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INVESTMENTS IN RENEWABLES AND IMPACT ON GLOBAL FOSSIL FUEL TRADE

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Abstract

The paper motivates an additive linear power supply model in which solar and wind power with diminishing returns are deployed alongside constant returns fossil fuel-based generation that meets residual demand. This aligns with industry realities and provides plausible predictions. A novel instrumental variable strategy that interacts exogenous country-specific renewable potentials with global generation trends is used to overcome endogeneity. Using various coefficients, the paper shows that wind and solar power generations have reduced global fossil fuel imports by USD300 billion to USD1 trillion. A reduction in fossil fuel imports is particularly evident in high-income countries. Evidence of substitution is more mixed for developing economies but points in the same direction. While the results are encouraging, production and trade of fossil fuels remain dominant.

Keywords: Fossil fuels; import dependency; renewable energy

JEL classification: D00; F18; O25; Q4

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1. Introduction

Investments in renewable energy have surged with the green transition. This is especially evident in the solar and wind power sectors over the past two decades, with improvements in technical efficiency, reduction in manufacturing costs, and greater integration into national grids.

With rising geopolitical tensions, concerns about energy security are growing. The trilemma of environmental sustainability, energy security, and affordability has become more salient. Renewable power has been touted as the solution to both climate change mitigation and energy security goals. The International Energy Agency (IEA) states that “climate and energy security policies in 140 countries have played a crucial role in making renewables competitive with fossil-fired power plants” [IEA (2024)].

Research into energy substitution (and transition) from fossil fuels to renewables is hardly new. Nevertheless, as the paper later reviews, many existing studies focus on localized transitions, and relatively little is known about how renewable energy generation interacts with fossil fuel trade and import dependency on a global scale. In the backdrop, fossil fuel-based generation still accounts for more than 60 percent of global power produced. In many economies, fossil fuel-based power continues to rise despite climate concerns. This source of power remains critical to economic development, with massive subsidies for the sector.

The question this paper explores is whether investments in renewable power have, in fact, reduced global imports of fossil fuels (oil, natural gas, and coal). The issue extends beyond energy security. As renewable power grows, it will fundamentally impact the global fossil fuel trade and potentially bring about structural changes to the current accounts and macroeconomic performance of both fossil fuel exporting and importing economies.

The paper first provides an aggregate stylized model that incorporates industry characteristics to guide subsequent empirical work. Aggregate economic output is modeled using a standard, constant returns to scale Cobb-Douglas production function. Power demand becomes a function of energy intensity and the size of the aggregate economy. Within the power sector, there are two (or more) sources of renewable energy, each facing diminishing returns, and a fossil fuel-based power source characterized by constant returns to scale.

The model employs a “quasi-linear” approach, in which the power generated by these sources is linearly additive, though they remain imperfect substitutes. As renewable power sources face diminishing returns, they are used in some quantities but cannot fully meet the power demand of the economy. Given its constant returns to scale, fossil fuel-based power acts to meet residual demand and clears the market. Implicitly in the model, ceteris paribus, the rise of renewables replaces fossil fuel power only if total power demand is growing by less. The paper argues that while this model is simplified to achieve tractability, its key features align with industry realities.

Modelling power sources as linearly additive simplifies the demand function for fossil fuels considerably. Fossil fuel usage can be derived tractably as a linear function of renewable power generation. This simplification supports subsequent empirical work and allows for an instrumental variable (IV) strategy to be implemented relatively easily to address potential endogeneity.

The instrument in this paper is novel, leveraging the interaction between country-level renewable energy potentials with global renewable power generation trends across time. The identification strategy relies on the exogenous geographic attributes of renewable potentials. These potentials affect deployment incentives and, in turn, correlate with renewable assets at the country level. They otherwise do not directly affect fossil fuel use. This paper shows that IV estimation yields plausible estimates of the impact each unit (megawatt hour) of renewable power has on fossil fuel dependency.

1.1 Literature Review

At a broad level, this paper stands at the intersection of two areas of economic research: energy economics and international trade and macroeconomics.

As mentioned, whether renewables can substitute for fossil fuel-based power on an economy-wide scale is at the heart of climate change mitigation [Acemoglu et al. (2012); Foster et al. (2017); Marques, Fuinhas and Pereira (2018); Holechek et al. (2020)]. In recent years, reducing exposure to concentrated geopolitical fossil fuel risks has provided an additional motivation on top of climate change concerns [see Hille (2023); Yan et al. (2024)]. Renewable power potentials tend to be more widespread, unlike fossil fuel endowments which are more concentrated geographically resulting in import dependency [Overland, Juraev and Vakulchuk (2022); Wang, Fan and Zhou (2022)]. Hence, the path toward renewable energy is potentially open to more economies and not just a few. In principle, given the sharp increase in renewable power in recent years, one should be able to detect the impact this has on global fossil fuel trade.

The literature also suggests that renewable power can potentially reduce economic vulnerability. Renewable power assets, once constructed, require little material inputs and hence little trade to sustain them [Krane and Idel (2021)]. Post-construction, there is a negligible risk of supply-side shocks. Some policymakers further hold that a reduction in fossil fuel imports would improve current accounts, promote growth, and reduce other macroeconomic vulnerabilities such as inflation passthrough. Nevertheless, evidence is also relatively limited. Andini, Cabral, and Santos (2019) find some evidence that renewables have driven economic growth in Portugal through import substitution. An IMF study by Millischer et al. (2024) finds little evidence that renewables have shielded economies from price fluctuations driven by fossil fuels.

This paper posits several reasons why. First, growing economies and rising energy demand mean that fossil fuel-based power generation grows alongside renewable investments [Yadav and Mahalik (2024)]. Large subsidies continue to support fossil fuel use. These mask any potential reduction in fuel imports. Country heterogeneity in renewable potentials, capacity, and economic structures, as with macroeconomic factors such as interest rates, oil prices, carbon pricing policies, and renewable subsidies, also affect renewable investments and fossil fuel use. These present confounding effects.

Second, renewable power still faces intermittency in generation and other constraints [Holechek et al. (2020)]. Many developing economies still lack the necessary transmission and distribution infrastructure to bring power from geographically distant renewable sources to demand centers. Without sufficient transmission between regions or storage capacity, the unpredictability of renewables could lead to unplanned load shedding.[1] In extreme cases, intermittency can cause voltage instability, leading to power outages and blackouts. Land constraints and the environmental impacts of renewables present further constraints. Many policymakers continue to view fossil fuel-based power as necessary to meet baseload demand.[2]

The stylized model in this paper aligns with industry characteristics. It recognizes the deployment of renewables as a key addition to the power system but leverages the fossil fuel sector to clear the market. With a simplified demand structure, it allows fossil fuel usage to be a tractable function of renewable power generation. As mentioned, import dependence could also motivate renewable deployment. Hence, as recognized in the literature, renewable investments are potentially endogenous to fossil fuel import dependency. The empirical strategy would have to address this.

For empirical work, this paper provides a clear identification strategy using a novel instrument. As briefly mentioned earlier, potentials are based on country-specific and exogenous geographical attributes (e.g., solar irradiance, wind speeds, and land area). Borrowing a similar technique in Lu, Tao, and Zhu (2017), these potentials are further interacted with global generation trends (for solar and wind) over two decades to obtain a set of country-year instruments. To the best knowledge of this research, this is also the first instance in which renewable potentials are used as IVs.

Existing works tend to focus on a single country or a relatively small number of countries. This paper uses a larger dataset that covers most economies, thereby providing estimates that are more representative of global averages. The paper shows that the IV strategy yields more plausible estimates compared to ordinary least squares (OLS) regressions, which return wrong-signed or insignificant coefficients. The paper shows that across a range of regression specifications, one megawatt hour of power generated by wind and solar could have reduced fossil fuel imports by as much as USD310. The aggregated impact over thousands of megawatt hours each year (per megawatt of installed capacity) is considerable, and even more so over the useful life of the initial renewable investment.

The results for developing economies are more mixed but still point to the potential of such a reduction. Taken together, this implies that the rise of renewables is already having a sizeable impact on fossil fuel trade. Based on 2022 trade data, the paper estimates that around USD300

[1] Load shedding is documented in many developing economies. It occurs due to inadequate generation, transmission, and distribution, in addition to a lack of robust pricing and demand management. Renewables can add to existing power production, especially during peak daylight hours, thereby reducing load shedding. Nonetheless, it is generally acknowledged that a more volatile renewable supply into the grid can pose a challenge to grid stability [Sundarajoo and Soomro (2023)].

[2] There are concerns among industry experts and policymakers that intermittency would lead to grid instability as the share of renewables grows. Moreover, older fossil fuel plants are also unable to respond as quickly to sudden drops in the output from renewable sources. There will continue to be a risk of load shedding of peak demand or curtailment of renewable power to reduce instability [Henriot (2015); Zhao et al. (2020)]. Because of these technical realities, many policymakers continue to see fossil-fuel power sources as baseload. Nevertheless, this baseload view is also increasingly being challenged given technological progress—inter alia, renewable energy sources (including those facilitated by cross-border trading) have become more diversified with intermittencies evened out, storage solutions have become more economically feasible, and real-time monitoring and artificial intelligence are being deployed to better predict renewable energy output to match demand and supply [Cosgrove, Roulstone, and Zachary (2023)].

billion to USD1 trillion of fossil fuel imports are removed from the global market with the rise of solar and wind power (though fossil fuel production and trade remain dominant).

Section 2 describes the data and key trends. The model and its properties are developed in Section 3, while Section 4 presents and discusses the results from various regressions. Section 5 offers some concluding thoughts.

2. Data and Key Trends

2.1 Installed Capacity and Generation

Data on the deployment capacity and generation of various types of renewable power and fossil fuels are provided by the International Renewable Energy Agency (IRENA). The dataset covers the period from 2000 to 2022.

This section first presents some statistical trends. As shown in Figure 1, there has been a sharp increase in the deployment capacity of solar and wind power in high-income countries (HICs), while fossil fuel-based power has largely stagnated.[3] Power generated from fossil fuels has also started to decline (Figure 2). However, for developing economies, fossil fuel-based power capacity and generation continue to rise (Figures 3 and 4).

[3] The income status of countries (high-income, upper-middle-income, lower-middle-income, and low-income) is based on the World Bank's classification.

Figure 1: Installed Capacity of Fossil Fuels and Renewables (HICs)

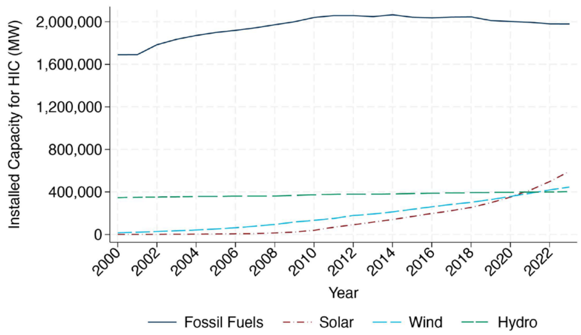


Figure 2: Electricity Generated by Fossil Fuels and Renewables (HICs)

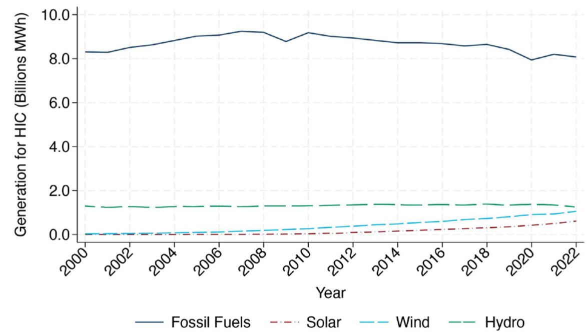


Figure 3: Installed Capacity of Fossil Fuels and Renewables (Developing Countries)

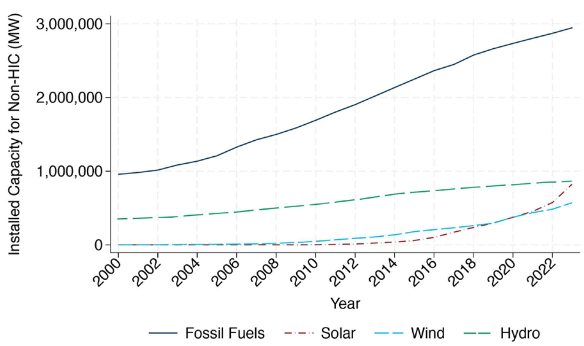
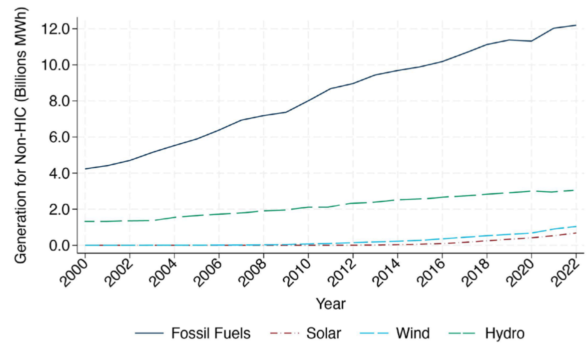


Figure 4: Electricity Generated by Fossil Fuels and Renewables (Developing Countries)



Globally, one megawatt of installed fossil fuel capacity generates 4,000 megawatt hours (or four gigawatt hours) on average. For wind and solar power, the generation-to-capacity ratios are around 2,500 and 1,200, respectively, in high-income economies (Figure 5), with slightly lower ratios in developing countries (Figure 6). Unless otherwise stated, all power units in this paper are reported in megawatts for capacity and megawatt hours for generation.

As expected, a single unit of installed capacity for fossil fuel-based technology generates significantly more than the respective installed capacity of wind and solar. It is also worth noting that the generation ratio has gradually declined for fossil fuel-based power, especially in HICs, while the generation ratios continue to increase for wind and solar. To be clear, the declining generation ratio for fossil fuel assets is likely due to decarbonization pressures (e.g., regulations and carbon taxes) rather than a decline in technological capacity. In fact, the modern combined-cycle gas turbine is highly efficient, with possible use of mixed fuels such as hydrogen or biofuels. Increasingly, gas-fired power plants are expected to be highly flexible, providing insurance for the overall system as the share of less predictable renewable energy increases [IRENA (2019)]. The decline in the generation ratio also reflects this, in part.

Figure 5: Generation-to-Capacity Ratio (HICs)

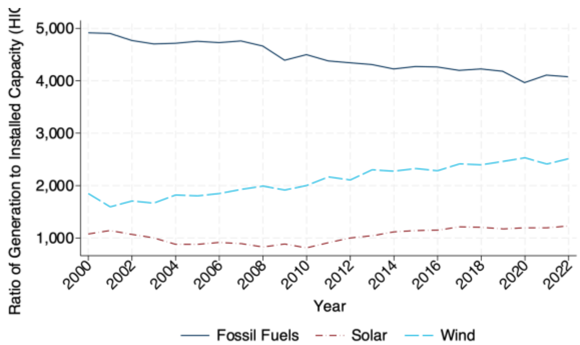
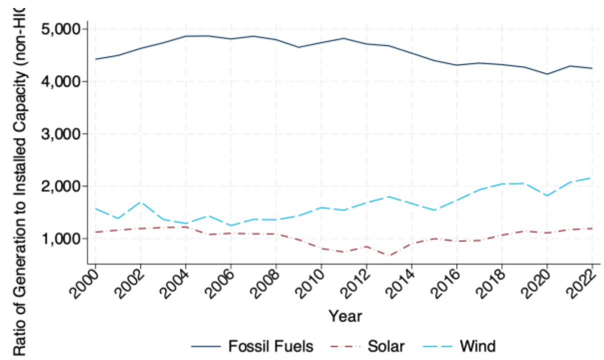


Figure 6: Generation-to-Capacity Ratio (Developing Countries)



The distribution of power generated globally in 2022 is provided in Table 1, while the number of countries with positive generation of such power is provided in Table 2. Coal power remains dominant among developing countries. Oil-based power is small but widely used, as seen in the number of countries with positive generation.

Table 1: Global Power Generation in 2022 by Source (megawatt hours, millions)

Source	High-Income Countries	Developing Countries
Total Non-Renewable Energy	8,169	12,012
Nuclear	*1,808*	*844*
Coal	*2,117*	*7,811*
Natural Gas	*3,761*	*2,616*
Oil	*389*	*325*
Total Renewable Energy	3,374	5,179
Solar	*603*	*679*
Wind	*1,054*	*1,044*
Hydro	*1,264*	*3,058*
Biofuels	*289*	*236*
Geothermal	*43*	*53*

Table 2: No. of Countries with Positive Generation in 2022

Source	High-Income Countries	Developing Countries
Total Non-Renewable Energy	73	133
Nuclear	*19*	*13*
Coal	*37*	*44*
Natural Gas	*51*	*65*
Oil	*68*	*121*
Total Renewable Energy	72	135
Solar	*72*	*132*
Wind	*64*	*82*
Hydro	*45*	*110*
Biofuels	*48*	*82*
Geothermal	*12*	*15*

2.2 Fossil Fuel Production and Trade

Data on the fossil fuel trade are obtained from UN Comtrade. As shown in Figure 7, the fossil fuel trade is dominated by oil. Notwithstanding volatility, HICs' imports of fossil fuels have largely stagnated. However, fossil fuel imports by developing economies, starting from a lower base, continue to rise (Figure 8).

Fossil fuel production data is obtained from the IEA. The dataset contains country-year production of oil, gas, and coal, standardized to kilotons of oil equivalent. Coal production has declined in HICs (Figure 9), but has continued to rise rapidly in developing economies (Figure 10).

Figure 7: Imports of Fossil Fuels (HICs)

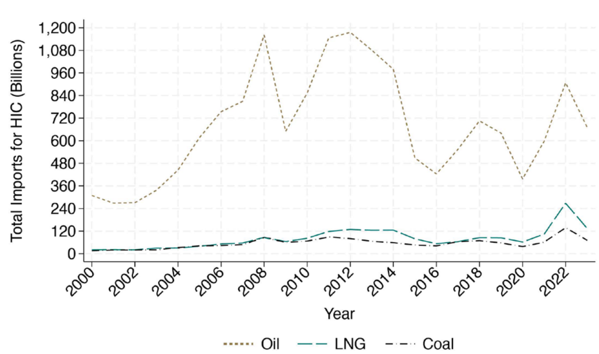


Figure 8: Imports of Fossil Fuels (Developing Countries)

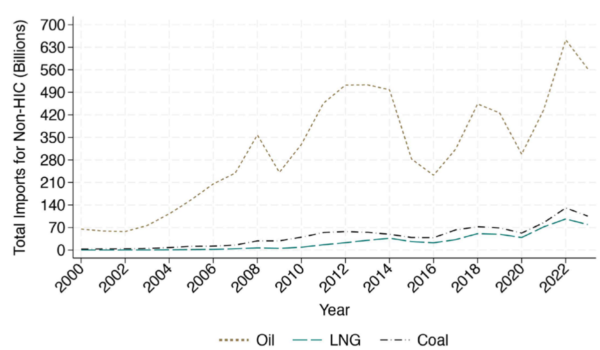


Figure 9: Production of Fossil Fuels (HICs)

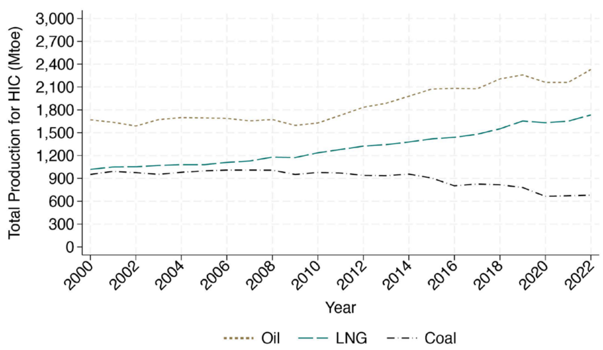
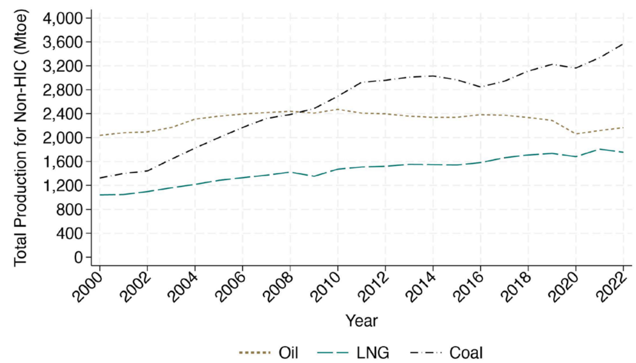


Figure 10: Production of Fossil Fuels (Developing Countries)



Notes: Mtoe = Million tonnes of oil equivalent

2.3 Renewable Potentials and IVs

The data for solar power potential is obtained from a public source, Global Solar Atlas), supported by the World Bank Group. The base data is provided by a private sector company, SOLARGIS, which uses satellite-tracked irradiance data and meteorological models to derive solar potentials, which are then validated through site testing. For this research, solar power potential for each country is the theoretical average kilowatt hour per square meter of photovoltaic (PV) potential of each country (which is provided), scaled up by its land area to arrive at the gross solar power potential for each country.[4]

Similarly, the data on wind power potential from the Global Wind Atlas is supported by the World Bank Group in collaboration with the Technical University of Denmark. The data provides the mean wind power density (at 50 meters in height), measured in watts per square meter. This is also scaled up by the land area to arrive at the gross wind power potential for each country. The IV measurement of wind power potential excludes offshore potential.[5]

2.4 The Role of Hydropower and Other Renewable Sources

Hydropower is the largest source of renewable power. Like solar and wind power, hydropower requires a large upfront investment, which is then matched by low marginal costs during operations. Though hydropower plants with storage reservoirs face fewer intermittency constraints,

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[4] Potential is based on the global horizontal irradiance (GHI) which measures the output of a horizontally laid solar panel at ground.

[5] In terms of installed capacity, a large majority of wind power is still deployed onshore. In 2022, onshore wind capacity was more than 800 gigawatts, compared to less than 80 gigawatts for offshore wind. While offshore capacity is more productive, deployment remains more costly. Nevertheless, offshore wind capacity is expected to rise significantly in the coming decades [Desalegn et al. (2023)]. Furthermore, offshore wind is often deployed close to the shore. In this paper, wind potential accounts for the land areas of countries and should sufficiently approximate for “nearshore” wind potential.

they are nonetheless affected by interseasonal variability in water flow and water level. Power output will also be constrained by longer-term dry weather patterns. Hydropower is also highly terrain-specific. It can be challenging to scale further once the best sites are already used.

Large hydropower infrastructure with stored reservoirs can also negatively impact the environment and biodiversity. Given these geographic and ecological constraints, hydropower is also likely to face diminishing marginal returns in the long run (this will be confirmed via a regression presented in a later section).

The analysis also excludes hydropower from the main regressions due to limited data on hydropower potential, which limits the implementation of IVs. Hydropower growth has been relatively slower than that of wind and solar over the past two decades.[6] Nonetheless, the paper includes hydropower in alternative regressions for robustness checks. Regression analysis also excludes other sources of renewable energy, such as biofuels or geothermal power, as these are generally too small in most countries to affect fossil fuel usage.

3. Energy Use and "Quasi-Linear" Power Supply Model

3.1 Model

Output of the economy is given as

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha} E_{i,t}^{\beta} L_{i,t}^{1-\alpha-\beta}$$

where $Y_{i,t}$ is given by the standard constant returns to scale Cobb-Douglas production function of the economy i at time t, $A_{i,t}$ the total factor productivity, $K_{i,t}$ the non-power capital stocks, $L_{i,t}$ the labor of the economy, and $E_{i,t}$ the power use in the economy.

The power sector supply function takes a "quasi-linear" form. Power generated by different sources is additive, but are imperfect substitutes

$$E_{i,t} = Q_{i,t} + a_{i,t}\left(N_{1,it}\right)^{\mu_1} + b_{i,t}\left(N_{2,it}\right)^{\mu_2}$$

with $Q_{i,t}$ representing the power generated by the fossil fuel sector, and $a_{i,t}\left(N_{1,it}\right)^{\mu_1}$ and $b_{i,t}\left(N_{2,it}\right)^{\mu_2}$ the power generated by the two respective renewable sources.[7]

To elaborate further, $N_{1i,t}$ and $N_{2i,t}$ are the two different renewable power assets with μ_1 and μ_2 representing the respective returns to scale, and $a_{i,t}$ and $b_{i,t}$ the respective productivity (or

[6] International Energy Agency (2021) projected a 230-gigawatt net capacity increase by 2030 (from 1330 gigawatts in 2020).

[7] Quasi-linear functions are most often used to model consumer demand. This paper adapts the useful properties of this functional form. While the paper provides a model with two renewable sectors, the quasi-linear additive setup allows additional renewable sources to be added to the model while preserving tractability.

scaling) factors.[8] For renewables, no operating cost will be required once the unit capital costs (P_1 and P_2, respectively) are invested. The costs of these renewable assets are assumed to be exogenously determined based on available technology and associated installation costs.

The production function of fossil fuel power takes on a Leontief function,

$$Q_{i.t}^{P} = min\left[\frac{F_{i,t}}{c_{i,t}}, \frac{M_{i,t}}{d_{i,t}}\right]$$

where $Q_{i.t}^{P}$ represents the unit quantity (a megawatt hour in the context of this paper) of power generated. Here, $F_{i,t}$ is the installed capacity, which together with inverse productivity $c_{i,t}$, represents the capacity $\frac{F_{i,t}}{c_{i,t}}$ for each megawatt hour generated. Similarly, $\frac{M_{i,t}}{d_{i,t}}$ represents the per-period fossil fuel requirement per unit of power. Note that a higher parameter $d_{i,t}$ implies that more fossil fuel is needed per megawatt hour generation (i.e., low productivity).

The Leontief production function is chosen for analytical convenience. This also aligns with the operational constraint of little substitution possibility between fixed power plants and variable fossil fuels. Generation requires installed capacity be matched to fuels in some fixed proportions. As will be explained later, this is a simplification but not an overly restrictive one. The paper later discusses an alternative production function based on Cobb-Douglas and shows that it further simplifies the estimated equation while preserving the conclusion.

The analysis assumes that all power generated by various sources is sold at the same price. End users are thus indifferent to power generated by various sources, consistent with the supply assumption that power from these sources is additive.

3.2 Key Model Properties and Discussion

First, the parameter β is the overall energy intensity of the economy. This pins down the size of the power sector. To be clear, output $Y_{i,t}$ depends on only the power generated regardless of source. Power use is thus constant returns to scale with respect to other factors in the aggregate production function $Y_{i,t}$, but the power sector itself is not necessarily constant returns to scale.

Second, the functional form also implies that where renewables are feasible, there will always be positive quantities of energy produced by these sources. However, renewable assets should have diminishing returns ($\mu_1, \mu_2 < 1$) to avoid "corner" equilibrium solutions where only a single type of power generation is deployed. Despite diminishing returns, technical efficiencies as measured by $a_{i,t}$ and $b_{i,t}$ (acting like TFP terms) can continue to increase over time, thereby raising renewable production. In a later section, the paper presents evidence of these with a set of ancillary regressions before the main results.

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[8] The scaling factors are required to translate installed capacity to power generated over the year. As mentioned, on average, 1 megawatt of installed wind power capacity can generate around 2,200 megawatt hours over the year.

It is worth stating that it is not merely a modeling convenience to assume renewables face diminishing returns. The various sources of power are in reality imperfect substitutes. Power needs to be matched to demand, which often peaks at different times during the day. The intermittent nature of renewable power sources means they cannot always meet peak demand. There are also seasonal peaks that renewables cannot match. Traditional power sources from fossil fuels can scale up (or down) more predictably to match demand fluctuations.

Deployment of renewable assets is also likely to face land, ecological, or other constraints as these assets scale up. These reasons also justify the modeling approach of, on the one hand, assuming power is additive to the economy regardless of source, while, on the other hand, imposing diminishing returns on renewable investments.

Third, fossil fuel-based generation, operating under constant returns to scale, absorbs whatever power demand renewables cannot meet (a convenient property of the functional form). To encourage renewables and to reduce greenhouse gas emissions, many economies have assigned renewable power priority dispatch–i.e., power generated from a renewable source is given priority to enter the grid to meet demand. Renewable power generation has negligible marginal costs in any case and is thus utilized first. This provides further support for the model setup in this paper, where renewables are used to their respective limits (given diminishing returns) and fossil fuel generation then clears the market of any demand that cannot be met by renewables.

3.3 Equilibrium and Fossil Fuel Use

Dropping subscripts for brevity, the maximizing problem for the economy is

$$\max E \;\; s.t \; \beta Y = R(Q^*) + rP_1N_1 + rP_2N_2$$

where βY represents, as with a Cobb-Douglas aggregate production function, the final expenditure in the economy directed to power generation. This pins down the aggregate revenue for the entire power sector. $R(Q^*)$ is the total revenue or factor payment directed to fossil fuel generation, with Q^* the fossil fuel-generated power required to clear the market and meet βY. Here, r is the interest rate, and P_1 and P_2 the cost of investments of the respective renewables—the two terms on the RHS are thus the factor payments to the respective renewable source. For simplicity, the model normalizes the output price to unity (numeraire) and assumes that electricity is sold at the same price P_E regardless of source (how P_E is determined will be discussed later in the paper).

For the fossil fuel power sector, the following equations pin down the equilibrium:

Equation 1

$$Q^* = \frac{F^*}{c} = \frac{M^*}{d}$$

where F^* is the total fixed asset for the fossil fuel sector, and M^* the per-period fossil fuel use. For renewables, the FOC equates marginal revenue $P_E\mu_1 a(N_1)^{\mu_1-1}$ to servicing cost rP_1, resulting in the following equilibrium conditions:

Equation 2

$$rP_1N_1 = P_E\mu_1 a(N_1)^{\mu_1} \qquad rP_2N_2 = P_E\mu_2 b(N_2)^{\mu_2}$$

The investment demands of N_1 and N_1 depend only on their own respective prices, productivity and interest r . As long as P_1 and P_2 are not prohibitive, there will be positive quantities of generation from both renewable sources. Substituting these back into the power sector's revenue constraint pins down equilibrium $R(Q^*)$; the total revenue for fossil fuel power becomes

$$R(Q^*) = \beta Y - P_E\mu_1 a(N_1)^{\mu_1} - P_E\mu_2 b(N_2)^{\mu_2}$$

This matches the total cost function, which, given the production function, is expressed as

$$C(Q^*) = rP_F cQ^* + P_M dQ^*$$

where P_F is the unit cost of fixed asset and P_M the unit cost of fossil fuel. The first term on the RHS ($rP_F cQ^*$) is the per-period servicing cost for all fossil fuel assets required to produce Q^* while the second term ($P_M dQ^*$) is the total cost of fossil fuels per period. Matching revenue to cost for fossil fuel-based generation gives

Equation 3

$$(rP_F c + P_M d)Q^* = \beta Y - P_E\mu_1 a(N_1)^{\mu_1} - P_E\mu_2 b(N_2)^{\mu_2}$$

Imposing equilibrium quantity from Equation 1 ($Q^* = \frac{M^*}{d}$) expresses costs in terms of fossil fuels and gives

Equation 4

$$\theta P_M M^* = \beta Y - P_E\mu_1 a(N_1)^{\mu_1} - P_E\mu_2 b(N_2)^{\mu_2}$$

where $\theta = \left[\frac{rP_F c + P_M d}{P_M d}\right]$ is a function of parameters, which is the ratio of total unit cost to fossil fuel cost.

One can further separate fossil fuel use M^* into imports (I^*) and domestic production (D^*) as $P_M M^* = I^* + D^*$. Normalizing by population

Equation 5

$$\frac{I^*}{L} = \frac{\beta}{\theta}\frac{Y}{L} - \frac{P_E\mu_1}{\theta}\frac{a(N_1)^{\mu_1}}{L} - \frac{P_E\mu_2}{\theta}\frac{b(N_2)^{\mu_2}}{L} - \frac{D^*}{L}$$

where $\frac{a(N_1)^{\mu_1}}{L}$ and $\frac{b(N_2)^{\mu_2}}{L}$ are simply the per-capita generation of the respective renewable source.

Equation 5 is the key one to be estimated.

Fossil fuel use (and hence imports) has a linear and decreasing relationship with renewable power generation. The $\frac{P_E\mu_1}{\theta}$ and $\frac{P_E\mu_2}{\theta}$ coefficients are expected to be negative, reflecting the model properties where power sources are substitutes.

One can consider a few comparative static analyses. Recall that parameter d is the inverse productivity of fossil fuels—a low d implies less use of fossil fuel inputs per megawatt unit of power (i.e., fossil fuel technology has high productivity). This translates to a higher θ parameter (i.e., a smaller fraction of total costs goes toward fossil fuels), which then has an attenuating effect, as seen in the coefficients of $\frac{P_E\mu_1}{\theta}$ and $\frac{P_E\mu_2}{\theta}$.

To state it in economic terms: A marginal unit of renewable power generated would reduce fossil fuel use by a smaller amount if fossil fuel technology is more efficient. If this is coupled with the diminishing returns of renewables, it can become more difficult for renewables to fully substitute fossil fuel use.[9]

It is possible to further characterize P_E. Taking the reasonable assumption that the market-clearing fossil fuel sector sets the market price, one can characterize the electricity price as $P_E = z(rP_Fc + P_Md)$, a function of $z$markup over the unit cost of fossil fuel power generation. With this, the coefficients $\frac{P_E\mu_1}{\theta}$ and $\frac{P_E\mu_2}{\theta}$ will be reformulated as $z\mu_1P_Md$ and $z\mu_2P_Md$, respectively. This reformulation provides an even more intuitive understanding of the coefficients—their size depends on fossil fuel prices and technical efficiency P_Md. Directionally, the economic interpretation of d is unchanged—i.e., a lower d parameter attenuates the effects of renewable generation impact on fossil fuel use. A similar effect holds for fossil fuel price: A lower price implies a smaller impact that renewables have on fossil fuel use.

Furthermore, note that a more efficient fossil fuel sector will imply a lower unit cost ($rP_Fc + P_Md$). If the power price is set by the market-clearing fossil fuel sector, this translates to a lower power price P_E and results in lower renewable investments through the revenue conditions (Equation 2).

[9] The higher technical efficiencies of renewable power assets (higher a and b)—via scaling up renewable generation per asset—reduce fossil fuel use. Though these parameters are not directly captured in the main estimated equation, they can be recovered separately.

This aligns with the insights of Acemoglu et al. (2012), where a highly productive "dirty" sector may make the green transition more difficult.

There are a few additional comparative static predictions arising from the model. Ceteris paribus, higher energy intensity β or a larger economy Y increases fossil fuel use (rather than renewables) because the constant return fossil sector meets residual demand. If fossil fuel technology is productive, the $\frac{\beta}{\theta}$ coefficient is smaller—any increase in overall demand will also boost fossil fuel use less proportionately.

Another property of the supply model is that N_1 and N_2 are determined only by their own prices and productivities—they are, all things considered, not correlated with each other or with economy-wide variables such as Y. However, correlation can, in fact, be reintroduced by policy measures or other factors. For example, a common incentive program, policy support, or the use of a common technology could cause both investment types to become correlated. If the incentive program is dependent on the state of the economy, correlation can be introduced with Y. In the estimation of Equation 5, one still needs to be cautious about the potential of omitted variables, even though the model is, in principle, more robust to such omission.

As is now clear, the additive supply function has resulted in considerable simplification of the fossil fuel demand function. Even though the model is based on a general equilibrium framework, fossil fuel demand is linear in the economy's energy intensity and renewable power generation. This allows for the implementation of a simple IV strategy to recover the coefficients.

Finally, it is worth discussing the Leontief function for fossil fuel power generation. An alternative formulation could be to assume a Cobb-Douglas production function $Q^P = (\frac{F}{c})^{1-\gamma}(\frac{M}{d})^{\gamma}$ in line with the main model s setup of constant returns to scale. With standard cost shares, $P_M M^* = \gamma d R(Q^*)$. Hence, one can proceed to implement a simpler form of Equation 3. Payments to fossil fuels is a function of elasticity γ and efficiency d. Nonetheless, the paper argues that the Leontief case remains more economically intuitive and continues to use this as the base case for the analysis.

4. Estimation Results and Discussion

4.1 Returns to Scale for Solar, Wind, and Fossil Fuel-Based Generation

The paper presents regressions to estimate returns to scale for solar and wind power. Take N_1, the generated power is given as $a(N_1)^{\mu_1}$. In log, this is $\log a_{1,it} + \mu_1 \log N_{1,it}$ over the sample period. The first term highlights TFP-type efficiency, which can improve over time. There could also be yearly variations due to weather conditions affecting generation efficiency. The second term highlights the return to scale of installed capacity.

It is straightforward to recover the estimates of μ_1 and μ_2 by running log regressions of generated power against the logs of capacities. The panel regressions (within estimators) for solar and wind power are provided in Table 3 below, together with fossil fuel-based power generation for completeness. Over the past two decades, fossil fuel-based generation has had an elasticity of around 1, indicating constant returns to scale. Formal tests of the respective capacity coefficients in Table 3 show that null hypotheses of coefficients being less than 1 can be rejected for solar and hydropower with 10 percent confidence. For wind power, the same test falls slightly short of rejection at 10 percent confidence.

Table 3: Regressions of Installed Capacity and Energy Generation

	Log Solar PV Generation	Log Wind Power Generation	Log Hydropower Generation	Log Fossil Power Generation
Log Solar PV Capacity	0.979***			
	(0.0149)			
Log Wind Power Capacity		0.920***		
		(0.0690)		
Log Hydropower Capacity			0.938***	
			(0.0432)	
Log Fossil Fuels Capacity				1.004***
				(0.122)
Constant	6.750***	6.006***	7.471***	7..919***
	(0.276)	(1.064)	(0.428)	(1.049)
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	3,307	2,357	3,569	4,690
R-squared Overall	0.971	0.942	0.942	0.878
Number of Countries	204	148	158	208

Standard errors in parentheses clustered by country. *** p<0.01, ** p<0.05, * p<0.1

4.2 Control Variables

To obtain a more precise estimation of Equation 5, good estimates of the control variables are required. The first is the energy intensity of an economy. This can be proxied by total power consumption per population. For completeness, GDP per capita (in current USD terms) is also included as a control variable to account for income from the exchange rate effects of fossil fuel imports.

The third control variable is the value of domestic fossil fuel production D. As the production of various fossil fuels is reported by the IEA in standardized kilotons of oil equivalents, these can be aggregated at the country-year level, multiplied by a standard factor of 7,250 barrels per ton, and then multiplied by the average annual global oil price to derive the country-year value approximation of domestic production value. This is further normalized by population to obtain $\frac{D}{L}$ per Equation 5.

4.3 Instrumental Variables

While Equation 5 is linear and can be estimated using OLS, there will be endogeneity concerns as mentioned. The instrument construction follows these steps.

Gross renewable power potentials (for solar and for wind separately)—which are time invariantare are computed for each country. Potentials are uncorrelated with fossil fuel imports. Each country's share of its respective global potentials for solar and wind is then computed as a percentage of the global total potential. The respective shares are then multiplied by global solar and wind power generation across time to derive a set of country-time IVs for solar and wind separately.

The assumption here is that global power generation depends on global technology availability, manufacturing costs, or other relevant trends. Global renewable power generation is hence uncorrelated with any country's fossil fuel import dependency (i.e., exogenous to any country's specific circumstances). The IVs thus represent the scaling up of solar and wind power generation in each country based on its share of potential. These are further normalized by country population so that IVs are on a per capita basis and comparable across countries.

This set of country-year interaction terms thus reflects the key idea that countries with higher renewable solar or wind potential would also invest in and generate from these sources more quickly. The countries with the highest gross and per capita potential for solar and wind are listed in Appendix 1.

While potentials are, by construct, exogenous, there may be a concern that scaling up across time via global generation may result in IVs that do not satisfy exclusion. Global renewable generation could directly influence a country's fossil fuel use. For example, a country may import renewable energy from neighboring countries, creating a channel through which global generation directly affects domestic fossil fuel use. Disruptions in global fossil fuel markets may reduce fossil fuel imports and accelerate global renewable use simultaneously.

In Appendix 2, the paper provides an alternative construct for the IVs, leveraging constant average growth rates (CAGRs) as opposed to actual year-to-year generation. The regression results with the alternative IVs are consistent with the main regressions. Finally, regressions between the dependent variable (fossil fuel imports) against both sets of IVs are conducted, and the results reported in Appendix 2 show that the IVs do not have any direct explanatory power. This provides greater confidence that the IVs broadly satisfy the exclusion criterion.

4.4 Unit Roots

A formal Dickey-Fuller test for panel data rejects the null hypothesis that all panels contain a unit root for 0-to-3-year lags for fossil fuel imports per capita (the dependent variable). It is more mixed for wind power. The same test rejects the hypothesis that all panels have unit root at 2 and 3 lags. The data for solar power do not reject the hypothesis that all panels have a unit root at various lags. Further tests showed the error terms were generally stationary when including 1 to 2 lags, indicating some autocorrelation.

4.5 Results

Having completed the preliminaries, this sub-section presents the various regression results for

Equation 5.

All regressions are conducted using the fixed effect estimator (within) to remove time-invariant factors, with clustered errors by country. Major fossil fuel exporters are excluded from the regressions so that the analysis captures the impact renewables have on fossil fuel importers only.[10] Not including major fossil fuel exporters also avoids the need to deal with cases of zero fossil fuel imports, or, in some cases, exporters with large petrochemical industries where fossil fuel imports are not for domestic consumption but for industrial processing and re-export.

The paper presents the preliminary results (prefix A) with the most parsimonious set of regressors in Table 2. A1 documents the naïve regression results in which solar and wind power generation are used as explanatory variables for fossil fuel imports, together with energy intensity and domestic fossil fuel production, without using instrumental variables. The coefficients are insignificant, with solar returning an unexpected positive sign.

Regression A2 shows the results in which solar and wind power generation are instrumented using the IVs, as described. The coefficients for solar (-253) and wind (-358) are negative, with the latter being significant at the 10 percent level. Regression diagnostics are largely favorable: The overall regression is significant, and the LM statistic shows that the regression is identified, though the Wald statistic highlights that the instruments are potentially weak.

As mentioned, HICs and developing economies have different power generation mixes. In the latter group, fossil fuel-based power is still rising, and the share of renewables is relatively smaller. Regression A3 mimics regression A2 using only HIC samples, while regression A4 includes only samples from developing economies. All coefficients remain correctly signed, but only wind power is significant for HICs (-472) at 5 percent.

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[10] The definition of major fuel exporters is based on the UN World Economic Situation and Prospects report. A country is classified as a major fuel exporter if fuel exports (including oil, gas, and coal) are at least 20 percent of its total merchandise exports and 20 percent greater than its fuel imports. Major fuel exporters are Algeria, Angola, Azerbaijan, Bahrain, Bolivia, Brunei Darussalam, Cameroon, Chad, Colombia, Côte d'Ivoire, Ecuador, Egypt, Equatorial Guinea, Gabon, Indonesia, Iran, Iraq, Kazakhstan, Kuwait, Libya, Nigeria, Oman, Qatar, Republic of the Congo, Russia, Saudi Arabia, South Sudan, Trinidad and Tobago, Turkmenistan, United Arab Emirates, Uzbekistan, Venezuela, Viet Nam, and Yemen.

Table 4: Preliminary Regressions

	A1	A2	A3	A4
Solar Generation Per Capita	104.22	-252.62	-157.29	-425.91
	[170.14]	[168.37]	[215.12]	[490.46]
Wind Generation Per Capita	-35.36	-358.32*	-471.57**	-325.21
	[54.24]	[191.08]	[238.14]	[436.67]
Power Intensity of GDP	-492.04	-574.37	-4,917.58**	-252.15
	[344.00]	[374.39]	[2,274.41]	[199.67]
GDP Per Capita	0.01***	0.02***	0.02**	0.02**
	[0.00]	[0.01]	[0.01]	[0.01]
Domestic Fossil Fuel Production Per Capita	-0.01	-0.03	-0.03	-0.01
	[0.02]	[0.02]	[0.02]	[0.01]
Constant	101.60			
	[70.43]			
Instruments	No	Yes	Yes	Yes
Observations	2,489	2,430	999	1,431
R-squared	0.09	-0.01	-0.04	0.03
Number of Countries	156	151	52 (HICs)	99 (Non-HICs)
Prob > F	0.000308	0.000156	0.000	0.230
Kleibergen-Paap LM		6.028	4.385	1.820
Kleibergen-Paap Wald F		3.050	4.031	20.49

Errors clustered by countries in brackets *** p<0.01, ** p<0.05, * p<0.1

Table 5 presents the same set of regressions (prefix B) but also includes the global fossil fuel trade index. This index is created with the year 2000, the first year of the dataset, as the base year (=100). This index then tracks annual data on global fuel imports with respect to the base year. The inclusion of this index thus absorbs annual market conditions shaped by global macroeconomic factors and specific shocks, such as a sharp drop in fuel imports during the Great Recession in 2009 and the outbreak of COVID in 2020. This variable effectively serves as the time fixed effect to capture yearly changes in global import trends.[11] Given that this index absorbs global market variations, its inclusion improves regression R^2 significantly.

Again, the relevant coefficients are negative. For all country samples in B2, solar (-317) and wind (-294) are significant at 1 percent and 10 percent, respectively. The LM statistic indicates that regression is identified, though instruments remain weak. For the subgroup regressions, wind power (-285) is significant at the 10 percent level for HICs. Coefficients for developing economies in B4 have the correct sign and are larger than the USD300 range in regression B2, but are insignificant.

[11] The regressions are conducted on level terms. Given large country heterogeneity in import dependence between large and small importers, simple year dummies would result in averaging across varying economies into common year effects. A common level term time fixed effect thus weakens the regressions' explanatory power considerably. Instead, the use of a global index here captures year-to-year changes in the global market and, when used as a regressor, absorbs changes in imports from year to year that reflect global market trends. It is essentially year fixed effects, but in an index sense.

Table 5: Regressions (with Control on Global Fossil Fuel Use)

	B1	B2	B3	B4
Solar Generation Per Capita	82.60	-317.25***	-143.60	-368.24
	[153.16]	[118.74]	[152.10]	[398.84]
Wind Generation Per Capita	-29.43	-294.46*	-284.60*	-330.89
	[45.30]	[160.84]	[159.20]	[354.13]
Power Intensity of GDP	330.34	236.83	-58.33	-197.16
	[274.18]	[283.53]	[1,986.69]	[190.89]
GDP Per Capita	0.01*	0.01**	0.00	0.01*
	[0.00]	[0.01]	[0.01]	[0.01]
Domestic Fossil Fuel Production Per Capita	-0.01	-0.03*	-0.04**	-0.01
	[0.01]	[0.02]	[0.01]	[0.01]
Global Fossil Fuel Production Index	0.75***	0.73***	1.83***	0.10***
	[0.14]	[0.15]	[0.34]	[0.03]
Constant	-85.76			
	[74.10]			
Instruments	No	Yes	Yes	Yes
Observations	2,489	2,430	999	1,431
R-squared	0.21	0.12	0.31	0.08
Number of Countries	156	151	52 (HICs)	99 (Non-HICs)
Prob > F	0.000	0.000	0.000	0.00220
Kleibergen-Paap LM		6.025	4.394	1.837
Kleibergen-Paap Wald F		3.041	4.042	19.54

Errors clustered by countries in brackets *** p<0.01, ** p<0.05, * p<0.1

The set of regressions (prefix C) includes hydropower generation, still the largest source of renewable power globally. Given the supply function, it is straightforward to include other sources of renewable power generation, and the inclusion of hydropower addresses potential omitted variable bias.

Table 6 shows that the coefficients are largely unchanged. Solar (-316) and wind (-305) power are significant at 1 percent and 10 percent, respectively, for all country samples. Breaking down further into country subgroups, coefficients are correctly signed but only significant for wind (-294) at 10 percent for HICs. The coefficients for developing economies (C4) are again slightly larger than USD300 but remain insignificant.

Hydropower does not appear to have a significant effect in reducing fossil fuel imports over the sample period. As mentioned, hydropower growth has been relatively modest over the past two decades compared to that of solar and wind power. Furthermore, hydropower is developed by relatively fewer economies (resulting in fewer sample points). This explains the lack of significance for the coefficients.

Table 6: Regressions (with Control on Global Fossil Fuel Use and Hydropower)

	C1	C2	C3	C4
Solar Generation Per Capita	82.60	-315.72***	-136.01	-335.41
	[153.16]	[121.35]	[159.85]	[393.03]
Wind Generation Per Capita Power Intensity	-29.43	-305.37*	-293.99*	-346.35
	[45.30]	[166.75]	[167.27]	[360.67]
of GDP	330.34	267.43	-22.73	-212.95
	[274.18]	[290.02]	[2,013.76]	[206.09]
GDP Per Capita	0.01*	0.01**	0.00	0.01*
	[0.00]	[0.01]	[0.01]	[0.01]
Domestic Fossil Fuel Production Per Capita	-0.01	-0.03*	-0.04**	-0.01
	[0.01]	[0.02]	[0.01]	[0.01]
Global Fossil Fuel Production Index	0.75***	0.74***	1.83***	0.10***
	[0.14]	[0.15]	[0.35]	[0.03]
Renewable Hydro Generation Per Capita		-17.51	-10.48	7.66
		[13.25]	[16.42]	[7.50]
Constant	-85.76			
	[74.10]			
Instruments	No	Yes	Yes	Yes
Observations	2,489	2,430	999	1,431
R-squared	0.21	0.12	0.31	0.09
Number of Countries	156	151	52 (HICs)	99 (Non-HICs)
Prob > F	0.000	0.000	0.000	0.00233
Kleibergen-Paap LM		6.181	4.197	1.848
Kleibergen-Paap Wald F		3.112	3.824	19.09

Errors clustered by countries in brackets *** p<0.01, ** p<0.05, * p<0.1

In general, partitioning the regressions into subgroups to account for heterogeneity also reduces the strength of the instruments across the board (sample points are reduced for each subgroup). In this context, it should also be noted that subgroup regressions for HICs (A3, B3, and C3) tend to show that instruments are sufficiently strong, whereas subgroup regressions for developing economies (A4, B4, and C4) point to weaker instruments. This can be explained by the fact that the correlation between renewable potentials and the actual deployment of renewable power investments is more uneven in developing economies, as the data show.

4.6 Discussion

The paper first contextualizes and compares the regression estimates against observed electricity prices at the retail level. Here, the World Bank provides a survey of electricity prices across many developed and developing economies [Foster and White (2020)]. There is substantial variation due to factors, including geography, resource availability, and tax and subsidy policies. The average electricity price stands at USD150 per megawatt hour for large fossil fuel exporters (which are not included in the regression estimates), around USD230 for HICs, and around

USD150-160 for middle- and low-income countries. Some of the highest tariffs in the world are found in small island developing states, averaging USD260 per megawatt hour due to a reliance on small-scale oil-fired power generation and high transport costs.

Based on the coefficients for solar and wind power across A2, B2, and C2, a megawatt hour of solar and wind power reduces fossil imports by around USD310. The fossil fuel import savings in these regressions appear to be on the high side–i.e., the average import savings per megawatt hour of power generated by renewables is higher than the retail price. This can be reconciled by a few factors.

First, fossil fuel subsidies are substantial, amounting to USD1.3 trillion in explicit subsidies per year and up to USD7 trillion if implicit subsidies are included [Black et al. (2023)]. [12] Many economies thus do not fully recover power costs through retail prices. The higher estimates in this paper may thus reflect the true "shadow" cost of fossil fuel-based power for importers, rather than the observed retail price.

Second, it is likely that the oldest and least efficient fossil fuel-based power plants have been replaced with the rollout of renewable generation. It is also important to note that among fossil fuels, oil-based generation is relatively small compared to coal and gas, but remains widely used, especially in smaller developing countries. To the extent that renewables can replace some oil-fired plants, there would be a reduction in oil import dependency.

There are also other second-order reasons that could explain the high estimates. The rise of renewable generation reduces the need for costly fossil fuel transport. Renewables also facilitate the switch to more efficient electricity-powered transportation. These contribute to a reduction in fossil fuel imports.

The regressions by country subgroups yielded less conclusive results. An issue with such partitioning is that the sample sizes for each subgroup become considerably smaller, leading to inefficient IV estimates. The coefficients for subgroup regressions continue to have the correct negative sign, thereby providing some comfort. The results are strongest for HICs (and wind power).

For developing economies, the results are more mixed. Economically, the reduction in fossil fuel use seen in HICs may simply be the result of "carbon leakage," in which high-emission production is simply shifted to some developing economies. Again, the fact that the coefficients for developing economies are also negative (albeit less significant) is reassuring.

Globally, power generation from solar and wind amounted to around 3.38 billion megawatt hours in 2022 (Table 1). Taking these figures with the estimate of USD310 reduction per megawatt hour, the paper estimates that slightly more than USD1 trillion in fossil fuel imports have been removed from the global market.

A more conservative estimate would consider only subgroup coefficients. Here, only wind power is significant for HICs, and a megawatt hour of wind power reduces imports by around USD290.

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[12] Explicit subsidies are expected to be reduced to less than USD1 trillion, still substantial, with the withdrawal of various fiscal support measures to cope with price shocks in 2022.

With wind power generation of 1.05 billion megawatt hours for this subgroup (Table 1), this implies that around USD300 billion in imports have been removed from the market.

These figures highlight the promise of renewables in reducing dependence on fossil fuel imports. Nevertheless, it should be seen against the backdrop of an enduring large global market for fossil fuels, with USD8.6 trillion in production in 2022 and around USD2.9 trillion in total imports.

Even as renewable energy investments and generation increase, fossil fuel use in developing economies continues to rise to meet growing economic needs. Some commentators have highlighted that the rise of renewable power has amounted to an “energy addition” rather than “energy transition” [York and Bell (2019); Yergin, Orszag and Arya (2025)]. Breaking the patterns of fossil use and trade would require significantly more scaling up of renewable and related investments.

5. Conclusions

There has been surprisingly little evidence on how renewables have shaped the global fossil fuel trade. This paper provides a stylized power sector supply model in which power produced from fossil fuels and various renewable sources are additive but imperfect substitutes, nested within a general equilibrium aggregate production function.

Renewable power sources face diminishing returns, while the constant returns to scale fossil fuel power sector produces to meet remaining demand. The paper argues that the chosen functional form aligns with industry realities. It also provides a tractable demand function for fossil fuel imports that simplifies empirical work.

Using a longitudinal dataset and novel IVs, the paper finds that increases in renewable power have reduced global fossil fuel imports. Using the all-country estimated coefficient of USD310 per megawatt hour, the paper suggests that around USD1 trillion worth of fossil fuel imports have been removed from the global market due to solar and wind power generation. Even if USD310 appears on the high side (relative to average retail prices) and one applies a discount to it, the impact on global fossil fuel trade will still be substantial. With the most conservative assumption, which includes only HICs and considers only wind power, the paper suggests that around USD300 billion in fossil fuel imports have been removed.

While these estimates point to the positive impact of renewables in reducing fossil fuel dependency, it is worth reemphasizing that fossil fuel-based generation remains dominant at present, especially in developing economies. The paper also points to the tension that, while a more productive fossil fuel sector reduces fossil fuel use for power generation, it can potentially result in lower renewable investments by lowering the equilibrium price of power and reducing the marginal substitution impact of renewable power generation on fossil fuel use.

Globally, fossil fuel production and trade remain several times larger than the reduction estimates provided in this paper. Renewable power must be scaled up many times to replace fossil fuels and to meet rising power demand. The paper nevertheless presents a clear motivation for policymakers to accelerate this transition. Countries with large fossil fuel exports will also need to prepare for further export reductions.

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Appendix 1: Renewable Energy Potentials

Table 7: Top 10 Countries for Solar Potential

Top 10 Countries with Highest Total Solar PV Potential	Top 10 Countries with Highest Solar PV Potential Per Capita
Russia	Namibia
Australia	Mongolia
Brazil	Australia
USA	Libya
China	Suriname
Canada	Mauritania
India	Botswana
Algeria	Guyana
Argentina	Canada
Saudi Arabia	Central African Republic

Table 8: Top 10 Countries for Wind Potential

Top 10 Countries with Highest Total Wind Power Potential	Top 10 Countries with Highest Wind Power Potential Per Capita
Russia	Mongolia
Canada	Libya
USA	Mauritania
China	Canada
Australia	Australia
Argentina	Namibia
Kazakhstan	Kazakhstan
Algeria	New Zealand
Brazil	Norway
Libya	Botswana

Appendix 2: Alternative IVs

First, time invariant gross renewable power (shares) potentials (for solar and for wind separately) are computed for each country as in the main paper. Second, the CAGRs of global solar and wind power generation are computed. Based on the data, solar and wind generation registered a CAGR of 40 and 21 percent per annum, respectively, between 2000 and 2022. Third, the renewable potentials of countries for solar and wind are separately scaled across time-based global trajectories anchored to their respective CAGRs (rather than actual year-to-year data in the main IVs). Finally, country IVs are normalized by population, as per the main paper.

The key idea is as follows. As CAGRs are effectively averaged growth rates, the resulting country IVs follow long-term growth trends but otherwise do not capture the year-to-year changes in global renewable generation. This delinks the resulting country-year IVs from year-to-year changes in global renewable generation. Naturally, this also delinks the IVs from year-to-year changes in fossil fuel use. The results of regressions using alternative IVs are presented in T with prefix D.

Table 9: Regressions (with Control on Global Fossil Fuel Use and Hydropower)– Alternative IVs

	D1	D2	D3	D4
Solar Generation Per Capita	82.60	-169.32	-160.94**	-2,307.23
	[153.16]	[160.87]	[64.93]	[7,923.25]
Wind Generation Per Capita	-29.43	-409.42**	-425.20***	1,162.61
	[45.30]	[199.70]	[113.46]	[3,837.04]
Power Intensity of GDP	330.34	287.87	-263.97	-378.04
	[274.18]	[291.08]	[2,135.57]	[599.41]
GDP Per Capita	0.01*	0.01**	0.01	0.00
	[0.00]	[0.01]	[0.01]	[0.01]
Domestic Fossil Fuel Production Per Capita	-0.01	-0.03*	-0.04**	-0.01
	[0.01]	[0.02]	[0.02]	[0.03]
Global Fossil Fuel Production Index	0.75***	0.74***	1.83***	0.11***
	[0.14]	[0.15]	[0.35]	[0.04]
Renewable Hydro Generation Per Capita		-23.50	-21.12	6.71
		[15.28]	[17.49]	[9.86]
Constant	-85.76			
	[74.10]			
Instruments	No	Yes	Yes	Yes
Observations	2,489	2,430	999	1,431
R-squared	0.21	0.09	0.25	-0.82
Number of Countries	156	151	52 (HICs)	99 (Non-HICs)
Prob > F	0.000	0.000	0.000	0.00201
Kleibergen-Paap LM		2.682	3.252	0.150
Kleibergen-Paap Wald F		1.422	18.31	0.0601

Errors clustered by countries in brackets *** p<0.01, ** p<0.05, * p<0.1

Compared to OLS in D1, the regression D2 with instruments returns the correct signs (with significance for wind at 5 percent). The subgroup regression for HICs returns negative and significant coefficients for solar (-161) and wind (-425). However, the use of alternative IVs based on CAGRs also results in weaker instruments, as evidenced by the lower LM statistic compared to regression C3. This is expected because the alternative IVs by construct do not capture year-to-year changes in renewable generation; thus, there is a loss of information relative to the main IVs.

Regression D4 (for developing economies) produces non-plausible coefficients because the alternative IVs are very weak, as indicated by the near-zero LM statistic, which suggests little correlation between the alternative IVs and regressors. The rollout of renewable power in developing economies, already more uneven than in HICs, is insufficiently instrumented by the CAGR-based alternative IVs.

Table 10 presents regressions for fossil fuel imports (the dependent variable) against the main IVs (E1) and the alternative IVs (E2). The coefficients show that the main IVs have little direct explanatory power on the dependent variable. The R2 is essentially zero, and the F statistic further confirms the lack of explanatory power of the model. This provides evidence that the IVs satisfy the exclusion requirement. Similarly, the alternative IVs also hold little explanatory power (the coefficients are near zero, as expected).

Table 10: Regressions of Fossil Fuel Imports Against IVs

	E1	E2
Solar Generation IV Wind	-0.036	
	[0.420]	
Generation IV	0.030	
	[0.190]	
Solar Generation (alternative IV)		-0.000
		[0.000]
Wind Generation (alternative IV)		-0.000
		[0.000]
Constant	229.875***	231.240***
	[1.103]	[1.136]
Observations	3,586	3,586
R-squared	0.000	0.000
Number of Countries	186	186
Prob > F	0.973	0.614
Corr (Xb, u)	-0.00541	0.00253