Mitigating Load Shedding in South Africa: The Role of Intermittent Renewable Energies

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Abstract: Developing countries often have to ration electricity when demand exceeds supply. This empirical study determines to what extent electricity from renewable resources mitigates load shedding in South Africa. This effect is easily underestimated if demand is unobserved, and because of the positive relationship of demand and solar electricity – both of which peak during daytime. To address these endogeneity problems, we employ an instrumental variables approach, yielding more accurate cost-benefit analyses for renewable energy investments. Our results also show that every additional MWh of wind power reduces the extent of load shedding reliably by up to 0.74 MWh. However, wind power alone typically does not bridge the entire gap between supply and demand. This gap may be closed by an additional supply of solar electricity, reducing the probability of load shedding events at critical periods of the day despite being out-of-sync with demand at other times.

Keywords: Load shedding; renewable electricity; South Africa

JEL Classification: L94, O13, Q41

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1 Introduction

Load shedding refers to the practice of disconnecting parts of the power grid at specific times and in specific regions when electricity demand exceeds the available capacity for electricity supply. This form of demand rationing protects the electricity system from an undersupply of electricity, with the potential consequence of cascading brownouts, up to a total blackout. In South Africa, it could take up to two weeks to restore full power supply after a blackout.[1] But also in the USA and Canada, cascading outages affected nine US states and most of Ontario for more than a week in 2003 following the unplanned shutdown of a mid-sized power plant (Borenstein et al., 2023).

While those events are the exception in OECD countries, they are prevalent in regions such as Sub-Saharan Africa, India, Pakistan, and China (Fried and Lagakos, 2023), often resulting in disastrous consequences across multiple dimensions. Load shedding not only disrupts industrial production, education, and households, but also interferes with the provision of essential services such as payment systems, telecommunications, and traffic lights, while also causing food safety issues as there are risks to the cold chain. The South African Research Bank (SARB, 2022) reports that load shedding increased from less than 10% of the time in 2015 to more than 33% of the time in 2022, translating to approximately 3 to 10 calendar days per month.

The South African Government (2023) hopes that the deployment of decentralized renewable energies, primarily wind and solar power, will help alleviate load shedding and simultaneously decarbonize electricity supply. Our study aims to quantify these effects, answering two primary research questions: (i) To what extent does electricity from decentralized and intermittent renewable resources reduce load shedding in South Africa? (ii) Which source, wind or solar power, is more effective in reducing load shedding?

An empirical investigation of these questions is relevant because theory does not predict an unequivocal effect of electricity from renewable resources on load shedding. Load shedding would even be exacerbated if wind and solar energy were mostly available when demand is low, and missing when demand is high (the so-called duck curve problem; Schmalensee, 2022; Elliott, 2024). Evidence suggests, indeed, an increase in both the supply of electricity from renewable resources and the increase in load shedding events in recent years in South Africa. Yet, this correlation is hardly causal because much of the increase in load shedding may be attributed to

[1] Eskom (2024). "What is load shedding?" `https://bit.ly/3RGJK6X` (accessed on 19 January 2024).

an aging fleet of coal-fired power plants, which causes increasing outages, higher maintenance requirements, and a decrease in the electricity generation capacity from conventional resources. Our main regression controls for these effects.

The impact of electricity from renewable resources on load shedding is still likely underestimated because we can only observe the equilibrium quantity of electricity in the market (load), while electricity demand remains unobserved. If now, over the course of a day, the supply of renewable electricity increases while demand also rises, the probability of a load shedding event and the extent of load shedding may increase, even despite the greater electricity supply. Under such circumstances, the effect of renewable electricity on load shedding would be underestimated, unless one tackles the simultaneity problem caused by the omitted variable demand. Moreover, demand is endogenous because electricity users may shift their consumption patterns in response to their expectations about electricity supply and load shedding.

There is, indeed, a correlation between demand and electricity from renewables. Daytime demand exceeds nighttime demand, which coincides with solar electricity, which is only available during daytime and zero at night. Electricity demand typically peaks in the evening, coinciding with higher wind electricity production as wind speeds tend to be highest during that time. To identify the true effect of renewable electricity on load shedding, we utilize an ex-post econometric model within an instrumental-variables framework. We employ wind speed and solar radiation measured at the locations of the renewable power stations as instruments for wind and solar electricity infeed. This allows us to separate exogenous changes in renewable electricity production and accurately assess the impact of additional renewable capacity on load shedding.

Our findings indicate that one additional MWh of wind electricity reduces load shedding by 0.29 MWh, while an additional MWh of solar electricity reduces load shedding by 0.66 MWh. Neglecting the simultaneity of changes in renewable electricity generation and demand would have led to an incorrect conclusion, according to which one additional MWh of wind electricity would have reduced load shedding by only 0.25 MWh, and merely 0.47 MWh for solar electricity. A naive OLS regression without control variables even suggests a positive impact of wind and solar electricity on load shedding.

We further examine the effect of electricity from renewable resources on both the probability of load shedding (the extensive margin) and the extent of load shedding (the intensive margin) for every hour of the day. Analyzing these intra-day patterns is insightful because wind power exhibits a relatively flat infeed profile throughout the day, with a moderate peak coinciding with the evening electricity demand peak. Solar power, on the other hand, is limited to daylight hours and also experiences significant intermittency, further reducing resource availability. While wind and solar power can help mitigate load shedding, their contribution is constrained by resource availability and its alignment with demand.

We find that wind power acts mainly as a baseload technology, generating a smaller effect on the probability of load shedding compared to solar power. However, when load shedding does occur, up to 74% of every additional MWh of wind power can be used to reduce its extent. Solar power has an even stronger effect on the extent of load shedding than wind power, particularly in the afternoon when solar electricity is still available while demand begins to rise. However, there is virtually no effect of solar power on load shedding around noon, when solar production is high but demand is only moderate.

Our findings demonstrate that investing in solar power is generally more effective in reducing load shedding. However, wind and solar power complement each other due to their disparate resource availability profiles. Additionally, the excess electricity generated by wind and solar power displaces coal-fired electricity from the merit order, leading to substantial CO_2 emissions abatement. Therefore, in addition to the economic value of mitigating load shedding, wind and solar power also offer significant environmental benefits.

These patterns have already had a significant qualitative impact on the ongoing policy discussion. It is our contribution to the field to quantify these effects based on a theory model of the South African electricity market, while adequately addressing the issue of endogeneity. That way, our results serve as inputs both for the policy discussion and for future research.

The paper is organized as follows: Section 2 provides a review of related literature and discusses the contributions of our analysis. Section 3 presents descriptive statistics on South Africa's electricity sector and explains the causes and consequences of load shedding. Section 4 presents our theoretical model, outlining how load shedding occurs in a market with regulated prices. We derive our regression equations from this model, as explained in Section 5. Our results are presented in Section 6. Policy implications are derived in Section 7. Section 9 concludes.

2 Literature Review and Contributions

This article contributes to the existing body of literature pertaining to the domain of electricity reliability. By quantifying the impact of renewable resource-derived electricity on load shedding, our findings enable us to draw policy conclusions regarding grid investments. Moreover, we gain insights into the environmental ramifications of transitioning towards sustainable energy sources. Our study is also relevant given the wider implications of electricity reliability on macroeconomic dynamics.

Electricity reliability – In their recent review, Borenstein et al. (2023, p. 183) identify electricity reliability as an important, yet underresearched topic, pointing out that electricity markets "are facing new challenges as they use less 'dispatchable' generation, like natural gas, coal, or nuclear, and more 'intermittent' sources that fluctuate exogenously, like wind and solar." Our study adds to this emerging literature by analyzing the contribution of intermittent renewables to electricity reliability in a transition economy. While this topic has received much attention in practice, our paper is one of the first academic studies in economics to analyze the effect of variable renewable energies on load shedding.

Our empirical study also builds on and contributes to earlier theoretical literature. For example, based on their model of retail competition (Joskow and Tirole, 2006), Joskow and Tirole (2007) provided a model of electricity reliability in oligopolistic markets. They derived optimal prices and investment decisions when oligopolistic power companies face one group of customers, whom they charge real-time prices depending on supply and demand conditions, and another group of customers, who pay a fixed price but may be rationed if demand exceeds supply. Different from those studies, prices are fixed in South Africa – and in our study.

Investment policy – Our results have implications for regulatory and industrial policy addressing investments in renewable electricity generation capacity, especially because "there is less agreement on the role of markets versus regulation. [... Investment decisions in this market are particularly challenging] due to the physics of grid stability, the high cost of storage, the shared network of transmission, the mix of for-profit companies with nonprofit or heavily regulated firms, and the critical role this product plays in the functioning of an economy" (Borenstein et al., 2023, p. 182).

Our results are important ingredients in calculating how much load shedding can be avoided when investing in renewable generation capacity. Those calculations indicate that the costs of avoiding demand rationing are considerably lower than the value of lost load, that is, the costs that would be incurred otherwise.

Environmental effects – In addition to these economic effects, there is a growing literature on the environmental benefits of renewable energies (e.g., Cullen, 2013; Fell et al., 2021; Fell and Kaffine, 2018; Gowrisankaran et al., 2016; Novan, 2015, to name some prominent examples). We contribute to this literature by determining the impact of wind and solar power on the reduction of greenhouse gases in South Africa, finding that investments into solar power, on average, help reduce greenhouse gases more efficiently than investments into wind power.

Macroeconomic effects – Our microeconomic analysis of the electricity market also contributes to the macroeconomic analysis of electricity reliability in developing countries. Macroeconomic data suggest a strong positive correlation between GDP per capita and electrification (Burke et al., 2018; Lee et al., 2020), so that a reduction in load shedding may have a positive effect on economic development. This is because, otherwise, power outages may cause idle resources, a depressed scale of incumbent firms, and reduced entry of new firms.

The long-run general-equilibrium effects of power outages may even be between three and five times larger than those short-run partial-equilibrium effects (Fried and Lagakos, 2023). Cole et al. (2018) find, using an instrumental-variables framework, that power outages in Sub-Saharan Africa deter economic activity by, on average, 2.1% of GDP. Andersen and Dalgaard (2013) estimate the effect of unplanned outages on GDP growth in a panel of countries in Sub-Saharan Africa over the period 1995–2007. Using lighting density as an instrument to account for endogeneity, they find that "an increase in outages by one standard deviation ([...] approximately 2.3 outages) instigates a reduction in growth of about 1.5 percentage points" (Andersen and Dalgaard, 2013, p. 21).

Regarding South Africa, an industry report by Hartley and Mills (2023) estimates that the economy is 8–10% smaller than it would be without rolling blackouts. Dinkelman (2011) finds that electrification significantly raises employment, especially for females, in rural South Africa. We contribute to this strand of literature by showing that renewable energies help avoid load shedding, so that they have economic benefits beyond emission abatement.

Load shedding is also relevant outside Sub-Saharan Africa. Allcott et al. (2016), using an instrumental-variables framework, estimate that electricity shortages reduce the average Indian manufacturing plant's revenues and producer surplus by 5–10%. They also find that the shortages distort the plant size distribution because there are economies of scale in generator costs. Chakravorty et al. (2014) find that grid connection and higher-quality electricity supply (hours of daily supply) significantly increase rural household incomes in India.

Timilsina and Steinbuks (2021) infer that the economic costs of load shedding in Nepal during 2007–2017 were enormous: Power outages of 14 hours per day in 2016 resulted in a severe welfare loss (6% of its GDP annually), posed a major barrier to economic development, impeded poverty reduction progress and hindered investments and, thus, industrial output. Planned outages also occur in China. Fisher-Vanden et al. (2015) analyze data for 23,000 energy-intensive, Chinese firms from 1999 to 2004, finding that companies respond to electricity scarcity by substituting materials for energy. They also outsource production to regions with more reliable electricity instead of investing into self generation of electricity.

3 Data on the Electricity Sector in South Africa

The South African electricity market is dominated by the vertically integrated, state owned power utility Eskom that owns and operates the country's entire conventional electricity supply capacity. Eskom generates approximately 95 percent of electricity used in South Africa and, thus, holds a near-monopoly position in electricity generation. In the retail market, Eskom has a market share of about 45%, while the remaining consumers are mostly supplied by their municipalities that, again, receive the electricity from Eskom.[2] Electricity prices are regulated by the *National Energy Regulator of South Africa* (NERSA). Considering social aspects, many municipalities use inclining block tariffs, where the price per kWh rises with a household's monthly electricity consumption.[3]

In recent years, the South African government has been striving for the deployment of renewable energy via the Renewable Independent Power Producer Programme (REIPPP; South African Government, 2024), which facilitates contracts (so-called "power purchase agreements") between Eskom and decentralized independent power producers. Eskom is also pursuing the replacement of decommissioned coal-fired power plants with renewable energy sources, supported in part by

[2]International Trade Administration (26 January 2024). "South Africa – Country Commercial Guide – Energy." https://www.trade.gov/country-commercial-guides/south-africa-energy (accessed on 16 August 2023)

[3]nersa.org.za. "Approved municipal electricity tariffs 2022/23." https://www.nersa.org.za/wp-content/uploads/bsk-pdf-manager/2022/10/Approved-Municipal-Electricity-Tariffs-2022-23.pdf (accessed on 8 February 2024).

the World Bank.[4]

Our study uses data on electricity supply and load shedding provided by Eskom. The data are country aggregates in hourly resolution, covering the time period from April 1, 2018, to January 31, 2023. Summary statistics are provided in Table 1. This data indicates that the South African electricity sector exhibits three distinctive trends, as depicted in Figure 1. Firstly, there has been a steady rise in load shedding (interruption of supply, IOS), which experienced a notable surge in 2022. Secondly, this trend can be attributed, in part, to a decrease in the supply of electricity as aging conventional power plants are decommissioned. Lastly, there is a noticeable increase in electricity generation from renewable sources. These trends align with the historical account of the sector's development as outlined, for example, in Walsh et al. (2020).

Table 1: Sample statistics

Variable	Obs.	Mean	S.D.	Min.	Max.
Dependent variables: load shedding					
Interruption of supply, IOS (MWh)	42,408	364.82	888.21	0.00	8736.94
Variables of interest					
Wind electricity infeed (MWh)	42,408	875.10	473.28	15.66	3,028.06
Solar electricity infeed (MWh)	42,408	478.43	606.42	0.00	2,099.49
Control variables					
Coal electricity (MWh)	42,408	21,400.42	2,256.09	13,774.00	30,136.00
Hydropower electricity (MWh)	42,408	174.62	228.81	0.00	610.00
Nuclear electricity (MWh)	42,408	1,311.57	444.29	90.00	1,854.00
Pumped-storage electricity (MWh)	42,408	549.88	630.31	0.00	2,746.00
Instrumental variables					
Solar radiation (W/m^2)	42,408	731.60	955.93	0.00	3,380.28
Wind speed (m/s)	42,408	5.83	1.83	1.42	15.27

Notes: Sample period: April 1, 2018, h1 – January 31, 2023, h24.

Figure 1 illustrates that both the prevalence of IOS and its magnitude have increased over the sample period (solid black line). To provide additional information, load shedding accounts for the predominant share of IOS, which includes all contracted and mandatory demand reductions utilized by Eskom, as well as interruption of supply due to transmission network faults (4.4% of IOS). The contracted demand reductions (interruptible load shed, ILS) account for 1.6% of IOS. Those reductions are based on agreements of Eskom with large industrial customers whose demand can be contractually interrupted without notice or reduced by remote control or on instruction from Eskom. The predominant share of IOS (94%) falls on manual load reduction (MLR), which is the demand reduced due to load shedding and/or curtailment.[5]

[4] worldbank.org (5 June 2023). "Factsheet: Eskom Just Energy Transition Project in South Africa." `https://bit.ly/3Ssganl` (accessed on 24 January 2024).

[5] Walsh et al. (2020, p. 16) validate Eskom's approach for measuring load shedding. They contrast it with own bottom-up calculations using data on curtailment by Eskom's top customers and data on monthly electricity sales and the incidence and duration of load shedding. Their own estimates and the load shedding calculations

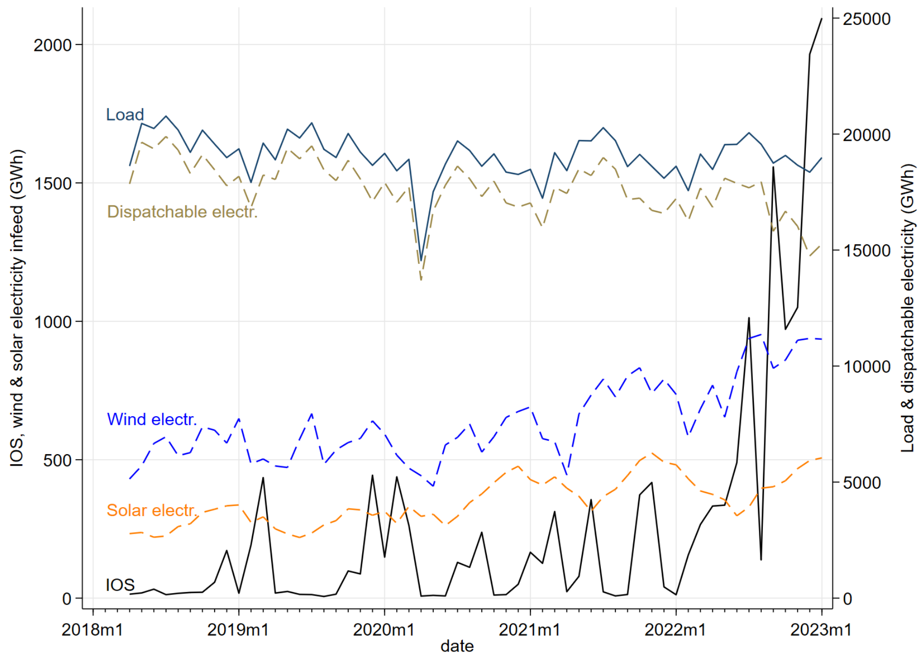


Figure 1: Developments of key variables

Notes: The figure shows developments of interruption of supply (IOS), wind and solar electricity (left y-axis), and dispatchable generation and load (right y-axis). Monthly frequency.

The supply of electricity from wind and solar have also risen over the study period (see the dashed blue and orange lines in Figure 1). While, in 2013, renewable energy contributed merely 0.5% of total electricity production in South Africa, its share rose to 6.1% in 2021. One, thus, observes a positive relationship between load shedding and electricity from renewables. These observations motivate our first research question: To what extent does electricity from decentralized and intermittent renewable resources reduce load shedding in South Africa?

The quantitative effect of wind and solar electricity on load shedding can hardly be derived from theory alone because the generation of electricity from wind hinges upon wind conditions, while the generation of solar electricity relies on solar radiation. Both wind speed and solar radiation are exogenous factors that do not always align with demand patterns. Consequently, these characteristics may impose difficulties on grid stability, as renewable energy may not be available during peak demand periods. Moreover, there are instances where the surplus electricity generated from renewables exceeds demand, further exacerbating the challenge.

These considerations, however, are paralleled by a further factor contributing to the increase in load shedding. This factor is the reduction in the supply of dispatchable electricity (dashed

provided by Eskom resemble each other closely.

brown line in Figure 1). It sums up electricity from all sources other than wind and solar, and consists of 89% coal-fired electricity. The decline in dispatchable energy is mostly due to old coal plants reaching the end of their lifetime without being replaced.

One prominent factor contributing to this issue is the financial predicament of Eskom, which has struggled to generate sufficient revenue to cover costs and service its debt obligations, thus relying on state bailouts for its sustenance.[6] This predicament is not uncommon among electricity providers in developing countries (Fried and Lagakos, 2023). To address this challenge, the South African government introduced a debt relief plan for Eskom in 2023.[7] Additionally, Eskom's aging fleet of conventional power plants has resulted in lower electricity generation in 2021 compared to 2004.[8]

Our second research question asks: Is wind or solar power more effective in reducing load shedding? This question has several elements. Wind and solar power may have an effect on the *extent of load shedding.* That is, one MWh of electricity may reduce load shedding by this amount. But this supply may not suffice to avoid load shedding altogether. Therefore, we also study how wind and solar electricity affect the *probability of load shedding* events. We study the differences between wind and solar power on the extent and probability of load shedding, performing this analysis for the different hours of a day.

The relevance of this endeavor can be seen particularly well from Figure 2 that presents the average of electricity load for every hour of a day. By averaging out differences between weekdays and different seasons this graph is informative about overall patterns. One sees that demand peaks in the morning around 8 am and, even more so, in the evening at about 7 or 8 pm. A similar pattern has been reported for other countries, with Australia being just one example (Elliott, 2024, Figure 2).

The generation of dispatchable electricity does not always suffice to supply demand, so that load shedding (IOS, black solid line) is especially pronounced during the evening peak. Electricity from wind (blue dashed line) is particularly suited to mitigate load shedding during this time because wind speed also peaks in the evening. However, electricity from wind is also generated at night, when demand is low. Solar electricity (orange dashed line) reflects this

[6]businesstech.co.za (29 June 2023). "Silver lining in Eskom debt relief plan: Moody's." https://bit.ly/3OgpwQr (accessed on 24 January 2024).

[7]reuters.com (1 November 2023). "South Africa amends Eskom debt relief, making loans interest-bearing." https://bit.ly/3vG4WCE (accessed on 24 January 2024).

[8]statssa.gov.za (3 November 2022). "The state of the electricity, gas & water supply industry (2021)." https://bit.ly/48K5DcV (accessed on 24 January 2024).

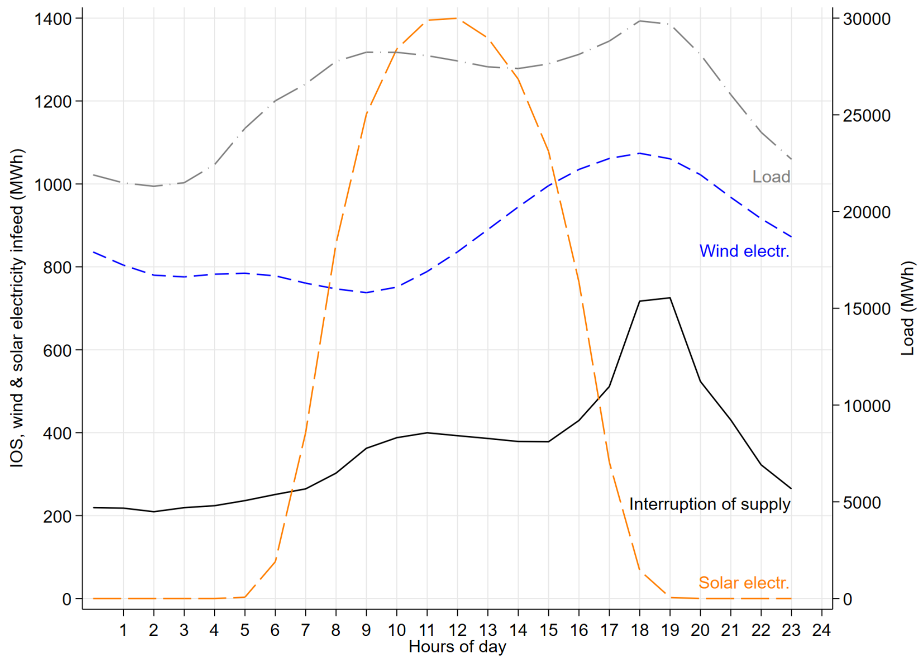


Figure 2: Infeed profiles and load by hour of day

Notes: The figure shows sample averages of interruption of supply (IOS), wind and solar electricity (left y-axis), and load (right y-axis).

day/night pattern better. Yet, only a medium amount of solar electricity is available when demand peaks in the morning, and it is unavailable when demand peaks in the evening. Solar electricity production is particularly high at noon, coinciding with only modest demand.

4 Theory

This section presents a theoretical model of electricity production (Subsection 4.1) that is used to derive our regression equations (Subsection 4.2).

4.1 Optimization problem

In most markets, the price rises if demand exceeds supply, and it falls if supply exceeds demand, until an equilibrium is attained. Yet, as the retail electricity price p in South Africa is regulated by Nersa, it cannot be used for equilibrating the market.[9] At every point in time t, Eskom rather chooses the quantities of electricity from wind W_t, solar S_t, nuclear N_t, coal K_t, hydropower H_t, and pumped storage R_t (= reservoir), to balance demand D_t and supply. If electricity gener-

[9]A similar setting also applies in other countries. Elliott (2024), for example, assumes that the Australian retail electricity price is constant in the short-run and determined by average prices in the electricity wholesale market.

ation from these sources cannot be extended to meet demand, demand rationing, that is, load shedding IOS_t (interruption of supply), is required.

We model the optimization problem of electricity production subject to the constraints of balancing supply and demand, and operating efficiently. To make this problem more manageable and consistent with the available data, we have made certain simplifications. These include considering aggregate quantities of electricity by source and overlooking the specific supply from individual plants. We have also not taken into account that wind and solar power often come from independent power producers with different profit objectives compared to Eskom. Rather than attempting to capture every detail of the South African electricity market, our model serves as a theoretical foundation for deriving the regression equations that form the basis of our analysis. By making these simplifications, we are able to focus on the key mechanisms that underpin our study.

Therefore, consider the following optimization problem with (in)equality constraints. The quantities of W_t, S_t, N_t, K_t, H_t, R_t, and load shedding IOS_t are chosen such as to maximize the profit π_t, subject to the constraints (2) and (3), where C_W, C_S, C_N, C_K, C_H, and C_R denote the total costs of the different sources of energy, and $W_{max}, \ldots, R_{max}$ the installed generation capacities, which are assumed to be exogenous.

$$\pi_t = p(W_t + S_t + N_t + K_t + H_t + R_t) - (C_W + C_S + C_N + C_K + C_H + C_R) \tag{1}$$

$$W_t \leq W_{max}, \ldots, R_t \leq R_{max} \tag{2}$$

$$D_t = W_t + S_t + N_t + K_t + H_t + R_t + IOS_t \tag{3}$$

The inequality constraints stated in (2) ensure that the amount of electricity produced from any source does not surpass its maximum generation capacity. The equality constraint presented in equation (3) enforces a balance between the electricity supply and demand at all times.

Let $E_t \in \{W_t, S_t, N_t, K_t, H_t, R_t\}$ be a variable indicating the different sources of electricity, so that the Lagrangian of the optimization problem can be written as follows:

$$L = \pi_t + \sum_E \lambda_E(E_{max} - E_t) + \lambda_{IOS}(D_t - IOS_t - \sum_E E_t) \tag{4}$$

The first order conditions of the Kuhn-Tucker Lagrangian with complementary slackness are given by (5) to (11), where we drop the index t for notational convenience.

$$\frac{\partial L}{\partial E} = p - \frac{\partial C_E}{\partial E} - \lambda_E - \lambda_{IOS} \leq 0 \tag{5}$$

$$E \cdot \frac{\partial L}{\partial E} = 0 \tag{6}$$

$$\frac{\partial L}{\partial \lambda_E} = E_{max} - E \geq 0 \tag{7}$$

$$\lambda_E \cdot \frac{\partial L}{\partial \lambda_E} = 0 \tag{8}$$

$$\frac{\partial L}{\partial IOS} = -\lambda_{IOS} \leq 0 \tag{9}$$

$$IOS \cdot \frac{\partial L}{\partial IOS} = 0 \tag{10}$$

$$\frac{\partial L}{\partial \lambda_{IOS}} = D - IOS - \sum_E E = 0 \tag{11}$$

If the marginal costs are rising in E ($\partial^2 C_E/\partial E^2 > 0$), the first order conditions (5) and (6) imply that electricity supply from a certain source is zero if its marginal costs are too high at $E = 0$, that is, $\partial C_E(E = 0)/\partial E \geq p - \lambda_E - \lambda_{IOS}$. If the marginal costs are below this threshold, the optimal supply of electricity from this source is positive and chosen such that (5) holds in equality. If the optimal electricity production is below the maximum capacity E_{max}, $\partial L/\partial \lambda_E$ from (7) is positive, and the shadow price of capacity is zero ($\lambda_E = 0$), as follows from (8). If the marginal costs $\partial C_E/\partial E$ are so small that optimal electricity production is at full capacity ($E = E_{max}$), condition (7) holds in equality. The shadow price of capacity is positive ($\lambda_E > 0$) such that (5) holds in equality, too.

Due to their (almost) zero marginal costs, solar, wind, and nuclear power should be generated at full capacity according to the first-order conditions. Conversely, electricity production from coal and pumped storage is expected to be demand-driven due to their higher marginal costs. In the case of South Africa, hydropower functions as a run-off river technology, operating at maximum capacity, but also incorporates aspects of a dam technology to generate electricity during peak demand periods. These patterns are supported by our data (see Appendix Figure **??**).

Condition (11) implies $IOS = D - \sum_E E$, so that load shedding occurs if demand exceeds supply. If $IOS > 0$, the shadow price λ_{IOS} of an increase in demand D is zero, as follows from (9) and (10). In this model, the cost of load shedding is merely the revenue foregone. A social planner would also consider additional economic effects such as the disruption of business activity, interruptions of the cold chain, or negative effects on medical treatment (Schmalensee, 2022). We will discuss aspects related to this value of lost load in Section 7. For the moment, we focus on using these relationships to derive our regression equations, as is shown next.

4.2 Regression equations

Equilibrium condition (3) can be re-written as in (12), where the indicator function I_t takes a value of one if demand exceeds supply, which implies $IOS_t > 0$, and zero otherwise. Also consider that the production of electricity from wind and solar is a function of wind speed ws_t and solar radiation sr_t.

$$IOS_t = I_t \cdot [D_t - \beta_{W,t} W(ws_t) - \beta_{S,t} S(sr_t) - \beta_{N,t} N_t - \beta_{K,t} K_t - \beta_{H,t} H_t - \beta_{R,t} R_t] \qquad (12)$$

$$I_t = \begin{cases} 1 & \text{if } D_t > \sum_E E_t \\ 0 & \text{otherwise} \end{cases} \qquad (13)$$

Theory predicts that the β-coefficients take a value of 1 if load shedding occurs ($I_t = 1$), and if one additional MWh of electricity reduces the extent of load shedding by exactly one MWh. In reality, however, one MWh of electricity in one part of the country may not necessarily help reduce load shedding in other parts of the country. There may also be lags, grid bottlenecks, or technical constraints that prevent sudden changes in supply when load shedding occurs. It may also be difficult calling off load shedding when supply goes up. Hence, the value of the β-coefficients cannot be determined from theory alone.

We estimate those coefficients for every hour h of the day using variation across the different days in our sample, so that equation (12) can be written as in (14).

$$IOS_t = \overline{I}_h \cdot [D_t - \beta_{W,h} W(ws_t) - \beta_{S,h} S(sr_t) - \beta_{N,h} N_t - \beta_{K,h} K_t - \beta_{H,h} H_t - \beta_{R,h} R_t] + u_t \quad (14)$$

Because load shedding occurs only at some days, the variable $\overline{I}_h$ measures the average frequency of load shedding events at this hour. The variable u_t stands for the error that one makes by averaging load shedding responses for a certain hour.

Quite importantly, demand D_t is unobserved in our sample. Let $D_t = \alpha + z_t$, where α measures average demand and z_t the deviation from this average at any particular point in time. Equation (14) can, therefore, be written as in (15), with $\epsilon_t = u_t + \overline{I}_h \cdot z_t$.

$$IOS_t = \overline{I}_h \cdot [\alpha - \beta_{W,h}W(ws_t) - \beta_{S,h}S(sr_t) - \beta_{N,h}N_t - \beta_{K,h}K_t - \beta_{H,h}H_t - \beta_{R,h}R_t] + \epsilon_t \quad (15)$$

A reduced-form regression equation, therefore, follows as is shown by (16), where $\delta_W = \overline{I}_h \cdot \beta_{W,h}$ and $\delta_S = \overline{I}_h \cdot \beta_{S,h}$.

$$IOS_t = \delta_W W_t + \delta_S S_t + X_t'\delta + \epsilon_t, \quad (16)$$

The variable X denotes a vector of control variables (different types of electricity supply) and fixed effects for the sample years, months of year, days of week, hours of day, and holidays. The coefficients δ_W and δ_S measure the aggregate effect of one additional MWh of wind or solar electricity on load shedding.

We, then, disaggregate this effect by decomposing equation (15) in two parts: We estimate the coefficients of a linear probability model (17) for all observations $t \in [1, T]$, which is the *probability of load shedding* (the extensive margin).

$$I_t = \gamma_{W,h}W(ws_t) + \gamma_{S,h}S(sr_t) + X_t'\gamma_h + \iota_t \quad (17)$$

We also estimate the coefficients of load shedding equation (18) conditional on $IOS_t > 0$. This equation measures the *extent of load shedding* (the intensive margin).

$$IOS_t = \beta_{W,h}W(ws_t) + \beta_{S,h}S(sr_t) + X_t'\beta_h + \sigma_t \quad (18)$$

This distinction is important because while adding one additional MWh of renewable electricity can help reduce the extent of load shedding by one MWh, it might not have a significant impact on the probability of a load shedding event occurring. This is especially true if the overall capacity is too low, meaning that adding more capacity may not entirely prevent a load shedding event, even if it mitigates the extent of load shedding. Due to demand being an omitted variable, identifying the β-, γ-, and δ-coefficients is not straightforward. Our approach to tackling this problem is presented in Section 5.

5 Instrumental Variables

Subsection 5.1 describes why an endogeneity problem may bias our results, and how we address this problem using an instrumental variables approach. The construction of the instruments is described in Subsection 5.2, with the identifying assumptions being evaluated in Subsection 5.3. Subsection 5.4 presents the results of the first-stage regressions.

5.1 Endogeneity

Our goal is to estimate the causal effect of variable renewable electricity infeed on load-shedding events in South Africa. Therefore, we estimate the coefficients of regression equations (16), (17), and (18), using heteroskedasticity and autocorrelation consistent (HAC) error terms. Theory indicates that demand should be included in these regressions as a control variable. However, since demand is unobserved, it causes an endogeneity problem.

More specifically, greater demand increases the need for load shedding and, thus, raises both the probability and the extent of load shedding. Greater demand will, however, also typically be matched by higher supply, which reduces load shedding. This results in a "bad control" problem (Angrist and Pischke, 2009). Given the negative correlation between electricity supply and load shedding, the positive correlation between load shedding and demand, and the positive correlation between demand and equilibrium supply, the β-, γ-, and δ-coefficients will be biased towards zero if one does not appropriately account for endogeneity.

To take care of this problem, we estimate a two-stage least squares (2SLS) model, using wind speed and solar radiation to instrument for wind and solar electricity production. Wind speed and solar radiation are measured for the exact locations of the renewable power stations, as described in more detail in Subsection 5.2. This allows for estimating unbiased and causal effects of wind and solar electricity on load shedding. The two first-stage regressions are:

$$W_t = \delta_{ws}^{1a} ws_t + \delta_{sr}^{1a} sr_t + X_t' \delta^{1a} + \epsilon_t^{1a} \tag{19a}$$

$$S_t = \delta_{ws}^{1b} ws_t + \delta_{sr}^{1b} sr_t + X_t' \delta^{1b} + \epsilon_t^{1b} \tag{19b}$$

Then, the second stage for our reduced form model (16) includes the predicted values of wind and solar electricity infeed, $\hat{W}_t$ and $\hat{s}_t$, respectively:

$$IOS_t = \delta_W^{2nd} \hat{W}_t + \delta_S^{2nd} \hat{S}_t + X_t' \delta^{2nd} + \epsilon_t^{2nd}. \tag{20}$$

The regression equation for the probability of load shedding (the extensive margin) is:

$$I_t = \gamma_W^{2nd}\hat{W}_t + \gamma_S^{2nd}\hat{S}_t + X_t'\gamma^{2nd} + \epsilon_t^{2nd}. \tag{21}$$

The regression equation for the extent of load shedding (the intensive margin) is:

$$IOS_t = \beta_W^{2nd}\hat{W}_t + \beta_S^{2nd}\hat{S}_t + X_t'\beta^{2nd} + \epsilon_t^{2nd} \text{ if } IOS_t > 0. \tag{22}$$

5.2 Instruments

Our dataset comprises 37 operational onshore wind parks and 42 PV or solar thermal installations in South Africa, which were identified using the Global Wind and Solar Power tracker from Global Energy Monitor.org. This tracker provided us with details such as capacities, commencement year of operations, and geographical coordinates for each facility. This information allowed us to precisely locate each installation and incorporate it into our analysis.[10]

Given that South Africa is divided into three distinct weather zones, we recognized the importance of accounting for the regional variations in weather conditions. To address this, we obtained simulated weather data specific to the exact locations of the wind and solar PV installations in our sample. To achieve this, we accessed wind and solar radiation data from ERA5, the European Centre for Medium-Range Weather Forecasts' fifth-generation atmospheric reanalysis of the global climate. ERA5 provides data with a resolution of 0.25° x 0.25° which ensures high accuracy and reliability in our analysis (Hersbach et al., 2020).

To calculate the average wind speed, we squared both the 100m u-component of wind and the 100m v-component of wind, summed these squared values, and then extracted the square root of this sum.[11] Additionally, we used the surface net solar radiation to determine solar radiation levels.

We aligned every wind or solar facility with the nearest grid point in the ERA5 dataset. This alignment was based on the installations' longitude and latitude. By doing so, we were able to accurately associate the weather data from ERA5 with each specific installation. Subsequently, we computed capacity-weighted hourly averages for both wind speed and solar radiation. Wind

[10] globalenergymonitor.org/projects/global-solar-power-tracker/tracker-map/ and globalenergymonitor.org/projects/global-wind-power-tracker/tracker-map/ (accessed on August 16, 2023)

[11] A detailed description of the variables can be found here: cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview (accessed on August 16, 2023)

speed metrics are presented in meters per second, while solar radiation is expressed in Watts per square meter.

5.3 Identifying assumptions

The instrumental variables method produces unbiased estimates, assuming that two assumptions are satisfied: (i) instrument relevance and (ii) the exclusion restriction, as are explored next.

Instrument relevance – This assumption requires wind speed and solar radiation to be sufficiently correlated with the endogenous variables (that is, wind and solar electricity infeed) to serve as valid instruments. This can be tested on empirical grounds. The first-stage regressions show indeed statistically significant partial coefficient estimates. Moreover, the Kleibergen-Paap first-stage F statistic is sufficiently high (i.e., 3,837), rejecting the null hypothesis of weak instruments.

Exclusion restriction – This assumption requires the instruments (wind speed and solar radiation) to impact the outcome variable (load shedding) only through the endogenous variables (wind and solar electricity infeed). Otherwise, the error term would be correlated with the endogenous variables, leading to estimation bias. The exclusion restriction cannot be tested empirically, but must be assessed by means of economic rationale. It is highly plausible that wind and solar electricity infeed are determined by wind speed and solar radiation, whereas the amount of load shedding is likely to be independent of wind speed and solar radiation.

There may be some concern regarding a potential relationship between solar radiation and electricity demand. For instance, some might posit that days characterized by intense solar radiation may coincide with heightened electricity demand, particularly for space cooling. However, several factors challenge this assumed correlation. Firstly, solar radiation is measured at the locations of solar power installations, which are usually situated in remote areas far away from demand centers. Secondly, these installations are often located in different climate zones compared to the large cities where electricity demand is high. Thirdly, there is no stable relationship between solar radiation and demand across the year. Even if high solar radiation led to higher electricity demand in summer, one would expect lower electricity demand for space heating in winter.

Figure 3 shows a scatter plot of solar radiation and load shedding, indicating no clear rela-

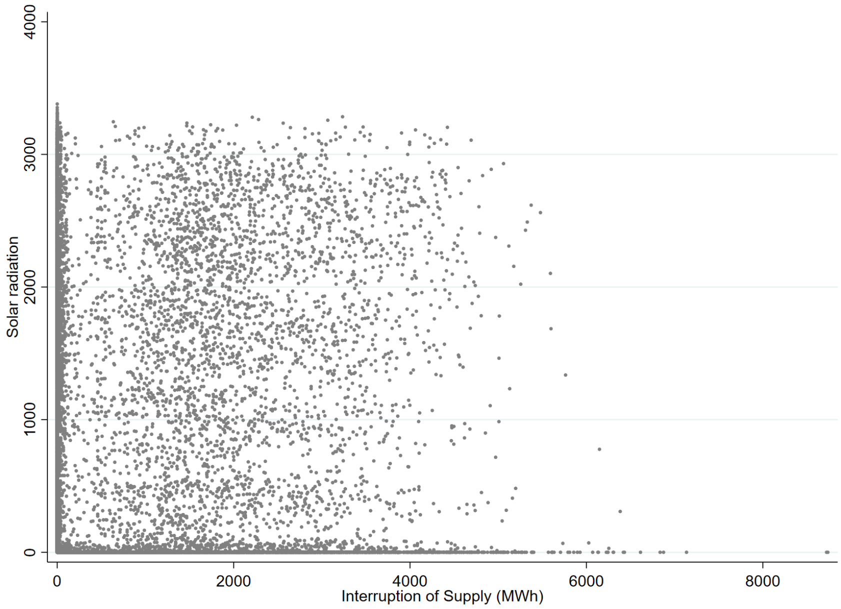


Figure 3: Scatter plot of solar radiation and load shedding

tionship between those two variables. This suggests that the exclusion restriction is satisfied, so that solar radiation can be treated as a suitable instrument for solar electricity infeed. Overall, the data and analysis provide evidence that there is no direct relationship between solar radiation and electricity demand. This supports the assumption that solar radiation can serve as a valid instrument in studying the effects of solar electricity infeed.

5.4 First-stage regression

The results of the first-stage regression are provided in Table 2. The instruments are strongly correlated with the endogenous variables.

Table 2: First-stage estimates

	(1) Wind electr.	(2) Solar electr.
Wind speed	197.2***	-1.287**
	(250.96)	(-2.82)
Solar radiation	-0.180***	0.293***
	(-45.70)	(89.64)
Coal electr.	-0.0198***	-0.0128***
	(-25.12)	(-22.44)
Hydro electr.	-0.0648***	0.0727***
	(-8.35)	(13.18)
Pumped-storage electr.	-0.0516***	-0.0699***
	(-19.36)	(-33.59)
Nuclear electr.	0.0473***	0.00231
	(16.20)	(1.10)
FE hours of day	yes	yes
FE days of week	yes	yes
FE months of year	yes	yes
FE years	yes	yes
Observations	42,408	42,408

*Notes: First stage estimates. Standard errors in parentheses are robust to heteroskedasticity and allow for first-order autocorrelation (HAC-robust Newey-West SE). *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$.*

6 Results

This section discusses how load shedding responds to wind and solar electricity infeed. Subsection 6.1 presents our main results and discusses special cases (e.g., daytime vs. nighttime), before we distinguish between the extensive margin (Subsection 6.2) and the intensive margin (Subsection 6.3).

6.1 Main results

Table 3 presents the main findings of our study. As hypothesized in Subsection 5.1, a naive OLS regression without any control variables, as presented in column (1), results in positive and statistically significant coefficient estimates on wind and solar electricity. This merely reflects the increasing trends of both load shedding and electricity from renewables. After controlling for the supply of other forms of electricity and, thus, for the decline in electricity from coal, the coefficients on wind and solar electricity turn out to be negative; see the OLS specification in column (2). However, those coefficients are still biased biased towards zero if one does not appropriately address endogeneity. This aspect is solved by our IV regression, as is presented in column (3). The absolute values of the coefficients on wind and solar electricity rise after controlling for endogeneity, and one finds that the bias had been particularly pronounced for

Table 3: Main regression estimates

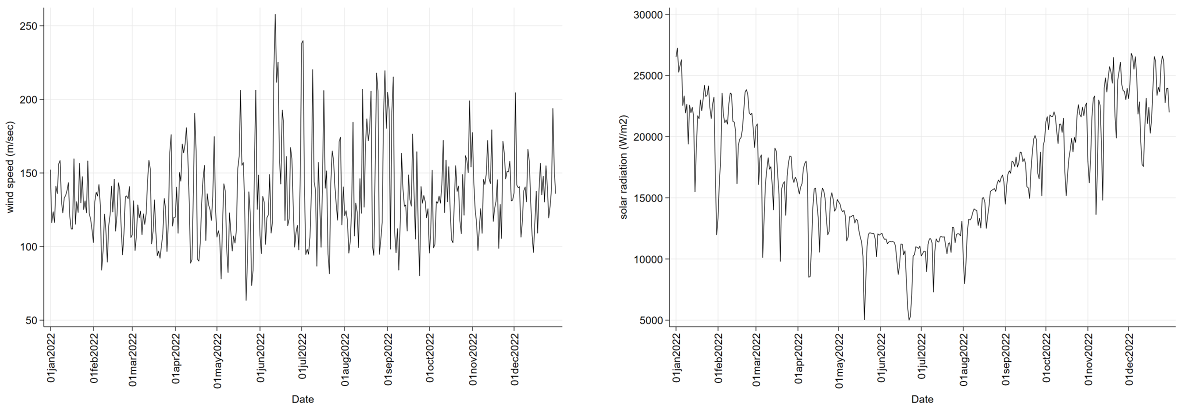
	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS h7–h17	(5) 2SLS h21–h4
Wind electr.	0.30736***	-0.25224***	-0.28920***	-0.31116***	-0.20391***
	(0.01498)	(0.01244)	(0.01280)	(0.01852)	(0.01616)
Solar electr.	0.09737***	-0.47126***	-0.66038***	-0.64449***	
	(0.01112)	(0.02695)	(0.05478)	(0.06748)	
Coal electr.		-0.18600***	-0.19137***	-0.20628***	-0.17492***
		(0.00438)	(0.00462)	(0.00673)	(0.00748)
Hydro electr.		-0.49988***	-0.49063***	-0.64151***	-0.39262***
		(0.03230)	(0.03256)	(0.05268)	(0.04844)
Pumped-storage electr.		-0.30375***	-0.32444***	-0.38421***	-0.55515***
		(0.01237)	(0.01348)	(0.01724)	(0.05843)
Nuclear electr.		-0.20064***	-0.20099***	-0.24018***	-0.18858***
		(0.01292)	(0.01294)	(0.01914)	(0.01886)
FE holidays	no	yes	yes	yes	yes
FE hours of day	no	yes	yes	yes	yes
FE days of week	no	yes	yes	yes	yes
FE months of year	no	yes	yes	yes	yes
FE years	no	yes	yes	yes	yes
Observations	42,408	42,408	42,408	19,437	14,136
R-squared	0.031	0.4443	0.4427	0.4455	0.3868
K.P. first-stage F stat.			2,162	1,285	11,000
D.W.H. endog. test, p-val.			0.000	0.000	0.000
Elasticity of wind electr.	+0.74%	-0.61%	-0.69%	-0.75%	-0.49%
	+2.69 MWh	-2.21 MWh	-2.53 MWh	-2.72 MWh	-2.00 MWh
Elasticity of solar electr.	+0.13%	-0.62%	-0.87%	-0.85%	
	+0.47 MWh	-2.25 MWh	-3.16 MWh	-3.08 MWh	

*Notes: Dependent variable: interruption of supply (IOS) in MWh. Standard errors in parentheses are robust to heteroskedasticity and allow for first-order autocorrelation (HAC-robust Newey-West SE). *** p < 1%, ** p < 5%, * p < 10%. Column 3–5: instrumented for wind and solar electricity by wind speed and solar radiation. Sample period: 01apr2018,01h–07mar2023,24h. At the bottom of the table, we present the effects of a 1% partial change in wind or solar electricity infeed on IOS (in % and in MWh), ceteris paribus, evaluated at sample means. "K.P." ... Kleibergen-Paap, "D.W.H." ... Durbin-Wu-Hausman.*

the solar coefficient.

The reported statistics suggest that the IV approach is relevant and well executed. The Durbin-Wu-Hausman test for endogeneity (Davidson and MacKinnon, 1993) rejects the null hypothesis that the variables wind and solar electricity infeed are exogenous at a p-value of 0.000. Hence, wind and solar electricity infeed should be treated as endogenous. Moreover, the instruments are strongly correlated with the endogenous variable and are rejected to be weak, indicated by the high value of the Kleibergen-Paap first-stage F statistic.

To interpret our main results, the IV estimates (column (3) of Table 3) suggest that wind and solar electricity infeed decrease IOS. The coefficient on wind electricity is -0.29, so that an increase in wind electricity by one MWh reduces IOS by 0.29 MWh. The coefficient on



(a) Wind speed **(b) Solar radiation**

Figure 4: Resource availability

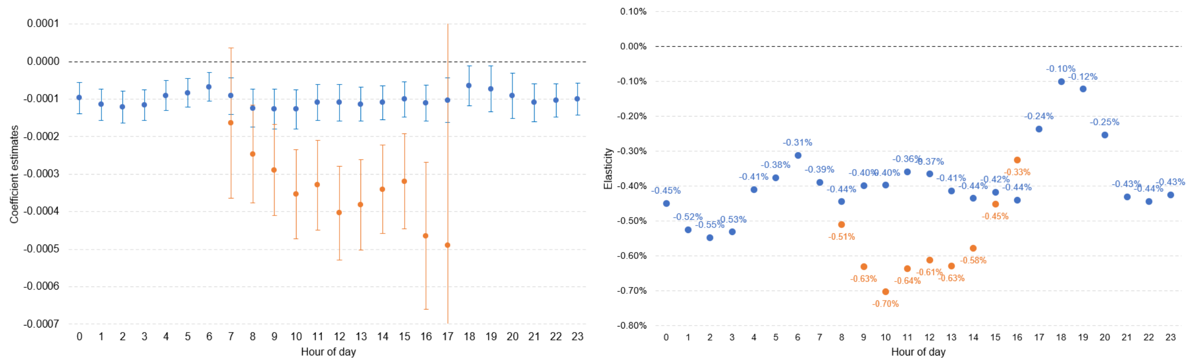
Notes: Figures 4a & 4b display daily aggregates for the year 2022.

solar electricity is -0.66 – more than twice as large. This indicates that a 1% increase in wind power (8.75 MWh) reduces load shedding by 0.69% (2.53 MWh). A 1% increase in solar power (4.78 MWh) reduces load shedding even by 0.87% (3.16 MWh).

As a likely explanation for these diverse effects, wind electricity is, on average, rather constant across the day. Hence, wind also feeds in electricity at night, when there is no need for load shedding. Solar electricity, however, tends to be load-following (see Figure 2) and, thus, better aligns with load-shedding events. Additionally, solar electricity infeed can be more accurately predicted compared to wind electricity, allowing it to effectively bridge the gap between dispatchable electricity generation and load. This combination of factors likely contributes to the diverse effects observed.

Overall, the two technologies have quite heterogeneous infeed profiles and, therefore, tend to complement each other. Wind power has features of a baseload technology (see Figure 2). However, there are severe intraday, day-to-day, and seasonal fluctuations, which, again, limit the baseload-characteristic of wind power (see Figure 4a). Solar radiation, however, is limited to daylight hours, again with significant intermittency across hours, days, and seasons (see Figure 4b), which limit the resource availability considerably.

Table 3 provides a breakdown between estimates for daytime (column (3)) and nighttime (column (4)). Wind power reduces load shedding by 0.20 to 0.31 MWh, depending on the time of day. Evidently, the effectiveness of wind power tends to be more pronounced during daytime (h7–h17), when load shedding is more prevalent, and weaker at night, when load shedding happens only infrequently. Solar power reduces load shedding by up to 0.64 MWh during the



(a) Effect on probability of load shedding **(b) Elasticities**

Notes: Figure 5a displays the estimated effects of an additional MWh of wind (blue) and solar (orange) power on the probability of load shedding per hour of the day. Each coefficient estimate multiplied by 100 represents the percentage-point change in the probability of load shedding. Figure 5b illustrates the percentage response in the probability of load shedding for a one percent increase in wind (blue) or solar (orange) electricity generation. Statistically insignificant estimates were omitted from the elasticities.

day, but has obviously no contribution during the night. The absence of solar electricity during the evening is especially problematic, because it cannot alleviating the peak in load shedding.

6.2 Extensive margin: probability of load-shedding events

We now focus on the extensive margin, examining whether wind and solar power decrease the probability of load-shedding events. To this end, we estimate the linear probability model defined in Equation (17), where the dependent variable I_t is a binary indicator if load shedding occurs ($IOS_t > 0$) or not ($IOS_t = 0$); see equation (13). For daylight hours, the regression is estimated for wind and solar, whereas solar is dropped for the hours after sundown.

Figure 5a provides a visual representation of the estimates.[12] It demonstrates that wind power has a steady potential to reduce the probability of load shedding, although this potential is somewhat constrained. In contrast, the effect of solar on the probability of load shedding is about 2 to almost 5 times stronger. This effect is particularly pronounced during the afternoon, when demand begins to rise. However, it is important to note that solar radiation diminishes considerably during the period when load shedding is most prevalent, typically occurring between 6 and 8 pm.

To improve the interpretability of the results, the estimated coefficients were converted into elasticities. Figure 5b illustrates that during daylight hours, solar is more effective than wind in reducing the load-shedding probability. A one percent change in solar electricity infeed can reduce the likelihood of a load-shedding event by up to 0.7% at 10–11 am. This coincides with

[12] Each coefficient estimate multiplied by 100 gives the percentage-point change in the load-shedding probability per additional Mwh of wind or solar electricity infeed.

moderate load-shedding activity (see Figure 2).

On the other hand, wind electricity is most effective in reducing the load-shedding probability during the night, with an elasticity of -0.55% at 2–3 am. This happens, however, when the load-shedding happens only rarely (see Figure 2). Nevertheless, during the hours 17–20, when load shedding is at its peak, wind has a low and solar no contribution to reducing the load-shedding probability.

6.3 Intensive margin: extent of load shedding

Turning to the intensive margin, we are interested in the extent of load shedding that can be avoided by an additional MWh of wind and solar electricity infeed during times of load-shedding ($IOS_t > 0$). Figure 6 visualizes the coefficient estimates of equation (18) by hour of day.

One additional MWh of wind power reduces load shedding by up to 0.74 MWh at 11 am. The effect of solar power is typically smaller. It is only more pronounced in the late afternoon, when a rising electricity demand (a necessity of load shedding) coincides with sunlight hours. However, the effect of solar is volatile across the day, and it almost vanishes around noon, when there is much solar power but only moderate demand.

These patterns underscore the complementary relationship between wind and solar power in mitigating load shedding. While wind power exhibits baseload characteristics and significantly impacts load shedding, it often operates at an infra-marginal level, meaning it alone may not entirely prevent load shedding. Solar power can help avoid load shedding. Yet, this effect is strongest in the afternoon when the generation of solar electricity is already on the decline.

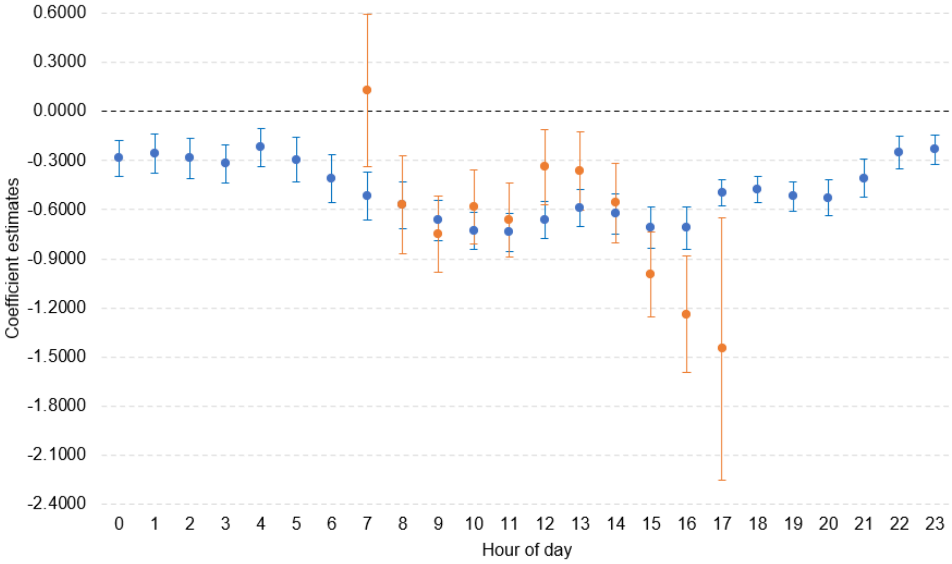


Figure 6: Effect on extent of load shedding

Notes: The figure shows the estimated coefficient of one MWh of wind (blue) or solar (orange) power on the extent of load shedding, during load-shedding events ($IOS > 0$) across the hours of day. Coefficient estimates lower than -1 are implausible; yet these estimates are quite imprecisely measured (as indicated by the large confidence intervals), given the low number of observations during these hours, and include the value of -1.

7 Policy implications

Our results show how much load shedding can be avoided per MWh of electricity generated from wind or solar. Subsection 7.1 demonstrates to what extent electricity from renewable resources helps avoid externalities from carbon emissions, as it replaces electricity from conventional resources. The costs and macroeconomic benefits of extending renewable electricity capacity are explored in Subsection 7.2. Subsection 7.3 elaborates on demand shifting.

7.1 Environmental effects

Whenever wind and solar power generate electricity, this extra supply can be used to either reduce load shedding by filling latent demand or, if there is no load shedding, to replace other forms of electricity production at the margin, where supply meets demand (Gugler et al., 2021). The largest share of South Africa's electricity is produced from coal. Throughout the year, coal represents the marginal electricity generation technology to meet demand. Coal has a particularly high emission factor of about 340 tCO_2 per MWh (DEA, 2019, Table 3.8, ref. "bituminous coal"). Therefore, the environmental value of wind and solar is high whenever it is not used for load-shedding mitigation, because each MWh can offset 340 tCO_2 of a MWh of coal-based electricity.

Our main results show that, on average, one MWh of wind or solar electricity reduces load shedding by 0.29 or 0.66 MWh, respectively. This, in turn, implies that, on average, every MWh replaces 0.71 ($= 1 - 0.29$) or 0.34 ($= 1 - 0.66$) MWh of coal-based electricity, which equals 241 tCO_2 avoided per MWh of wind power or 116 tCO_2 avoided per MWh of solar power.

This back-of-the-envelope calculation illustrates not only the economic value of mitigating load shedding through wind and solar power, but also underscores the considerable environmental value they offer. Importantly, in opportunity, one MWh of load shedding, which is offset by one MWh of wind or solar power, has also environmental value evaluated against the counterfactual of filling this gap by means of thermal energy.

7.2 Cost-benefit analysis

From a policy perspective, it is also informative to assess the extent to which investment in one MW of wind or solar PV electricity generation capacity can reduce load shedding. Our data enables the calculation of capacity factors for wind and solar PV stations in South Africa, which stand at 34% for wind and 25% for solar.[13] This implies that for every additional MW of wind or solar capacity, on average, 0.34 MWh of wind electricity and 0.25 MWh of solar electricity are generated per hour. Consequently, the addition of one MW of wind or solar power capacity would contribute to reducing load shedding by 0.0986 MWh ($= 0.28924 \cdot 0.34$) or 0.165 MWh ($= 0.66040 \cdot 0.25$), respectively. Thus, solar PV demonstrates greater effectiveness in reducing load shedding overall.

Latest available data indicate that capital investment costs for a typical wind power station and a utility-scale solar PV station in South Africa in 2019 were reported as 1,877 USD/kW (IEA, 2020b) and 1,321 USD/kW (IEA, 2020a), respectively. This implies that for an investment of USD 1 million in wind or solar power, 0.0178 MWh or 0.0312 MWh of load-shedding reduction can be bought, respectively. Reichenberg et al. (2018, Table 1) report an expected lifetime of 25 years for both wind and solar installations.[14] Therefore, over a 25-year period, load shedding could be reduced by 3,898 MWh ($= 0.0178 \cdot 8,760 \cdot 25$) or 6,833 MWh ($= 0.0312 \cdot 8,760 \cdot 25$).

Investment decisions require a comparison of costs and benefits. With increasing marginal investment costs and decreasing marginal benefits, optimal capacity investment occurs when

[13] In 2022, this was 1,106 MWh per hour of wind electricity output relative to 3,277 MW installed wind capacity and 553 MWh per hour of solar PV electricity output relative to 2,228 MW installed solar PV capacity.

[14] GWEC (2023, p. 27) also report a 25-year lifetime of a utility-scale wind asset in Africa.

marginal benefits equate to marginal costs. In principle, the benefits of avoiding load shedding can be assessed through the value of lost load (VoLL), which quantifies the loss in consumer and producer surplus in the electricity market resulting from a temporary shutdown. Measuring the VoLL is, however, difficult for a variety of reasons:

A shutdown has a different impact on a company (idle capacity) compared to a private household. A long shutdown, which, for example, impairs the cold chain, may have an exponentially greater effect than a short shutdown. A shutdown in an entire city may be more severe than a shutdown in just one street, when the residents of this street may continue their activities (work, shopping etc.) elsewhere. Also, macroeconomic multiplier effects are hard to measure. Hence, estimates of VoLL can differ by several orders of magnitude (Gorman, 2022).

A recent estimate for South Africa has been provided by Walsh et al. (2020) in a study commissioned by Eskom. Using the variation in GDP growth and load shedding, they estimate the VoLL at R 9.53/kWh in the period 2018-19. About 40% of those costs were shouldered by the manufacturing sector. Transport & Communication, Wholesale & Retail Trade, and Agriculture, Hunting, Forestry & Fishing bore another 40% of those costs.

Earlier, we calculated that investing USD 1m in wind power reduces 3,898 MWh over the average lifetime of a plant, which is USD 0.26 or R 3.9 per kWh.[15] Investing USD 1m in solar power reduces 6,833 MWh over the average lifetime of a plant, which is USD 0.15 or R 2.25 per kWh, indicating that the investment costs are about 2.5 to 4 times smaller than the gains as measured by the VoLL.

7.3 Demand shifting

To increase wind and solar power's effectiveness in mitigating load shedding, it would be helpful to shift demand so that it coincides with the resource profiles of wind or solar radiation more closely. Energy storage would, thus, be an ideal complementary strategy to extending the capacity of renewable electricity. Eskom is already investing in such storage solutions. In November 2023, it brought online a 1,440MWh battery energy storage system, which is just the first out of eight utility-scale storage projects.[16] Yet, "if prices are capped below reasonable

[15] The USD-R exchange rate was about 15:1 in 2018-19, which is the exchange rate used for this calculation. Since then, the Rand has further depreciated with an exchange rate of about 19:1 in early 2024.

[16] engineeringnews.co.za (9 November 2023). "Eskom's Hex battery the first of eight utility-scale projects being deployed across four provinces." https://www.engineeringnews.co.za/article/eskoms-hex-battery-the-first-of-eight-utility-scale-projects-being-deployed-across-four-provinces-2023-11-09 (accessed on 2 February 2024).
eskom.co.za (10 November 2023). "Eskom unveils a first of its kind largest

estimates of the value of lost load [...] revenues from sales in energy markets will provide inadequate incentives for investment in generation" and also in electricity storage (Schmalensee, 2022, p. 15).

Dynamic electricity tariffs, which incentivize end-users to shift demand from peak to off-peak times, would also be beneficial. Electricity prices are currently regulated by Nersa. In such a heavily regulated system, dynamic pricing, where different prices are charged in peak and off-peak times, might even be easier to introduce than in other economies, where private, profit-maximizing retailers set their tariff rates. While dynamic electricity tariffs are uncommon in South Africa, to date,[17] Eskom is currently investing in smart meters that will allow for dynamic pricing.[18]

The increasing use of electric vehicles may shift demand patterns, too. In California, for example, the users of electric vehicles charge them most frequently between 10pm and 6am (Burlig et al., 2021). In South Africa, such a demand pattern might correspond well to the nighttime supply of wind energy. Yet, sales of electric vehicles are low in South Africa. In 2019, conventional motorcars represented about two thirds of the 11.5m road vehicles in the country. But only 560 were battery electric vehicles, and 680 plug-in hybrid vehicles (Tongwane and Moeletsi, 2021).

8 Planned extensions

To be done:

- We will use estimates of the fixed costs or Levelized Costs of Energy (LCOE) of wind and solar power from external sources to evaluate how much load shedding reduction one could by for one Rand of investment in wind or solar power.

- We will also say more about the CO_2 abatement effect of wind and solar power in South

battery storage project in the African continent." https://www.eskom.co.za/eskom-unveils-a-first-of-its-kind-largest-battery-storage-project-in-the-african-continent/ (accessed on 2 February 2024).
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[17] nersa.org.za. "Approved municipal electricity tariffs 2022/23." https://www.nersa.org.za/wp-content/uploads/bsk-pdf-manager/2022/10/Approved-Municipal-Electricity-Tariffs-2022-23.pdf (accessed on 8 February 2024).

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Africa. It is most likely that one additional unit of wind and solar power would abate one MWh of coal-electricity whenever this MWh of wind or solar power is not used to reduce load shedding. Hence, there may be a tradeoff between load-shedding reduction and carbon offset: an additional MWh of renewable energy can either be used to meet demand or, if demand is already met, to offset coal-electricity supply.

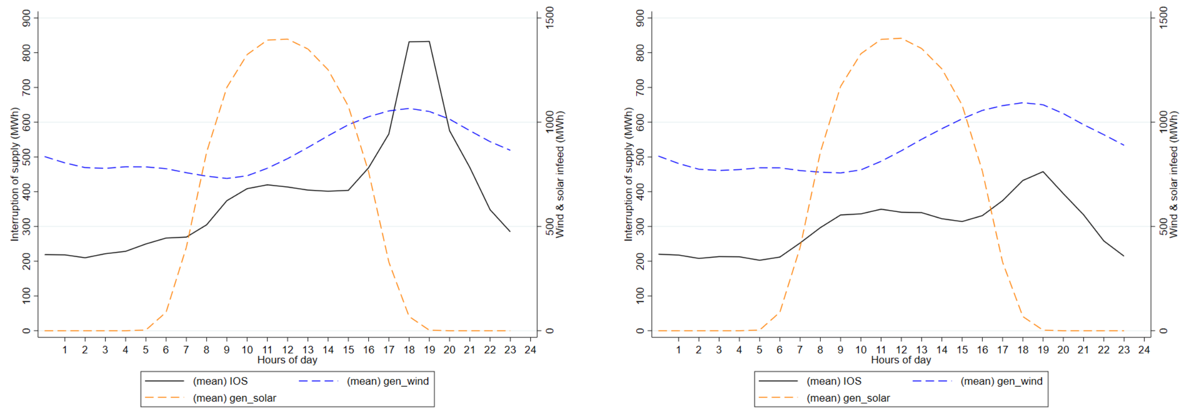
- We will also analyze the differences between workdays and weekends.

Table 4: 2SLS estimates: work days vs weekend

	(1) Mon–Fri 2SLS: 2nd stage IOS	(2) Sat, Sun 2SLS: 2nd stage IOS
Wind electr.	-0.30211***	-0.26372***
	(0.01127)	(0.01550)
Solar electr.	-0.77786***	-0.46030***
	(0.04933)	(0.06827)
Coal electr.	-0.20666***	-0.16990***
	(0.00413)	(0.00580)
Hydro electr.	-0.54994***	-0.35936***
	(0.02970)	(0.04123)
Pumped-storage electr.	-0.37192***	-0.32098***
	(0.01290)	(0.01966)
Nuclear electr.	-0.21467***	-0.18215***
	(0.01142)	(0.01497)
FE holidays	yes	yes
FE hours of day	yes	yes
FE days of week	yes	yes
FE months of year	yes	yes
FE years	yes	yes
Observations	30,288	12,125
K.P. first-stage F stat.	2,632	1,188

*Notes: Dependent variable: interruption of supply (IOS) in MWh. Standard errors in parentheses are robust to heteroskedasticity and allow for first-order autocorrelation (HAC-robust Newey-West SE). *** p < 1%, ** p < 5%, * p < 10%. Column 2: instrumented for wind and solar electricity by wind speed and solar radiation. Sample period: 01apr2018,01h–07mar2023,24h. "K.P." ... Kleibergen-Paap.*

Figure 7: IOS & wind and solar infeed profiles: work days vs. weekends



(a) **Work days** (b) **Weekends**

9 Conclusion

In this study, we investigated two research questions: To what extent does electricity from decentralized and intermittent renewable resources reduce load shedding in South Africa? And if so, is wind or solar power more effective in reducing load shedding?

This inquiry bears significance due to the growing prevalence of load shedding in South Africa, which has had detrimental effects on both economic development and the quality of life. In recent years, the frequency of rolling blackouts has intensified markedly. This escalation can be attributed to the decline in electricity generation from conventional resources, as aging plants approach the end of their useful life – a trend that is projected to persist in the future. Concurrently, South Africa has set incentives, particularly for independent power producers, to bridge this gap by harnessing electricity from intermittent renewable resources.

While wind and solar power contribute to addressing the supply-demand gap, it remains uncertain to what extent they alleviate load shedding, as their generation does not necessarily align with times of peak demand. Drawing upon data provided by South African electricity provider and grid operator Eskom, our analysis reveals that both wind and solar power reduce load shedding. Furthermore, these effects have significant economic implications. Even modest investments can yield substantial results, although substantial investments would be required to achieve nearly zero load shedding.

Nonetheless, the intraday patterns of wind and solar power differ markedly. Wind power exhibits a relatively stable supply throughout the day, with a moderate peak in the evening

– when demand is highest. Consequently, wind power serves as a baseload technology, with approximately three-quarters of each MWh of electricity generated contributing to load shedding reduction.

However, wind power is rarely pivotal for avoiding load shedding altogether. Even at full capacity, demand may still outstrip supply. On occasion, this shortfall is supplemented by solar power, which exerts a more pronounced impact on the load shedding probability, particularly during the afternoon when demand begins to rise towards its evening peak.

The baseload characteristics of wind power underscore the importance of continued investment in this technology. However, constructing wind power plants necessitates substantial investments from corporate entities, whereas solar power can be developed in smaller installments. Nevertheless, the impact of solar power on load shedding is more volatile. Consequently, it is vital to complement investments in solar power with the development of storage technologies or demand shifting.

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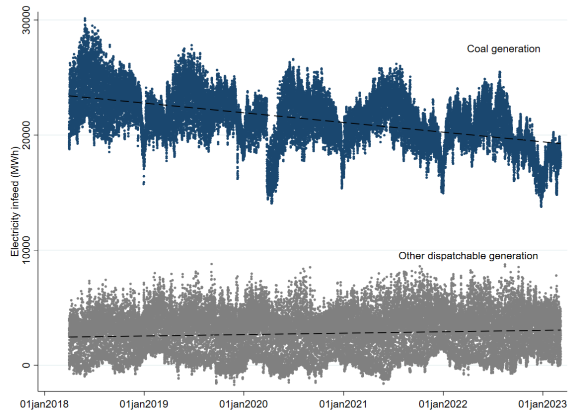
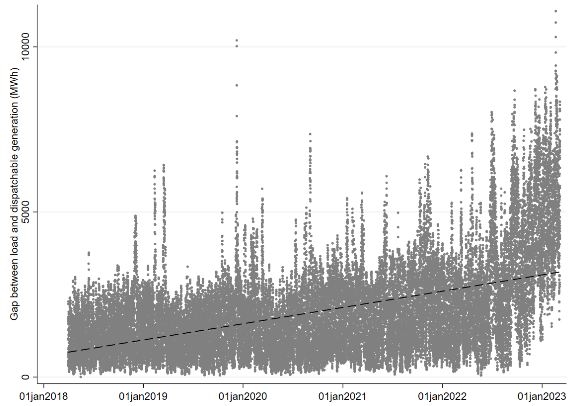
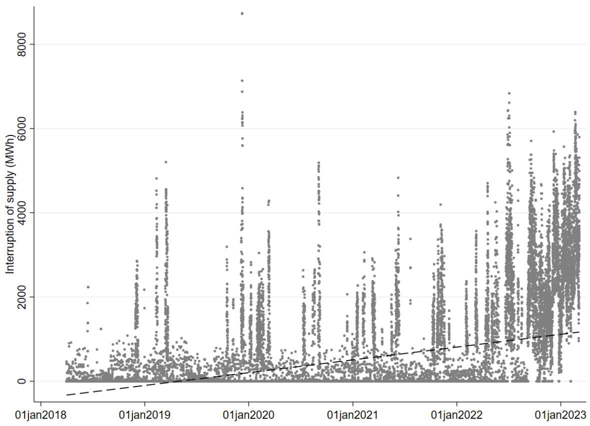
Appendix



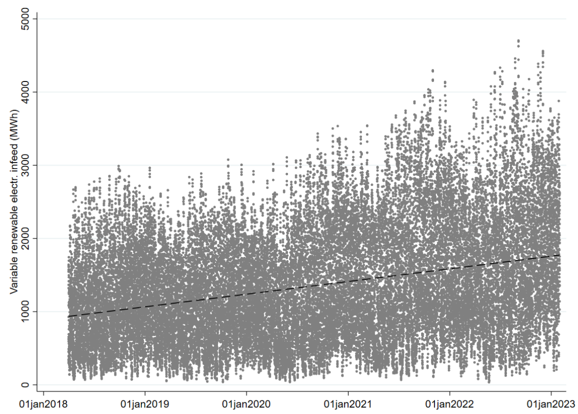
(a) Dispatchable electricity



(b) Gap betw. demand and disp. electr.



(c) Interruption of supply



(d) Variable renewable electricity

Figure A1: Dispatchable electricity, load shedding, and renewables