

How Does the Unequal Adoption of Solar Power Trigger a Pricing ‘Death Spiral’ in Lebanon’s Informal Generator Cartels, and What Are Its Effects on Middle and Low-Income Households? An Agent-Based Simulation

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ABSTRACT

Lebanon's 2019 economic collapse left the country's electricity sector in crisis. The state utility, Électricité du Liban, provides only around three to four hours of power per day, forcing households to depend on private generator cartels that charge unregulated prices, while solar energy has begun to emerge as an alternative for those who can afford it. This paper uses an Agent-Based Model to simulate how 500 households across five income brackets interact with these three energy sources over a six-year period. The simulation produces several findings that were not built into the model's rules, the most significant is that middle-income households, not the poorest, end up carrying the heaviest energy burden. Low-income households ration almost immediately, while wealthier households escape to solar, leaving the middle class to absorb rising generator costs in what this study terms "the death spiral." A One-At-a-Time sensitivity analysis shows that generator cartel greed has the largest effect on energy poverty out of all parameters tested, and that tighter enforcement of existing tariff regulations alone could ease the pressure on the most affected households. The model's parameters map directly to real policy decisions, making it possible to simulate the effects of regulatory changes before they are applied.

INTRODUCTION

Lebanon is a country that has faced many hardships throughout its history. From colonization to invasions to civil wars, and most recently, a catastrophic economic collapse. The 2019 economic crisis affected Lebanese households in many different sectors, but the most visible impact was on electricity. For roughly one to two years, most Lebanese citizens were living in near-complete darkness. After this period, the electricity system was reshaped entirely: EDL (Électricité du Liban) could barely keep the lights on, private generator owners rushed in to fill the gap and profit off the shortage, and solar-powered households began to emerge as an alternative. For households already struggling under devalued salaries

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and a collapsing cost of living, the added weight of generator bills pushed many past their financial limits. Electricity is not optional, which leaves households with no choice but to make difficult decisions about their energy consumption on a monthly basis.

LITERATURE REVIEW

Several studies have examined this crisis and its effects on Lebanese citizens. Dagher et al. (2023) documented the extreme energy poverty Lebanese households are now experiencing. The International Monetary Fund (IMF, 2019) showed how far below demand EDL's supply has fallen and how private generator owners exploit this gap for extra profit. Human Rights Watch (2023) demonstrated that energy bills now consume a dangerously large share of household income, especially for the poorest families. And Dagher and Ruble (2011) used Long-range Energy Alternatives Planning (LEAP) simulations to show that renewable energy and natural gas scenarios would be both cheaper and cleaner than the current baseline. However, none of these studies simulate the interaction between all of these factors at once - how generator pricing, solar adoption, income inequality, and social networks feed back into each other and reshape the energy system over time. This is exactly what this study's Agent-Based Model (ABM) does: it simulates these interactions together to identify who is most vulnerable to this crisis and why.

METHODOLOGY

Traditional mathematical models that study electricity markets tend to treat all households as one average consumer. This does not work for Lebanon because the whole problem is that different income classes react in completely different ways to the same price change, and those individual reactions feed back into each other. A rich household switching to solar is not just a personal decision; it directly raises the generator bill for the poor household next door. To capture this kind of chain reaction, this study uses an ABM, where each household is its own independent decision-maker that responds to its environment and to the choices of its neighbors. This approach follows Weidlich and Veit's (2008) argument that agent-based modeling is better suited for electricity market research than traditional equilibrium-based methods because it allows individual agents to make autonomous decisions based on their own conditions.

The python model runs for 2,190 days (6 years), with each time step representing a single day. A fixed random seed (42) is used so that results are fully reproducible.

The model starts with assigning the percentage of the Lebanese people across different income ranges: low (30%), lower-middle (25%), middle (20%), upper-middle (15%), and high (10%). Income ranges were set based on estimates of post-crisis Lebanon, with low-income households earning between 200-500\$/month, lower-middle earning 500-1,000\$/month, middle households between 1,000-2,000\$/month, upper-middle earning between 2,000-4,000\$/month, and high-income households

earning between 4,000-10,000\$/month. A total of 500 household agents are created and distributed across 10 neighborhoods.

Households are connected through a "small-world" network. This network type means each household is mostly connected to others in the same neighborhood from the same street, with a few random long-distance connections representing family, coworkers, or friends. The network is built using a Watts-Strogatz small-world structure with an average degree of 6 connections per household and a rewiring probability of 0.1, meaning each local connection has a 10% chance of being replaced by a long-distance link to a household in a different neighborhood. This network structure matters because when a household sees its neighbors adopting solar and being satisfied with it, it lowers their own perceived risk of making the switch. This social influence is one of the main drivers of adoption cascades in the model.

The model then defines the three electricity types, all with their unique attributes:

EDL: The state utility provides heavily subsidized electricity at a fraction of the cost of private generators, but is highly unreliable, averaging around 1–3 hours per day (consistent with reported supply levels outside Beirut; Human Rights Watch, 2023). EDL supply fluctuates daily with random noise and seasonal variation, and has a slight downward trend over the simulation to reflect continued infrastructure decay. The 3-hour baseline and deterioration trend are based on publicly reported EDL supply schedules across different Lebanese regions.

Private Generators: Generator owners set their prices based on the demand for their service. The baseline price starts at 0.40\$/kWh (within the 0.37–0.50 range documented in the Ministry of Energy and Water (MoEW, 2024, 2025) monthly tariff circulars). This number is then multiplied by 1.7x to represent the “enforcement gap” that reflects the well documented reality that generator operators routinely ignore government pricing and overcharge their customers (Human Rights Watch, 2023).

When richer households move towards solar, generator owners must now split their fixed costs (diesel, maintenance, equipment) between fewer remaining subscribers. This forces the price per person up, which then forces lower-income households to start rationing their usage and squeezes the middle class, who cannot ration because of their needs but also cannot move directly to solar because of the high upfront cost. This feedback loop is what the model refers to as the "death spiral."

Solar: The solar setup scales based on each household's energy demand, which means richer households end up paying a higher upfront cost because their lifestyle requires a bigger system. The base cost for a standard 8 kWh system is set at \$3,000 (reflecting average market prices for residential rooftop systems in Lebanon as of 2024–2025). Solar output varies by season and by random daily weather conditions, and panels degrade slightly each year (0.5% annual efficiency loss, consistent with industry standards; Jordan and Kurtz, 2013). Not every household can install solar panels. Renters, apartment dwellers without roof access, and those needing co-owner consent are excluded. Based on Lebanon's 88% urbanization rate and

roughly 50% tenancy rate, only about 35% of households in the model are eligible for rooftop solar installation (World Bank, 2022).

The model then computes all hours of electricity and kWh that each household gets from EDL, private generators, and solar (if they have it). Households use EDL first since it is the cheapest, then solar if available, then the generator fills whatever gap is left. The total monthly cost as a share of income gives the energy burden for each household.

The energy burden is the main metric used to define energy poverty in this model. Any household spending more than 10% of their monthly income on electricity is classified as energy poor, following the commonly used threshold in energy poverty literature (Boardman, 1991). Other studies have proposed stricter or more complex definitions, such as Hills' "Low Income High Costs" indicator, which factors in residual income after energy spending. However, the 10% threshold was chosen here because it is straightforward to calculate from the model's output and remains the most widely recognized benchmark in the field.

Following that, the model evaluates whether a household can adopt solar based on their savings. Richer households can afford to adopt with less savings relative to the system cost (high-income households need 30% of the cost saved up, while lower-middle need 80%). The adoption decision also factors in the household's risk tolerance, environmental awareness, and how many of their neighbors have already adopted (social influence).

The next function evaluates a household's decision to drop out of private generators. If the generator cost pushes a household's energy burden past 20% of their income, they start rationing. Low-income households ration down to 15% of their normal electricity use (basically just a light bulb), while lower-middle- and middle-class households ration to 30% (fridge, a light, maybe a fan). Middle-class households have a higher pain threshold of 30% before they start rationing, reflecting their stronger dependence on electricity for daily needs. If a household is already rationing and the cost still exceeds 50% of their income, they have a small daily probability of dropping out of the generator entirely. Solar adopters can also voluntarily cancel their generator subscription once they feel their solar system covers enough of their needs.

The Gini coefficient is also calculated, but specifically for electricity inequality (how unequal the actual kWh consumed are across households) rather than the standard income-based Gini.

[Sensitivity Analysis] To test whether the results depend too heavily on any single assumption, a One-At-a-Time (OAT) sensitivity analysis was performed. Five parameters were selected for testing: cartel greed (markup slope), solar eligibility rate, enforcement gap (overcharge multiplier), solar installation cost, and middle-class adoption speed. Each parameter was tested at a low and high bound while all other parameters stayed at their default values. Because the model is stochastic, each parameter setting was run 5 times with different random seeds, and the results were averaged to filter out noise from random variation. The energy poverty rate baseline was also averaged over the last 90 days of the

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simulation rather than taken from a single day, since daily fluctuations in weather and costs can cause this metric to change daily. The results are presented as tornado charts showing how much each parameter shifts three output metrics: energy poverty rate, solar adoption rate, and generator peak price.

Parameter	Description	Low Bound	Baseline	High Bound
Cartel Greed	Generator markup slope	0.7	1	1.3
Solar Eligibility	Percentage of households eligible	25%	35%	45%
Enforcement Gap	Multiplier over official tariff	1.3	1.7	2
Solar Install Cost	Upfront cost of system (USD)	\$2,000	\$3,000	\$4,500
Middle-Class Adoption	Speed/friction of adoption	0.04	0.08	0.15

After everything runs, six graphs are generated to visualize the results: solar adoption rate by income bracket, generator price paired with generator subscriber percentage (showing the death spiral feedback), percentage of every income bracket that is subscribed to generators, energy burden by income bracket with a 10% energy poverty line, the Gini coefficient for energy access paired with the energy poverty rate, and energy satisfaction by income bracket. The sensitivity analysis produces an additional figure with three tornado charts (one per output metric).

Code: [majdghayzi-cloud/lebanon_ABM](https://github.com/majdghayzi-cloud/lebanon_ABM)

RESULTS

The following figures illustrate the simulation's output over a six-year period. Two dynamics stand out across the results: the inverse correlation between solar adoption and generator subscribers, and the positive correlation between solar adoption and generator price.

Figure 1

How Does the Unequal Adoption of Solar Power Trigger a Pricing 'Death Spiral' in Lebanon's Informal Generator Cartels, and What Are Its Effects on Middle and Low-Income Households? An Agent-Based Simulation

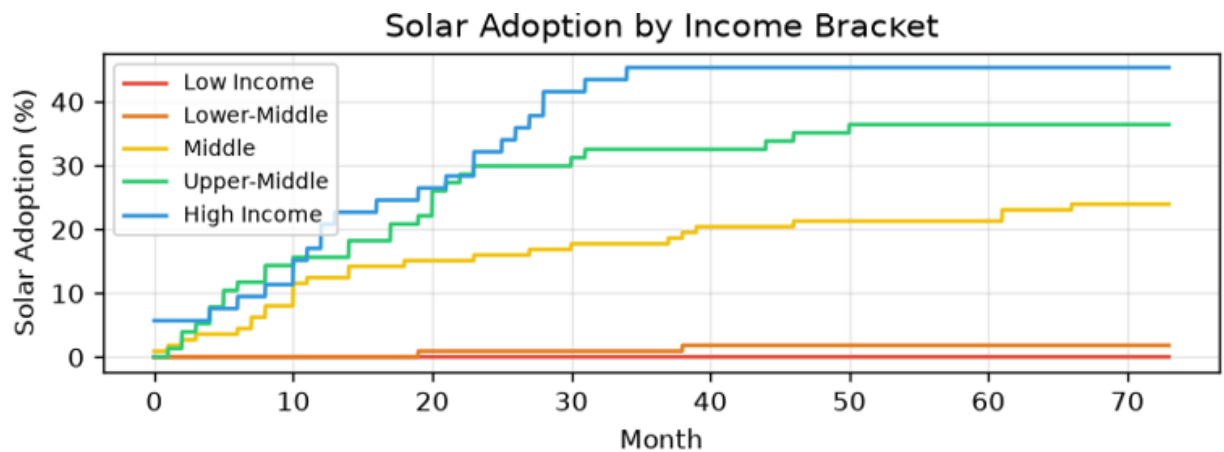


Figure 2

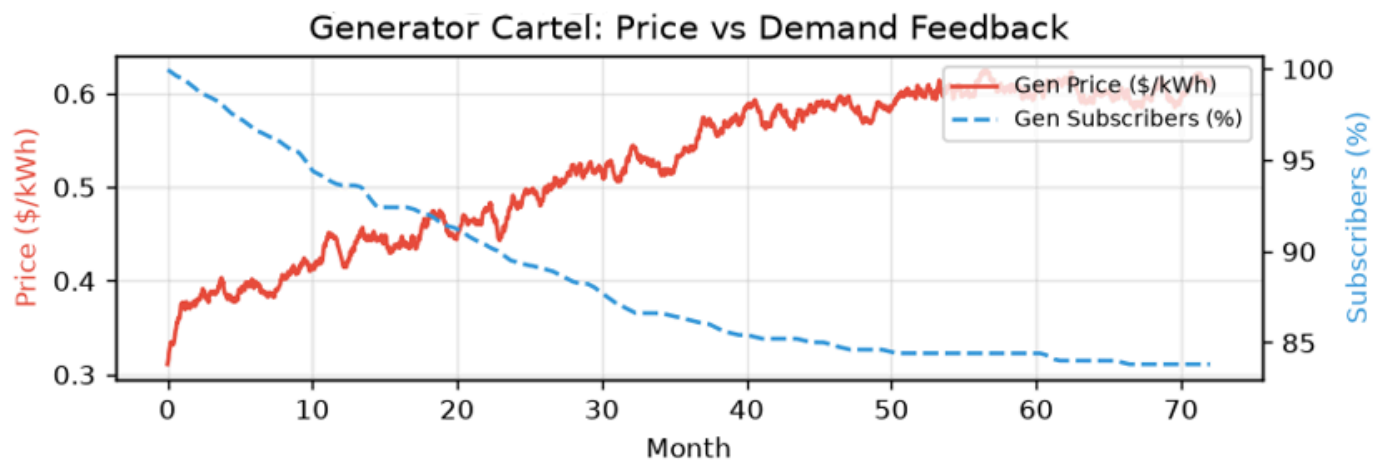


Figure 3

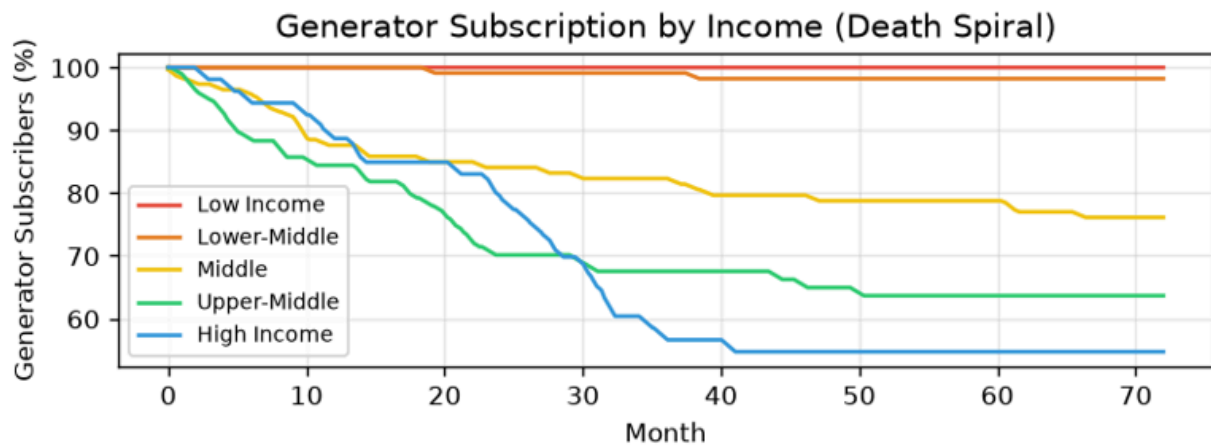


Figure 4

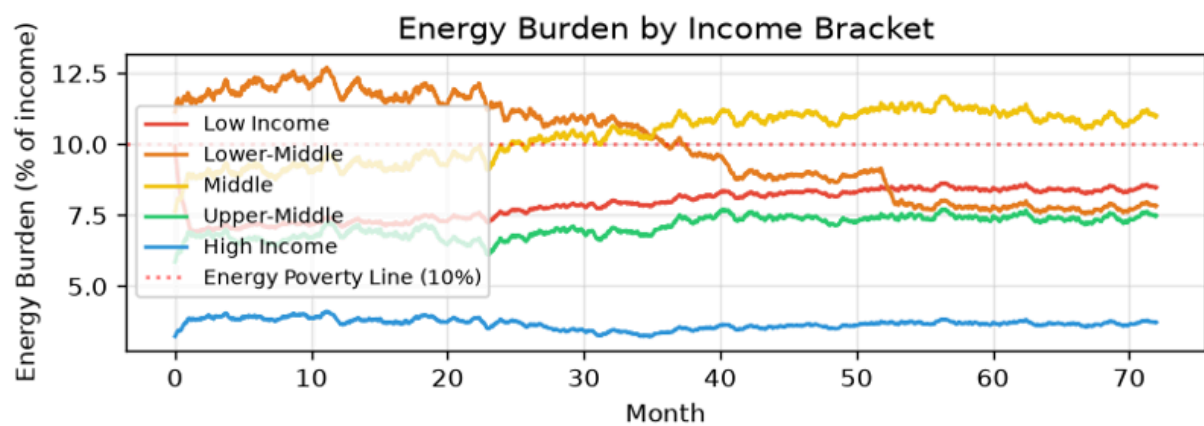


Figure 5

How Does the Unequal Adoption of Solar Power Trigger a Pricing 'Death Spiral' in Lebanon's Informal Generator Cartels, and What Are Its Effects on Middle and Low-Income Households? An Agent-Based Simulation

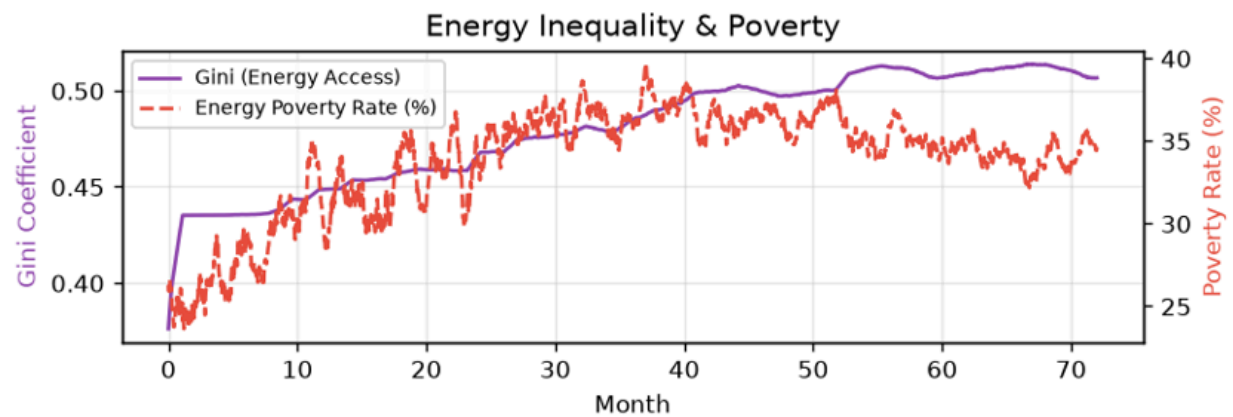


Figure 6

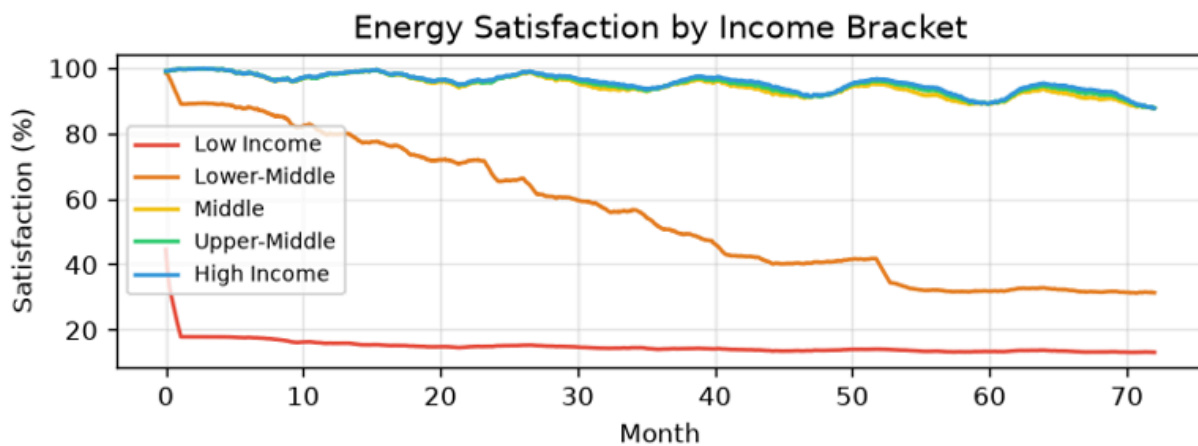


Figure 7

How Does the Unequal Adoption of Solar Power Trigger a Pricing ‘Death Spiral’ in Lebanon’s Informal Generator Cartels, and What Are Its Effects on Middle and Low-Income Households? An Agent-Based Simulation

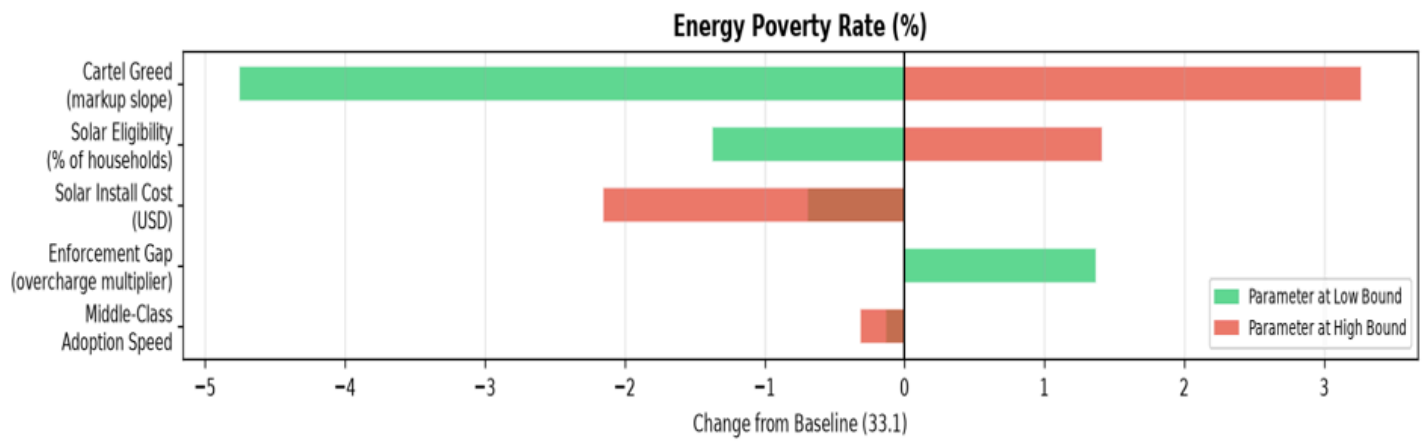


Figure 8

How Does the Unequal Adoption of Solar Power Trigger a Pricing ‘Death Spiral’ in Lebanon’s Informal Generator Cartels, and What Are Its Effects on Middle and Low-Income Households? An Agent-Based Simulation

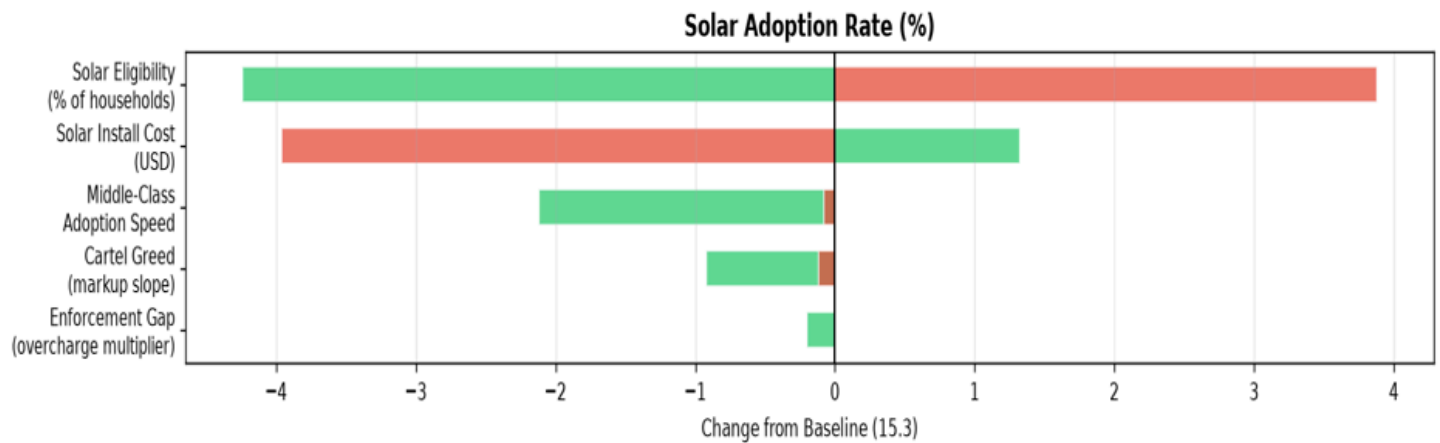
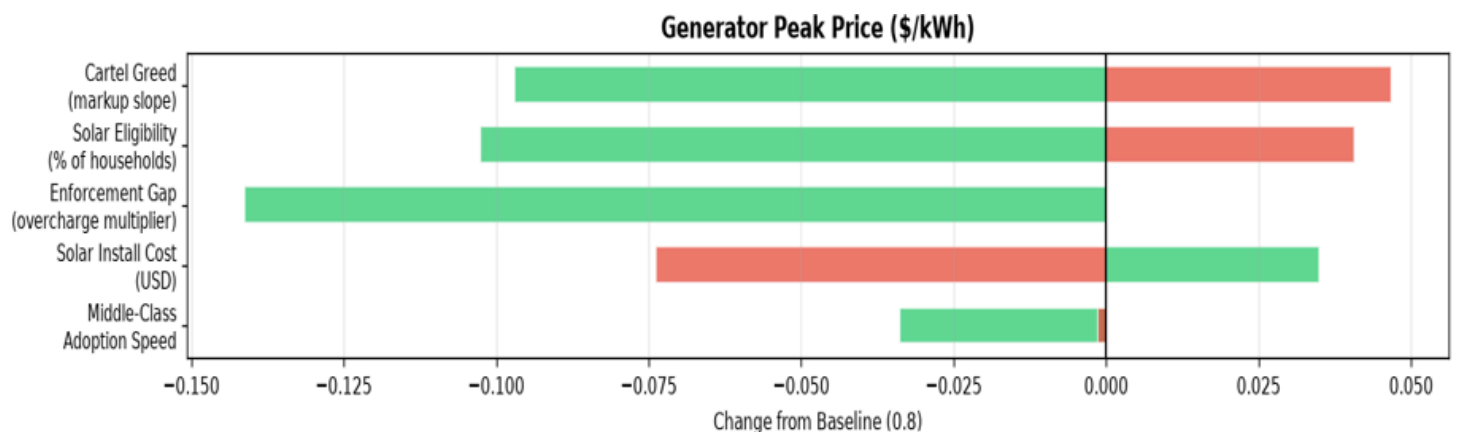


Figure 9



DISCUSSION

The simulation results show a clear chain reaction. As cartel greed drives generator prices upward, upper-middle and high-income households are the first to transition to solar (figure 1). Their departure from the generator network forces the cartel to redistribute its fixed costs onto fewer subscribers (figure 2), primarily middle-class and lower-income households. This cost redistribution triggers two distinct responses among the lower income groups: low-income households begin rationing almost immediately from the start of the simulation because they cannot absorb even a small increase in their energy bill, while lower-middle-income households endure the financial strain for a much longer period before they are eventually forced to cut their consumption (figure 4).

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The middle class turns out to be the most vulnerable group in this crisis. Unlike lower-income households, middle-class families cannot simply ration their electricity because their daily needs and lifestyle are heavily dependent on consistent power access. At the same time, they cannot quickly adopt solar the way upper-income households can because the upfront installation cost requires years of saving on a middle-class budget. This dynamic creates what this study classifies as "the death spiral": generator owners raise prices in response to subscriber dropouts and shrinking demand (figure 2), and the middle class absorbs the largest share of that increase. Their energy burden remains the highest of any income group throughout the entire simulation (figure 4), yet they lack the financial capacity to escape.

The solar adoption results confirm this class divide (figure 1). High-income and upper-middle-income households show the steepest adoption curves, both plateauing once they hit the solar eligibility ceiling. Middle-class adoption follows later, picking up only after households have accumulated enough savings to afford the down payment. A very small fraction of lower-middle-income households manage to adopt solar by the end of the simulation, but this requires a level of saving that barely any household in that bracket can realistically achieve. Low-income households do not adopt solar at all.

The Gini coefficient for energy access reaches approximately 0.51 by the end of the simulation (figure 5), which reflects a sharp disparity between income groups. Upper-class households have full access to the electricity they need, whether from solar panels or private generators. Lower-class households, by contrast, are forced to ration heavily just to prevent their electricity bill from consuming their entire income.

The energy poverty rate stabilizes at around 35% (figure 5), driven primarily by the lower-middle and middle classes spending the majority of the simulation above the 10% energy poverty threshold. This confirms the central finding: the middle class is the income group most trapped by this crisis, caught between an inability to afford solar and an inability to escape rising generator costs.

Energy satisfaction scores reinforce this pattern (figure 6). Low-income households show very low satisfaction from early in the simulation because they begin rationing almost immediately. Lower-middle-income households experience a gradual decline as they are squeezed for a longer period before eventually cutting their consumption. The middle class and upper classes maintain high satisfaction rates throughout the simulation because, despite the financial pressure on the middle class, these households continue to access the electricity they need. Toward the final months, satisfaction for upper-class households begins to oscillate as solar-dependent homes experience reduced output during winter, when solar generation drops.

The sensitivity analysis tested five parameters to determine which assumptions have the strongest effect on the model's outputs. For energy poverty (figure 7), cartel greed is by far the most influential parameter. Solar eligibility ranks second: at a lower eligibility rate, fewer upper-class households move to solar, which keeps more subscribers on the generator network and slightly reduces pricing pressure, lowering energy poverty. The opposite is true at the higher eligibility rate. Solar installation cost produces a result where both bounds lead to a decrease in energy poverty. A lower installation cost allows middle-class

households to adopt solar faster, which directly reduces their energy burden. A higher installation cost slows upper-class adoption, which keeps generator demand more stable and prevents the aggressive price hikes that push borderline households into poverty. The enforcement gap at its low bound increases energy poverty because a lower price ceiling keeps generator bills "affordable enough" that lower-middle-class households remain subscribed and financially strained for longer, rather than being forced to disconnect and stop spending altogether. Middle-class adoption speed has a minimal effect on energy poverty because the middle class remains constrained by solar eligibility limits and installation costs regardless of how quickly they are willing to adopt.

For solar adoption (figure 8), the two most influential parameters are solar eligibility and installation cost, as expected. Middle-class adoption speed produces a surprising result: both its low and high bounds decrease total solar adoption. At the low bound, slower adoption simply means fewer middle-class households transition within the simulation period. At the high bound, rapid middle-class adoption triggers an early collapse in generator demand, which causes prices to spike so quickly that lower-middle-class households are financially crushed before they can save enough for solar, reducing total adoption. Cartel greed follows a similar pattern. At the low bound, prices stay relatively affordable, so households feel less urgency to invest in solar. At the high bound, prices rise so aggressively that middle-class households cannot accumulate the savings needed for the down payment before their budgets are consumed by generator bills. The enforcement gap does not significantly affect total solar adoption at either bound.

For generator peak price (figure 9), the three most influential parameters are cartel greed, solar eligibility, and enforcement gap. At a higher solar installation cost, middle-class households have to wait longer before they can afford solar, which keeps them on the generator network and prevents the demand collapse that triggers the most extreme price increases. A lower installation cost has the opposite effect: faster solar adoption shrinks the subscriber base and drives generator prices higher. The low bound for middle-class adoption speed keeps more middle-class households subscribed to generators for longer, which stabilizes demand and results in a lower peak price. The high bound shows an effectively negligible change from the baseline, as that tiny red bar is statistical noise produced by random fuel price fluctuations across different simulation seeds causing both the baseline and fast-adoption scenarios to push the generator price into the same regulatory ceiling.

This model is not only a simulation of the crisis, but also a tool for testing policy. None of the behaviors described above were hard coded into the model. The death spiral, for example, was not written as a rule. It showed up on its own because when wealthier households left the generator network for solar, the cartel had to spread its fixed costs across fewer people, which pushed prices up for everyone still connected. The middle-class trap, where middle-income households ended up carrying the heaviest energy burden despite not being the poorest income group, was not a built-in rule but a direct consequence of the middle class being too wealthy to ration and too poor to escape. The class-specific rationing sequence, where low-income households cut their consumption almost immediately while lower-middle-income households held on for months longer, emerged from each household individually reacting to its own

financial pressure. The finding that both very fast and very slow middle-class solar adoption reduces total adoption, because one removes the urgency to switch and the other triggers a price collapse that financially traps the lower classes, was entirely unexpected and could not have been predicted by a traditional equation-based model. Each of the parameters tested in the sensitivity analysis maps directly to a real policy decision. Cartel greed corresponds to how strictly the government regulates generator pricing. The enforcement gap reflects whether meters are installed and whether tariff circulars are actually enforced on the ground. Solar installation costs can be reduced through government subsidies, lower import tariffs on panels, or subsidized financing programs. Solar eligibility can be expanded through changes in building codes or the creation of community solar programs for apartment dwellers and renters who currently have no roof access. Middle-class adoption speed can be accelerated through targeted microloans or public awareness campaigns. Any of these changes can be directly entered into the model as a modified parameter value, and the simulation will produce a new set of outputs showing how that specific policy would affect energy poverty, solar adoption, and generator pricing across every income group. This is what gives the model its practical value: in a country where experimenting with real energy policy carries real consequences for real households, the ability to test a policy change inside a simulation before implementing it is not just useful, it is necessary.

COMPARISON WITH PRIOR LITERATURE

The energy burden pattern the model produces, where lower-income households carry a heavier share of their income on electricity than wealthier ones, matches what the IMF (2019) documented in its report, where generator spending in Lebanon's poorest regions consumed roughly six times the income share that it did in the wealthiest regions. The scale of energy poverty is shown in the model and in line with what Dagher et al. (2023) found in their survey of 931 households, where the majority faced extreme energy poverty across multiple indicators, though the model's 35% rate is lower because it only captures electricity spending and not total energy costs such as heating and cooking fuel. The overcharging mechanism at the heart of the death spiral, generators charging above the regulated tariff because enforcement is weak, is exactly what Human Rights Watch (2023) documented in its survey of 1,200 households. And the escape route that solar provides for households who can afford it lines up with Dagher and Ruble's (2011) earlier finding that renewable energy scenarios outperform the baseline both economically and environmentally.

LIMITATIONS

This model has limitations. The generator market is treated as a single entity with one price, when in reality every neighborhood in Lebanon has its own generator owner setting prices based on local conditions. Geographic variation is also absent; electricity access, solar potential, and income levels differ between Beirut, the Bekaa, and the South, and the model groups them into one population. The sensitivity analysis tests each parameter independently, meaning it does not capture interaction effects between

parameters that could produce different outcomes when changed simultaneously. And while the model does incorporate randomness in weather, fuel prices, and individual decisions, real human behavior includes factors that no equation can fully account for including fear, stubbornness, family pressure, political ties to a generator owner, or simply not knowing that solar is an option. Most of these limitations likely cause the model to underestimate the severity of the crisis, particularly for the most vulnerable households. Adding geographic variation, for example, would almost certainly increase the inequality the model measures, since rural areas face lower incomes and less access to solar installers than urban centers.

CONCLUSION

Lebanon's electricity crisis is not just a story about power outages. It is a story about how the absence of a functioning state pushes millions of households into an informal market that was never designed to be fair, and how the consequences of that market fall hardest on the people least equipped to escape it. The central finding shows that the middle class, not the poorest households, bears the heaviest energy burden in this crisis. This was not built into the model but emerged from the interactions between households responding to their financial reality on their own. The sensitivity analysis reinforces this: of all parameters tested, the regulation of generator pricing has the largest effect on energy poverty, meaning that even modest enforcement of existing tariff rules could produce measurable relief. Whether the Lebanese government will take on the responsibility of fixing the energy sector remains an open question, but the simulation makes one thing clear: solutions do exist, and their effects can be measured before they are ever implemented. Further research that addresses the limitations outlined in this study, particularly by incorporating geographic variation, income dynamics, and validating the model against actual household survey data, could bring this type of modeling closer to becoming a practical instrument for energy policy in Lebanon and in other countries facing similar crises.

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