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Intermittency or Uncertainty? Impacts of Renewable Energy in Electricity Markets

Abstract

Renewable energy resources possess unique characteristics—intermittency and uncertainty— that pose challenges to electricity grid operations. We study these characteristics and find that uncertainty, represented by wind forecast error, has larger grid impacts than intermittency, or hourly generation changes. Uncertainty yields roughly double the price effects and roughly double the number of conventional generator start-ups, as compared to perfectly forecast wind. While this finding is important given the persistence of wind forecast error over the study period, reducing wind forecast error to the level of demand forecast error would lower costs by a modest half a million dollars per year.

JEL-Codes: Q400, Q420, Q470.

Keywords: renewable energy, electricity prices and price dispersion, electricity grid management.

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1 Introduction

Renewables in the United States electricity sector have experienced rapid growth over the last decade, increasing from less than 2% of the generation mix in 2001 to greater than 12% in 2020.[1] This trend is poised to continue, with renewables accounting for a majority of capacity expansions in 2021 and planned expansions in 2022.[2] Renewables offer the potential for a dramatic reduction in electricity sector pollution, and continued cost reductions in these technologies may provide lower electricity prices. Yet, the growth of renewables is not without concern. Predominant renewable resources—wind and solar energy—possess unique characteristics that may pose both technical and economic challenges to the operation of electricity grids: intermittency in generation stemming from exogenous changes in resource availability and uncertainty in generation due to forecast error.[3]

In this paper, we decompose the overall effects of renewable resources on electricity markets outcomes by separately estimating the impacts of renewables' intermittency and renewables' uncertainty. Previous work has estimated the overall effect of wind and solar resources on prices, and a smaller subset of this work includes effects on price dispersion.[4] In addition, we separately identify the role of each of these characteristics on price levels and price dispersion. In doing so, we provide novel estimates of how renewables' forecast error impacts wholesale electricity prices. We also estimate how each of these characteristics affects the operations of non-renewables generators, which further identifies how renewables' forecast error imposes costs on electricity markets.

We find that an additional one GWh of wind generation reduces wholesale electricity prices in Texas by around $2.27 per MWh, and these effects are highly heterogeneous with the largest effects occurring in hours with high residual demand for conventional generators, defined as consumer demand less renewable energy. We also find that wind generation decreases dispersion of hourly prices because of its impact on decreasing prices by reducing residual demand. However, when controlling for this residual demand price dampening effect, renewables increase price dispersion. As with the price effect, the price dispersion effects are highly heterogeneous across the hours of the day and are larger when the residual demand is greater.

1. We exclude hydroelectric generation in our calculation of renewables output. Data, currently available through 2020, are from the U.S. Energy Information Administration's Electric Power Monthly: `https://www.eia.gov/electricity/monthly/`.

2. Data are from the U.S. Energy Information Administration's Preliminary Monthly Electric Generator Inventory (Form EIA-860M): `https://www.eia.gov/electricity/data/eia860m/`.

3. Resources such as hydroelectric power and geothermal power are not intermittent and hence do not share all the characteristics that wind and solar possess. We use the term "conventional" generation to refer to fossil-based resources and other dispatchable power plants.

4. See Woo et al. (2011), Ketterer (2014), and Bushnell and Novan (2021), among many others. Würzburg, Labandeira, and Linares (2013) provides a comprehensive review of the early literature on this topic.

In our decomposition analysis, we find heterogeneous effects by each of wind generation's unique characteristics. We estimate that one GWh of unforecast wind generation has a bigger effect on prices and price dispersion than one GWh of forecast generation, a result that we attribute to differences in the conventional supply curve that is available when market conditions are predicted well versus hours with substantial forecast error. In addition, we find that the effect of wind forecast error on wholesale electricity prices is larger than the effect of demand forecast error, indicating a difference in the way grid operators manage uncertainty in residual demand coming from renewables versus demand.

We also examine the mechanisms generating these results and find that wind forecast error leads to a greater extensive margin response from non-wind generators—particularly natural gas turbines—as compared to forecast wind. That is, when wind generation is poorly forecast, more units must start up or shut down to balance the market as compared to when wind is perfectly forecast. These findings are particularly important given two key descriptive findings about error. One, although demand in Texas is around seven times the size of wind generation, the magnitude of average hourly forecast error for wind is roughly 50% larger than the forecast error for demand. Two, while both raw error and error rate in demand forecasting has been improving over time, the same trend is not observed for wind forecasting.[5]

The goal of our work is to prepare policy makers and grid operators for the anticipated impacts of a new electricity portfolio. Understanding the unique effects of intermittency and uncertainty allows for a clearer and market-specific set of predictions about the future grid impacts from renewables. For example, our estimates of forecast error's impacts demonstrate the potential value of investing to improve grid operators' forecasts of renewable energy. We find that improving wind generation forecasts to the quality of demand forecasts—a 33% reduction in wind forecast error—would reduce integration costs by an estimated $550,000 per year in the Texas electricity market. Further, our estimates of the effect of hourly intermittency on price levels and dispersion provide insight into the potential role of storage technologies in smoothing hourly prices. Additionally, our estimates of renewables effects on price dispersion indicate a new co-benefit of increasing renewable energy penetration, to the extent that dampening price dispersion provides value to consumers and producers. The descriptive trends we find in our data during this study period with respect to intermittency and forecast error are also useful for preparing for an increasingly decarbonized electricity grid. In particular, we find that wind generation forecasts did not improve during our

5. Further detail on these descriptive findings is provided in Section 2.

study period while wind generation steadily increased. Hour-to-hour changes in wind generation, or hourly intermittency, increased as wind generation in the market increased, though at a decreasing rate per unit of wind.

We develop a simple theoretical framework to predict how each of the unique characteristics of renewables—zero marginal cost, intermittency, and uncertainty—impact market outcomes. Because renewables have zero marginal cost, they will always be prioritized for meeting consumer demand.[6] Additional renewable generation reduces residual demand—consumer demand less renewable generation—that must be supplied by conventional generators. This shift in residual demand lowers the marginal cost of electricity generation and, hence, the wholesale electricity price. This residual demand price effect is expected to dampen price dispersion as lower prices yield greater price stability in this market; at the same time, however, more renewables have greater intermittency, which would be expected to increase price dispersion. Thus, *ex ante* it is not clear if more renewable generation will increase or decrease price dispersion. Additionally, when residual demand deviates from what was expected due to uncertainty in renewable generation, maintaining grid reliability requires an immediate response that can only be provided by a limited set of producers. The limited effective supply curve in these cases means unforecast renewable generation yields larger price effects than perfectly forecast generation, intermittent or not.

We test each of these hypotheses using hourly and sub-hourly data from the Texas electricity market for the years 2012–2019. The data include sub-hourly wholesale prices, hourly wind generation and hour-ahead forecasts of wind generation, and hourly electricity demand and hour-ahead demand forecasts. This market has one of the highest penetrations of wind energy among US electricity markets, growing from roughly 9% in 2012 to more than 24% in 2021.[7] Additionally, the Texas electricity grid has little capacity for trade with adjacent electricity markets, making it well suited for use as an isolated laboratory in which to study these effects of wind generation on electricity market outcomes.

Our work contributes to a growing literature seeking to anticipate and prepare for the transition to an increasingly decarbonized electricity grid. There are a number of papers that have estimated the price effect of renewables stemming from their zero-marginal cost property, often termed the "merit-order effect." A survey of this literature by Würzburg, Labandeira, and Linares (2013) finds

6. The fuel inputs to electricity generation from wind and solar resources come at zero cost. There are some variable operational costs in solar and wind production, but these costs are sufficiently small enough that wind and solar resources are treated as zero marginal cost.

7. Data are from the Electricity Reliability Council of Texas's Fuel Mix Reports, which are available at: `http://www.ercot.com/gridinfo/generation`.

the estimated effects of one additional GWh of renewable energy have ranged from around to \$0.40 to \$13.00 per MWh in empirical settings across Europe and the US from studies written from 2001 to 2009.[8] Sakaguchi and Fujii (2021) study the merit-order effects of wind and solar in Japan in the years 2016–2020 and find that wind has a larger price effect in hours with higher prices using quantile regression binning on price. Quint and Dahlke (2019) study the price effects on wind in the U.S. Midwest and document evidence of a lower marginal effect over time, attributed to an increase in wind generation. Cludius et al. (2014) and Zipp (2017) estimate price impacts from merit-order effects in Germany, and Clò, Cataldi, and Zoppoli (2015) estimate these effects in Italy.

The theoretical framework presented in Section 3 highlights that price effects across geographies and time need not be comparable in magnitude, as they are a function of the local supply curve elasticity where it intersects the residual demand, both of which are clearly unique across electricity markets. Yet, our estimate of wind generation's margin effect on price—1 GWh of wind reduces prices by \$2.27 per MWh—falls within the range of estimates found in the literature. To demonstrate the mechanism generating differences across time and space, we estimate price effects separately in hours with high and low residual demand and show that price effects are larger in periods with higher residual demand. In describing these two sets of results, we avoid the term "merit-order effects" as this embeds several mechanisms in which renewables impact price outcomes. Rather, we distinguish between price effects coming from renewables reducing residual demand and those coming from the known and unknown quantity of renewables supply, where the second two effects can lead to price outcomes from changes in the effective supply curves of conventional generators. In that regard, perhaps our more important contribution is our decomposition of price effects and price dispersion effects based on the unique characteristics of renewables, including novel estimates of the impact of error in renewable energy forecasts on wholesale electricity prices.

In terms of renewables and price dispersion, Woo et al. (2011) and Mallapragada et al. (2021) also study price dispersion effects of wind in ERCOT. Compared with Woo et al. (2011), our paper studies Texas's market in more recent years, 2012–2019, which allows us to study a period with higher wind penetration, reaching 20% in our sample compared to 10% in their earlier study period. Further, we use a different approach to study the impact of renewables on price variance, and we also decompose the effects by the characteristics of renewables. The Woo et al. (2011) approach predicts how an increase in wind generation would impact price dispersion using the estimated

8. These estimates are taken from the minimum and maximum price effect listed from column 8 in Table 2 of Würzburg, Labandeira, and Linares (2013), 0.35 to 11.60 Euro per MWh, and then converted to USD using exchange rate as of December 15, 2021.

variance from a linear model of price as a function of wind generation, which by construction is always positive. Our approach, on the other hand, directly estimates the impact of renewables on price dispersion using observed data to measure price dispersion. Notably, we find that overall renewable energy reduces price dispersion through its dampening effect on prices. Mallapragada et al. (2021) simulate wholesale electricity price distributions to 2050 under alternative constraints on carbon emissions. Their results indicate that more renewables increase price dispersion, increasing the frequency of periods of both very low and very high prices. Our estimation of current outcomes, however, indicates that renewables in Texas have had a dampening effect on price dispersion as they reduce the amount of energy demanded from conventional resources.

This paper also contributes to the literature that estimates the impact of renewable energy policy on consumer costs. Sensfuß, Ragwitz, and Genoese (2008) find that the price effect of renewables in Germany in 2006 exceeded the costs of the feed-in-tariff policy used to induce renewable energy. Meanwhile, renewables may also affect the producers of conventional generation sources; Bushnell and Novan (2021) study the impacts of solar energy generation on market outcomes in California, and they find that over the long term renewables decrease the economic value of traditional baseload units. They also conclude that little market value is generated by policies to promote the proliferation of renewable technologies that provide energy in periods with low prices. Fell, Kaffine, and Novan (2021) study how transmission and congestion impact the social value of renewables, showing that wind energy in Texas has a larger environmental benefit when transmission is unconstrained. Novan (2015) points out that renewables have heterogeneous environmental benefits depending on the technology and level of installed capacity. Jha and Leslie (2021) study the competitive effects of renewable energy, finding that increases in solar capacity reduce competition during sunset hours. The role of start-up costs in their paper is highly connected to one of the outcomes here—we find that the larger price effects of wind forecast error are due to the need to start up or shut down producers in order to maintain a balanced grid.

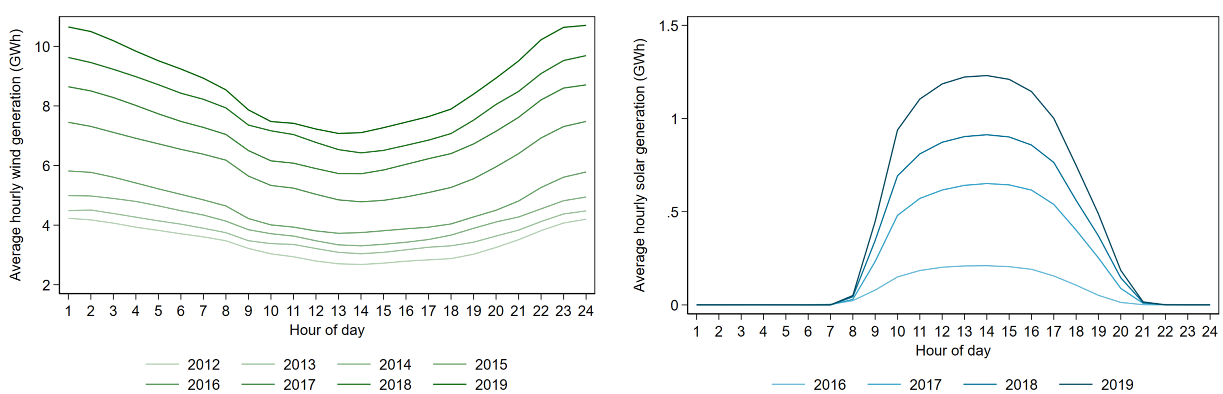
2 Data and descriptive analysis

The data for this paper come from the electricity grid operator in Texas, the Electric Reliability Council of Texas (ERCOT), which makes these data publicly available by request. These data include hourly wind and solar generation, wind and solar forecasts, demand, and wholesale electricity prices over the period of 2012–2019. Generation and forecast data are available at the region and marketwide level; we focus on marketwide observations in this work. Electricity prices are also available at the 15-minute level, which we use for one of our measures of dispersion. The forecast data come from ERCOT's Short-term Wind Power Forecast (STWPF) and Short-term Photovoltaic Power Forecast (STPPF), hourly forecasts of the generation from all available wind and solar resources, respectively.[9] These forecasts are first made available several days in advance and are updated every hour to reflect new information. We use the final forecast made in the hour preceding operations, which corresponds to the last opportunity for market participants to adjust their operating plans.

Figure 1a shows wind energy generation by hour and year, demonstrating a steady monotonic increase in the quantity of wind over the study period.[10] Wind energy varies throughout the day, with larger generation coming in the evening and early morning hours. However, on average wind exhibits less variation over the day compared to solar, shown in Figure 1b, which produces only during daylight hours, peaking between hours 12 to 16 (4pm). The solar time series starts in 2016; before that ERCOT did not produce solar resource reports because it did not have much utility-scale solar on the grid (ERCOT 2021b). Over the years 2016–2019 we see almost 10 times as much wind as solar, with wind generation reaching 10.7 GWh in some hours in 2019, compared to solar reaching just over 1.7 GWh in 2019. For this reason, our empirical strategy in Section 4 focuses only on the effect of wind generation.

Figure 1: Average hourly renewable generation in ERCOT by year

(a) ERCOT wind generation (b) ERCOT solar generation



Notes: Panel (a) shows average hourly wind generation in ERCOT by year for 2012–2019. Panel (b) shows average hourly solar generation in ERCOT by year for 2012–2019.

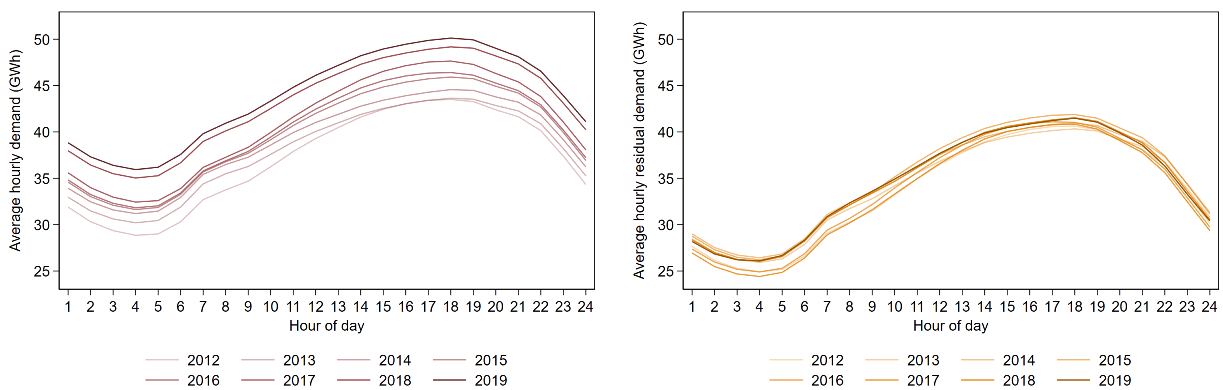
9. The STWPF and STPPF correspond to ERCOT's 50% probability of exceedance forecast for generation from all available units of the wind and solar resources, respectively (ERCOT 2021b, 2021a).

10. Hour numbers in this figure and elsewhere denote the hour-ending number.

Wind and solar have close to zero marginal cost, so they are scheduled first to meet demand, which we discuss in more detail in Section 3. Residual demand, demand less wind and solar generation, is thus the demand curve facing conventional generating units. Figure 2a plots hourly electricity demand over time showing a steady annual increase in demand in all hours over the time series. On average demand per hour was 18 percent higher in 2019 compared to 2012. Meanwhile, the increase in renewable generation dampens the increase in residual demand shown in Figure 2b, which rose on average by only 3 percent over this time period.

Figure 2: Impact of renewables on residual demand

(a) Demand (b) Residual demand



Notes: Panel (a) shows average hourly demand in ERCOT by year for 2012–2019. Panel (b) shows average hourly residual demand, demand less wind and solar generation, in ERCOT by year for 2012–2019.

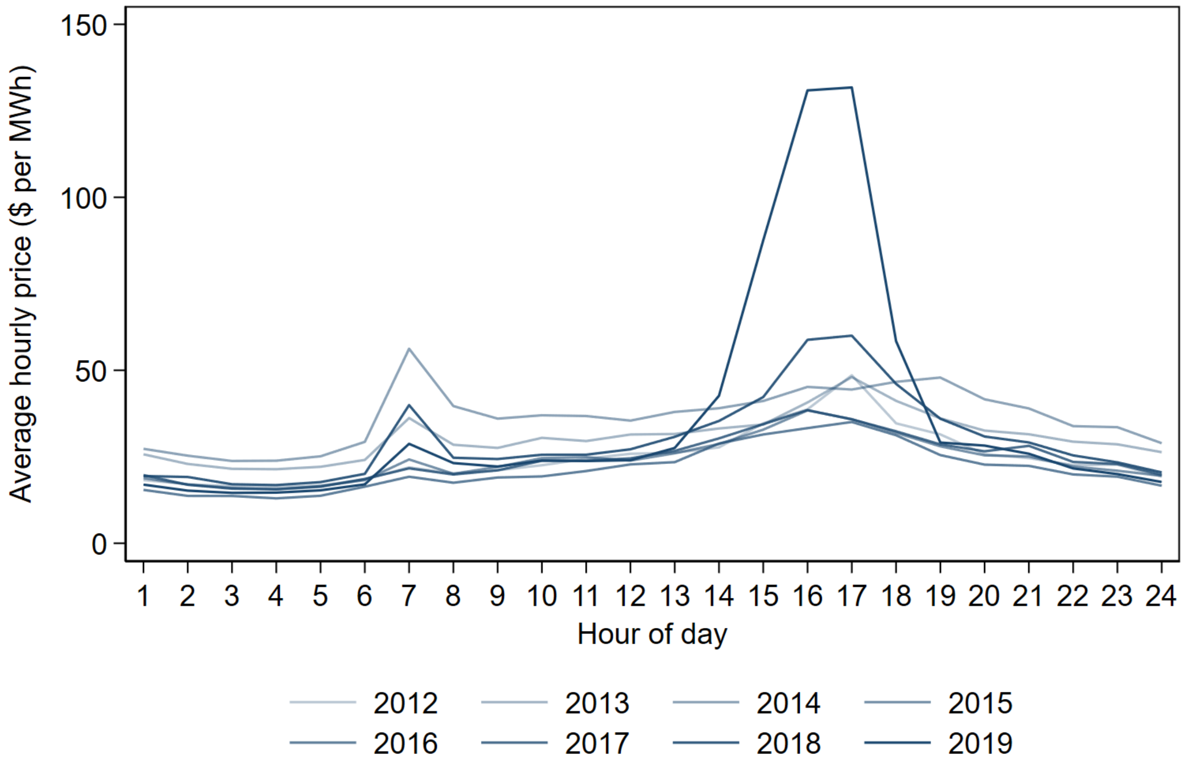
Figure 3 plots average hourly prices over this period, which do not follow monotonic trends.[11] This lack of trend occurs despite the monotonic trends in renewables and demand, highlighting the importance of other changing factors that impact prices over the study period, such as macroeconomic and weather-related shocks. Figure 3 also shows the variation in prices throughout the hours of the day: we see a morning peak around 6 to 8am, and then a larger early evening peak, with the price increase starting as early as 1pm, peaking around 4 to 6pm, and then decreasing by 7pm and staying low through the night and early morning until 6am.

With these wholesale price data, we construct four measures of price dispersion, which measure price variation within an hour, within a day, across the same hour-of-day within a month, and across the same hour-of-day within a year. We calculate these measures as:

$$\sigma_t = \sqrt{\frac{1}{T}(P_t - \bar{P}_h)^2}. \tag{1}$$

11. We compute the average price from the settlement points LZ North, LZ South, LZ West, and LZ Houston.

Figure 3: Average hourly prices in ERCOT



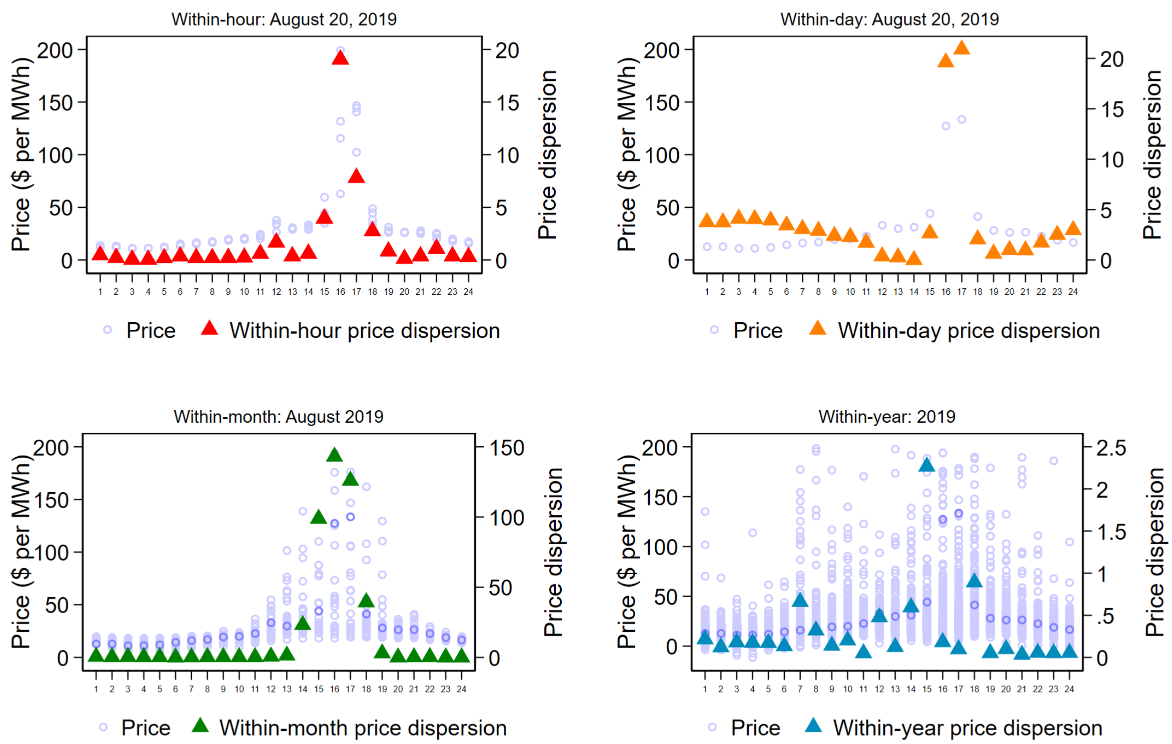
Notes: This figure shows average hourly wholesale electricity price in ERCOT by year for 2012–2019. The average is calculated as the mean of prices across the four load zones in Texas: LZ North, LZ South, LZ West, and LZ Houston.

For the month and year dispersion measures, P_t is the hourly wholesale electricity price and $\bar{P}_h$ is the average price in hour-of-day h over a longer time horizon—month and year, respectively. T is the number of hourly prices that go into the calculation for each time horizon; for example, $T = 365$ for the annual dispersion metric. For the hourly metric, P_t is the 15-minute interval wholesale electricity price, $\bar{P}_h$ is the average price across the four 15-minute interval prices in the hour, and $T = 4$. The daily price measure indicates price dispersion within a day, unconditional on hour of the day. In this case, $T = 24$, and $\bar{P}_h$ is the average price in the day.

Figure 4 plots these four measures of dispersion for an illustrative day, month, and year. The light blue dots show the number of price observations that enter the mean price value in Equation (1). For the within-month and within-year measures, the darker blue dots show the price for a particular day. The triangles give our calculated price dispersion measure for that day. All the measures show a peak in price dispersion in the afternoon and early evening hours, 2–6pm. The measure of interest depends on the research question—for example, the daily measure provides an indicator of price fluctuations throughout the day and could be relevant to questions about storage, while the annual measure provides a measure of how prices in the same hour vary across the year and could be relevant to long-run entry and exit decisions.

Figure A1 in the Appendix plots the within-month measure of price dispersion over the years for the study period. As with prices, we do not see a monotonic trend for dispersion over time. In fact, annual variation in dispersion looks quite similar to the annual price variation in Figure 3.

Figure 4: Four measures of price dispersion, averaged over 2012–2019

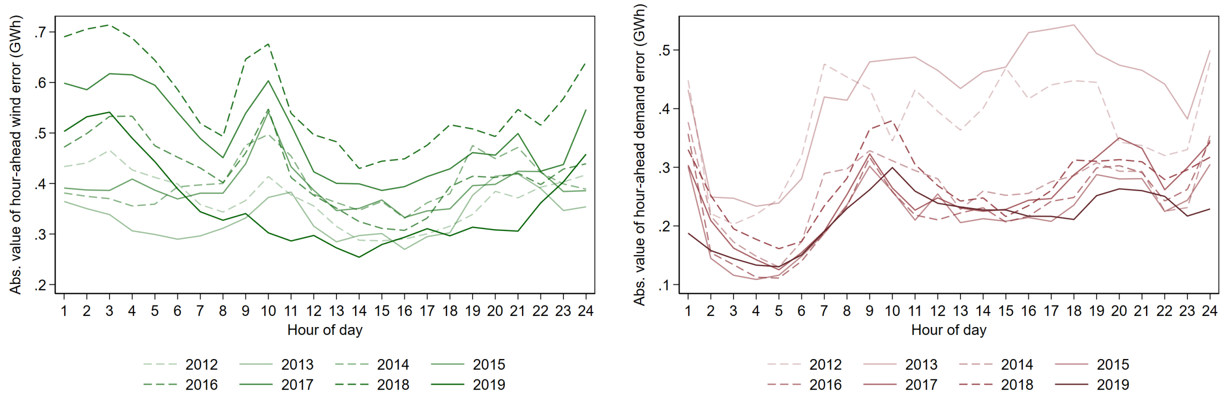


Notes: This figure shows four measures of price dispersion for illustrative time periods in 2019 with hour of day on the x-axis. The top-left panel depicts the within-hour measure of price dispersion on August 20; the top-right panel depicts the within-day measure on August 20; the bottom-left panel depicts the within-month measure in August; the bottom-right panel depicts the within-year measure. The light blue circles give all price observations used to calculate the mean price in Equation (1). In the bottom panels, the dark blue circles give prices for one particular day. The triangles show our calculated price dispersion metrics for that day. The lefthand y-axis for price is truncated at $200 per MWh for visual purposes.

Figure 5a and 5b plot forecast error—*ex post* observed values less the hour-ahead forecast—in absolute value over time for wind generation and demand. The figure shows some evidence of wind error increasing over time, yet the relationship is not monotonic; for example, 2019 exhibits the second to lowest average error in absolute value across hours, with 2013 having the lowest average error. On the other hand, demand error has a clearer time trend, with less error in more recent years. Interestingly, even though there is roughly 7 times more electricity demand than wind generation, the average magnitude of wind error is larger than that of demand error: 417 MWh of wind error per hour compared to 281 MWh of demand error per hour on average over the study period. Section 3 presents several hypotheses for expected trends in forecast error over time as wind capacity increases. On one hand, error could decrease over time as grid operators gain experience in wind forecasting. Further, geographic expansion of wind resources could dampen system-wide variation in wind generation, reducing forecasting error. On the other hand, as wind capacity is continually deployed, error could increase if the uncertainty of new investments is positively correlated with that of the existing capacity.

Figure 5: Average hourly forecast error in ERCOT by year

(a) Wind error (b) Demand error

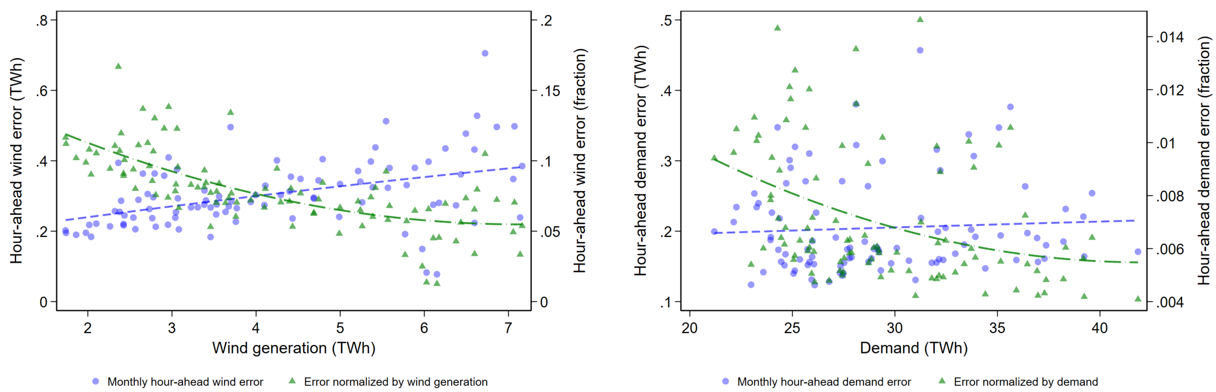


Notes: Panel (a) shows the absolute value of the average hourly error in hour-ahead wind generation forecasts in ERCOT by year for 2012–2019. Panel (b) shows the absolute value of the average hourly error in hour-ahead demand forecasts in ERCOT by year for 2012–2019.

Figure 6a provides another view of the relationship between error and the quantity of wind generation on the grid. We plot total monthly wind generation on the x-axis and two measures of monthly wind error on the y-axis. The blue dots plot the sum of the absolute value of error over the month, and this metric shows that forecast error tends to be larger when wind generation is greater. The green triangles plot this error normalized by monthly wind generation, which shows a decrease in error per unit of generation, providing some modest evidence of learning. Overall, the figure does not provide strong evidence of the experience hypothesis or the resource expansion hypothesis, which predict that forecast error decreases as wind resources expand. However, those two effects could be occurring together under the hypothesis that error increases as wind is developed due to positively correlated uncertainty. Figure 6b plots the corresponding metrics for demand error. We see a small positive trend with error and quantity of demand, with error decreasing per unit of demand when demand is larger. As previewed earlier, the error rate for demand is much smaller than for wind, 6–9 MWh of demand error per 1 GWh of demand, compared to 50–100 MWh of wind error 1 GWh of wind.

Figure 6: Monthly forecast error, raw and normalized

(a) Wind error (b) Demand error

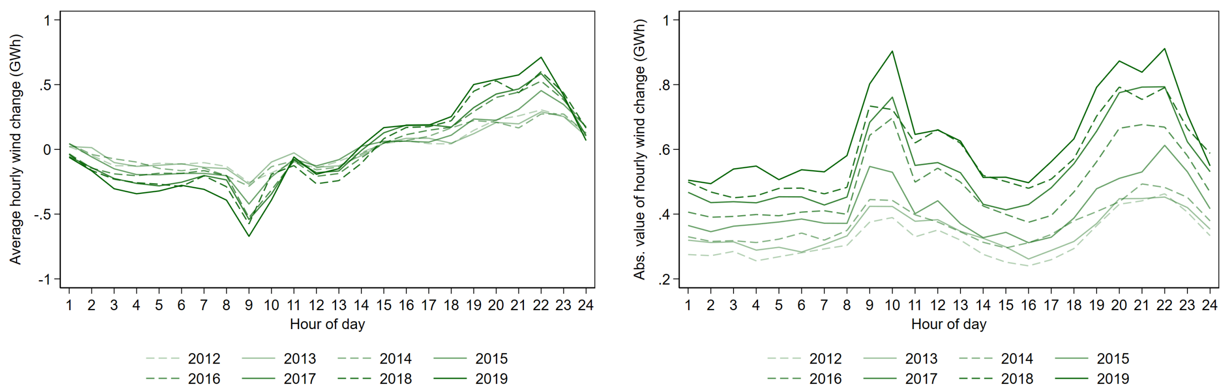


Notes: Panel (a) plots monthly wind generation and wind forecast error. Panel (b) plots monthly electricity demand and demand forecast error. The x-axes give wind generation and monthly electricity demand, respectively, aggregated for each month of our data. In each panel, the blue dots give the aggregate magnitude of error over the month and are plotted on the left y-axes. The green triangles normalize this aggregate error by the total monthly quantity and are plotted on the right y-axes. The dashed lines denote quadratic fits for the respective data series.

Next, we consider how intermittency—the changes in wind generation from hour to hour—has changed over the study period. Figure 7 plots the average hourly change in wind generation by year in the left panel, as well as the average hourly change in absolute value in the right panel. We see that the direction of change in a particular hour tends to persist across years, and the absolute value of change is increasing monotonically over years. This increase, however, occurs slower than the increase in renewables. While this provides some evidence of intermittency dampening as the scale of wind increases, from a grid management perspective, one is arguably more interested in the raw intermittency—which notably has increased over the study period—and not intermittency as a fraction of wind generation. Figure 8 plots the corresponding metrics for electricity demand; demand intermittency increases only modestly over time.

Figure 7: Wind generation intermittency over time

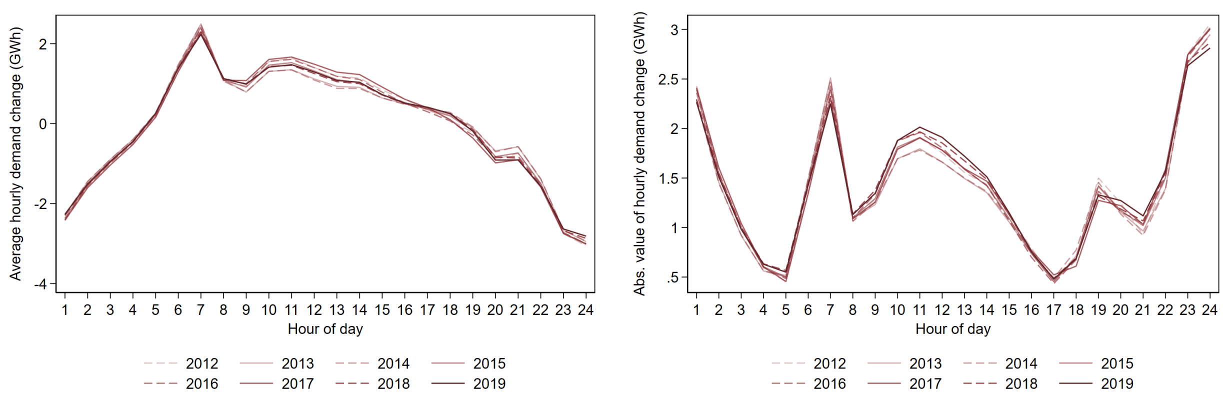
(a) Average hourly wind change (b) Absolute value of wind change



Notes: Panel (a) plots the average hour-to-hour changes in wind generation in ERCOT by year for 2012–2019. Panel (b) plots the absolute value of the average hour-to-hour changes in wind in ERCOT by year for 2012–2019.

Figure 8: Demand intermittency over time

(a) Average hourly demand change (b) Absolute value of demand change



Notes: Panel (a) plots the average hour-to-hour changes in demand in ERCOT by year for 2012–2019. Panel (b) plots the absolute value of the average hour-to-hour changes in demand in ERCOT by year for 2012–2019.

3 Theoretical framework

In this section, we provide intuition for how each of the unique characteristics that renewable resources possess—zero marginal cost, intermittency, and uncertainty—are expected to affect wholesale electricity price and price dispersion as renewable generation grows, and we generate testable hypotheses based on this intuition.

3.1 Zero marginal cost

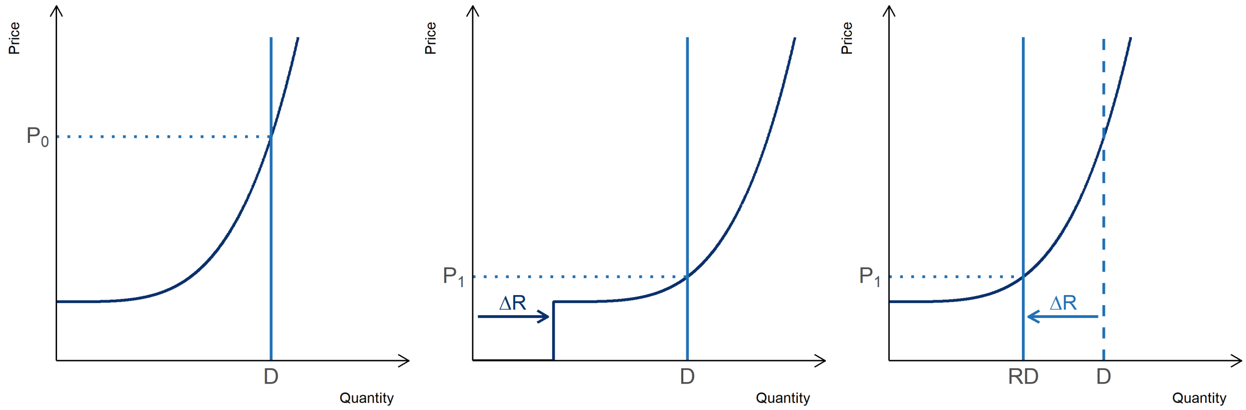
Renewable electricity generators face no marginal cost of electricity generation because they capture energy from existing resources, such as the wind or sun, in contrast to conventional generators that require fuel to generate electricity.[12] With zero marginal cost, renewable generators enter the market at the bottom of the supply curve—or merit order—pushing out the supply of electricity from conventional generators.

We show this effect of renewables on the electricity supply curve in Figure 9, with the left panel depicting a stylized market with no renewables and the middle panel adding renewables to the market. This addition of renewables, ΔR, pushes out the supply curve of conventional generators. For a given hourly electricity demand, D, these renewables change the marginal generator and, hence, the marginal cost of electricity generation, lowering the market-clearing price from P_0 to P_1. We can see the same effect by looking at the residual demand, or the amount of generation that must come from conventional generators, which we show in the right panel of Figure 9. We plot a supply curve that includes only conventional generators, and we indicate the residual demand, RD—calculated as total demand minus renewable generation—that must be generated by these conventional generators. A reduction in residual demand, while holding the conventional supply curve constant, yields the equivalent price effect as shifting the supply curve by the same amount. This effect of residual demand on price is theoretically the same for an increase in renewables or a comparable decrease in demand.

This simple intuition provides our first two testable hypotheses. First, the marginal effect of increased renewable generation is to reduce the wholesale electricity price. Further, an increase in renewables should have the same price effect as a comparable decrease in load. Second, the magnitude of this price reduction will depend on the slope of the supply curve, with larger price effects occurring at higher levels of residual demand—that is, at times of less renewables and/or greater demand. This price effect of renewables is often described as the "merit-order effect" (Sensfuß, Ragwitz, and Genoese 2008), but we will refer to it as the "residual demand effect" to highlight that it operates by changing the residual demand that must be supplied by conventional generators and the magnitude of the effect depends on the level of residual demand, which determines the slope of the supply curve at the margin. Further, the term merit-order effect beckons the question, do

12. As described previously, we exclude hydroelectric generation from our definition of renewables. Hydroelectric generation incurs an opportunity cost because a unit's long-run aggregate generation is constrained by water availability, so each MWh generated in one time period precludes a MWh of generation in a different time period.

Figure 9: Theoretical foundation for the residual demand effect



Notes: The figure on the left shows an illustrative hourly market-clearing price for the depicted supply curve and a given amount of inelastic demand, D. The center figure shows the price reduction that occurs from a shift in the supply curve to the right due to an increase in zero marginal cost renewables, ΔR. The right figure shows an equivalent price reduction, modeled as a shift in the demand curve to the left creating the residual demand curve, RD.

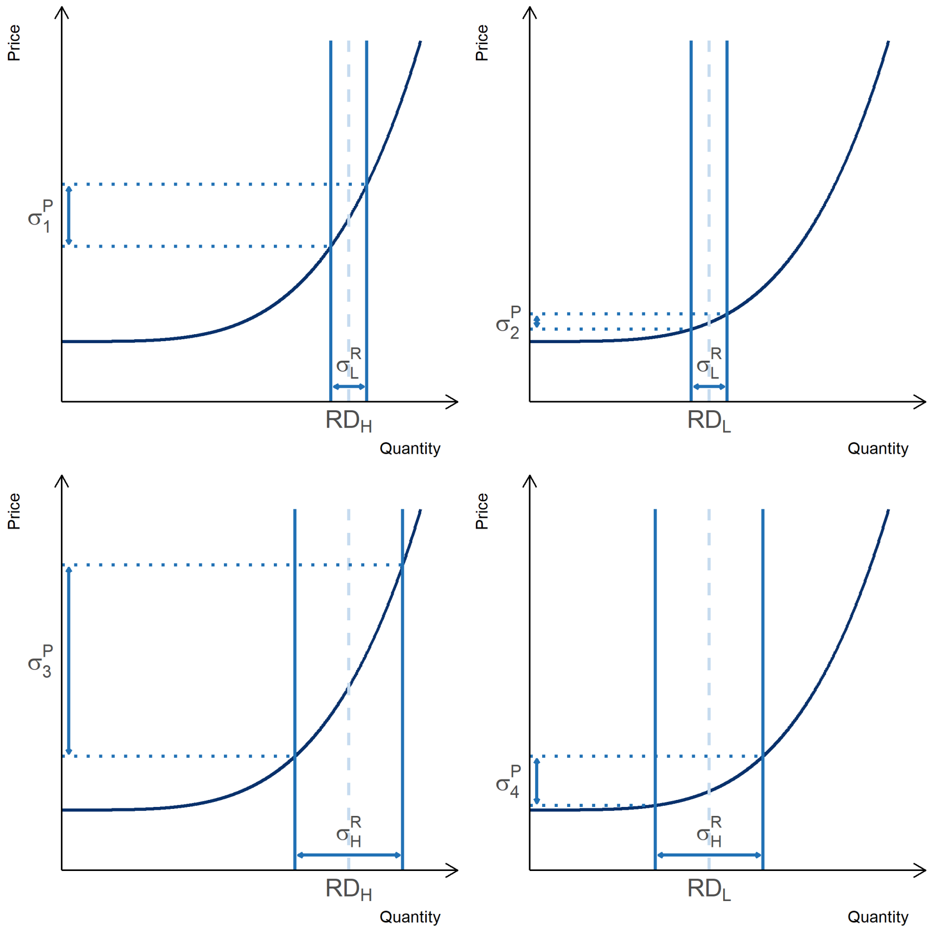
renewables change the ordering of conventional generators along the supply curve? We will study the supply-side responses—changes in the ordering of the conventional supply curve—stemming from the intermittent and uncertain characteristics of renewables.

3.2 Known intermittency

Renewable electricity generators depend on exogenous weather-related factors, such as wind speed and solar irradiation, which are highly variable across hours and seasons. Thus, the energy provided by a given amount of built renewable capacity is variable across time periods, a characteristic we term intermittency. We think of renewable generation, W_t, consisting of forecast generation, WF_t, and generation that was not forecast—or forecast error—WE_t, with $W_t = WF_t + WE_t$. In this subsection, we momentarily assume there is no uncertainty, $WE_t = 0$, in order to describe how known exogenous variation affects price levels and dispersion. In the next subsection, we describe the additional effects due to uncertainty.

Known intermittency and price dispersion Known intermittency, or variation in renewable generation, for a given level of demand, maps to variation in residual demand that must be met by conventional resources. As a result, this variation in renewable generation—even if perfectly forecast—is expected to cause dispersion in the market-clearing price, holding both demand and the conventional generation supply curve constant. We focus on two specific channels for this effect, both of which can be viewed as shifts or variation in the residual demand curve.

Figure 10: Theoretical foundation for effects of known intermittency on price dispersion



Notes: The top-left figure shows the price dispersion, σ_1^P, that results from a high level of residual demand, RD_H, and a low level of variation in renewable generation, σ_L^R. The top-right figure shows the lower level of price dispersion, σ_2^P, that results from a reduction in the residual demand curve from RD_H to RD_L, while holding the amount of variation in renewable generation at σ_L^R. The bottom-left panel shows the price dispersion, σ_3^P, that results from an increase in the variation of renewable generation, from σ_L^R to σ_H^R, at the higher residual demand level, RD_H. The bottom-right figure shows the price dispersion, σ_4^P, that results from the greater variation in renewable generation, σ_H^R, at the lower residual demand level, RD_L. Our empirical setting studies the impact of moving from the top-left to the bottom-right, which yields an ambiguous change in price dispersion.

We first describe how the level of renewables affects the relationship between renewables intermittency and price dispersion, which we depict in the top panels of Figure 10. These plots have the same renewables intermittency—a low amount of intermittency given by σ_L^R—but different levels of residual demand. The top-left panel has high residual demand, RD_H, and the top-right panel has low residual demand, RD_L, so moving from top-left to top-right corresponds to an increase in renewables. As with the residual demand effect, adding these renewables to the grid lowers residual demand, which flattens the slope of the conventional supply curve at the margin. When the supply curve is flatter, a given amount of renewables intermittency yields less price dispersion, as shown in these plots. Thus, this addition of renewables reduces price dispersion from σ_1^P to σ_2^P if renewables intermittency were to remain the same.[13]

As shown in Section 2, however, the level of renewables on the grid affects the amount of intermittency. Specifically, we find that a greater level of renewables increases renewables intermittency over these longer-run time frames. In the left panels of Figure 10, we show the theoretical effect of greater renewables intermittency on price dispersion. These plots have the same residual demand, RD_H, but different amounts of intermittency; the top-left panel has low intermittency, σ_L^R, and the bottom-left panel has high intermittency, σ_H^R. This increase in renewables intermittency, holding constant residual demand, increases price dispersion from σ_1^P to σ_3^P. Thus, if an addition of renewables could increase intermittency but leave residual demand unchanged, it would increase price dispersion.[14]

This intuition provides our next two testable hypotheses. First, holding constant residual demand—or holding constant the market-clearing price, which is a function of residual demand—but allowing longer-run intermittency to vary, the marginal effect of increased renewable generation is to increase the dispersion of wholesale electricity prices. Conversely, the marginal effect of lower prices—due to lower residual demand—is to reduce the dispersion of wholesale electricity prices. We will empirically test each of these hypotheses.

The full effect of renewables on price dispersion incorporates both of these channels, effectively moving from the top-left panel of Figure 10 to the bottom-right panel. Because these two channels drive dispersion in opposite directions, we cannot ascertain the direction of this effect using theory alone. Instead, this overall marginal effect of renewables on price dispersion is an empirical question, and we will estimate the direction and magnitude of the effect.

Known intermittency and price level Known intermittency in renewable generation also has the potential to affect the level of wholesale electricity prices by inducing changes in the composition and shape of the conventional supply curve. For a given level of demand, an hourly change in renewable generation—that is, $\Delta WF_t = WF_t - WF_{t-1}$, while still assuming renewables generation is perfectly forecast—yields an hourly change in residual demand for conventional resources, so conventional generators must be able to respond quickly to ensure that demand is met at every moment. This immediate need for supply can change the effective supply curve of conventional

13. The bottom panels of Figure 10 depict a similar effect for a high amount of renewables intermittency (σ_H^R). Holding constant this intermittency, the addition of renewables reduces price dispersion from σ_3^P to σ_4^P.

14. The right panels of Figure 10 depict a similar effect for a low level of residual demand (RD_L). Holding constant this residual demand, an increase in renewables intermittency increases price dispersion from σ_2^P to σ_4^P.

generators available to respond to intermittent renewable generation, even if that intermittency is known.

An hourly reduction in renewable generation, which causes an hourly increase in the residual demand that must be supplied by conventional generators, has two types of effects on the conventional supply curve: one on the extensive margin and one on the intensive margin. On the extensive margin, some conventional generators are simply not able to be dispatched rapidly to meet the increasing residual demand, which effectively removes those units from the supply curve of conventional generators. On the intensive margin, as conventional generators come online to meet the increase in residual demand, some generators incur start-up costs—beyond the marginal cost of generation depicted in previous supply curves—which increases the price at which those generators are willing to supply electricity. Both of these effects reduce the effective supply of conventional generators.[15]

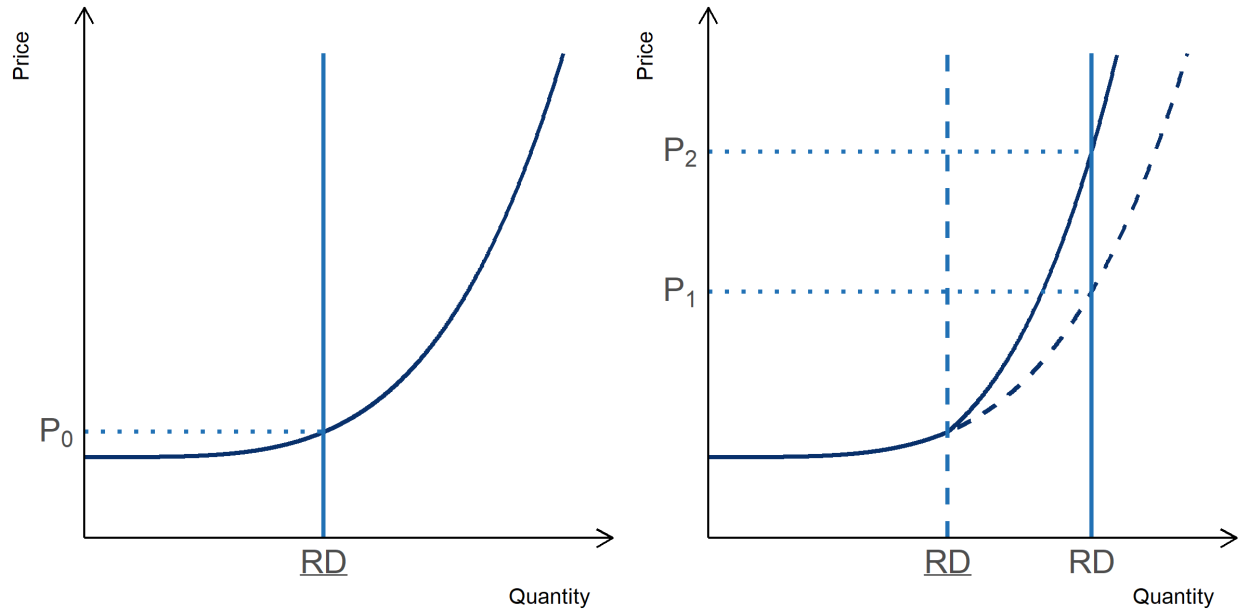
In Figure 11, we plot the market in two sequential hours to show how this hourly reduction in renewable generation affects the conventional supply curve and the resulting wholesale price of electricity. The left panel depicts the market in the previous hour, and the right panel depicts the market in the current hour. In the previous hour, conventional generators up to the level of residual demand $\underline{RD}$ generate, yielding a price of P_0. When residual demand increases to RD in the current hour, these units are already generating, so their supply curve remains the same as the previous hour. Some of the units that are not already generating, however, may not be able to respond quickly enough or may face large start-up costs, decreasing the supply curve from the dashed line to the solid line in the right panel. If there were no change in the conventional supply curve, the residual demand effect would cause the price to increase from P_0 to P_1. However, the immediate need for conventional generators further pushes the price up to P_2.[16]

This intuition provides our next testable hypotheses. When controlling for the level of renewables—or the residual demand effect—the marginal effect of hourly decreases in renewable generation is to further increase the wholesale electricity price due to the conventional supply curve response. Conversely, the marginal effect of an hourly increase in renewables is to further decrease the price.

15. Conversely, an hourly increase in renewable generation increases the effective supply of conventional generators. On the extensive margin, some conventional generators that are already producing are not able to shut down rapidly. On the intensive margin, other conventional generators incur a shutdown cost if they were to cease production, so those generators are willing to supply electricity at a lower price to avoid shutting down. Both of these effects increase the effective supply of conventional generators.

16. If renewables were instead to increase, the residual demand price effect would cause the price to fall. This rapid increase in renewables would also increase the effective supply of conventional generators—see the previous footnote—which causes an additional decline in the price.

Figure 11: Theoretical foundation for effect of intermittency and uncertainty on price level



Notes: The figure on the left shows the hourly clearing price, P_0, for a given conventional supply curve and an expected residual demand level, $\underline{RD}$. The figure on the right plots the actual residual demand level, RD, which exceeds the expected level. In this case the effective conventional supply curve—solid line—is steeper than the dashed supply curve that would have been available had the actual residual demand been accurately forecast. The price increase from P_0 to P_1 occurs due to the residual demand effect, and from P_1 to P_2 due to the change in the effective conventional supply curve. A second interpretation is that the left figure represents the preceding hour and the right figure represents the current hour, with an hour-over-hour change in residual demand from $\underline{RD}$ to RD. In that case, the effective supply curve becomes steeper due to the immediate need for additional generation.

Further, these larger price effects correspond to greater price dispersion. Thus, when controlling for the level of renewables, the marginal effect of an hourly change in renewable generation is to further increase price dispersion.

3.3 Uncertainty

Intermittency in renewables generation, which is due to exogenous weather-related factors, is not perfectly known or forecastable. This uncertain component of intermittency has additional effects on the conventional supply curve. Electricity grid operators must dynamically manage the supply of electricity throughout the day, making forecasts of both electricity demand and renewable generation. Firms also dynamically optimize their generation resources throughout the day in the face of this uncertainty. Any error in the forecast of renewables generation may result in deviations from the *ex ante* optimal dispatch of conventional generators that would have occurred absent the forecast error, resulting in different wholesale electricity prices and price dispersion.

Figure 11 is again helpful for demonstrating the intuition for how forecast error—due to uncertain intermittency—affects prices and dispersion. In this context, the left panel depicts the forecast of the market in an hour, and the right panel depicts the actual realization of the market in that hour. In this example, less renewable generation is realized than was forecast, so realized residual demand exceeds its forecast. The market is prepared to supply conventional generation to meet the forecast residual demand, $\underline{RD}$, and the conventional generators beyond that level are not expecting to generate. In reality, however, more conventional generation must be supplied to meet this greater residual demand. Some of the units that were not expecting to generate may not be able to respond quickly enough or may face large start-up costs, similar to the effects of known intermittency. As described previously, the inflexibility and higher costs of these generators decrease the supply curve from the dashed line to the solid line in the right panel. If there were no changes in the conventional supply curve, the residual demand effect would cause the price to increase from the expectation of P_0 to the realization of P_1. However, the uncertainty in residual demand further pushes the price up to P_2.[17]

This intuition provides our final testable hypotheses. When controlling for the level of renewables that were forecast—or the forecast of the residual demand effect—and the forecast amount of intermittency, the marginal effect of over-forecasting renewables is to increase the wholesale electricity price due to the conventional supply curve response. Conversely, the marginal effect of under-forecasting renewables is to further decrease the price. Further, these larger price effects correspond to greater price dispersion. Thus, when controlling for the forecast of renewables and intermittency, the marginal effect of forecast error in renewable generation is to further increase price dispersion.

4 Empirical approach and results

4.1 Price effects

We first present a benchmark estimate of the overall effect of wind generation and electricity demand on wholesale electricity prices, and then we move on to our decomposition of these benchmark price effects.

17. If more renewable generation is realized than was forecast, the residual demand price effect would cause the realized price to be below the expected price. This forecast error would also increase the effective supply of conventional generators, which causes an additional decline in the price.

Benchmark overall price effects The overall marginal effects of wind generation and electricity demand on wholesale electricity prices can be estimated with the following regression equation:

$$P_t = \beta W_t + \theta D_t + \alpha_h + \gamma_m + \delta_y + \varepsilon_t \qquad (2)$$

where P_t is hourly wholesale electricity price, W_t is hourly wind generation, and D_t is hourly electricity demand in hour t, and ε_t is an idiosyncratic hourly shock. The terms α_h, γ_m, and δ_y flexibly control for diurnal and seasonal patterns and long-run trends by hour-of-day, month-of-year, and annual fixed effects, respectively.[18] The identifying assumption is that, after controlling for demand and these fixed effects, the remaining residual variation in wind generation is exogenously determined, such as by idiosyncratic variation in the speed and direction of the wind. Similarly, this specification assumes that after controlling for fixed effects and wind generation, variation in electricity demand is exogenously determined.

Table A1 in the appendix shows the results from the benchmark estimating Equation (2) and alternate specifications. We find that one additional GWh of wind generation causes the wholesale electricity price to fall by \$2.27 per MWh on average, and this effect is highly statistically significant. We estimate that the price effect of demand has the same magnitude, \$2.27 per MWh, but with the opposite sign, consistent the hypothesis presented in Section 3 regarding the similarity of effects from one more unit of wind and one less unit of demand. We also estimate how these effects vary by hour of the day by separately estimating Equation (2) for each of the 24 hours of the day, and we plot the resulting hourly coefficients in Figure A2 in the appendix. We find these hourly price effects of wind generation and of electricity demand follow a similar pattern, largest in the afternoon during 2–6pm and in the morning from 6–7am. These hourly price effects are suggestive of the hypothesis we proposed in Section 3: the magnitude of the price effect is determined by the slope of the conventional supply where it intersects the residual demand curve, with greater price effects at times of greater residual demand or times when the conventional supply curve is steeper.[19]

We also test this hypothesis directly by splitting our sample based on the percentile of residual demand. We estimate the regression in Equation (2) separately for each of these subsamples, with results shown in Table 1. We estimate that the causal price effects of wind generation and electricity

18. In alternate specifications, we include more granular time-fixed effects to more flexibly control for confounding factors.

19. We see larger price effects from 6–7am, which has a relatively low residual demand. During this hour, however, we see a rapid increase in demand, which causes the price to spike, as shown in Figure 3. Due to the convexity of the conventional supply curve, this high price indicates the slope of the conventional supply curve is steep on the margin, so we would expect the marginal price effect to be large.

demand are substantially larger when residual demand is relatively high; for example, one additional GWh of wind generation reduces the price by \$10.94 per MWh when residual demand is in the 95th to 99th percentile, as compared to \$1.28 per MWh when residual demand is below the 25th percentile. This result further confirms our hypothesis that greater price effects occur during times of greater residual demand. Comparing the price effects of wind generation and electricity demand, however, we see that the price effects of wind generation are larger in each subsample, presenting some initial evidence that the market effects of wind generation may be distinct from those of electricity demand in some circumstances, even though the average price effects are comparable in magnitude.

Table 1: Price effect heterogeneity by residual demand

	< 25th %	25–75th %	75–90th %	90–95th %	95–99th %	> 99th %
	(1)	(2)	(3)	(4)	(5)	(6)
Wind (GWh)	-1.28^{***}	-1.23^{***}	-2.24^{***}	-5.53^{**}	-10.94^{**}	-206.10^{**}
	(0.05)	(0.10)	(0.38)	(1.77)	(2.82)	(39.44)
Demand (GWh)	1.17^{***}	0.88^{***}	1.40^{***}	4.62^{**}	3.27^{***}	163.69^{**}
	(0.05)	(0.11)	(0.27)	(1.61)	(0.74)	(30.39)
Subsample definition:						
Residual demand (GWh)	< 27.0	27.0–39.9	39.9–49.6	49.6–54.6	54.6–61.5	> 61.5
Observations	17,434	34,870	10,461	3,484	2,786	698

Notes: This table reports the results of estimating Equation (2) on subsamples of our dataset. The outcome in each regression is the hourly wholesale electricity price in \$ per MWh. Column (1) includes hours with residual demand less than the 25th percentile, column (2) includes hours with residual demand between the 25th and 75th percentiles, column (3) includes hours with residual demand between the 75th and 90th percentiles, column (4) includes hours with residual demand between the 90th and 95th percentile, column (5) includes hours with residual demand between the 95th and 99th percentile, and column (6) includes hours with residual demand greater than the 99th percentile. All columns include hour-of-day, month-of-year, and annual fixed effects. Standard errors clustered by hour of day are shown in parenthesis. Significance: * $p < 0.001$, $p < 0.01$, * $p < 0.05$.

The causal price effects of wind generation and electricity demand that we have estimated thus far represent the *overall* marginal effects that include all economic and technical aspect of wind generation. As we describe in Section 3, however, the different characteristics of wind generation and electricity demand may have different effects on wholesale electricity prices. We now turn our attention to decomposing these overall price effects.

Decomposition of price effects To decompose the price effects of wind generation and electricity demand into those stemming from the residual demand effect, predicted intermittency, and forecast error, we decompose the hourly quantities of wind generation and electricity demand across two dimensions: the quantity that persists from hour to hour versus the hourly change, and the quantity that is forecast versus forecast error. We rewrite the W_t and D_t terms as:

$$W_t = WF_{t-1} + \Delta WF_t + WE_{t-1} + \Delta WE_t$$
$$D_t = DF_{t-1} + \Delta DF_t + DE_{t-1} + \Delta DE_t$$

where WF_{t-1} is forecast hourly wind generation in hour $t-1$, ΔWF_t is the forecast change in wind generation from hour $t-1$ to hour t, WE_{t-1} is the error in the forecast in hour $t-1$, and ΔWE_t is the change in forecast error from hour $t-1$ to hour t, so these four terms sum to hourly wind generation in hour t. Likewise for electricity demand, DF denotes demand forecast and DE denotes demand error. Substituting these terms into Equation (2) yields our estimating equation:

$$\begin{aligned} P_t = {} & \beta_1 WF_{t-1} + \beta_2 \Delta WF_t + \beta_3 WE_{t-1} + \beta_4 \Delta WE_t \\ & + \theta_1 DF_{t-1} + \theta_2 \Delta DF_t + \theta_3 DE_{t-1} + \theta_4 \Delta DE_t \\ & + \alpha_h + \gamma_m + \delta_y + \varepsilon_t \end{aligned} \tag{3}$$

Then β_1 (θ_1) gives the causal price effect of predicted and consistent wind generation (demand), β_2 (θ_2) gives the causal price effect of a predicted hourly change in wind generation (demand), β_3 (θ_3) gives the causal price effect of consistently unpredicted wind generation (demand), and β_4 (θ_4) gives the causal price effect of an hourly change in unpredicted wind generation (demand).

We report the estimated coefficients in Table 2. We find that one additional GWh of predicted and consistent wind generation reduces the wholesale electricity price by \$2.22 per MWh. By controlling for aspects of intermittency and uncertainty in this specification, this estimate most closely reflects the residual demand effect described in Section 3. The magnitude of the estimate is not statistically different than the impact of consistent and forecasted demand—\$2.24 per MWh—which further confirms our hypothesis that the magnitude of the residual demand effect is the same for wind generation and electricity demand.

We find that a one-GWh hourly increase in forecast wind generation, shown in the second row of Table 2, reduces the wholesale electricity price by \$2.28 per MWh. This coefficient estimate is very close to the marginal effect of consistent and predicted wind generation, and the estimates are not statistically distinguishable, indicating that predicted intermittency of wind generation has no additional effect on price outcomes beyond its residual demand effect.

Table 2: Full decomposition of price effect

		Heterogeneity by residual demand		
	Full sample	< 25th %	25–75th %	> 75th %
	(1)	(2)	(3)	(4)
Wind forecast in previous hour (GWh)	-2.22^{***}	-1.22^{***}	-1.10^{***}	-7.40^{**}
	(0.41)	(0.05)	(0.09)	(2.29)
Wind forecast hourly change (GWh)	-2.28^{**}	-2.78^{***}	-2.67^{***}	-8.10
	(0.79)	(0.22)	(0.55)	(4.26)
Wind error in previous hour (GWh)	-5.05^{***}	-0.57^{*}	-3.80^{***}	-14.78^{***}
	(1.17)	(0.23)	(0.61)	(2.96)
Wind error hourly change (GWh)	-4.86^{***}	-2.12^{***}	-4.30^{***}	-15.07^{**}
	(1.08)	(0.34)	(0.67)	(4.19)
Demand forecast in previous hour (GWh)	2.24^{***}	1.11^{***}	0.84^{***}	5.29^{***}
	(0.47)	(0.04)	(0.09)	(1.38)
Demand forecast hourly change (GWh)	3.97^{**}	1.87^{***}	2.09^{***}	9.17^{***}
	(1.12)	(0.18)	(0.47)	(2.25)
Demand error in previous hour (GWh)	3.54^{***}	0.67^{**}	2.42^{***}	4.42^{*}
	(0.86)	(0.18)	(0.58)	(1.68)
Demand error hourly change (GWh)	3.84^{*}	1.68^{***}	1.82^{**}	8.81^{**}
	(1.53)	(0.34)	(0.48)	(2.91)
Subsample definition:				
Residual demand (GWh)	All	< 27.0	27.0–39.9	> 39.9
Observations	69,739	17,434	34,870	17,435

Notes: This table reports the results of estimating Equation (3) on the full sample or subsamples of our dataset. The outcome in each regression is the hourly wholesale electricity price in $ per MWh. Column (1) includes the full sample of hours, column (2) includes hours with residual demand less than the 25th percentile, column (3) include hours with residual demand between the 25th and 75th percentiles, and column (4) includes hours with residual demand greater than the 75th percentile. All columns include hour-of-day, month-of-year, and annual fixed effects. Standard errors clustered by hour of day are shown in parenthesis. Significance: * $p < 0.001$, $p < 0.01$, * $p < 0.05$.

We further estimate that one additional GWh of consistent but unforecast wind generation—that is, consistent forecast error—reduces the wholesale electricity price by $5.05 per MWh, and a one-GWh hourly increase in wind forecast error increases the price by $4.86 per MWh. These estimates for wind forecast error are not statistically different from one another, but they are more than twice as large as wind generation's residual demand effect. Thus, forecast error in wind generation causes a relatively larger price effect than forecast wind generation, as depicted in Figure 11. Because we control for the residual demand effect and others aspects of wind generation and electricity demand, this result can be explained by a change in the conventional supply curve that is induced by wind generation's uncertainty.

Turning to the decomposition of electricity demand's price effect, we find that a one-GWh hourly increase in forecast electricity demand increases the wholesale electricity price by $3.97 per

MWh. We also find that an additional GWh of consistent but unforecast electricity demand—that is, consistent demand error—increases the wholesale electricity price by \$3.54 per MWh, while a a one-GWh hourly increase in demand forecast error increases the price by \$3.84 per MWh. These three estimates are not statistically different from one another, and each is larger in magnitude than the estimate for consistent and forecast demand. Thus, we conclude that both hourly intermittency and forecast error in demand cause a relatively larger price effect than consistent and forecast electricity demand. These effects are also depicted in Figure 11 and explained by a change in the conventional supply curve that is induced by electricity demand's hourly variability and uncertainty. Note, however, that these price effects are smaller than the price effect of wind forecast error.

We further estimate the full decomposition of wind generation separately for quartiles of residual demand. Table 2 reports these results in columns (2)–(4). Each decomposed price effect tends to increase with residual demand, just as we found for the overall price effects and as expected given the convex shape of the conventional supply curve. At the highest levels of residual demand, an additional one GWh of error in wind forecasts reduces prices by roughly \$15 per MWh. Interestingly, at this level of residual demand, consistent demand error does not have an additional effect. Instead, hourly changes in demand—either forecast or not—have larger price effects, nearly double the effect of consistent and forecast demand. In fact, all of the fully decomposed effects are larger when residual demand is greater.

In summary, we confirm several of our testable hypotheses about price effects, but some of our estimated effects are less intuitive. First, the residual demand effect is negative and depends on the level of residual demand, with greater residual demand yielding a larger price effect. Second, the residual demand effect of wind generation is statistically indistinguishable from the residual demand effect of electricity demand. Third, uncertainty in wind generation—as measured by forecast error—yields a price effect that is larger in magnitude than the residual demand effect, while error in demand forecast causes a smaller price effect or no additional price effect in some hours. Fourth, intermittency in electricity demand—as measured by hourly changes—has a larger price effect than a consistent level of demand, but intermittency in wind generation does not have an additional effect beyond the expected residual demand effect.

4.2 Effects on Price Dispersion

We next estimate the causal effects of wind generation and electricity demand on the dispersion of wholesale electricity prices. As with price effects, we first estimate the overall effect as a benchmark and then decompose this result into the constituent effects described in Section 3.

Benchmark overall effect on price dispersion We estimate the overall marginal effect of wind generation on the dispersion of wholesale electricity prices with a regressions similar to Equation (2) but with outcome variable σ_t, a measure of price dispersion defined in Equation (1); in some regressions, we also control for the hourly wholesale price to effectively control for the price effects that we identified above.[20] The relevant measure of price dispersion depends on the research question. Short-term measures of dispersion are useful metrics to determine the potential value of storage or load shifting to facilitate intraday price arbitrage, while longer-term measures may be more relevant when thinking about how price dispersion affects firm entry decisions. We estimate wind generation's impact on four measures of price dispersion: within-hour, within-day, within-month, and within-year.

Table A2 in the appendix shows the results for wind's overall effect on price dispersion, using these four measures of dispersion, as indicated in the column headings. The odd-numbered columns report the overall price dispersion effects of wind generation and electricity demand. Across all four price dispersion measures, we find that additional wind generation reduces the dispersion of wholesale electricity prices and additional electricity generation increases the dispersion. At the shortest time scale, one additional GWh of wind generation reduces within-hour price dispersion by \$0.37 per MWh, and an additional GWh of electricity demand increases dispersion by a statistically similar amount. At the longest time scale, one additional GWh of hourly wind generation reduces within-year price dispersion by \$0.05 per MWh, while an additional GWh of hourly electricity demand increases price dispersion by approximately the same magnitude.[21] The even-numbered columns of Table A2 report results from the regressions that control for price, effectively controlling for the price effects we estimated above. At the shortest time scale, we find that wind generation and electricity demand have no effect on price dispersion after controlling for the price level. At

20. The identifying assumption is again that, after flexibly controlling for time-varying market characteristics through time fixed effects and, in some cases, hourly price, the remaining residual variation in wind generation and electricity demand is exogenously determined, such as by idiosyncratic variation in weather-related factors.

21. These price dispersion effects are correlated with the time scale of the dispersion measure due to the inherent importance of a single observation in each measure. A 15-minute period represents one quarter of within-hour price dispersion, whereas a single hour represents only a small fraction of within-year price dispersion.

longer time scales, however, when controlling for the wholesale electricity price, additional wind generation increases price dispersion, whereas additional electricity demand decreases dispersion. For example, one additional GWh of hourly wind generation increases within-month price dispersion by \$0.18 per MWh, and one additional GWh of hourly electricity demand decreases within-month price dispersion by \$0.04 per MWh, conditional on the price. Across all price dispersion measures, price dispersion is positively correlated with the price level, which we previously found is causally a function of wind generation and electricity demand.

These results show that wind generation and electricity demand affect price dispersion through two channels, as we describe in Section 3, which support two of our hypotheses. First, additional wind generation reduces the wholesale electricity price, which yields lower price dispersion. Controlling for this effect, however, additional wind generation increases price dispersion due to wind generation's long-run variability. While *ex ante* it is unclear whether the overall marginal effect of wind generation on price dispersion is positive or negative, empirically we find this overall effect is negative across all time scales.

We also estimate how the causal effects on electricity price dispersion vary by hour of day. Figure A3 in the appendix plots the 24 hourly coefficients for wind generation, unconditional on price in the left panel and conditional on price in the right panel. In this and all future regressions, we focus on only the within-month measure of price dispersion for brevity.[22] The pattern of hourly price dispersion effects in the left panel is similar to the price effects in Figure A2: all hourly effects are negative, and the largest effects occur in the afternoon during 2–7pm and in the morning at 6–7am. As described previously, these large effects in the afternoon and morning correspond to times when residual demand is either high or increasing rapidly, which increases prices. When we control for hourly price to focus on the effect of wind generation's long-run variability—as shown in the right panel of Figure A3—the marginal effect of wind generation on price dispersion becomes positive, but the general pattern is roughly the same: effects are largest in the morning at 6–7am and in the afternoon during 2–7pm. Thus, during these hours, the long-run variability of wind generation greatly moderates the extent to which its price effect would reduce price dispersion.

Decomposition of effects on price dispersion The estimated effects above represent the *overall* effect of wind generation on wholesale electricity price dispersion. Next, we decompose these price dispersion effects into the constituent effects by decomposing hourly wind generation and

22. We report results for the other measures of price dispersion in the appendix.

hourly electricity demand as we did previously. As before, we will estimate specifications with and without controlling for price. The results are shown in Table 3, using the monthly measure of price dispersion as the dependent variable.

Table 3: Full decomposition of within-month dispersion effect

	(1)	(2)
Wind forecast in previous hour (GWh)	-0.18^{**}	0.17^{***}
	(0.06)	(0.01)
Wind forecast hourly change (GWh)	0.23	0.60^{***}
	(0.19)	(0.13)
Wind error in previous hour (GWh)	-0.87^{***}	-0.06
	(0.20)	(0.07)
Wind error hourly change (GWh)	-0.55^{**}	0.23^{**}
	(0.16)	(0.06)
Demand forecast in previous hour (GWh)	0.31^{**}	-0.05^{**}
	(0.09)	(0.02)
Demand forecast hourly change (GWh)	0.70^{**}	0.06
	(0.22)	(0.05)
Demand error in previous hour (GWh)	0.32^{*}	-0.24^{**}
	(0.13)	(0.08)
Demand error hourly change (GWh)	0.59^{*}	-0.02
	(0.25)	(0.06)
Price ($ per MWh)		0.16^{***}
		(0.00)
Observations	69,739	69,739

Notes: This table reports the results of estimating Equation (3). The outcome in each regression is a measure of within-month dispersion of hourly wholesale electricity prices. Column (2) adds a control for the hourly wholesale electricity price. All columns include hour-of-day, month-of-year, and annual fixed effects. Standard errors clustered by hour of day are shown in parenthesis. Significance: * $p < 0.001$, $p < 0.01$, * $p < 0.05$.

Column (1) reports the coefficients from estimating Equation (3) with within-month price dispersion as the outcome. We find that the decomposed price dispersion effects are qualitatively similar to the decomposed price effects, which we would expect because price dispersion is correlated with the price level. For wind generation, the important dimension of decomposition is forecast wind versus forecast error: forecast wind generation yields relatively modest effects, while forecast error has much larger effects on price dispersion. For electricity demand, on the other hand, the important dimension is consistent demand versus hourly changes: consistent demand has smaller effects on price dispersion, while hourly changes in demand yield larger effects on price dispersion.

Column (2) reports these price dispersion effects when controlling for the hourly price. These results, which show how individual components affect price dispersion beyond their effect on the price level, are more nuanced. For example, an hourly change in forecast wind generation has a large and positive coefficient, indicating that predicted intermittency of wind greatly moderates the effect of wind generation on price dispersion, yielding a dispersion effect that is smaller in magnitude than would be expected from the price effect. At the opposite extreme, consistent error in wind forecast has no additional effect on price dispersion beyond its effect on price. Conversely, when looking at decomposed electricity demand, consistent error in demand forecast is the only component that has a substantial effect on price dispersion after controlling for hourly price.

In summary, we confirm many of our testable hypotheses about price dispersion effects and estimate effects that could not be determined *ex ante*. First, the marginal effect of lower wholesale electricity prices—due to the residual demand effect—is to reduce price dispersion. Second, when controlling for the residual demand effect, the marginal effect of wind generation is to increase price dispersion. The net effect of these two channels, which we could not ascertain based on theory alone, is that wind generation reduces price dispersion. In terms of the decomposition, when not controlling for prices, we see many of the same channels of effect identified in Table 2. When controlling for these price effects, we find more nuanced effects on price dispersion.

4.3 Effects on Non-Wind Operations

As we describe in Section 3, the estimated effects of wind and demand on price and price dispersion stem from how changes in wind and demand impact the operation of conventional generators, and which generators are on the margin. To better understand the heterogeneity in our price effects—such as why wind error has the largest price effect—we now estimate how hourly wind generation and electricity demand affect the contemporaneous operations of non-wind generators. To do so, we estimate regressions similar to Equation (3)—using decomposed wind generation and electricity demand—but with outcomes that describe the operations of non-wind generators.[23] We consider four such outcomes for each unit type:[24] generation, average within-hour capacity factor, average intensive margin capacity factor of operating units, and number of operating units. We further estimate these regressions separately for the different bins of residual demand, as in Table 1.

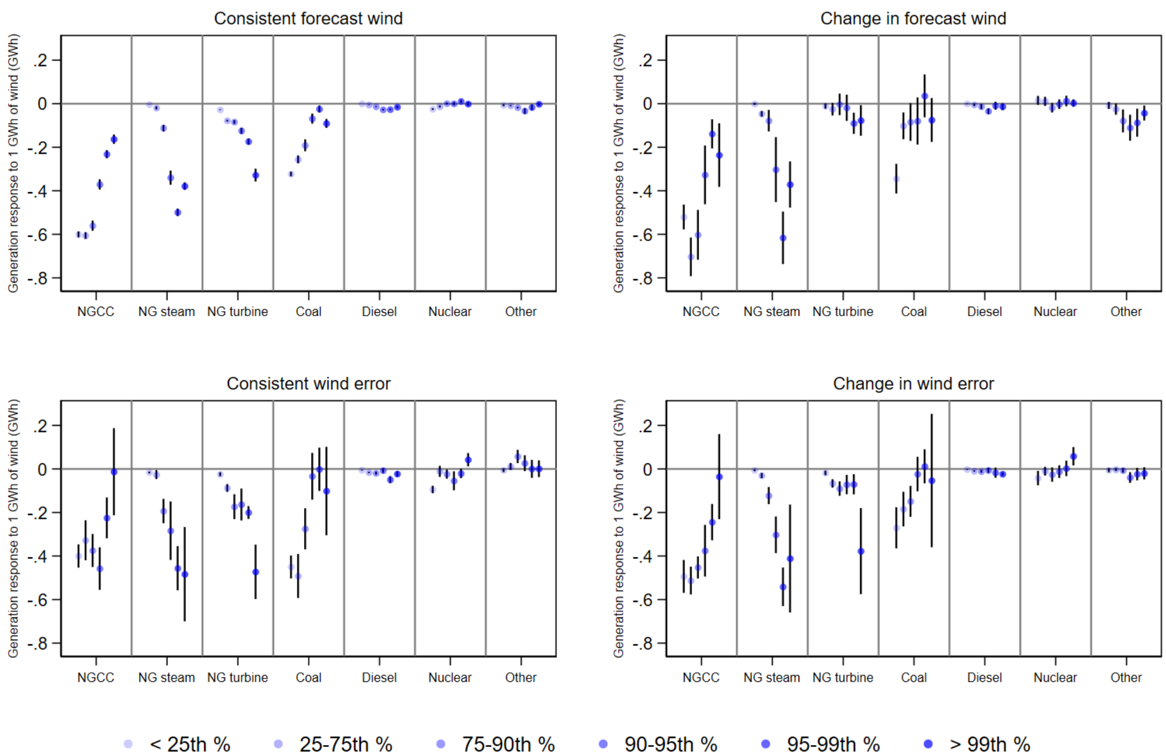
Decomposed effects Figure 12 depicts the decomposed effects of wind generation with generation by unit type as the outcome variable. In each panel of this figure, each point represents a coefficient

23. We also estimate regressions similar to Equation (2) that correspond to the benchmark overall effects. These results are in the appendix.

24. We group all non-wind generators into seven unit types: natural gas combined cycle (NGCC), natural gas (NG) steam, NG turbines, coal, diesel engines, nuclear, and all others. The other category includes biomass, hydro, solar, and storage.

estimate from a different regression. The first six points correspond to total generation by natural gas combined cycle (NGCC) units, and then for other non-wind technologies as labeled on the x-axis. Within each grouping of points, the lightest point on the left gives the estimated coefficient for hours with less than the 25th percentile of residual demand, and so on as shown in the legend. Each panel corresponds to one of the four components of wind generation from Equation (3): the upper-left panel gives the marginal effect of consistent forecast wind, the upper-right panel gives the marginal effect of an hourly change in forecast wind, and the bottom panels are similar but for error in the wind forecast.

Figure 12: Decomposed effects of wind on generation at non-wind generators



Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed wind variables on generation by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

For generation from both NGCC and coal, we see a positive slope across the estimated coefficients in most panels, where the estimated coefficient is *largest* in magnitude for the *smallest* levels of residual demand. For NG steam and NG turbine generation, however, the slope across the coefficients tends to be negative, indicating that aggregate generation from these technologies responds by a larger magnitude in response to wind generation at higher levels of residual demand. Taking these results together, they suggest that NGCC and coal units are more likely to be on the margin during low residual demand hours, while NG steam and NG turbine units are more likely to be on the margin during high residual demand hours. The heterogeneity in marginal costs of these two groups of technologies creates the heterogeneity in price effects at different residual demand levels.

As before, by comparing consistent forecast wind to consistent wind error, we can focus on how error impacts operations at non-wind generators. Interestingly, we see that the generation response from NGCC units shown in Figure 12 is *smaller* in magnitude when responding to wind error as compared to forecast wind generation, while NG turbine and coal generation is *more* responsive to wind error from a generation perspective than to forecast wind in some hours. By comparing the top-left panel to the top-right, we can isolate the role of forecast intermittency. We find that forecast changes in wind generation are mostly balanced by generation at NGCC and NG steam units.[25]

Figure 13 plots the decomposed intensive margin response to wind generation, which we estimate as the average capacity factors of units by technology, conditioning on units that are operating in a given hour.[26] The average intensive margin response for most unit types is small, even in response to wind error and changes. In most cases, one GWh of wind generation can be balanced by adjusting generation at operating units by only a few percentage points. Thus, what may appear to be a large aggregate generation response corresponds to a relatively small response at individual units that are already operating. NG steam and diesel units, however, have particularly large intensive responses, especially to wind error and changes.[27]

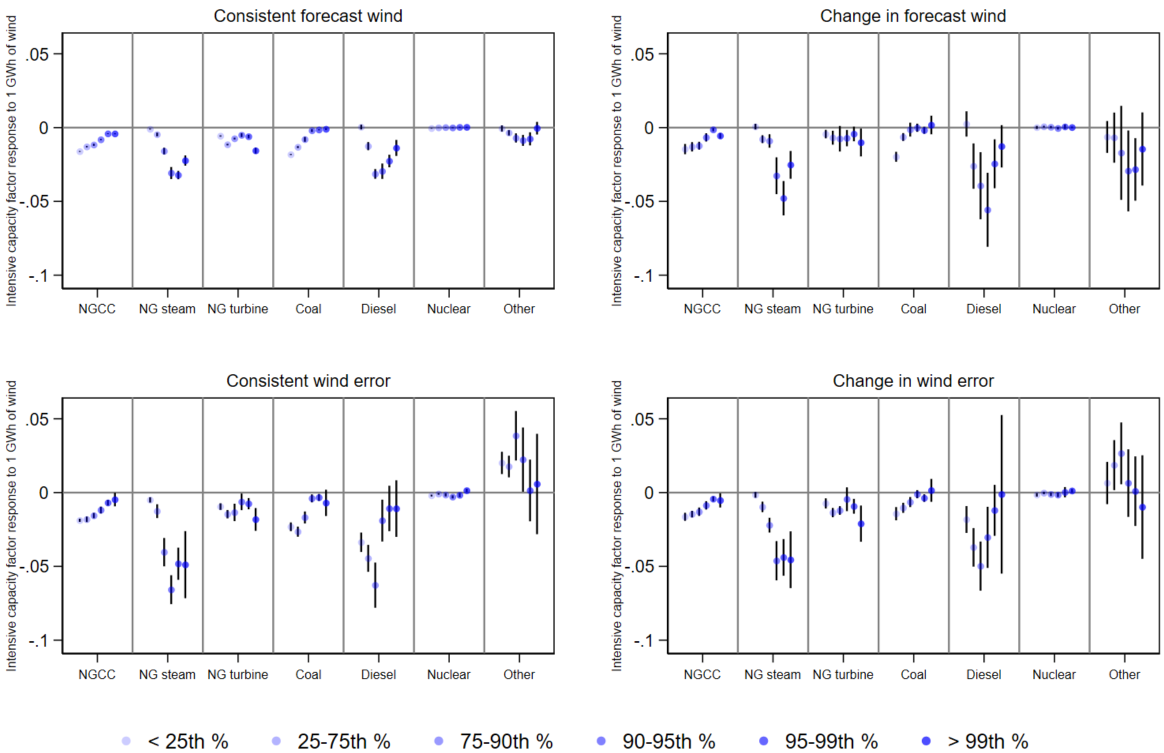
Finally, Figure 14 shows the decomposed extensive margin response to wind generation, which we estimate as the number of units operating. Extensive margin responses are small or nonexistent for all technologies except for NG turbines. In fact, there is essentially no extensive margin response to changes in wind generation, and only NG turbines have a meaningful extensive margin response to wind error. These extensive margin results demonstrate that any additional start-up costs induced by wind generation are primarily accruing at NG turbines, which have smaller start-up costs than most other technologies, particularly NGCC and coal units (Kumar et al. 2012). Notably, for NG

25. Figure A11 in the appendix shows the comparable generation responses to electricity demand. The coefficients are similar with some notable differences: the generation response from NG turbines is less for demand error than for wind error, and coal generation is more responsive to demand error and demand changes in some hours.

26. Technology-specific intensive margin capacity factors are calculated as the total generation from that technology in each hour divided by the total capacity of that technology that is operating in that hour, with unit-level capacity estimated as the maximum observed unit operating level.

27. We show capacity factor responses inclusive of non-operating units in Figure A12 in the appendix, and the results are generally consistent with these intensive margin results. The corresponding results for decomposed demand are in Figures A13 and A14 in the appendix, which are also broadly consistent with these results for decomposed wind.

Figure 13: Decomposed effects of wind on intensive margin at non-wind generators



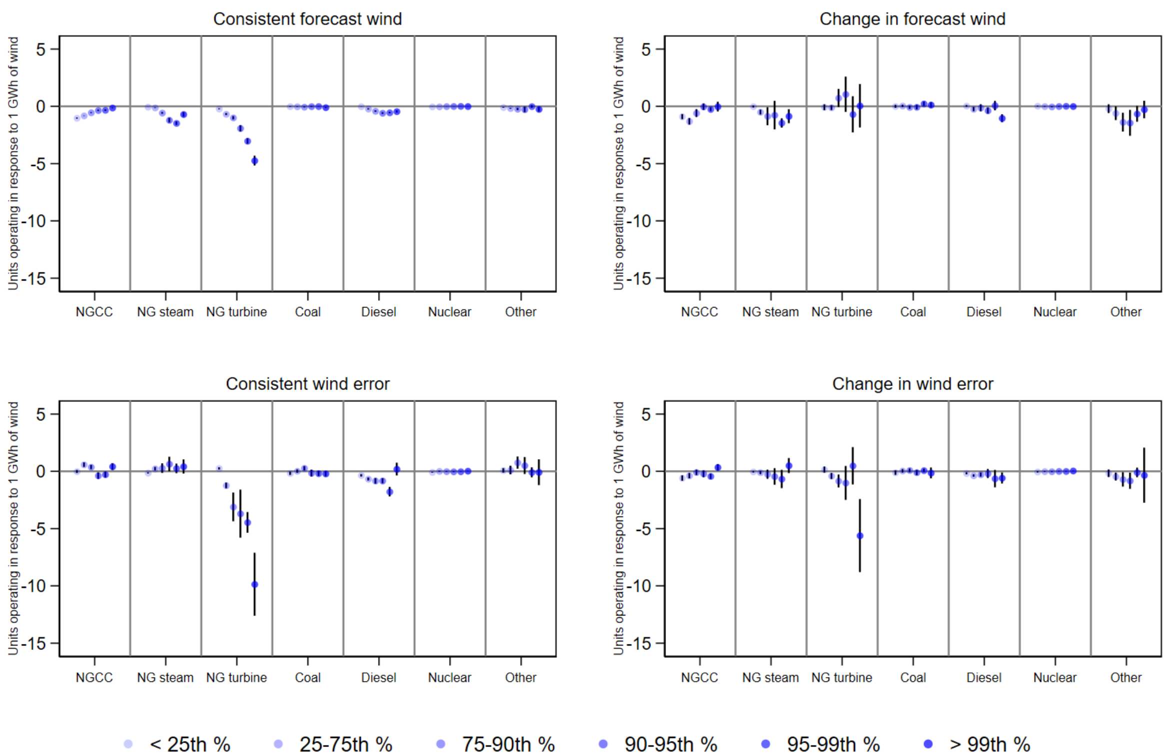
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed wind variables on intensive margin capacity factor—aggregate generation divided by aggregate capacity of operating units—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

turbines, the extensive margin response to unforecast wind is about twice as large as the response to forecast wind. Thus, the key characteristic driving an extensive margin response is whether the wind generation was forecast or not.[28]

Overall, these results demonstrate that there are important differences between how the grid balances forecast versus unforecast wind generation, and how it does so depends on the amount of residual demand. We find that at low levels of residual demand, much of the balancing of wind generation occurs through small intensive margin generation responses, changing within-unit generation by less than 3 percentage points typically, which is technically simple to accomplish and relatively low cost. High levels of residual demand, however, elicit extensive margin responses among NG turbines, and these responses are twice as large for unforecast wind than forecast. As described

28. Figure A15 shows the corresponding results for decomposed demand, and we do not observe a statistical difference in the response of NG turbines for forecast versus unforecast demand. This distinction mirrors the distinction we saw in the price effects: wind forecast error yields roughly double the price effect of forecast wind, while demand forecast error did not have a statistically different impact than forecast demand. These findings provide more evidence that grid operators are responding to error in wind forecasts uniquely compared to error in demand forecasts.

Figure 14: Decomposed effects of wind on extensive margin at non-wind generators



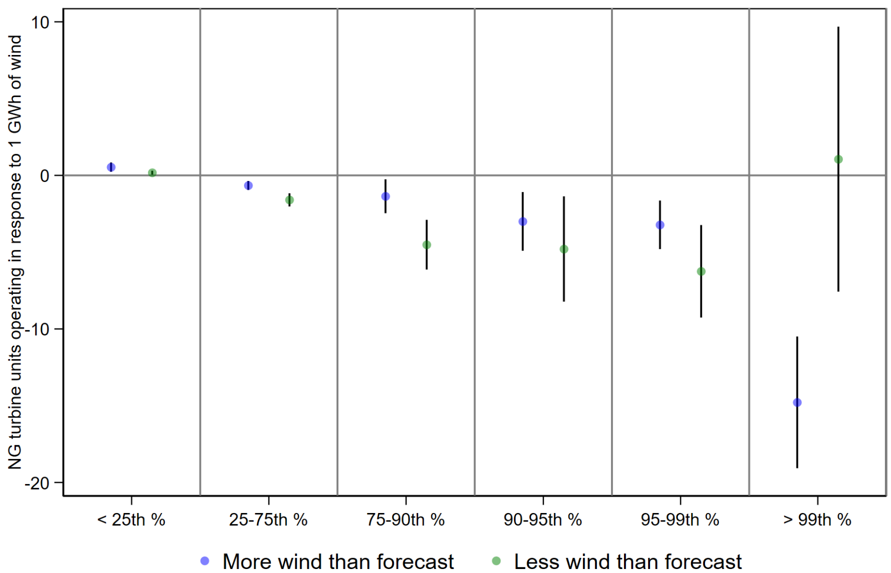
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed wind variables on the extensive margin—the number of units operating—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

previously, this extensive margin response incurs start-up costs, but NG turbines have lower start-up costs than other predominant technologies. Thus, error in wind forecasts may generate additional costs for the operation of the grid, but the use of NG turbines to balance wind error minimizes these costs, as compared to the use of NGCC or coal units.

Start-up costs due to uncertainty To conclude our analysis, we further examine this most costly response of non-wind generators: the start up and shut down of NG turbines to balance error in forecasts. In particular, we investigate whether effects are asymmetric across hours in which wind error is positive or negative—that is, there is more wind than forecast or less wind than forecast. When more wind generation occurs than was forecast, so less conventional generation is required to meet demand, we would expect units to be shut down. Conversely, when less wind generation occurs than was forecast, we expect that additional units must start up. The magnitude of these responses may differ, and they each impose different costs on the operation of the grid.

To investigate any potential asymmetries in the grid response to more versus less wind than forecast, we first re-estimate the decomposed extensive margin effects for NG turbines, shown in Figure 14, but allow the coefficients on consistent error to differ for positive and negative values. Figure 15 plots the resulting coefficients for this heterogeneity.[29] We find that over most hours, having less wind generation than forecast yields an extensive margin response that is roughly double the response when more wind occurs than forecast.[30] In other words, the number of NG turbines that start up when there is a shortfall of wind generation is double the number of NG turbines that shut down when there is an excess of wind.[31]

Figure 15: Asymmetric effects of wind error on extensive margin at natural gas turbines



Notes: This figure shows the coefficient estimates and 95% confidence intervals of the impact of wind error on the number of NG turbines operating. We estimate heterogeneous effects for hours with more wind than forecast (blue) or less wind than forecast (green). We separately estimate these effects for different levels of residual demand, as indicated on the x-axis.

These extensive margin responses include both start ups and shut downs, but only start ups are directly costly. Shutting down a unit may be costly if that unit or another unit must then start back up in a subsequent hour, but a shut down does not directly incur a cost. Thus, to accurately capture the cost of these extensive margin responses, we finally examine the effect of forecast error on NG turbine starts. Because shut downs in one hour could lead to start up in subsequent hours,

29. Figure A16 in the appendix shows the comparable results for demand forecast error. We find that any asymmetry is less pronounced for demand error.

30. Estimates are imprecise for the 90th to 99th percentile of residual demand, but the relative magnitudes of these point estimates are consistent with the more precise estimates at lower levels of residual demand.

31. When less wind generation occurs than was forecast, the value of wind error is negative. Thus, a larger amount of error in these hours corresponds to error that is more negative. Multiplying this negative value by a negative coefficient indicates that *more* units operate.

we estimate the effect of forecast error in one hour on starts in the contemporaneous hour and the subsequent four hours:

$$\begin{aligned} \sum_{k=0}^{4} S_{t+k} = \beta_1 W_t + \beta_2 WE_t \times \mathbb{1}[WE_t > 0] + \beta_3 WE_t \times \mathbb{1}[WE_t < 0] \\ + \theta_1 D_t + \theta_2 DE_t \times \mathbb{1}[DE_t > 0] + \theta_3 DE_t \times \mathbb{1}[WE_t < 0] \\ + \eta X_t + \alpha_h + \gamma_m + \delta_y + \varepsilon_t \end{aligned} \tag{4}$$

where S_t is the number of NG turbine starts in hour t that we sum over the contemporaneous hour and the subsequent four hours. The remaining variables are as described previously. Unit starts over the subsequent four hours will also depend on market conditions in those four hours, so we also control for wind, wind error, demand, and demand error in those hours, represented by X_t. Importantly, we allow the effects of error to differ if the value is positive or negative. As before, we estimate this regression for different levels of residual demand.

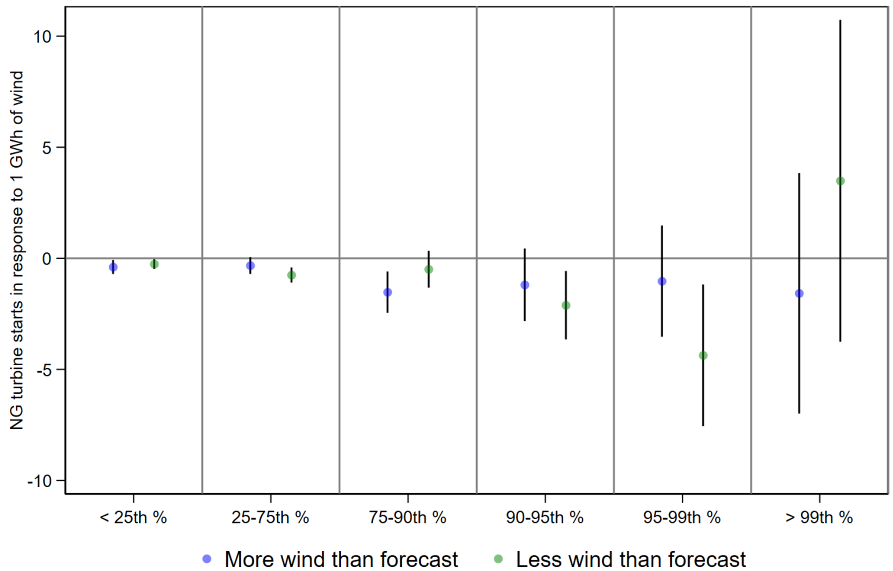
The coefficients of interest are β_2 and β_3, which give the additional effect of wind forecast error, compared to if the that wind generation was accurately forecast. Figure 16 plots these coefficients.[32] We find that a greater amount of negative error—when less wind generation occurs than was forecast—increases the number of NG turbine starts,[33] while positive error reduces the number of starts. In most hours, the additional starts due to negative error are roughly twice as large as the number of fewer starts due to positive error. One implication of this result is that, if wind forecasts were to improve so the magnitude of wind forecast error is reduced, then the number of NG turbines starts would change. In hours with negative error, better forecasts would reduce starts; in hours with positive error, better forecasts would increase starts. The identified asymmetry indicates that, if forecasts improved comparably in hours with negative error and hours with positive error, the reduced number of starts in hours with negative error would be larger in magnitude than the increased number of starts in hours with positive error, so NG turbine starts would be reduced overall.

To summarize the benefits of improving wind generation forecasts, we consider how aggregate NG turbine starts would change if wind generation forecasts were improved to be as good as electricity demand forecasts. The average magnitude of wind error is 0.417 GWh, and the average magnitude

32. Figure A17 in the appendix shows these effects over other time horizons, ranging from contemporaneous effects only to 12 subsequent hours. Figure A18 in the appendix shows the comparable effects for demand error.

33. As described previously, both the variable and the coefficient are negative, so the product yields an increase in the number of starts.

Figure 16: Asymmetric effects of wind error on starts in current and next four hours at natural gas turbines



Notes: This figure shows the coefficient estimates and 95% confidence intervals of the impact of wind error on the total number of NG turbines that start up in the current and next four hours. We estimate heterogeneous effects for hours with more wind than forecast (blue) or less wind than forecast (green). We separately estimate these effects for different levels of residual demand, as indicated on the x-axis.

of demand error is 0.281 GWh, so this improvement corresponds to a roughly 33% reduction in wind forecast error. To calculate this aggregate effect, we apply the relevant coefficient from Figure 16 to each hour of our dataset, and then use that estimated marginal effect to calculate the change in NG turbine starts due to a 33% reduction in wind error in that hour.

We find that improving wind generation forecasts to the quality of electricity demand forecasts would yield 1750 fewer NG turbine starts over the eight years of our study. The median cost of starting up an NG turbine is $32 per MW of capacity (Kumar et al. 2012), and the average capacity of an NG turbine unit in our data is 79 MW, yielding a start-up cost of $2528 per start. Thus, this improvement in wind generation forecasts would reduce start-up costs by $4.4 million over eight years, or roughly $550,000 per year. For comparison, more than $10 billion is transacted annually in the ERCOT wholesale electricity market, so the cost of wind generation uncertainty corresponds to less than 0.01% of the overall market.

5 Conclusion

We conclude by highlighting the key takeaways from the estimation results, which generally confirm the predictions of our theoretical model, and we discuss implications for policy. First, we find that the average magnitude of an increase in renewable generation leads to a price effect similar to a commensurate decrease in demand. Next, we find that the magnitude of this price effect depends on other market characteristics, becoming larger during periods where the residual demand curve shifts to the right and intersects steeper regions of the non-renewable supply curve, and smaller when the residual demand curve shifts to the left and intersects flatter regions of the non-renewable supply curve. Third, we find that hourly changes in wind generation that are forecast affect prices in a very similar magnitude as consistent wind generation. Errors in wind forecasts, however, have statistically larger price effects than forecasted wind. On the other hand, for electricity demand, the additional price effect of demand forecast error is similar to the effect of forecast demand, while intermittency in demand has larger price effects. When looking at price dispersion, we find that overall wind generation reduces the variation in wholesale electricity prices because of the residual demand price effect. Conditional on the price level, however, wind, hourly wind intermittency, and wind forecast error all increase price dispersion, as does demand forecast error. We note that the price and price dispersion impacts studied here are exclusively in the wholesale electricity market. There may be other important impacts occurring outside of this market, such as in bilateral contracting and ancillary service markets, which we leave to future research.

These price and price dispersion effects are generated by operational responses at non-wind generators. During many hours, variation in wind generation can be balanced by small intensive margin adjustments of roughly 1–3 percentage points at operating units, which is low cost and technically easy to achieve. Error in wind forecast, however, typically requires an extensive margin response—starting up or shutting down non-wind generators—which incurs a greater cost. This result points to the value of renewables forecasts: balancing the grid with low-cost intensive margin adjustments rather than high-cost extensive margin responses. Further, we find that the extensive margin responses occur exclusively among NG turbines.

Overall, we find that a key dimension of wind generation's impact on grid outcomes stems from uncertainty in generation—indicated by error in generation forecasts. Wind's price effect from the residual demand effect mirrors the impact of electricity demand, and the impact of hourly changes in wind is similar to the impact of constant wind. Additionally, the effects of demand error are similar to the effects of forecast demand. The effects of wind error, however, are unique among all electricity market outcomes we study. These findings are particularly salient given the trends observed in demand versus wind forecast error, with demand error steadily decreasing over time while similar improvements are not as marked for wind forecast error. Thus, in preparing for an increasingly decarbonized electricity system, grid operators would do well to focus on improving wind forecasts, which would dampen price variation and alleviate the need for costly extensive margin responses to wind generation.

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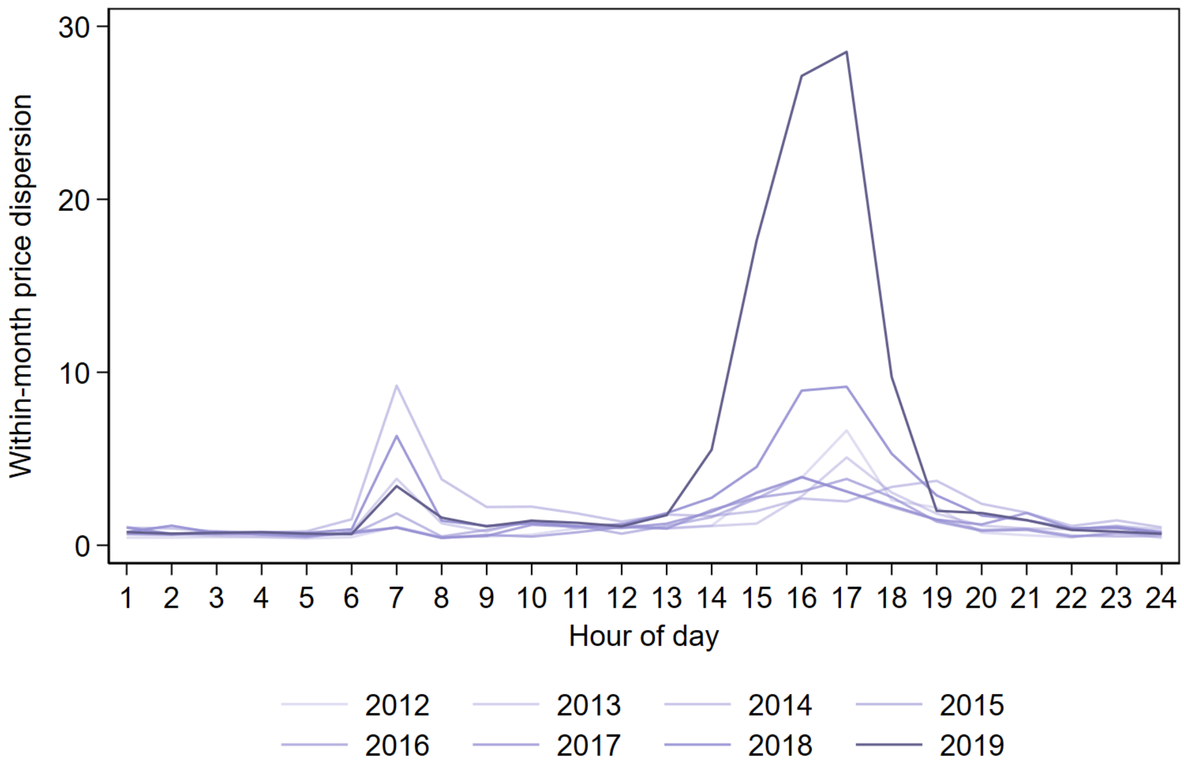
Appendix

Figure A1: Monthly measure of price dispersion, by year 2012–2019



Notes: This figure plots average hourly price dispersion in ERCOT by year for 2012–2019 using the within-month metric of price dispersion.

Table A1: Overall effects on wholesale electricity price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wind (GWh)	-2.27^{***}	-2.10^{***}		-2.23^{***}	-2.19^{***}	-2.27^{***}	-2.27^{***}
	(0.41)	(0.37)		(0.40)	(0.37)	(0.22)	(0.22)
Demand (GWh)	2.27^{***}		2.21^{***}	2.24^{***}	2.03^{***}	2.27^{***}	2.27^{***}
	(0.48)		(0.47)	(0.46)	(0.36)	(0.29)	(0.28)
Fixed effects:							
Hour-of-day (HoD)	Yes	Yes	Yes			Yes	Yes
Month-of-year (MoY)	Yes	Yes	Yes			Yes	Yes
Year	Yes	Yes	Yes	Yes		Yes	Yes
HoD × MoY				Yes			
HoD × MoY × Year					Yes		
Standard errors:							
Clustered by HoD	Yes	Yes	Yes	Yes	Yes		
Clustered by date						Yes	
Newey-West, 24 lags							Yes
Observations	69,739	69,739	69,739	69,739	69,739	69,739	69,739

Notes: This table reports the results of estimating Equation (2) and alternate specifications. The outcome in each regression is the hourly wholesale electricity price in $ per MWh. Column (1) directly corresponds to Equation (2); this regression includes hour-of-day, month-of-year, and year fixed effects, and standard errors are clustered by hour of day. Column (2) includes only wind generation as a regressor, and column (3) includes only demand as a regressor. Columns (4) and (5) include more flexible fixed effects specifications: hour-of-day-by-month-of-year and year fixed effects in column (4) and hour-of-day-by-month-of-year-by-year fixed effects in column (5). Columns (6) and (7) estimate alternate standard errors: standard errors clustered by date in column (6) and Newey-West standard errors with 24 lags in column (7). Standard errors are shown in parenthesis. Significance: * $p < 0.001$, $p < 0.01$, * $p < 0.05$

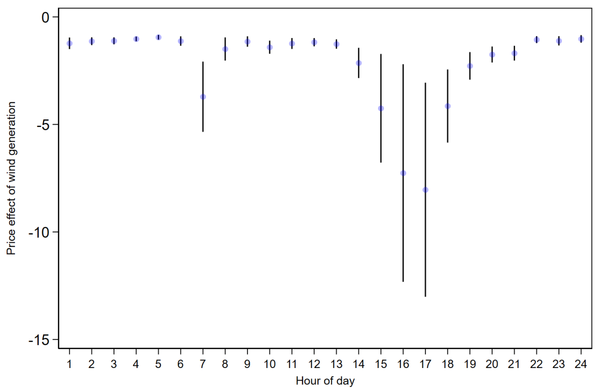
Table A2: Overall effects on wholesale electricity price dispersion

	Within-hour		Within-day		Within-month		Within-year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wind (GWh)	-0.37^{***}	-0.12	-0.29^{**}	0.11^{***}	-0.19^{**}	0.18^{***}	-0.05^{**}	0.06^{***}
	(0.08)	(0.07)	(0.08)	(0.01)	(0.06)	(0.01)	(0.02)	(0.00)
Demand (GWh)	0.33^{***}	0.09	0.34^{***}	-0.06^{**}	0.32^{**}	-0.04^{*}	0.06^{**}	-0.05^{***}
	(0.08)	(0.07)	(0.08)	(0.02)	(0.09)	(0.02)	(0.02)	(0.01)
Price ($ per MWh)		0.11^{**}		0.18^{***}		0.16^{***}		0.05^{***}
		(0.03)		(0.00)		(0.00)		(0.00)
Observations	69,739	69,739	69,739	69,739	69,739	69,739	69,739	69,739

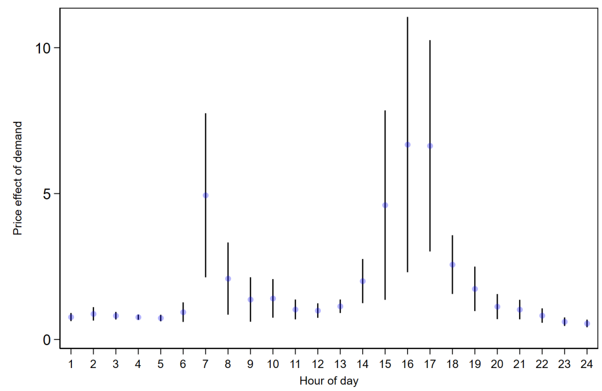
Notes: This table reports the results of estimating Equation (2). The outcome in each regression is a measure of hourly wholesale electricity price dispersion, as given in the column headings. All columns include hour-of-day, month-of-year, and annual fixed effects. Some columns also control for hourly wholesale electricity price. Standard errors clustered by hour of day are shown in parenthesis. Significance: * $p < 0.001$, $p < 0.01$, * $p < 0.05$.

Figure A2: Price effects by hour of day

(a) Wind generation



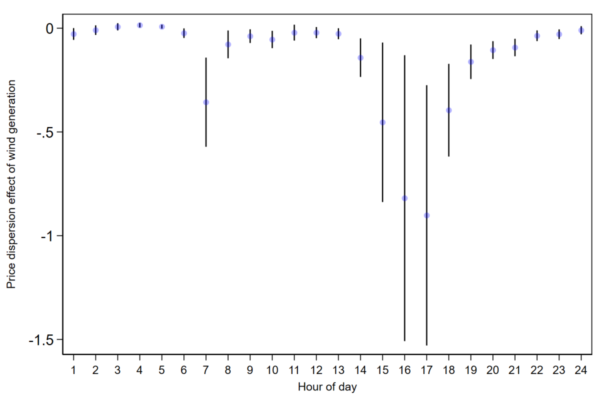
(b) Electricity demand



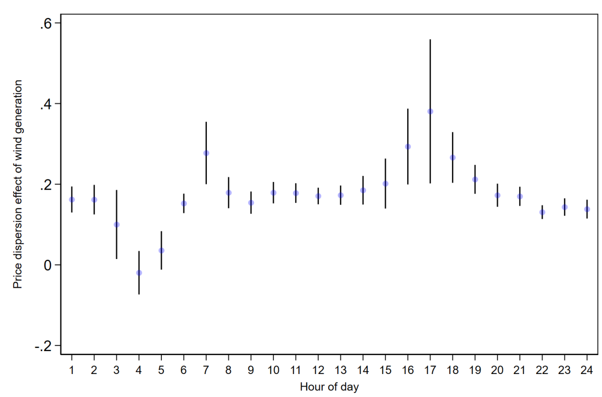
Notes: Panel (a) shows the estimated coefficients and 95% confidence intervals of wind generation on price by hour of day. Panel (b) shows the estimated coefficients and 95% confidence intervals of electricity demand on price by hour of day. All specifications include month-of-year and annual fixed effects.

Figure A3: Price dispersion effects by hour of day

(a) Unconditional on price

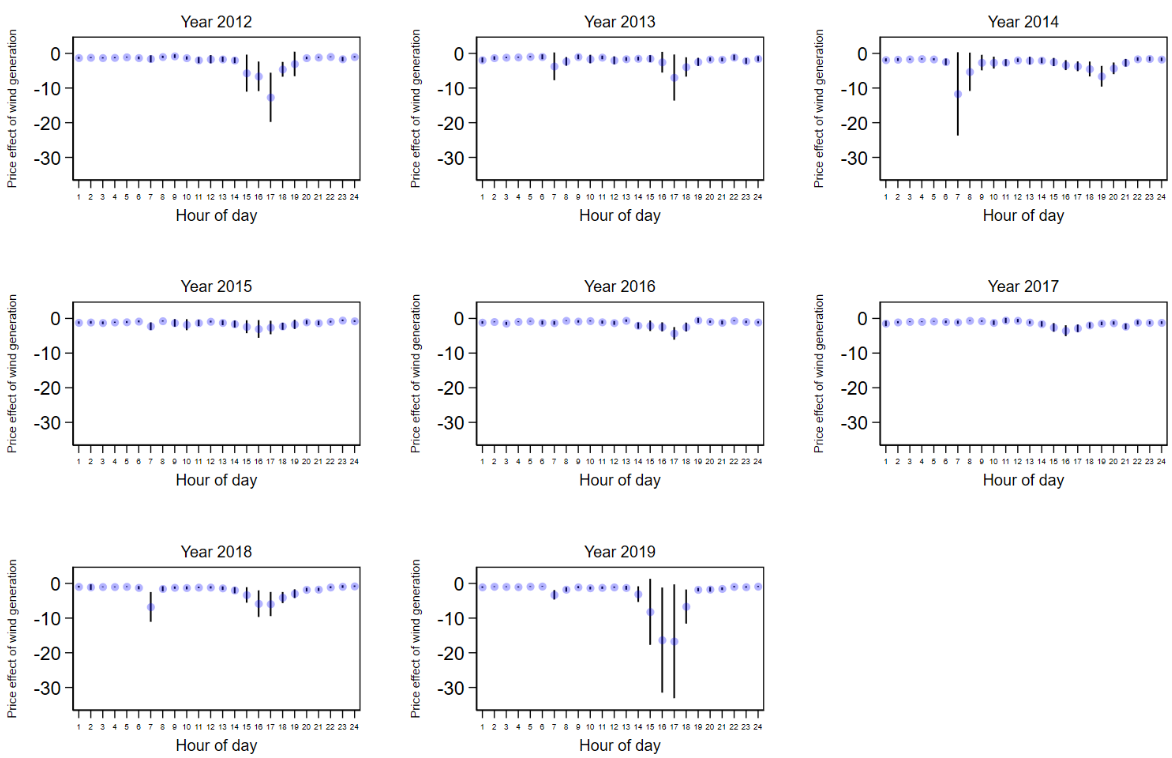


(b) Conditional on price



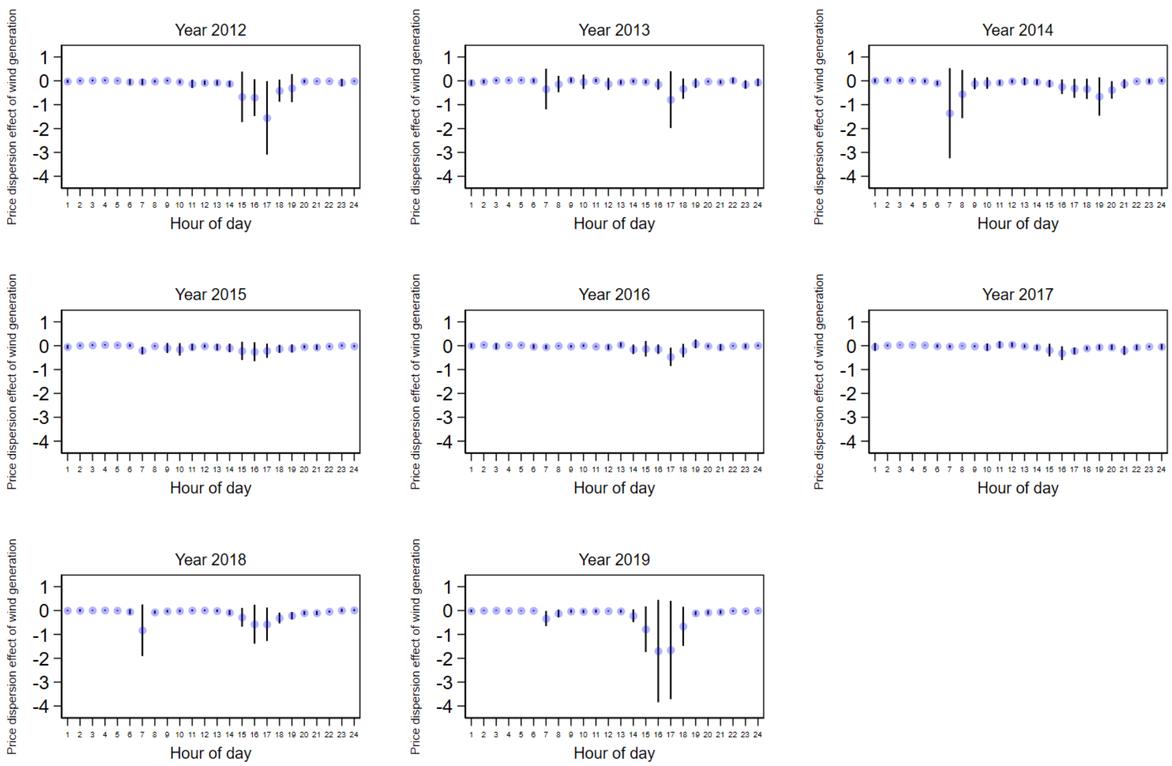
Notes: Panel (a) shows the estimated coefficients and 95% confidence intervals of wind generation on within-month price dispersion by hour of day, unconditional on price. Panel (b) shows the estimated coefficients and 95% confidence intervals of electricity demand on within-month price dispersion by hour of day, conditional on price. All specifications include month-of-year and annual fixed effects.

Figure A4: Hourly effect of wind on prices by year



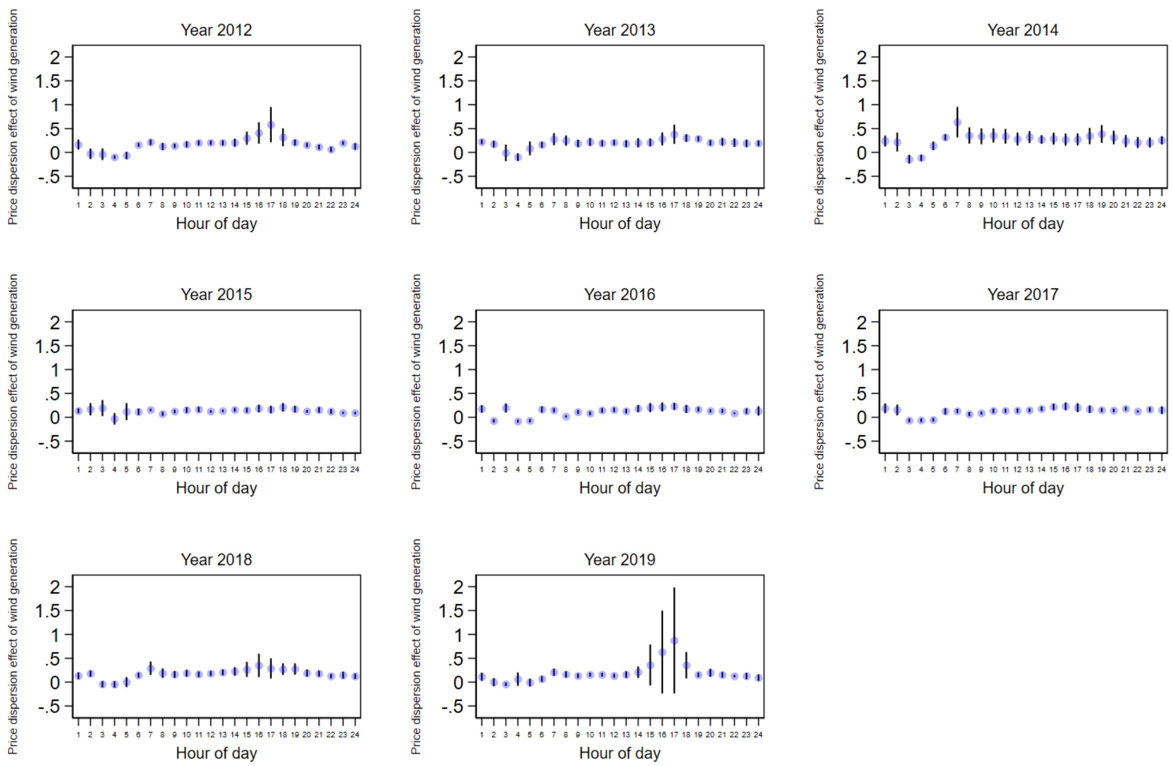
Notes: These figures show the estimated coefficients and 95% confidence intervals of wind generation on price by hour of day and year. All specifications control for electricity demand and include month-of-year fixed effects.

Figure A5: Hourly effect of wind on price dispersion by year, unconditional on price



Notes: These figures show the estimated coefficients and 95% confidence intervals of wind generation on within-month price dispersion by hour of day and year, unconditional on price. All specifications control for electricity demand and include month-of-year fixed effects.

Figure A6: Hourly effect of wind on price dispersion by year, conditional on price

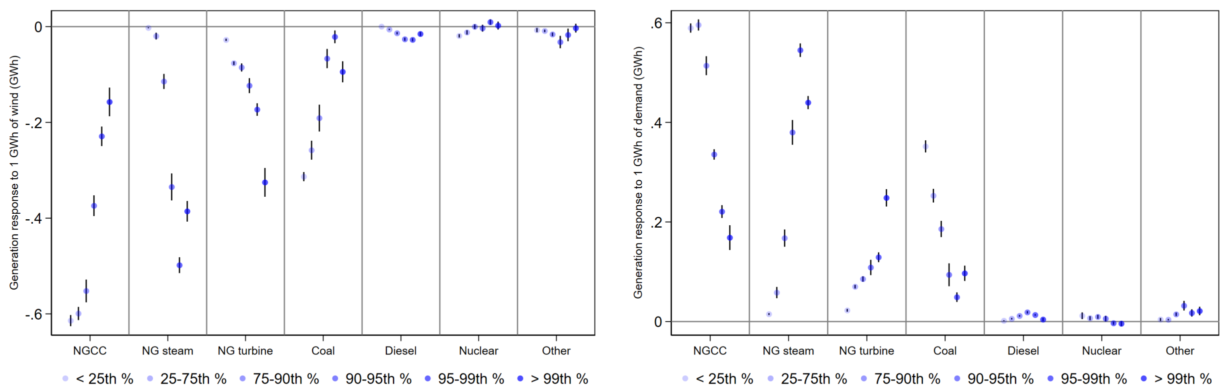


Notes: These figures show the estimated coefficients and 95% confidence intervals of wind generation on within-month price dispersion by hour of day and year, controlling for price. All specifications control for electricity demand and include month-of-year fixed effects.

A.1 Additional results for non-wind generators

Figure A7: Overall effects on generation at non-wind generators

(a) Wind generation (b) Electricity demand



Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of wind generation and electricity demand on generation by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

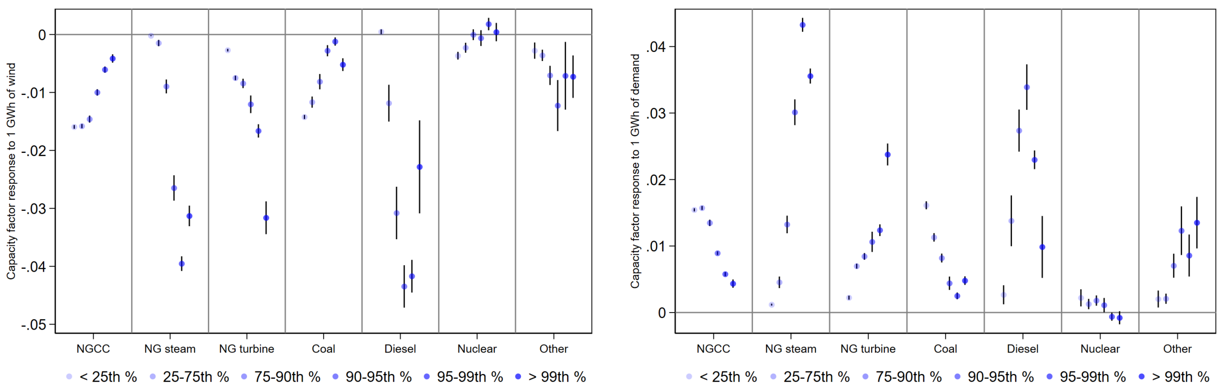
Figure A7 depicts the results of estimating Equation (2) with generation by unit type as the outcome variable. In each panel of this figure, each point represents a coefficient estimate from a different regression. The first six points correspond to total generation by natural gas combined cycle (NGCC) units, and then for other non-wind technologies as labeled on the x-axis. Within each grouping of points, the lightest point on the left gives the estimated coefficient for hours with less than the 25th percentile of residual demand, and so on as shown in the legend. The left panel gives the marginal effects of wind generation and the right panel of electricity demand, and the corresponding points in each panel come from the same regression. In other words, the leftmost point in each panel comes from the same regression, which regresses systemwide NGCC generation on wind generation and electricity demand in hours when residual demand is less than the 25th percentile.

For both NGCC and coal, Figure A7 shows a positive slope across the estimated coefficients for wind generation, where the estimated coefficient is *largest* in magnitude for the *smallest* levels of residual demand. For NG steam and NG turbines, however, the slope across the coefficients is negative, indicating that aggregate generation from these technologies responds by a larger magnitude in response to wind generation at higher levels of residual demand. There is no clear slope in estimated coefficients for diesel, nuclear, and other technologies, and most of the estimated coefficients are close to zero. Taking these results together, they suggest that NGCC and coal units are more likely to be on the margin during low residual demand hours, while NG steam and NG turbine units are more likely to be on the margin during high residual demand hours. The heterogeneity in marginal costs of these two groups of technologies creates the heterogeneity in price effects at different residual demand levels. The estimated generation responses to electricity demand follow a similar pattern, where NGCC and coal generators are more likely to respond at low levels of residual demand, and NG steam and NG turbine generators are more likely to respond at higher levels of residual demand.

Figure A8 plots non-wind technology capacity factor responses unconditional on operating status. Figure A9 plots intensive margin responses, which we estimate as the average capacity factors among units that are operating. These results are generally similar to the intensive margin re-

Figure A8: Overall effects on capacity factor at non-wind generators

(a) Wind generation (b) Electricity demand



Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of wind generation and electricity demand on capacity factor—aggregate generation divided by aggregate capacity—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

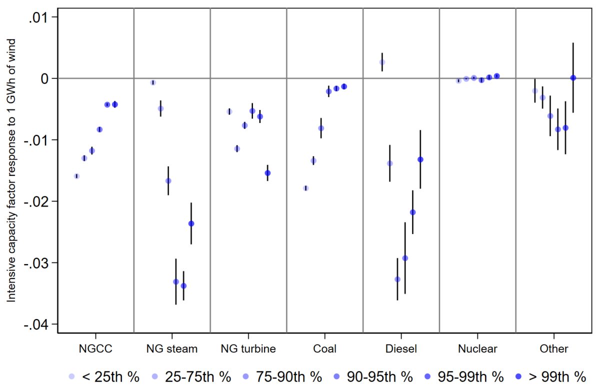
sponses described here, suggesting that much of the total response occurs on the intensive margin. We find that while aggregate generation from NGCC units decreases by around 0.6 GWh when wind increases by one GWh and residual demand is low, each operating NGCC unit adjusts its capacity factor by less than 2 percentage points on average. Thus, what may appear to be a large aggregate response corresponds to a relatively small response at individual units that are already operating. NG steam and diesel units have larger intensive unit responses compared to the other technologies, especially during hours with higher levels of residual demand, but even these largest intensive margin responses are less than 4 percentage points.

Figure A10 plots the extensive margin responses, which we estimate as the number of units operating. At high levels of residual demand, we find that NG turbines have the largest extensive margin response, or the number of NG turbines that start up or shut down in response to an additional GWh of wind or demand. At lower levels of residual demand, the extensive margin response is small for all non-wind technologies, with less than one unit starting up or shutting down in response to wind generation or electricity demand, and this smaller extensive margin response accounts for only a small portion of the overall generation response. These extensive margin results demonstrate that any additional start-up costs induced by wind generation are primarily accruing at NG turbines, which have smaller start-up costs than most other technologies, particularly NGCC and coal units.

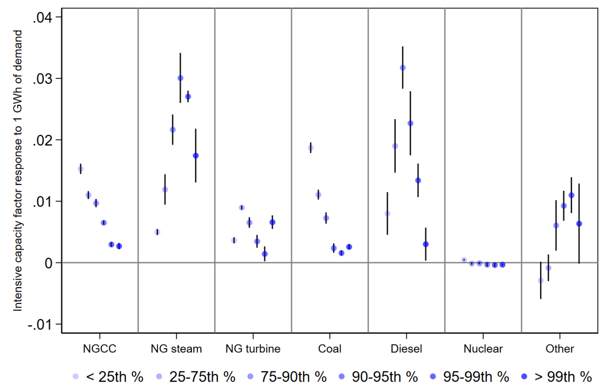
Looking across these three sets of results, we conclude that much of the variation in wind and demand is being balanced by small intensive margin generation responses, changing within-unit generation by 1–3 percentage points on average, which is technically simple to accomplish and relatively low cost. At higher levels of residual demand, however, the grid relies importantly on starting up and shutting down NG turbines, which incurs a greater cost than intensive margin adjustments but is not as costly as starting up and shutting down other technologies.

Figure A9: Overall effects on intensive margin at non-wind generators

(a) Wind generation



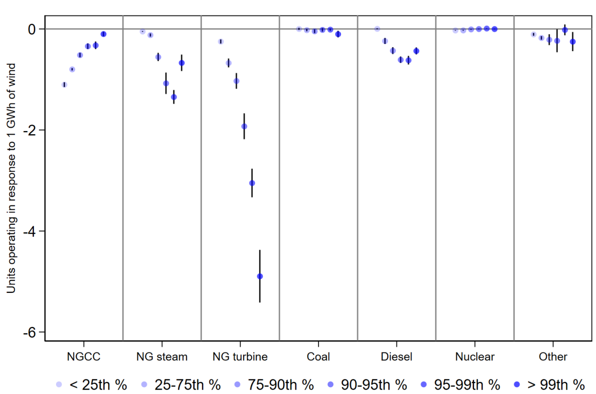
(b) Electricity demand



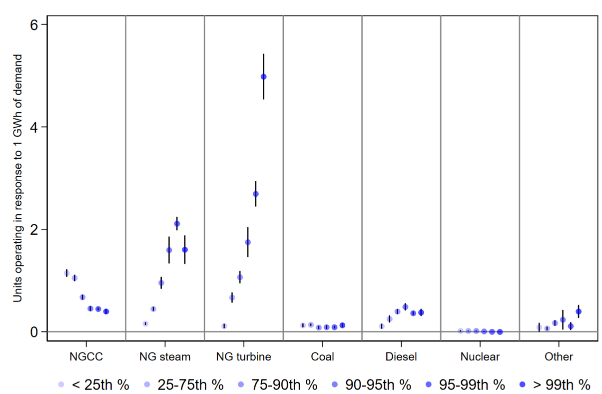
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of wind generation and electricity demand on intensive margin capacity factor—aggregate generation divided by aggregate capacity of operating units—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

Figure A10: Overall effects on extensive margin at non-wind generators

(a) Wind generation

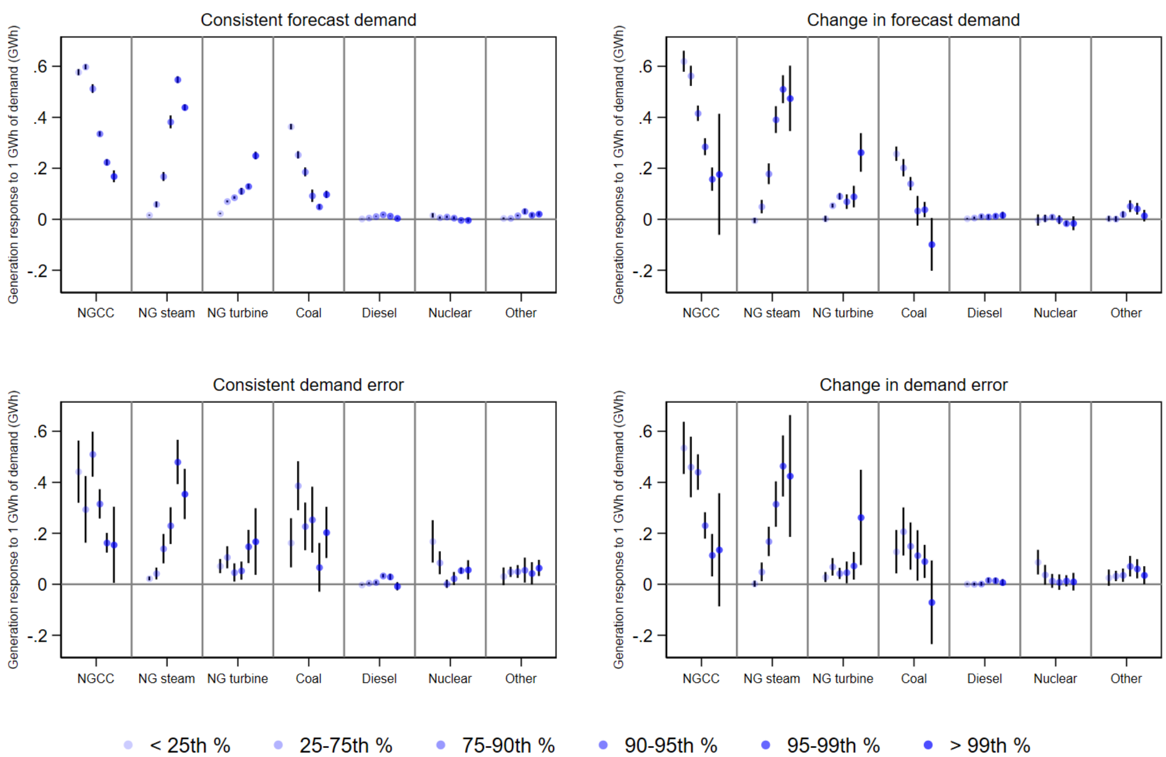


(b) Electricity demand



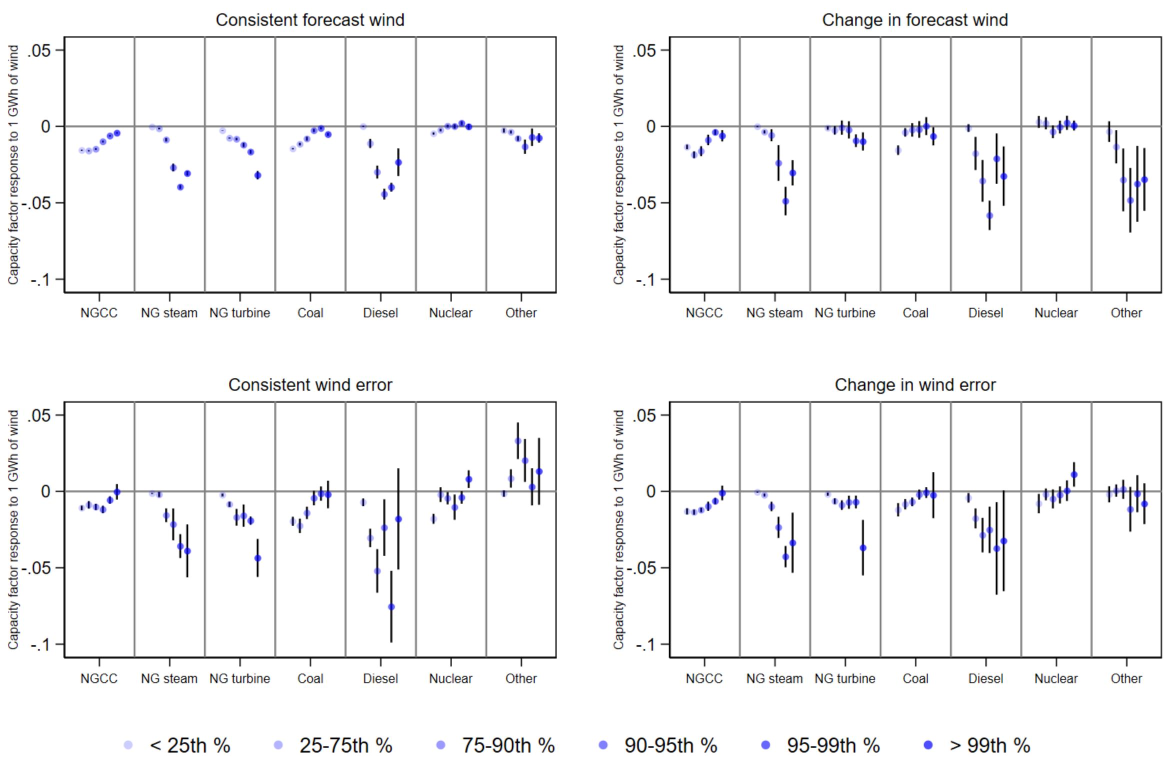
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of wind generation and electricity demand on the extensive margin—the number of units operating—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

Figure A11: Decomposed effects of demand on generation at non-wind generators



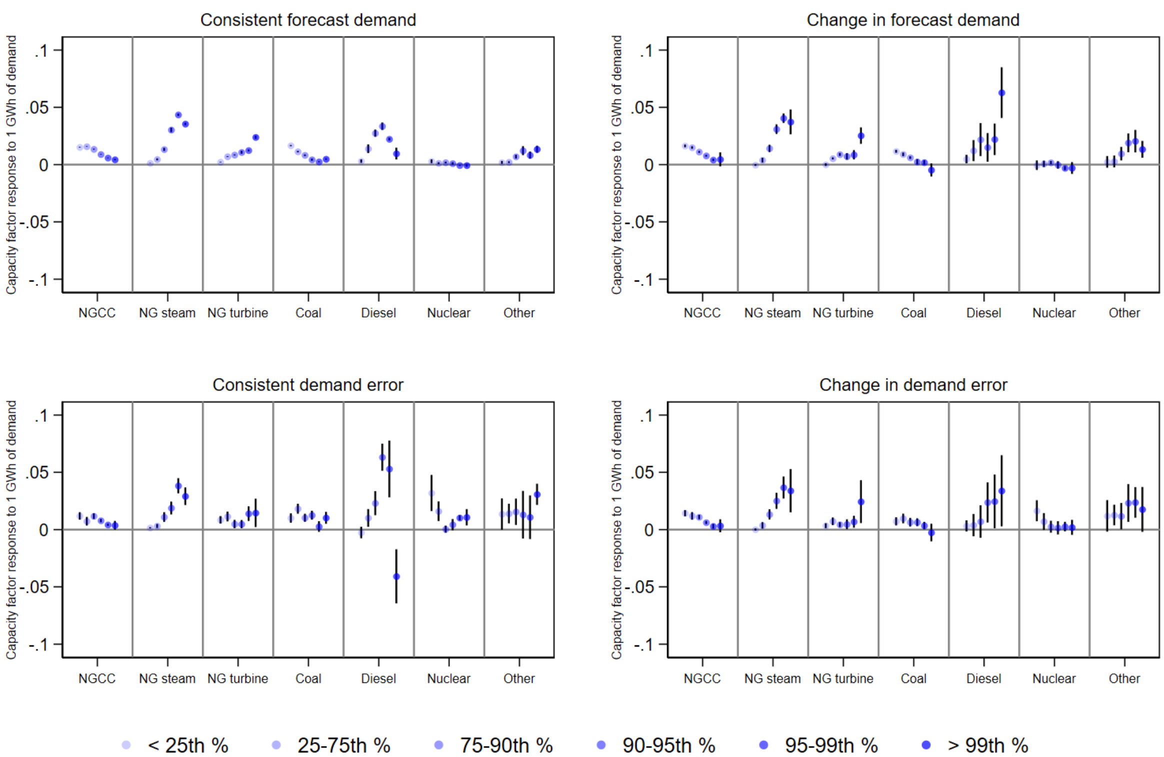
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed demand variables on generation by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

Figure A12: Decomposed effects of wind on capacity factor at non-wind generators



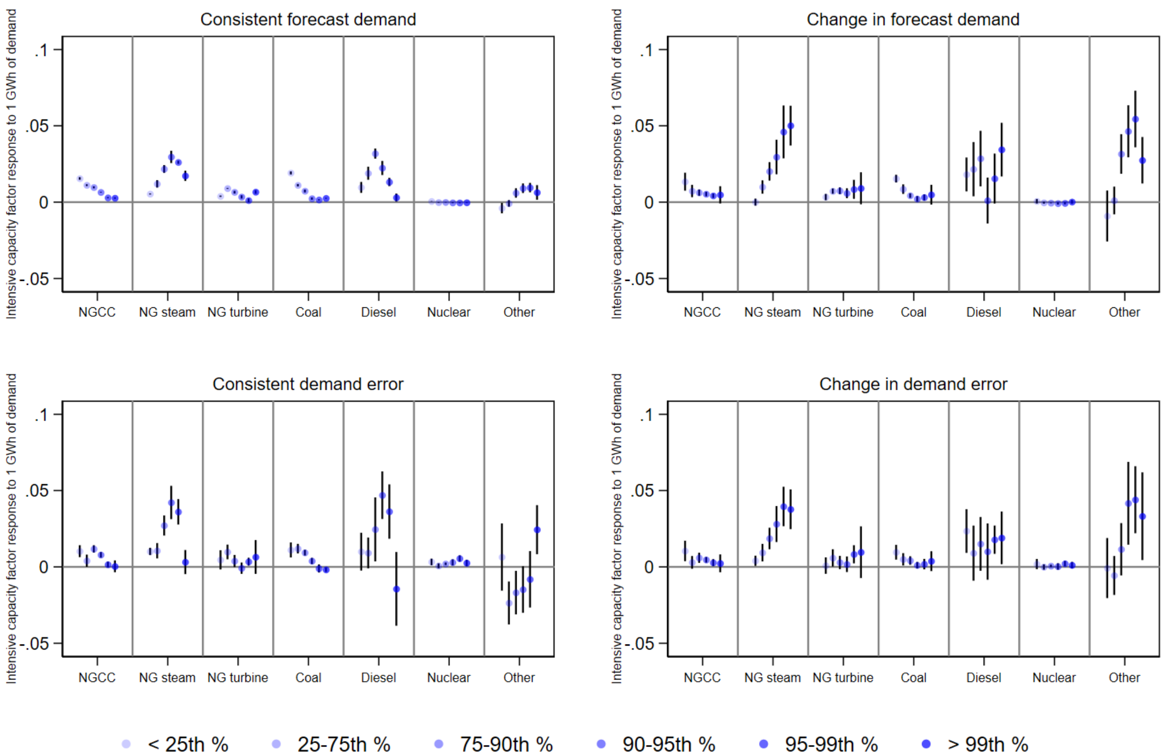
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed wind variables on capacity factor—aggregate generation divided by aggregate capacity—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

Figure A13: Decomposed effects of demand on capacity factor at non-wind generators



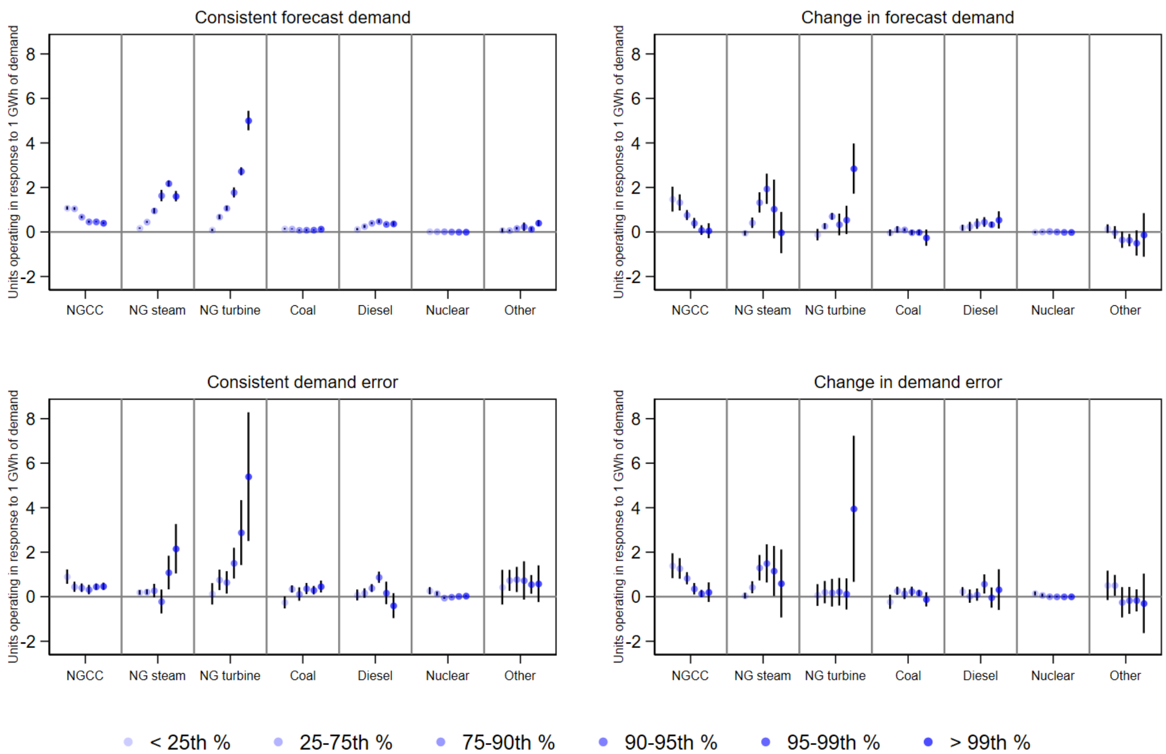
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed demand variables on capacity factor—aggregate generation divided by aggregate capacity—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

Figure A14: Decomposed effects of demand on intensive margin at non-wind generators



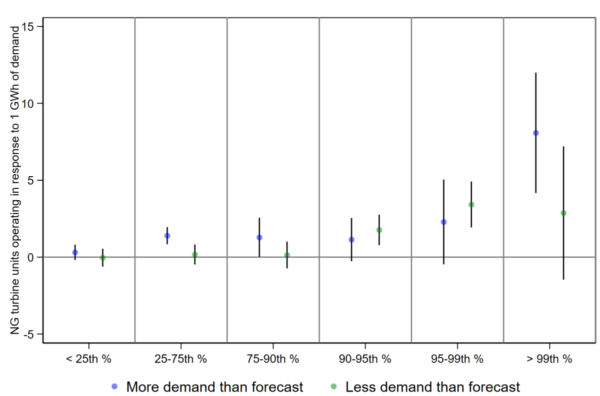
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed demand variables on intensive margin capacity factor—aggregate generation divided by aggregate capacity of operating units—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

Figure A15: Decomposed effects of demand on extensive margin at non-wind generators



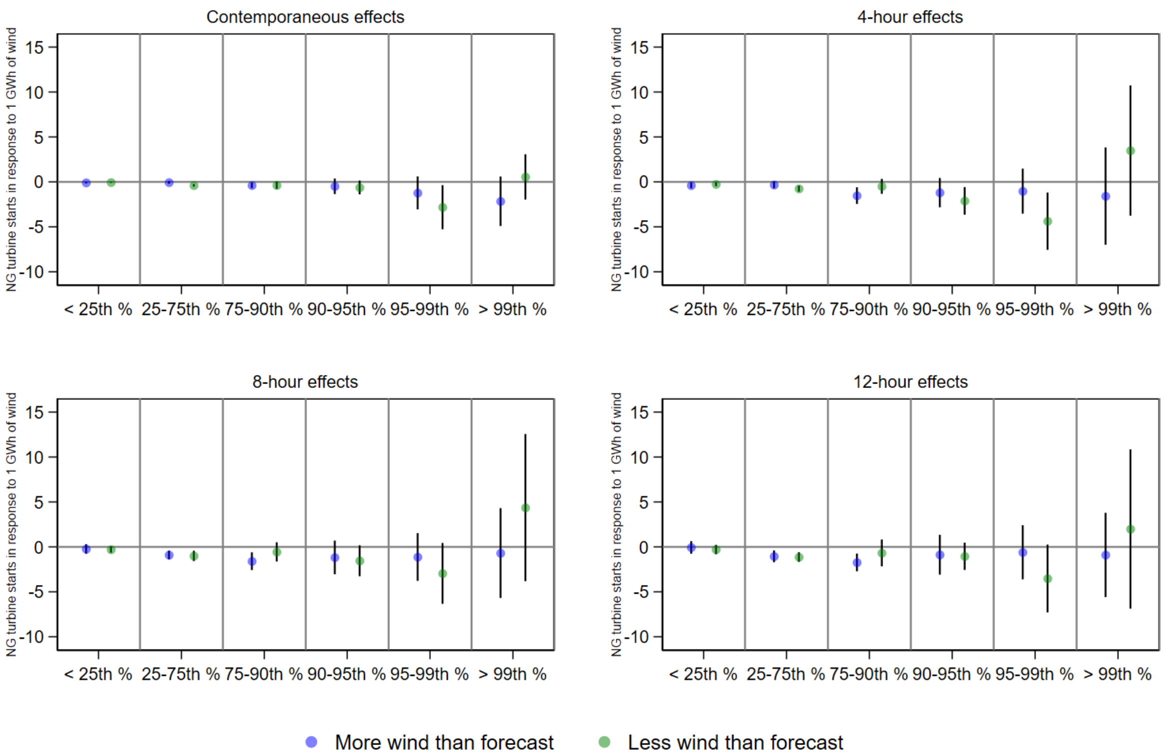
Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of decomposed demand variables on the extensive margin—the number of units operating—by technology type. We separately estimate these effects for different levels of residual demand, as indicated by the color of each shaded blue dot.

Figure A16: Asymmetric effects of demand error on extensive margin at natural gas turbines



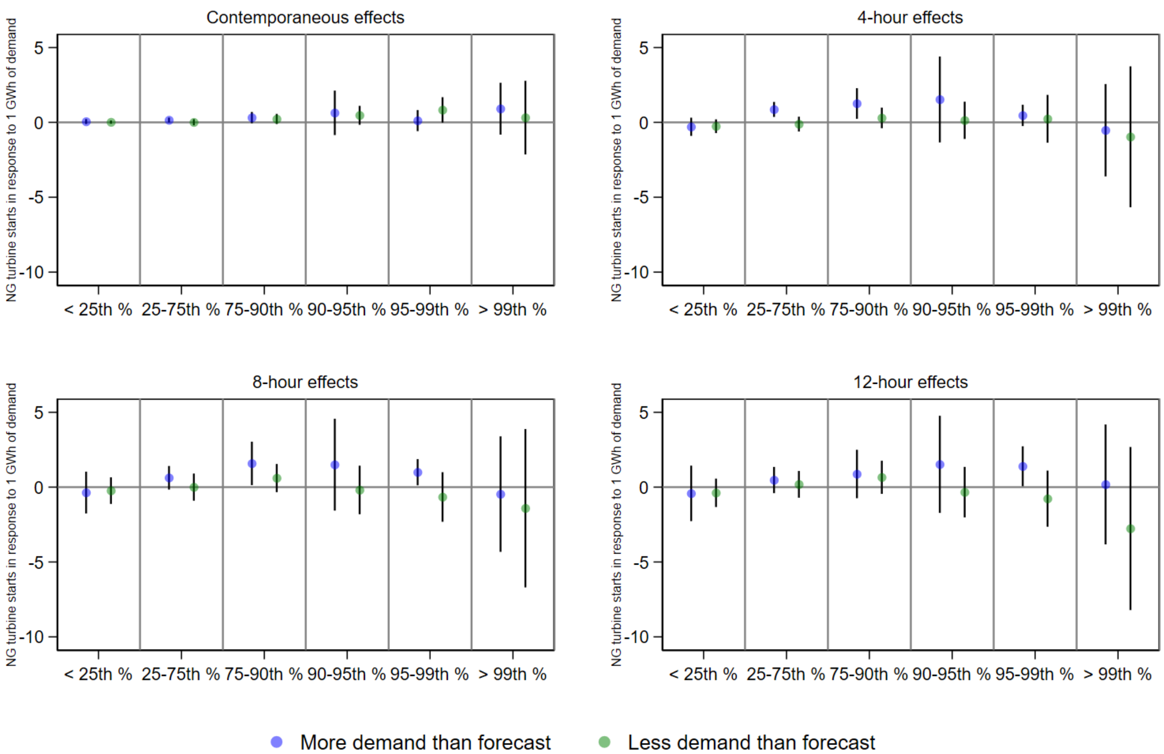
Notes: This figure shows the coefficient estimates and 95% confidence intervals of the impact of demand error on the number of NG turbines operating. We estimate heterogeneous effects for hours with more demand than forecast (blue) or less demand than forecast (green). We separately estimate these effects for different levels of residual demand, as indicated on the x-axis.

Figure A17: Asymmetric effects of wind error on starts at natural gas turbines



Notes: This figure shows the coefficient estimates and 95% confidence intervals of the impact of demand error on the total number of NG turbines that start up in the current hour, current and next four hours, current and next 8 hours, and current and next 12 hours. We estimate heterogeneous effects for hours with more demand than forecast (blue) or less demand than forecast (green). We separately estimate these effects for different levels of residual demand, as indicated on the x-axis.

Figure A18: Asymmetric effects of demand error on starts at natural gas turbines



Notes: These figures show the coefficient estimates and 95% confidence intervals of the impact of wind error on the total number of NG turbines that start up over different time horizons, as indicated above each figure. We estimate heterogeneous effects for hours with more wind than forecast (blue) or less wind than forecast (green). We separately estimate these effects for different levels of residual demand, as indicated on the x-axis.

A.2 Additional study of demand error

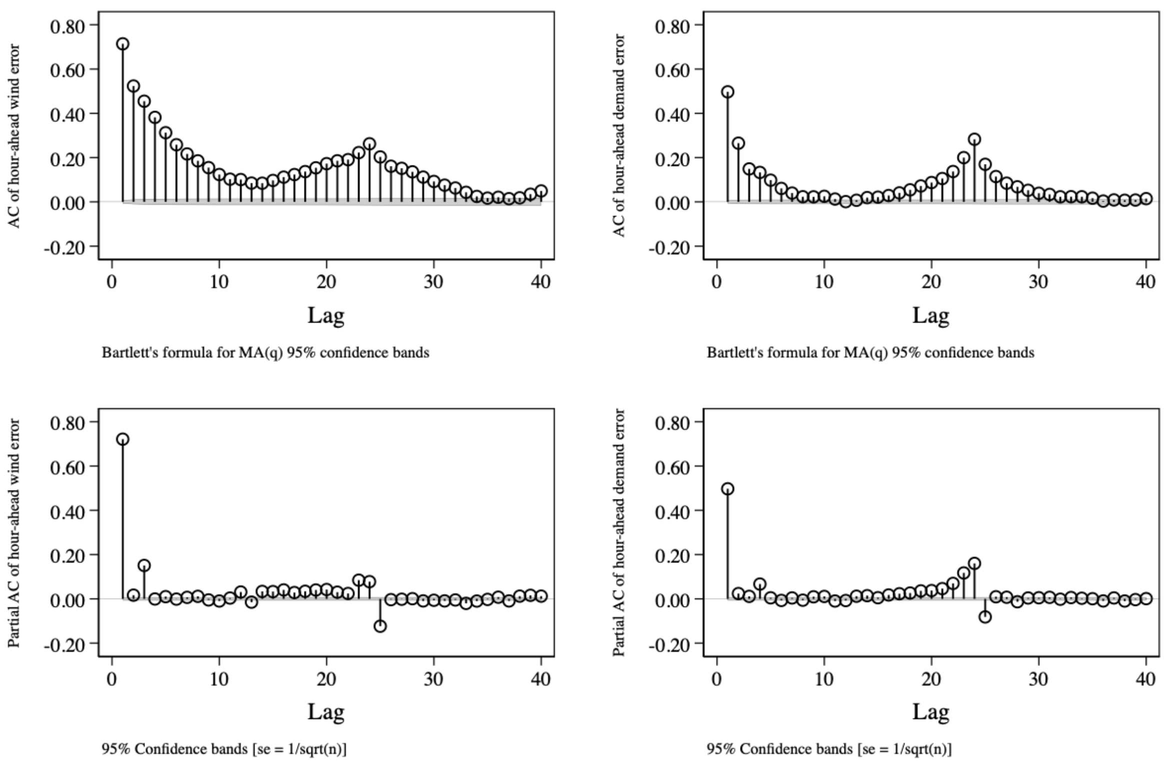
One hypothesis for the fact that we fail to identify an additional effect of demand forecast error on wholesale prices could be from nonlinearities in how forecast error affects prices—for example, if forecast error only impacts prices at higher levels of error. Wind has higher forecast error in our study period on average, at 0.42 GWh in absolute value per hour, compared to demand forecast error's average of 0.28 GWh. To test this hypothesis, we estimate Equation (3) binning demand forecast error by size. Even at the larger sizes of demand error, when conditioning on the subset of hours with demand forecast error above the 75th (0.38 GWh) and 95th percentiles (0.62 GWh), we still fail to identify an additional effect—beyond the residual demand effect—of demand forecast error on wholesale prices.[34]

Another potential explanation for the dissimilarity of demand and wind forecast error's effect on prices could be from differences in their respective error processes, in particular their autoregressive properties. If this were the case, we could expect one GWh of wind forecast error to have a different impact on market participants' expectations of future prices and market operations, as compared to one GWh of demand forecast error. To explore this potential explanation, we estimate the autocorrelations and partial autocorrelations for demand and wind forecast error, allowing for 40 lagged-hour errors to impact current period error; we plot the estimated coefficients in Figure A19. The shape of both the autocorrelations and partial autocorrelations over the lagged period for the two types of error look quite similar. Notably, both show that the current hour's error is most correlated with the prior hour's error, and we see a spike in the correlation between current hour error and error 24 hours prior, or the same hour-of-day on the day before. The autocorrelation and partial autocorrelation between the current hour and the previous hour is statistically larger for wind error than for demand error. It could then be the case that, because wind forecast error is more highly correlated with the next period's wind forecast error as compared to demand forecast error, the identified price effects from wind error occur from changing expectations about future market conditions. In other words, more wind than forecast leads to a larger update in firms' expectation of next period's residual demand, as compared to less demand than forecast. These different expectations would yield price effects from conventional supply curve responses—decisions to bid into the market in any hour are dynamic, based on their expectations of future periods' prices and residual demand.

A final potential explanation is that short-term deviations in electricity demand, compared to its forecast, are addressed outside of the wholesale electricity market. Because demand forecast errors tend to be smaller and less autocorrelated than wind forecast errors, it could be that demand forecast error is primarily addressed through ancillary service markets, which are intended to correct for small imbalances between supply and demand. Conversely, wind forecast error, which tends to be larger and more autocorrelated, affects outcomes in the wholesale electricity market.

34. A table with estimates of this robustness test is not included in this draft but is available by request.

Figure A19: Autocorrelations and partial autocorrelations of forecast errors



Notes: These figures show the autocorrelations and partial autocorrelations of wind forecast error and demand forecast error. We estimate these correlations for 40 hours of lags.