What's killing nuclear power in U.S. electricity markets?
Drivers of wholesale price declines at nuclear generators in the PJM Interconnection

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Abstract

Electricity market prices across organized wholesale electricity markets in the United States have declined significantly in recent years, prompting several nuclear power stations to consider early retirement before the end of their licensed operation or useful lifespans. This paper explores three possible explanations for observed declines in day-ahead electricity prices received by 19 nuclear generators in the PJM electricity market region: (1) the impact of declining natural gas prices; (2) the growth of wind generation in the American Midwest; and (3) stagnant or declining demand for electricity. I employ time series linear regression with time fixed effects to empirically estimate the effect of each explanatory variable on the average day-ahead locational marginal price (LMP) earned by 19 nuclear generating stations (with 33 individual reactors) located in PJM (encompassing roughly one-third of the U.S. nuclear fleet) as well as weighted average PJM day-ahead market prices. The paper uses daily average observations from January 1, 2008 to December 31, 2016 (n = 3,288). I employ a variety of alternative specifications to further explore geographic heterogeneity in causal effects on different generators across the PJM region and interrogate the impact of using price time series from different natural gas trading hubs. I find that natural gas price declines are the dominant driver of reduced electricity prices at the 19 nuclear power stations over this period. The growth of wind energy has an order of magnitude smaller cumulative effect and is only statistically significant for nuclear generators located in the western portion of the PJM region (in proximity to vast majority of installed wind capacity in the region). Finally, declining demand also has a relatively small but statistically significant effect on prices across all generators.

Keywords: Wind energy, natural gas, nuclear power, merit-order effect, electricity markets, electricity prices, econometrics, time-series regression, fixed effects, energy economics

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1. Introduction

Electricity prices across organized wholesale electricity markets in the United States have declined significantly in recent years. These low power prices have already contributed to the retirement of several nuclear power stations before the end of their licensed operation or useful lifespans, and roughly half (BNEF 2016) to two-thirds (Haratyk 2017) of the U.S. nuclear fleet may be operating at a loss in current market conditions. Nuclear power plants generate 20 percent of U.S. electricity and constitute the nation's largest source of emissions-free power (EIA 2017a). As such, determining the causes of deteriorating economic conditions at these nuclear plants has important implications for both the future of U.S. electricity markets and state and national efforts to reduce CO_2 emissions and conventional pollutants in the electric power sector.

This paper thus provides the first empirical estimates of the causal effect of three primary explanatory factors – declining or stagnant electricity demand, growth in wind energy generation, and declines in natural gas prices – on wholesale day-ahead electricity market prices received by 19 nuclear generating stations across the PJM electricity market region. These power plants are home to 33 individual reactors and encompass roughly one-third of the U.S. nuclear fleet, including 11 reactors currently facing possible retirement (see Table 1). In addition, the location of the 19 nuclear plants spans from New Jersey, Pennsylvania, Maryland, and Virginia in the east to Ohio, Michigan, and Illinois in the west (see Figure 1), permitting exploration of geographic heterogeneity in the effects of each explanatory variable.

In this paper, I employ a time series ordinary least squares (OLS) regression with time fixed effects using 3,288 daily observations for the nine-year period from January 1, 2008 to December 31, 2016.[1] I directly estimate coefficients for the effect of changes in daily natural gas spot market prices and daily average electricity demand and wind generation in PJM and the adjoining MISO market region on daily average day-ahead market prices at the locations of the 19 nuclear plants in PJM. I also estimate effects on a measure of the generation-weighted average day-ahead price across the PJM region. I then use the resulting coefficients to estimate the cumulative effect of changes in the three explanatory factors from 2008 to 2016 on average annual market prices for each nuclear generator over this period. In short, this paper seeks to provide an empirical answer to the question: what is killing the profitability of nuclear power plants in U.S. organized electricity markets?

Since 2013, six nuclear reactors in the United States have closed permanently, and up to 23 additional reactors have announced that they plan to retire or are considering retirement before the end of their licensed operation or useful lifespans (Table 1). While three reactor closures were forced by botched repairs (Crystal River 3 and San Onofre 2 and 3) and two large dual-reactor plants represent negotiated political settlements (Diablo Canyon and Indian Point), low electricity market prices and declining economic conditions contributed to the remainder of recent and planned

[1] Three nuclear plants – Davis Besse and Perry in Ohio and Beaver Valley in western Pennsylvania – are located in the ATSI control area (Ohio Edison and PennPower transmission systems), which joined PJM on June 1, 2011. I therefore estimate regression for these three plants for the period June 1, 2011 to December 31, 2016 only (n=2,041).

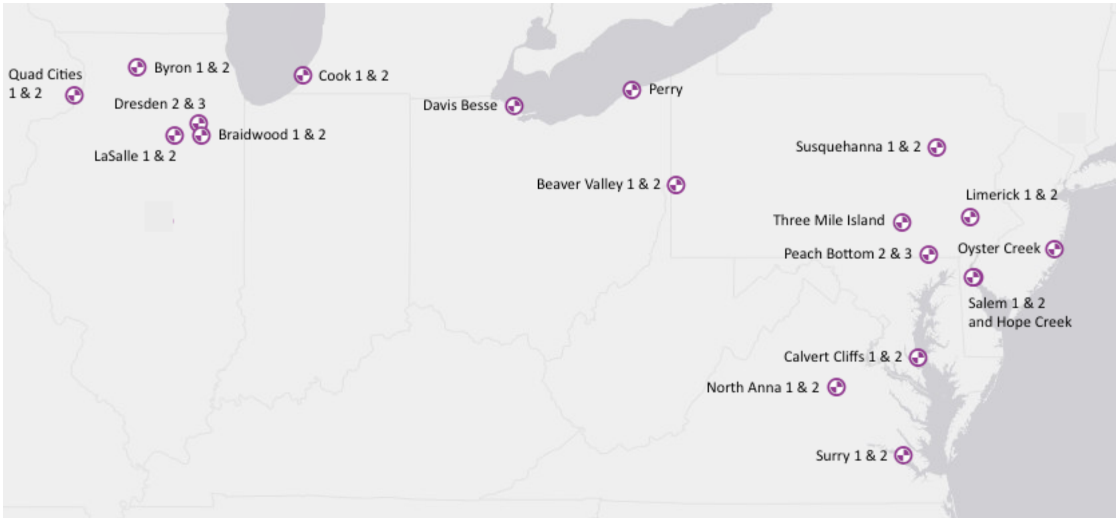


Figure 1: Location of nuclear generation facilities considered in this analysis [2]

retirements. In total, plants currently considering or planning retirement represent one-fifth of total U.S. nuclear capacity and are capable of producing about 12 percent of U.S. carbon-free electricity generation.

To date, these trends have prompted policy actions in two states (New York and Illinois) to prevent retirement of financially troubled reactors (DiSavino 2016; Maloney 2016b). Several other states are now considering similar policies, and in September 2017, the U.S. Department of Energy directed the Federal Energy Regulatory Commission to consider a proposed "grid resiliency pricing rule" designed to guarantee cost recovery for beleaguered nuclear and coal-fired power plants (DOE 2017a). The DOE notice of proposed rule-making followed an earlier staff review of conditions in wholesale electricity markets launched in amidst "concerns about the erosion of critical baseload resources," including nuclear plants, on the reliability of U.S. electricity systems. In an April 2017 memo announcing the DOE staff review (DOE 2017b), Secretary of Energy Rick Perry expressed concern about "the market-distorting effects of federal subsidies that boost one form of energy at the expense of others"—a reference to subsidies for renewable energy sources, which also receive support from various state-level policies. Completed in August 2017, the DOE report identified three factors contributing to declining economic conditions and pending retirements of nuclear and other baseload generators: (1) low-cost natural gas; (2) low growth in electricity demand; and (3) increased generation from variable renewable energy sources such as wind and solar energy (DOE 2017c). While the report concluded that natural gas was the largest contributing factor, neither the DOE nor any previous literature has produced an empirical estimate of the causal effect of each factor on declining revenues for U.S. nuclear generators.

Recent work by Haratyk (2017) employs a simulation-based approach to decompose and estimate

[2]Image source: (EIA 2017b) (annotated by author)

the effect of various explanatory factors on revenues received by nuclear plants in the Midwest and Mid-Atlantic regions of the United States over the period 2008 to 2015. The present work is complementary and employs empirical methods for causal inference based on observed data from the MISO and PJM regions. In addition, Haratyk (2017) does not consider the geographic heterogeneity introduced by transmission network power flows, which is considered in this paper.

Table 1: Recent and announced retirements of U.S. nuclear reactors

Reactor	**Capacity (MW)**	**State**	**Market Region**	**Primary Owner**	**Age (yrs)***	**Retirement Date**
Crystal River 3	860	FL	Southeast	Duke Energy	36	February 2013
Kewaunee	556	WI	MISO	Dominion	39	May 2013
San Onofre 2	1,070	CA	California	SCE & SDG&E	30	June 2013
San Onofre 3	1,080	CA	California	SCE & SDG&E	29	June 2013
Vermont Yankee	620	VT	New England	Entergy	42	December 2014
Fort Calhoun	469	NE	SPP	Omaha PPD	43	October 2016
FitzPatrick	847	NY	New York	Entergy	42	2017 (h)
Ginna	582	NY	New York	Exelon	46	2017 (h)
Nine Mile Point 1	637	NY	New York	Exelon	47	2017 (h)
Clinton	1,065	IL	MISO	Exelon	30	2017 (h)
Quad Cities 1	934	IL	**PJM**	Exelon	44	2018 (h)
Quad Cities 2	937	IL	**PJM**	Exelon	44	2018 (h)
Davis-Besse	889	OH	**PJM**	FirstEnergy	38	2018 (s)
Perry	1,231	OH	**PJM**	FirstEnergy	29	2018 (s)
Beaver Valley 1	970	PA	**PJM**	FirstEnergy	41	2018 (s)
Beaver Valley 2	920	PA	**PJM**	FirstEnergy	30	2018 (s)
Three Mile Island 1	837	PA	**PJM**	Exelon	43	2019 (p)
Oyster Creek	608	NJ	**PJM**	Exelon	47	2019 (p)
Pilgrim	677	MA	New England	Entergy	44	2019 (p)
Indian Point 2	1,032	NY	New York	Entergy	43	2020 (p)
Indian Point 3	1,051	NY	New York	Entergy	41	2021 (p)
Palisades	800	MI	MISO	Entergy	45	2022 (p)
Diablo Canyon 1	1,118	CA	California	PG&E	32	2024 (p)
Diablo Canyon 2	1,122	CA	California	PG&E	31	2025 (p)
Salem 1	1,174	NJ	**PJM**	PSEG	40	after 2019 (?)
Salem 2	1,130	NJ	**PJM**	PSEG	36	after 2019 (?)
Hope Creek	1,059	NJ	**PJM**	PSEG	31	after 2019 (?)
Millstone 2	882	CT	New England	Dominion	41	no date (?)
Millstone 3	1,155	CT	New England	Dominion	31	no date (?)
Total retired	4,655					
Total pending	21,657					
Total	26,312					

* Age reported at date of retirement for closed reactors; current age for operating reactors
(h) - previously announced retirement on hold due to pending state policy action
(p) - planned retirement date
(s) - sale of plant or retirement date
(?) - economic retirement under consideration
Updated January 3, 2018

In addition, the empirical literature on the "merit order effect" of renewable energy on average electricity market prices is relatively extensive. However, most of this prior work has focused on European contexts and on the impact of changing electricity prices on consumer surplus. This literature includes Gelabert et al. (2011), Würzburg et al. (2013), Cludius et al. (2014) and Luňáčkováa et al. (2017), which all use OLS with time fixed effects to study the effect of growing production from wind and/or solar energy on market prices in Spain, Germany, Austria, and the Czech Republic, respectively. In addition to OLS techniques, Jónsson et al. (2010) use non-parametric regression to assess the merit order effect of wind generation in western Denmark using data from 2006-2007, and Ketterer (2014) employs a generalized autoregressive conditional heteroskedasticity (GARCH) model to estimate the merit-order effect of wind energy in Germany from 2006-2012. Clò et al. (2015) use a generalized least squares (GLS) autoregressive (AR1) model with time fixed effects to estimates the effect for wind and solar in Italy for 2005-2013. In addition to these studies focused on European contexts, Woo et al. (2011) and Forest & MacGill (2013) use GLS autoregressive models with time fixed effects to study the impact of wind generation on wholesale electricity prices in the Electricity Reliability Corporation of Texas market and the Australian National Electricity Market, respectively. Finally, Woo et al. (2016) use similar techniques to estimate the impact of wind and solar on day-ahead and real-time prices in California as well as the impact of renewable energy forecast errors on the spread between day-ahead and real-time prices.

In this paper. I extend this literature to a novel and timely context by employing OLS regression with time fixed effects to empirically estimate not only the merit-order effect of wind generation but also the impact of declining natural gas prices and electricity demand on day-ahead electricity market prices earned by nuclear generators in the PJM market over the nine-year period from January 1, 2008 to December 31, 2016. Unlike previous work, which focuses largely on implications for electricity consumers, this work aims to explain changes in market prices received by suppliers, in this case a set of economically vulnerable nuclear power stations. In addition, where previous studies explore impacts on general market price trends, this paper estimates impacts on locational marginal prices at the sites of 19 nuclear power stations spread across the PJM market region, which accounts for and explores geographic heterogeneity in the effects of each explanatory factor.

Empirically estimating the causes of changing electricity market prices for these generators can shed light on the likely fate of nuclear power plants in U.S. organized electricity markets going forward and has important implications for energy and environmental policy decisions. The transition from coal to natural gas in the U.S. electricity mix, the rise of wind generation, and declining electricity consumption have all helped reduce emissions of both carbon dioxide and criteria pollutants in recent years (EIA 2017e). Yet nuclear power plants currently provide the largest source of emissions-free electricity in the United States by far (EIA 2017a). Nuclear generators in the PJM region alone produce roughly as much electricity as all wind and utility-scale solar power plants in the U.S. as of 2016 (ibid.). If cheap natural gas, growing wind generation, or lower electricity demand eventually lead to widespread retirement of existing nuclear plants, the net environmental benefits of these trends would be significantly reduced.

The rest of this paper proceeds as follows: Section 2 provides additional background and theory on determinants of wholesale electricity prices. Section 3 describes the data and causal inference method employed to estimate the effects of each explanatory variable. Section 4 provides results for the primary formulation, which uses Henry Hub spot prices for natural gas and total demand

and wind generation aggregated for both PJM and MISO regions. Sections 5-6 present alternative model specifications and results that explore the geographic heterogeneity of effects across the 19 nuclear plants by disaggregating wind generation and demand in PJM and MISO separately as well as employing price series from natural gas trading hubs at different locations across the region. Finally, Section 7 presents conclusions and discusses possible future work.

2. Background and Theory

In U.S. organized electricity markets, independent system operators (ISOs, also known as regional transmission organizations) are responsible for running a series of temporally-linked wholesale electricity markets (e.g., day-ahead, real-time, and ancillary services markets) that foster competition between wholesale power producers. ISOs are also responsible for planning and operating the transmission system and centrally dispatching power plants to ensure reliable and affordable electricity supply across their service territory.

The PJM Interconnection operates the largest electricity market in the United States (as measured by total delivered electricity). As of 2017, the PJM marketplace serves approximately 65 million customers and encompasses Pennsylvania, New Jersey, Maryland (constituting the original "P" "J" and "M"), Delaware, the District of Columbia, Virginia, West Virginia, Ohio, and portions of North Carolina, Kentucky, Indiana, Michigan, and Illinois (see Figure 2). The western portions of the PJM system are also strongly interconnected with the Midcontinent Independent System Operator (MISO) market region, which spans all or part of 15 U.S. states and the Canadian province of Manitoba.

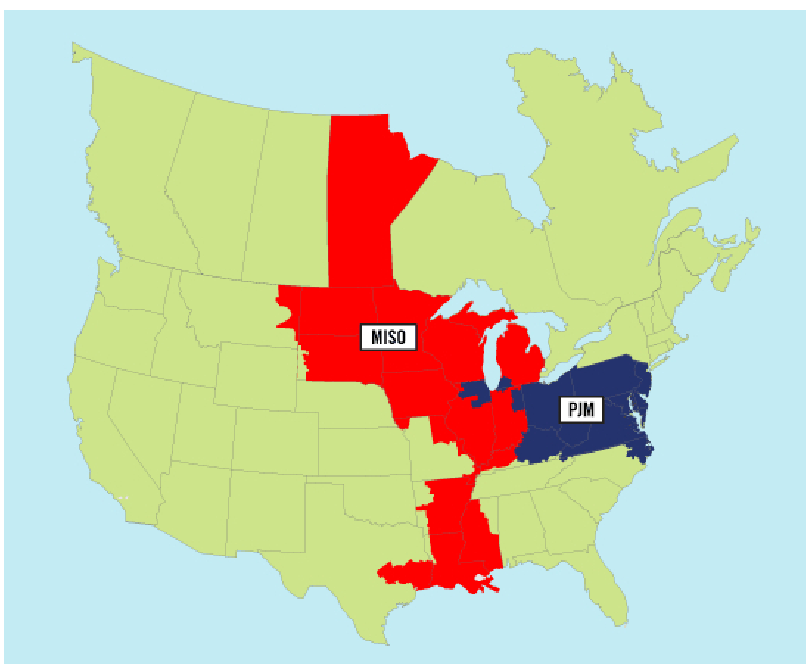
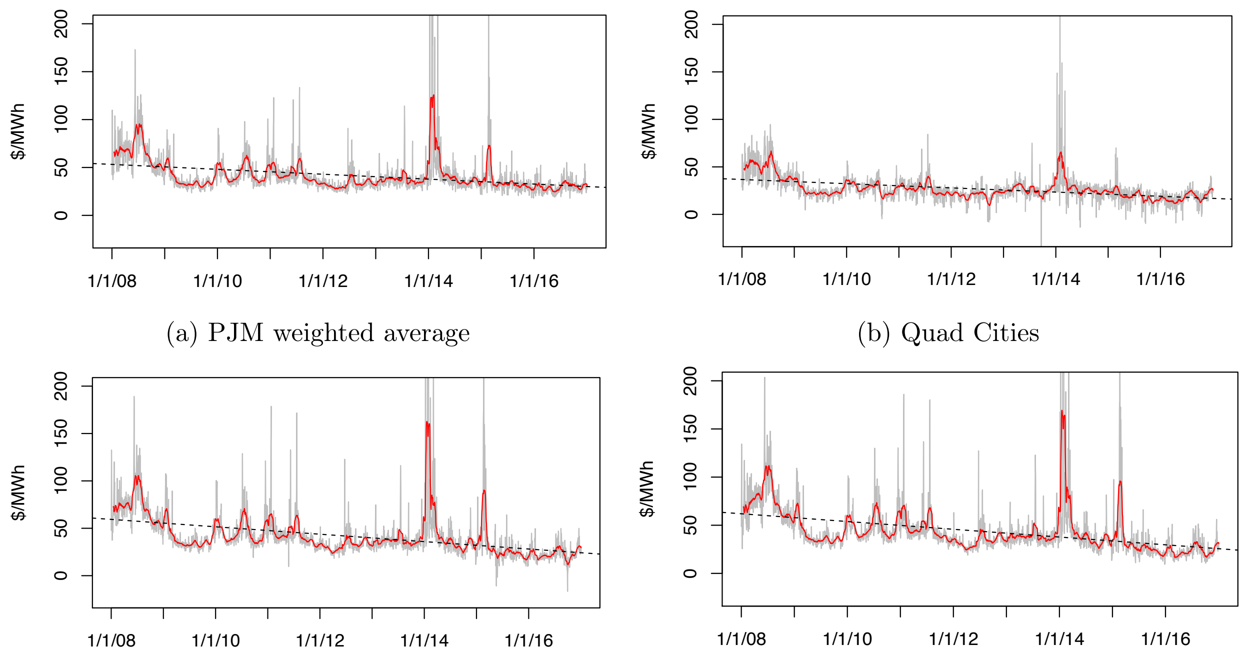


Figure 2: Midcontinent and PJM market regions[3]

Average day-ahead electricity market prices across the PJM market fell 55 percent from 2008 to 2016, with prices at individual nuclear plants in the PJM region declining between 47 and 69 percent or \$22.65 to \$51.70 per megawatt-hour (MWh) (PJM 2017c). Figure 3 presents the evolution of day-ahead electricity prices for the weighted average of prices across the PJM system (a) and prices at the locations of three representative nuclear plants spanning the region: Quad Cities in western Illinois (b); Three Mile Island in Pennsylvania (c); and Oyster Creek in eastern New Jersey (d).



(a) PJM weighted average

(b) Quad Cities

(c) Three Mile Island

(d) Oyster Creek

Figure 3: Daily average (grey) and 31-day rolling average (red) day-ahead electricity market prices, January 1, 2008 to December 31, 2016[4]

ISOs receive economic bids from competitive generators and clear wholesale electricity markets by dispatching the least-cost combination of generators in "merit order" (or from lowest to highest marginal cost) necessary to meet demand, subject to a number of transmission network and system reliability-related constraints.[5] All cleared generators then receive a locational marginal price reflecting the cleared bid of the generator capable of serving a marginal increment of demand at that location, adjusted to reflect the impact of transmission losses. Figure 4 depicts an illustrative

[3] Image source: http://www.miso-pjm.com/.

[4] Image is author's own, created with data from (PJM 2017c)

[5] U.S. ISOs use a two-stage market settlement process, in which a "day-ahead" market initially clears for each hour of expected demand for the following day. Next, a second "real-time" market clearing process is conducted after generators are physically dispatched to meet actual demand. Generators are then settled for any changes or deviations in actual dispatch relative to their day-ahead position at the real-time market price. Day-ahead and real-time markets are typically co-optimized with ancillary services markets used to procure various classes of operating reserves. This process facilitates commitment of thermal generators with long start-up times and maintenance of sufficient operating flexibility to adjust to forecast errors or unexpected generator or transmission failures.

supply stack or merit order curve consisting of generator bids from wind, nuclear, coal, natural gas combined cycle, and natural gas combustion turbine power plants. This supply curve is hypothetical, but reflects fuel prices circa 2008 and common variable operating and maintenance costs and heat rates for generators of each type.

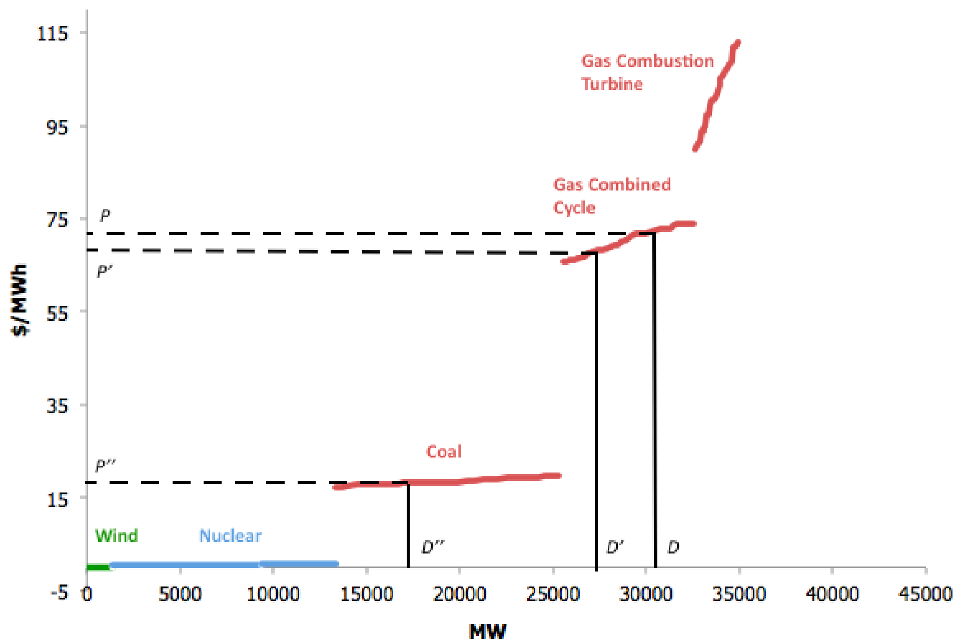


Figure 4: Hypothetical electricity supply curve with circa 2008 fuel prices. Three levels of demand (*D, D', D"*) are depicted with associated clearing prices (*P, P', P"*).

Changes in aggregate electricity demand have straightforward effects on electricity prices, as illustrated by the three demand levels (*D, D', D"*) and corresponding market clearing prices (*P, P', P"*) in Figure 4. All else equal, a decline (or increase) in demand results in a lower (or higher) market clearing price as a different generator with a lower (or higher) marginal cost of generation is dispatched on the margin. Furthermore, changes in clearing prices affect the revenues collected by any inframarginal generators, which typically includes nuclear units (due to their low variable costs and quasi-fixed fuel costs[6]). Indeed, average retail sales of electricity in states served by the PJM and MISO markets declined approximately 3.5 percent from 2008 to 2016 (Figure 5) (EIA 2017c).[7] In contrast, prior to the onset of the Great Recession, electricity demand in these states

[6]Nuclear plants are refueled on a pre-planned schedule, typically every 18 to 24 months. Fuel costs are thus generally a function of the frequency of refueling schedules and are thus treated more like a fixed O&M cost, rather than a true marginal cost of each MWh of generation

[7]Both the PJM and MISO markets expanded between 2008 and 2016 to include additional control areas. PJM added the Ohio Edison and PennPower territories (zone ATSI) on June 1, 2011, Duke Energy Ohio/Kentucky (zone DEOK) joined PJM on January 1, 2012, and East Kentucky Power Cooperative (zone EKPC) joined PJM on June 1, 2013. MISO's Southern region joined the market on December 19, 2013. This makes it difficult to rely on the demand time series from each ISO to depict trends in electricity demand. Instead, I use state-level monthly retail

grew by 9.1 percent from 2001 to 2008 (ibid.). Stagnant or declining demand is thus one possible cause of the observed decline in electricity market prices across PJM over this time period and a likely contributor to declining revenues for nuclear plants in the region (especially as compared to a counterfactual in which demand grew at pre-recession levels).

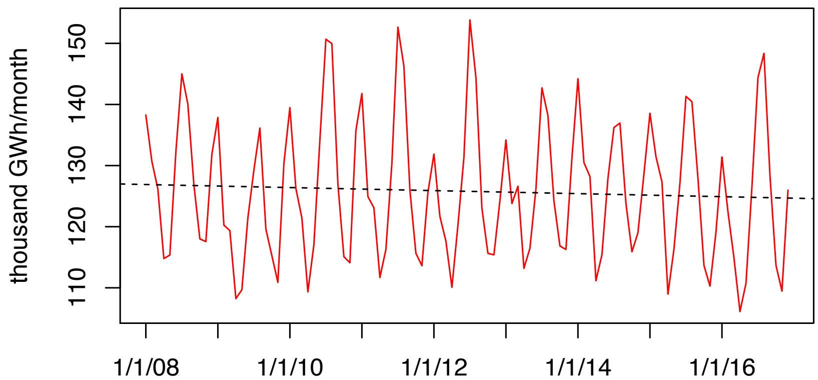


Figure 5: Monthly retail electricity sales from January, 2008 to December, 2016 in states served entirely or significantly by MISO and PJM as of 2016[8]

Wind energy generation is also growing rapidly in the United States, particularly in the American Midwest. Buoyed by supportive state and federal policies and declining technology costs, annual average wind energy generation in the MISO and PJM market regions grew more than five-fold from 1.35 average gigawatts (avg-GW) in 2008 to 7.31 avg-GW in 2016 (Figure 6) (MISO 2017a,b; PJM 2015, 2017a). In total, wind energy supplied 4.4 percent of MISO and PJM demand in 2016 (MISO 2017b,d; PJM 2017a,b). As wind energy generators have approximately zero marginal cost, they effectively shift the remainder of the electricity supply curve to the right (or equivalently, shift the net demand curve to the left) whenever they produce electricity (Figure 7). This price suppression or "merit order effect" (Felder 2011; Hirth 2013; Sensfuß et al. 2008) can result in a different generator setting the market clearing price, resulting in a lower price for a given level of demand and reducing inframarginal rents earned by nuclear generators (see Figure 7).

electricity sales data from EIA (2017c) for 19 states and the District of Columbia served entirely or to a substantial degree by the PJM or MISO markets as of 2016. This data excludes sales in Montana, Texas, and North Carolina, as only a small portion of these states resides within the PJM or MISO markets, and it also excludes demand in Manitoba, as EIA data are only available for U.S. territories.

[8]Image is author's own, created with data from (EIA 2017c). See footnote 7 above.

[9]Image is author's own, created with data from (MISO 2017a,b; PJM 2015, 2017a)

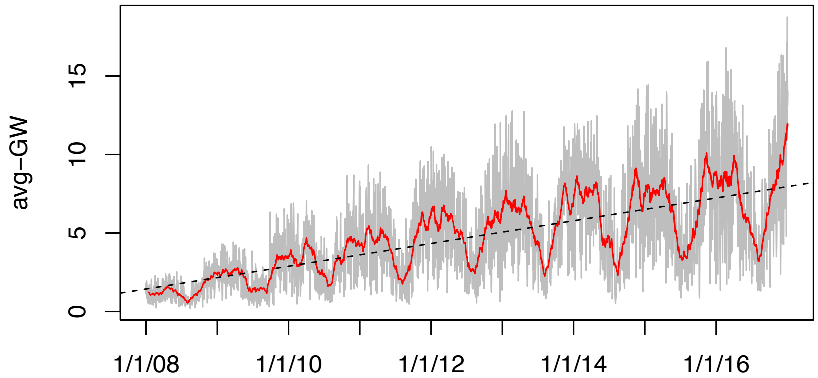


Figure 6: Daily average (grey) and 31-day rolling average (red) wind energy generation in MISO and PJM market regions, January 1, 2008 to December 31, 2016[9]

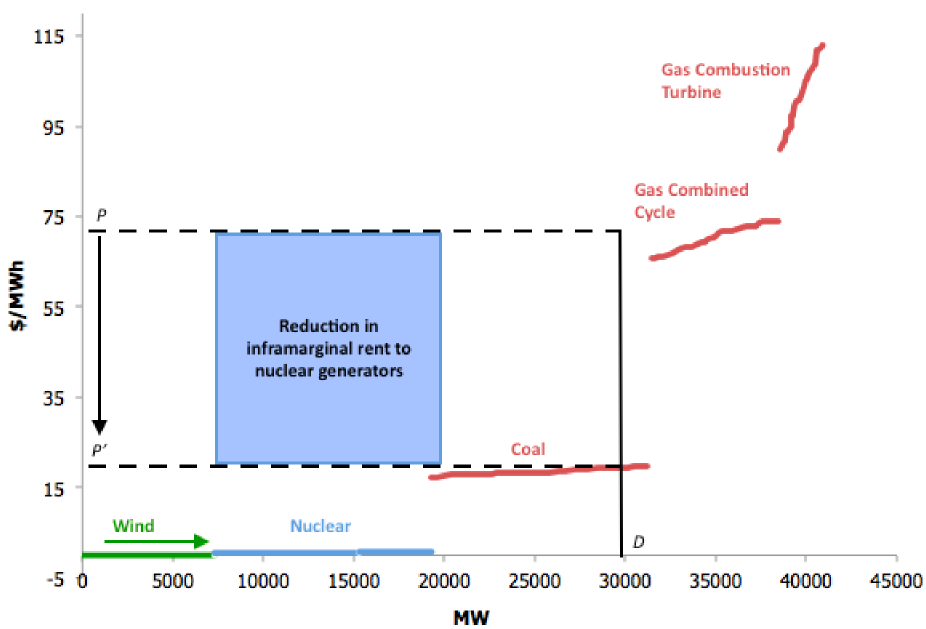


Figure 7: Hypothetical electricity supply curve and "merit order effect" of wind generation. Increased wind generation shifts the supply curve to the right, reducing the market clearing price at demand D from P to P'.

In addition to the merit order effect, production subsidies for wind energy can induce wind generators to bid negative prices in wholesale electricity markets. Negative bids reflect the opportunity cost to the generator of forgoing production subsidies awarded per megawatt-hour of electricity generated. Wind generators in the U.S. are currently eligible to receive a federal production tax credit (PTC) valued at $23 per megawatt-hour (equivalent to approximately $35-43 per megawatt-hour in pre-tax revenue[10]). In addition, 27 states and the District of Columbia have enacted renewable energy procurement mandates (known as renewable portfolio standards), which typically award tradable compliance certificates (or renewable energy credits) for each megawatt-hour of production by qualifying generators, including wind generators (DSIRE 2015). At hours when wind generators set the market clearing price, these production-based subsidies can result in negative wholesale electricity prices.[11] Any generators producing energy during these periods actually pay a penalty equal to the negative clearing price times the quantity generated. As wind energy market penetration remains modest to date, negative prices occur relatively rarely, although their frequency is increasing in some portions of the PJM marketplace (Figure 3 depicts a handful of instances of negative average prices across entire days at Quad Cities and Three Mile Island, for example).

There is a third likely explanation for the decline in nuclear plant revenues in the United States, however: cheap natural gas. Due to surging domestic production of gas unlocked by hydraulic fracturing and horizontal drilling techniques, daily spot market prices for natural gas at the Henry Hub declined from an average of $8.89 per million British thermal units (MMBtu) in 2008 to $2.51 per MMBtu in 2016 (Figure 8) (SNL 2017). Thus, while wind generation grew from 0.9 percent to 4.4 percent of combined MISO and PJM annual demand during this period,[12] gas prices simultaneously declined by 72 percent.

As fuel prices fell, natural gas-fired power generation increased market share in the United States, from 21.4 percent of total U.S. electricity generation in 2008 to 33.8 percent in 2016 (EIA 2017a). Natural gas plants now set wholesale electricity market prices in the PJM market 42.5 percent of the time in 2016, up from 16.9 percent in 2008.[14] Moreover, as the electricity supply curve is not linear (see Figure 4) and gas-fired plants make up much of the steeper portion of the curve, market prices set by marginal gas-fired generators are responsible for a disproportionate share of total revenues for inframarginal generators. Figure 9 depicts the impact of declining gas prices

[10]Assumes a combined marginal corporate tax rate of 35-42.8 percent–e.g., a federal income tax of 35 percent and state and local taxes of 0-12 percent, with federal taxes paid deducted from taxable income at the state level.

[11]Market prices can occasionally reach negative levels absent distortions from production subsidies as well. During periods of very low demand, if all online generators are operating at their minimum stable output, some thermal generators may bid negative prices to avoid shutting down. These negative bids reflect direct costs (e.g., fuel burn and wear and tear during start-up) and opportunity costs (e.g., lost revenue due to the inability to immediately restart a generator after shutdown due to thermal stress) incurred by shutting down and restarting large thermal generators such as pulverized coal plants, combined cycle gas plants, and nuclear plants.

[12]Note that both the MISO and PJM markets expanded between 2008 and 2016 to include additional control areas. By 2016, wind energy provided 5.4 percent of energy consumed in the MISO and PJM territories that were part of the markets as of January 1, 2008.

[13]Image is author's own, created with data from (SNL 2017)

[14]Author's analysis of data from Monitoring Analytics (2015)

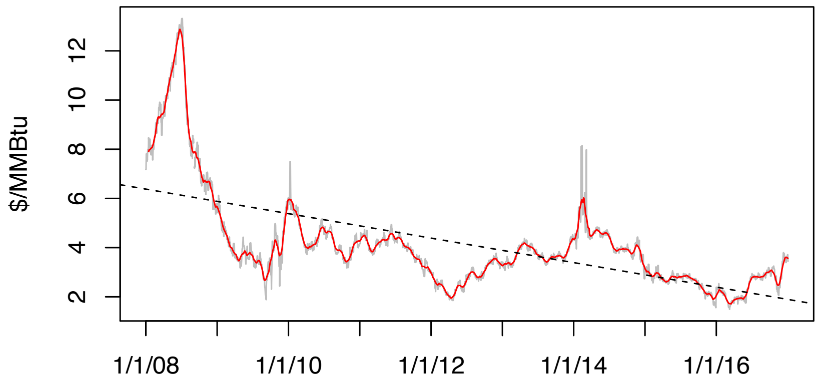


Figure 8: Daily average (grey) and 31-day rolling average (red) natural gas spot market prices at Henry Hub, January 1, 2008 to December 31, 2016.[13]

on the hypothetical supply curve. In this illustrative figure, the same generating units presented in Figure 4 are considered while fuel prices are adjusted to circa 2016 levels. As can be seen, the supply curve is significantly transformed, with combined cycle gas plants displacing and intermingling in the supply curve with less efficient coal plants and the overall supply curve flattening significantly. The decline in gas prices since 2008 could thus account for a substantial decline in the revenues collected by nuclear power plants in the PJM region.

Finally, it is important to note that electricity markets in the United States do not produce a uniform clearing price for the entire market region. All organized electricity markets in the United States employ locational marginal pricing in both day-ahead and real-time electricity markets as a way to accurately reflect the value of electricity generation (and cost of consumption) at different locations in the transmission system, accounting for the impacts of energy losses as electricity moves across transmission lines[15] as well as the effect of physical limits in transmission power flows (Schweppe et al. 1988; Rivier & Pérez-Arriaga 1993; Hogan 2014). As a result, electricity prices differ at each "node" in the transmission system, where a node is typically defined at each substation connecting generators or the lower-voltage distribution networks that serve end customers to the high-voltage transmission grid. Losses introduce only modest variation in prices, while physical constraints or congestions in transmission lines can cause marked differences in prices. Whenever a transmission constraint is binding, electricity markets effectively segment or split, with prices on each side of the constraint reflecting the cost of the marginal generator capable of serving

[15] As electricity flows across transmission networks, some of the energy is lost to ohmic losses or resistive heating. LMPs are thus adjusted to reflect the relative value or cost of producing or consuming electricity at a given location in light of marginal energy lost during transmission to end consumers.

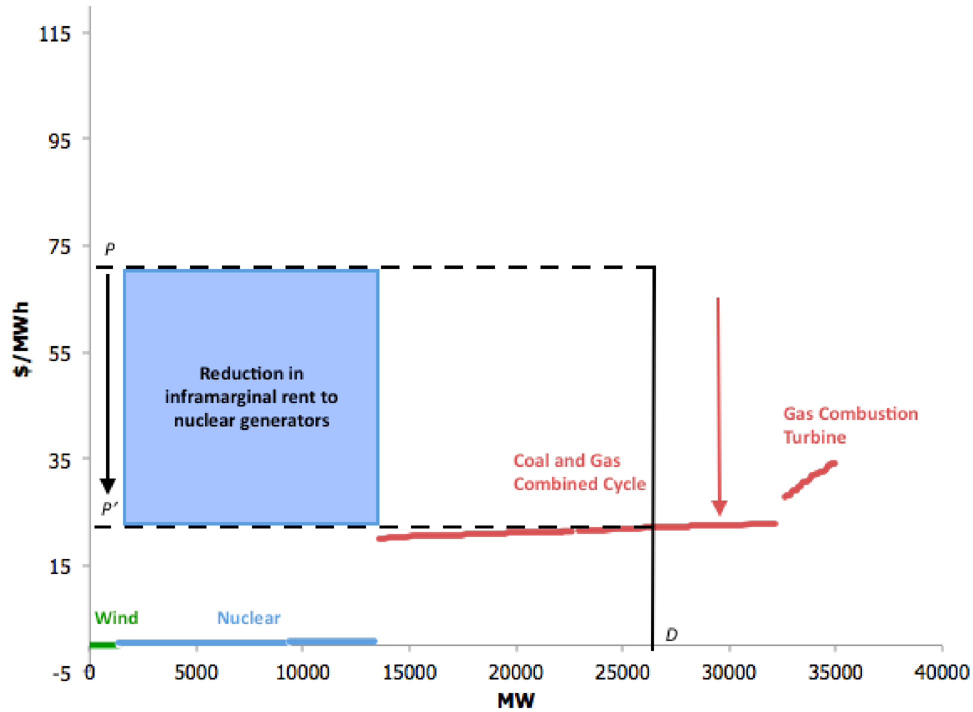


Figure 9: Hypothetical electricity supply curve with circa 2016 fuel prices. Marginal prices for natural gas-fired generators are significantly lower, flattening the supply curve and reducing the market clearing price at demand D from P to P'.

load in that portion of the system. As a result of transmission constraints, the impacts of changes in demand or supply across an organized electricity market may not be uniform, which means that the effects of each of the three explanatory factors described above may vary across the different nuclear plants in the PJM region.

3. Data and Methods

Figure 10 illustrates a causal diagram for the determination of electricity prices in the wholesale day-ahead electricity market. As depicted in Figure 4, market clearing prices (LMPs) are caused by the intersection of demand with the electricity supply curve, which is in turn co-determined by generation supply offers from wind generators and other operating generation. Supply offers from these other generators are in turn influenced by natural gas prices and the prices of other inputs (e.g., coal, labor, other consumables). Weather patterns influence both demand for electricity and for gas heating, as well as wind speeds.

While nuclear generator revenues are the final outcome of interest here, data on daily reactor operating status is not readily available.[16] I therefore use the daily average day-ahead market

[16]The Nuclear Regulatory Commission does report daily reactor operating status at NRC (2017), but not in an

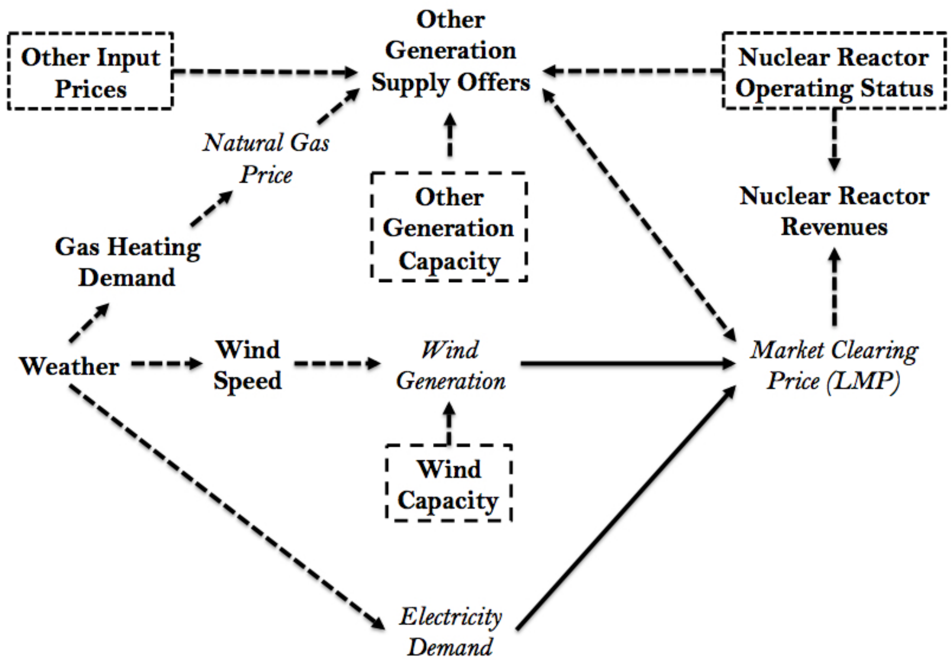


Figure 10: Causal diagram (directed acyclic graph) for wholesale electricity market prices. Italicized elements indicate observed variables; outlined elements are unobserved variables controlled for using time fixed effects; other unobserved variables (i.e., weather, wind speeds, and gas heating demand) are controlled for by conditioning on observed variables (i.e., wind generation, gas prices, and demand).

clearing price or LMPs at the nodes where each reactor is connected to the transmission system as a proxy outcome variable.[17] As nuclear generators operate at maximum rated power when online (excepting brief periods immediately after start-up and before shutdown), operate continuously for 18-24 month periods between refueling, and schedule planned refueling outages long in advance, average daily LMPs at the reactor nodes should be a reasonable proxy for average revenues for the reactors.[18] Additionally, as network related constraints and losses lead to a different effect of wind generation on the LMP seen by each nuclear power station, we cannot assume constant treatment across units (i.e., across nuclear plants). The effect of electricity demand, wind generation, and natural gas prices on LMPs is thus estimated independently for each of the 19 nuclear power

easily machine-readable format. In future analysis, I will scrape and include this data and conduct further analysis. However, I maintain that LMPs are a reasonable proxy outcome variable at this point.

[17]While U.S. electricity markets employ a two-stage market settlement process (as explained in Footnote 5 above), nuclear power stations in the U.S. traditionally operate as "must run" or "baseload" resources that produce constant output at their maximum rated capacity whenever operating. As such, final dispatch of nuclear power plants does not deviate from their day-ahead market position, and therefore they do not participate in real-time settlement. Going forward, flexible operation of nuclear plants may allow nuclear plants to adjust their dispatch in response to changes in real-time prices (see Jenkins et al. (forthcoming)), but this is not common practice to date. Day-ahead market prices are thus the most appropriate proxy for revenue earned by nuclear plants in the U.S. markets.

[18]If reactor refueling outages are significantly correlated with one or more regressors used to predict wholesale market prices at the reactor nodes, the effect of wind, gas, or electricity demand on wholesale prices may be a somewhat biased proxy for the final effects on reactor revenues.

stations.

The data set consists of 78,912 hourly observations from January 1, 2008 to December 31, 2016 for wind generation (MISO 2017a,b; PJM 2015, 2017a), electricity demand (MISO 2017c,d; PJM 2017b), and LMP at each nuclear reactor node (PJM 2017c).[19] I then average hourly observations for wind, demand, and nodal prices into 3,288 daily average observations to align with the frequency of natural gas spot price observations.[20] Daily natural gas spot prices for the Henry Hub and a set of other regional trading hubs – Chicago, Dominion South (near Pittsburgh), and M3 (near Philadelphia) – for each trading day from January 1, 2008 to December 31, 2016 from SNL (2017) complete the data set. For non-trading days (weekends and holidays), I use the most recent previous trading day price.

I estimate the effect of wind generation, natural gas prices, and electricity demand on the LMPs seen by each nuclear power station using ordinary least squares (OLS) linear regression with time fixed effects for week of time series and day of week. The primarily specification used in this analysis is presented in Equation 1:

$$ln(P_d) = \beta ln(D_d) + \gamma W_d + \delta N_d + \sum_{k=1}^{470} \alpha_{week,k} dw_k + \sum_{n=1}^{7} \alpha_{day-of-week,n} dd_n + \sum_{i=1}^{4} \eta_i z_i + \epsilon_d \qquad (1)$$

where P_d is the daily average hourly LMP at the node associated with each nuclear plant, D_d is daily average hourly market-wide demand across the PJM and MISO markets, W_d is daily average hourly market-wide wind energy generation across PJM and MISO, and N_d is the daily natural gas spot price. Binary variables α_{week} and $\alpha_{day-of-week}$ are time fixed effects for the week (dw_k) and day-of-week (dd_n) that each observation falls within. To control for the addition of several control areas to the PJM and MISO market footprints over the course of the time series, additional binary dummy variables, z_i, signify each market footprint expansion.[21] Finally, ϵ_d is the idiosyncratic error term (assumed to be orthogonal across the time series after controlling for time fixed effects, inclusion of new PJM and MISO zones, and conditioning on observables).

This inference strategy rests on the assumption that potential outcomes are independent after

[19]Dual reactor plants have multiple nodes (one for each reactor), but prices at the adjacent nodes are extremely highly correlated (correlation coefficient near 1.0), so in the interest of brevity, regressions are presented for only one node for each dual reactor nuclear plant. LMPs correspond to the following PJM nodes associated with each of the nuclear power stations: Illinois – Braidwood (32417599), Byron (32417635), Dresden (32417545), La Salle (32417525), and Quad Cities (32417629); Michigan – Donald C. Cook (40243801); Ohio – Davis Besse (98370477) and Perry (87901631); Pennsylvania – Beaver Valley (98370523), Limerick (50542), Peach Bottom (50557), Susquehanna (50654), and Three Mile Island (50759); New Jersey – Salem (50489), Hope Creek (1097732449), and Oyster Creek (50724); Maryland – Calvert Cliffs (50661); Virginia – North Anna (34887819) and Surry (34887859).

[20]The Davis Besse, Perry and Beaver Valley plants are located in the ATSI control area (Ohio Edison and PennPower transmission systems), which joined PJM on June 1, 2011. Data for these plants spans the period June 1, 2011 to December 31, 2016 only (n=2,041).

[21]PJM added the Ohio Edison and PennPower territories (zone ATSI) on June 1, 2011, Duke Energy Ohio/Kentucky (zone DEOK) joined PJM on January 1, 2012, and East Kentucky Power Cooperative (zone EKPC) joined PJM on June 1, 2013. MISO's Southern region joined the market on December 19, 2013. Dummy variables for each of these four market footprint expansions are thus added to the model to adjust for any discontinuities due to inclusion of these additional regions.

conditioning on time-variant observable variables (electricity demand, wind generation, and natural gas spot prices) and controlling for other unobservables (e.g., installed generation capacity, other input prices, and nuclear reactor operating status) by using time fixed effects (see Figure 10).

Directly conditioning on wind generation, natural gas prices, and electricity demand avoids potential confounding due to weather patterns, which affect demand for both heating and electricity and thus natural gas and electricity prices, as well as wind speeds.

Natural gas spot prices change daily, as gas prices are relatively volatile. While the majority of power plants secure long-term contracts for fuel, these contracts are assumed to track changes in average spot prices over time. In addition, as long as generators do not hold take-or-pay contracts, rational bidding behavior should internalize the spot price for gas in market bids, as any unused gas can be resold at spot prices. This model thus exploits daily variation in gas prices as an explanatory variable for changes in electricity market prices.

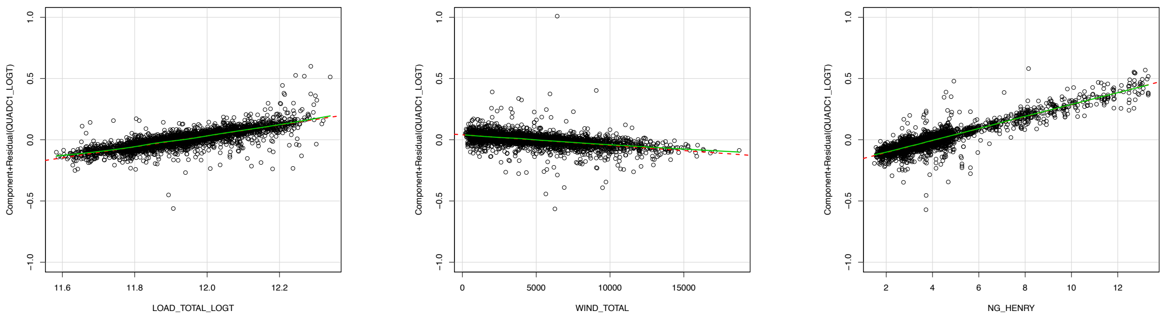
Other fuel and input prices vary much less frequently than gas. Week fixed effects are thus assumed to control for changes in other relevant inputs, chiefly coal prices, which lack liquid daily spot prices and instead trade on weekly spot markets with futures markets for delivery by month (CME Group n.d.). Oil-fired generation is de minimus in the MISO and PJM regions, so oil price changes are ignored (MISO 2017e; PJM 2017e).

In addition, installed capacity of wind farms and other power plants can reasonably be considered invariant on a weekly time scale, as construction times for wind generators span many months (and longer for other power plants). Week fixed effects also control for nuclear plant refueling schedules and offline maintenance schedules for other power plants. Day of week fixed effects further control for cyclicality in weekly electricity demand patterns and their effect on the operating status of other thermal generators (e.g., shut down of coal units over weekends).

This model thus exploits variation in electricity demand, wind generation, and gas prices within each week and across each day of week cycle to estimate the causal effect of each observed regressor on LMPs at each nuclear power station. The model in Equation 1 will produce an unbiased and consistent estimator of these effects so long as there are no additional unobserved confounders that are: (1) correlated with electricity demand, wind output, or gas prices; (2) also correlated with electricity market prices; and (3) are time-variant *within* the time fixed effects periods.

Please note that the use of time fixed effects in this inference strategy may mask the longer-term influence of these explanatory variables on the structural composition of the generation stock (e.g., retirements, additions) over time, which may in turn affect prices received by nuclear generators. The estimates produced by this inference strategy should therefore be interpreted as reflecting only the effect of variation in demand, wind generation, or natural gas prices on electricity prices by virtue of (a) shifting the demand curve, (b) shifting the supply curve horizontally due to exogenous variation in wind generation, (c) shifting the supply curve vertically due to changes in factor prices (e.g., natural gas) and resulting substitution between generators in the merit order, and (d) changing power flows across transmission networks and any resulting changes in losses and congestions—all *after* controlling for any changes in the generation stock over time (which will be absorbed by the week fixed effects terms).

Assuming conditional independence of potential outcomes, OLS produces unbiased estimates given four additional assumptions. First, no perfect co-linearity between parameters is required, which is easily verified.[22] Second, effects must be linear. Effects are linear for all three regressors, after log-transformation of electricity demand levels and prices at each reactor, as illustrated for the Quad Cities plant in Figure 11.



(a) $\ln(D_d)$ (demand) (b) W_d (wind generation) (c) N_d (natural gas price)

Figure 11: Example component residuals plots for regression on data for the Quad Cities nuclear power station demonstrating strong linearity of each parameter

Third, the time series for each parameter must be stationary. Given the use of time fixed effects, stationarity must hold after de-meaning within each time period (e.g., subtracting the mean for each time period from each observation within that time period). Example results for augmented Dickey-Fuller (ADF) tests (Dickey & Fuller 1979) for stationarity before and after de-meaning by week are presented in Table 2[23] and illustrate that while the original demand and natural gas price time series are not stationary, de-meaning results in stationarity for all parameters.

Finally, this strategy requires no simultaneity between the regressors and the outcome variable (i.e., regressors should be strictly exogenous from the outcome variable). In most markets, demand is not plausibly exogenous from price (the outcome of interest here), but electricity markets are distinct. In electricity markets, however, the overwhelming majority of retail customers in the United States are subject to regulated tariffs that do not reflect hourly changes in wholesale market prices.[24] Electricity demand is accordingly highly price inelastic at short time frames (e.g., hourly or

[22]This is implemented using the 'vif()' function in R, ensuring that the square-root of the variance inflation factors does not exceed 2.0 for any combination of explanatory variables.

[23]To select the number of lags to use in the ADF test, I follow Banerjee et al. (1999) and select the integer portion of $12(N/100)^{1/4}$, where N is the number of observations (e.g., 3,288 daily observations). This results in 28 lags.

[24]As of 2015, 96.4 percent of electricity customers in the PJM and MISO footprints were on fixed price rates that provide no time-differentiated price signal and are subject to change on an annual basis at most (EIA 2017f). Of the 3.6 percent of customers receiving some kind of time-varying rates, nearly all are on "time-of-use" rates with fixed peak and off-peak prices that also do not reflect actual hourly changes in wholesale prices. Commonwealth Edison and Ameren in Illinois run the largest hourly pricing programs in the United States where hourly rates change based on wholesale market prices. As of December 2015, these programs had enrolled roughly 1 percent of total customers representing about 5.5 percent of annual demand for these two utilities (Illinois CCC 2016). Enrollment in hourly

Table 2: Results of ADF test for stationarity of parameters

Parameter	Original time series (p-value)	After de-meaning by week (p-value)
$\ln(P_d)$ - PJM Average	-4.59 (<0.01)	-18.88 (<0.01)
$\ln(P_d)$ - Quad Cities	-4.02 (<0.01)	-17.41 (<0.01)
$\ln(P_d)$ - Three Mile Island	-4.49 (<0.01)	-18.75 (<0.01)
$\ln(P_d)$ - Oyster Creek	-4.39 (<0.01)	-18.81 (<0.01)
$\ln(D_d)$ - MISO & PJM	**-2.21 (0.235)**	-18.18 (<0.01)
W_d - MISO & PJM	-5.69 (<0.01)	-17.41 (<0.01)
N_d - Henry Hub	**-2.10 (0.275)**	-16.92 (<0.01)
N_d - Chicago Hub	**-2.73 (0.073)**	-18.11 (<0.01)
N_d - Dominion South Hub	-3.11 (0.027)	-17.32 (<0.01)
N_d - Columbia Hub	**-2.41 (0.16)**	-16.87 (<0.01)

daily time scales). The exception is during very high price periods induced by supply scarcity (e.g., when demand exceeds available generation capacity), when so-called "demand response" resources may be called upon and can set market prices well above the marginal price of the highest cost generators. However, day-ahead LMPs are above $200 per MWh less than 0.1 percent of hours and above $300 per MWh less than 0.03 percent of hours across the time series. It is thus plausible to treat demand as exogenous of price in this market, at least at the level of daily variations.[25] Long-term price trends may affect electricity demand (e.g., long-term demand elasticity is greater than very short-term elasticity), but this effect is controlled for through the use of week fixed effects.

Additionally, as wind generators have zero variable cost, they are dispatched virtually all hours when available. Exceptions occur during periods of severe negative prices, in which wind output may be curtailed. However, given the availability of production subsidies (including the federal Production Tax Credit and renewable energy certificates used for compliance with state Renewable Portfolio Standards), LMPs must go deeply negative (e.g., less than $35 per MWh) to induce economic curtailment of wind generators. This occurs less 0.05 percent of hours in the time series. Unlike generators with higher marginal costs, wind generation can thus be reasonably considered exogenous to market prices.[26]

Given the time series used in this estimation strategy, the resulting OLS residuals exhibit serial autocorrelation. In addition, steady growth in wind capacity during the time series results in increased variation and thus heteroskedasticity. Statistical inference is thus performed using Newey-

pricing programs is significantly lower across the rest of PJM and MISO. Therefore, it is reasonable to assume very little retail response to changes in wholesale electricity pricing at this time.

[25]Note that in a future version of this paper, I intend to exploit measures of heating/cooling degrees and hours of daylight as instrumental variables for the effect of changes in demand on electricity prices, in order to address further any remaining concerns about endogeneity. As this is unlikely to produce significantly different estimates, I present the current work for consideration as a working paper at this time.

[26]As with demand (see note above), a future version of this paper will exploit measures of wind speeds as an instrumental variable for the effect of changes in wind generation on electricity prices, in order to address further any remaining concerns about endogeneity.

West heteroskedasticity and autocorrelation consistent (HAC) standard errors (Newey & West 1987).[27] In the presence of autocorrelation and heteroskedasticity, OLS remains unbiased and consistent (Woolridge 2012), but is no longer the most efficient unbiased linear estimator. Other time-series regression formulations (i.e., various vector autoregression models) may be more efficient, but the OLS framework remains flexible and produces unbiased point estimates in this context without requiring specification of the form of autocorrelation. In addition, the relatively large sample size in this study (N=3,288) permits use of OLS for statistical inference using Newey-West HAC errors while retaining sufficient statistical power (although as we will see, resulting confidence intervals for the effect of natural gas price changes are relatively large).

4. Results

4.1. Model specification

Table 3 presents OLS estimates for the model specification described in Section 3, with each regressor added in turn. Results are presented only for the two representative plants from across the PJM region (one in the west and one in the east) to save space as results are similar for the remaining plants. Given the presence of heteroskedasticity and autocorrelation of the residuals, as discussed in Section 3, Newey-West HAC standard errors are presented for all specifications.

Model 1 includes only the weekly time fixed effects, which alone explain about 66 to 76 percent of the variance in the model. Adding the day-of-week fixed effects in Model 2 increases the explanatory power by an additional 2 to 3 percentage points. Model 3 includes the binary variables for each expansion of the PJM and MISO market footprints (e.g., addition of the PJM ATSI, DEOK and EKPC zones and MISO South).

Adding the natural log of total MISO and PJM electricity demand ($ln(D_d)$) in Model 4 increases the explanatory power of the model further, with greater predictive power for plants in the eastern portion of the PJM region. The estimated effect of demand on price is positive, as expected. Model 5 adds total MISO and PJM wind generation (W_d), which as expected, has a negative effect on price. However, the inclusion of wind has very little explanatory power for plants in the eastern portion of PJM, and the estimated effect has less statistical significance for these plants. Section 5 explores this geographic heterogeneity further. Model 6 adds Henry Hub natural gas spot market prices to the model, resulting in the full specification described in Eq. 1. Natural gas price has a positive effect on electricity price, as expected, and this specification explains about 75 to 85 percent of the variation in observed daily average electricity price. Estimates of the effect of natural gas price are all statistically significant at >99 percent confidence across all reactors.

Models 7 and 8 demonstrate the importance of the time fixed effects specifications for unbiased estimation of the effects. Model 7 removes the day-of-week fixed effects, which has a noticeable

[27] Newey-West HAC errors are implemented using the 'sandwich' package in R. See Lumley & Zeileis (2015). The maximum lag is set as per Newey & West (1987) to $4(N/100)^{1/4}$, where N is the number of observations (e.g., 3,288 daily observations). This results in 9 lags.

impact on the estimated effect of demand and natural gas prices (although the estimated wind effect remains largely unchanged). This result indicates the potential impact of accounting for weekly cyclicality in demand patterns and resulting unit commitment of various thermal generators throughout the week. However, the explanatory power of Models 6 and 7 are approximately equal, and time series are stationary in both specifications, indicating that day-of-week fixed effects may be optional. The same cannot be said of week fixed effects. Model 8, which removes week fixed effects, results in dramatically different estimates for all variables. In addition, as Table 2 illustrates, demand and natural gas price time series are not stationary before de-meaning by weekly averages. The estimates in Model 8 should therefore be considered biased. Indeed, the effect of wind generation on electricity price in this specification is positive, which is a nonsensical result.[28] This model is presented here only to verify the importance of accounting for time fixed effects.

Finally, Model 9 drops the binary variables denoting PJM and MISO footprint expansions. As this specification illustrates, removing these variables has a very small impact (if any) on the estimated effects of demand, wind, and gas prices and the predictive power of the model. However, this more parsimonious formulation does not reduce the standard errors of the estimated effects of demand, wind, or gas either. As the footprint expansion variables produce statistically and substantively significant estimated effects on nodal prices for many nuclear plants and the more extensive specification in Model 6 is equally precise in estimating the effects of the other explanatory variables, I employ Model 6 as the primary model formulation.

While I retain the binary variables for footprint expansions in the primary specification, it is important to note that these variables are included only as controls and the estimated effects should not be interpreted as causal. Expansion of the footprint of an electricity market to include a new control area brings additional demand and generation into the organized electricity marketplace. This can result in increased efficiency due to gains from trade—facilitated by both improved awareness of network congestion externalities (Mansur & White 2012) and lower transaction costs—and re-dispatch of generators towards lower cost units (Cicala 2017). For example, Mansur & White (2012) demonstrate that when PJM expanded to include the American Electric Power (AEP) and Dayton Power & Light (DPL) control areas in October 2004, trade between these regions and the pre-existing PJM zones roughly tripled during peak demand periods and increased more than 140 percent in off-peak periods (nights and weekends). In addition, the authors estimate that economic gains from trade between these regions more than doubled. Additional gains from trade can be expected to reduce average prices in importing regions and increase average prices in exporting regions, all else equal. However, significant changes in power flows associated with reconfiguration of trade across the region may change the patterns of transmission network congestions and thus significantly impact locational marginal prices at some nodes. This means that the directional effect of footprint expansions on locational prices at individual plants is ambigous *a priori*. Thus,

[28] This is presumably due to the consistent increasing time trend in the wind time series, which when estimated in a model that also includes a non-stationary regressor and outcome variable will produce highly biased estimates.

Table 3: Results of alternative time series OLS specifications for estimated effects on percent change in daily average price ($ln(P_d)$) at two representative nuclear plants

Variable (Units)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quad Cities									
$ln(D_d)$ - $\hat{\beta}$ (per percent change)				0.47	0.47	**0.45**	0.42	0.29	0.44
(st. err)				0.046	0.046	**0.043**	0.031	0.026	0.043
W_d - $\hat{\gamma}$ (per avg-GW)					-0.86	**-0.86**	-0.86	-0.30	-0.85
(st. err)					0.065	**0.063**	0.063	0.069	0.063
N_d - $\hat{\delta}$ (per \$ per MMBtu)						**4.89**	4.68	3.42	4.92
(st. err)						**1.471**	1.455	0.266	1.468
PJM ATSI - $\hat{\eta_1}$ (June 1, 2011)			$0.50^{\ddagger}$	$2.13^{\dagger}$	$-0.09^{\ddagger}$	$\mathbf{-1.30}^{\ddagger}$	$-1.98^{\dagger}$	$-0.60^{\ddagger}$	
(st. err)			1.61	0.95	0.77	**0.85**	0.84	0.82	
PJM DEOK - $\hat{\eta_2}$ (Jan. 1, 2012)			-6.33	-6.59	-2.98	**-2.88**	-2.82	$-1.49^{\ddagger}$	
(st. err)			1.09	0.78	0.65	**0.67**	0.63	1.00	
PJM EKPC - $\hat{\eta_3}$ (June 1, 2013)			-16.70	-20.37	-21.17	**-20.78**	-20.36	$-2.05^{\ddagger}$	
(st. err)			2.67	2.36	2.09	**2.10**	2.04	1.29	
MISO South - $\hat{\eta_4}$ (Dec. 19, 2013)			-4.31	-5.17	-6.79	**-6.48**	-6.56	$-2.47^{\dagger}$	
(st. err)			1.00	1.06	0.54	**0.54**	0.54	1.20	
Adjusted R^2	0.655	0.690	0.691	0.729	0.752	**0.758**	0.756	0.565	0.756
Three Mile Island									
$ln(D_d)$ - $\hat{\beta}$ (per percent change)				0.90	0.90	**0.87**	0.65	0.57	0.87
(st. err)				0.077	0.077	**0.071**	0.041	0.059	0.071
W_d - $\hat{\gamma}$ (per avg-GW)					$-0.14^{\ddagger}$	$\mathbf{-0.13}^{\ddagger}$	$-0.13^{\ddagger}$	$0.64^{\ddagger}$	$-0.12^{\ddagger}$
(st. err)					0.085	**0.081**	0.081	0.190	0.081
N_d - $\hat{\delta}$ (per \$ per MMBtu)						**7.59**	8.08	4.82	7.58
(st. err)						**1.631**	1.715	0.291	1.631
PJM ATSI - $\hat{\eta_1}$ (June 1, 2011)			$-8.36^{\ddagger}$	-5.22	-5.58	**-7.46**	-7.97	$-1.65^{\ddagger}$	
(st. err)			6.41	0.95	1.73	**1.79**	1.79	1.10	
PJM DEOK - $\hat{\eta_2}$ (Jan. 1, 2012)			$-0.23^{\ddagger}$	$-0.74^{\ddagger}$	$-0.16^{\ddagger}$	$\mathbf{0.00}^{\ddagger}$	$1.79^{\ddagger}$	$-1.84^{\ddagger}$	
(st. err)			8.28	0.54	0.67	**0.61**	0.56	1.13	
PJM EKPC - $\hat{\eta_3}$ (June 1, 2013)			$2.15^{\ddagger}$	-4.91	-5.04	**-4.44**	-0.86	$-1.63^{\ddagger}$	
(st. err)			6.41	1.41	1.34	**0.61**	0.71	0.92	
MISO South - $\hat{\eta_4}$ (Dec. 19, 2013)			$-11.28^{\ddagger}$	-12.93	-13.19	**-12.71**	-11.58	-9.03	
(st. err)			5.85	0.75	1.34	**0.48**	0.60	1.03	
Adjusted R^2	0.763	0.785	0.785	0.848	0.848	**0.854**	0.848	0.604	0.854
Weekly fixed effects	Yes	Yes	Yes	Yes	Yes	**Yes**	Yes	No	Yes
Day-of-week fixed effects	No	Yes	Yes	Yes	Yes	**Yes**	No	No	Yes

Notes: Standard errors (in parenthesis) are Newey-West HAC standard errors (Newey & West 1987).
† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other coefficients statistically significant at >99 percent confidence.

while expansions of the PJM and MISO market footprints very likely contributed to meaningful changes in average locational prices at nuclear plants across PJM during the time period considered in this paper, the inference strategy used herein is not appropriate to produce unbiased estimates of the effects of market footprint expansions. In particular, week fixed effects are likely to absorb a significant portion of the actual impact of footprint expansions (along with other unobservables), biasing the estimated effect of footprint expansions. As such, in the interest of brevity and to avoid potentially misleading interpretation of the results, I omit estimates for the footprint expansion variables throughout the remainder of this results section.[29] An inference strategy appropriate to producing an unbiased estimate of the effect of footprint expansions could reveal further interesting and heterogenous impacts on prices received by PJM nuclear plants, but this will have to be the subject of future research.

4.2. Primary results

Table 4 presents estimated effects of changes in demand and wind generation in the PJM and MISO market footprints and natural gas prices at the Henry Hub (along with Newey-West HAC standard errors) on day-ahead electricity prices for all 19 nuclear power stations in PJM using Model 6 (as per Eq 1). As the table illustrates, estimates for each regressor exhibit clear geographic variation across the plants.

For each percent increase in total PJM and MISO electricity demand, daily average nodal prices increase by approximately 0.45 to 0.93 percent across the different nuclear plants, *ceteris paribus*. This significant variation in estimated effect exhibits a clear geographic trend. Changes in demand (D_d) have the smallest influence on nodal prices seen by nuclear plants in the western zones of PJM (e.g., Illinois and Michigan, see Figure 2), while the influence of demand on day-ahead electricity prices increases steadily the more to the east a given plant is located (see Figure 1). Prices at plants located closer to major demand centers (e.g., major metropolitan areas) exhibit greater dependence on changes in demand. This can be seen in the general west-to-east trend (wherein the majority of demand in the MISO and PJM markets is located along the Atlantic coast) as well as in the variation within a given state (e.g., the greater estimate for Braidwood, Byron, Dresden and Cook, each of which is proximate to the Chicago metro area, as compared to Quad Cities, located at the western edge of Illinois). Variation in the elasticity of price to changes in aggregate demand across the MISO and PJM regions is the result of constraints on power flows across transmission lines, which can segment the market and insulate plants in congested regions from the influence of changes in demand on the opposite side of the constraint (see Section 2). Section 5.1 further explores geographic heterogeneity in the estimated influence of demand on prices. Note also that all demand estimates are statistically significant at greater than 99 percent confidence and are tightly estimated, with 95 percent confidence intervals ranging $+/-$ 0.08 to 0.14 percentage points around the central estimate across the plants. The estimated effect on weighted average PJM nodal prices

[29] Estimated effects of footprint expansions are available from the author upon request.

Table 4: Results of time series OLS estimate for effect of changes in demand, wind generation, and natural gas prices on percent change in daily average price ($ln(P_d)$) at 19 nuclear power stations in PJM - Henry Hub gas price series used (see Eq. 1)

Plant	Regressor Estimator State	$ln(D_d)$ $\hat{\beta}$ (per percent change)	 st. err	W_d $\hat{\gamma}$ (per avg-GW)	 st. err	N_d $\hat{\delta}$ (per \$ per MMBtu)	 st. err	Adjusted R^2
Quad Cities	IL	0.45	0.043	-0.86	0.063	4.89	1.471	0.757
Byron	IL	0.58	0.043	-0.51	0.058	4.99	1.428	0.784
LaSalle	IL	0.59	0.041	-0.32	0.051	5.26	1.324	0.772
Dresden	IL	0.61	0.040	-0.29	0.048	5.22	1.348	0.786
Braidwood	IL	0.61	0.040	-0.35	0.057	5.14	1.346	0.764
Cook	MI	0.59	0.041	-0.19	0.050	5.55	1.328	0.782
Davis Besse*	OH	0.70	0.066	-0.13†	0.058	8.86	1.948	0.744
Perry*	OH	0.74	0.068	-0.13†	0.058	8.67	1.847	0.740
Beaver Valley*	PA	0.76	0.073	-0.11‡	0.059	9.03	1.869	0.742
Three Mile Island	PA	0.87	0.071	-0.13‡	0.081	7.59	1.631	0.854
Susquehanna	PA	0.88	0.072	-0.09‡	0.074	7.47	1.644	0.837
Peach Bottom	PA	0.89	0.071	-0.09‡	0.075	7.75	1.621	0.862
Limerick	PA	0.89	0.071	-0.08‡	0.075	7.63	1.652	0.860
Salem	NJ	0.90	0.071	-0.07‡	0.076	7.78	1.651	0.863
Hope Creek	NJ	0.90	0.071	-0.07‡	0.076	7.79	1.653	0.863
Oyster Creek	MD	0.92	0.073	-0.07‡	0.077	7.64	1.621	0.861
Calvert Cliffs	MD	0.99	0.072	-0.07‡	0.079	7.90	1.673	0.838
North Anna	VA	0.93	0.066	-0.11‡	0.072	7.83	1.571	0.842
Surry	VA	0.91	0.064	-0.12‡	0.069	7.53	1.498	0.838
PJM Average	N/A	0.83	0.057	-0.14†	0.060	6.90	1.388	0.847

Notes: Standard errors are Newey-West HAC standard errors (Newey & West 1987).

† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other coefficients statistically significant at >99 percent confidence.

* - Estimates based on observations from June 1, 2011 to December 31, 2016 only.

is 0.83 percent increase in price per 1.0 percent increase in demand (with a 95 percent confidence interval of 0.72 to 0.94 percent).

The estimated effect of wind generation (W_d) also exhibits significant geographic variation, with another clear trend from west to east, indicating that transmission topology also plays an important role in the impact of wind generation growth on nodal prices at each nuclear plant. For each avg-GW in daily average wind generation in PJM and MISO, nodal prices at each plant are reduced by 0.07-0.86 percent, depending on the plant. However, despite a relatively tight estimate (the 95 percent confidence interval spans $+/-$ 0.09 to 0.16 percent per avg-GW change in wind generation across plants), the estimated effect of wind on price is only statistically significant at greater than 95 percent confidence for plants in Illinois, Michigan and Ohio, as well as the PJM weighted average price. The greatest effect is observed for the Quad Cities plant (0.86 percent change in average nodal price per avg-GW change in wind generation), which is located at the western edge of PJM in proximity to the significant installed wind capacity in the MISO region. The Byron plant in north-central Illinois sees the second greatest effect from wind (0.55 percent change per avg-GW), while the remainder of plants in Illinois, Michigan, and Ohio see an estimated 0.28 to 0.35 percent change per avg-GW increase in wind generation. For all other plants, the estimated effect is too small to be considered statistically significant at greater than 95 percent confidence. This geographic variation is consistent with the fact that the large majority of wind generation in the MISO and PJM regions is located either in MISO or in the western zones of PJM that are embedded in MISO and the fact that transmission constraints across the Appalachian range frequently segment the PJM market into western and eastern zones. See Section 5.2 for further discussion of geographic heterogeneity in the effect of wind generation on nodal prices across the PJM plants.

Finally, the estimated effect of natural gas price changes on nodal prices across the PJM nuclear plants is large and statistically significant (greater than 99 percent confidence for all plants), although again exhibits geographic variation. For plants in Illinois and Michigan, each $ per MMBtu increase (or decline) in the price of natural gas causes an estimated 4.9 to 5.6 percent increase (or decline) in the average day-ahead electricity price at these nodes. For the three plants in the ATSI control area – Davis Besse, Perry, and Beaver Valley – the estimated effect is 8.7 to 9.0 percent per $ change in natural gas price.[30] Finally, each $ per MMBtu change in gas price has an estimated 7.5 to 7.9 percent effect on the electricity price at plants located east of the Appalachian Mountains. Variance in the estimated effect of gas is significant, however, with the 95 percent confidence intervals spanning 2.6 to 3.8 percentage points per $ change in gas price across the plants. See Section 6 for further exploration of the impact of using time series from alternative natural gas trading hubs in lieu of the Henry Hub on the estimated effect of gas price changes on electricity prices earned by PJM reactors.

[30]Note that the estimate for these plants derives from observations from June 1, 2011 to December 31, 2016 only.

4.3. Estimated effect of cumulative observed changes from 2008 to 2016

Using the estimated coefficients in Table 4 and Equation 2 below, I predict counterfactual 2016 daily average prices for 16 nuclear plants in PJM for which a complete time series from 2008 to 2016 is available[31] (as well as the PJM weighted average nodal price) wherein each counterfactual is "as if" demand, wind generation, and/or natural gas prices had remained at average 2008 levels.

$$\begin{aligned} ln(\widehat{P_{d,2016}}) = {} & \hat{\beta} ln(D_{d,2016}) \times (\frac{\sum ln(D_{d,2008})}{366} / \frac{\sum ln(D_{d,2016})}{366}) \times \tau_D + \hat{\beta} ln(D_{d,2016}) \times (1 - \tau_D) \\ & + \hat{\gamma} W_{d,2016} \times (\frac{\sum W_{d,2008}}{366} / \frac{\sum W_{d,2016}}{366}) \times \tau_W + \hat{\gamma} W_{d,2016} \times (1 - \tau_W) \\ & + \hat{\delta} N_{d,2016} \times (\frac{\sum N_{d,2008}}{366} / \frac{\sum N_{d,2016}}{366}) \times \tau_N + \hat{\delta} N_{d,2016} \times (1 - \tau_N) \\ & + \sum_{k=418}^{470} \widehat{\alpha_{week,k}} dw_k + \sum_{n=1}^{7} \alpha_{\widehat{day-of-week,n}} dd_n + \sum_{i=1}^{4} \hat{\eta}_i \times 1 \end{aligned} \tag{2}$$

The binary variables τ_D, τ_W, τ_N in Equation 2 indicate whether or not to employ a counterfactual time series for demand, wind energy generation, and natural gas prices, respectively. In the case that $\tau = 1$, the corresponding time series of 2016 daily observations are each adjusted by multiplying by the ratio between the time series's annual average 2008 values and annual average 2016 values. This produces a counterfactual 2016 time series that preserves daily and seasonal variation in the 2016 series, but adjusts values to reflect average changes in the independent variables from 2008 to 2016. The difference between the counterfactual 2016 nodal price series and actual observed 2016 prices at each nuclear plant (e.g., $ln(\widehat{P_{d,2016}}) - ln(P_{d,2016})$) thus constitutes the estimated effect of cumulative observed changes in a given regressor from 2008 to 2016.

Appendix 1 depicts the resulting counterfactual 2016 daily average electricity price time series estimates for each nuclear plant (as well as the PJM weighted average nodal price),[32] while Figure 12 summarizes the estimated effect of cumulative changes in demand, wind energy generation, and natural gas price from 2008 to 2016 on the average annual day ahead electricity prices at each plant. Figure 12 also presents 95 percent confidence intervals for each estimate as well as the total observed change in annual average prices from 2008 to 2016 for each plant.

From 2008 to 2016, annual average demand across the PJM and MISO regions fell by approximately 3.5 percent (see Figure 5). Employing Equation 2 with $\tau_D = 1, \tau_W = 0, \tau_N = 0$, I thus produce a counterfactual estimate of 2016 electricity prices for each nuclear plant with demand in each day 3.5 percent higher than actual 2016 values. In this manner, I estimate that, due to declin-

[31] Estimates for Davis Besse, Perry, and Beaver Valley plants are excluded as the data series for these plants begins in 2011.

[31] Note that both 2008 and 2016 are leap years and thus contain 366 days.

[32] As Eq. 2 produces a counterfactual prediction $ln(\widehat{P_{d,2016}})$, I employ Duan's Smearing Estimator (Duan 1983) to produce an unbiased and consistent counterfactual prediction on the original untransformed price scale $\widehat{P_{d,2016}}$. That is, $\widehat{P_{d,2016}} = exp(ln(\widehat{P_{d,2016}})) \times \frac{1}{N} \sum_{i=1}^{N} exp(e_i)$ where e_i are the residuals from the original model Eq. 1.

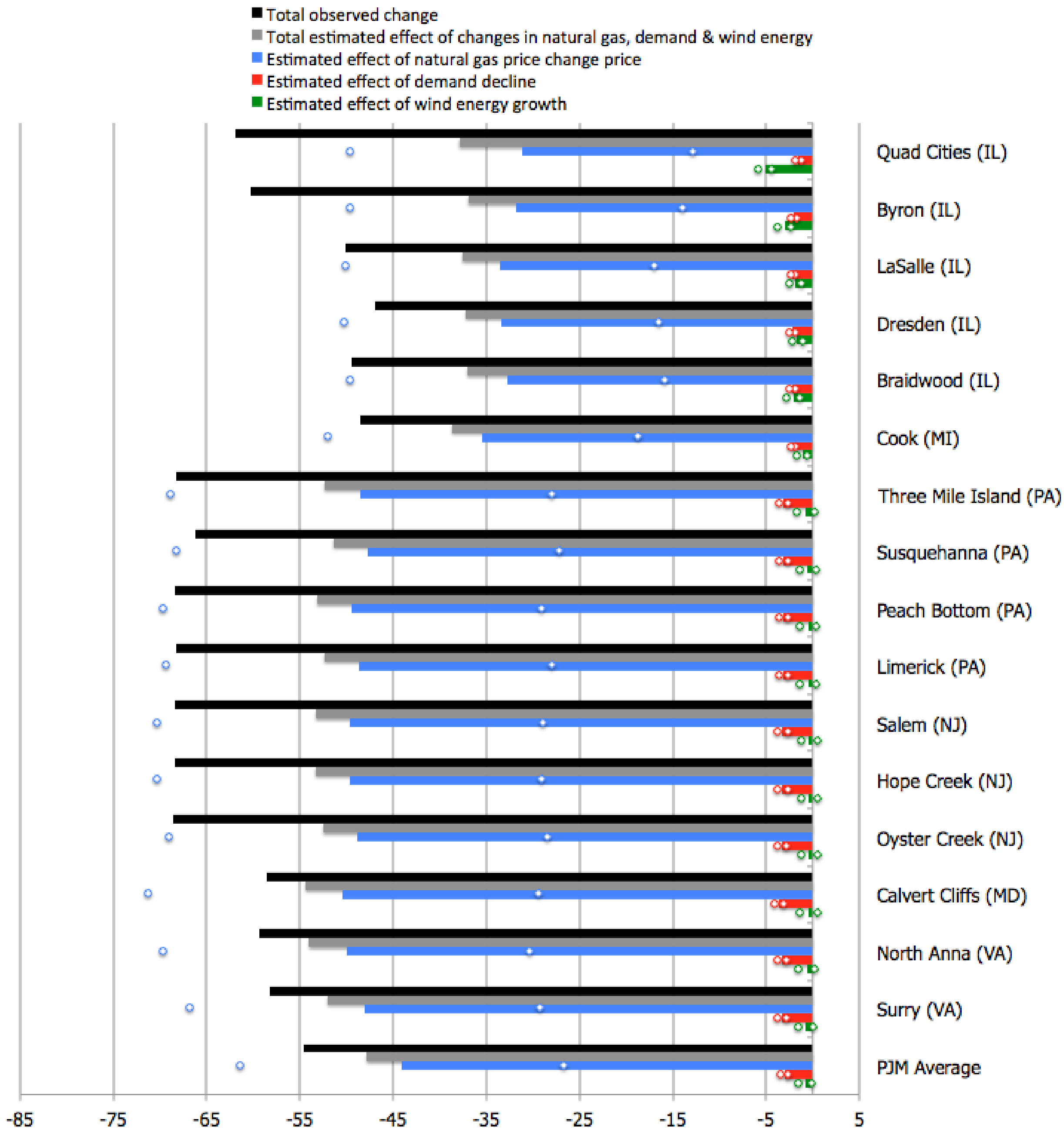


Figure 12: Estimated effect of cumulative observed changes in average demand, wind generation, and natural gas prices from 2008 to 2016 on annual average day-ahead electricity market prices for 16 nuclear generators in PJM[31]. Circles depict 95 percent confidence intervals for each estimate (using Newey-West HAC standard errors). Estimates based on counterfactual 2016 predictions adjusting 2016 daily observations to reflect percent change between annual average 2008 values and annual average 2016 values for each time series as per Equation 2. Total observed change in annual average prices from 2008 to 2016 presented for comparison. See Appendix 1 for depiction of counterfactual time series.

ing demand, wholesale electricity prices earned by reactors in Illinois and Michigan were 1.6 to 2.2 percent lower than they would otherwise have been, while prices were 3.1 to 3.6 percent lower at nuclear plants in the eastern portions of PJM. On average, declining electricity demand appears to be responsible for a roughly 3.0 percent decline in weighted average PJM day-ahead market prices. 95 percent confidence intervals for these estimates span approximately plus or minus 0.2 to 0.5 percentage points.

Wind generation in MISO and PJM also increased by 5.95 avg-GW from 2008 to 2016 (see Figure 6). Using Equation 2 with $\tau_W = 1, \tau_D = 0, \tau_N = 0$, I estimate that for plants in Illinois, the cumulative impact of wind energy growth on electricity prices over this period appears to be of a similar magnitude as the effect of declining demand. Growth in wind generation appears to have driven down prices for the Quad Cities plant by roughly 4.4 to 5.8 percent over this period, 2.4 to 3.7 percent at Byron and 1.1 to 2.8 percent at the remaining three Illinois nuclear plants. Wind generation likewise reduced prices at the Cook plant in Michigan by roughly 0.5 o 1.7 percent. The impact of wind generation on all other PJM nuclear plants is much more modest, however, with estimated cumulative effects of as little as zero to no more than 1.7 percent. None of the estimated effects of wind on plants east of the Appalachians are statistically significant. Finally, increasing wind generation appears to have reduced weighted average PJM prices by roughly 0.8 percent overall over the period (95 percent confidence interval from -0.1 to -1.5 percent).

While declining demand and growing wind generation both contribute to lower prices at nuclear plants across PJM, Figure 12 illustrates that lower natural gas prices are the primary driver of observed price declines from 2008 to 2016. Annual average natural gas prices at the Henry Hub decreased by \$6.38 per MMBtu from 2008 to 2016 (declining from \$8.89 per MMBtu in 2008 to \$2.51 per MMBtu in 2016, see Figure 8). Using Equation 2 with $\tau_N = 1, \tau_D = 0, \tau_W = 0$, I estimate that changes in natural gas prices reduced annual average day-ahead prices at PJM nuclear stations by roughly 31 to 50 percent across all units. The estimated effect of gas price changes is not as precise as the estimates for wind or demand, however, with 95 percent confidence intervals ranging from approximately 13 to 70 percent declines (with the upper end of that range exceeding observed changes in nodal electricity prices for most plants). Still, while the exact effect is less precise, the estimated impact of declining natural gas prices on average electricity prices at PJM nuclear power plants is clearly an order of magnitude greater than the estimated effect of wind growth or declining electricity demand over this time period. In addition, gas prices declines are responsible for a larger decline in prices at plants in the eastern portion of PJM (where point estimates range from 48 to 50 percent reductions in electricity price) than those plants in the west (where point estimates range from 31 to 35 percent). Cheaper natural gas appears responsible for a 44 percent decline in weighted average prices across PJM (95 percent confidence interval: 27 to 61 percent).

Finally, by setting $\tau_D = 1, \tau_W = 1, \tau_N = 1$, Equation 2 produces a counterfactual price series reflecting the cumulative impact of reversing observed changes in all three regressors. Using the difference between this counterfactual and observed 2016 prices, I estimate that the total effect of changes in electricity demand, wind generation, and natural gas prices from 2008 to 2016 was to reduce prices earned by nuclear plants in the PJM footprint by 51 to 54 percent in the east and 37 to 39 percent in the western portion of the region. Weighted average wholesale prices in PJM were approximately 48 percent lower due to these observed changes. Overall, this estimated total effect of demand, wind generation, and gas price changes accounts for roughly 61 to 93 percent of the observed decline in prices from 2008 to 2016 across the PJM plants.

5. Geographic Heterogeneity in the Effect of Demand and Wind Generation

5.1. Disaggregating demand by ISO region

The primary model specified in Equation 1 aggregates demand across both the PJM and MISO regions to estimate the effect of changes in electricity demand on electricity market prices. In this section, the demand time series is further disagreggated into separate time series for demand in the MISO ($D_{d,miso}$) and PJM ($D_{d,pjm}$) regions, as per Equation 3:

$$\begin{aligned} ln(P_d) =& \beta_{miso} ln(D_{d,miso}) + \beta_{pjm} ln(D_{d,pjm}) + \gamma W_d + \delta N_d \\ &+ \sum_{k=1}^{470} \alpha_{week,k} dw_k + \sum_{n=1}^{7} \alpha_{day-of-week,n} dd_n + \sum_{i=1}^{3} \eta_i z_i + \epsilon_d \end{aligned} \tag{3}$$

This specification does not increase the explanatory power of the model (R^2 coefficients are nearly identical to those for Equation 1 for all nuclear plants). However, this specification allows further exploration of the geographically heterogenous effects of demand on different reactors.

As Table 5 illustrates, demand in MISO has the greatest impact on prices for nuclear plants located in the western portion of PJM (Illinois, Michigan, Ohio), which is to be expected given the significant interconnection between these PJM zones and the MISO region (see Figure 2). In contrast, MISO demand has little to no effect on prices at eastern plants, with estimates for most of these plants exhibiting no statistical significance. This indicates that transmission congestions are sufficient to insulate prices at nuclear plants in the east from the influence of demand in the MISO region. This explanation is consistent with the lack of any statistically significant effect of wind generation on prices at reactors in the east, as 95.5 percent of total wind generation in MISO and PJM in 2016 was located in either MISO or the western zones of PJM.

Conversely, the influence of PJM demand is statistically significant for all plants and the magnitude of the estimated effect on electricity prices increases steadily from west to east, consistent with the concentration of PJM demand centers along the Atlantic coast. Thus, it is clear that prices received by plants in the western portion of PJM are influenced by demand in both ISO regions, while plants in the east are affected overwhelmingly by changes in demand in PJM.

Finally, estimates for the effects of wind and natural gas are largely the same for both model specifications, particularly for those estimates with higher statistical significance. However, the covariance of PJM and MISO demand increases the standard errors of these estimates when using Equation 3, which reduces the statistical significance of the estimated effect of wind for some plants.

Table 5: Comparison of results of time series OLS estimate for effect on percent change in daily average price ($ln(P_d)$) at 19 nuclear power stations in PJM when aggregating demand (D_d, Eq. 1) vs disaggregating demand by ISO region ($D_{d,miso}, D_{d,pjm}$, Eq. 3) - Henry Hub gas price series used

	Regressor	$ln(D_d)$	$ln(D_{d,miso})$	$ln(D_{d,pjm})$	W_d		N_d		Adjusted R^2	
	Estimator	$\hat{\beta}$	$\widehat{\beta_{miso}}$	$\widehat{\beta_{pjm}}$	$\hat{\gamma}$		$\hat{\delta}$			
	Model	Eq. 1	Eq. 3		Eq. 1	Eq. 3	Eq. 1	Eq. 3	Eq. 1	Eq. 3
Plant	State	(per percent change)			(per avg-GW)		(per \$ per MMBtu)			
Quad Cities	IL	0.45	0.38	0.12	-0.86	-0.88	4.89	4.85	0.757	0.757
Byron	IL	0.58	0.44	0.19	-0.51	-0.54	4.99	4.95	0.784	0.784
LaSalle	IL	0.59	0.36	0.26	-0.32	-0.33	5.26	5.24	0.772	0.772
Dresden	IL	0.61	0.37	0.27	-0.29	-0.30	5.22	5.21	0.786	0.787
Braidwood	IL	0.61	0.38	0.26	-0.35	-0.36	5.14	5.12	0.764	0.764
Cook	MI	0.59	0.27	0.32	-0.19	-0.19	5.55	5.55	0.782	0.782
Davis Besse*	OH	0.70	0.24	0.45	-0.13†	-0.12†	8.86	8.84	0.744	0.744
Perry*	OH	0.74	0.23	0.48	-0.13†	-0.13†	8.67	8.65	0.740	0.740
Beaver Valley*	PA	0.76	0.25	0.49	-0.11‡	-0.10‡	9.03	9.01	0.742	0.742
Three Mile Is.	PA	0.87	-0.04‡	0.81	-0.13‡	-0.08‡	7.59	7.57	0.854	0.854
Susquehanna	PA	0.88	-0.04‡	0.82	-0.09‡	-0.04‡	7.47	7.57	0.837	0.837
Peach Bottom	PA	0.89	-0.07‡	0.85	-0.09‡	-0.03‡	7.75	7.85	0.862	0.862
Limerick	PA	0.89	-0.07‡	0.84	-0.08‡	-0.03‡	7.63	7.73	0.860	0.860
Salem	NJ	0.90	-0.07†	0.85	-0.07‡	-0.01‡	7.78	7.88	0.863	0.863
Hope Creek	NJ	0.90	-0.07†	0.85	-0.07‡	-0.01‡	7.79	7.89	0.863	0.863
Oyster Creek	NJ	0.92	-0.05‡	0.86	-0.07‡	-0.02‡	7.64	7.74	0.861	0.861
Calvert Cliffs	MD	0.99	-0.08†	0.94	-0.07‡	-0.01‡	7.90	8.01	0.838	0.838
North Anna	VA	0.93	-0.05‡	0.87	-0.11‡	-0.06‡	7.83	7.93	0.842	0.842
Surry	VA	0.91	-0.03‡	0.84	-0.12‡	-0.07‡	7.53	7.62	0.838	0.838
PJM Average	N/A	0.83	0.07†	0.69	-0.14†	-0.10‡	6.90	6.96	0.847	0.847

† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other coefficients statistically significant at >99 percent confidence.
* - Estimates based on observations from June 1, 2011 to December 31, 2016 only.

Demand in MISO states fell 3 percent from 2008 to 2016, and demand in PJM states declined 5.9 percent in this period. Using the same approach as in Equation 2 above, I produce alternate counterfactual time series using observed changes in demand in MISO and PJM states[33] to produce an estimate of the cumulative effect of declining demand in each ISO from 2008 to 2016 on average electricity prices at the 16 PJM nuclear plants with complete time series. Table 6 also presents the sum of predicted changes in each ISO region and compares this value to the effect of cumulative changes in aggregate demand produced in Section 4.3 using estimates derived from Equation 1.

Table 6: Comparison of estimated effect of cumulative observed changes in electricity demand on daily average price ($ln(P_d)$) from 2008 to 2016 at 16 nuclear power stations in PJM[31] when aggregating demand (Eq. 1) vs disaggregating demand by ISO region (Eq. 3) - Henry Hub gas price series used

Plant	State	D_d Eq. 1	Total	$D_{d,miso}$ Eq. 3	$D_{d,pjm}$
Quad Cities	IL	-1.62	-1.51	-1.16	-0.35
Byron	IL	-2.09	-1.92	-1.34	-0.58
LaSalle	IL	-2.12	-1.88	-1.09	-0.79
Dresden	IL	-2.19	-1.94	-1.12	-0.82
Braidwood	IL	-2.19	-1.94	-1.16	-0.79
Cook	MI	-2.12	-1.81	-0.83	-0.98
Three Mile Island	PA	-3.15	-2.34	0.14‡	-2.47
Susquehanna	PA	-3.19	-2.37	0.14‡	-2.50
Peach Bottom	PA	-3.21	-2.37	0.21‡	-2.58
Limerick	PA	-3.20	-2.36	0.20‡	-2.57
Salem	NJ	-3.23	-2.38	0.22†	-2.60
Hope Creek	NJ	-3.23	-2.38	0.22†	-2.60
Oyster Creek	NJ	-3.31	-2.45	0.17‡	-2.62
Calvert Cliffs	MD	-3.58	-2.64	0.23†	-2.87
North Anna	VA	-3.36	-2.50	0.16‡	-2.65
Surry	VA	-3.29	-2.45	0.11‡	-2.56
PJM Average	n/a	-3.00	-2.31	-0.20†	-2.11

† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other estimates statistically significant at >99 percent confidence.

As Table 6 illustrates, both models produce estimates of a similar magnitude for the total impact

[33]As per note 7, changes in the footprint of MISO and PJM from 2008 to 2016 make a direct use of the demand time series from each ISO to depict trends in electricity demand. Instead, I use state-level monthly retail electricity sales data from EIA (2017c) for states served entirely or to a substantial degree by the PJM or MISO markets as of 2016. For PJM, this includes New Jersey, Pennsylvania, Illinois, Indiana, Michigan, Ohio, Delaware, the District of Columbia, Maryland, Virginia, West Virginia and Kentucky. For MISO, this includes Illinois, Indiana, Michigan, Wisconsin, Iowa, Minnesota, Missouri, North Dakota, South Dakota, Kentucky, Mississippi, Arkansas, and Louisiana. States may appear in both ISOs if substantial portions of the state reside in both market regions. Note that this data excludes sales in Montana, Texas, and North Carolina, as only a small portion of these states resides within the PJM or MISO markets, and it also excludes demand in Manitoba, as EIA data is only available for U.S. territories.

of declines in aggregate demand across the two ISO regions from 2008 to 2016. In general, the sum of estimated effects when disaggregating demand by ISO region as per Equation 3 produces a slightly smaller estimated impact than predictions that aggregate demand into a single time series, as per Equation 1. Using Equation 3 predicts that declining demand across MISO and PJM is responsible for a 1.5 to 1.9 percent decline in average prices earned by plants in Illinois and Michigan, with most of this estimated decline due to changes in demand in the MISO region. For plants in the eastern portion of PJM, this model predicts that total changes in demand are responsible for a roughly 2.3 to 2.6 percent decline in prices at these locations. However, note that the estimated effect of MISO demand in Equation 3 is slightly positive and of marginal statistical significance for plants in the eastern portion of PJM. For these plants, the impact of changes in demand in the PJM region alone is likely to be a more accurate estimate, and ranges from a roughly 2.5 to 2.9 percent decline in average prices.

5.2. Disaggregating wind by ISO region

As previous results above illustrate, the presence of transmission congestions can influence the impact of changes in wind generation on electricity prices at different nodal locations. This section thus disaggregates the wind time series by ISO region to further illuminate geographic differences in the effect on nodal prices at PJM nuclear plants, as per Equation 4:

$$\begin{aligned} ln(P_d) =& \beta ln(D_d) + \gamma_{miso} W_{d,miso} + \gamma_{pjm} W_{d,pjm} + \delta N_d \\ &+ \sum_{k=1}^{470} \alpha_{week,k} dw_k + \sum_{n=1}^{7} \alpha_{day-of-week,n} dd_n + \sum_{i=1}^{3} \eta_i z_i + \epsilon_d \end{aligned} \tag{4}$$

Once again, neither the predictive power (as measured by R^2) nor the point estimates for demand or natural gas prices change meaningfully when wind generation is disaggregated by ISO region as in Equation 4. However, as Table 7 illustrates, the estimated effect of wind generation from each ISO varies across geography.

First, wind generation in MISO has a statistically significant effect on prices at the nuclear plants in Illinois only. In addition, wind generation in PJM has a greater effect on prices at these Illinois plants than wind in the adjacent MISO region, which is consistent with the fact that 84 percent of wind generation in PJM as of 2016 was located in the ISO's western zones immediately proximate to these plants. Wind in the PJM region also has a statistically significant effect (at greater than 95 percent confidence) on all plants located west of the Appalachians (including Beaver Valley). This again indicates that persistent constraints on transmission lines stretching across the Appalachian ranges effectively insulates nuclear generators in the east from the effects of wind generation (and demand) located in the western portion of the PJM market and neighboring MISO.

Table 8 compares the estimated effect of cumulative changes in wind generation from 2008 to 2016 when wind generation is aggregated as in Equation 1 and disaggregated at the ISO level as in Equation 4. Wind generation grew from 0.97 avg-GW in MISO in 2008 to 5.30 avg-GW in 2016 MISO (2017a,b), while wind generation in PJM grew from 0.39 avg-GW to 2.01 avg-GW over the

Table 7: Comparison of results of time series OLS estimate for effect on percent change in daily average price ($ln(P_d)$) at 19 nuclear power stations in PJM when aggregating wind generation (W_d, Eq. 1) vs disaggregating wind generation by ISO region ($W_{d,miso}, W_{d,pjm}$, Eq. 4) - Henry Hub gas price series used

	Regressor	$ln(D_d)$		W_d	$W_{d,miso}$	$W_{d,pjm}$	N_d		Adjusted	
	Estimator	$\hat{\beta}$		$\hat{\gamma}$	$\widehat{\gamma_{miso}}$	$\widehat{\gamma_{pjm}}$	$\hat{\delta}$		R^2	
	Model	Eq. 1	Eq. 4	Eq. 1	Eq. 4		Eq. 1	Eq. 4	Eq. 1	Eq. 4
Plant	State	(per percent change)		(per avg-GW)			(per $ per MMBtu)			
Quad Cities	IL	0.45	0.45	-0.86	-0.83	-0.95	4.89	4.88	0.757	0.757
Byron	IL	0.58	0.58	-0.51	-0.45	-0.71	4.99	4.97	0.784	0.784
LaSalle	IL	0.59	0.59	-0.32	-0.21	-0.67	5.26	5.23	0.772	0.772
Dresden	IL	0.61	0.61	-0.29	-0.17	-0.67	5.22	5.19	0.786	0.787
Braidwood	IL	0.61	0.61	-0.35	-0.21	-0.79	5.14	5.10	0.764	0.764
Cook	MI	0.59	0.59	-0.19	-0.12‡	-0.41	5.55	5.53	0.782	0.782
Davis Besse*	OH	0.70	0.70	-0.13†	-0.05‡	-0.39†	8.86	8.82	0.744	0.744
Perry*	OH	0.74	0.74	-0.13†	-0.05‡	-0.39†	8.67	8.63	0.740	0.740
Beaver Valley*	PA	0.76	0.76	-0.11‡	-0.03‡	-0.37†	9.03	8.99	0.742	0.742
Three Mile Island	PA	0.87	0.87	-0.13‡	-0.07‡	-0.31‡	7.59	7.58	0.854	0.854
Susquehanna	PA	0.88	0.88	-0.09‡	-0.06‡	-0.18‡	7.47	7.47	0.837	0.837
Peach Bottom	PA	0.89	0.89	-0.09‡	-0.06‡	-0.18‡	7.75	7.74	0.862	0.862
Limerick	PA	0.89	0.89	-0.08‡	-0.03‡	-0.25‡	7.63	7.62	0.860	0.860
Salem	NJ	0.90	0.90	-0.07‡	-0.03‡	-0.18‡	7.78	7.77	0.863	0.863
Hope Creek	NJ	0.90	0.90	-0.07‡	-0.03‡	-0.17‡	7.79	7.78	0.863	0.863
Oyster Creek	MD	0.92	0.92	-0.07‡	-0.06‡	-0.11‡	7.64	7.64	0.861	0.861
Calvert Cliffs	MD	0.99	0.99	-0.07‡	-0.05‡	-0.15‡	7.90	7.89	0.838	0.838
North Anna	VA	0.93	0.93	-0.11‡	-0.09‡	-0.20‡	7.83	7.83	0.842	0.842
Surry	VA	0.91	0.91	-0.12‡	-0.11‡	-0.17‡	7.53	7.52	0.838	0.838
PJM Average	N/A	0.83	0.83	-0.14†	-0.08‡	-0.33†	6.90	6.88	0.847	0.847

† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other coefficients statistically significant at >99 percent confidence.
* - Estimates based on observations from June 1, 2011 to December 31, 2016 only.

same period (PJM 2015, 2017a). Using the same general method as in Equation 2 and the estimates produced by Equation 4, I estimate the cumulative effect of these changes in wind generation in each ISO on average prices for each of the 16 reactors with complete 2008-2016 time series, as well as weighted average PJM prices.

Table 8: Comparison of estimated effect of cumulative observed changes in wind generation on daily average price ($ln(P_d)$) from 2008 to 2016 at 16 nuclear power stations in PJM[31] when aggregating wind generation (Eq. 1) vs disaggregating generation by ISO region (Eq. 4) - Henry Hub gas price series used

Plant	State	W_d Eq. 1	Total	$W_{d,miso}$ Eq. 4	$W_{d,pjm}$
Quad Cities	IL	-5.11	-5.13	-3.60	-1.53
Byron	IL	-3.06	-3.11	-1.95	-1.16
LaSalle	IL	-1.91	-2.00	-0.91	-1.08
Dresden	IL	-1.70	-1.80	-0.72	-1.08
Braidwood	IL	-2.09	-2.20	-0.92	-1.28
Cook	MI	-1.13	-1.19	-0.52‡	-0.67
Three Mile Island	PA	-0.77‡	-0.82	-0.31‡	-0.51‡
Susquehanna	PA	-0.53‡	-0.55	-0.27‡	-0.28‡
Peach Bottom	PA	-0.52‡	-0.55	-0.25‡	-0.30‡
Limerick	PA	-0.49‡	-0.53	-0.13‡	-0.40‡
Salem	NJ	-0.41‡	-0.43	-0.15‡	-0.28‡
Hope Creek	NJ	-0.40‡	-0.43	-0.15‡	-0.28‡
Oyster Creek	NJ	-0.41‡	-0.42	-0.25‡	-0.18‡
Calvert Cliffs	MD	-0.43‡	-0.46	-0.21‡	-0.25‡
North Anna	VA	-0.67‡	-0.69	-0.37‡	-0.32‡
Surry	VA	-0.73‡	-0.75	-0.47‡	-0.28‡
PJM Average	n/a	-0.82†	-0.87	-0.34‡	-0.53†

† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other estimates statistically significant at >99 percent confidence.

As Table 8 illustrates, the sum of the disaggregated effects from wind generation in each ISO is very similar in magnitude to the estimated effect of aggregated change in wind generation produced using estimates from the primary model specification in Equation 1. Both methods thus have very similar predictive ability. However, the disaggregated model (Equation 4) provides further insight on which plants are most affected by wind generation in MISO and PJM, respectively. Interestingly, for nuclear plants in Illinois where wind generation has a statistically significant impact, the estimated effect of per unit changes in wind generation is greater for an avg-GW of wind generation in PJM ($\widehat{\gamma_{pjm}}$) than in MISO ($\widehat{\gamma_{miso}}$, see Table 7). However, due to the larger cumulative increase in wind generation in MISO from 2008 to 2016, wind generators in MISO appear to have had a larger impact on revenues for plants like Quad Cities and Byron and a similar magnitude impact for the remainder of Illinois plants as more proximate generation in PJM.

6. Exploring the Use of Time Series from Different Natural Gas Trading Hubs

The North American natural gas market has a highly active spot market, where buyers and sellers can trade natural gas for delivery to a variety of trading hubs physically located at different point across the continent. These trading hubs are usually located at the intersection of multiple interstate pipelines, which facilitates liquidity, and contracts for delivery to other locations are typically indexed against prices at one of these trading hubs. In addition, a variety of futures products and long-term contracts for gas delivery are also traded and are typically priced based on expected prices at one or more of these trading hubs (API 2014).

The Henry Hub in Louisiana has long been the primary benchmark hub for North American natural gas trading, including all NYMEX gas futures and the majority of spot market trades. However, as North American natural gas production has shifted in recent years from the Gulf Coast to other regions, including the Marcellus and Bakken formations (spanning parts of New York, Pennsylvania, and Ohio, and North Dakota, Montana, and Saskatchewan, respectively), several other trading hubs have recently surpassed the Henry Hub in trading volume, including the Chicago Citygate Hub and the Dominion South and Columbia TCO Pool hubs in Appalachia (API 2014; DiSavina & Krishnan 2014; FERC 2017). Indeed, these three gas hubs are more physically proximate to the PJM electricity marketplace than the Henry Hub (see Figure 13) and may serve as referents for natural gas contracts or spot market purchases for power plants in the PJM region. It is therefore relevant to explore whether using prices from alternative gas hubs has a significant impact on the estimated effect of natural gas price changes and other regressors on electricity market prices received by nuclear generators in PJM. In this section, I thus present results of regressions using Equation 1 with natural gas price time series from the Henry, Chicago Citygate, Dominion South, and Columbia Appalachia TCO Pool hubs. All gas prices series are from SNL (2017).

As Figure 14 and Table 9 illustrate, the original price time series at the four gas hubs are closely correlated, with two exceptions. First, prices at the Dominion South hub are consistently lower than the other trading hubs after January 2014, although variation in prices at the Dominion hub remain highly correlated with variations at the other hubs (Table 9 (a)). Second, price shocks caused by extremely cold weather and high heating demand during the so-called "Polar Vortex" of January-March 2014 were both much more severe and more sustained at the Chicago Citygate than the three other hubs (see Figure 14 (b)). After de-meaning the gas price time series by weekly mean (representing the effect of using weekly time fixed effects), this difference in the duration of price shocks at the Chicago hub stands out, and results in a much lower correlation between the Chicago hub and all other hubs.

Given strong correlations between the Henry, Dominion South and Columbia hubs, one would expect that the explanatory power of the regression model would be similar when using any of these three series, while it may differ somewhat for the less correlated Chicago hub. In addition, any

[34]Image is author's own, based on locations of Top 25 North American Gas Trading Locations (based on volume traded) from API (2014)

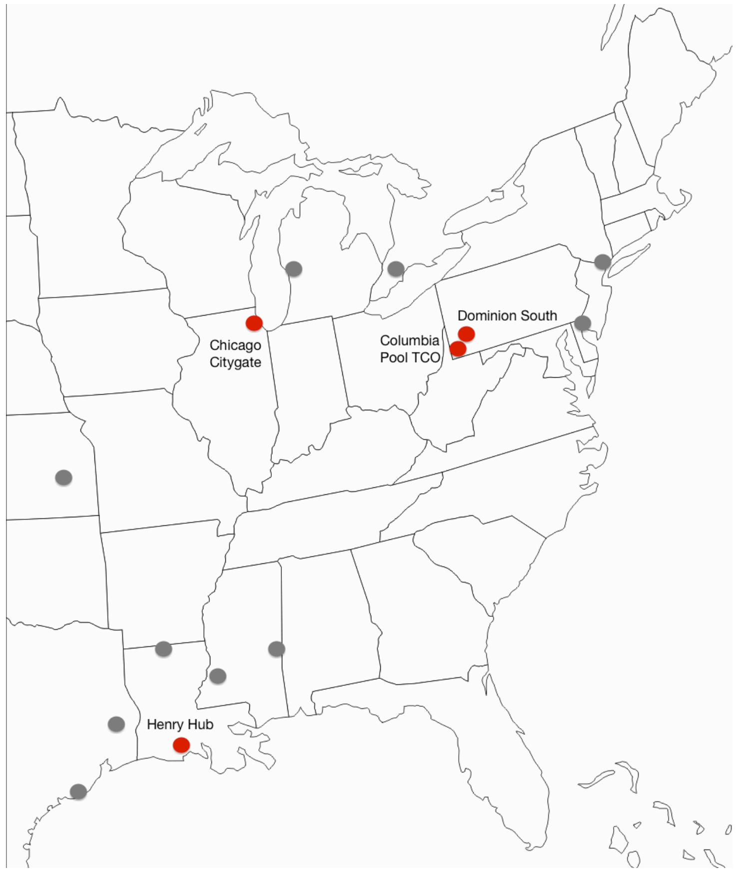


Figure 13: Physical location of four major natural gas trading hubs used in this study. The location of several other major eastern trading hubs are shown in grey.[34]

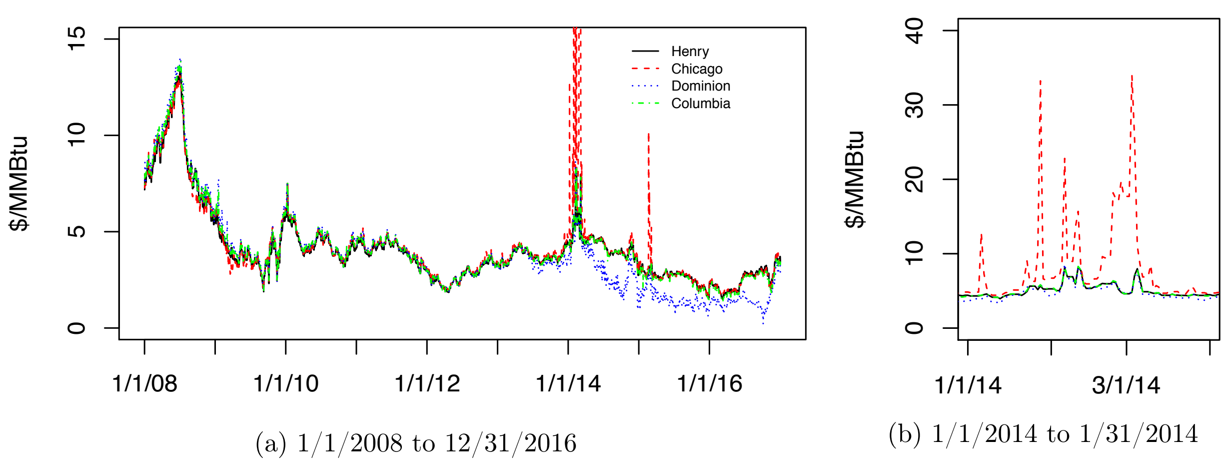


Figure 14: Daily natural gas spot prices at four major trading hubs SNL (2017)

Table 9: Correlation matrix for natural gas trading hub time series

	(a) Original Time Series				(b) After De-Meaning by Week			
	Henry	Chicago	Dominion S	Columbia	Henry	Chicago	Dominion S	Columbia
Henry	1.000	0.885	0.966	0.998	1.000	0.300	0.803	0.943
Chicago	0.885	1.000	0.858	0.883	0.300	1.000	0.356	0.305
Dominion S	0.966	0.858	1.000	0.975	0.803	0.356	1.000	0.859
Columbia	0.998	0.883	0.975	1.000	0.943	0.305	0.859	1.000

variation in the magnitude of correlated price shocks at the different hubs would lead to a difference in the magnitude of the estimated effect of changes in natural gas prices produced by the regression.

Indeed, both expectations are reflected in a comparison of the results of time series OLS regressions using the four natural gas price series, as depicted in Table 10. The Chicago Citygate time series has somewhat greater explanatory power than prices from the other hubs, particular for plants in western PJM. In addition, the estimated effects of gas price changes on electricity prices at the 19 nuclear plants varies depending on the gas price series used. The estimated effects of changes in natural gas prices produced using time series from the Henry and Columbia hubs are nearly identical, while the Dominion South hub tends to produce slightly higher estimated effects. However, given the large variance in the natural gas estimator, the 95 percent confidence intervals for these estimates overlap substantially. However, estimates produced using the Chicago hub are uniformly lower and exhibiting less geographic heterogeneity than estimates using prices from other hubs. Indeed, the differences in estimates produced using the Chicago time series for plants in the eastern portion of PJM are significantly different (at 95 percent confidence) from the estimates produced using prices from the Dominion South and Columbia hubs and, for most plants, the Henry Hub as well.

Finally, in contrast to the variation in estimated effects of natural gas price changes, the estimated effects of changes in demand and wind generation are of similar magnitude across results for all four natural gas price series, which further increases confidence in the approximate magnitude of the effects of these explanatory variables.

Table 10: Comparison of results of time series OLS estimate for effect of changes in demand, wind generation, and natural gas prices on percent change in daily average price ($ln(P_d)$) at 19 nuclear power stations in PJM using price time series from four different natural gas trading hubs

		D_d				W_d			
Plant	State	Henry	Chicago	Dominion S	Columbia	Henry	Chicago	Dominion S	Henry
Quad Cities	IL	0.45	0.40	0.41	0.44	-0.86	-0.82	-0.85	-0.86
Byron	IL	0.58	0.54	0.53	0.57	-0.51	-0.48	-0.51	-0.51
LaSalle	IL	0.59	0.55	0.54	0.58	-0.32	-0.29	-0.32	-0.32
Dresden	IL	0.61	0.57	0.56	0.60	-0.29	-0.25	-0.28	-0.29
Braidwood	IL	0.61	0.56	0.56	0.60	-0.35	-0.32	-0.35	-0.35
Cook	MI	0.59	0.55	0.54	0.58	-0.19	-0.16	-0.19	-0.19
Davis Besse	OH	0.70	0.64	0.63	0.69	-0.13†	-0.09‡	-0.12†	-0.13†
Perry	OH	0.74	0.68	0.67	0.72	-0.13†	-0.09‡	-0.13†	-0.13†
Beaver Valley	PA	0.76	0.71	0.69	0.75	-0.11‡	-0.07‡	-0.10‡	-0.11‡
Three Mile Island	PA	0.87	0.84	0.80	0.86	-0.13‡	-0.10‡	-0.12‡	-0.13‡
Susquehanna	PA	0.88	0.85	0.81	0.87	-0.09‡	-0.06‡	-0.08‡	-0.09‡
Peach Bottom	PA	0.89	0.85	0.81	0.87	-0.09‡	-0.06‡	-0.08‡	-0.09‡
Limerick	PA	0.89	0.85	0.81	0.87	-0.08‡	-0.05‡	-0.07‡	-0.08‡
Salem	NJ	0.90	0.86	0.82	0.88	-0.07‡	-0.04‡	-0.06‡	-0.07‡
Hope Creek	NJ	0.90	0.86	0.82	0.88	-0.07‡	-0.04‡	-0.06‡	-0.07‡
Oyster Creek	MD	0.92	0.88	0.84	0.90	-0.07‡	-0.04‡	-0.06‡	-0.07‡
Calvert Cliffs	MD	0.99	0.96	0.92	0.98	-0.07‡	-0.04‡	-0.07‡	-0.07‡
North Anna	VA	0.93	0.89	0.86	0.92	-0.11‡	-0.08‡	-0.11‡	-0.11‡
Surry	VA	0.91	0.87	0.84	0.90	-0.12‡	-0.09‡	-0.12‡	-0.12‡
PJM Average	N/A	0.83	0.79	0.77	0.82	-0.14†	-0.10‡	-0.13†	-0.14†
		N_d				Adjusted R^2			
Plant	State	Henry	Chicago	Dominion S	Columbia	Henry	Chicago	Dominion S	Henry
Quad Cities	IL	4.89	3.25	5.98	4.71	0.757	0.805	0.762	0.757
Byron	IL	4.99	3.25	6.51	4.87	0.784	0.829	0.790	0.784
LaSalle	IL	5.26	3.25	6.50	5.26	0.772	0.832	0.780	0.772
Dresden	IL	5.22	3.27	6.57	5.24	0.786	0.850	0.795	0.787
Braidwood	IL	5.14	3.27	6.49	5.15	0.764	0.824	0.772	0.764
Cook	MI	5.55	3.27	6.82	5.65	0.782	0.846	0.791	0.783
Davis Besse	OH	8.86	3.36	11.09	9.48	0.744	0.826	0.766	0.747
Perry	OH	8.67	3.37	11.15	9.30	0.740	0.822	0.762	0.743
Beaver Valley	PA	9.03	3.47	11.58	9.68	0.742	0.822	0.764	0.745
Three Mile Island	PA	7.59	3.27	10.72	8.52	0.854	0.872	0.864	0.856
Susquehanna	PA	7.47	3.20	10.58	8.57	0.837	0.854	0.847	0.839
Peach Bottom	PA	7.75	3.29	10.89	8.73	0.862	0.880	0.871	0.864
Limerick	PA	7.63	3.23	10.83	8.59	0.860	0.877	0.870	0.862
Salem	NJ	7.78	3.24	10.98	8.76	0.863	0.880	0.873	0.865
Hope Creek	NJ	7.79	3.25	10.99	8.77	0.863	0.880	0.873	0.865
Oyster Creek	MD	7.64	3.35	10.92	8.69	0.861	0.879	0.870	0.863
Calvert Cliffs	MD	7.90	3.33	10.56	8.70	0.838	0.858	0.847	0.840
North Anna	VA	7.83	3.36	10.20	8.44	0.842	0.865	0.851	0.844
Surry	VA	7.53	3.31	9.81	8.13	0.838	0.862	0.847	0.840
PJM Average	N/A	6.90	3.27	9.16	7.42	0.847	0.878	0.857	0.848

† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other estimates statistically significant at >99 percent confidence.

The low correlation exhibited between prices at the Chicago hub and the other time series after removing time trends by de-meaning by week facilitates one additional regression specification, described by Equation 5:

$$\begin{aligned} ln(P_d) = &\beta\ ln(D_d) + \gamma W_d + \delta_{Chicago} N_{d,Chicago} + \delta_{Columbia} N_{d,Columbia} \\ &+ \sum_{k=1}^{470} \alpha_{week,k} dw_k + \sum_{n=1}^{7} \alpha_{day-of-week,n} dd_n + \sum_{i=1}^{3} \eta_i z_i + \epsilon_d \end{aligned} \tag{5}$$

This specification includes natural gas price series from both the Chicago and Columbia hubs. I select this pair of hubs because they exhibit the smallest covariance amongst the three hubs located within the PJM market footprint and do not exhibit significant collinearity.[35] As with the specifications disaggregating electricity demand and wind generation series geographically, this specification provides coefficients for two relatively uncorrelated natural gas price series for trading hubs located in the western and eastern portions of the PJM region, which allows further exploration of the geographically heterogenous effects of changes in gas prices on electricity prices in PJM. Table 11 depicts estimated coefficients for this specification and compares to results for the primary specification using the Henry Hub price series.

The explanatory power of Eq. 5 (as measured by adjusted R^2) is superior to Eq. 1 when using Henry, Dominion South, or Columbia hub gas prices, and it is comparable to (if not slightly better than) using the Chicago hub alone. Estimated effects of changes in demand and wind generation are largely consistent with the primary specification using Henry Hub prices. These estimates tend to be slightly smaller, although not enough to be considered significantly different (at 95 percent confidence). Using Eq. 5, the effect of natural gas price changes at Chicago Citygate are statistically significant for all 19 PJM nuclear plants. The estimated effect per $ change in the price of gas (per MMBtu) at the Chicago hub under this specification tends to be more modest than the estimated effect of changes at Henry using Eq. 1, just as when using Chicago Citygate alone. As discussed above, this is presumably due to the more severe price shocks at the Chicago Citygate hub during the Polar Vortex period. The effect of price changes at the Chicago hub is slightly higher for plants in the western PJM region than in the east, although there is much less geographic variation than estimates for other gas price series. Finally, the estimated effect of changes in gas price at the Columbia Appalachia hub are statistically significant only for plants in the eastern portion of PJM (as well as the PJM weighted average nodal price series). This is consistent with the fact that,

[35] After de-meaning by week, variance inflation factors exceed 2.0 for gas price series (indicating significant multicollinearity) using regressions featuring the following pairs of gas hubs: Henry and Dominion; Henry and Columbia; and Dominion and Columbia. The presence of multicollinearity is not surprising, given the high correlation coefficients between these three hubs (Table 9). Henry and Columbia and Chicago and Dominion would also be possible specifications that do not exhibit significant collinearity. However, I disregard combinations featuring Henry Hub here as it is not physically proximate to the PJM market footprint, and I select the Chicago and Columbia pairing over Chicago and Dominion as this pair of series exhibits has the least correlation and thus smallest collinearity between them.

until only recently, gas pipelines in the region flowed almost exclusively into the Northeast and not westward (EIA 2014).

Table 11: Comparison of results of time series OLS estimate for effect on percent change in daily average price ($ln(P_d)$) at 19 nuclear power stations in PJM when using natural gas price series from Henry Hub (N_d, Eq. 1) vs using prices from both Chicago Citygate ($N_{d,Chi.}$) and Columbia Appalachia TCO Pool ($N_{d,Col.}$) hubs (Eq. 5)

Regressor		$ln(D_d)$		W_d		N_d	$N_{d,Chi.}$	$N_{d,Col.}$	Adjusted	
Estimator		$\hat{\beta}$		$\hat{\gamma}$		$\hat{\delta}$	$\hat{\delta_{Chi.}}$	$\hat{\delta_{Col.}}$	R^2	
Model		Eq. 1	Eq. 5	Eq. 1	Eq. 5	Eq. 1	Eq. 5		Eq. 1	Eq. 5
Plant	State	(per percent change)		(per avg-GW)		(per $ per MMBtu)				
Quad Cities	IL	0.45	0.40	-0.86	-0.82	4.89	3.23	$0.36^‡$	0.757	0.805
Byron	IL	0.58	0.53	-0.51	-0.48	4.99	3.22	$0.53^‡$	0.784	0.829
LaSalle	IL	0.59	0.54	-0.32	-0.28	5.26	3.19	$0.97^‡$	0.772	0.832
Dresden	IL	0.61	0.56	-0.29	-0.25	5.22	3.21	$0.92^‡$	0.786	0.851
Braidwood	IL	0.61	0.56	-0.35	-0.32	5.14	3.21	$0.82^‡$	0.764	0.824
Cook	MI	0.59	0.54	-0.19	-0.16	5.55	3.18	$1.35^‡$	0.782	0.847
Davis Besse*	OH	0.70	0.63	$-0.13^†$	$-0.08^‡$	8.86	3.18	$3.80^‡$	0.744	0.829
Perry*	OH	0.74	0.67	$-0.13^†$	$-0.09^‡$	8.67	3.20	$3.57^‡$	0.740	0.824
Beaver Valley*	PA	0.76	0.69	$-0.11^‡$	$-0.06^‡$	9.03	3.29	$3.79^‡$	0.742	0.825
PJM Average	N/A	0.83	0.78	$-0.14^†$	$-0.10^‡$	6.90	3.05	3.35	0.847	0.880
Three Mile Island	PA	0.87	0.82	$-0.13^‡$	$-0.10^‡$	7.59	2.97	4.61	0.854	0.874
Susquehanna	PA	0.88	0.83	$-0.09^‡$	$-0.06^‡$	7.47	2.89	4.76	0.837	0.857
Peach Bottom	PA	0.89	0.84	$-0.09^‡$	$-0.05^‡$	7.75	2.98	4.81	0.862	0.882
Limerick	PA	0.89	0.83	$-0.08^‡$	$-0.05^‡$	7.63	2.92	4.74	0.860	0.879
Salem	NJ	0.90	0.84	$-0.07^‡$	$-0.04^‡$	7.78	2.92	4.92	0.863	0.882
Hope Creek	NJ	0.90	0.84	$-0.07^‡$	$-0.03^‡$	7.79	2.92	4.92	0.863	0.882
Oyster Creek	MD	0.92	0.86	$-0.07^‡$	$-0.03^‡$	7.64	3.05	4.68	0.861	0.881
Calvert Cliffs	MD	0.99	0.94	$-0.07^‡$	$-0.04^‡$	7.90	3.02	4.73	0.838	0.860
North Anna	VA	0.93	0.88	$-0.11^‡$	$-0.08^‡$	7.83	3.07	4.41	0.842	0.867
Surry	VA	0.91	0.86	$-0.12^‡$	$-0.09^‡$	7.53	3.05	4.12	0.838	0.864

† - Estimate statistically significant at 95 percent confidence. ‡ - Estimate not statistically significant. All other coefficients statistically significant at >99 percent confidence.
* - Estimates based on observations from June 1, 2011 to December 31, 2016 only.

Figure 15 compares the estimated effect of cumulative changes in natural gas prices over the 2008-2016 period on electricity prices at PJM nuclear plants when using the various gas time series and specifications presented in this section. The point estimates vary substantially, with changes in gas prices from 2008-2016 responsible for anywhere from on the order of 20 percent to 80 percent declines in electricity prices, depending on the specification. In addition, all point estimates exhibit large standard errors. As such, one should treat the quantitative estimate of the effect of changes in gas prices on electricity prices at PJM nuclear plants with some caution. However, it is notable that changes in gas price produce an estimated effect on electricity prices that is always an order of magnitude greater than the cumulative effect of changes in demand or wind generation in the region. Thus, while it is difficult to estimate the precise magnitude, it appears that changes in gas prices are responsible for the majority of observed changes in electricity prices at all PJM nuclear plants.

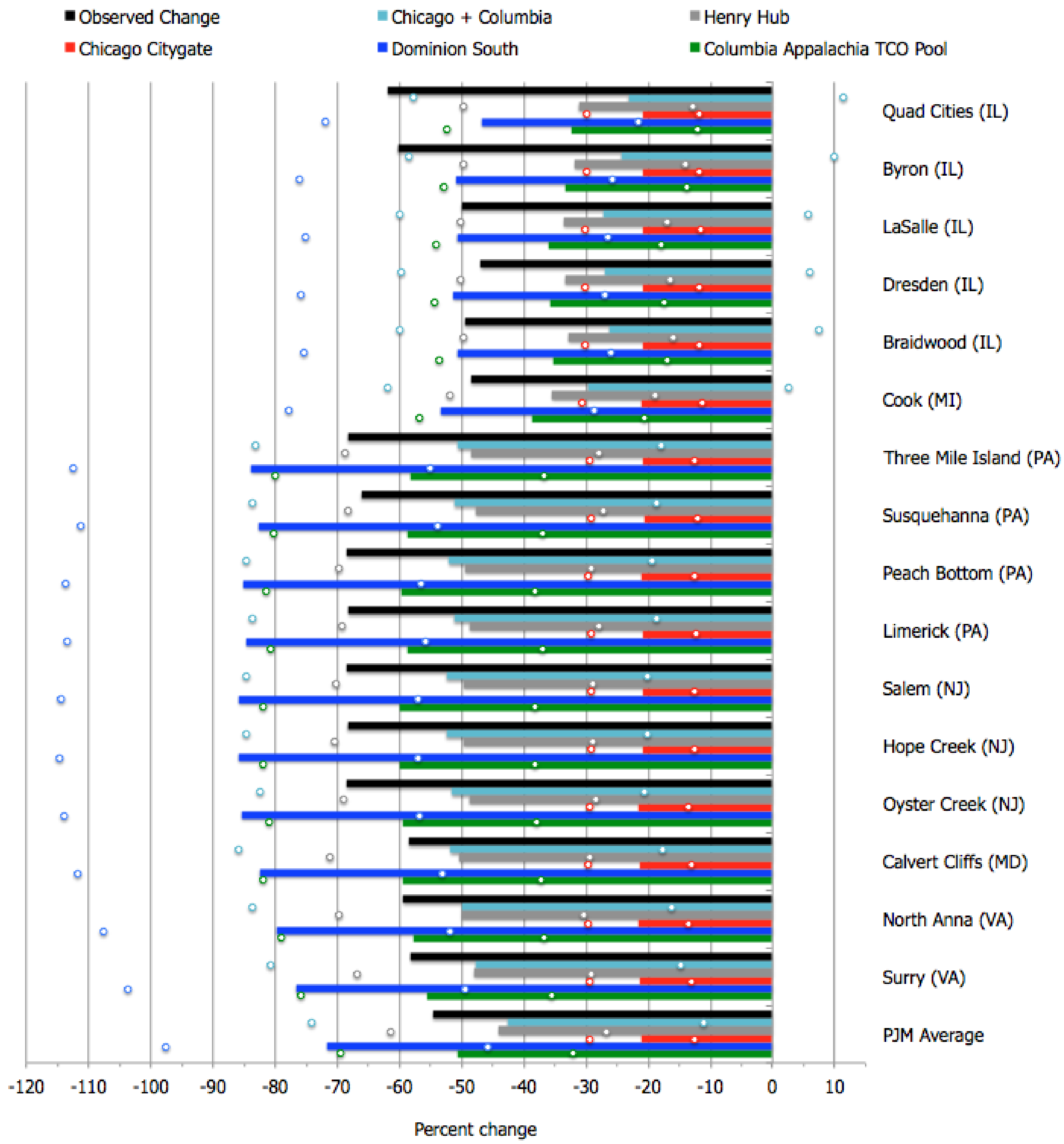


Figure 15: Comparison of estimated effect of cumulative observed changes in natural gas prices on daily average price ($ln(P_d)$) from 2008 to 2016 at 16 nuclear power stations in PJM[31] when using prices time series from different natural gas trading hubs. Circles depict 95 percent confidence intervals for each estimate (using Newey-West HAC standard errors). Estimates based on counterfactual 2016 predictions adjusting 2016 daily observations to reflect percent change between annual average 2008 values and annual average 2016 values as per Equation 2. Total observed change in annual average prices from 2008 to 2016 presented for comparison.

7. Conclusions, Limitations, and Future Work

This paper offers the first empirical estimate of the effect of significant changes in electricity demand, wind generation, and the price of natural gas over the period 2008 to 2016 on electricity market prices earned by 19 economically-challenged nuclear power plants in the PJM electricity market region. In addition, this paper takes advantage of the fact that these nuclear plants are dispersed across the PJM region from Illinois to the Atlantic coast to explore the geographically heterogenous effects of each explanatory variable.

I find that an approximately 3.5 percent decline in electricity demand across the PJM and MISO electricity market footprints from 2008 to 2016 is responsible for a statistically significant but modest decline in electricity prices at all 19 nuclear plants in PJM. The cumulative effect of changes in electricity demand from 2008 to 2016 on the average prices earned by these plants is on the order of a 1.5 to 4.0 percent decline. The impact of declining demand on electricity prices is greater at plants in the east (closer to major population centers) than those in the western portion of PJM. The various specifications explored in this paper provide relatively precise estimates for the effect of demand on electricity prices (e.g., estimates exhibit small standard errors), and these estimates are consistent across all specifications. Subject to the assumption that demand is overwhelmingly inelastic and thus exogenous to price on daily time scales, the estimated effect of demand on electricity prices earned by PJM nuclear plants can thus be treated with some confidence.

Annual average wind energy generation in the MISO and PJM market footprints grew more than five-fold from 1.35 avg-GW in 2008 to 7.31 avg-GW in 2016, enough to supply 4.4 percent of electricity demand in the two market regions. Across various specifications used in this paper, this growth in wind generation appears to have had a modest and statistically significant effect on electricity market prices only at nuclear plants in the eastern portion of PJM (e.g., in Illinois, Michigan, and Ohio). Wind generation is estimated to have had the greatest impact on prices earned by the Quad Cities nuclear plant located in western Illinois, driving down prices there by somewhere between 4.2 to 6.0 percent over this period. The cumulative effect of wind generation on other plants in western PJM is more modest, ranging from roughly 1 to 4 percent across the Byron, LaSalle, Dresden, and Braidwood plants in Illinois, with even smaller effects for plants in Michigan (Cook) and Ohio (Perry and Davis Besse). For all other nuclear plants in PJM, growth in wind generation does not appear to have had a statistically significant effect. Frequent transmission constraints likely insulated plants in the east from the effects of changes in wind generation in western PJM and MISO. Note that these estimated effects encompass both the merit order effect of wind and the impact of any negative prices induced by subsidized wind generation. As with estimates for changes in demand, the estimated effects of changes in wind generation are tightly estimated and consistent across all specifications presented in this paper.

Finally, natural gas prices fell substantially from 2008 to 2016, declining by $6.38 to $7.82 per

[35]This range represents the range of 95 percent confidence intervals for the cumulative effect of changes in wind generation from 2008 to 2016 exhibited across all specifications presented in this paper.

MMBtu across the Henry, Chicago Citygate, Dominion South, and Columbia Appalachia TCO Pool hubs considered in this paper. Across a variety of specifications presented in this paper, this decline in the price of natural gas appears responsible for the majority of observed declines in electricity prices across the 19 PJM nuclear plants over this period. However, the methods I employ herein produce much less precise estimates for the effects of declining gas prices than they do for demand or wind generation. Point estimates for the cumulative effect of changes in gas prices from 2008 to 2016 range from a roughly 20 to 85 percent decline across different plants and model specifications. In addition, these estimates exhibit significant variance across all specifications—e.g., 95% confidence intervals for the cumulative impact of changes in gas prices span +/- 8 to 29 percentage points around these point estimates, depending on which natural gas trading hub and model specification is used. Despite these wide intervals, one can confidently conclude that the estimated effect of natural gas prices on electricity prices at all PJM nuclear plants is an order of magnitude greater than the impact of either declining electricity demand or the growth in wind energy generation in the MISO and PJM markets over this same time period. Changes in gas prices also appear to have had a greater impact on nuclear plants in the eastern portion of PJM, although effects are large and significant for all plants in the PJM footprint.

It is important to note that this analysis is limited to estimated effects on *day-ahead* electricity prices. As nuclear units in the United States currently operate in a baseload or must-run manner and do not change output in response to changes in electricity prices between day-ahead and real-time markets, this focus on day-ahead prices should be sufficient. However, the effect of each explanatory variable on real-time prices in the PJM region may be relevant to the revenues of other generators (e.g. fossil fueled power plants). In addition, U.S. nuclear generators may begin to operate plants more flexibly in the future as variable renewable energy sources increase the prevalence of zero or negative electricity prices (Maloney 2016a). Future analysis could therefore explore whether demand, wind generation, or gas price changes had different impacts on real-time prices.

In addition, please note that this paper estimates the effect of demand, wind generation, and natural gas price changes on electricity *prices* at the locations of 19 PJM nuclear power stations. Actual *revenues* earned by nuclear stations may differ for two reasons.

First, since nuclear plants operate at full output whenever possible, it is plausible that day-ahead prices are a reasonable proxy for impacts on nuclear plant operating revenues. This assumption holds so long as shutdowns for refueling or other planned or forced outages at nuclear stations are not correlated with explanatory variables. In the case of wind output and gas prices changes, this seems plausible. However, nuclear generators tend to plan refueling and maintenance shutdowns for periods of low demand (e.g. in the spring or fall). Nuclear plant output and thus revenues may therefore be correlated with demand, which may make the effect of changes in demand on prices a biased proxy for the corresponding effect on actual revenues. Future work could compile time

[35] There is simply less variation in the gas price time series to exploit for regression analysis than there is in the demand and wind generation series, particularly after employing time fixed effects to help account for confounders and ensure stationarity of the time series.

series data on nuclear plant operating status to verify this assumption and/or directly account for operating status to estimate effects on operating revenues as well as prices.

Second, while day-ahead market sales represent the majority of revenues for nuclear generators, they also earn money in PJM's capacity market, an annual competitive auction wherein the system operator procures capacity (in the form of firm commitments to provide electricity supply or reduce demand) sufficient to meet expected peak demand three years in the future (PJM n.d.). Changes in demand, wind generation, and natural gas prices may have also impacted capacity market clearing prices and even resulted in some nuclear plants not clearing in the auction. Indeed, the Quad Cities and Three Mile Island plants failed to clear in the 2017 auction (for capacity to be delivered in 2020-2021) (Walton 2017). However, analyzing the impact of these explanatory variables on PJM capacity market outcomes is beyond the scope of this paper.

Finally, the use of time fixed effects in this paper may mask the longer-term influence of explanatory variables on the structural composition of the electricity generation stock (e.g., retirements, additions) over time, which may in turn affect prices received by nuclear generators. The estimated effects presented herein should therefore be interpreted as reflecting only the effect of variation in demand, wind generation, or natural gas prices on electricity prices *after* controlling for any changes in the generation stock over time (which will be absorbed by the week fixed effects terms). It is plausible that declining demand, increasing wind generation, and (in particular) changes in gas prices may have resulted in retirements of generation capacity over this period. For example, declining demand and a significant decline in natural gas prices has no doubt contributed to deteriorating economic conditions for coal-fired power plants as well. Between 2010 and 2017, 63 GW of coal capacity retired (MJB & A 2017). Using a simulation-based approach, Haratyk (2017) estimates that coal-fired power plant retirements increased average electricity prices 6 percent in the Midwest and 23 percent in the Mid-Atlantic states, offsetting some of the declines in price due to natural gas prices, wind generation, and declining demand. Some portion of these retirements may be causally attributable to natural gas price changes, wind generation, or declining demand. Unfortunately, empirically estimating any such causal effects is beyond the scope of this analysis.

To conclude, noting the limitations above, it nevertheless appears clear that significant declines in natural gas prices have had the dominant impact on declining wholesale electricity market prices for nuclear power plants in the PJM market region in recent years. The estimated effect of natural gas prices on power prices at PJM nuclear plants from 2008 to 2016 is uniformly an order of magnitude greater than the estimated effect of declining demand, or growth in wind energy generation. Furthermore, point estimates for the effect of gas explain the majority (approximately 50 to 86 percent across plants in the primary specification) of observed changes in average day-ahead prices

[35] Haratyk defines this region as including Iowa, Illinois IL, Indiana, Michigan, Minnesota, Missouri, North Dakota, and Wisconsin. This is roughly comparable to the northern MISO and western PJM regions discussed in this analysis.

[35] Haratyk defines this region as including the District of Columbia, Deleware, Kentucky, Maryland, New Jersey, Ohio, Pennsylvania, Virginia, and West Virgina. This is roughly comparable to eastern PJM region discussed in this paper.

at these locations.

That said, declining electricity demand also had a statistically significant effect on prices across PJM. It is fair to say that electricity prices earned by nuclear plants in PJM would have been a few percentage points higher had electricity demand in PJM and MISO remained steady at 2008 levels. Prices would have been higher still had demand continued to grow at over 1 percent per year, as projected by many analysts prior to the Great Recession (see e.g., EIA (2008)).

In addition, wind generation appears to have had a small but material effect on electricity prices at nuclear stations in Illinois and, to a lesser degree, plants in Michigan and Ohio. While the historical impact of growing wind generation in MISO and PJM from 2008 to 2016 alone is not responsible for the declining economic condition of nuclear power stations in the region, these results indicate that any rebound in electricity prices due to future increases in natural gas prices would have to overcome further declines in price due to continued wind growth in the region. The expectations of further wind power additions could thus negatively impact financial decisions today concerning capital expenditures to refuel, retrofit, or repair nuclear plants in western PJM for continued service—particularly amidst expectations of a modest near-term rebound in gas prices and stagnant electricity demand growth (EIA 2017d).

In short, cheap natural gas may be killing the profitability of nuclear power producers in the PJM Interconnection, but stagnant electricity demand and expectations of future growth in wind generation going forward may be accomplices.

As these factors act in combination to reduce wholesale electricity prices and thus generator revenues, nuclear power plants in U.S. markets are likely to be under greater economic pressure and may be driven to retirement. To the extent that natural gas or coal-fired power plants increase production to replace retiring nuclear plants, the net environmental benefits of expanded renewable energy, reduced demand, and cheap natural gas may be significantly diminished. Whether this outcome can be prevented is an active question for public policy makers across the United States. Formulating effective policy will ultimately benefit from an accurate assessment of the proximate causes of the deteriorating economic outlook for U.S. nuclear plants. This analysis thus contributes valuable insight on the interaction of low gas prices, stagnant electricity demand, and growing wind generation on the economics of nuclear power in the PJM Interconnection, with implications that likely extend to other organized U.S. electricity markets.

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Appendix A. Counterfactual 2016 Wholesale Electricity Price Predictions

(see Section 4.3)

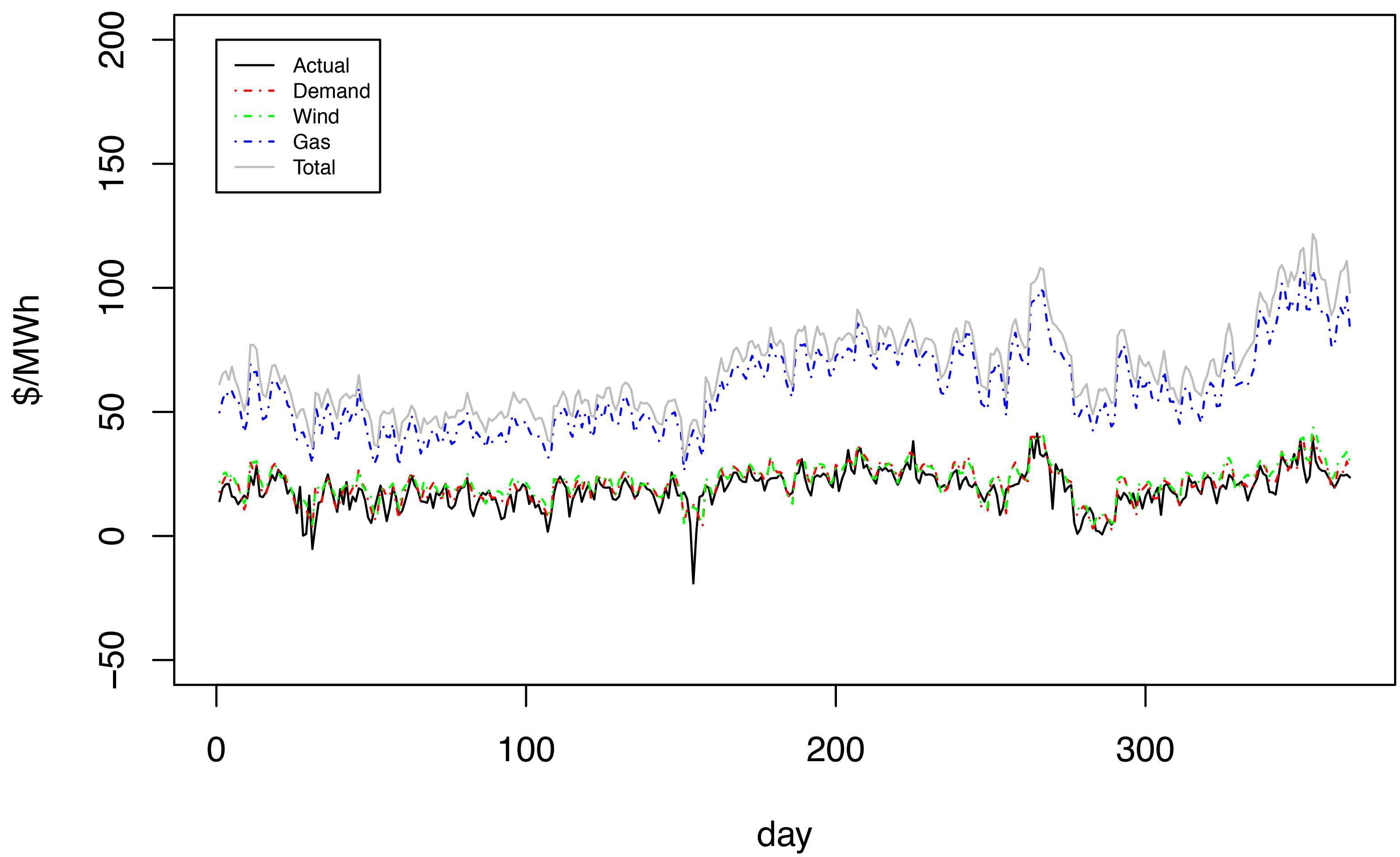

Figure Appendix A.1: Quad Cities (IL)

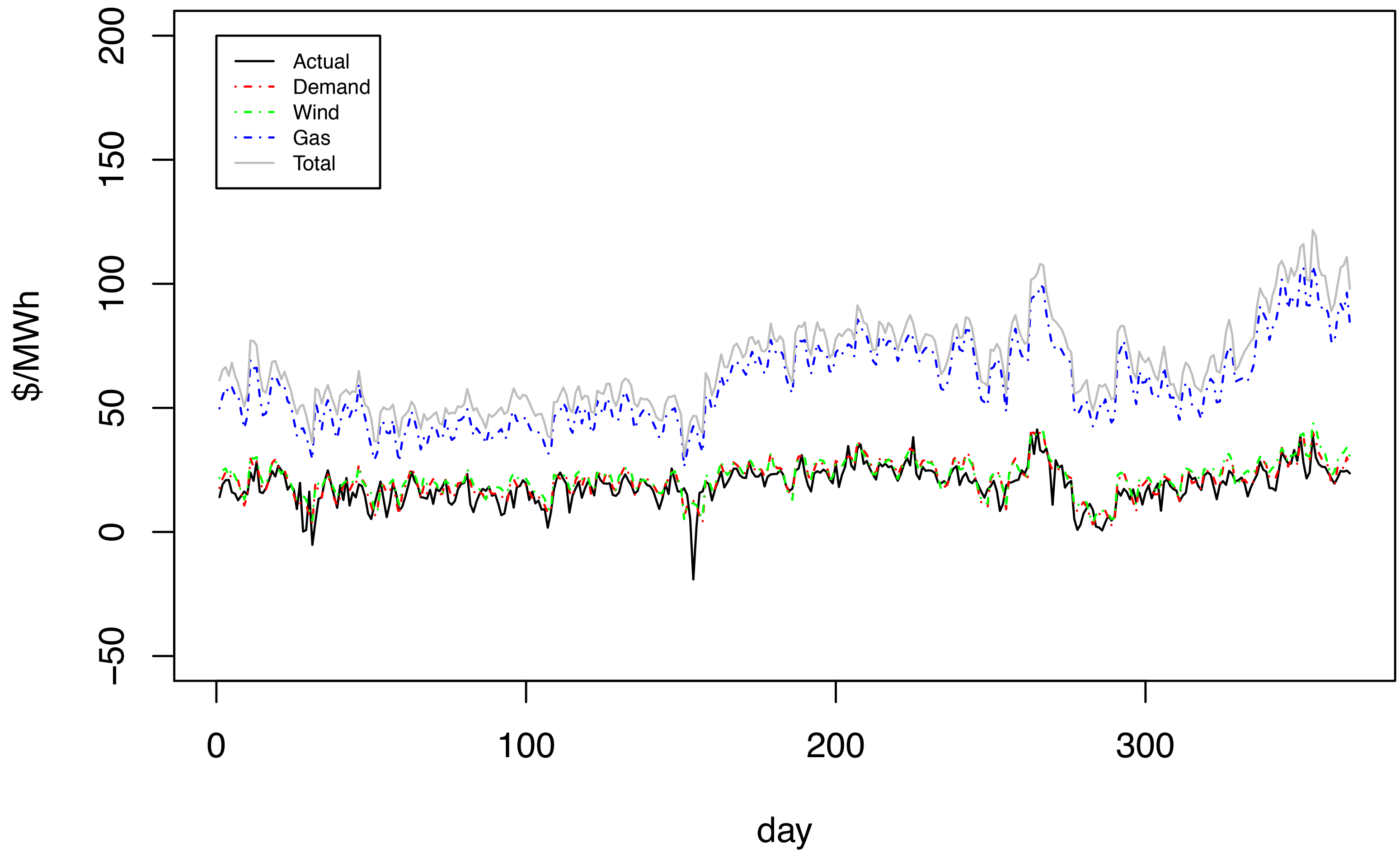

Figure Appendix A.2: Byron (IL)

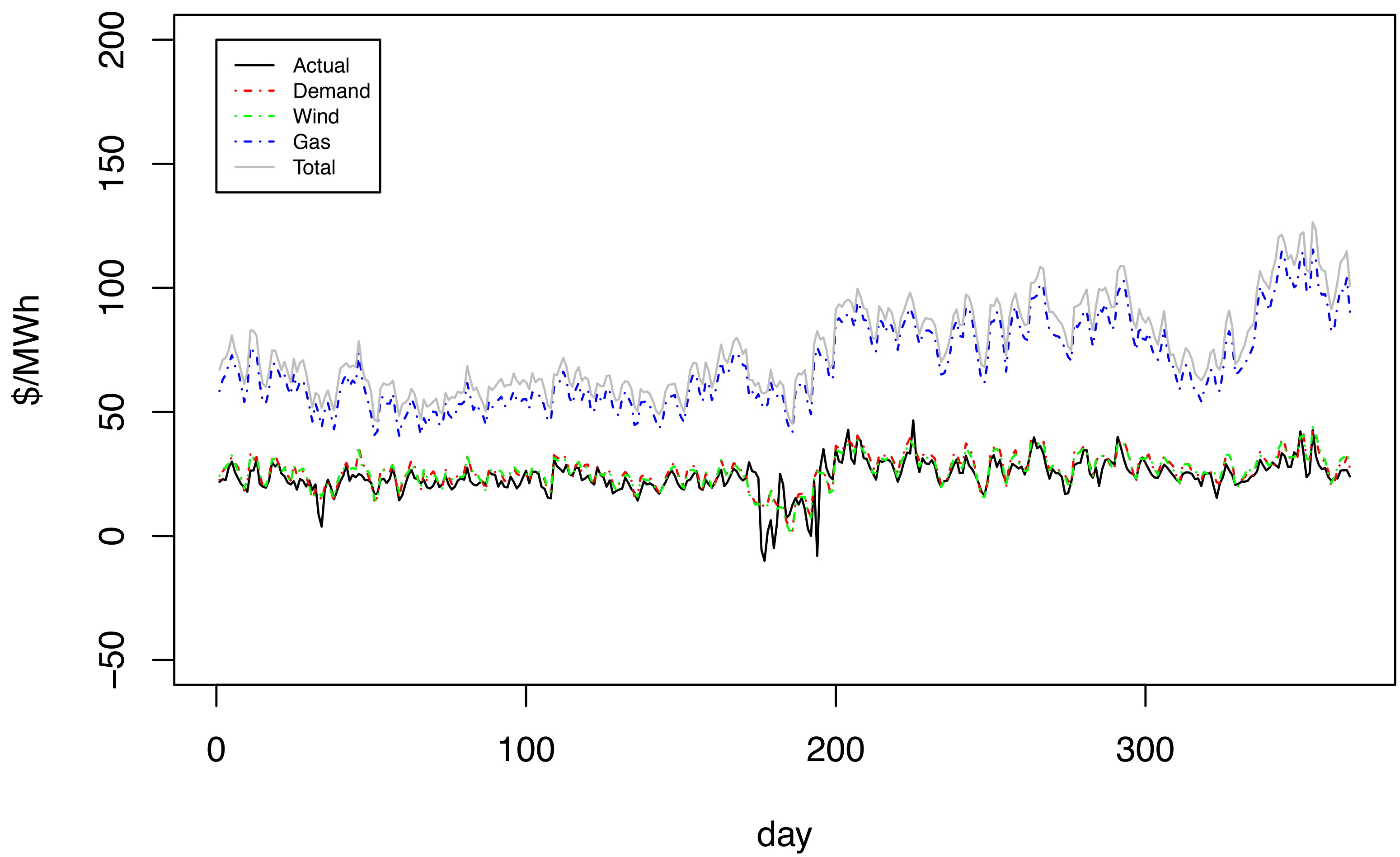

Figure Appendix A.3: LaSalle (IL)

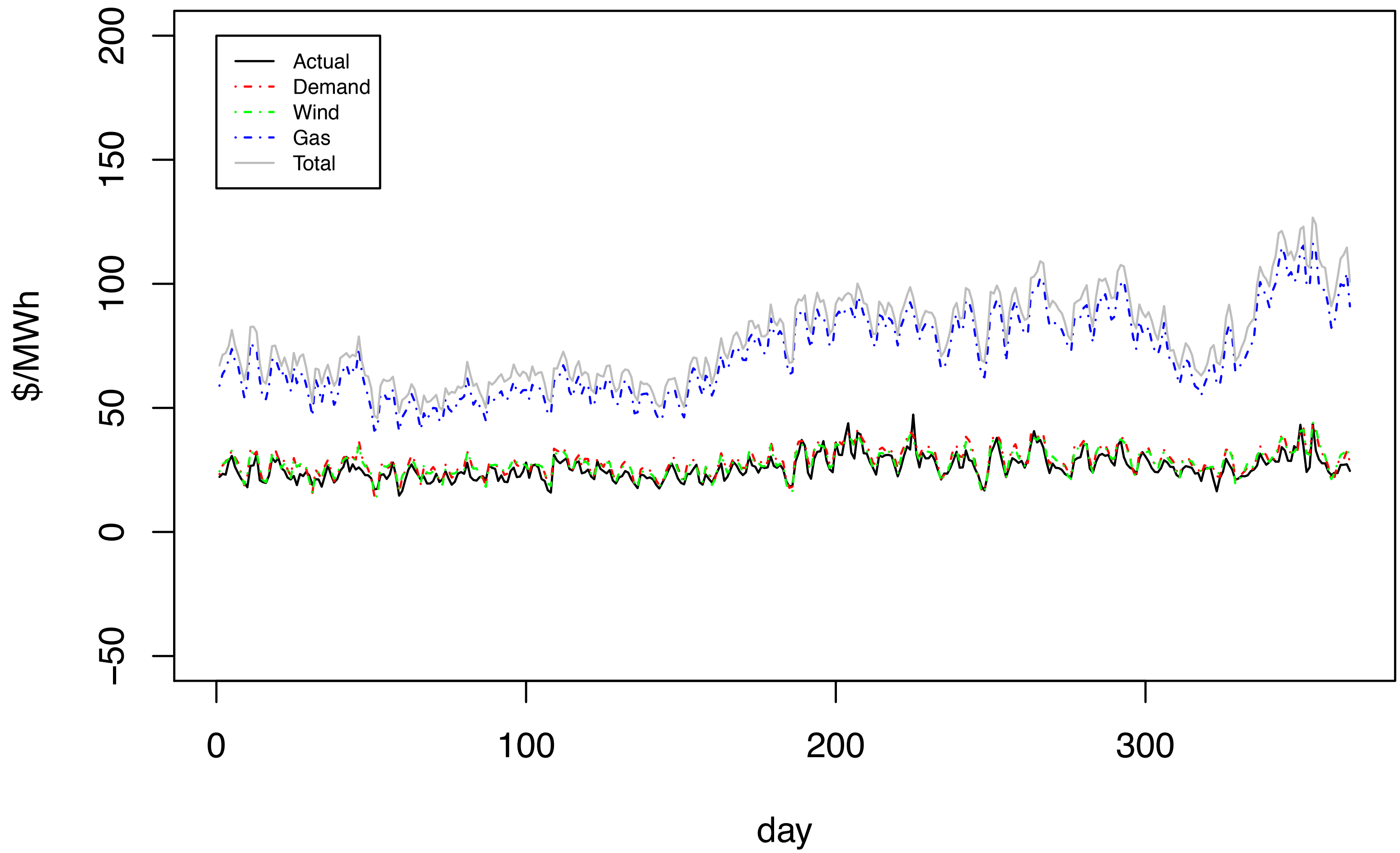

Figure Appendix A.4: Dresden (IL)

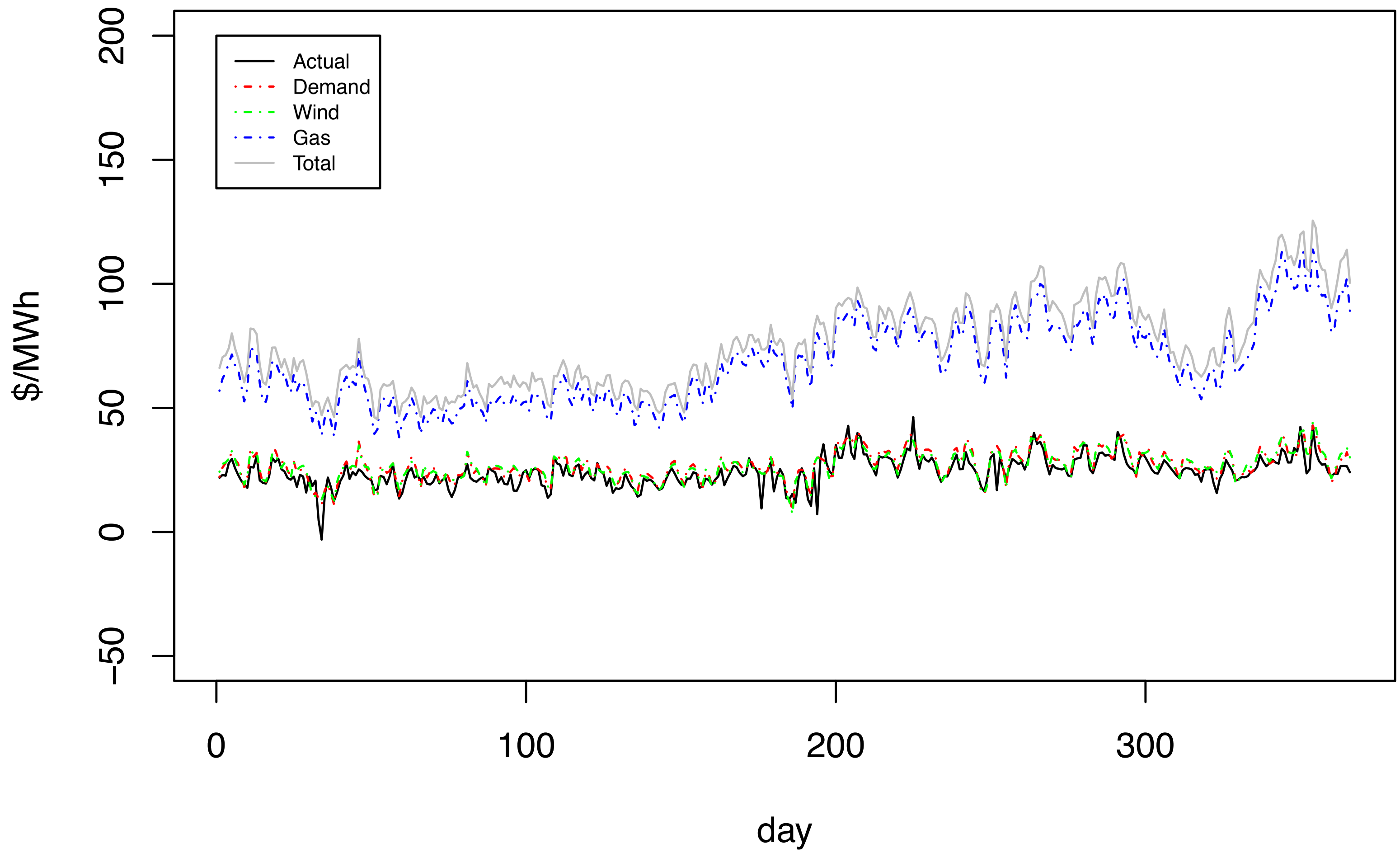

Figure Appendix A.5: Braidwood (IL)

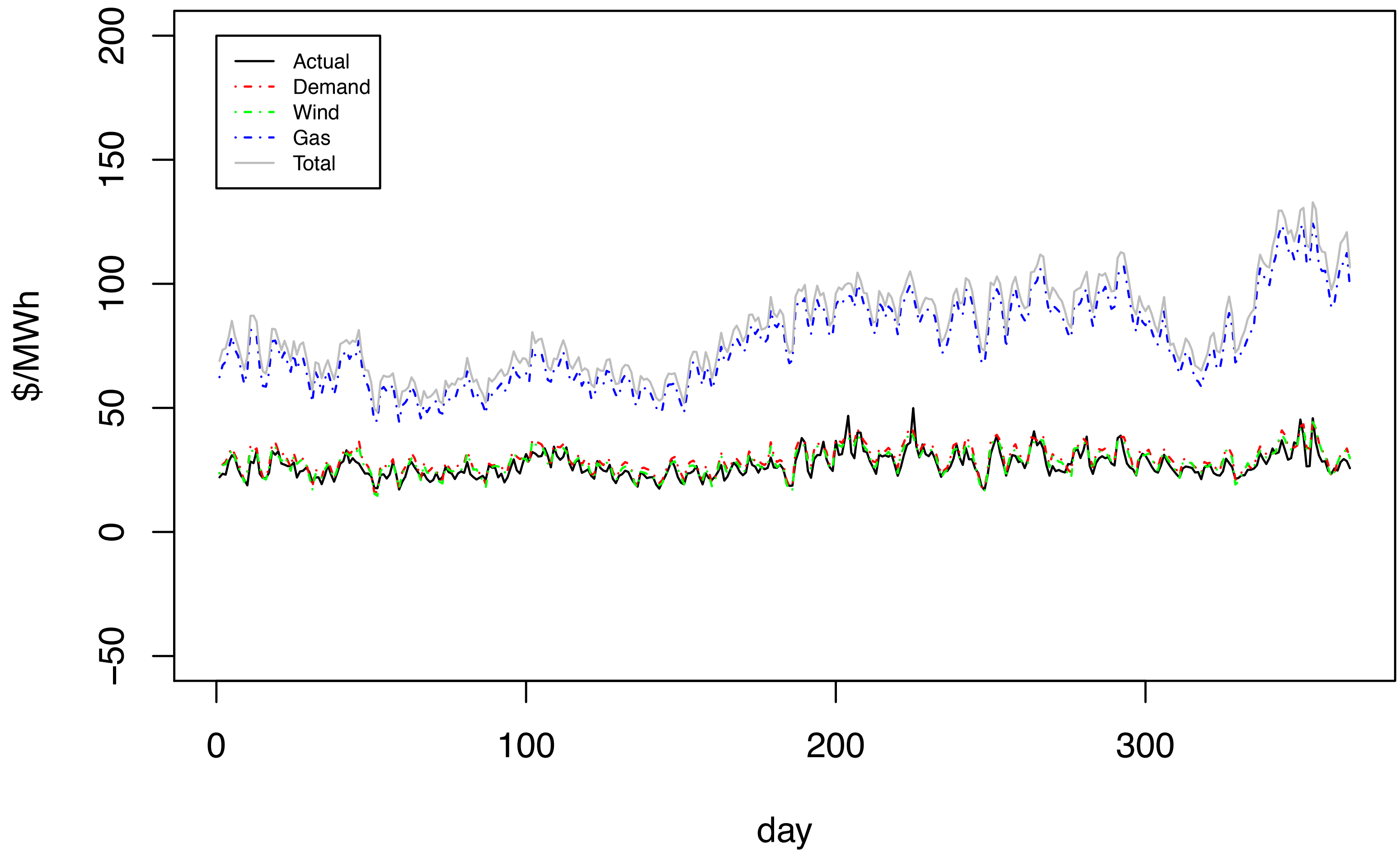

Figure Appendix A.6: Cook (WI)

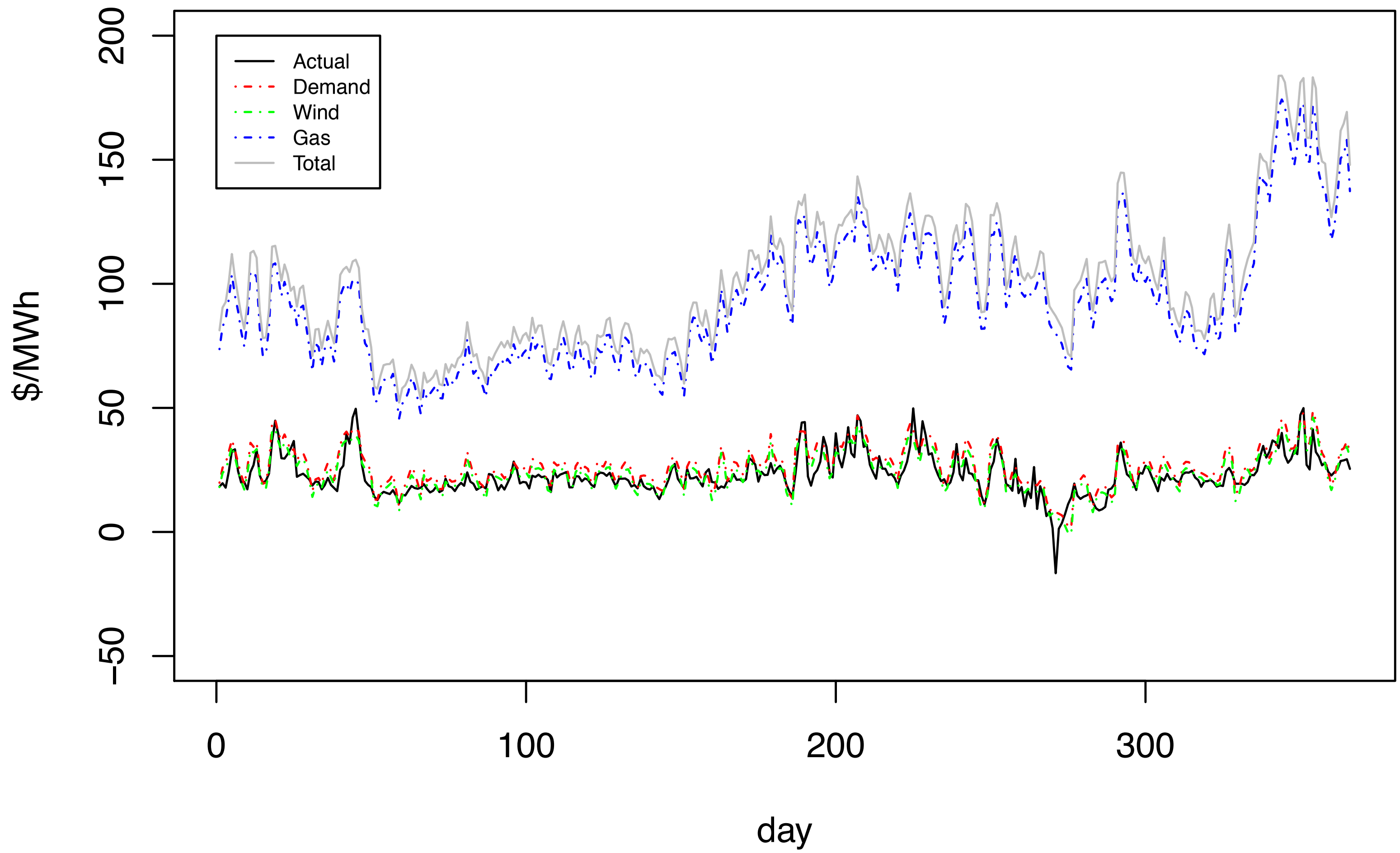

Figure Appendix A.7: Three Mile Island (PA)

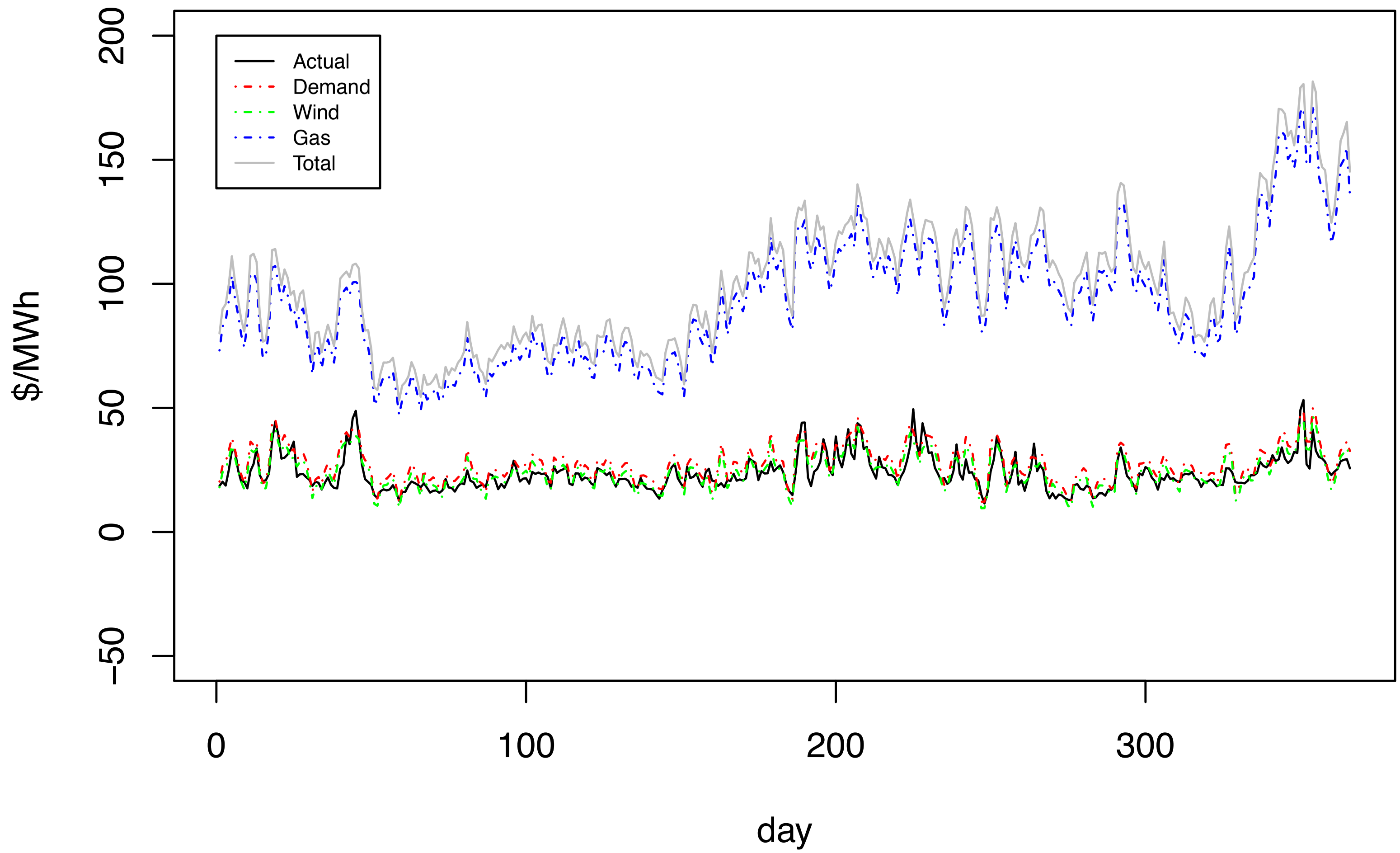

Figure Appendix A.8: Susquehanna (PA)

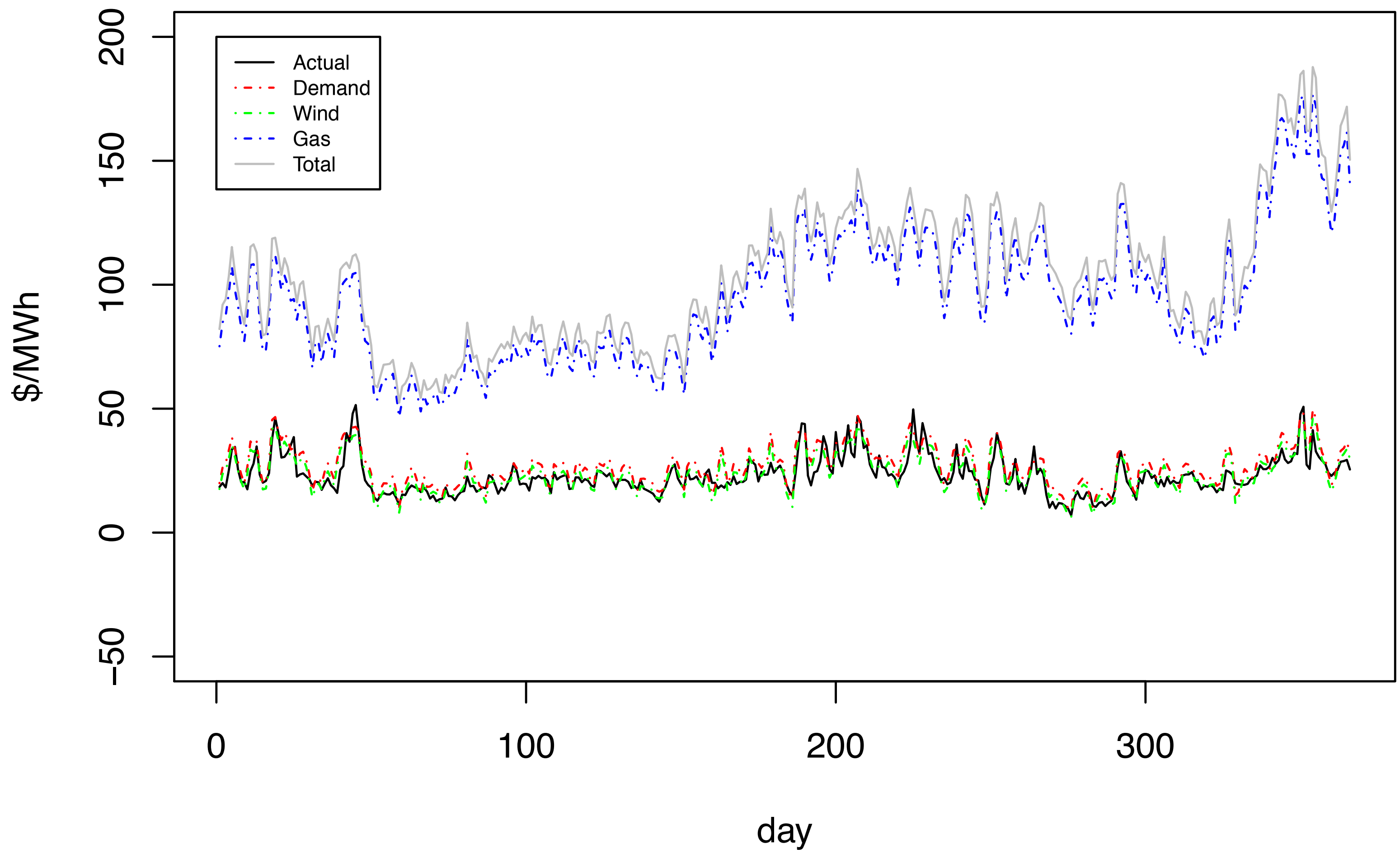

Figure Appendix A.9: Peach Bottom (PA)

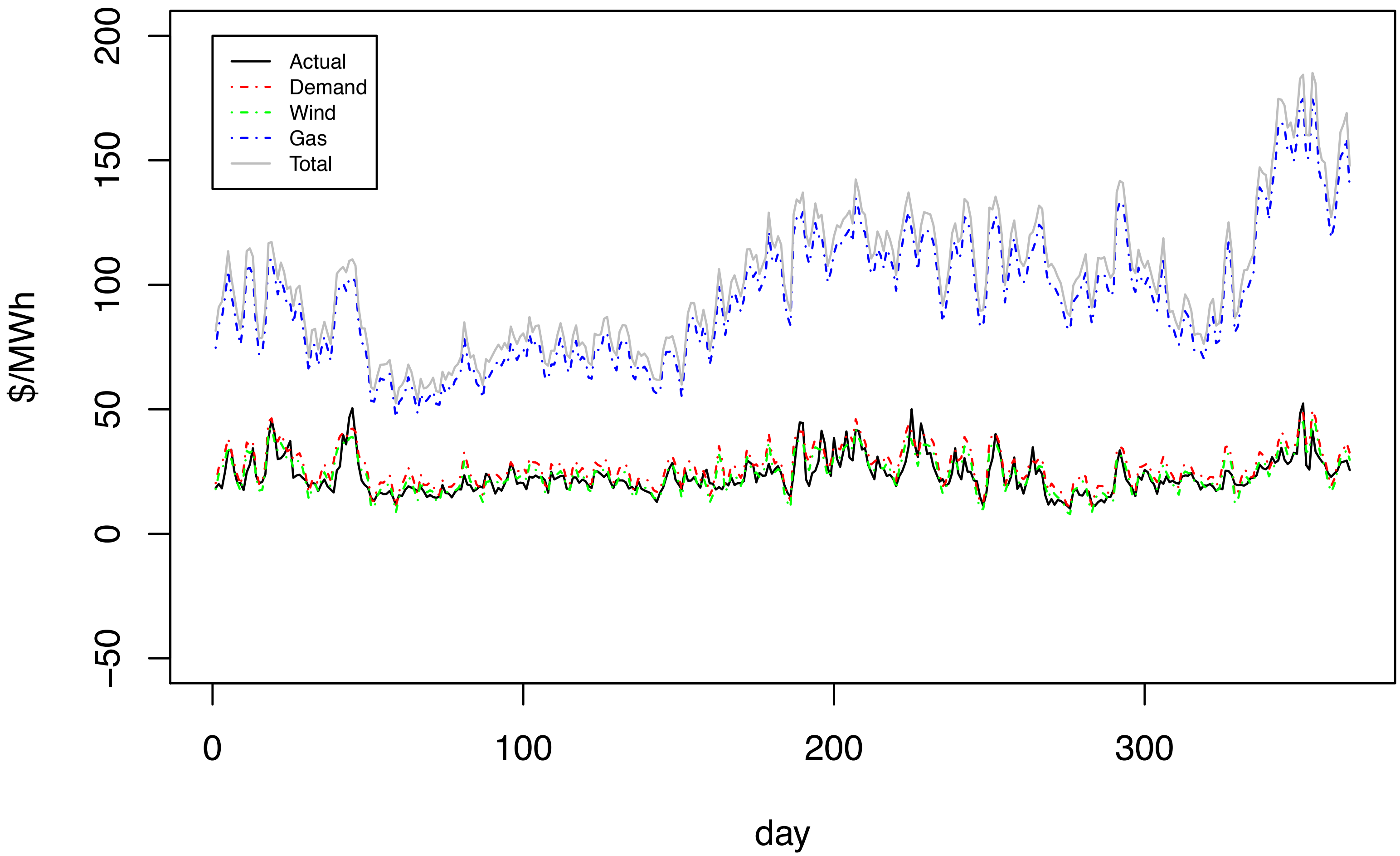

Figure Appendix A.10: Limerick (PA)

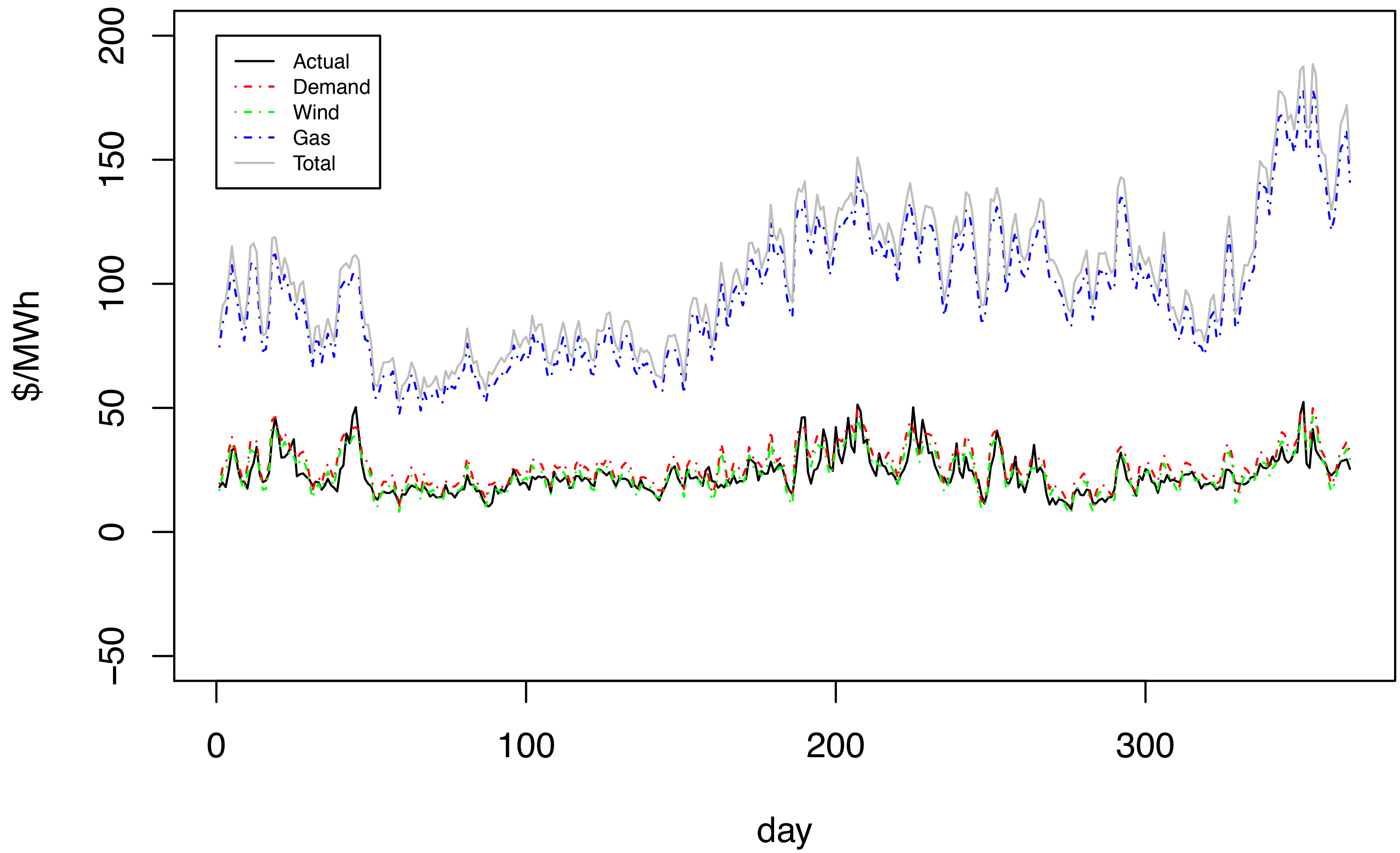

Figure Appendix A.11: Salem (NJ)

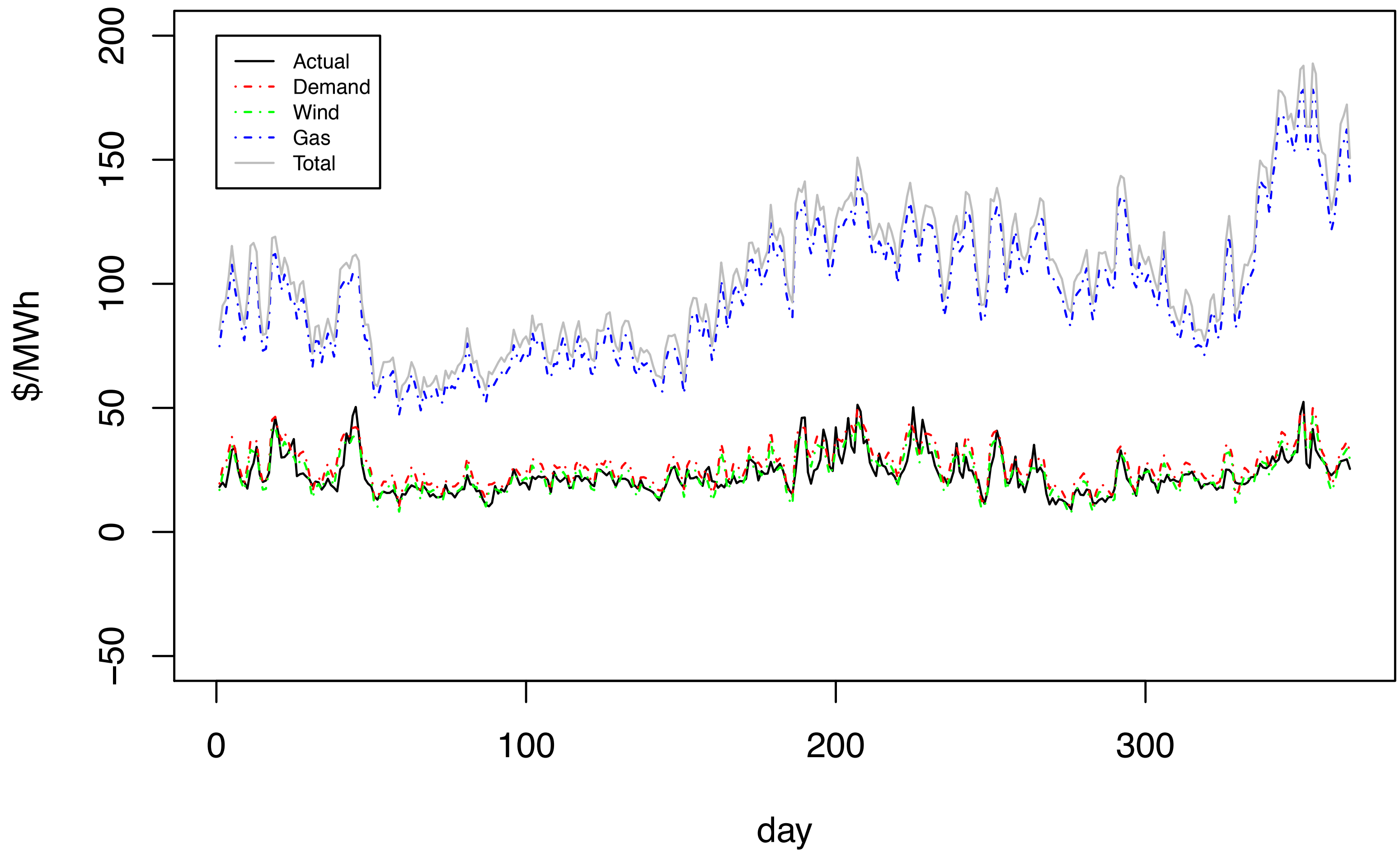

Figure Appendix A.12: Hope Creek (NJ)

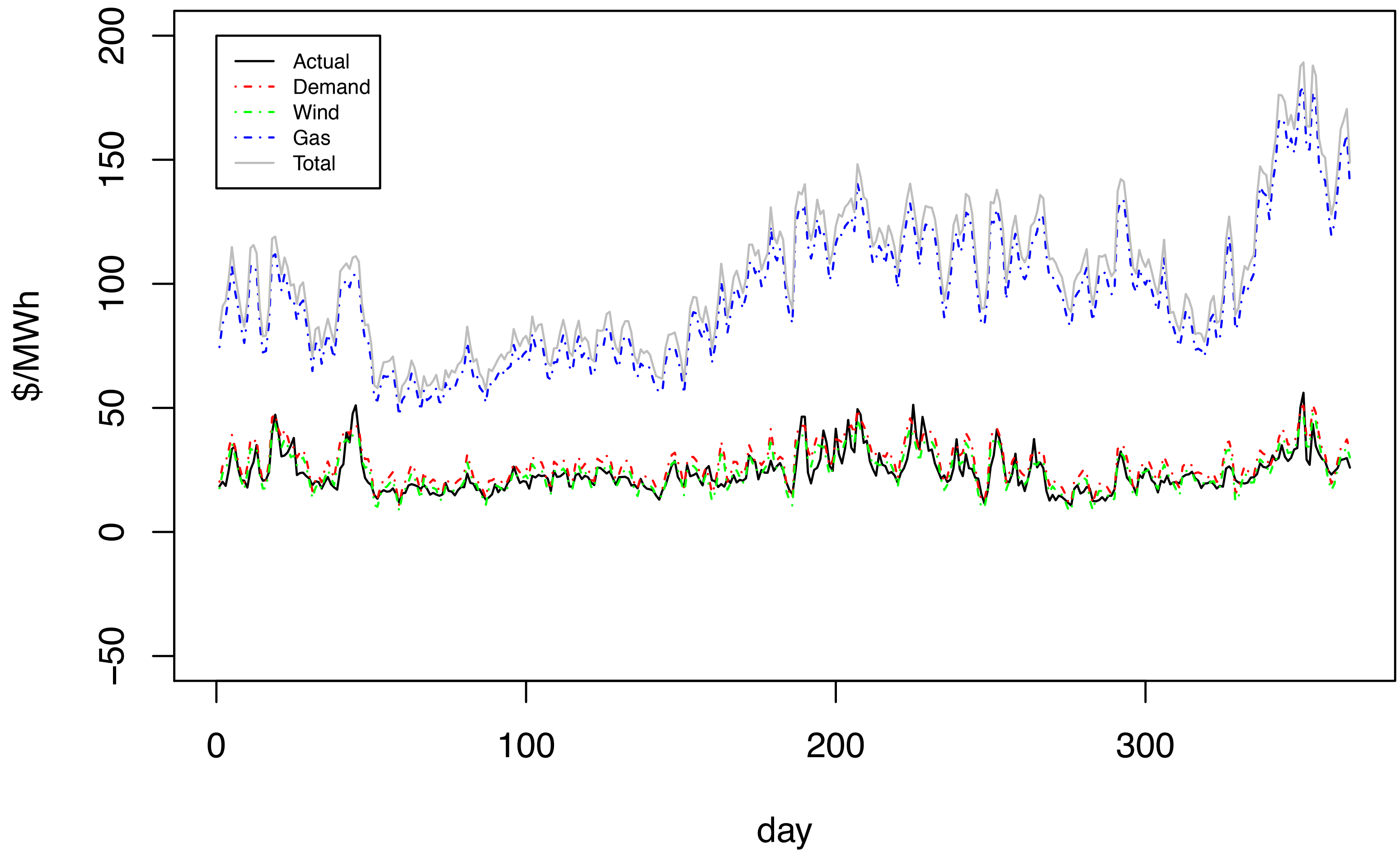

Figure Appendix A.13: Oyster Creek (NJ)

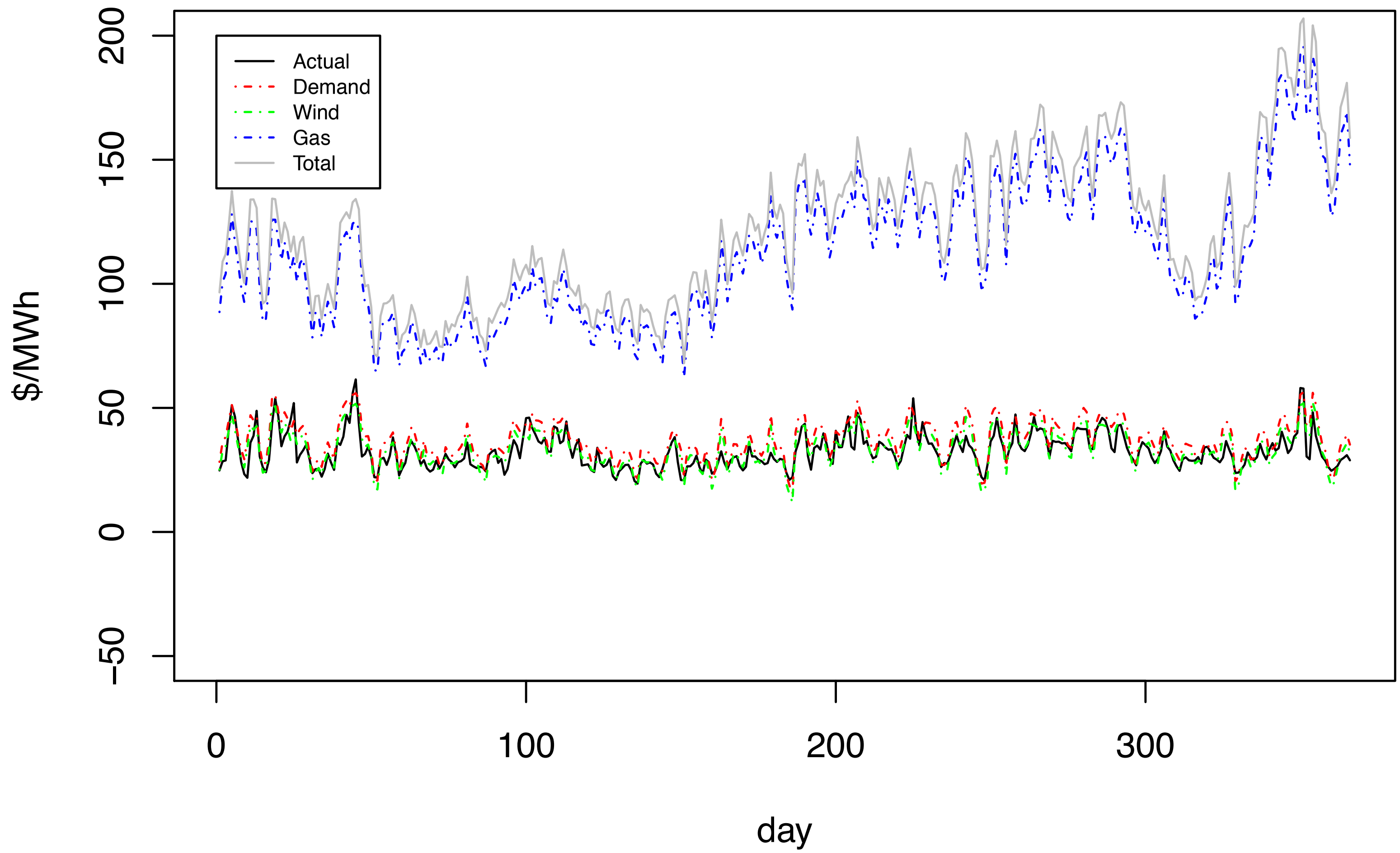

Figure Appendix A.14: Calvert Cliffs (MD)

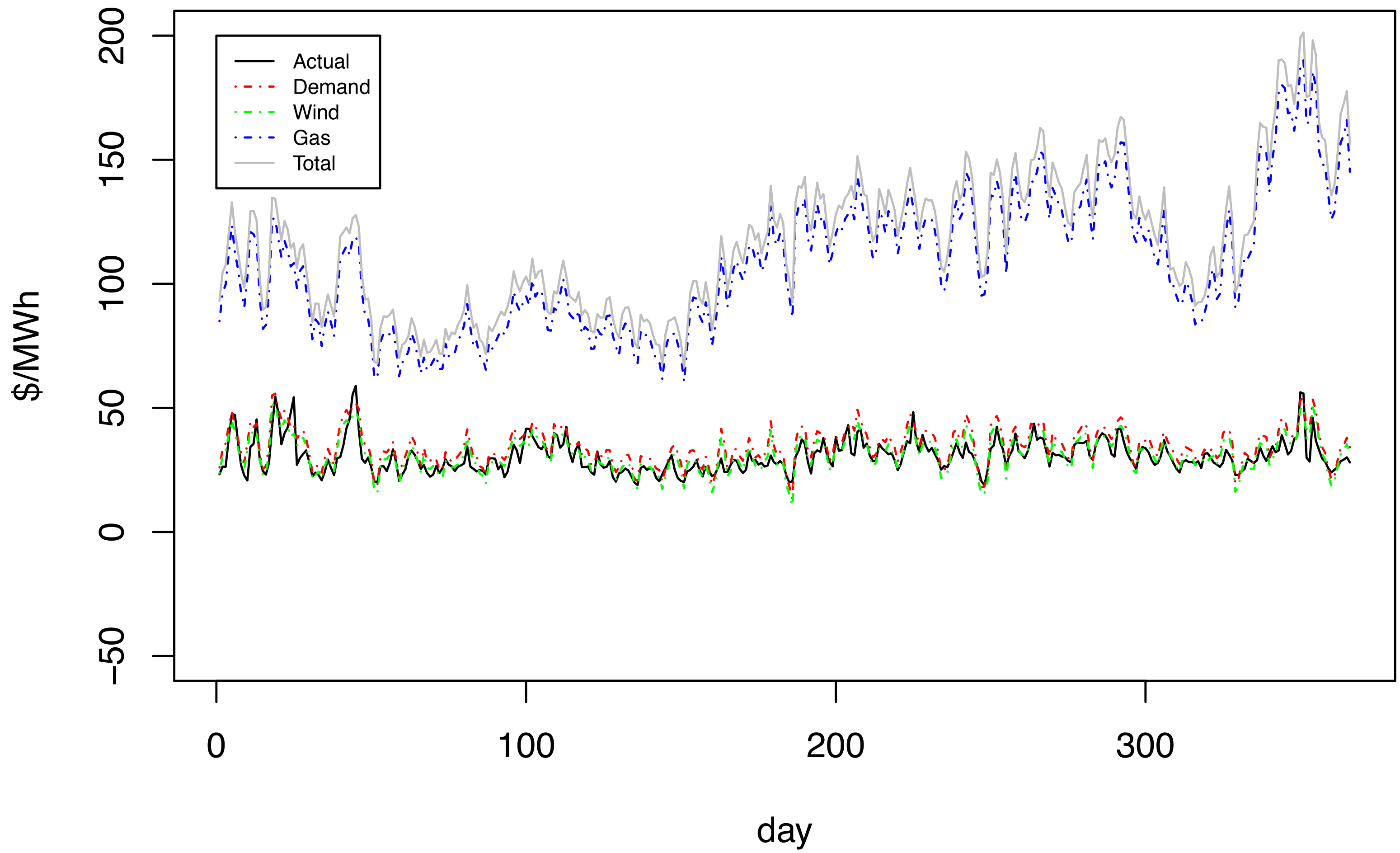

Figure Appendix A.15: North Anna (VA)

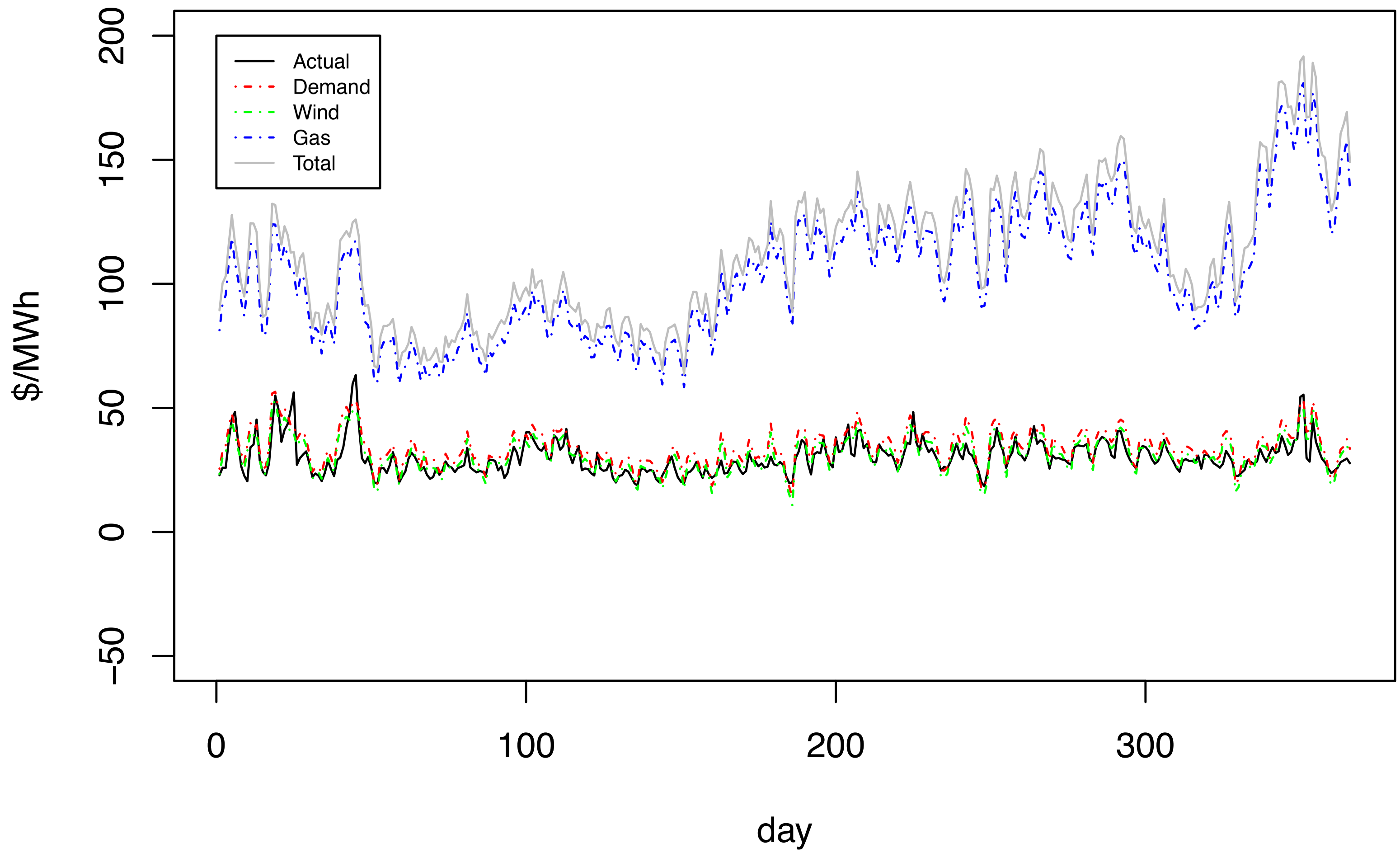

Figure Appendix A.16: Surry (VA)

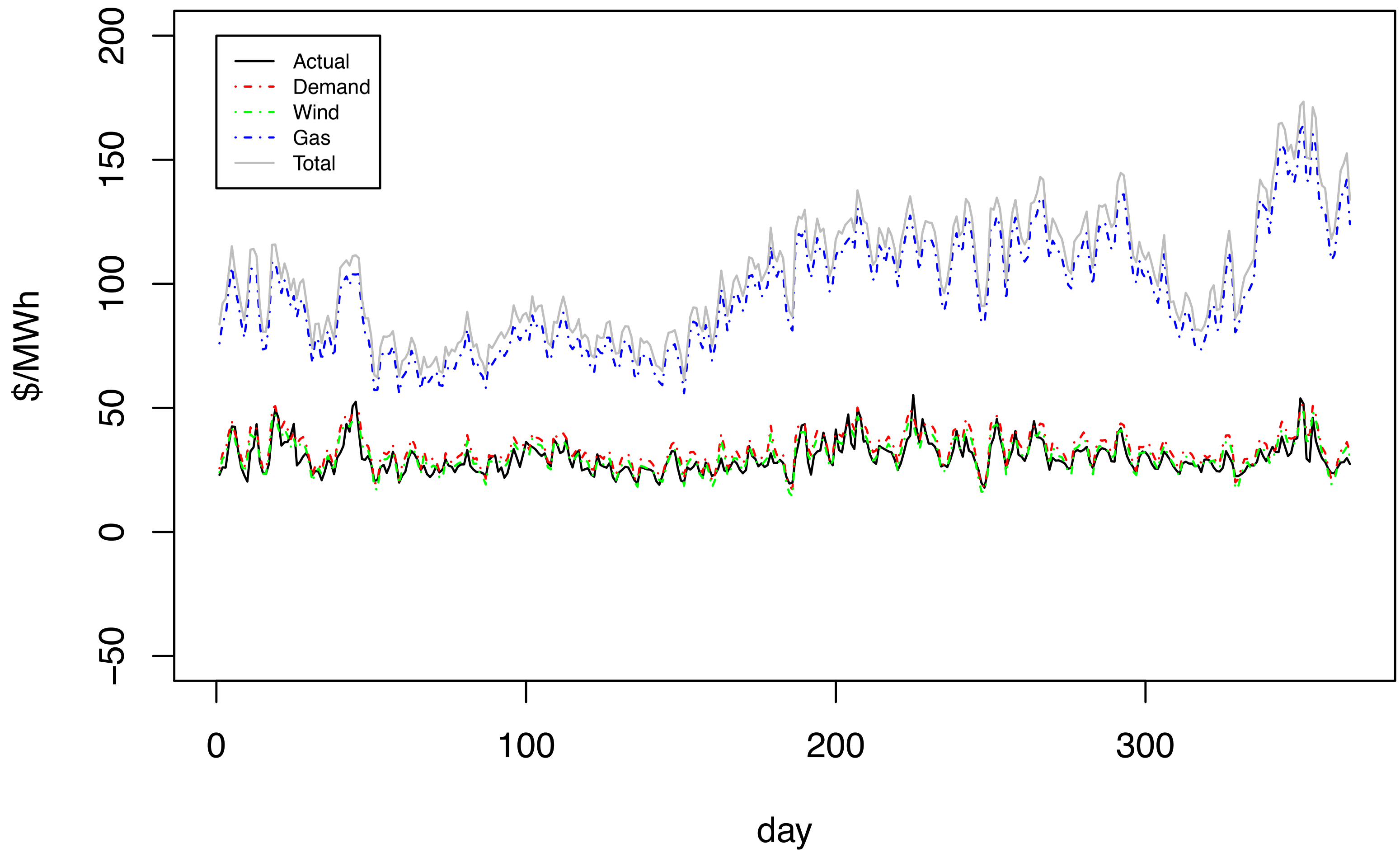

Figure Appendix A.17: PJM Weighted Average Nodal Price