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"Wind Power in the United States: Prospects and Consequences"

by

Peter R. Hartley

RICE
Department of Economics
Baker Hall, MS22
6100 Main Street, Houston, Texas 77005
https://economics.rice.edu

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Peter R. Hartley*
George & Cynthia Mitchell Professor of Economics
and Rice Scholar, James A. Baker III Institute for Public Policy
Rice University

1. Introduction

Wind power generating capacity installed in the United States has grown at an average annual rate of around 30% since 2000. A consequence of this rapid growth is that the demands for fossil fuels to generate electricity are likely to be lower than they otherwise would be. In order to understand the consequences for natural gas and coal demand, however, it is important to know whether the recent rapid growth in wind generation is likely to be maintained and what types of fossil fuel plants will be displaced by wind generation.

We examine these questions using data from Texas and the mid-west, where wind generation currently is concentrated. We find that in both locations, average wind capacity utilization[1] (hereafter called the *wind capacity factor*) has declined in recent years presumably despite continued technological change and operating improvements that might have led one to expect the opposite.

An important explanation in the case of Texas is that the construction of transmission capacity has lagged behind the construction of new wind farms, leading to substantial curtailment of wind generators. Texas has initiated a program to upgrade its transmission system, which will alleviate this problem. Nevertheless, the intermittent nature of wind output means that the new lines are likely to be under-utilized much of the time, making them very expensive. The high costs of connecting wind to the grid may ultimately limit the number of sites that will be developed.

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[1] This is defined as the actual amount of wind generation over a given time period (for example, hour, week, month or year) divided by the maximum possible output assuming all available wind had operated at full capacity throughout that time period.

By contrast, there was very little curtailment of wind generation in MISO, where the extent of wind development, and therefore the strain on transmission capacity, has not been as great as in west Texas. Furthermore, since major load centers are more dispersed in MISO than in ERCOT (where they are concentrated on the eastern edge of the region), power flows in MISO tend to be less unidirectional. Hence, new transmission lines in MISO are likely to operate at higher capacity. If so, the need to add transmission lines should also be less of a constraint on future wind development in MISO.

There is also some evidence that average wind speeds were lower in both regions in 2009 than in 2008. As we explain in more detail below, however, it is less clear that such a drop in average wind speed could explain a statistically significant drop in average hourly capacity utilization.

A third explanation for the recent drop in capacity utilization in both regions is that the most prospective sites that were not ruled out of contention by environmental or other considerations were chosen for development first. If so, future development might be constrained by fewer good sites being available.

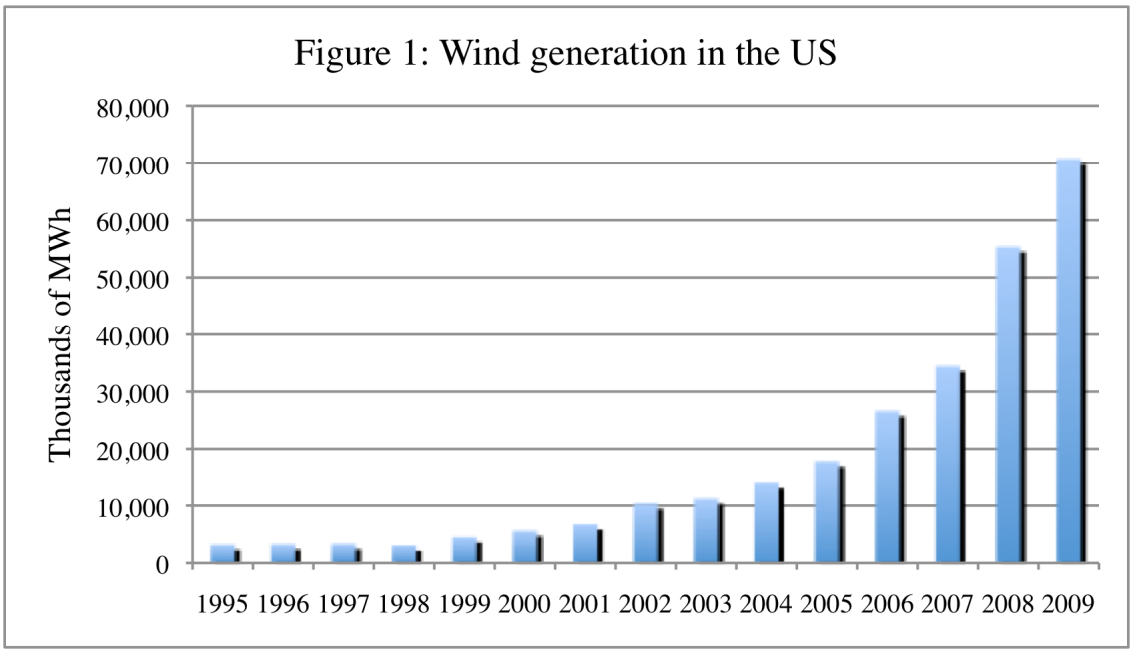
Simultaneously with the decline in the wind capacity factor, we find that wind capacity utilization has tended to vary less from one hour to the next. The most likely explanation is that as wind generation sites have become more dispersed, the correlation in output from different sites has declined. The reduced correlation across sites will assist with the assimilation of wind generation into the grid by making output from wind generators as a whole more predictable. On the other hand, the reduction in maximum wind capacity factor that has accompanied the decline in variability implies that wind can be relied upon less to provide significant output at times of emergency.

We also find some conflicting evidence on the types of fossil fuels that expanding wind generation will likely displace. On the one hand, we cite a number of studies that have shown that wind generation has, to date, displaced natural gas more than coal. This response, however, takes existing investments in different types of generating capacity as fixed. In the longer run, investors in new fossil fuel plants will respond to the pattern of demand for power *net* of anticipated wind output. We argue that this is likely to reduce the demand for new coal-fired capacity more than new natural gas capacity, while at the same time favoring single cycle gas

turbines over combined cycle natural gas plants. The net effect on the demand for natural gas in particular is likely to depend on the details of the power generating system. In particular, the ages and relative efficiencies of the different types of thermal plants currently operating in the system will have a significant effect on future investments made in response to anticipated increases in wind output.

2. Growth in wind generation in the US

Figure 1 shows net generation from wind in the US from 1995–2009. In the last decade the *annual* growth in wind generation has averaged almost 33%. Since the growth in wind generation has exceeded the growth in overall electricity output, the *proportion* of electricity generated from wind has grown from around 0.9% in the mid-1990s to almost 1.8% in 2009.



Source: Energy Information Administration

There are three major reasons for the observed growth in wind generation. First, most of the states have introduced financial incentives and regulations to encourage the use of renewable energy. Table 1 summarizes various financial incentives encouraging renewable energy production, while Table 2 summarizes rules and regulations supporting or actively promote renewable energy sources.

Table 1: Financial Incentives for Renewable Energy

	Personal tax	Corporate tax	Sales tax	Property tax	Rebates	Grants	Loans	Industry recruiting	Bonds	Production incentives
Federal	3	4				3	5	1		1
Alabama	1-S				2-U	1-S	1-S, 1-U			1-U
Alaska						1-S	2-S			1-U
Arizona	3-S	1-S	1-S	2-S	6-U		1-U	1-S		
Arkansas					1-S, 1-U		1-U			
California				1-S	6-S, 38-U, 2-L		2-S, 1-U, 2-L	1-S		1-S, 2-U
Colorado			2-S, 1-L	2-S	9-U, 1-L	1-S, 1-L	1-S, 3-U, 1-L			
Connecticut			2-S	1-S	3-S, 2-U	2-S	2-S, 1-P	2-S		
Delaware					1-S	2-S				
Florida		2-S	2-S		1-S, 10-U, 1-L		1-S, 5-U	1-L		2-U
Georgia	1-S	1-S	1-S		1-S, 9-U		1-U			2-U
Hawaii	1-S	1-S		1-L	1-S, 1-U		2-S, 2-U, 1-L	1-S		1-S
Idaho	1-S		1-S	1-S	1-S	1-P	1-S		1-S	1-P
Illinois			1-S	2-S	1-S, 3-U	1-S, 1-L, 1-P	1-S		1-S	1-P
Indiana	1-S			1-S	1-S, 4-U	1-S	1-U			1-U
Iowa	1-S	2-S	1-S	3-S	11-U	1-S	2-S, 1-U			1-U
Kansas				1-S	2-U		1-S	1-S		
Kentucky	1-S	2-S	1-S		7-U	1-S	1-S, 1-L, 1-P			1-U
Louisiana	1-S	1-S		1-S			2-S			
Maine			1-S		2-S	1-S	1-S, 1-P			1-S
Maryland	3-S	3-S	2-S	4-S, 7-L	4-S, 1-L	1-S	3-S	1-S		1-S
Massachusetts	1-S	2-S	1-S	1-S	3-S, 5-U	4-S	1-S, 1-U, 1-P	3-S		1-S, 1-P
Michigan				2-S	2-S, 3-U	2-S		4-S		1-U
Minnesota			2-S	1-S	4-S, 23-U	2-S, 2-U	6-S, 2-U			1-S, 1-U
Mississippi					4-U		1-S, 2-U			1-U
Missouri		1-S			1-S, 9-U		1-S, 1-U			
Montana	3-S	1-S		3-S	4-U	1-U	1-S	2-S		1-P
Nebraska			1-S		2-U		1-S			
Nevada			1-S	3-S	1-S, 1-U		1-S			
New Hampshire				1-S	1-S, 4-U		3-S, 1-P			

	Personal tax	Corporate tax	Sales tax	Property tax	Rebates	Grants	Loans	Industry recruiting	Bonds	Production incentives
New York	3-S	1-S	1-S	2-S, 1-L	6-S, 4-U	2-S	3-S, 1-L	2-S		
North Carolina	1-S	1-S	1-S	2-S	5-U	1-S	3-S, 1-U			3-U, 1-P
North Dakota	1-S	1-S		2-S	1-U		2-U			
Ohio		1-S	1-S	1-L	5-U, 1-P	6-S	2-S, 1-U, 1-L	1-S		
Oklahoma		1-S			3-U		4-S, 2-U	1-S		
Oregon	1-S	1-S		1-S	8-S, 21-U	2-S, 1-P	3-S, 9-U	1-S		1-S, 1-U, 1-P
Pennsylvania				1-S	1-S, 1-U, 1-L	8-S, 1-U, 2-L	6-S, 1-U, 5-L	3-S		
Rhode Island	1-S	1-S	1-S	2-S	1-U	1-S	1-S, 1-P			1-P
South Carolina	1-S	2-S	1-S		1-S, 5-U		1-S, 5-U			1-S, 2-U, 1-P
South Dakota			1-S	2-S	1-S, 4-U		2-U			
Tennessee				1-S	1-U	2-S	2-S, 1-U	1-S		1-U
Texas		1-S		1-S	20-U, 2-L	2-S	2-S	1-S		2-U
Utah	1-S	1-S	1-S		6-U			1-S		
Vermont	1-S	1-S	1-S	1-S	1-S	2-S, 1-U	2-S, 1-P			1-S, 2-U
Virginia				1-S	3-S		1-S	2-S		1-U
Washington			1-S		16-U	1-L, 1-P	13-U	1-S		1-S, 3-U, 1-P
West Virginia	1-S	1-S		1-S						
Wisconsin			1-S	1-S	7-S, 4-U	1-S, 2-U	2-S, 1-U, 1-L	2-S		5-U
Wyoming			1-S		1-S, 3-U		2-U			
D.C.					1-S					
Totals	37	38	37	60	340	68	162	36	3	59

Source: Energy Information Administration, DSIRE database. Note that S = State/Territory, L = Local, U = Utility, P = Private

Table 2: Rules, Regulations & Policies for Renewable Energy

	"Pubic benefit fund" (PBF) surcharge to support rebates	Renewable Portfolio Standards	Net metering (retail prices paid for self-generated power)	Inter-connection standards for renewables	Licensing for renewable energy contractors	Equipment certification requirements	Laws safe-guarding access to solar or wind resources	Construction and design energy codes	Utilities required to offer a green power option
Federal				1				1	
Alabama									
Alaska			1-S				1-S		
Arizona		1-S	1-S, 1-U	1-S	1-S	1-S	1-S	3-S, 4-L	
Arkansas			1-S	1-S				1-S	
California	1-S	1-S	1-S	1-S	1-S		2-S, 8-L	3-S, 8-L	
Colorado	1-L	1-S, 1-L	1-S	1-S			1-S, 1-L	3-S, 4-L	1-S
Connecticut	1-S	1-S	1-S	1-S	1-S			2-S	
Delaware	1-S, 2-U	1-S	1-S	1-S			1-S	1-S	1-S
Florida		1-U	1-S	1-S	1-S	1-S	1-S, 1-L	1-S	
Georgia			1-S	1-S			1-S	1-S, 1-L	
Hawaii	1-S	1-S	1-S	1-S	1-S		1-S	2-S	
Idaho			3-U				1-S		
Illinois	1-S	1-S	1-S	1-S				2-S	
Indiana			1-S	1-S			1-S	1-S, 1-L	
Iowa		1-S	1-S	1-S			1-S		1-S
Kansas		1-S	1-S	1-S			1-S	1-L	
Kentucky			1-S	1-S			1-S		
Louisiana			1-S, 1-L	1-S					
Maine	1-S	1-S	1-S	1-S	1-S		2-S	2-S	1-S
Maryland		1-S	1-S	1-S			1-S	1-S	
Massachusetts	2-S	1-S	1-S	1-S			1-S	3-S	
Michigan	1-S	1-S	1-S	1-S	1-S			2-S, 1-L	
Minnesota	1-S	2-S	1-S	1-S		1-S	1-S	1-S	
Mississippi									
Missouri		1-S, 1-L	1-S	1-S			1-S	1-S	
Montana	1-S	1-S	1-S, 1-U	1-S			1-S		1-S
Nebraska			1-S	1-S			1-S		
Nevada		1-S	1-S, 1-U	1-S	1-S		1-S		
New Hampshire		1-S	1-S	1-S			1-S		
New Jersey	1-S	1-S	1-S	1-S			2-S	4-S	
New Mexico		1-S	1-S, 1-U	1-S			1-S	1-S	1-S
New York	1-S	1-S, 1-U	1-S, 1-U	1-S			1-S	2-S, 1-L	
North Carolina		1-S	1-S	1-S			1-S, 1-L	2-S, 11-L	

	"Pubic benefit fund" (PBF) surcharge to support rebates	Renewable Portfolio Standards	Net metering (retail prices paid for self-generated power)	Inter-connection standards for renewables	Licensing for renewable energy contractors	Equipment certification requirements	Laws safe-guarding access to solar or wind resources	Construction and design energy codes	Utilities required to offer a green power option
North Dakota		1-S	1-S				2-S		
Ohio	1-S	1-S	1-S	1-S			1-S	1-S	
Oklahoma			1-S					1-S	
Oregon	1-S	1-S	1-S, 1-U	1-S	1-S	1-S	1-S, 2-L	3-S, 1-L	1-S
Pennsylvania	1-S	1-S	1-S	1-S				1-S	
Rhode Island	1-S	1-S	1-S				1-S	1-S	
South Carolina			3-U	1-S				1-S	
South Dakota		1-S		1-S			1-S	2-S	
Tennessee							1-S		
Texas		1-S, 1-U, 1-L	1-U	1-S				2-S, 5-L	
Utah		1-S	1-S, 3-U	1-S	1-S		1-S	1-L	
Vermont	1-S	1-S	1-S	1-S			1-S		
Virginia		1-S	1-S	1-S			2-S	1-S, 1-L	1-S
Washington		1-S	1-S, 1-U	1-S			1-S	1-S, 1-L	1-S
West Virginia		1-S	1-S						
Wisconsin	1-S	1-S	1-S	1-S	1-L		1-S1-L	1-S	
Wyoming			1-S	1-S					
D. C.	1-S	1-S	1-S	1-S				1-S	
Totals	23	43	63	43	11	4	56	97	9

Source: Energy Information Administration, DSIRE database. Note that S = State/Territory, L = Local, U = Utility, P = Private

The most significant financial and regulatory provisions are production tax credits, other favorable tax provisions and renewable portfolio standards. Currently the production tax credit is a $21/MWh benefit that can be used to offset other tax liabilities for the first ten years of operation of a renewable energy facility. As of August 2009 firms can instead take an investment tax rebate, or take a grant from the US Treasury Department, for 30% of capital costs. Renewable generation also benefits from a 5-year accelerated depreciation schedule. In other words, the cost can be depreciated over a 5-year period even though the useful life of the installation is much greater.

Renewable portfolio standards (RPS) require specified percentages of power sold in the state to be produced from renewable sources. As of April 2010, 29 states and the District of Columbia have legislated an RPS. Although the definition of "renewable" varies from state to state, in every state wind generation is included.

As an example of an RPS, Electric Reliability Council of Texas (ERCOT) region[2] implements its RPS using a renewable energy credit (REC) trading program. The state has established targets of 4264 MW of renewable capacity by January 2011, 5256 MW by January 2013 and 5880 MW by January 2015. These MW goals originally were translated into MWh energy requirements by assuming renewable facilities operated at 35% capacity, but are now based on the actual performance of the resources in the REC-trading program for the previous two years. Each retailer in Texas is required to purchase a quantity of RECs equal to the overall state mandate for renewable sources multiplied by that retailer's pro rata share of statewide retail energy sales. RECs can be banked for three years, and all renewable additions have a minimum of 10 years of credits to recover over-market costs. An administrative penalty of $50 per MWh has been established for providers that do not meet the RPS requirement. The market value of the RECs provides an additional subsidy to renewable energy production.

The second explanation for the dramatic growth in wind generation in recent years is that, among sources of renewable energy covered by the financial incentives and regulations (which generally do not include the largest renewable energy source, hydroelectricity), wind is currently the least uncompetitive with fossil fuels. The *Annual Energy Outlook*, 2009 from the Energy

[2] The ERCOT region is a subset of the state of Texas, with some counties in the panhandle, east and southeast border area and the far west included in neighboring North American Electric Reliability Corporation (NERC) regions.

Information Administration (EIA) provides estimates of the costs of new central station electricity generating technologies. Their figures imply that the cost of new onshore wind capacity is about double the cost of combined cycle gas turbines (CCGT), while offshore wind is around four times as expensive. By comparison, solar thermal is more than five times, and solar photovoltaic more than six times, as expensive.[3] In addition, fixed operating and maintenance (O&M) cost of onshore wind is around two and a half times the corresponding fixed O&M for CCGT, although the latter also has fuel costs. The corresponding ratio is around 7 for offshore wind, while fixed O&M costs for solar photovoltaic are similar to the fixed O&M costs for CCGT. Overall, however, onshore wind has the lowest costs of the renewable energy sources covered by the regulations and subsidies.

Although wind generation is closer to competing with fossil fuel generation than the other technologies covered by the financial incentives and regulations, it still requires assistance to compete with conventional plants on a cost basis. This was seen, for example, in 2000, 2002 and 2004 when new wind capacity additions declined following the expiration of the production tax credit in each preceding year. In each case, new capacity additions increased again as soon as the tax credits were re-authorized.

A third explanation for the dramatic growth in wind generation in recent years is that the US has substantial wind resources close enough to large markets that development was possible at reasonable cost. Specifically, as Figure 2 from NREL indicates, large parts of the central plains have "good" to "excellent" wind generating resources (corresponding to a wind speed of 7–8 m/s, at 50 meters).

[3] These costs do not account for the lower average capacity factor of intermittent sources such as wind or solar, which would make the capital costs of the renewable sources even more expensive per unit of effective capacity.

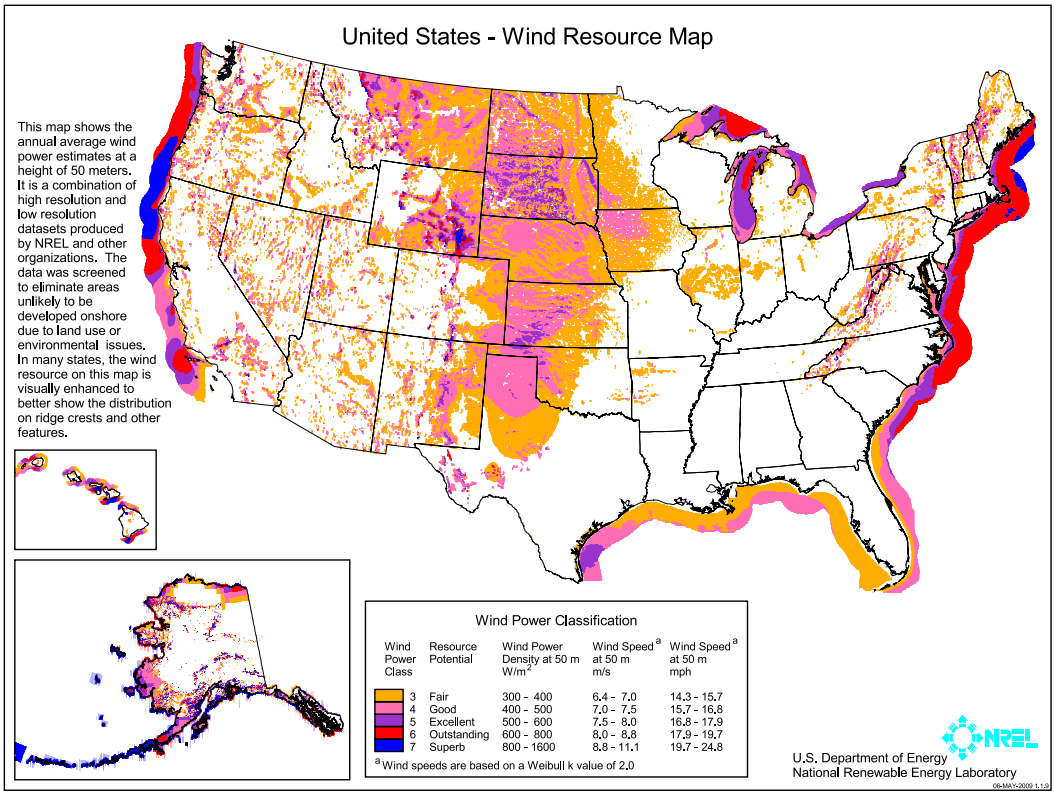


Figure 2: United States wind resources

Parts of the east and west coasts and the Great Lakes have even better resources. However, as we saw above, offshore wind is more expensive to develop than onshore wind farms. Furthermore, substantial parts of the northeast, California and Lake Michigan coasts have already been, or no doubt will be, ruled out for development based on objections that the wind towers would be unsightly to nearby residents[4] and may interfere with plane or shipping movements.[5] Some have also objected to wind development on the Gulf of Mexico coast on the

[4] People would object more strongly if the structures stop producing significant electricity output. Where firms have not been required to post a bond to guarantee they can decommission wind generators, there is a concern that dismantling wind farms may burden future taxpayers. A recent study in West Virginia (available at http://www.wind-watch.org/documents/wind-decommissioning-costs-lessons-learned/) suggested that the value of salvaged material would not be sufficient to pay for decommissioning costs. In another recent study (http://puc.sd.gov/commission/dockets/electric/2008/el08-031/Appendix%20h.pdf), the Public Utilities Commission of South Dakota reached a similar conclusion, but concluded that since the firm constructing the project "is the world's fourth largest electric utility and an A-rated company" a bond would not be required.

[5] Studies have shown that wind turbines can interfere with radar, potentially raising concerns about air traffic control, weather warning systems based on radar and, especially in the case of offshore installations, national security. These issues were discussed in a 2006 Department of Defense report to Congress (http://www.defense.gov/pubs/pdfs/WindFarmReport.pdf). It concludes that, "Only three methods so far have been

grounds that it may adversely affect migratory birds. In addition, the effect of hurricanes on offshore oil and gas platforms has raised doubts about the viability of wind generators along the Gulf of Mexico and south Atlantic coastlines. The relatively low population densities in the plains states, however, have made them less susceptible to objections and planning constraints.

Wind resources alone are not sufficient to make wind commercially viable. Access to a suitable market also is necessary. Furthermore, the generally low capacity factor of wind generators raises the costs of electricity transmission. The capacities of the lines have to be sufficient to handle maximum output from the wind generators, but for much of the time the lines will be utilized at far below their rated capacity. The remoteness of the areas with at least "good" wind resources, especially in Texas, means that existing transmission lines in those regions have low capacity. Hence, new lines need to be constructed to accommodate the wind output. As a result, wind resources that are remote from suitable markets generally will cost far too much to develop relative to the revenue derived from the electricity that they produce.

Figure 3 illustrates the location of the major electricity demand centers in the US. More specifically, it gives the location and size of the major generating facilities regardless of fuel source or type. While these do not necessarily correspond to large demand sinks, they tend to be located in or near the large population centers or centers of industry. Also, electricity demand in Arizona and the Southeast is larger than population alone might indicate in part because of the heavy demand for air conditioning.

Table 3 presents the total wind capacity in MW and also wind generation as a percentage of total generating capacity in each state in 2007 and 2008. Juxtaposing Figures 2 and 3, it is not surprising that Texas has the largest wind capacity of any state. In addition, the Public Utility Commission of Texas reports[6] that as of December 28, 2009 Texas had a total of 9,652 MW of wind generation capacity, with 150 MW of wind generation capacity under construction and an additional 9,340 MW announced. The states with the highest *proportions* of wind capacity are Iowa, North Dakota, Minnesota and Wyoming (in that order) followed by Oregon and Colorado before Texas in 7th place.

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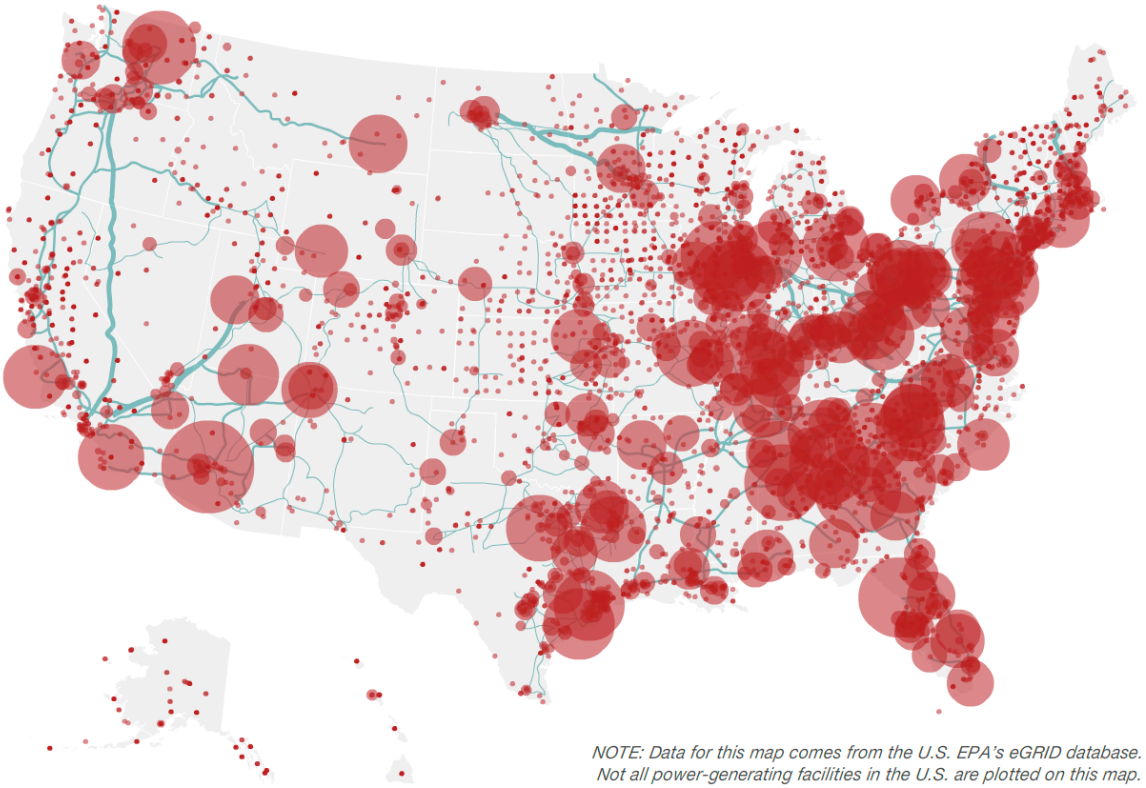
proven to be completely effective in preventing any impairment of primary radar systems. Employment of these or other approaches that could produce marginal, but acceptable, impacts on defense capabilities need to be assessed on a case-by-case basis."

[6] See the report on New Electric Generating Plants in Texas available at http://www.puc.state.tx.us/electric/maps/index.cfm



Source: http://www.npr.org/news/graphics/2009/apr/electric-grid/

Figure 3: Major generating facilities in the US

Wind generation is, however, spreading beyond the plains states. The three states with the largest percentage growth in wind capacity between 2007 and 2008 were Michigan, Wisconsin and West Virginia, followed by the plains states of South Dakota, Missouri, Wyoming, Iowa, Kansas and North Dakota.

In the subsequent more detailed analysis we will focus on the ERCOT and Midwest Independent System Operator (MISO) NERC regions. The latter covers the states of Minnesota, North Dakota, Wisconsin and parts of Montana, South Dakota, Iowa, Missouri, Illinois, Indiana, Michigan and Ohio.

Table 3: Wind generation capacity (MW) in the United States, 2007, 2008

	2007			2008		
	All capacity	Wind capacity	Wind percent	All capacity	Wind capacity	Wind percent
AK	2163	3	0.139	2190	3	0.137
AL	33230	0	0	33936	0	0
AR	16462	0	0	16461	0	0
AZ	28730	0	0	29034	0	0
CA	68522	2318	3.383	68695	2371	3.451
CO	13735	1065	7.754	14178	1065	7.512
CT	8561	0	0	8604	0	0
DC	868	0	0	850	0	0
DE	3525	0	0	3525	0	0
FL	63145	0	0	63318	0	0
GA	39767	0	0	39641	0	0
HI	2674	64	2.393	2675	64	2.393
IA	13389	1170	8.739	14842	2661	17.929
ID	3518	75	2.132	3751	117	3.119
IL	48654	740	1.521	48980	962	1.964
IN	30050	0	0	30133	131	0.435
KS	12200	363	2.975	13037	812	6.228
KY	23351	0	0	23617	0	0
LA	30158	0	0	30153	0	0
MA	15299	2	0.013	15225	2	0.013
MD	13442	0	0	13548	0	0
ME	4522	42	0.929	4529	47	1.038
MI	33037	2	0.006	33164	124	0.374
MN	13984	1139	8.145	15678	1481	9.446
MO	22195	57	0.257	22320	163	0.730
MS	18184	0	0	17826	0	0
MT	5658	165	2.916	5756	271	4.708
NC	29654	0	0	29647	0	0
ND	5346	383	7.164	5804	841	14.490
NE	7422	71	0.957	7421	71	0.957
NH	4494	0	0	4518	24	0.531
NJ	20154	8	0.040	20136	8	0.040
NM	7934	494	6.226	8794	496	5.640
NV	11526	0	0	13024	0	0
NY	42769	425	0.994	42248	707	1.673
OH	36707	7	0.019	36442	7	0.019
OK	21901	689	3.146	22266	708	3.180
OR	13802	886	6.419	13910	1068	7.678
PA	49176	293	0.596	49374	361	0.731
RI	2022	0	0	2020	0	0
SC	25078	0	0	25698	0	0
SD	3127	43	1.375	3374	193	5.720
TN	22962	29	0.126	22997	29	0.126
TX	111098	4490	4.041	113688	7431	6.536
UT	7521	0	0	7555	19	0.251
VA	25270	0	0	25642	0	0
VT	1090	6	0.550	1108	6	0.542
WA	28720	1163	4.049	29912	1366	4.567
WI	16976	53	0.312	18472	365	1.976
WV	16986	66	0.389	17250	330	1.913
WY	7036	287	4.079	7524	680	9.038
US total	1087791	16596	1.526	1104486	24980	2.262

Source: Environmental Protection Agency, State Historical Tables, 2008

3. Previous analyses of the effect of wind generation on other fuel use

A major issue of concern in this paper is how a continued expansion in wind generation is likely to affect the demand for fossil fuels. A number of studies have looked at this question. The ERCOT region has been the focus of the most detailed analysis. The general conclusion has been that wind has primarily displaced generation from combined-cycle natural gas facilities.

Using an economic simulation, GE Energy (2008) projected that about 80 percent of wind generation would displace output from combined cycle facilities. Reductions in coal generation accounted for most of the remaining 20 percent. This contrasts with the fact that the proportion of natural gas in the fuel mix was 42.1 percent in 2009 (ERCOT 2010). Cullen (2008) uses historical ERCOT data from April 2005 through April 2007 to reach a very similar result that every MWh of wind production reduced natural gas and coal generation by 0.81 and 0.19 MWh respectively. Both analyses found that nuclear and hydro were unaffected by wind.

An overview of how generation by fuel type has changed over the past couple of years in ERCOT also provides support for the hypothesis that wind has primarily affected natural gas. Between 2007 and 2009, natural gas generation fell 3.4 percentage points, while coal only fell by 0.8 percentage points to 36.6 percent and nuclear actually rose by 0.2 percentage points (ERCOT 2010).

GE Energy (2008) explains that much combined cycle generation is likely to be turned off during overnight hours, with wind displacing it. In its high-wind scenario (15,000 MW), combined cycle output occasionally fell to near zero during nighttime periods with low load.[7] Assuming 75 percent of wind generation displaces gas in ERCOT, the natural gas capacity factor in ERCOT could fall from 30 percent to 21 percent by 2013 (Blossman, Followill, and Chipman 2009).

Several analyses have suggested that wind will displace proportionally more coal outside of ERCOT. Wynne et al. (2009) examined four Regional Transmission Organizations (RTOs), namely ERCOT, the Midwest Independent System Operator (MISO), Southwest Power Pool

[7] The *load* on an electricity network is essentially a measure of the "strain" on the system. Specifically, it equals find demand plus the transmission losses, and therefore the power input from generators needed to keep the network operating. Strictly speaking, the geographical distribution of the demand sinks and generator inputs, the configuration of the transmission network and other factors also are relevant to keeping the power supply from the network within specified voltage and frequency tolerances.

(SPP) and PJM Interconnection West (PJM W). They concluded that, although wind will primarily displace natural gas in ERCOT, over 60 percent of the wind capacity built from 2009 through 2011 in all four regions should displace coal. In particular, they project that wind generation will displace decidedly more coal than natural gas in the other three RTOs. Similarly, a 2005 study for New York (GE Energy 2005) found that 65 percent of electricity displaced by wind would be from natural gas, with the remainder from coal, oil and imported electricity. While this did not show coal being the primary fuel displaced, the displacement was more balanced than in ERCOT.

We shall argue, however, that the evidence of wind displacing natural gas more than coal is a short-term result. Specifically, the above studies have all looked at operating choices made using existing generating facilities. We shall instead focus on the longer-term investment decisions made in response to a larger anticipated supply of wind energy.

Fewer studies have focused on the potential longer-term implications of increased wind penetration. The Public Utility Commission of Texas (Smitherman 2009) predicts that, with roughly equal amounts of new coal and natural gas capacity installed between now and 2013, natural gas generation will fall dramatically to 27 percent of generation while coal generation will rise quite substantially to 44 percent. Oswald, Raine and Ashraf-Ball (2008) argue that, in the United Kingdom, wind will lead to more construction of single cycle combustion turbines as opposed to CCGT because natural gas plants will be utilized less in the presence of wind. This disadvantages the CCGT plants that have a higher capital cost. Additionally, they believe CCGT plants that must ramp up and down frequently (a process known as load cycling) may be at greater risk for reliability issues such as thermal stress cracking. If the cost of running CCGT plants increases, the desire to build them will decrease.

Gross and Heptonstall (2008) agree that high penetration of wind power could lead to lower capacity factors for combined cycle natural gas plants. However, they note that new plants generally operate at or close to their maximum load factor, while older plants are used less frequently. Hence, increased wind output may reduce the capacity factor of older plants more than younger plants and the fuel mix of those plants will depend on the history of the generating system. Furthermore, the tradeoff between flexibility (the combustion turbine) and efficiency (the CCGT) would depend on many factors, including opportunities for load shedding and

curtailments, the availability of hydroelectric capacity and the shape of the load curve, and likely would vary on a case-by-case basis.

While these discussions have focused on the trade-off between intermediate and peaking load plant, we shall argue that, in the currently developed locations in the United States, increased wind capacity should significantly negatively affect investment in new base-load sources of power such as coal. The basic reason is that wind tends to generate most of its supply in off-peak hours. As a result, wind capacity steepens the load duration curve[8] faced by the thermal generating system, which disadvantages base-load thermal plants relative to intermediate and peaking load plants.

As Oswald, Raine and Ashraf-Ball argue, the intermittent nature of wind generation reinforces the tendency to favor natural gas as the primary fuel for the thermal generating system. System operators need to maintain standby capacity when wind generators are operating to compensate for sudden decreases in wind speed. Single cycle gas turbines, or combined cycle gas turbines operated in single cycle mode, are the most suitable thermal plants for providing quick start and load following capacity. Thus, as the proportion of intermittent renewable energy in the system increases, operators are turning more to natural gas plants to provide back-up power.

In the next two sections of the paper we present and discuss some data on wind generation in ERCOT and MISO. We then return to the issue of the effect of wind on investment in new capacity. We present a simple model of electricity capacity investment decisions. This is followed by an analysis of the likely effects of the expansion of wind using both the evidence of what has happened in ERCOT and MISO and the theoretical analysis.

4. Wind capacity utilization in ERCOT and MISO

Although California has had significant wind generation for a longer time, Texas has now become the center of the wind industry in the United States. As Figures 2 and 3 show, north

[8] The *load duration curve* is a graph showing the *proportion* of time (measured on the horizontal axis) over some time interval, such as a year, that the load (measured on the vertical axis) exceeds a given value. The maximum load will occur at the left edge of the graph, since it is attained for a very small fraction of the time. The height of the right edge of the graph will give the minimum load during the time interval since by definition the minimum is equaled or exceeded in all hours of the time interval. A relatively flat load duration curve means the generating requirements tend to fall within a small range. A steep curve means that usage varies widely over the time interval.

Texas is well suited to wind development for natural and economic reasons. We therefore examined the Texas, or more specifically the ERCOT, experience in some detail.

Table 4: Distributions of hourly wind capacity utilizations in ERCOT, 2007–09[9]

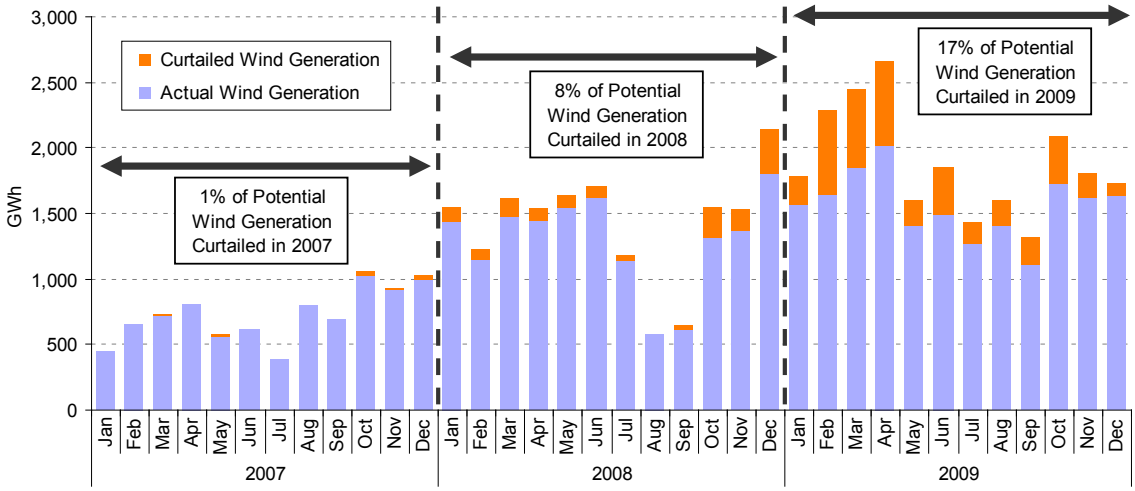
				Percentiles									
	Mean	Std dev	Min	1	5	10	25	50	75	90	95	99	Max
2007	0.2630	0.2075	-0.0013	-0.0003	0.0078	0.0215	0.0777	0.2175	0.4319	0.5791	0.635	0.7208	0.7989
2008	0.2966	0.2019	-0.0016	0.0018	0.0122	0.0286	0.1076	0.2925	0.4613	0.5717	0.6267	0.7103	0.7932
2009	0.2445	0.1441	0.0016	0.0122	0.0348	0.0518	0.1147	0.2414	0.3641	0.4368	0.4713	0.5400	0.6793

Table 4 provides some statistics on the distribution of wind capacity utilization in ERCOT from 2007–2009. These statistics were calculated from hourly data. The strongest feature in the data in Table 4 is the substantial reduction in standard deviation of capacity utilization from around 20% in 2007 and 2008 to 14.4% in 2009. At the same time, there was a decline in the maximum capacity utilization in any single hour from almost 80% to around 68%. In addition, the number of hours with very low capacity utilization, and also the number with high utilization, both declined. This pattern can be explained by a reduction in the correlation of wind speed across the different sites as the sites become more dispersed. Very low or high wind speeds are then unlikely to occur at all the sites at the same time. In particular, wind speeds at new wind generators in the coastal region south of Corpus Christi in 2009 tend to have a low correlation with wind speeds at previously developed sites in west Texas. The reduction in correlation of production across sites is a positive outcome in so far as it will assist with managing network stability in the face of variable wind production. We will return to this point when we discuss maintenance of network stability in more detail below.

The other notable feature of the data in Table 4 is the reduction in mean hourly capacity utilization in 2009. These are means calculated across 8,760 hourly observations in 2007 and 2009 and 8,784 observations in 2008 (a leap year). Hence, we would not expect the mean to vary much from one year to the next unless there has been a significant change in circumstances.

[9] The negative values for capacity utilization in Table 4 seem like an error, but the statistics measure any power purchased to run on-site operations as a negative supply. In 2007, at least 1% of the hours were characterized by a net positive demand for electricity from wind generating entities.

Formally, one can test for the differences in the mean utilization rates in Table 4 using *t*-tests. The resulting statistics are 6.85 for the difference between 2007 and 2009 and 19.68 for the difference between 2008 and 2009. These clearly are statistically significantly different from zero, implying that the decline in average capacity utilization in 2009 is extremely unlikely to have occurred simply by chance. Continued technological change in the wind generation industry should *increase* capacity utilization over time as useful generation output can be obtained from lower wind speeds.



Source: Wiser and Bolinger (2009) based on personal communication from ERCOT

Figure 4: Wind Energy Curtailment within ERCOT: 2007-2009

One explanation for a significant part of the decline in average capacity utilization is that the amount of curtailment increased in 2009. Figure 4, from Wiser and Bolinger (2009) shows that while 8% of potential wind generation was curtailed in 2008, 17% was curtailed in 2009. Curtailments result primarily from inadequate transmission capacity and occur either at the request of the system operators (in order to prevent line overload) or voluntarily in response to negative prices.[10]

[10] The latter also partly reflect insufficient transmission capacity to get power to parts of the state where prices are positive. In some cases, however, excess generation can be so large that wholesale prices everywhere in ERCOT are negative, in which case the "lost" wind output actually has negative social value. Adding it to supply would force other generators to incur substantial costs to further back down their output, which is presumably the reason they are bidding such large negative prices in the first place.

If we augment the wind output in 2008 by 8% and the output in 2009 by 17% the average capacity utilizations would increase approximately to 0.320 in 2008 and 0.286 in 2009.[11] This is still a decline of more than 10.6%. Increasing the standard deviations of output by hour by the same proportions,[12] we find that the difference between the mean capacity utilization rates in 2009 and 2008 after eliminating the effects of curtailment remain statistically significant (t = 11.64). It would be reasonable to postulate as a null hypothesis that the measured standard deviation across the hours within a year ought to account for normal variations in wind speed as a result of weather, including from one year's group of hours to the group of hours that constitute the following year. After all, the cut-off day between the two years of December 31 is arbitrary. The result that the remaining difference in means (after correcting for curtailment) is statistically significant despite measured fluctuations in output from hour to hour would then suggest that the difference is not due to normal fluctuations in weather. Wiser and Bolinger (2009) claim to the contrary that "in part as a result of El Niño" 2009 was "considered to be a generally poor wind year throughout much of the United States" while 2008 "was generally considered to be a good wind year."[13] This amounts to a claim that the year-to-year fluctuation in wind speed is outside the bounds represented by the standard deviations of the hourly fluctuations within each year. This may be possible, since weather patterns do undergo longer-term trends and cycles, but it seems unlikely to account for all the remaining reduction in capacity utilization in 2009 relative to 2008.

Economics suggests another possible explanation. Even in a region generally suitable for wind power generation, some sites will be better than others. While site selection is influenced by many factors apart from wind speeds, including grid access, proximity to residential

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[11] This would only be valid if the percentage increase was uniformly distributed across the year. As can be seen in Figure 4, this is not the case. Percentage curtailments tended to be higher in months when actual generation also was higher. A consequence is that the above adjustments would tend to understate the effects of curtailment on average capacity utilizations.

[12] The pattern in curtailments in Figure 4, whereby output is more likely to be curtailed in months where its average is greatest, suggests that if wind generators had supplied all the energy they could generate under the prevailing wind conditions the standard deviation of output would have increased more than 8% in 2008 and 17% in 2009. Even so, since the t-statistic is so large, the difference in means is likely to remain statistically significantly different from zero.

[13] Maps of average annual wind speed variance from average are available from *3Tier* at http://www.3tier.com/en/support/resource-maps/ For 2008, these show that average wind speeds in the parts of Texas where wind farms are located were about 5% above normal, while in 2009 they were about 2–3% above normal. In MISO they were 0–2% above normal in 2008 and about 2% below normal in 2009. Since we do not have measures of standard deviations in average annual wind speeds we do not know whether these deviations are statistically significantly different from zero.

population, access for construction equipment and the presence of significant environmental resources to name a few, we would expect that, among the available sites, those most favorable for wind generation would be exploited first. As the industry expands, therefore, less favorable sites will tend to be used, resulting in a reduction in average output per unit of capacity.

While substitutability between potential sites might be greatest at the local level, there may also be a tendency to choose the best regions within the state as locations for the initial wind farms. If so, subsequent farms would be in less favorable locations and average utilization would decline over time. Texas experience provides some evidence consistent with this hypothesis. Even though demand is in the east of the state, the initial wind farms were in the west where the highest average wind speeds are found. In 2009, the first wind farms outside the western region were established on the coast south of Corpus Christi. Although this is rated as having lower average wind speed than the western regions developed earlier, it had the offsetting benefit that its wind speeds were much less correlated with those of other farms in western regions of the state.

More systematic evidence can be gathered on whether regional location choices indicate declining site quality over time. A list of wind turbine locations, and the quarter in the period 2007–09 when they were brought online, was constructed based on data from the American Wind Energy Association.[14] The latitudes and longitudes were then plotted on a wind power map from AWS Truepower available for each state from the US Department of Energy (2010). The average annual wind speeds from AWS Truepower are grouped in 0.5 meter/second (m/s) increment bands. The band that each new farm fell into was gauged from the map.[15] We then obtained an approximate capacity-weighted average annual wind speed for the new farms added in a given quarter. The results are presented in Table 5.

[14] The majority of the data came from the AWEA Market Reports: http://www.awea.org/projects/pdf/Market_Report_Jan08.pdf (2007), http://www.awea.org/publications/reports/3Q08.pdf (2008), and http://www.awea.org/publications/reports/4Q09.pdf (2009)

[15] These assessments are crude since the maps are large-scale approximations. Indeed, there is an industry devoted to assessing sites for suitability for wind generation. The advisory industry could not survive if sites could be selected simply by looking at a map.

Table 5: Average annual wind speed (m/s) for new farms in ERCOT

Quarter	Assessed average annual wind speed of new wind farms
2007 Q2	8.15
2007 Q3	8.00
2007 Q4	7.61
2008 Q1	7.71
2008 Q2	7.59
2008 Q3	7.96
2008 Q4	7.57
2009 Q1	7.78
2009 Q2	7.16
2009 Q3	7.75
2009 Q4	7.24

A simple regression of the average assessed wind speed of new farms against time yields (standard errors in parentheses)

$$s = \underset{(0.150)}{8.051} - \underset{(0.022)}{0.061}t$$

which implies a statistically significantly ($t = -2.768$, $p = 0.022$) decline of 0.061 per quarter in assessed average wind speed of new farms.

Table 6 presents summary measures of the distribution of hourly wind capacity utilizations in MISO for 2008 and 2009. Since the industry is developing later in MISO than in ERCOT, data for 2007 is less meaningful and we have presented data only for 2008 and 2009. The MISO data reveals similar changes in wind generating capacity utilization to those observed in ERCOT. Once again, the reduction in standard deviation of capacity utilization, and the decline in the number of hours with very high capacity utilization, suggest that the wind output across sites is becoming less correlated over time. This is likely as sites become more dispersed geographically.

Table 6: Distributions of hourly wind capacity utilizations in MISO, 2008–09

				Percentiles									
	Mean	Std dev	Min	1	5	10	25	50	75	90	95	99	Max
2008	0.3413	0.2152	0.0020	0.0220	0.0561	0.0840	0.1521	0.3039	0.5123	0.6578	0.7221	0.8280	0.9576
2009	0.2806	0.1746	-0.0005	0.0129	0.0398	0.0636	0.1349	0.2539	0.4095	0.5445	0.5941	0.6600	0.7272

Although the average hourly capacity utilization is higher in MISO than it was in ERCOT in the same years, the MISO data also shows a reduction in mean hourly capacity utilization from 2008 to 2009. The *t*-statistic for the difference (20.52) is highly statistically significant. Since only about 1% of wind output in MISO was curtailed in 2009, this is a much less important factor than it was in ERCOT for explaining the decline in capacity utilization.

Carrying out a similar mapping exercise for the MISO states as was done above for ERCOT, we can again obtain an approximate capacity-weighted average annual wind speed for the new farms added in a given quarter. The results are presented in Table 7. A simple regression of the average assessed wind speed of new farms against time yields (standard errors in parentheses)

$$s = \underset{(0.226)}{6.934} + \underset{(0.033)}{0.052}\,t$$

which now implies a *increase* of 0.052 per quarter in assessed average wind speed of new farms. This slope coefficient, however, is not statistically significantly different from zero ($t = 1.572$, $p = 0.150$). Furthermore, the positive slope comes mainly from the low values in the first two quarters in the sample. When these are removed, the estimated slope falls to 0.0067.

Table 7: Average annual wind speed (m/s) for new farms in MISO

Quarter	Assessed average annual wind speed of new wind farms
2007 Q2	6.70
2007 Q3	6.83
2007 Q4	7.32
2008 Q1	7.21
2008 Q2	7.54
2008 Q3	7.00
2008 Q4	7.48
2009 Q1	7.64
2009 Q2	7.75
2009 Q3	6.75
2009 Q4	7.50

As in the case of ERCOT, these analyses relate only to whether the broad sub-regions within ERCOT or MISO that are best for wind generation tend to be developed first. Since substitutability between sites is likely to be higher at the local level, the economic analysis might instead imply that site quality *within* each broadly defined sub-region is likely to deteriorate over time as the best sites are developed first. Furthermore, in both cases it is important to note that power output is a non-linear function of wind speed. Specifically, power output depends on the cube of wind speed at low levels, asymptotes to a maximum level at higher speeds, and then drops to zero at very high speeds when the plant is turned off to avoid damage. As a result, power output will depend on the entire distribution of wind speed, so the average annual wind speeds presented in Tables 5 and 7 might not necessarily be a good indicator of site quality.

Finally, as already noted, factors such as grid access, proximity to residential population, access for construction equipment and the presence of significant environmental resources will also affect location decisions. An additional relevant issue in MISO is that it incorporates many states with different laws governing the subsidies for wind, regulatory and environmental regulations and so on. These legal and institutional differences will also influence location

choices. If changes in some of these other factors open up new areas for development it is possible that higher quality sites could become available in later years. Nevertheless, if these other changes are uncorrelated with wind speed characteristics we would expect the quality of sites that are developed to decline on average over time.

5. The distribution of wind output over time

The average hourly wind capacity factor (or the average utilization rate of the available wind generating capacity) is of interest to developers of wind projects, to competing suppliers and also to system operators. The capacity factor influences the amount of electricity a developer can expect to sell to cover the up-front costs of investment, maintenance costs and dismantling costs at the end of the project. Competing suppliers need to forecast how much and what types of capacity they could profitably build given their expectation of the competition they are likely to face from wind generation. In turn, the latter depends on the actual output from wind generation projects, not the maximum feasible production determined by capacity. Finally, system operators need to know how much actual output they can expect to obtain from wind generation projects in order to judge the adequacy of the available generating capacity and the transmission network to meet fluctuations in demand or supply.

In each of these cases, however, the *average* capacity factor is not the only relevant issue. For developers of wind projects, anticipated revenue depends not only on the amount of electricity they expect to sell but also on the wholesale price they expect to obtain, and the latter will closely follow the overall system demand.

Other suppliers need to know the time profile of wind output relative to system demand in order to decide whether they should invest in base, intermediate or peaking load plant. For system operators, the amount of transmission capacity needed to support wind projects depends on the *maximum* anticipated output from the project, not the average value. In addition, the contribution of wind generation to maintaining network stability depends on the likely *minimum* supply of wind output *during peak periods* when demand more closely approximates available generating capacity and supply resources are most strained. Even if wind is not blowing in other periods, alternative suppliers can be called upon to make up the difference. In peak periods, however, all available generators likely already will be producing and there is little room to compensate for a sudden drop in wind output.

More generally, operators design the system with a *reserve margin* so the sum of the rated capacities of the generating plants exceeds the anticipated maximum load on the system by a specified percentage (12.5% is the value used by ERCOT, for example). Thus, when judging the adequacy of supply to meet extreme levels of demand, operators discount the rated capacity of a plant for the likelihood that the plant might not be able to operate at full capacity when additional output is needed. In the case of ERCOT, this implicit "capacity value" of wind generation is set at only 9% of its maximum value.

To investigate these issues further, we calculated the pattern of wind capacity utilization as a function of the system load. More specifically, we calculated a kernel density estimate of the joint probability density of wind capacity utilization and overall load factor. A kernel density estimate can be considered as a smoothed, generalized form of histogram. In a histogram based on bivariate data, the two data ranges are divided into non-overlapping intervals, which then form a set of non-intersecting rectangles. The number of points falling within each rectangle is then tallied and graphed as a three dimensional bar chart. In a kernel density estimate, the ranges of data are still divided into rectangles and estimates of the density at the center of each rectangle are produced. Now, however, the rectangles can overlap, while the contribution of a point to a given rectangle is a number between 0 and 1 depending on how far the point is from the center of the rectangle. Specifically, the weights are determined by a function K known as the kernel. In our application we used the Gaussian kernel.[16] We estimated the density at 2500 points, (x_{1i}, x_{2j}), $i = 1, 2, \ldots, 50$, $j = 1, 2, \ldots, 50$ where x_{1i} is the i-th load factor (load in an hour relative to maximum load any hour in the year), and x_{2j} is the j-th wind generation capacity factor (wind generation in an hour relative to available wind generation capacity), at which the probability density is estimated. The estimate at $\mathbf{x} = (x_{1i}, x_{2j})$ is given by:

$$\hat{f}(\mathbf{x};\mathbf{H}) = \frac{1}{n}\sum_{k=1}^{N}|\mathbf{H}|^{-1/2} K\left(\mathbf{H}^{-1/2}(\mathbf{x}-\mathbf{X}_k)\right)$$

[16] This is given by $K(\mathbf{x}) = \frac{1}{2\pi}\exp(-\frac{1}{2}\mathbf{x}'\mathbf{x})$ for a vector $\mathbf{x} = (x_1, x_2)$.

where $\mathbf{X}_k$ represents the observed ERCOT load factor and wind capacity factor in hour $k = 1, 2, \ldots, 8760$ in the year and $\mathbf{H}$ is a symmetric positive-definite bandwidth matrix.[17]

Figures 5–9 present the resulting estimated probability density functions for ERCOT in each of the years 2007, 2008 and 2009, followed by similar results for MISO in 2008 and 2009.

Measured along the axis labeled as going from –0.2 to 1.2 (Figures 5, 6 and 8) or –0.2 to 0.8 (Figures 7 and 9) we have the range of wind capacity factors observed in each of the hours in the year. Measured along the axis labeled as going from around 0.3 to 1.1 (Figures 5, 7 and 9), 0.2 to 1.2 (Figure 6) or 0.4 to 1.1 (Figure 8), we have the range of ERCOT or MISO load factors observed in the different hours of each year. Since these are expressed as a ratio to the maximum hourly load in the year, the largest observed value is 1.0. Hence, the maximum extent of the figure in this dimension is actually 1. It looks slightly larger because the surface is sitting slightly above the "floor" of the figure.

The height of the surface in Figures 5–9 represents the value of the probability density function at the corresponding values of ERCOT or MISO load factor and wind capacity factor. Thus, to obtain the probability of observing any range of values for system load $[x_{11}, x_{12}]$ and wind capacity factor $[x_{21}, x_{22}]$ one would integrate the surface over these two ranges of values. The integral of the total volume beneath the surface and above the floor of the figure has to be 1.0 since this is a probability density function.

[17] The bandwidth in $\mathbf{H}$ for component $i = 1, 2$ was set equal to the default value in STATA, namely $h_i = 0.9m_i/n^{1/6}$ where $m_i = \min(\text{standard deviation}_i, \text{interquartile range}_i/1.349)$.

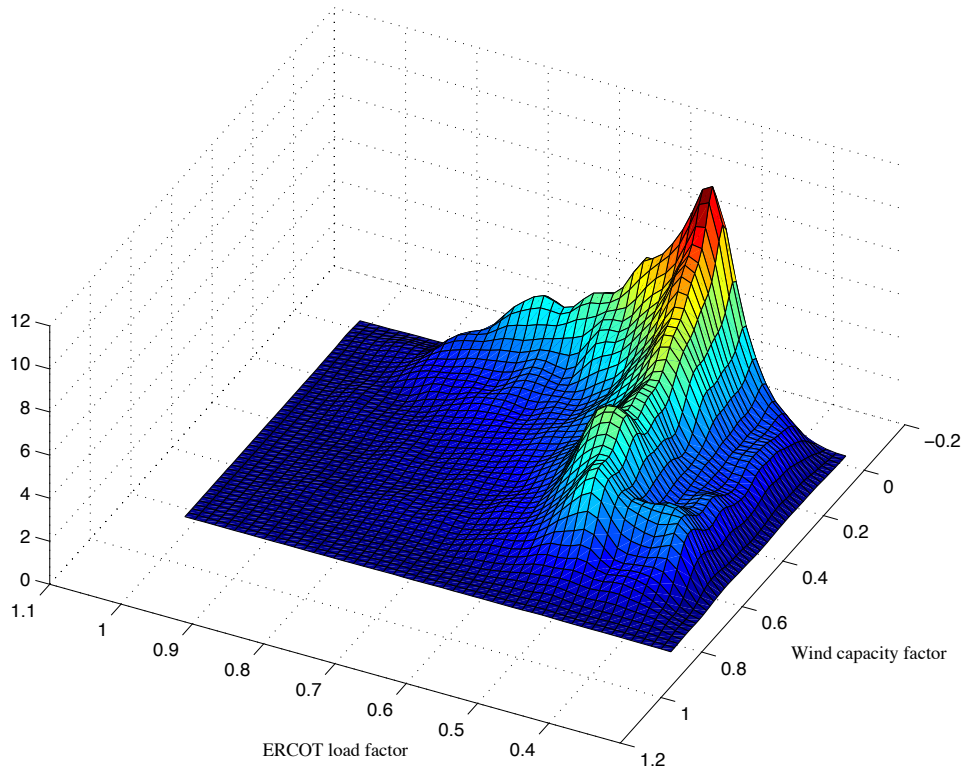

Figure 5: 2007 ERCOT load and wind capacity factor kernel density estimate

If we ignore the wind capacity factor dimension and imagine projecting the surface against the back wall of the figure, we would obtain the probability density for the system load factor over the year. Similarly, if we ignore the system load factor dimension and imagine projecting the surface against the left wall of the figure, we would obtain the probability density for wind capacity factor across hours of the year that also was examined numerically in Tables 4 and 6.

With these preliminaries out of the way, we can now describe the implications of Figure 5 in more detail. The prominent "ridge" in Figure 5 implies that during most of those hours when at least 20% of wind capacity was in use, the ERCOT system load was close to 50% of its maximum. This is not far above the minimum of a little over 35% load factor and is approximately equal to the lower quartile of the distribution of ERCOT hourly loads. In other words, around 75% of the hours in 2007 had an ERCOT system load greater than 50% of the maximum load. Thus, although wind capacity factors in quite a few hours were between 40%

and 80%, in almost all these hours, the ERCOT system load was less than 60% of its maximum hourly value for 2007.

The other significant feature of Figure 5 is the large flat area in the front left hand corner and along the left hand edge. This means that during those hours when the total ERCOT load was highest there was very little wind generation.

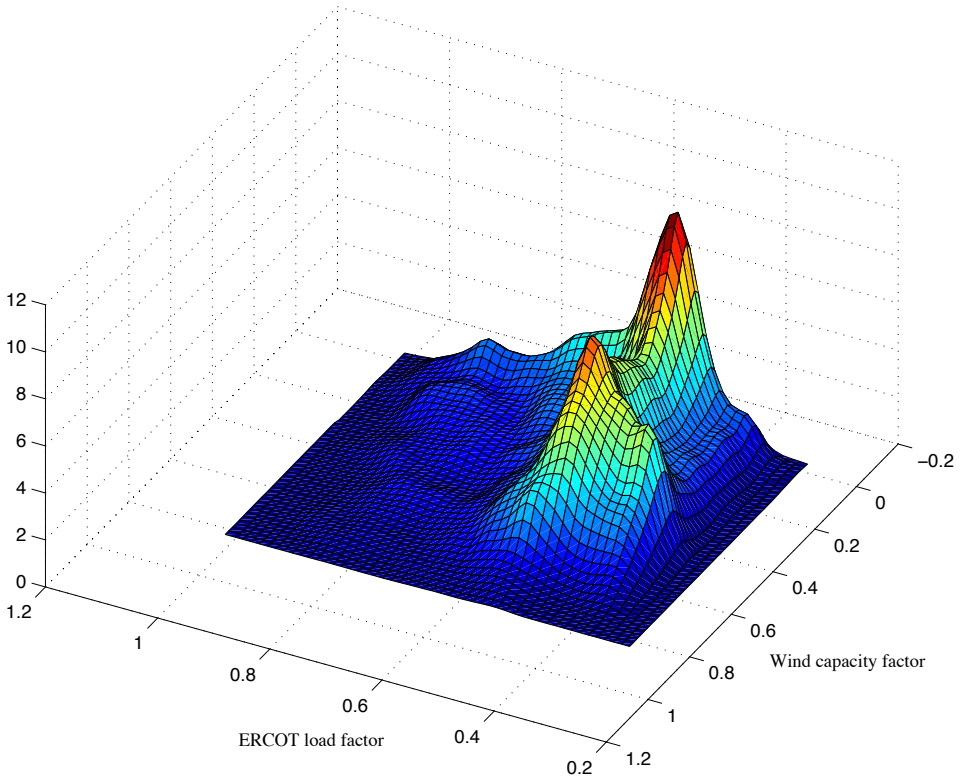

Figure 6: 2008 ERCOT load and wind capacity factor kernel density estimate

Figure 6 presents the corresponding joint probability density function for ERCOT in 2008. We see that, once again, there was a prominent ridge around a system-wide load factor of about 50%, which again corresponds approximately to the lower quartile of 2008 load factors. In contrast to 2007, however, the 2008 data shows that there was a somewhat higher tendency for more of the wind capacity to be used during those hours than was the case in 2007. In particular, the secondary peak in wind generation capacity factors around 50%, which was barely visible in Figure 5, is much more pronounced in the 2008 data in Figure 6.

The relative lack of wind generation at times when total system load is high was also slightly less pronounced in 2008. The generally flat area in the front, left hand end of the graph has a few more slight undulations than the corresponding area in the 2007 data in Figure 5.

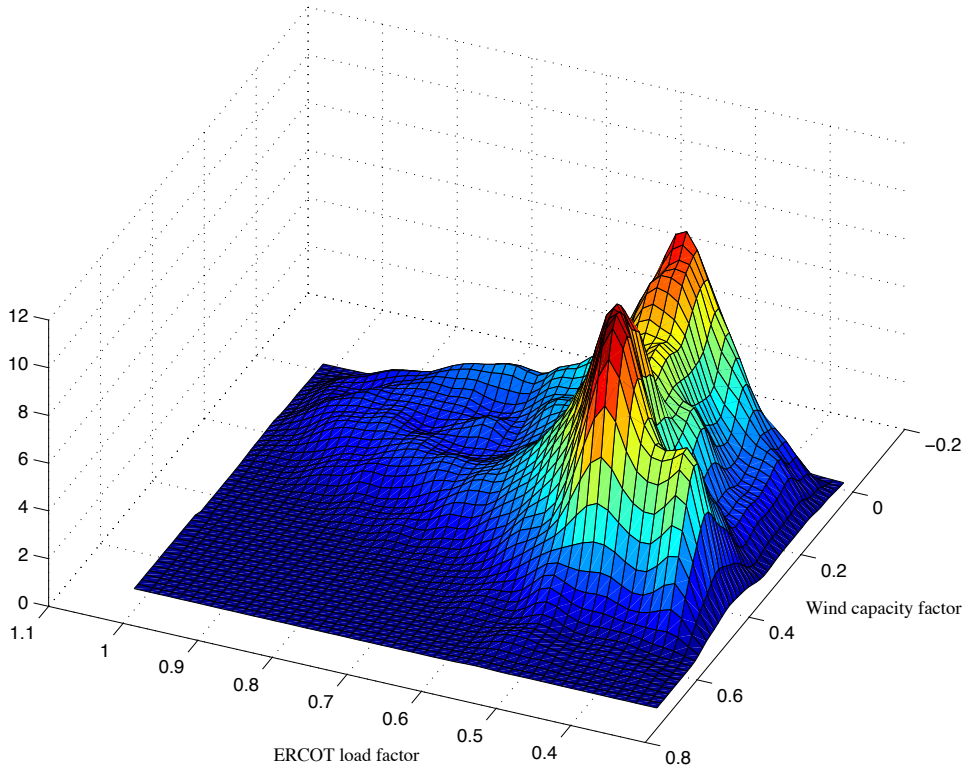

Figure 7: 2009 ERCOT load and wind capacity factor kernel density estimate

Figure 7 shows that the tendencies evident in the changes from 2007 to 2008 continued into 2009. The peak in the ridge at higher wind capacity factors has increased further so the mode of the distribution now occurs at a wind capacity factor of around 30% rather than zero as in 2007 and 2008. This alone would tend to raise average wind capacity factors. However, we saw previously that the overall mean wind capacity factor declined significantly in 2009 relative to the previous two years. One explanation is that the peak at 30% wind capacity factor in 2009 was centered on a higher wind capacity factor of around 50% in 2008.[18] Second, the wind

[18] This fact tends to conflict with the assertion, discussed above, that curtailment explains a large amount of the reduced wind capacity utilization in 2009 relative to 2008. Curtailment would truncate the distribution of wind capacity utilizations at high levels but should not produce a large shift from the proportion of hours with 50% capacity utilization to the proportion with 30% utilization.

capacity factors in 2009 have a maximum value below 80% compared with 100% in 2007 and 2008.[19] Wind capacity factors in 2009 rarely rose above 60%, with the flat area to the front and left of the graph now extending all the way across the front. These changes are consistent with the hypothesis that the growth of wind generation has resulted in less correlation in output across the now more dispersed wind farms. In the limit, if output were uncorrelated across wind farms, we would expect a central limit theorem result to imply aggregate wind capacity use would converge to a normal distribution (a "cone shape" symmetric about the mode) centered on the average value per hour (around 24% in 2009).

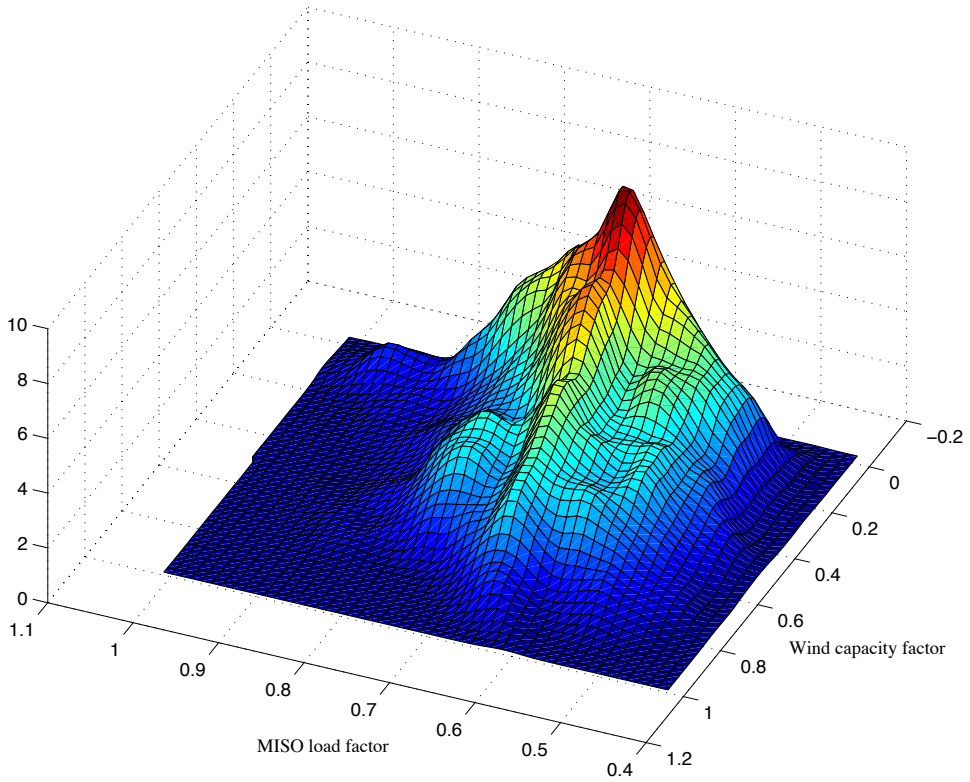

Figure 8: 2008 MISO load and wind capacity factor kernel density estimate

[19] This fact is consistent with the claim that curtailment can explain some of the reduction in capacity utilization in 2009 relative to 2008 and 2007.

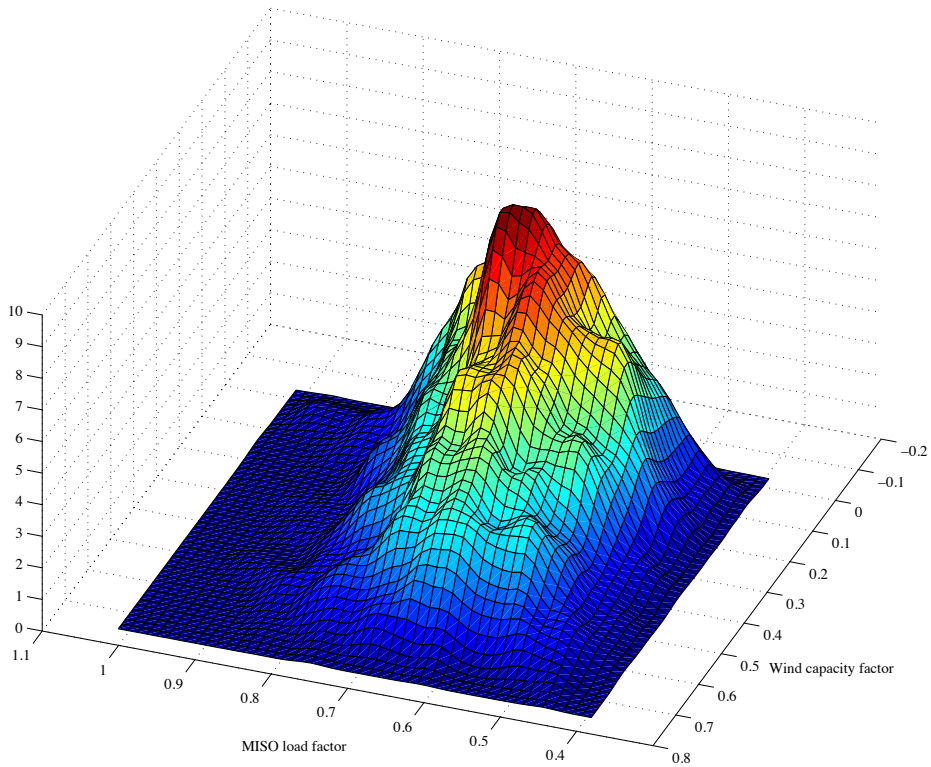

Figure 9: 2009 MISO load and wind capacity factor kernel density estimate

Figures 8 and 9 present corresponding probability density estimates for MISO in 2008 and 2009. Consistent with the notion that MISO development is lagging somewhat behind development in Texas, the MISO pattern in 2008 looks similar to the ERCOT pattern in 2007 presented in Figure 5. The modal wind capacity utilization (that is, the most likely value, or the value where the surface attains a peak) is again zero, although in the case of MISO, the mode of the distribution occurs at a system load of around 65% (the MISO load factor value at the peak in Figure 8 is approximately 0.65) compared with a value closer to 50% for ERCOT in 2007. In both cases, a ridge extends to higher wind capacity factors at roughly the same level of system load as the modal value. Consistent with the higher average wind capacity factor in MISO revealed in Table 6, the MISO wind capacity generally extends to higher values in Figure 8 than does the corresponding surface for ERCOT in 2007. In addition the ridge in MISO is broader at higher wind capacity values. As in ERCOT in 2007, however, there is also a flat area on the

surface at the front and left hand edge of the figure implying that very little wind output was available when system loads were at a peak.

Comparing the estimated 2009 MISO joint probability density function in Figure 9 with the 2008 function in Figure 8 we again see some similarities with developments in ERCOT. The maximum wind capacity factors in 2009 were lower than 2008, with the change in scale on the graph again reflecting the drop in maximum capacity factor.[20] The nascent development of a secondary peak in wind capacity factor around a level of 30% can also be detected in Figure 9. In general, however, the MISO ridges are broader and less peaked than the ERCOT surfaces suggesting, perhaps, that wind output is somewhat less correlated across sites in the MISO region.

Both the ERCOT and the MISO data indicate that wind output tends to be highest when the load on the system is modest. To better understand why, we looked for systematic tendencies in wind capacity utilization. Table 8 presents results of estimating simple time series models to explain wind capacity utilization. These models include indicator variables for each hour of the day (the hour beginning with midnight being the excluded category). Thus, the coefficient on Hour01, for example, measures whether wind capacity factors were significantly different on average from 1am to 2am relative to the midnight to 1am hour.

In ERCOT in 2007, all hourly indicator coefficients were negative except for the 11pm to midnight hour, which was positive. Also, the coefficients from 11pm to midnight and 1am to 2am were not statistically significantly different from zero. The interpretation is that wind capacity factors are similar in the three hours from 11pm to 2am, but in all other hours they tend to be significantly *less* than these hours in the middle of the night. In 2008 and 2009, the 11pm to midnight hour also has significantly lower average wind capacity factors than the midnight to 1am hour, but the morning hours that are not significantly different from midnight to 1am extend to 3am to 4am in 2008 and 5am to 6am in 2009.

[20] Once again this is consistent with some curtailment of wind output, but it also may reflect decreased correlation of output as sites become more dispersed.

Table 8: Estimated time pattern of wind generation in ERCOT and MISO*

	ERCOT 2007	ERCOT 2008	ERCOT 2009	MISO 2008	MISO 2009
Hour01	-0.00185	0.00278	0.00627	0.00198	-0.00054
	(0.00263)	(0.00284)	(0.00197)	(0.00213)	(0.00155)
Hour02	-0.00901	0.00028	0.00708	-0.00163	-0.00244
	(0.00422)	(0.00453)	(0.00307)	(0.00371)	(0.00275)
Hour03	-0.02072	-0.00542	0.00387	-0.00416	-0.00622
	(0.00544)	(0.00582)	(0.00401)	(0.00506)	(0.00379)
Hour04	-0.03210	-0.01429	0.00187	-0.00805	-0.01044
	(0.00640)	(0.00683)	(0.00472)	(0.00617)	(0.00464)
Hour05	-0.04499	-0.02390	-0.00607	-0.00803	-0.01469
	(0.00722)	(0.00753)	(0.00531)	(0.00704)	(0.00531)
Hour06	-0.05577	-0.03663	-0.01064	-0.00950	-0.01851
	(0.00791)	(0.00811)	(0.00577)	(0.00772)	(0.00584)
Hour07	-0.07185	-0.05010	-0.01465	-0.01243	-0.02584
	(0.00840)	(0.00855)	(0.00612)	(0.00823)	(0.00627)
Hour08	-0.08955	-0.06775	-0.02715	-0.02153	-0.03604
	(0.00870)	(0.00878)	(0.00639)	(0.00862)	(0.00661)
Hour09	-0.10289	-0.08511	-0.03621	-0.03923	-0.04984
	(0.00887)	(0.00893)	(0.00655)	(0.00889)	(0.00684)
Hour10	-0.11274	-0.10109	-0.04951	-0.05120	-0.061347
	(0.00897)	(0.00904)	(0.00663)	(0.00905)	(0.00698)
Hour11	-0.12343	-0.11158	-0.06273	-0.04711	-0.06488
	(0.00903)	(0.00913)	(0.00665)	(0.00911)	(0.00703)
Hour12	-0.13092	-0.11904	-0.07524	-0.03845	-0.06221
	(0.00905)	(0.00920)	(0.00666)	(0.00908)	(0.00699)
Hour13	-0.13617	-0.12233	-0.08512	-0.03308	-0.05852
	(0.00905)	(0.00914)	(0.00662)	(0.00900)	(0.00692)
Hour14	-0.13903	-0.12357	-0.08675	-0.02790	-0.05331
	(0.00892)	(0.00895)	(0.00653)	(0.00880)	(0.00675)
Hour15	-0.13939	-0.12325	-0.08503	-0.02144	-0.04772
	(0.00864)	(0.00863)	(0.00639)	(0.00853)	(0.00645)
Hour16	-0.13658	-0.11861	-0.08060	-0.01694	-0.04423
	(0.00835)	(0.00821)	(0.00614)	(0.00812)	(0.00614)
Hour17	-0.13261	-0.11652	-0.07676	-0.018630	-0.04370
	(0.00785)	(0.00768)	(0.00580)	(0.00759)	(0.00566)
Hour18	-0.12861	-0.11124	-0.07623	-0.02422	-0.04546
	(0.00740)	(0.00714)	(0.00539)	(0.00698)	(0.00520)
Hour19	-0.10853	-0.09906	-0.07036	-0.03099	-0.04680
	(0.00681)	(0.00655)	(0.00497)	(0.00637)	(0.00473)
Hour20	-0.07080	-0.06983	-0.05849	-0.03478	-0.04412
	(0.00609)	(0.00586)	(0.00451)	(0.00575)	(0.00426)
Hour21	-0.03485	-0.04194	-0.03930	-0.02934	-0.03171
	(0.00507)	(0.00499)	(0.00384)	(0.00487)	(0.00366)
Hour22	-0.01199	-0.01509	-0.01714	-0.01578	-0.01631
	(0.00394)	(0.00385)	(0.00310)	(0.00371)	(0.00285)
Hour23	0.00049	-0.00785	-0.00596	-0.00536	-0.00382
	(0.00236)	(0.00254)	(0.00193)	(0.00217)	(0.00158)
Constant	0.33973	0.36170	0.28385	0.36299	0.31425
	(0.01503)	(0.01495)	(0.01036)	(0.01646)	(0.01416)
AR(-1)	1.25458	1.20335	1.17786	1.51777	1.53416
	(0.00745)	(0.00763)	(0.00758)	(0.00693)	(0.00690)
AR(-2)	-0.29662	-0.24671	-0.22570	-0.54310	-0.55595
	(0.00682)	(0.00694)	(0.00716)	(0.00664)	(0.00667)
MA(12)	0.05703	-0.04363	-0.02306	0.00837	
	(0.00977)	(0.01017)	(0.01034)	(0.00941)	
MA(24)		0.04822	0.05694	0.08944	0.09159
		(0.00943)	(0.01020)	(0.00954)	(0.00941)
σ	0.04759	0.04994	0.03752	0.03173	.02327
	(0.00021)	(0.00025)	(0.00019)	(0.00016)	(.00012)

* Estimated standard errors in parentheses below each estimated coefficient.

The general conclusion, the implications of which will be further discussed below, is that average wind generation is much higher in the early hours of the morning on most days of the year. It tends to reach a maximum around 1am and a minimum around 2 or 3 in the afternoon, when demand is likely to be high, especially in the summer months when air conditioning dominates the load.[21]

The average wind capacity factors in MISO also tend to be lower during the day than at night. However, since the coefficients are smaller in magnitude, the deviations are smaller. Also, the minimum wind capacity factors tend to occur a little earlier in the day (10am to 11am in 2008 and 11am to noon in 2009) than in ERCOT. The hours where wind capacity factors are not statistically significantly different from the values they take from midnight to 1am extend to 6am to 7am in 2008 but only 3am to 4am in 2009.

In summary, the results in Table 8 imply that wind speed, and thus wind generator output, in the plains states tends to be highest at night. By contrast, peak demand tends to be in the early afternoon when wind production is lowest. In order to ensure security of supply, system operators need to have other capacity available to meet fluctuations in excess demand during peak periods. In the case of ERCOT, for example, installed wind capacity is only rated at 9% of its maximum value when assessing its contribution to meeting peak demands.

We can focus more narrowly on the issue of a "safe" allowance for wind capacity from the perspective of ensuring supply security by looking at the distribution of wind capacity factors at the very highest levels of demand. Table 9 presents statistics on the distribution of wind capacity factors analogous to the ones presented in Tables 4 and 6 but restricted to the hours when system hourly demand was among the 1% or 5% highest values for the year.

The most notable feature of Table 9 is that in both ERCOT and MISO and in both years, the mean wind capacity utilization in the peak 1% of hours is less than the mean utilization in the peak 5% of hours, which in turn is less than the mean utilization in all hours. Once again, this

[21] The models in Table 8 also allow for an autoregressive moving average structure in the error term. In all cases, only two autoregressive lags proved significantly different from zero at conventional levels of significance. The coefficients imply that if wind generation is high relative to average in a particular hour it will tend to deviate further from average over the next few hours, but then decay exponentially until it disappears after about 48 hours. The moving average coefficients imply that a deviation in one hour tends to be (positively or negatively) correlated with deviations 12 or 24 hours later.

emphasizes that wind output does not correlate well with peak demands for electricity in either region.

Table 9: Distributions of wind capacity utilizations during peak hours in 2008, 2009

				Percentiles									
	Mean	Std dev	Min	1	5	10	25	50	75	90	95	99	Max
ERCOT 2008													
Top 5%	0.2183	0.1835	0.0013	0.0031	0.0109	0.0230	0.0720	0.1664	0.3343	0.4790	0.6129	0.7290	0.7531
Top 1%	0.1441	0.1305	0.0035	0.0035	0.0079	0.0110	0.0448	0.1079	0.2092	0.3735	0.4021	0.5696	0.5696
ERCOT 2009													
Top 5%	0.1584	0.0823	0.0177	0.0243	0.0350	0.0492	0.0931	0.1578	0.2172	0.2763	0.3069	0.3365	0.3835
Top 1%	0.1448	0.0708	0.0294	0.0294	0.0350	0.0473	0.0892	0.1478	0.1852	0.2446	0.2705	0.3077	0.3077
MISO 2008													
Top 5%	0.2275	0.1924	0.0084	0.0180	0.0389	0.0558	0.0942	0.1444	0.3207	0.5620	0.6666	0.7525	0.7720
Top 1%	0.1289	0.0733	0.0333	0.0333	0.0469	0.0553	0.0913	0.1104	0.1446	0.1923	0.3114	0.4328	0.4328
MISO 2009													
Top 5%	0.2523	0.1861	0.0039	0.0146	0.0312	0.0440	0.0822	0.2178	0.4011	0.5398	0.5779	0.6597	0.6920
Top 1%	0.1935	0.1628	0.0165	0.0165	0.0340	0.0403	0.0548	0.1305	0.2998	0.4921	0.5166	0.5555	0.5555

Looking at the changes over time, the statistics in Table 9 show that, if we consider only the peak period hours defined by the highest 5% of system load, the mean wind capacity factors declined substantially in ERCOT between 2008 and 2009, although they increased slightly in MISO over the same period. If we further restrict the definition of peak period hours to just the top 1% of system load, the mean wind capacity factor in ERCOT was unchanged between 2008 and 2009, but increased from 12.9% to 19.4% in MISO. It should be noted, however, that as the number of hours in the sample declines, the statistics would be more affected by unsystematic "outlier" events and changes from one year to the next could represent little more than statistical noise.

Table 9 also shows a fall between 2008 and 2009 in dispersion measures for wind capacity utilization in ERCOT peak hours. This again suggests a decline in correlation in output across different wind farms. Whether we focus on the top 1% or top 5% of hours by system load, the standard deviation of wind capacity utilization declined, the minimum utilization increased and the maximum utilization decreased.

The situation in MISO is again more ambiguous. Although Table 6 showed that the dispersion of wind generator output in MISO declined between 2008 and 2009 when considering

all hours, the distributions in Table 9 do not show this for the peak 1% of hours defined by system load.

Returning to the issue of the capacity value of wind generation from the perspective of ensuring network stability and power quality, we are interested in the proportion of peak hours when wind capacity will be below the value it is assigned for network planning purposes. Taking the 9% value used by ERCOT, for example, the 2009 ERCOT data in Table 8 implies that for around one quarter of the peak hours (defined as either the maximum 1% or 5% of system load), the actual wind capacity will be less than that value. The 2008 ERCOT data implies that wind capacity utilization will be less than 9% of the installed value for considerably more than 25% of the peak hours. For the MISO 2008 data, at least 9% of the available wind capacity was utilized for slightly more than 75% of the peak hours, but in the 2009 data, at least 9% was available for considerably less than 75% of the peak hours. While the definition of "prudence" is subjective, assigning more than 9% capacity value to wind generation runs a substantial risk that supply will not be adequate to meet unusual levels demand.

For an electricity network, we can define "supply security" as a level of capacity sufficient to ensure a low probability of blackouts, or voltage or frequency fluctuations in the face of unforeseen events. To gauge the effect of wind generation on supply security, one can also look at its effect on the variability of the *net* demand (demand less wind output) faced by the rest of the system. The reason is that the rest of the system will need to cope with fluctuations in both demand and in wind output, and provide increased power in emergencies.

In the case of ERCOT, the mean overall hourly demand in 2008 was 35,365.98MW, with a standard deviation of 8,357.114MW. The mean hourly demand *net of wind supply* was more than 4.8% lower at 33,650.35MW, but the standard deviation was almost 3.4% higher at 8,639.491MW. Wind generation thus substantially increased the variability of demand faced by the rest of the system. In 2009, the mean hourly demand was 35,073.38MW, with a standard deviation of 8,763.766MW. The mean demand on the system apart from wind was more than 5.8% lower at 35,073.38MW but once again the standard deviation was more than 4.7% higher at 9,179.48MW.

Very short-term fluctuations in wind generator output, known as ramp-up and ramp-down events, can cause particular difficulty for supply security. Rapid changes in wind output occur

when various weather events, such as the passage of cold fronts or sudden pressure gradient changes, cause dramatic changes in wind speed. ERCOT has experienced a number of these events over the last few years. As an example, from 10pm on March 10 to the early hours of March 11, 2009 a southward moving cold front caused large system-wide ramp ups. The episode included 15-minute increases in wind generation of 921–961MW, a 1-hour ramp of 3,226MW and a 3-hour ramp of 4,259MW.

Accommodating such sudden large swings in supply requires an inventory of plants that can increase or decrease output quickly and at low cost. A recent study by Bentek (2010) found that in both ERCOT and Colorado the amount of capacity suitable for cycling has become insufficient to accommodate swings in wind output, particularly at night. Specifically, they found that coal as well as natural gas plants were cycled to accommodate wind output. They noted that while natural gas turbines and, to a lesser extent, CCGT are designed to cycle and follow the load, coal plants are not. Cycling makes the plants less efficient so they end up requiring more fuel to produce the same power output. They also produce more emissions per unit of power output as cycling de-stabilizes the emission control systems. The report notes, for example that "there are often over 50 required adjustments, involving everything from fuel-to-air mixes to the lime-slurry mixtures for proper SO_2 absorption that must be made in response to changing generation output" (p 32). The Bentek report also notes that cycling coal plants can damage the plant and thus increase maintenance costs and reduce plant life.

In some cases, ramp-up events may be handled at least cost by curtailing some of the wind output. In particular, if the load on a thermal plant drops to its minimum generation level (that is, it can not go lower without shutting down), it may be cheaper to curtail the wind than to incur start up costs for the thermal plant when the wind speed subsequently declines. Of course, frequent curtailment of wind generators also reduces the value of adding wind capacity to the system in the first place. It also limits the renewable generation credits that wind can supply. In some cases, system operators may also be able cope with sudden declines in wind output using mechanisms to shed demand, such as interruptible supply contracts or real-time pricing implemented with smart meters, but in today's markets such options are limited. In practice, it would appear that cycling of thermal power plants has been the primary response to short-term fluctuations in wind generator output.

Handling ramp-up and ramp-down events also requires forecasts and monitoring of wind conditions and the power curves (the translation between wind speed and power output) for wind farms. Although this caused difficulty for system operators in early years, there is some evidence that forecasting accuracy has improved with experience. Of course, operators also need to forecast temperatures (which have a big influence on demand), and monitor variables that can affect outages of plants or transmission lines or variables. It is not clear that forecasting wind speeds is in principle any more difficult than forecasting these other variables. However, since wind generator output depends on the cube of wind speed over much of the operating range of the turbine, fluctuations in wind power output magnify wind speed fluctuations by a factor of three. This may make it more critical to obtain more accurate forecasts of wind speed than other variables.

The relationship between wind output and system demand is also of interest to the owners of wind farms. The reason is that wholesale electricity prices in spot markets are closely related to system load. In particular, prices are typically very low at night and in the early hours of the morning when wind generation also tends to be higher.[22]

In this regard, a peculiar feature of the ERCOT market is that prices in the spot "balancing market" (where excess demands or supplies relative to contracted levels are reconciled) in recent years have often been *negative* in the middle of the night or early hours of the morning when demand is low. A negative price means that instead of having to pay generators to provide electricity, generators pay buyers to consume power. In effect, suppliers are willing to pay money in order to avoid cutting back output. In other wholesale electricity markets, negative prices occasionally occur when base load plants bid in a negative price that reflects the fact that they would prefer to pay to supply power than to incur the costs of shutting down and re-starting. If demand falls low enough to make these plants the marginal suppliers, equilibrium prices will be negative.

In ERCOT in recent years, however, the prices have been negative unusually often, especially in the west zone where the wind generation is concentrated. Prices were negative in 0.965% of the 15-minute market intervals in 2007, 13.94% of the intervals in 2008 and 8.76% of

[22] For example, the price-weighted average capacity utilization in ERCOT in 2008 was just 20.09% compared with the un-weighted average of 29.66%.

in 2009. Many of the settlement prices also approximated the amount of subsidies provided to wind generators through production tax credits and renewable energy credits. In order to have output that can be used to receive the production credits, wind generators were willing to pay up to the amount of the subsidies.

Some of the prices were much more negative. The minimum 15-minute price in the ERCOT west zone was –$999.01 in 2007, –$1981.81 in 2008 and –$1000.00 in 2009. The large absolute values of these prices are an indication of the costs that other generators incur as a result of cycling, or shutting down and re-starting, as discussed above. They are willing to pay a very large sum of money if they can avoid having to reduce their output.

A shortage of transmission capacity has also affected both the prices in the west zone of ERCOT and the utilization of installed wind generating capacity. Prior to the development of wind generation, there was little need to transport power between east and west Texas. Both the major sources of supply and the major demand centers were located in east Texas. The large expansion of wind generation quickly overwhelmed the capacity of the existing transmission lines.

In response to this situation, the Texas Legislature voted to introduce a transmission upgrade scheme, known as the Competitive Renewable Energy Zones (CREZ) initiative, to be paid for by all Texas electricity consumers. The various upgrades involved in CREZ are illustrated in Figure 10.

An increase in transmission capacity between west and east Texas should reduce the incidence of negative prices since there are many more sources of elastic demand and supply of power in east Texas. The cost of the new links per unit of electricity supplied will be quite high, however, because the links will need to have sufficient capacity to accommodate maximum wind output but will for most of the time be used to carry much smaller amounts of power.

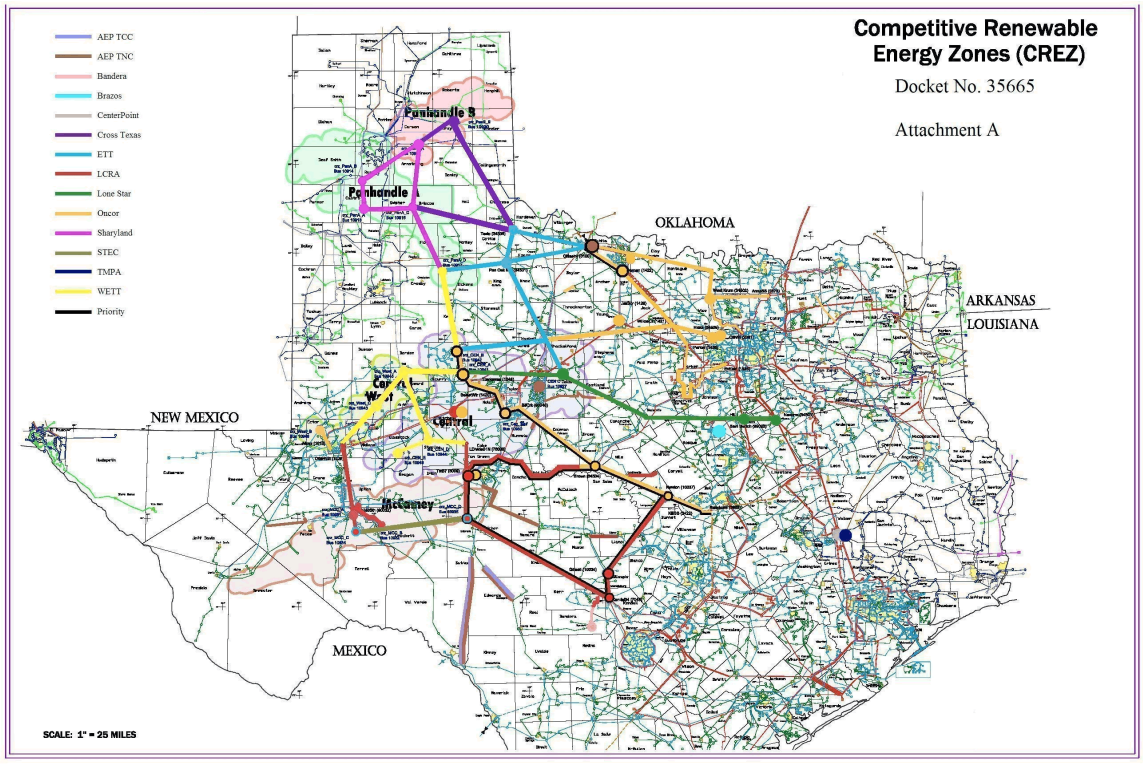

Figure 10: The CREZ transmission upgrade initiative

6. The effect of wind on long-term investment decisions

Decisions about what types of conventional plants to build in the face of expanding wind output depend on when the wind output will be supplied to market. The perspective we take is that conventional thermal capacity is chosen to meet the demand for electricity *net* of the supply from wind output. The assumption is that the operating cost of wind generation is sufficiently low that it always makes sense to dispatch the wind generation when the wind is blowing.[23] From this perspective, the stochastic nature of wind output simply adds to the stochastic nature of total system-wide demand. Indeed, wind, and other exogenously variable sources of supply, can be thought of as "negative demand."

[23] In practice, transmission constraints or the cost of curtailing other types of generating plant may limit the amount of wind generation dispatched. Nevertheless, wind output (like run-of-river hydroelectricity, solar, geothermal, tidal and other sources of supply that have miniscule variable operating costs) will generally be worth using whenever it is available.

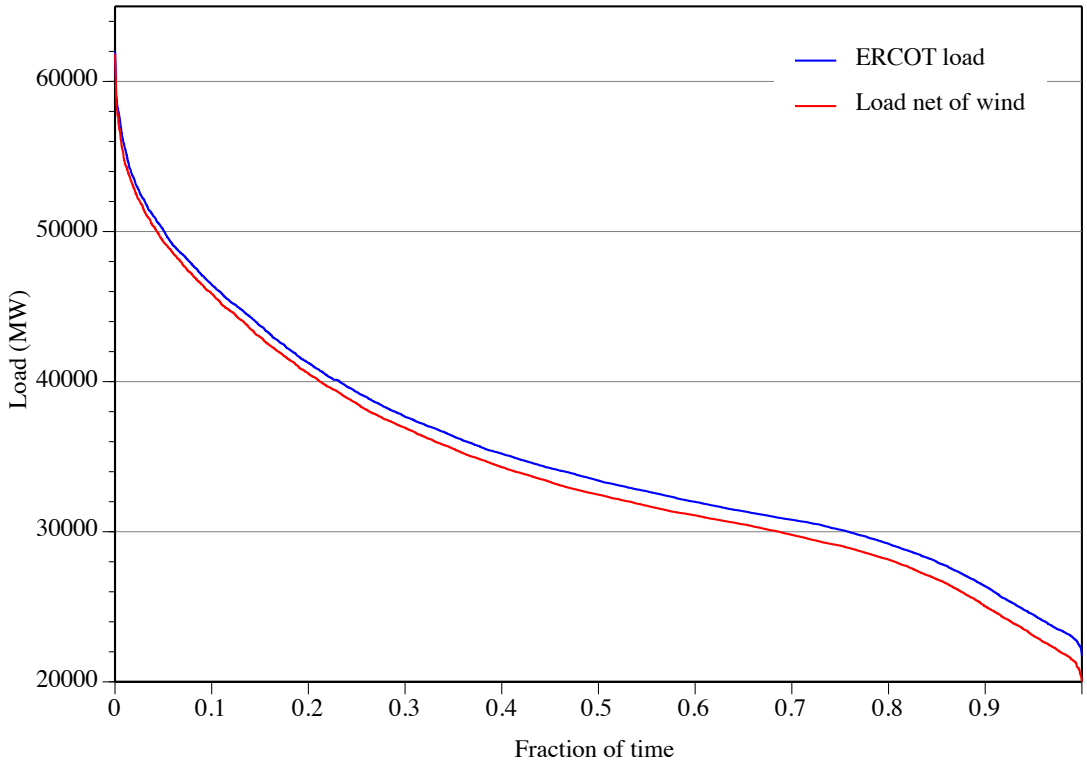

Figure 11: ERCOT load and net load duration curves, 2007

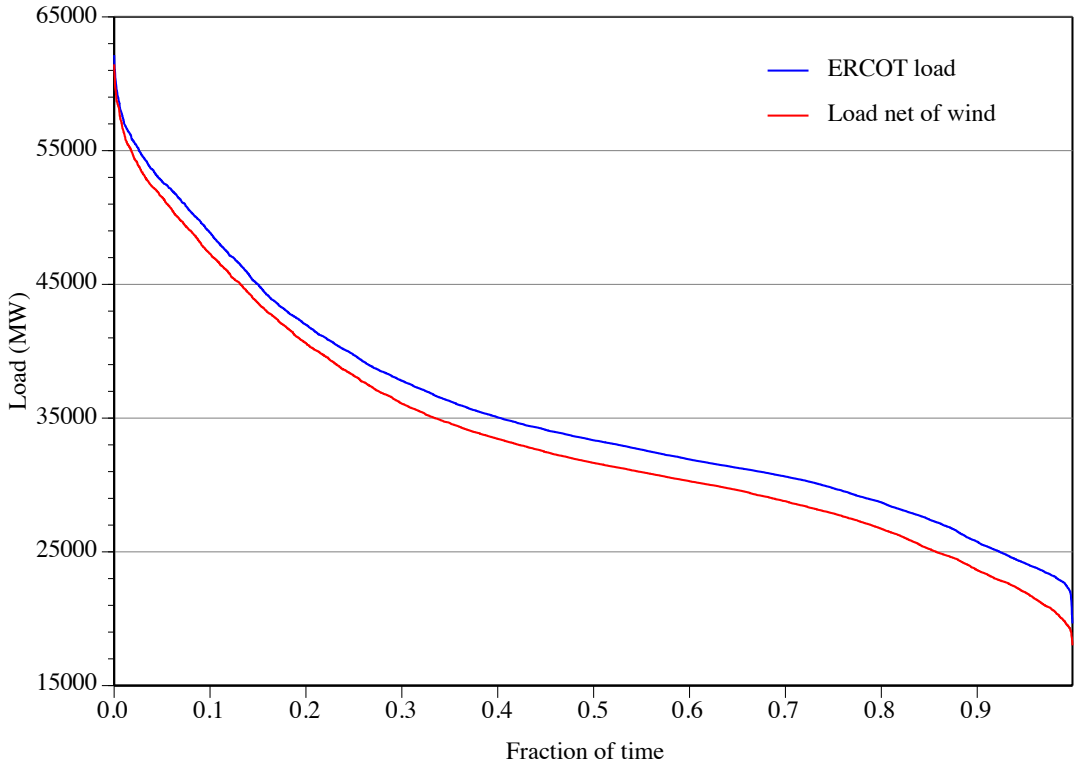

Figure 12: ERCOT load and net load duration curves, 2008

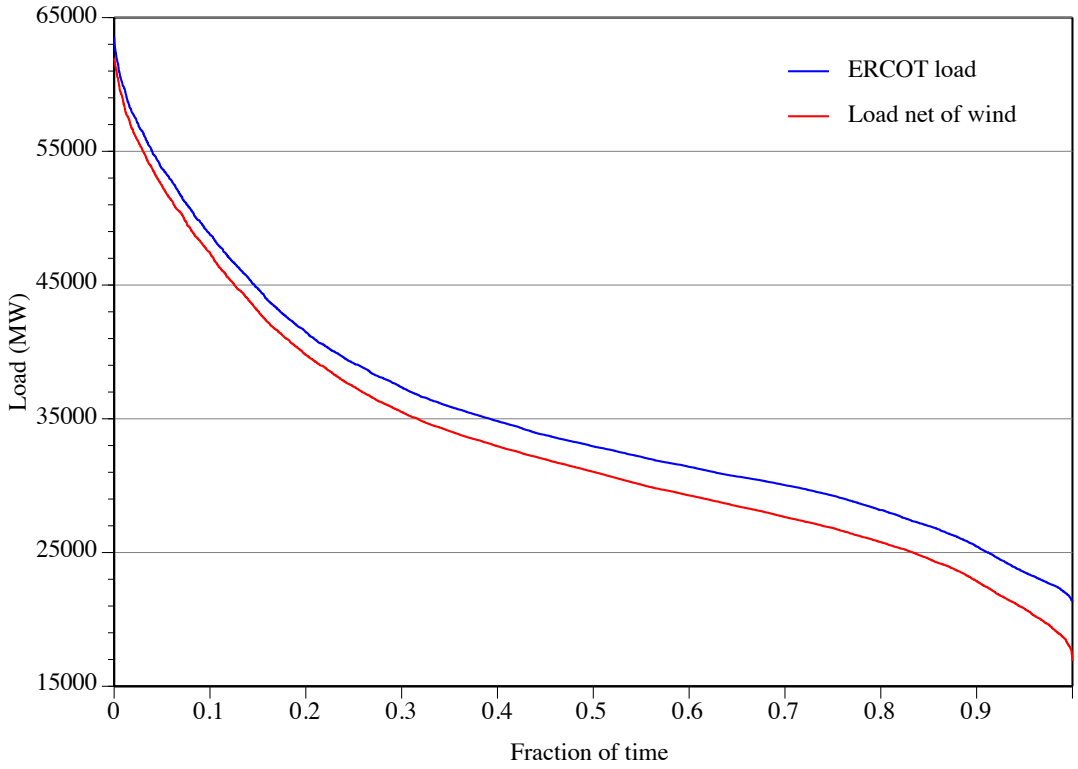

Figure 13: ERCOT load and net load duration curves, 2009

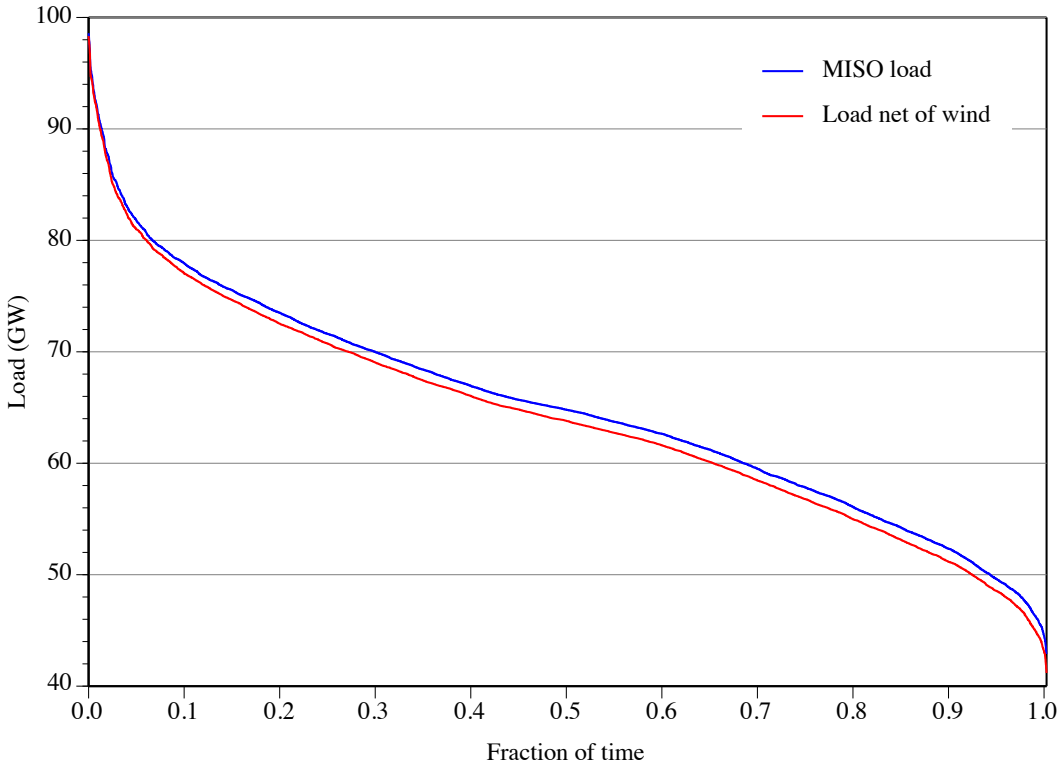

Figure 14: MISO load and net load duration curves, 2008

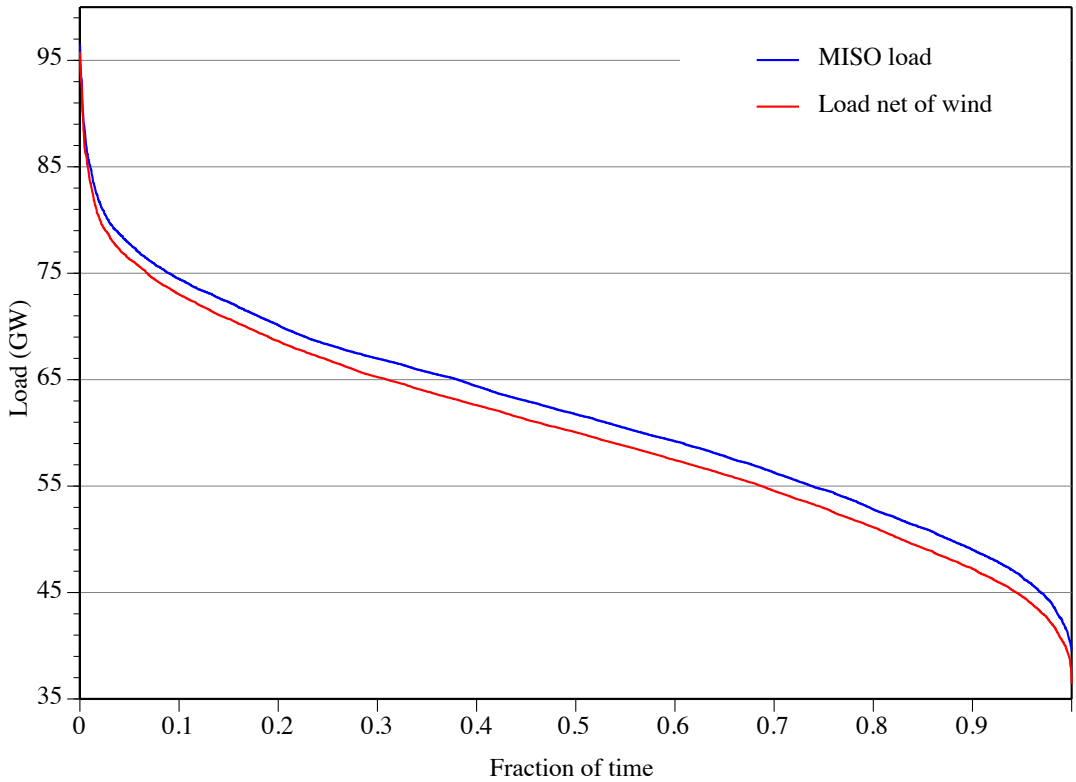

Figure 15: MISO load and net load duration curves, 2009

The usual approach to thinking about the mix of capacity needed to meet a given demand load involves calculating a load duration curve. As noted earlier, this is analogous to a cumulative probability distribution function and gives the fraction of time that load exceeds a given value. Figures 11–15 give the load duration curves, and the load duration curves net of wind generation, for ERCOT in 2007–09 and MISO in 2008–09.

Base load is defined as the amount of power that is demanded throughout the year. In Figure 11, this is slightly above 22GW. Base load demand can be supplied by plants that operate continuously. Peak load is the amount of power demanded in the 1% or 5% of hours when demand is greatest. Peak demand is supplied by plants that operate for only a few hundred hours each year. In between, we have various levels of intermediate demand that can be served by plants that are operating for an increasing number of hours as the demand level declines.

Since we have already seen that wind generation tends to supply more power in off-peak periods, it is not surprising that the *net* demand facing the rest of the system after wind output has been subtracted involves a larger reduction in base load than intermediate or peaking load.

The load duration curve effectively rotates clockwise around the peak demand level as more wind capacity is added over time.

In order to understand how firms using other fuel inputs are likely to react to increased wind output *in the longer term* one simply cannot look at the recent history of the effects of wind output on the demand for other fuels. The reason is that those reactions reflect the options afforded by the currently available capacities of different types of generating plants. In the longer run, however, the firms can, and in general will, alter the mix of generating capacity in response to the new demand situation they expect to face. The altered mix of types of plants will in turn change operating decisions.

The very rapid recent development of wind capacity also limits the extent to which we can use historical experience to gauge how investment policies will respond to an increase in wind generation. The experience is too new, and the relevant history too short, to make any observations very meaningful. Some changes in the historical record may share characteristics with the changes occasioned by increased wind output, but generally it will not be possible to find exact analogs of the recent experience.

We thus need to use a model of how electricity-generating firms generally make investment decisions to predict how they are likely to react to the changes resulting from increased wind output. A model allows us to characterize the influences on investment decisions at a more abstract level and apply those lessons to derive the likely response to increased wind generation. For this paper, we will keep the model as simple as possible. However, the basic conclusions of the analysis will apply to a more general model.

We assume that any one firm can choose two types of thermal capacity. Base load power has a relatively low operating cost per unit of output c_1 but a relatively high capital cost per unit of capacity K_1. By contrast, "peaking load" (in reality intermediate and peaking periods together) plants have a higher operating cost $c_2 > c_1$ per unit of output but a lower capital cost per unit of capacity $K_2 < K_1$. We also assume that either type of capacity has the same useful life span time of T periods, with the length of each period normalized to 1. Each of these periods is divided into two sub-periods. The first, off-peak, sub-period covers $[0, t]$ while the second peak sub-period covers $[t, 1]$. The off-peak period is characterized by a lower demand for electricity (net of wind) d_1 and a lower wholesale electricity price p_1. The peak period has both higher demand $d_2 > d_1$ and

a higher wholesale price $p_2 > p_1$. Denote the relevant risk adjusted continuously compounded interest rate by r. For simplicity, we assume that the operating and investment decisions of each firm are small enough relative to the market that none of them will affect the operating or capital costs, or the wholesale prices of electricity.[24] Let X_1 denote the base load capacity and X_2 peak load capacity. Use $0 \le x_{11} \le X_1$ to denote the anticipated aggregate output from the base load plants in the base load sub-period, $0 \le x_{12} \le X_1$ the output from the base load plants in the peak load sub-period, $0 \le x_{21} \le X_2$ output from the peak load plants in the base load period and $0 \le x_{22} \le X_2$ output from peak load plants in the peak load sub-period. The capacities X_1, X_2 and outputs x_{11}, x_{12}, x_{21} and x_{22} would then be chosen to maximize expected discounted profits

$$\sum_{i=0}^{T} e^{-ri} \int_0^t e^{-r\tau}[p_1(x_{11}+x_{21}) - c_1x_{11} - c_2x_{21}]d\tau + \int_t^1 e^{-r\tau}[p_2(x_{12}+x_{22}) - c_1x_{12} - c_2x_{22}]d\tau$$
$$-K_1X_1 - K_2X_2$$

subject to the constraints

$$0 \le x_{11} \le X_1,\ 0 \le x_{12} \le X_1,\ 0 \le x_{21} \le X_2,\ 0 \le x_{22} \le X_2$$

Define the Lagrangian function:

$$L = PV_1[p_1(x_{11}+x_{21}) - c_1x_{11} - c_2x_{21}] + PV_2[p_2(x_{12}+x_{22}) - c_1x_{12} - c_2x_{22}] - K_1X_1 - K_2X_2$$
$$+\lambda_{11}(X_1 - x_{11}) + \lambda_{12}(X_1 - x_{12}) + \lambda_{21}(X_2 - x_{21}) + \lambda_{22}(X_2 - x_{22}) + \mu_{11}x_{11} + \mu_{12}x_{12} + \mu_{21}x_{21} + \mu_{22}x_{22}$$

where, for notational convenience, we also have defined the present value factors

$$PV_1 = \frac{1-e^{-r(T+1)}}{1-e^{-r}}\frac{1-e^{-rt}}{r},\ PV_2 = \frac{1-e^{-r(T+1)}}{1-e^{-r}}\frac{e^{-rt}-e^{-r}}{r}$$

The first order conditions for maximizing L can then be written

$$PV_1(p_1 - c_1) - \lambda_{11} + \mu_{11} = 0,$$

with $$\lambda_{11}(X_1 - x_{11}) = 0,\ x_{11} \le X_1,\ \lambda_{11} \ge 0,\ \mu_{11}x_{11} = 0,\ x_{11} \ge 0,\ \mu_{11} \ge 0 \qquad (1)$$

$$PV_2(p_2 - c_1) - \lambda_{12} + \mu_{12} = 0,$$

[24] If this assumption were relaxed, prices and costs would change to marginal revenues and marginal costs. However, if we make the assumption that a new investment is large enough to significantly affect prices or costs we would need to modify the analysis to allow for strategic considerations. Hartley and Kyle (1989) examine a model along these lines, but without peak and off-peak sub-periods. Extending that model to allow for peak and off-peak sub-periods is the subject of further research.

with $$\lambda_{12}(X_1 - x_{12}) = 0,\ x_{12} \le X_1,\ \lambda_{12} \ge 0,\ \mu_{12}x_{12} = 0,\ x_{12} \ge 0,\ \mu_{12} \ge 0 \tag{2}$$

$$PV_1(p_1 - c_2) - \lambda_{21} + \mu_{21} = 0,$$

with $$\lambda_{21}(X_2 - x_{21}) = 0,\ x_{21} \le X_2,\ \lambda_{21} \ge 0,\ \mu_{21}x_{21} = 0,\ x_{21} \ge 0,\ \mu_{21} \ge 0 \tag{3}$$

$$PV_2(p_2 - c_2) - \lambda_{22} + \mu_{22} = 0,$$

with $$\lambda_{22}(X_2 - x_{22}) = 0,\ x_{22} \le X_2,\ \lambda_{22} \ge 0,\ \mu_{22}x_{22} = 0,\ x_{22} \ge 0,\ \mu_{22} \ge 0 \tag{4}$$

$$-K_1 + \lambda_{11} + \lambda_{12} = 0 \tag{5}$$

$$-K_2 + \lambda_{21} + \lambda_{22} = 0 \tag{6}$$

In addition, if there is free entry into the industry, the discounted expected operating surplus from the optimal investments must be zero:

$$PV_1\left[p_1(x_{11} + x_{21}) - c_1x_{11} - c_2x_{21}\right] + PV_2\left[p_2(x_{12} + x_{22}) - c_1x_{12} - c_2x_{22}\right] = K_1X_1 + K_2X_2 \tag{7}$$

Using these conditions, we first show that the lower operating cost base-load plants will be used "first" in the sense that it will only be worthwhile incurring the higher operating costs of the peak-load plants when no more lower operating cost capacity is available:

Proposition 1: Peak-load plants will not be used in any sub-period unless base-load plants are fully utilized in that sub-period.

Proof: Suppose to the contrary that $x_{2i} > 0$ and $0 < x_{1i} < X_1$. Then $\mu_{2i} = 0$ and $\mu_{1i} = 0 = \lambda_{1i}$ and from (1) and (2) $p_i = c_1$ while (3) and (4) imply $\lambda_{2i} = PV_i(p_i - c_2) \ge 0$. But this contradicts the assumption that the base load plants have lower operating cost, $c_1 < c_2$.

We next show that, except for a special set of parameter values, base load capacity will be fully utilized in the base period:

Proposition 2: Unless the cost parameters, discount rate and time split t between base and peak periods satisfy $K_1 - K_2 = PV_2(c_2 - c_1)$, base-load plants will be fully utilized in the base period.

Proof: If base-load plants are less than fully utilized in the base period, $0 < x_{11} < X_1$, and from (1), $\mu_{11} = 0 = \lambda_{11}$ and $p_1 = c_1$. Also, since $x_{12} > 0$ from Proposition 1, (2) implies $\mu_{12} = 0$ and hence from (5) and (2) we would have $K_1 = \lambda_{12} = PV_2(p_2 - c_1)$. From Proposition 1, we must also have

$x_{21} = 0$ and hence from (3) $\lambda_{21} = 0$. Then (6) would imply $\lambda_{22} = K_2 > 0$ and we conclude from (4) that $x_{22} = X_2$ and peak plant must be fully utilized in the peak period. Equation (4) also implies $\lambda_{22} = PV_2(p_2 - c_2)$. Thus,

$$K_1 - K_2 = PV_2(p_2 - c_1) - PV_2(p_2 - c_2) = PV_2(c_2 - c_1)$$

Remark 1: Observe that the parameter restriction in Proposition 2 says that the difference in capital cost of the two types of plant per unit of capacity equals the present value of the saving in operating cost during peak periods alone. Since in this special situation there is no loss from using base load plant to provide output in all periods, it is reasonable that base load capacity could exceed base period demand.

Remark 2: Notice that we also showed in the proof of Proposition 2 that if capacity of a given type is not fully utilized in a period then the wholesale price of electricity in that period must equal the operating cost of the under-utilized plant. This relies on the assumption that the market is competitive and might not hold in a model where competition is imperfect.

Proposition 3: Unless the cost parameters, discount rate and time split t between base and peak periods satisfy $K_1 - K_2 = (PV_1 + PV_2)(c_2 - c_1)$, peak-load plants will not be used to supply output in the base period.

Proof: If $x_{21} > 0$ then (3) implies $\lambda_{21} = PV_1(p_1 - c_2)$. Also, from Proposition 1, we must have x_{11}, $x_{12} > 0$. Since total demand is higher in the peak than in the base load period, and from Proposition 1 base load plant will be fully utilized in both periods, we must also have $x_{22} > x_{21} > 0$. In particular, we conclude that (1) implies $\lambda_{11} = PV_1(p_1 - c_1)$, (2) implies $\lambda_{12} = PV_2(p_2 - c_1)$, and (4) implies $\lambda_{22} = PV_2(p_2 - c_2)$. Thus, from (5) and (6)

$$K_1 = PV_1(p_1 - c_1) + PV_2(p_2 - c_1) \text{ and } K_2 = PV_1(p_1 - c_2) + PV_2(p_2 - c_2)$$

and hence,

$$K_1 - K_2 = PV_1(p_1 - c_1) + PV_2(p_2 - c_1) - PV_1(p_1 - c_2) - PV_2(p_2 - c_2) = (PV_1 + PV_2)(c_2 - c_1)$$

Remark: The parameter restriction in Proposition 3 says that the difference in capital cost of the two types of plant per unit of capacity exactly equals the present value of the saving in operating cost during both periods. In this special situation, the levelized total costs of the two types of

plant are identical and thus it is not surprising that optimal investment in either type is indeterminate.

Proposition 4: Unless the cost parameters, discount rate and time split t between base and peak periods satisfy either of the special conditions given in Proposition 2 or Proposition 3, base load plants will supply all the output in the base load period and both types of plants will be fully utilized in the peak load period.

Proof: The first part of this Proposition follows from Propositions 2 and 3. For the second part, observe from (3) that $x_{21} = 0$ implies $\lambda_{21} = 0$ and hence from (6) $\lambda_{22} = K_2 > 0$ so (4) also implies that $x_{22} = X_2$.

Remark: Observe that with $x_{21} = \lambda_{21} = 0$, $x_{11} = x_{12} = X_1$ and $x_{22} = X_2$, discounted expected profits will be zero as required by the free entry condition (7) since

$$PV_1(p_1 - c_1)x_{11} + PV_2[(p_2 - c_1)x_{12} + (p_2 - c_2)x_{22}] = (\lambda_{11} + \lambda_{12})X_1 + \lambda_{22}X_2 = K_1X_1 + K_2X_2$$

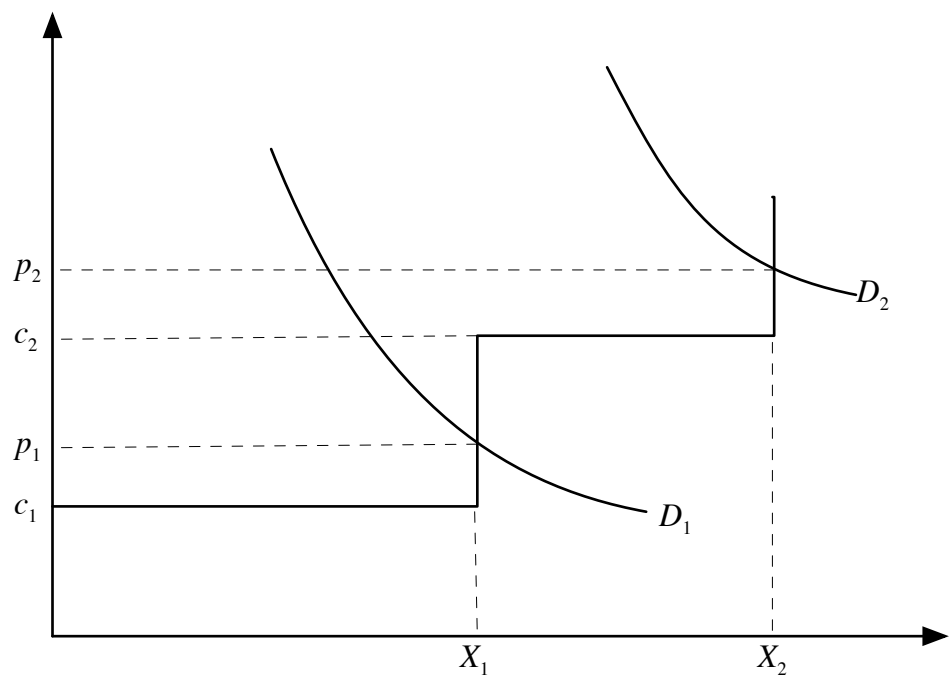

Figure 16: Competitive equilibrium with peak and off-peak periods

The resulting competitive equilibrium can be illustrated as in Figure 16. We can interpret $PV_2(p_2 - c_2)$ as the present value of "rents" accruing to scarce peak load capacity in peak periods. These have to be sufficient to cover the up-front capital costs of investing in such capacity.

Similarly, $PV_1(p_1 - c_1) + PV_2(p_2 - c_1)$ equals the present value of "rents" accruing to the scarce base load capacity in both periods. These have to compensate for the larger up-front capital costs of investing in base load capacity.

Although these results have been derived assuming perfect competition in the wholesale electricity market, similar results will hold in an imperfectly competitive environment with free entry. In particular, marginal revenues, and therefore prices, will have to exceed short run marginal costs by enough to yield a present value of rents sufficient to compensate for up-front capital investment costs. In addition, the conclusion that base load plants will be used first should be robust to many changes in the competitive environment since the lower operating cost of such plants gives them a competitive advantage in the short run.

These results have all followed solely from the assumed differences in cost structure of base load and peak load plants and the assumption that prices and demand are higher in peak than off-peak periods. Another difference between the technology of base load and intermediate or peaking load plants should accentuate the results we have derived. As noted above, base load plants typically have higher cycling costs than smaller plants designed to meet intermediate and peak demand. As a result, large base-load plants are designed to operate 24 hours a day, 7 days a week, apart from planned maintenance periods. This also will limit the maximum capacity of such plants to the expected minimum demand for their output in off-peak periods. In this context, the assumed pattern of demand in the simple model above represents the best situation for enabling variable output from base load plants. The model assumed that the peak periods were contiguous, so that all the base demand in each period was followed by all the peak demand. In reality, demand will fluctuate much more than this, which will further disadvantage base load capacity and tend to restrict its maximum level to the minimum demand prevailing in the off-peak periods.

Now consider the implications of the theoretical model in the context of the data analysis. We found from both the ERCOT and the MISO data that wind generation tends to be much larger in the off-peak periods at night than in the peak periods during the day. A consequence, as shown by the altered load duration curves in Figures 11–15, is that increased wind generation will produce a demand pattern facing the rest of the supply system that has a much higher ratio of peak to off-peak demands than would be the case without wind. The model implies, however,

that once investment adjusts to the demand pattern, the amount of base load capacity will be limited by the amount of base load demand net of wind. Hence, a future electricity market with more wind will have less base load capacity than otherwise would have been the case. In short, in the long run, we expect increased wind capacity primarily to reduce base load capacity.

This conclusion raises the question as to why previous researchers have found that wind generation has to date primarily displaced gas-fired generation. As already noted, those studies looked at the short run effects of wind taking existing facilities in operation as given. By contrast, the above argument was based on what is likely to happen in long run equilibrium as investments adjust in response to the new situation.

Paradoxically, the fact that wind has primarily reduced natural gas generation in the short run is consistent with the hypothesis that it will likely favor new investments in natural gas generation in the longer run. As we also noted above, wind output is highly variable. Hence, it is not surprising that increases and decreases in wind output primarily impact conventional generation capacity that is more flexible and can be ramped up and ramped down more cheaply. From a longer run perspective, however, this makes such plants a much better complement to wind. Hence, we would expect more wind to result in more, not less, investment in natural gas fired generation capacity.

This argument does not necessarily imply, however, that more wind generation will increase the demand for natural gas to produce electricity. Although the investment in natural gas *capacity* may be higher, the fact that the output from natural gas plants will be fluctuating as wind output varies will tend to reduce the capacity factors of natural gas plants below what they otherwise would be. This would reduce the demand for natural gas. On the other hand, cycling of gas plants reduces their efficiency and that would tend to raise the demand for natural gas. Furthermore, the intermittency of wind will tend to favor natural gas combustion turbines rather than combined cycle plants. Since the combustion turbines have higher heat rates, this will also increase the demand natural gas when the wind is not blowing. Finally, the disincentive to invest in base load capacity as a result of increased wind output is likely to favor increased gas generation in base periods as well as intermediate and peaking periods. The net effect on natural gas demand will depend on the size of the increased capacity of different types of natural gas-

fired plants on the one hand and any diminution in capacity factors for natural gas fired generating plants on the other.

7. Concluding remarks and policy implications

We began the paper by noting that there has been a large growth in wind generation capacity in recent years. However, wind generation also has been heavily subsidized, both directly and indirectly, over this period. Despite technological advances in wind generation, it remains more expensive than other conventional forms of generating electricity. Projections of the likely future costs of different generation technologies by the EIA also do not have the costs of wind becoming competitive with fossil fuels for some time.

The data from ERCOT and MISO suggest that some of the best sites for wind generation in the US have already been developed. In particular, average wind capacity factors in both ERCOT and MISO have declined in recent years. Furthermore, many of the favorable sites that have not been developed are in locations that will be more expensive, and also more environmentally sensitive, to develop than existing sites.

Limited transmission capacity may also have prevented the exploitation of some otherwise favorable sites. Transmission upgrades may alleviate this problem. Improved transmission links also would reduce the incidence of negative prices and increase the profitability of some existing wind farms. However, some of the best locations for wind are remote from markets, raising the cost of new transmission links. Low capacity factors for wind generation exacerbate the problem. The capacities of the transmission lines have to be large enough to accommodate peak levels of production while very little of that capacity will be used for much of the time. While it would be more desirable to add or upgrade lines that have another purpose, such as arbitraging price differences between two markets, increasing network stability, or accommodating additional types of generating capacity, such opportunities are limited.

The intermittent nature of wind generation also limits how much can be included in a network without jeopardizing network stability. Providing backup capacity is expensive. More flexible market mechanisms, including a market for ancillary services that permits voluntary load shedding, can mitigate these problems. In addition, as system operators gain more experience with accommodating wind generation they may develop better forecasting tools and other

techniques to minimize the threat to network stability. On the other hand, as wind generators age, the tightness of the relationship between wind speed and generator output may decline. This would reduce the ability to predict output fluctuations using weather data and weather forecasting models alone.

Putting these considerations together, we conclude that current targets for aggressive expansion in wind generation are unrealistic. As the various costs of the policies mount, there is likely to be a political backlash. If subsidies and regulatory policies are then moderated or withdrawn, the vigorous expansion that the industry has seen in recent years will abate, with negative consequences for parties who have invested heavily in expectation of the boom continuing. Any financial difficulties for the industry will also have negative consequences for the maintenance, and ultimately replacement or dismantling of existing facilities.

While there are reasons to question continued political sponsorship of the industry in the intermediate term, the plans for new capacity that have already been approved will still imply a substantial increase in wind generating capacity over the next few years. In addition, in the longer term, unsubsidized wind generation is likely to become competitive with fossil fuels as the price of the latter rise through depletion. This raises the question of what alternative energy source increased wind is likely to displace.

A number of studies have shown that the expansion of wind has thus far displaced natural gas more than coal. We argued, however, that this was a short run outcome based on optimal behavior taking existing capacity as given and recognizing that gas generation is more flexible than coal and thus more suitable as a backup for fluctuating wind output. In the longer run, the intermittency of wind and the fact that wind generation satisfies base load demand more than intermediate or peaking loads should discourage investment in base load coal and nuclear capacity and encourage investment in natural gas capacity.

If our argument is correct, natural gas can be seen as a “transition fuel” for more than one reason. Not only is natural gas the least carbon-intensive fossil fuel, and thus a bridge to an energy supply system that is less dependent on carbon-based fuels. It also is a good complement to renewable sources such as wind that are highly variable.

Finally, even if natural gas capacity is larger than it would be without an expansion in wind, the demand for natural gas to generate electricity need not rise. On the one hand, the

intermittency of wind means that natural gas plants will operate at a lower average capacity factor than they would in the absence of wind generation, thus reducing the demand for natural gas. On the other hand, the same intermittency may increase the cycling of gas plants and encourage the use of natural gas turbines at the expense of combined cycle plants. The reduced efficiency with which the natural gas is used then would raise the demand for natural gas. The net effect is likely to vary from one supply system to the next and could only be gauged via detailed modeling of each system.

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