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The Impact of Wind, Solar, and Other Factors on the Decline in Wholesale Power Prices in the United States

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Abstract

Across multiple organized wholesale power markets in the United States, annual average prices declined by $19–64/MWh between 2008 and 2017 while retirements of thermal power plants accelerated. Several prominent changes over the last decade are often discussed as contributors to this decline in prices. These include growth in wind and solar, a reduction in the price of natural gas, and weakened load growth. Here we construct a fundamental supply curve model for each of seven organized wholesale market regions and use counterfactual simulations to assess the degree to which wind and solar—among other factors—have influenced wholesale electricity prices. We find that growth in wind and solar since 2008 reduced average annual wholesale electricity prices by less than $3/MWh. In contrast the decline in natural gas prices reduced wholesale prices by $7–53/MWh, depending on the region. This suggests that recent thermal-plant retirements in the U.S. are primarily due to low natural gas prices, not growth in wind and solar. Fully isolating the impact of individual factors, however, is limited by non-linear interactions between factors.

Keywords: variable renewable energy, wholesale power market prices, grid integration, electricity policy

1. Introduction

Across the organized wholesale markets in the United States, average annual wholesale prices at major trading hubs declined by $19–64/MWh between 2008 and 2017. Oft-noted causes include the steep reduction in natural gas prices, the rise of variable renewable energy (VRE, inclusive of wind and solar), and moderating load growth (DOE 2017). One consequence of the reduced prices has been growth in thermal-plant retirements (Haratyk 2017; Shawhan and Picciano 2019). The change in the generating mix in the seven organized wholesale market regions in the U.S. between 2002 and 2016 shows the parallel reduction in coal generation and increase in natural gas and VRE generation, Figure 1.

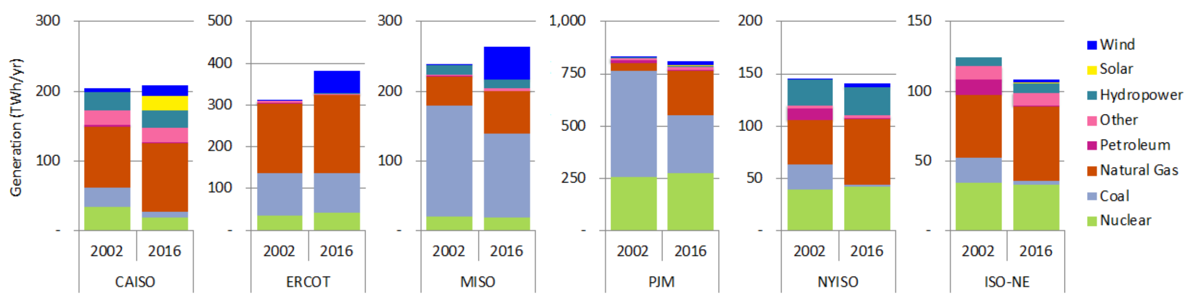


Figure 1. Change in annual generation mix across the organized wholesale market regions of the United States between 2002 and 2016 (DOE 2017)

Considerable attention has been placed on the impacts of VRE on wholesale power prices. After all, wind and solar power have both grown rapidly, and each has unique characteristics that may have distinctive impacts on wholesale pricing patterns. This literature consistently confirms the so-called 'merit order' effect—namely, that the addition of VRE with low marginal costs leads to lower market-clearing prices. And yet, estimates of the absolute magnitude of the effect vary, in part due to various approaches applied to different regions, making comparisons difficult; a summary of the empirical U.S. literature is provided in Table 1, showing a range of historical impacts from $0–12/MWh. Much of the literature has focused on VRE impacts, without consistently considering the wide array of other possible price drivers. The U.S.-focused literature is a subset of the broader literature on the price effect of wind and solar in Europe, with many of the studies summarized by Welisch *et al* (2016) and Würzburg *et al* (2013). Csereklyei et al. (2019) find that wind and solar in Australia put downward pressure on prices in the context of overall increasing average prices between 2010 and 2018.

Studies that have considered a wide array of other drivers often use a fundamental model rather than a statistical model. Haratyk (2017) develop a simple fundamental model to estimate the impact of changes in natural gas prices, installed wind capacity, demand, and other factors on wholesale prices in the Midwest and Mid-Atlantic regions of the U.S. Kallabis, Pape, and Weber (2016) build a simple supply curve model of the price of electricity futures contracts in Germany to determine the drivers of the decline between 2007 and 2014. While the decline is frequently attributed to the increase in renewable generation, they find that emissions prices had a greater impact. Bublitz et al. (2017) finds the impact of changes in carbon permit and coal prices were twice the impact of renewable expansion in Germany using both an agent based model and a statistical regression model. Using a fundamental model, Hirth (2018), in contrast, finds that growth in renewables was the largest single driver of the wholesale price decline in Germany and Sweden between 2008 and 2015. Hirth explains that differences in conclusions across the European studies stem from differences in the time horizon, geographic coverage, and whether studies focus on futures or spot prices.

We build on the approach described in Kallabis, Pape, and Weber (2016) and Hirth (2018) to quantify the relative impact of VRE and other factors on annual, market-wide average historical wholesale prices between 2008 and 2017 in the U.S. In contrast to much of the previous U.S. literature, our approach allows for the application of a consistent method across multiple regions, and enables us to compare the influence of wind and solar to many other factors. To do this, we develop a relatively simple, fundamental supply-curve model for all seven centrally organized wholesale markets in the United States: the California Independent System Operator (CAISO), the Electric Reliability Council of Texas (ERCOT), the Southwest Power Pool (SPP), the Midcontinent Independent System Operator (MISO), the PJM Interconnection (PJM), the New York Independent System Operator (NYISO), and the New England Independent System Operator (ISO-NE). Collectively, these seven markets cover more than two thirds of the load in the U.S. Our use of a fundamental model allows explicit representation of non-linear relationships between changes in factors and average prices, a feature missing from much of the previous U.S. literature.

Each of the ISOs runs an energy market and various ancillary service (i.e., reserve) markets, and many also have capacity markets or related resource adequacy obligations. The energy markets clear on at-least an hourly basis, with both a day-ahead financial market and a real-time balancing market to account for changes that occur in near-real-time. We focus exclusively on prices in energy markets at major trading hubs, and primarily on hourly real-time (not day ahead) prices. In order to draw connections between energy prices at major trading hubs and changes to revenues of generators it is important to recognize that the aggregate revenue of a generator participating in a wholesale market depends on a locational marginal price (LMP) at the generator location, which may differ from prices at major trading hubs due to transmission congestion. Total generator revenue also depends on ancillary service prices, capacity prices, and the dispatch of that generator. Moreover, many contracts between generators and loads exist outside of centrally organized wholesale spot markets, in which case the LMPs reflect the grid value of power and establish the opportunity cost of not selling into or buying from the wholesale market but do not necessarily have a direct impact on the contracting parties.

With these supply curve models, we estimate counterfactual prices where one factor is changed at a time. We find that growth in wind and solar since 2008 reduced average annual wholesale electricity prices by less than $3/MWh, a level within the range of the estimates in the literature summarized in Table 1, and on par with several other secondary factors. The primary contributor to the reduction in wholesale prices is the decline in natural gas prices, which, depending on the region, drove prices $7–53/MWh lower over this same period.

Table 1. Average wholesale power energy price reduction associated with VRE growth in the U.S.

Study	Applicable Region	Time Period	Average VRE Penetration (% of demand)	Decrease in Average Wholesale Power Energy Price from Average VRE
Woo et al. (2011)	ERCOT	2007-2010	Wind: 5.1%	Wind: $2.7/MWh (ERCOT North) Wind: $6.8/MWh (ERCOT West)
Woo et al. (2013)	Pacific NW (Mid-C)	2006-2012	N/A	Wind: $3.9/MWh
Woo et al. (2014)	CAISO (SP15)	2010-2012	Wind: 3.4% Solar: 0.6%	Wind: $8.9/MWh Solar: $1.2/MWh
Woo et al. (2016)	CAISO (SP15)	2012-2015	Wind: 4.3% Solar: 2.6%	Wind: $7.7/MWh Solar: $2.1/MWh
Gil and Lin (2013)	PJM	2010	Wind: 1.3%	Wind: $5.3/MWh
Wiser et al. (2016)[a]	Various regions	2013	RPS energy: 0%-16% depending on the region	RPS energy: $0 to $4.6/MWh depending on the region
Craig et al. (2018)	CAISO	2013-2015	DG Solar: ~5%	DG Solar: < $1/MWh
Tsai and Eryilmaz (2018)	ERCOT	2014-2016	Wind: 11%	Wind: $8-12/MWh
Quint and Dahlke (2019)	MISO	2014-2016	Wind: 6%	Wind: $6.7/MWh
Jenkins (2017)[b]	PJM	2008-2016	N/A	Wind: $1-2.5/MWh
Wiser et al. (2017)[b]	CAISO	2008-2016	Solar: ↑ 9.5% 2008-2016 Wind: ↑ 3.3% 2008-2016	Solar: $1.9/MWh Wind: $0.4/MWh
Wiser et al. 2017(2017)[b]	ERCOT	2008-2016	Wind: ↑ 10.8% 2008-2016 Solar: ↑ 0.3% 2008-2016	Wind: $0.7/MWh Solar: $0/MWh
Haratyk (2017)[b]	Midwest	2008-2015	Wind: ↑ 9% 2008-2015	Wind: $4.6/MWh
Haratyk (2017)[b]	Mid-Atlantic	2008-2015	N/A	Wind: $0/MWh
Bushnell and Novan (2018)[b]	CAISO	2012-2016	Utility-Scale Solar: ↑ 8.3% 2012-2016	Solar: $5.2/MWh
Zarnikau et al. (2020)	MISO	2014-2017	Wind: 8%	Wind: $1.3 to $10/MWh depending on the region

Notes: a – Price effect is estimated impact of RPS energy relative to price without RPS energy in 2013 before making adjustments due to the decay effect discussed by the authors. b – Decrease in average wholesale price is based on change in wind or solar energy from beginning to end of the time period, rather than the decrease from average wind or solar reported in other rows.

2. Methods and Data

2.1 Quantifying the Relative Impact on Average Wholesale Prices

Building on the approach outlined by Kallabis, Pape, and Weber (2016) and Hirth (2018), we use a fundamental supply curve model, described below, to estimate the change in annual average wholesale prices from changing one factor at a time. In particular, we compare modeled annual average prices when all factors are set to their 2017 levels to counterfactual annual average prices when changing one factor at a time to its 2008 level. For example, we estimate the impact of growth in wind over 2008 to 2017 on average wholesale prices in 2017 by changing the wind to its 2008 level while keeping all other factors constant at their 2017 level. By individually changing each factor from its 2017 level to its 2008 level we can estimate the relative contribution of different factors to the observed decline in average annual wholesale prices between 2008 and 2017. The different factors summarized in Table 2 include wind and solar deployment, changes in natural gas prices, thermal plant retirements and additions, changes in electricity load, permit prices for pollution emissions, and hydropower water levels.

Table 2. Summary of factors considered in fundamental supply curve model

Factor	Summary of change	Implementation
Wind	Growth in wind generation	Scale 2017 hourly wind profile by annual average wind in 2008
Solar	Growth in utility-scale and distributed solar generation	Scale 2017 utility-scale and distributed solar profile by annual average solar in 2008
Other RE	Change in other non-hydropower renewable energy generation	Replace other renewable energy generation by 2008 levels
Thermal Additions	Growth in new thermal capacity	Exclude all new thermal power plant capacity since 2008
Thermal Retirements	Retirements of existing thermal capacity	Exclude all retirements of thermal power plant capacity since 2008
Heat Rate	Change in efficiency of existing thermal generation	Replace the monthly average heat rate of thermal power plants with 2008 heat rates
Emissions Price	Change in emission permit prices for CO_2, NO_x, and SO_2 emissions	Replace emissions permit prices, applicable to each region, with permit prices in 2008
Natural Gas Price	Reduction in natural gas prices	Scale daily natural gas price profile at major trading hubs for each region with annual average natural gas price at the trading hub in 2008
Petroleum Price	Reduction in petroleum fuel prices for oil-fired generation	Replace annual average price of petroleum fuel with 2008 price
Coal Price	Change in coal prices	Replace monthly coal prices with 2008 monthly prices

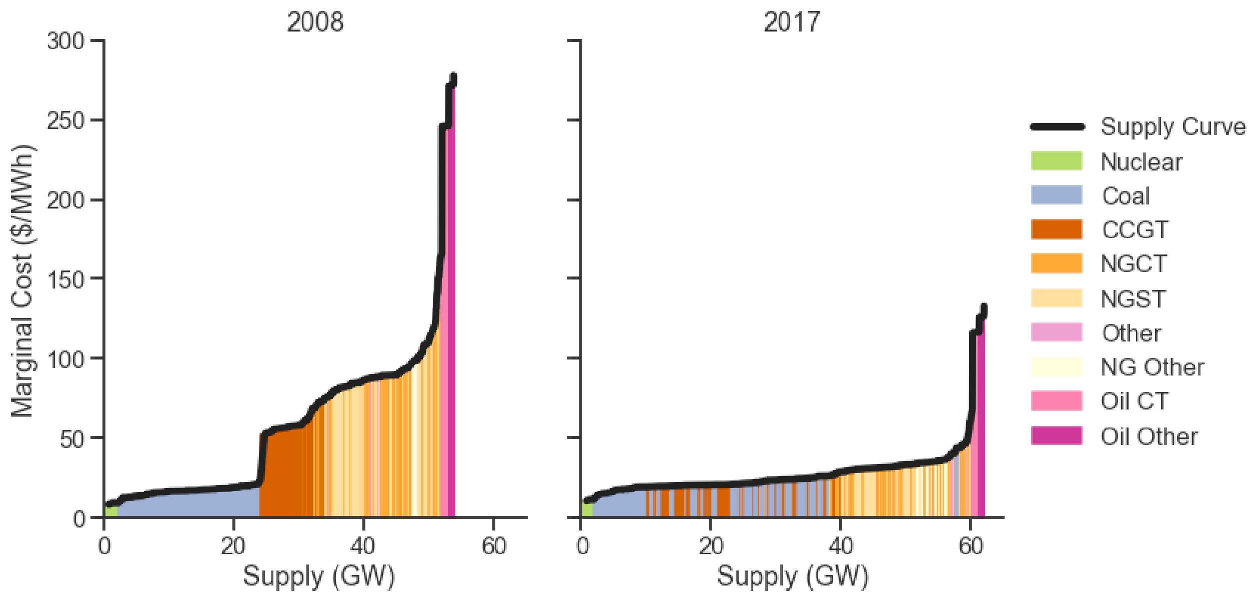
Uranium Price	Change in uranium prices	Replace annual average price of uranium with 2008 price
Demand	Change in demand for electricity, excluding the impact of distributed PV	Scale 2017 demand profile by annual average demand in 2008
Imports	Change average net imports	Adjust relationship between imports and net demand by monthly import levels in 2008
Hydro	Change in hydropower availability	Adjust relationship between hydropower and net demand by monthly precipitation levels in 2008

Owing to non-linearities, the sum of changes in wholesale prices from individual factors does not equal the change in prices from changing all factors simultaneously, leading to an interaction term. The interaction illustrates limits on the ability to disentangle the relative contribution of individual factors to the observed decline in wholesale prices. This non-linear interaction has been noted in the studies that use similar methods to understand the relative contributions of individual factors to changes in wholesale prices (Kallabis, Pape, and Weber 2016; Hirth 2018). It is important to note that this limitation is not a measure of the accuracy of the fundamental model. Even a perfectly accurate model of prices would have non-linear interactions between individual factors.

2.2 Supply-Curve Model

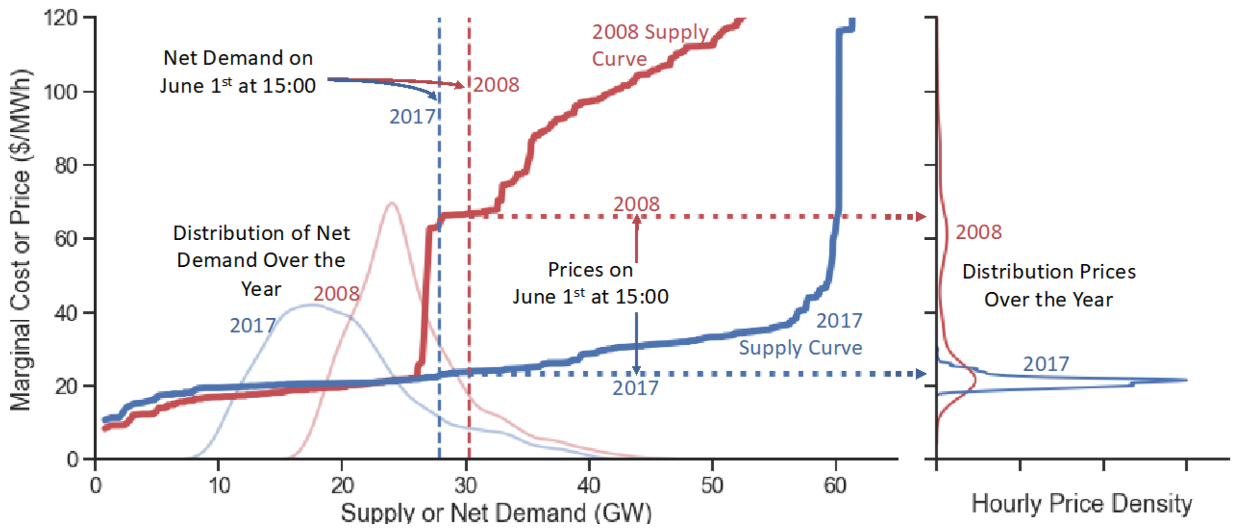
To estimate the impact of VRE and other factors on market-wide, annual average wholesale prices, we created a simple fundamental model for each of the seven centrally organized wholesale power markets in the United States. The simple supply-curve model estimates hourly market-clearing prices from the intersection of the non-linear supply curve with net demand (demand net of wind and solar). This hourly price is then averaged over the year to estimate the annual average reported in the analysis.

Supply curves, as illustrated in Figure 2, are constructed by ordering all generation capacity from lowest marginal cost to highest marginal cost (the "merit-order") with the cumulative thermal generator capacity along the horizontal axis and the marginal cost of the generator on the vertical axis. The example supply curves are based on the set of thermal generators and the estimated marginal fuel costs in SPP on June 1, 2008 and June 1, 2017. Because several different types of generators make up the supply curve, the supply curve is non-linear. Higher gas prices in 2008 compared to 2017 led to a steeper supply curve and a clear difference between the marginal cost of natural-gas fired combined cycle generators and coal generators. The electricity price in each hour is calculated as the marginal cost of the generator where the supply curve intersects with the hourly net demand as illustrated in Figure 3 using the net demand on June 1 at 15:00 local time in 2008 and 2017. Figure 3 also shows the full distribution of hourly net demand in SPP over the year for 2008 and 2017. The distribution of hourly net demand across the year leads to a distribution of hourly prices for 2008 and 2017, also illustrated in Figure 3. The mean of the distribution is the annual average price and the standard deviation of the distribution reflects the hour-to-hour variability of prices.



Notes: Area is colored based on the type of generator with the width based on the capacity of the generator. Generator types in this illustration include nuclear, coal, natural gas-fired combined cycle gas turbines (CCGT), natural gas combustion turbines (NGCT), natural gas steam turbines (NGST), other natural gas-fired generators (NG Other), oil-fired combustion turbines, (Oil CT), other oil-fired generators, and other thermal generators.

Figure 2. Examples of supply-curves in SPP for June 1, 2008 and June 1, 2017



Notes: Hourly net demand is represented as a probability distribution across all hours of the year. Hourly prices, based on the intersection of the net demand and the supply curve, are also represented as a probability distribution across all hours of the year.

Figure 3. Illustration of the method for estimating hourly prices based on the intersection of supply and net demand

In the model, electricity demand, wind, and solar vary by hour based on historical weather patterns. Demand is the ISO-reported hourly demand with our estimate of hourly distributed solar generation added back into the demand profile. The solar profile therefore includes both utility-scale solar and distributed solar. The estimated marginal cost of each thermal plant in the supply curve is based on the heat rate of the unit, the fuel cost, and other variable operations and maintenance costs. Variable costs also include emissions costs based on the emissions rate of the unit and annual average costs of emissions permits (CO_2, SO_2, and NO_x), where applicable. Natural gas fuel costs vary on a daily basis following the trading price at major natural gas trading hubs. Coal fuel costs vary on a monthly basis following average delivered costs of coal in each plant's state as reported by the U.S. Energy Information Administration (EIA). The capacity of each generator, reported in ABB's Velocity Suite, is based on its summer or winter capacity, depending on the season, de-rated by a seasonal availability factor. We de-rate the summer capacity using only the forced outage rate whereas the winter capacity is de-rated by both the forced outage rate and the scheduled outage rate. By applying the scheduled outage rate to the winter capacity we, in effect, assume that scheduled maintenance occurs only in the winter season. Outage rates are technology specific (rather than unit specific). Dispatch of hydropower and imports cannot be modeled following the simple merit-order concept used for thermal generators. Instead, we assume their generation levels vary by hour based on inferred relationships between historically observed hydropower, monthly precipitation and net demand, or imports and net demand, respectively. Other renewable energy is treated as a static hourly profile. The hourly generation from hydropower, imports, and other renewable energy are then used to shift the net demand curve to the left for the purposes of calculating the intersection with the merit-order supply curve.

With two exceptions, this simple supply curve ignores numerous real constraints including unit specific minimum generation levels, startup times, ramp rates, transmission limits, heat rate variation based on loading, etc. The first exception is that we assume nuclear plants are always at full capacity (accounting for de-rates) and that generation from combined heat and power units cannot be below 35% of their capacity (Denholm, Brinkman, and Mai 2018). The second exception is that we include a transmission constraint between PJM East and PJM West (additional details in the Supplementary Information note 1) since modeling PJM as a single market consistently deviated from actual historical prices. During rare oversupply or scarcity conditions, prices are not set by the marginal generator in the supply curve and are instead based on assumed penalty prices.

The data required even for this relatively simple supply-curve model are extensive. The Supplementary Information (note 1) summarizes the sources and details of the data employed in our analysis.

3. Results

3.1 Supply-Curve Model Validation

To validate the supply-curve model, we compare the wholesale prices from the model to actual wholesale power energy prices from major trading hubs in each region. The major trading hubs used for the actual annual average wholesale prices in the real-time market are listed in Table 3. Day-ahead prices from the same hubs are used for years in which the day-ahead market existed. Some of the markets have seen major design changes between 2008 and 2017. In particular, several of these markets did not have centrally organized day-ahead markets in the earlier years of this period. We therefore do not show a comparison of day ahead and modeled prices for 2008 for CAISO, ERCOT, and SPP and we also do not show day-ahead prices for 2012 for SPP. All markets had both day-ahead and real-time prices by 2017. Another important market evolution for the CAISO was the introduction of the Energy Imbalance Market (EIM), which enabled real-time balancing with utilities outside of the CAISO starting in 2015. Our fundamental model considers only CAISO generation and loads and does not include the broader EIM.

Table 3. Major wholesale electricity price hubs used to validate modeled wholesale prices

Market	Years	Major Trading Hub Name
CASIO	2008-2017	SP15
ERCOT	2008-2017	North
SPP	2008-2012	OKGE
SPP	2017	South Hub
MISO	2008	Cinergy
MISO	2012-2017	Indiana Hub
PJM	2008-2017	Western Hub

NYISO	2008-2017	Hudson Valley Zone G
ISO-NE	2008-2017	Mass. Hub

By fixing all supply curve model parameters to their historical levels in 2008, 2012, and 2017, the model replicates actual average annual wholesale energy prices within 13% except for certain years in SPP (2008, 2017), MISO (2017), and NYISO (2012) where the modeled prices are 16-21% lower than the actual real-time prices (Figure 4). These errors between actual and modeled annual average wholesale prices are on par with the levels in other studies based on similar methods (Haratyk 2017; Kallabis, Pape, and Weber 2016; Hirth 2018). This validation confirms that, for the purpose of understanding drivers of changes in the annual average wholesale prices, this simple and transparent approach can be applied consistently across multiple regions of the U.S. and capture the impact of multiple factors on average prices—a major contribution of the current work.

In contrast, comparison of the standard deviation of modeled hourly prices to the standard deviation of actual hub prices shows that the model is not as effective in representing hour-to-hour variability, though the variability of the modeled prices is closer to the variability of day-ahead prices than it is to the variability of real-time prices. In particular, the distribution of prices from the simple supply curve model tends to be much more narrow than actual real-time prices (i.e., the model shows fewer very high price or low price events than the number of events observed in actual real-time prices). This result is due to the simple model not accounting for all transmission constraints and many of the flexibility attributes and constraints embedded in real markets. As a consequence, we utilize the model in this analysis solely to assess the impact of various drivers of market-wide average annual wholesale prices, and not to explore geographic and temporal variability in those prices. Additional discussion of the distribution of prices and the hour-to-hour match between prices from the supply curve model and actual historical prices is in the Supplementary Information (note 2).

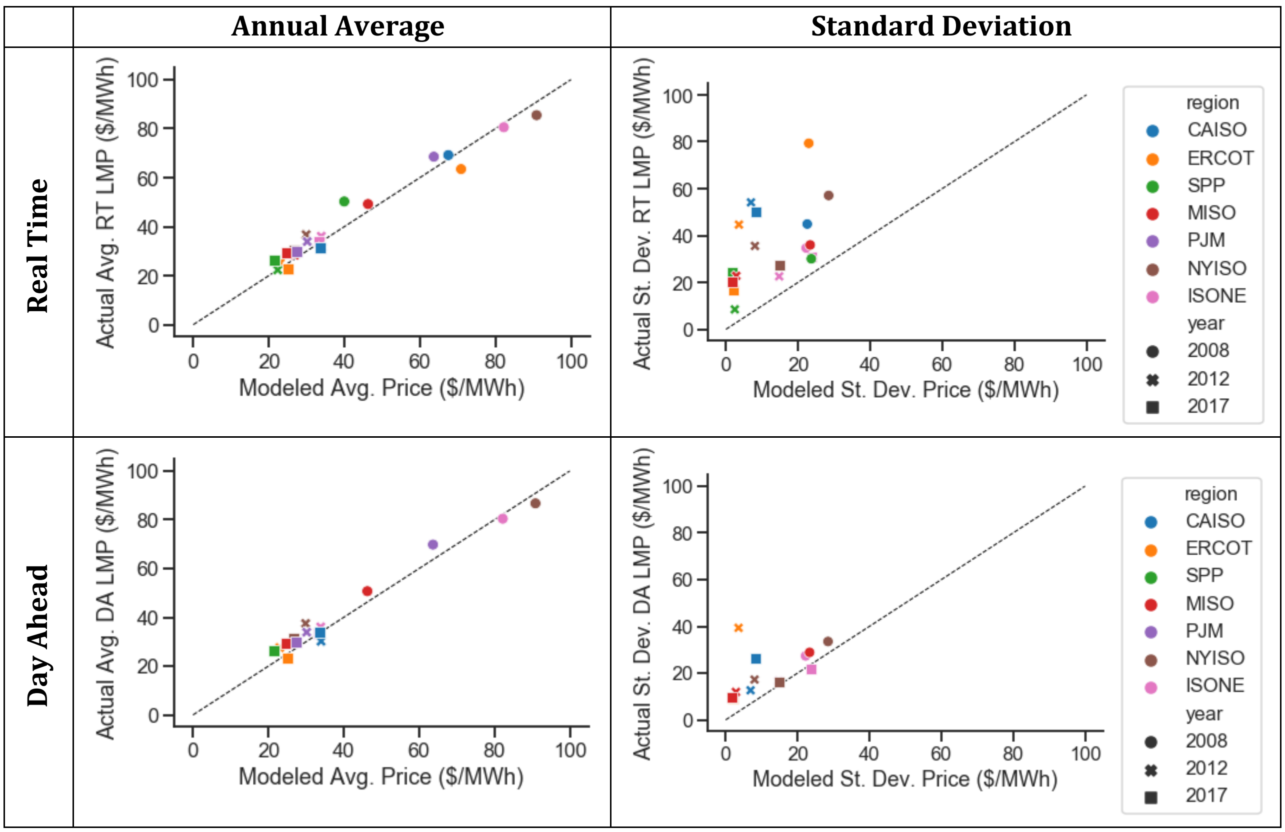
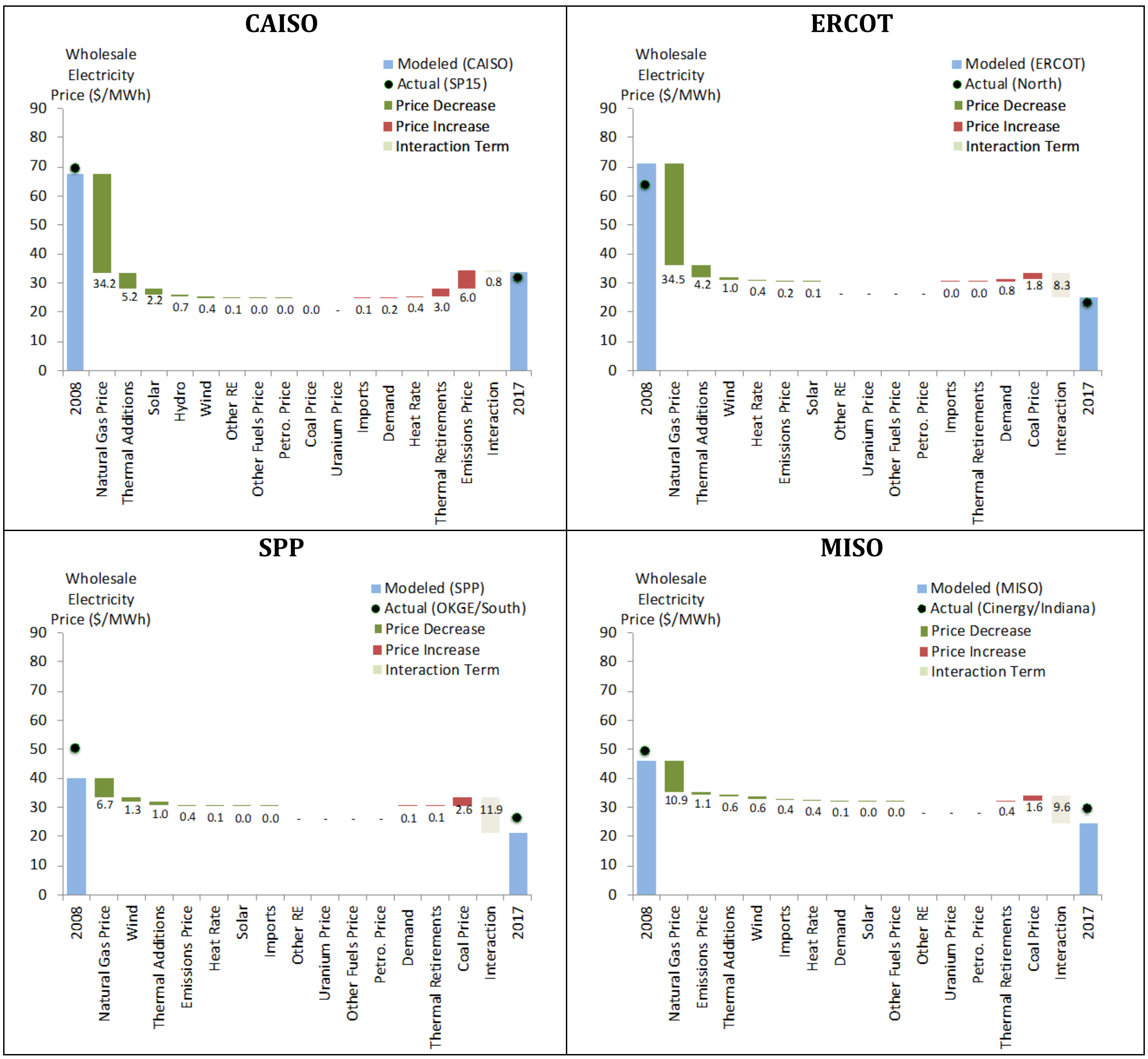
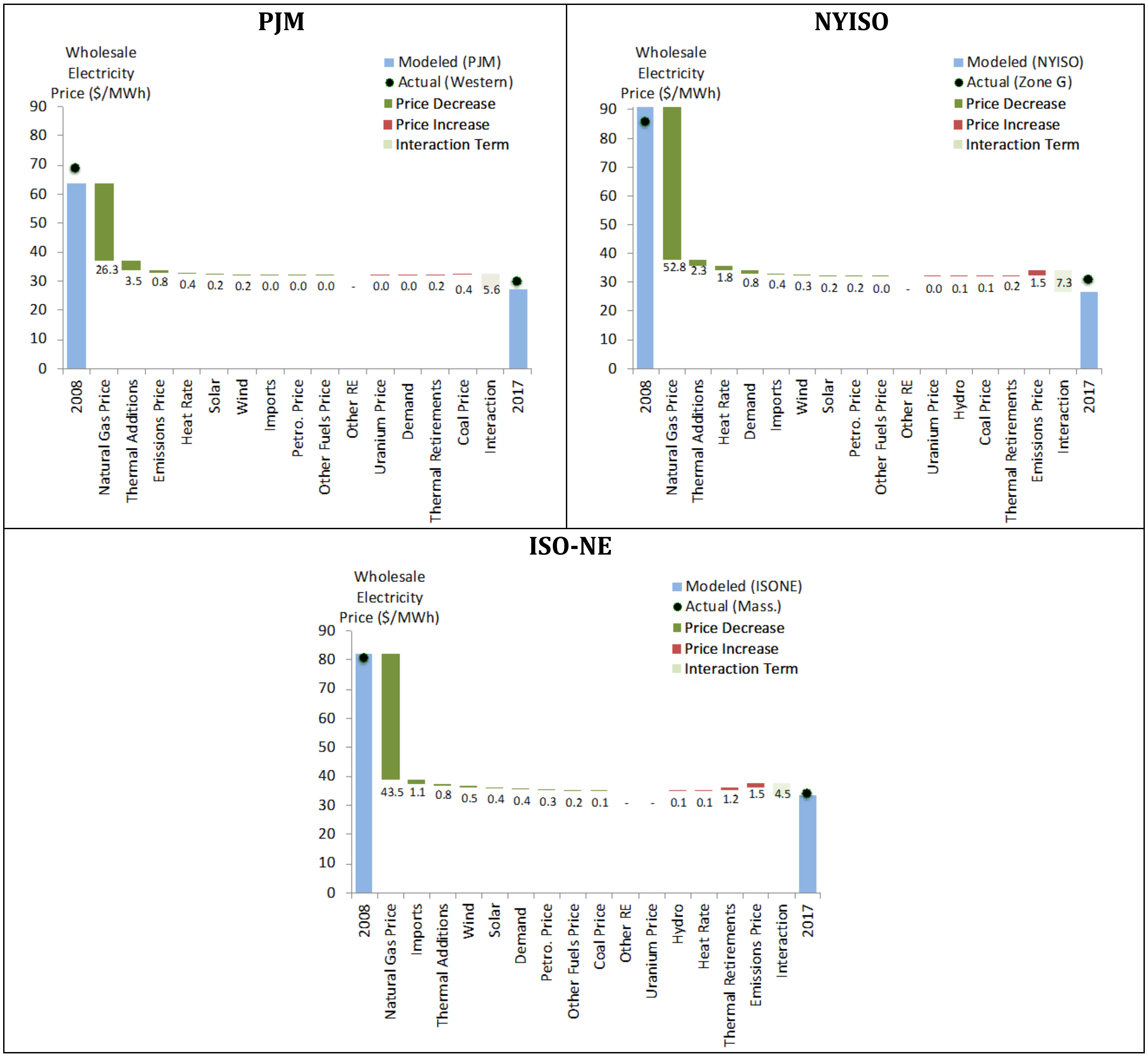


Figure 4. Comparison of modeled and actual real-time (top) and day-ahead (bottom) average annual wholesale power energy prices (left) and the standard deviation of wholesale prices (right) for different historical years and market regions.

3.2 Drivers of Average Annual Market-Wide Prices

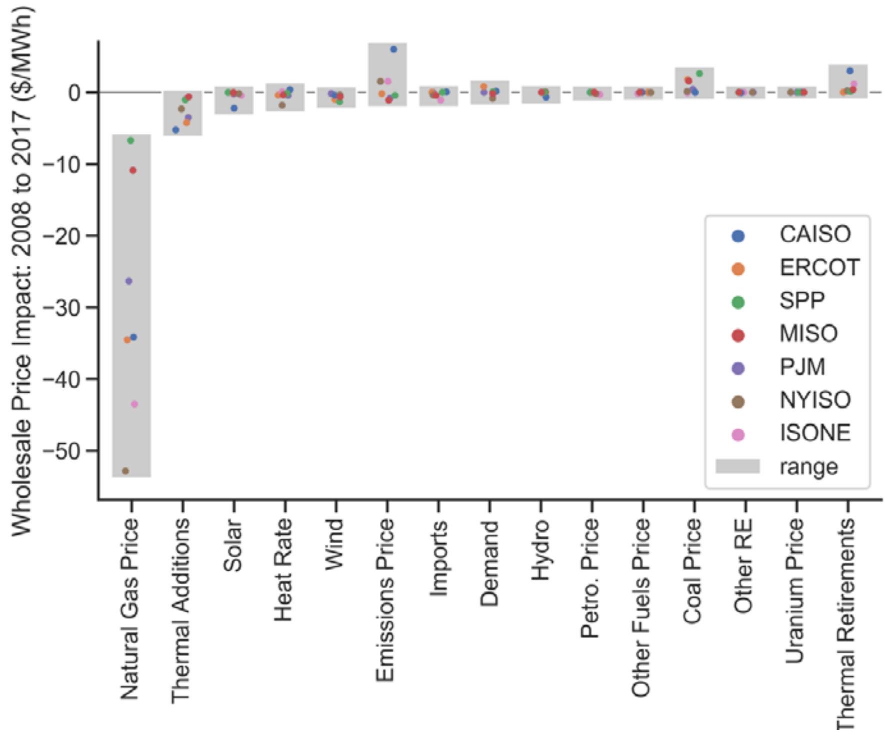
We estimate the relative contribution of different factors to the observed decline in average annual wholesale prices between 2008 and 2017 by individually changing each factor from its 2017 level to its 2008 level as shown in Figure 5. Owing to non-linearities, the sum of changes in wholesale prices from individual factors does not equal the change in prices from changing all factors simultaneously, leading to the interaction term. The implications of non-linear interactions are discussed further in Section 3.4.





Notes: Modeled price bars (blue) represent the annual average modeled price when setting all factors to their 2008 or 2017 level. The actual prices (black dots) are the observed annual average prices in the same years. The middle bars represent the change in average annual prices from changing one factor at a time from its 2017 level to its 2008 level while keeping all other factors at their 2017 level. The interaction term is the difference between the sum of the individual factor bars and the total modeled reduction in annual average prices between 2008 and 2017 found from simultaneously setting all factors to their 2008 or 2017 level.

Figure 5. Relative contribution of different factors to the observed wholesale power energy price decline between 2008 and 2017 for each market region



Notes: Individual points represent the impact on annual average wholesale prices of changing one factor. The gray bars represent the range of impacts across all seven centrally organized wholesale markets in the United States, including the California Independent System Operator (CAISO), the Electric Reliability Council of Texas (ERCOT), the Southwest Power Pool (SPP), the Midcontinent Independent System Operator (MISO), the PJM Interconnection (PJM), the New York Independent System Operator (NYISO), and the New England Independent System Operator (ISO-NE).

Figure 6. Summary of average wholesale power energy price impact of various factors that changed between 2008 and 2017 across all markets

Across all seven centrally organized wholesale markets, the dominant driver of the decline in average annual wholesale prices between 2008 and 2017 is the fall in natural gas prices (Figure 6). Not surprisingly, the impact of changing gas prices is highest in markets where natural gas-fired generators are marginal in the supply stack even with higher gas prices. For CAISO, ERCOT, PJM, NYISO, and ISO-NE, for example, falling gas prices from 2008 to 2017 reduced average annual wholesale prices by $26–53/MWh. As shown in the Supplementary Information (note 3), even after the shale-gas boom caused a sustained reduction in natural gas prices, changes in average gas prices continued to be the largest driver of changes in average wholesale prices in many regions.

The impact of wind and solar on market-wide average annual wholesale prices since 2008 has been secondary compared to natural gas, but amongst the biggest drivers in a second tier of factors with similar magnitudes of impact that also include expansion and retirement of other generation capacity, changes in demand, generator efficiency, coal prices, variations in hydropower, and emissions prices.

3.3 Impact of Wind and Solar on Average Wholesale Prices

The magnitude of the estimated impact of wind and solar on average wholesale prices primarily depends on the incremental level of penetration, where a higher share of wind or solar leads to a greater impact on prices, as shown in Figure 7. Across all markets, each incremental percentage-point increase in wind or solar penetration since 2008 reduces average wholesale prices in 2017 by approximately \$0.14/MWh. In most markets, the total impact on average prices in 2017 is below \$1.3/MWh; California is an exception, where solar growth is estimated to have reduced prices by \$2.2/MWh—perhaps foreshadowing greater impacts from solar in other regions as solar penetrations grow.

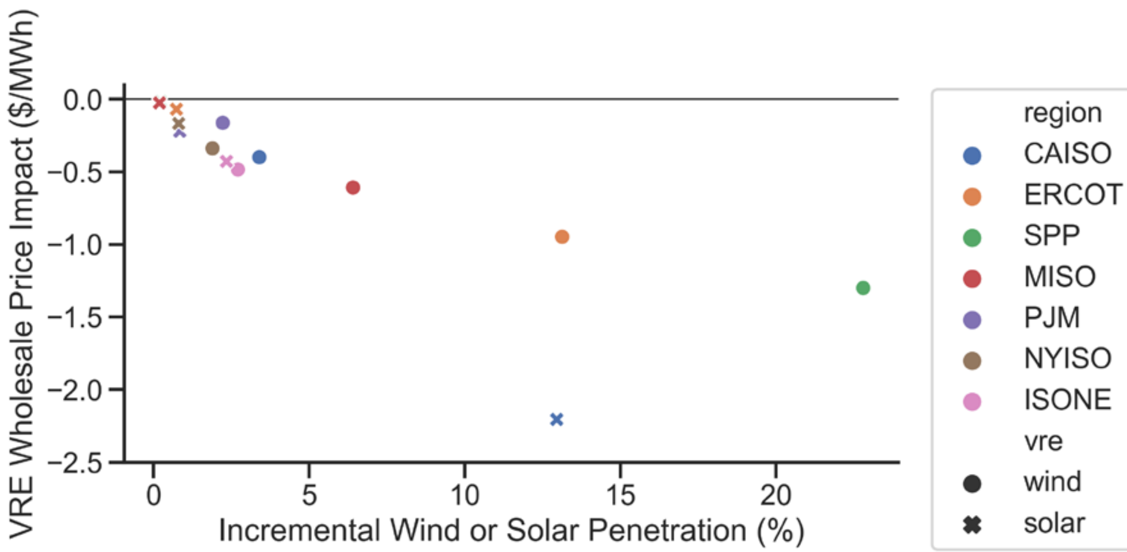


Figure 7. The impact of VRE growth between 2008 and 2017 on annual average wholesale prices in each market region

The relatively greater impact of solar in CAISO compared to the similar share of wind in ERCOT is driven by solar more frequently shifting the net demand in the steeper part of the supply curve and therefore having a larger impact on prices. The alignment with the steeper part of the supply curve is due to solar in California reducing net demand during the summer afternoons when marginal generators tend to be higher cost peaker plants. Wind in ERCOT, on the other hand, is less likely to reduce net demand in the summer afternoon and more likely to reduce it at night when the supply curve is flat.

With projected increases in the deployment of wind and solar by 2022, we expect the downward pressure of VRE on average wholesale prices to increase. Based on EIA projections of demand, VRE growth, thermal-plant additions, thermal-plant retirements, and fuel price changes (along with regional projections of changes in CO_2 emissions prices), we modeled wholesale price changes between 2017 and 2022 for all seven markets.

Impacts of VRE on annual average wholesale prices between 2017 and 2022 particularly stand out in regions where VRE generation increasingly occurs at times when oversupply conditions exist and prices become negative (e.g., CAISO, SPP, ERCOT, and NYISO). Most notable, the projected doubling of solar in California by 2022 in EIA's Annual Energy Outlook for 2018 may have substantial, non-linear additional impacts on average prices ($5–7/MWh reduction). Storage and other forms of flexibility not otherwise captured in the supply-curve model may mitigate these impacts (Mills and Wiser 2015). Even with this growth in VRE, however, changes in natural gas prices remain the dominant price influencer leading to an expected net increase in average wholesale prices between 2017 and 2022. Further details on this forward-looking analysis can be found in the Supplementary Information (note 4).

3.4 Non-linear Interactions

The large interaction terms relative to the overall decline in wholesale prices in some markets, particularly SPP, ERCOT, and MISO, illustrate limits on the ability to disentangle the relative contribution of individual factors to the observed decline in wholesale prices. In SPP, for example, summing the impacts of all individual factors leads to a net price decline of $6.7/MWh, whereas changing all of the factors simultaneously leads to a price decline of $18.6/MWh. Owing to the interaction of multiple factors, the combined impact of each individual factor understates the combined price decline by $11.9/MWh.

One source of interactions between multiple factors is changes in the net demand with increasing wind at the same time as changes in natural gas prices affect the slope of the supply curve. Again using the example of SPP, the sum of the individual contributions of wind and natural gas to wholesale prices was \$8.0/MWh, while the impact of changing wind and natural gas simultaneously was \$14.9/MWh. The interaction of wind and natural gas is therefore more than half of the overall interaction observed in SPP (e.g., (14.9-8.0)/11.9 = 0.57). Similar interactions between wind and natural gas were observed in ERCOT and MISO.

Another consequence of interactions between factors is that estimates of the magnitude of the wholesale price impacts of individual factors depend on the choice of base year. The previous results began with the system as it was in 2017 and changed one factor at a time to its 2008 levels. For most regions, the low natural gas prices in 2017 meant that the supply curve was relatively flat, muting the impacts of various factors on wholesale prices. Alternatively, the analysis could have started with the system as it was in 2008 and changed individual factors to their 2017 levels. In this case, the considerably steeper supply curve in 2008 amplifies the impact of individual factors, but does not alter the finding that changes in natural gas prices was the largest contributor (Figure 7). For example, had things remained the same as in 2008, with a very steep supply curve in many regions, the impact on average prices of increasing VRE from 2008 to 2017 levels could be almost five times higher (a price decrease of up to \$12.5/MWh instead of \$2.6/MWh). Not only would VRE impacts have been greater, but also the impact of nearly all other factors would have been greater. Using a 2008 base year therefore overstates the contribution of individual factors, and it leads to an interaction term with the opposite sign.

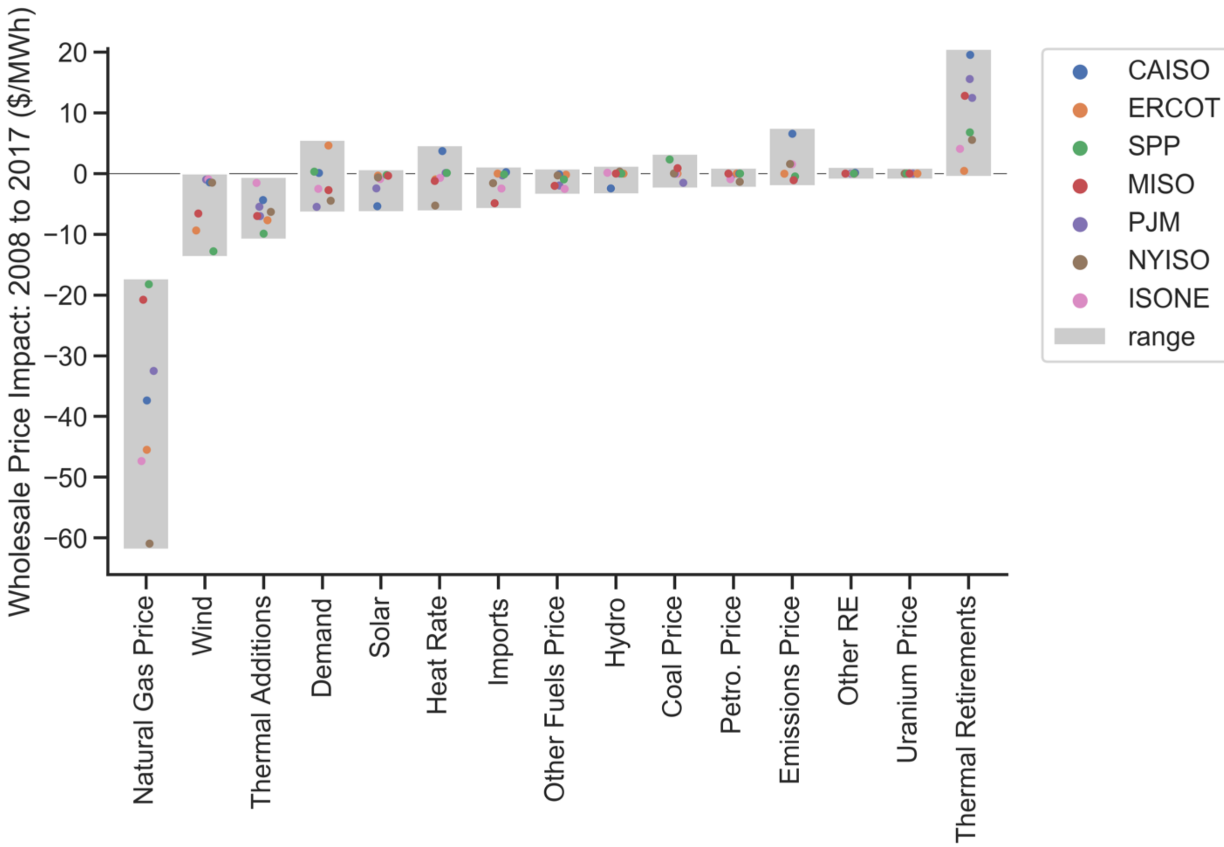


Figure 7. Impact of individual factors on average prices when keeping all factors at their 2008 level and changing one at a time to its 2017 level.

4. Discussion

The finding that the reduction in natural gas prices was the primary contributor to the fall in wholesale electricity prices since 2008 is consistent with an emerging literature that has similarly focused on decomposing factors impacting average wholesale prices in the United States, albeit generally focused on a smaller set of possible drivers and a subset of regions. For example, Jenkins (2017) estimated the relative impact of different drivers for wholesale price reductions from 2008 through 2016, finding that the decline in natural gas prices was the dominant factor, resulting in wholesale price reductions of roughly $20/MWh; growth of wind was found to have a much smaller effect of $1–2.5/MWh.

Haratyk (2017) similarly demonstrated that the declining price of natural gas was a larger influence on wholesale prices than was growth in VRE between 2008 and 2015 in both the Midwest and Mid-Atlantic regions of the U.S..

The impact of VRE on average wholesale prices reported here is within but often on the lower end of estimates in the previous literature (see Table 1). In some cases, this can be explained by a different choice of starting year. Haratyk (2017), for example, starts with all parameters at a 2008 level then changes individual factors to their 2015 levels. In other cases, the time period for the analysis includes years with higher gas prices and therefore a steeper supply curve. Impacts have declined with time on a marginal basis as the supply curve has flattened (Quint and Dahlke 2019). In still other instances, differences may be caused by our use of a simplified fundamental model, as opposed to regression models used in much of the other literature. Finally, differences may exist due to improper or imprecise methods used in some of the previous literature.

It is also clear that non-linear interactions between factors place a limit on isolating the effect of changes in individual factors. We bound the impact of non-linear interactions by estimating the impact of factors both with 2008 and 2017 as the starting year. Either way, we find that the impact of the decline in natural gas prices was greater than the impact of any other factor, including the growth of wind and solar.

Finally, growth in wind and solar impact not only average annual prices, but also temporal and geographic pricing patterns. Since the simple fundamental model used here does not account for many constraints embedded in real markets we did not use the model to quantify the impact of wind and solar on geographic and temporal variability in those prices. These changing pricing patterns clearly have important implications for valuing VRE: the fact that wind and solar suppress prices during periods of high VRE output means declining grid-system value with penetration (Hirth 2013; Sivaram and Kann 2016). An emerging literature has only just begun to explore the influence of VRE on temporal and geographic pricing patterns (Levin and Botterud 2015; Bushnell and Novan 2018; Woo et al. 2011; Mills and Wiser 2012).

5. Conclusions

Wholesale power markets in the United States experienced several major shifts over the past decade, with growth in wind and solar, a steep reduction in the price of natural gas, limited growth in electrical load, and an increase in the retirement of thermal power plants. Building on related work, this article has assessed the degree to which growth in variable renewable energy has influenced wholesale power energy prices in the United States, not in isolation but in comparison to other possible drivers.

Consistent with past literature, we find that wind and solar have contributed to reductions in overall average annual wholesale power energy prices. However, our multi-region and multi-factor analysis focused on seven regions of the United States adds considerable nuance to this finding, demonstrating that falling natural gas prices have been the dominant driver. In fact, the influence of variable renewable energy on annual average prices so far has been rather modest, and is similar in rough magnitude to a wide range of other secondary factors that include expansion and retirement of other generation capacity, changes in demand, generator efficiency, variations in hydropower, and emissions prices.

While impacts are anticipated to increase as wind and solar penetrations grow, our analysis suggests that variable renewable energy has not been the primary cause of thermal-plant retirements to this point. As such, any policy and market-design changes that seek to slow 'baseload' thermal-plant retirements should be thought-of primarily as a reaction to low, market-driven natural gas prices, and not (so far, at least) a consequence of policy-driven deployments of variable renewable energy. On economic grounds, it may be harder to justify additional support for at-risk generation if the drivers are primarily decreased competitiveness relative to other resource options, rather than being primarily driven by policy-induced variable renewable energy growth.

Additional research is warranted along multiple directions. First, VRE and other factors are likely to impact other grid services priced in wholesale markets, including capacity and ancillary services. Similar to wholesale energy prices, the price of these services varies by region and has changed over time. While the analysis presented in this paper focuses exclusively on energy prices, additional assessments might usefully also address capacity and ancillary service markets. Second, price changes have differential impacts on the revenue earned by different resources depending on whether the resource operates at a near-constant output irrespective of grid conditions (e.g., nuclear), the resource flexibly responds to changing grid conditions as signaled by changing prices (e.g., combustion turbines), or the resource dispatch is variable and largely driven by weather (e.g., wind and solar). Future research might therefore further explore the implications of price changes on the net revenue of different generation assets, depending on their typical dispatch patterns. Analysis might also usefully extend beyond generation to explore how pricing changes are already impacting the relative attractiveness of different forms of demand-side flexibility and storage investments. Third, investigations on longer-term power-sector transformation scenarios and related impacts on pricing and market design will require more sophisticated tools than employed in the present paper. Use of such tools can enable a more thorough assessment of future temporal and geographic pricing patterns under a range of future assumptions and conditions. Of particular interest might be assessments of the impact of VRE on price volatility and the subsequent impact on revenues of flexible resources, with important implications for policy interventions seeking to extract additional flexibility from both electricity supply and demand.

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Competing Interests

Declarations of interest: none

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The Impact of Wind, Solar, and Other Factors on Recent Changes in Wholesale Power Prices

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Supplementary Note 1

Hourly 2008-2017 load profiles, net of distributed PV (DPV), for each market are from ABB's Velocity Suite database (ABB 2017). For CAISO, ERCOT, PJM East, NYISO, and ISO-NE, these demand profiles are used directly. For other regions, the historical demand does not match with the current generation assigned to that market in ABB Velocity Suite as the market footprint changed over the historical period considered. In these cases, we scale up the ISO-reported demand in earlier years to match the more recent ratio of EIA reported sales in states currently covered by the ISO to the ISO-reported demand, similar to an approach used by Haratyk (2017). The result is that we effectively model each ISO based on its 2017 footprint, even in earlier years. Demand is calculated by adding DPV profiles, described below, to the demand net of DPV.

Hourly 2008-2017 wind data for MISO, SPP, ERCOT, and PJM are from ABB's Velocity Suite database. ABB does not have data from 2008 for CAISO nor for 2008 and 2012 for ISO-NE and NYISO. Aggregate wind profiles for 2012 for ISO-NE and NYISO are directly provided by the respective ISO. We estimate CAISO, NYISO, and ISO-NE wind profiles for 2008 using a regression based on wind and weather data from representative sites in NREL's Wind Tool Kit (Draxl et al. 2015). The regression was trained using overlapping aggregate profiles and Wind Tool Kit data from 2011-2012.

We use a variety of data sources to build the utility-scale PV (UPV) profiles. For ERCOT (2012-2017) and CAISO (2017), hourly UPV data are from ABB's Velocity Suite database. ABB data are used for solar shapes in PJM (2017) and ISO-NE (2017); however, we scale the ABB data with solar production estimates from GTM Research (GTM Research 2018), following an approach described elsewhere (Wiser et al. 2017), as the ISO provided hourly data covers only a fraction of the utility-scale solar capacity installed in these regions. For all other years and ISO regions, we simulate solar shapes using a combination of irradiation data from NREL's National Solar Radiation Database (NSRDB)(Sengupta et al. 2018), utility-scale solar plant characteristics from EIA Form 860, and NREL's System Advisor Model (SAM) (SAM 2018). After calculating the hourly solar shapes, we scale them to match the total annual solar energy production for a given year and region. For each ISO region, we first used installed UPV capacity (2008-2017) by date from ABB's Velocity Suite generator database. We use the resulting output for every year of UPV data for MISO and SPP where a changing ISO footprint would have made the alternative of scaling the output to state-based estimates solar less accurate. For the other regions, which had stable ISO footprints, we scale the energy amount using total UPV energy production estimates from GTM Research. Similar to the majority of UPV profiles, we use a combination of NREL's

NSRDB and estimates of DPV energy production for each ISO from GTM Research to generate DPV profiles.

Data for thermal generators is primarily obtained directly from the ABB Velocity Suite database, including the ISO where the generator operates, summer and winter capacity, forced outage rate, scheduled outage rate, whether or not the generator is a combined heat and power unit, and variable O&M costs. The heat rate and emissions rate for each unit is based on U.S. Environmental Protection Agency Continuous Emissions Monitoring (CEMS) data similarly accessed through ABB Velocity Suite. We use the CEMS data to develop unit-specific heat rates and emissions rates for each month of 2008, 2012, and 2017. Where data was not directly available for a particular month or year, we rely on averages for similar plants in the same market region.

Daily natural gas prices from major trading hubs in each region are from ABB's Velocity Suite. Hubs are selected largely based on guidance from market monitoring reports for each ISO. We calculated monthly coal fuel costs as the average delivered cost of coal in each state and month as reported to EIA and accessed through ABB's Velocity Suite. Similarly, we calculate annual fuel costs for other fuels (petroleum, uranium, renewable/biomass, etc.) as the average fuel costs in each region for each fuel as reported to EIA and accessed through ABB Velocity Suite.

We model the effects of emissions prices for NOx, SO2, and CO2 in each region depending on whether a majority of plants in the specific ISO region faced those costs, as reported in

ABB's Velocity Suite generator database. Historical NOx and SO2 emissions prices are from SNL Financial from 2008-2017(SNL Financial 2018). California carbon prices are from the Climate Policy Initiative(Climate Policy Initiative 2018) and RGGI prices are from SNL (2017) and from EIA (2008 and 2012) (EIA 2017).

We include hydropower for CAISO, ISO-NE, and NYISO assuming hydropower dispatch occurs in response to the net demand (demand less wind and solar in this case) and as a function of precipitation. We model hydropower dispatch as responsive to net demand because, in contrast to VER, hydropower is a dispatchable resource whose output can be scheduled based on economic considerations. Hydropower does, however, have limits that influence this dispatch such as minimum stream-flow requirements, limited energy storage capacity, and coupling constraints between reservoirs on the same river system. Rather than attempt to incorporate such constraints directly in the simple model, we use historical observations of hydropower dispatch to estimate its response. The relationship between hydropower, net demand, and precipitation is based on simple linear regressions over an historical period depending on data availability. In the regression, hourly hydropower levels are based on hourly net demand and a monthly value of the moving average of precipitation measured at a USGS gauge in each region with a window of one year. Hydropower was excluded altogether in all other regions, given its small share in total generation.

Similar to hydropower, imports change in response to system conditions, though many factors affect the capabilities of imports. Rather than attempt to model those factors directly, we similarly use historical observations of imports to estimate its response to system conditions. In particular, hourly import levels are based on a simple linear regression of hourly net demand, the square of net demand, and monthly imports estimated from EIA. For most regions, the hourly import data used to develop the regression is from the total net actual hourly interchange from EIA's U.S. Electric System Operating Data (using data from 2016-2017) (EIA 2018b). For CAISO and PJM, we use longer histories of hourly import profiles provided by ABB. For MISO, major changes in the market footprint result in large differences in the amount of imports predicted by the regressions relative to the annual average imports reported by the MISO market monitor in years prior to 2016 (Potomac Economics 2017). In this case, we scale the imports from the regression by the historical annual average reported by the market monitor.

In PJM, we include a transmission constraint to more accurately represent the flow of energy between PJM West and PJM East during constrained hours. We use PJM's transfer limits and flows database to identify a 5,000 MW transfer capability between the regions(PJM 2018). Then, we simulate the market clearing price in the PJM East region, where our price hub of interest for PJM is located, using methods to model centralized trading in a two-bus system described by Kirschen and Strbac (2004). The transmission constraint limits the ability of generators located in one region from supplying load in the other region. Inclusion of the transmission limit improves the supply-curve model's estimate of annual average prices in PJM East relative to a model without a transmission limit between the two regions of PJM.

When the net load is below the minimum generation level, prices fall to the level of negative bids. Specifically, if the intersection of the supply curve and demand falls below the minimum generation level, based on nuclear and combined heat-and-power capacity, prices are assumed to equal a negative bid price between -$3 to -$17/MWh, depending on the region. The negative bid prices are based on the actual observed average negative price in 2017 for each region. Alternatively, if the demand plus an assumed operating reserve margin of 5% exceeds estimated supply, prices are assumed to increase to a penalty price of $1,000/MWh. This value was chosen to be above the marginal variable costs of generators and in the range administratively-set scarcity prices in U.S. ISOs.

Projections for 2022 are based on scaling 2017 shapes from each ISO by ISO-specific growth rates from EIA's Annual Energy Outlook 2018 (EIA 2018a). As an alternative to EIA's reference case, we examine a separate case where we use the planned generation additions and retirements from ABB's Velocity Suite. This alternative results in greater VRE in all markets than EIA's reference case except for CAISO where EIA projects greater wind and solar. To project CO_2 prices to 2022, we relied on California Energy Commission projections for California's cap-and-trade program(California Energy Commission 2018) and NYISO projections for RGGI carbon prices(Cohen 2018). We held NO_x and SO_2 prices constant between 2017 and 2022.

Supplementary Note 2

One way to validate the modeled prices is to compare the price distribution curves of the modeled prices to the price distribution curves of the actual RT market prices at the hubs. These are shown for each region below, along with a comparison of the average modeled and actual RT prices (Figures 1–7)..

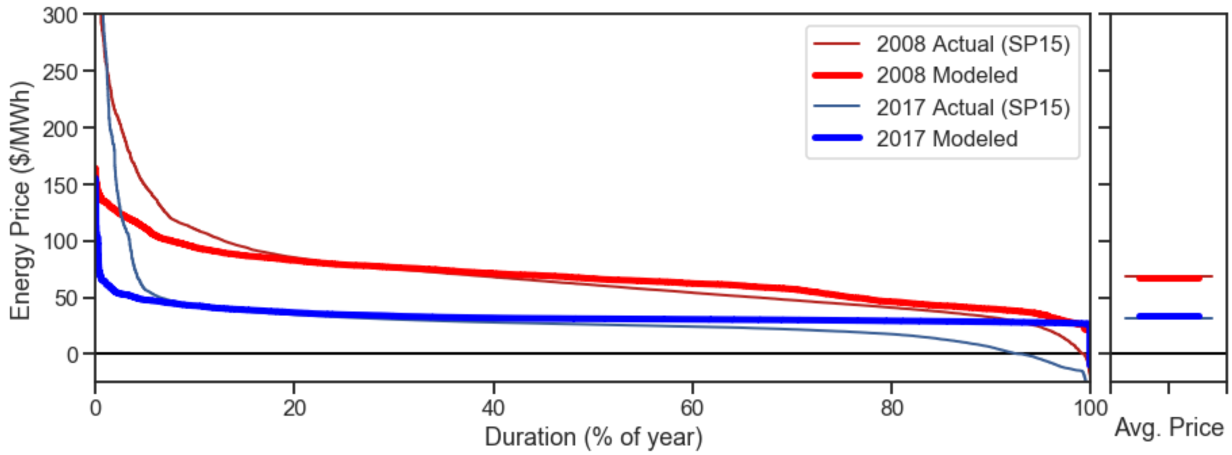

Figure 1. Price duration curves for modeled and actual RT prices for CAISO.

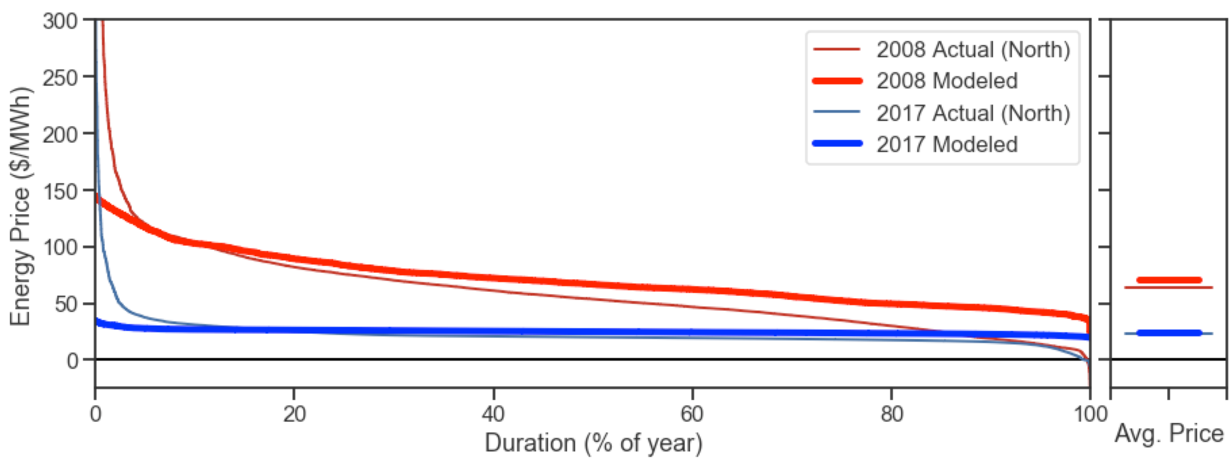

Figure 2. Price duration curves for modeled and actual RT prices for ERCOT.

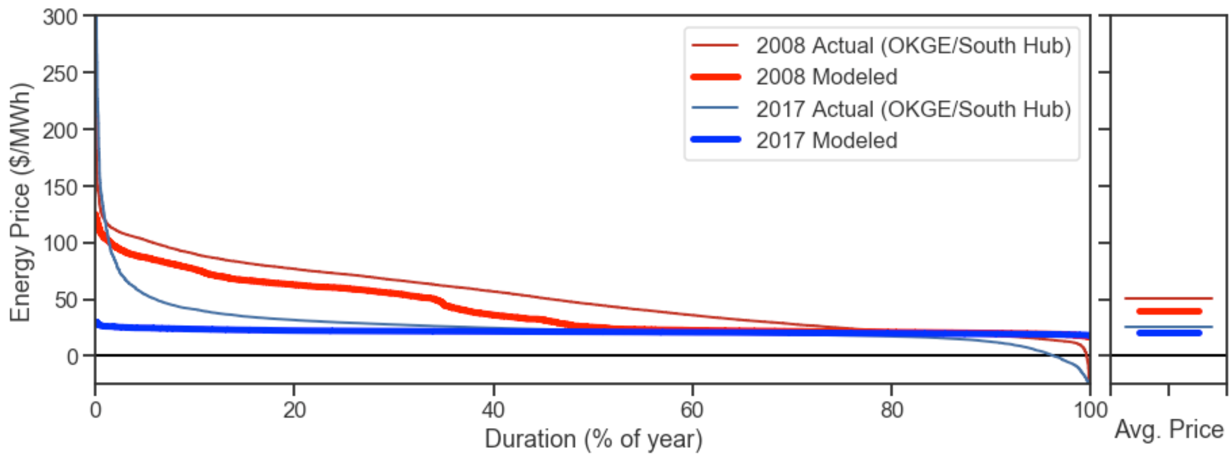

Figure 3. Price duration curves for modeled and actual RT prices for SPP.

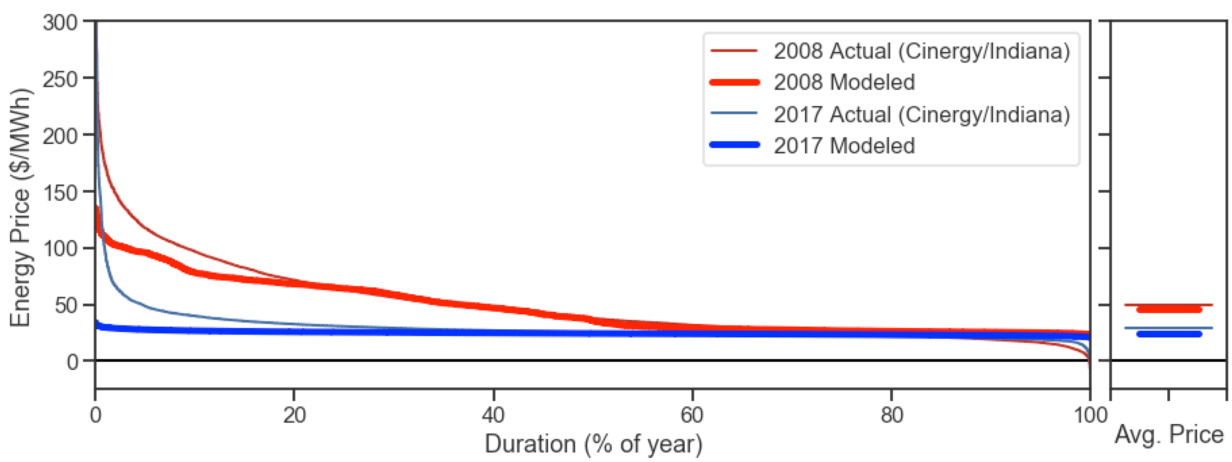

Figure 4. Price duration curves for modeled and actual RT prices for MISO.

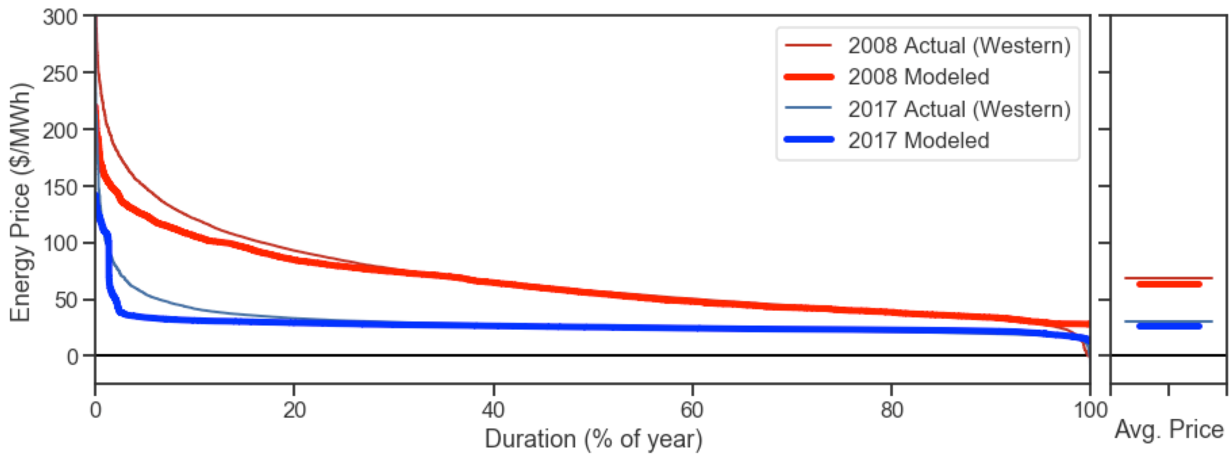

Figure 5. Price duration curves for modeled and actual RT prices for PJM.

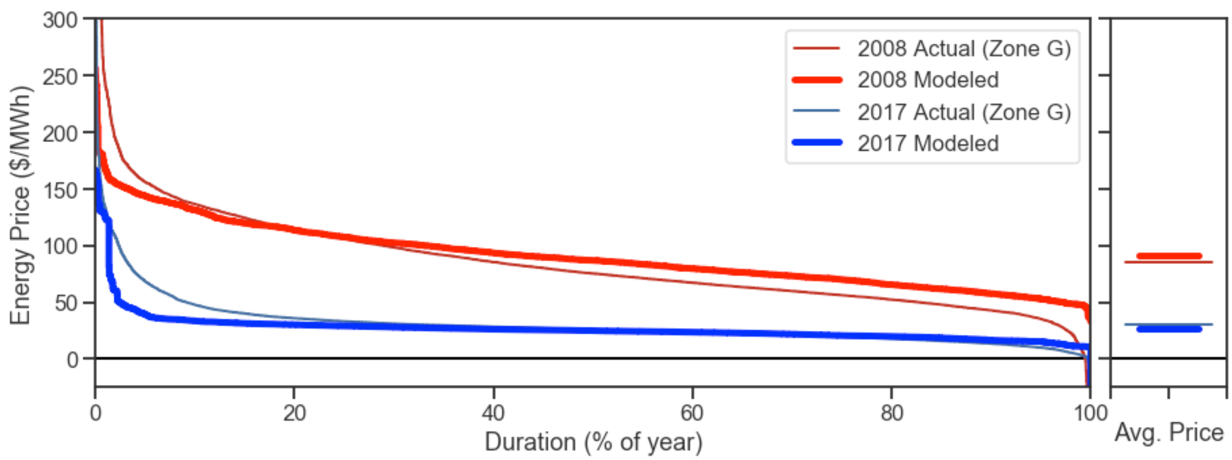

Figure 6. Price duration curves for modeled and actual RT prices for NYISO.

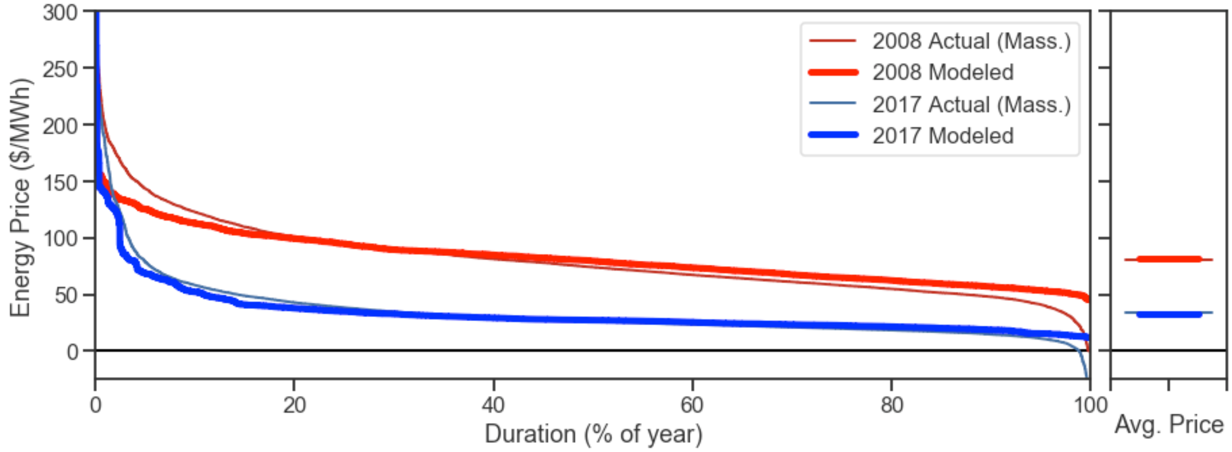

Figure 7. Price duration curves for modeled and actual RT prices for ISO-NE.

Another way to validate the model is to compare the actual real-time price in a particular hour to the modeled price for the same hour. In addition to having a matching annual average price, ideally, the modeled price in each hour would match the actual price in each hour. The degree to which hourly prices do not match is measured by the normalized mean absolute error (NMAE) for each region and year, Figure 8. Across all regions, hourly errors were higher on average in 2008, a period with generally higher prices and a steeper supply curve, than in 2017. Normalizing the mean absolute errors by dividing by the actual annual average real-time price yields relatively stable normalized mean absolute errors across regions and years in the range of about 15-40% with the exception of CAISO. Normalized mean absolute errors approach 60% in California for 2012 and 2017 where, as shown in Figure 8, the variability of prices is higher than other regions as measured by the standard deviation of real-time prices.

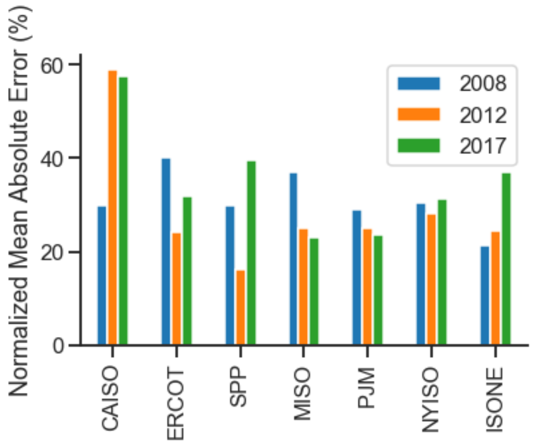

Figure 8. Normalized mean absolute error between hourly actual prices and hourly modeled prices.

As a final diagnostic exercise, we also compare the correlation of hourly price errors to hourly estimates of several time varying parameters in the model including gas prices, demand, hydro, imports, solar, wind, and 1-3 hour ramps in the net demand, Figure 9. Error is defined as positive when the modeled hourly price exceeds the actual hourly real-time price. The positive correlation between wind and model error suggest that modeled prices tend to be greater than actual prices when wind is high. Furthermore, the correlation of errors and wind increased in many regions that saw increased growth in wind between 2008 and 2017. Similarly, solar in CAISO and ISO-NE began to see a positive correlation of solar and errors in 2017. This suggests that the model may be understating the effect of wind and solar on hourly prices and that further model improvements in representing minimum generation levels would be valuable.

Demand is negatively correlated with the errors. This suggests that modeled prices tend to be lower than actual prices when demand is high and that further model improvements in representing a tightening of the supply curve during high demand periods would be valuable. Hydro and Imports similarly have a negative correlation with errors, though the hourly patterns for Hydro and Imports are modeled as being dispatched in response to net demand. The correlation of natural gas prices and errors do not have a consistent direction and magnitude across regions and years.

Net demand ramps are for the most part negatively correlated with errors. CAISO, which has experienced significant growth in solar, shows a large degrease in the correlation of net demand ramps and errors in prices. This suggests that modeled prices tend to be lower than actual prices when net demand ramps are high and that further model improvements in representing ramping constraints on thermal generators would be valuable.

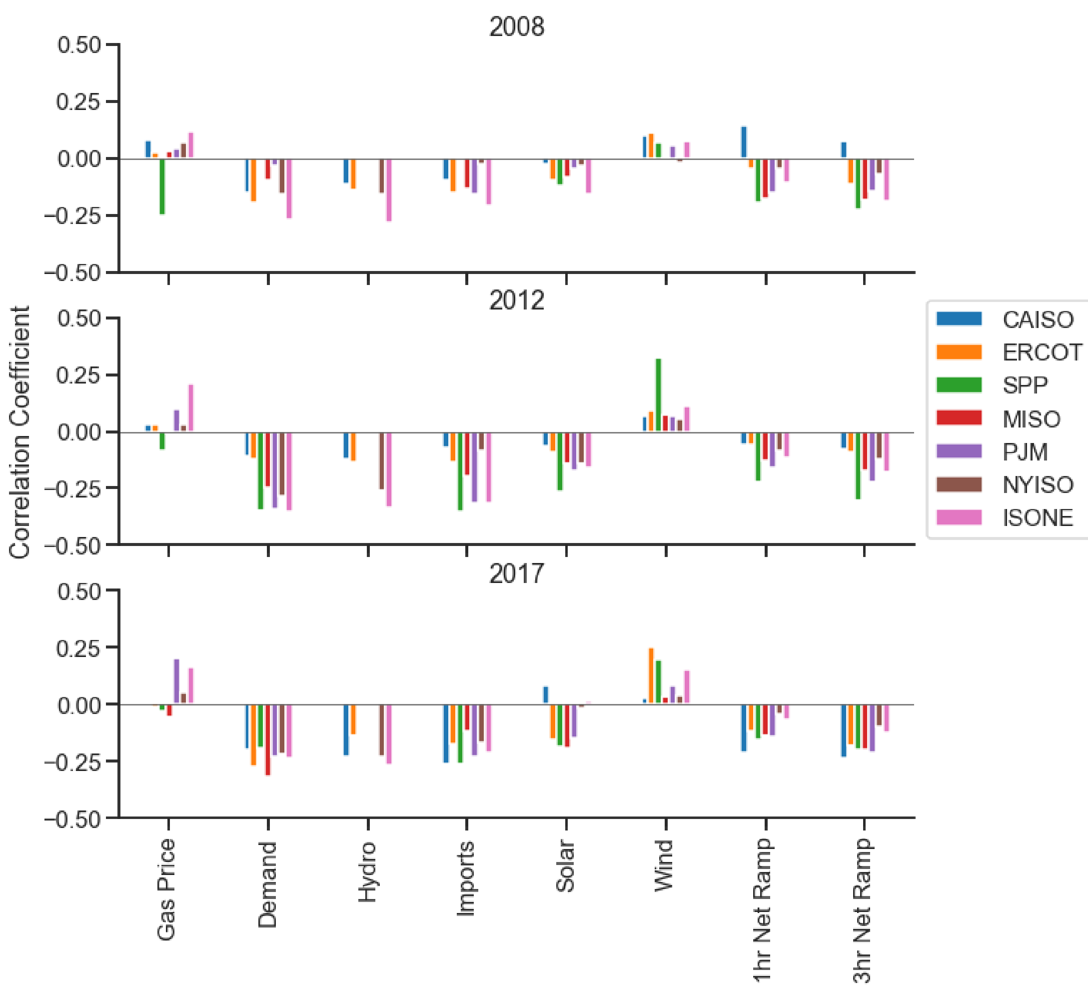

Figure 9. Correlation between hourly error and hourly values for several factors in 2008, 2012, and 2017.

Supplementary Note 3

Since 2008, annual average natural gas prices have fallen and remained at much lower levels, whereas shares of VRE generation have expanded rapidly in some markets. Here we examine the relative impacts of different factors on wholesale prices over a period with low gas prices and relatively stable wholesale prices: 2012-2017. The results of our analysis, conducted in the same fashion as the earlier results for 2008-2017, are presented in Figure 10.

Overall, the net impact of all factors considered was to either modestly increase (ERCOT) or—more commonly—to modestly decrease (all other regions) annual average prices.

Even though natural gas prices are on average much lower in 2012 than 2008, natural gas prices are found to still be the largest driver of changes in wholesale prices in some regions from 2012 to 2017. Increases in natural gas prices between 2012 and 2017 contributes to increases in wholesale prices in CAISO and ERCOT. In contrast, decreases in natural gas prices between 2012 and 2017 decrease wholesale prices in NYISO.

Factors that decrease prices on par with the estimated VRE impacts include thermal generation additions (PJM, CAISO, and ERCOT), decreases in coal prices (PJM and MISO), and more precipitation and therefore hydropower production (CAISO).

Factors other than natural gas price changes that are found to have increased wholesale prices include higher coal prices in ERCOT, less precipitation and therefore less hydropower production in NYISO, marginal combined cycle units in CAISO and ISO-NE that were less efficient in 2017 than in 2012, generation retirements in ISO-NE, higher emissions prices in NYISO and ISO-NE, and increased demand in ERCOT.

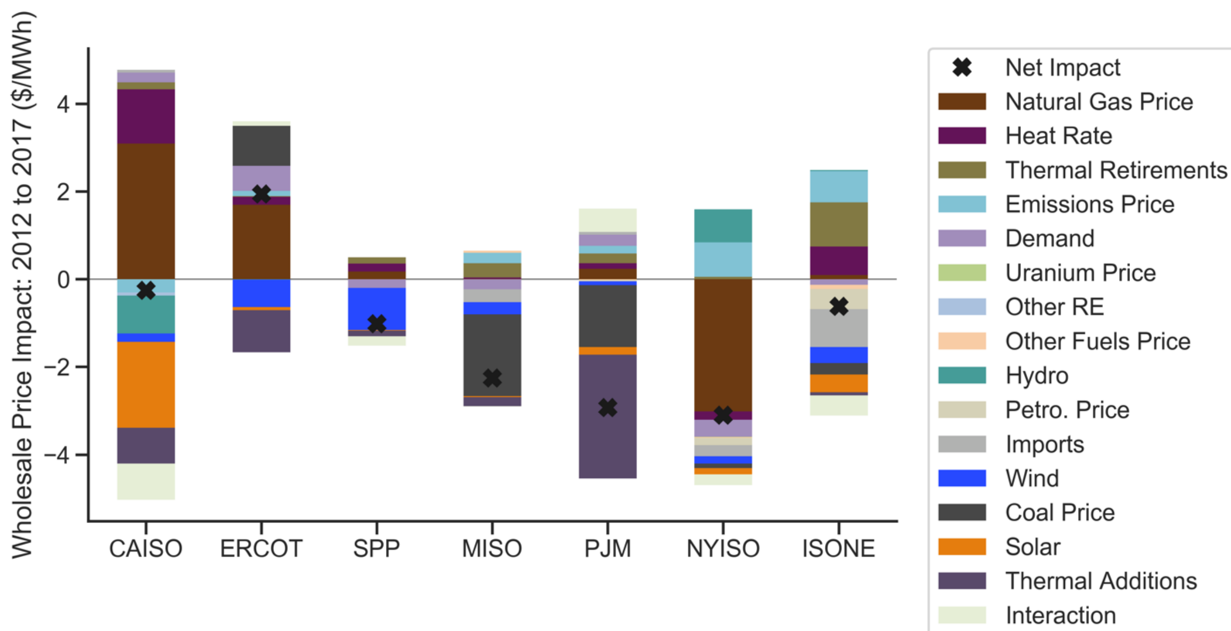

Figure 10. Price impact of various factors that changed between 2012 and 2017 across all markets.

Supplementary Note 4

Based on EIA projections of demand, VRE growth, thermal additions, thermal retirements, and fuel price changes (along with regional projections of changes in CO_2 emissions prices), we modeled wholesale electricity price increases between 2017 and 2022 for all seven markets (Figure 11).

The major contributors to the increase in prices vary by region, though the expected increase in natural gas prices is consistently one of the largest contributors to increases in average estimated wholesale prices. The projected increase in carbon prices in California and RGGI leads to estimated wholesale price increases in CAISO, ISO-NE, and NYISO. The increase in coal prices leads to notable increases in estimated wholesale prices in MISO, ERCOT, and SPP. The increase in prices due to the retirement of thermal generation is substantial in CAISO and NYISO. Finally, the expected increase in electricity demand is found to boost wholesale prices modestly in most regions.

Growth in VRE, on the other hand, is found to mitigate the price increases, particularly in the case of solar growth in California. EIA projects that solar penetration will double in California between 2017 and 2022, leading to several instances in the simple supply curve model where net demand is less than minimum generation levels for nuclear and combined heat and power units. Prices in these hours are therefore set by the assumed negative bid price for curtailing renewables. As this future negative bid price is uncertain, we show the

CAISO results both assuming curtailment occurs at a price of zero and assuming curtailment occurs only when prices are below -$10/MWh.

The estimated impact of solar on wholesale prices in California far exceeds the anticipated impact of wind and solar in all other markets, even with solar curtailment assumed to occur at a price of $0/MWh. In other regions, the decrease in average wholesale prices from wind and solar is on par with or less than the decrease in prices due to other thermal generation additions.

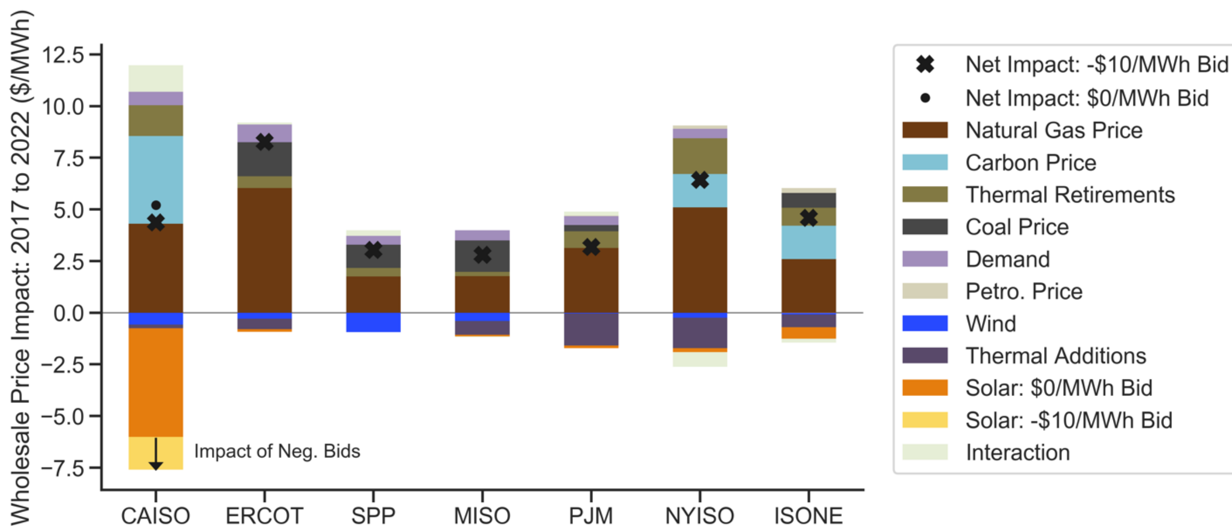

Figure 11. Average wholesale power energy price impact of various factors that are expected to change between 2017 and 2022 across all markets.

These results are based on a simple supply curve model, and EIA reference case assumptions for the change in various possible price drivers to 2022. They should not be construed as precise forecasts for future regional wholesale prices or price trajectories. In particular, the lack of storage in the simple supply curve model will tend to overstate the magnitude of the impact of solar.

Many factors can impact generation expansion and retirement decisions, including expansion of VRE, across U.S. markets making it difficult to rely on only one source for future projections. Projections from other sources (BNEF 2018) include considerably greater wind and solar deployment in most markets than EIA's reference case by 2022. One major exception is that Bloomberg New Energy Finance (BNEF) projects less wind and solar growth in CAISO than projected in EIA's reference case. The BNEF projections for utility-scale solar and wind are more in line with planned projects in ABB's Velocity Suite (including projects identified as "feasible" and "proposed"). We therefore examined wholesale price impacts for an alternative set of generation expansion and retirements projections for 2022, with greater VRE deployment in all regions except CAISO. The results in Figure 12 show that using this alternative to the EIA's reference case results in overall similar conclusions as presented above, with a smaller impact of solar in CAISO and greater impacts of wind relative to impacts based on EIA's projections, particularly in SPP, NYISO, and ERCOT. The greater impact of wind in the alternative case is in part due to more frequent negative prices with the growth of wind. Solar growth in CAISO still has the greatest impact on decreasing prices. However, other factors that tend to increase prices (e.g., natural gas prices, emission prices, and thermal retirements) are still overall greater, leading to a net wholesale price increase in each market.

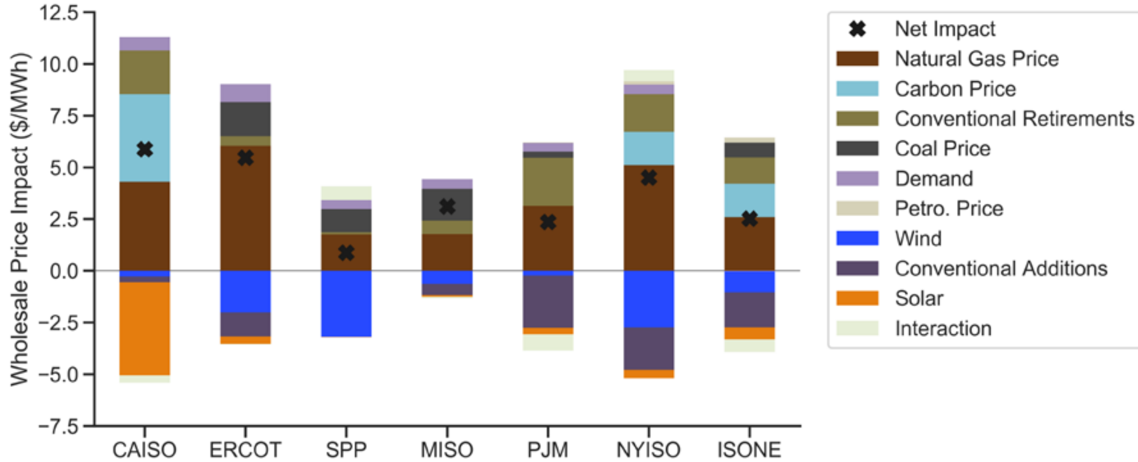

Figure 12. Average wholesale power energy price impact of various factors that are expected to change between 2017 and 2022 across all markets using ABB Velocity Suite data rather than EIA.

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