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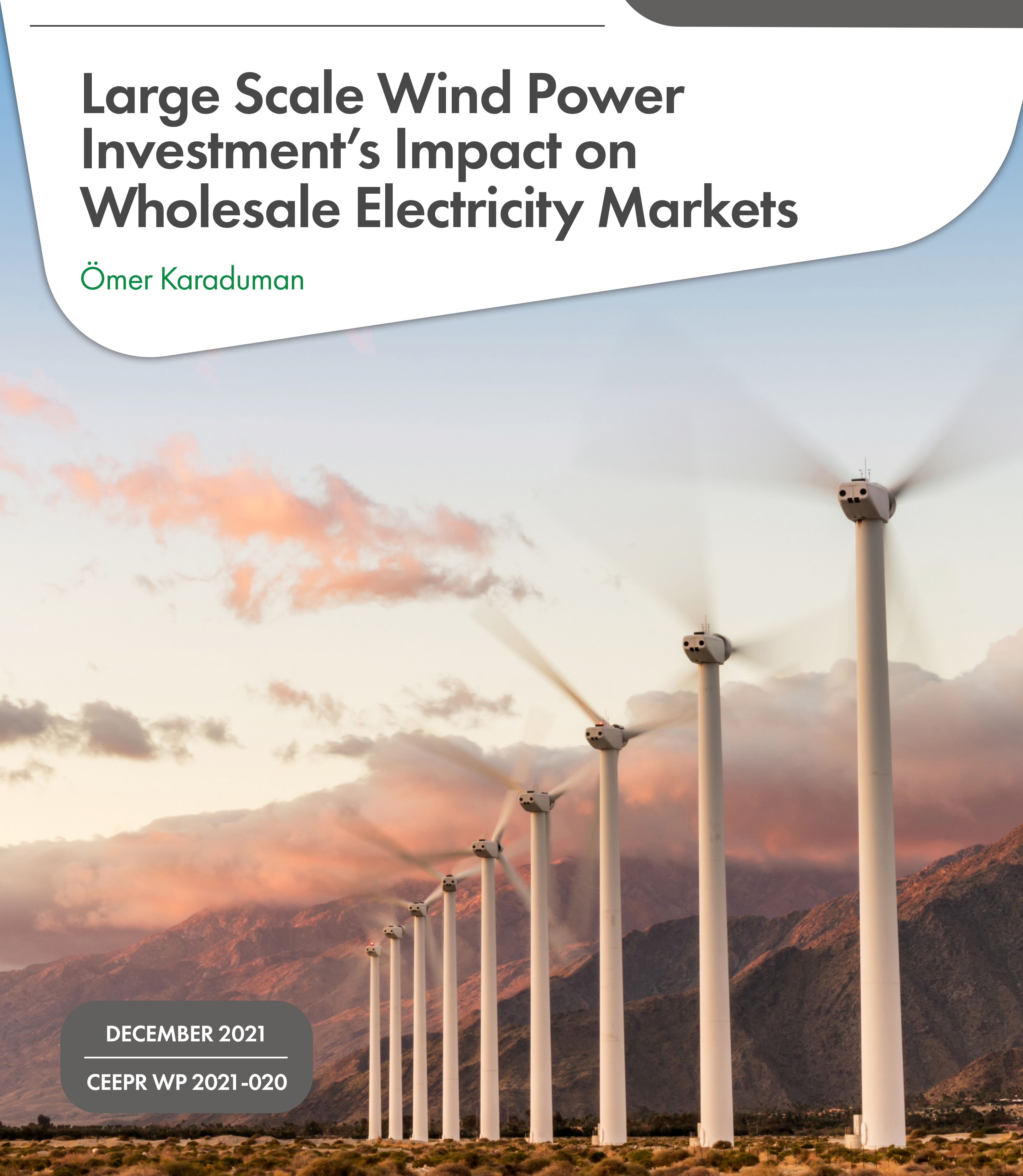

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Large Scale Wind Power Investment's Impact on Wholesale Electricity Markets

Ömer Karaduman *

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Abstract

Renewable subsidies are an influential device for wind power investment. These policies help lower emissions by offsetting high-emitting electricity generation with clean energy. For zero-emission targets, the transition towards renewable power should be accompanied by the retirement of thermal generators to clean the energy mix in the power sector. In this paper, I build a framework to quantify the offset and revenue impact of large-scale wind power investment in a wholesale electricity market and apply it to study the South Australian Electricity Market. The equilibrium framework computes a supply function equilibrium using estimated best responses from conventional sources to observed variation in the residual demand volatility. I first show that reduced-form methods are biased as the scale of the additional capacity increases. My results highlight that with different investment sizes, the substitution patterns and revenue impact of wind power differ considerably. As the penetration level of wind power increases, the electricity becomes cheaper. The offset and negative shock shifts from low-cost inflexible generators to high-cost flexible generators, while the negative revenue impact is the highest on existing renewable generation. These impacts exhibit heterogeneity in price impact among different potential wind power projects. These results have some policy implications on renewable targets' long-run effects on the generation mix and the project selection given the subsidy scheme.

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1 Introduction

Wind energy plays a critical role in reducing greenhouse gas emissions by providing carbon-free and low marginal cost energy. Investments around the globe dramatically increased in the last two decades. In 2018, a quarter of all additional power capacity in the world was wind energy, and it is expected to become one of the dominant sources of power in the next couple of decades (*IRENA Renewable Capacity*, 2019). Much of the rising interest is related to cost reduction in installing a wind power plant and subsidies as a part of climate policies. As wind power plants produce clean electricity, it offsets some thermal generators' production. These substitution patterns of wind generation effectively determine its value climate policies.

As more wind energy is deployed, it should be accompanied by the retirement of high carbon emitter thermal power plants to achieve higher decarbonization. Although wind energy investments are driven mainly by subsidies, power plant retirements generally result from changing market dynamics. In 2018 wind generation only accounts for 5% of world electricity consumption. Nevertheless, increasing wind generation is already affecting generators' revenue in the wholesale market by lowering the prices due to its low marginal cost (Ketterer, 2014). Understanding this revenue impact of renewable generation is essential for determining the path for decarbonization in the future. For instance, if wind generation leads to the retirement of high-cost low-carbon emitting generators, it can diminish its impact on emissions or decrease the value of existing renewable generation, hurting future investments in renewable technologies.

In this paper, I ask what the substitution patterns for large-scale wind generation are and how they affect existing firms' revenues. To answer this question, I use Karaduman (2020)'s framework to quantify the potential effects of large-scale wind generation in the wholesale electricity market. My model uses data from an electricity market to simulate the equilibrium effects of a wind capacity expansion in electricity markets. I account for the price impact of wind generation and find a new market equilibrium in which I allow incumbent firms to respond to wind capacity increases. [1]

To model firms' decisions, I represent the electricity market as a multi-unit uniform price auction. Each day, before the auction, firms observe a public signal containing information such as publicly available demand and renewable production forecasts. They then bid into the electricity market a day ahead of the actual production. I simulated wind generation and modeled it as a decrease in demand for a given wind generation profile. I estimate incumbent firms' best responses to this shift in demand by using observed variation in demand and renewable production in a market without wind expansion. In this research, I use South Australia Electricity Market data from

[1] My model is not exclusive to wind or renewable. The impact of any stochastic change on either side of the market, such as solar expansion, energy efficiency, electric cars, etc. can be incorporated into the model.

2017 – 2018. In the observed period, almost 35% generation comes from wind energy, one of the highest wind energy ratios among electricity markets. The current high penetration level creates a considerable variation in residual demand, which helps my model recover firms' best responses.

First, I compare offset by wind patterns with reduced form analysis for different wind expansion scenarios by using Cullen (2013). I decompose offsets by the wind into two parts, merit order effect, due to price change, and market power effect, due to market power change. For small-sized wind expansion, my model and Cullen (2013) give similar results, as market power changes are insignificant. However, as the new wind generator's capacity increases, marginal units that new wind generation offsets change, and the market power effect amplify the difference between estimates of my model and Cullen (2013)'s. Surprisingly, I find a similar carbon emission decrease with both models, 1.05 tons per MWh.

Next, I evaluate substitution patterns for wind generation at a much larger scale, up to 100% of the market generation capacity. South Australia trades with its neighbor region Victoria, which has a lot of brown coal generation. For a low level of wind generation investment, gas power plants with flexible technologies adjust their strategies and do not get replaced by wind generation much. Most of the renewable generation is exported to Victoria to replace brown coal. However, as the penetration level increases, the transmission between the two regions gets congested, and almost half of the renewable production gets curtailed. On the other hand, all other power plants' production in South Australia is cut almost half. In terms of emissions, large-scale wind generation cuts South Australia's carbon emissions by 60% and two times more in terms of tons in Victoria.

The impact of wind generation on different generators' revenue varies a lot at different expansion scales. For small capacity expansion, generators with flexible technologies lose the least by adjusting their bids. However, as the penetration level increases, wind generation suppresses prices, and flexible but high-cost generators stop producing. Some gas technologies lose up to 90 percent of their revenue. The existing wind generation gets the most considerable reduction in revenue and loses up to 91% of its revenue. These results have some policy implications. In a pathway with an aggressive wind capacity target, low carbon emitting generators may exit due to price reduction. On the other hand, as new renewable generation cannibalizes existing renewable technologies, it can be more costly to incentivize further investment in renewable technologies.

Lastly, I find that wind project production differs from each other based on their capacity factor, and this can affect the potential value of a wind generation investment (Novan, 2015), (Gillingham and Ovaere, 2020). I look for potential heterogeneity between 18 existing wind projects in South Australia, and I find a significant dispersion in projects' price effects, 35%, and revenue effects, 30%. This heterogeneity leads to a policy discussion. If a policymaker has a particular concern about the capacity, price impact, or revenue impact of a project, a policy must differentiate between competing investments to ensure that the socially optimal renewable investments are made.

Related Literature This paper contributes to a few different pieces of literature. First, it explores the impact and environmental benefits of renewable power. Cullen (2013) finds that environmental benefits of wind-generated electricity exceed the cost only when the value of emissions is high. Novan (2015) finds a significant heterogeneity in carbon offset between solar and wind-generated electricity and Gillingham and Ovaere (2020) extends a similar research question to across countries setting. Ketterer (2014) and Bushnell and Novan (2018) looks at the price impact of wind and solar generation, respectively. The aforementioned papers follow a marginal analysis for the impact of renewable substitution patterns. This paper confirms the papers' findings in the South Australia context and extends the analysis to a more structural setting, allowing for a larger scale of renewable investment.

The methods in this paper contribute to the growing literature on structural empirical approaches that utilizes large available bidding dataset, and electricity market clearing algorithms ((Wolak, 2003) , Hortacsu and Puller (2008), Reguant (2014))). This paper also contributes to another growing literature about long-run dynamics in electricity market. Impact of coal power plant retirements ((Kim, 2019)), carbon price ((Cullen and Shcherbakov, 2011), (Chyong et al., 2020)), nuclear power closure ((Davis and Hausman, 2016), (Jarvis et al., 2019)), and environmental regulations ((Linn and McCormack, 2019)).

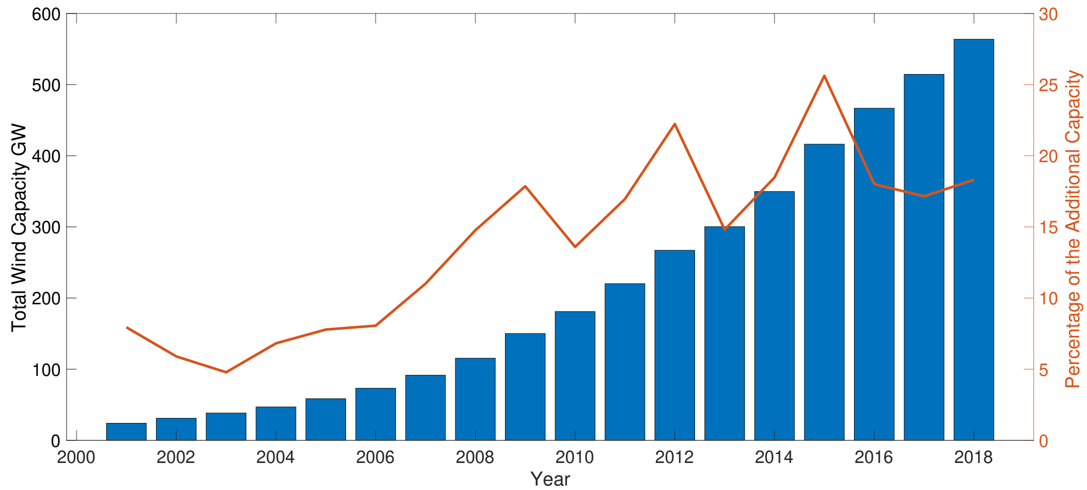
2 Wind Energy in Electricity Markets

2.1 Wind Power Investment

Wind power is an important part of the decarbonization agenda for many countries as it provides clean and green energy. Over the last three decades, wind generation capacity increased almost from zero to one quarter of the total renewable capacity and one-fifth of the renewable generation in 2018 (*IRENA Renewable Capacity*, 2019). Especially in the last decade, wind power became a more significant part of the added capacity to power generation. Figure 1 shows the total wind power capacity and wind power as the share of additional annual capacity. In 2015, wind power capacity investments among all technologies, including thermal power plants such as gas and coal, made up a quarter of that year's total capacity investments (*IRENA Renewable Capacity*, 2019).

Wind resources are only available when the wind is blowing at operational speeds; they are non-dispatchable and intermittent. Their production patterns are hard to predict. Wind production varies depending on the geography, hours, days, seasons. They produce electricity only when the wind is blowing. This production inflexibility causes some technical problems and affects its economic value, especially for large-scale penetration (Gowrisankaran et al., 2016). One measure to calculate the efficiency of a renewable generator is a capacity factor, a ratio of an average actual

Figure 1: Wind Power Capacity and As a Percentage of the Additional Yearly Capacity in the World



Source: IRENA Renewable Capacity 2019

electrical energy output over its capacity.

Like many other renewable technologies, fixed costs are high and marginal costs are low. A large part of the cost for wind power is an upfront fixed installment cost, with no fuel cost and low O&M cost. Low marginal costs prioritize renewable technologies over thermal generators once installed. Thus renewable production can offset pollution that otherwise would have been emitted by conventional fossil fuel generators' production.

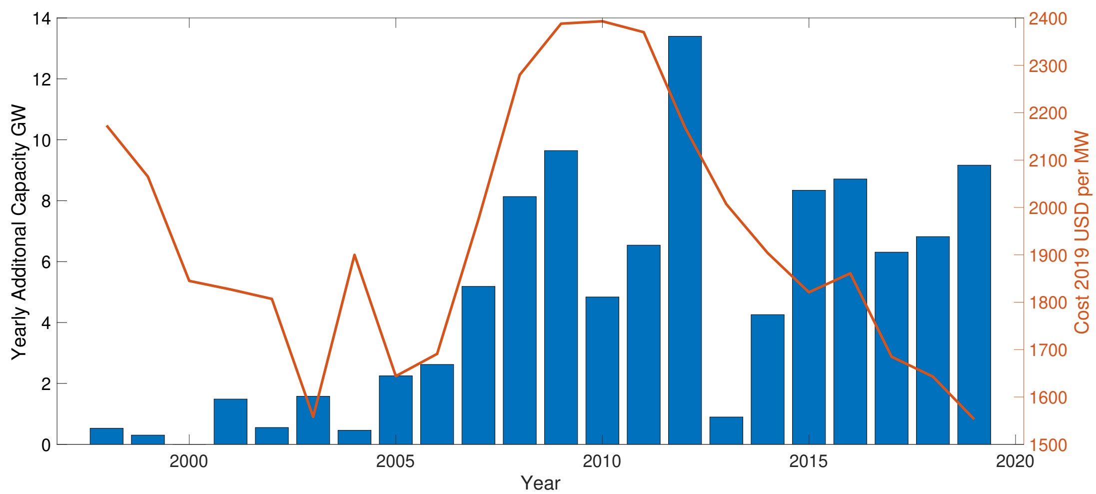
Subsidies Across the globe, subsidies play a significant role in deploying new wind capacity. Lots of local and federal incentives programs around the world make renewable generation more competitive and try to achieve carbon emission reduction policy goals[2]. These incentive programs primarily differ based on their payment scheme. Most countries adopt some version of feed-in tariff policies, a long-term contract to renewable energy producers based on renewable production (Germany, Spain, Australia). Some others adopt feed-in-premium, a premium on top of the market price of their electricity production, tax credits, renewable mandates or standards [3].

At the federal level, in the United States, Production Tax Credit (PTC) plays a crucial role in financing renewable resources through a per-kilowatt-hour tax credit for a unit of electricity gen-

[2] The cost of building a wind power plant significantly reduced in the 1980s and 1990s, nearly by tenfold (Lantz et al., 2012)

[3]For instance, in the US, at the state level, there are Renewable Portfolio Standards (RPS), in which renewable producers receive a renewable energy certificate (REC) for each MWh generated.

Figure 2: Annual Wind Capacity Additions and Cost of 1 MW installment in the United States



Source: IRENA Power Generation Cost 2019

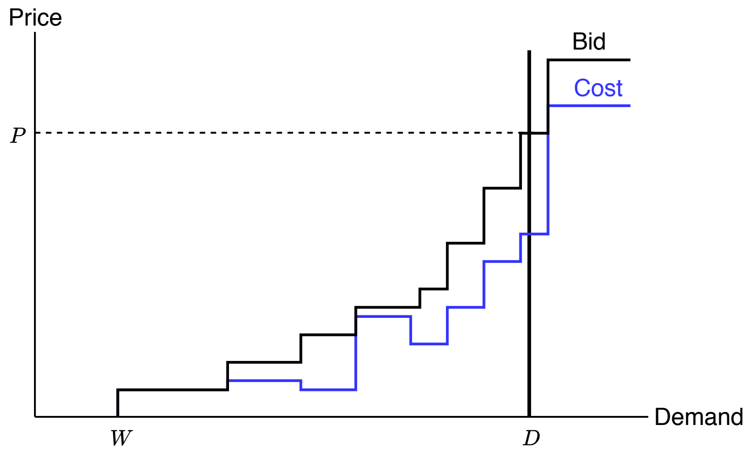
eration. Figure 2 shows the annual additional wind generation capacity and cost of installment per MW in the United States, and investment does not follow the installment cost closely. In the USA, tax credits' expiration and uncertainties drive most of the fluctuation in the capacity investment. In other countries, like Australia, Renewable Energy Targets (RETs) have been very influential in the early adoptions of renewable technologies.

The nature of these incentives plays a significant role in selecting renewable projects. Production-focused subsidies such as PTC can bias wind investment towards high-producing sites with lower covariance of their variable output with market prices (Schneider and Roozbehani, 2017). Similarly, capacity-oriented policies can lead to projects with lower capacity factor (Schmalensee, 2016). Therefore understanding the heterogeneity of projects and tailoring the incentives accordingly can play a vital role (Novan, 2015), (Gillingham and Ovaere, 2020).

2.2 Electricity Markets

The nature of the electricity makes it very expensive to store; therefore, real-time electricity demand and supply need to be balanced. System operators coordinate the producer and consumer sides via a centralized mechanism to maintain the grid's stability. System operators usually run complex algorithms to balance the market, considering technical constraints such as generators and grid's capacity, loss factors, etc. These algorithms search for the lowest possible cost for consumers, following merit order ranking within producers.

Figure 3



Aggregated demand curve does not necessarily align with the aggregated cost curve.

In deregulated markets, such as Australia's National Electricity Market (NEM), producers submit their willingness to produce at specified prices, their "bids", to the system operator in advance. The system operator ranks the merit order based on bids from different producers and clears the market where demand meets supply. These bids do not necessarily reflect the generator's production cost. Some producers may have incentives to bid higher than their production costs because of their market power, leading to differences in merit order and production cost ranking. Figure 3 shows an example of an aggregated bid and cost curve. In this example, the merit order does not follow the cost order, as some firms exercise their market power and bid higher than the following cheapest generators bid. These types of market power exercises can lead to significant market inefficiencies (Borenstein et al., 2002).

An increase in generation from wind power plants effectively shifts the electricity supply curve outward due to their merit order ranking. This shift replaces some marginal generators' production. The identity of the offset of the conventional generator depends on the price setter unit at the time of wind production. This shift in supply also reduces wholesale prices. This change leads to revenue reduction for marginal units, whose production has been offset by wind generation, and for inframarginal units, whose per MWh revenue is decreased. If the total renewable production exceeds electricity demand, then the remaining energy must be curtailed or stored for the power grid's security.

3 Institutions and Data

I use Australia's National Electricity Market (NEM) data in 2017 to study the impacts of additional large-scale wind generation. In this section, I first introduce NEM and its generation mix. Then, I show related summary statistics of electricity demand, prices, and production profiles.

3.1 Australia's National Electricity Market

In Australia, the Australian Energy Market Operator (AEMO) operates the electricity market, the National Electricity Market (NEM). The NEM connects five regional market jurisdictions: Queensland, New South Wales, Victoria, South Australia, and Tasmania. AEMO operates an energy market that produces between 15,000 and 65,000 MW, with around 85,000 MW of installed capacity. The market serves more than 22 million people and collects over AU$16 billion in gross charges per year.

The NEM is an energy-only pool; it only compensates power that has been produced. The NEM matches generation's supply schedules with demand[4] in the most cost-efficient way for each 5-minute period. The NEM averages the 5-minute prices and posts spot prices every 30 minutes for each of the five trading regions. In the NEM, the minimum and maximum market prices are $AU14,500/MWh and –$AU1,000/MWh, respectively. AEMO uses the spot price as the basis for settling financial transactions for all energy traded in the NEM.

In the NEM, generating units submit their bids every 30 minutes for the following day before 12:30 pm. The NEM uses these bids to clear the market and construct a production agenda for the day. The day starts at 4:30 am. Every 5 minutes, the AEMO releases the NEM Dispatch overview, which includes prices, demand, generation, renewable production, and trade between regions for the last five minutes.

NEM regions have a heterogeneous generation mix. Historically the electricity sector in Australia has been dominated by coal-fired plants due to its rich coal resources. However, in the last two decades, thanks to aggressive RETs, there has been a steady shift towards natural gas and renewables in some regions. On the one hand, South Australia has a generation mix in which almost half of the electricity comes from renewable resources and the other half from natural gas. On the other hand, Victoria's electricity production is still dominated by brown coal, 85% of the production.

[4] There is no bidding on the demand side in the NEM.

3.2 Data

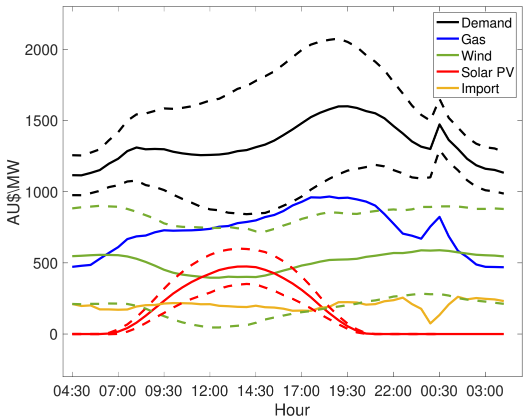
I construct a dataset from publicly available data from the AEMO. South Australia is a part of the NEM, connected only with the Victoria region. In the counterfactual analysis, I use data from 2017. There are two primary motivations for using this period. First, South Australia is one of the wind generation technology leaders, as a percentage of their generation mix, 40%. Second, during this period, the South Australia generation mix is stable; there is no entry or exit of thermal generators. I also use data from 2018 to test my counterfactual fit. In 2018 there has been some additional renewable investment in the wind (100 MW), rooftop solar (200 MW), and grid-scale solar (150 MW) without exits or entries by thermal generators from 2017.

The main variables in the data set are bids, production, demand data, and forecasts for demand and renewable production. The bidding data includes daily bids and can be mapped to the generation units in Victoria and South Australia. The production data has actual quantities generated from all units in the market for each 5 minute period. The demand data has realized the demand and a proxy for residential solar production for each 30 minute period. I also have data on generator characteristics, such as the type of fuel used, thermal rates, age, location, carbon emission, and ownership—a more detailed explanation of the data can be found in the Appendix of Karaduman (2020).

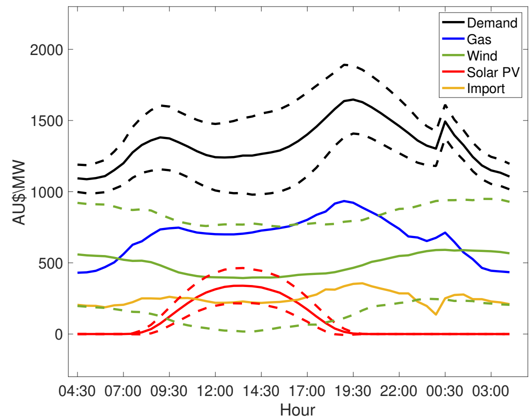
Generation Mix Although coal dominates the electricity production in Australia, in South Australia, production mainly comes from two types of resources: gas and renewables. This generation mix is considered a good candidate for the economically optimal low-carbon electricity production portfolio (De Sisternes et al. (2016)). There are 13 thermal units with two fuel types: natural gas and diesel oil. Gas-fired generators generate almost all of the dispatchable electricity, with relatively low CO_2 emission rates.

Gas technologies in South Australia include closed cycle (CCGT), open cycle (OCGT), and steam sub-critical (Steam). On top of the dispersion in CO_2 emission rates within natural gas-fueled generators due to fuel efficiency, environmental regulation compliance, and production profiles, they vary in terms of their production flexibility. CCGT is relatively more flexible than OCGT, which is more flexible than Steam. Diesel oil-fueled generators, peaker plants are only active for a few hours each month to meet peak demand, with high costs and high CO_2 emission rates. As Table 1 shows, wind production constitutes around 35%, gas generators 45%, and Solar PV 10% of electricity production. Imports from the Victoria region mostly come from brown coal generators. In South Australia, AGL, Pelican Energy, and Origin Energy produce almost 95% of thermal generation.

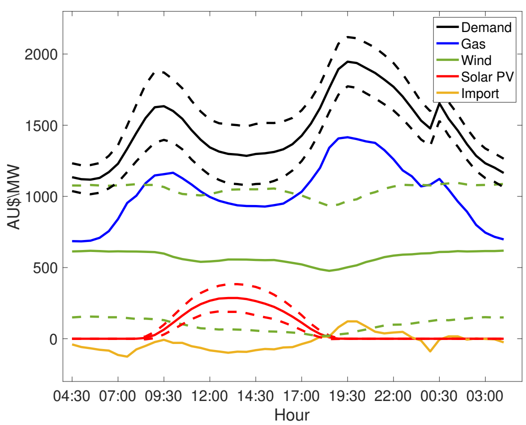
Figure 4: Daily Production and Demand Profiles in South Australia in 2017



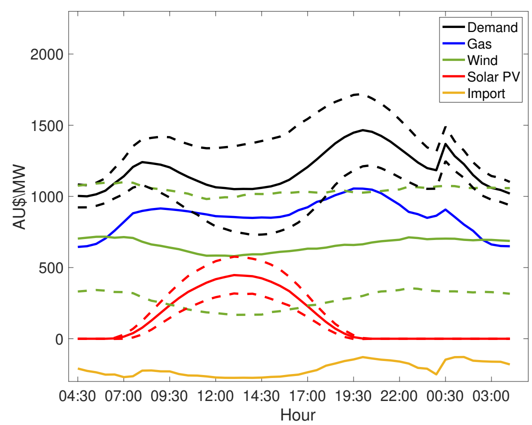
(a) Summer



(b) Fall



(c) Winter



(d) Spring

Table 1: Generation Mix for South Australia

Generator Name	Average Production (MW)	Capacity (MW)	CO2 Emission Rates (ton per MWh)	Units	Fuel Type	Technology	Owner
Torrens Island	333.0	1320	0.72	8	Natural Gas	Steam Sub-Critical	AGL
Pelican	287.6	529	0.48	1	Natural Gas	CCGT	Pelican Power
Osborne	151.2	204	0.57	1	Natural Gas	CCGT	Origin Energy
Quarantine	24.5	233	0.84	5	Natural Gas	OCGT	Origin Energy
Ladbroke	22.9	100	0.66	2	Natural Gas	OCGT	Origin Energy
Hallett	4.0	220	1.19	1	Natural Gas	OCGT	EnergyAustralia
Mintaro	2.3	105	0.96	1	Natural Gas	OCGT	Synergen
Dry Creek	0.8	171	1.36	3	Natural Gas	OCGT	Synergen
Pt Stanvac	0.6	65	1.49	1	Diesel oil	Compression	Lumo
Angaston	0.4	50	1.01	1	Diesel oil	Compression	Lumo
Lonsdale	0.2	21	1.49	1	Diesel oil	Compression	Lumo
Snuggery	0.1	69	1.49	1	Diesel oil	OCGT	Synergen
Port Lincoln	0.1	78	1.56	2	Diesel oil	OCGT	Synergen
Rooftop PV	116.5	800	0	-	Solar	Renewable	Miscellaneous
Wind	557.3	1700	0	13	Wind	Renewable	Miscellaneous
Import from VIC	52.6	800	1.12	-	Brown Coal	Steam Sub-Critical	Miscellaneous

Notes: The sample is from the South Australia Electricity Market January 2017 – December 2017. Rooftop PV is AEMO's estimation. Import from Victoria's emissions rate is the quantity-weighted region average.

Production Profiles Figure 4 displays the average daily profile of demand, import, wind production, Solar PV production, and gas power plant production in South Australia in different seasons. Dotted lines show a standard deviation from the mean. South Australia's peak-time demand is consistently after sunset due to high solar energy production, similar to the "duck curve" in California. On average, wind production is steady throughout the day, with up to 30% changes in average production between seasons. However, solar production varies much more between seasons, around 120% changes between winter and summer.

Even though these average production and demand profiles show some familiar patterns in power systems, the variation from day to day is very high. Dashed lines in Figure 4 show one standard deviation in the daily profile of demand and renewable production. Regardless of the time of day, wind production has very high volatility, and this variability leads to different substitution patterns with wind generation on the merit order. On the other hand, gas power plants follow demand very closely. The variability in intermittent resources and demand helps the model recover firms' best responses to renewable production. In particular, I exploit variation in residual demand (which includes both renewables and demand) to estimate firms' best responses to new renewable investment.

The price in South Australia is set by a generator from Victoria more often than one of its gas power plants. Therefore modeling trade plays an essential role in any counterfactual exercise in

South Australia. There is also a high correlation between export and renewable production, 0.69, which suggests that the trade with the Victoria region handles some variability due to renewables. South Australia's wind generation in trade usually replaces the brown coal production from Victoria. This trade has significant implications for the carbon emission impact of renewable generation in South Australia.

4 Reduced-form Analysis

This section presents reduced-form evidence on offset by wind power generation by using Cullen (2013)'s approach. This reduced form approach takes advantage of the exogeneity of wind power plant production to identify average substitution patterns between each generator and wind power production. However, there can be common factors in wind production patterns and a generator's production decision. To deal with this potential bias Cullen (2013) controls for factors that can lead to changes in both thermal and wind production. It also uses lagged versions of the controls to take the dynamic factors into account.

For the estimation, I run the following regression for each generator i's production.

$$q_{it} = \beta_{i0} + \beta_{i1}\text{Wind}_t + \beta_{i2}\text{Wind}_t^2 + \textbf{Controls}_t\gamma_{\mathbf{i}} + \textbf{Lagged}_t\omega_{\mathbf{i}} + \alpha_i\text{Day}_t + \epsilon_{it} \tag{4.1}$$

where q_{it} is realized quantity produced by generation i in period t, Wind_t is the total wind power production, $\textbf{Controls}_t$ including, demand, temperature, wind speed and humidity, $\textbf{Lagged}_t$ lagged version of controls extending back to 6 hours [5], and Day_t is a dummy for the observation day.

The goal of using such an extensive set of lagged controls is to control dynamic constraints and firms' expectations. The quadratic function form of interaction of wind generation allows for some nonlinearity in the substitution patterns. The regression does not impose the sum of marginal impacts to be one. Potentially different comparative transmission line losses between gas and renewable generation and curtailments can lead the sum of the offsets to be less or more than one.

Given estimations of regressions for each generator, marginal substitution parameters for wind power can be calculated. The total marginal effect can be represented as $\frac{\partial \triangle q_{it}}{\partial \text{Wind}_t} = \beta_{i1} + 2\,\text{Wind}_t\beta_{i2}$. For changes in carbon emission, I multiply the average carbon emission rate of each generator with its estimated change in production.

Table 2 shows the offsets for each fuel type. Since transmission constraints within South Aus-

[5] Cullen (2013) extends the lagged controls for 25 hours prior. In my dataset, generators can adjust their production within 6 hours. Therefore I used only 6 hours prior. Adding the extra 18 hours does not change the main substitution patterns.

Table 2: Offset by Wind

Fuel	Offset MWh (MWh/MWh Wind)	Offset CO_2 (ton/MWh Wind)
All gas	-0.28	-0.24
	(0.03)	(0.03)
OCGT	-0.04	-0.04
	(0.02)	(0.01)
CCGT	-0.08	-0.06
	(0.02)	(0.01)
Steam	-0.16	-0.14
	(0.03)	(0.03)
Diesel	-0.002	0.008
	(0.001)	(0.001)
Comp	-0.002	0.007
	(0.001)	(0.000)
OCGT	0.000	0.001
	(0.001)	(0.000)
Import	-0.74	-0.83
	(0.02)	(0.03)
Market	-1.02	-1.05
	(0.02)	(0.04)

Note: Standard errors in parentheses. Gas technologies include open cycle (OCGT), closed cycle (CCGT) and steam sub-critical (Steam). Diesel technologies include compression (Comp) and open cycle (OCGT). The sample is from South Australia Electricity Market 2017.

tralia are not significant, the total offset for wind production is near -1. Also similar to the patterns in the data, net import accounts for three-fourth of the overall reduction due to wind production. The high negative correlation between wind production and net import already shows that the Victoria region buys most of the renewable production in the region. For different gas technologies, the offset patterns are different. Steam gas power plants reduce their production two times more than CCGT and four times for than OCGT.

The change in imports is the main driver for carbon emission offsets by wind power. An increase in renewable production in South Australia replaces high carbon emitter brown coal power plants in Victoria.

The reduced form method finds the impact of wind power on carbon emission using observed generating behavior. However, the estimated effects may not be valid for large-scale renewable investment. The substitution patterns at a more significant margin can be drastically different from the patterns in the data, especially with very high penetration. Therefore, to further specify the mechanics of the offset, I model the electricity market, account for the change in the generator's bidding strategies, find a new equilibrium, and calculate new prices under a large-scale renewable investment policy.

5 Model

In this section, I build a model of strategic behavior in the electricity market. To formalize firms' decisions, I represent the pricing mechanism in the electricity market as a uniform price multi-unit auction. My model closely follows Karaduman (2020).

I first describe the electricity demand, renewable production, and information structure. Next, I lay out payoffs, information structure, and strategies for thermal technologies. Then, I derive the equilibrium conditions for my model. Finally, I construct a mapping to account for changes in market equilibrium due to additional renewable investment.

5.1 Electricity Demand

In the electricity market, the System Operator runs a daily individual multi-unit uniform price auction for each of the H periods of the following day. I take electricity demand for each period h of the day d, D_{dh}, to be inelastic. In electricity markets, the bulk of demand is from utilities. The end consumer usually pays a fixed price per MWh, which makes the demand very inelastic in the short run [6].

Each day, before the auction, firms observe a discrete public signal $X_d \in \mathcal{X}$. The public information set contains information such as publicly available demand and renewable production forecasts. The $H \times 1$ demand vector D_d has probability density function $f_D(D_d|X_d)$ conditional on X_d. The signal X_d and the publicly known function f_D inform firms about the distribution of the electricity demand and renewable production for the next day. Conditional on X_d, the signal X_{d+1} has the probability density function $f_X(X_{d+1}|X_d)$. This Markovian structure links demand profiles across days.

Each firm k submits a bid to the market each day for the following day. These bids are supply schedules $S_{kd}(p) = \big(S_{kd1}(p), \ldots, S_{kdH}(p)\big)$, where $S_{kdh} : \mathbb{R} \to \mathbb{R}$ for the period h of the day d. The bid, S_{kdh}, should be increasing in p. For each period h, the market clearing price p^c_{dh} satisfies the condition $\sum_k S_{kdh}(p^c_{dh}) = D_{dh}$. I assume there is no transmission constraint within the market.[7] The vector p^c_d represents the price vector for the day d. Firm k gets paid $\sum_{h=1}^{H} S_{kdh}(p^c_{dh})p^c_{dh}$ for the day d.

5.2 Firms' Payoff and Strategies

There are $k = 1, \ldots, N$ firms that maximize their profit. Each firm owns $u = 1, \ldots, U_k$ generators to produce electricity with some technological capacity, e.g., a maximum/minimum production

[6] Any type of nonstrategic flexible demand can be easily incorporated into the model.
[7] Later I specify the transmission constraint between markets.

level. For ease of exposition, I assume each firm owns one generator. I denote firm k's bidding strategy σ_k, and the market strategy $\sigma = (\sigma_1, \ldots, \sigma_N)$. There are two types of generators in the electricity market: thermal and renewable, for which I use i, r to represent each type of generator, respectively.

Thermal firm i submits daily bids to maximize their expected daily profit conditional on their information set and their beliefs about other players' strategies, given by σ_{-i}. Firm i's information set, I_{id}, contains the public signal, X_d, and a signal $\epsilon_{id} \in \mathbb{R}$. This private signal can be interpreted as any shocks to firm i's daily profit, such as cost shocks and information about demand or other firms. Also, it explains variation in data in thermal firms' bids conditional on the public signal.

Assumption 5.1. *The signal ϵ_{id} is a private signal and $\epsilon_{id} \perp\!\!\!\perp \epsilon_{id'} | X_d \neq X_{d'}\ \forall i$.*

This assumption allows for the correlation of private signals conditional on the demand distribution signal. However, the model does not allow for firm-specific persistent shocks across days.

The model also assumes no cost complementarities across days for thermal generators, such as start-up and ramp-up costs, but allows for within-day cost complementarities. In the case of high start-up and ramp-up costs, these complementarities can impact the generator's profit. However, Reguant (2014) shows that start-up and ramp-up costs for gas power plants are not significant.[8]

The bidding strategy function of the thermal firm is a mapping from the private and public signal to supply schedule vectors, $\sigma_i : \mathcal{X} \times \mathbb{R} \rightarrow \mathcal{S}_i^H$, where $\mathcal{S}_i$ represents sets of supply schedules that satisfy the technological constraints of the firm i and the market rules. If other firms' strategies are given by a strategy profile σ_{-i}, firm i's expected daily profit given a signal X_d and bid S_{id} is

$$\mathbb{E}[\pi_{id}|\sigma_{-i}, X_d, \epsilon_{id}] = \mathbb{E}\Big[\sum_{h=1}^{H} \pi_{idh}(S_{idh}, p^c_{dh}, \epsilon_{id})|\sigma_{-i}, X_d, \epsilon_{id}\Big] =$$

$$\sum_{h=1}^{H} \int\int \pi_{idh}(S_{idh}, D_h, S_{-idh}, \epsilon_{id}) f_D(D_h|X_d)\sigma_{-i}(S_{-idh}|X_d) dD dS_{-idh}. \tag{5.1}$$

The ex post profit of firm i is $\pi_{id} = \sum_{h=1}^{H} S_{idh}(p^{c*}_{dh})p^{c*}_{dh} - C_i(S_{id}(p^{c*}_d), \epsilon_{id})$, where C_i is the cost function of firm i and p^{c*}_d is a vector of market prices. The cost function for each day is a function of the production vector for the day $S_{id}(p^{c*}_d)$ and the private signal, which allows for within-day cost complementarities.

[8]Since South Australia only has gas power plants as thermal generators, these low-cost links between days do not affect a firm's daily optimization decision.

Trade South Australia trades electricity with its neighbor region, Victoria. I model Victoria as firm bidding in the South Australia electricity market to incorporate trading into the model. Like the other thermal firms, firm Victoria submits supply schedule $S_{VIC}(p)$ into the market. However, unlike other thermal generators, I allow firm Victoria to purchase electricity when $p_{VIC} > p_{SA}$. This flexibility enables South Australia to sell electricity when prices are lower relative to Victoria. Also, it mitigates curtailment at some capacity when renewable production is higher than demand in South Australia. I use transmission line capacity as the capacity of the firm Victoria, $S_{VIC} \in [-800, 700]$. This allows for differences between the two regions' prices.

I use the market-clearing condition for Victoria to calculate S_{VIC}. I assume Victoria's renewable production, demand, and trade with other regions are exogenous. Therefore, the market-clearing condition in Victoria is

$$S_{VIC,dh}(p) = Trade_{SA}(p) = \sum_{k \in VIC} S_{kdh}(p) - Export_{Others,dh} - Renewable_{VIC,dh} - Demand_{VIC,dh},$$

where $S_{VIC,dh}(p)$ is a bid of firm Victoria in day d and period h. Notice that if the price in South Australia is lower (higher) than Victoria, firm Victoria buys (sells), $S_{VIC,dh}(p_{VIC} - \epsilon) \leqslant 0$ ($S_{VIC,dh}(p_{VIC} + \epsilon) \geqslant 0$) for any $\epsilon > 0$.

Renewable Production As a part of greenhouse-gas-emission mitigation targets, most countries have programs to support renewable production and investment: e.g., Renewable Portfolio Standards (RPS), Renewable Energy Targets (RET), Production Tax Credits (PTC), and Feed-in Tariffs. Most of these policies are output-based subsidies rather than investment subsidies, and these financial supports disincentivize a potential strategic reduction in renewable production.

I assume renewable generator r with $\overline{a}_r$ capacity is non-strategic and its production is exogenous, $a_{rdh} \in [0, \overline{a}_r]$, distributed $f_r(a_{rh}|X)$. Acemoglu et al. (2017), Genc and Reynolds (2019) and (Samano and Sarkis, 2020) show that firms with diverse energy portfolios may have incentives to manipulate renewable production or under-produce from their thermal generators. Therefore, I assume output-based subsidies, such as PTC, feed-in-tariffs are large enough for the renewable generator to not under-produce.[9]

5.3 Equilibrium

In this section, I define equilibrium in the daily electricity market. For every day d, thermal generators simultaneously bid into the electricity market ahead of actual production. For every realized

[9]In my dataset, the owners of renewable generators do not have thermal generators in their portfolios.

demand level in every period h, the System Operator aggregates supply bids and clears the market at the lowest possible price.

Definition 5.1. *The strategy profile σ^* is a Markov Perfect Equilibrium if*

$$\sigma_i^*(X, \epsilon_i) = \underset{S_{id}(p) \in \mathcal{S}_i^H}{\text{argmax}} \ \mathbb{E}[\pi_{id} | \sigma^*, X, \epsilon_i], \forall i \in N \textit{ and } \forall X, d, \epsilon_i, \tag{5.2}$$

$$D_{dh} = \sum_{i=1}^{N \setminus \{i\}} S_{idh}(p_{dh}^{c*}) + a_{rdh} \ \forall d, h. \tag{5.3}$$

Equation 5.2 requires that thermal generators maximize their expected daily profits. Since the public signal is the only relevant information for demand, thermal generators only condition their strategy on the public and private signals. Thermal generators form their expectations on demand conditional on public signal X. The System Operator runs a multi-unit auction, and the electricity market clears at p_{dh}^{c*}, where demand equals the sum of renewable production and thermal firms' supply, as Equation 5.3 shows.

Solving the thermal generator's problem, Equation 5.2, involves supply function equilibrium, which is usually computationally intractable and not unique (Klemperer and Meyer (1989), Green and Newbery (1992)). In the next subsection, I propose computationally tractable re-formulation to find σ^*.

5.4 An Equivalent Best Response Mapping

5.4.1 Net Demand After Renewable Investment

Let us define market equilibrium strategies in a market without additional renewable generation as σ, in which thermal firm i's strategy is σ_{is}. The strategy σ satisfies Definition 5.1, and it can be observed in data. When new wind investment enters the market, it produces at its total capacity.

Wind production is inelastic and has a lower merit order than thermal generators. Therefore, the System Operator starts clearing the demand by using wind production.

New wind investment's production for period h, $\widehat{a}_{rh}$ is distributed conditional on X with probability distribution $f_r(a_{rh}|X)$. Thermal firm i forms an expectation about the new net demand, D'_h. Since charge level is private information, the only relevant information about renewable production is the signal X. Recall the market clearing condition for period h after renewable production a_{rh},

$$\sum_{i=1}^{N} S_{ih}^r(p_h^c) = D_h - a_{rh} = D'_h,$$

where S_{ih} is a bid of firm i under the strategy σ, and D'_h is the net demand after wind investment. Since the System Operator first clears renewable production, thermal generators compete to meet net demand, D'_h, instead of D_h. The new net demand after after the investment D'_h consists of the difference of two random variables, D_h and a_h, with distribution conditional on X, $f_r(a_{rh}|X)$ and $f_D(D_h|X)$, respectively.

Let us define the probability density function of net demand after new wind investment conditional on signal X, $f^r_{D'}(D'|X) = \int_0^{\overline{a}_r} f(D-a|X)f_r(a|X)da$. Now, new net demand, D', is a more relevant object for thermal generators' residual demand than demand, D. Therefore thermal generators' respond to the new distribution $f^r_{D'}(D'|X)$.

5.4.2 Thermal Generators' Response

Thermal generators compete to meet net demand, D'_h, given the new wind production distribution $f_r(a_{rh}|X)$. Let us define another signal X^r from the same set as $X \in \mathcal{X}$, which conveys information about the distribution of D'.

Definition 5.2. *If two signals X^r, X belong to the same set $X^r, X \in X_m$, then the distribution of D' conditional on X^r is the same as the distribution of D conditional on X,*

$$f^r_{D'}(D'|X^r) = f(D|X),\ \forall X, X^r.$$

Notice that this definition implicitly assumes that the distribution of D' can be partitioned into sets conditional on a signal X^r , $f^r_{D'}(D'|X^r)$, such that these new distributions can fit into partitioned distributions of D conditional on signal X, $f(D|X)$. Renewable production often reduces demand. Therefore, if $\mathcal{X}$ is rich enough in terms of demand levels, such a signal can be defined. A further discussion on this issue can be found in Karaduman (2020).

I assume thermal generators observe X^r but not X. Given a day with $X_d \in X_m$, the signal X^r_d does not necessarily belong to set X_m. For some realization of net demand D_d, new wind generation can be large enough to shift D'_d, and signal X^r_d can belong to a different set $X_{m'}$. With the new signal X^r and given other firms' strategies σ_{-i}, the thermal generator i's problem becomes

$$\underset{S_{id}(p)\in\mathcal{S}_i^H}{\text{argmax}} \Big[\sum_{h=1}^{H} \int\int \pi_{idh}(S_{idh}, D'_h, S_{-idh}, \epsilon_{id}) f^r_{D'}(D'_h|X_d)dD'dS_{-idh}\Big].$$

By Definition 5.2, conditional on two signals belonging to the same category, the distribution of net demand after new wind production is the same as the distribution of net demand. Therefore, I use the firms' strategies σ_{-is} to find a new equilibrium.

Proposition 5.1. *If two signals X^r and X belong to the same category X_m, and a strategy set σ_i is firm i's equilibrium strategies in a market without additional wind generation, define*

$$\widehat{\sigma}_i(S_{id}|X_d^r) = \sigma_{is}(S_{id}|X)\ \forall i, X_m \in \mathcal{X}.$$

Then market strategies for firms, $\widehat{\sigma}$, is an equilibrium for firms in a market new wind generation.

Since X^r, X both belong to the same set X_m, the thermal generator's net demand distribution under both signals is the same. Therefore if thermal generators use their strategies under signal X^r in the same way as under signal X, their strategies constitute an equilibrium, as they were in the market without additional renewable investment. A further discussion and the proof can be found in Karaduman (2020).

6 Empirical Strategy

This section introduces my empirical strategy to quantify a renewable entry's impact on the electricity market. First, I decompose offset by the wind into two parts and discuss the difference. Then, I discuss my estimation procedure for public signal X, the conditional distribution of demand, and wind production. Finally, I present the algorithm for finding the equilibrium in a market with new wind investment.

6.1 Decomposition of Offset Wind

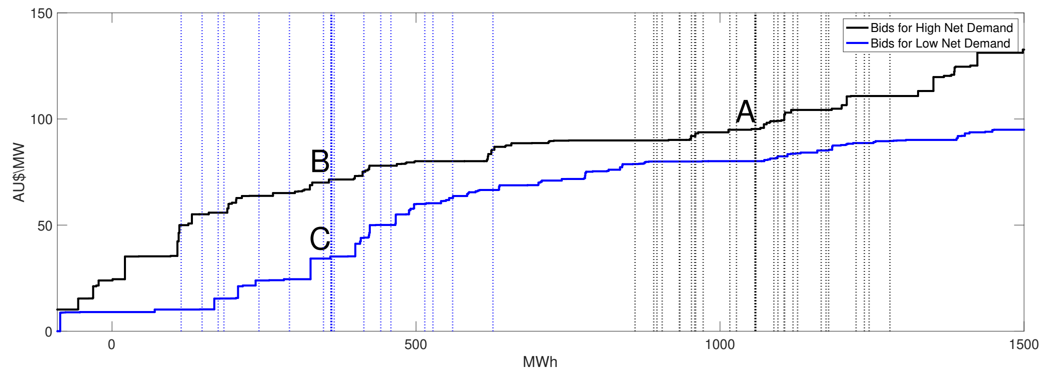
An increase in wind generation effectively shifts the aggregated electricity supply curve outward due to the merit order. Renewable generation replaces the marginal units at the time of production. This shift reduces wholesale electricity prices, reducing the inframarginal unit's revenue. This reduction can lead to a change in the market power of some generators; in return may lead to a change in their bidding strategies.

Due to the low O&M cost of wind generation and inelastic demand, the shift in electricity supply can be modeled as a shift in net electricity demand. In supply function equilibrium literature, the response to demand reduction usually leads to a reduction in market power, resulting in firms bidding closer to their marginal cost[10]. I decompose the change in the production of generators into two parts: merit order and market power effect.

$$\triangle q_i = \{ \underbrace{S_i(p) - S_i(p')}_{\text{Merit Order Effect}} \} - \{ \underbrace{S_i(p') - S_i'(p')}_{\text{Market Power Effect}} \}$$

[10]Results in the literature are theoretical results. I am not aware of an empirical study regarding this issue.

Figure 5: Aggregated Bids and Demand for some days in 2017 at 18:00



Firms respond to change in net demand by changing their bids.

where p and p' market prices before and after the renewable production, S_i is the bid of the generator i, and S'_i is the updated bid of the generator i after renewable production.

Figure 5 shows average aggregated bids for two sets of days for the same period in South Australia. Vertical black dashed lines are high net demand days, whereas the vertical blue dashed line is low net demand days. Bold dashed lines show the average net demand.[11].

Large-scale investment in wind generation can lead to a shift in net demand, similar to the difference in high and low demand days. If firms do not respond to these changes, in other words, keep their bids, the market equilibrium shifts from point A to point B. However, if firms adjust their strategies to use those in too low demand days with low market power, they bid more aggressively, and the market equilibrium shifts from point A to point C. This can lead to underestimating price and revenue effect wind investment, especially for a substantial level of wind generation investment with the reduced-form method. My model incorporates a shift from point A to point C. I discuss the differences in Section 7.1.

6.2 Estimation Details

In electricity markets, renewable resources have lower merit order. Therefore, the System Operator clears the demand with renewables before thermal generators. I define a new variable, net demand, the difference between demand and renewable production, and net demand is a more relevant variable since thermal generators compete for the net demand.

[11]In the dataset, firms bid more aggressively when the demand is lower. However, some exceptions in which firms bid less aggressively in response to lower demand. This potentially can lead to overestimation of the price and revenue effect of wind investment.

There are two renewable resources in South Australia; solar and wind. All the solar generation in South Australia comes from rooftop solar PVs in 2017. Customers directly consume this electricity; therefore, they buy less from the grid. The demand in the dataset is demand after solar PV production, and I calculate net demand in data as the difference between demand and wind generation. In the dataset, I do not observe curtailment for renewable. According to the AEMO's Quarterly Energy Dynamics reports (AEMO (2018)), wind curtailment around this period is less than 5 % in South Australia; therefore, I assume there is no curtailment for the baseline.

In order to define the signal X, I assign observed half hourly net demand vectors D_d (size 48×1) to N_X groups $\mathcal{X} = \{X_1, \ldots, X_{N_X}\}$ by using their corresponding forecast vector FD_d. I use the k-median clustering algorithm to group days and construct $\mathcal{X}$. For a given number of clusters, this algorithm partitions vectors into clusters. The objective of this algorithm is to minimize within-cluster sum of squares,

$$\underset{\mathcal{X}}{\operatorname{argmin}} \sum_{m=1}^{N_X} \sum_{d \in X_m} ||FD_d - \boldsymbol{\mu_{X_m}}||^2,$$

where $\boldsymbol{\mu_{X_m}}$ is the median vector in X_m.

I use the elbow method to pick the optimal number of clusters, N_X. The elbow method looks at the total within-cluster sum of squares as a function of the number of clusters and picks a point in which a new cluster does not improve the objective much. I pick the number of clusters to be $N_X = 16$. The observed data shows a wide variety of net demand patterns. For the transition of signal X I assume and estimate a Markov process $f_X(X_{d+1}|X_d)$.

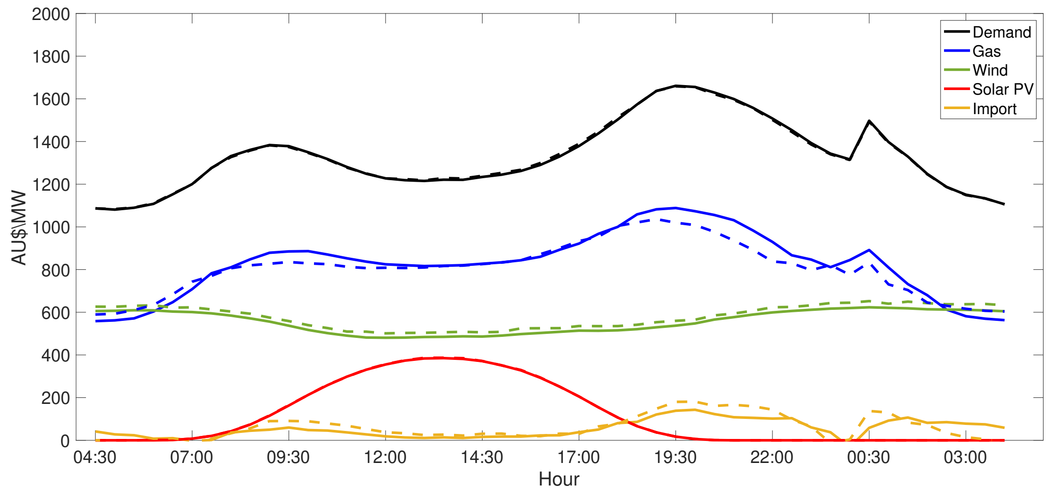
In order to fully characterize $f_D(D|X)$, I estimate the distribution of net demand conditional on signal X. Within the day, I assume demand, solar PV, wind generation follow a random effect model conditional on the signal X,

$$y_{dt} = C + \alpha_t + \xi_d + \epsilon_{dt} \tag{6.1}$$

where d is observed day and t is time period, α is the period fixed effect, ξ is random day effect, where $\xi \sim N(0, \sigma_\xi)$, and ϵ_{dt} is idiosyncratic period shock.

Since I assume firms submit their bid conditional on the signal X; I use the conditional empirical distribution to estimate $\sigma_i(X)$. By combining simulated demand, renewable production, and firm strategies, I simulate the market for 2000 days. Figure 6 shows daily patterns for all the processes. Solid lines are observed, dashed lines are simulated variables. Random processes match almost perfectly, whereas bid-based variables, gas production, and import match by a small error.

Figure 6: Comparing Data and Simulated Production and Demand Profiles 2017



Curtailment If net demand with the additional renewable production exceeds the total demand trade capacity of South Australia with Victoria, $a'_{rdh} > D_{dh} + 700$, System Operator curtails the difference. I define updated net demand by

$$D^r_{dh} = \begin{cases} D_{dh} - a'_{rdh}, & \text{if } D_{dh} + 700 - a'_{rdh} \geqslant 0 \\ 0, & \text{if } D_{dh} - a'_{rdh} + 700 < 0. \end{cases}$$

Simulation Details for Wind Investment To model an increase in wind capacity, I use the observed wind production profiles in the data. For an $M\%$ increase in wind capacity of technology j, I calculate the additional wind production a^r_{rdh} by $a^r_{rdh} = a_{jrdh} * (1 + \frac{M}{100})$.

As I describe in Section 5.4.1, additional wind production changes the net demand. I first simulate the existing renewable production, demand, and additional wind production. Then I calculate the new demand vector for the simulated day. Then I look for the closest cluster in the set of $\mathcal{X}$ by using Euclidean distance to assign the simulated day.

Here the identifying assumption is firms' best response to changes in the distribution net demand. If the additional wind production is large enough, it can affect the signal X. To identify firms' best response to renewable entry, I use observed shocks to residual demand. The source of the observed variation is the changes in levels of renewable availability or demand. As Section 3.2 shows, South Australia has a large variance in renewable production.

This process potentially creates a bias, especially for extensive wind penetration. One concern is that if the market has not experienced extensive renewable production, manifest as low net demand, it is challenging to identify firms' strategies for a large wind investment case. This, out of the scope of data concern, creates a bias for only the "market power" impact. In my dataset, South Australia experiences much of the variation in renewable production, and there are days in which thermal generators produce only a tiny fraction of their capacity. However, in the other type of markets, with the assumption that firms bid more aggressively (less market power) when demand is lower, my model can find an upper bound for prices and a lower bound on the revenue impact of the renewable expansion.

Another concern is the potential long-run impact of large-scale renewable investment. With a large reduction in revenues, some generators may exit the market, which potentially increases incumbent firms' market power exercise opportunities. Market exit and entry dynamics must be modeled to account for the full long-run impact. My method calculates the changes in wholesale revenues of generators, and these estimates can be used as part of a flow payoff of a firm. Also, if there are many generator maintenances in the market, this can allow identifying market competition with fewer players. This can be especially useful for base-load technologies like coal, which does take long maintenance breaks.

7 Results

In this section, I present my estimates of the impact of a large-scale wind investment. Given the calculated market equilibrium strategies σ^*, I simulate the electricity market for 2000 consecutive days. First, I discuss the fit of my model in the baseline case. Here, I compare the summary statistics of my estimates for 2017. Then I compare my model's fit for the generation mix in 2018 with a particular renewable investment in South Australia. Second, compare models of offset by wind and demonstrate how a reduced-form analysis can lead to biases, especially for large-scale renewable investments. Later, I show substitution patterns and, subsequently, the revenue impact of different sizes of investments in wind technology. Last, I discuss the impact of the heterogeneity in different wind generation technologies and its implication on renewable project selection under different renewable subsidy schemes.

7.1 Model Assessment

Before turning to estimates of large-scale renewable effects, it is important to check the model's validity in the baseline case. First, my model assumes firms condition their strategies on public signal X_d. I calculate the variation explained in thermal generators' bids by the estimated clustering

(a) Price Fit 2017 (b) Price Fit 2018

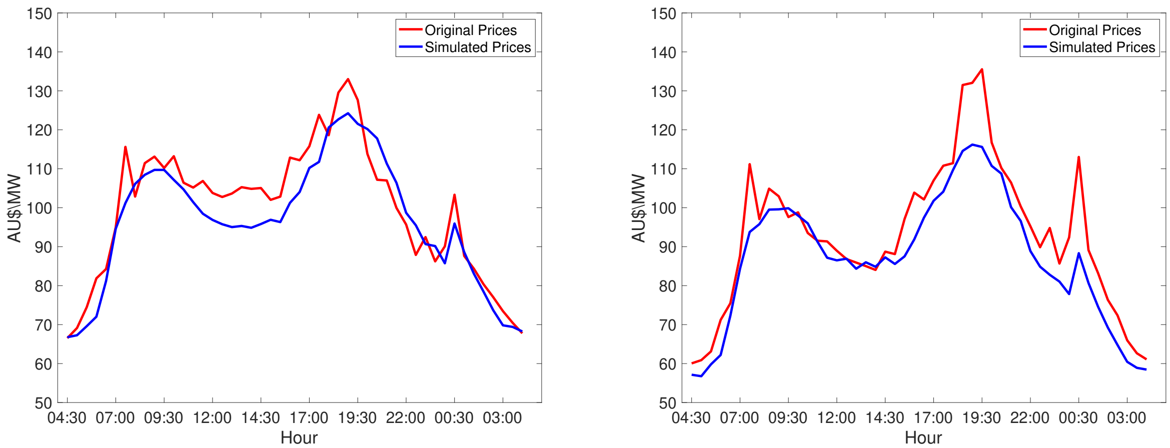


Figure 7: Comparing Data and Simulated Prices

to check the public signal's validity for a firm's decisions. The calculation includes comparing supply schedules, S_{id}. To construct the distance measure, I use L^2 distance for each observed market price. Clusters explain 89% of the firms' bids' variation and 87% of the variation in the daily demand vector, D_d. Karaduman (2020)'s Appendix shows details of the k-medians algorithm and constructed L^2 distances.

To check the validity of the simulations, I run two exercises. First, in the baseline case with no additional wind capacity, I simulate the market and compare observed and simulated market prices for 2017. Second, I simulate the effect of additional renewable generation capacity in 2018 in South Australia (100 MW wind, 200 MW rooftop solar, and 150 MW grid-scale solar), then compare observed and simulated market prices for 2018. The first exercise primarily tests the validity of the estimation of the market signal X_d, and the second exercise tests the framework's validity for firms' best responses to net demand shocks via increasing renewable capacity.

Electricity price patterns are critical for wind generations' impact on the incumbent generators' revenue. Note that the model does not use price moments but uses observed bids and demand conditional on the public signal. Figure 7 presents the simulated average daily prices against the actual data in 2017 and 2018. The simulated price pattern is comparable to the observed data, despite missing some price spikes, especially in 2018. My model fails to match periods with a price above AU$1000. These extreme price periods only occur 0.2% of the time in 2017 and 0.3% in 2018.

Table 3: Production Offsets by Wind Energy

	Offset by Wind				
		Additional Wind Generation Capacity			
		100 MW		1000 MW	
	Cullen (2013)	No Response	Best Response	No Response	Best Response
Gas	-0.28	-0.23	-0.21	-0.15	-0.13
Diesel	-0.002	-0.003	-0.001	-0.001	-0.001
Import	-0.74	-0.77	-0.78	-0.79	-0.81
Carbon Emissions	-1.05	-1.05	-1.05	-1.06	-1.07
Curtailment	-	-0.004		-0.06	

Note: For the additional wind generation I use capacity factor of overall wind generation. The sample is from South Australia Electricity Market 2017. Change in production types are in MWh/MWh Wind. Change in emissions are in ton/MWh Wind.

7.2 Comparing Models for Offsets Wind

Reduced form methods to find offsets by wind can be biased for large-scale renewable investments. In this section, I compare reduced form estimates using Cullen (2013) with my approach, for 100 MW and 1000 MW additional wind generation capacity, which correspond to 6% and 60% increase in wind generation capacity, respectively, in South Australia. I first do not allow firms to adjust their strategies for renewable entry, then compare results, allowing them to best respond and use the new equilibrium strategies. As a generation profile, I use the profile of overall wind production in South Australia. Table 3 presents substitution patterns for the additional wind production.

There are some differences in offsets by wind between estimates from my model and the Cullen (2013) model for 100 MW, and even more significant differences for 1000 MW. Cullen (2013) does not change for any size of the renewable investment. Therefore potential biases are inevitable, especially for large-scale investments. Cullen (2013) cannot predict curtailment for any scale of renewable investment, and this creates an upward bias for offset estimations. In my model, as renewable production increases, trade accommodates more of the renewable output, as it becomes electricity in South Australia gets cheaper. The change in the direction of the trade changes the substitution patterns between 100 MW and 1000 MW cases.

Allowing firms to change their responses also affects the offsets by wind. The No Response column only accounts for the 'Merit Order' effect, whereas the Best Response column also accounts for a 'Market Power' effect. Allowing gas and diesel power plants to adjust their strategies decreases their offset. This result supports the exercising of market power claims for thermal generators in

Table 4: Change in Production

	Unit	Additional Wind Generation Capacity 100 MW	1000 MW	5000 MW
Generation of the Wind Entry	Million MWh	0.30	3.00	15.00
Curtailment of Wind Generation	%	0.6%	6.4%	46.2%
Change in Generation of All Gas	Million MWh	-0.06	-0.39	-3.70
	%	-0.9%	-5.4%	-51.1%
Change in Generation of Diesel	Million MWh	0.00	0.00	-0.01
	%	-1.9%	-17.7%	-31.4%
Change in Import	Million MWh	-0.23	-2.43	-4.38
	%	-50.6%	-528.3%	-952.2%
Change in Carbon Emission (SA)	Million Ton	-0.06	-0.39	-2.51
	%	-1.5%	-9.1%	-58.3%
Change in Carbon Emission (SA and VIC)	Million Ton	-0.32	-3.11	-7.41
	%	-0.7%	-6.5%	-15.4%

Note: Changes are compared to baseline case. For the additional wind generation I use capacity factor of overall wind generation. The sample is from South Australia Electricity Market 2017.

South Australia. The market power effect is even more significant for diesel generators, which generate only when the price is high and constitute 0.1% of production in South Australia.

Notice that roughly 6% of the wind generation is curtailed for the 1000 MW investment. However, the carbon emission offsets are similar in both 100 MW and 1000 MW cases. In 1000 MW, cleaner power plants adjust their strategies and decrease their production. On the other hand, trade accommodates more of the renewable output, which causes more offset of brown coal generators production in Victoria.[12] This mechanism drives the unaffected carbon emission offset across different models.

7.3 Large Scale Wind Impact on Incumbent Production and Revenues

Due to merit order and low marginal costs, average daily electricity prices decrease as renewable penetration increases. To understand the long-term implications of renewable expansion via renewable subsidies, we need to investigate the impact of renewable expansions on incumbent firms' revenues. This section considers the effect of 100, 1000, and 5000 MW (correspond to 6%, 60%, 300% increase in wind capacity in South Australia) wind investments on different generator production and revenue. As a generation profile, I use the profile of overall wind production in South Australia.

production Table 4 shows the production of new wind investments, curtailments, change in the generation of different technologies, and changes in carbon emission. As the size of the additional

[12] Notice that I allow for Victoria to respond to net demand changes in South Australia.

(a) 100MW (b) 1000MW (c) 5000MW

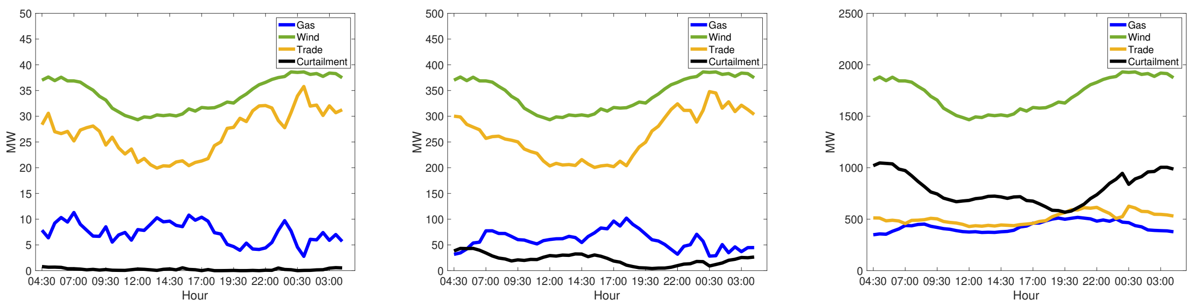


Figure 8: Offset Patterns for Different Size of Wind Investment

capacity increases, its impact on different technologies' production patterns is changing. Although gas generators lose half of the production, they still produce a considerable amount of the market demand even at 5000 MW wind additional investment case, and diesel generators keep 70% of their production.[13] Overall offsets of diesel and gas generators lead to a 58% decrease in carbon emission in South Australia.

For 1000 MW and 5000 MW wind generation investment cases, South Australia becomes a net exporter. As the investment size reaches 5000 MW, much of the production goes to the Victoria region and replaces brown coal production. This trade helps to decrease carbon emissions in Victoria by around one-tenth.[14] However, the transmission capacity of 700 MW between two regions limits the further carbon emission gains as almost half of the renewable investment's production is curtailed at 5000 MW expansion case. Figure 8 shows the offset patterns within a day. Curtailments are the highest at night when the wind blows the fastest and demand is the lowest. The avoided curtailment can lead to further gains in emissions and fuel costs by offsetting thermal generation. Karaduman (2020) shows that energy storage supports renewable revenues considerably when there is curtailment.

Revenue The price effect of renewable entry is crucial to understanding the long-run implication of renewable subsidies for electricity markets. While new renewable production offsets marginal units, inframarginal units also lose revenue due to the price change. The change in the profitability of some generators can lead to exits, which may increase or decrease the overall carbon emission and reliability of the power grid and compromise long-run goals of decarbonization policies. Table 5 shows the price impact and the changes in revenue of incumbents for 100, 1000, 5000 MW wind

[13] This result supports the argument for the very high cost for 100% renewables, and a need for technologies like storage, thermal generators with CCS, or nuclear power (De Sisternes et al., 2016).

[14] This result can be upward bias since I assume fix 1.12 carbon emission per MWh for Victoria. Especially when renewable generation increases by 5000 MW, the marginal producer may change, and potentially CO_2 can decrease.

Table 5: Change in Revenue

	Unit	Additional Wind Generation Capacity 100 MW	1000 MW	5000 MW
Change in Average Price	AUS$	-2.2	-17.5	-67.1
	%	-2.1%	-16.7%	-63.9%
Revenue of the Wind Entry	Million AUS$	21	92	26
Change in Revenue All Gas	Million AUS$	-21	-186	-721
	%	-2.3%	-20.4%	-79.1%
Steam	%	-3.2%	-27.2%	-58.8%
OCGT	%	-2.4%	-22.6%	-81.1%
CCGT	%	-1.6%	-13.4%	-91.4%
Change in Revenue Diesel	Million AUS$	-0.288	-2.1408	-5.496
	%	-2.4%	-17.8%	-45.8%
Change in Import Expense	Million AUS$	-32	-201	-253
	%	-22.5%	-141.5%	-178.2%
Change in Existing Wind Revenue	Million AUS$	-21	-154	-377
	%	-5.1%	-37.4%	-91.5%
Change in Total Electricity Cost	Million AUS$	-54	-451	-1331
	%	-3.6%	-30.5%	-90.0%

Note: Changes are compared to baseline case. For the additional wind generation I use capacity factor of overall wind generation. The sample is from South Australia Electricity Market 2017.

generation investment.[15]

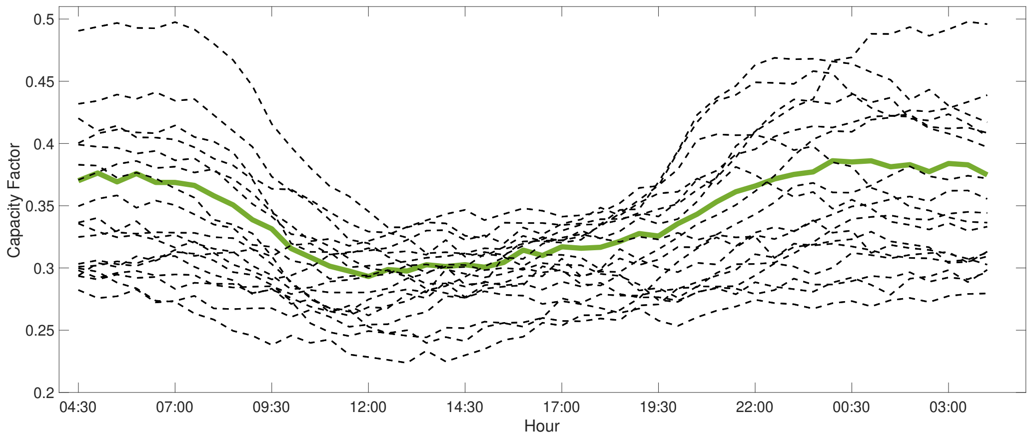
The price effect of the wind generation is not linear in additional capacity; it is 2.1% for 100 MW and 63.9 % for 5000 MW. This result is due mainly to the convexity nature of the aggregated supply curve. In South Australia, wind production already accounts for 35% of the overall production. The new wind generation affects prices when there is already a lot of renewable production and supply is relatively inelastic.[16]. On the other hand, the total electricity cost in South Australia decreases by 90 % with a 5000 MW investment. Although the main driver of this result is the change in prices, the shift in trade's direction also plays an important role. South Australia starts to sell to the Victoria region; therefore, overall, electricity cost in South Australia further decreases.

There is significant heterogeneity between the revenue reduction of different incumbent generators. For a low penetration level, wind generation's main impact is on the marginal units due to the replacement by the wind generation. In this case, firms with more flexible technologies, CCGT, lose the least, while less flexible technologies, Steam, suffer the most. For a high level of penetration, the price effect becomes more dominant. In the case of a high price drop, high-cost

[15]For this exercise, I set the price floor to be 0. In my data, prices go below zero, only 0.8% of the periods. These negative prices are not consistent, on average, for 2.2 periods. Therefore many firms bid to produce when the prices are below 0 not to adjust their production for the short-term. However, as more renewable is introduced, these firms update their strategies accordingly.

[16]Weighted the average price for gas production is 126.01 AUS$; for wind production, it is 84.43 AUS$

Figure 9: Capacity Factors of 18 Wind Power Plants in South Australia in 2017



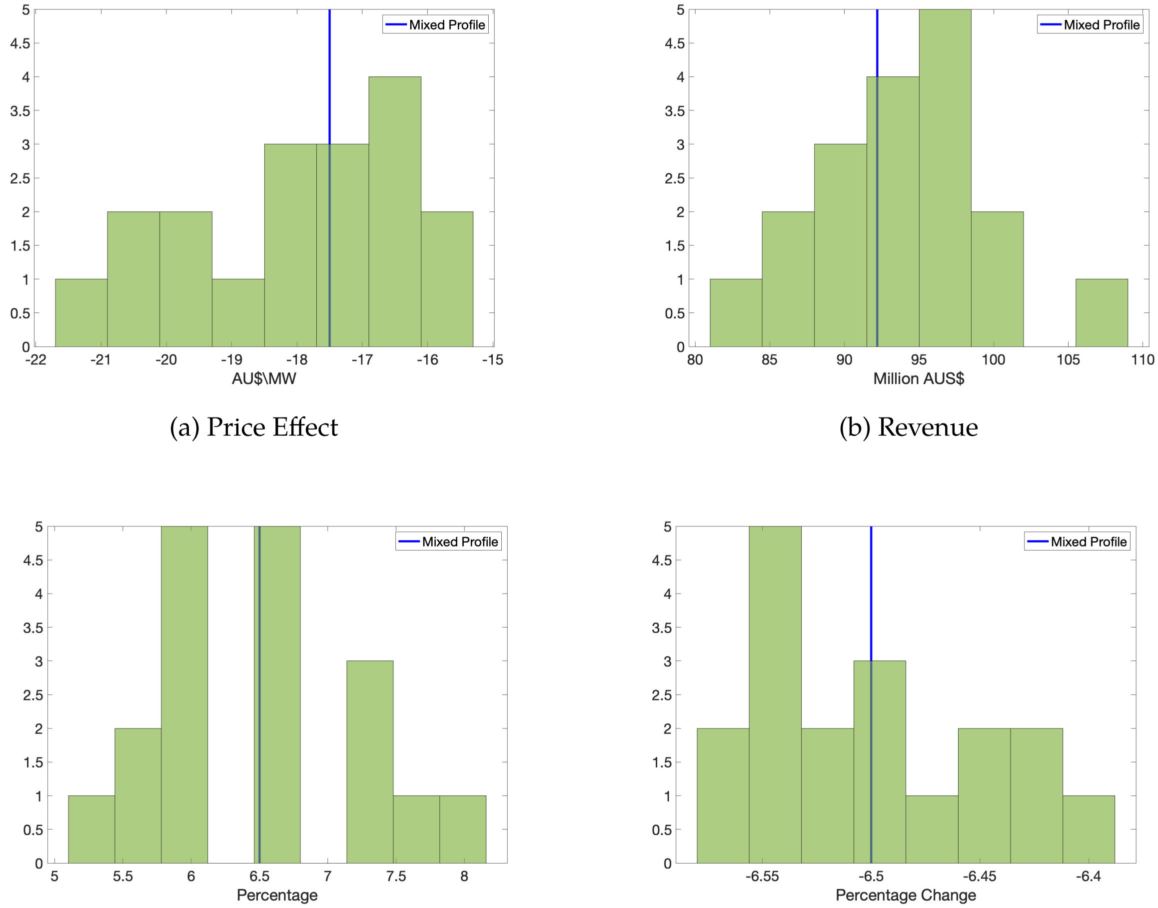
technologies such as CCGT and OCGT stop producing and lose the most. Due to low prices, only the very cheapest units and existing renewable generators produce electricity.

The existing wind generation gets the largest reduction in revenue, loses up to 91% of its revenue. For renewables, curtailment causes further revenue loss. I assume uniform curtailment across all renewable generators, proportional to their production at the time of curtailment. Therefore as the curtailment increases, existing renewables lose a part of their production. This also has implications for future renewable investment. As the revenue in the electricity market goes down for renewables, subsidies should compensate more of the upfront cost; therefore, clean electricity policies can get more expensive.

With very high penetration, in a long-run model, I expect many firms to exit and remaining firms to exert their market power. Market exit and entry dynamics must be modeled to account for the full long-run impact. The simulated changes in wholesale revenues of generators can be used as part of a firm's flow payoff and help specify future exit patterns.

7.4 Heterogeneity Between Different Projects

The value of the renewable projects differs by their size, capacity factor, and production's correlation with market prices. This section considers the impact of 1000 MW (correspond to 60%, increase in wind capacity) for various wind investments. I use 18 different existing wind production profiles in South Australia as a generation profile. Figure 9 shows the capacity factor of different projects,



(a) Price Effect

(b) Revenue

(c) Curtailment

(d) Carbon Emission Effect

Figure 10: Histogram of Impact of 1000 MW Wind Investment on 18 Different Projects

with a bold green line representing the overall region's wind capacity factor.

Figure 10 presents the heterogeneity of different projects on four different aspects. There is a significant dispersion in the price effect, 35%, and the revenue, 30%, of projects. This heterogeneity leads to an important policy discussion. Depending on the policymaker's social objective, a policy must differentiate between competing investments to ensure that the socially optimal renewable investments are made. For instance, a market price-oriented subsidy such as a feed-in tariff should be used if a policymaker is concerned about high market prices. If a policymaker wants the most competitive projects to be undertaken, it should give out lump-sum payments to ensure only the most profitable investments are made.

Even though the price effect varies, there is only a slight difference in the carbon emission impact of different projects. This low variance is primarily due to similar offset patterns between projects, as South Australia's thermal generation mainly uses gas. At a high price elasticity period, the marginal gas power generator can have a similar carbon emission rate with another marginal gas power generator at a low price elasticity period. This difference between carbon emission and price effect shows that pecuniary externalities can be much larger than the real production effect.

8 Conclusion

This paper introduces a framework to model and estimates the effects of introducing large-scale renewable generation into a wholesale electricity market. The model allows for a new equilibrium arising due to incumbent firms' responses to new renewable generation. I use estimated responses from thermal generation sources to observe variation in demand volatility in the baseline market, recomputing the new equilibrium when new renewable capacity is introduced.

My results about changing offset and revenue impact on different generators by wind generation have several policy implications. With very high penetration, in the long run, some generators can exit, and the remaining ones may exert their market power more. A policy with aggressive carbon emission targets should account for retirement dynamics. On the other hand, the existing wind generation gets a large reduction in revenue. As the revenue in the electricity market goes down for renewables, subsidies will have to compensate more of the upfront cost; therefore, clean electricity policies can get more expensive. Lastly, there is a significant dispersion in the price that affects the revenue between projects. Depending on the policymaker's concern, a policy must differentiate between competing investments to ensure that the socially optimal renewable investments are made.

This paper motivates two lines of future work. First, the generator market exit and entry dynamics must be modeled to estimate the whole pathway for decarbonization in the electricity market. This paper's results on simulated changes in wholesale revenues of generators can be used as a part of the generator's objective function. Second, given a subsidy scheme, one can use my model to simulate the revenue of different projects; therefore, it can identify the selection caused by a particular subsidy structure.

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