NBER WORKING PAPER SERIES

SETTING WITH THE SUN:
THE IMPACTS OF RENEWABLE ENERGY ON WHOLESALE POWER MARKETS

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Working Paper 24980
http://www.nber.org/papers/w24980

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2018

We thank participants in seminars at the University of California Energy Institute. We also thank Severin Borenstein, Paul Joskow, Aaron Smith, and Frank Wolak for helpful comments. James Bushnell is a member of the Market Surveillance Committee (MSC) of the California Independent System Operator (CAL ISO). The MSC is an independent advisory committee to the Governing Board of the Cal ISO. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. L5,L94,Q41,Q42

ABSTRACT

Policies supporting investment in renewable electricity have been a cornerstone of climate policy in many parts of the world. While previous empirical work explores the economic and environmental impacts of renewable production, the focus has exclusively been on the short-run impacts of expanding renewable supply. In this paper, we shed light on the longer run impacts of renewable expansions. Focusing on the California electricity market, we estimate how wholesale electricity prices have responded to a dramatic increase in utility-scale solar capacity. While a substantial decline in daily average prices can be attributed to the solar capacity expansion, this average price impact masks a substantial decrease in mid-day prices combined with an increase in shoulder hour prices. These results imply that short-term power markets are responding to the renewable expansion in a fashion that could sustain more flexible conventional generation, while seriously undermining the economic viability of traditional baseload generation technologies.

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1 Introduction

Within the electricity industry, a wide array of policies are being adopted with the goal of reducing emissions, particularly of carbon dioxide. In addition to measures that target stationary sources of emissions, a variety of alternative interventions that promote energy efficiency, renewable generation, and the electrification of transportation and heating are playing increasing roles in climate policy around the world. A growing strand of environmental economics literature has naturally come to look at the economic and environmental impacts of these policies.[1] However, econometric studies of these measures tend to focus on quantifying the short-run reductions in emissions, leaving a gap in understanding of the medium to long-term impacts of such policies. To date, attempts to measure longer-term impacts have been dominated by forward-looking, simulation based approaches.

In this paper, we attempt to capture the medium term impacts of the most significant of the electricity sector policies to date, the promotion of renewable electricity generation. While our setting is California, such policies have been a cornerstone of climate policy in many parts of the world for at least a decade. In the United States the result has been a dramatic increase in generation capacity from renewable energy sources. Much of the existing economic literature has focused on the short-run, marginal impacts of increasing renewable production (Cullen (2013), Kaffine, McBee and Lieskovsky (2013), Novan (2015), Fell and Kaffine (2018), Callaway, Fowlie and McCormick (2018)). However, as policymakers continue to push for ever increasing levels of renewables, it is becoming increasingly important to understand how the composition of conventional generation capacity (e.g., fossil fuel units) will respond to the growth in renewable capacity.

In particular, another major industry trend in the last decade has been growing financial distress of the traditional power plants that had previously formed the backbone of the nation's power supply. These plants, primarily powered by coal or nuclear fuel, constitute some of the largest capital investments made by utilities, as well as the largest sources of employment in the generation sector. Concerns over the financial future of these "baseload" generation plants has prompted a series of controversial proposals at the state and Federal level. The political current that has given momentum to proposals to assist traditional generation sources has been the view that subsidies for renewable energy have played a non-trivial role in depressing wholesale power prices. Under this narrative, subsidies for conventional, and particularly nuclear, production can be justified as leveling the playing field with renewables. Implicit in all of these proposals has been the assumption that power

[1] See for example, Fowlie, Greenstone and Wolfram (2018) on energy efficiency, Cullen (2013) on renewable generation, and Holland et al. (2016) on electric vehicles.

markets will continue to depend upon traditional baseload sources and that power markets as they are currently constituted are incapable of unlocking the implicit value these plants provide.[2]

This paper examines how expansions in renewable capacity affect wholesale electricity prices and, as a result, the potential profits earned by conventional generators (e.g., fossil fuel or nuclear units). The standard economic argument is that an increase in near-zero marginal cost renewable output will result in a reduction in the wholesale price – an outcome referred to as the 'merit-order effect' (Sensfuß, Ragwitz and Genoese, 2008). However, we present evidence that growth in renewable capacity does not uniformly decrease wholesale prices. In particular, while expansions in solar capacity push wholesale prices down during daylight hours, prices are found to increase during non-daylight hours.

Our analysis focuses on California's electricity market overseen by the California Independent System Operator (CAISO). California provides a unique laboratory for these effects since a substantial amount of output is already produced by solar and wind.[3] During 2016, 10% of the total electricity produced in California came from utility-scale solar and 6.8% came from wind. In the case of solar in particular, there has been dramatic growth in recent years – with installed capacity increasing from 0.6 GW at the beginning of 2012 to over 10 GW by 2017. The large levels of existing renewable capacity, as well as the recent rapid growth in solar capacity, make the CAISO market an excellent setting to explore the impacts of renewable capacity expansions.

Using our estimates of the heterogeneous response of the wholesale price to renewable growth, we explore how the profits earned by conventional generating technologies are affected by expansions in renewable capacity. Ultimately, firms' incentives to invest in – or retire – specific types of generation capacity are driven by the future profits. Therefore, by exploring how profits respond to renewable capacity additions, we are able to provide insights into how the composition of conventional capacity may endogenously respond to growth in renewables. Our estimates suggest that expansions in solar capacity will indeed decrease the profits earned by conventional generators with low marginal generation costs. In contrast, generators with higher marginal costs may experience constant, or even increasing, profits.

[2]The environmental attributes of different generation sources, of course, provide part of the rational for renewable energy subsidies, but renewable sources provide no distinct air quality benefits relative to nuclear energy. In addition, power plant emissions of NO_X, SO_2, and to a lesser extent CO_2, are subject to a series of Federal and State regulations, although in the case of CO_2 those regulations impose costs well below Federal estimates of the social cost of carbon.

[3]As of May, 2017, California had 5.7 GW of wind capacity – the third most behind only Texas' 20.9 GW and Iowa's 6.7 GW. In terms of utility-scale solar capacity, California is far and away the nation's leader. Over 10 GW of solar capacity had been installed – 43% of the total utility-scale solar installed in the U.S. North Carolina had the second most utility-scale solar capacity with 2.7 GW. Texas has less than a GW of utility-scale solar and Iowa only has 2.6 MW of solar.

In the case of California, this suggests that there will be a long-run shift towards a stock of less fuel-efficient, and thus dirtier, conventional generators.

Moreover, we are able to explore how the value of the renewable capacity investments themselves vary with the level of renewable penetration. Given that the expansion in solar capacity has caused sizable reductions in midday prices, we find that the marginal revenue generated by the tenth gigawatt of California's grid-level solar capacity is less than half of the marginal revenue generated by the second gigawatt of capacity. This finding highlights a key shortcoming inherent with the current policies subsidizing the production of renewable output. Specifically, renewable portfolio standards and production tax credits continue to incentivize investment in renewable capacity that has little to no market value. In contrast, under a first-best environmental policy (i.e. a non-trivial price on GHG emissions), there will be little incentive to continue to invest in clean energy sources that are only able to produce during periods that are already experiencing a glut of clean energy.

Finally, this paper contributes a methodological point that has subtle but important implications for interpreting the results of studies such as ours. A common approach used to quantify the impact of electricity supply or demand shifts on electricity system outcomes (e.g., wholesale prices, fossil generation, emissions) has been to utilize a large degree of fixed effects in order to control for potentially confounding trends and isolate the impact of the variables of interest (e.g. wind or solar production). These include both annual, seasonal, and hourly fixed effects. This approach, while appropriate for identifying the impacts of short-run variation in electricity demand or renewable output, can be misleading when trying to identify long-run impacts.

In section two we review the policy developments influencing the economics of both renewable and non-renewable generation over the last decade. We also discuss the previous literature that has addressed various aspects of renewable energy impacts and trends in power markets. In section three we describe the data and methodology we deploy to examine the impact of renewable growth in California. Sections four and five provide our results and conclusions, respectively.

2 Background and Previous Literature

A combination of state-level mandates and federal tax credits have driven a surge in U.S. renewable electricity capacity.[4] Utility-scale solar and wind farms, which produced less than

[4]Capacity and generation data are available from the U.S. Energy Information Administration. From 2006 through 2015, utility-scale solar capacity increased from 0.8 gigawatts (GW) to over 27 GW and wind capacity grew from 22 GW to 145 GW. Schmalensee (2011) summarizes the renewable energy policies. For studies exploring the policy impacts, see Bird et al. (2005), Yin and Powers (2010), and Hitaj (2013).

0.7% of total U.S. electricity in 2006, accounted for nearly 7% of output in 2015. Figure 1 illustrates the growth in renewable energy production in California since 2000. While California had a substantial amount of renewable generation before 2000 distributed between geothermal, biomass, and wind generation, the growth in the last 5 years has been dominated by utilty-scale solar photo-voltaic (PV) capacity. California's renewable portfolio will continue to expand under recent legislation that mandates 50% of electricity come from renewable sources by the year 2030. With ambitious renewable mandates being passed in many states, the growth in renewables across the US shows no signs of slowing.[5] These policy measures, combined with the rapid decline of utility-scale solar PV costs, imply that California's experiences may very well foreshadow those of markets across the US.

To quantify how the CAISO wholesale price responded to the growth in renewable capacity, we largely follow the strategy used by numerous studies that have sought to uncover the short-run impacts of renewable generation on a variety of outcomes (e.g., wholesale prices, emissions, fossil generation). Previous studies have taken one of two broad approaches to this question. Within the economics literature, several simulation studies have explored the potential long-run response to renewable capacity growth (Lamont (2008), Bushnell (2010), Fell and Linn (2013), Gowrisankaran, Reynolds and Samano (2016)). However, these studies have had to impose fairly strong simplifying assumptions. For example, the simulation studies typically abstract from dynamic operating costs and constraints faced by conventional generators, effectively ruling out the possibility that wholesale prices could increase in response to renewable capacity growth.[6]

A second strand of literature applies econometric approaches to high frequency electricity markets data.[7] Several studies use the same general strategy to identify the short-run impact of wind generation on emissions (Cullen (2013), Kaffine, McBee and Lieskovsky (2013), and Novan (2015)) as well as the impact of wind on coal-fired generation (Fell and Kaffine (2018)). Specifically, these studies identify how variation in the daily level of renewable output affects the wholesale price. However, three key features differentiate our analysis from the previous work. First, we exploit different variation in renewable generation. Over our sample period (January, 2013 through May, 2017), daily CAISO renewable output – and particularly solar – steadily increased as a result of capacity growth.

Rather than controlling for the trend in renewable output, we use this variation in output

[5]Of the 76 GW of net capacity additions planned for 2016 through 2020, almost half (37 GW) comes from planned solar and wind additions. Planned capacity additions by fuel source are provided by the EIA.

[6]In recent work examining the long-run impacts of low natural gas prices on electricity generation and investment, Linn and McCormack (2017) demonstrate the importance of considering dynamic constraints faced by fossil fuel generators.

[7]Würzburg, Labandeira and Linares (2013) provides a recent overview of the empirical merit-order effect studies. We discuss this literature in greater detail in the following Section.

across years to identify the impact of renewable output on prices. In contrast, the previous studies sweep away capacity-driven changes in renewable production and instead rely on short-run, largely weather-driven, fluctuations in renewable output.[8] In our setting, the previous strategies would identify how prices differ, for example, on a sunny day versus on a similar day, with the same level of solar capacity, but substantial cloud cover. Ultimately, prices may respond differently to shifts in renewable output caused by capacity additions as opposed to less predictable, weather-driven fluctuations in renewable production. As a result, exploiting short-run swings in output to identify price responses may be less meaningful for answering the question in which we are interested – how does capacity growth affect wholesale prices?

Second, while the existing studies largely focus on estimating the average change in the wholesale price, we examine how the price response differs across hours of the day and across seasons. Ultimately, this allows us to predict how renewable expansions affect the profits of conventional generators that operate during a subset of hours, specifically when the price exceeds their variable costs. Third, we do not assume that the wholesale price in a given hour can only respond to the contemporaneous level of renewable output. In the case of solar, this proves to be particularly important as we find evidence that solar capacity expansions increase wholesale prices during the early morning and late evening hours, despite the fact that no solar generation occurs during these hours.

3 Data and Empirical Strategy

In this section we review the primary sources of supply and price data and present summary analysis of their trends. As described above, our focus is on large, utility-scale generation whose production is sold directly into wholesale markets. However, much of the attention solar investment has received in the economic literature, as well as in the media, has focused on small scale, distributed solar generation – and in particular, residential solar. In particular, much of the focus has been on the growth of distributed solar capacity in California. By the end of 2016, California had an estimated 5.36 GWh of distributed solar capacity – 41% of the total distributed solar capacity installed in the U.S. at the end of 2016.[9]

While the aggregate output from the distributed solar capacity is not measured, the impact can clearly be seen by examining the average quantity of electricity demanded (load). Distributed, "behind-the-meter", solar output effectively serves as negative load. The upper

[8] This is achieved using a variety of approaches – e.g., first-differencing the data, including annual fixed effects, or estimating models with lagged dependent variables.

[9] Estimates of distributed solar capacity by state by month are provided by the U.S. Energy Information Administration's Electric Power Monthly reports.

left panel of Figure 2 plots the average load in the CAISO market by hour-of-day during 2012 and 2016. During the hours with limited to no solar potential – i.e. 6pm through 7am – the average hourly loads are nearly identical during 2012 and 2016. However, with the growth in distributed solar capacity from 2012 through 2016, there has been a clear decrease in load during the sunny, daytime hours. This difference peaks at an average of 1,479 MWhs between noon and 1pm, specifically when the average generation from the distributed solar capacity would reach its maximum daily output.

While distributed solar capacity growth has clearly reduced the midday demand for electricity in the CAISO market, recent growth in large, utility-scale solar generation capacity has dwarfed the distributed solar production. At the beginning of 2012, California had 0.6 GW of utility-scale solar capacity installed. By April, 2017, over 10 GW of utility-scale solar capacity was installed in the state.

In contrast to output from distributed sources, electricity generated by grid-connected, utility-scale technologies is publicly available. In our analysis, we use data provided by CAISO that reports the hourly aggregate generation by technology, which includes aggregate hourly utility-scale solar and wind production. In addition, to explore how output from wind and solar generators has impacted production from different fossil fuel generating technologies, we supplement the CAISO data with two additional data sources: EPA CEMS data which provides hourly gross generation and fuel consumed at nearly every fossil fuel unit and EIA 923 data which provides the monthly net generation and fuel consumed by fossil fuel generators.

The top right panel of Figure 2 displays the average generation from utility-scale solar thermal and solar PV generators by hour-of-day during 2012 and 2016. The average solar generation during the noon hour has grown over the 5 year period from 640 MWh to over 6,400 MWh. Over the same time period, 2012 through 2016, installed wind capacity in California has grown much more modestly. At the beginning of 2012, there was 4 GW of installed wind capacity. By the end of 2016, that number had increased to 5.7 GW of wind. The bottom right panel of Figure 2 highlights the resulting modest growth in average daily wind generation across 2012 and 2016.

3.1 Wholesale Electricity Prices

The primary objective of our empirical analysis is to uncover how growth in utility-scale solar capacity impacts wholesale electricity prices in the CAISO market. For the sake of comparison, we also present estimates of the impact of wind growth on wholesale prices.[10]

[10] However, given the limited growth in wind capacity that occurs over our sample period, the estimates of the impact of wind capacity growth on prices requires a larger our-of-sample extrapolation.

Using the estimates of the wholesale price responses to solar and wind, we explore how growth in renewable capacity affects the revenue earned by a variety of generating technologies. We focus on the price impacts in the real time market (RTM).[11] Rather than exploring how the price impacts may vary across locations within the CAISO market, we focus on estimating how the average hourly, CAISO-wide RTM price responds to renewables.[12]

To provide initial evidence for how wholesale prices have responded to growth in renewable capacity, the bottom left panel of Figure 2 plots the average RTM price by hour-of-day during 2012 and 2016. Two clear patterns emerge. First, during the midday hours, when solar generation has increased dramatically, the average hourly prices show a clear decrease in 2016 relative to 2012. Second, during the hours when there is limited to no solar production (6pm through 7am), the average RTM prices increased between 2012 and 2016. Of course, changes in a variety of other determinants of wholesale prices, aside from renewables, could be contributing to the observed price differences. To quantify the effect of solar and wind output on hourly wholesale prices, it will be vital to control for these factors.

3.2 Empirical Strategy

Ours is certainly not the first analysis to estimate how wholesale electricity prices are affected by renewable generation.[13] However, three features of our empirical analysis differentiate it from the existing studies. First, while the vast majority of studies estimate the average change in the wholesale price caused by renewable generation, we estimate how the price response varies across hours of the day and across seasons.[14] Ultimately, if our objective was to predict how renewable growth affects the revenue earned by baseload units operating at 100% capacity every hour, it would be sufficient to uncover the average price change. However, few generators produce at full capacity all the time. To explore how renewable

[11]In an Appendix B.2, we examine how prices in the day-ahead market (DAM) are affected.

[12]CAISO reports the hourly RTM price across four Default Load Aggregation Points (DLAP). The price within each DLAP is the sum of the marginal energy price, which is constant across DLAPs, and the congestion and loss prices, which can vary across DLAPs. Ultimately, the energy component of the DLAP accounts for 99% of the average hourly DLAP level price. As a result, the correlation between the hourly average prices in any two DLAPs never falls below 0.92.

[13]Numerous empirical studies provide evidence that renewable generation reduces wholesale prices across many different markets. For example, Gelabert, Labandeira and Linares (2011) focus on the Spanish market; O'Mahoney and Denny (2011) study the impact of wind in Ireland; Würzburg, Labandeira and Linares (2013) and Ketterer (2014) focus on the German market; Forrest and MacGill (2013), Cludius, Forrest and MacGill (2014) study the Australian market; Clò, Cataldi and Zoppoli (2015) examines Italy's market. In the U.S., Woo et al. (2011), Woo et al. (2013), and Woo et al. (2016) estimate the average impact of renewable output in Texas, the Pacific Northwest, and California, respectively.

[14]One notable exception is Jónsson, Pinson and Madsen (2010). The authors estimate how the distribution of prices in the Danish market would be impacted by growth in wind capacity. However, the authors do not examine how revenues are affected by the resulting price changes.

expansions affect the revenues of a wide range of generating technologies, it is necessary to uncover how the full distribution of wholesale prices is affected by growth in renewables.

Second, we allow renewable output to have non-contemporaneous impacts on wholesale prices. To do so, we estimate how the price during a specific hour of the day is affected by the total daily solar or wind output.[15] That is, we seek to identify how the daily profile of prices differs on a day with high solar output versus on a day with low solar output. In contrast, the majority of existing studies estimate how the hourly, or sub-hourly, wholesale price responds to the contemporaneous level of renewable output.[16] In the case of solar, this is quite restrictive. During the period we study, no solar output occurred before 8am or after 8pm. Therefore, if we were to restrict hourly prices to respond solely to the contemporaneous solar generation, we would be assuming that growth in solar capacity has not affected pre-8am or post-8pm prices. However, the comparison of the average RTM prices from the bottom left panel of Figure 2 suggests that solar growth has potentially increased prices during non-daylight hours – a finding which is supported by our subsequent empirical results.

Finally, the third difference between our analysis and the previous empirical studies stems from the fact that we exploit different variation in renewable output – particularly in the case of solar. Specifically, we estimate how prices have responded to variation in solar output across multiple years (January, 2013 through May, 2017). In contrast, the previous studies almost exclusively estimate how prices respond to short-run variation in renewable generation – e.g., changes in renewable output from one day to the next.

To understand why the response of wholesale prices to short-run and long-run variation in

[15]In the case of solar output, very little information is lost by using the daily aggregate solar output as opposed to the hourly solar output. From January 1, 2013 through May 31, 2017, the correlations between the daily aggregate solar output and the hour-specific levels of solar generation are all above 0.89 for 9am through the 5pm hour – which, combined, account for over 90% of the total solar output. Given that the within-day wind pattern is less regular than solar output, the correlation between the daily wind output and the hourly output is not consistently as high. Over the full sample period, the 24 correlation coefficients between the daily aggregate wind output and the hour-specific wind output oscillates between 0.81 and 0.94. For the sake of comparison, we also conduct the analysis using the hourly levels of wind, imposing the assumption that wind only has contemporaneous impacts on the wholesale price. The subsequent results for wind are robust across the two specifications.

[16]An alternative strategy used to estimate how average daily, or within-day (e.g., hourly or interval), wholesale prices respond to renewable output has been to include the lagged wholesale price as an additional independent variable (see Woo et al. (2011), Woo et al. (2013), Forrest and MacGill (2013), Ketterer (2014), Cludius, Forrest and MacGill (2014), and Woo et al. (2016)). With the inclusion of the lagged wholesale price as an explanatory variable, these partial adjustment models impose a very strict dynamic relationship between renewable output and wholesale prices. Specifically, the price in the present period can be impacted by the contemporaneous level of renewable output as well as the lagged levels of renewable output. Moreover, the most recent lagged renewable output has more influence on the price than prior lags, and the rate of decay in the relative weights is assumed to be constant. The partial adjustment framework also imposes the assumption that future levels of renewable output do not impact the current price, an assumption which is relaxed in our analysis.

renewable output could potentially differ, it is helpful to be very specific about the different sources of temporal variation in renewable generation. Figure 3 displays the daily aggregate solar and wind production from January 1, 2013 through May 31, 2017. For both solar and wind, there is clear seasonal and day-to-day variation in daily output. In addition, in the case of solar, there is also a steady upward trend driven by growth in solar capacity.

To identify how the daily level of solar and wind output affects the wholesale price, our analysis, as well as the previous studies, rely on the fact that the seasonal and day-to-day variation in renewable output is driven almost entirely by exogenous factors (e.g., sunlight and wind speeds).[17] Therefore, we do not need to worry that short-run swings in renewable production are endogenously caused by changes in the wholesale price. Of course, while short-run changes in renewable output are exogenous, they are not random. The seasonal patterns in renewable output can be correlated with seasonal variation in electricity demand and non-renewable supply. Moreover, daily weather conditions can drive day-to-day variation in renewable output and demand. Therefore, similar to the previous studies, we must control for wholesale price variation driven by seasonality and daily fluctuations in demand.

Where our empirical approach differs from the previous studies lies not in how we deal with the seasonal and day-to-day variation in renewable output, but rather the longer-run trends – in our case specifically, the steady increase in solar output. Previous studies do not exploit this longer-run variation in renewable output. Instead, the existing studies strip away year-to-year variation using a variety of approaches – e.g., first-differencing, including month-by-year fixed effects, or including lagged prices as an additional explanatory variable. By doing so, the existing studies estimate how prices respond exclusively to short-run fluctuations in renewable generation. In Appendix A, we highlight that short-run (i.e. within-month) variation in daily solar generation is driven almost entirely by days with abnormally low solar capacity factors (e.g., cloudy days). Moreover, we demonstrate that the RTM price increases substantially on these days with abnormally low solar output. Consequently, exclusively exploiting short-run (within-month) variation in solar generation results in estimates that suggest the wholesale price responds dramatically to changes in the daily level of solar output.

Ultimately, our objective is not to estimate how short-run, weather driven fluctuations in renewable output affect wholesale prices. Instead, we seek to answer the following question:

[17]One concern arises from the fact that effectively zero marginal cost output from solar and wind is often curtailed – i.e. intentionally reduced – in order to prevent problems related to congestion and/or over-supply. In an appendix, we present estimates from an alternative estimation strategy in which we instrument for the observed renewable output using the potential renewable output – the observed output plus the curtailed renewable output. The results from the instrumental variable approach reveal that endogeneity arising from curtailments do not bias the estimates of the wholesale price changes in any meaningful way.

how would hourly wholesale prices differ on a day with a low level of installed renewable capacity versus on the same day with a higher level of installed renewable capacity? The difference is subtle but important. Weather-driven fluctuations in renewable output are transitory and certainly less forecastable than shifts in renewable supply caused by renewable capacity growth. If the response of prices to unforecastable swings in renewable output differs from the response to more forecastable, long-run changes, then exploiting short-run swings in output to identify price responses may be less meaningful for answering our question.

Rather than focusing on how prices respond exclusively to short-run fluctuations in daily renewable output, we take advantage of the fact that solar generation has grown considerably over our four and a half year sample. In particular, we do not sweep away the variation in prices and renewable output across years using annual fixed effects, time trends, or by differencing the data. This of course raises a clear concern – we estimate how wholesale prices, which may exhibit trends over the sample period, respond to a non-stationary time series of observed solar generation. This opens the door for us to uncover a spurious relationship between the trending solar output and prices. To address this concern, we rely on the assumption that we can directly control for the factors that drive longer-run trends in wholesale electricity prices in the CAISO market.

Trends in wholesale prices could be driven by long-run patterns in electricity demand or supply. Controlling for demand-driven price trends is straightforward – we simply include the hourly CAISO load as a control in our empirical specification.[18] The inclusion of the hourly load also controls for weather-driven demand shifts that could be correlated with renewable production. Supply-driven price trends could arise for a variety of reasons. First, there could be trends in fuel prices – particularly the price of natural gas, the dominant fuel source among California's thermal generators.[19] To control for this possibility, we include the daily Henry Hub spot price in our model.[20] Second, wholesale price trends could be driven by patterns in hydroelectric output.[21] Given that hydroelectric generation can respond to

[18]This assumes that demand is perfectly inelastic with respect to the CAISO wholesale price.

[19]Table A1 summarizes the share of California generation by fuel source from 2013 through 2016. The natural gas spot prices also control for shifts in the supply curve for electricity imports into the State. It is important to note that during our sample period, the Western Energy Imbalance Market (EIM) was introduced to reduce barrier to real-time trade between California and other markets in the Western Interconnection. While we do not directly control for the EIM introduction, we test the robustness of our empirical findings during the pre- and post-EIM periods.

[20]Gas spot prices are reported by the U.S. EIA. To proxy for the daily spot price on weekends and holidays, we use the daily price from the most recent preceding date for which a spot price is reported.

[21]Aside from natural gas generation, large hydroelectric output and nuclear output are the only other major in-state sources of non-renewable production. However, unlike natural gas and hydroelectric supply, nuclear capacity is fixed over the period we examine and does experience trends in the marginal cost of production. Finally, there are small declines in natural gas generation capacity over the period we examine (see Table A2). However, given that there is excess thermal capacity, this is unlikely to drive meaningful

renewable output, we cannot directly control for hydroelectric production. Instead, we use a measure of monthly hydroelectric potential to control for variation in wholesale prices.[22] Assuming these set of controls account for any non-renewable driven trends in the hourly wholesale prices from 2013 through mid-2017, we can conclude that our estimates of the response of the wholesale price to variation in renewable output is not biased by a spurious relationship.

4 Wholesale Electricity Price Changes

In this section we estimate the impacts of renewable expansion on wholesale power market outcomes. To determine the average impact of utility-scale solar and wind production on RTM prices, we estimate the following model separately for each hour of the day:

$$P_{h,d} = \alpha_{h,m} + \beta_h^s \cdot Solar_d + \beta_h^w \cdot Wind_d + \beta_h^g \cdot Spot_d + \boldsymbol{\theta}_h \cdot \mathbf{X_{h,d}} + \varepsilon_{h,d}, \tag{1}$$

where h indexes each hour-of-day, d indexes each day in the sample spanning January 1, 2013 through May 31, 2017, and m indexes each month of the year. $P_{h,d}$ represents the average hourly RTM price (\$/MWh) in the CAISO market for hour h of day d. $Solar_d$ and $Wind_d$ are the aggregate daily levels of CAISO solar and wind generation (GWh).

To control for wholesale price changes driven by demand or non-renewable supply shifts that may be correlated with daily solar and wind production, we include $Spot_d$, the daily Henry Hub natural gas spot price (\$/MMBtu). In addition, $\mathbf{X_{h,d}}$ includes the hourly load in the CAISO market as well as a proxy for hydroelectric potential. Finally, to control for seasonal shifts in supply that may be correlated with the seasonal patterns in wind and solar production, we include monthly fixed effects.

The key coefficients of interest, β_h^s and β_h^w, represent the average changes in the RTM price during hour h caused by a 1 GWh increase in the daily level of CAISO solar or wind generation. To get a sense of the relative magnitude of the price changes caused by renewable

trends in wholesale prices. In addition, given that the capacity changes could be driven in part by renewable capacity growth, we choose not to directly control for the capacity changes.

[22]Variation in precipitation drives trends in hydroelectric potential. During 2015, the peak of the State's most recent drought, large hydroelectric damns accounted for 5.9% of output (see Table A1). In 2016, after much of the State had emerged from drought conditions, hydroelectric output accounted for 12.3% of generation. To control for precipitation driven changes in hydroelectric output, we use NOAA estimates of the statewide, monthly precipitation. The data are available from NOAA's Climate at a Glance website, `https://www.ncdc.noaa.gov/cag/`. The monthly precipitation measure is a weighted average of the monthly aggregate precipitation measured in the seven climate-divisions in California. The weights are proportional to the area within each division. Ultimately, we proxy for hydroelectric potential in a given month using the simple average of the current month's precipitation and the precipitation over the preceding 11 months.

production, we compare the estimated solar and wind driven price changes to estimates of β_h^g, the average impact of a \$1/MMBtu increase in the spot gas price on the wholesale price during hour h. Recall, the model specified by Eq. 1 is estimated separately for each hour of the day. To account for serial correlation, we report Newey-West standard errors allowing the errors for hour h to be correlated over a 7-day lag.

Recall that a key assumption used to identify the parameters specified in Eq. 1 is that the daily level of wind and solar output varies exogenously with respect to the wholesale price. There are two main threats to this assumption. First, over long periods of time, renewable capacity can change in response to shifts in the wholesale price. However, in our setting, this is unlikely to be a serious concern. For one, we directly control for the factors that drive long-run variation in wholesale prices (e.g., fuel prices, demand). Moreover, the growth in renewable capacity observed over our sample period may be entirely driven by policies (i.e. California's renewable portfolio standard) as opposed to market forces.

The more serious threat to our exogeneity assumption is the fact that renewable output can be curtailed. Curtailments occur in order to reduce system-wide oversupply or mitigate congestion issues on the grid. From CAISO, we observe the levels of wind and solar generation curtailed for the period spanning May 1, 2014 through May 31, 2017. Over that period, an average of 577 MWh of solar output was curtailed per day and 153 MWh of wind output was curtailed per day. It is certainly possible that the timing and level of curtailments are correlated with wholesale prices. For example, during periods of unexpectedly low demand, and consequently low wholesale prices, the grid operator may require solar output to be curtailed in order to prevent oversupply. In this case, our estimate of the negative relationship between solar output and wholesale prices would be biased towards zero. In Appendix B.1, we present alternative estimates of the model specified by Eq. 1 using the daily solar and wind potential – i.e. the observed daily generation plus the curtailed output – as instruments for $Solar_d$ and $Wind_d$. The results reveal that the potential bias introduced by endogenous curtailments has no meaningful affect on the estimates of the price changes.

4.1 Average Change in Hourly Prices

The top panel of Figure 4 displays the 24 point estimates of β_h^s, the average change in the RTM price during hour h in response to a 1 GWh increase in daily solar production.[23] The corresponding 95% confidence intervals are also shown in the figure. The estimates

[23] Re-estimating the model using data exclusively from before December 2015, prior to NV Energy joining the Western Energy Imbalance Market (EIM), we find very similar qualitative results. This finding provides strong evidence that the pattern of midday price reductions and afternoon/morning price increases was not driven by the introduction of the EIM.

reveal that, from 9am through 4pm, the hours which account for 83% of the solar output, increases in daily solar generation result in significant reductions in the hourly RTM prices. For example, during the 2pm hour, the wholesale price falls an average of \$0.39/MWh for each additional GWh of daily solar production. To get a sense of the magnitude of this estimate, the average daily utility-scale CAISO solar generation was 5.5 GWh during 2012 and 57.8 GWh during 2016 – an average increase of 52.3 GWh. Multiplying the estimate of $\hat{\beta}^s_{12pm} = -0.39$ by the average change in daily solar suggests that the growth in solar pushed the average 12pm wholesale prices down by \$20.40/MWh during 2016 relative to 2012. Referring back to the top left panel of Figure 2, the average RTM price during the 12pm hour of 2016 was \$22.05/MWh and \$34.25/MWh during 2012 – a decline of \$12.24/MWh.

The top panel of Figure 4 also highlights that, on average, an increase in the daily level of solar generation results in significant increases in the average RTM prices during the 6am and 7am hours and during the 7pm and 8pm hours. For example, during the 7pm hour, the average RTM price increases by \$0.30/MWh for each additional GWh of daily solar production. This suggests that, from 2012 through 2016, the observed growth in utility-scale CAISO solar production pushed the average 7pm RTM price up by \$15.62/MWh during 2016 relative to 2012.[24] Overall, taking the simple average across all hours of the day, the results from the top panel of Figure 4 reveal that the average RTM price decreases by \$0.10/MWh in response to a 1 GWh increase in daily solar production.

The middle panel of Figure 4 displays the point estimates of the average change in the hourly RTM price caused by a 1 GWh increase in daily aggregate wind generation. In contrast to the impacts of solar, increases in wind output result in decreases in the RTM price throughout the day. The profile of the average price changes across hours is driven by two main factors. First, production from wind turbines is, on average, higher in the early morning and late night hours. Therefore, an additional 1 GWh of wind will not be evenly distributed across hours, but rather will result in larger increases in wind during the non-daytime hours. Second, and most importantly, during the sample period we examine, the average hourly RTM prices peaked in the late afternoon and fell to their lowest levels overnight and early in the morning. Ultimately, while an additional GWh of daily wind will not disproportionately occur during the late afternoon hours, the conventional output that is offset during the late afternoon tends to have a higher marginal cost and thus, the late afternoon RTM prices experience the largest average declines.[25]

[24]For comparison, the average 7pm RTM price during 2012 was \$41.11/MWh and \$50.62/MWh during 2016 – an increase of \$9.51/MWh. This suggests that, had other determinants of the wholesale price (e.g., natural gas prices which fell slightly between 2012 and 2016; see Figure A1) been held constant across the years, the growth in solar production would have resulted in even larger increases in the 7pm RTM price than was actually observed.

[25]Appendix Figure A7 presents estimates of the impact of wind generation on RTM prices from an al-

For the sake of comparison, the bottom panel of Figure 4 displays the point estimates of the average change in the hourly RTM prices caused by a $1/MMBtu increase in the Henry Hub natural gas spot price. The fuel efficiency of natural gas generators varies by technology and is measured by the heat rate – the fuel input (MMBtu) required to generate a MWh of output. Relatively fuel efficient combined cycle natural gas units typically have heat rates around 7 MMBtu/MWh. In contrast, gas turbines, which tend to be on the margin more heavily during higher demand periods, have heat rates closer to 11 MMBtu/MWh. Therefore, if the natural gas price increased by $1/MMBtu, we would expect to see wholesale prices increase by approximately $7/MWh during low demand hours (e.g., the very early morning hours) when combined cycle units are the marginal suppliers. In contrast, during high demand hours (e.g., late afternoon), we would expect to see wholesale prices increase by closer to $11/MWh. This is exactly the pattern we see in the bottom panel of Figure 4.

The estimates of the RTM price changes caused by changes in the natural gas spot price also provide another way for us to highlight the magnitude of the impacts of renewable production. Recall, our estimates suggest that the growth in utility-scale solar between 2012 and 2016 pushed the average 7pm RTM price up by $15.62/MWh. This is equivalent to the average 7pm RTM price increase we would expect to see in response to a $1.52 increase in the Henry Hub spot price – approximately a 46% increase relative to the average spot price ($3.28/MMbtu) observed over our sample period.

4.2 Substitution Between Renewables and Non-Renewables

In addition to estimating how renewable generation has impacted wholesale prices, we also explore how output from the renewable sources affects production from non-renewable sources. Examining the substitution patterns between renewable output and non-renewable sources allows us to accomplish two objectives. First, we can test whether our estimation strategy is in fact uncovering the impact of renewables. Second, we can examine why growth in solar output is pushing wholesale prices up during the non-daylight hours.

To estimate how increases in daily renewable generation affect hourly production from

ternative model. Rather than including the daily level of wind generation (in GWhs) as an independent variable in the model specified by Eq. 1, we instead include the wind generation that occurs specifically in the corresponding hour (in MWhs). The top panel of Figure A7 displays the estimates of the average change in the hour-specific RTM price caused by an additional 1 MWh of wind supplied during the corresponding hour. To compare the estimates to the results displayed in the middle panel of Figure 4, we multiply the estimates of the impact of a MWh of wind on the contemporaneous hourly RTM price by the additional MWhs of wind that would occur, on average, during each hour if the daily wind generation grew by 1 GWh (the middle panel of Figure A7). Using this procedure, we predict the average changes in the hourly RTM prices caused by an additional GWh of wind. The bottom panel of Figure A7 reveals that the estimates are very similar across the two approaches – i.e. using the daily aggregate wind generation or the hourly wind output.

other sources, we reestimate the model specified by Eq. 1. Instead of including the hourly price as the dependent variable, we now include the hourly quantity of electricity supplied to the CAISO market (in MWh) from a variety of alternative sources. We focus on the hourly quantity of energy supplied by thermal sources in the CAISO region (i.e. fossil fuel units), large hydroelectric dams in the CAISO region, CAISO nuclear units, other renewables (i.e. non-wind and non-solar), and net imports into the CAISO market. Table 1 summarizes the hourly output from the various sources. From January, 2012 through May, 2017, thermal, large hydro, nuclear, and net-imports accounted for 44%, 9%, 9%, and 31% of the CAISO load not met by CAISO solar and wind output, respectively. Other renewables accounted for the remaining 7% of residual load.[26] To examine how output from the various sources are affected during different hours of the day, we again estimate the model separately for each hour-of-day.

The top panel of Figure 5 displays the estimates of the average changes in the quantity of electricity supplied (in MWh) during each hour of the day in response to a 1 GWh increase in the daily aggregate solar generation. During the daylight hours when the solar output occurs, the quantity of electricity supplied by CAISO thermal and large hydroelectric sources falls. In addition, imports into the market also experience sizable decreases. On the other hand, output from nuclear generators, which have very low marginal costs, are unaffected by increases in solar output. Consistent with the previous finding that growth in solar affects prices outside of the hours when the sun is shining, there are shifts in the composition of electricity supplied to the CAISO market during the non-daylight hours – e.g., CAISO thermal output falls in the early morning hours while the quantity supplied by imports and large hydroelectric increase.[27]

The results presented in the top panel of Figure 5 also enable us to conduct two tests of whether our empirical approach is accurately uncovering the impacts of solar. First, given that the quantity of electricity supplied to the market must always be equal to the quantity of electricity demanded (load), a 1 GWh increase in daily solar output must offset 1 GWh of daily output from all other sources. Summing the changes in the hourly output from each of the other sources, we estimate that a 1 GWh increase in daily solar output reduces the quantity of electricity supplied by all other sources by an average of 0.998 GWh per day, which does not differ significantly from 1 GWh. Second, given that no solar output occurs

[26]Among the 'other renewables', 55% is from geothermal, 19% from biomass, 11% from biogas, and 15% from small scale hydroelectric.

[27]It is worth nothing that the fact that hydroelectric output is being shifted away from the daytime hours to the overnight/early-morning hours is consistent with the predicted price changes displayed in the top panel of Figure 4. Effectively, storable energy is being used to supply electricity during the overnight hours when increases in solar output are pushing the wholesale prices up.

between the hours of 8pm through 6am, the net change in electricity supplied by all other sources must equal zero during these hours. Summing the estimates of the change in thermal, large hydroelectric, nuclear, and imports during each separate hour of the day between 8pm through 6am, we find no significant changes in output occur during these hours in response to an increase in daily solar.

The estimates displayed in the bottom panel of Figure 5 show how the quantity of electricity supplied by alternative sources responds to a 1 GWh increase in daily wind output. Again, CAISO thermal output and net imports experience the largest average declines. There are smaller, yet still significant, reductions in large hydroelectric output during the late afternoon hours when wind causes the largest average price decreases. Again, aggregating across all sources and all hours, we find that a 1 GWh increase in daily wind output results in an average reduction of 1.002 GWh of daily output from other sources.

4.3 Why Does Solar Increase Prices?

To explore why growth in daily solar generation increases wholesale electricity prices during certain hours of the day, we further explore how the composition of output supplied by conventional sources is affected by solar output. In particular, we focus on how different types of thermal (i.e. fossil fuel fired) generators are affected by increases in solar output.

Fossil fuel units in California use natural gas almost exclusively. Within the set of natural gas fired units in the CAISO region, there are three broad technologies: combined cycle gas turbines (CCGT), gas turbines (GT), and steam turbines (ST). For nearly all of the natural gas generating units in the CAISO market, the U.S. Environmental Protection Agency uses Continuous Emissions Monitoring Systems (CEMS) to record the hourly gross electricity generation (MWh), fuel input (MMBtu), and emissions. The gross generation reported by the CEMS data includes electricity consumed at the plant. In addition, for many combined cycle natural gas units, the gross generation does not include output from both generation cycles. To convert the reported gross generation to the net, hourly quantity of electricity supplied to the grid by each generating unit, we use unit-level net-to-gross conversion factors.[28]

Table 2 summarizes the heat rates – the MMBtu's required to generate a MWh of output – as well as the CO_2 emission rates for the three types of natural gas generating units in

[28]To convert the observed hourly gross generation to the hourly net generation, we first group units at each plant based on the primary fuel source and technology. For each plant, we calculate the total gross and net (from EIA Form 923) generation by fuel-technology pairing over the sample period. Dividing the total net generation by the total gross generation, we produce net-to-gross ratios at the plant-by-fuel-by-technology level. To convert the hourly gross generation to hourly net generation, we multiply each unit's observed gross generation by the resulting net-to-gross ratios.

the CAISO market (CCGT, GT, and ST). The CCGT units have the lowest heat rates and CO_2 emission rates. Compared to the CCGT units, the GT units have heat rates that are approximately 43% higher. Given that fuel costs account for the majority of the variable generation costs, this pattern highlights that the marginal generation costs of GT units exceed the marginal generation costs of CCGT units.

While the CCGT technology has the lowest average marginal cost, it is also the least flexible natural gas technology. Baseload generation technologies in general are designed to run for long contiguous stretches of time. They have relatively high fixed start-up costs, increase or 'ramp' their production relatively slowly, and become very inefficient when run at low levels of output relative to their design maximum. By contrast, combustion turbines are designed to be nimble, but relatively costly, sources of power over shorter periods. They are "quick-start" plants that can be brought up to full output in as few as ten minutes. From these characteristics, one might expect that CTs would be a complementary technology to renewable variable energy resources.

To determine how output from the various natural gas generating technologies is impacted by growth in daily solar generation, we again reestimate the model specified by Eq. 1 separately for each hour using the net hourly generation from CAISO CCGT, GT, or ST units as the dependent variable. Figure 6 presents the point estimates of the average change in net generation by technology for each hour of the day.[29] Overall, the results follow closely with the estimates of the aggregate hourly changes in CAISO thermal generation from the top panel of Figure 5. During the daylight hours, there are reductions in output from CCGT, GT, and ST units. Overnight, there are small reductions in the aggregate output supplied by the natural gas units.

Focusing still on the estimates displayed in Figure 6, a key insight emerges. During several early morning hours (6am, 7am, and 8am) and evening hours (7pm, 8pm, and 9pm), there are significant increases in the net generation from the less fuel efficient GT units. These are the same six hours where we found that increases in daily aggregate solar generation results in significant increases in wholesale electricity prices. These results provide strong support for the conclusion that the wholesale price increases are caused by a change in the composition of output from natural gas units. Leading up to the morning ramp up in solar generation, and at the tail end of the evening ramp down in solar production, there is a shift away from more fuel efficient CCGT production and towards less fuel efficient, higher marginal cost GT production.

[29] Figure A10 provides the point estimates with the corresponding 95% confidence intervals. We again allow the errors in the hour specific models to be correlated across a 7-day lag.

5 Profit Impacts

The preceding section provides estimates of how growth in daily renewable generation affects wholesale prices during different hours of the day. In this section, we use the estimates to predict how wholesale prices during 2016, the last full year of our sample, would have differed had there been different levels of solar or wind capacity installed in the CAISO market. Using the predicted counterfactual prices, we explore how solar capacity expansions affect the profit earned by different conventional generating technologies as well as the revenue earned by the marginal renewable capacity added to the market.

5.1 Counterfactual Scenarios

Recall, Eq. 1 specifies the hour-specific wholesale electricity price as a linear function of the daily levels of solar and wind output, hourly load, daily gas price, and lagged precipitation. In reality, the relationship between hourly prices and the control variables will likely be non-linear and non-separable. For example, the impact of daily solar output on prices can likely differs as a function of the daily natural gas spot price. Nonetheless, the simple model provides a reasonable approximation for how prices vary with renewable output. Moreover, the parsimonious model allows us to produce very straightforward predictions of the hourly wholesale electricity prices with different levels of solar or renewable capacity installed.

To predict the counterfactual 2016 wholesale prices, we first reestimate the model specified by Eq. 1 separately by hour-of-day (h) and by season (q).[30] By doing so, we are able to capture the potentially heterogeneous seasonal impacts of renewable generation on hourly prices. Using the hour and season-specific estimates of $\{\hat{\alpha}_{h,m}, \hat{\beta}^s_{h,q}, \hat{\beta}^w_{h,q}, \hat{\beta}^g_{h,q}, \hat{\boldsymbol{\theta}}_{h,q}\}$ and the observed residuals $\{\hat{\varepsilon}_{h,d}\}$ as our best estimate of the unobserved errors, we predict the counterfactual wholesale price ($\tilde{P}_{h,d}$) during each hour h of day d during 2016 for different counterfactual levels of daily solar generation ($\widetilde{Solar}_d$) – or similarly, for different levels of wind generation ($\widetilde{Wind}_d$). For example, assuming the daily wind, hourly load, daily gas spot price, lagged precipitation level, and error remain unchanged, the predicted counterfactual hourly wholesale price ($\tilde{P}_{h,d}$) given the counterfactual solar generation ($\widetilde{Solar}_d$) is given by,

$$\tilde{P}_{h,d} = \hat{\alpha}_{h,m} + \hat{\beta}^s_{h,q} \cdot \widetilde{Solar}_d + \hat{\beta}^w_{h,q} \cdot Wind_d + \hat{\beta}^g_{h,q} \cdot Spot_d + \hat{\boldsymbol{\theta}}_{h,q} \cdot \mathbf{X_{h,d}} + \hat{\varepsilon}_{h,d}. \tag{2}$$

[30] We define the quarterly seasons as follows: December-February is winter; March-May is spring; June-August is summer; September-November is fall. The point estimates of $\beta^s_{h,q}$ and $\beta^w_{h,q}$, the average changes in the hour-specific wholesale prices by season caused by an additional GWh of daily solar or wind, are displayed in Figures A8 and A9. To calculate the confidence intervals of each point estimate, we again use Newey-West standard errors with a 7-day lag.

In addition to imposing the simplifying assumption that, for a given hour of the day in a given season, wholesale prices vary linearly with the daily level of solar or wind generation, the approach we use to predict the counterfactual wholesale prices imposes an additional assumption. Specifically, by holding the unexplained portion of the wholesale price (i.e. the residual $\hat{\varepsilon}_{h,d}$) constant across counterfactual levels of renewable output, we are assuming that the distribution of the unobserved error term is independent of the daily level of solar or wind generation.[31]

Under the assumptions highlighted above, Eq. 2 predicts the wholesale electricity price that would have been observed given any counterfactual level of daily solar generation. The question now is what counterfactual levels of daily solar, or wind, generation should be considered? Recall, the goal is to understand how growth in renewable capacity affects wholesale prices. One option would be to focus on how wholesale prices during the last year of our sample would differ had the level of solar or wind capacity increased above the observed 2016 levels. This is unappealing however because the counterfactual levels of solar and wind generation would be larger than the daily levels of wind and solar generation that were observed during our sample period (January, 2013 through May, 2017), requiring us to extrapolate the estimates of Eq. 1 beyond the observed support. Therefore, we take a different approach. We examine how 2016 wholesale prices would have differed had the installed solar or wind capacity been lower than the levels we observed at the end of our sample. In particular, we predict the wholesale electricity assuming that the installed solar capacity during 2016 was equal to 2 GW, 6 GW, or 10 GW for the full year.[32] Similarly, we predict the counterfactual 2016 wholesale prices had wind capacity been equal to 1 GW, 3 GW, or 6 GW for the entire year.[33]

To predict the daily solar or wind generation that would have occurred given the counterfactual levels of renewable capacity, we could simply calculate the daily solar and wind capacity factors – the daily generation divided by the actual installed capacity – and mul-

[31]In reality, it is certainly possible that, as the daily level of solar or wind changes, the variance of the error may change. As a robustness check, we relax this assumption by directly modeling the variance of the hour-specific error term as a linear function of the level of daily wind and solar generation. Using the estimates of the relationship between the hour-specific error variance and daily renewable output, we predict the counterfactual prices without the assumption of homoskedastic errors. While we find evidence of mild heteroskedasticity, the resulting predictions of the counterfactual wholesale prices are effectively unchanged.

[32]By the end of 2016, there were over 9.8 GW of solar capacity installed – and over 10 GW by May, 2017. During 2013, solar capacity increased from 1.2 GW to 3.2 GW. During 2015, roughly the midpoint of our sample, solar capacity increased from 5.8 GW to 7 GW.

[33]In contrast to solar capacity which grew over the full sample, wind capacity remained between 5.6 GW and 6 GW during our sample period. Therefore, the 1 GW and 3 GW counterfactual levels of wind capacity are not in sample. Nonetheless, because the daily capacity factors for wind generation vary dramatically, often falling close to zero (see 3), the resulting counterfactual levels of wind generation are certainly within the observed levels of daily wind generation.

tiply these capacity factors by the counterfactual levels of solar or wind capacity. However, this approach imposes the unrealistic assumption that curtailments would be independent of the level of installed solar or wind capacity. In reality, the frequency and levels of solar and wind curtailment increases with installed renewable capacity.

To predict the counterfactual levels of daily solar or wind generation, we instead use the following procedure. First, we calculate the daily solar and wind potential capacity factors during 2016. The potential capacity factor is the daily potential output – i.e. the daily observed solar generation plus the daily curtailed solar output – divided by the actual installed capacity. Imposing the assumption that the potential capacity factors are independent of the installed solar and wind capacity, the counterfactual potential generation is simply equal to the product of the daily potential capacity factors and the counterfactual solar or wind capacity. Finally, to determine the daily solar or wind generation from the predicted potential generation, we estimate daily curtailment as a function of the daily renewable potential and subtract the predicted curtailment from the potential generation. A detailed explanation of the curtailment estimation procedure is provided in Appendix C.

5.2 Counterfactual Prices

Figure 7 displays the average predicted RTM prices by hour-of-day during 2016 for the three counterfactual levels of solar capacity and the three levels of wind capacity. Focusing first on the top panel, the figure highlights that increasing from 2 GW to 10 GW of solar capacity would cause the 2016 RTM prices to decrease by approximately $20/MWh during the middle of the day when the solar output occurs. During the early morning (6am-7am), when solar production is about to begin, and the evening, when solar production is just ending, the expansion in solar capacity is predicted to increase wholesale prices.

Overall, increasing solar capacity from 2 GW to 10 GW would cause the distribution of hourly wholesale prices to become wider. The distribution of the counterfactual wholesale prices is displayed by season in Figure A11. With the decrease in midday prices, the left tail of the wholesale price distribution increases and shifts left, particularly during the Spring and Fall months. In addition, with the increase in the late afternoon, early evening prices, the right tail of the price distribution shifts slightly outwards with the increase in solar capacity – again, particularly during the Spring and Fall.

While solar capacity expansions are predicted to cause the distribution of wholesale prices to become wider, expanding from 1 GW to 6 GW of wind capacity is predicted to shift the distribution of wholesale prices leftwards. As the bottom panel of Figure 7 highlights, increasing wind capacity results in lower average wholesale prices during each hour of the day.

5.3 Profit Changes for Conventional Generators

In this section, we explore how the profit earned by different types of conventional generators during 2016 would differ with the level of installed solar and wind capacity. To do so, we impose a key simplifying assumption. Specifically, we assume that conventional generators face no dynamic costs or constraints (e.g., start-up costs, ramping constraints). During a given hour, a generating unit will produce zero output if the wholesale price falls below the unit's constant marginal generation cost. If the hourly price exceeds the unit's marginal generation cost, the generator will operate at full capacity.

Using the simple static framework, we explore how conventional generators with different marginal generation costs are affected by expansions in renewable capacity. In particular, for the different counterfactual levels of renewable capacity K_r, for $r = \{\text{Solar, Wind}\}$, we calculate the predicted annual profit for conventional generating units with marginal generation costs (c) ranging from \$0/MWh (i.e. a pure baseload technology) up to \$70/MWh. Given the predicted counterfactual wholesale electricity prices ($\tilde{P}_t(K_r)$), the counterfactual profit over the 8,784 hours during 2016 is given by the following expression:

$$\text{Revenue}(c, K_r) = \sum_{t=1}^{8,784} max\Big(\tilde{P}_t(K_r) - c, 0\Big). \tag{3}$$

To summarize how the predicted profits change as with the level of solar capacity, the top panel of Figure 8 displays the percentage changes in the 2016 profits for different technologies and for different levels of solar capacity relative to the case with 2 GW of solar. Increasing from 2 GW to 6 GW of solar reduces the profit across all conventional technologies considered. A hypothetical unit with a marginal cost of \$0 loses 10% of their profit while a unit with a marginal cost of \$30/MWh loses 23%. As the marginal costs increases, the share of profit lost due to solar capacity expanding from 2 GW to 6 GW falls. For example, a unit with a marginal cost of \$60/MWh experiences a 4% decrease in profits as solar capacity grows to 6 GW. Interestingly, increasing from 6 GW to 10 GW of solar does not uniformly decrease the profits for all technologies. While an increase from 6 GW to 10 GW reduces profits for units with marginal costs below \$45/MWh, generators with marginal costs above \$45/MWh begin to recover some of the initial profit declines caused by the expansions from 2 GW to 6 GW of solar. This is driven by the fact that as solar capacity increases from 6 GW to 10 GW, the share of hours with prices above \$40/MWh effectively stabilizes. While there are fewer hours with prices above \$30 to \$40/MWh in the Summer and Winter with 10 GW of solar, the share of hours with high prices increases in the Spring and Fall (see Figure A11). As a result, the higher marginal cost units, which only operate during the hours with the highest prices, continue to operate the same number of hours, and earn stable profits, as solar capacity expands from 6 GW to 10 GW (see Figure A12).

The bottom panel of Figure 8 highlights how 2016 profits for conventional generators would change as wind capacity grows beyond 1 GW of installed capacity. Consistent with the estimates presented in the middle panel of Figure 4, increasing wind generation uniformly decreases prices and, as a result, decreases profits. For a hypothetical unit with a marginal generation cost of $0/MWh, expanding wind capacity from 1 GW to 6 GW reduces 2016 profit by 17%. For a unit with a marginal cost of $30/MWh, the expansions from 1 GW to 6 GW of wind reduces 2016 profit by 30%.

5.4 Marginal Revenue of Renewable Capacity Additions

In addition to exploring how renewable expansions impact the revenue earned by conventional generators, we also explore how growth in renewable capacity affects the returns to the renewable investments themselves. In particular, we predict how the annual revenue earned by the marginal unit of solar or wind capacity added to the CAISO market varies with the total level of solar or wind capacity installed in the region.

To estimate the revenue earned by the marginal unit of solar or wind capacity, we first need to predict how much output the marginal renewable generators would supply to the market during each individual hour of 2016. To do so, we calculate the observed 2016 hourly solar and wind capacity factors – the actual solar or wind output (MWhs) supplied to the market divided by the installed capacity (MW). We assume that, regardless of the level of installed renewable capacity, the observed hourly capacity factors represent the amount of electricity that would be supplied by an additional MW of solar or wind capacity. Effectively, this imposes an assumption regarding the amount of output that would be curtailed during each hour from the marginal solar or wind capacity. Specifically, we assume that, regardless of the level of installed renewable capacity, the fraction of the marginal solar or wind capacity's hourly output curtailed is equal to the share of potential hourly solar or wind output that was curtailed during the corresponding hours of 2016.[34] To predict the annual revenue earned by the marginal solar or wind capacity added to the market, we simply multiply the hourly

[34]This assumption likely overstates the level of output curtailed form the marginal capacity for low levels of renewable capacity. However, it is a reasonable approximation for the upper end of the counterfactual solar and wind capacities considered – which were similar to the observed capacity installed during 2016. Therefore, while the subsequent results demonstrate that marginal revenues decline with solar and wind capacity growth, these reductions likely understate the decrease in marginal revenue that occurs with capacity growth.

solar or wind capacity factors by the predicted hourly counterfactual prices ($\tilde{P}_t(K_r)$) for solar capacities between 2 GW and 10 GW and for wind capacities between 1 GW and 6 GW. Summing across all the hours in 2016, we are able to estimate the annual revenue earned by the electricity supplied by the marginal renewable capacity.[35]

To summarize how the revenue earned by the marginal solar or wind generators vary with the level of renewable capacity, Figure 9 plots the percentage change in the revenue earned by an additional MW of solar or wind capacity relative to the case where there is only 2 GW of solar or 1 GW of wind. Focusing first on the top panel, as solar capacity increases, the revenue earned by the marginal unit of solar capacity consistently falls. While the revenue losses experienced by the higher marginal cost conventional generators are mitigated by the morning and evening wholesale price increases that are caused by solar expansions, the solar generators themselves do not benefit from these price increases that occur outside of their primary hours of production. Compared to the 2,000$^{\text{th}}$ MW of solar capacity installed in the market, the 10,000$^{\text{th}}$ MW of solar capacity earns 52% less revenue.

The bottom panel of Figure 9 reveals a similar decline in the revenue earned by additional wind capacity added to the market. Compared to the 1,000$^{\text{th}}$ MW of wind capacity, the 6,000$^{\text{th}}$ MW of wind capacity achieves almost 20% less annual revenue. With regards to both wind and solar investment, therefore, the marginal value of new capacity has declined substantially as the amount of existing capacity has grown over the last half-decade.

To further highlight how the returns to renewable capacity investment decline, we also calculate the average revenue earned per MWh of solar generation – or wind generation – for different counterfactual levels of renewable capacity. Specifically, for each counterfactual level of solar or wind capacity, we multiply the predicted hourly RTM price by the share of annual solar, or wind, output that would occur during the corresponding hour. Aggregating across each hour during 2016 results in the average revenue earned per MWh of solar or wind output generated. Figure 9 plots the average revenue per MWh for various levels of renewable capacity. The top panel reveals that, had there been 2 GW of solar capacity during 2016, each MWh of solar output generated would earn an average of $39/MWh. Had there been 10 GW of solar capacity installed, each MWh of solar output would earn an average of $19/MWh.

[35]By summing across all hours, we are assuming that the renewable output is supplied even during hours when the wholesale price is predicted to be negative. This is in fact reasonable given that renewables receive financial incentives that make it rational supply output even when prices are negative. Ultimately however, this assumption has limited impact on our revenue estimates. Even in the case with 10 GW of solar capacity installed, the predicted wholesale price falls below zero less than 1% of the hours.

6 Conclusion

We have examined the impact of the major influx of investment in renewable energy technology on western US electricity prices. It is worth considering our results in the context of the claims and controversies that have swirled around this topic in recent years. First, defenders of traditional power sources have claimed that their industry has been grossly distorted by policies favoring renewable energy. In contrast, a recent string of studies that have focused on eastern US markets have concluded that declines in natural gas prices, rather than renewables, are responsible for the bulk of the decline in power prices. We find, studying a different market and deploying a different methodology, that renewable investment has indeed had a significant impact on power prices, and appears to be responsible for the majority of price declines over the last half-decade in California. To the extent that California's renewable goals are even partially followed east of the Mississippi, we can expect that their impact on wholesale prices will be substantial.

A second view has been that wholesale power markets, as currently designed, are ill-positioned to absorb large amounts of renewable capacity and properly reward sources of energy that provide critically needed services for maintaining reliable operations. Concerns over the fate of baseload generation, when they extend beyond private interest, have been focused on the reliability risks to power systems of plant retirements. Even in regions like the northeastern US and California that have allowed nuclear capacity to retire, there are concerns about the commercial viability of more flexible generation technologies in a high-renewable system. For example, the CAISO has an ongoing proceeding exploring separate procurement requirements for "flexible" generation that would be mandated of all customer serving utilities.

Our results provide a counter-weight to the view that current markets "don't work." On the one hand, it is true that baseload generation sources throughout the country are in financial distress, and that renewable energy either currently is, or will be, partly to blame for this situation. However, this is the result of, rather than the cause of, renewable investment. These are in turn strongly influenced by state and federal policy decisions regarding the promotion of renewable energy. The two most prominent policies pushing renewable energy right now are Federal tax credits for renewable energy production and state-level renewable portfolio standards that mandate growing percentages of supply come from renewable energy sources. Both policies effectively subsidize renewable production. The remarkably rapid decline in procurement prices for renewable energy can also be attributed to the fact that they are increasingly cost-competitive even without subsidies. Therefore wholesale power markets are accurately reflecting the "facts on the ground," given the reality of substantial renewable capacity. These include the fact that nimble generation with low capital, but high marginal, cost is complimentary to renewable energy, while high capital cost baseload plants are not. Our finding that higher marginal cost CT technologies are much less negatively impacted by renewable expansion than other sources of generation indicates that the market is indeed rewarding the technologies that are providing value, conditioned on the amount of renewable energy hitting the system.

The California market is also signaling the rapidly declining returns to further investment in renewable capacity, particularly solar. The level of investment has reached a point where it is strongly shaping market outcomes. Because the output of solar plants is so strongly correlated, additional capacity investment will continue to concentrate production in hours of the day that are already featuring the lowest power prices on average.

Our results therefore reinforce the perception of many environmental economists that subsidizing the production of "green" power is inferior to placing a positive cost on the production of negative externalities such as greenhouse gasses. A non-trivial price on GHG would also reward renewable energy by giving it a relative cost advantage and raising energy prices in periods where fossil generation is still marginal. Clean energy sources that are able to target periods of the highest remaining prices would be rewarded more than sources that produce during periods that are already experiencing a glut of clean energy. At the same time, baseload generation may or may not be cost-competitive, depending upon both its emissions profile and its ability to adapt to system needs for more flexibility. The results in California signal that baseload generation is indeed being penalized by renewable expansion, but that fact is consistent with the view that this market does not need baseload generation. In contrast, the market does need flexible generation, and the market responses are reflecting that this value is, at least qualitatively if not fully, reflected in prices.

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Table 1: Hourly Quantity Supplied to CAISO

Source	Average Hourly Quantity Supplied (MWh)	Standard Deviation (MWh)
Thermal	10,198	3,987
Nuclear	2,054	434
Large Hydroelectric	2,044	1,107
Solar	1,633	2,323
Wind	1,484	1,133
Other Renewables	1,671	118
Net Imports	7,215	1,424

Hourly CAISO market data spans January 1, 2013 through May 31, 2017. Other renewables includes output from small-scale hydroelectric units, geothermal, biomass, and biogas.

Table 2: Heat and Emission Rates by Technology

	Combined Cycle Gas Turbine (CCGT)	Gas Turbine (GT)	Steam Turbine (ST)
Number of Units	85	94	25
Median Heat Rate *(MMBtu/MWh)*	7.51	10.73	12.76
Median CO_2 Rate *(tons/MWh)*	0.44	0.63	0.76

Median heat and CO_2 rates are equal to the 50th percentiles of the unit-level, average heat and emission rates between January 1, 2013 and March 31, 2017. The units include all of the generating units in the CEMS dataset that are part of the CAISO power control area.

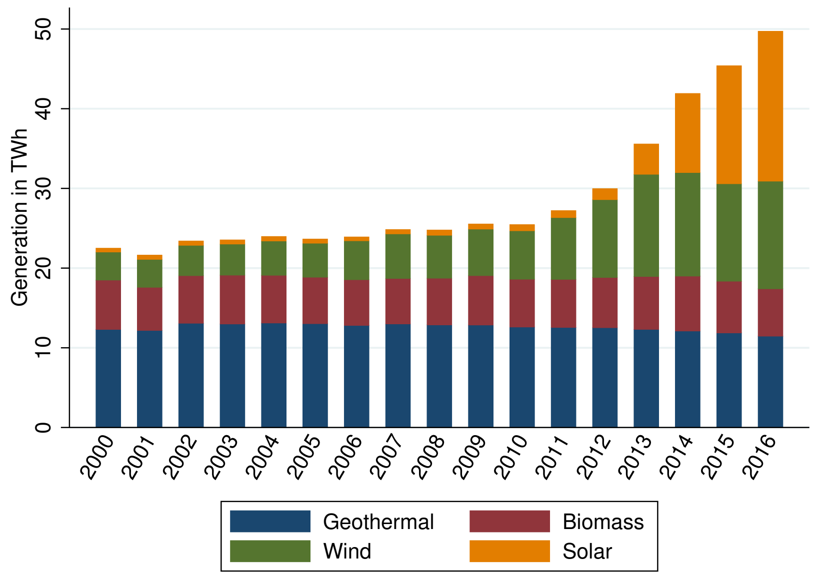


Figure 1: Renewable electricity production in California.

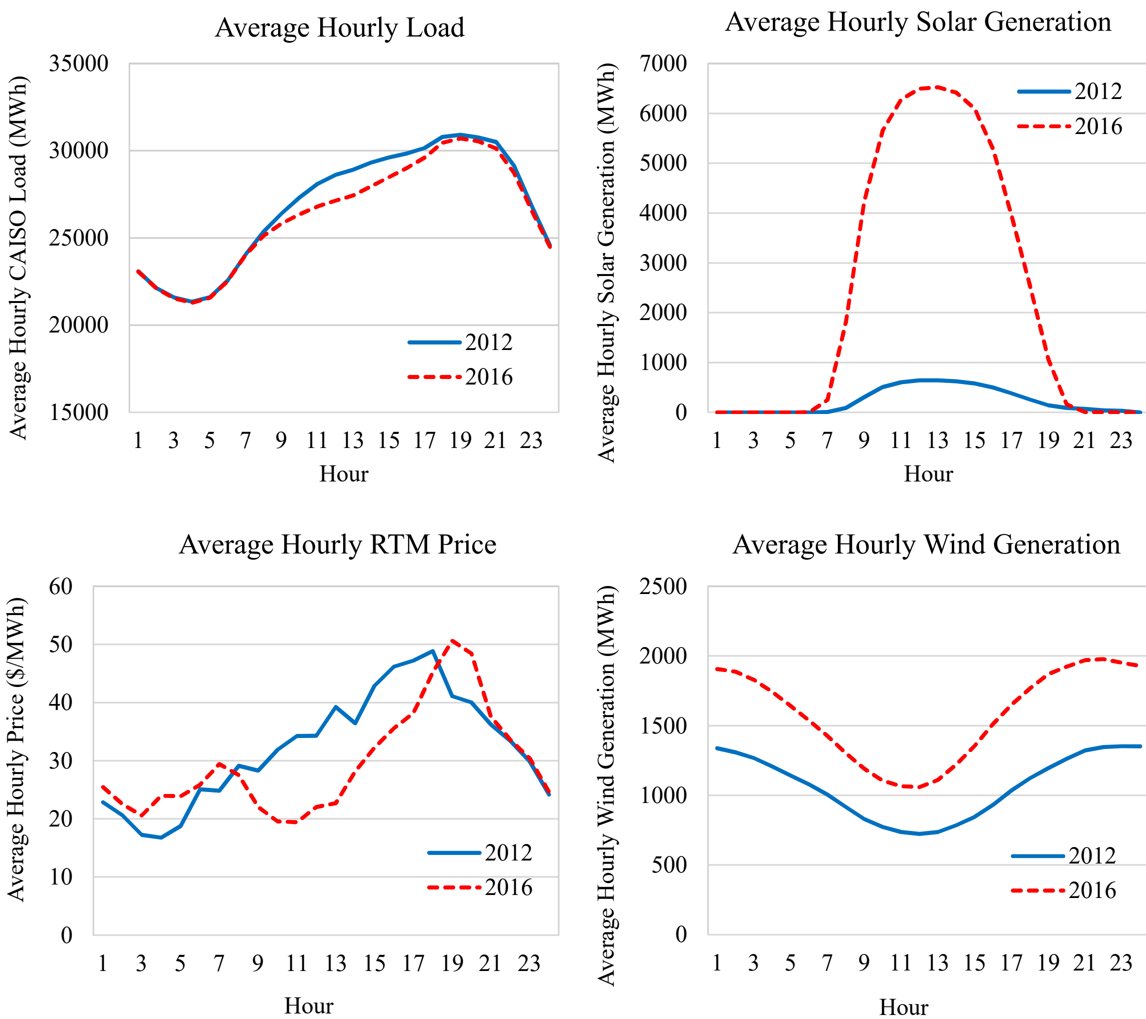


Figure 2: The upper left panel displays the average hourly CAISO load during 2012 and 2016. The bottom left panel displays the average hourly day ahead market energy prices in the CAISO market (the simple average across the DLAPs). The right panels display the average hourly grid-level solar and wind generation.

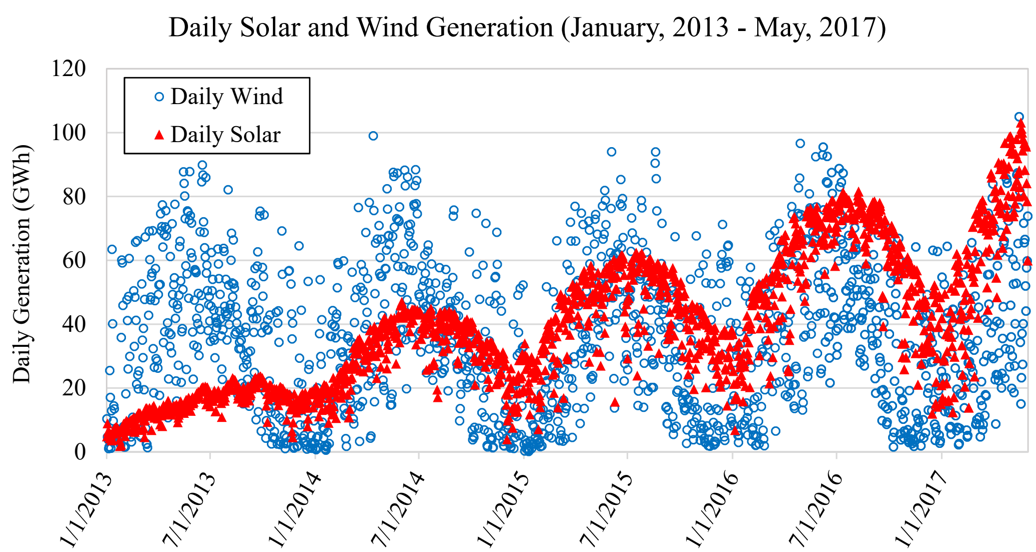


Figure 3: The plot displays the aggreate daily solar and wind generation from January 1, 2013 through May 31, 2017.

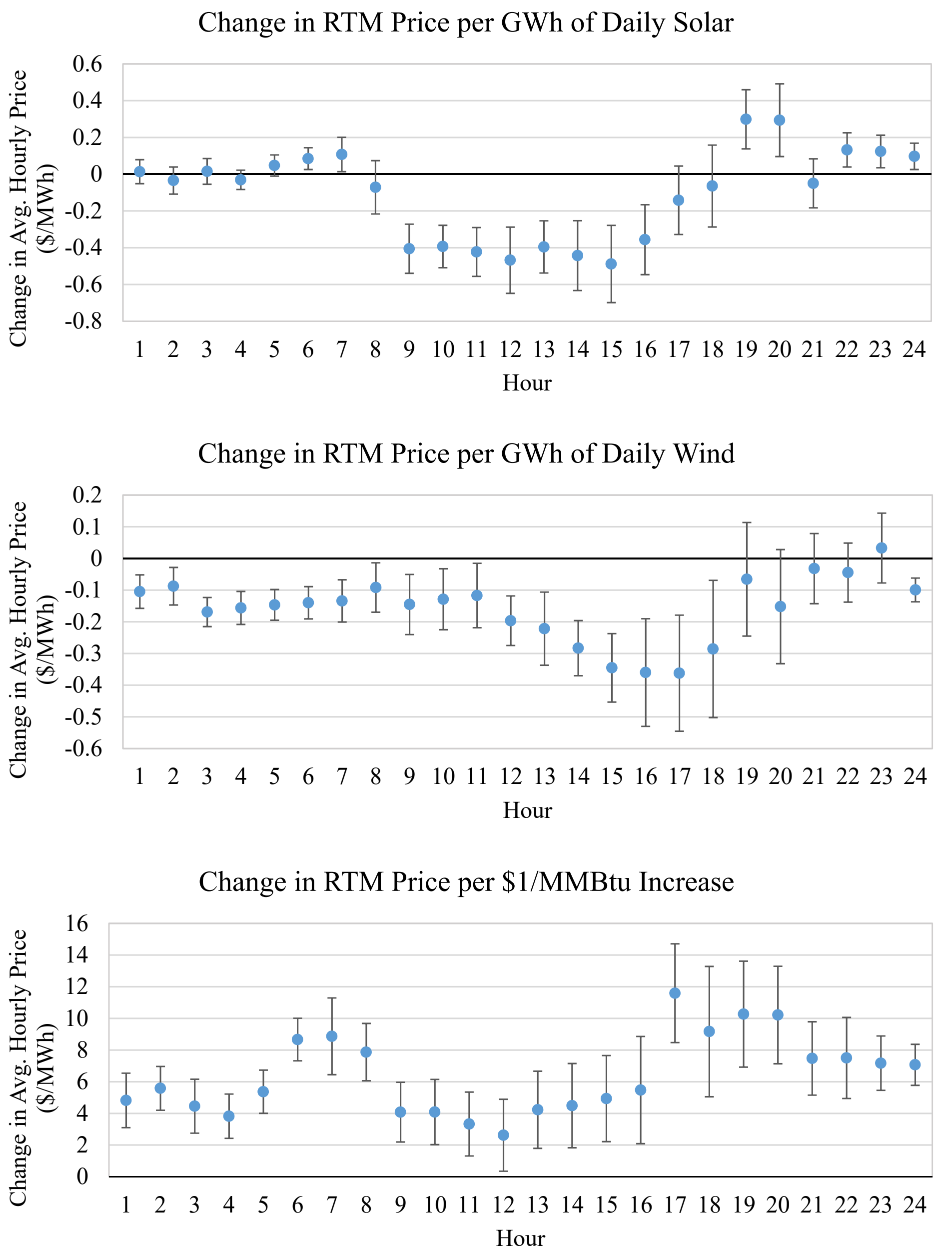
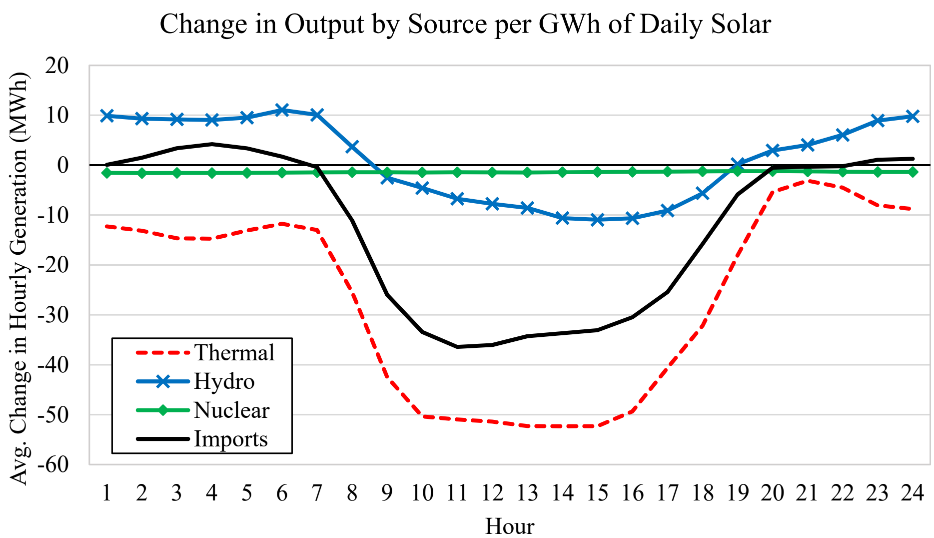


Figure 4: The panels display the point estimates of β_h^s, β_h^s, and β_h^g (from the model specified by Eq. 1) and the corresponding 95% confidence intervals.



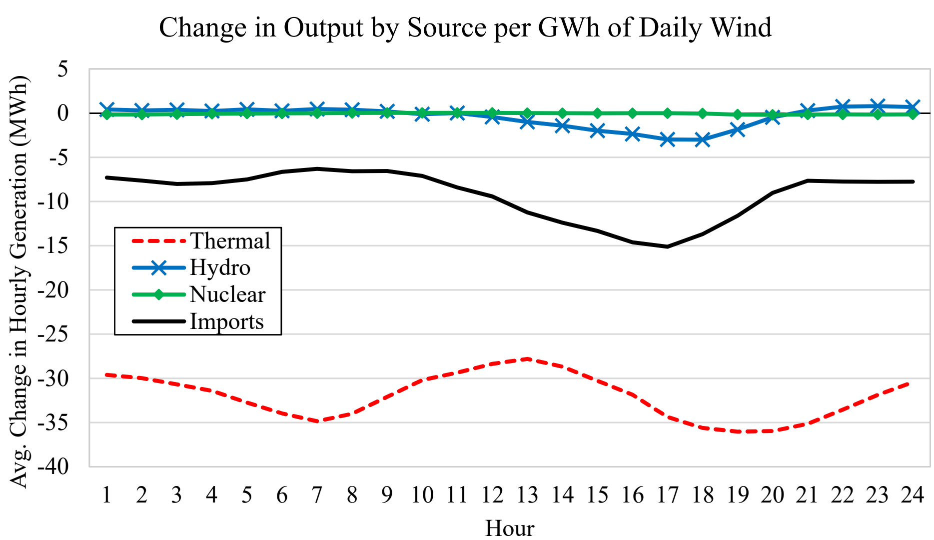


Figure 5: The top panel displays the average impact of an additional GWh of daily solar generation on the hourly level of generation from CAISO thermal, hydro, and nuclear units as well as net-imports into the the CAISO market. The bottom panel displays how the CAISO units and net-imports respond on average to an additional GWh of wind generation.

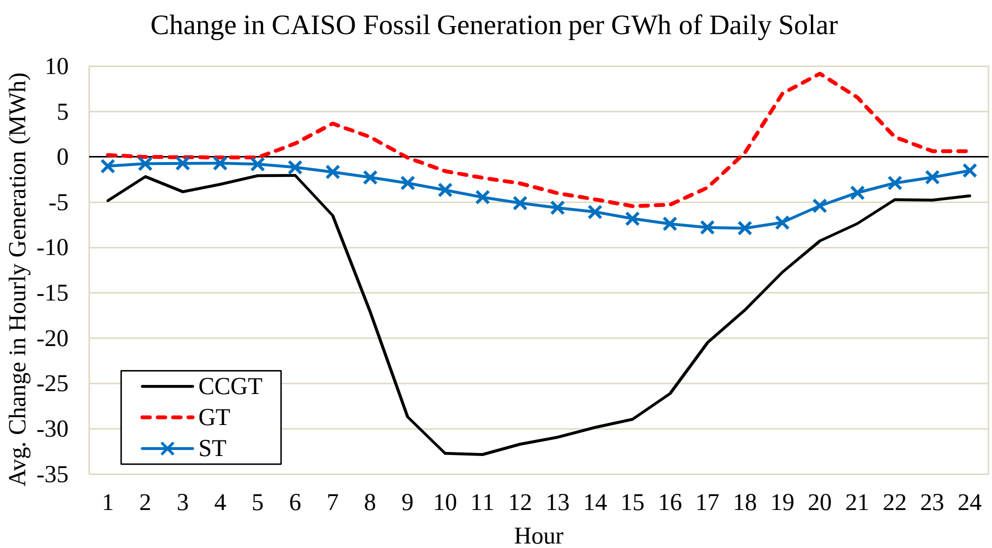
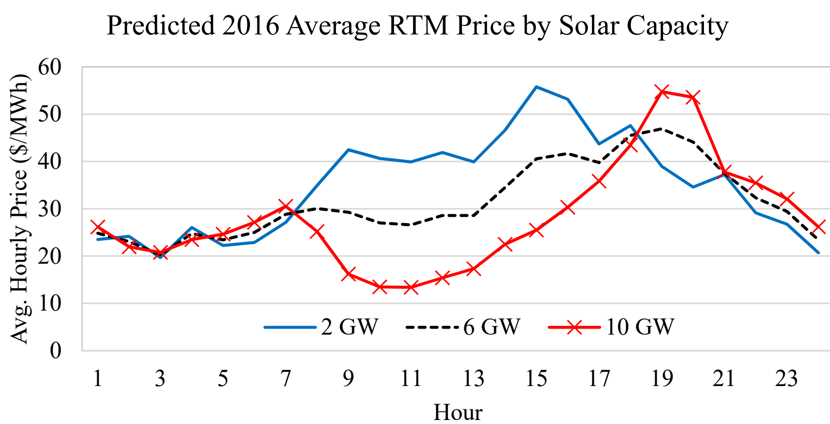


Figure 6: The figure displays how an additional GWh of daily solar generation affects the average level of gross generation from CAISO fossil units in the EPA CEMS dataset. The fossil fuel units are separated into combined cycle gas turbined (CCGT), gas turbines (GT), and steam turbines (ST).



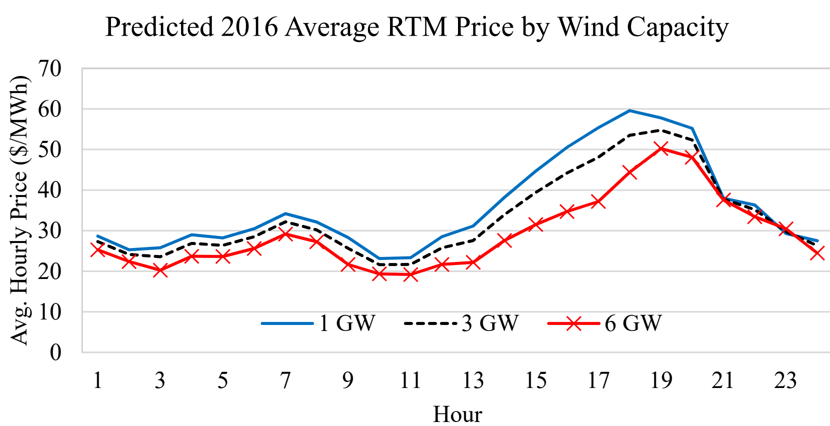


Figure 7: The top panel displays the average predicted DAM price by hour-of-day during 2016 under three counterfactual levels of solar capacity (2 GW, 6 GW, and 10 GW). The bottom panel displays the predicted DAM prices by hour-of-day during 2016 for three different counterfactual levels of wind capacity.

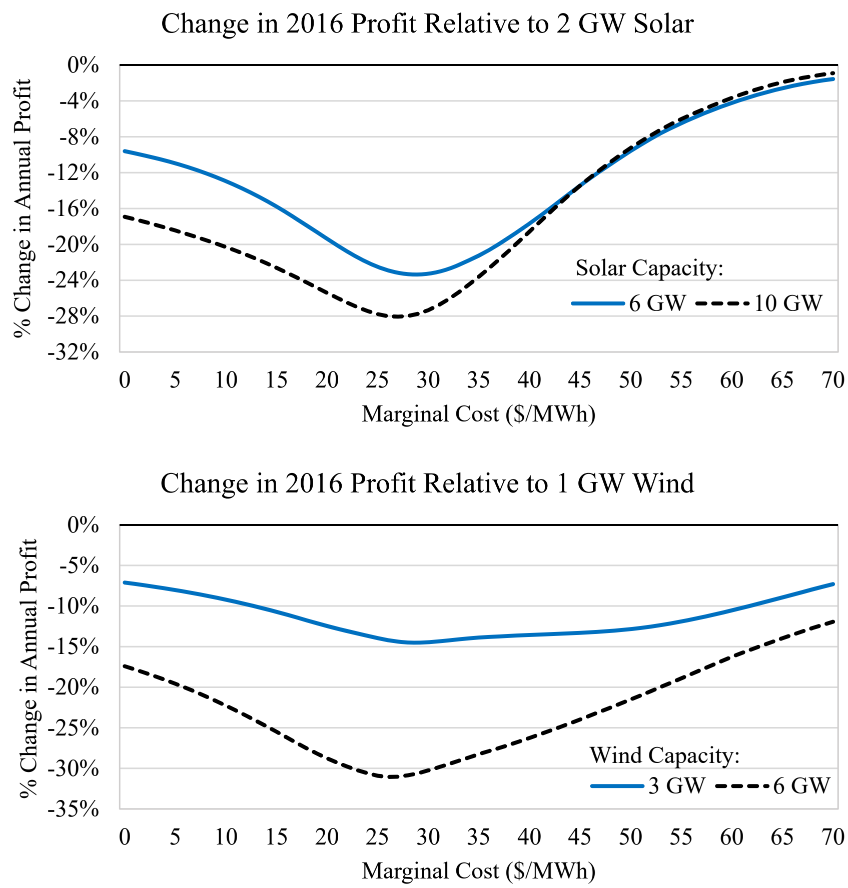


Figure 8: The top panel displays the percentage change in the predicted profit a conventional generator would earn during 2016 given different levels of solar capacity. The profit changes are displayed for hypothetical conventional generators with variable generaiton costs ranging from $0 to $70/MWh. The bottom panel displays the predicted percentage changes in profits under different levels of installed wind capacity.

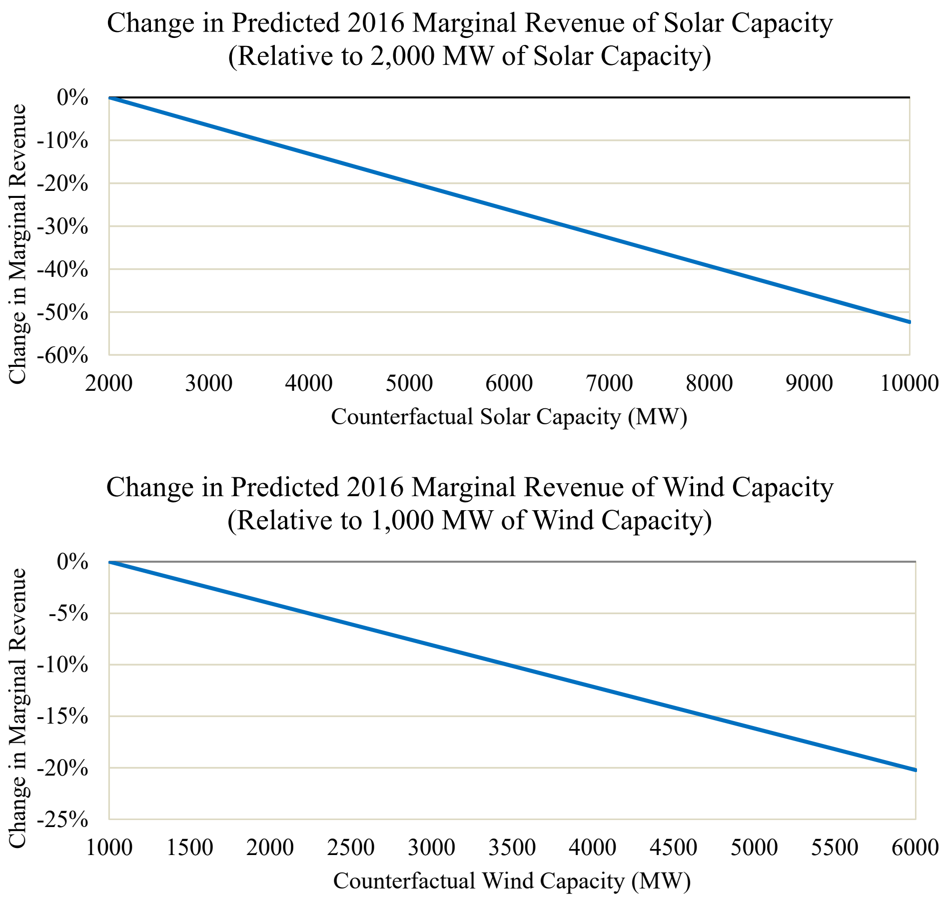


Figure 9: The top panel displays the predicted percentage change in the 2016 revenue earned by the marginal solar generator (i.e. the last MW of installed solar capacity) for different aggregate levels of solar capacity. The bottom panel displays how the 2016 revenue earned by the marginal wind generator varies as aggregate wind capacity increases.

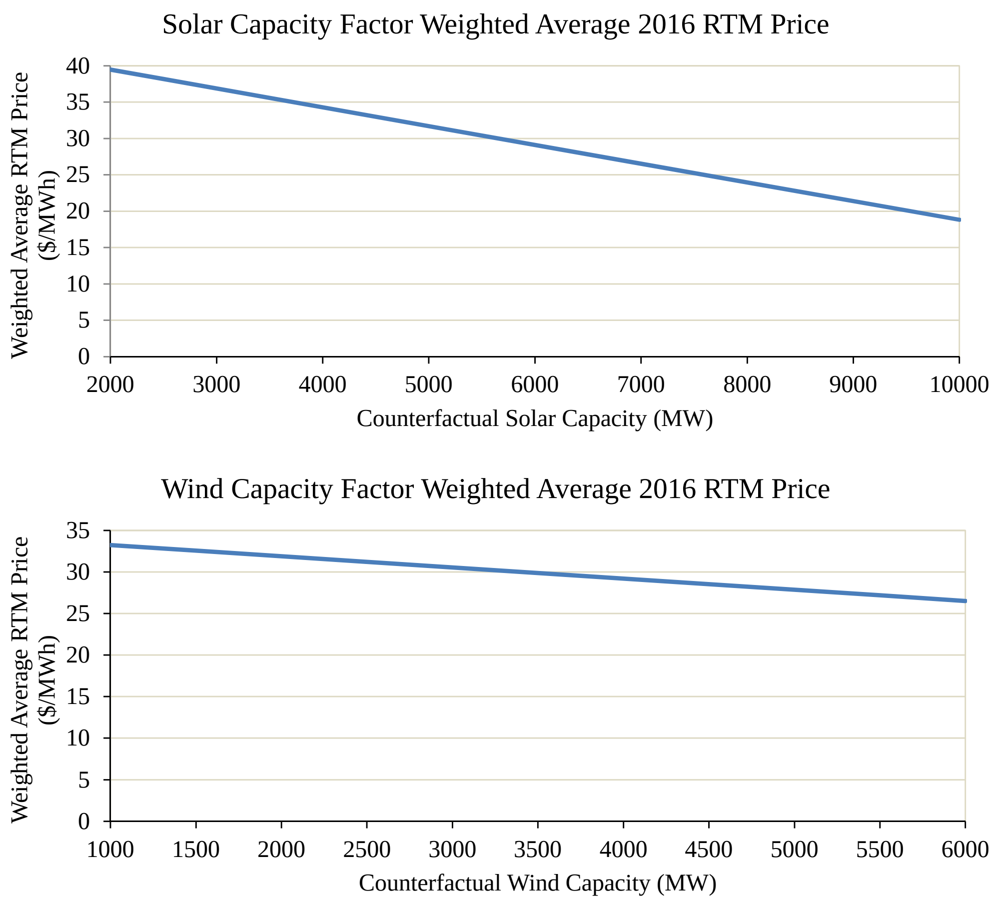


Figure 10: The top panel displays the weighted average of the predicted 2016 hourly RTM prices for different levels of installed solar capacity. Each hourly predicted price is weighted by the share of 2016 solar generation that would occur during the specific hour. Similarly, the bottom panel displays the weighted average of the predicted 2016 RTM prices for different levels of wind capacity. Again, the weights are the share of total annual wind generation that occurs during the specific hour.

Appendix

A Exploiting Short-Run Solar Fluctuations

Recall, the objective of our empirical analysis is to quantify how growth in solar capacity has affected wholesale electricity prices. To do so, we take advantage of the fact that solar generation has grown considerably over our four and a half year sample. In particular, we do not sweep away the variation in prices and renewable output across years using annual fixed effects, time trends, or by differencing the data. In this section, we examine how the estimates of the impact of renewable output on wholesale prices differ if we solely exploit short-run variation in renewable output (e.g., within-month variation in solar output).

To explore how the estimates differ, we re-estimate the model specified by Eq. 1 using a larger set of fixed effects. In particular, instead of including a fixed effect that flexibly varies across hour-of-day and across months of the year, we allow the fixed effect to vary by hour-by-month-by-year. In particular, we estimate the following model:

$$P_{h,d} = \alpha_{h,m,y} + \beta_h^s \cdot Solar_d + \beta_h^w \cdot Wind_d + \beta_h^g \cdot Spot_d + \boldsymbol{\theta}_h \cdot \mathbf{X_{h,d}} + \varepsilon_{h,d}, \tag{A1}$$

where h indexes each hour-of-day, d indexes each day in the sample spanning January 1, 2013 through May 31, 2017, m indexes each month of the year, and y indexes each year in the sample. $P_{h,d}$ represents the average hourly RTM price (\$/MWh) in the CAISO market for hour h of day d. $Solar_d$ and $Wind_d$ are the aggregate daily levels of CAISO solar and wind generation (GWh). We continue to include the same set of additional controls in $\mathbf{X_{h,d}}$.

The key coefficient of interest, β_h^s, still represents the average change in the RTM price during hour h caused by a 1 GWh increase in the daily level of CAISO solar generation. However, in the model specified by Eq. A1, these coefficients are now being identified exclusively based off of variation in the daily level of solar output relative to the average daily solar in that specific month and year. As a result, we are no longer exploiting the long-run growth in solar output that has occurred as a result of solar capacity additions. Instead, we are relying largely on daily fluctuations in renewable output – which is largely driven by weather conditions, not renewable capacity. Again, to account for serial correlation, we report Newey-West standard errors allowing the errors for hour h to be correlated over a 7-day lag.

Figure A2 displays the point estimates of the average impact of an additional GWh of daily solar or wind generation on RTM prices across each hour of the day. The blue point estimates display the estimates from Eq. 1, the specification that does not sweep away variation in renewable output across years. The red line displays the point estimates from Eq. A1, the specification that exclusively exploits within month-of-year variation in the daily levels of solar or wind generation.

In the case of solar, there is a stark difference in the estimates of the price impacts based on the variation that is ultimately exploited. Most notably, the estimates from Eq. A1 reveal that, as the daily level of solar generation deviates from the average daily generation in the corresponding month, the wholesale price also deviates dramatically from the average hourly price during the corresponding month.

However, the estimates from Eq. A1 ultimately do not reflect how the RTM price responds to growth in the solar output caused by increasing solar capacity. Instead, the hour-by-month-by-year fixed effects estimates are driven by how wholesale price respond to large weather-driven drops in daily solar production. To see why this is the case, we first highlight the distribution of the short-run (i.e. within-month) deviations in the daily level of solar generation. Focusing on the last full year of our sample (2016), we regress the daily level of solar generation on a monthly fixed effect and the daily observed levels of wind generation, CAISO load, and the natural gas spot price. Figure A3 displays the distribution of the residuals from the model – i.e. the unexplained short-run variation in the daily level of solar. The figure reveals that the deviations of the daily solar output from the monthly mean is quite skewed – there is a long left tail of negative residuals (i.e. cloudy days). Ultimately, when estimating the impact of the RTM price to short-run fluctuations in the daily level of solar output, the days with uncharacteristically low solar output will be very influential.

The fact that the days with large, downward deviations in the daily level of solar output are influential in the hour-by-month-by-year fixed effect model is quite important because there is a clear, non-linear response of wholesale prices to within-month deviations in daily solar output. To see this fact, we focus on the 12pm hourly wholesale prices during the last full year of our sample (2016). To isolate the unexplained, within-month variation in wholesale prices, we regress the hourly RTM price on a monthly fixed effect and the daily observed levels of wind generation, CAISO load, and the natural gas spot price. To focus on the impact of short-run (i.e. within-month) fluctuations in daily solar output on deviations in RTM prices, we explore the relationship between the residuals from the RTM price model with the previous residuals from the daily solar output model described in the previous paragraph.

Figure A4 displays a kernel-weighted local polynomial fit to the price and solar output residuals. The plot focuses days with daily solar output up to 20 GWh below the predicted daily level (the 5^{th} percentile) up to days with over 12 GWh more than expected (the 95^{th} percentile). For days with relatively small deviations from the within-month expected level of solar output – e.g., plus or minus 10 GWh per day, roughly 80% of the days – there is a clear negative relationship between daily solar output and the 12pm RTM price. However, for days with large negative deviations in daily solar output – e.g. deviation below -10 GWh per day – the negative relationship becomes dramatically more pronounced. Ultimately, these days with large negative deviations in the daily level of solar output – which are very influential in the hour-by-month-by-year fixed effect model – explain the large discrepancy between the midday point estimates displayed in Figure A2 in the case of solar.

In contrast, in the case of wind, the estimates of the average price impacts do not differ meaningfully across the two specifications. This is consistent with the fact that, during our sample period, there was very little change in wind capacity. As a result, both models (i.e. including monthly fixed effects or including month-by-year fixed effects) ultimately rely on variation in the daily level of wind generation that is driven by weather variation – not long-run capacity growth.

B Robustness

B.1 Instrumental Variable Estimates

Throughout the analysis, we have assumed that the variation in the daily level of wind and solar generation did not respond endogenously to the wholesale electricity price. There are two main potential threats to this assumption. First, in the long run, changes in renewable capacity can clearly respond to the wholesale price. For example, if prices increase, there could be an acceleration in the growth of wind and solar capacity. However, this is unlikely to be a serious concern due to the fact that we directly control for the non-renewable drivers of wholesale prices (i.e. fuel prices, demand, hydroelectric potential). Moreover, the growth in renewable capacity observed over our sample period may be entirely driven by policies (e.g., California's renewable portfolio standard) as opposed to market forces.

The second threat to our key identifying assumption is potentially more serious. Specifically, output from wind and solar generators could respond to short run variation in the wholesale price through the level of wind or solar output curtailed. For example, during periods of high solar production (and consequently low wholesale prices), the grid operator may require additional solar output to be curtailed. In this setting, the negative relationship between solar output and wholesale prices would be biased towards zero, resulting in potential underestimation of the price reductions caused by solar output.

For the period spanning May 1, 2014 through May 31, 2017, we observe the level of wind and solar generation curtailed at the 5-minute level from CAISO. Aggregating the curtailments up to the daily level, we find that during the period we observe curtailments, the average curtailed solar and wind output were 577.4 MWh per day and 152.7 MWh per day, respectively.

To examine whether our estimates of the impact of solar and wind output on the DAM price are biased by the curtailments, we reestimate the model specified by Eq. 1. Now, rather than assuming the observed daily solar and wind output ($Solar_d$ and $Wind_d$) are exogenous, we instrument for the observed daily output using the potential daily solar and wind output. The potential daily solar output is equal to $Solar_d$ plus the aggregate GWhs of curtailed solar output on day d. Similarly, the potential wind output is the sum of $Wind_d$ and the daily curtailed wind production.

We estimate the model using the data spanning May 1, 2014 through May 31, 2017. For each hour of the day, we estimate the model specified by Eq. 1 twice – once using the instrumental variables and again using ordinary least squares (i.e. continuing to assuming $Wind_d$ and $Solar_d$ vary exogenously with respect to the wholesale price). Figure A5 presents the estimates of the average change in the hourly DAM price using IV and OLS approaches.[36] The results reveal that imposing the assumption that the daily level of wind and solar vary exogenously does not result in any meaningful bias in the resulting estimates of the response of the RTM price to renewable output.

B.2 Day-Ahead Market Impacts

The main analysis presented in this paper focuses on the impacts of daily wind and solar production on hourly prices in the real-time market. To explore how an increase in daily solar or wind output is related to changes in the day-ahead market (DAM) price, we reestimate the model specified by Eq. 1 separately for each hour the day – again using all days spanning January 1, 2013 through May 31, 2017. Rather than using the hourly average RTM price as the dependent variable, we use the observed hourly average DAM price.

Figure A6 presents the point estimates of the average change in the hour-specific mean DAM price caused by increasing daily utility-scale solar or wind generation by 1 GWh. Comparing the estimates to the average changes in the RTM price (Figure 4), the same qualitative patterns emerge. Increases in solar output depress the midday prices and cause prices to increase during the mid-morning (6am-7am) and early evening (7pm-8pm).

[36]The 95% confidence interval for the IV estimates is also reported. The standard errors are robust to clustering at the weekly level.

C Predicting Counterfactual Curtailment

To predict the DAM prices under counterfactual levels of installed solar or wind capacity, we first need to predict how much solar and wind output would be supplied to the market. Rather than assuming that curtailment would be independent of the installed renewable capacity, we instead allow the curtailment to vary as a function of capacity as well. To do so, we first calculate the daily solar and wind potential capacity factors during 2016. The potential capacity factor is the daily potential output – e.g., the daily observed solar generation plus the daily curtailed solar output – divided by the actual installed capacity. Imposing the assumption that the potential capacity factors are independent of the installed solar and wind capacity, the counterfactual potential generation is simply equal to the product of the daily potential capacity factors and the counterfactual solar or wind capacity. To determine the daily solar or wind generation from the predicted potential generation, we estimate daily curtailment as a function of the daily renewable potential and subtract the predicted curtailment from the potential generation.

To predict curtailment, we estimate the following tobit model:

$$Curtailment_d^* = \alpha_m + \beta_1 \cdot Potential_d^{solar} + \beta_2 \cdot Potential_d^{solar} \cdot Load_d + \boldsymbol{\theta} \cdot \mathbf{X_d} + \varepsilon_d, \quad \text{(A2)}$$

where $Curtailment_d^*$ is a latent variable (described below), $Potential_d^{solar}$ is the potential daily solar production, $Load_d$ is the daily CAISO load, and $\mathbf{X_d}$ is a set of controls including the Henry Hub gas spot price, the lagged measure of precipitation, and the daily CAISO load. Rather than observing the latent variable $Curtailment_d^*$, we observe $Curtailment_d$ which equals $Curtailment_d^*$ if $Curtailment_d^* > 0$ and zero otherwise. By estimating the Tobit model specified by Eq. A2, we allow the level of curtailment to vary not only as a function of the potential renewable output (which varies with renewable capacity), but also with the interaction between renewable potential and load.

Estimates of the Tobit model are made using the observed solar potential and solar curtailments as well as the observed wind potential and wind curtailments. With the resulting coefficient estimates, we are able to predict the counterfactual solar or wind curtailments for different levels of solar and wind potential that would be realized with different levels of installed capacity. Finally, subtracting the resulting predicted daily curtailments from the predicted daily solar or wind potential, we are able to construct the counterfactual daily solar and wind series ($\widetilde{Solar}_d$ and $\widetilde{Wind}_d$).

Table A1: California Generation by Fuel

	Year			
Fuel	2013	2014	2015	2016
Coal	0.4%	0.4%	0.2%	0.2%
Large Hydro	10.2%	6.9%	5.9%	12.3%
Natural Gas	60.6%	61.1%	59.7%	49.9%
Nuclear	8.9%	8.5%	9.4%	9.6%
Oil	0.02%	0.02%	0.03%	0.02%
Petroleum Coke	0.1%	0.1%	0.1%	0.1%
Waste Heat	0.1%	0.1%	0.1%	0.1%
Biomass	3.3%	3.4%	3.2%	3.0%
Geothermal	6.3%	6.1%	6.1%	5.8%
Small Hydro	1.9%	1.4%	1.2%	2.3%
Solar PV	1.9%	4.6%	6.6%	8.7%
Solar Thermal	0.3%	0.8%	1.2%	1.3%
Wind	6.0%	6.6%	6.2%	6.8%

Annual California generation by fuel source is provided by the California Energy Commission (`http://www.energy.ca.gov/almanac/electricity_data`).

Table A2: California Capacity (MW) by Fuel

	Year			
Fuel	2013	2014	2015	2016
Coal	247	139	101	63
Large Hydro	12,155	12,244	12,252	12,252
Natural Gas	47,089	46,190	44,524	42,629
Nuclear	2,393	2,393	2,393	2,393
Oil	325	326	326	326
Petroleum Coke	36	36	36	36
Waste Heat	53	53	53	53
Biomass	1,212	1,296	1,287	1,325
Geothermal	2,703	2,703	2,716	2,694
Small Hydro	1,750	1,749	1,741	1,743
Solar PV	3,102	4,778	6,081	8,619
Solar Thermal	925	1,292	1,249	1,249
Wind	5,785	5,869	5,984	5,644

Annual California capacity by fuel source is provided by the California Energy Commission (`http://www.energy.ca.gov/almanac/electricity_data`).

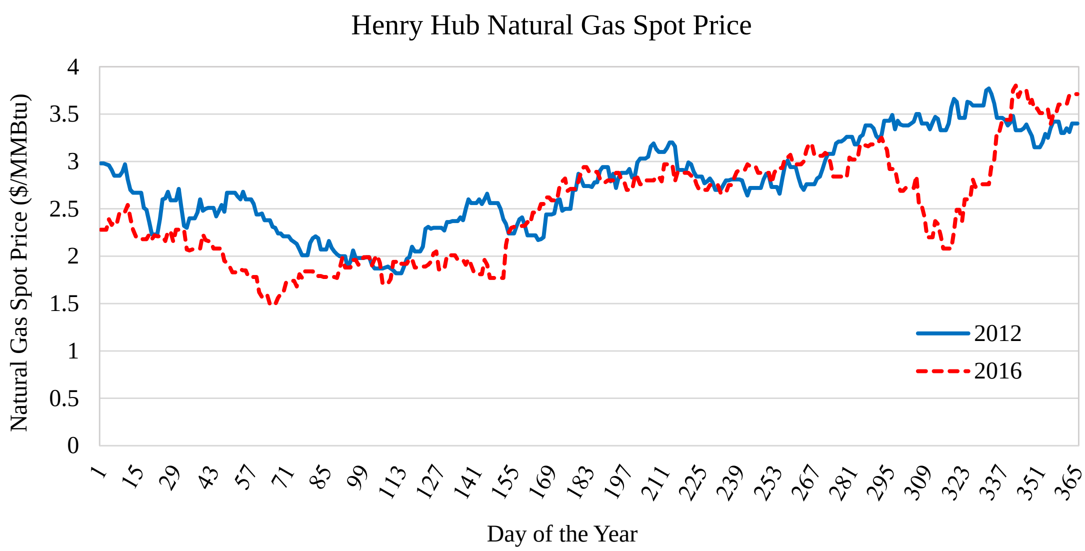


Figure A1: The plot displays the daily Henry Hub spot prices, reported by the U.S. EIA, during 2012 and 2016. To proxy for the daily spot price on weekends and holidays, we use the daily price from the most recent preceding date for which a spot price is reported.

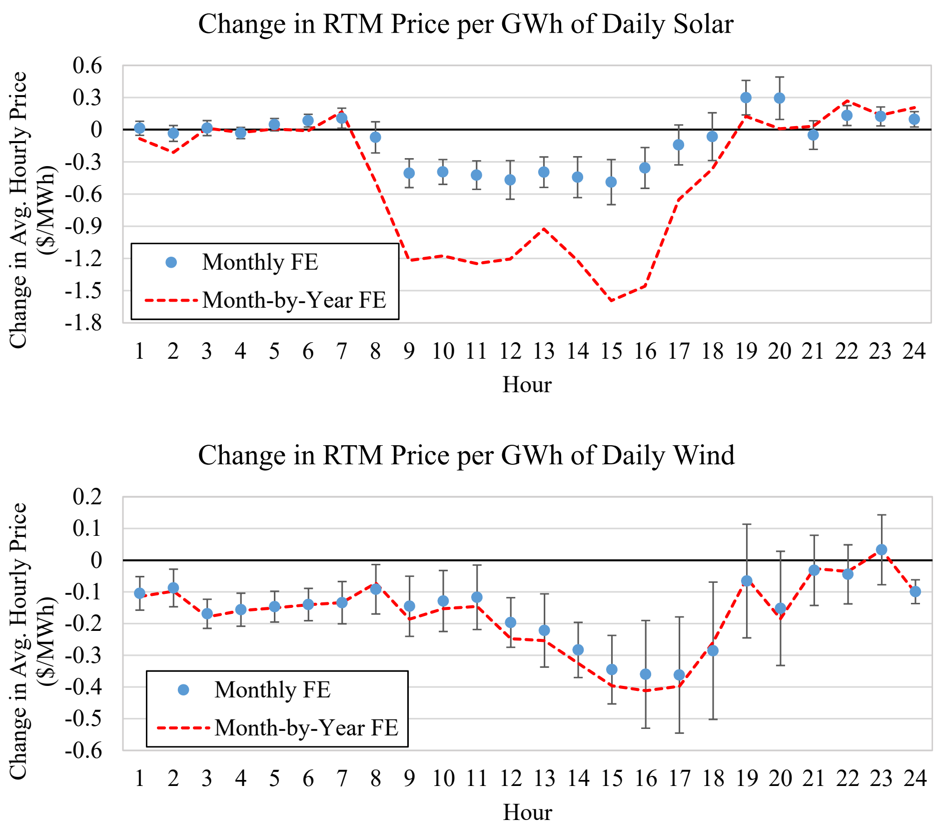


Figure A2: The figure displays the point estimates of the impact of an additional GWh of daily solar or wind output on the hourly average RTM price from two different specificaitons. The first includes hourly fixed effects that are allowed to flexibly vary by month. The second specificaiton includes hourly fixed effects that are allowed to flexibly vary by month-by-year.

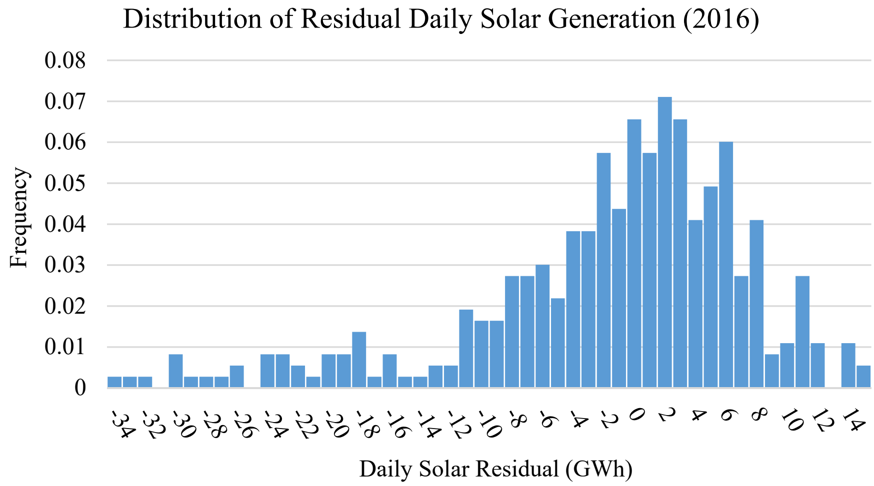


Figure A3: The plot displays the histogram of the residuals from the daily level of solar generation (throughout 2016) regressed on a monthly fixed effect and the daily observed levels of wind generation, CAISO load, and the natural gas spot price.

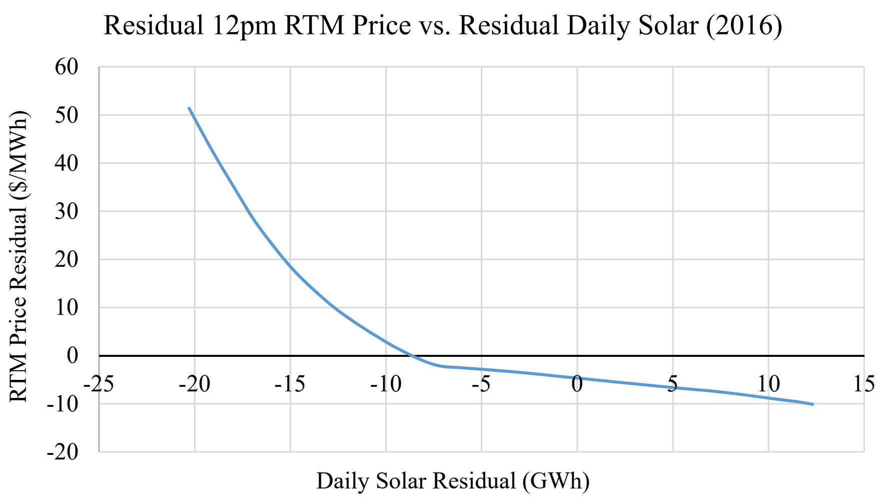
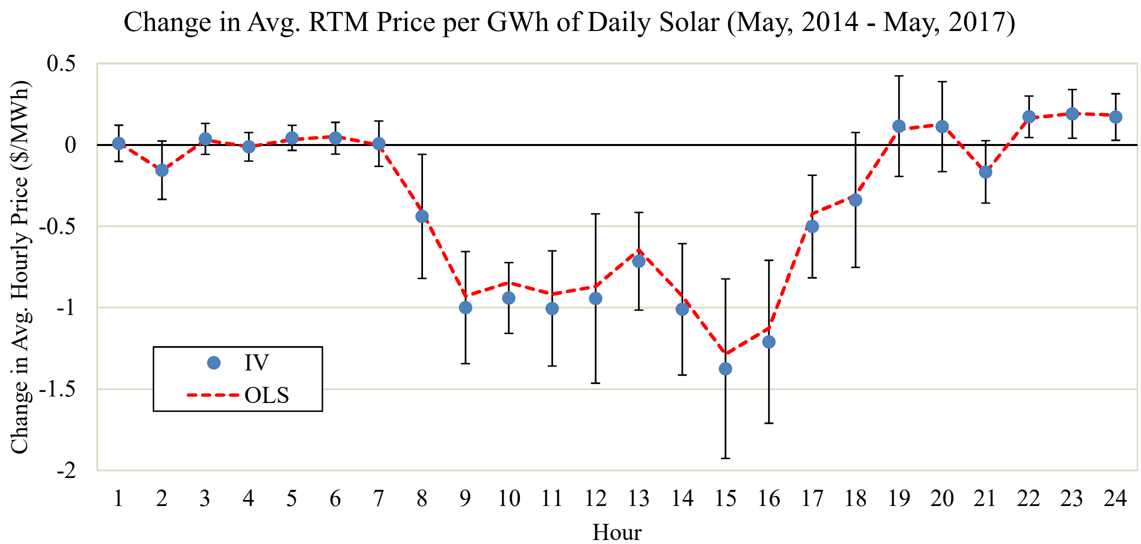


Figure A4: The figure displays a kernel-weighted local polynomial fit to the price and solar output residuals – i.e., the residuals stemming from the daily solar output and the noon hour RTM prices regressed on a monthly fixed effect and the daily observed levels of wind generation, CAISO load, and the natural gas spot price. The plot focuses days with daily solar output up to 20 GWh below the predicted daily level (the 5^{th} percentile) up to days with over 12 GWh more than expected (the 95^{th} percentile).



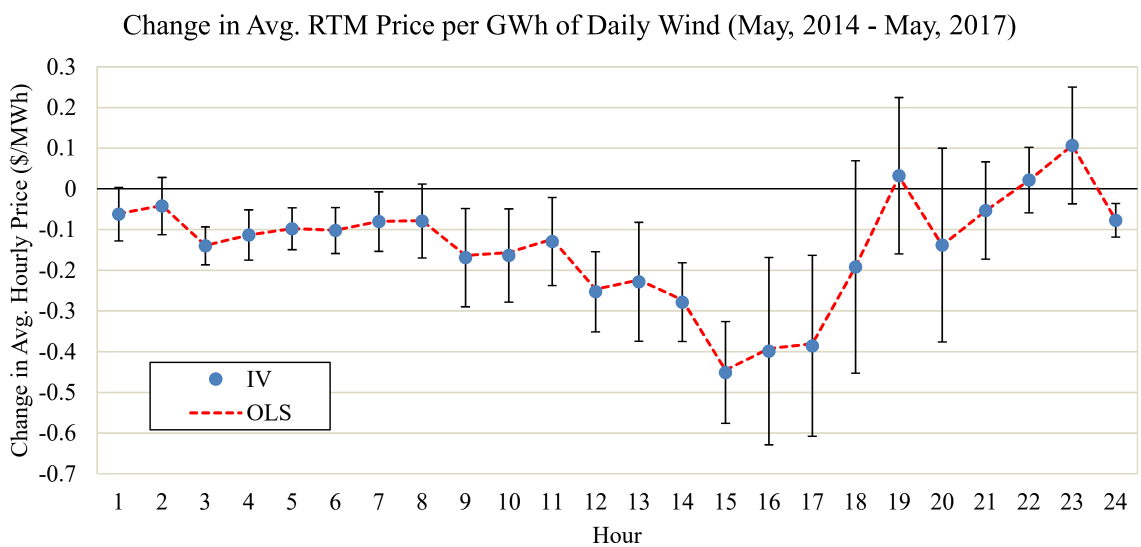


Figure A5: The figure displays the point estimates of the impact of an additional GWh of daily solar or wind output on the hourly average RTM price from two different specificaitons. The blue circles, and the corresponding 95% confidence intervals, represent the estimates from the model using daily potential wind and solar output as excluded instruments. The dashed red line plots the point estimates from the primary OLS model specified in the main text.

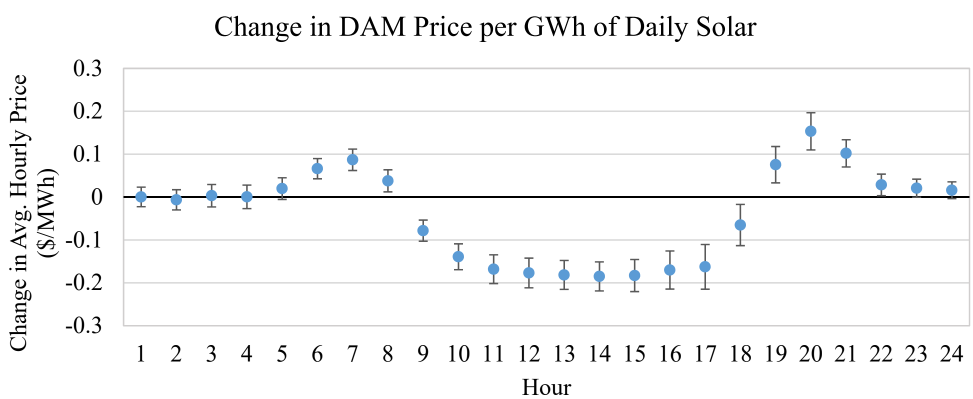


Figure A6: The plot displays the average hourly change in the Day-Ahead Market price for a given hour of the day given a 1 GWh increase in the corresponding daily level of realized solar output.

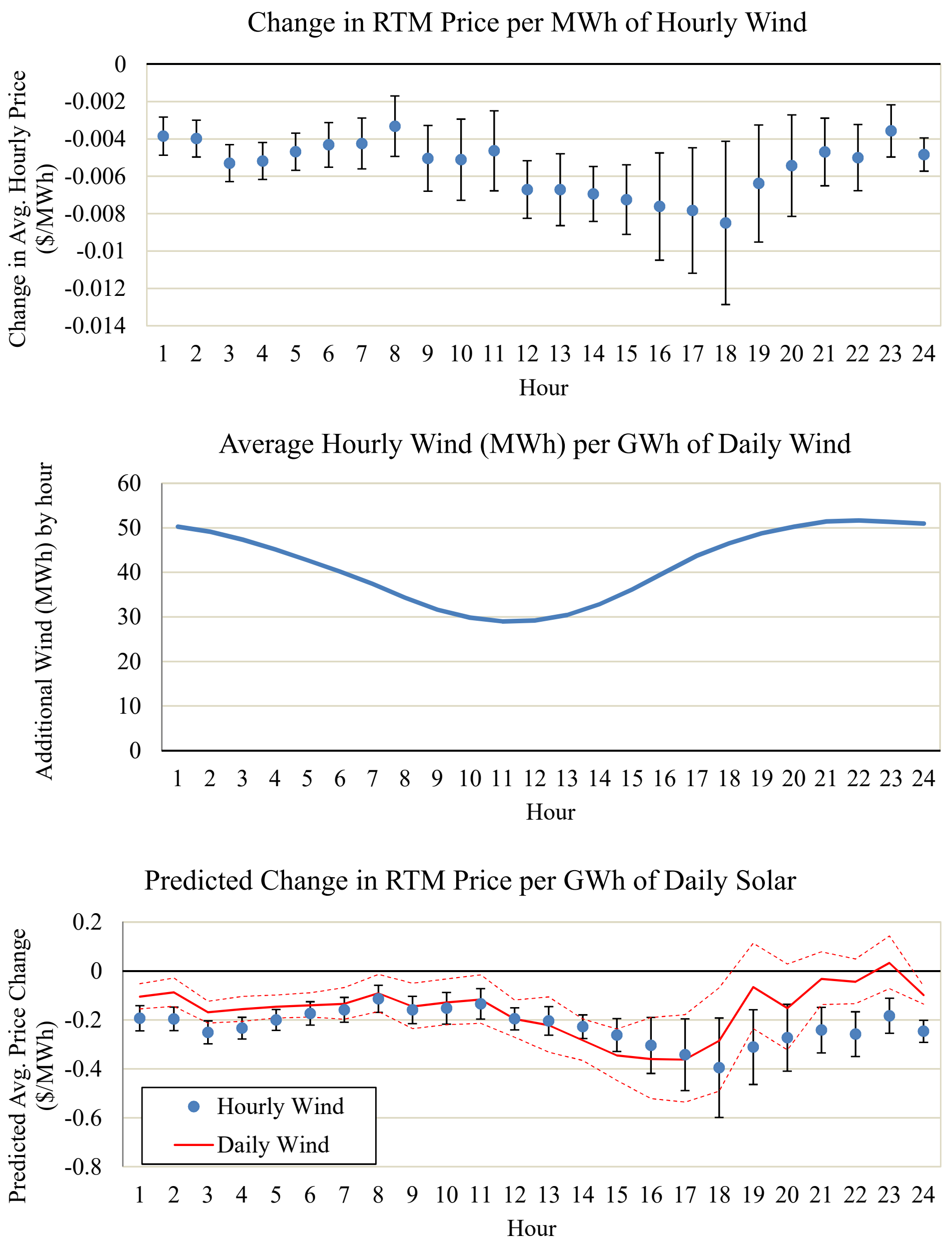


Figure A7: The top panel displays the average change in the hourly RTM price caused by a 1 MWh increase in the level of wind generation during the corresponding hour. The middle panel displays the average increase in wind generation by hour-of-day that would occur with a 1 GWh increase in the aggregate daily wind generaiton. Finally, the bottom panel displays the estimates from the top panel (using hourly wind levels) weighted by the middle panel (the increase in wind generation by hour-of-day) to predict the change in hourly RTM prices caused by a 1 GWh increase in daily wind production.

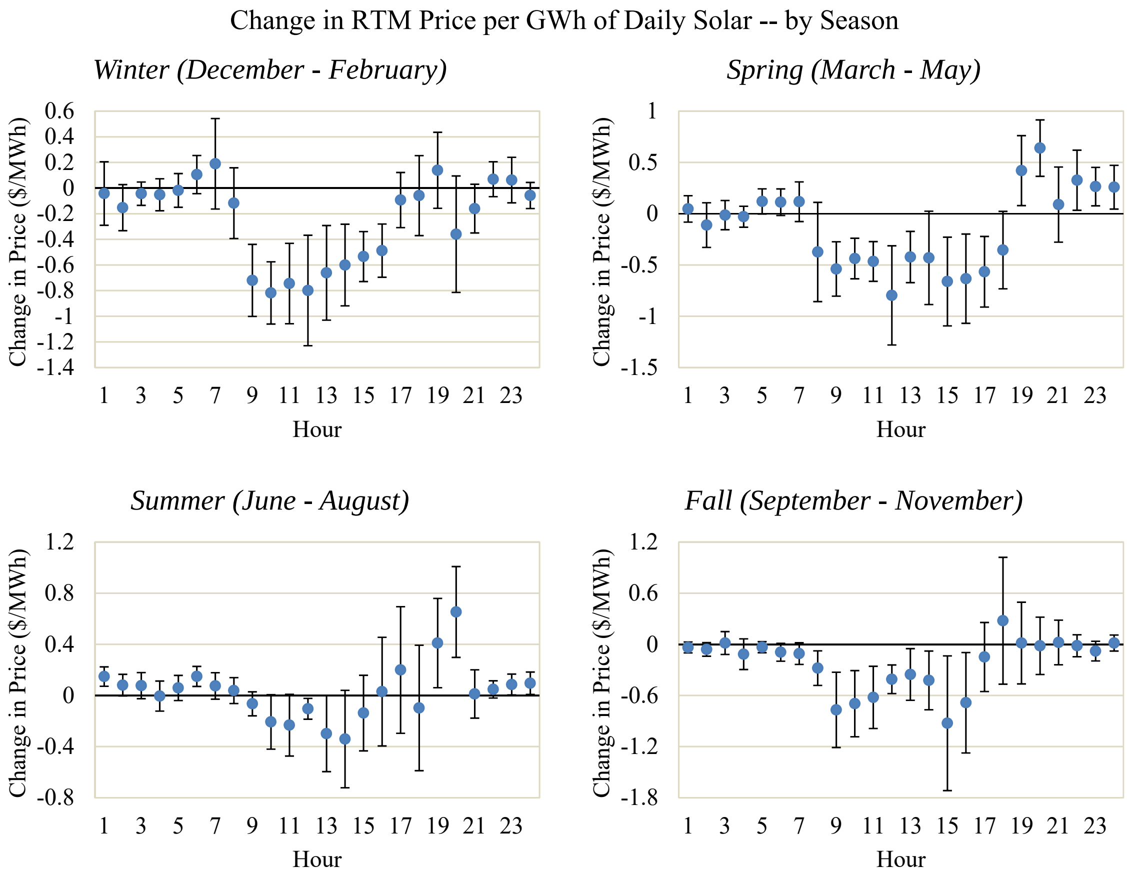


Figure A8: The four panels display the point estimates, and the corresponding 95% confidence intervals, of the average hourly change in the RTM price caused by an additional GWh of daily solar output by season.

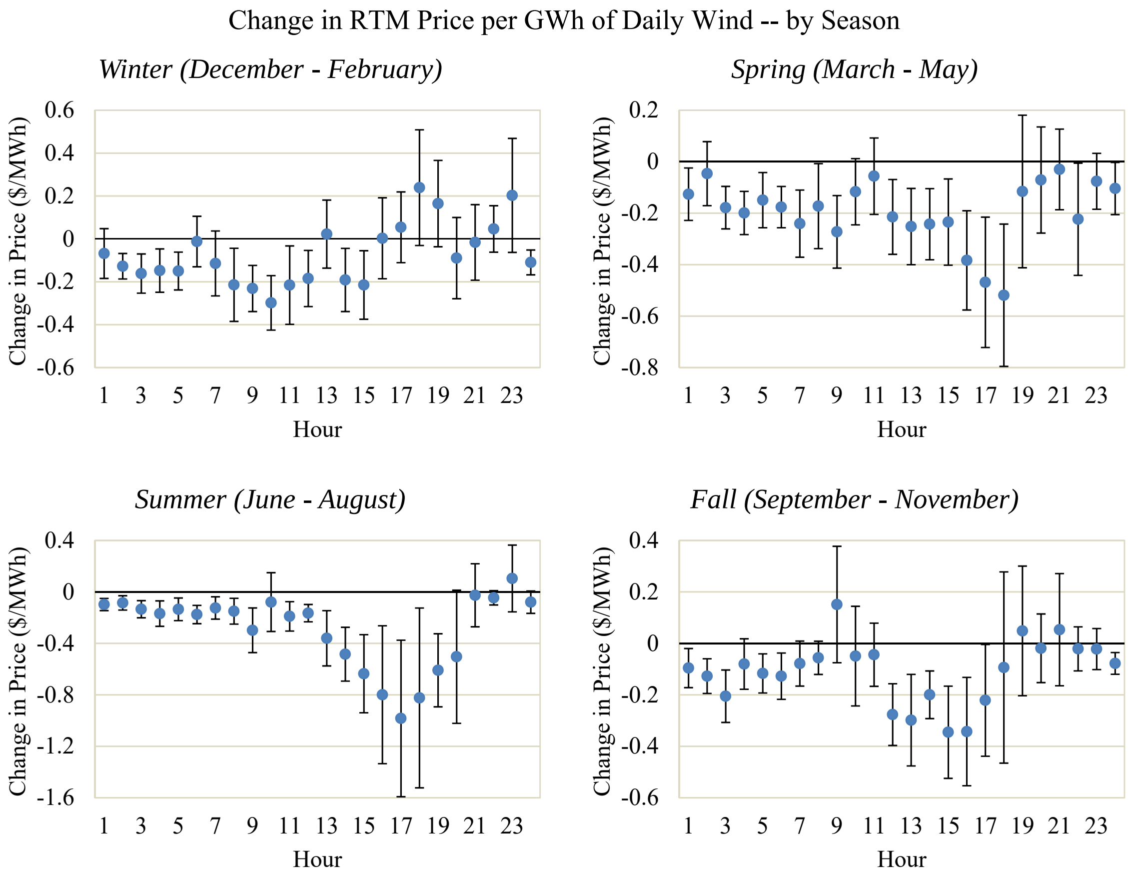


Figure A9: The four panels display the point estimates, and the corresponding 95% confidence intervals, of the average hourly change in the RTM price caused by an additional GWh of daily wind output by season.

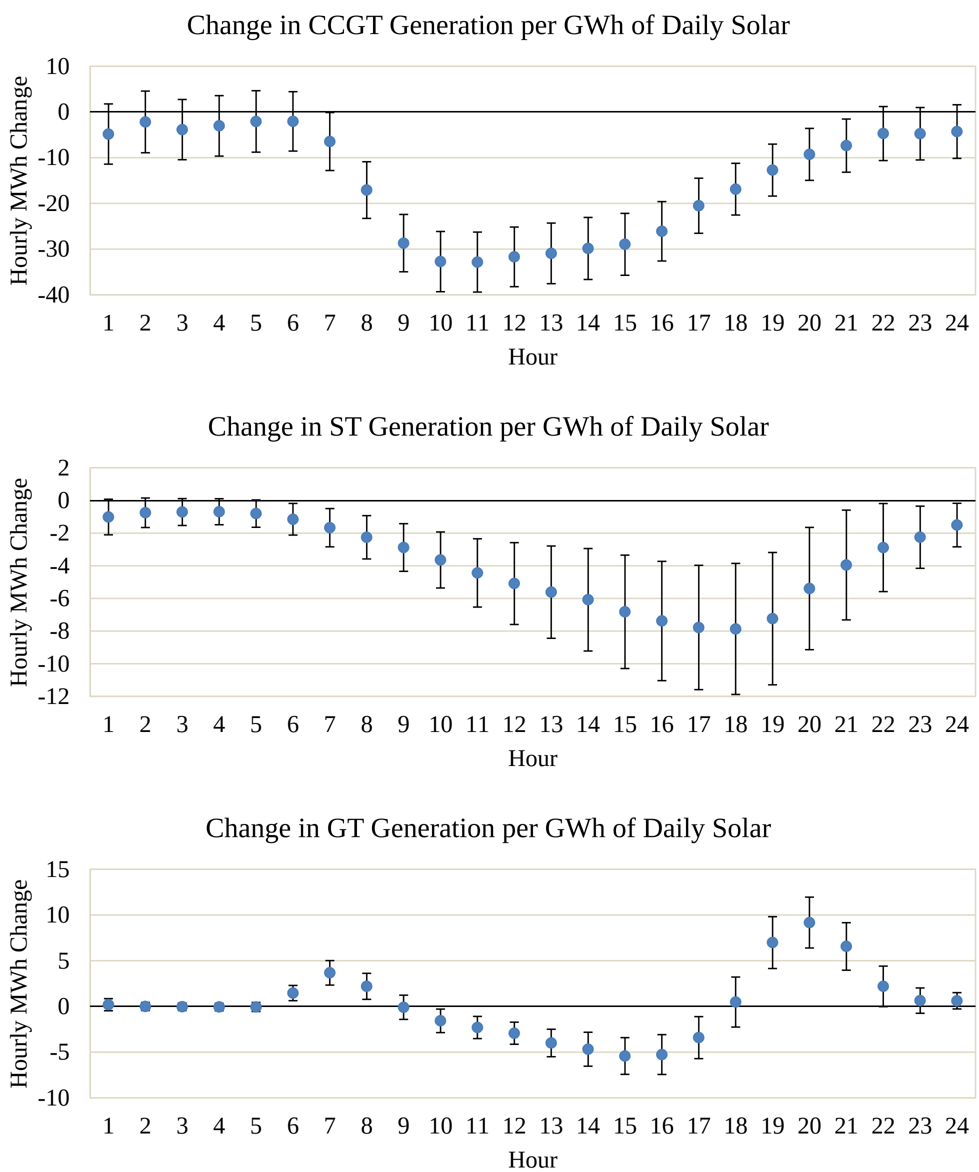


Figure A10: The figures re-plot the point estimates from Figure 5 – the average changes in hourly production from combustion, steam, and gas turbines caused by an additional GWh of daily solar output – along with the corresponding 95% confidence intervals.

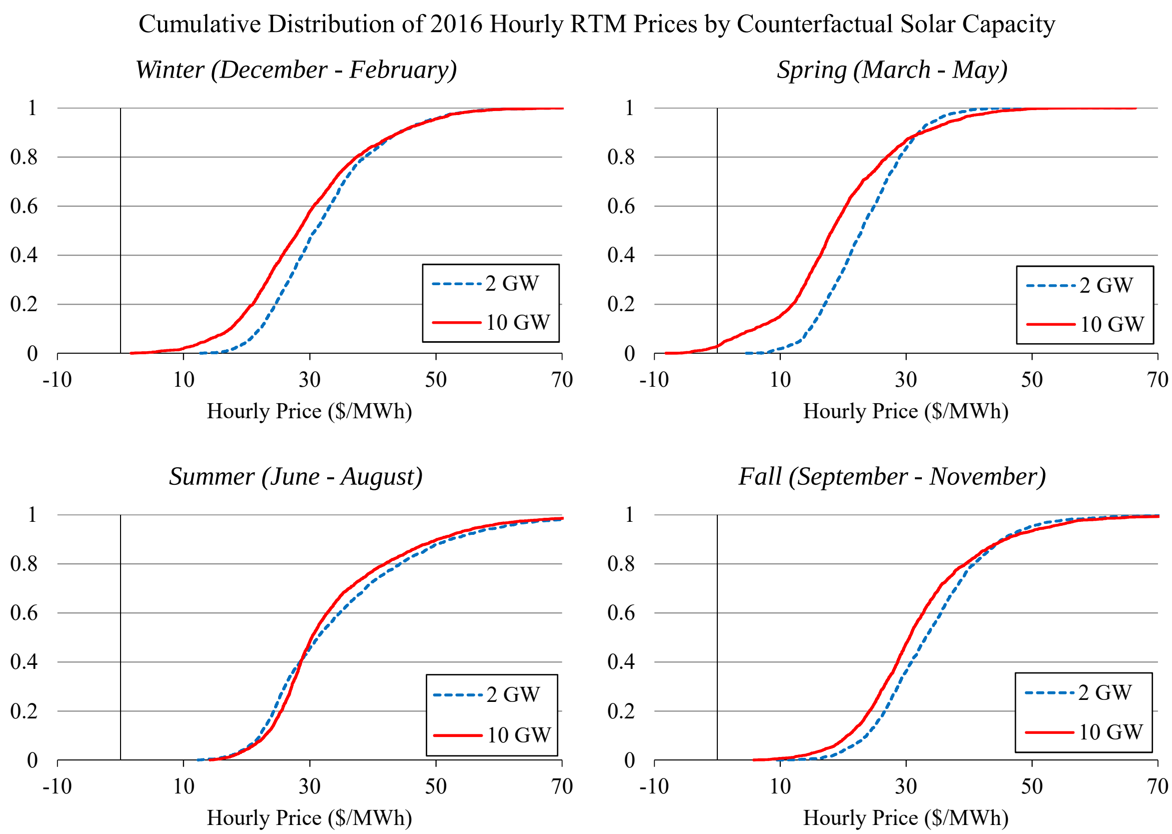
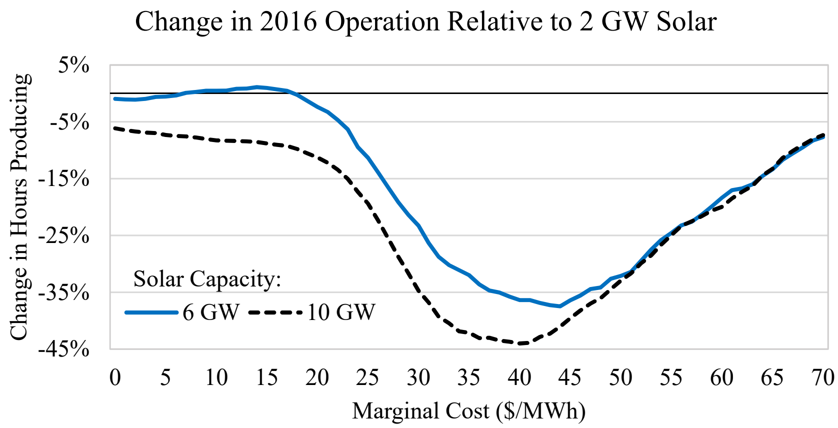


Figure A11: The figures display the cumulative distributions, by season, of the counterfactual 2016 hourly RTM prices under two scenarios: one in which there was 2 GW of solar capacity installed all year and another in which there was 10 GW of solar capacity installed all year.



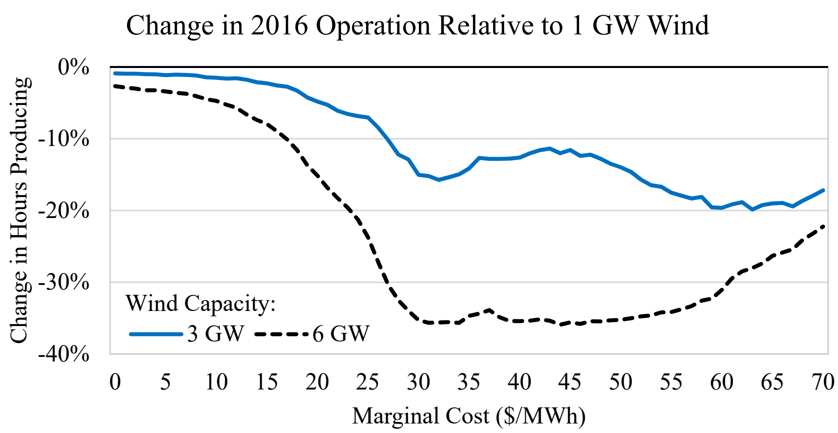


Figure A12: The figures display the percentage change in the number of hours a coventional generator, with a given variable cost, would operate during 2016 for different levels of installed solar or wind capacity. We assume that the conventional unit would operate during any hour in which the predicted price exceeds their constant marginal cost of production.