher value of $Z_{c,d}$ induces a persistent increase in prices, a decline in domestic generation, a shift from the shocked technology towards fossil, a reduction in energy exports and an increase in imports.

We then move to monthly frequency and study their impact on baseline and core inflation, producer prices, interest rates, and industrial production. We find that the shocks significantly increase both

Figure 4: Model Simulated Impact of Own Supply Shock



Note. The figure shows log deviations from baseline following a one-standard-deviation permanent negative energy supply shock. Grey lines denote individual country responses (excluding the country of origin of the shock), the blue line shows the cross-country average.

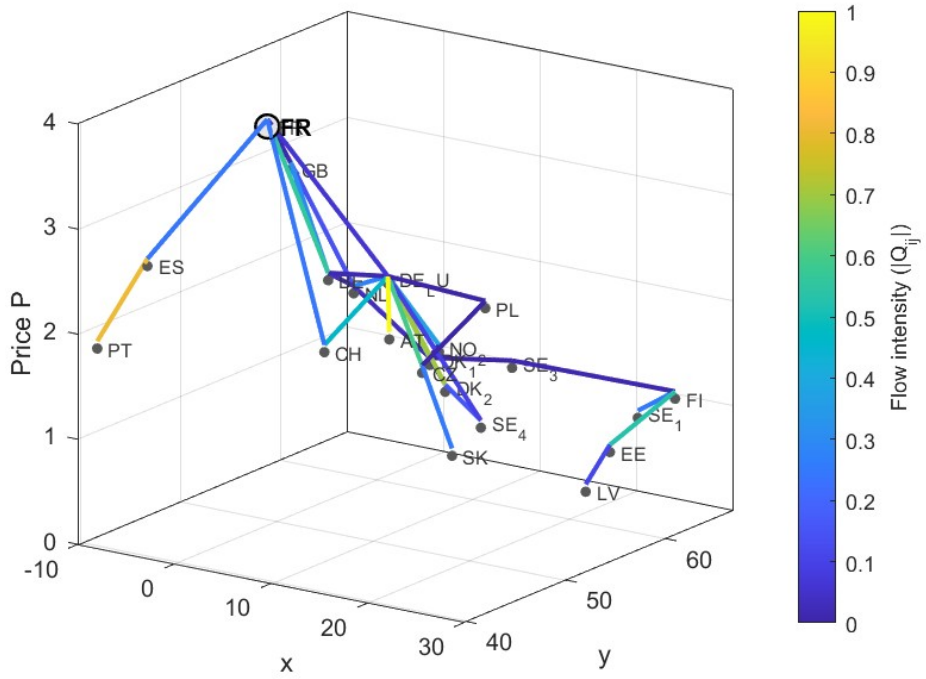
headline and core inflation and PPI, tighten financial conditions, and reduce industrial production; these results are robust to a wide range of specifications.

5.1 Effects on electricity markets

Let c index countries (bidding zones) and d index calendar days. We aggregate hourly data to daily. Results are robust to equal weighted aggregation of prices and load-weighted, as well as to using average generation/load in a day or total generation/load. For each country-day pair we then observe total generation $G_{c,d}$, load $L_{c,d}$, the day-ahead wholesale energy price $P_{c,d}$, energy inflows $I_{c,d}$ and outflows $E_{c,d}$ as well as the shares of different technologies in generation, $\mathrm{S}^k_{c,d}$ for technology k. We estimate panel local projections where the shock enters directly. For each outcome $Y_{c,d}$ of interest, in turn total generation, load, the day-ahead price, energy inflow, outflow and the fossil share of generation, we estimate, for horizons $h = 0, 1, \ldots, H$:

$$Y_{c,d+h} = \alpha_c^Y + \lambda_d^Y + \beta_h^Y Z_{c,d} + \sum_{l=1}^{L_Y} \Phi_{l,h} Y_{c,d-l} + \sum_{l=1}^{L_Z} \Psi_{l,h} Z_{c,d-l} + \sum_{f=1}^{F_Z} \Lambda_{f,h} Z_{c,d+f} + \varepsilon^Y_{c,d+h}. \tag{16}$$

Figure 5: Model Impact of Energy Supply Shock in France



Note. The figure plots the model-implied price surface and cross-border electricity flows across European bidding zones. Node height denotes equilibrium electricity prices, while colored edges represent net bilateral flows. X and Y are normalised latitude and longitude coordinates of the countries in the spatial model. The simulation is based on the calibrated network model described in the text.

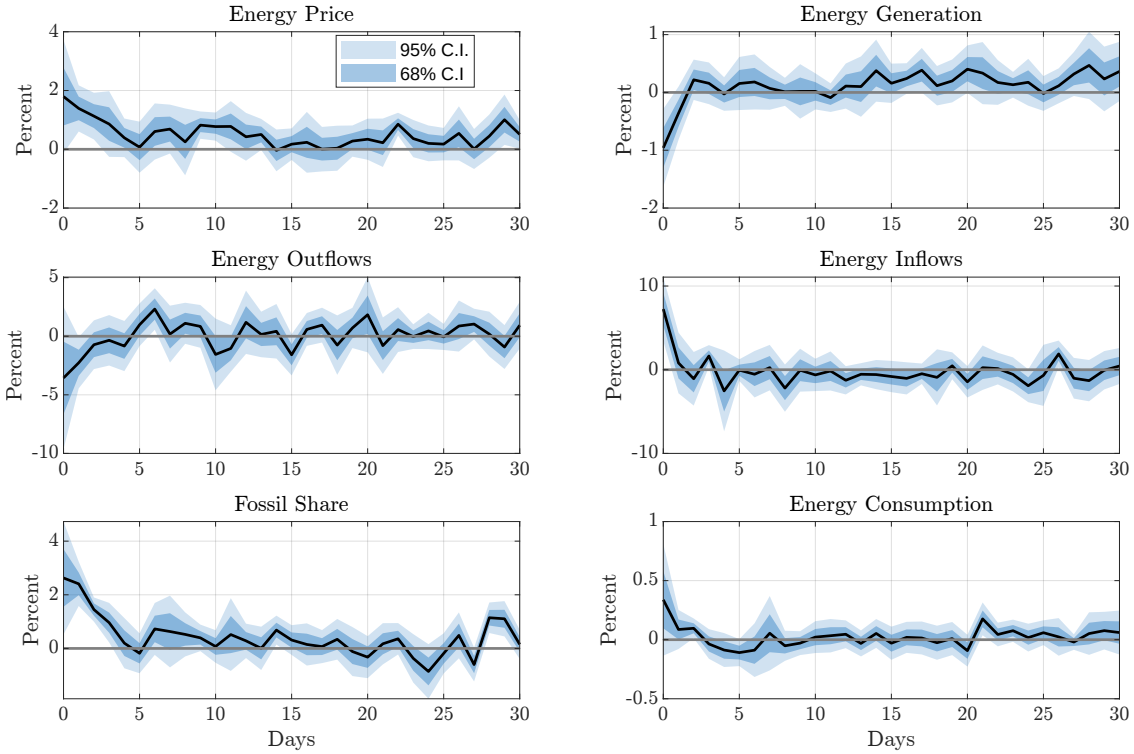
Here α_c^Y are country fixed effects and λ_d^Y are common time effects (e.g. day-of-sample or month-by-year fixed effects) that absorb shocks common to all countries such as fuel prices or EU-wide policy changes. Lagged values of the outcome $Y_{c,d-\ell}$ and of the shock $Z_{c,d-\ell}$ flexibly account for persistence and for multi-day outage spells. For this we also add leads of the shock We typically set $L_Y = L_Z = F_Z = 30$ (one month), and verify robustness to alternative lag lengths.

The coefficients β_h^Y trace out the impulse response of variable Y at horizon h to a shock on day d. The shock is scaled such that the reported $\hat{\beta}_h^Y$ correspond to the cumulative percent change in $Y_{c,d}$ as a response to a shock of 1% of average generation. Equation (16) is estimated for each h separately, with standard errors clustered at the country level.

5.1.1 Results

I present now the results of the baseline specification on energy markets. Figure 6 shows the estimated dynamic causal impact of energy supply shocks, normalised so that it corresponds to a 1% reduction in average generation, on energy markets. All variables are in logs so that the IRFs can be interpreted as percent cumulative change. The solid black lines are the point estimates and the shaded areas are 68 and 95 percent confidence intervals based on standard errors clustered by

Figure 6: Daily impacts of energy supply shocks on energy markets



Note. The figure reports impulse responses of electricity prices, generation, cross-border inflows and outflows, fossil generation share, and energy consumption to an adverse energy supply shock, estimated using panel local projections at the daily frequency. Shaded areas denote 68 and 95 percent confidence intervals, standard errors clustered at the country level. These results are robust to a battery of different specifications and to using the shock as an instrument instead of directly in the specification. The results are also replicable using a country-level proxy SVAR instead of local projections.

country. A negative supply shock that reduces generation by 1% leads to a significant immediate 2% increase in energy prices, which then falls sluggishly, but remains significant for 20 days after the supply shock has reverted. Energy inflows rise significantly by 10% to make up for the loss in generation, and similarly outflows fall. These effects are however short-lived and go back to steady state in the space of 3 days, in line with the timing of the shock. Interestingly, energy consumption does not significantly respond. There is a signifcant response of the share of fossil in the energy mix, which goes up by 2%. These results are robust to different specification of the local projections, to using the shock as an instrument for generation instead of directly, and to using country-by-country proxy SVARs instead of local projections.

5.2 Effects on the macroeconomy

We now move from high-frequency electricity market outcomes to monthly macroeconomic aggregates. The goal is to quantify how the identified supply shocks propagate into inflation, producer prices, industrial activity, and interest rates. First, we aggregate the daily country-level shocks $Z_{c,d}$ to a monthly frequency. Second, we estimate panel local projections for macro variables. Third, we

consider a country by country Proxy SVAR specification where the shocks instrument for energy prices.

5.2.1 From daily outages to monthly shocks

Our daily country-level outage series $Z_{c,d}$ measures the fraction of installed capacity that is unexpectedly offline. To avoid double-counting multi-day outage spells when aggregating to the monthly frequency, we work with the *innovation* in outages rather than the level.

Specifically, for each country c we first residualise $z_{c,d}$ on own lags and calendar, controls to obtain $r_{c,d}$:

$$Z_{c,d} = \sum_{l=1}^{30} Z_{c,d-l} + u_{c,d}, \tag{17}$$

and interpret the residuals $u_{c,d}$ as daily outage innovations. Our monthly energy supply shock is defined as the sum of these innovations

$$Z_{c,m} = \sum_{d \in m} u_{c,d}. \tag{18}$$

This construction ensures that a long-lasting outage that keeps capacity offline for several days is treated as a single shock, rather than a sequence of mechanically repeated shocks.

5.2.2 Panel local projections for macro variables

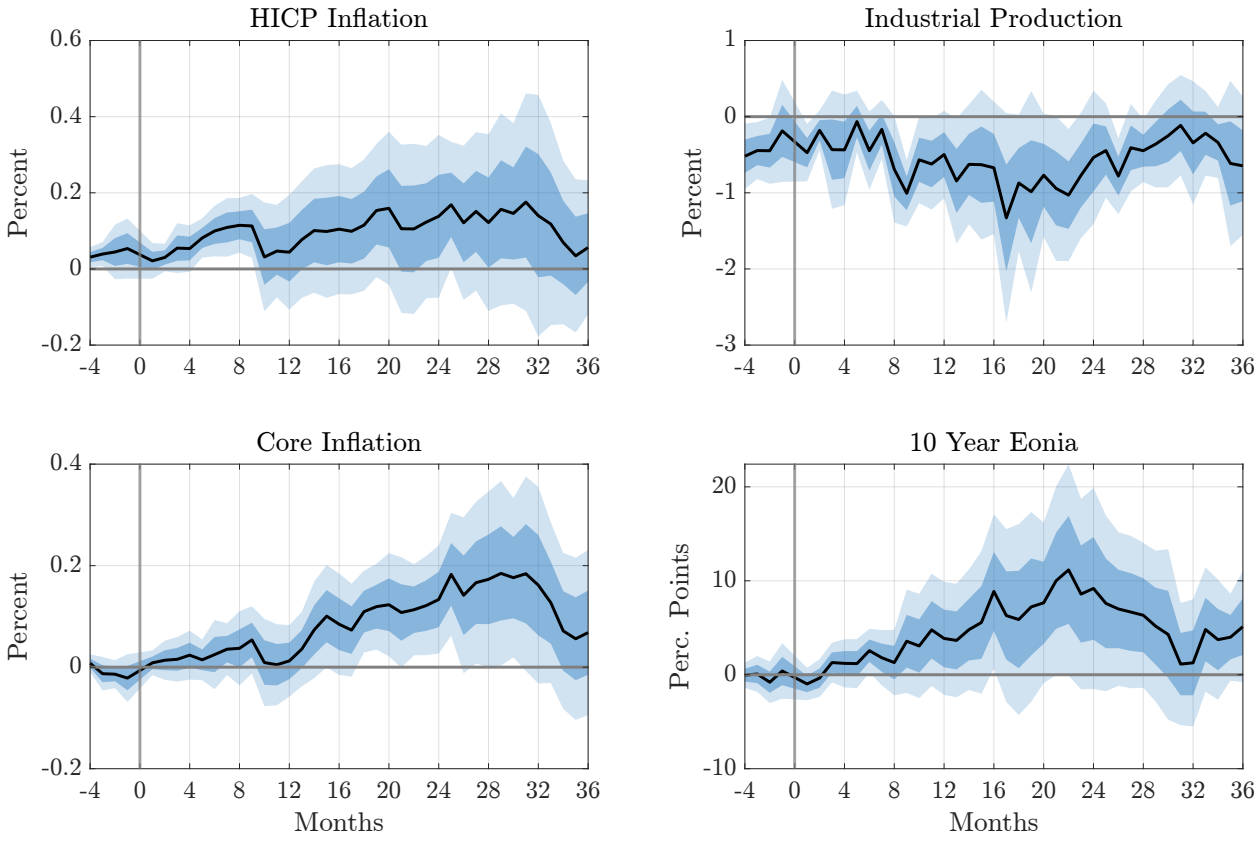
The baseline specification includes five variables: We focus on the following monthly macro outcomes: headline CPI inflation $\pi^H_{c,m}$, core inflation $\pi^C_{c,m}$, producer price inflation $\pi^{PPI}_{c,m}$, industrial production $ip_{c,m}$, and EONIA long-term nominal interest rates (10 year yields) $i_{c,m}$. For each outcome $Y_{c,m}$ we estimate horizon-specific panel local projections of the form

$$Y_{c,m+h} - Y_{c,m-1} = \alpha^Y_c + \lambda^Y_m + \beta^Y_h \log(Z_{c,m}) + \Gamma^Y_h X_{c,m} + u^Y_{c,m+h}, \tag{19}$$

for horizons $h = 0, 1, \ldots, H$. In this specification, $Y_{c,m+h}$ is the log of each of the 5 macro variables at horizon $m+h$, α^Y_c are country fixed effects, λ^Y_m are time fixed effects (month-by-year dummies).$X_{c,m}$ is a vector of controls that includes all other variables in the specification except for Y, mirroring a VAR setting. For instance, for industrial production, $X_{c,m}$ will include inflation, PPI and interest rates. As persistence is already cleansed in the aggregation to monthly, we do not include lags in the baseline specification, but results are robust to doing so.

Equation (19) is estimated with standard errors clustered at the country level. Our coefficients of interest are β^Y_h, which trace out the percent response of macro outcome Y at horizon h to a one percent energy supply shock. We report $\{\hat{\beta}^Y_h\}_{h=0}^H$ as impulse response functions, together with 68 and 95 percent confidence bands.

Figure 7: Macroeconomic effects of energy supply shocks

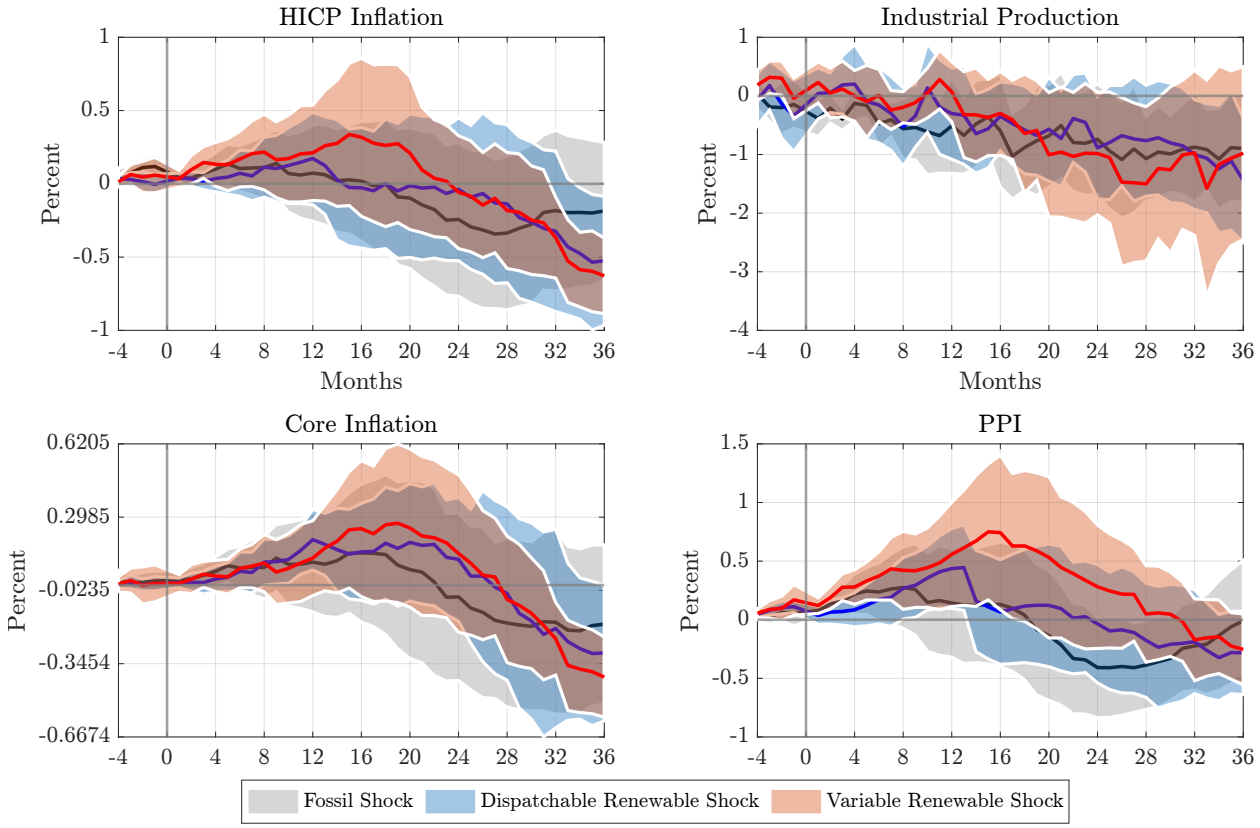


Note. The figure shows impulse responses of headline inflation (HICP), core inflation, industrial production, and long-term interest rates to a monthly energy supply shock obtained by aggregating daily outages. Responses are estimated using panel local projections; shaded areas denote 68 and 95 percent confidence intervals. These results are robust to a battery of different specifications and to using the shock as an instrument insted of directly in the specification. The results are also replicable using a country-level proxy SVAR instead of local projections.

5.2.3 Results

The results are presented in the four panels of Figure 7. A one standard deviation adverse energy supply shock leads, on impact, to an increase in headline inflation which peaks at around 0.2%, persistently for around 32 months before going back to 0. The response of core inflation is similar, with a slower build-up and later peak also around 0.2%. Industrial production declines gradually over a 20 months horizon, bottoming at -1% before reverting to 0. The response of interest rates, possibly because of the absence of variation in the cross section, are noisier, but point to a hump shaped positive response of long-run interest rates peaking at 100 basis points.

Figure 8: Macroeconomic effects by generation technology.



Note. The figure compares the macroeconomic responses to energy supply shocks originating from fossil, variable renewable, and dispatchable renewable generation; shaded areas denote 68 percent confidence intervals.

5.2.4 Effect of fossil vs renewable shocks

My novel shock measure allows disaggregation by generation technology. We can therefore examine the heterogeneity in macroeconomic impact of fossil, dispatchable renewable and variable renewable shocks. Figure 8 presents the IRFs to fossil shocks in black, dispatchable renewables in blue and variable renewables in red.

We see that the response to the different shocks follow similar trajectories quantitatively but differ in their magnitudes. In agreement with the idea that variable renewables have virtually zero marginal cost, and reduction in renewable supply causes a higher increase in inflation and PPI, as well as more pronounced medium-run fall in industrial production. This also lines up with the finding from Figure 6 that in general a negative energy supply shocks will result in increase reliance on fossil, increase the marginal cost of energy production.

6 Conclusion

This paper studies the macroeconomic effects of energy supply disruptions in the integrated European energy market. I construct a new high-frequency measure of energy supply shocks based on unplanned generation outages, which improves on existing measures in the literature along three dimensions: identification, granularity and generation-type breakdown. I then develop a spatial general equilibrium model to trace the transmission of supply shocks through the electricity network.

Empirically, I show that the newly estimated shocks raise wholesale electricity prices, shift generation toward fossil sources, and increase cross-border imports. At the monthly frequency, these shocks lead to persistent increases in both headline and core inflation, alongside a decline in industrial production. The model accounts for these patterns by showing how network congestion turns localized supply disturbances into union-wide cost-push shocks and amplifies their macroeconomic effects.

The results highlight electricity networks as an important channel through which supply shocks propagate within a currency union. They point to transmission capacity and market integration as key determinants of the inflationary and real effects of energy disruptions. Future work will use the framework to study optimal policy and infrastructure design in the presence of network-transmitted energy shocks.

References

Fajgelbaum, Pablo D and Edouard Schaal (2020). "Optimal transport networks in spatial equilibrium". In: *Econometrica* 88.4, pp. 1411–1452.

Känzig, Diego R (2021). "The macroeconomic effects of oil supply news: Evidence from OPEC announcements". In: *American Economic Review* 111.4, pp. 1092–1125.

Kilian, Lutz (2009). "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market". In: *American economic review* 99.3, pp. 1053–1069.

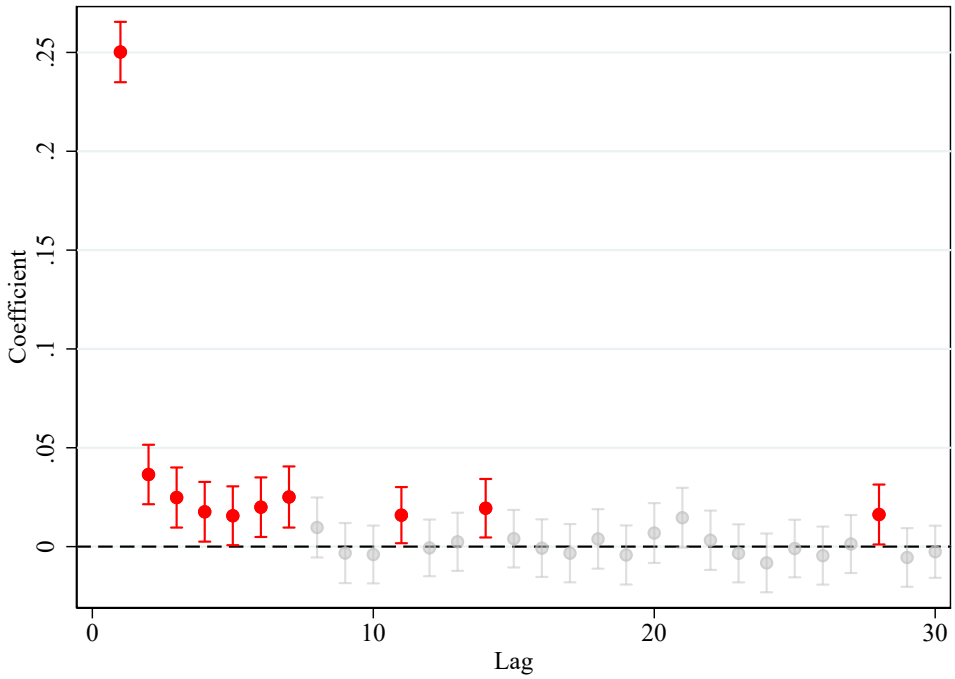
Patzelt, Paula (2025). *Renewable Energy Supply Shocks from Wind Electricity*. Tech. rep. CESifo Working Paper.

Online Appendix for

The Macroeconomic Effects of High-Frequency Energy Supply Shocks and their propagation in Spatial Equilibria

by Giovanni Rosso

Figure B1: Autocorrelation of supply outage shocks



Note. This figure plots coefficients from regressions of the daily supply outage shock on its own lags up to 30 days. The shock is defined as total supply outages scaled by average daily generation within each area and expressed in percentage points. Regressions include area, date, day-of-week, and month fixed effects. Dots denote point estimates and vertical bars indicate 95% confidence intervals. Coefficients that are statistically significant at the 5% level are shown in red; insignificant coefficients are shown in light gray. Standard errors are heteroskedasticity-robust.

A Model Appendix

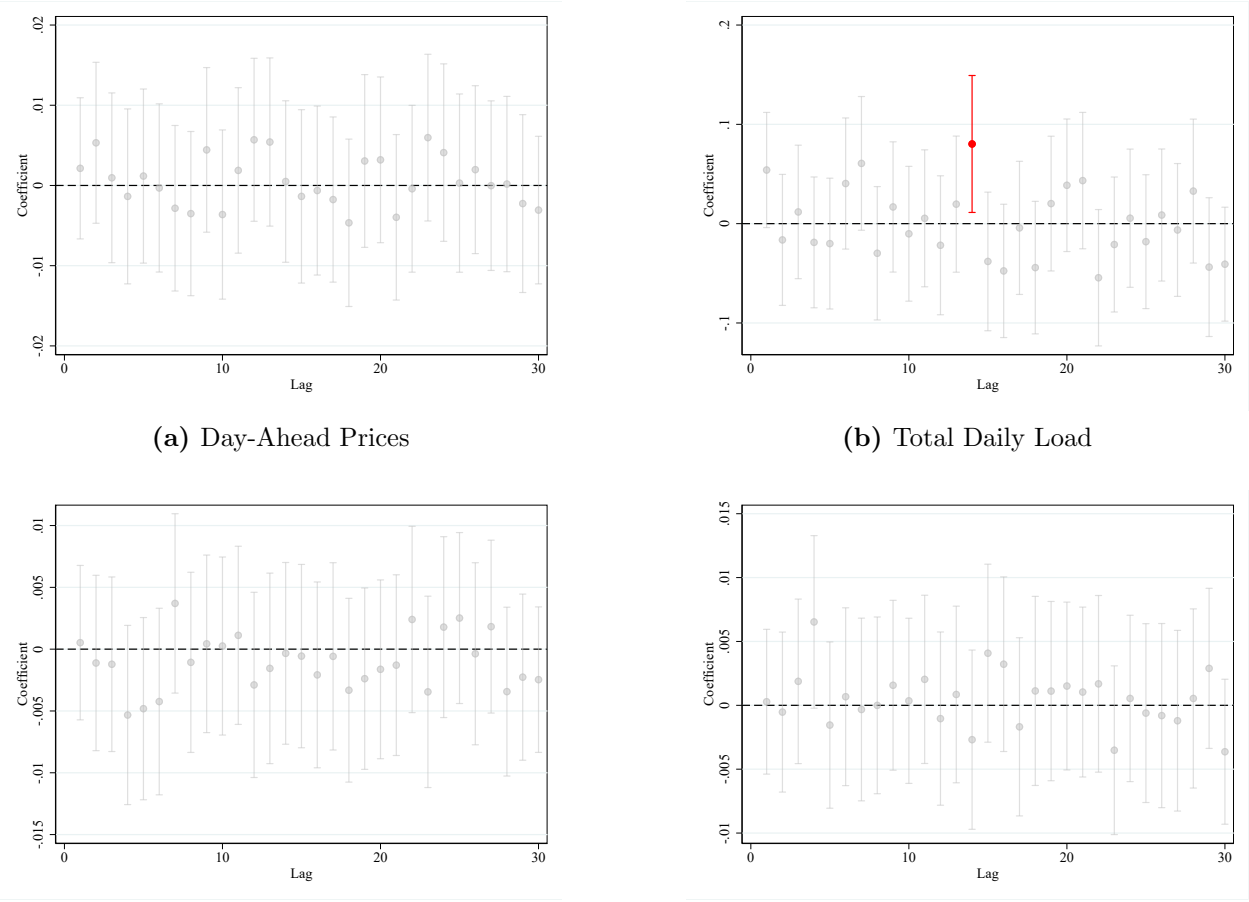
B Details on Construction of the Shock and Diagnostics

B.1 Construction of Shock

B.2 Diagnostics

C The shock for all Bidding Zones

Figure B2: Shock is not predicted by lagged energy variables



(a) Day-Ahead Prices

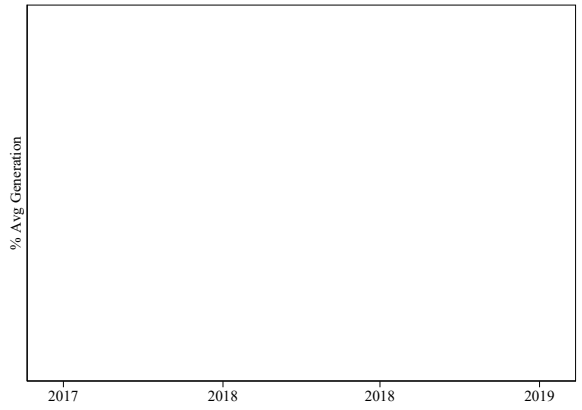
(b) Total Daily Load

(c) Cross-Border Energy Inflows

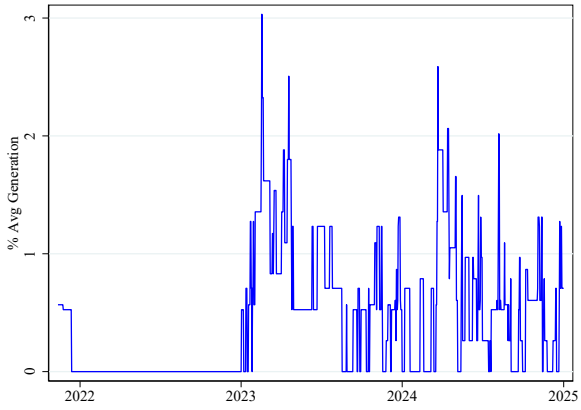
(d) Cross-Border Energy Outflows

Note. Each panel reports coefficients from regressions of the daily supply outage shock on lags (1–30 days) of the indicated variable: total load, wholesale electricity prices, and cross-border flows. All regressions include area, date, day-of-week, and month fixed effects. Coefficients are plotted with 95% confidence intervals. Red markers indicate coefficients that are statistically significant at the 5% level; light gray markers indicate insignificant estimates. Standard errors are heteroskedasticity-robust.

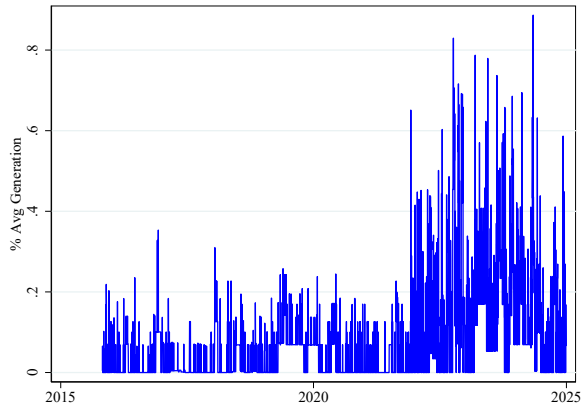
Figure C3: Energy Supply Shock for All Bidding zones



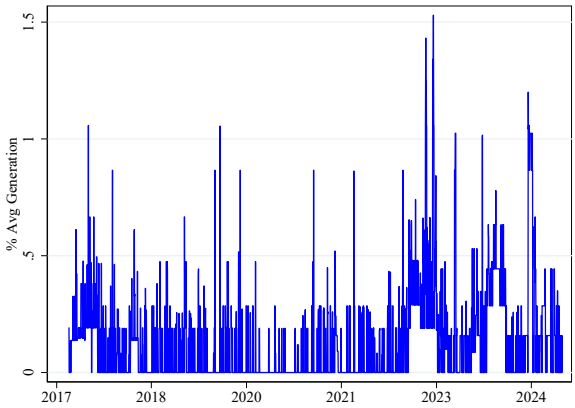
(1) Albania



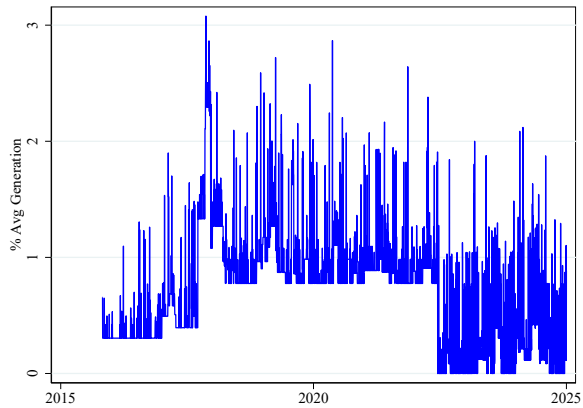
(2) Bosnia



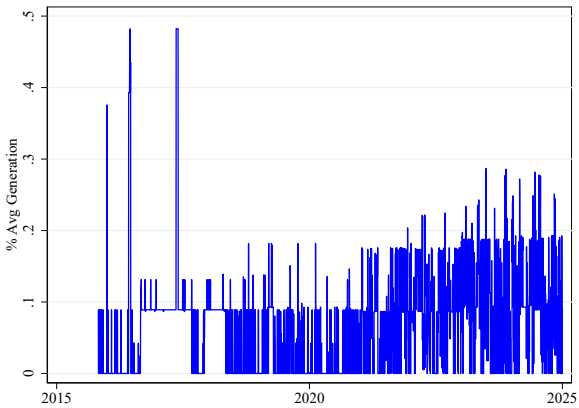
(3) Belgium



(4) Bulgaria



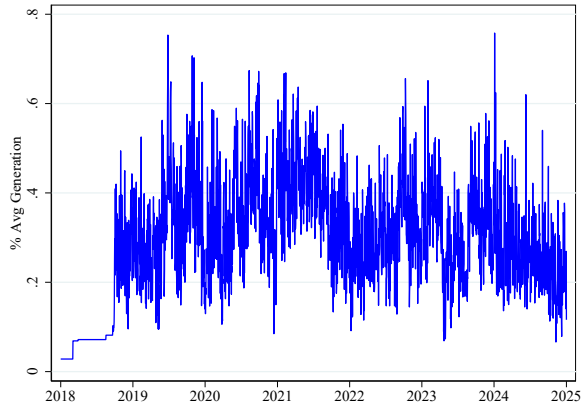
(5) Switzerland



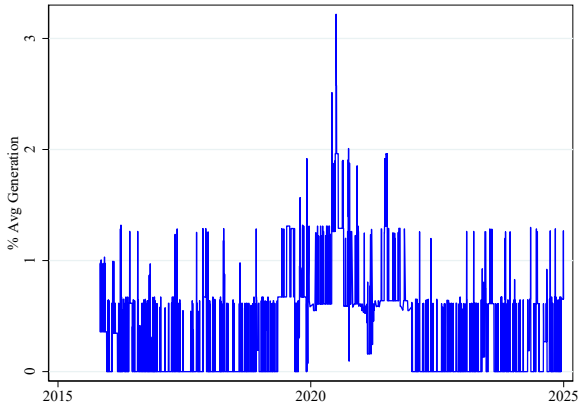
(6) Czech Republic

Note. This figure plots the daily supply outage shock for each area in the sample. The shock is defined as total supply outages scaled by average daily generation within the area and expressed in percentage points.

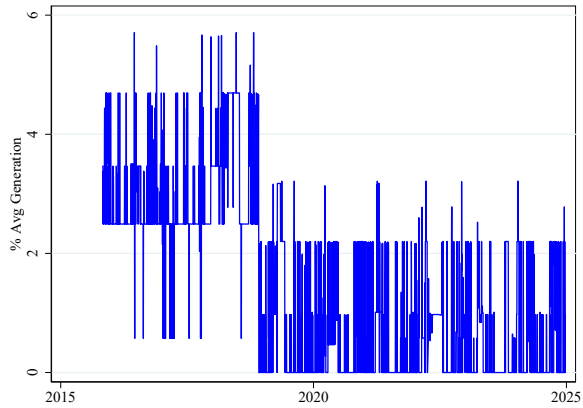
Figure C3: Energy Supply Shock for All Bidding zones (continued)



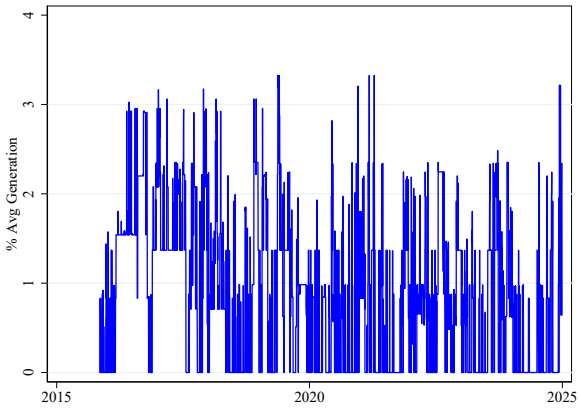
(7) Germany-Luxemburg



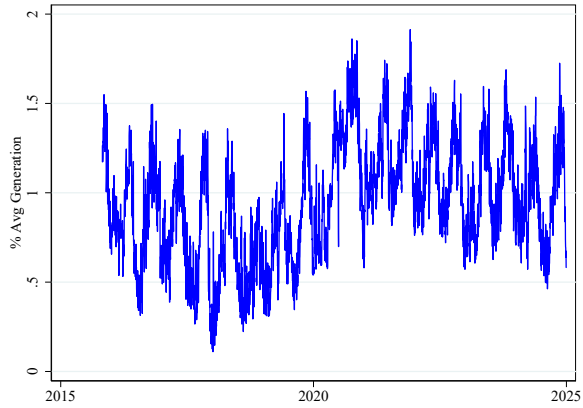
(8) Denmark 1



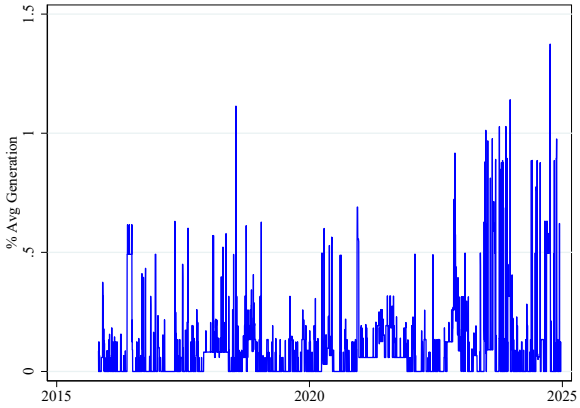
(9) Denmark 2



(10) Estonia



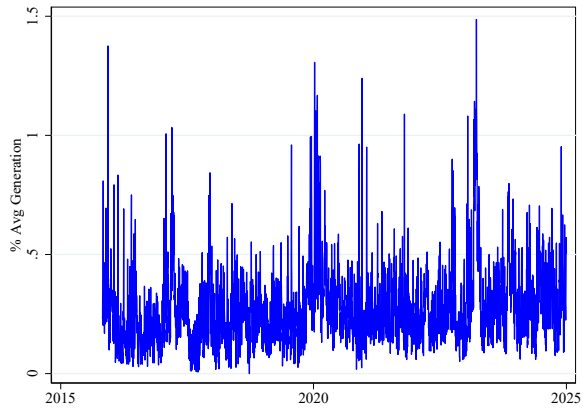
(11) Spain



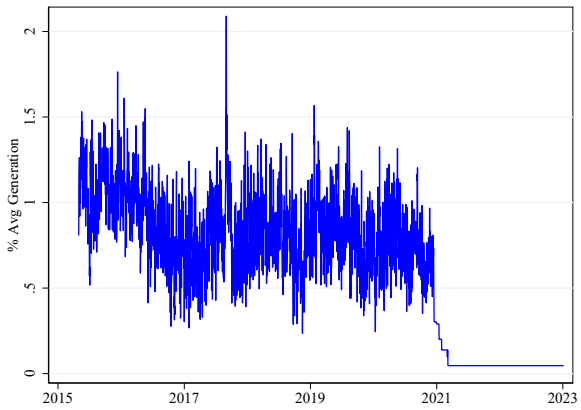
(12) Finland

Note. This figure plots the daily supply outage shock for each area in the sample. The shock is defined as total supply outages scaled by average daily generation within the area and expressed in percentage points.

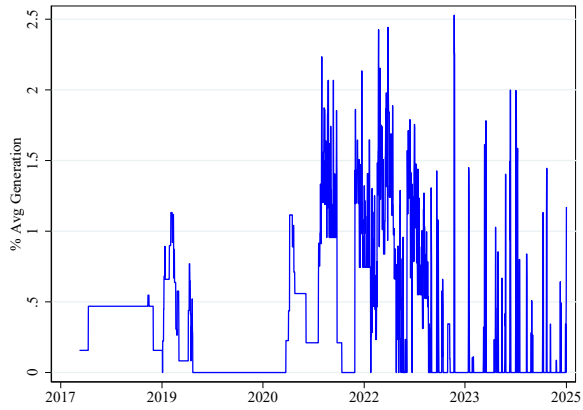
Figure C3: Energy Supply Shock for All Bidding zones (continued)



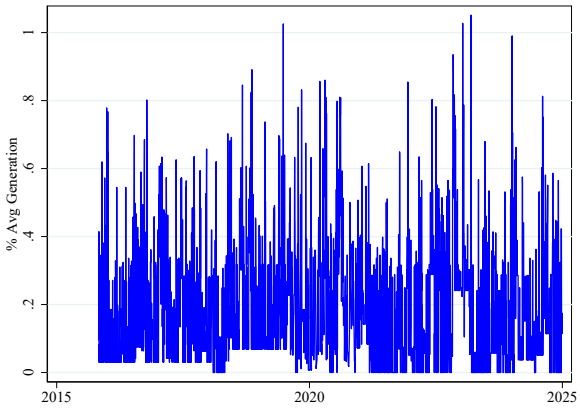
(13) France



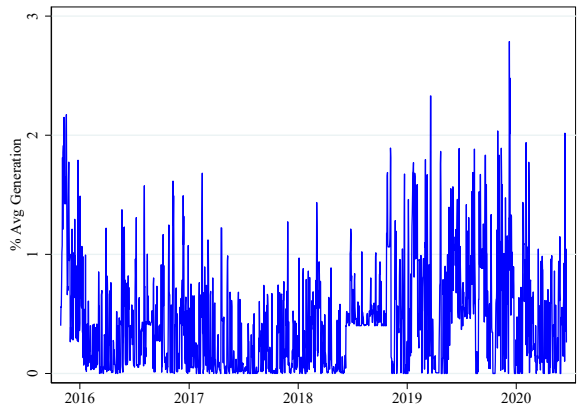
(14) United Kingdom



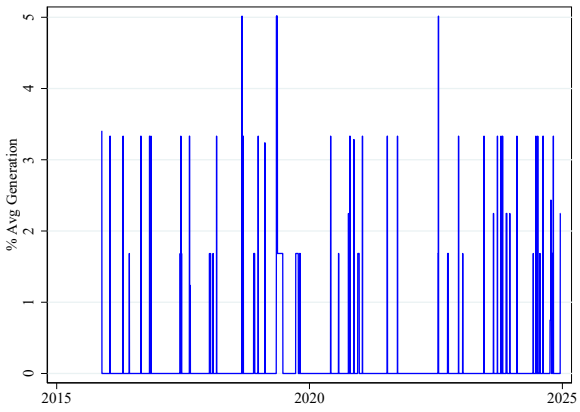
(15) Greece



(16) Hungary



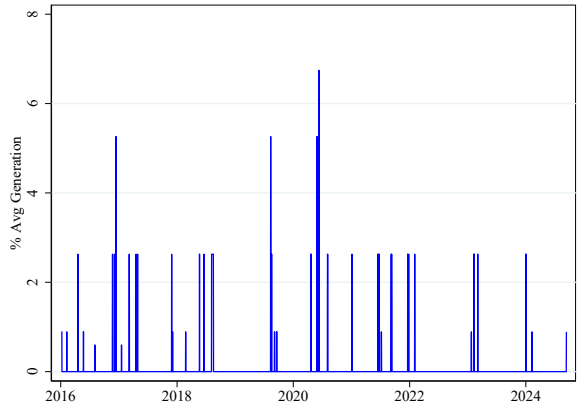
(17) Ireland



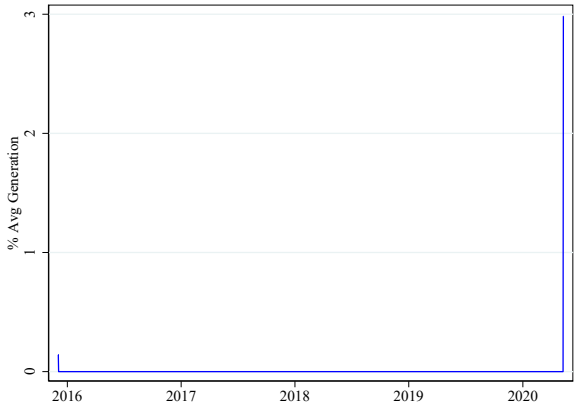
(18) Lithuania

Note. This figure plots the daily supply outage shock for each area in the sample. The shock is defined as total supply outages scaled by average daily generation within the area and expressed in percentage points.

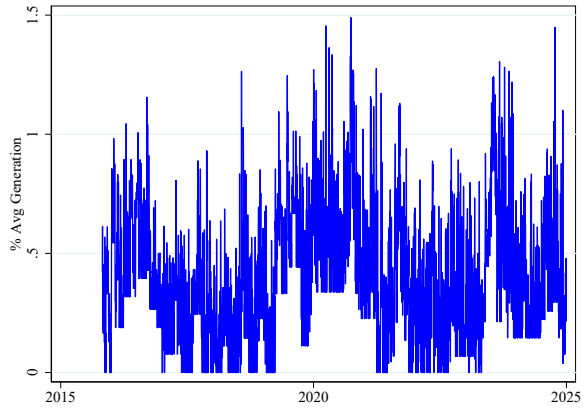
Figure C3: Energy Supply Shock for All Bidding zones (continued)



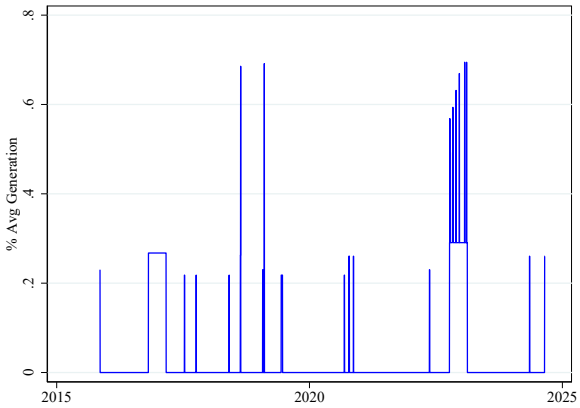
(19) Latvia



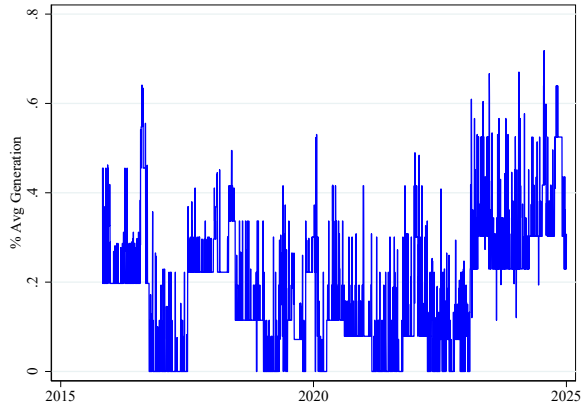
(20) Montenegro



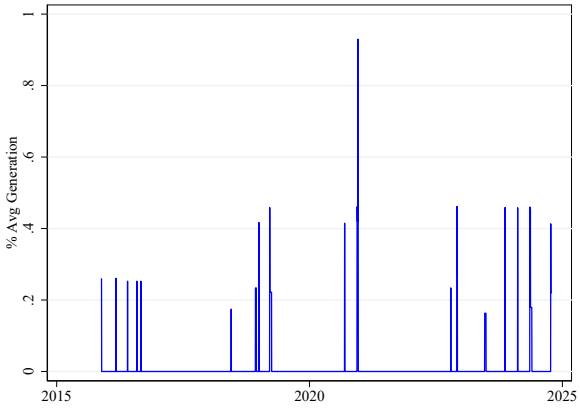
(21) Netherlands



(22) Norway 1



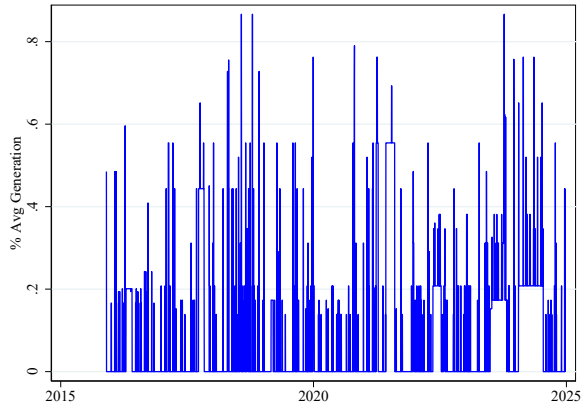
(23) Norway 2



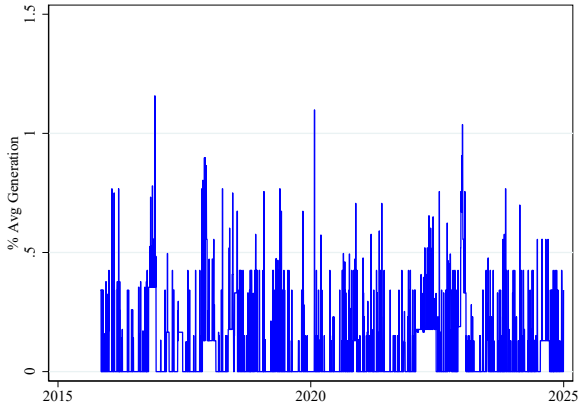
(24) Norway 3

Note. This figure plots the daily supply outage shock for each area in the sample. The shock is defined as total supply outages scaled by average daily generation within the area and expressed in percentage points.

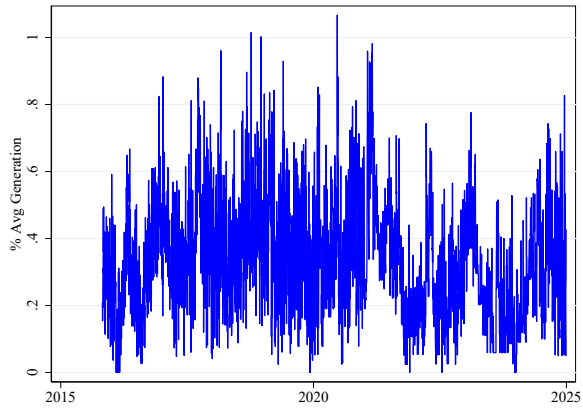
Figure C3: Energy Supply Shock for All Bidding zones (continued)



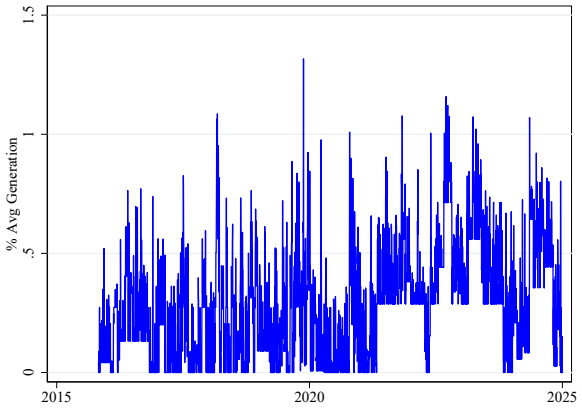
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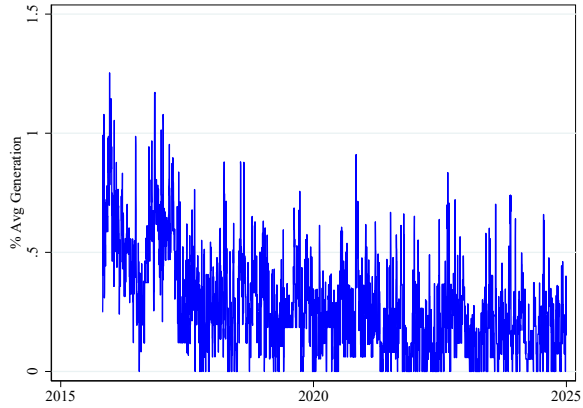
(26) Norway 5



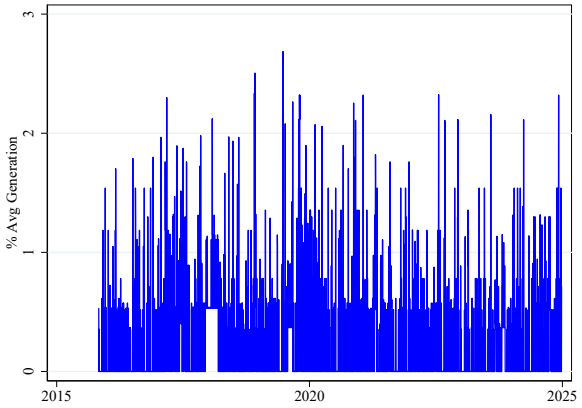
(27) Poland



(28) Portugal



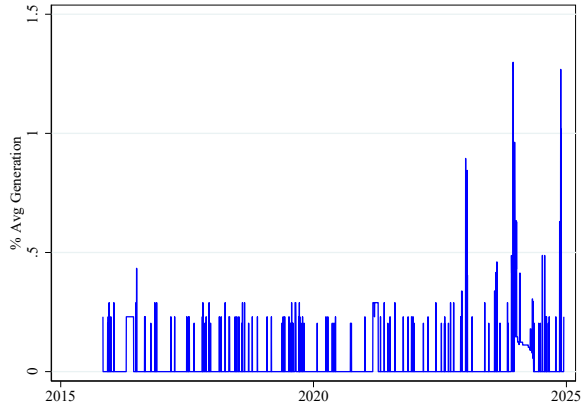
(29) Romania



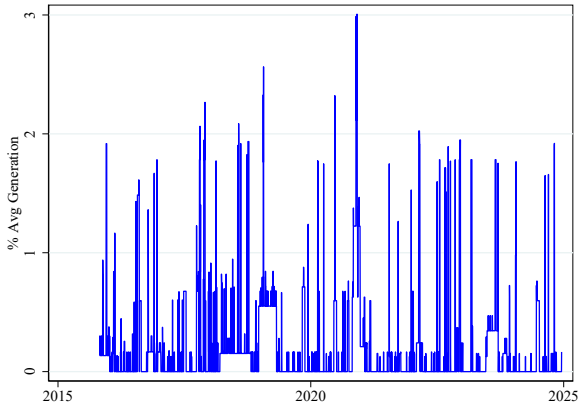
(30) Sweden 1

Note. This figure plots the daily supply outage shock for each area in the sample. The shock is defined as total supply outages scaled by average daily generation within the area and expressed in percentage points.

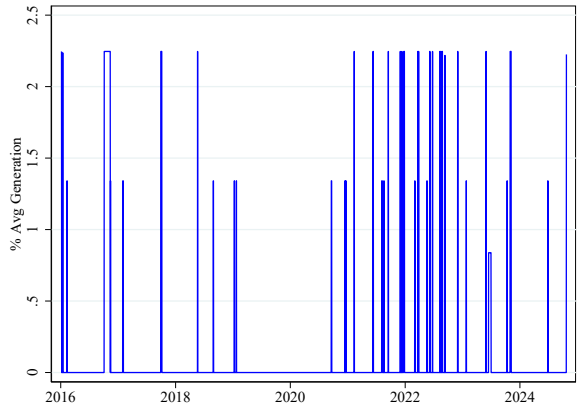
Figure C3: Energy Supply Shock for All Bidding zones (continued)



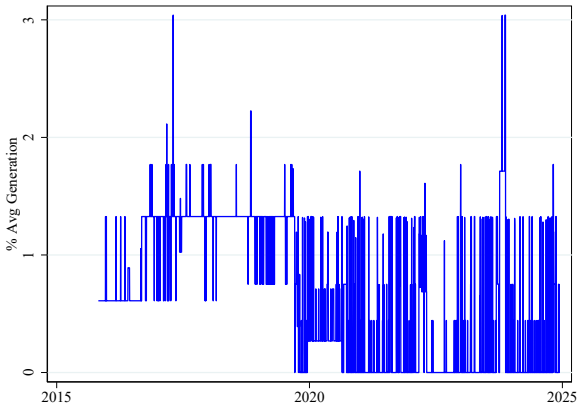
(31) Sweden 2



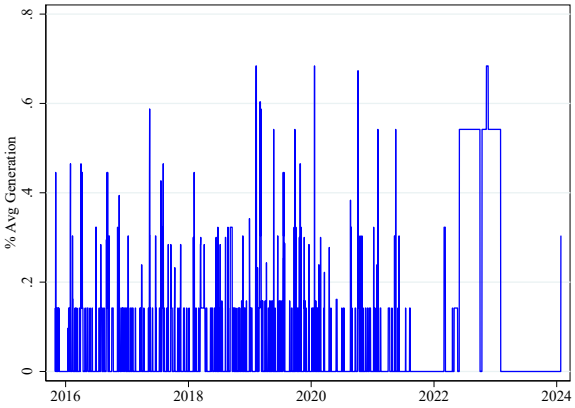
(32) Sweden 3



(33) Sweden 4



(34) Slovenia



(35) Slovakia

Note. This figure plots the daily supply outage shock for each area in the sample. The shock is defined as total supply outages scaled by average daily generation within the area and expressed in percentage points.