Start-up Costs and Market Power: Lessons from the Renewable Energy Transition

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Abstract

Firms expect to recover the fixed costs required to start production by earning positive operating profits in subsequent periods. We develop a dynamic measure of competition that accounts for start-up costs, showing that static markups overstate the rents attributable to market power in an electricity market where power plants frequently stop and start production in response to output from solar panels. We estimate that increases in solar capacity correspond to *increases* in the aggregate operating profits earned by fossil-fuel plants because competition softens at sunset – plants displaced by solar during the day must incur start-up costs to compete in the evening.

JEL Codes: L11, L13, L94, Q41, Q42

Keywords: Start-up Costs, Dynamic Production Function, Market Power, Wholesale Electricity Markets, Renewables, Rooftop Solar, Intermittency

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1 Introduction

Firms that incur the fixed costs required to enter a market expect to recover these costs by earning revenues in excess of their variable costs (Bresnahan and Reiss, 1990, 1991). This presents two challenges for studying competition. First, market power is traditionally measured based on the markup in prices above the short-run cost of producing the marginal unit. However, assuming that prices would be equal to the marginal cost of production if the market was competitive ignores the requirement that prices must be sufficient for firms to recover their fixed costs and rationalize their entry. Second, entry costs represent a barrier to competition; decisions on the extensive margin to enter or exit a market impact the intensity of competition in subsequent periods.

In this paper, we develop a dynamic framework to measure market power in wholesale electricity markets. This setting provides an ideal opportunity to study the interplay between fixed costs and market power because fossil-fuel plants start and stop production far more frequently than firms enter or exit a market. In addition, high frequency data on input fuel use and output allow us to calculate a competitive benchmark – a counterfactual time series of plant output and market prices – that accounts for the recovery of the fixed costs required for plants to start up. Specifically, our dynamic framework minimizes the daily total costs of dispatching power plants to satisfy demand in each hour of the day while setting prices that allow each plant to recover both its variable costs and its start-up costs. This approach extends static methods that estimate price-cost markups using data on inputs and output

(Borenstein et al., 2002; De Loecker and Warzynski, 2012; Syverson, 2019; De Loecker et al., 2020). In contrast to existing work that estimates market power accounting for fixed costs, our approach does not rely on an economic model of conduct to recover estimates of the rents captured by firms from exercising market power.[1]

Accounting for dynamics when assessing competition in electricity markets is especially important in light of the global transition away from polluting fossil fuels in favor of production from intermittent renewables (IEA (2020)). Namely, fossil-fuel plants are increasingly being forced to stop and start production in response to changes in output from renewables (Schill et al., 2017). Static price-cost markups do not account for the recovery of start-up costs and can thus overestimate the rents captured due to the exercise of market power (Mansur, 2008), especially in settings where large amounts of production from renewables make starts more common. Moreover, an increase in output from renewables in an hour does not just affect competition in that hour – plants displaced by intermittent renewables must decide whether to incur the start-up costs necessary to compete at a later time.

Our first key finding is that using the marginal cost of production as the competitive benchmark price can result in substantial overestimates of the share of operating profits earned due to the exercise of market power. We show this by applying our dynamic framework to a setting with world-leading rooftop solar penetration rates: Western Australia (WA).[2] Fossil-fuel plants in WA often shut down during the day

[1]Examples of studies that assume a model of conduct to estimate market power in settings with fixed costs include Reguant (2014) for electricity, Bresnahan and Reiss (1990) for automobile dealers, and Ryan (2012) for cement.

[2]Australia has the highest rooftop solar penetration rate in the world (Australian Energy Council, 2016). Over 25% of dwellings in WA in particular have adopted rooftop solar as of the end of

in response to output from solar panels, starting back up in the evening when solar stops producing. These plants expect to recover the fixed costs associated with starting production by earning revenues in excess of their variable costs in subsequent hours. Due to this, the competitive benchmark prices calculated using our dynamic framework are 30% higher at sunset on average than those derived from traditional static methods that set the competitive price equal to the marginal cost of the marginal unit produced.

Our second key finding relates to how the clean energy transition affects competition in wholesale electricity markets. Namely, we demonstrate that increases in rooftop solar capacity correspond to increases in the exercise of market power in the evening. This is because some of the fossil-fuel plants displaced by output from solar panels during the day choose not to incur the start-up costs necessary to produce at sunset, softening competition in the evening. This solar-induced increase in market power has meaningful aggregate impacts: the annual operating profits earned by fossil-fuel plants increased by 14% coincident with the doubling of rooftop solar capacity between 2015 and 2018, with the bulk of these increases concentrated in the evening. In contrast, we estimate that operating profits would have *fallen* by 22% from 2015 to 2018 under the counterfactual implied by our dynamic competitive benchmark. This indicates that the increase in operating profits over our sample period is driven primarily by increases in the exercise of market power in the evening.[3]

2018 (Roberts et al., 2019). Rooftop solar production totalled 6.5% of all electricity generated in WA's market in 2018 and over 20% of electricity generated in the middle of the day.

[3] As further evidence that increases in solar capacity correspond to increases in the exercise of market power in the evening, we show that the average number of fossil fuel units operating in the

Results from two additional empirical approaches further support that solar-induced increases in operating profits are likely to stem from increases in the exercise of market power rather than increases in the prices that would prevail under our dynamic competitive benchmark. The first empirical approach is a regression framework similar to Davis and Hausman (2016) and Bushnell and Novan (2021) that links marginal additions of rooftop solar capacity to changes in market outcomes. The second approach is a simulation analysis that explores the impact of larger-scale counterfactual changes in solar capacity on the market outcomes that would prevail under our dynamic competitive benchmark. The findings across the empirical approaches suggest that employing technologies that can more cost-effectively compensate for fluctuations in output from renewables can improve the competitiveness of markets. We discuss the policy implications of our findings in more detail in Section 8.

Related literature: Our paper contributes to two strands of existing literature: (1) the measurement of market power and (2) the market impacts of increases in renewable energy production.

Traditional measures of market power are based on the slope of the residual demand curve (Reiss and Wolak, 2007); for applications to wholesale electricity, see Wolfram (1999); Wolak (2003, 2007); Hortacsu and Puller (2008); and McRae and Wolak (2014). However, these approaches do not account for the presence of dynamic start-up costs. Studies that examine market power in concert with sunk costs tend

evening fell between 2015 and 2018 while the absolute value of the slope of the residual demand curve faced by large suppliers increased at sunset over this sample period (McRae and Wolak, 2014).

to focus on capital-intensive entry decisions in industries such as automobile dealers (Bresnahan and Reiss, 1990), ready-mix concrete (Syverson, 2004, 2007) or cement (Ryan, 2012). Closest to our work, Reguant (2014) utilizes bid-level data and an assumed model of conduct in order to jointly estimate dynamic cost functions and market power in the Spanish wholesale electricity market.

A feature of our approach is that it does not rely on an assumed model of conduct.[4] Instead, we make use of temporally granular data on electrical output and gas input for each power plant, allowing us to estimate each plant's start-up cost and marginal cost. We use these estimates to formulate a time series of competitive benchmark prices that recognizes that each plant must recover both their variable and start-up costs. This approach builds on recent work that uses accounting data to measure static price-cost markups across a range of different industries (De Loecker and Warzynski, 2012; Syverson, 2019; De Loecker et al., 2020), including electricity (Wolfram, 1999; Borenstein et al., 2002; Joskow and Kahn, 2002). Relative to this existing literature, the availability of high-frequency data on inputs and output allows us to identify market power in the presence of start-up costs.[5] Mansur (2008) motivates the need for our dynamic framework by showing that static competitive benchmark methods that do not incorporate unit commitment constraints or non-convexities in unit-level cost functions overstate the welfare loss from the exercise of

[4]In support of our approach based on calculating a dynamic competitive benchmark, Hortaçsu et al. (2019) argues that assuming expected profit maximization in order to estimate costs from bid-level data may be unsuitable for small suppliers in Texas' wholesale electricity market.

[5]Previous work discusses the need to account for dynamic adjustment costs when attributing differences in productivity to the exercise of market power (Hsieh and Klenow, 2009; Asker et al., 2014).

market power.[6]

We also contribute to a growing literature that estimates the impacts of increases in production from renewables on pollution emissions (Kaffine et al. (2013); Novan (2015)), coal-fired production (Fell and Kaffine, 2018), and the private and social value of electricity storage (Karaduman, 2020; Butters et al., 2021).[7] Closest to our paper, Bushnell and Novan (2021) demonstrates for California's wholesale electricity market that increases in utility-scale solar capacity correspond to decreases in wholesale prices during the day but increases in wholesale prices in the evening. We contribute to this existing work by providing evidence in favor of a specific mechanism for solar-induced increases in wholesale prices at sunset. Specifically, we show that some of the fossil-fuel plants displaced by solar during the day choose not to start up at sunset, weakening competition in the evening.[8,9] Moreover, our simulation analysis reveals that the reductions in system-wide production costs from increases in solar capacity exhibit slightly decreasing returns to scale at high baseline solar penetration rates. This simulation analysis contributes to a separate strand of literature that employs modeling approaches to assess longer-run responses to investment

[6]Other work that documents the importance of accounting for start-up costs and non-convex production constraints such as minimum safe operating levels when simulating market prices include Hogan and Ring (2003); O'Neill et al. (2005); Gribik et al. (2007); and Buchsbaum et al. (2020).

[7]The benefits from a rooftop solar panel in particular can vary substantially based on where the solar panel is sited (Lamp and Samano, 2020; Sexton et al., 2021).

[8]Previous work provides evidence on the importance of accounting for fixed costs when designing environmental policy targeting fossil fuel power plants (Cullen (2015); Cullen and Reynolds (2016)) and cement producers (Fowlie et al., 2016).

[9]Increases in *utility-scale* solar capacity can result in increases in the exercise of market power if solar is part of a large supplier's portfolio of units (Bahn et al., 2021) or if the supplier has access to cheap electricity storage (Karaduman, 2020). These sources of market power are less relevant in our setting because WA did not have meaningful amounts of either utility-scale solar capacity or electricity storage during our sample period.

in renewables (Bushnell (2010); Fell and Linn (2013); Gowrisankaran et al. (2016)).

The rest of the paper proceeds as follows. The next section outlines a stylized model of how rooftop solar penetration impacts the measurement of market power with versus without accounting for start-up costs during the day and evening. Section 3 discusses our empirical setting. We detail how we estimate marginal costs and start-up costs for each gas-fired unit in Section 4. Section 5 describes our methodology for calculating competitive prices accounting for start-up costs; this section also presents a decomposition of revenues into costs and rents based on these prices. In Section 6, we more formally link increases in solar penetration to market outcomes using a regression framework. Section 7 reports results from simulations of how market outcomes under the competitive benchmark would be impacted by large changes in solar capacity. Finally, Section 8 discusses the policy implications of our findings.

2 Conceptual Framework: Start-up Costs, Market Power, and Solar Penetration

This section introduces the core economic concepts underpinning our analysis. We present a stylized two-period example that demonstrates the major differences between a static competitive framework that sets the competitive price equal to the marginal cost of the marginal unit and a dynamic competitive framework that accounts for the fact that units must recover their start-up costs. This example also serves to highlight the increased importance of accounting for dynamics in settings with large levels of production from solar resources. We formalize the 2-period example in Section 5.1.

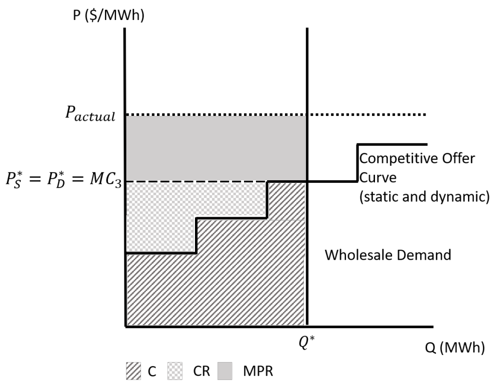
Consider a market with two periods: daylight hours and evening hours. This market has four power plants. We assume that each plant $i \in \{1, 2, 3, 4\}$ has constant marginal cost conditional on having started up. Consistent with the engineering trade-off inherent to electricity production technology, plants with lower indices have lower marginal costs but higher start-up costs ($\text{MC}_i < \text{MC}_j$ but $S_i > S_j$ for $i < j$).

Figure 1 plots the aggregate supply curve and wholesale electricity demand corresponding to the solar versus no-solar scenarios during the day versus evening. Wholesale demand is equal to the total quantity of electricity demanded by end-users minus the quantity of this electricity demand that is satisfied by rooftop solar panels instead of the wholesale market. Since rooftop solar panels have near-zero marginal cost and produce only when the sun is out, output from these panels is not sensitive to the wholesale electricity price.

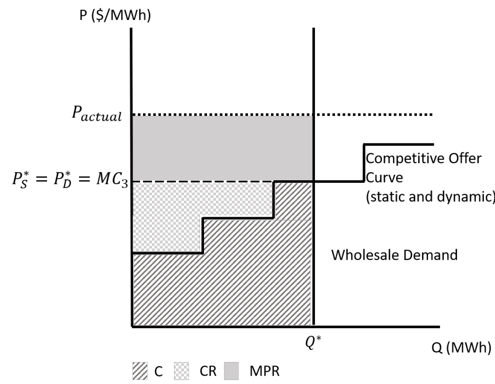
Focusing first on the no-solar scenario in the top row of Figure 1, we assume that plants 1-3 are operating entering the day and thus do not incur start-up costs. Using the static framework specified in Borenstein et al. (2002), the competitive price for both the day and evening is equal to the marginal cost of the marginal unit (i.e., $P_S^* = MC_3$). For the no-solar scenario, the dynamic competitive price (P_D^*) is equal to the static competitive price (P_S^*) in both periods because plants 1-3 were assumed to have entered the day operating and thus no start-up costs were incurred.

Revenues earned by suppliers in the market can be decomposed into three com-

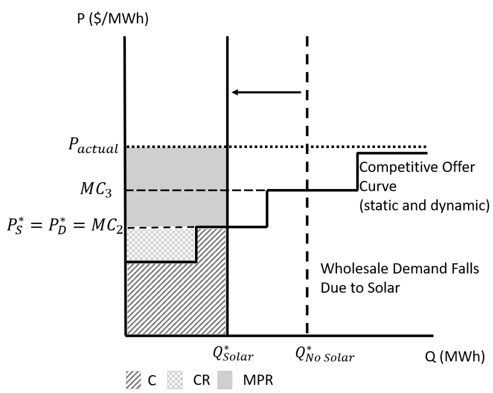
Figure 1: The Impact of Rooftop Solar Penetration Using Static versus Dynamic Competitive Frameworks



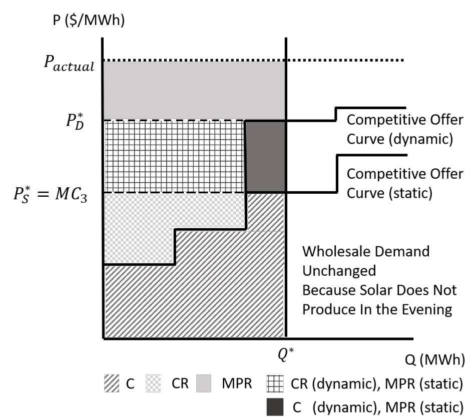
(a) Daylight Hours: No Solar



(b) Evening Hours: No Solar



(c) Daylight Hours: With Solar



(d) Evening Hours: With Solar

Notes: The wholesale electricity market is assumed to operate in two periods: daylight hours and evening hours. This market has four power plants ($i = 1,2,3,4$) with marginal cost MC_i and start-up cost S_i; plants 1-3 are assumed to be operating prior to the start of the day. The dynamic (static) competitive offer curve stacks the supply bids submitted by each plant assuming perfect competition accounting (not accounting) for the recovery of start-up costs. C denotes operating costs, CR denotes competitive rents, and MPR denotes market power rents. P_{actual} is the observed market price while P_S^* (P_D^*) denotes the competitive price implied by the static (dynamic) framework. Panels (a) and (b) depict the scenario with no rooftop solar penetration. Panels (c) and (d) depict the scenario with rooftop solar penetration, which shifts the demand to be served by the wholesale market down during the daylight hours but does not shift wholesale demand in the evening when solar stops producing.

ponents. First, the aggregate operating costs incurred by plants is the area under the competitive offer curve (denoted by C in Figure 1). Next, the competitive rents earned by the inframarginal units if prices are set competitively are calculated as the area below the competitive price and above the competitive offer curve (denoted by CR). Finally, the market power rents earned in excess of competitive rents are calculated as the area between the competitive price and the observed market clearing price (denoted MPR).

The bottom row of Figure 1 considers how the market would be impacted by the addition of rooftop solar capacity. Adding solar capacity shifts wholesale electricity demand during the day to the left – less energy from power plants is required due to the output produced by solar resources (see panel c). This leftward shift in wholesale demand results in only plants 1 and 2 producing to meet demand during the day. In both the static and dynamic frameworks, the competitive price during the day is equal to the marginal cost of the marginal plant (which is plant 2). This is because both plants 1 and 2 are assumed to be operating at the start of the day and thus do not have to incur start up costs.

Wholesale demand in the evening in the solar scenario is unchanged from the no-solar scenario (see panel d). This is because rooftop solar capacity does not produce when the sun is not shining. However, the third plant operated during the day in the no-solar scenario but does not operate during the day in the solar scenario. Consequently, either plant 3 or plant 4 must start up for wholesale demand to be satisfied in the evening.

Due to this, the competitive prices implied by the dynamic and static frameworks are different in the evening in the scenario with solar penetration. The static framework ignores start-up costs and sets the competitive price equal to MC_3, noting that plant 3 is assumed to be the marginal plant because plant 3 has a lower marginal cost than plant 4. However, plant 3 would earn negative profits if forced to operate at a price of MC_3 since it would not recover its start-up costs.

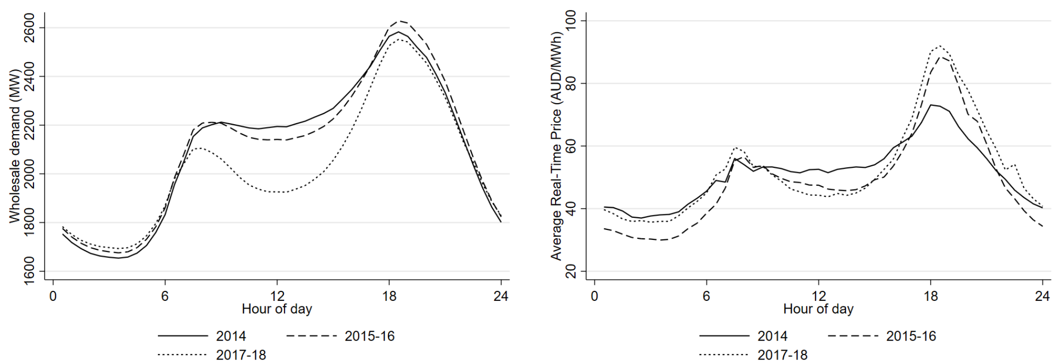
In contrast, the dynamic framework sets the competitive price equal to the lowest price that ensures that all plants earn weakly positive profits (i.e., recover their start-up costs). We depict this dynamic competitive price as being set by the fourth plant, with $P_D^* = MC_4 + (S_4/Q_4)$. By setting a higher competitive price, the dynamic framework will attribute less of the total revenues earned in the wholesale market to market power rents than the static framework and will attribute more revenues to operating costs and competitive rents.

In sum, a static competitive framework for studying market outcomes is inclined to overstate market power rents because it does not account for the recovery of start-up costs. Differences between static and dynamic frameworks are likely to be especially large in electricity markets with high solar penetration rates. This is because solar production during the day displaces fossil-fuel plants, forcing them to start up to produce in the evening.

To motivate the importance of considering dynamics in markets with high rooftop solar penetration rates, Figure 2a plots hourly average wholesale demand in Western Australia separately for the year 2014, the years 2015-2016 and the years 2017-

2018. Figure 2a documents that, coincident with the rooftop solar boom from 2015-2018, average wholesale demand fell precipitously during the day when rooftop solar produces electricity but remained similar in the evening when rooftop solar ceases production.

Figure 2: Wholesale Electricity Demand and Wholesale Prices



(a) Wholesale Electricity Demand (b) Real-Time Wholesale Price

Notes: The left panel plots hourly averages of wholesale electricity demand, which is overall electricity consumption minus "behind-the-meter" production from rooftop solar panels. The right panel plots demand-weighted hourly averages of wholesale prices. These averages are calculated using half-hourly data on demand and prices from the wholesale electricity market of the South West Interconnected System of Western Australia (SWIS).

Consistent with the intuition in our stylized model, Figure 2b documents that wholesale prices fell from 2014 to 2018 during the day but increased in the evening over this sample period.[10] As highlighted by our framework, this increase in wholesale prices potentially reflects both increases in the competitive price and increases in the markup between observed and competitive prices (i.e., the exercise of market power). Indeed, Appendix Figures B.3a and B.3b provide evidence that evening peak demand

[10] Appendix Section B documents descriptive trends in wholesale prices and demand over our 2014-2018 sample period.

was increasingly met by units with low start-up costs but high marginal costs. This is consistent with some of the units with high start-up costs displaced by solar during the day choosing not start up at sunset. Assessing the role played by market power in the increase in wholesale prices in the evening thus hinges on properly calculating competitive prices accounting for the start-up costs incurred by plants.

3 Empirical Setting: Western Australia

We study the Wholesale Electricity Market (WEM) of the South West Interconnected System of Western Australia (SWIS). This covers Perth and its surrounding cities. The WEM is an ideal empirical setting to study how rooftop solar penetration impacts wholesale market outcomes. Specifically, between 2014-2018, there was no entry or exit of major generating units, and there was no major investment in electricity transmission capacity. Moreover, there are no transmission interconnections between WA and other markets. Finally, the total amount of rooftop solar capacity in WA more than doubled between 2014 and 2018 to world-leading penetration rates by 2018.[11]

Production from rooftop solar panels, typically owned by small end-users, reduces the amount of electricity demand that must be satisfied in the wholesale market. During our sample period, approximately 49% of electricity demand in the WEM

[11]Output from rooftop solar panels accounted for approximately 6.5% of all energy generated in 2018 and approximately 20% of all energy generated in the 1pm-1:30pm interval in 2018. Details on the half-hourly data on rooftop solar capacity and output used in this paper can be found in Appendix Section A.

was met by coal-fired sources, with 41% and 8.4% of overall electricity production coming from gas-fired and wind sources respectively (AEMO (2018)). There was very little utility-scale solar capacity and no utility-scale electricity storage capacity in the WEM during our sample period.[12]

Participants in the WEM submit their willingness to supply energy in both day-ahead and real-time markets. In contrast to wholesale markets in the United States, the WEM sets one uniform day-ahead price and one uniform real-time price when clearing day-ahead and real-time markets rather than allowing these prices to vary by location.[13] The WEM has three major suppliers: Synergy, Alinta and NewGen. Synergy owns roughly half of the production capacity in the market; Alinta and NewGen own roughly 13 percent and 11.5 percent of the capacity in the market respectively.[14]

4 Start-up Costs and Operating Costs

4.1 Estimating Dynamic Production Functions

This section discusses how we estimate each gas-fired unit's production function. To do so, we utilize data from the Australian Energy Market Operator (AEMO) on the

[12] The 10MW Greenough River Solar Farm is the only utility-scale solar resource in WA during our sample period.

[13] The market operator can adjust the real-time dispatch of power plants to account for physical operating constraints such as transmission congestion.

[14] Synergy is also the retail provider of electricity for most end-users in WA, which potentially reduces its incentive to exercise market power in the wholesale market (Leslie, 2018). That being said, Synergy has come under scrutiny in the past for exercising market power in order to raise prices in the WEM (Hastie (2019); Perpitch (2019)).

electrical output $O_{i,t}$ (in MWh) produced by each unit i in each half-hour-of-sample t and daily feeder-level data on gas use (in GJ). The ensuing discussion focuses on how we estimate production functions for feeders linked to only one generating unit. Appendix Section C discusses how we adjust our estimation strategy for the feeders associated with multiple generation units.

We model each unit's production technology as:

$$G_{i,t} = \alpha_i O_{i,t} + \gamma_i S_{i,t} + \epsilon_{i,t} \tag{1}$$

where $G_{i,t}$ is the gas used by unit i in half-hour-of-sample t.[15] The "start-up" term $S_{i,t}$ is equal to one if the unit started up in half-hour t and is equal to zero otherwise (i.e., $S_{i,t} \equiv 1[O_{i,t} > 0] \times 1[O_{i,t-1} = 0]$).

We sum Equation (1) over the 48 half-hours of the day since we only observe gas use at the daily level:

$$\sum_{t=1}^{48} G_{i,t} = \alpha_i \sum_{t=1}^{48} O_{i,t} + \gamma_i \sum_{t=1}^{48} S_{i,t} + \sum_{t=1}^{48} \epsilon_{i,t} \tag{2}$$

Equation (2) is estimated using ordinary least squares. Appendix Table C.1 reports the parameter estimates for each of the gas-fired generating units in the market.[16] The parameters are precisely estimated. Moreover, our estimates of unit-level heat

[15] In contrast to Wolak (2007) and Reguant (2014), we do not model ramping because most gas units in our setting start up at most one time in a day and do not ramp up or ramp down production much within a day other than when starting up or shutting down. It is consequently difficult to separately identify ramping costs and start-up costs for most units with data on daily gas use.

[16] Gas-fired cogeneration units that produce both electricity and useful heat energy are not included in this table.

rates (α_i) are similar to engineering estimates of heat rates from SKM-MMA (2014).

Table 1: Input Gas Use and Electrical Output by Technology Type

	CCGT	**OCGT**	
	Low HR	Medium HR	High HR
Annual Average Output (GWh)	2,358	1,189	665
Average Hours Running per Start	106	33	11
Capacity Factor	0.48	0.15	0.08
Aggregate Heat Rate (GJ/MWh)	8.0	10.9	15.6
Percentage of Gas Used on Starts	1%	1%	5%

Variable definitions: The capacity factor is calculated as the total output produced by all units in the category from 2015-2018 divided by the total output that would have been produced by all units in the category from 2015-2018 if the units were producing at their nameplate capacity. The aggregate heat rate is calculated as the total fuel use (in GJ) across all units in the category divided by the total output across all units in the category (in MWh). The percentage of gas used on starts is calculated as 100 times the ratio of: (1) our estimate of the total gas used for start-ups summed across all units in the category and (2) the total quantity of gas used by all units in the category.

Category definitions: Generating units are categorized by their heat rate ranking, with "Low HR", "Medium HR", and "High HR" corresponding to the lowest, middle and highest heat rate groups. The COCKBURN and N'GEN_K'ANA combined-cycle gas turbine (CCGT) units have the lowest heat rates (i.e., heat rates less than 7.9 GJ/MWh). The ALINTA_WGP, KWINANA and N'GEN_N'BUP open-cycle gas turbine (OCGT) units are in the "Medium HR" group (i.e., heat rates between 10.5-11.3 GJ/MWh), and the remaining OCGT units are in the high heat rate group (i.e., heat rates greater than 12.8 GJ/MWh).

The estimates presented in Appendix Table C.1 indicate that each unit must burn non-trivial quantities of fuel to start up production. This highlights the importance of accounting for dynamics when calculating the fuel use associated with different patterns of output. To further emphasize this point, Table 1 reports summary statistics for combined-cycle gas turbines (CCGT) with low heat rates ("Low HR") and therefore low marginal costs versus open-cycle gas turbines (OCGT) that have lower start-up costs but higher marginal costs. The OCGT units with lower marginal costs are classified as medium heat rate ("Medium HR") while the OCGT units with higher marginal costs are classified as “High HR”.

Units in each of these three categories produce for 106, 33, and 11 hours on average per start-up respectively. Units in the low heat rate category have large start-up costs, but start up so infrequently that they burn less fuel due to starts as a proportion of total gas use than OCGT units. Start-ups are a small proportion of overall gas use for all three types of units, representing 1%, 1%, and 5% of total gas use for low, medium and high heat rate units respectively. Though the gas use required for start-ups is small relative to total gas use, start-up costs could easily be sufficient to deter entry from a unit that expects to produce only for a short amount of time.[17]

4.2 Operating Costs

We calculate the operating costs $TC_{i,f,t}$ incurred by unit i that produces output $O_{i,f,t}$ by burning fuel f in half-hour-of-sample t as:

$$TC_{i,f,t} = P_t^f E_{i,f,t} + \text{VOM}_{i,f} O_{i,f,t}$$

where P_t^{f} is the price of fuel f in AUD per GJ, $E_{i,f,t}$ is unit i’s fuel use in the half-hour (in GJ), and VOM_i is unit i’s non-fuel variable operating and maintenance costs (in AUD per MWh). Appendix Section A provides further information on the data used for fuel prices and VOM_i.

[17]If the average OCGT unit started up, produced at capacity, and shut down in the same hour, the percentage of total gas use attributable to the unit starting up would be 19%.

The previous subsection detailed how we estimate the fuel used by each gas-fired unit in each half-hour. By focusing on fuel use, we ignore the nonfuel costs of starting up a unit such as those associated with depreciation as well as the use of auxiliary power, chemicals, and water (Kumar et al., 2012; Schill et al., 2017). This is primarily due to a lack of data or estimates on these costs for units in WA.

That being said, the nonfuel components of start-up costs are likely to be small relative to the fuel component of start-up costs for three reasons. First, engineering estimates suggest that the depreciation costs from start-ups are small relative to the fuel cost of start-ups (Schill et al., 2017). Second, the competitive prices from our dynamic framework are likely to be set by OCGT units; engineering estimates of nonfuel start-up costs are largest for steam-based technologies and smallest for OCGT units (Kumar et al., 2012; Schill et al., 2017). Third, our estimates of start-up costs for CCGT units based on fuel use are similar to those in Reguant (2014), which assumes a model of conduct to estimate start-up costs inclusive of all components. The advantage of our approach relative to Reguant (2014) is that we can recover estimates of start-up costs without assuming a model of firm conduct, an assumption that may be less likely to hold for smaller firms (Hortaçsu et al., 2019).

We calculate the fuel used by each coal-fired unit as the product of the unit's output in the half-hour times its heat rate at maximum output (i.e.:, $E_{i,f,t} = O_{i,f,t}\mathrm{HR}_{i,f}$).[18] We cannot estimate start-up costs for coal-fired units because we do not observe unit-level data on coal consumption. Though the start-up costs for

[18] A unit's heat rate at maximum output is the amount of input heat energy required to produce one MWh of electricity given that the unit is producing at capacity.

coal-fired units can be quite large (Reguant, 2014), these units typically have far lower marginal costs than gas-fired units.[19] Consequently, coal-fired power plants are very rarely forced to start up, and when they do, it is typically because they shut down to perform planned maintenance.[20] Start-up costs are thus unlikely to be a meaningful portion of the operating costs incurred by any coal-fired unit in WA over our sample period.

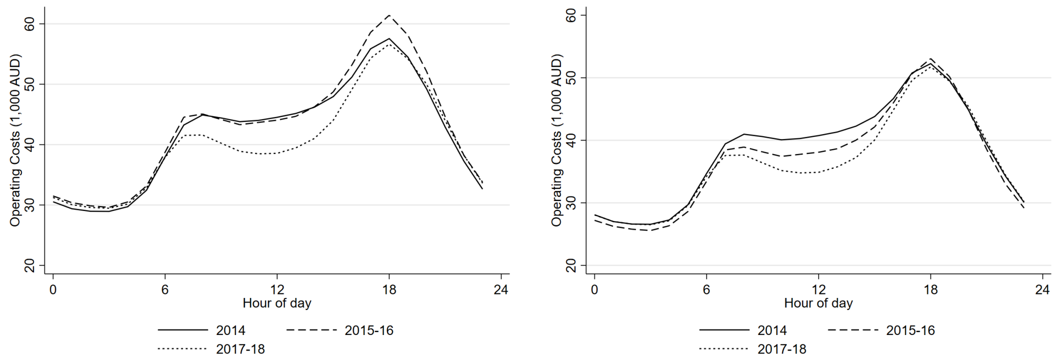
Figure 3a plots aggregate operating costs averaged over half-hours-of-sample for each hour of the day for the year 2014, the years 2015-2016, and the years 2017-2018. This figure documents that aggregate operating costs fell for all hours of the day from 2014 to 2018. Indeed, annual total operating costs across the fossil fuel units in our sample were 23 million dollars (6%) lower in 2018 relative to 2015.

To account for changes in coal and natural gas prices over time, Figure 3b displays hourly average operating costs holding fuel prices fixed at 2013 levels. This measure of operating costs is lower during the day in 2018 relative to 2014, consistent with output from rooftop solar increasingly displacing production from fossil-fuel units. However, solar resources do not produce in the evening. Consistent with this, hourly average operating costs in the evening remain largely unchanged from 2014 to 2018 after holding fuel prices fixed.

[19] Per the engineering estimates in Sinclair Knight Merz MMA (2014), the marginal cost of the coal-fired unit with the highest marginal cost is 27.55 AUD/MWh. This is substantially smaller than the marginal costs of the CCGT unit with the *lowest* marginal cost (37.62 AUD/MWh) and the OCGT unit with the lowest marginal cost (45.62 AUD/MWh).

[20] Coal-fired units run for 625 hours (almost one month) per start on average over our sample period. In contrast, even low marginal cost CCGT gas-fired units operate for only 106 hours per start on average.

Figure 3: Average Operating Costs By Hour of the Day: 2014-2018



(a) Operating Costs

(b) Operating Costs Fixing Fuel Prices at 2013 Levels

Notes: This figure plots averages over half-hours-of-sample of the aggregate operating costs across coal-fired and gas-fired units (excluding co-generation units). The left panel focuses on aggregate operating costs while the right panel focuses on aggregate operating costs calculated after fixing fuel prices at 2013 levels.

5 Competitive Rents and Market Power Rents

This section is split into two parts. First, we develop a methodology to construct a competitive benchmark that extends existing static frameworks by allowing for the recovery of start-up costs. Second, we apply our methodology to WA, presenting trends in competitive rents and market power rents over 2014-2018.

5.1 Calculating a Competitive Benchmark that Satisfies Start-Up Cost Recovery

In this subsection, we calculate a competitive price for each of the 24 hours of the day that (a) accounts for minimum safe operating levels, and (b) ensures that all units recover their start-up costs. By including these two features, we extend traditional static methods to calculate the price that would prevail in a perfectly competitive market (for example, Borenstein et al., 2002).

To begin, we consider a social planner that minimizes the total daily costs incurred by the gas-fired fleet of serving demand in each of the 24 hours of the day. We set the residual demand to be served in each hour equal to wholesale demand less production from non-gas sources operating in the wholesale market. This treats generation from other resources as negative inelastic demand. We exclude coal-fired units when applying this methodology to WA for two reasons. First, every half-hour interval in our sample has multiple gas-fired units operating, all of which have substantially higher marginal costs than the coal unit in WA with the lowest marginal cost (Sinclair Knight Merz MMA, 2014).[21] Therefore, a gas-fired unit is likely to be setting the market clearing price in every hour of the day. Second, we only have estimates of start-up costs for the gas-fired fleet.

The social planner minimizes the following objective function:

$$\begin{aligned}\min_{\{O_{i,h}\}_{h=1}^{24}} \sum_{h=1}^{24}\sum_{i=1}^{G} &\underbrace{P^{NG}\alpha_i O_{i,h} + \mathrm{VOM}_i O_{i,h}}_{\text{Static Operating Costs}} \\ &+ \sum_{h=1}^{24}\sum_{i=1}^{G} \underbrace{P^{NG}\gamma_i S_{i,h}}_{\text{Start-up Costs}}\end{aligned} \tag{3}$$

[21] Wind and solar resources have near-zero marginal cost and can produce only when the wind is blowing or the sun is shining. Since production from renewables is determined primarily by prevailing weather conditions rather than wholesale prices, we treat generation from these resources as negative inelastic demand as well.

where P^{NG} is the price of natural gas (in AUD per GJ), α_i is the heat rate for unit i (in GJ per MWh), $O_{i,h}$ is the output of unit i in hour h (in MWh), VOM_i is the non-fuel operating cost for unit i (in AUD per MWh), γ_i is the fuel used by unit i when starting up, and the start-up term $S_{i,h} \equiv 1[O_{i,h} > 0] \times 1[O_{i,h-1} = 0]$ is equal to one if and only if unit i started up in hour h.[22]

The production and balancing constraints are:

$$\underbrace{O_{i,h} \in \{0\} \cup [\underline{M_i}, \overline{M_i}] \text{ for all } (i,h)}_{\text{Minimum and Maximum Output Constraints}} \tag{4}$$

$$\underbrace{\sum_{i=1}^{G} O_{i,h} = \mathrm{RD}_h \text{ for all h}}_{\text{Total Output Equals Residual Demand}} \tag{5}$$

In words, Equation (4) states that each unit i can be either on or off. If unit i is on, it can only produce at levels above its minimum safe operating level $\underline{M_i}$ and below maximum capacity $\overline{M_i}$.

We note two differences between our formulation of the cost minimization problem and common static formulations. First, start-up costs are not considered in static methods (see the second line of Equation 3). Consequently, static methods can simply take a period-by-period approach, assigning units to produce from lowest marginal cost to highest marginal cost until supply equals residual demand.

Second, the minimum output constraint is usually not imposed in a static framework (see Equation 4). This constraint is a crucial component of our dynamic

[22]We plug each unit's observed output into this problem for $h = 0$ (i.e., $O_{i,0}$ is equal to the value observed in the data for unit i in the last hour of day $d - 1$).

methodology - without the minimum output constraint, the least-cost solution may involve units running at tiny output levels in order to avoid start-up costs. This strategy is technologically infeasible.[23] Each unit's minimum and maximum feasible output levels (i.e., $\underline{M_i}$ and $\overline{M_i}$) are found empirically by taking the minimum and maximum values of output observed for the unit over the sample period.[24]

We solve this mixed-integer programming problem separately for each day-of-sample d using KNITRO optimization software.[25] The solution gives us optimized output $O^*_{i,h}$ for each unit i and hour h, which we use to calculate the competitive price p_h for each hour of the day. We set prices in order to minimize daily total wholesale payments, which is consistent with the objective function used by electricity market operators in practice.

Specifically, competitive prices are set by minimizing the daily total payments associated with satisfying wholesale demand D_h in each hour $h = 1, 2, ..., 24$:

$$\underset{\{p_h\}_{h=1}^{24}}{min} \quad \underbrace{\sum_{h=1}^{24} p_h \mathrm{D}_h}_{\text{Wholesale Payments}} \tag{6}$$

[23]Buchsbaum et al. (2020) demonstrates that minimum output constraints play an important role in how units respond to changes in the amount of electricity generating capacity required to provide frequency regulation.

[24]When finding these minimum and maximum values, we include only observations for which the unit neither started up nor shut down in the adjoining hours.

[25]We consider the set of plants that are available to produce in day t as those that were observed operating on day t. This removes the possibility that the model is dispatching plants that are on outage that day (ex: a plant choosing to shut down to perform maintenance). The decision to exclude plants that do not operate on day t will increase costs and competitive rents, leading us to remain conservative on the portion of operating profits attributable to the exercise of market power.

subject to a dynamic rationality constraint that each unit makes non-negative profits in the day:

$$\underbrace{\sum_{h=1}^{24} p_h O_{i,h}}_{\text{Total Revenues}} \geq \underbrace{\sum_{h=1}^{24} [P^{NG}\alpha_i O_{i,h} + \text{VOM}_i O_{i,h} + \gamma_i S_{i,h}]}_{\text{Total Cost}} \text{ for all } i \tag{7}$$

and subject to a static rationality constraint that each unit producing more than their minimum in an hour cannot increase their profits by producing at the minimum:

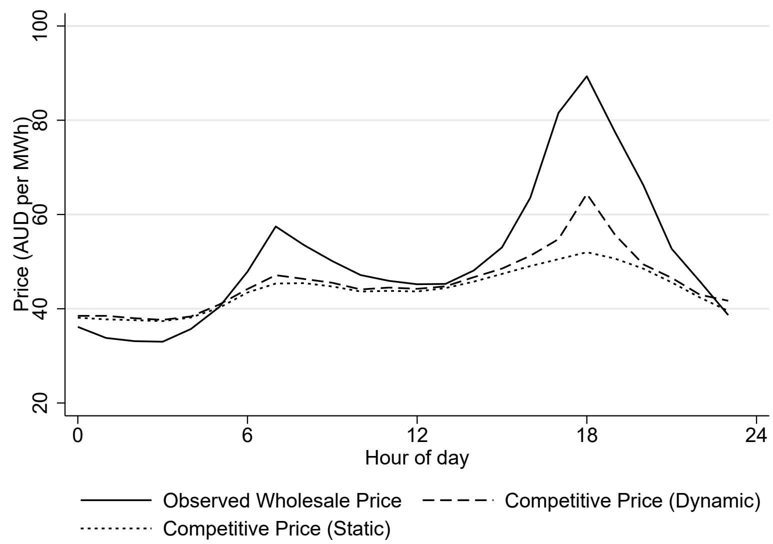
$$p_h \geq \underbrace{P^{NG}\alpha_i + \text{VOM}_i}_{\text{Marginal Cost}} \text{ if } O_{i,h} > \underline{M}_i \text{ for all } (i,h) \tag{8}$$

The competitive prices from our dynamic framework will typically be larger than the corresponding static competitive prices because of the additional constraint in the dynamic framework that units must recover their start-up costs. However, the dynamic competitive price may be lower in some hours than the corresponding static price because units may rationally incur a loss in an hour in order to remain operating and thus avoid having to incur start-up costs later in the day.

Figure 4 displays the hourly average competitive price from applying this framework to WA; the hourly averages of observed real-time prices and the competitive prices from the static framework are plotted for comparison. We see that the static and dynamic methods yield roughly similar results for nearly all hours of the day with the exception of a small departure around 7am and a larger departure at 6pm.

These patterns in price reflect the fact that wholesale demand increases in the

Figure 4: Hourly Averages of Observed Prices and Competitive Prices Calculated Using the Static and Dynamic Frameworks



Notes: This figure plots the hourly averages of competitive prices calculated using the static framework that ignores start up costs versus the dynamic framework from Section 5.1. We also plot the hourly averages of the real-time price. All averages are taken over hours-of-sample from 2014-2018.

early morning as people wake up and go to work and then significantly increases in the evening as (a) production from rooftop solar decreases and (b) people come home from work and use electricity in their homes. Power plants must start up to meet increasing demand during these two periods. However, only our dynamic framework sets competitive prices that are high enough for these plants to recover their start-up costs.

The differences between dynamic and static competitive prices are largest at sunset, demonstrating the increased importance of accounting for start-up costs when measuring market power in settings with high solar penetration rates. Specifically, the average competitive price at 6pm is approximately 30% higher when using the dynamic framework rather than the static framework. This provides evidence supporting the concerns raised in Mansur (2008) that market power rents will be overstated when using conventional static methods based on markups over marginal cost.

5.2 Trends in Competition Measures

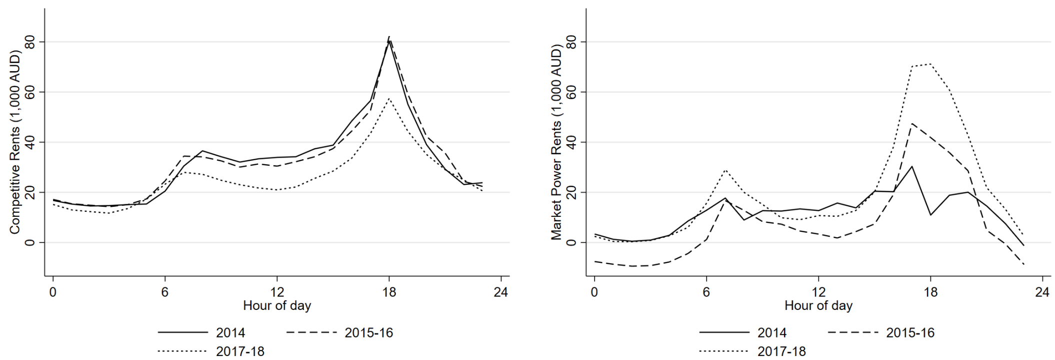
We calculate aggregate operating revenues by multiplying the spot electricity price in each half-hour by the total output across all coal- and gas-fired units in the half-hour.[26] Aggregate operating profits are simply equal to aggregate operating revenues minus the aggregate operating costs incurred by coal- and gas-fired units. Competitive rents are the operating profits that would be earned in aggregate if wholesale prices were equal to the competitive prices discussed in the previous subsection. Finally, market power rents are defined as observed operating profits minus competitive rents.

Coincident with the rooftop solar boom in WA from 2015-2018, annual total operating profits were 14% higher (49 million dollars higher) in 2018 than in 2015. This increase in operating profits is not driven by changes in operating costs: operating costs only fell by 6% (23 million dollars) from 2015 to 2018. Moreover, competitive rents also fell by 21% (59 million dollars) over the sample period, as shown in Figure 5a. This decline in competitive rents is driven by (a) output from rooftop solar displacing higher marginal cost units during the day, and (b) gas prices falling by

[26] A limitation we share with most of the previous work studying wholesale electricity markets is that this measure of aggregate operating revenues may differ from the actual revenues received by suppliers due to long-term bilateral contracts between electricity suppliers and retailers (Wolfram, 1999; Borenstein et al., 2002).

approximately 15% in 2017-18 (see Appendix Figure B.1c).

Figure 5: Hourly Average Competitive Rents and Market Power Rents: 2014-2018



(a) Competitive Rents (b) Market Power Rents

Notes: This figure plots hourly average aggregate competitive rents and market power rents for coal-fired and gas-fired units (excluding co-generation units). The left panel considers competitive rents: the operating profits that would be earned if the wholesale price was set at the competitive price described in Section 5.1. Market power rents, presented in the right panel, are the operating profits earned in excess of competitive rents.

In contrast, market power rents were 157% higher (108 million dollars higher) in 2018 relative to 2015. These increases in market power rents are concentrated primarily in the evening (see Figure 5b). In fact, similar to Reguant (2014), market power rents are sometimes near zero or even negative during the day and overnight, with prices less than the marginal cost of production for 4% of hours in the sample. This suggests that units are sometimes willing to suffer small losses to continue operating overnight or during the day in order to avoid having to incur start up costs to operate during the morning or evening demand peaks.

The descriptive trends in Figure 5b are consistent with the intuition that increases in solar output displace fossil-fuel-fired production during the day, leading to increases in market power in the evening because some of these displaced units choose not to incur the start-up costs necessary to compete. In Appendix Figure B.4, we document that other competition measures support this claim, with (a) less fossil-fuel units operating both during the day and evening in 2018 relative to 2014; and (b) suppliers facing less competition at the sunset demand peak, as demonstrated by increases over the sample period in suppliers' inverse semi-elasticities of residual demand.[27]

6 Linking Market Outcomes to Solar Penetration

The previous sections examined changes over 2014-2018 in operating costs, competitive rents and market power rents. As discussed in Section 3, there were no major changes to market conditions such as investments in generating or transmission capacity during this sample period. Based on this, changes in market outcomes from 2014 to 2018 are likely to stem primarily from the doubling of rooftop solar capacity over this period.

In this section, we explicitly link increases in rooftop solar capacity to changes in market outcomes using a regression framework. The first and second subsections discuss the methodology and results respectively.

[27] A supplier's inverse semi-elasticity is interpretable as the increase in market prices (in AUD per MWh) that would result from a 1% decrease in the supplier's quantity sold (McRae and Wolak, 2014).

6.1 Methodology

We assume that total electricity demand is inelastic with respect to wholesale prices because the retail price faced by end users in WA does not vary with short-run fluctuations in wholesale prices. In addition, rooftop solar panels generate electricity at zero marginal cost when the sun is out, lowering the amount of electricity that needs to be purchased from the wholesale market. Consequently, wholesale electricity demand (i.e., total electricity demand minus production from rooftop solar) is also price inelastic.

Based on this, we specify a regression framework in order to estimate the impact of changes in wholesale demand on market outcomes.[28] We then predict how market outcomes change when adding 10 MW of rooftop solar capacity to the system by adjusting wholesale demand down to reflect the increased production from this solar capacity. The patterns identified in the previous section suggest that changes in rooftop solar production impact market outcomes both during the day and during the evening. Therefore, we model market outcomes as being a function of both wholesale demand in the current hour-of-sample and wholesale demand in the previous 24 hours-of-sample.[29]

[28] Bushnell and Novan (2021) and Davis and Hausman (2016) employ a similar approach to estimate how market outcomes in California are impacted by increases in solar output and the shut down of the San Onofre nuclear power plant respectively.

[29] Appendix Section D.6 documents that the regression model without lagged demand does a poor job of predicting how market outcomes change with increases in solar capacity, particularly in the evening. This is because market outcomes in the evening are a function of daytime demand: power plants displaced by solar during the day must start up in order to meet demand in the evening.

Specifically, we estimate:

$$Y_t = \alpha + \sum_{s=0}^{24} \gamma_{s,h} D_{t-s} + \epsilon_t \tag{9}$$

where t indexes hour-of-sample and h indexes hour of the day. Standard errors are clustered by week-of-sample.

Following Davis and Hausman (2016), our primary specification does not include any fixed effects. Appendix Section D.1 documents that the results remain similar if we include (1) quarter-of-sample fixed effects, (2) month-of-sample fixed effects, (3) year, hour-of-day, and month-of-year fixed effects, or (4) month-of-sample and hour-of-day fixed effects.

The prediction model specified in Equation (9) allows us to estimate changes in market outcomes due to marginal additions of rooftop solar capacity. To do this, we first divide observed total production from rooftop solar panels in hour-of-sample t by the aggregate output implied by these solar panels producing at capacity in the hour. Using this capacity factor CF_t, we subtract the output from a counterfactual increase in rooftop solar capacity of 10MW from observed wholesale demand in each hour-of-sample (i.e. $D_t^S \equiv D_t - 10\text{CF}_t$). Finally, we take the difference in predictions from the estimated version of Equation (9) when plugging in the adjusted time series of wholesale demand $\{D_t^S\}_t$ versus the observed time series of wholesale demand $\{D_t\}_t$.

6.2 Results

Figure 6 plots the hourly average change in model predictions from adding 10MW of rooftop solar capacity to the system. The bars presented are 95% confidence intervals based on standard errors clustered by week-of-sample. Figure 6a indicates that the aggregate operating costs incurred by the coal- and gas-fired fleet in WA fall precipitously during the day when solar capacity is increased by 10MW. This reduction in operating costs is driven largely by production from solar displacing production from coal- and gas-fired sources during the day (see Appendix Figure D.7). Consistent with this, a 10MW increase in solar capacity corresponds to decreases in predicted operating profits, competitive rents, market power rents, wholesale prices, and competitive prices during the day (see Figures 6b-6f).

However, Figures 6b and 6f indicate that a 10MW increase in solar capacity corresponds to *increases* in operating profits and wholesale prices in the evening and early morning. There is no corresponding change in operating costs outside of daylight hours. As discussed in Section 2, this increase in operating profits in the evening could be due either to changes in competitive rents or market power rents.

Namely, production from rooftop solar displaces production from fossil-fuel plants during the day. Displaced fossil-fuel plants must incur start-up costs in order to produce in the evening. Competitive prices in the evening must be sufficient for these displaced plants to recover their start-up costs. In addition, some displaced plants may choose not to start up, leading to less competition in the evening in the scenario with additional solar capacity. The extent to which increases in operating profits and wholesale prices are driven by increases in competitive prices versus market power rents is thus an empirical question.

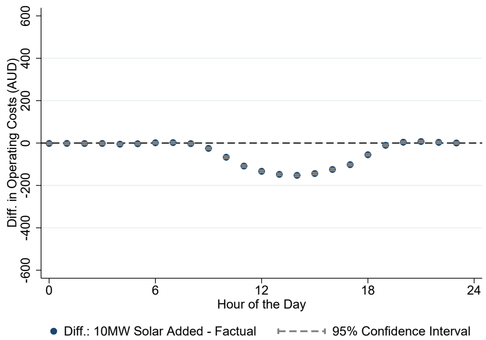
Comparing Figures 6c and 6d, we see that increases in predicted operating profits in the evening are due primarily to increases in market power rents rather than competitive rents. Buttressing this point, competitive prices outside of daylight hours do not change much on average with increases in solar capacity (see Figure 6e).[30] Taken together, Figures 6c-6e provide evidence that the bulk of the increases in wholesale prices and operating profits in the evening are driven by increases in the exercise of market power.

6.3 Robustness Checks and Sensitivity Analyses

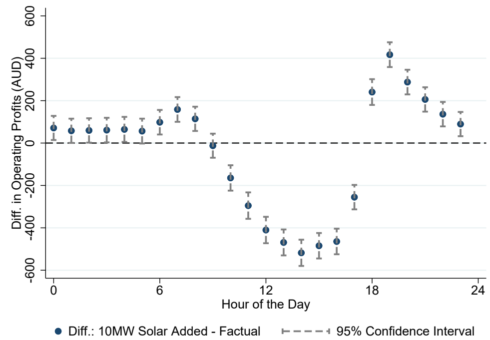
Appendix Section D.1 documents that the results remain similar when including different sets of fixed effects in the regression model. The estimates also remain similar in magnitude and statistical significance when the top 1% and bottom 1% of the outcome is trimmed prior to estimating the model and calculating average predicted differences (see Appendix Figure D.2). Finally, in Appendix Section D.3, we estimate the regression model for each outcome using a randomly selected 80% of the data and predict outcomes using the remaining 20% of the data. Appendix

[30] Appendix Figure D.7 documents that a 10 MW increase in solar capacity results in decreases in total output from both baseload and peaker units during the day. However, we estimate that increases in solar capacity result in *increases* in output from peaker units in the evening, with no corresponding increase for baseload units. This explains the slight increase in competitive prices and competitive rents in the evening: peaker units have smaller start-up costs but higher marginal costs than baseload units. Peaker units are thus better equipped to start up to produce in the evening when solar stops producing.

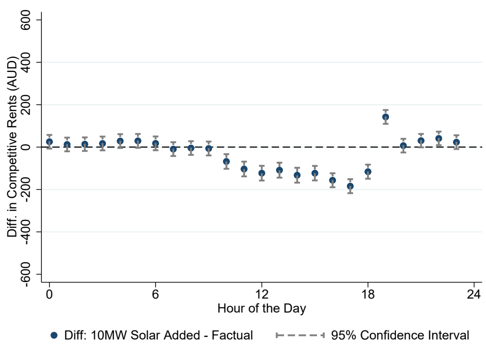
Figure 6: Hourly Average Changes in Predicted Market Outcomes From Adding 10 MW of Rooftop Solar Capacity



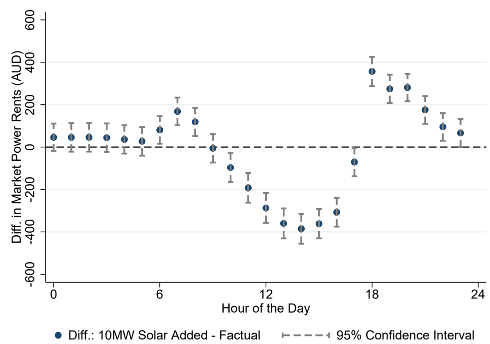
(a) Operating Costs (AUD)



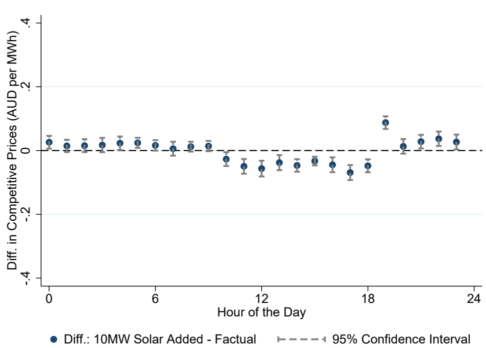
(b) Operating Profits (AUD)



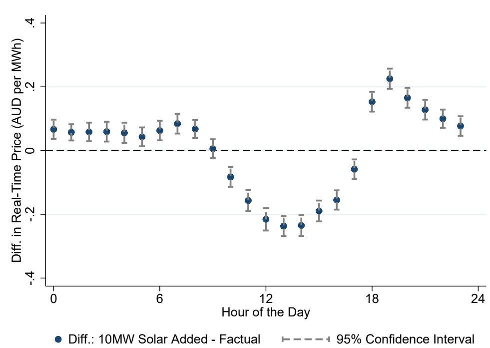
(c) Competitive Rents (AUD)



(d) Market Power Rents (AUD)



(e) Competitive Price (AUD per MWh)



(f) Real-Time Price (AUD per MWh)

Notes: This figure plots the hourly average differences in predictions of market outcomes with versus without adding 10MW of rooftop solar capacity to the system. The bars presented are 95% confidence intervals based on standard errors clustered by week-of-sample. Panel (a) considers the total operating costs incurred by coal- and gas-fired units (excluding co-generation units). Panels (b), (c), and (d) report averages for operating profits, competitive rents and market power rents. Panels (e) and (f) focus on competitive prices and real-time wholesale market prices. Competitive rents, market power rents, and competitive prices are calculated using the dynamic framework discussed in Section 5.1.

Figure D.3 documents that out-of-sample predictions from the regression model track observed values well on average for all hours of the day.

Appendix Section D.4 presents two additional sets of results suggesting that increases in solar capacity lead to increases in the exercise of market power in the evening. First, Appendix Figure D.4a documents that a 10 MW increase in solar capacity corresponds to decreases in the average number of fossil fuel units operating during the day as well as smaller but still statistically significant reductions in the number of units operating in the evening. This suggests that some of the fossil-fuel units displaced by solar during the day choose not to start up in the evening, leading to a decrease in effective competition. In addition, Appendix Figure D.4b indicates that the three major suppliers in WA face steeper residual demand curves on average as a consequence of adding solar capacity to the system.[31] This again suggests that increases in solar capacity lead to increases in the exercise of market power in the evening.

Finally, Appendix Section D.5 documents how our estimated differences in predicted outcomes with versus without 10 MW of additional solar capacity vary by season. A 10 MW increase in solar capacity results in the largest decreases in predicted operating costs, operating profits, and wholesale prices during the day in the summer. This is to be expected: production from rooftop solar panels is tied to solar irradiance; the sun is the brightest and out the longest in the summer relative to the other seasons.

[31] Formally, Appendix Figure D.4b predicts that increases in solar capacity correspond to larger inverse semi-elasticities at sunset. A supplier's inverse semi-elasticity is the increase in market prices (in AUD per MWh) that would result from a 1% decrease in the supplier's quantity sold.

In contrast, we estimate that increases in solar capacity correspond to increases in predicted operating profits, market power rents and real-time prices in the evening for every season *except* summer. This is because the sun is out for longer in the summer, resulting in a more gradual decline in output from solar than in other seasons. Consequently, in the summer, more units start up in the hours leading up to the evening demand peak, resulting in more effective competition in the evening.

7 Market Impacts from Large-Scale Solar Penetration

We conclude our analysis by simulating least-cost market outcomes for counterfactual levels of solar penetration using the dynamic competition framework outlined in Section 5.1. The simulation results inform: (a) the returns to scale of reductions in operating costs from increases in solar penetration; and (b) the extent to which the large increases in operating profits coincident with the solar boom from 2015-2018 could have occurred in a competitive market.

7.1 Methodology

We simulate plant output levels and prices using the dynamic competitive framework outlined in Section 5.1. However, we use counterfactual rather than observed values for the demand to be satisfied in the wholesale market. Namely, our simulations vary the level of rooftop solar capacity in the system, modifying wholesale demand in line with the output from this counterfactual level of solar capacity.

To do this, we divide the aggregate production from rooftop solar panels in each hour-of-sample by the total output implied by these panels producing at capacity in the hour (termed a "capacity factor"). Let CF_t denote the capacity factor for hour-of-sample t. In words, adding (subtracting) X MW of solar capacity in hour t results in an increase (decrease) in solar production of $X \times \text{CF}_t$. We subtract this counterfactual change in rooftop solar production from observed wholesale demand. Namely, for the counterfactual scenario where installed solar capacity is changed by X MW, wholesale demand D_t^X is equal to $D_t^0 - X \cdot \text{CF}_t$.

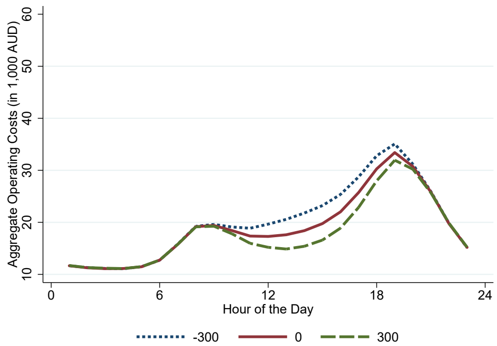
7.2 Results

Figure 7 plots the hourly averages of market outcomes simulated under the dynamic competitive benchmark for each counterfactual solar scenario. The three counterfactual scenarios considered are the removal of 300MW of rooftop solar capacity from the system, keeping the observed level of solar capacity, and the addition of 300MW of solar capacity.[32] As a benchmark for interpreting the magnitudes from this counterfactual analysis, the amount of rooftop solar capacity in WA increased from 544MW to 1102MW from December 1st 2015 to December 1st 2018.

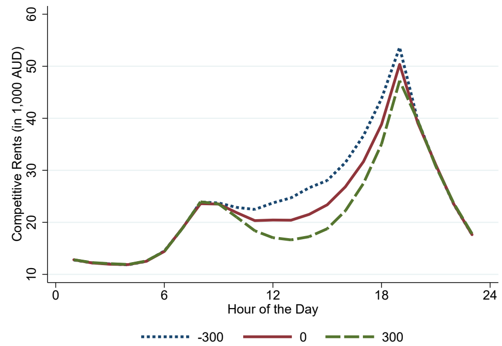
Figures 7a and 7b document that operating costs and competitive rents decrease with solar penetration during the day, consistent with increases in output from solar displacing fossil-fuel production. We also see from these figures that increases in

[32]We do not consider scenarios with larger additions of solar capacity to avoid cases where the total output from solar is larger than the residual demand to be served by the gas-fired fleet.

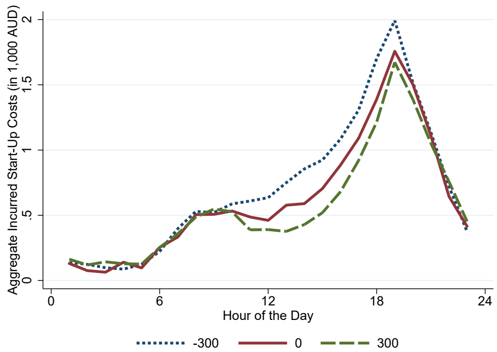
Figure 7: Hourly Averages of Simulated Competitive Market Outcomes for Different Changes in Solar Capacity



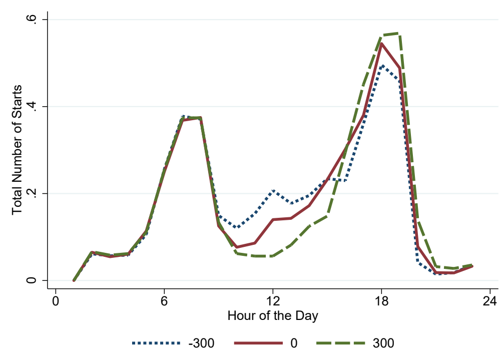
(a) Operating Costs (1,000 AUD)



(b) Competitive Rents (1,000 AUD)



(c) Aggregate Incurred Costs from Starts (1,000 AUD)



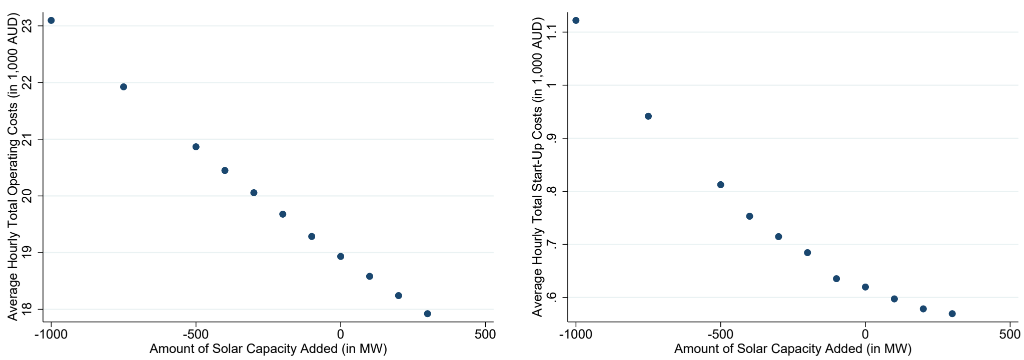
(d) Number of Starts By Gas-Fired Units in the Hour

Notes: This figure plots the hourly averages of market outcomes simulated using the dynamic competition framework outlined in Section 5.1. -300 (300) corresponds to a counterfactual scenario with 300MW less (more) solar capacity than is actually in the system, while 0 corresponds to simulating market outcomes based on the observed level of solar capacity.

solar penetration correspond to decreases in operating costs and competitive rents in the evening. This is due to reductions in the aggregate start-up costs incurred at sunset (see Figure 7c). These results further suggest that solar-induced increases in prices and operating profits in the evening are attributable to increases in market power rents rather than increases in competitive rents.

Figure 7d shows that, under the competitive benchmark, increases in solar capacity lead to less units starting up in the middle of the day, but more units starting up in the late afternoon and early evening. This is intuitive: increases in solar output reduce the need for fossil-fuel units to start up during the day, but these displaced units must start up in the evening when solar stops producing. Despite there being *more* starts at sunset, aggregate incurred start-up costs are *lower* in the evening. This is due to shifts in the least-cost composition of the fleet towards peaker units with lower start-up costs but higher marginal costs.

Figure 8: Averages of Competitive Market Outcomes Simulated for Different Changes in Solar Capacity



(a) Aggregate Operating Costs (1,000 AUD)

(b) Aggregate Incurred Costs from Starts (1,000 AUD)

Notes: This figure plots average market outcomes simulated using the dynamic competition framework outlined in Section 5.1. We consider various changes in rooftop solar capacity relative to observed levels (ex: -300 corresponds to a counterfactual scenario with 300MW less solar capacity than is actually in the system). The left panel plots the average over the sample period of hourly total operating costs across the gas-fired fleet for each counterfactual scenario. The right panel plots the average of the hourly total costs associated with the fuel used for starts.

Figure 8a plots the average of hourly total operating costs across the sample period by counterfactual solar scenario. We see from this figure that the reductions in operating costs from increased solar penetration exhibit slightly decreasing returns to scale as baseline solar penetration rates reach observed levels. This is due to the decreasing returns to scale in solar-induced reductions in aggregate incurred start-up costs, as seen in Figure 8b. This highlights the increasing importance of accounting for dynamics in production as the share of electricity production from renewable resources grows in markets around the world.

8 Conclusions and Policy Implications

Studies of market power commonly examine the extent to which market prices exceed the marginal cost of production (Reiss and Wolak, 2007). However, firms require positive price-cost markups to recover their fixed costs of production (Bresnahan and Reiss, 1990, 1991; Mansur, 2008). This paper develops a framework to calculate a competitive benchmark for the electricity supply sector that accommodates the recovery of the start-up costs incurred by power plants. We empirically demonstrate the importance of accounting for start-up costs when measuring market power for Western Australia, a setting with world-leading rooftop solar penetration rates.

The competitive prices from our dynamic framework are higher than the marginal cost of production, especially in the evening when demand is high and the ability to exercise market power is large. Static price-cost markups can thus substantially overstate the rents captured by firms due to the exercise of market power. In addition, we document that static price-cost markups are negative in a nontrivial percentage of hours, suggesting that fossil-fuel plants are willing to incur short-term losses in order to avoid the costs associated with shutting down and starting back up. Combined, our findings highlight that firms may be earning close to zero profits even while setting prices in excess of their marginal costs in industries with substantial fixed costs.

Measuring market power accounting for start-up costs is becoming increasingly important as policymakers around the world subsidize renewables in their push to transition away from producing electricity by burning polluting fossil fuels (Borenstein, 2012; Greenstone and Nath, 2019). Namely, descriptive trends coincident with the solar boom from 2015-2018 in WA, regression estimates, and results from least-cost simulations all tell the same story: fossil-fuel plants displaced by solar output during the day must incur start-up costs to produce in the evening. Some plants choose not to incur these start-up costs, leading to increases in the exercise of market power in the evening.

The dynamic impacts of rooftop solar penetration on market outcomes speak to the growing importance of designing markets that properly account for the benefits associated with technologies that can rapidly adjust production or consumption. This can be accomplished through the following market design features that are not currently implemented in many wholesale electricity markets around the world. First, all U.S. wholesale markets allow suppliers to submit bids specifying their willingness to start up their units; as increased solar penetration makes starts more relevant, the benefits from co-optimizing across multiple periods by incorporating start-up bids into the market clearing process become more pronounced. Second, many market operators outside of the United States use regulatory mechanisms to procure the "ancillary services" required to quickly adjust consumption or production in order to ensure that supply meets demand at every instant. Integrating the procurement of ancillary services into day-ahead and real-time market clearing processes will yield larger benefits as these services become more important due to increased production from renewables (Wolak, 2019; Buchsbaum et al., 2020; Leslie et al., 2020).

Further, previous work documents that allowing financial participation in the day-ahead market results in lower production costs and decreases in the exercise of market power (Saravia, 2003; Jha and Wolak, 2020; Mercadal, 2020). The benefits from financial trading are especially large in contexts where: (1) physical operating constraints are more likely to bind and (2) market participants have a large degree of market power. Settings with high solar penetration rates often exhibit these two characteristics: increases in solar penetration can exacerbate physical operating constraints tied to generation unit starts, allowing some suppliers to exercise a greater degree of market power in the evening.[33]

Finally, most end-users of electricity around the world face retail prices that do not vary contemporaneously with wholesale prices and often not even by hour of the day (Borenstein and Holland, 2005; Borenstein, 2007; Leslie et al., 2021). Allowing retail prices to reflect hourly variation in wholesale prices will likely shift some demand from the evening to the day (Borenstein, 2005; Holland and Mansur, 2008). As a result of this shift in demand, less fossil fuel units would need to start up

[33] For example, the real-time market clearing solution must account for the amount of time required for units to start up and reach minimum safe operating levels.

in the late afternoon in order to effectively compete at sunset. Our findings suggest that this could reduce the ability of firms to exercise market power, leading to lower wholesale prices in the evening and perhaps ultimately decreases in the retail prices paid by consumers.

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Appendices

A Data Appendix

This Appendix section provides details on the data collection and construction process. Summarizing, our analysis uses publicly-available data on daily fuel usage by gas-fired electricity generation units, half-hourly electricity output from each unit, generation unit characteristics, wholesale electricity market outcomes, fuel prices, and rooftop solar installations. Estimates of the half-hourly aggregate output from rooftop solar panels are sourced from a subscription service.

We obtained fuel consumption data for gas-fired units from August 1st 2013 through December 31st 2018 from the Gas Bulletin Board at the Australian Energy Market Operator (AEMO).[34] This database lists the daily total amount of gas consumed from each "feeder". Feeders are matched to generating units in order to estimate each unit's production function including the fuel used for starts; see Appendix Section C for more details.

Wholesale electricity market (WEM) data were obtained from AEMO.[35] These data are available for each 30 minute interval and include information on day-ahead and real-time prices, load, and the output produced by each generating unit. Further, the offer curves submitted to the day-ahead and real-time markets for each half-hour are available either at the portfolio level or the generation unit level.

Unit characteristics were collected from annual reports compiled for the WEM market operator. These reports, such as SKM-MMA (2014), include engineering

[34] These data can be accessed at `https://gbbwa.aemo.com.au/#reports/largeUserConsumption`

[35] These data can be accessed at `http://data.wa.aemo.com.au/`

estimates of the heat rate at maximum output for each unit but do not include estimates of start-up costs. We document that the heat rate estimates listed in these reports are similar to our econometric estimates for gas-fired units. We also use the engineering estimates of heat rates from SKM-MMA (2014) to calculate the fuel used by coal-fired units. Finally, each unit's fuel cost in each half-hour is calculated by multiplying fuel use by the relevant quarterly fuel price reported by the Western Australian Department of Mines and Petroleum (WA-DMP (2018)).[36]

The Australian Photovoltaic Institute provided us with half-hourly data on the capacity of rooftop solar installed in Western Australia as well as an estimate of the aggregate output from rooftop solar panels in each half-hour-of-sample.

[36]The fuel prices listed in WA-DMP (2018) are the prices paid to producers by all gas customers. Consequently, we scale the gas price time series by $\frac{4.32}{4.96}$ to align this series with the prices paid by gas-fired generation units provided by AEMO (2017) for the year 2017.

B Descriptive Trends in Market Outcomes: Additional Figures and Tables

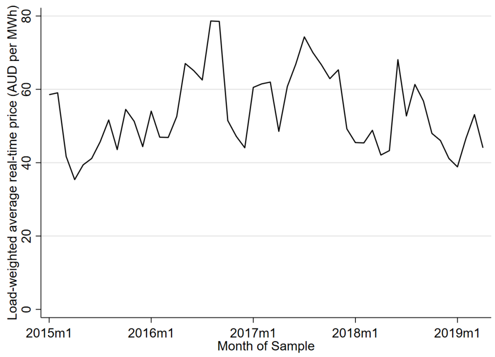
Appendix Figures B.1a-B.1d present trends in real-time wholesale prices, aggregate heat rate for the gas-fired fleet, and fuel prices over 2015-2018. Each series is relatively flat, with only slight upward trends in electricity prices, heat rates and coal prices over time. Gas prices also remained relatively stable with the exception of a 15% reduction in 2017.

Installed rooftop solar capacity increased by 133% from 2015 to 2018 (Appendix Figure B.2). Coincident with this solar boom, wholesale electricity prices in the day-ahead market increased by 15% while real-time prices increased by 6%.[37] However, the annual aggregate heat rate for the gas-fired fleet only changed by 1% from 2015 to 2018. The increase in wholesale prices also cannot be explained by changes in fuel prices: natural gas prices decreased by 17% and coal prices decreased by 5% from 2015 to 2018. This motivates an analysis of start-up costs and market power: rooftop solar production displaces fossil fuel units during the day, forcing these units to start up in order to effectively compete at sunset. Both increases in the marginal cost of the marginal unit and increases in the exercise of market power can result in the increases in wholesale prices observed at sunset.

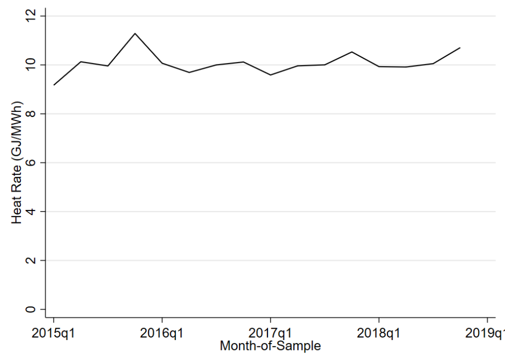
Appendix Figures B.3a and B.3b plot hourly average aggregate output from baseload and peaker units respectively. Coal and combined cycle gas turbine (CCGT)

[37]Day-ahead prices increased from 43.20 AUD/MWh in 2015 to 49.80 AUD/MWh in 2018 while real-time prices increased from 47.40 AUD/MWh to 50.20 AUD/MWh. Both sets of prices are load-weighted annual averages for the years 2015 versus 2018.

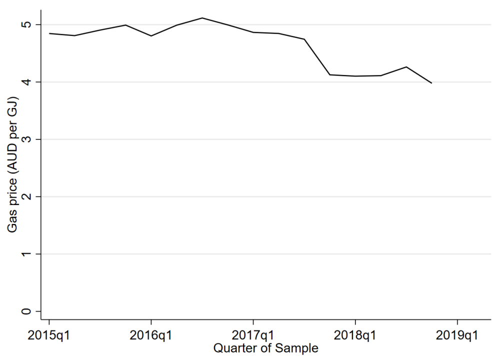
Figure B.1: Electricity Prices, Heat Rate and Fuel Prices: 2015-2018



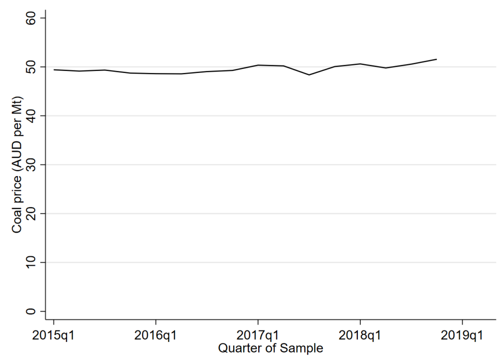
(a) Load-Weighted Average Real-Time Electricity Price (AUD per MWh)



(b) Aggregate Heat Rate for the Gas-Fired Fleet (GJ/MWh)



(c) Natural Gas Price (AUD per GJ)

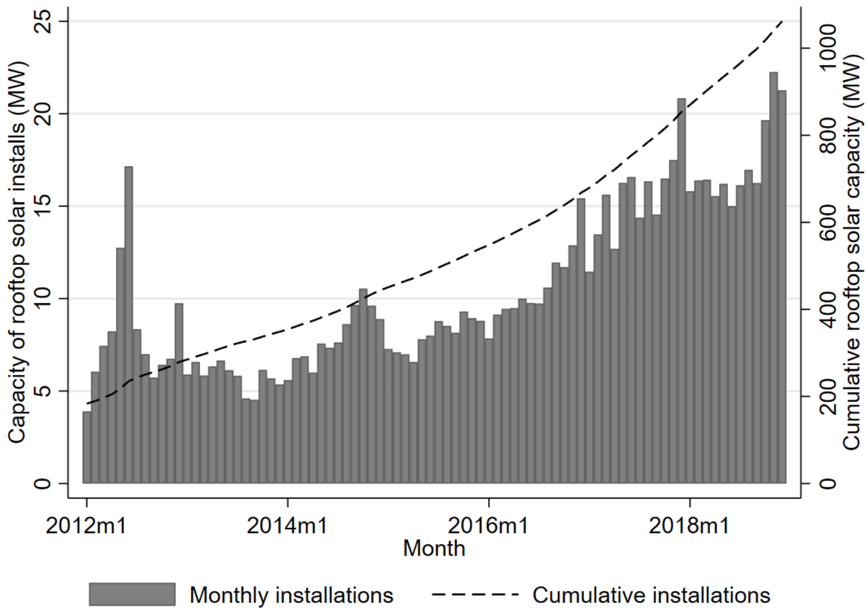


(d) Coal Price (AUD per MT)

Notes: Panel (a) of this figure plots the monthly load-weighted average price in the balancing market (i.e., the "real-time" price); note that wholesale electricity demand is called "load". Panel (b) of this figure plots the monthly total fuel consumed by the gas-fired fleet (in GJ) divided by the monthly total output produced by the gas-fired fleet (in MWh). We exclude gas-fired units that produce both electricity and useful heat (i.e., "co-generation units") when calculating this aggregate heat rate. Panels (c) and (d) report quarterly average natural gas prices and coal prices in AUD per GJ and AUD per MT respectively. The sample period considered for all panels is 2015-2018.

units are considered "baseload" technologies while open cycle gas turbine (OCGT) units are considered "peakers". Peaker units tend to have lower start-up costs but higher marginal costs than baseload units. We see from Appendix Figures B.3a and

Figure B.2: Trends in the Installation of Rooftop Solar Capacity

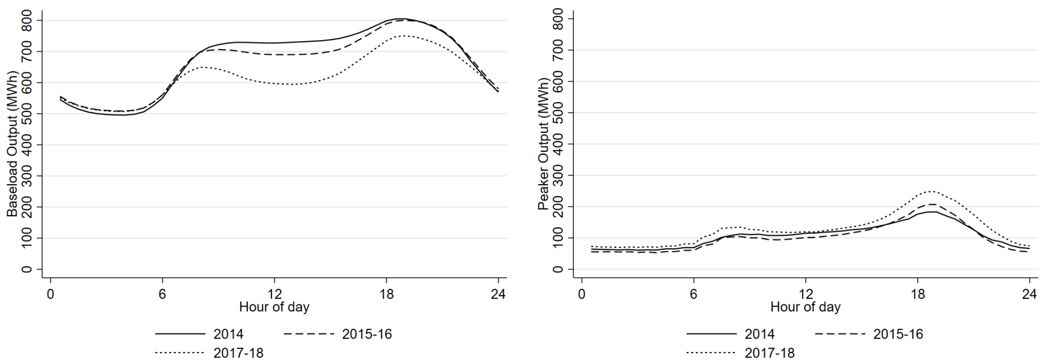


Notes: This figure displays monthly total capacity of new installations of rooftop solar panels (the histogram) and the total cumulative amount of rooftop solar capacity installed up to that month-of-sample (the dashed line).

B.3b that the decreases in wholesale demand from 2015-2018 correspond to reductions in output mostly from baseload units during the daylight hours. Consistent with baseload technologies having higher start-up costs, we see increases in output from peaker units substituting for decreases in output from baseload units in the evening.

Finally, we consider two measures relevant to suppliers' ability to exercise market power. First, Appendix Figure B.4a documents that the average total number of fossil fuel units operating falls from 2014 to 2018 for all hours of the day. This reduction in the number of units running is most pronounced during the day, consis-

Figure B.3: Hourly Average Aggregate Output by Technology: 2014-2018



(a) Output from Coal and CCGT Units (b) Output from OCGT Units

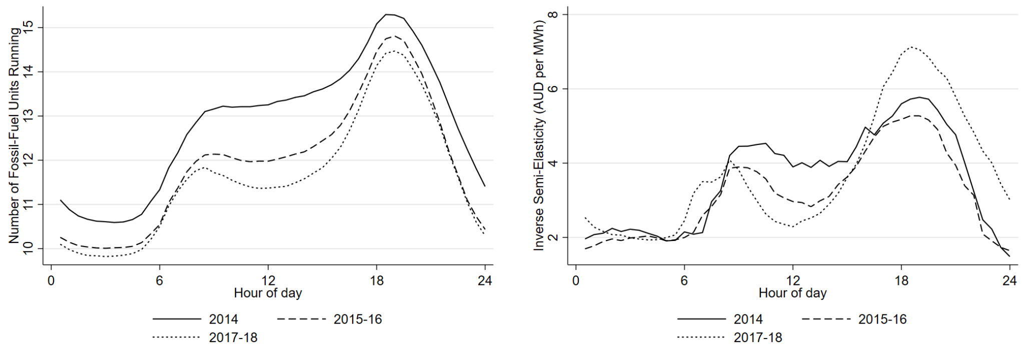
Notes: This figure plots the hourly average aggregate output from baseload and peaker generating units. Specifically, we sum output across units in each category and then average across half-hours-of-sample separately for each hour of the day and separately for the year 2014, the years 2015-2016, and the years 2017-2018. Coal-fired units and combined-cycle gas turbine (CCGT) units are classified as "baseload" because they operate consistently throughout the year, shutting down primarily for maintenance. Open-cycle gas turbine (OCGT) units are classified as "peakers"; peaker units typically have lower start-up costs but higher marginal costs than baseload units.

tent with increased production from rooftop solar capacity displacing fossil-fuel-fired production.

We measure the ability to exercise market power using the output-weighted average inverse semi-elasticity across the three major suppliers in the market: Synergy, Alinta, and NewGen.[38] In words, the inverse semi-elasticity facing a given supplier is the increase in wholesale prices (in AUD per MWh) that results from the supplier reducing the amount they sell into the market by one percent (McRae and Wolak, 2014). Appendix Figure B.4b indicates that the ability of suppliers to ex-

[38]Each supplier s faces inverse semi-elasticity in half-hour-of-sample t equal to $\eta_{s,t} = -\frac{1}{100}P_t^*[\frac{\partial P_t^*}{\partial Q_{s,t}}][\frac{Q_{s,t}^*}{P_t^*}]$. We take the difference in residual demand evaluated at $0.9q_{s,t}^*$ versus $1.1q_{s,t}^*$ in order to numerically estimate the derivative $\frac{\partial P_t^*}{\partial Q_{s,t}}$ (McRae and Wolak (2014); Leslie (2018)).

Figure B.4: Hourly Averages of Competition Measures: 2014-2018



(a) Number of Fossil Fuel Units Running

(b) Output-Weighted Average Inverse Semi-Elasticity

Notes: This figure plots hourly averages of two measures relevant to suppliers' ability to exercise market power. These averages are calculated across half-hours-of-sample separately for the year 2014, the years 2015-2016, and the years 2017-2018. The left panel focuses on the total number of fossil fuel units running: we count the number of coal-fired and gas-fired units (excluding co-generation units) producing positive output for each half-hour-of-sample and then average over half-hours-of-sample for each hour of the day. The right panel displays the output-weighted average inverse semi-elasticity across the three major suppliers in the market: Synergy, Alinta, and NewGen. For this panel, we take the output-weighted average of each supplier's inverse semi-elasticity across suppliers and half-hours-of-sample for each hour of the day. The inverse semi-elasticity facing a supplier is the increase in market clearing prices associated with a 1% reduction in their output.

ercise market power increased at sunset over the sample period. This is consistent with the evidence from Appendix Figure B.4a that the increased production from solar from 2014 to 2018 causes more fossil fuel units to have to start up in order to effectively compete at sunset. The resulting decrease in effective competition leads to an increased ability to exercise market power in the evening.

C Dynamic Production Function: Additional Detail on Methods and Estimates

We assume that each unit's production function takes the form specified in Equation (1) in Section 4.1. This functional form is similar to the ones used in Wolak (2007) and Reguant (2014). Specifically, both of these papers specify start-up costs as in Equation (1). However, we do not consider ramping costs since we focus on the gas-fired fleet. Gas-fired units in WA do not face significant ramping constraints over the course of an hour. In addition, ramping costs are difficult to separately identify from start-up costs since we only have daily data on gas use.

Both Wolak (2007) and Reguant (2014) include higher order polynomials in output. We do not include higher order terms for two reasons. First, the heat rates estimated using our linear specification are comparable to the engineering estimates reported in SKM-MMA (2014). Second, estimates from polynomial specifications are unreasonable for some generating units; nonlinear specifications can predict very low or negative fuel use for reasonable levels of output.

The sample period used to estimate each unit's production function spans from August 1st 2013 to December 31st 2018. Only days with positive gas use are included when estimating each unit's production function. We estimate each unit's production function using ordinary least squares and report heteroskedasticity-consistent standard errors.

For the ALINTA_WGP, KEMERTON, KWINANA and MUNGARRA facilities, there are multiple generating units at each plant site. For each of these facilities, generating units at the same site have the same production technology and are thus likely to have similar production functions (SKM-MMA (2014)). Therefore, we estimate the following equation for each feeder i providing gas to J identical generating units:

$$\sum_{t=1}^{48} G_{i,t,d} = \alpha_i \sum_{j=1}^{J} \sum_{t=1}^{48} O_{i,j,t,d} + \gamma_i \sum_{j=1}^{J} \sum_{t=1}^{48} S_{i,j,t,d} + \sum_{j=1}^{J} \sum_{t=1}^{48} \epsilon_{i,j,t,d}$$

where $O_{i,j,t,d}$ is unit j's output in half-hour-of-day t of day d. As before, start-up term $S_{i,j,t,d} \equiv 1[O_{i,j,t,d} > 0] \times 1[O_{i,j,t-1,d} = 0]$ is equal to one if and only if unit j started up in half-hour t.

For the PINJAR facility, there are six generating units that use the same technology (PINJAR1-PINJAR7) while a different technology is used for three other generating units (PINJAR9-PINJAR11). For this facility, we estimate the following equation for feeder i providing gas to J generating units of type 1 and K generating units of type 2:

$$\begin{aligned}\sum_{t=1}^{48} G_{i,t,d} =& \alpha_1 \sum_{j=1}^{J} \sum_{t=1}^{48} O_{i,j,t,d} + \gamma_1 \sum_{j=1}^{J} \sum_{t=1}^{48} S_{i,j,t,d} + \sum_{j=1}^{J} \sum_{t=1}^{48} \epsilon_{i,j,t,d} \\ & \alpha_2 \sum_{k=1}^{K} \sum_{t=1}^{48} O_{i,k,t,d} + \gamma_2 \sum_{k=1}^{K} \sum_{t=1}^{48} S_{i,k,t,d} + \sum_{k=1}^{K} \sum_{t=1}^{48} \epsilon_{i,k,t,d}\end{aligned}$$

Appendix Table C.1 compares each unit's parameter estimates from their production function to the engineering estimates reported in SKM-MMA (2014). Specifically, this report lists each unit's capacity as well as engineering estimates of each unit's heat rates when producing at its minimum safe output level and at capacity.

Note that each facility can be home to multiple units; for example, a facility with 6 units, each of which has 35MW of capacity, would be listed as 35×6. The last two columns of Appendix Table C.1 list the parameter estimates corresponding to each unit's production function: heat rate ($\hat{\alpha}_i$) and start-up fuel requirement ($\hat{\gamma}_i$). We report heteroskedasticity-consistent standard errors for each parameter estimate in parentheses.

From Appendix Table C.1, we see that the engineering estimate of heat rate at maximum output is similar to the parameter estimate listed in the "HR" column for all of the units listed in SKM-MMA (2014). Moreover, our econometric estimates demonstrate that gas-fired units must use non-trivial quantities of fuel in order to start up. Finally, there is significant heterogeneity in heat rates and start-up costs across gas-fired units. Combined Cycle Gas Turbine (CCGT) units are considered "baseload" because they have small heat rates but require larger amounts of fuel to start up. In contrast, Open Cycle Gas Turbine (CCGT) units are considered "peakers" because they are characterized by higher heat rates but smaller amounts of fuel required to start up.

Table C.1: Engineering versus Econometric Estimates of the Parameters of Each Gas-Fired Unit's Production Function

Facility	Capacity (MW)	**Engineering Estimates** HR@min ($\frac{GJ}{MWh}$)	HR@max ($\frac{GJ}{MWh}$)	**Econometric Estimates** HR ($\hat{\alpha}_i$) ($\frac{GJ}{MWh}$)	Start Up ($\hat{\gamma}_i$) (GJ)
Combined Cycle Gas Turbine (CCGT) Units					
COCKBURN	237×1	9.4	9	7.7	841.8
				(0.011)	(33.4)
N'GEN_K'ANA	324×1	.	.	7.9	2916.7
				(0.006)	(628.1)
Open Cycle Gas Turbine (OCGT) Units					
ALINTA_WGP	190×2	16.2	11.5	11.3	492.5
				(0.032)	(36.6)
KEMERTON	154×2	13.3	12.2	12.8	237.9
				(0.1)	(34.4)
KWINANA	100×2	15.2	9.4	10.5	66.1
				(0.01)	(23.1)
MUNGARRA	37×3	21.9	13.5	15.8	147
				(0.29)	(39.8)
N'GEN_N'BUP	342×1	.	.	11.1	452.1
				(0.226)	(351.4)
PINJAR1-7	38×6	22.5	13.2	13.8	168.3
				(0.373)	(31.9)
PINJAR9-11	116×3	19.3	12.1	15.1	577.5
				(0.033)	(18.9)

Notes: This table lists each unit's capacity (in MW), engineering estimates of heat rates when producing at minimum and maximum output (in GJ/MWh), and our parameter estimates from the production function specified in Equation (1). Each facility can be home to multiple units; for example, a facility with 3 units, each of which has 37MW of capacity, would be listed as 37×3. Each unit's capacity and engineering estimates of heat rate are listed in SKM-MMA (2014). Engineering estimates for N'GEN_K'ANA and N'GEN_N'BUP are not available. We estimate each unit's production function using the methodology discussed in Section 4.1. The last two columns of this table report the parameter estimates corresponding to the increase in fuel use in GJ corresponding to a 1 MWh increase in output ignoring starts ("HR"), and the gas required to start up the unit ("Start Up"). The sample period used to estimate each unit's production function spans from August 1st 2013 to December 31st 2018. Only days with positive gas use are included when estimating each unit's production function. Heteroskedasticity-consistent standard errors are reported in parentheses.

D Linking Market Outcomes to Solar Penetration: Additional Results

This Appendix section presents additional results pertaining to the regression analysis in Section 6.

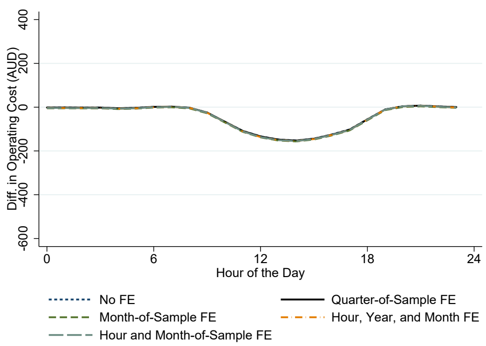
D.1 Robustness to Different Sets of Fixed Effects

The differences in average predictions plotted in Figure 6 were calculated by estimating Equation (9) in Section 6.1. In this subsection, we show that the patterns in predictions remain similar if we predict outcomes after adding different sets of fixed effects to Equation (9). Specifically, Appendix Figure D.1 plots the hourly average differences in predictions with versus without adding 10 MW of solar capacity from 5 different regression models including: (1) no fixed effects (our primary specification), (2) quarter-of-sample fixed effects, (3) month-of-sample fixed effects, (4) year fixed effects, hour-of-day fixed effects, and month-of-year fixed effects, and (5) month-of-sample fixed effects and hour-of-day fixed effects.

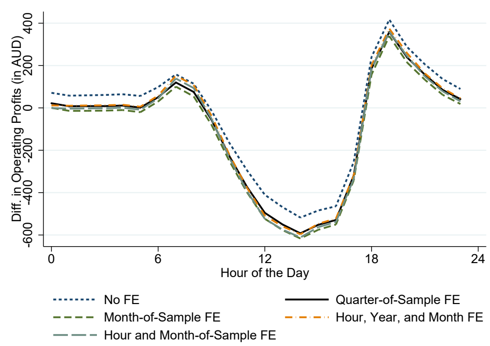
D.2 Trimming the Top 1% and Bottom 1% of the Outcome

In this subsection, we trim the top 1% and bottom 1% of the relevant market outcome before estimating Equation (9) from Section 6.1. We predict the market outcome with versus without adding 10 MW of solar capacity to the system for each hour-of-sample for the observations remaining after trimming. The average differences in

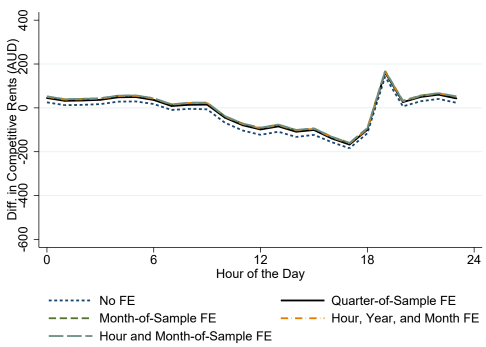
Figure D.1: Hourly Average Differences in Predicted Outcomes: Different Sets of Fixed Effects



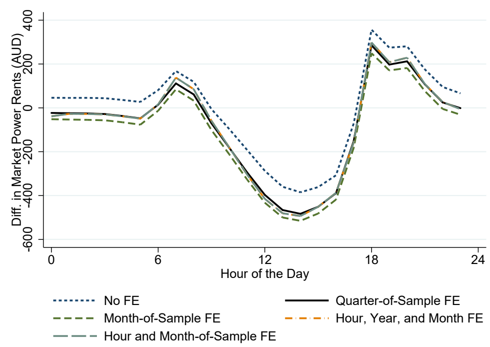
(a) Aggregate Operating Cost (AUD)



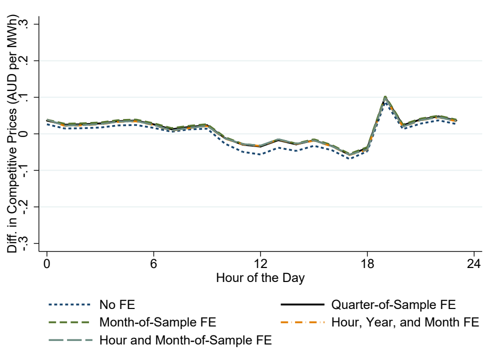
(b) Aggregate Operating Profits (AUD)



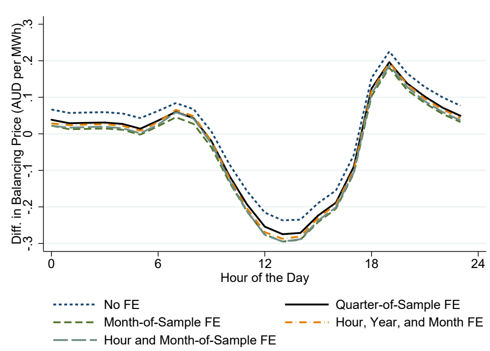
(c) Competitive Rents (AUD)



(d) Market Power Rents (AUD)



(e) Competitive Price ($\frac{\text{AUD}}{\text{MWh}}$)



(f) Real-Time Wholesale Price ($\frac{\text{AUD}}{\text{MWh}}$)

Notes: This figure plots the hourly average differences in predictions of market outcomes with versus without adding 10MW of rooftop solar capacity to the system. In each panel, predictions are calculated using five different regression specifications which include (1) no fixed effects, (2) quarter-of-sample fixed effects, (3) month-of-sample fixed effects, (4) year fixed effects, hour-of-day fixed effects, and month-of-year fixed effects, and (5) month-of-sample fixed effects and hour-of-day fixed effects. Panel (a) considers the total operating costs incurred by coal- and gas-fired units (excluding co-generation units). Panels (b), (c), and (d) report average predicted differences for operating profits, competitive rents and market power rents. Panels (e) and (f) focus on competitive prices and real-time wholesale market prices. Competitive rents, market power rents, and competitive prices are calculated using the dynamic framework discussed in Section 5.1.

predictions for each hour of the day are presented in Appendix Figure D.2.

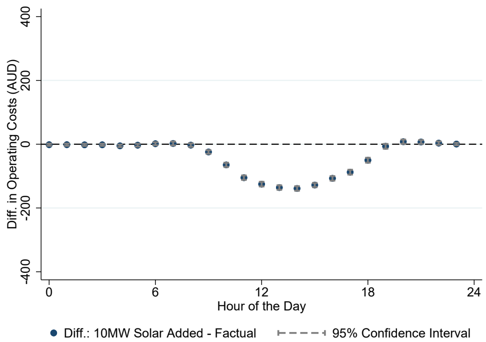
The story remains the same regardless of whether the outcomes are trimmed or not. Namely, Appendix Figure D.2 indicates that adding 10 MW of solar capacity to the system corresponds to reductions in all of our market outcomes during the day. However, operating profits and wholesale prices are larger in the evening when adding 10 MW of solar capacity. As with Figure 6 in the main text, increases in operating profits and wholesale prices in the evening are driven primarily by increases in market power rents rather than increases in competitive rents or competitive prices (see Appendix Figures D.2c-D.2e).

D.3 Predicted versus Observed Outcomes

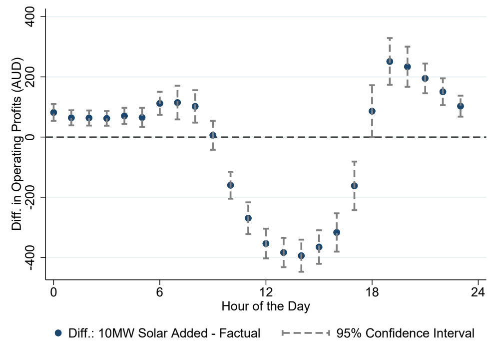
Appendix Figure D.3 plots hourly averages of observed market outcomes versus market outcomes predicted using Equation (9) from Section 6.1. As in the machine learning literature, we focus on "out-of-sample" prediction in this figure (Jarvis et al. (2019); Burlig et al. (2020)). Specifically, we estimate Equation (9) on a randomly chosen 80% of the data-set and assess observed versus predicted outcomes for the other 20% of the data-set. The out-of-sample R^2 is reported underneath each panel.

Panel (a) of Appendix Figure D.3 focuses on the total operating costs incurred by coal- and gas- fired units (excluding co-generation units) while Panel (b) focuses on the total operating profits earned by these units. Competitive rents and market power rents are plotted in Panels (c) and (d) respectively. Finally, Panel (e) focuses on the price in the balancing market (i.e., the "real-time" wholesale price) while

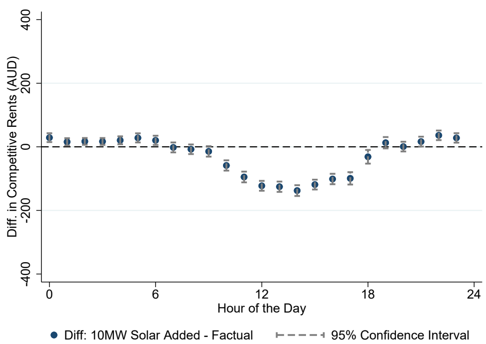
Figure D.2: Hourly Average Predicted Changes in Trimmed Market Outcomes when Adding 10MW of Rooftop Solar Capacity



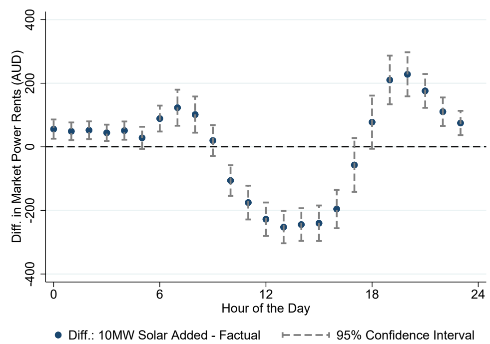
(a) Operating Costs (AUD)



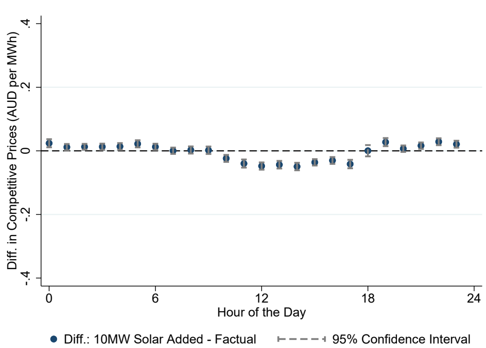
(b) Operating Profits (AUD)



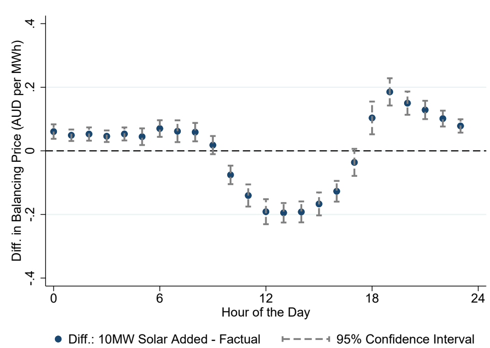
(c) Competitive Rents (AUD)



(d) Market Power Rents (AUD)



(e) Competitive Price (AUD per MWh)



(f) Real-Time Price (AUD per MWh)

Notes: This figure plots the hourly average differences in predictions of market outcomes with versus without adding 10MW of rooftop solar capacity to the system. We trim the top 1% and bottom 1% of the market outcome prior to estimating the regression model. The bars presented are 95% confidence intervals based on standard errors clustered by week-of-sample. Panel (a) considers the total operating costs incurred by coal- and gas-fired units (excluding co-generation units). Panels (b), (c), and (d) report average predicted differences for operating profits, competitive rents and market power rents. Panels (e) and (f) focus on competitive prices and real-time wholesale market prices. Competitive rents, market power rents, and competitive prices are calculated using the dynamic framework discussed in Section 5.1.

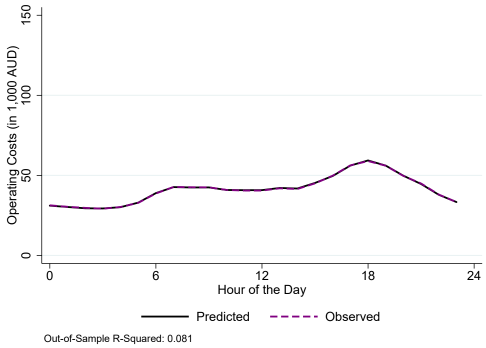
Panel (f) focuses on competitive prices. For Panels (c), (d), and (f), the relevant magnitude is constructed using the time series of competitive prices from the dynamic framework presented in Section 5.1.

Appendix Figure D.3 demonstrates that our linear regression model predicts all six market outcomes well on average even out-of-sample. The linear regression model includes only current and lagged wholesale demand; it does not include any sets of fixed effects or control variables. Despite this, the out-of-sample R^2 is above 0.49 for all of the outcomes except for operating costs. Even in this case, the hourly averages of observed versus predicted operating costs track each other quite closely. This is especially comforting because we compare the hourly averages of predictions from Equation (9) with versus without adding 10MW of rooftop solar capacity to the system.

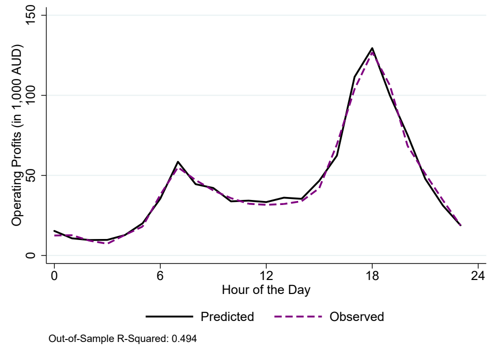
D.4 Effects on Other Competition Measures

Appendix Figure D.4a plots hourly average differences in predicted total number of fossil fuel units running with versus without adding 10MW of rooftop solar capacity to the system. This figure documents that a 10 MW increase in rooftop solar capacity corresponds to decreases in the total number of fossil fuel units operating during the day. This figure also shows that increases in solar capacity result in smaller but still statistically significant declines in the number of fossil fuel units operating in the evening. This suggests that some of the fossil fuel units displaced by solar during the day choose not to start up to produce in the evening, leading to less competition

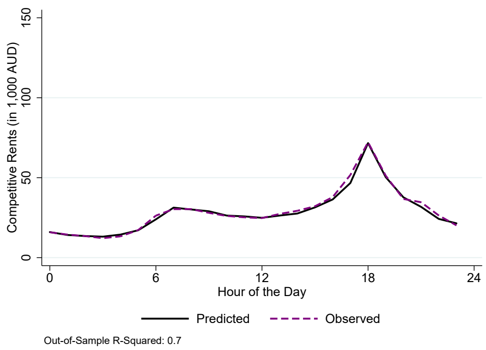
Figure D.3: Hourly Average Predicted and Observed Market Outcomes



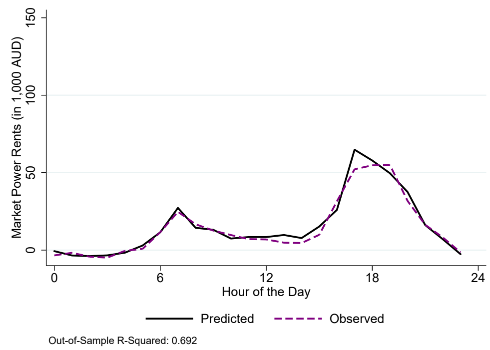
(a) Aggregate Operating Costs (AUD)



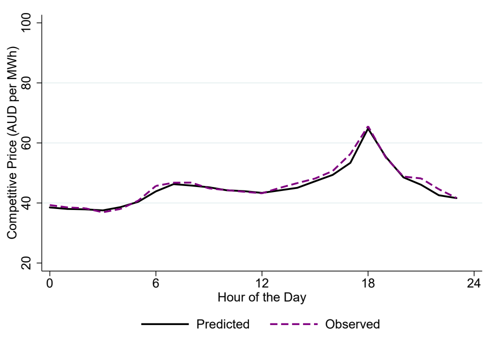
(b) Aggregate Operating Profits (AUD)



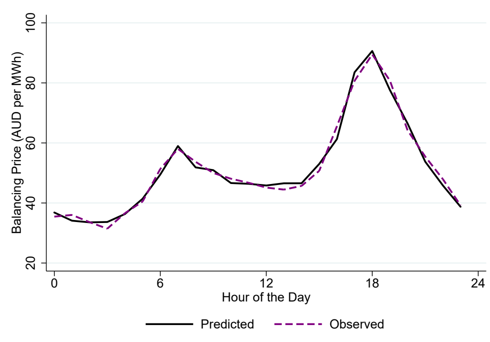
(c) Competitive Rents (AUD)



(d) Market Power Rents (AUD)



(e) Competitive Price ($\frac{\text{AUD}}{\text{MWh}}$)

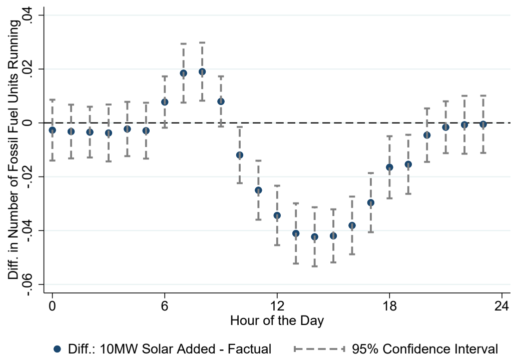


(f) Real-Time Wholesale Price ($\frac{\text{AUD}}{\text{MWh}}$)

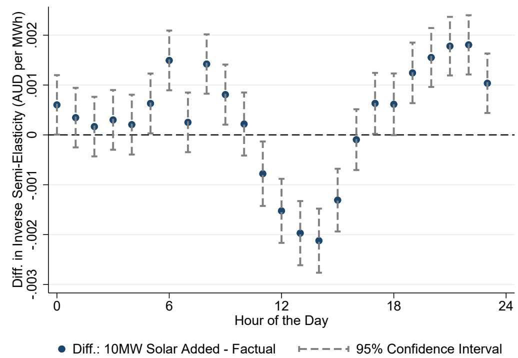
Notes: This figure plots the hourly averages of observed and predicted outcomes. We estimate Equation (9) on a randomly chosen 80% of the data-set and compare observed versus predicted outcomes for the other 20% of the data-set. Panel (a) considers the total operating costs incurred by coal- and gas-fired units (excluding co-generation units). Panels (b), (c), and (d) report averages for operating profits, competitive rents and market power rents. Panels (e) and (f) focus on competitive prices and real-time wholesale market prices. Competitive rents, market power rents, and competitive prices are calculated using the dynamic framework discussed in Section 5.1.

among suppliers in the evening.

Figure D.4: Hourly Average Changes in Other Competition Measures From Adding 10MW of Rooftop Solar Capacity



(a) Number of Fossil Fuel Units Running



(b) Output-Weighted Average Inverse Semi-Elasticity

Notes: This figure plots hourly average differences between model predictions of (a) the number of fossil fuel units running, and (b) output-weighted average inverse semi-elasticity, with versus without adding 10MW of rooftop solar capacity to the system. The bars presented are 95% confidence intervals based on standard errors clustered by week-of-sample. The inverse semi-elasticity facing a supplier is the increase in market clearing prices associated with a 1% reduction in their output.

To explore this more formally, Appendix Figure D.4b displays hourly averages of the differences in predicted output-weighted average inverse semi-elasticity across the three major suppliers in WA: Synergy, Alinta, and NewGen. A supplier's inverse semi-elasticity is interpretable as the increase in market prices (in AUD per MWh) that would result from a 1% decrease in the supplier's quantity sold (McRae and Wolak, 2014). We estimate that adding 10 MW of solar capacity to the system leads to decreases in average inverse semi-elasticities during the day. This is consistent with production from solar capacity resulting in less residual demand to be satisfied by fossil-fuel units, leading to increased competition among suppliers during the day.

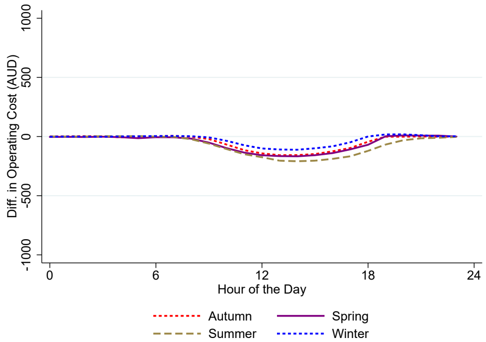
In contrast, in the evening, we see that increases in rooftop solar capacity correspond to increases in inverse semi-elasticities. This again is intuitive: as discussed above, some of the fossil fuel units that shut down due to solar output during the day choose not to start up in the evening when solar no longer produces. Consequently, suppliers exercise a greater degree of market power in the evening when solar capacity is added to the system.

D.5 Effects of Solar By Season

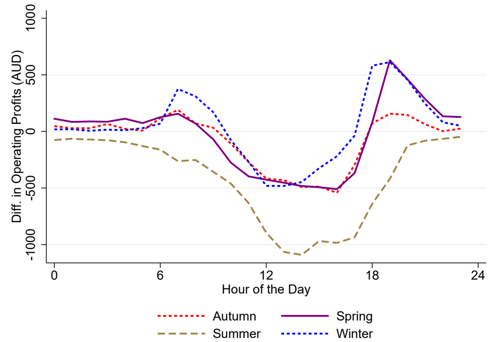
This Appendix subsection explores how hourly average differences in predicted outcomes with versus without adding 10MW of solar capacity to the system vary by season. We see from Appendix Figure D.5 that a 10MW increase in solar capacity corresponds to the largest reductions in operating costs, operating profits, and market power rents during daylight hours in the summer relative to the other seasons. This is intuitive: production from solar is tied both to how long the sun is out and how brightly the sun shines; output from a given amount of solar capacity will be largest in the summer. Of course, increases in rooftop solar output directly correspond to decreases in the residual demand to be served by the fossil-fuel fleet.

Interestingly, we see the *smallest* declines in competitive prices during the day from increases in solar capacity in the summer. Moreover, unlike the other seasons, operating profits, market power rents, and wholesale prices do not increase with solar capacity in the evening in the summer. This suggests that the market impacts of a given increase in solar capacity are tied not only to the level of output from this

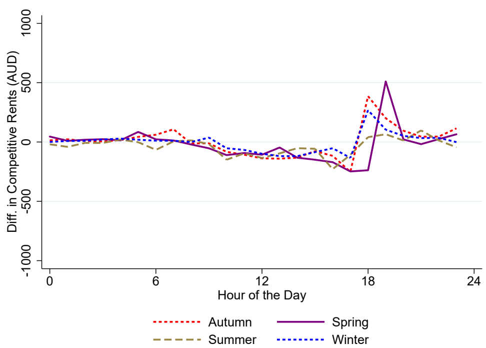
Figure D.5: Hourly Average Changes in Predicted Market Outcomes From Adding 10MW of Rooftop Solar Capacity By Season



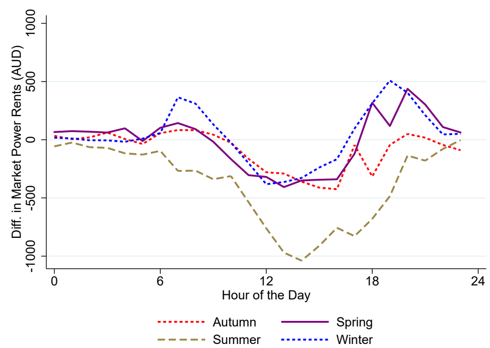
(a) Operating Costs (AUD)



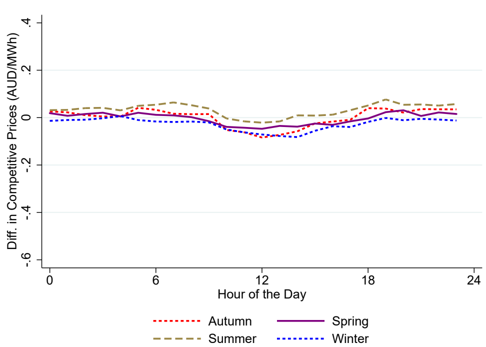
(b) Operating Profits (AUD)



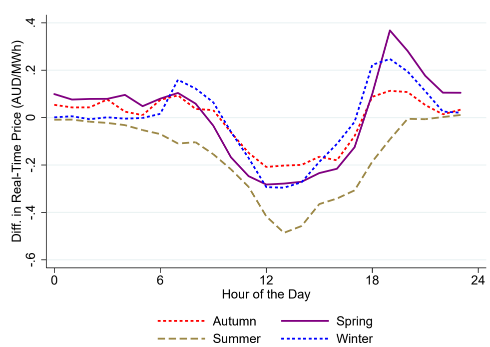
(c) Competitive Rents (AUD)



(d) Market Power Rents (AUD)



(e) Competitive Price (AUD per MWh)



(f) Real-Time Price (AUD per MWh)

Notes: This figure plots hourly average differences in predictions of market outcomes with versus without adding 10MW of rooftop solar capacity; these averages are calculated separately for each season. The bars presented are 95% confidence intervals based on standard errors clustered by week-of-sample. Panel (a) considers the total operating costs incurred by coal- and gas-fired units (excluding co-generation units). Panels (b), (c), and (d) report averages for operating profits, competitive rents and market power rents. Panels (e) and (f) focus on competitive prices and real-time wholesale market prices. Competitive rents, market power rents, and competitive prices are calculated using the dynamic framework discussed in Section 5.1.

capacity, but also the pattern of solar output across hours of the day.

Namely, 10 MW of solar capacity produces the most during the day in the summer. However, the sun also sets at a later hour in the summer, leading to a more gradual increase in wholesale demand from day to evening. This in turn leads to a more gradual increase in the number of fossil-fuel units starting up in the hours before peak evening demand. A supplier deciding whether to start their unit up to meet evening demand has a good sense of the level of competition they will face given this gradual increase in the number of units operating as the sun sets.

In contrast, in the other seasons, the sun sets relatively earlier and so suppliers must make quick decisions regarding which units to start up to meet demand in the evening. If many units decide to start up, competition will be especially fierce, leading to prices that may be insufficient to cover start-up costs. For this reason, some units choose not to start up, leading to less effective competition in the evening and thus increases in the degree of market power exercised.

D.6 Estimation Excluding Lagged Wholesale Demand

In this subsection, we estimate the relationship between current wholesale demand and market outcomes excluding the terms corresponding to lagged demand. Specifically, we estimate:

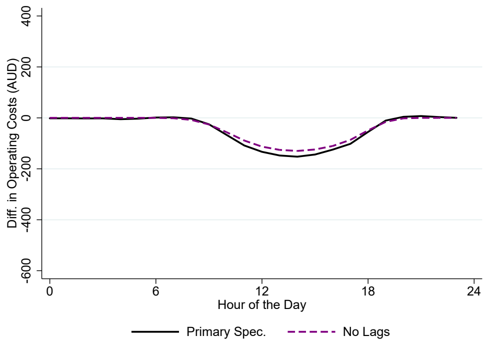
$$Y_t = \gamma_h D_t + \epsilon_t \tag{D.1}$$

where t indexes the hour-of-sample corresponding to hour of the day h. Appendix

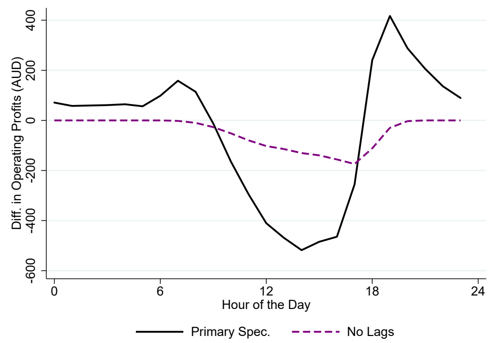
Figure D.6 plots the hourly average differences in predictions with versus without adding 10 MW of solar capacity for predictions calculated in two different ways: (1) using Equation (9) which includes the 24 lags of hourly wholesale demand versus (2) using Appendix Equation (D.1) without lagged wholesale demand.

Including versus excluding lagged wholesale demand in the regression framework substantially changes the predicted impacts of solar capacity on operating profits and market power rents. Namely, relative to the static framework, the dynamic framework predicts a much larger drop in operating profits and market power rents during the day from a 10MW increase in solar capacity. Moreover, a 10 MW increase in solar capacity results in increases in predicted operating profits and market power rents in the evening when using the dynamic regression model but not the static regression model. This highlights the importance of accounting for start-up costs when assessing the market impacts of solar penetration.

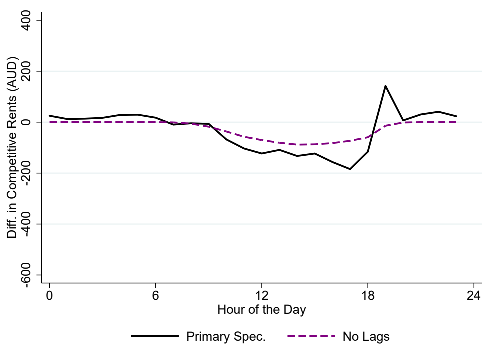
Figure D.6: Differences in Hourly Average Outcomes Predicted Using Regression Models with versus without Lagged Wholesale Demand



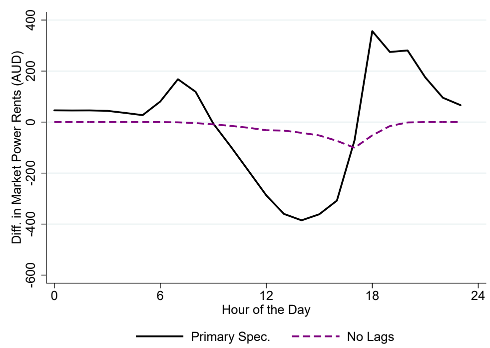
(a) Operating Costs (AUD)



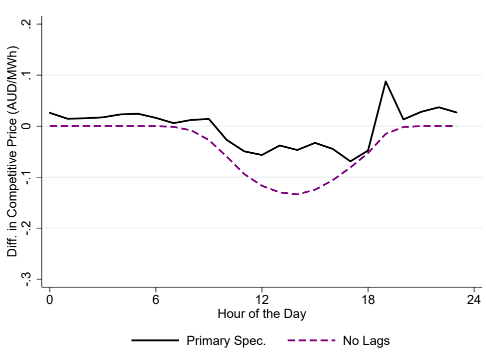
(b) Operating Profits (AUD)



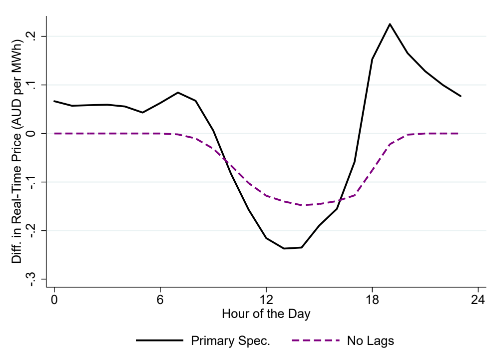
(c) Competitive Rents (AUD)



(d) Market Power Rents (AUD)



(e) Competitive Price (AUD per MWh)



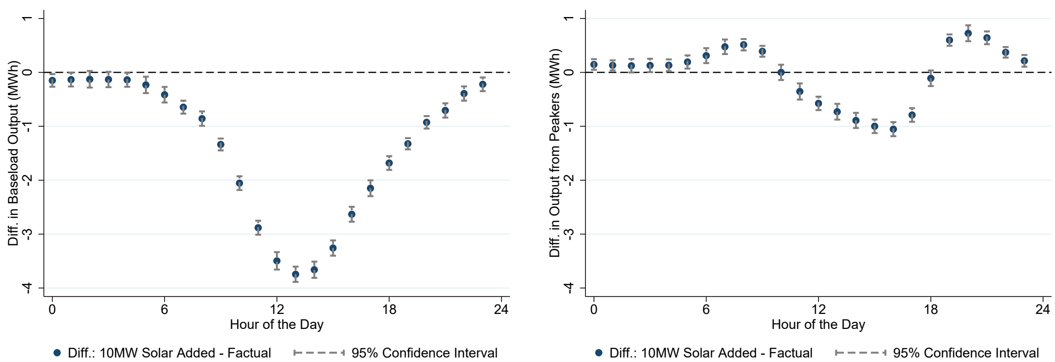
(f) Real-Time Price (AUD per MWh)

Notes: This figure plots the hourly average differences in predictions of market outcomes with versus without adding 10MW of rooftop solar capacity. In each panel, predictions are calculated using two different regression specifications: (1) specifications including the 24 lags of hourly wholesale demand (see Equation 9) versus (2) specifications excluding lagged wholesale demand (see Appendix Equation D.1). Panel (a) considers the total operating costs incurred by coal- and gas-fired units (excluding co-generation units). Panels (b), (c), and (d) report averages for operating profits, competitive rents and market power rents. Panels (e) and (f) focus on competitive prices and real-time wholesale market prices. Competitive rents, market power rents, and competitive prices are calculated using the dynamic framework discussed in Section 5.1.

D.7 Effects on Total Output By Type of Plant

To explore how rooftop solar impacts production from more versus less flexible units, Appendix Figures D.7a and D.7b plot hourly average differences in predicted total output from baseload units and peaker units respectively.[39] These figures indicate that average total output from both peaker and baseload units fall during the day due to a 10MW increase in rooftop solar capacity.

Figure D.7: Hourly Average Changes in Predicted Total Output from Baseload and Peaker Units when Adding 10MW of Rooftop Solar Capacity



(a) Output from Baseload Units (MWh) (b) Output from Peaker Units (MWh)

Notes: This figure plots hourly average differences between model predictions of total output with versus without adding 10MW of rooftop solar capacity to the system. The bars presented are 95% confidence intervals based on standard errors clustered by week-of-sample. Panels (a) and (b) consider hourly average changes in predicted total output from baseload units and peaker units respectively. All coal-fired units and combined-cycle gas turbine (CCGT) units are classified as “Baseload”. All open-cycle gas turbine (OCGT) units are classified as “Peaker”. See Appendix Table C.1 for the full list of CCGT and OCGT units in Western Australia (excluding co-generation units).

However, peaker units are better equipped than baseload units to quickly start up

[39] All coal-fired units and combined-cycle gas turbine (CCGT) units are classified as “Baseload”. All open-cycle gas turbine (OCGT) units are classified as “Peaker”. See Appendix Table C.1 for the full list of CCGT and OCGT units in Western Australia (excluding co-generation units).

production to meet evening peak demand. This is because peaker units have smaller start-up costs than baseload units. Consistent with this intuition, Appendix Figure D.7b documents that there are **increases** in output from peaker units in the evening due to a 10MW increase in solar capacity. We see no such increase in the output from baseload units in the evening in Appendix Figure D.7a. This is consistent with the hypothesis that increases in solar capacity incentivize shifts in production from baseload units with higher start-up costs to peaker units with lower start-up costs.