Does Wind Generation Really Reduce GHG Emissions?

Talat S. Genc* and M. Ege Yazgan‡

September 1, 2017

Abstract

We study the relationship between greenhouse gas (GHG) emissions and wind generation. We provide empirical evidence on the questions of a) whether the relationship between the wind generation and GHG emissions is linear, which is commonly assumed in the literature; b) whether the marginal impact of wind generation on emissions is positive or not; c) whether relying on a renewable energy source (e.g., wind) in electricity production helps reduce the aggregate emission in the system. Using hourly actual generations by all generators and actual emissions data covering all hours of 2006-2010 in the Ontario wholesale electricity, we observe that the relation between emissions and wind outputs is non-linear and non-monotonic. At the very low and very high wind generation levels the emissions increase while wind generation increases and at the in between levels the emission is decreasing in wind output. While we employ a semiparametric approach to examine the effect of wind output on GHG emissions, we perform several robustness checks in the presence of different covariates to explain this relation.

Keywords: Renewable energy; greenhouse gas emissions; electricity markets; semiparametric methods.
JEL Classification: C12, C22, Q40, Q51.

*Department of Economics and Finance, University of Guelph, Guelph, ON, N1G2W1, Canada. Corresponding author. Phone: 1.519.8244120 ext:56106. Email: tgenc@uoguelph.ca

†Department of Economics, Istanbul Bilgi University, Istanbul, Turkey

‡We thank Fuat C. Beylunioglu for excellent research assistance.

1 Introduction

Environmental consciousness has gained momentum among consumers, policy makers, NGOs, governments, and investors. The reflections of this on the energy sector are that consumers now demand more of green products (such as energy efficient appliances, electric cars/bikes, wind/solar generated electricity); governments issue “Clean Power Plan”, or “Green Energy Acts” or “Renewable Energy Laws”; and investors expand their renewable energy investments and/or portfolios. One common goal of those initiatives is to reduce air emissions and provide alternative clean products. Wind turbine investments, feed-in-tariff programs, and wind generated electricity are part of this goal. In that regard, this paper focuses on wind generation, which is celebrated and promoted as a clean and cost effective energy choice, and questions whether it has really contributed to reductions in air emissions such as greenhouse gases (GHG).

To address this issue we examine Ontario wholesale electricity market, in which wind generation has been growing at a fast-pace since 2006. Due to the Ontario’s Green Energy Act the government has signed a contract with a consortium in 2010 to construct new green energy facilities which plans to triple Ontario’s renewable wind and solar energy generation. In 2010 Ontario had about 1,200 MW installed wind generation capacity and 40 MW of solar capacity.[1] This new project which will entail the construction of 2,000 MW of wind power and 500 MW of solar power is expected to provide 110 million MWh emissions-free electricity over 25 years. Ontario’s energy plan aims to reach 10,700 MW wind and solar energy installed, corresponding to 20 percent of the total production capacity, by 2020. This energy act also targets 33 percent of total generation to come from renewable resources, including 10 percent generation from wind by 2030.

Several studies have examined the relation between wind generation and market and environmental outcomes including the analyses of market prices, outputs of conventional generators, hydropower storage, power trade, investment, and emissions. The examples include Denny and O’Malley (2006), Benitez et al. (2008), Callaway and Fowlie (2009), Traber and Kemfert (2009, 2010), Cullen (2013), Novan (2015), Genc and Aydemir (forthcoming), Acemoglu et al. (2017), Genc and Reynolds (2017). Most of these papers assume perfect competition (exceptions are Traber and Kemfert, Genc and Aydemir, Genc and Reynolds, Acemoglu et al., who consider market power) and show that under certain market conditions wind generation causes emissions reductions. To alleviate the intermittency issues of wind generation and increase the supply security, some peaking units with high ramp-up rates are needed, but the investment incentives by the thermal units could be low due to lower market prices. These papers mainly find that wind generation reduces emissions. For example, Traber and Kemfert (2009) study the impact of German feed-in tariff program on emissions and prices. They find that this FIT program increases consumer (end-user) prices by 3% but decreases producer (or market) price by 8%. Also emissions from electricity generators in Germany go down about 11%, but this does not impact aggregate emissions levels in Europe. In another study, Traber and Kemfert (2011) examine the relationship between wind generation and investment behavior of peaking technologies. They apply their equilibrium model using a German market data and find that although wind supply reduces market prices more than 5% it reduces incentives to invest in natural gas fired generators which are the spinning reserves that supply power when wind generation fails to produce electricity due to its nature of intermittency. Therefore, expansion in wind investments and generations could cause supply security problem in the market. Benitez et al. (2007) investigate the impact of wind generation on the environment and market outcomes and assess the extent to which hydropower storage would offset wind power intermittency. They also show that the cost of wind generated energy is high; vary from \$37 to \$68 per MWh in the Alberta market; but this cost can be

[1] As of July 2015, the installed wind generation is 2,925 MW, which is about 8% of the total installed capacity.

reduced if hydropower generators are used in place of peaking high-cost natural gas-fired generators. Denny and O'Malley (2005) investigate whether wind emissions cause an increase in emissions (CO2, NOx, SO2) of conventional plants. Using a unit commitment model for Irish power market they find that wind generation cause reduction in CO2 emission but do not much affect the levels of other emissions. Cullen (2013) estimates generator start-up costs, and uses these estimates in a perfect competition model to run counter-factual simulations to assess the impact of additional wind power on the Texas wholesale market. Genc and Aydemir (forthcoming) calibrate Ontario power market model and find that 0.62 lbs of NOx, 1.99 lbs of SO2, and 0.3 tons of CO2 could be avoided per MWh imports in 2007-2008 in Ontario. The current paper is similar in vain to Kaffine et al. (2013) who also examine the impact of wind generation on emissions. In OLS model, Kaffine et al. find that the coefficient of the right hand side variable which is wind generation is negative; that is wind generation reduces air emissions. In particular, they find in OLS estimation that emission savings from wind power in Texas (ERCOT) are 1.3 lbs for SO2, 0.79 lbs for NOx, and 0.52 tons for CO2 per MWh wind generation. Genc and Reynolds (2017) investigate the market implications of ownership of a new low-cost production technology. They measure the impact of renewable energy penetration into electricity markets and examine how the ownership of renewable capacity changes market outcomes. They find that consumers enjoy better air quality under the largest firm's ownership of new generation, but at the expense of higher prices. Acemoglu et al. (2017) analyze a model of wholesale electricity market with symmetric Cournot firms of conventional generation and renewable generation capacity that may be owned by either the Cournot suppliers or non-strategic firms. They show that the merit order effect, that is wind capacity depresses the price due to dispatch order, holds in their model and that shifting ownership of a fixed amount of renewable capacity toward strategic Cournot suppliers yields higher wholesale prices and lower welfare.

Our main difference from the above mentioned literature is that while we empirically examine the actual wholesale electricity market outcomes we do not impose a linear relation between wind generation and emissions nor assume a parametric model. Indeed data shows that the relationship between wind outputs and emissions are highly non-linear and non-monotonic. Therefore, we utilize a non-parametric estimation procedure to quantify this relation. Although we focus on wind generation and examine its impact on greenhouse gas (GHG) emissions, the methodology can be extended to include any generation type (solar, coal, nuclear) or unit (specific plant). We find that the emission levels exhibit a complex and non-monotonic relation with wind and depend on the level of wind generation. In particular, the emissions tend to decrease in low levels of wind outputs and tend to increase in high levels of wind generations. This behavior is consistent across the peak and off-peak seasons over the years.

The structure of the paper is as follows. In Section 2 we briefly explain the Ontario wholesale electricity market and give details of the hourly data sets. In Section 3 we introduce the non-parametric econometric methodology applied to the Ontario market. We explain the regression results in connection with the market interactions in Section 4. In the final section we briefly conclude with a policy implication of our results.

2 Market Structure and Data

We examine the Ontario wholesale electricity market, the most diverse (in terms variety of production technologies) and one of the largest power markets in Canada, where electricity consumption is significant as it is the manufacturing hub of Canada. In Ontario there is a single settlement market in which electricity transactions (purchase, sale, export/import) are carried out in the "pool" type real-time wholesale market. There is no day-ahead forward market and the share of bilateral contracts is tiny (due to the market design which mandates real-time power exchange). The system operator, so called the Independent Electricity System Operator (IESO), is mainly responsible from running the auction, clearing the market and managing the transmission network. The IESO also employs a dispatch scheduling and optimization algorithm to determine (predicted) pre-dispatch sequence of prices and demand quantities for the future periods so that market participants could use the pre-dispatch data to reform their operations, planning and participation in the real-time market.

In Ontario there are several dominant firms (each with more than 1000 MW installed capacities) such as Ontario Power Generation Inc (OPG), Bruce Nuclear Inc (Bruce), and Brookfield Renewable Energy Inc (Brookfield), and a large number of firms and generators which are small and competitive suppliers (whose capacities are mostly less than 100 MW). The OPG has operated hydro, nuclear, coal, natural gas fueled generators, and wind farms. The total available capacity of OPG generators changes every hour. For instance, the minimum available total capacity was 12,900 MW, the maximum was 19900 MW, and the average was almost 16,900 MW per hour in 2007.[2] Bruce Nuclear has six nuclear generators/stations with the identical heat rates. Total production capacity from these six nuclear stations changes every hour, and in year 2007 its average total capacity was around 4,200 MW. Brookfield mainly runs hydro, wind and natural gas–fired generators. Its total available capacity varies from hour to hour, and its total production capacity was on average 1,000 MW. The rest of the firms operate small-scale hydro (some are run-of-the river), wind, biomass, and natural gas production technologies. They have different gas-fired generators with different heat rates, emission rates and capacities.

We employ a detailed plant and market level data provided by the Environment Canada, the Statistics Canada, and the Independent Electricity System Operator (IESO). These data sets include hourly export/import quantities, hourly production and emissions and available capacities of all generators, hourly market clearing prices and demand quantities, temperature, as well as technical features of the generators.

We use five-year hourly data accounting for 43,824 hourly observations for each variable starting from January 1, 2006, the time that the wind generators has started to operate, and ending with December 31, 2010. In the Ontario market there were over 500 registered generators (over time some generators were phased off and some new ones were constructed) of which we have their efficiency rates, emission rates (of NOx, SO2, CO2, N2O, CH4 and others) and available hourly production capacities.

In our regressions, we directly utilize the actual emissions of generators reported by the Environment Canada. This is a better approach than the one employed by Genc and Aydemir (forthcoming) who estimated the emission quantities in 2007-8 using model predicted production data and generator technical characteristics such as emission rate, fuel content, and heat rate. We examine greenhouse gasses including CO2, N2O, and CH4, as opposed to Genc and Aydemir who studied CO2, NOx and SO2 for measuring the impact of electricity trade on emissions. In this study, we ignore NOx and SO2 emissions as they have only local impacts, and focus on GHG emissions which are significant and exhibit global environmental degradation. The greenhouse gasses are emitted by the generators which are fueled by diesel, refinery gas, wood and wood waste, landfill gas, coal (lignite, bituminous, sub-bituminous), natural gas, and oil. The CO2 emission rates of generators vary across generation units in Ontario and the CO2 fuel contents can even greatly change for a given fuel type. For example, coal has several subcategories with different CO2 contents depending on whether it is anthracite, lignite, sub-bituminous or bituminous. Due to these reasons, instead of calculating the emissions from

[2] As of late 2015, all of the coal-fired plants in Ontario have been phased out. They have been replaced by renewables and gas-fired generators.

the production data, we directly employ the actual emissions quantities reported by the Environment Canada.

We divide the hourly data into seasons, where winter spans December through March, spring covers April and May, summer includes June through August, and the rest of the months are part of fall. In Table 1 we present hourly average descriptive statistics including electricity output by production technology, demand and import (MWh), air temperature (Celsius) and GHG (pounds) emissions.

Table 1 demonstrates that the peak seasons are winter and summer where high demand is accompanied by higher imports, higher temperature in summer (and lower temperature in winter), higher productions by fossil-fuel technologies (coal and natural gas) and hence higher GHG emissions. Clearly, coal production is highly correlated with GHG emissions, and its share goes down over time in our data. On the other hand, Wind output increases monotonically after its introduction in 2006 and but due to its intermittency it may not be productive whenever it is most needed, especially in peak times. Nuclear, hydro and oil outputs show similar movements over the periods. There is no clear pattern for imports over the seasons, however they are increasing in demand. Moreover, GHG emissions reached the maximum in summers almost all years, except 2009 during which the coal generation sharply went down.

< Table 1 >

3 Methodology

In this study we analyze the relation between GHG emissions and wind generation. Our aim is to provide empirical evidence about whether a) the relationship between the wind generation and GHG emissions is linear (which is commonly assumed in the literature without any justification); b) the marginal impact of wind generation on emissions is positive or not; c) relying on a renewable energy source (e.g., wind) in electricity production helps reduce the aggregate emission in the system or not. In Figure 1 we plot actual hourly average wind generation and actual hourly average GHG emissions over the years encompassing 2006-2010 in Ontario.

<Figure 1>

This figure shows that the relation is non-linear and non-monotonic. At very low and very high wind generation levels the emissions are increasing in wind generation and at in-between levels GHG emission is decreasing in wind generation. This relation could be due to changes in market demand conditions over the years. To control this demand effect we correct the variables for demand.

<Figure 2>

In Figure 2 we normalize the actual hourly average GHG emissions with the actual hourly average load in the y-axis and use the hourly average wind output over the years in the x-axis. Similar to Figure 1, we find the same non-linear and non-monotonic relationship between aggregate emissions and wind generation. This finding provides a justification for our modeling choice as delineated below.

These figures indicate that the relationship between wind generation and GHG emission is non-linear; not only because of the changes in the slope but also in the sign of the relationship. While GHG emissions and wind generation are negatively associated for some production levels, they are positively correlated for some other production levels. That is GHG emission can increase as wind production expands.[3]

[3]We also plot GHG emissions versus wind generation over the seasons using the disaggregated data. We find the same non-linear and non-monotonic patterns across the seasons as we have seen for the entire sample.

The figures suggest that modeling the relationship between wind generation and GHG emissions by using simple linear regression is clearly inappropriate. As an alternative modeling strategy, conformable with the evidence shown in the figures, we will make use of non-parametric regression techniques to capture the non-linear features of this observed pattern.[4] As is widely accepted, functional form (non-linear or linear) for the relationship between variables is generally unknown and parametric models are only implemented due to their simple estimation procedures and ease of interpretation. However, the relationship between the variables could be highly complicated and a parametric model may only present a deceptive picture of this relationship. To avoid the potential disadvantages of adopting a parametric model, we utilize a semi-parametric approach. Semi-parametric estimation procedures are appealing because they preserve the simplicity of parametric models and the flexibility of nonparametric ones. They are also more informative than their alternatives such as threshold models that impose a piece-wise linear structure on the underlying function.

The semi-parametric regression model can be expressed in its following general additive form.

$$y_t = m_1(x_{1t}) + \cdots + m_k(x_{kt}) + \beta_{k+1}x_{k+1t} + \cdots + \beta_n x_{nt} + \epsilon_t$$

where $\epsilon_t \sim NID(0, \sigma^2)$ and k nonparametric regressors enter additively whereas the rest is allowed to enter linearly. The partial regression functions $m_j(x_{jt})$ are assumed to be smooth and are to be estimated from the data by fitting a smoother.[5] This combined feature of semi-parametric model brings many advantages together; first the model relaxes linearity assumption by containing a non-linear part but also contains linear analysis in itself. Therefore, some features of linear regressions such as dummy variables can be incorporated to the analysis. Second, it offers flexibility on adapting various cases in the same model formulation as we show below.

In this study, to analyze the effect of wind electricity output on GHG emissions, we consider the above partially linear regression model in which production by wind (represented by W_t) has an unknown functional form whereas other regressors enter the model linearly. By considering different covariates in addition to production by wind, we estimate the following alternative 11 models:

[4] Needless to say a non-linear relation can also be modeled parametrically. As explained below, the choice of non-parametric regression is also related with its flexibility in addition to its capability of capturing non-linear relations as well as linear ones.

[5] There are several methods for estimating nonparametric and semi-parametric regression models such as local averaging, kernel estimations or local polynomial regressions. Among them, smoothing spline method leaps out because of ease of adaptiveness to different types such as additive nonparametric and semi-parametric models. Instead of fitting a local polynomial regression, it optimizes an explicit function, *penalized sum of squares*, to find the best fit and offers certain advantage over others. The estimation of generalized additive models is accomplished using spline smoother as described in Wood (2004, 2006, 2011) which also features automatic selection of smoothing parameters and carried out by using mgcv package in R (The name of the package comes from the method employed to pick the smoothing parameters: **m**ultiple **g**eneralized **c**ross-**v**alidation, see also Fox and Weisberg (2011)).

$$y_t = \alpha + m(W_t) + \epsilon_t \tag{1}$$
$$y_t = \alpha + m(W_t) + \beta_1 D_t + \epsilon_t \tag{2}$$
$$y_t = \alpha + m(W_t) + \beta_1 D_t + \beta_2 T_t + \epsilon_t \tag{3}$$
$$y_t = \alpha + m(W_t) + \beta_1 (D_t - W_t - I_t) + \epsilon_t \tag{4}$$
$$y_t = \alpha + m(W_t) + \beta_1 (D_t - W_t - I_t) + \beta_2 T_t + \epsilon_t \tag{5}$$
$$y_t = \alpha + m(W_t) + \beta_1 N_t \tag{6}$$
$$y_t = \alpha + m(W_t) + \beta_1 (D_t - W_t - N_t - I_t) + \beta_2 N_t + \epsilon_t \tag{7}$$
$$y_t = \alpha + m(W_t) + \beta_1 N_t + \beta_2 (D_t - W_t - N_t - I_t) + \beta_3 T_t + \epsilon_t \tag{8}$$
$$y_t = \alpha + m(W_t) + \beta_1 N_t + \beta_2 H_t + \epsilon_t \tag{9}$$
$$y_t = \alpha + m(W_t) + \beta_1 N_t + \beta_2 H_t + \beta_3 (D_t - W_t - N_t - H_t - I_t) + \epsilon_t \tag{10}$$
$$y_t = \alpha + m(W_t) + \beta_1 N_t + \beta_2 H_t + \beta_3 (D_t - W_t - N_t - H_t - I_t) + \beta_4 T_t + \epsilon_t \tag{11}$$

where $W_t, N_t, H_t, C_t, G_t, B_t, O_t$ denote electricity outputs of Wind, Nuclear, Hydro, Coal, Natural Gas, Biomass and Oil generators for a given hour, t, respectively. D_t, I_t and T_t denote total market demand (which includes Ontario demand and exports), imports and Ontario temperature. GHG emission for a given hour is represented by the dependent variable y_t.

In all of these models the partial regression function, $m(W_t)$, where the effect of wind output on GHG emission is captured non-parametrically, is our main interest. The models from (2) to (11) are included to evaluate the robustness of the estimate of $m(W_t)$ in the presence of different covariates in the regression. The second model includes total electricity demand as an additional regressor to control its effect on GHG emissions. The third one considers temperature in addition to total demand quantity. The fourth redefines a modified residual demand by deducing imports and wind output from the total demand. Similarly other models follow. In total we consider 11 different models and the main objective is to check the robustness of (1) so as to examine whether the inclusion of these new variables change the form of the function $m(W_t)$ that represents the effect of wind output on emission.

4 Results

The estimation results of $m(W_t)$ along with the 95 percent confidence bands for the 11 models proposed above are illustrated in Figures 3 to 7. Figure 3 presents the results for all data covering all hours of 2006-2010. Figures 4 to 7 provide the estimates of seasonal data separately (winter, spring, summer and fall).[6]

<Figure 3 - 7>

The figures show the estimates of $m(W_t)$ at different wind output levels that are indicated in the x-axis. The frequency bars on the x-axis of each figure depicts the intensity of data points with different levels of wind output. For example, in all springs (Figure 5) and all summers (Figure 6) the frequency decreases above the level of 800 and 600 MWh, respectively, whereas for winters and falls it is typically above 1000 MWh. This indicates the fact that there is less windy days in summers and springs compared to other seasons. This fact also leads to widening confidence intervals for a

[6] In Tables A1 and A2 of the Appendix, for illustrative purposes, we have included additional output on the estimation results of the 11 regression models illustrated in Figure 3.

level of wind production due to decreasing number of data-points. To be more specific about the figures, note that the values on the y-axis refer to the values of $m(W_t)$ function and should not be interpreted as the total value of GHG emission, which is y_t, with respect to different wind output levels. Instead they are interpreted as the contribution of wind generation to the total value GHG emissions among other variables included in the model under investigation. For example, in the first figure (Model 1) of Figure 3, when wind output reaches its highest level, close to 1200 MWh (x-axis), the contribution of wind output on GHG emission, represented by $m(W)$ (y-axis), points a negative value around 1500. This indicates that the additional contribution of wind on total GHG emission results in a reduction in total GHG by 1500 pounds per hour. Similarly, when the wind output is equal to 600 MWh, $m(W)$ indicates a reduction in total GHG by approximately 750 pounds per hour. Therefore, using the estimated values in Table 1 of the Appendix (Model 1), for a given wind level equal to 600 MWh, we can calculate, the total GHG emission y_t as being equal to $2929.30 + m(600)$, which approximately yields $2929.30 - 750 = 2179.3$ pound per hour in GHG emissions.

The results displayed in Figure 3 suggests that for all models, the effect of wind output on GHG emission is negative for the majority of wind levels captured in our data sets. Moreover, for the majority of the models, as seen from almost steady downward pattern of $m(W_t)$, this negative effect becomes larger and larger as the wind output increases. But this steady pattern is discontinuous and reverts backs in some output levels and the negative contribution starts to diminish leading to positive marginal effects (captured by the positive slopes). The negative marginal effects (negative slopes) decelerates and turns into positive ones between 400 MWh and 600 MWh for the majority of the models. For 4 models (models 7,8,10, and 11) out of 11, the negative marginal effects turns into positive ones after wind production attains a level around 1000 MWh.

The analyses are also carried over the seasonally disaggregated data in Figure 4 - 7. The graphs in Figure 4 displays the results obtained using the data for winter season only. The results are similar to those of entire data (Figure 3), however, the opposite effect observed in the high wind output levels seems to disappear. However, in graph of spring season (Figure 5), the reverse effect in the higher wind outputs, observed especially in models 7, 8, 10 and 11 in Figure 3, becomes more apparent and the shape of the curve becomes a reminiscent of U-shaped with a bottom value corresponding to the wind level of 600 MWh. The positive marginal effects appearing after this level of wind production reduce the negative marginal contribution up to minus 100 in general.

As can be followed from Figure 6, this U-shaped characteristic of the curves becomes more clearly visible for almost all models in the summer data, where the bottom of U-shaped appears to correspond to a wind level around 400 MWh. After this point positive marginal effects help the contribution of wind turn into positive numbers. For example, for model 1, the contribution of wind (the value of $m(W_t)$) reaches to a level higher 1000 pound per hour.

The behaviors of $m(W_t)$ in fall data (Figure 7) is similar to those of the entire data (Figure 3) with more erratic movements around wind levels 400 MWh and 600 MWh and after 1000 MWh.

Overall the results do not support the premise that wind production does lead to decrease in GHG level in all circumstances. After certain level of wind production, the assumed negative effect of wind production on GHG emission seems to be reversed and higher level of wind production becomes associated with more pollution. The clear U-shaped figures of $m(W_t)$ estimates found especially in summer data suggest that increasing wind production after an approximate optimum level of 400 MWh per hour only contributes more pollution. Although to a lesser extent this type of U-shaped curves are also found in spring data at around the optimum level 600 MWh per hour. Similar nonlinear effects are found in other seasons except winter where no reverse effect seems to be present. It should be emphasized that the revers effects are valid for models 7, 8, 10 and 11 in all seasons excluding winter. This finding suggests that, especially in summers, due to low penetration of wind generation and very low levels of wind speed, increasing wind output doesn't prevent the usage of fossil-fuel based units, especially coal generators, and hence causing more emissions.

Note also that among all models considered for robustness purpose, models 10 and 11 appear to be the most powerful in terms of explanatory power (see the Appendix). This latter result further consolidates the conclusion that the reverse effect is not limited to summer season, but the other seasons with varying degrees except winters.

5 Conclusions

One of the main contributions of this paper is to estimate the marginal contribution of each MWh wind generation on the GHG emissions for all levels of wind production. Using a nonparametric estimation technique we estimate the impact of wind generation on GHG emissions in the Ontario wholesale electricity market covering all hours of 2006-2010. We show that there are non-linear and non-monotonic relations between wind generation and GHG emissions, and the marginal impact of wind generation is non-linear. In contrast, the econometric models in the literature mainly using parametric estimation methods to explore the relationship between wind generation and emissions find that this marginal contribution is constant. The competition models also assume that the marginal contribution of wind is constant. Second, we expand the base model to control for conventional generation (including hydropower, nuclear, and fossil-fuel fired generators) as well as demand and temperature in several semiparametric regressions. We find that our results are robust.

While we find that the marginal contribution of wind output on emissions is in general positive, that is wind generation helps reduce emissions, penetration of high wind output into the electricity market does not imply that aggregate emissions should be decreasing. Indeed, as we observe in summers (in the summer figures for all models in the Appendix) that, the relationship between wind generation and aggregate emissions are U-shaped. At low levels of wind generation, the aggregate emissions tend to decrease in wind output. However, most interestingly, as wind output increases the aggregate GHG emissions go up. This result is associated with the market conditions: in summers demand is high and hydro output is low, so output of fossil-fuel fired generators is high and hence causing emissions increase. Therefore, in summers when wind generations are at its highest levels the aggregate emissions are also at their highest levels. We also observe this relation in fall seasons and overall data.

A policy implication of this paper is that wind generation does not necessarily associated with air emission reductions. Furthermore, contribution of each MWh wind generation has a non-constant effect on emissions released in the system. Although wind capacity investments and wind generations go up, emission targets set by policy makers may not be reached. This is due to growing demand for electricity and intermittency of the renewable energy.

References

[1] Acemoglu, D., Kakhbod, H., and Ozdaglar, A., (2017). “Competition in Electricity Markets with Renewable Energy Sources”, The Energy Journal, 38: 137-156.

[2] Benitez, L., Benitez, P. and van Kooten, C., (2008). “The economics of wind power with energy storage”, Energy Economics, 30(4): 1973–1989.

[3] Callaway, D., M. Fowlie (2009). “Greenhouse Gas Emissions Reductions from Wind Energy: Location, Location, Location?”, working paper, University of Michigan.

[4] Cullen, J. (2013). “Measuring the Environmental Benefits of Wind-Generated Electricity”, American Economic Journal: Economic Policy, 5(4): 107-33.

[5] Denny, E. O’Malley, M., (2006). “Wind generation, power system operation and emissions reduction”, IEEE Transactions on Power Systems, 21(1): 341-347.

[6] Fox, J. and Weisberg, S. (2011). An R Companion to Applied Regression. Sage, Thousand Oaks, CA, second edition.

[7] Genc, T.S., Aydemir, A, (forthcoming). “Power Trade, Welfare and Air Quality”, Energy Economics.

[8] Genc, T.S., S. Reynolds, (2017). “Who Should Own a Renewable Technology? Ownership Theory and an Application”, working paper, University of Guelph.

[9] Kaffine, D., B. McBee, and J. Lieskovsky, (2013). “Emissions Savings from Wind Power Generation in Texas”, Energy Journal, 34(1): 155-175.

[10] Novan, K.,(2015), "Valuing the Wind: Renewable Energy Policies and Air Pollution Avoided,"American Economic Journal: Economic Policy, 7: 291-326.

[11] Renewables (2014). "Global Status Report", available at `http://www.ren21.net/portals/0/documents/resources/gsr/2014/gsr2014\_full\%20report\_low\%20res.pdf`

[12] Traber, T. and Kemfert, C., (2011). “Gone with the Wind?: Electricity Market Prices and Incentives to Invest in Thermal Power Plants under Increasing Wind Energy Supply”, Energy Economics, 33(2): 249-256.

[13] Traber, T. and C. Kemfert, (2009). “Impacts of the German Support for Renewable Energy on Electricity Prices, Emissions, and Firms”, The Energy Journal, 30 (3): 155-178.

[14] Wood, S.N. (2004) Stable and efficient multiple smoothing parameter estimation for generalized additive models.Journal of the American Statistical Association. 99:673-686.

[15] Wood, S.N. (2006) Generalized Additive Models: An Introduction with R. Chapman and Hall/CRC

[16] Wood, S.N. (2011) Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. Journal of the Royal Statistical Society (B) 73(1):3-36

Tables and Figures

Table 1: Descriptive Statistics

Period		GHG	Wind	Nuclear	Hydro	Coal	Nat. Gas	Bio Engy.	Oil	Demand	Imports	Temp.
	Winter	3404.88	44.55	9981.23	4232.63	3001.60	1100.61	60.14	13.37	19364.98	777.39	-3.66
	Spring	2433.95	27.23	9047.63	4594.73	2027.12	1008.03	66.73	28.65	17545.89	548.01	4.66
2006	Summer	4014.98	31.23	10104.77	3388.62	3469.20	1251.46	116.97	119.64	19331.76	735.61	15.88
	Fall	3063.31	87.54	8863.68	3578.43	2627.80	1168.90	122.64	27.01	17323.68	689.26	7.27
	Overall	3311.23	49.01	9577.72	3917.30	2863.41	1140.19	91.15	46.11	18543.67	706.55	5.38
	Winter	4002.22	154.95	9519.06	4004.67	3459.04	1452.40	137.85	91.74	19808.66	849.50	-6.35
	Spring	3001.84	106.00	9082.13	3971.55	2631.51	1121.30	99.83	9.83	17629.44	481.44	3.32
2007	Summer	4109.44	64.90	9474.65	3608.29	3609.39	1235.83	103.73	187.21	19158.84	715.59	14.66
	Fall	3535.31	132.25	8440.79	3355.89	3028.67	1376.26	128.91	88.88	17790.69	1123.07	8.08
	Overall	3745.65	118.41	9166.01	3737.47	3251.34	1323.49	120.67	101.40	18777.56	822.44	4.16
	Winter	3530.06	212.25	10030.54	4290.41	2958.82	1397.08	136.50	31.10	20283.18	1108.69	-5.43
	Spring	2593.91	149.43	8339.08	5066.90	2171.78	1020.26	97.47	8.30	19066.40	1985.89	3.79
2008	Summer	3446.10	81.91	9692.56	4528.42	3023.68	1059.35	25.38	93.09	20083.94	1424.46	15.91
	Fall	2674.58	182.50	9551.93	3561.46	2170.80	1330.20	106.69	28.41	17961.95	920.92	6.97
	Overall	3140.23	161.62	9544.67	4298.41	2648.02	1232.76	94.65	42.21	19453.16	1287.58	4.55
	Winter	2807.46	298.15	10261.96	4256.86	1948.02	1743.89	136.89	17.49	19326.71	514.37	-6.46
	Spring	1744.73	317.71	7517.89	4722.54	947.69	1482.43	124.19	81.88	15735.45	363.92	3.08
2009	Summer	1475.61	161.05	9769.90	4320.42	663.54	1765.97	112.53	14.50	17631.17	647.61	14.65
	Fall	1500.15	270.35	8984.32	3874.81	610.44	1975.33	134.04	0.70	16579.42	635.60	7.69
	Overall	1968.22	259.93	9360.80	4255.46	1123.61	1763.46	127.92	23.31	17614.22	553.03	3.98
	Winter	2346.27	357.59	10075.96	4164.44	1529.19	1883.97	141.57	4.80	19008.45	803.01	-5.43
	Spring	2155.66	313.30	8062.53	3386.20	1189.80	2146.95	129.44	16.80	15817.70	540.55	5.51
2010	Summer	3812.25	190.84	9358.04	2789.63	2407.33	3048.35	113.26	41.05	18742.77	771.52	17.00
	Fall	1530.74	469.68	9675.09	3433.78	491.48	2354.52	126.06	2.76	17224.58	708.27	6.92
	Overall	2480.60	336.10	9458.57	3505.69	1435.09	2338.72	128.54	15.43	17963.49	727.59	5.13

Note: Yearly or seasonal averages per hour. GHG and Temperature are expressed in pounds and Celsius, respectively. The remaining variables are expressed in MWh.

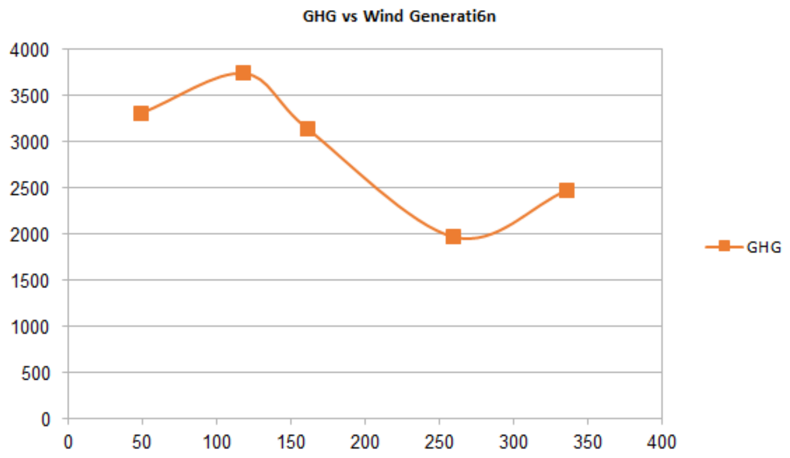


Figure 1: Actual hourly average GHG (pounds) versus actual hourly average wind generation (MWh) over years (2006-2010)

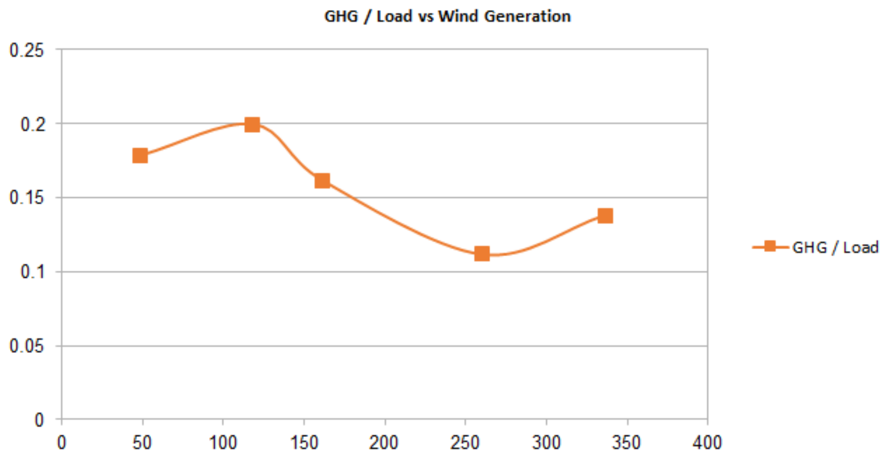
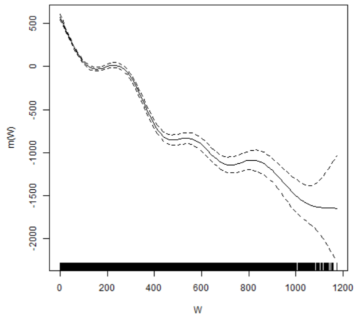
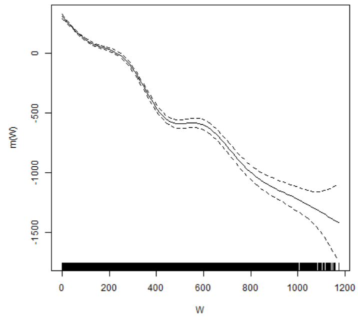


Figure 2: Actual hourly average GHG (pounds) corrected for load versus actual hourly average wind generation (MWh) over years (2006-2010)

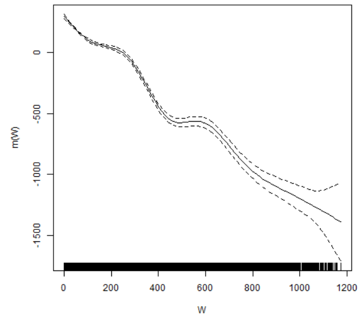
Figure 3: Overall Data, $m(W_t)$ estimates



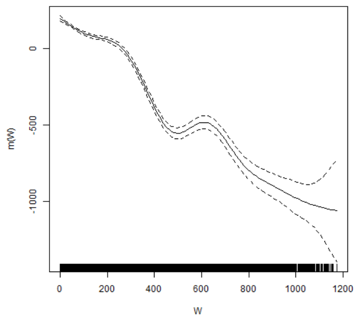
Model 1



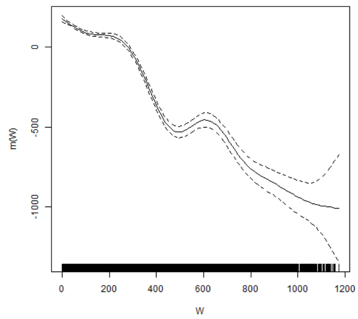
Model 2



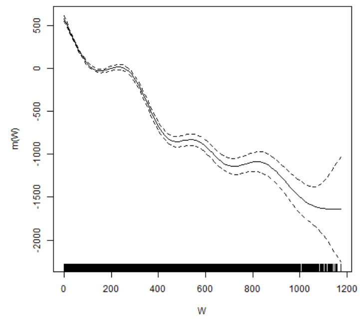
Model 3



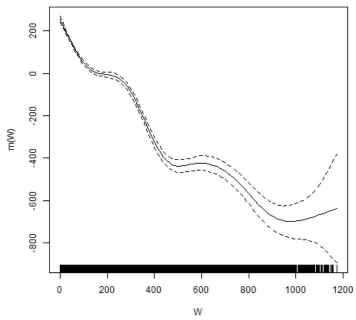
Model 4



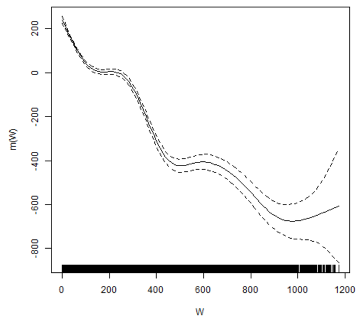
Model 5



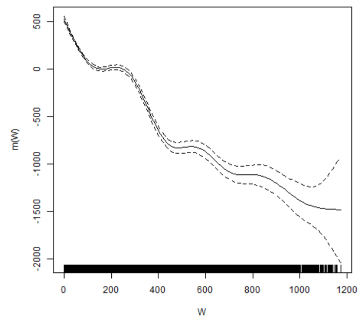
Model 6



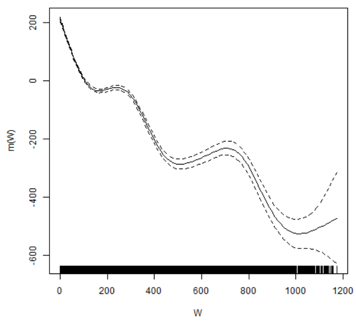
Model 7



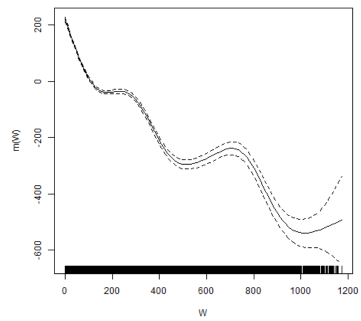
Model 8



Model 9

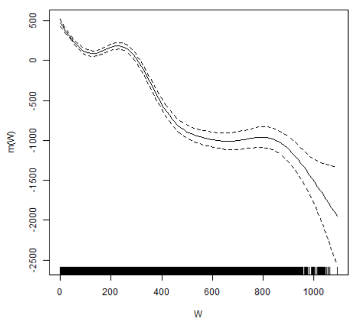


Model 10

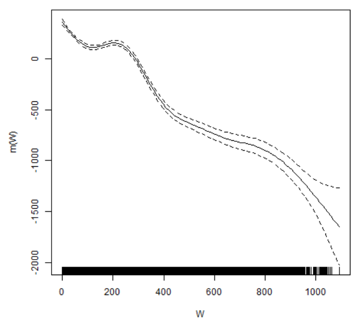


Model 11

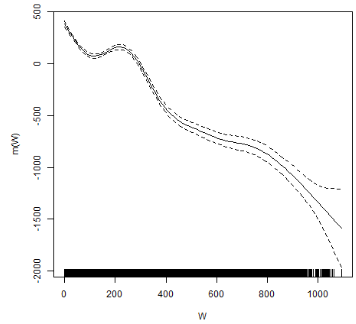
Figure 4: Winter Data $m(W_t)$ estimates



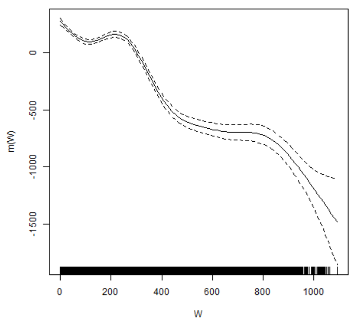
Model 1



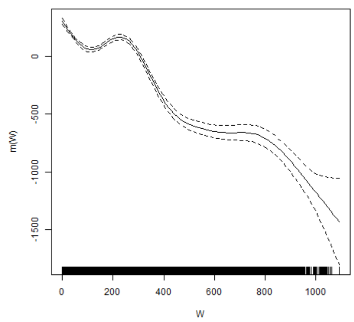
Model 2



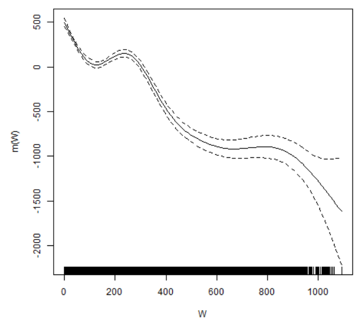
Model 3



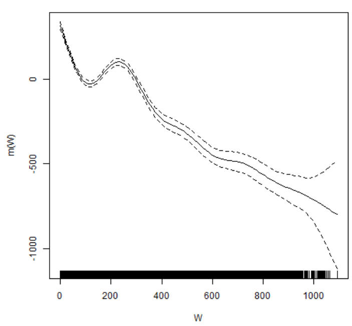
Model 4



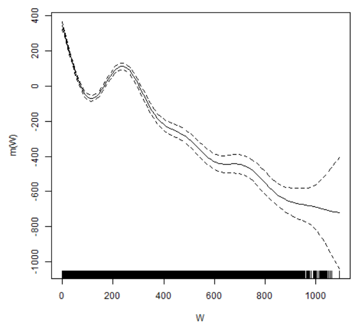
Model 5



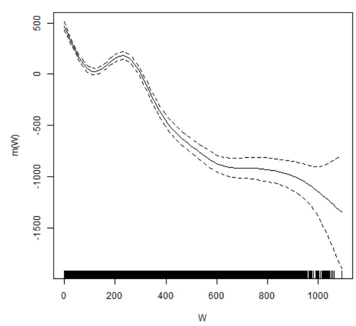
Model 6



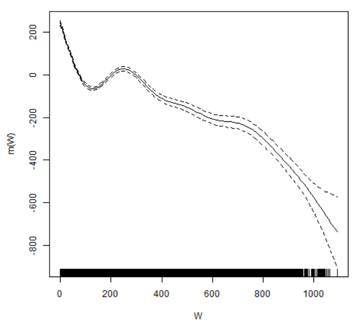
Model 7



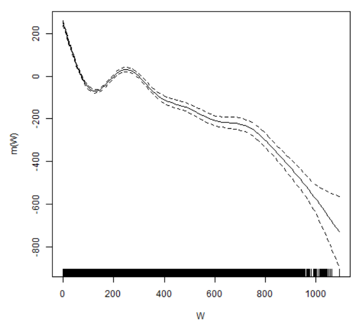
Model 8



Model 9

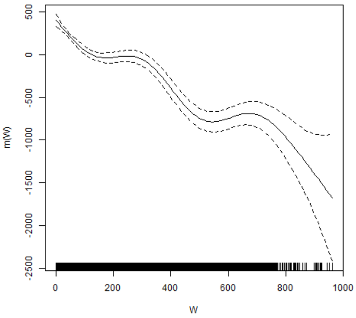


Model 10

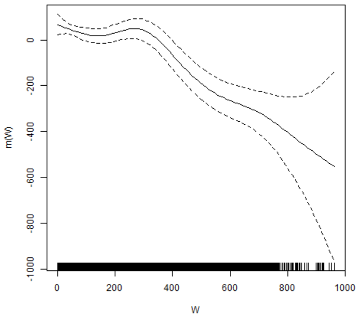


Model 11

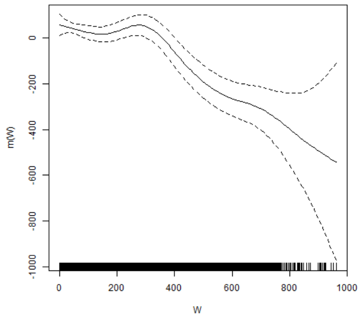
Figure 5: Spring Data $m(W_t)$ estimates



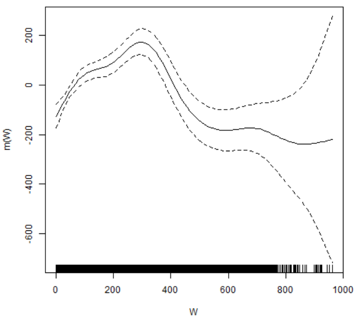
Model 1



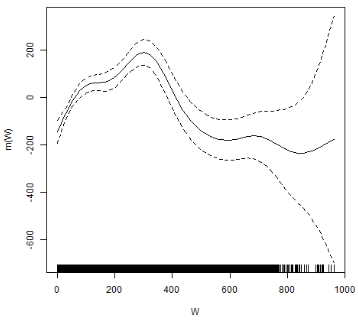
Model 2



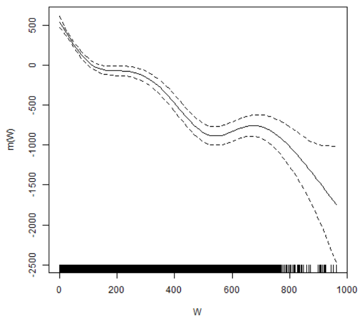
Model 3



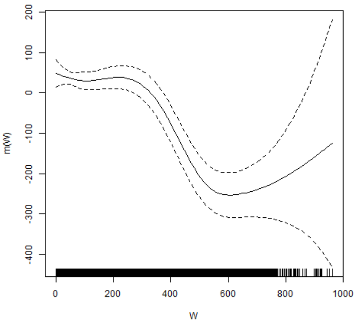
Model 4



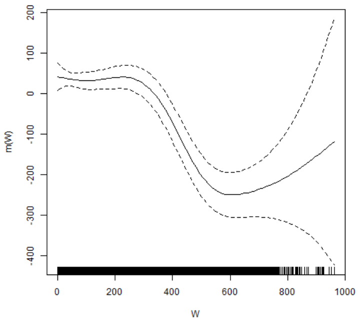
Model 5



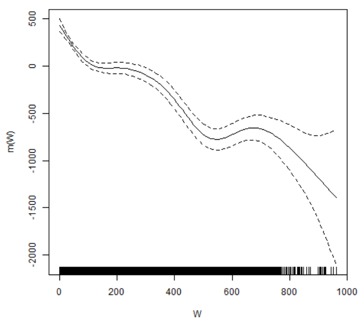
Model 6



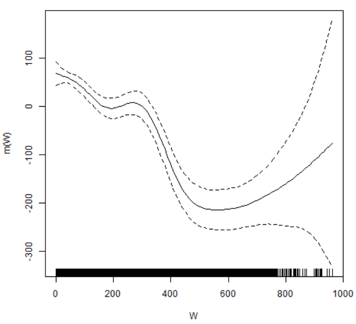
Model 7



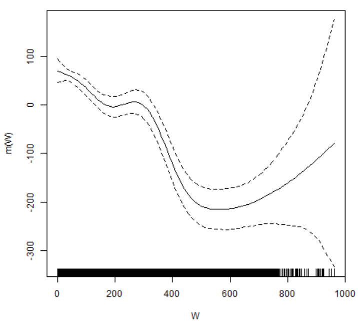
Model 8



Model 9

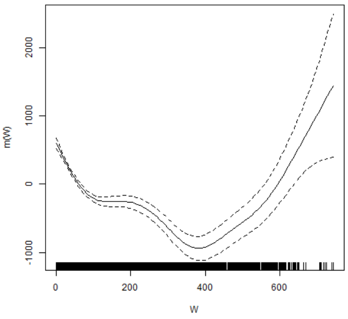


Model 10

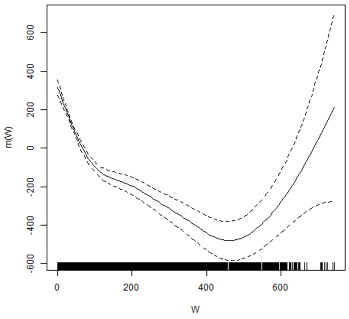


Model 11

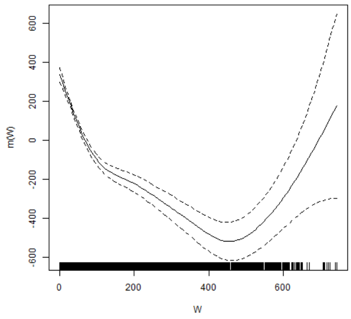
Figure 6: Summer Data $m(W_t)$ estimates



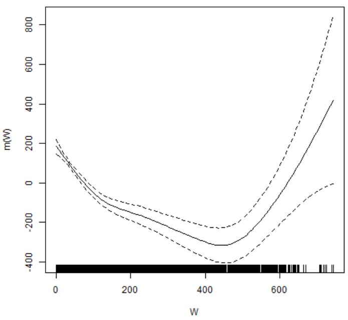
Model 1



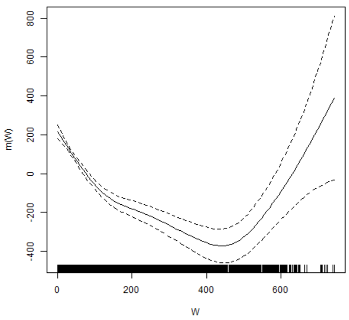
Model 2



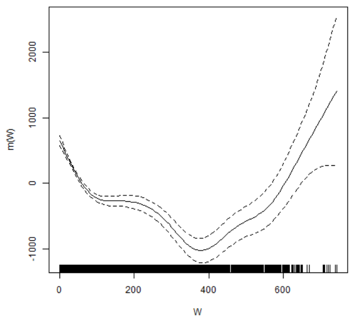
Model 3



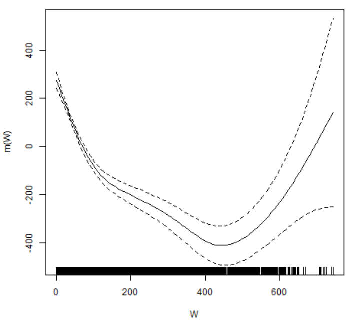
Model 4



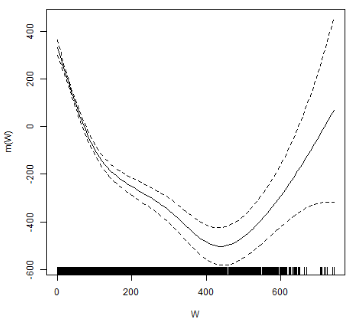
Model 5



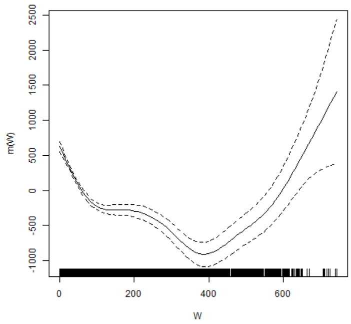
Model 6



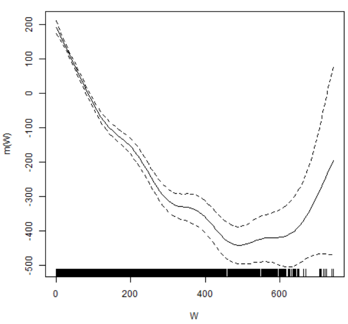
Model 7



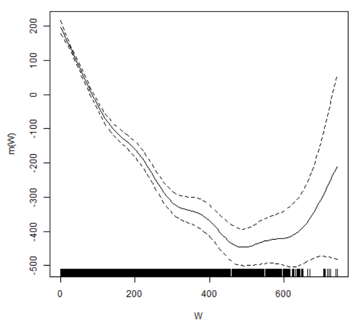
Model 8



Model 9

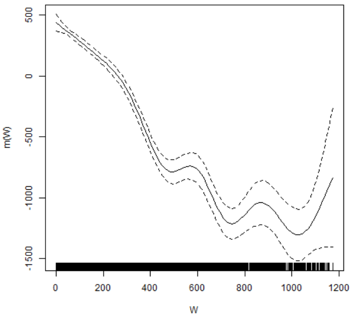


Model 10

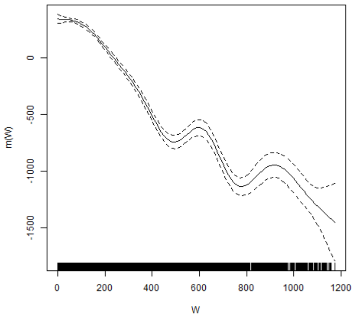


Model 11

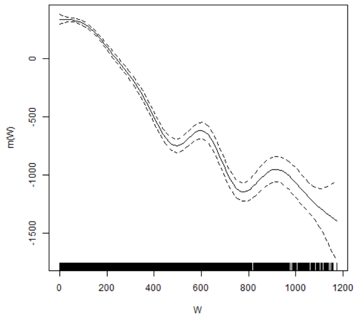
Figure 7: Fall Data $m(W_t)$ estimates



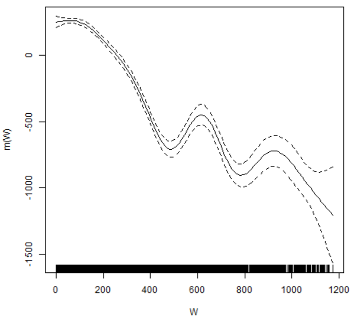
Model 1



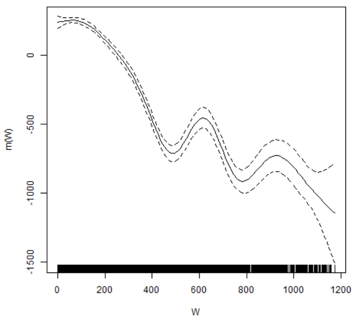
Model 2



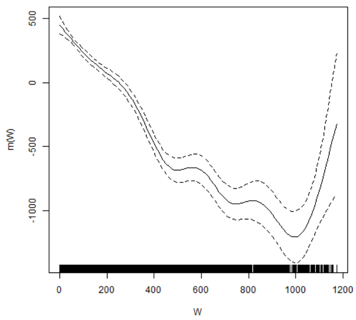
Model 3



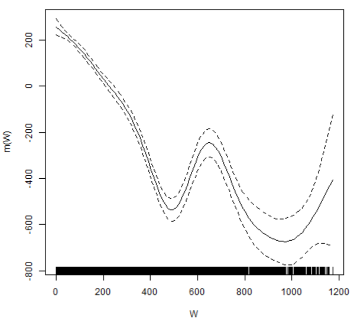
Model 4



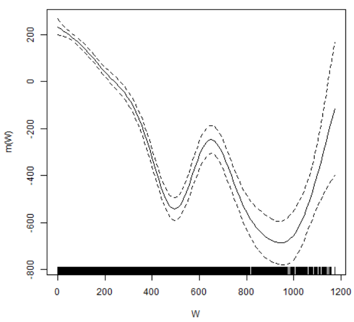
Model 5



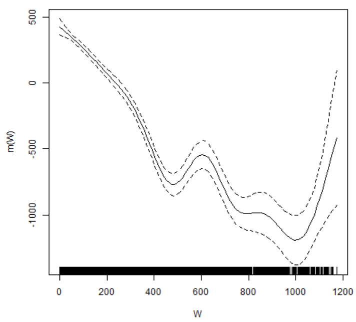
Model 6



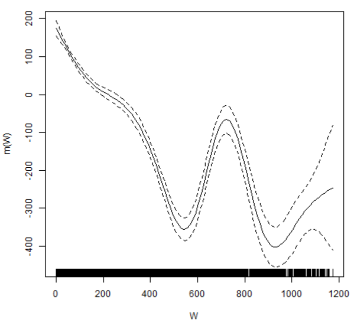
Model 7



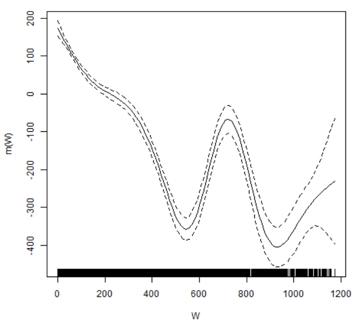
Model 8



Model 9



Model 10



Model 11

Appendix: Regression Details

Table A1: Regressions for Overall Data, Models 1 to 6

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	2929.30^{***}	-5188.46^{***}	-5295.09^{***}	-5309.89^{***}	-5456.29^{***}	3020.00^{***}
	(6.86)	(28.07)	(28.44)	(28.42)	(28.80)	(64.26)
Demand		0.44^{***}	0.44^{***}	0.47^{***}	0.48^{***}	
		(0.00)	(0.00)	(0.00)	(0.00)	
Temp			8.08^{***}		10.10^{***}	
			(0.40)		(0.40)	
Nuclear						-0.01
						(0.01)
EDF: s(Wind)	8.49^{***}	7.85^{***}	7.91^{***}	8.13^{***}	8.18^{***}	8.49^{***}
AIC	761542.16	714168.32	713764.22	714038.72	713405.71	761542.12
BIC	761633.25	714262.60	713867.68	714135.43	713511.52	761641.91
Log Likelihood	-380760.59	-357073.31	-356870.20	-357008.23	-356690.68	-380759.57
Deviance	90341862999.23	30648446172.32	30365677838.24	30557557098.06	30117908343.49	90337648978.19
Deviance explained	0.09	0.69	0.69	0.69	0.70	0.09
Dispersion	2061916.32	699510.27	693073.15	697440.28	687422.25	2061867.26
R^2	0.09	0.69	0.69	0.69	0.70	0.09
GCV score	2062362.70	699667.57	693245.71	697601.56	687597.65	2062360.76
Num. obs.	43824	43824	43824	43824	43824	43824
Num. smooth terms	1	1	1	1	1	1

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, See Fox and Feisberg (2011) for the details of the above output

Table A2: Regressions for Overall Data, Models 7 to 11

	Model 7	Model 8	Model 9	Model 10	Model 11
(Intercept)	-2005.08^{***}	-2141.48^{***}	963.72^{***}	-571.12^{***}	-442.69^{***}
	(34.13)	(34.58)	(67.77)	(18.99)	(19.35)
Nuclear	0.06^{***}	0.07^{***}	0.03^{***}	0.03^{***}	0.02^{***}
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Demand	0.54^{***}	0.54^{***}		0.79^{***}	0.79^{***}
	(0.00)	(0.00)		(0.00)	(0.00)
Temp		7.05^{***}			-5.30^{***}
		(0.34)			(0.19)
Hydro			0.44^{***}	-0.01^{**}	-0.02^{***}
			(0.01)	(0.00)	(0.00)
Coal					
Gas					
Bio					
Oil					
EDF: s(Wind)	7.58^{***}	7.65^{***}	8.25^{***}	8.30^{***}	8.29^{***}
AIC	698717.59	698283.44	756955.06	644910.69	644105.40
BIC	698818.21	698393.34	757061.52	645026.21	644229.57
Log Likelihood	-349347.21	-349129.07	-378465.28	-322442.05	-322038.41
Deviance	21541589388.54	21328198499.02	81357196845.07	6309850901.23	6194680708.84
Deviance explained	0.78	0.78	0.18	0.94	0.94
Dispersion	491666.49	486807.91	1856929.86	144022.04	141396.50
R^2	0.78	0.78	0.18	0.94	0.94
GCV score	491785.24	486937.36	1857406.82	144062.46	141439.40
Num. obs.	43824	43824	43824	43824	43824
Num. smooth terms	1	1	1	1	1

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, See Fox and Feisberg (2011) for the details of the above output