Setting with the Sun: The impacts of renewable energy on conventional generation.

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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 been on the short-run impacts of expanding renewable supply. In this paper, we shed light on the potential longer run impacts of renewable expansions. Focusing on California's electricity market, we estimate how wholesale electricity prices have responded to a dramatic increase in utility-scale solar capacity. While an overall decline in daily average prices can be attributed to the solar expansion, this reduction in the average price 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 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 CO_2. 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. A growing strand of 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 longer term impacts of such policies. To date, attempts to explore the long-run impacts have been dominated by forward-looking, simulation based approaches.[2]

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. 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 et al. (2013), Novan (2015), Fell and Kaffine (2018), Callaway et al. (2018)). However, as policymakers continue to push for higher 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 industry trend in the last decade has been growing financial distress of the traditional power plants that had previously formed the backbone of US power supply. These plants, primarily coal or nuclear, constitute some of the largest capital investments made by utilities, as well as the largest current sources of employment in the generation sector. Concerns over the financial future of these "baseload" plants has prompted a series of controversial proposals at the state and Federal level.[3] 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

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

[2] Lamont (2008), Bushnell (2010), Linn and McCormack (2018), and Gowrisankaran et al. (2016) explore the long-run impacts of environmental policies and renewable expansions.

[3] The Trump administration has pursued several policies aimed at supporting baseload generation (Plummer, 2018). New York and Illinois have implemented credit systems designed to support nuclear(NEI, 2018). Efforts by Ohio to support coal generation (DiSavino, 2019) have been ongoing but unsuccessful thus far.

these proposals has been the assumption that power markets will continue to depend upon baseload sources and that power markets as they are currently constituted are incapable of unlocking the implicit value these plants provide.[4]

This paper examines how expansions in renewable capacity affect wholesale electricity prices and, as a result, the potential operating margins 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 et al., 2008). However, we present evidence that growth in renewable capacity does not uniformly decrease prices across all hours of the day. In particular, we find that, 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 produced by renewables.[5] During 2016, 10% of the 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 recently – capacity increased from 0.6 GW in 2012 to over 10 GW by 2017. The rapid growth in solar capacity makes the CAISO market an excellent setting to explore the impacts of renewable capacity expansions.

To understand why solar growth has had heterogeneous impacts on wholesale prices across different periods of the day, we examine the short-run substitution pattern between solar and non-renewable generation. During the daylight hours when solar generation is being supplied, there are large reductions in output from natural gas generators in California as well as reductions in electricity imports into the state. We find that these reductions in conventional generation have resulted not only in meaningful reductions in midday wholesale prices in both the real-time and day-ahead markets, but also sizable reductions in CO_2 and NO_X emissions from the region. At the same time, we find that the growth in solar production has driven an increase in generation from flexible, high marginal cost natural gas turbines during the early morning hours – prior to the morning ramp up in solar output – and during the early evening hours – following the daily ramp down in solar. While the aggregate output from natural gas turbines has remained largely unchanged, the increased early morning and early

[4]The environmental attributes of different generation sources, of course, provide part of the rationale 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.

[5]As of May, 2017, California had 5.7 GW of wind capacity – the third most behind only Texas and Iowa. In terms of utility-scale solar capacity, California leads the nation. Over 10 GW of solar capacity had been installed – 43% of the total utility-scale solar installed in the U.S.

evening production from the high marginal cost generators correspond precisely with the hours in which prices in the real-time and day-ahead markets have increased.

Using our estimates of the response of the wholesale price to renewable growth, we explore how the operating profits earned by conventional technologies may be affected by renewable capacity expansions. Our estimates suggest that, over the observed range of solar capacity in California, expansions in solar continually decrease the operating profits low marginal cost conventional generators can earn in the real-time and day-ahead markets. In contrast, higher marginal cost generators may begin to experience constant, or even slightly increasing, operating profits in the real-time and day-ahead markets. There are two important caveats that must be stressed. First, while we are able to estimate how revenues earned through the real-time and day-ahead markets may be affected by growth in solar capacity, we are not able to estimate the impact solar expansions have on the revenue earned through bilateral contracts. Nonetheless, given that we expect bilateral contracts to adjust over time to reflect the market value of energy revealed in the daily wholesale markets, it is reasonable to assume that the profits earned through bilateral contracts will change in a similar pattern. Second, we do not explore how revenues earned through capacity and ancillary service markets are affected by solar expansions. However, given that upwards of 90% of the revenue earned by generators in the CAISO market comes from the sale of energy, our analysis is able to provide insights into how the main source of profits are being affected by solar expansions.[6]

Ultimately, firms' incentives to invest in, or retire, generation capacity are driven by the future profits. Therefore, by exploring how operating 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. In the case of California, our estimates suggest that, absent increases in demand response or storage, over the long-run less fuel-efficient, and thus dirtier, conventional generators may comprise a growing share of the remaining stock of thermal generation. This contrasts with other regions, where the reduced profits of baseload generation could accelerate the retirement of coal-plants, thereby reducing the average emission intensity of the remaining conventional generation stock.

Moreover, we are able to explore how the value of renewable capacity investments vary with the level of renewable penetration. Using our estimates of the real-time market price changes caused by growth in solar, we find that the market value of power generated by the tenth gigawatt of California's grid-level solar capacity is less than half of the market value

[6]CAISO (2019) estimates that, during 2018, $156 million was paid to generators through the CAISO capacity market and $189 million was paid to generators providing ancillary services. Combined, the payments in the capacity and ancillary service markets account for 3.2% of the estimated total cost ($10.8 billion) of serving load in CAISO. Similarly, Borenstein and Bushnell (2018) find that approximately 90% of wholesale cost of serving load in CAISO during 2015 was made up by the energy costs.

of power generated by the second gigawatt of capacity.[7] This finding highlights a potential concern inherent with policies that subsidize the production of renewable output regardless of where or when that output is produced.Specifically, renewable portfolio standards, investment, and production tax credits can incentivize investment in renewable capacity that may not be the most cost-effective way to address climate change or other environmental goals.[8]

Finally, this paper contributes a methodological point that has 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 various outcomes (e.g., prices, generation, emissions) has been to utilize a large degree of fixed effects (e.g., annual, seasonal, hourly) to control for confounding trends and isolate the impact of the variables of interest (e.g. wind or solar output). We highlight that this approach, while appropriate for identifying the impacts of short-run, weather-driven variation in renewable output, can be misleading when trying to identify longer-run impacts caused by growth in renewable capacity.

In section two we review the policies influencing the economics of 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 present our results uncovering how wholesale prices and emissions have been affected by growth in renewable capacity. Section six explores how the resulting wholesale price changes have impacted the operating profits earned by conventional generators and section seven summarizes our conclusions.

2 Background and Previous Literature

A combination of state-level mandates and federal tax credits have driven a surge in U.S. renewable capacity.[9] Utility-scale solar and wind farms, which produced less than 0.7% of total U.S. electricity in 2006, accounted for nearly 7% of output in 2015. While California had

[7]The incidence of this reduced value, reflected in lower energy prices, largely falls upon the utilities and other buyers of renewable energy, rather than renewable producers themselves. Renewable energy is mostly procured under fixed price long-term power purchase agreements, making the buyers of this energy the residual claimants to the spot market value of that energy.

[8]In the case of RPSs and production tax credits, the credits are accrued on a per-MWh basis. Among other issues, production-based subsidies are seen as contributing to the phenomenon of negative electricity prices since plants prefer to keep running as long as the subsidy magnitude exceeds the level of the negative price. This is one reason why curtailment is controversial.

[9]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).

a substantial amount of renewable generation before 2000 distributed between geothermal, biomass, and wind generation, the growth since 2011 has been dominated by utilty-scale solar photovoltaic (PV) capacity.[10] California's renewable portfolio will continue to expand under recent legislation that mandates 60% of electricity come from renewable sources by the year 2030, and 100% by 2045. With ambitious renewable mandates being passed in many states, the growth in renewables across the US shows no signs of slowing.[11] 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 U.S.

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 two approaches to this question. Within the economics literature, simulation studies explore the long-run response to renewable capacity growth (Lamont (2008), Bushnell (2010), Fell and Linn (2013), Gowrisankaran et al. (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.[12]

A second strand of literature, and the one the present paper extends, applies econometric approaches to high frequency electricity markets data.[13] Specifically, these studies identify how variation in the daily, or within-day, level of renewable output affects the wholesale price. Several studies use the same general strategy to identify the short-run impact of wind generation on emissions (Cullen (2013), Kaffine et al. (2013), and Novan (2015)) as well as the impact of wind on coal-fired generation (Fell and Kaffine (2018)). However, three key features differentiate our analysis from these previous empirical studies.

First, we exploit different variation in renewable generation. Over our sample period, daily CAISO renewable output, and particularly solar, steadily increased as capacity grew. Rather than controlling for the trend in renewable output, we use this variation in output across years to identify the impact on prices. In contrast, the previous studies sweep away capacity-driven changes in renewable production and instead rely on short-run, largely

[10]Figure A1 illustrates the growth in renewable energy production in California since 2000.

[11]Of the 104 GW of net capacity additions planned for 2019 through 2023, over half (56 GW) comes from planned solar and wind additions. Planned capacity additions by fuel source are provided by the EIA.

[12]Examining the long-run impacts of low natural gas prices on electricity generation and investment, Linn and McCormack (2018) demonstrate the importance of dynamic constraints faced by fossil fuel generators.

[13]Würzburg et al. (2013) provides a recent overview of the empirical merit-order effect studies. We discuss this literature in greater detail in the following Section.

weather-driven, fluctuations in renewable output.[14] 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 seasons. This allows us to predict how renewable expansions affect the operating profits of conventional generators that operate during a subset of hours, when the price exceeds their marginal cost. Third, we do not assume that the wholesale price can only respond to the contemporaneous level of renewable output. This proves to be 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. While our focus is on large, utility-scale generation whose production is sold directly into wholesale markets, much of the attention solar 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. 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.[15]

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). The upper left panel of Figure 1 plots the average load in the CAISO market by hour-of-day during 2012 and 2016. The load reported by CAISO measures the total quantity of electricity consumed minus any distributed generation. 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, there has been a clear decrease in load during the sunny, daytime hours. This difference peaks at an average of 1,479 MWh between noon and 1pm, specifically when the average generation from the

[14]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.

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

distributed solar capacity would reach its maximum daily output.

While distributed solar capacity growth has reduced the midday load in the CAISO market, recent growth in utility-scale solar generation capacity has dwarfed distributed solar production. At the beginning of 2012, California had 0.6 GW of utility-scale solar capacity. By April, 2017, over 10 GW of utility-scale solar capacity was installed.[16] In contrast to output from distributed sources, data on utility-scale generation is publicly available. We use data provided by CAISO that reports the hourly aggregate generation by technology, which includes aggregate hourly utility-scale solar and wind production. The top right panel of Figure 1 displays the average generation from utility-scale solar 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. To explore how output from renewable 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 emissions at nearly every fossil fuel unit and EIA 923 data which provides the monthly net generation and fuel consumed by fossil fuel generators.

3.1 Real-Time Market Electricity Prices

The primary objective of our empirical analysis is to uncover how growth in utility-scale solar capacity impacts wholesale electricity prices. For the sake of comparison, we also present estimates of the impact of wind growth on wholesale prices.[17] Using the estimates of the wholesale price responses to solar and wind, we explore how growth in renewable capacity affects the operating profits earned by a variety of generating technologies.

There are two relevant wholesale market prices: the real-time market (RTM) price and the day-ahead market (DAM) price.[18] While we expect prices in the RTM and DAM to respond similarly to growth in solar and wind, the DAM responses would be driven by changes in market participants' expectations of the day-ahead solar and wind output, not the actual realizations of daily solar and wind production. Given that we do not observe measures of market participants' expectations of future solar and wind production, we focus primarily on how RTM prices respond to realized solar and wind output. In Appendix 2.2, we demonstrate that growth in solar generation has driven the same pattern of price changes in the day-ahead market (DAM).[19] Rather than exploring how the price impacts may vary

[16]Over the same time period, California's wind capacity has grown much more modestly, growing from 4 GW at the beginning of 2012 to 5.7 GW at the end of 2016.

[17]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 out-of-sample extrapolation.

[18]Roughly 90 to 95 percent of power is scheduled through the DAM and the remainder through the RTM.

[19]Growth in solar has caused RTM and DAM prices to decline midday and increase during the shoulder

across locations within the CAISO market, we focus on estimating how the average hourly, CAISO-wide RTM price responds to renewables.[20]

To provide initial evidence for how RTM prices have responded to growth in solar capacity, the bottom left panel of Figure 1 plots the average RTM price by hour-of-day during 2012 and 2016.[21] Two patterns emerge. First, during the midday hours, which have seen dramatic growth in solar, the average hourly prices were lower in 2016 relative to 2012. Second, during the hours without solar production (6pm through 7am), the average RTM prices increased between 2012 and 2016. Of course, changes in other determinants of prices could be contributing to the observed price differences. To quantify the effect of renewables on 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.[22] However, three features of our empirical analysis differentiate it from the existing studies. First, while the 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.[23] If our objective was to predict how renewable growth affects the revenue earned exclusively by baseload units operating at 100% capacity every hour, it would be sufficient to uncover the time-weighted average price change. However, few generators produce at full capacity all the time. To explore how renewable 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.

hours. However, the estimates of the DAM price changes are attenuated towards zero. This attenuation is likely due to measurement error bias. The realized solar and wind output is a noisy measure of market participants' day-ahead expectations for renewable output. By using the realized solar and wind as proxies for the day-ahead forecasts, we expect our estimated DAM price changes will be biased towards zero.

[20]CAISO reports the hourly RTM price across four Default Load Aggregation Points (DLAP). We take the unweighted average across the DLAPs. 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 price. As a result, the correlation between the hourly average prices in any two DLAPs never falls below 0.92.

[21]Figure A2 displays the median hourly RTM prices during 2012 and 2016. The median profile is smoother and lower than the average prices due to the fact that there is a long, right tail in the RTM distribution.

[22]Numerous studies provide evidence that renewable generation reduces wholesale prices across many different markets. For example, Gelabert et al. (2011) focus on the Spanish market; O'Mahoney and Denny (2011) study the impact of wind in Ireland; Würzburg et al. (2013) and Ketterer (2014) focus on the German market; Forrest and MacGill (2013), Cludius et al. (2014) study the Australian market; Clò et al. (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.

[23]One notable exception is Jónsson et al. (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.

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.[24] 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.[25] 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 1 suggests that solar growth has potentially increased prices during non-daylight hours – a finding which is supported by our subsequent empirical results.

The third difference between our analysis and the previous empirical studies stems from the fact that we exploit different variation in renewable output. 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 renewable output could potentially differ, it is helpful to be very specific about the different sources of temporal variation in renewable generation.[26] First, due primarily to variation in weather conditions, there will be seasonal and day-to-day variation in daily solar and wind output. In addition, in the case of solar in our sample period, there is also a steady upward trend driven by growth in solar capacity.

[24]In the case of solar output, very little information is lost using daily output as opposed to hourly output. From January 1, 2013 through May 31, 2017, the correlations between the daily aggregate solar and the hour-specific solar levels are all above 0.89 for 9am through 5pm – which account for over 90% of solar output. Given that the within-day wind pattern is less regular than solar, the correlation between the daily wind output and the hourly output is not as consistently high. The 24 correlation coefficients between the daily wind output and the hour-specific output oscillates between 0.81 and 0.94. For 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.

[25]An alternative strategy to estimate how average daily, or within-day, 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 et al. (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.

[26]Figure A3 displays the daily solar and wind production from January 1, 2013 through May 31, 2017.

To identify how the daily level of solar and wind output affects the wholesale price, our analysis, as well as the previous studies, relies 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).[27] 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, weather conditions 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, the steady increase in solar output. Previous studies do not exploit this longer-run variation in renewable output. Instead, they 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 explanatory variable. 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: 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

[27] 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.

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 grew over our 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 demand or supply. Controlling for demand-driven price trends is straightforward – we simply include the hourly CAISO load as a control.[28] The inclusion of the hourly load also controls for weather-driven demand shifts that could be correlated with renewable production. In addition, because the measure of load is equal to the quantity demanded less behind-the-meter, distributed generation, this will also control for shifts in output from distributed solar. 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.[29] To control for this, we include the daily Henry Hub spot price in our model.[30] Second, wholesale price trends could be driven by patterns in hydroelectric output.[31] Given that hydroelectric generation can respond to renewable output, we cannot directly control for hydroelectric production. Instead, we use a measure of monthly hydroelectric potential. Assuming these set of controls account for any non-renewable driven trends in wholesale prices from 2013 through mid-2017, we can conclude that our estimates of wholesale price response to renewable output are not biased by a spurious relationship.

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

[29]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 imports into the State. During our sample period, the Western Energy Imbalance Market (EIM) was introduced to reduce barrier to real-time trade between California and the remaining Western Interconnection. While we do not directly control for the EIM introduction, we test the robustness of our findings during the pre- and post-EIM periods.

[30]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 reporting date.

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

4 Real-Time Market Price Changes

In this section we estimate the impacts of renewable expansions 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 shifts in demand and supply, we include monthly fixed effects, the daily Henry Hub natural gas spot price ($Spot_d$), and vector $\mathbf{X_{h,d}}$ which includes two additional controls – the hourly CAISO load and a proxy for hydroelectric potential.[32] Recall, the hourly load measures the total quantity of electricity consumed minus behind-the-meter distributed generation. Therefore, its inclusion will control for changes in residential solar production.

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 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 RTM price during hour h. 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.

A key assumption used to identify the parameters specified in Eq. 1 is that daily wind and solar output varies exogenously with respect to the RTM price. There are two threats to this assumption. First, in the long-run, 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 RTM prices (e.g., fuel prices, demand). Moreover, the growth in renewable capacity over our sample period may

[32]The proxy for hydro potential is a measure of the aggregate, state-level precipitation over the preceding twelve months. During 2015, the peak of the State's most recent drought, large hydroelectric 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 precipitation measured in the seven climate-divisions. 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.

be entirely driven by policies (i.e. California's RPS) as opposed to market forces.

The more serious threat to our exogeneity assumption is the fact that renewable output can be curtailed. Curtailments occur to reduce system-wide oversupply or to mitigate grid congestion. From CAISO, we observe wind and solar curtailments 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.[33] It is certainly possible that the timing and level of curtailments are correlated with prices. For example, during periods of low demand, and low RTM prices, the grid operator may curtail solar output in order to prevent oversupply. In this case, our estimate of the negative relationship between solar output and prices would be biased towards zero. In Appendix 2.1, 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 effect on the estimates of the price changes.

4.1 Average Change in Hourly Prices

The top panel of Figure 2 displays the 24 point estimates, and 95% confidence intervals, 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.[34] The estimates reveal that, from 9am through 4pm, the hours which account for 83% of solar output, increases in daily solar generation result in significant reductions in the RTM price.[35] For example, during the 1pm hour, the RTM price falls an average of \$0.39/MWh for each additional GWh of daily solar production. To get a sense of this magnitude, the average daily utility-scale CAISO solar generation was 5.5 GWh during 2012 and 56.8 GWh during 2016 – an increase of 51.3 GWh. Multiplying the estimate of $\hat{\beta}_{1pm}^s = -0.39$ by the change in average daily solar suggests that the growth in solar reduced the average 1pm RTM price in 2016 by \$19.98/MWh relative to 2012. Referring back to the top left panel of Figure 1, the average RTM price during the 1pm hour of 2016 was \$22.68/MWh and \$39.23/MWh during 2012 – a decline of \$16.55/MWh.

The top panel of Figure 2 also highlights that an increase in the daily level of solar generation results in significant increases in the average RTM prices during the 6am and 7am

[33]These curtailments represent 1.19% and 0.42% of the actual daily solar and wind generation, respectively.

[34]In Appendix 2.2, we demonstrate that growth in solar caused the DAM prices to change in the same pattern as the RTM prices. Figure A14 presents the estimates of the average change in hourly DAM prices.

[35]Recall, the RTM price is comprised of the marginal energy price, the marginal loss price, and the marginal congestion price. Figure A4 displays the 24 point estimates of β_h^s from Eq. 1 using only the marginal energy price as the dependent variable. The plot highlights that almost all of the resulting changes in the RTM price stem from changs in the marginal energy price – not from changes in the loss or congestion components.

hours and during the 7pm and 8pm hours.[36] 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 solar production pushed the average 7pm RTM price up by \$15.30/MWh.[37] Overall, taking the simple average across all hours of the day, the results from the top panel of Figure 2 reveal that the average RTM price decreases by \$0.10/MWh in response to a 1 GWh increase in daily solar production.

For comparison, the bottom panels of Figure 2 display estimates of the average change in the hourly RTM prices caused by a 1 GWh increase in daily wind generation and a \$1/MMBtu increase in the Henry Hub spot price. The fuel efficiency of natural gas units 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 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 RTM prices increase by approximately \$7/MWh during low demand hours (e.g., 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 RTM prices increases closer to \$11/MWh – precisely the pattern displayed in the bottom panel of Figure 2.

The estimates of the RTM price changes caused by changes in the natural gas spot price also provide a way to highlight the magnitude of the impacts of renewable production. Recall, our estimates suggest that growth in utility-scale solar between 2012 and 2016 increased the average 7pm RTM price 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 – a 46% increase relative to the average spot price (\$3.28/MMbtu) over our sample period.

4.2 Substitution Between Renewables and Other Sources

Using the same empirical strategy, we explore how solar output affects production from other sources. Examining these substitution patterns allows us to test whether our estimation strategy is uncovering the impact of solar as well as to understand why growth in solar output is pushing wholesale prices up during the non-daylight hours.

[36]Re-estimating the model only using data before December 2015, prior to NV Energy joining the 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.

[37]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 A5) 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.

To estimate how an increase in daily solar generation affects hourly production from other sources, we re-estimate 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' renewable sources in CAISO, 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 7% of output from Januarly 2012 through May 2017. Among the other renewables, 55% is from geothermal, 19% from biomass, 11% from biogas, and 15% from small scale hydroelectric. To examine how output from these 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 3 displays the estimates of the average changes in the quantity of electricity supplied during each hour of the day in response to a 1 GWh increase daily 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. Output from nuclear generators and other renewables are not meaningfully affected by increases in solar output. Consistent with the previous finding that growth in solar affects prices outside of the daylight hours, 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.[38]

The estimates from the top panel of Figure 3 reveal that, on average, an additional GWh of daily solar increases daily generation from large hydro sources by 26.6 MWh. Consequently, for each GWh of solar supplied on a given day, conventional generation must increase by 26.6 MWhs on different days. Because this change in conventional generation could be distributed across many days, and even seasons, the resulting impacts on the marginal cost, and therefore prices, on any given day will be trivially small. However, aggregating over time, the non-contemporaneous change in conventional generation will result in meaningfully changes in total generation costs. In the subsequent section, we account for these dynamic spillovers when estimating the impact of solar on emissions.

[38]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 2. Effectively, storable energy is being used to supply electricity during the overnight hours when increases in solar output are pushing the wholesale prices up.

The results in the top panel of Figure 3 provide two tests for 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 supplied by all other sources by an average of 0.998 GWh/day, which does not differ significantly from 1 GWh.[39] Second, given that no solar output occurs 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, other renewables, and imports during each separate hour of the day between 8pm through 6am, we find no significant changes in aggregate output during these hours.

4.3 Why Does Solar Increase Prices During Some Hours?

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 natural gas units in the CAISO region, there are three technologies: combined cycle gas turbines (CCGT), gas turbines (GT), and steam turbines (ST). For nearly all of the gas units in the CAISO market, the U.S. EPA uses Continuous Emissions Monitoring Systems (CEMS) to record the hourly gross electricity generation (MWh), fuel input, and emissions.[40] Table 2 summarizes the heat rates as well as the CO_2 and NO_X emission rates for the three types of natural gas generating units in the CAISO market (CCGT, GT, and ST). The CCGT units have the lowest heat rates and emission rates. Compared to the CCGT units, the GT units have heat rates that are approximately 43% higher. Given that fuel costs account

[39]Figure A6 displays the corresponding estimates for a 1 GWh increase in daily wind generation. 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.

[40]The gross generation reported by the CEMS data includes electricity consumed at the plant and, for many combined cycle natural gas units, 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.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.

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. They have relatively high fixed start-up costs, increase their production relatively slowly, and become very inefficient when run at low levels of output. By contrast, combustion gas 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 GTs would be a complementary technology to renewable variable energy resources.

To determine how output from the various technologies is impacted by solar generation, we re-estimate 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. The bottom panel of Figure 3 presents the estimates of the average change in net generation by technology for each hour of the day.[41] The results follow closely with the estimates of the aggregate hourly changes in CAISO thermal generation from the top panel of Figure 3. 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.

A key insight emerges from the estimates displayed in the bottom panel of Figure 3. During the early morning (6am-8am) and evening hours (7pm-9pm), there are significant increases in generation from the less fuel efficient GT units. These are the same six hours where we found that increases in daily solar generation increase wholesale electricity prices. These results provide strong support for the conclusion that the wholesale price increases during these hours 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.

5 Impacts on Emissions

This section uses the empirical approach employed in the previous section to identify how growth in solar output has affected emissions.[42] To accurately estimate the emissions avoided

[41]Figure A17 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.

[42]It is important to keep in mind that California has capped the emissions of CO_2 from the electric and other sectors. Consequently, the subsequent estimates of changes in CO_2 emissions do not necessarily represent real, long-run changes in aggregate CO_2. At first glance, therefore, it might appear that reductions in CO_2 due to renewable generation would be offset by increases in other sectors facilitated by the extra room under the cap. However, the California carbon market also featured a floor-price mechanism that effectively

in the short-run, two challenges must be confronted. First, as the results in Figure 3 highlight, increasing solar generation in California impacts net imports into the state, suggesting that the impact on emissions will occur both inside and outside of California. Second, because solar generation affects generation from large hydroelectric sources, the resulting changes in emissions will not be confined to the same day the solar output occurs. To address these challenges, we estimate the impact of solar generation on emissions in two steps. First, we re-estimate the model specified by Eq. 1 using the aggregate hourly emissions of CO_2 and NO_X from fossil fuel generators in CAISO as the dependent variables. The resulting estimates of β_h^s represent the average impact of an additional GWh of daily solar generation on the emissions exclusively from CAISO generators and limited to the same day.

Next, to uncover how much emissions change (a) in the surrounding Western U.S. grid and (b) during different time periods, we use the estimates of Eq. 1 using the aggregate hourly net-imports into CAISO and the hourly supply from CAISO hydroelectric sources as the dependent variables. Intuitively, if CAISO solar generation causes a reduction in net-imports, there would be a reduction in emissions outside of CAISO – assuming fossil fuel fired units are on the margin. Similarly, if solar output reduces hydroelectric production, the conserved hydroelectric output would offset emissions at a different point in time.[43]

To quantify the resulting changes in CO_2 emissions outside of CAISO, we multiply the change in the MWhs of net-imports by 0.428 tons of CO_2 per MWh – the emission intensity the California Air Resources Board applies to unspecified imports coming into California for compliance with the State's cap-and-trade program. This unspecified import emission rate is roughly equal to the emission intensity of a combined cycle gas turbine (see Table 2), which effectively means we are assuming that the CCGTs are on the margin outside of CAISO. To quantify the change in non-CAISO NO_X emissions, we multiply the change in net-imports by 0.06 pounds of NO_X per MWh – which again is the median NO_X emission rate for CAISO combined-cycle gas turbines (Table 2). Finally, to quantify how much emission are altered on different days, we multiply the resulting changes in CAISO hydroelectric generation by the same emission factors – 0.428 tons of CO_2 and 0.06 pounds of NO_X per MWh.

Figure 4 displays the estimates of β_h^s from Eq. 1 – how an additional GWh of daily solar generation affects the emissions of CO_2 from CAISO generators on the same day. To highlight the heterogeneity in the emission impacts, the model is estimated separately for each season. During Summer (June-August) and Fall (September-November), increases in daily solar output cause sizable reductions in daily CAISO CO_2 emissions during the daylight

reduced allowance sales in response to low demand (Borenstein et al., 2019).

[43]This assumes that the reduction in hydroelectric output is not the result of simply spilling water out of reservoir. Given that we do not observe spillage, we cannot test for this possibility.

hours and have no meaningful impacts outside of the daylight hours. In contrast, during the Winter (December-February), daily CAISO CO_2 emissions fall across all hours of the day while during the Spring (March-May), daily CAISO CO_2 emissions increase during the evening hours. To estimate how much daily CAISO emissions change in response to an additional GWh of daily solar, we aggregate the 24 hourly point estimates of β_h^s for each season. The top two rows of Table 3 display the estimates of the average change in daily CAISO CO_2 and NO_X emissions, again highlighting the heterogeneity across seasons.

To understand why solar output affects daily CAISO emissions so differently across seasons, it is important to explore how the substitution pattern between solar and other sources differs across seasons. Figure 5 displays the point estimates of β_h^s from Eq. 1 using hourly CAISO hydroelectric and hourly net-imports into CAISO as the dependent variables. During the Winter and Fall, when a GWh of daily solar generation offsets the largest amount of CO_2 from CAISO generators, we find that there is also an aggregate increase in daily electricity supplied by hydroelectric sources and net-imports (see Table 3). Consequently, supplying an additional GWh of solar generation will cause positive leakage – CO_2 and NO_X emissions would increase on different days and/or in different markets. In contrast, during the Spring and Summer, we find that an additional GWh of daily solar causes sizable reductions in the aggregate daily supply from hydroelectric units and net-imports – implying negative leakage (i.e. emissions will fall on different days and/or in different markets).

Assuming each additional MWh imported increases non-CAISO CO_2 and NO_X emissions by 0.428 tons and 0.06 pounds, and assuming that using an additional MWh of CAISO hydroelectric output increases emissions on a different day by the same amount, we are able to quantify not only how large these temporal and spatial leakage effects are, but we can estimate the resulting net changes in CO_2 and NO_X per GWh of daily solar output. The bottom two rows of Table 3 display the estimates of the aggregate change in CO_2 and NO_X per GWh of solar generation. Across the year, a GWh of solar output offsets approximately 300 tons of CO_2.[44] During the Winter, Spring, and Fall, an additional GWh of solar generation reduces aggregate NO_X emissions by 41 to 94 pounds. During the high demand Summer months, when very emission intensive gas turbines are far more likely to be on the margin, an additional GWh of daily solar reduces an estimated 277 pounds of NO_X.

By directly accounting for the emission impacts that spillover to other markets and to different time periods, the preceding estimates contribute to a large literature estimating

[44]The results from Figure 3 highlight that, on net, solar generation largely offsets CCGT output in the short-run. While the emission rate of these CCGT units is approximately 0.4 tons of CO_2 per MWh, solar is offsetting closer to 0.3 tons/MWh. Previous work (Kaffine et al. (2013), Novan (2015)) similarly highlights that the emissions avoided by intermittent output from wind generation is lower than what would be implied by the average emissions rates of fossil units.

the impact of renewable output on emissions (e.g., Callaway et al. (2018), Fell and Kaffine (2018), Novan (2015), Cullen (2013), Kaffine et al. (2013)). However, all of these estimates focus on the short-run impacts. The focus of the next section is to use these well-established empirical approaches to begin to explore how growth in renewable capacity may begin to reshape the composition of the fleet of generation capacity going forwards.

6 Impacts on Operating Profits

To shed light on the potential impacts renewable capacity expansions can have as we move away from the short-run and allow for changes in the stock of generation capacity, we proceed in two steps. First, we use the estimates of the short-run price impacts to predict how RTM 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. Second, using the predicted counterfactual RTM prices, we explore how renewable capacity expansions affect the operating profit earned by different conventional generating technologies. In Appendix 2.2, we perform the same analysis using estimates of the impact of solar generation on day-ahead market prices. Ultimately, the predicted impacts on operating profits are qualitatively unchanged whether we focus on the RTM or DAM price impacts.

It is important to highlight two key caveats. First, while we are able to provide estimates of how the profits earned in the RTM and DAM are affected by expansions in solar capacity, we are unable to estimate the impact on profits earned through bilateral contracts. However, given that the contracts can be expected to adjust over time to reflect the market value of electricity revealed through the DAM and RTM prices, we would expect profits earned through bilateral contracts to change in a very similar pattern. The second key caveat is that our estimates of the operating profit changes do not capture any profit changes arising from the capacity or ancillary service markets. However, combined, revenues from the capacity and ancillary service markets account for less than 10% of the total estimated revenue earned by serving load in the CAISO market CAISO (2019). Therefore, our results provide insights into how the main profit streams may be affected by expanding solar capacity.

6.1 Counterfactual Scenarios

Eq. 1 specifies the RTM price as a linear function of the daily levels of solar and wind, hourly load, daily gas price, and lagged precipitation. While the relationship between hourly prices and the control variables will certainly be non-linear and non-separable, the simple model provides a reasonable approximation for how prices vary with renewable output. Moreover, the parsimonious model allows us to produce straightforward predictions of the hourly RTM prices with different levels of solar or renewable capacity installed.

To predict the counterfactual 2016 RTM prices, we first re-estimate the model specified by Eq. 1 separately by hour-of-day (h) and by season (q).[45] 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 RTM 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 RTM price ($\tilde{P}_{h,d}$) given the counterfactual solar generation ($\widetilde{Solar}_d$) is given by,

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

In addition to imposing the assumption that, for a given hour of the day in a given season, RTM prices vary linearly with the daily level of solar or wind generation, the approach we use to predict the counterfactual prices imposes an additional assumption. Specifically, by holding the unexplained portion of the RTM price (i.e. $\hat{\varepsilon}_{h,d}$) 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.[46]

Eq. 2 predicts the RTM price given any counterfactual level of daily solar generation. The question now is what counterfactual levels of generation to consider? One option would be to focus on how prices during the last full year of our sample would differ had the level of solar or wind capacity increased above the observed 2016 levels. This is unappealing because the counterfactual levels of solar and wind generation would be larger than the levels of generation that were observed during our sample period, requiring us to extrapolate the estimates of Eq. 1 beyond the observed support. Therefore, we take a different approach. We examine how 2016 RTM prices would have differed had the installed solar or wind capacity been lower than the levels observed at the end of our sample. In particular, we predict the RTM price assuming the installed solar capacity during 2016 was equal to 2 GW, 6 GW, or

[45]The seasons are winter (Dec.-Feb.), spring (March-May), summer (June-Aug.), and fall (Sep.-Nov.). The point estimates of $\beta^{s}_{h,q}$ and $\beta^{w}_{h,q}$ are displayed in Figures A15 and A16. To calculate the confidence intervals of each point estimate, we again use Newey-West standard errors with a 7-day lag.

[46]As a robustness check, we relax this assumption by 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 assuming homoskedasticity. While we find evidence of mild heteroskedasticity, the resulting counterfactual wholesale prices are effectively unchanged.

10 GW for the full year.[47] To predict the counterfactual prices, we assume that the daily wind generation remains unchanged from the observed 2016 levels. Similarly, we predict the counterfactual 2016 RTM prices had wind capacity been equal to 1 GW, 3 GW, or 6 GW for the entire year.[48] Again, to predict these counterfactual prices, we assume that the daily solar generation remained unchanged from the observed levels.

To predict the daily solar or wind generation given the counterfactual levels of capacity, we could calculate the daily solar and wind capacity factors – the daily generation divided by the actual capacity – and multiply these capacity factors by the counterfactual 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, 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 – the daily observed solar generation plus the daily curtailed solar output – divided by the actual capacity. Assuming 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 counterfactual generation from the counterfactual potential generation, we predict daily curtailment as a function of the daily renewable potential and subtract the predicted curtailment from the potential generation. Appendix 3 discusses curtailment estimation approach.

6.2 Counterfactual Prices

Figure 6 displays the average predicted RTM prices by hour-of-day during 2016 for the counterfactual levels of renewable capacity. Focusing on the top panel, we estimate that the increase from 2 GW to 10 GW of solar capacity reduced 2016 midday RTM prices by approximately $20/MWh. 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 have increased RTM prices. In Appendix Section 2.2, we highlight that the same pattern of price changes (i.e. price declines during the middle of the day and price increases during the early morning and evening) is found using the day-ahead market.

[47] During 2013, solar capacity grew from 1.2 GW to 3.2 GW. During 2015, capacity increased from 5.8 GW to 7 GW. By the end of 2016, there was over 9.8 GW of solar capacity and over 10 GW by May, 2017.

[48] 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 Figure A3), the resulting counterfactual levels of wind generation are certainly within the observed levels of daily wind generation.

Overall, this exercise predicts that increasing solar capacity from 2 GW to 10 GW caused the distribution of hourly RTM prices to become wider.[49] With the decrease in midday prices, the left tail of the RTM price distribution shifts left. With the increase in the late afternoon and early evening prices, the right tail of the price distribution shifts to the right. While solar capacity expansions are estimated to have caused the distribution of RTM prices to become wider, expanding from 1 GW to 6 GW of wind capacity is estimated to shift the distribution of RTM prices leftwards. As the bottom panel of Figure 6 highlights, increasing wind capacity resulted in lower average RTM prices during each hour.[50]

6.3 Operating Profit Changes for Conventional Generators

This section explores how the operating profits conventional technologies could earn in the real-time market 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). Consequently, a generator will produce zero output if the RTM price falls below the unit's marginal generation cost. If the price exceeds the unit's marginal cost, the generator will operate at full capacity.[51]

Using the static framework, we explore how conventional generators with different marginal generation costs may be affected by expansions in renewable capacity. In particular, for the different counterfactual levels of renewable capacity K_r, for $r \in \{\text{Solar, Wind}\}$, we calculate the predicted annual operating 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 RTM prices ($\tilde{P}_t(K_r)$), the counterfactual operating profit over the 8,784 hours during 2016 is given by the following expression:

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

To summarize how the predicted operating profits change with the level of solar capacity, the top panel of Figure 7 displays the percentage changes in the 2016 operating profits for different levels of solar capacity, and for different technologies, relative to the case with 2

[49]The distribution of the counterfactual prices is displayed by season in Figure A18.

[50]Figure A7 compares the average counterfactual prices to the actual average 2016 prices. The top panel highlights that the actual RTM prices during 2016 fell between the 6 GW and 10 GW counterfactuals. During 2016, the average level of solar capcaity was 8.1 GW. The bottom panel displays the counterfactual prices for different levels of wind capacity. The actual prices line up very closely with the 6 GW counterfactual. This is expected given that there was 5.7 GW of wind capacity throughout all of 2016.

[51]This static optimization assumption is reasonable for a flexible GT unit. However, for baseload units, abstracting from dynamic costs will lead us to understate the losses incurred by expanding renewables.

GW of solar. The operating profit changes are displayed for conventional technologies with marginal costs ranging from $0/MWh to $52/MWh. For reference, the average marginal generation cost for nuclear units as well as the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the marginal generation costs for CCGT and GT units, are displayed.[52] In addition, while there are no coal units in CAISO, we include the variable cost for further reference.

Increasing from 2 GW to 6 GW of solar reduces the operating profit across all technologies. A hypothetical unit with a marginal cost of $0 loses 10% of their operating profit while a unit with a marginal cost of $30/MWh loses 23%. As the marginal cost increases beyond $30/MWh, the share of operating profit lost due to solar capacity expanding from 2 GW to 6 GW falls. For example, a GT with a marginal cost of $50/MWh experiences a 10% decrease in operating profits as solar capacity grows to 6 GW. Interestingly, increasing from 6 GW to 10 GW of solar does not uniformly decrease the operating profits for all technologies. While an increase from 6 GW to 10 GW reduces operating profits for units with marginal costs below $45/MWh, units with marginal costs above $45/MWh recover some of the initial operating 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 $45/MWh stabilizes.[53] As a result, high marginal cost units continue to operate the same number of hours, and earn stable operating profits, as solar capacity expands from 6 GW to 10 GW (see Figure A19). In Appendix 2.2, we repeat the counterfactual analysis using the day-ahead market and find the results are qualitatively unchanged.

The results displayed in the top panel of Figure 7 have potentially important implications for the emission intensity of the stock of conventional generators going forward. The results suggest that, in response to growth in solar capacity, the share of remaining conventional generation may be comprised of higher marginal cost, lower fixed cost technologies – e.g., there may be relatively less disinvestment (or increased investment) in gas turbines compared to combined cycle and nuclear units.[54] Importantly, in the CAISO market, the higher marginal cost generators (i.e. gas turbines) have higher emission rates. Recall from Table 2,

[52]For nuclear and coal, the mean variable generation cost comes from NREL's Annual Technology Baseline – https://atb.nrel.gov/electricity/. For CCGT and GT, we use the variable O&M costs reported by NREL – and assume that variable O&M costs do not vary within CCGT or GT. To compute the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the variable fuel costs for both technologies, we solve for the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the heat rates among CAISO CC and GT units using the CEMS data. We then mulitply by the average price of natural gas delivered to electricity generators in California during 2016.

[53]While there are fewer hours with prices above $30/MWh in the Summer and Winter, the share of hours with high prices increases in the Spring and Fall (see Figure A18).

[54]It is important to note that the long-run impact of renewable expansions depends on other market responses as well. If demand were to become more elastic, or storage capacity were to meaningfully increase, then the impact of solar additions on wholesale prices would be dampened and much more uniform across hours. Ultimately however, response from demand has yet to materialize and storage capacity remains low.

the typical gas turbine emits 41% more CO_2 and 150% more NO_X per MWh compared to the typical combined cycle unit. The difference in emission rates is even starker comparing gas turbines to zero-emitting nuclear units. These results suggest that, as solar capacity continues to grow in California, the stock of remaining conventional generators may become steadily more carbon intensive. While supplying solar output to the market will continue to reduce emissions from the generators on the margin, some of these environmental benefits may be partially offset in the long-run if emissions from the inframarginal units begin to increase. In markets with substantial baseload coal capacity, similar changes in wholesale prices could drive a different pattern. As solar capacity grows, there could be greater incentive to disinvest in lower private marginal cost, and substantially dirtier, coal capacity.

The bottom panel of Figure 7 highlights how operating profits for conventional generators would change as wind capacity grows beyond 1 GW. Consistent with the estimates presented in Figure 2, increasing wind generation uniformly decreases prices and, as a result, operating profits. For a unit with a marginal generation cost of \$0/MWh, expanding wind capacity from 1 GW to 6 GW reduces operating profit by 17%. For a unit with a marginal cost of \$30/MWh, the expansions from 1 GW to 6 GW of wind reduces operating profit by 30%.

6.4 Marginal Energy Value of Renewable Capacity Additions

We can also use our counterfactuals to explore how the benefits provided by marginal increases in renewable capacity vary with the level of installed capacity. Importantly, our objective is not to quantify the revenue earned by the owner of the marginal unit of renewable capacity. Instead, we are interested in quantifying the market value of the additional renewable output achieved by expanding capacity. The difference between these two measures is important. As renewable capacity increases, the aggregate level of renewable output curtailed will grow. Which units experience these curtailments – i.e. the infra-marginal units or the newest, marginal unit – will affect how large the private returns are to the owners of the marginal capacity. In contrast, the measure we are interested in – the market value of the additional, aggregate renewable output – is independent of which units are being curtailed.

To estimate the energy value of a 1 MW increase in solar or wind capacity, we first need to predict how much renewable output would increase during each hour of 2016. To do so, we first calculate the observed 2016 hourly solar and wind capacity factors. For simplicity, we assume that the observed hourly capacity factors represent the amount of electricity that would be supplied by an additional MW of solar or wind capacity, regardless of the level of installed renewable capacity.[55] To predict the annual value of the additional renewable

[55]This assumes that, regardless of the renewable capacity, the fraction of hourly output curtailed is equal to the share of potential hourly output curtailed during the corresponding hours of 2016. This assumption

output achieved by expanding solar or wind capacity, we simply multiply the hourly 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 value of the additional energy supplied by an additional MW of renewable capacity.[56]

Figure 8 plots the percentage change in the value of the energy supplied 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 value of the energy supplied by the marginal unit of solar capacity 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 market value of the energy supplied by the 2,000$^{\text{th}}$ MW of solar capacity installed in the market, the market value of the energy supplied by the 10,000$^{\text{th}}$ MW of solar capacity is 52% lower. At the same time, costs of new wind and solar power purchase agreements declined from around 8 cents/kWh in 2013 to 5 cents/kWh in 2017. The net value of new renewable agreements will depend upon the rate at which these costs continue to decline relative to the decline in energy value. By comparison, the CAISO price, weighted by hourly solar output, declined from 4.5 to 2.6 cents/kWh from 2013-2016.

The bottom panel of Figure 8 reveals a similar decline in the market value of the energy supplied by additional wind capacity. Compared to the 1,000$^{\text{th}}$ MW of wind capacity, the 6,000$^{\text{th}}$ MW of wind capacity produces energy that has 20% less market value. 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.

7 Conclusion

We have examined the impact of the major influx of investment in renewable energy technology on electricity prices in California's electricity market. It is worth considering our results in the context of the claims and controversies that have swirled around this topic in recent

likely overstates curtailments for low levels of renewable capacity. However, it is a reasonable approximation for the upper end of the counterfactual capacities considered – which were similar to the capacity during 2016. Therefore, while the results demonstrate that marginal energy value declines with renewable growth, these reductions will understate the decrease in the value of the energy supplied by renewable additions.

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

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 U.S. markets have concluded that declines in natural gas prices, rather than renewables, are largely responsible for the tenuous economic position of many baseload generation plants.[57] We find, studying a different market and deploying a different methodology, that renewable investment has indeed had a significant impact on electricity prices. 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 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 U.S. 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 renewables either are, or will be, partly to blame. However, this is the result of the market properly capturing the new reality of high renewable penetration – influenced in turn by state and federal policy – rather than a sign of market failure. 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 complementary to renewable energy. Our finding that higher marginal cost combustion turbines are much less negatively impacted by renewable expansion than other technologies indicates that the market is indeed rewarding generators that are providing value, conditioned on the amount of renewable energy hitting the system.

The California market may also be signaling 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.

[57] See, for example, Tierney (2012), Jenkins (2018), and Fell and Kaffine (2018).

While a comprehensive cost-benefit analysis of California's renewable policies is beyond the scope of this paper, these results may demonstrate the declining marginal benefits associated with those policies as they continue to expand. More reliance upon a carbon price would have the advantage of potentially better aligning the environmental benefits provided by renewable production with the financial benefits enjoyed by renewable producers. Clean energy sources that are able to target periods of the highest prices, or highest carbon intensity, would be rewarded based upon the carbon they displace rather than their renewable attributes. 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. In this way, carbon pricing would be more likely to discourage counter productive outcomes like the closure of nuclear generators in response to low overall energy 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	90	25
Median Heat Rate *(MMBtu/MWh)*	7.50	10.36	12.77
Median CO_2 Rate *(tons/MWh)*	0.44	0.62	0.76
Median NO_X Rate *(lbs/MWh)*	0.06	0.15	0.13

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

Table 3: Aggregate Change in Emissions per GWh of Daily Solar

	Season			
	Winter	Spring	Summer	Fall
Change in Daily CAISO CO_2 (tons)	-346.52***	-81.46	-242.98***	-299.55***
	(60.21)	(50.76)	(59.22)	(78.62)
Change in Daily CAISO NO_X (lbs)	-46.16***	-61.91**	-264.63**	-73.37***
	(14.16)	(28.32)	(111.90)	(25.15)
Change in Daily Quantity Supplied by:				
Hydroelectric (MWh)	187.98**	-163.25	-22.80	28.91
	(83.32)	(42.33)	(41.14)	(45.48)
Net Imports (MWh)	-104.70	-382.08***	-184.38*	172.10
	(105.41)	(94.57)	(102.04)	(130.17)
Hydro + Imports (MWh)	83.27	-545.32***	-207.17*	201.01
	(110.74)	(108.94)	(115.84)	(122.97)
Predicted "Leakage" in CO_2 Emissions (tons)	35.64	-233.40	-88.67	86.03
Predicted "Leakage" in NO_X Emissions (lbs)	5.00	-32.72	-12.43	12.06
Predicted Total Change in CO_2 Emissions (tons)	-310.88	-314.86	-331.66	-213.52
Predicted Total Change in NO_X Emissions (lbs)	-41.17	-94.63	-277.06	-61.31

The first two rows report the average change in the aggregate daily CO_2 and NO_X emissions from CAISO fossil fuel units in response to a 1 GWh increase in daily aggregate solar generation. The following three rows report the change in aggregate daily generation from CAISO hydroelectric units and net imports into CAISO in response to a 1 GWh increase in daily solar generation. To predict the quantity of CO_2 emissions that "leak" into surrounding markets, in response to a change in net imports, or across days, due to a change in hydroelectric generation, the predicted "leakage" row multiplies the total change in daily CAISO hydroelectric generation and net imports by an emission rate of 0.428 tons of CO_2 per MWh – the emission intensity the California Air Resources Board applies to unspecified imports coming into California for compliance with the State's carbon cap-and-trade program. Newey-West standard errors allowing for correlation in the errors over a 7-day lag are reported in parentheses. * =Signficant at the 10% level; ** =Signficant at the 5% level; *** =Signficant at the 1% level.

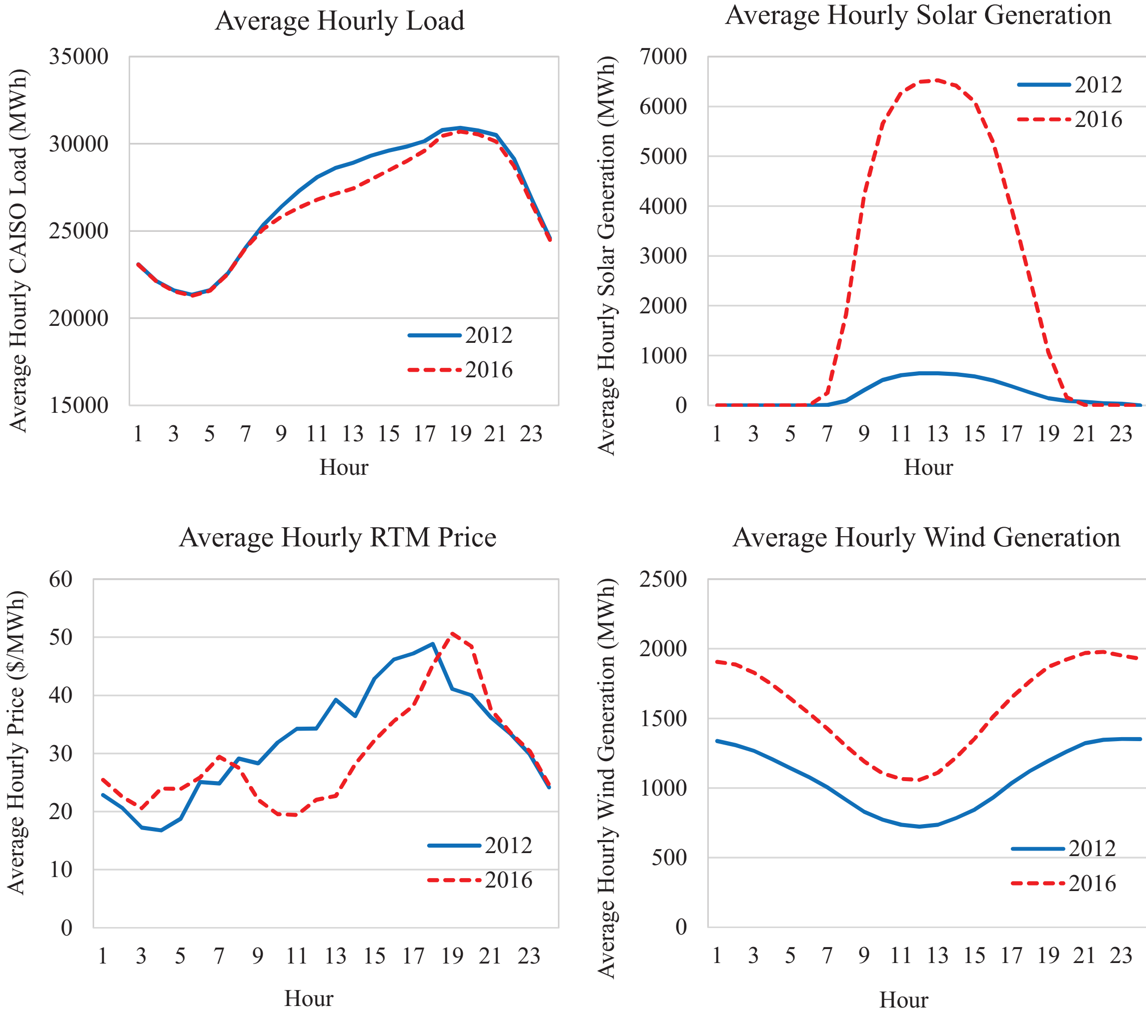

Figure 1: The upper left panel displays the average hourly CAISO load during 2012 and 2016. The bottom left panel displays the average hourly real time market (RTM) prices in the CAISO market (the simple average across the DLAPs). The right panels display the average hourly grid-level solar and wind generation.

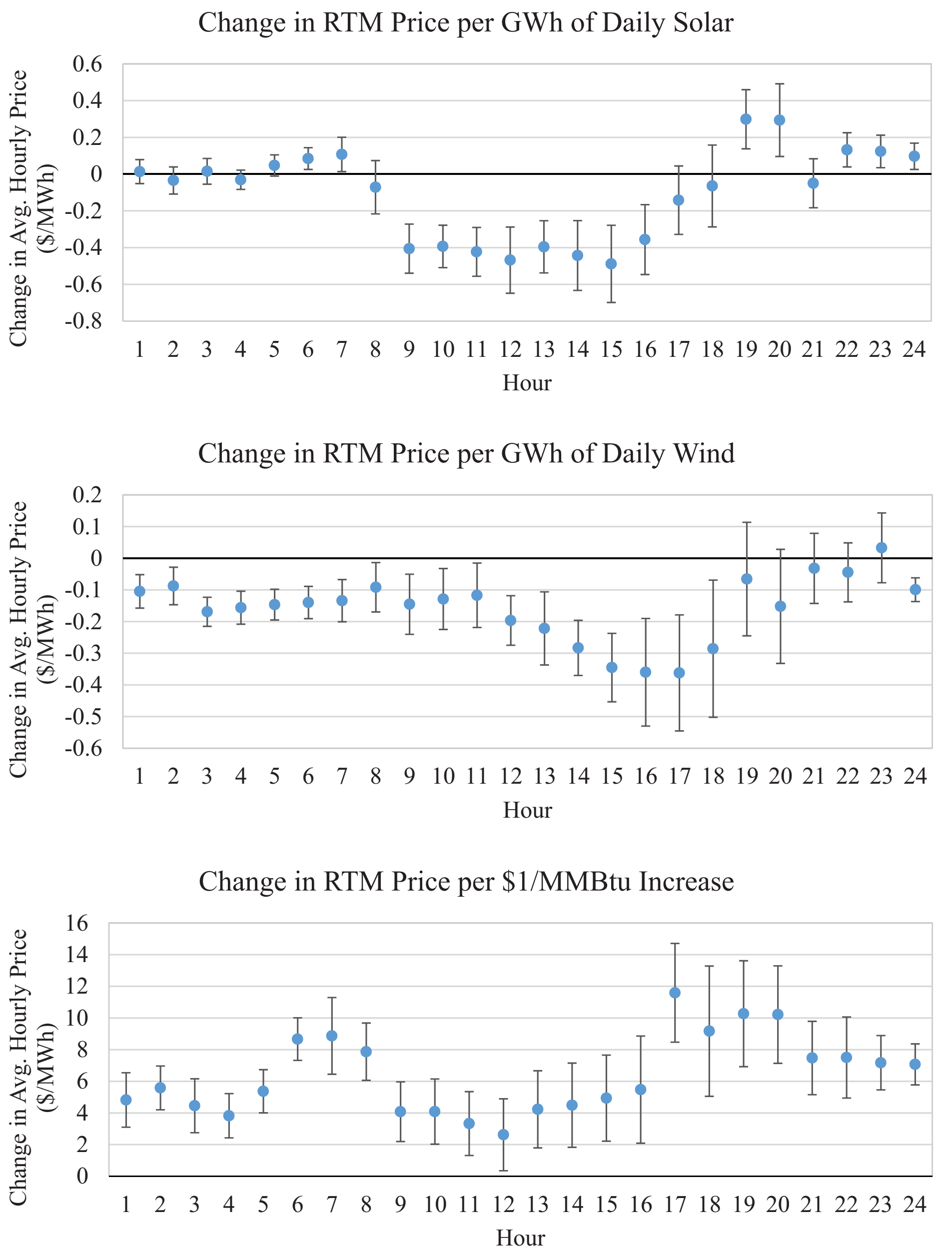

Figure 2: The panels display the point estimates of β_h^s, β_h^s, and β_h^g (from the model specified by Eq. 1) and the corresponding 95% confidence intervals.

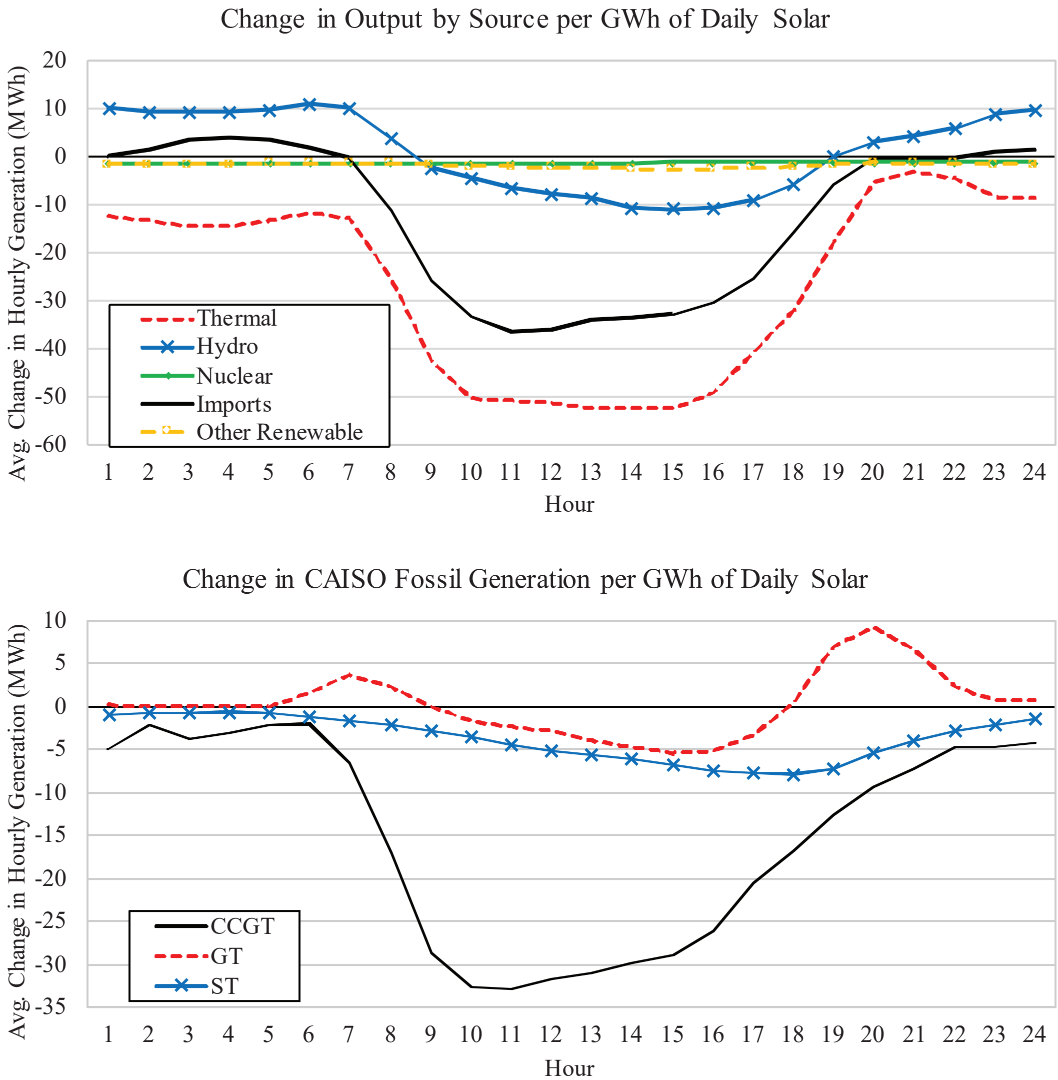

Figure 3: The top panel displays the average impact of an additional GWh of daily solar generation on the hourly level of generation from CAISO thermal, hydro, nuclear, and 'other' renewable sources as well as net-imports into the the CAISO market. The bottom panel displays how an additional GWh of daily 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 turbines (CCGT), gas turbines (GT), and steam turbines (ST).

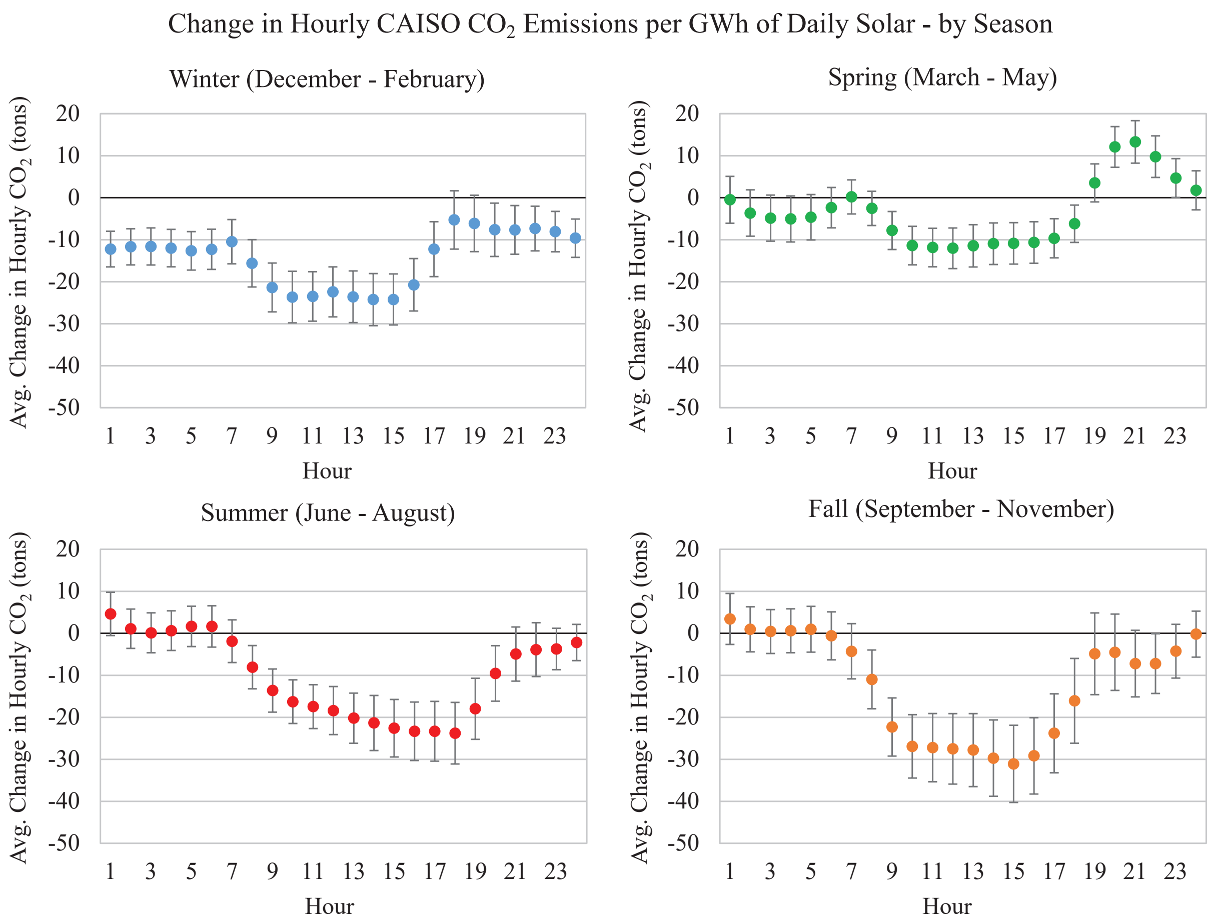

Figure 4: The figure displays how an additional GWh of daily solar generation affects the average hourly level of CO_2 emitted during different seasons by CAISO fossil units in the EPA CEMS dataset.

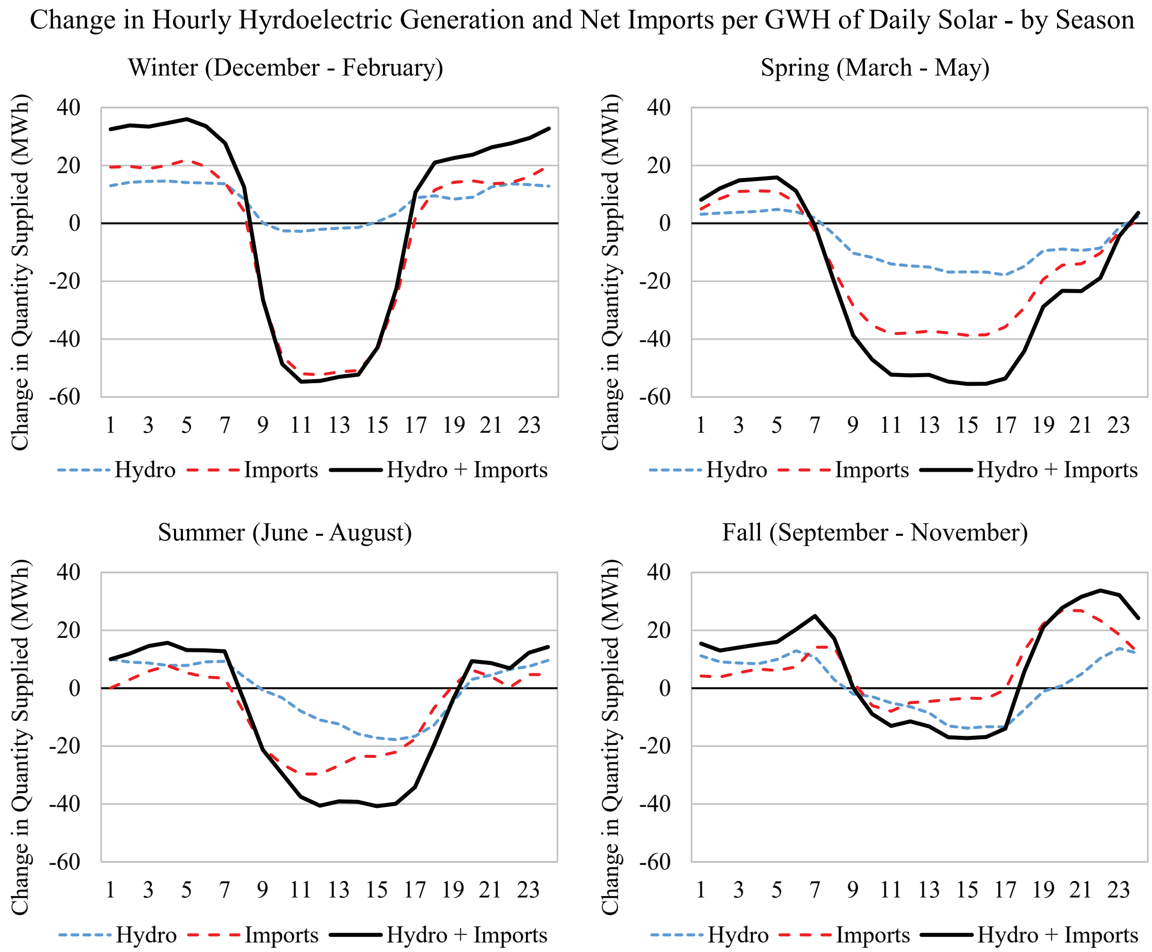

Figure 5: The figure displays how an additional GWh of daily solar generation affects (A) the average hourly quantity of electricity supplied to the CAISO market by large hydroelectric generators in California, (B) the average hourly net imports into CAISO, and (C) the sum of the hourly hydroelectric generation and net imports.

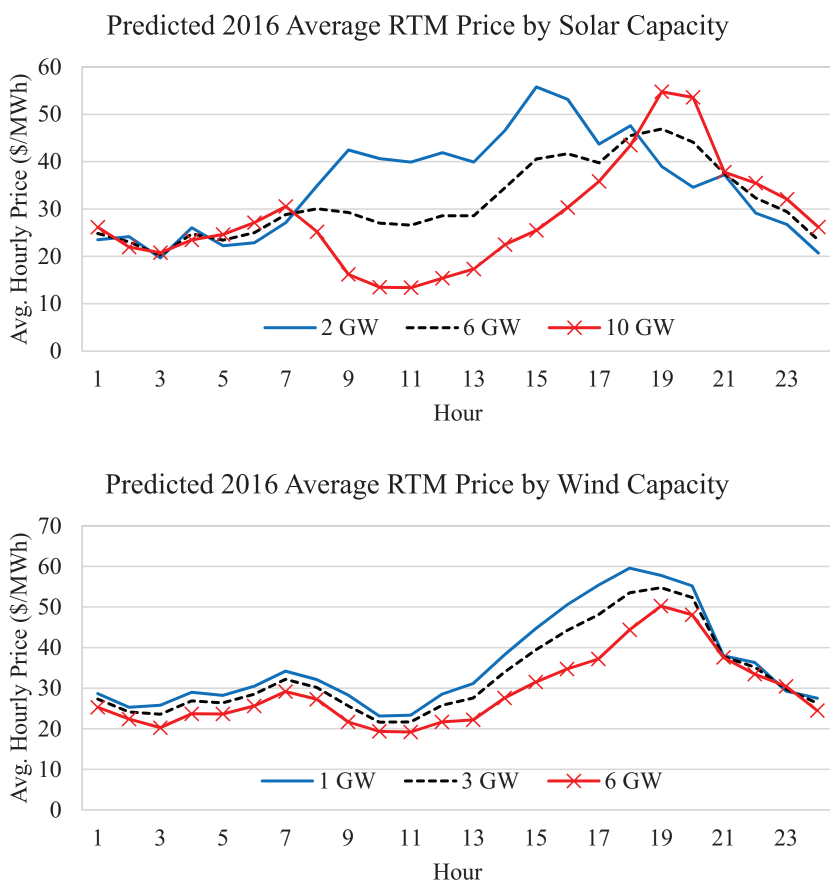

Figure 6: The top panel displays the average predicted RTM price by hour-of-day during 2016 under three counterfactual levels of solar capacity (2 GW, 6 GW, and 10 GW). The bottom panel displays the predicted RTM prices by hour-of-day during 2016 for three different counterfactual levels of wind capacity.

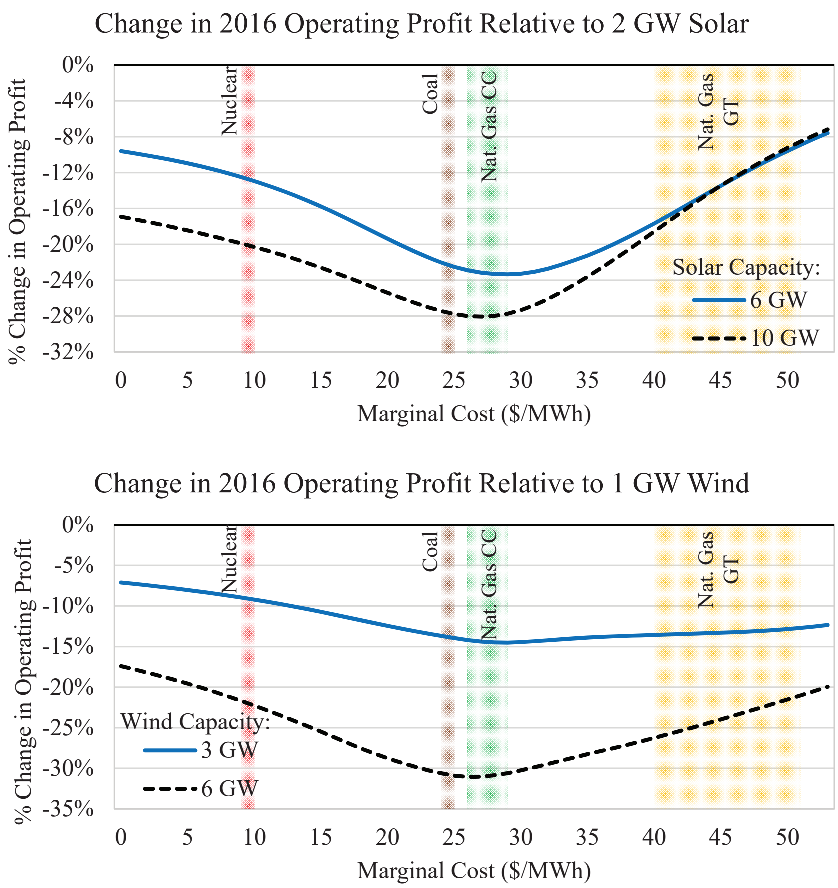

Figure 7: The top panel displays the percentage change in the predicted operating profits a conventional generator could earn in the real-time market during 2016 given different levels of solar capacity. The operating profit changes are displayed for hypothetical conventional generators with variable generation costs ranging from \$0 to \$52/MWh. The bottom panel displays the predicted percentage changes in operating profits under different levels of installed wind capacity. The vertical bars represent the predicted mean variable generation costs for nuclear and coal units and the 25^{th} to 75^{th} percentiles of the predicted variable generation costs for natural gas combined cycle units and natural gas turbines.

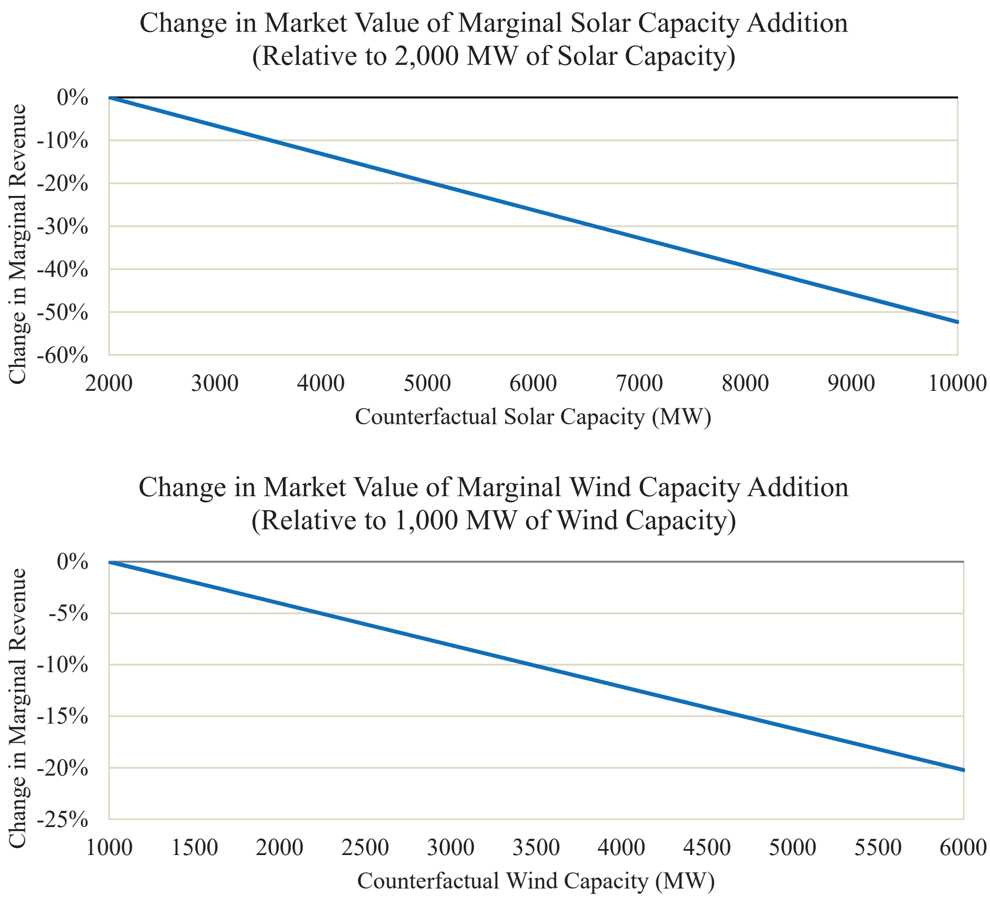

Figure 8: The top panel displays the predicted percentage change in the 2016 revenue earned by the marginal solar generator (i.e. the last MW of installed solar capacity) for different aggregate levels of solar capacity. The bottom panel displays how the 2016 revenue earned by the marginal wind generator varies as aggregate wind capacity increases.