Power Decarbonization in a Global Energy Market: The Climate Effect of U.S. LNG Exports

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Abstract. Investment in clean power depends on the price of internationally traded fossil fuels. To what extent can major fossil fuel exporters such as the U.S. influence global electricity decarbonization through their trade policy? To answer this question, I develop and estimate a dynamic, multi-country model of power asset investment, where the carbon intensity of electricity generation is affected by the entry and exit of plants using alternative fuels and the local price of fossil inputs is determined in a global trade equilibrium. Using this model, I assess the climate impact of granting federal approval to all proposed U.S. liquified natural gas (LNG) export terminal projects, which would double U.S. export capacity by 2030. Results indicate a net decrease in global emissions through 2070, primarily due to higher local gas prices in the U.S., leading to lower domestic gas generation and accelerated renewable adoption. In the rest of the world, short-term emissions fall as reliance on coal drops, yet delayed renewable uptake drives long-term emissions up. Combining the LNG expansion with carbon policies in importing countries substantially boosts carbon savings. Conversely, reverting LNG capacity to baseline by 2050 shows little impact, underscoring the risk of carbon lock-in in settings with long-lived infrastructure.

Keywords: energy transition, global energy markets

JEL Codes: F13, O33, Q42

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1 Introduction

Reducing the carbon intensity of electricity production is fundamental to achieve climate goals, as electricity currently accounts for 40% of global CO_2 emissions (International Energy Agency, 2022). Transitioning towards cleaner sources of electricity generation requires large investments in renewable energy and storage infrastructure, in tandem with a phase-out of existing fossil fuel generation assets. In order to achieve this goal, many countries have enacted policies ranging from the introduction of carbon taxes and renewable energy mandates to the provision of subsidies to solar and wind installation costs. The majority of these policies have targeted domestic power emission reductions. However, because fossil fuel inputs used in electricity generation are globally traded commodities, domestic policies affecting their prices can create cross-border spillover effects and influence decarbonization incentives in power sectors across the world.

Global fossil fuel markets have become increasingly interconnected in the last decade due in part to the US emergence as the world's largest liquified natural gas (LNG) exporter. LNG —natural gas cooled into liquid form to facilitate its transportation over long distances —currently accounts for 60% of natural gas interregional trade, and has become the largest mode of natural gas imports for Asia and Europe (Energy Institute, 2024). Beginning in 2016, the U.S. has undergone a rapid LNG export infrastructure expansion process that could accelerate in the coming decade, with proposed projects that would more than double U.S. LNG export capacity by 2030. In January 2024, the U.S. Department of Energy, which oversees approvals for export terminal projects, paused new project reviews to revise its environmental impact assessment approach. Two primary environmental concerns have been identified. First, LNG exports may increase gas reliance in importing countries, delaying the adoption of renewables (Cahill and Majkut, 2024). Second, LNG emits methane, a greenhouse gas over 8 times more potent than CO_2 (Howarth, 2024). On the other hand, LNG proponents argue that cheaper gas internationally could help reduce coal reliance in import countries, and that exporting gas could hasten the U.S. transition to renewables by increasing local gas prices (Dalena et al., 2022; Rapier, 2024).

Is this expansion of U.S. LNG exports a challenge or an opportunity for global electricity decarbonization? My project tackles this question by building a novel dynamic model of investment in electricity generation infrastructure in a world with internationally traded fossil fuels. In the model, the entry and exit of generators of different carbon intensities (gas, coal, renewables), depends on expected local fossil fuel prices, which are influenced by production and trade conditions worldwide.[1,2] From the per-

[1]The model also introduces endogenous investment in electricity storage assets, which offset the intermittency of renewable generation.

[2]Market structure and the characteristics of transmission infrastructure are also relevant for power sector prices and profits. In this project, I focus on modeling supply-side investment determinants for electricity generation and instead consider a simplified market setting with perfect competition in spot wholesale markets and no transmission constraints. For work on how transmission infrastructure impacts renewable penetration, see Arkolakis and Walsh (2023). An extensive literature has studied electricity production choices and price determination in settings with market power and strategic bidding (Reguant,

spective of electricity investment, my model captures a key dynamic trade-off posed by natural gas in the transition to renewables: a decrease in gas prices can incentivize a higher entry rate of gas-fueled generators, which compete in electricity markets with higher-emitting coal generators and might drive their exit. At the same time, cheaper gas generation might generate carbon lock-in by delaying the adoption of newer clean technologies, such as solar generation or electricity storage. From the perspective of global climate policy, my model captures a trade-off generated by domestic decarbonization initiatives under a lack of international coordination: policies that might induce a faster energy transition in one country might also delay the transition in others.

Assessing the impact of fossil fuel trade policy on global decarbonization requires examining the key factors driving electricity investment worldwide. To make progress on this front, I collect and harmonize data for the 26 largest electricity markets in the world, which account for 80% of global electricity generation. My data includes country-level information on fossil fuel prices, production, consumption, and trade, as well as information on electricity demand, carbon taxes, renewable potential and generator installation costs. I complement this country-level data with a panel on worldwide electricity assets that allows me to track the entry and exit of generators by fuel type, age, and other generator-specific characteristics.

I leverage this data to structurally estimate the main parameters governing electricity generation and investment in my model. A first important element is the elasticity of power generation to input price fluctuations, which influences intensive margin responses to fossil fuel supply shocks and is also a key determinant of generator profits. To estimate this parameter, I combine data on electricity prices, fossil fuel prices and the observed capacity use of fossil fuel generators. I use shocks to oil prices and the availability of renewable generation as instruments to deal with the potential endogeneity of production decisions to unobserved supply shocks. To recover maintenance costs —important determinants of exit decisions in power markets —I exploit variation in the timing of exit of generators operating in different markets and with varying age.[3] To capture unobserved shifters to installation costs —which explain generator entry decisions conditional on observed profits —I solve for paths of electricity investment using the full structure of my model and find the parameters that reduce the distance between model-predicted patterns and observed entry rates.[4]

2014; Bushnell, Mansur and Saravia, 2008; Wolfram, 1998; Borenstein, Bushnell and Wolak, 2002). For an interesting recent study on energy transition policy in the context of rate-of-return regulation, see Gowrisankaran, Langer and Reguant (2024).

[3]The structure of my model allows me to use discrete Euler methods (Arcidiacono and Miller, 2011; Hsiao, 2022; Hall, 1978; Scott, 2013) to recover exit determinants from linear regressions. This approach requires deriving equations that compare the exit probability of a generator in subsequent years. Continuation values difference out by finite dependence, which holds because exit is a terminal action.

[4]My setting is one with complex transitional dynamics that feature non-stationarity, particularly because renewable entry costs are decreasing over time. To deal with this feature when solving the model, I leverage the nonstationary equilibrium concept recently developed in Benkard, Jeziorski and Weintraub (2024). This approach allows me to capture the short and medium-run market dynamics of power sector investment in a computationally-light way. It relies on a finite horizon approximation to the infinite-horizon problem, a method also used in the macroeconomics literature (Maliar et al., 2020).

The extent to which an export capacity shock spills over to domestic and foreign markets depends critically on the price elasticity of fossil fuel supply and on the magnitude of fossil fuel trade costs. I recover upstream fossil fuel supply elasticities from IV regressions that exploit shifts in prices coming from changes in electricity demand conditions. Finally, I use data on the capacity use of fossil fuel export terminals, freight rates and customs prices to obtain a measure of the variation of trade costs across time and space.

I use my estimated model to consider the potential effect of an expansion in U.S. LNG export capacity. I simulate the evolution of global fossil fuel prices, electricity generation capacity, and emissions from 2025 to 2070 under two scenarios: one in which all LNG projects under review get built and one in which only LNG export terminals currently operating or under construction are ever active. The shock generates a cumulative reduction in global power-related CO2 emissions over the period of analysis that translates into global social savings of USD 314bn when using recent estimates of the monetized value of emission damages from the U.S. Environmental Protection Agency (EPA, 2023).[5]

A major driver of this decarbonization effect is the increase in U.S. local gas prices generated by the export shock, which reduces gas-fueled power generation locally. This effect is consistent with reduced-form evidence on the negative relationship between fossil fuels prices and the production choices of the generators that use them, presented in Section 2. The shock also induces an increase in the domestic pace of renewable adoption which more than offsets a gas-to-coal substitution effect. As a result, cumulative U.S. power-sector emissions are reduced by 6% compared to the baseline scenario.[6] In the rest of the world, the effect of the policy varies across time and space. Cheaper LNG prices first generate emission reductions in importing countries by incentivizing a less intensive use of coal-based electricity plants in countries with large coal fleets, but later drive a widespread delay in the adoption of renewable energy and storage. Long-term emission increases out-weight short-term reductions in the rest of the world, generating cumulative emission gains in importing countries.[7]

Given that the decarbonization effect of the U.S. LNG export expansion is mitigated by the long-term emission increase in importing countries, are there policies that could limit this effect in the rest of the world? I first consider whether coordinating the

[5]In addition to the effect of LNG on worldwide power sector emissions, an important concern related to the environmental footprint of this form of natural gas export is the fact that the liquefaction and transport of LNG generates additional methane and CO2 emissions relative to the local consumption of natural gas (Howarth, 2024). Using EPA's measure of climate damages, I show that social savings from the shock are still positive when taking into account the additional methane emissions generated by increased LNG exports. As discussed in Section 8, life-cycle assessments of the LNG expansion are, however, sensitive to how climate damage from methane emissions is valued relative to carbon damage.

[6]In contemporaneous work, Stock and Zaragoza-Watkins (2024) argues that the start of LNG exports in 2016 reconnected local U.S. gas prices to world market prices, after a hiatus of "shut-in" fracked gas. Projecting local natural gas and coal prices under scenarios with and without recoupling and feeding these projections to the NREL ReEDS model, this work estimates that the price reconnection reduces U.S. 2030 power sector emissions by around 145 million metric tons. My findings on the local effect of a further LNG export expansion are in line with these results.

[7]Results hold under alternative assumptions on the evolution of renewable and storage installation costs, as discussed in Section 8.

LNG export capacity expansion with domestic carbon policies in climate-concerned LNG importers could induce a larger cumulative reduction in emissions. I find that, if the EU, the UK and Japan impose a binding carbon cap in response to the export expansion, global social cost savings from emission reductions are increased by 62%.

I next consider whether, in the absence of international coordination, the U.S. could reduce long-term emission impacts by simply reverting the LNG expansion by 2050, once international emissions begin to grow. I find that this policy reversal is not effective in reducing global emissions, and actually increases emissions in the rest of the world relative to the case where U.S. LNG export capacity is permanently higher. This finding highlights the risk of carbon-lock in a setting with sunk investments and long-lived assets: once importing countries have invested in building new gas power infrastructure because of lower LNG prices, this early capacity increase permanently increases gas generation even under higher future LNG prices. The lock-in of gas generation occurs even if the U.S. can fully commit to shutting down additional LNG export infrastructure in the future, but is even more pronounced when commitment is not possible and agents do not anticipate the infrastructure reversal.

My work contributes to a growing empirical IO literature studying how industry dynamics shape the effects of environmental and energy policy (Fowlie, Reguant and Ryan, 2016; Ryan, 2012; Elliott, 2022; Chen, 2024). Relative to existing papers, I introduce endogenous fossil input prices and allow for multiple technological types in a model of firm entry and exit. My findings also connect to the literature on directed technical change and the environment (Acemoglu et al., 2012, 2016; Aghion et al., 2016). Most closely connected to my project, Acemoglu et al. (2023) builds a dynamic closed economy model in which natural gas prices affect both the use of coal in electricity generation and the pace of innovation in renewable technologies.[8] In my model, natural gas poses a similar trade-off in terms of current and future emissions, but this trade-off arises from the specific nature of electricity infrastruture investment, which involves large sunk costs and long-lived assets. The extent to which this trade-off operates in practice is governed by the distribution of generator entry and exit costs over time and space, which I structurally estimate.

Given its focus on fossil fuel trade policy as a driver of global decarbonization, my project also builds on a rich literature on international environmental policy coordination (Nordhaus, 2015; Böhringer, Carbone and Rutherford, 2016; Hsiao, 2022; Farrokhi and Lashkaripour, 2022; Kortum and Weisbach, 2022; Barrett, 2006) and the environmental effects of trade policy (Copeland and Taylor, 2003; Shapiro, 2020; Kortum and Weisbach, 2016). I contribute to these works by proposing a quantitative model of global energy markets and showing how to leverage publicly available data to esti-

[8]Harstad and Holtsmark (2024) refers to this dynamic trade-off as the "gas trap", and argues that it generates a time-inconsistency problem for policy design: a "climate-friendly" gas producer has an optimal long-term policy of curtailing gas production to incentivize renewable investment, but faces the temptation of expanding gas production in the short-term to outcompete coal. Market anticipation of this short-term incentive generates a long-term increase in emissions. Gerlagh and Smulders (2024) also discusses the long-term environmental risks imposed by the position of natural gas as a cleaner alternative to coal, focusing on implications for the U.S. shale gas revolution.

mate the main parameters governing agents' production and investment decisions. A related paper that has followed a similar approach is Arkolakis and Walsh (2023), which provides a spatial quantitative model of global electricity transmission networks but abstracts from the heterogeneous availability of fossil fuels across space, a key aspect to take into account to understand the effect of a fossil fuel export supply shock. Finally, my work is connected to a growing theoretical literature on supply-side environmental policies (Hoel, 1994; Harstad, 2012; Harstad and Holtsmark, 2024; Holtsmark and Midttømme, 2021), which has highlighted the importance of addressing time-inconsistency and international coordination problems in the design of supply-side fossil fuel policies. I quantitatively evaluate these forces in the context of the U.S. LNG expansion and propose a framework that, more broadly, can be used to think about supply-side policy design in a global equilibrium.

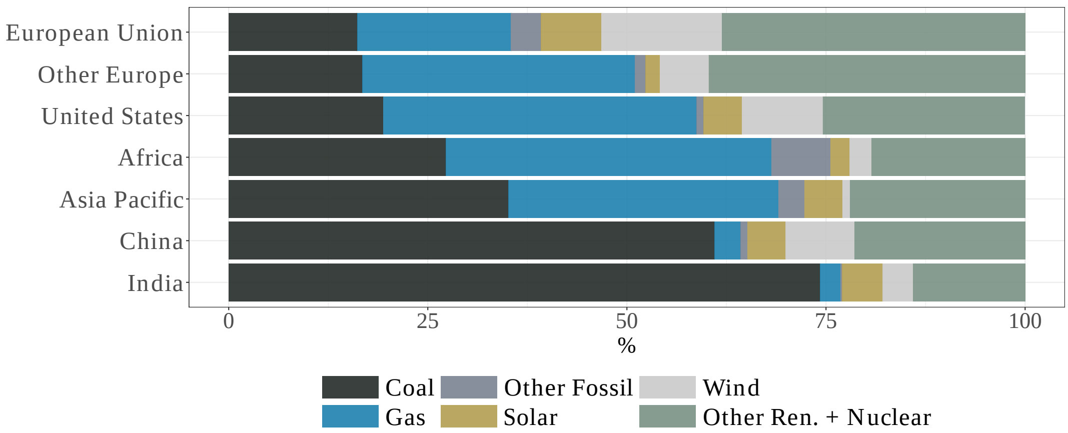
Interest in the climate impacts of U.S. LNG exports is rapidly growing, as reflected in contemporaneous work examining their effects on U.S. power sector emissions (Stock and Zaragoza-Watkins, 2024) and their greenhouse gas footprint (Howarth, 2024). My research, to the best of my knowledge, is the first to provide a comprehensive global analysis of the climate impacts of U.S. LNG exports, taking into account both local and global spillovers and considering dynamic effects on investment incentives as well as potential substitution effects across generators of different carbon intensities. This work aims to contribute to the ongoing re-assessment of the environmental impact of LNG terminal projects and to broaden the discussion on the role of fossil fuel trade policy in global decarbonization.

2 Background

2.1 Drivers of power sector decarbonization

The carbon intensity of power generation varies widely across the world.[9] This heterogeneity is primarily explained by differences in the type of power generators that are installed in each country. While coal-fueled generators produce more than twice the emissions per unit than gas-fueled generators, both are carbon-intensive electricity sources relative to renewables. Although the share of renewables in the global electricity has increased rapidly in the last ten years, driven in large part by a decline in the installation cost of renewable generation, fossil fuels still accounted for 61% of electricity generation worldwide in 2023. The pace of decarbonization in the power sector has been uneven across countries, with some regions making significant progress in reducing the carbon intensity of their electricity production, while others have seen little change or even an increase in carbon emissions.[10]

Figure 1: Electricity generation breakdown by source (2022)



Note: Breakdown of electricity generation by energy source based on annual data at the country level from Ember.

Building a power generator involves large sunk costs and generators are long-lived assets, which means that investment decisions can have long-lasting effects on emissions. Data on retirement episodes of coal and gas generators across the world in 2000-2023 show that the average age of retired coal generators was 38 years, while the average age of retired gas generators was 36 years.[11] This propensity of fossil fuel generators to stay active in a market for a long period means that the age distribution of generators in a given market is relevant to predict future transition dynamics. Figure 2 shows that the age distribution of fossil generators exhibits a lot of variation

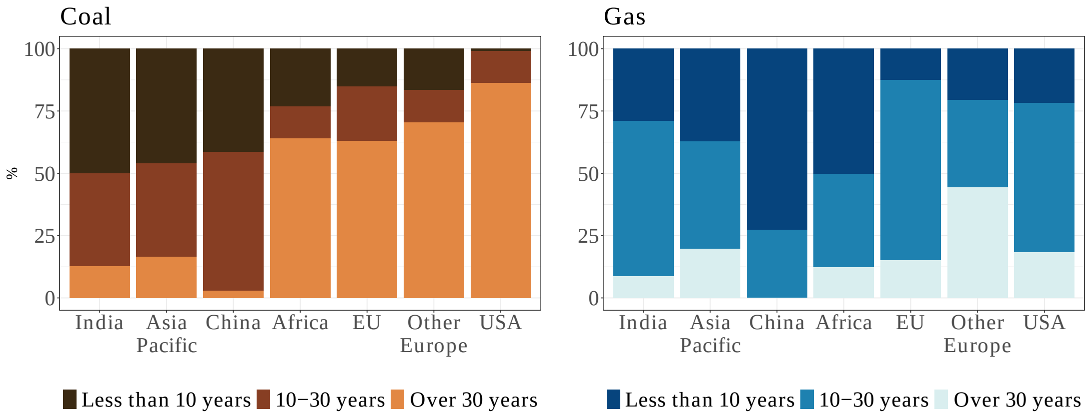
[9] As an example, India generated almost twice as many carbon emissions per unit of electricity in 2022 than the U.S., and 2.5 times as many than the European Union. Appendix Figure A1 shows a map of power carbon intensity across the world.

[10] Figure A2 in the Appendix shows the evolution of power emission intensity across world regions. The European Union, China and the U.S. have exhibited the largest reductions in carbon intensity since 2005. Meanwhile, Asia Pacific has experienced an increase in carbon intensity relative to the same year.

[11] See section 5 for a description of the generator-level data used throughout this project.

across the world, with India and China having a younger fleet of both coal and gas generators than the European Union and the U.S.[12]

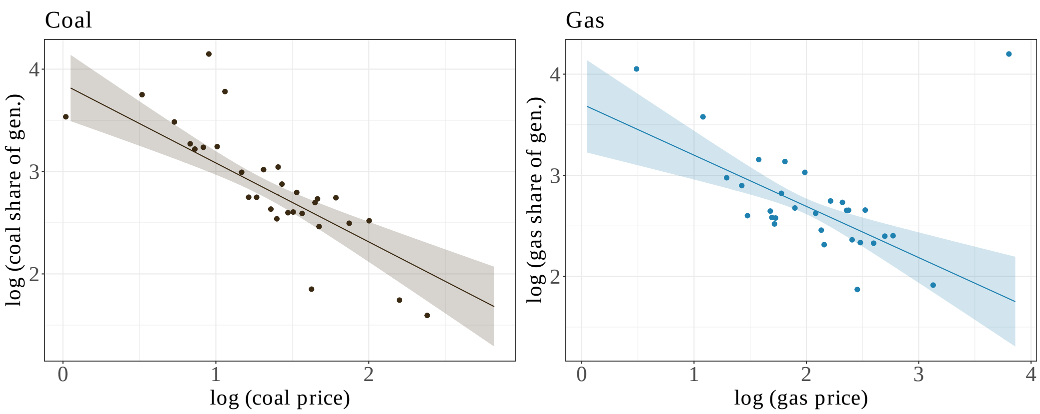
Figure 2: Fossil generator installed capacity by age (2022)



Note: Installed capacity breakdown by age constructed from generator-level data on coal and gas generators from Global Energy Monitor Infrastructure Tracker. See Section 5 for a description of this data source.

Fossil fuel prices are an important determinant of profits in the power sector, and thus a major driver of technological choice. In the U.S., for example, fuel costs accounted for an average 78% of the total operating expenses of fossil fuel power plants in 2012-2022.[13] Across the world, lower fossil fuel prices are associated with higher reliance on fossil fuels for electricity generation, as depicted in figure 3. This partly explains why electricity mixes vary widely across countries with different resource endowments. However, the price of fossil fuels is not only determined by local supply and demand conditions, but also by international trade. The next section provides an overview of fossil fuel trade, with a particular focus on LNG as a driver of natural gas trade expansion.

Figure 3: Fuel share of electricity generation and local fuel prices



Note: Binscatter regression using annual data on fuel share of electricity generation and fuel prices by country for 51 countries in 2000-2023. Controls include GDP, other fossil fuel prices, and region and year fixed effects. See Appendix Table A1 for regression results, including a version using coal and gas reserves as instruments for prices.

[12]In my model, I account for generator age as a determinant of exit decisions. See section 3 for a detailed description of the model.

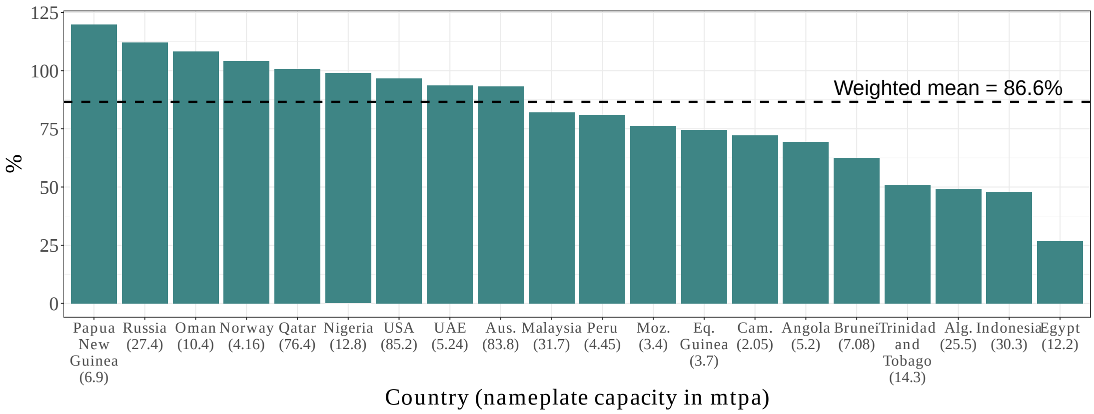
[13]https://www.eia.gov/electricity/annual/html/epa_08_04.html

2.2 LNG and the U.S. export boom

The main fossil fuels used for electricity generation, thermal coal and natural gas, are both internationally traded commodities. 16% of global thermal coal production and 30% of natural gas production was traded internationally in 2023. Although natural gas trade was historically limited to intra-regional flows through long-distance pipelines, the development of liquified natural gas (LNG) infrastructure has led to the creation of new, cross-regional trade links. Today, around half of global natural gas trade is conducted through LNG, with the U.S. being the world's largest LNG exporter in 2023, closely followed by Qatar and Australia.

LNG is natural gas that has been cooled to -162 degrees Celsius, which reduces its volume by 600 times and allows it to be transported across the world through long distances. Exporting and importing LNG requires specialized infrastructure, namely liquefaction plants (in charge of turning gas into liquid form), LNG carriers (specialized tank ships), and regasification terminals (which turn LNG back into gaseous form to allow local transportation through pipelines). Around the world, the construction of this specialized infrastructure is subject to government approval. This gives governments' an important policy tool to influence fossil fuel international trade and prices specially since the industry operates under binding export capacity constraints. Figure 4 shows that the average capacity utilization rate of LNG export terminals ascended to 86.6% in 2023, with major exporters such as Qatar and the U.S. operating their facilities at almost full capacity.[14]

Figure 4: Capacity utilization in global LNG export terminals (2023)



Source: International Gas Union (2024). Nameplate export capacity, measured in million tonnes per annum (mtpa), specifies the amount of LNG produced in a calendar year under normal operating conditions, based on the engineering design of a facility. Export terminals can thus operate over full nameplate export capacity in a given year.

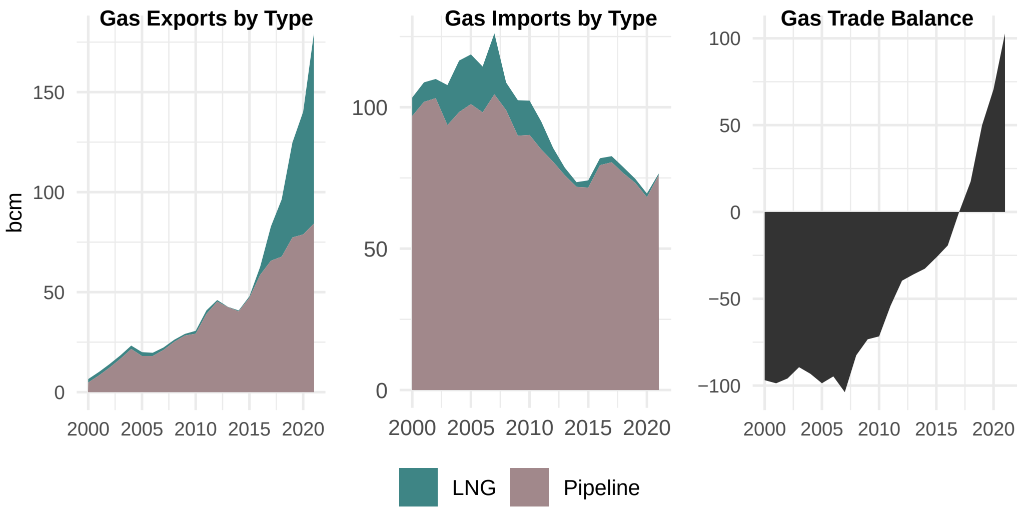
The question of how to regulate fossil fuel export infrastructure build-out in the context of the climate transition has become recently more salient due to the rise of U.S.

[14] The high capacity utilization of LNG liquefaction or export terminals contrasts with a much lower capacity utilization in LNG regasification or receiving terminals. Figure A3 in the Appendix shows that global regasification capacity utilization has stayed below 45% in the last two decades. Due to this reason, in my model I explicitly account for export-side LNG capacity constraints, but abstract from regasification capacity constraints.

LNG exports. The U.S. experienced a major shift in its natural gas trade balance in just one decade due to advent of fracking and the shale gas revolution (Figure 5). Faced with a surplus of local natural gas, the U.S. first started exporting natural gas as LNG in 2016 and quickly started ramping up LNG exports. By 2023, the U.S. was exporting 18% of its production and had become the world leader in LNG exports, with a pipeline of export terminal projects that could double its export capacity by 2030 (Figure 6). This dramatic shift was cited by the Biden Administration when, on January 26, 2024, it announced a pause on Department of Energy (DOE) export license approvals pending an update of its methodology to evaluate the economic and environmental impact of LNG projects.[15] As of November 2024 export approvals were still on hold, with DOE yet to release its new methodological guidelines. Meanwhile, public debate on the environmental implications of U.S. LNG exports are centered around two main discussion points. The first one focuses on emissions generated by the extraction and transportation of natural gas through the LNG supply chain (Howarth, 2024; Roman-White et al., 2019). The second one has to do with long-term implications for the domestic and international transition to renewables.

The remainder of this paper builds a quantitative model of global energy trade and electricity investment to adress both of these points. The next section introduces the open economy model of electricity investment that I use to analyze the potential effects of the pause on LNG export approvals. I first set up the investment problem of power producers in a closed economy, and then show how I endogenize fossil fuel prices within a global framework.

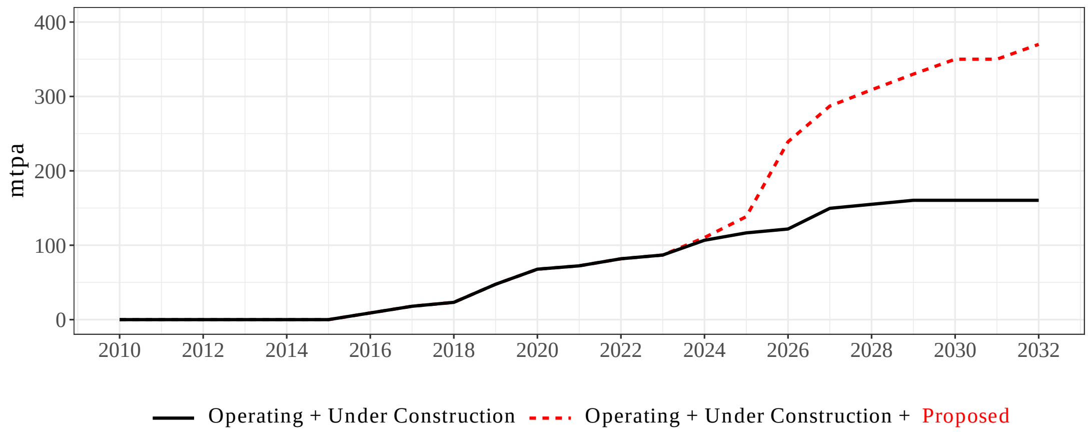
Figure 5: Evolution of U.S. natural gas trade trade flows and balance



Note: the left-most and center panel show the evolution of U.S. LNG exports and imports respectively in billion cubic meters. Trade flows in these panels are broken down by mode of transport (LNG or pipeline). The right-most panel show the evolution of the U.S. natural gas trade balance, adding across modes of transport.

[15]See https://www.whitehouse.gov/briefing-room/statements-releases/2024/01/26/fact-sheet-biden-harris-administration-announces-temporary-pause-on-pending-approvals-of-liquefied-natural-gas-exports/ for the official statement announcing this decision. For a detailed historical narrative of United States' emergence as a natural gas superpower, as well as on the regulatory process that underpins LNG export terminal approvals, see Stock and Zaragoza-Watkins (2024).

Figure 6: U.S. LNG Export Capacity



Note: Operating and under construction capacity is defined as the capacity in U.S. export LNG terminals that have received government approval and have reached a final investment decision. Proposed capacity indicates projects that have sought government approval but have not yet reached a final investment decision. Data on LNG current and projected capacity comes from EIA Liquefaction Capacity File and Global Energy Monitor Infrastructure Tracker.

3 A model of dynamic investment in electricity generation

Time is discrete and measured in years. Agents in the model are electricity generators, which operate in a given market $j \in \mathcal{J}$. In this section, I focus on how production and investment decision are made in a generic local market j. In the next section, I turn to the interaction between local markets when I specify how fossil fuel prices are determined.

Generators are characterized by their type f, which is given by the energy source the use as input. I first assume that there are four potential generator types: gas (g), coal (c), solar (s), and wind (w), and no intermittency in electricity supply.[16] In Appendix B, I present an extension to the baseline model where I incorporate intermittency and endogenous entry of storage facilities.

Generators at time t have a given age $a \in \{0, 1, ..., A\}$, which depends on their time of entry. In period t, the industry state space S_t contains the distribution of incumbent characteristics and exogenous determinants of demand and supply, which include the prices of fossil fuels.

The timing of the model is as follows. Every period, incumbents and potential entrants make entry and exit decisions after observing the industry state space S_{jt}, entry costs and scrap value draws. Following this, electricity markets open and incumbent players make their production choices. Lastly, entry and exit decisions are implemented and the state evolves.

[16] All other generator types in the data (.e.g. nuclear, oil, biomass) are taken as exogenous market supply.

3.1 Static game

Upon entering a market, an electricity generator ω is endowed with a capacity k_ω. Generator capacities cannot be adjusted over time. Every period, all incumbent generators in a market choose how much electricity to produce taking the price of electricity as given, i.e. electricity markets are perfectly competitive. Electricity demand is perfectly inelastic and given by D_{jt}.[17]

Solar and wind generators have constant zero marginal costs, so that they produce at their full available capacity whenever the wholesale electricity price is positive. The available capacity of a renewable generator ω of type f is given by

$$\tilde{k}_{\omega(f)jt} = \varphi_{fj} k_{\omega(f)jt} \qquad \forall f \in \{w, s\}$$

$\varphi_{fj} \in [0, 1]$ represents the capacity factor of solar/wind generators and varies across markets depending on natural characteristics (wind speed, sunshine hours per year).

Gas and coal generators have production costs that are a function of the price of their type-specific fossil fuel input and are increasing in their capacity use. I assume that a generator ω of type $f \in \{c, g\}$ chooses production by solving the following profit maximization problem:

$$\max_{q_{\omega(f)jt}} \pi_{\omega(f)jt} = p^{elec}_{jt} q_{\omega(f)jt} - \Big(\beta_{1f}\gamma_{1fjt}p_{fjt} + \beta_{2f}\frac{q_{\omega(f)jt}}{k_{\omega(f)jt}} + \chi_{fjt} + \epsilon_{fjt}\Big) q_{\omega(f)jt} \quad \forall \omega \in \Omega_{fjt}, \; \forall f \in \{c, g\} \tag{1}$$

where p^{elec}_{jt} is the price of electricity, p_{fjt} is the type-specific input price, and χ_{fjt} and ϵ_{fjt} are shocks to the marginal production cost of a generator of type f.[18] β_{1f} is the parameter governing the efficiency of fossil-fueled generators, while γ_{1fjt} is a time and market-varying shock to this efficiency.[19] Meanwhile, $\beta_{2f} > 0$ is a scale parameter, governing the extent to which production costs are increasing in capacity use. Note that I assume that all incumbent generators of the same type have a homogeneous efficiency and that capacity use enters marginal costs linearly. These assumptions imply that, in equilibrium, all generators of the same type in the same market will have the same optimal capacity use, i.e.

[17] Since I do not observe electricity prices for all the markets in my sample, I unfortunately cannot estimate a price-elastic demand function. In simulations, I allow electricity consumption to vary across markets and years according to observed demand patterns, and I use industry projections for future periods as detailed in Section D of the Appendix. When I extend my model to introduce storage and intermittency, I allow electricity consumption to vary within the year as explained in Appendix section B.

[18] Both shocks are observed by generators at the time of their production decision, but χ_{fjt} is observed by the econometrician while ϵ_{fjt} is not.

[19] Together, β_{1f} and γ_{1fjt} determine the number of units of input f required to generate one unit of electricity at a given moment in time.

$$\frac{q^*_{\omega(f)jt}}{k_{\omega(f)jt}} = \tilde{q}_{fjt}(p^{elec}_{jt}, p_{fjt}) \quad \forall \omega \in \Omega_{fjt}, \forall f \in \{c, g\} \tag{2}$$

Adding across the supply decisions of generators of all types, aggregate market supply of electricity can thus be written as

$$Q(p^{elec}_{jt}, \mathbf{K}_{jt}, p_{fjt}) = \varphi_s K_{sjt} + \varphi_w K_{wjt} + \sum_{f \in \{c,g\}} \tilde{q}_{fjt}(p^{elec}_{jt}, p_{fjt}, \epsilon_{fjt}) K_{fjt} \tag{3}$$

where $\mathbf{K}_{jt} = \{K_{gjt}, K_{cjt}, K_{sjt}, K_{wjt}\}$ contains the aggregate capacities of generators of each type at time t and market j.

3.2 State Transitions

State transitions in the model are affected by endogenous entry and exit of generators, as well as the evolution of electricity demand determinants and of generator entry costs. I now describe optimal entry and exit strategies conditional on a given belief on the evolution of industry and exogeneous state variables, and turn to describe how beliefs are formed in the next subsection.

Exit In order to be active next year, generators need to pay a per-unit of capacity maintenance cost that depends on their fuel type and age. At the start of every period, generators observe an IID logit shock ϕ to their maintenance cost and decide whether to pay it - in which case they will be incumbents next period - or exit the market.

The value function of an incumbent generator of age a and type f is given by

$$V_{aft}(S_{jt}) = \pi_f(S_{jt}) + \max\left\{0, \beta\mathbb{E}[V_{a+1ft}(S_{jt+1})|S_{jt}] - (F_{aft} + \phi)\right\} \tag{4}$$

where F_{aft} is the deterministic component of the maintenance cost. The expectation over continuation values is taken over all future maintenance shock draws and the strategies of current and future competitors.

An incumbent generator will exit the market if its maintenance cost is higher than its continuation value. This event occurs with probability[20]

[20]Given that most solar and wind capacity has been installed in the last 10 years, there is not enough data on their exit patterns to estimate the distribution of their fixed costs and endogenize their exit decisions. Instead, I assume that all non-fossil generators (and storage facilities) have fixed maintenance costs $\bar{F}_f$ and a fixed operating life $\bar{T}_f$, which I calibrate based on engineering estimates. I provide details on these assumptions in the Estimation section.

$$\zeta_{af}(S_{jt}) = Pr(\phi > \beta \mathbb{E}[V_{a+1f}(S_{jt+1})|S_{jt}] - F_{aft}) = 1 - F_{\phi}(\beta \mathbb{E}[V_{a+1f}(S_{jt+1})|S_{jt}] - F_{aft}) \tag{5}$$

Entry Every period there is a number $\overline{N}_f$ of potential entrants of each generator type that decide whether to enter the market or not based on the current value of the type-specific entry cost κ_{fjt} and a random IID logit shock $\bar{\phi}$.[21] The value of entry for a generator of type f is given by

$$VE_f(S_{jt}) = \beta \mathbb{E}[V_{0f}(S_{jt+1})|S_{jt}] - \kappa_{fjt} \tag{6}$$

A generator will thus enter the market if its entry cost shock draw $\bar{\phi}$ is lower than the net entry value, an event that occurs with probability

$$\bar{\zeta}_f(S_{jt}) = Pr(\bar{\phi} > VE_f(S_{jt})) = F_{\bar{\phi}}(VE_f(S_{jt})) \tag{7}$$

3.3 Equilibrium and Beliefs

I now turn to specifying how agents beliefs' about future state transitions and the actions of their competitors are formed, and describe the equilibrium concept that I use to solve my model. An important aspect of my setting is the fact that the entry costs of new renewable technologies are falling over time, i.e. the distribution of state variables is non-stationary. Accounting for the presence of non-stationarity is critical to capturing how short-term and medium-term transition dynamics respond to changes in fossil fuel prices, which is the focus of this project. To do so, I rely on the Nonstationary Oblivious Equilibrium (NOE) concept recently developed by Benkard, Jeziorski and Weintraub (2024).

NOE imposes two key assumptions. The first is that firms make decisions assuming that the industry state evolves deterministically. This can be thought as an approximation to a setting with an infinite number of firms, where firm-specific entry and exit shocks would wash out and the percentage of firms that transition from any individual state to another would be deterministic. NOE further assumes that firms believe the evolution of exogenous state variables, e.g. renewable installation costs and electricity demand, is also deterministic.

[21] Entry costs are per-unit of generation capacity (as are maintenance costs). Note that, because generators of type f in a given market are assumed to be homogeneous and because non-operating costs are per-unit of capacity, the exact distribution of capacity across market entrants in period t does not affect the current market equilibrium nor future transition dynamics. In my simulations, I assume that generators enter the market with one unit of capacity and set the maximum number of entrants $\overline{N}_f$ to be equal to 10 times the largest observed capacity entry in any of the markets in my sample during 2001-2021.

Under these assumptions —and further assuming symmetrical strategies across firms of the same type —the time period determines the industry state and any common shocks. The (expected) evolution of the aggregate capacity of generators of type f and age a can be written as

$$\tilde{K}_{afjt+1}(\zeta_{af}, \zeta_f^{entry}, K_{0afj}) = \begin{cases} \zeta_{af}(S_{jt})\tilde{K}_{afjt}(\zeta_{af}, \zeta_f^{entry}, K_{afj0}) + \bar{N}\zeta_f^{entry}(S_{jt}) & \text{if} \quad a = 0 \\ \zeta_{af}(S_{jt})\tilde{K}_{afjt}(\zeta_{af}, \zeta_f^{entry}, K_{afj0}) & \text{otherwise} \end{cases}$$
$$\forall f \in \mathcal{F}, \forall a \in \mathcal{A}_f \tag{8}$$

Equation (8) completely characterizes the evolution of the industry state. For a given starting state K_0, a NOE will consist on exit strategies ζ_{af} $\forall f, \forall a \in [1, \bar{A}_f]$, and entry strategies ζ_f^{entry} $\forall f$ characterized by (5) and (7), such that the expected evolution of the industry state is given by (8). I further assume, as in Benkard, Jeziorski and Weintraub (2024), that NOE becomes stationary as time progresses. Specifically, I assume that there is a terminal period $\bar{T}$ after which all firms believe that the industry enters into a steady state. In this way, finding a NOE becomes equivalent to solving a finite horizon problem. The solution algorithm I use is described in Appendix C.

4 Fossil Fuel Markets in an Open Economy

The electricity investment model presented in the preceding section highlights the importance of energy inputs for investment decisions in electricity sectors worldwide. To assess how global shocks to energy input supply affect decarbonization efforts across the world, I now bring my closed-economy electricity investment model into a framework where energy inputs are internationally traded and their price is endogenous. In Appendix B, I further show how I incorporate an endogenous carbon price for markets that operate a cap-and-trade emission trading scheme such as the EU and UK.

Energy demand Consider a country j that produces electricity under the model outlined in the previous section. Existing generation capacity and demand fundamentals determine the country's demand for gas and coal inputs to be used in electricity generation. In equilibrium, the quantity of fossil fuel f used to produce electricity is given by:

$$D_{fjt}^{elec} = D_f^{elec}(p_{fjt}, K_{fjt}, p_{jt}^{elec}) \quad \forall f \in \{coal, gas\} \tag{9}$$

where the electricity price, p_{jt}^{elec}, is itself a function of demand fundamentals, the prices of all energy inputs and the available capacity of all types.

In country j, energy inputs are also demanded for other local uses (e.g. residential heating and manufacturing). The overall demand for input f for other local uses in a period is given by

$$D_{fjt}^{other} = D_f^{other}(p_{fjt}, X_{jt}) \tag{10}$$

where X_{jt} is a vector of exogenous country characteristics that affects demand for fossil f in non-electricity sectors.

Lastly, an exporting country j has $\mathcal{K}_{fjt}$ export terminals that purchase input f domestically, transform it and ship it internationally.[22] I assume that the profit of a terminal $k \in \mathcal{K}_{fjt}$ is given by the following expression

$$\pi_{kfjt} = p_{fjt}^{export} X_{kfjt} - c^{export}\left(p_{fjt}, \frac{X_{fjt}}{K_{fjt}^{export}}\right) X_{kfjt} \qquad \text{s.t.} \qquad X_{kfjt} \leq K_{kfjt}^{export} \tag{11}$$

Where K_{kfjt}^{export} is the export capacity of terminal k, and p_{fjt}^{export} is the price at which it exports the processed input. $c^{export}(\cdot)$ is a unit cost function that is increasing in the domestic price of the fossil fuel input f and increasing in the exporter's capacity use. I assume that export terminals choose the export quantity that maximizes their profits taking both domestic and export prices as given. Given this optimal choice, the aggregate demand for the local input is given by

$$X_{fjt} = X_f(p_{fjt}, K_{fjt}^{export}, p_{fjt}^{export}) \tag{12}$$

Overall demand for fossil fuel f in country j is then given by

$$D_{fjt} = D_f^{elec}(p_{fjt}, K_{fjt}, p_{fjt}^{elec}) + D_f^{other}(p_{fjt}, X_{jt}) + X_f(p_{fjt}, K_{fjt}^{export}, p_{fjt}^{export}) \tag{13}$$

Energy supply Countries have two ways of sourcing energy input f. First, they can produce it domestically, with production function

$$Q_{fjt} = Q_f(p_{fjt}, X_{jt}) \tag{14}$$

[22]Natural gas can be exported through pipelines or as LNG. In my simulation exercises, I take pipeline exports and imports as an exogenous component of fossil fuel f demand and supply for each country j, and only endogenize the decision to export natural gas as LNG.

Second, they can purchase it from international export terminals, at import price p_{fjt}^{import}. Overall supply is given by

$$\tilde{Q}_{fjt} = Q_f(p_{fjt}, X_{jt}) + M_f(p_{fjt}^{import}) \tag{15}$$

Equilibrium I start by assuming that there is one international market clearing price for each fossil fuel (p^*_{ft}). On top of this international market clearing price, the effective price that importers pay and exporters receive is also affected by trade costs. I introduce trade costs in a stylized way. I assume that effective import price and export prices are given by

$$p_{fjt}^{import} = \delta_j^{import}(p^*_{ft} + \tau_f) \tag{16}$$

$$p_{fjt}^{export} = \delta_j^{export} p^*_{ft} \tag{17}$$

where τ_f is a fuel-specific additive transport cost, and δ_j^{import} and δ_j^{export} are country-specific shifters that capture country heterogeneity in distance to markets, bargaining power, and other factors that might generate a deviation from average international prices.

In equilibrium, every domestic market for fossil fuel f has to clear, and trade has to be balanced. The equilibrium conditions are as follows:

$$\tilde{Q}_{fjt}(p_{fjt}, p^*_{ft}, \cdot) = D_{fjt}(p_{fjt}, p^*_{ft}) \quad \forall j \in \mathcal{J} \tag{18}$$

$$\sum_j M_f(p^*_{ft}) = \sum_j X_f(p^*_{ft}, p_{fjt}, K_{fjt}^{export}) \tag{19}$$

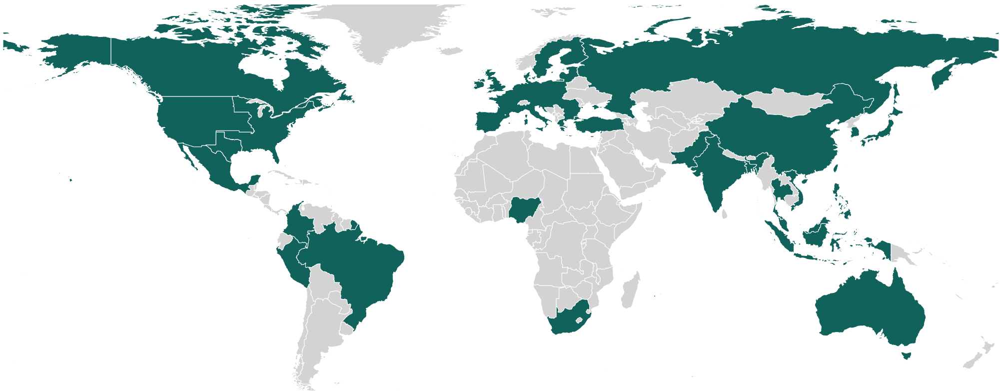
In essence, for each fossil fuel f there are $\mathcal{J}$ domestic markets and one international market that have to be cleared together.

5 Data

For my quantitative analysis, I split the world into regions that roughly correspond to electricity markets. My simulation sample is made up of 28 markets including 24 countries, the European Union, and three US regions (West, East and Texas, roughly corresponding to the existing US electricity interconnections). These markets, shown in figure (7), accounted for 87% of global electricity generation and were responsible for 86% of emissions produced in electricity generation in 2023.

To estimate the parameters of my model and conduct my simulation analysis, I collect and harmonize data on fossil and electricity markets from multiple sources. I provide an overview of my data sources below.

Figure 7: Markets in sample



Note: The map depicts the 28 markets included in my simulation sample. Each market is a country, with the exception of the U.S. (split into Eastern U.S., Western U.S., and Texas), and the European Union (aggregated into a single market). For a full list of sample markets, see Appendix D.

Electricity generation infrastructure & investment determinants My model features endogenous entry and exit of electricity generators. To estimate the parameters governing these choices, I build a dataset with detailed information on global electricity generation assets. For each electricity generator that has been active at any point between the years 2000 and 2023 in any market of my sample, I collect information on their fuel type, date of entry, date of exit, installed capacity, and other characteristics. The starting point of my data construction is the Global Energy Monitor (GEM) Infrastructure Tracker, which provides detailed information on the current fleet of global electricity generators. In order to get a full panel of electricity generation assets, which I need to identify entry and exit events, I extend this dataset with information from local electricity regulatory authorities.

Electricity investment determinants Electricity investment choices depend on market conditions and infrastructure costs. Annual market-level data on electricity demand and supply by generator type comes from Ember and the U.S. Energy Information Agency (EIA). In order to estimate electricity supply functions, I complement this data with monthly information on electricity demand, supply, wholesale electricity prices and carbon prices for a sample of selected markets, which I collect from local regulatory authorities. I also retrieve survey data on installation costs and fixed operating costs by generator type and market from the International Energy Agency (IEA) and the International Renewable Energy Agency (IRENA). Lastly, I use information on wind and solar potential by market from the Global Solar Atlas and the Global Wind Atlas.

Fossil fuel markets The local price of fossil fuels is a key determinant of electricity generation costs and input supply in my model. I build a panel of annual thermal coal and natural gas prices from 2001 to 2022 for the markets in my sample by collecting and harmonizing data from local regulatory agencies and international organizations (International Gas Union Wholesale Gas Survey, IEA, EIA). I complement this data with monthly information on trade prices and flows for both thermal coal and LNG from COMTRADE and WITS, together with information on LNG and coal freight rates from Refinitiv. Data on annual fossil fuel supply by market comes from IEA, and data on proved fossil fuel reserves from EIA.

Trade infrastructure Infrastructure constraints are a key determinant of thermal coal and LNG trade flows. Data on the location and capacity of both coal and LNG terminals comes from GEM's Infrastructure Tracker. A useful aspect of the GEM data is that it provides information on planned and under-construction terminals, which I use to construct counterfactual forward-looking scenarios.

6 Estimation

This section outlines my approach to recovering the parameters that govern equilibrium choices in my model. I begin by detailing the estimation of static supply and demand functions for electricity and fossil fuels, along with the determinants of trade costs. Given the existing electricity generation capacity, these elements are sufficient to determine global equilibrium quantities and prices in my quantitative simulation of fossil fuel and power markets. I then provide an overview of my method for identifying entry and exit determinants for electricity generators worldwide, which drive the transition dynamics in the model.

6.1 Electricity supply

Gas and coal generators From the profit function in (1), and given the assumption that all generators of the same type within a market are homogeneous in their production costs, the interior solution to the quantity choice problem of a generator of type f in market j can be written as

$$p_{jt}^{elec} = \beta_{1f}\gamma_{1fjt}p_{fjt} + \beta_{2f}\frac{q_{fjt}}{K_{fjt}} + \chi_{fjt} + \epsilon_{fjt} \qquad \forall f \in \{c, g\} \tag{20}$$

I obtain the parameters in (20) in two steps. First, I obtain a measure of γ_{1fjt} from IEA, which provides an indicator of the average annual efficiency of electricity plants by fuel and country for the period 2000-2022.[23] With estimates $\hat{\gamma}_{1fjt}$ in hand, I rewrite (20) as

$$p_{jt}^{elec} = \beta_{1f} \underbrace{\tilde{p}_{fjt}}_{\hat{\gamma}_{1fjt} p_{fjt}} + \beta_{2f} \frac{q_{fjt}}{K_{fjt}} + \chi_{fjt} + \epsilon_{fjt} \qquad \forall f \in \{c, g\} \tag{21}$$

I separately recover β_{1f} and β_{2f} for each electricity generation type (gas and coal) through IV regressions based on specification (21). To do so, I collect monthly electricity prices, fossil fuel prices, and aggregate capacity use of generators by type for a sample of global electricity markets. My estimation sample has monthly market-level information for 2016-2023.[24]

Generator capacity use is endogenous to unobserved supply shocks (ϵ_{ft}). To deal with this source of endogeneity, I instrument coal and gas generator capacity use with the capacity use of renewable generators in a given market and period. The underlying logic for this instrument is that changes in the availability of renewable electricity sources —which are largely driven by climate conditions and thus arguably uncorrelated with fossil fuel generation supply shocks —act as a shift in the residual demand faced by gas/coal generators.

In my setting, fossil fuel prices are also potentially endogenous to shocks to electricity supply. I address this source of endogeneity by instrumenting $\tilde{p}_{fjt}$ —the efficiency-adjusted price of fossil fuel f —with the monthly price of Brent oil. The relevance of the instrument comes from the fact that local natural gas prices are affected by global oil price shocks due to the existence of gas-oil co-extraction and the fact that natural gas contracts have been historically indexed to oil prices. Oil is almost not used for electricity generation in my sample, which limits the potential endogeneity of the instrument to electricity supply shocks. Relying on variation in a global price rather than on local oil prices also limits endogeneity concerns.[25]

Estimation results are presented in Table 1, with first stage results shown in Appendix Table A2. The coefficient associated with the efficiency-adjusted fossil fuel price, β_{1f}, is close to unity for both generator types. This implies that the average response of electricity prices to fossil fuel shocks is consistent with the generator efficiency measure

[23]In the case of OECD countries, IEA obtains this data through annual questionnaires to national administrations. For non-OECD countries, IEA constructs this indicator based on a mix of publicly reported data and questionnaires to national authorities. A full list of sources is available in International Energy Agency (2024*b*).

[24]In estimation, markets are defined as either countries (i.e. Japan, South Korea, and all countries in the European Union) or subnational units (i.e. U.S. balancing authorities). Details on how I construct my baseline sample are provided in Appendix D.

[25]Any exogenous shift to natural gas prices spills over to coal prices due to coal-to-gas substitution in electricity generation. Coal prices also react to oil price shocks because they affect the cost of coal transportation.

obtained from IEA. I recover positive estimates of β_{2f} for both coal and gas generators, consistent with the existence of increasing marginal costs.[26]

Table 1: Electricity supply parameters

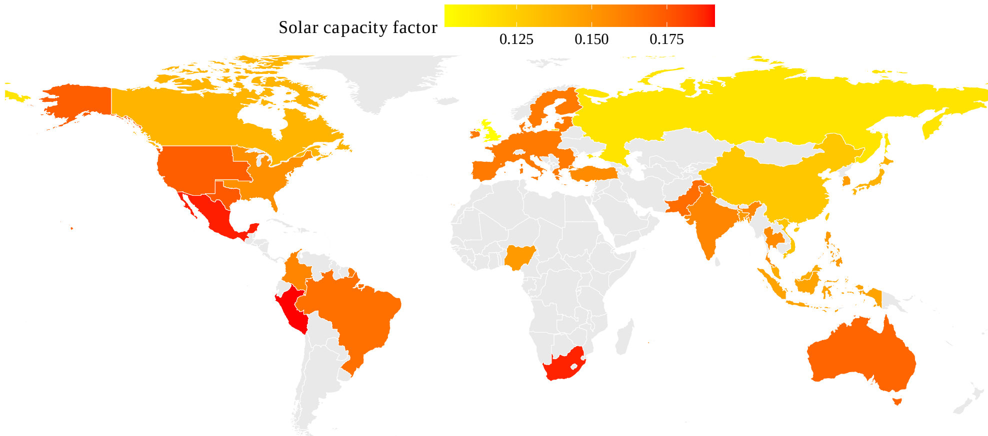
	Gas		Coal	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Efficiency-adj fuel price (β_{1f})	0.906***	0.992***	1.51***	0.975***
	(0.135)	(0.171)	(0.102)	(0.231)
Capacity use (β_{2f})	24.1***	37.8***	8.53***	46.5***
	(3.46)	(8.12)	(2.73)	(12.7)
Observations	2,226	2,226	2,226	2,226
Adjusted R^2	0.817	0.886	0.807	0.790
Within Adjusted R^2	0.502	0.691	0.474	0.429
F-test, Efficiency-adj fuel price (β_{1f})		14.9		207.1
F-test, Capacity use (β_{2f})		122.5		47.5
Region x year fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓

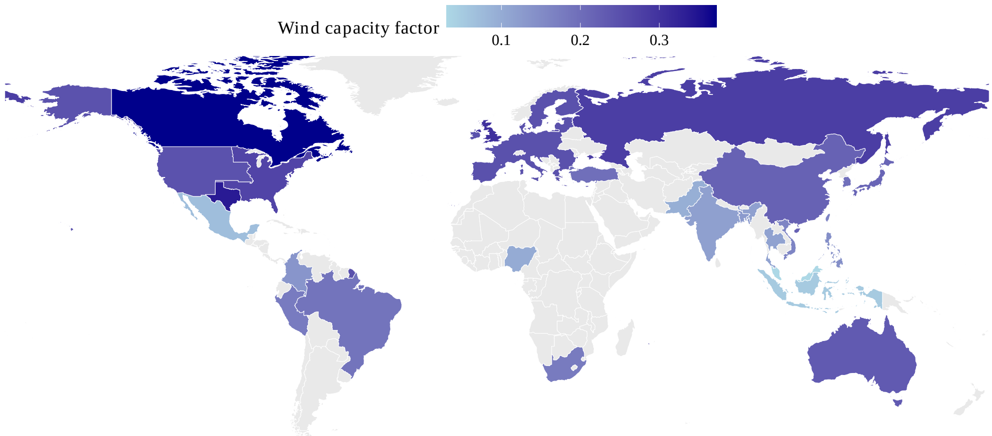
Notes: Elec. supply estimation draws on monthly data from 2016 to 2023 for electricity markets in US, EU, Korea and Japan. Robust standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Renewable generators I assume all wind and solar generators have zero marginal costs but differ in their capacity factor φ_{fj}, which determines what fraction of their installed capacity is effectively active in a given year. The Solar and Wind Atlas published by the World Bank contains detailed grid data on capacity factors for both renewable types. I compute φ_{fj} as the population-weighted average of the capacity factor of renewable type f within the geographical area of market j. Figure 8 shows the spatial distribution of φ_{fj} for both solar and wind.

[26] My estimation sample is limited to a subset of the markets and periods I use in my counterfactual analysis, and has a different time aggregation (monthly vs. annual). When simulating the full model equilibrium, I extrapolate β_{1f} and β_{2f} for all markets and years in my simulation sample. Appendix F details the approach I follow to extrapolate observed cost shifters in χ_{fjt}.

Figure 8: Renewable energy capacity factors





Note: capacity factors are population-weighted averages constructed based on grid data from the Global Solar Atlas and the Global Wind Atlas.

6.2 Fossil fuel supply

I parametrize the log supply curves of gas and coal as

$$\text{Gas}: \quad log(Q_{gjt}) = \alpha_1^g \log p_{gjt} + \alpha_2^g \log R_{gjt} + \alpha_{3,j}^g \log Q_{jt}^{oil} + \gamma_j^g + \epsilon_{gjt} \tag{22}$$

$$\text{Coal}: \quad log(Q_{cjt}) = \alpha_1^c \log p_{cjt} + \alpha_2^c \log R_{cjt} + \gamma_j^c + \epsilon_{cjt} \tag{23}$$

Market-level production of gas Q_{gjt} and coal Q_{cjt} are both functions of domestic prices p_{fjt}, available reserves R_{gjt}, and market fixed effects γ_j^f, where f denotes the respective fossil fuel. In addition, I account for the fact that natural gas is often extracted as a by-product of oil by including oil production into the natural gas supply function. Lastly, domestic fossil fuel prices are endogenous, as unobserved supply shocks ϵ_{fjt}

can decrease prices by reducing supply. Thus, I instrument for prices with the interaction between local electricity demand and the share of electricity generation that uses fossil fuel f in the year prior to the beginning of my sample. The use of this instrument is motivated by the fact that shifts in a markets' total electricity demand affect demand for fossil fuel f as an input, more so in countries that are initially more reliant on that fossil fuel for electricity generation. The exclusion restriction requires that shifts in aggregate electricity demand are orthogonal to fossil fuel supply shocks.[27]

I implement my estimation using annual data for 2000-2021 for a sample of markets that account for 82 % and 95% of global natural gas and coal supply throughout the period.[28] Results are presented in Table 2, while first stage results are shown in Appendix Table A4. Without instrumenting for the price of fossil fuels, I get price parameter estimates with a strong downward bias, particularly for coal. Under the IV specifications, I find that coal supply is around three times more elastic to price changes than natural gas supply. This has important implications for the potential effect of a global gas supply shock such as the expansion of LNG export capacity. First, because gas supply is relatively inelastic, an expansion in natural gas exports potentially leads to increases in the domestic gas prices of exporting countries. Second, because coal supply is elastic, a decrease in coal demand due to relatively lower LNG prices in importing countries will likely not lead to big declines in domestic coal prices, thus amplifying the effect of the gas supply shock on coal-to-gas substitution incentives.

[27] One potential concern is the fact that electricity prices could be affected by fossil fuel supply shocks and that aggregate electricity demand might be elastic to electricity prices in the long-term, biasing my estimates for price elasticities upwards. I obtain similar coefficients for both coal and gas when I use the evolution of population —a determinant of electricity demand that is arguably uncorrelated with prices —as an instrument.

[28] Markets in my full sample that are not included in the fossil fuel estimation mostly have zero or close to zero production during the period of my analysis. In counterfactuals, I fix their production of fossil fuel f at observed levels and assume that it remains constant at 2021 levels when projecting supply into the future.

Table 2: Fossil fuel supply parameters

	Gas		Coal	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
log(Price)	0.064***	0.239***	0.201***	0.769***
	(0.019)	(0.078)	(0.059)	(0.081)
log(Reserves)	0.087**	0.350***	-0.015	0.250**
	(0.035)	(0.074)	(0.052)	(0.098)
log(Oil production)	0.408***	0.333**		
	(0.060)	(0.138)		
Observations	310	310	298	298
Adjusted R^2	0.995	0.977	0.994	0.979
Within Adjusted R^2	0.845	0.305	0.748	0.039
F-test (1st stage), log(Price)		53.2		70.4
Country fixed effects	✓	✓	✓	✓
2016+ dummy x Country fixed effects	✓	✓	✓	✓

Notes: Supply estimation draws on annual data from 2000 to 2021 for markets accounting for 82% and 95% of natural gas and coal global production respectively. The IV columns instrument for fossil fuel prices with shocks to aggregate electricity demand interacted with the share of the fossil fuel in generation in 2000. Newey-West standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

6.3 Non-electricity fossil fuel demand

I assume the following log-linear function for the demand for natural gas for non-electricity uses:

$$\log(D_{gjt}^{other}) = \tilde{\alpha}_p^g \log p_{gjt} + \tilde{\alpha}_X^g X_{jt} + \epsilon_{gjt} \tag{24}$$

where X_{jt} is a vector of exogenous country characteristics that includes GDP, population, and country fixed effects. I use annual data on gas prices, non-electricity gas demand and country characteristics to estimate (24). To instrument for the gas price, I use the evolution of proven domestic gas reserves and global oil prices as supply shifters. Results are presented in Table 3. As expected, the elasticity of non-electricity gas demand to price changes is negative but relatively low.

Table 3: Non-electricity gas demand

	OLS	IV
	(1)	(2)
log(Price)	-0.030	-0.128*
	(0.031)	(0.071)
log(GDP p.c.)	1.19***	1.32***
	(0.166)	(0.182)
log(Population)	-0.042	0.084
	(0.646)	(0.652)
log(GDP p.c.) × OECD	0.552*	0.642**
	(0.296)	(0.297)
log(Population) × OECD	0.141	-0.190
	(0.753)	(0.746)
Observations	421	421
Adjusted R^2	0.993	0.993
Within Adjusted R^2	0.652	0.634
F (1st Stage), log(Price)		50.4
Country fixed effects	✓	✓
2016+ dummy x Country fixed effects	✓	✓

Notes: Column (2) uses per capita gas reserves and Brent oil price as an instruments for the gas price. Newey West standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

6.4 Trade determinants

My model features two types of fossil fuel trade costs, which I estimate separately. First, the model incorporates export costs that are increasing on export capacity use, which I estimate leveraging data on observed trade flows and infrastructure capacity. Second, the model includes origin- and destination-specific trade shifters, which I calibrate to match observed differences in export and import prices across countries. I provide details on both of these elements below.

Export supply functions In the model, each country j that exports fossil fuel f has a set of export terminals $\mathcal{K}_{fjt}$ that choose their optimal export quantity by optimizing the profit function in (11). I parametrize the unit export cost $c(\cdot)$ in (11) as follows:

$$c^{export}\left(p_{fjt}, \frac{X_{fjt}}{K_{fjt}^{export}}\right) = \gamma_{0fj} + \gamma_{1f}\frac{X_{fjt}}{K_{fjt}^{export}} + \epsilon_{kfjt} \tag{25}$$

Given this functional form for $c^{export}(\cdot)$, the interior solution to problem faced by an export terminal k that trades fossil fuel f can be written as

$$p^*_{fjt} - p_{fjt} = \gamma_{0fj} + 2\gamma_{1f}\frac{X_{fjt}}{K^{export}_{fjt}} + \epsilon_{kfjt} \tag{26}$$

I take (26) to the data to recover the parameters governing the export supply of LNG and coal for each exporting country. For LNG, I construct a panel of capacity use at the export terminal level by matching terminal capacity data from GEM Infrastructure Tracker with annual export quantity data at the terminal-level from Refinitiv. I get country-level average annual LNG export prices from COMTRADE, and assume that each export terminal faces the same price. I do not have data on export quantities at the terminal level for thermal coal, so in this case I aggregate export capacity data from GEM at the country level and match it to annual export quantity data from IEA. Country-level export prices again come from COMTRADE.

Results are presented in Table 4. I find that the unit cost of exporting both commodities is increasing in capacity use. At the mean capacity use, export costs are on average USD 4.20 per million British thermal unit (MMBtu)[29] for LNG and USD 1.90 per MMBtu for coal at 2021 constant prices.[30]

Table 4: Export cost parameters

	LNG (1)	Coal (2)
Export capacity use	0.560**	1.40***
	(0.216)	(0.476)
Observations	113	162
Adjusted R^2	0.555	0.279
Avg. sum FE	3.78	0.916
Mean capacity use	0.761	0.452
Country fixed effects	✓	
Region fixed effects		✓

Notes: Robust standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Trade costs and country-specific trade shifters I calibrate the trade cost τ_f for each fossil fuel using data on the daily freight rates paid in thermal coal and LNG trans-

[29]Throughout this paper, I measure both LNG and thermal coal prices in MMBtus, a common unit to measure the heating content and the value of a fuel.

[30]My estimates for LNG export costs are roughly in line with Zou et al. (2022), which reports global liquefaction fees in the range of 2-4 USD per MMBtu based on industry estimates for a sample of projects.

actions between major trading partners in 2012-2023, which I source from Refinitiv. I take the weighted average freight rate for each fossil fuel type, weighting country pairs by their share on global trade.[31] My calculation yields average freight rates of USD 0.75 per MMBtu and USD 0.41 per MMBtu for LNG and thermal coal respectively (in constant 2021 prices). Country-specific shifters δ_j^{export} and δ_j^{import} are calibrated to match average differences between the mean global FOB export price of fossil fuel f, country-specific FOB export prices and domestic fossil fuel prices in importing countries.

6.5 Transitions

Exit Incumbent gas and coal generators decide whether to exit the market based on their expected future path of profits and the maintenance costs they face. I parametrize the deterministic component of maintenance costs as

$$F_{afjt} = \gamma_{fj} + \gamma_{af} + \epsilon_{afjt} \tag{27}$$

γ_{fj} are market specific fixed effects, and γ_{af} are age group fixed effects. Given the structure of the model and the assumption that maintenance costs are subject to random IID logit shocks ϕ, I can recover the parameters in (27) through a linear structural regression, without having to compute continuation values (Arcidiacono and Miller, 2011; Hotz and Miller, 1993; Hall, 1978; Scott, 2013). Appendix F presents derivations. The structural equation that I obtain compares exit probabilities in a given market and for a given generator type in years t and $t+1$ and ages a and $a+1$:

$$\tilde{\zeta}_{afjt} - \beta\Big\{log\Big[\exp\tilde{\zeta}_{a+1fjt+1} + 1\Big] + \gamma\Big\} = \beta\frac{\pi_{fjt+1}}{\sigma_f} - \frac{\gamma^e_{fj}}{\sigma_f} - \frac{\gamma^e_{af}}{\sigma_f} + \tilde{\epsilon}_{afjt} \tag{28}$$

where $\tilde{\zeta}_{aft} = \log(1-\zeta_{afjt}) - log(\zeta_{afjt})$ is a transformation of the exit probability ζ_{afjt} and γ is the Euler constant. σ_f is the variance of fixed cost shocks. The larger σ_f is, the less coal and gas exit depends on future market conditions.

To take equation (28) to the data, I need first to construct a measure of exit probability by generator type, market, year and age. To do so, I rely on the data on global generator exit events from Infrastructure Tracker described in Section 4. I obtain exit probabilities from Probit regressions of exit events in the data on market-year fixed effects and generator age. To construct a measure of profits, I use my estimated electricity supply parameters together with data on observed capacity use by generator type, year and market, as well as data on market-specific fossil fuel prices. I instrument future profits with current period profits to account for expectational error in agents' decisions (Scott, 2013).

[31] Coal freight rates are reported in metric tonnes. To get a freight rate value in MMBtu, I use IEA annual data on the average caloric value of thermal coal exports for the exporters in my sample.

Results are presented in Table 5. For both gas and coal generators, maintenance costs are increasing in age, but more so for gas generators. Fixed costs represent an average 50% of variable profits in my sample.

Table 5: Generator maintenance cost parameters

	Gas (1)	Coal (2)
1-20 years	15,501.0***	26,661.0 ***
	(6,509.2)	(7,565.5)
21-40 years	19,639.4***	33,915.0***
	(7,252.0)	(10,665.9)
41-60 years	22,434.2***	40,363.34 ***
	(9,400.0)	(14,867.4)
61-80 years	26,185.4***	43,958.0***
	(12,325.5)	(18,954.2)
Logit scale (σ_f^{exit})	39,719.0***	32,549.0***
	(9758.2)	(7,140.3)
Observations	5,388	6,488

Entry The entry decision of generators depends both on expected future profits and generator installation costs. I obtain data from a survey on the installation costs of solar and onshore wind generators for selected countries from 2010 to 2022 from IRENA. I complement this data with information on the installation costs of gas and coal generators by region from IEA. None of these sources has information on taxes or subsidies applied to the installation of generators across countries. In addition, heterogeneity in regulatory barriers to entry might be relevant to explain differences in the rate of entry of generators of different types across countries.

To deal with the potential presence of unknown shifters to entry costs, I first parametrize the distribution of entry costs for fossil fuel f in country j and time t as

$$EC_{fjt} \sim G(s_{fj}IC_{fjt}, \mu IC_{fjt}) \tag{29}$$

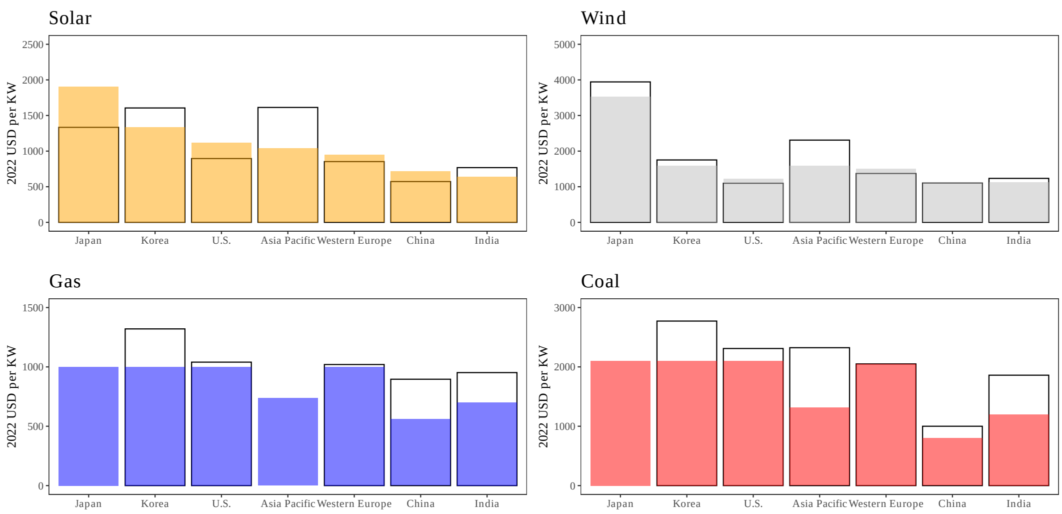
where G is the Gumbel distribution and IC_{fjt} are observed installation costs in my data. s_{fj} is a type and market-specific shifter to installation costs. In addition, I allow for a time-variant variance for entry costs that depends on observed installation costs and parameter μ.

Estimation of entry parameters proceeds in two steps. First, I recover μ using Euler methods. Intuitively, I identify μ from the correlation between differences in entry probabilities across time, fuels and markets and differences in profits (net of installation costs), similarly to the procedure I follow to recover the variance of maintenance costs.[32]

Next, I recover s_{fj} by minimizing the distance between the power capacity transitions predicted by the model and those observed in the data. The data moments I match are the absolute changes in electricity generation capacity by fuel type for each of the markets in my sample from 2001 to 2021. My estimation algorithm proceeds as follows. In each iteration, I start with a guess of LNG and international coal prices. Given this guess, I find the vector of market-specific parameters that minimizes the distance between model and data moments, performing this minimization independently market by market. Once I obtain a set of parameters for each market, I compute the full global equilibrium in my model and update the guess of equilibrium LNG and international coal prices. I repeat this process until the difference between LNG and international coal prices across successive iterations is below a tolerance level.

A summary of how mean market and fuel-level installation costs change when I multiply them by the estimated entry cost shifters is presented in Figure 9. Incorporating the estimated entry cost shifters lowers solar entry costs in the U.S., China, Japan and Western Europe relative to the gross installation costs reported by IRENA. Meanwhile, average installation costs across fuel types in Asia Pacific and India are higher than in my data when incorporating estimated cost shifters.

Figure 9: Installation Costs



Note: Color bars indicate average installation costs in 2021 per region and fuel type from IRENA and IEA data. Black bars denote the installation costs after adjusting for the shifter s_{fj}.

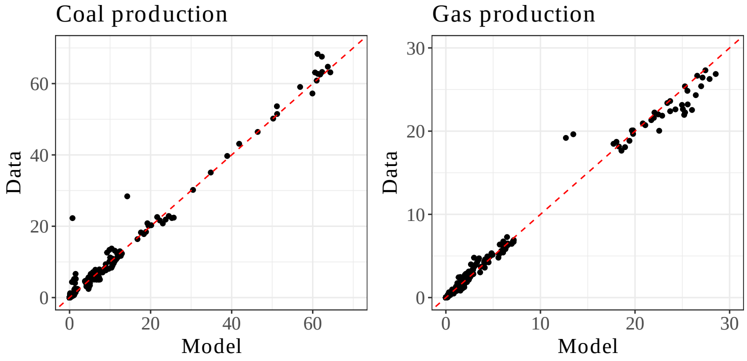
[32]As discussed before, I can construct a measure of realized profits by generator type, market and year using data on observed capacity use by generator type and fossil fuel prices, together with my electricity supply estimates. I recover realized entry probalities using the entry events reported in the Infrastructure Tracker data and assuming the same maximum capacity entry per year that I impose in my model simulations.

7 Model Fit

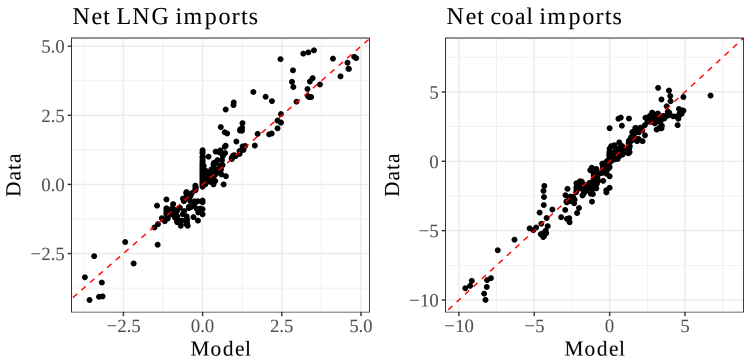
To assess the fit of my model, I simulate a global equilibrium using 2001 as a starting year and 2070 as a terminal year. Then I compare the evolution of the endogenous variables in my model to actual data on fossil fuel prices, consumption and trade, as well as on electricity generation and electricity capacity. Figures 10 and 11 compare my model predictions with observed data. Tables A5 and A6 in the Appendix show that my baseline projections for future electricity capacity and generation by market and fuel are in line with industry predictions to 2050 taken from the International Energy Agency (IEA) and the U.S. Energy Information Administration (EIA).

Figure 10: Model fit: fossil fuel markets

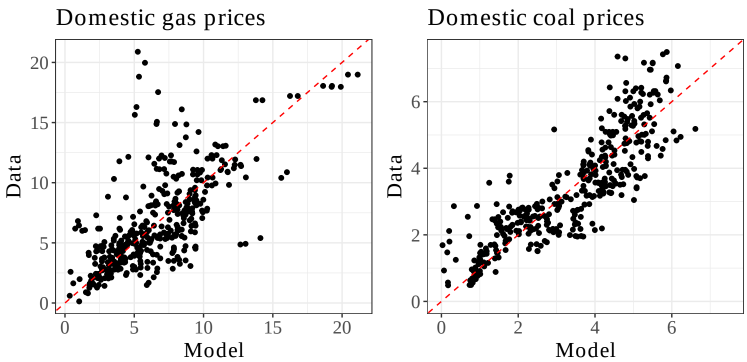
(a) Fossil fuel production (in exajoules)



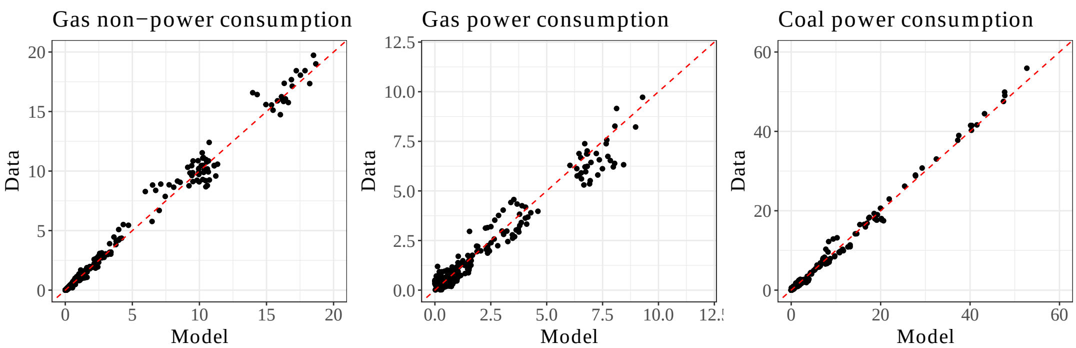
(b) Fossil fuel trade (in exajoules)



(c) Fossil fuel prices (in 2021 usd per mmBtu)

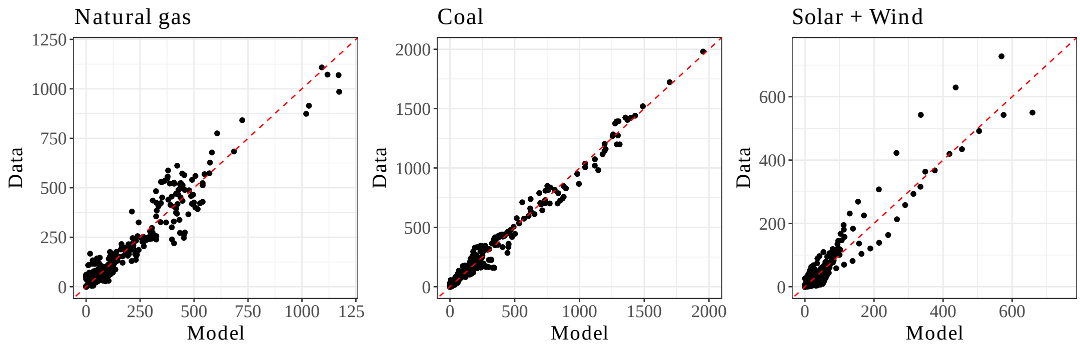


(d) Fossil fuel consumption (in exajoules)



Note: every point is a market-year pair. 45-degree line in dashed red.

Figure 11: Model fit: electricity generation by type (in TWh)



Note: every point is a market-year pair. 45-degree line in dashed red.

8 Effect of a shock in U.S. LNG export capacity

I use the full structure of my estimated model to analyze the decarbonization impacts of the proposed build-out of US LNG export terminals in the coming years. As described in Section 2, the U.S. Department of Energy is currently in the process of reviewing several export terminals projects that, if built, would more than double US LNG export capacity by 2030. My main counterfactual analysis compares the evolution of global fossil fuel prices, electricity generation capacity and emissions from 2025 to 2070 in two scenarios: one in which all LNG proposed projects get built and one in which only LNG export terminals currently operating or under construction are ever active. After providing an overview of my baseline results, I next discuss how different technological paths and alternative policy combinations would change the effect of the shock.[33]

8.1 Baseline results

Effect on prices and power generation Figures 12 provides an overview of my results. In response to the shock, U.S. LNG exports increase by an average 20% across 2025-2070 relative to the baseline scenario, generating an annual increase in global LNG trade of 6.4% on average.[34] Higher U.S. LNG exports reduce the gap between U.S. natural gas prices and the international price of LNG. I find that the export shock increases U.S. domestic gas prices by an average 5.4% throughout the period of anal-

[33] Details on the simulation algorithm and on assumptions about the future evolution of exogenous state variables in my model are provided in the Appendix to this document.

[34] This growth rate is small when compared to the sizable U.S. export capacity expansion that I feed into my counterfactual. Results are driven by the presence of slack in the LNG market under my baseline projections, with natural gas demand growing by less than global export capacity in 2025-2070 even in the absence of the U.S. LNG shock. This supply overcapacity aligns with industry analysts recently voicing corcerns about the heightened risk of LNG stranded assets (e.g. see https://www.reuters.com/markets/commodities/iea-says-unprecedented-supply-surge-could-lead-lng-glut-2025-2023-10-24/). In Appendix G I compare my baseline projections with a scenario where U.S. LNG export capacity stays constant at 2021 levels, a capacity shock of relatively the same magnitude than the one analyzed in this section. In this alternative counterfactual, I find similar results but in the opposite direction, with market effects that are twice as large in magnitude.

ysis, while decreasing international LNG gas prices by 2.5% on average. Due to the existence of gas-coal substitution in global power sectors, the shock also generates spillovers on coal prices.

How do electricity mixes react to this change in relative fossil fuel prices? Panel (b) of Figure G4 shows that in the U.S. the shock induces a decrease in gas generation that is equivalent to an average 3.5 percentage point reduction in the gas share of the electricity mix. Natural gas generation is almost exclusively replaced by renewable generation, with a very limited coal-to-gas substitution effect. Meanwhile, the rest of the world increases its reliance on gas-fired generation in response to the shock. Does higher gas generation mostly substitute for coal or for renewable energy sources in importing countries? Substitution patterns vary across time, with the shock inducing a larger short-run decline in coal generation, while mostly reducing the renewable share of the electricity mix in the long-run, by the time solar, wind and storage installation costs reach their minimum level.

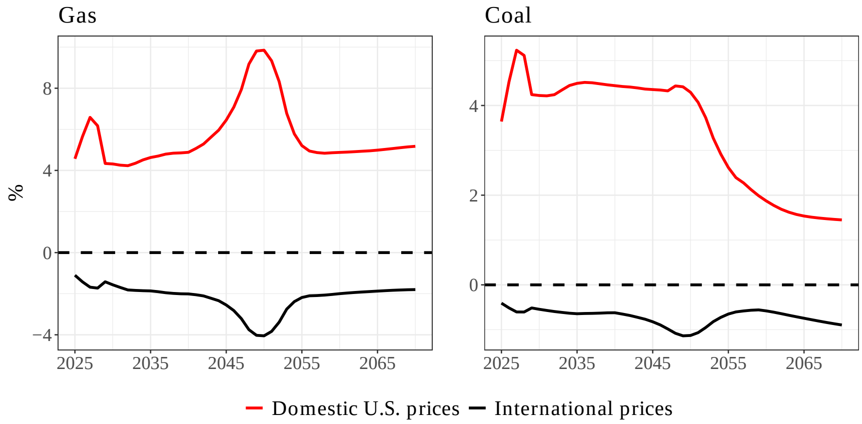
Effect on emissions The expansion of U.S. LNG capacity induces cumulative carbon emission reductions in the U.S. of 2240 million metric tonnes over 2025-2070, equivalent to a 6% reduction relative to baseline power sector emissions. Looking at the path of emission reductions over time, panel (c) of Figure 12 shows that U.S. emissions are always lower than in the baseline scenario, although the decarbonization effect tempers after 2055. Results are consistent with the fact that lower gas generation is mostly replaced by a higher adoption of renewables, with relative renewable growth rates under the LNG expansion being specially high before renewable installation costs reach their minimum level.

In the rest of the world, the effect of the shock on emissions reverses over time. In the short-term, emissions decrease relative to the baseline because gas mostly substitutes for coal in power generation. However, the change in emissions turns positive by 2035 and reaches a maximum around 2055. Long-term emission increases are consistent with lower international natural gas prices inducing lower renewable investment. The long-term emission increase offsets short-term reductions, and the cumulative effect on rest of the world emissions is an increase of 391.1 million metric tonnes of CO2, or 0.1% relative to the baseline.[35] This effect is small relative to U.S. emission reductions: globally, the shock induces a cumulative reduction in emissions of 1848 million metric tonnes, or 0.5% of baseline global power emissions.

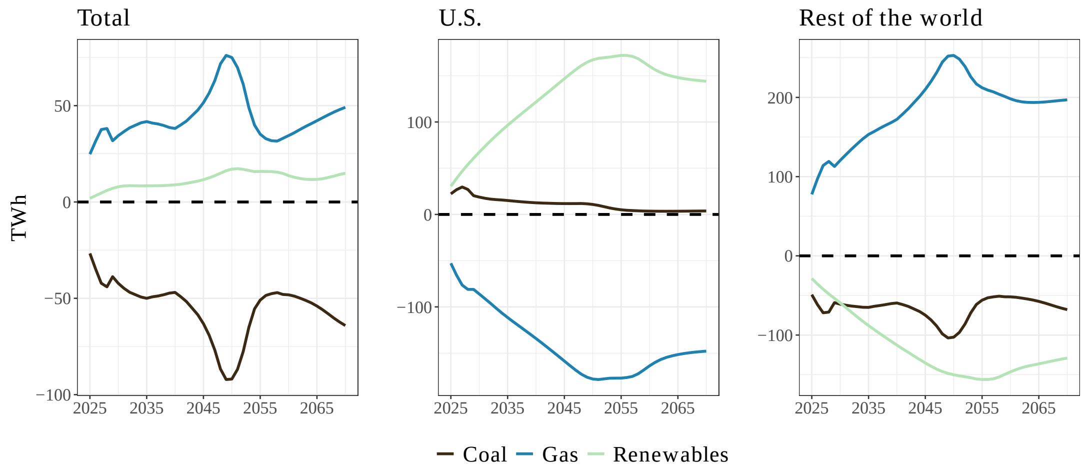
[35]The aggregate effect of the shock on LNG importers also hides important heterogeneities across countries. This heterogeneity is driven by the initial power capacity mix, the local availability of fossil and renewable resources, and also by the presence or absence of carbon pricing policies. Figure G5 in the Appendix shows how emissions change over time across the world.

Figure 12: Baseline counterfactual results: expansion of U.S. LNG export capacity

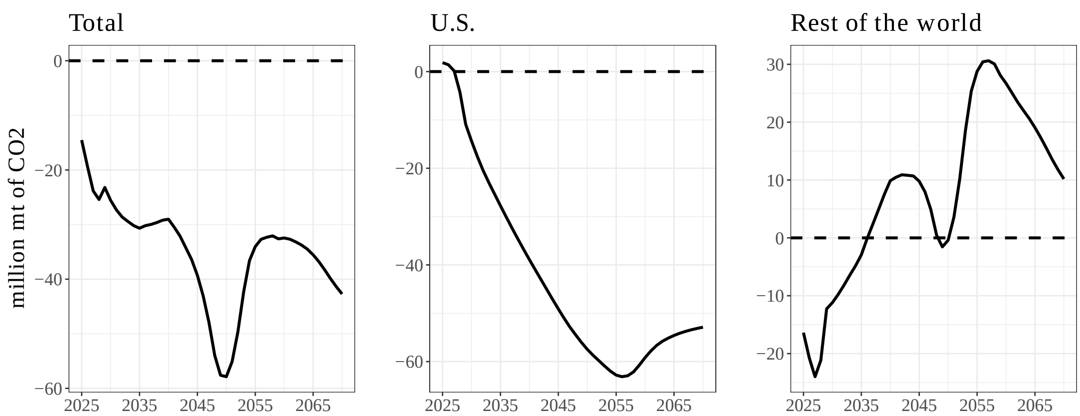
(a) Percentage change in fossil fuel prices



(b) Absolute change in generation by type



(c) Absolute change in annual emissions



Note: Panel (a) shows the evolution of annual price changes in the LNG expansion scenario relative to the baseline scenario for both U.S. and international fossil fuel prices. Panel (b)shows the absolute annual change in generation by fuel type and region relative to baseline. Renewables refers to solar and wind electricity production, with solar generation including both direct sales by generators and sales by storage facilities. Panel (c) shows the absolute change in annual emissions across regions relative to baseline.

I incorporate upstream and midstream CO2 and methane emissions to my analysis to provide a preliminary estimate of the life-cycle effect of the U.S. LNG export expansion. In addition to the CO2 generated through the combustion of fuels in power generation, fossil fuel production and transportation generate both carbon and methane emissions. As mentioned previously, discussion surrounding the potential environmental effect of U.S. LNG exports has placed a large focus on the potential for LNG trade to induce greater methane emissions. These additional emissions could offset the power sector decarbonization effect of the shock, especially if the methane leakage rate is high. To understand the extent to which this might be the case, I use existing estimates of the emission intensity of fossil fuel production, transportation and liquefaction from Howarth (2024), and apply them to the production and trade quantities I predict in the two alternative scenarios. I next use the U.S. Environmental Protection Agency's most recent estimates of the social cost of greenhouse gas emissions (EPA, 2023) to arrive to a monetary metric of the present value of the climate effect of the shock. Appendix E provides a detailed description of the methodology and assumptions used in this calculation.

Overall, I find that the U.S. LNG export shock generates cumulative social gains of over 75 billion dollars by 2050. Taking into account upstream and midstream emissions does not change the sign of the effect, but it does reduce the magnitude of the social gains by two-thirds. It is important to highlight, however, that there is considerable debate over the actual climate cost of methane emissions and the damage they generate relative to carbon emissions. Implicitly, the methodology I borrow from EPA (2023) values the social cost generated by a metric ton of methane to be 8-14 times the cost of a carbon metric ton, with variation over time. In columns 2 to 4 of Table 6 I show that different measures of methane carbon-equivalency imply very different emission changes from the shock. Under the worst-case assumption used in the literature (Howarth, 2024), in which a ton of methane generates over 80 times the climate damage of a ton of CO2, the expansion of U.S. LNG capacity actually induces an increase in carbon-equivalent emissions.

Table 6: Life-cycle effect of U.S. LNG expansion (2025-2070)

	Change in social cost	Change in CO2-equivalent emissions *Million mt*		
	2020 USDbn	GWP_{500}	GWP_{100}	GWP_{20}
Upstream				
Coal	-27.41	-132.65	-242.27	-535.15
Gas	72.28	366.64	584.55	1166.75
Midstream				
LNG trade	195.13	1078.93	1378.26	2177.98
Downstream				
Power	-309.44	-1848.4	-1848.4	-1848.4
Non-power	-5.69	-33.4	-33.4	-33.4
Total	-75.13	-568.88	-161.25	927.77

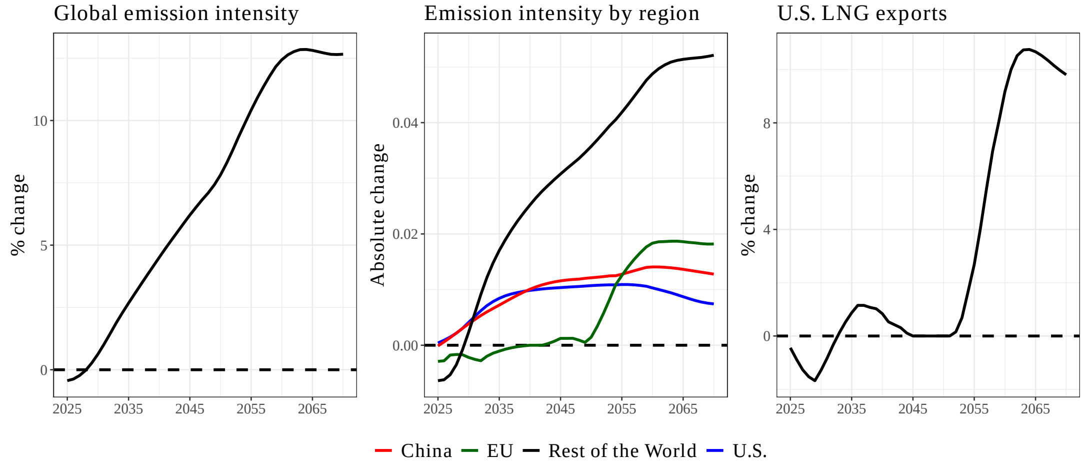
Notes: the change in the social cost of greenhouse gas emissions is calculated using the monetized emission damages provided by EPA (2023), with future emission damages brought to 2021 present values using a 2.5% discount rate. Columns 3 to 5 show the change in CO2-equivalent emissions under different global warming potentials (GWP) for methane according to the IPCC sixth assessment report (Intergovernmental Panel on Climate Change , IPCC).

8.2 The role of technological progress

In my baseline analysis, I assume that renewable installation costs decline over time according to current projections from industry analysts. However, the future evolution of renewable costs is highly uncertain, and projections have been consistently revised in the past. In this section, I explore how the effect of the U.S. LNG export shock changes when I assume a different trajectory for renewable installation costs.

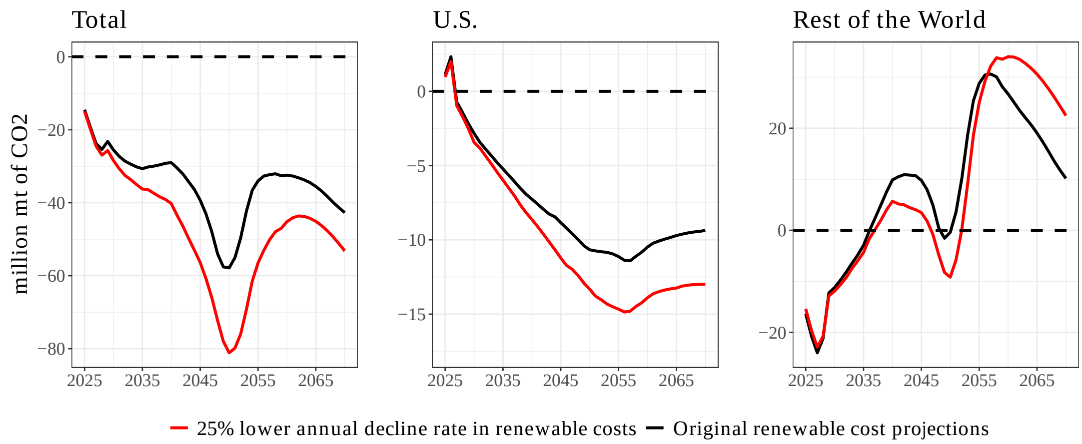
I consider a scenario in which renewable costs decrease at a 25% lower annual rate than in the baseline case in all countries. When comparing trajectories in the absence of the U.S. LNG shock, I find that higher future renewable installation costs increase future emission intensities everywhere: by 2070, the average global emission intensity is 12.5% higher than it would be under the original renewable cost projection. However, the increase in emission intensity is much less pronounced in markets that are already in a decarbonization path, such as the U.S., China or the EU.

Figure 13: Trajectories without LNG shock under higher renewable costs, relative to original projection



Note: Every plot shows the annual change in the variable of interest when comparing trajectories in the scenario with higher renewable costs relative to the original projection.

Figure 14: Emission changes under U.S. LNG export shock and higher renewable costs



Note: Each plot shows the annual change in aggregate emissions for a given region of interest relative to the baseline scenario of U.S. LNG export growth, both for the original renewable cost projections and the alternative case in which renewable costs decrease at a slower rate.

Since higher renewable installation costs reduces renewable entry more in the rest of the world than in the U.S., this alternative scenario features higher long-term baseline U.S. LNG exports, as shown in the rightmost panel of Figure 13. Because of this, the expansion of U.S. LNG export capacity has a larger effect in fossil markets: U.S. LNG exports now increase by 25% and U.S. gas prices grow by 6.5% (vs. increases of 20% and 5.4% under the original cost projections). When looking at global emission changes, I find that under higher renewable costs the long-term emission increase in the rest of the world due to the U.S. LNG shock is more pronounced. However, this is not enough to offset the higher emission reductions that are achieved domestically. In fact, assuming a slower rate of technological progress increases annual aggregate emission reductions from the U.S. LNG shock by an average 32%.

My model does not consider endogenous technological progress, and thus does not capture the possibility that the expansion of LNG exports might affect the rate of decline of renewable installation costs. However, note that both in the original version of my counterfactual and under the alternative scenario described above, global renewable installations increase on aggregate every year in response to the shock. In a model of technological progress with learning-by-doing and global technological diffusion, this increase in global renewable adoption would generate endogenously lower installation costs in the future, mitigating the long-term emission gains that the shock generates in importing countries.

8.3 Interaction with domestic carbon policies

The domestic price of fossil fuels is affected both by market forces and by domestic policy interventions. One form of intervention that has already been implemented or is under discussion in many countries are carbon cap-and-trade schemes. These schemes set a cap on the total amount of emissions that can be generated in given year, and allow firms to buy and sell permits to emit. The price of these permits is determined by the market, and is an important determinant of the cost of production for power generators of different types.[36] Can better decarbonization outcomes be achieved if U.S. LNG exports are combined with binding domestic carbon caps? Table 7 evaluates the cumulative social cost savings achieved under alternative policy combinations, relative to the baseline scenario where only U.S. export capacity currently under construction is ever built.

First, I ask whether emission social cost reductions would be higher if the U.S. implemented a carbon cap to achieve the same power-related emission reductions than under the LNG expansion, but without actually expanding its export capacity (Scenario 1 in Table 7). I find that, indeed, if the U.S. were able to implement this power sector carbon cap, total social cost reductions would be almost 5 times larger than those achieved through the expansion of LNG export capacity (Scenario 2 in Table 7). This is due to two main reasons. First, although the LNG expansion generates short-term emission reductions in the rest of the world, the present monetized value of this emission reduction is lower than the present cost of long-term emission increases. Second, LNG exports also generate additional midstream methane emissions that contribute to reducing social cost savings.

If implementing a carbon cap is not feasible in the U.S., would it be possible to mitigate long-term emission increases from the export shock if climate-concerned importers implemented their own carbon caps? In Scenario 3 of Table 7, I consider a case in which U.S. expands its LNG export capacity and the EU, UK and Japan impose a binding power sector carbon cap in response to avoid cheaper natural gas from re-

[36]In my baseline analysis I assume that the only markets that have a cap-and-trade scheme in place at any point in the future are the EU and the UK, and feed the existing schedule for the evolution of carbon allowances as a constraint in my model simulation. The allowance limit that I set based on projections is not always binding in these markets.

ducing renewable adoption.[37] I find that under this combination of policies, global social cost savings are 62% larger than under Scenario 2. The imposition of carbon caps in these importing countries both reduces long-term CO2 emission increases from global power generation and mitigates methane emission increases from the shock, by slightly reducing equilibrium LNG exports.

Table 7: Change in social greenhouse costs under alternative policy combinations

Scenario	Change in GHG social cost *Billion USD (2021 values)*	
	Power only	Total
(1) Baseline LNG capacity + U.S. CO2 cap	-352.26	-367.04
(2) Higher LNG capacity + no CO2 cap	- 309.44	-75.13
(3) Higher LNG capacity + allies CO2 cap	-349.65	-122.34

Notes: Greenhouse gas (GHG) social cost calculated using the methodology detailed in EPA (2023). See subsection text for details on each of the scenarios.

8.4 Policy reversal and carbon lock-in

In my baseline results, U.S. LNG exports increase emissions in the rest of the world after 2050, mitigating aggregate decarbonization gains from the policy. Could the U.S. avoid long-term emission increases in the rest of the world if it reverts its LNG export capacity back to baseline levels after that year?

In this section, I consider what would happen under a LNG capacity reversal in 2050. To focus just on the effect in the rest of the world, I assume that the U.S. can implement a carbon cap after that year to achieve the same emission gains than under the permanent LNG capacity expansion. I consider two possible scenarios of policy reversal. First, I assume that the U.S. can fully commit to a policy of reverting back LNG capacity by 2050, so that agents perfectly foresee the shock and adjust their strategies accordingly. Next I compare this scenario with one in which full commitment is not possible. Agents believe that U.S. LNG export capacity will be permanently higher until the capacity reversal shock hits in 2050, and they adjust their expectations only after this happens.

Results are presented in Figure 15. As panel (c) shows, the policy is ineffective in reverting long-term emissions in the rest of the world (in both the full-commitment and no-commitment cases) and actually induces higher emissions in some periods.

[37] In my baseline analysis I also assume that the EU and UK implement carbon cap-and-trade schemes, but carbon allowance levels in these markets remain constant after 2050, the last year for which I have data on allowance projections. In this exercise, I set carbon allowance levels that constrain annual power sector emissions to be at most those produced under the absence of the LNG export shock. This carbon cap effectively inhibits any future emission gains from the shock in these markets.

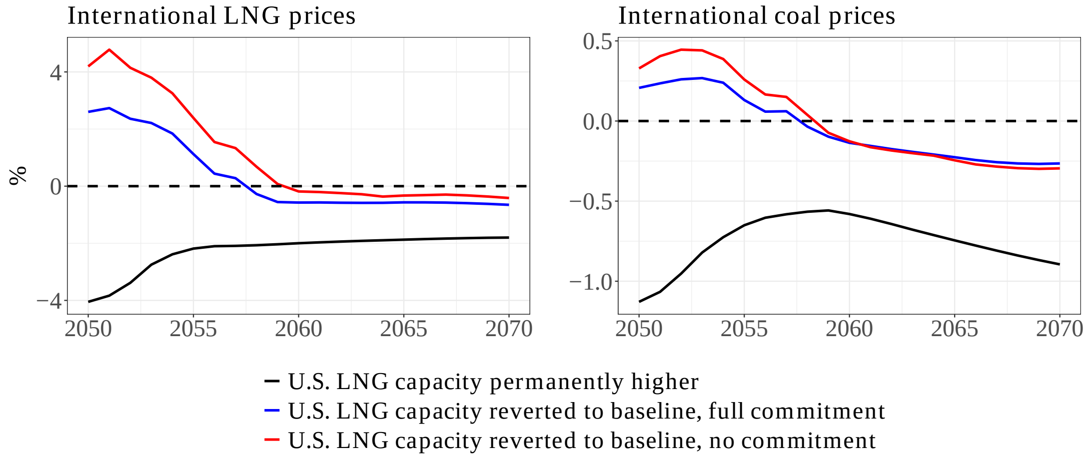
This finding highlights the risk of carbon lock-in in settings with sunk investments and long-lived assets. The expansion of U.S. LNG export capacity generates a long-term increase in gas generation capacity in the rest of the world, which is not easily reversible. Because gas generation capacity is higher by the time U.S. goes back to its baseline LNG export infrastructure, gas generation remains permanently higher in the future. The permanent increase in gas generation is even more pronounced if agents do not consider the future LNG reversal when making their investment decision before 2050.

How can the policy reversal induce even higher emissions than in the permanent expansion scenario? As discussed, when U.S. export capacity goes back to its baseline levels in 2050 it still faces a permanently higher gas demand from the rest of the world. This higher international gas demand is now combined with a lower LNG gas supply after 2050, which induces a sizable increase in LNG prices in the first years after 2050.[38] Because LNG prices increase, coal generators in LNG importing countries can now compete with gas generators in more favorable terms, which induces an increase in emissions from coal.

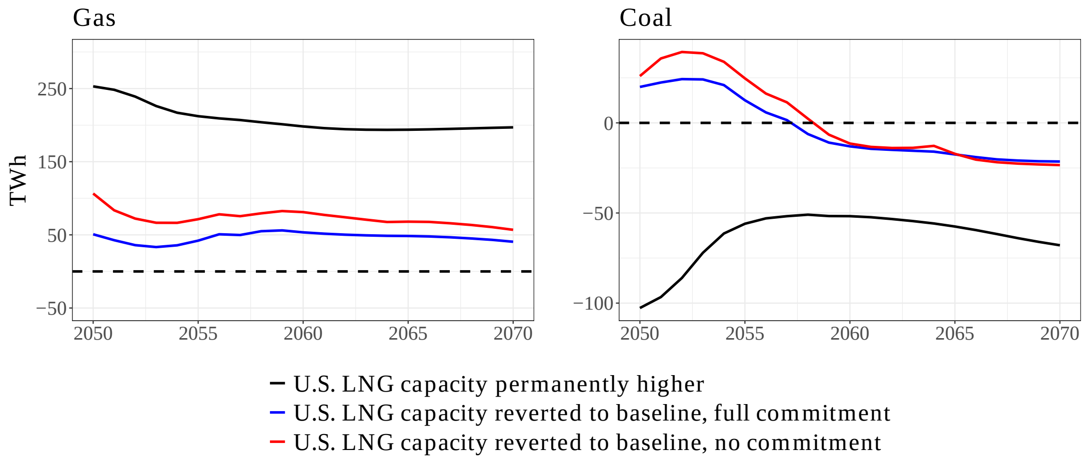
[38]The price increase vanishes in the long-term because by 2060 there is slack in U.S. baseline LNG capacity, which means that the additional global gas demand can be absorbed easily.

Figure 15: Effect of U.S. LNG expansion reversal in 2050

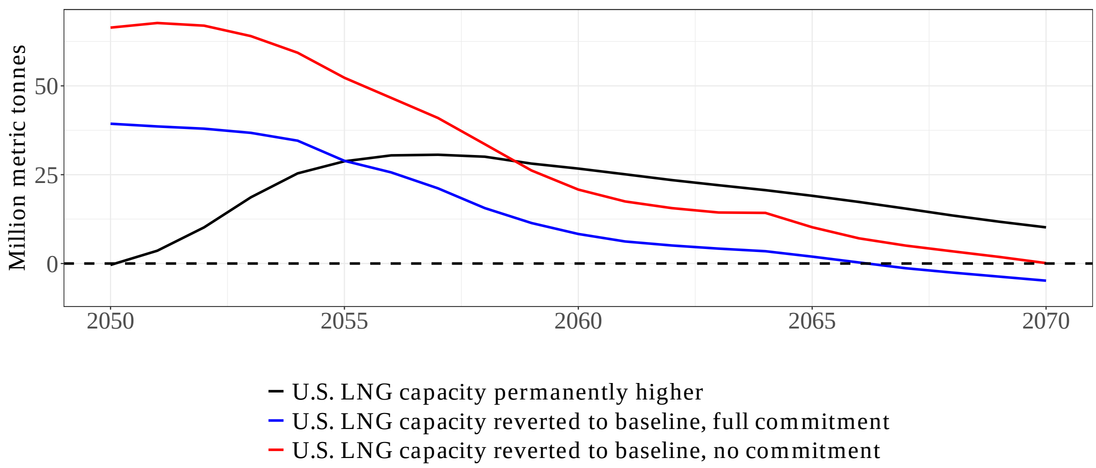
(a) Percentage change in fossil fuel prices relative to baseline



(b) Absolute change in generation by type relative to baseline



(c) Absolute change in annual emissions relative to baseline



Note: Every panel shows the evolution of a variable of interest in alternative scenarios relative to the baseline case in which only U.S. LNG export capacity currently under construction is ever built. "U.S. LNG capacity permanently higher" refers to the main counterfactual described in Subsection 8.1. "U.S. LNG capacity reverted to baseline, full commitment" refers to the case in which U.S. credibly announces it will revert export capacity back to baseline in 2050 at the start of the simulation period. "U.S. LNG capacity reverted to baseline, no commitment" is the case in which the reversal to baseline capacity in 2050 is not anticipated by market players.

9 Conclusion

Public and academic discussion on potential approaches to incentivize power decarbonization often focuses on domestic-oriented policies, such as the provision of subsidies to renewable generation or the imposition of carbon taxes. Furthermore, analyses of the effects of these policies seldomly take into account international spillovers. This paper develops a framework to study the determinants of power sector investment and decarbonization in a global context. It focuses on one particular driver of international policy spillovers: the globalized nature of fossil fuel markets.

Analyzing the potential effects of an expansion of U.S. LNG export capacity, I draw two main lessons. First, domestic regulation of fossil fuel trade infrastructure can have substantial effects on worldwide fossil fuel prices and, through them, on international power sector investment decisions. Second, this might generate a trade-off between local and global emission reductions. In my setting, the overall decarbonization effect of the U.S. LNG export shock is mitigated by long-term emission increases in importing countries. I find that this downside can be reduced by combining the U.S. LNG export increase with carbon caps in major importing countries, highlighting the importance of international climate policy coordination to achieve global emission reductions. A reversal of the LNG infrastructure expansion, on the contrary, is not successful at reducing long-term emission increases in foreign countries. The persistence of the shock under a policy reversal suggests that taking into account the long-term nature of infrastructure investments is critical to the design of succesful decarbonization policies.

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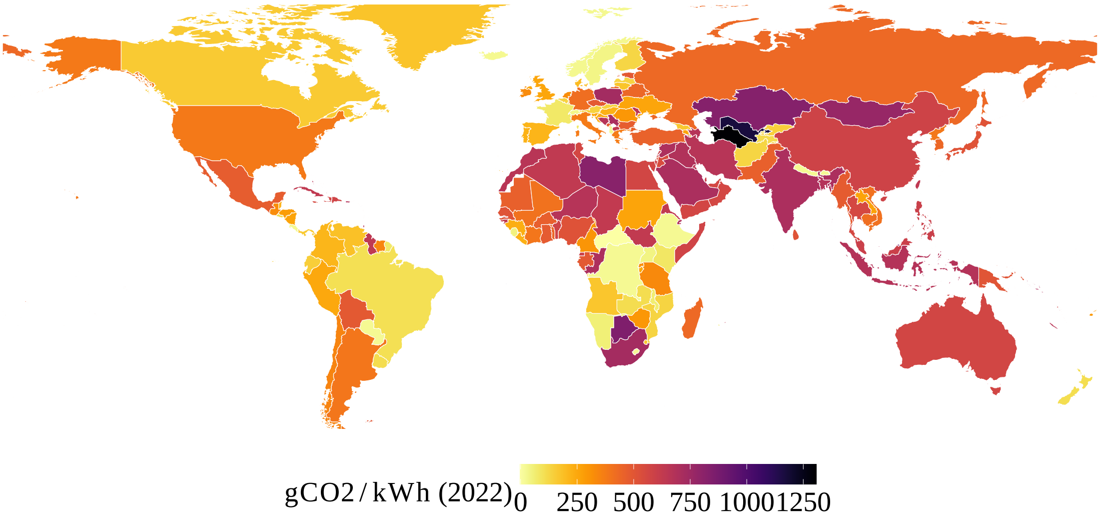
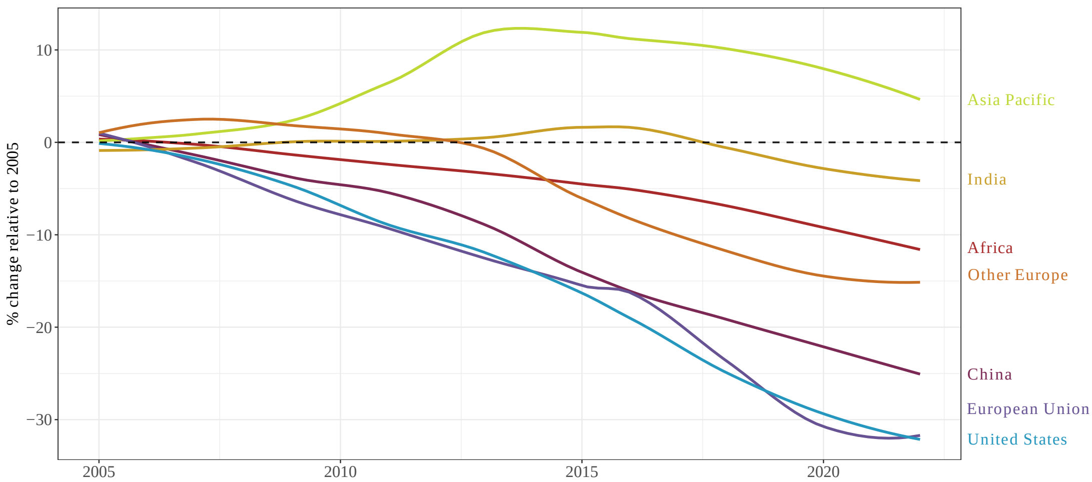
A Additional descriptive figures and tables

Figure A1: Carbon intensity of electricity production by country



Source: Ember.

Figure A2: Change in power sector emission intensity relative to 2005



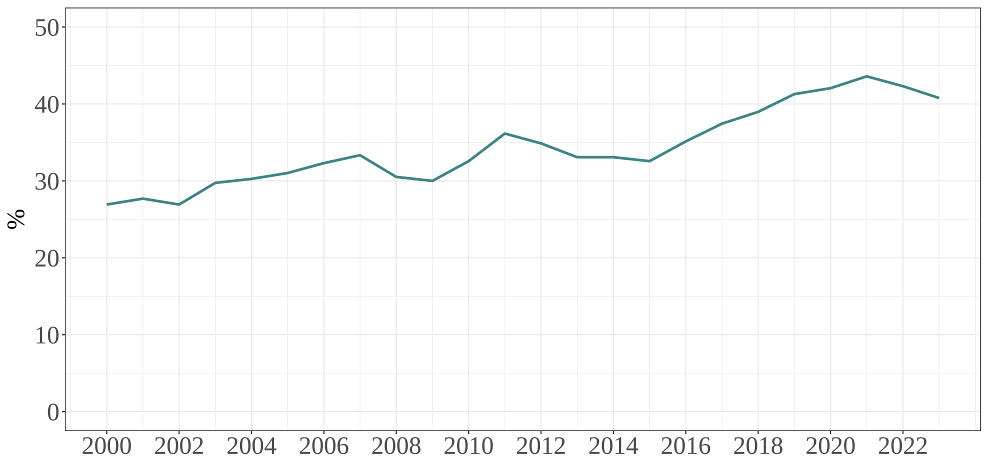
Source: Ember.

Table A1: Fuel share of electricity generation and local fuel prices

	log(Fuel share of elec.generation)			
	Gas		Coal	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
log(Gas price)	-0.568***	-2.44***	-0.0002	2.87*
	(0.113)	(0.507)	(0.120)	(1.57)
log(Coal price)	1.02***	3.62***	-0.397**	-3.36*
	(0.168)	(0.665)	(0.182)	(1.94)
log(GDP, 2015 prices and PPP)	-0.330***	0.028	0.544***	0.043
	(0.063)	(0.110)	(0.064)	(0.250)
Observations	259	252	257	250
Adjusted R^2	0.343	-0.177	0.495	-0.053
F-test (1st stage), log(Gas price)		104.0		86.6
F-test (1st stage), log(Coal price)		84.9		94.3
Region fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓

Notes: Standard errors in parentheses. Estimation draws on annual data from 51 countries for 2000-2023. IV columns instrument fossil fuel prices with local reserves. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Figure A3: Evolution of global LNG import capacity utilization



Source: International Gas Union (2024).

B Model extensions

B.1 Intermittency and storage

In the model outlined above, renewable generators can produce electricity at all times. This assumption rules out one of the main challenges to increasing the penetration of renewable power in electricity grids: intermittency. Because solar generators are unable to produce electricity during parts of the day, in the absence of electricity storage fossil-based generators have an incentive to remain in the market to fill this gap. The extension outlined below incorporates intermittency for solar generators, and adds endogenous entry of storage facilities.[39]

Static game I assume that every period in my model contains two sub-periods t_i: day (t_{day}) and night (t_{night}). Each sub-period has a different inelastic demand level, D_{t_i}. Gas, coal and wind generators have the same production function during both sub-periods, but solar generators are constrained to produce only during the day, i.e. the effective capacity of a solar generator is given by

$$\tilde{k}_{\omega(s)t_i} = \begin{cases} \varphi_f k_{\omega(f)t_i} & \text{if} \quad t_i = t_{day} \\ 0 & \text{if} \quad t_i = t_{night} \end{cases} \tag{A1}$$

There is a fifth type of agent that can be active in the market: storage facilities (b). If active, storage facilities can purchase electricity from solar generators during the day, store it and sell it during the night. I assume that storage facilities pay solar generators the price at which they are indifferent between selling electricity to them or selling it in the regular market, i.e. the day electricity price.

The aggregate supply function of storage facilities active during t is given by

$$Q_{bt_i}(p^{elec}_{t_{day}}, p^{elec}_{t_{night}}) = \begin{cases} 0 & \text{if} \quad t_i = t_{day} \\ \beta_b \min(K_{bt}, \varphi_s K_{st}) & \text{if} \quad t_i = t_{night} \quad \text{and} \quad p^{elec}_{t_{day}} \leq p^{elec}_{t_{night}} \end{cases} \tag{A2}$$

where $\beta_b \in [0, 1]$ is a parameter representing energy losses in storage. Note that storage facilities will only supply electricity during the night if they can purchase their input (solar power) at a price lower or equal to their selling price. Note also that storage supply is constrained by both the capacity of storage facilities and solar generators.

Given these assumptions, electricity market clearing in period t requires both of the following conditions to hold:

$$D_{t_{day}} = \varphi_s K_{st} - \frac{1}{\beta_b} Q_{bt_{night}}(p^{elec}_{t_{day}}, p^{elec}_{t_{night}}) + \varphi_w K_{wt} + \sum_{f \in \{c,g\}} \tilde{q}_{ft}(p^{elec}_{t_{day}}, p_{ft}, \epsilon_{ft}) K_{ft} \tag{A3}$$

$$D_{t_{night}} = Q_{bt_{night}}(p^{elec}_{t_{day}}, p^{elec}_{t_{night}}) + \varphi_w K_{wt} + \sum_{f \in \{c,g\}} \tilde{q}_{ft}(p^{elec}_{t_{night}}, p_{ft}, \epsilon_{ft}) K_{ft} \tag{A4}$$

[39] A similar stylized approach to intermittency and storage is used within a macro climate framework in Gentile (2024). Gowrisankaran, Reynolds and Samano (2016) and Elliott (2022) explicitly model the stochastic nature of renewable power generation, while Butters, Dorsey and Gowrisankaran (2021) studies battery storage adoption in an equilibrium industry model with dynamic supply choice.

Both day and night markets clear jointly, since storage demand for solar power reduces the supply of solar power during the day.

Dynamic strategies of storage facilities I assume that storage facilities that enter a market have a fixed operating lifetime $\overline{T}_b$ and fixed maintenance costs $\overline{F}_b$. The entry of storage facilities is decided in exactly the same way as all generator types. $\overline{N}_b$ potential entrants will observe time-varing storage entry costs κ_{bt} and a random entry shock, and decide whether to enter the market given their expected profits.

B.2 Cap-and-trade emission trading scheme

My sample of markets includes the European Union and the UK, both of which have implemented cap-and-trade emission trading schemes. If the limit of CO2 allowances in these markets is binding, a shock to the price of gas will not affect their aggregate level of CO2 emissions but will impact the relative demand for natural gas and coal, with potential implications for global fossil fuel prices. In order to properly account for this feature, I now extend my model to incorporate a cap-and-trade emission trading scheme.

Under a cap-and-trade scheme, the emission intensity of generators becomes a relevant factor in their production decisions. I modify the profit function in (1) as follows:

$$\max_{q_{\omega(f)jt}} \pi_{\omega(f)jt} = p_{jt}^{elec} q_{\omega(f)jt} - \Big(\beta_{1f}\gamma_{1fjt}p_{fjt} + \beta_{2f}\frac{q_{\omega(f)jt}}{k_{\omega(f)jt}} + p_{CO2jt}e_{fjt} + \chi_{ft} + \epsilon_{fjt}\Big) q_{\omega(f)jt}$$
$$\forall \omega \in \Omega_{fjt}, \forall f \in \{c, g\} \qquad \text{(A5)}$$

where e_{fjt} is the emission intensity of a generator of type f at time t and market j, and p_{CO2jt} is the price of CO2 allowances. The optimal production choice of fossil fuel generators will now imply an equilibrium demand for CO2 allowances, given by

$$D_{jt}^{CO2}(p_{jt}^{elec}, p_{fjt}, p_{C02jt}) = \Big(\sum_{f\in\{c,g\}} e_{fjt}\tilde{q}_{fjt}(p_{jt}^{elec}, p_{fjt}, p_{CO2jt})K_{fjt}\Big) + \overline{D}_{jt}^{C02} \qquad \text{(A6)}$$

where, as before, $\tilde{q}_{fjt}$ is the optimal capacity use of generators of type f at time t. Assuming all generators of the same type have the same emission intensity, this optimal capacity use is again homogeneous within a given generator type. $\overline{D}_{jt}^{CO2}$ is the demand for CO2 allowances from other sectors of the economy, which I assume to be exogenous.

The supply of CO2 allowances is set by the government, time-varying, and exogenous in my model. Given an aggregate CO2 allowance supply $\overline{Q}_{jt}^{CO2}$, the price of CO2 allowances is determined by the intersection of the aggregate demand for CO2 allowances and the supply of CO2 allowances. Equilibrium in a market with a cap-and-trade emission trading scheme will thus require that fossil fuel demand equals fossil fuel supply (for both gas and coal), and that the CO2 market clears, i.e.

$$D_{jt}^{CO2}(p_{jt}^{elec}, p_{fjt}, p_{C02jt}) = \overline{Q}_{jt}^{CO2} \qquad \text{(A7)}$$

C Model computation: algorithm description

In this section, I outline the algorithm I use to find the equilibrium in my model. The algorithm solves a nested problem. In the inner nest, it looks for the path of equilibrium domestic fossil fuel prices as a function of international fossil fuel prices. In the outer nest, it iterates over guesses for international fossil fuel prices until trade balance is satisfied every period.

I denote by $\mathbf{p}_g^{n*} = \{p_{gT_0}, p_{gT_0+1}, ..., p_{g\bar{T}}\}$ and $\mathbf{p}_c^{n*} = \{p_{cT_0}, p_{cT_0+1}, ..., p_{c\bar{T}}\}$ the guess n of the vector that contains the path of each international fossil fuel price.

Algorithm 1 Global equilibrium

Input: Number of periods T, initial vector of global fossil fuel prices $\mathbf{p}_g^*$ and $\mathbf{p}_c^*$, country set $\mathcal{J}$, convergence tolerance ϵ
Initialize convergence flag $err\_global = 1$
while $err\_global > 0$ **do**
  for each country $j \in \mathcal{J}$ **do**
    Initialize country convergence flag $err\_j = 1$ and electricity convergence flag $err\_elec\_j = 1$
    while $err\_j > 0$ **do**
      Guess vector of domestic fossil fuel prices $\mathbf{p}_g$ and $\mathbf{p}_c$
      Solve for fossil fuel supply and non-electricity fossil fuel demand
      Solve for electricity fossil fuel demand:
      while $err\_elec\_j > 0$ **do**
        Guess entry/exit strategies
        Compute state in each period given these strategies
        Compute electricity prices and profits given each state
        Compute value functions
        Update entry/exit strategies given value functions
        Check dynamic problem convergence: Determine if changes in entry and exit strategies are within tolerance ϵ
        if all changes $\leq \epsilon$ **then**
          $err\_elec\_j = 0$
        end if
      end while
      Check market clearing condition: Ensure there is no excess supply in domestic fuel markets
      if $D_{fjt} - S_{fjt} \geq \epsilon \; \forall t \in T, f \in \{c, g\}$ **then**
        $err\_j = 1$
      else
        Update vectors of domestic fossil fuel prices $\mathbf{p}_g$ and $\mathbf{p}_c$
      end if
    end while
  end for
  Compute trade deficit each period given $\mathbf{p}_g^{n*}$ and $\mathbf{p}_c^{n*}$ as the difference between total imports and total exports
  if $\sum_{j \in \mathcal{J}} M_{fj} - \sum_{j \in \mathcal{J}} X_{fj} \leq \epsilon \quad \forall f \in \{c, g\}$ **then**
    $err\_global = 0$
  end if
end while

D Data Appendix

D.1 Projections

In this section I provide detail on my approach to generate projections for the exogenous variables in my model up to 2050.

Electricity technologies Projections for generator installation costs by type (solar, wind, natural gas and coal) come from IEA I use the following projections to extend my time series I project electricity installation costs per market leveraging projections from International Energy Agency (2024*c*). I calculate an average implied compound annual growth rate (CAGR) based on IEA's projections and apply it to each market in my sample. For storage technologies, I rely on projections from the National Renewable Energy Laboratory (NREL, 2024). Their report contains projections for the U.S. for both installation costs and fixed operation and maintenance costs, up to 2050. To account for potential cross-country heterogeneity, I assume that the relative installation cost of storage in each market with respect to the U.S. is the same as the relative installation cost of solar generators.[40] Utility-scale batteries are installed alongside existing or new solar generating facilities. Motivated by this fact, I assume a per-country installation cost shifter s_b equal to the one I compute for solar generators.

LNG export capacity For countries excluding the U.S., I leverage data from the Global Energy Monitor (GEM) Infrastructure Tracker to obtain information on under-construction and proposed LNG terminals. GEM Infrastructure Tracker contains data on under-construction and proposed LNG export capacity by country and the expected completion year of each project. In my baseline exercise, I assume that only projects that have already reached Final Investment Decision (FID) will be completed.[41] In robustness checks, I also consider a scenario where all proposed projects that have not yet reached FID will also be built.

Electricity demand I build projections for the electricity demand faced by generators in my model using the most recent EIA outlooks for the U.S. and international markets (EIA, 2023*a*,*b*). For the U.S., EIA provides forecasts for annual electricity generation by fuel at the national level up to 2050. I substract all generation types that are taken as exogenous supply in my model from the annual expected electricity generation to arrive at a measure of projected residual demand. I use the same annual growth rates for my three markets in the U.S.. For markets excluding the U.S., EIA provides generation by type forecasts at 5-year intervals, up to 2050. I construct the implied CAGR from these projections and harmonize EIA's market classifications with mine.[42]

Fossil fuel supply and non-electricity demand intercepts I project the intercepts of the fossil fuel supply functions and the non-electricity gas demand function under the

[40]Surveys of utility-scale storage installation costs in different countries support this assumption, showing lower costs for storage in the European Union and China relative to the U.S. (IRENA, 2024).

[41]I exclude currently under construction Russian LNG export capacity, as economic sanctions have halted their development. See https://www.gem.wiki/Ust_Luga_LNG_Terminal and https://www.gem.wiki/Arctic_LNG_2_Terminal for details.

[42]EIA provides country-specific projections for China, India, Japan, South Korea, Mexico, Canada and Russia, which I take directly from this source. For other markets, I match my market definitions with EIA's, which is in general more aggregate (e.g. EIA has a single forecast for all Western Europe, which I apply both to the European Union and UK.)

assumption that expected supply and demand growth rates are a good proxy for the growth rate of non-price supply and demand determinants. To that end, I use EIA outlooks for the U.S. and international markets and follow the same annualization and harmonization procedure as for electricity demand.

Other exogenous variables Finally, I assume that trade costs, liquefaction costs, pipeline gas capacity, and coal export capacity remain constant at 2022 levels. I also assume no technological progress in the efficiency of fossil fuel generators or the capacity factor of wind and solar generators.

E Life-cycle emissions calculations

In this section, I provide details on the procedure and sources used to calculate life-cycle emissions per country and fuel type under counterfactual scenarios.

E.1 Natural gas

I calculate life-cycle greenhouse emissions as the sum of the following components:

$$E^{gas}_{\ell jt} = E^{up,mid}_{\ell jt} + E^{elec}_{\ell jt} + E^{other}_{\ell jt} + E^{LNG}_{\ell jt} \tag{A8}$$

where ℓ denotes a greenhouse gas, either methane (CH_4) or carbon dioxide (CO_2), j is a country, and t a year.

$E^{up,mid}_{\ell jt}$ are upstream and midstream emissions. I obtain CO_2 and CH_4 upstream and midstream emission factors (in grams of greenhouse gas per megajoule) from Howarth (2024). I multiply these factors by the amount of natural gas produced in each country and year to obtain aggregate emissions. Howarth (2024) focuses its analysis in the U.S., but upstream and midstream emissions are known to vary across the world due to the use of different abatement technologies. I adjust methane emission factors for countries other than the U.S. using estimates from International Energy Agency (2024*a*), which provides country-specific scaling factors for upstream methane natural gas emissions for the world's top producers. Given that these scaling factors only apply to methane, I assume that all countries have the same upstream and midstream CO_2 intensity.[43]

$E^{elec}_{\ell jt}$ are emissions from fuel combustion in electricity generation. I derive implicit CO_2 emission factors from EIA's 2023 International Energy Outlook. For the year 2022, EIA reports both electricity generation and power emissions by fuel for major countries and regions. Using this data, I calculate the CO_2 emission intensity of natural gas electricity generation per EIA country/region, and apply it to my sample. Following Howarth (2024), I assume no CH_4 emissions from downstream natural gas combustion.

$E^{other}_{\ell jt}$ are downstream emissions generated from activities excluding power generation. I follow a similar procedure than above, an obtain implicit CO_2 emission factors from 2022 data on aggregate emissions and total fuel consumption provided in EIA's 2023 International Energy Outlook. I substract power sector fuel consumption and emissions from the aggregate data to arrive to a non-power emission intensity.[44] As above, I assume no CH_4 emissions from non-electricity downstream fuel combustion.

Lastly, $E^{LNG}_{\ell jt}$ are emissions related to the liquefaction and transportation of natural gas. I assign all LNG emissions to the producer, using Howarth (2024) CO_2 and CH_4 LNG emission intensity estimates.

[43]For countries in my sample not included in International Energy Agency (2024*a*), I use the median IEA scaling factor for countries in the same region.

[44]Note that EIA uses the same non-power emission intensity per unit for all countries/regions excluding the U.S..

E.2 Coal

For coal, I calculate life-cycle emissions as follows:

$$E_{\ell jt}^{coal} = E_{\ell jt}^{up,mid} + E_{\ell jt}^{elec} \tag{A9}$$

Unlike in the case of natural gas, I do not have estimates for the emission intensity of thermal coal international trade or non-electricity uses.[45] For upstream and midstream emissions, I use estimates from Howarth (2024), which do not distinguish across countries. For electricity emissions, I follow the same procedure as for natural gas, using EIA data.

[45] Almost the entirety of thermal coal is used for electricity generation, and I hold non-electricity demand constant in my model across scenarios.

F Estimation appendix

F.1 Electricity supply estimation: coal and gas generators

The procedure detailed in sub-section 6.1 allows me to recover the two main parameters of interest in the supply function of coal and gas generators: β_{1f}, which captures the relationship between fuel prices and generator costs, and β_{2f}, the slope of the generator supply curve. The estimation sample I use differs to the sample used in full model simulations, both in terms of the time aggregation (monthly vs. annual) and in terms of the markets and years included. While I use the same estimates for β_{1f} and β_{2f} for my whole simulation sample, I calibrate market-specific cost shifters χ_{fjt} to better match the observed relationship between capacity use and fossil fuel prices in the data. This section details my calibration approach.

I first use the fact that, from the profit function in (1), the optimal interior solution to a generator's production problem in market j and time t is given by

$$\frac{q_{fjt}}{K_{fjt}} = \frac{p^{elec}_{jt} - \beta_{1f}\tilde{p}_{fjt} - \chi_{fjt} - \epsilon_{fjt}}{2\beta_{2f}} \qquad \forall \quad f \in \{c, g\} \tag{A10}$$

where I assume that ϵ_{fjt} are mean-zero errors that are uncorrelated across fuel types and time.

Consider a market where both coal and gas generators are active. Equation (A10) can be transformed to obtain an expression for the equilibrium electricity price as a function of the capacity use of gas generators:

$$p^{elec}_{jt} = 2\beta_{2g}\frac{q_{fjt}}{K_{fjt}} + \beta_{1g}\tilde{p}_{gjt} + \chi_{gjt} + \epsilon_{gjt} \tag{A11}$$

Subtituting this expression in the optimal capacity use choice of coal generators yields:

$$\frac{q_{cjt}}{K_{cjt}} = \frac{2\beta_{2g}\frac{q_{fjt}}{K_{fjt}} + \beta_{1g}\tilde{p}_{gjt} + \chi_{gjt} + \epsilon_{gjt} - \beta_{1c}\tilde{p}_{cjt} - \chi_{cjt} - \epsilon_{cjt}}{2\beta_{2c}} \tag{A12}$$

Which can be re-arranged to get

$$\chi_{cjt} - \chi_{gjt} = 2\beta_{2g}\frac{q_{gjt}}{K_{gjt}} - 2\beta_{2c}\frac{q_{cjt}}{K_{cjt}} + \beta_{1g}\tilde{p}_{gjt} - \beta_{1c}\tilde{p}_{cjt} + \epsilon_{cjt} - \epsilon_{gjt} \tag{A13}$$

and taking expectations over shocks ϵ_{fjt}

$$\mathbb{E}(\chi_{cjt}) - \mathbb{E}(\chi_{gjt}) = \mathbb{E}\Big(2\beta_{2g}\frac{q_{gjt}}{K_{gjt}} - 2\beta_{2c}\frac{q_{cjt}}{K_{cjt}} + \beta_{1g}\tilde{p}_{gjt} - \beta_{1c}\tilde{p}_{cjt}\Big) \tag{A14}$$

Equation (A14) identifies the difference between coal and gas unobserved shifters as a function of relative capacity uses and the relative price of the inputs used by both generator types. Coal and gas shifters cannot be identified separately without information on market electricity prices. I first normalize $\chi_{gjt} = \bar{\hat{\chi}}_{gt}$, where $\bar{\hat{\chi}}_{gt}$ is the median annual $\hat{\chi}_{gjt}$ recovered from my estimation in 6.1. Given χ_{gjt}, I recover χ_{cjt} using equation (A14) and my estimates for $\hat{\beta}_{1fc}$ and $\hat{\beta}_{2fc}$, together with data on annual capacity use by fuel and efficiency-adjusted fossil fuel prices.[46]

F.2 Firm exit estimating equation

Under the assumption that maintenace cost shocks are logit distributed, the probability that a generator of type f and age a in period t decides to remain in the market for an additional period is given by

$$1 - \zeta_{aft} = \frac{\exp\left(\frac{\beta \mathbb{E}[V_{a+1f}(S_{t+1})|S_t] - F_{af}}{\sigma_f^{exit}}\right)}{1 + \exp\left(\frac{\beta \mathbb{E}[V_{a+1f}(S_{t+1})|S_t] - F_{af}}{\sigma_f^{exit}}\right)} \tag{A15}$$

From this expression, solving for the expected value of staying in the market yields:

$$\sigma_f^{exit} \underbrace{\Big(\log(1-\zeta_{aft}) - \log(\zeta_{aft})\Big)}_{\tilde{\zeta}_{aft}} + F_{af} = \beta \mathbb{E}[V_{a+1f}(S_{t+1})|S_t] \tag{A16}$$

From equation (4) and under the logit shock assumption, the expected value of remaining as an incumbent in t+1, $\mathbb{E}[V_{a+1f}(S_{t+1})|S_t]$, has the following form:

$$\begin{aligned}\mathbb{E}[V_{a+1f}(S_{t+1})|S_t] =& \pi_{ft+1} + \\ & \sigma_f^{exit}\left\{ \log\left[exp\left(\frac{\beta \mathbb{E}[V_{a+2ft}(S_{t+2})|S_{t+1}] - F_{a+1f}}{\sigma_f^{exit}}\right) + 1\right] + \gamma \right\}\end{aligned} \tag{A17}$$

where γ is the Euler constant and the second term represents the inclusive value of drawing a maintenance cost shock. Plugging (A16) in (A17) yields

$$\frac{1}{\beta}\left(\sigma_f^{exit}\tilde{\zeta}_{aft} + F_{af}\right) = \pi_{ft+1} + \sigma_f^{exit}\left\{log\left[\exp \tilde{\zeta}_{a+1ft+1} + 1\right] + \gamma\right\} \tag{A18}$$

After re-ordering terms, (A18) becomes

$$\tilde{\zeta}_{aft} - \beta\left\{log\left[\exp \tilde{\zeta}_{a+1ft+1} + 1\right] + \gamma\right\} = \beta\frac{\pi_{ft+1}}{\sigma_f^{exit}} - \frac{F_{af}}{\sigma_f^{exit}} \tag{A19}$$

[46]In Appendix X I show that, in equilibrium, the profit of gas and coal generators depends on the difference between χ_{gjt} and χ_{cjt} but not on the level of the cost shifters, so that the normalization that I impose does not affect my estimation of fossil fuel generator profits. This normalization does, however, affect the level of electricity prices and, through it, the profit of renewable generators. A higher χ_{gjt} will imply a higher electricity price and, all else equal, should lead to a higher entry rate of renewable generators. When I estimate market-specific installation costs based on observed entry rates, the installation cost shifters that I recover will partially absorb this effect.

F.3 Additional estimation results

Table A2: Electricity supply: First stage results

	Gas		Coal	
	Eff-adj. fossil price	Capacity use	Eff-adj. fossil price	Capacity use
	(1)	(2)	(3)	(4)
Brent oil price	0.522***	0.0002	0.488***	0.001*
	(0.100)	(0.0004)	(0.031)	(0.0006)
Renewables cap. use	-9.62*	-0.502***	-6.91***	-0.468***
	(5.62)	(0.031)	(1.60)	(0.055)
Observations	2,226	2,226	2,226	2,226
Adjusted R^2	0.794	0.253	0.887	0.237
Within Adjusted R^2	0.061	0.100	0.159	0.040
F-test (1st stage)	14.9	122.5	207.1	47.5
Region x year fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓

Notes: Elec. supply estimation draws on monthly data from 2016 to 2023 for electricity markets in US, EU, Korea and Japan. Robust standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A3: Non-electricity gas demand: first stage results

	log(Price)
	(1)
log(Gas Reserves per capita)	-0.122**
	(0.050)
log(Brent oil price)	0.376***
	(0.061)
log(GDP p.c.)	0.794***
	(0.248)
log(Population)	1.74
	(1.97)
log(GDP p.c.) $\times$ OECD	0.790*
	(0.404)
log(Population) $\times$ OECD	-5.40**
	(2.15)
Observations	421
Adjusted R^2	0.852
Within Adjusted R^2	0.458
F (1st Stage)	50.4
Country fixed effects	✓
2016+ dummy x Country fixed effects	✓

Notes: Newey West standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A4: Fossil fuel supply estimation: first stage results

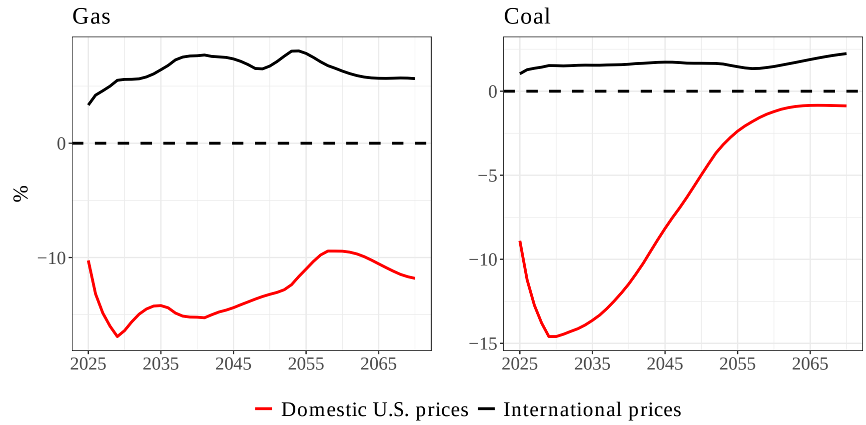
	log(Price)	
	Gas	Coal
	(1)	(2)
log(Elec. gen.) $\times$ f share (2000)	0.043***	0.013***
	(0.011)	(0.002)
log(Reserves)	-0.132	0.124**
	(0.097)	(0.053)
log(Oil production)	0.078	
	(0.194)	
Observations	310	298
Adjusted R^2	0.664	0.752
Within Adjusted R^2	0.141	0.228
F-test (1st stage)	44.2	60.2
Country fixed effects	✓	✓
2016+ dummy x Country fixed effects	✓	✓

Notes: Robust standard errors in parentheses. f share refers to the gas and coal share of electricity generation in columns (1) and (2) respectively. Supply estimation draws on annual data from 2000 to 2021 for markets accounting for 82% and 95% of natural gas and coal global production respectively. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

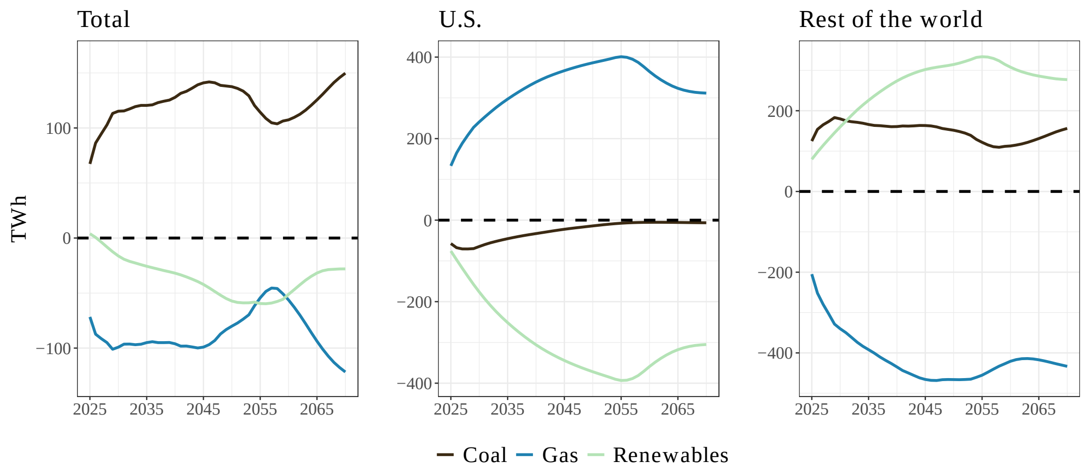
G Additional counterfactual results

Figure G4: Effect of keeping U.S. LNG export capacity constant at 2021 levels

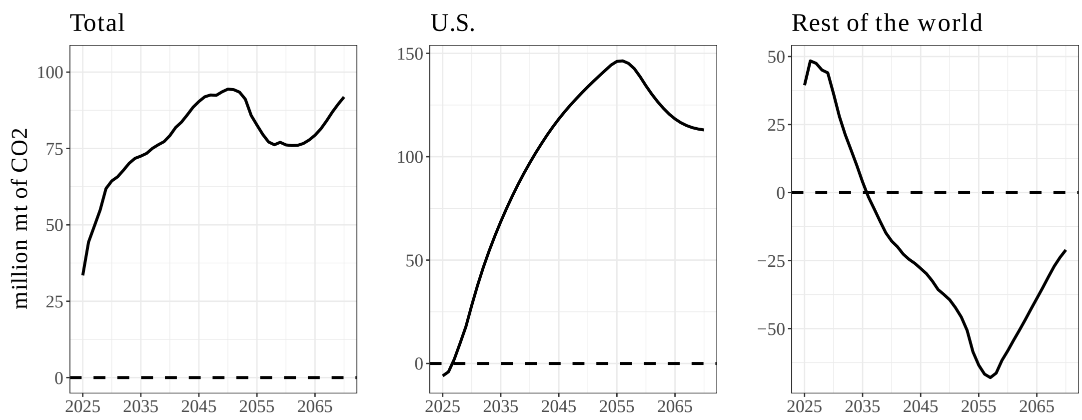
(a) Percentage change in fossil fuel prices



(b) Absolute change in generation by type

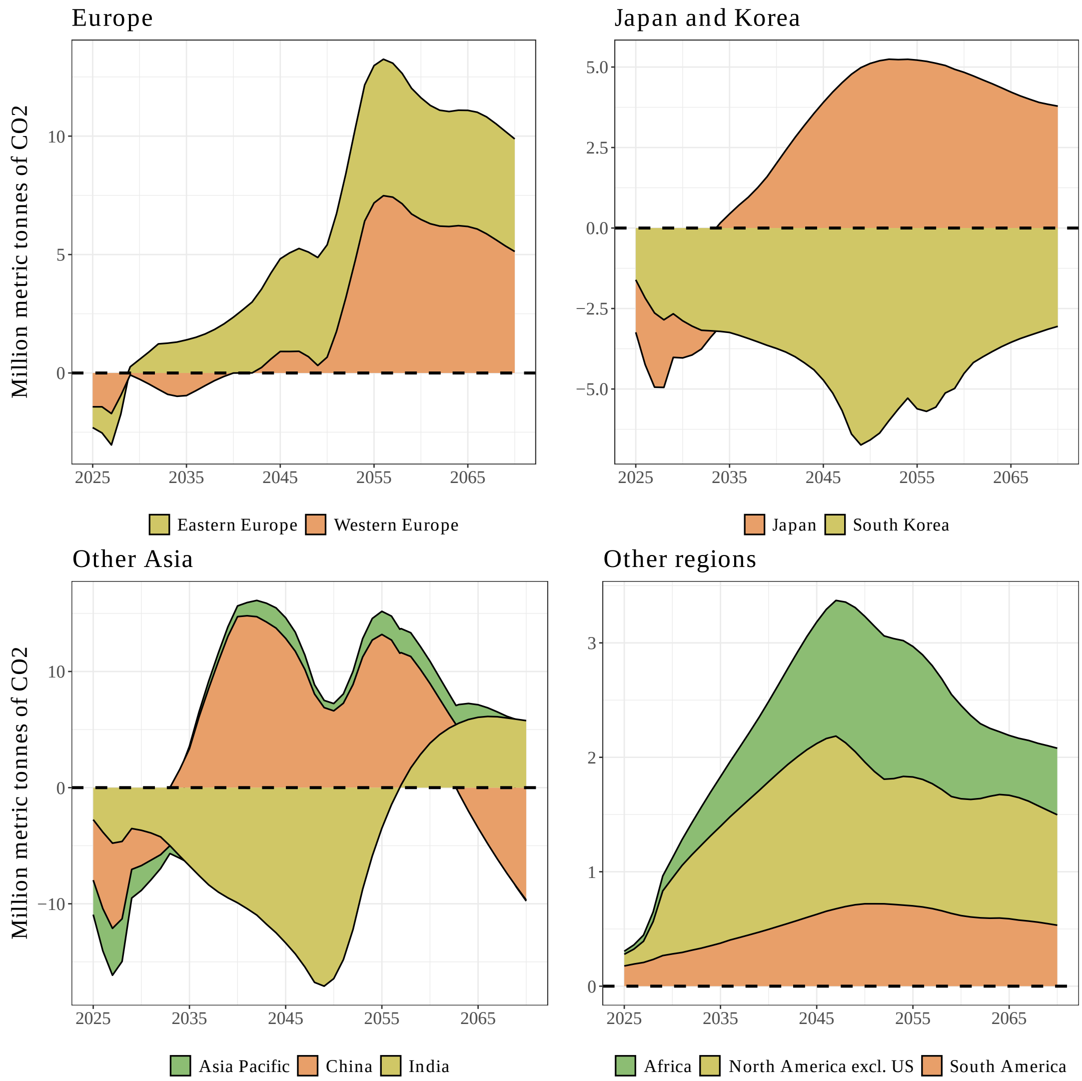


(c) Absolute change in annual emissions



Note: Panel (a) shows the evolution of annual price changes in the case where U.S. LNG export capacity is held at 2021 levels relative to the baseline scenario for both U.S. and international fossil fuel prices. Panel (b)shows the absolute annual change in generation by fuel type and region relative to baseline. Renewables refers to solar and wind electricity production, with solar generation including both direct sales by generators and sales by storage facilities. Panel (c) shows the absolute change in annual emissions across regions relative to baseline.

Figure G5: Baseline counterfactual results: effect heterogeneity



Note: Each panel shows, for a given selection of countries, the evolution of the annual absolute change in power sector emissions in the case of the U.S. LNG export expansion relative to the baseline scenario in which only U.S. LNG export capacity that is currently under construction is ever built.

H Comparison with other projections

Table A5: Power installed capacity projections: baseline vs. EIA (2023)

Country	Fuel	Installed capacity (GW)					
		EIA			Model		
		2022	2030	2050	2022	2030	2050
US	Coal	201.2	105.0	72.6	183.2	86.5	20.4
	Natural gas	444.9	526.0	675.6	535.3	573.2	585.8
	Solar + Storage	131.4	463.8	1084.0	161.7	450.7	1272.4
	Wind	145.0	300.8	374.1	118.7	299.5	446.5
Canada	Coal	5.8	0.0	0.0	9.4	6.5	7.3
	Natural gas	32.5	51.2	68.5	19.5	20.7	28.3
	Solar + Storage	3.6	3.6	3.6	5.0	24.7	187.5
	Wind	15.7	23.2	129.2	16.9	31.0	62.4
Mexico	Coal	8.6	8.6	8.6	4.6	4.4	4.5
	Natural gas	44.2	45.2	55.8	43.8	47.2	54.7
	Solar + Storage	7.5	10.5	45.5	9.3	32.6	133.9
	Wind	8.1	8.1	8.1	4.2	6.1	7.9
Brazil	Coal	5.9	4.1	4.1	4.9	1.7	0.0
	Natural gas	24.0	27.2	16.4	13.8	13.6	9.5
	Solar + Storage	13.0	13.0	13.0	20.7	32.5	82.3
	Wind	19.7	26.8	48.3	26.4	68.5	84.1
China	Coal	1163.7	1203.1	1203.1	1002.0	1053.7	923.3
	Natural gas	105.9	157.3	441.6	153.2	197.6	238.1
	Solar + Storage	466.0	887.5	1046.9	358.2	1108.6	3166.2
	Wind	355.8	428.3	745.7	255.3	672.3	1135.3
India	Coal	291.1	310.2	310.2	230.2	268.0	337.1
	Natural gas	30.6	36.1	56.0	35.5	58.1	147.8
	Solar + Storage	58.0	209.1	1730.8	58.8	404.7	2114.6
	Wind	39.0	104.3	250.0	64.3	121.3	179.6
Japan	Coal	63.7	42.1	40.8	55.0	55.0	37.5
	Natural gas	95.3	100.6	78.2	82.1	83.0	56.7
	Solar + Storage	76.2	85.8	110.8	77.4	182.4	561.4
	Wind	4.3	4.4	28.1	6.5	6.6	0.6
South Korea	Coal	42.6	45.8	45.8	36.4	36.8	34.1
	Natural gas	43.2	45.6	35.5	42.8	47.1	55.0
	Solar + Storage	15.7	15.7	16.0	37.0	70.2	214.8
	Wind	1.9	13.3	59.8	1.6	1.9	0.8

Note: EIA estimates come from the EIA International Energy Outlook 2023 (EIA, 2023*b*).

Table A6: Electricity mix projections: baseline run vs. IEA (2023) and EIA (2023)

Country	Fuel	Share of electricity mix (%)								
		Model			IEA			EIA		
		2022	2030	2050	2022	2030	2050	2022	2030	2050
US	Coal	26	9	2	28	6	0	27	11	6
	Natural gas	59	50	34	53	43	9	53	34	27
	Solar	7	18	37	6	23	56	6	27	41
	Wind	9	23	28	13	28	35	14	28	27
Brazil	Coal	21	2	0	8	4	1	7	4	3
	Natural gas	35	18	8	25	13	6	50	49	23
	Solar	18	22	28	18	33	33	11	10	7
	Wind	26	59	64	49	51	60	32	38	67
China	Coal	83	60	37	79	50	17	77	67	52
	Natural gas	4	7	5	4	4	3	4	5	13
	Solar	6	16	34	6	25	51	8	16	16
	Wind	7	16	25	11	21	29	10	11	19
India	Coal	91	65	36	85	66	22	81	67	29
	Natural gas	0	5	10	3	4	4	5	4	2
	Solar	5	24	49	7	22	52	6	17	56
	Wind	4	5	4	5	8	22	8	13	13
Japan	Coal	53	37	20	42	31	11	38	24	25
	Natural gas	35	34	18	45	34	15	47	55	41
	Solar	10	27	62	12	25	39	14	20	25
	Wind	1	2	0	1	10	35	1	1	10
EU27	Coal	27	8	3	29	4	0	-	-	-
	Natural gas	27	20	9	33	16	3	-	-	-
	Solar	18	35	60	12	31	38	-	-	-
	Wind	27	37	27	25	48	58	-	-	-
Russia	Coal	58	61	66	28	16	13	27	20	13
	Natural gas	42	39	34	71	81	77	72	79	86
	Solar	0	0	0	0	1	2	0	0	0
	Wind	0	0	0	1	2	9	1	0	1

Note: Electricity mix shares calculated excluding all electricity sources other than coal, natural gas, solar and wind. IEA estimates come from the IEA World Energy Outlook 2023 (International Energy Agency, 2024*c*), while EIA estimates come from the EIA International Energy Outlook 2023 (EIA, 2023*b*).