2011

The Impact of Weather Forecasts on Day-Ahead Power Prices

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SUBMITTED TO

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FOR

SENIOR THESIS

SPRING 2011

MAY 2, 2011

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1. Introduction

Power industry deregulation and electricity market restructuring, which began in Chile in the 1980s and then spread to Norway, New Zealand and the UK, were introduced in the United States with the passage of the Energy Policy Act (EPA) of 1992 (Jameson, 1997). The EPA and subsequent Federal Energy Regulatory Commission (FERC) Orders led to the restructuring of vertically integrated electric utilities, the establishment of Independent System Operators (ISO) and Regional Transmission Organizations (RTO) and the development of competitive wholesale power markets. Deregulation also led to the creation of various electricity contract–based financial derivative products. In 1996, the New York Mercantile Exchange (NYMEX) created the US's first electricity futures, the Palo Verde and California/Oregon Border contracts, which were traded for physical delivery (Warwick, 2002). While these products were eventually delisted in 2002, other exchange-traded and OTC contracts, for both physical and financial settlement, have been introduced on numerous exchanges, including the Intercontinental Exchange (ICE), Chicago Mercantile Exchange (CME) and markets operated by ISOs and RTOs. From the start, deregulation of the electricity industry has been a contentious and controversial subject, its economic, political and social ramifications hotly debated in the US and abroad. The debate continues, and as of September 2010, fifteen states and the District of Columbia have deregulated electricity markets, seven have suspended restructuring activities and twenty-eight have no deregulatory legislation or restructuring activities to speak of (FERC, 2010).

While the merits and faults of restructured power markets present the opportunity for many interesting and material discussions, this paper will instead focus on one of the markets borne of such deregulatory activities, the PJM Western Hub's Day-Ahead Power Market. Specifically, this paper will attempt to determine if the addition of weather forecast variables improves the predictive powers of electricity pricing models.

Electricity is considered a flow commodity, defined by its inherently non-storable nature and limited transportability. Unlike other commodities, it cannot be economically stored in large quantities and holding inventories is near impossible[1]. With traditional goods, inventories can be used as a buffer against supply and demand imbalances and can exert a smoothing effect on prices (Cartea, et. al., 2008). The impracticability of electricity storage requires that supply and demand be constantly and instantaneously coordinated, and the lack of inventories eliminates the possibility of any buffering effect. Electricity is also grid-bound, its transportation restricted not only by the location and extent of the power grid, but also by transmission line capacity limits, congestion and efficiency losses as distance increases (Wilkens, et. al., 2007). Such considerations make electricity a geographically concentrated regional good, produced and consumed relatively locally, and subject to local supply and demand conditions. These characteristics- non-storability and limited transportability- can explain some of the more distinct properties of electricity prices, and most importantly, all but preclude the ability to conduct arbitrage across time and space. These impediments to arbitrage complicate the valuation of electricity derivatives, especially futures, limiting the use of traditional

[1] Synthetic forms of storage are available, such as dams for hydroelectric generation or stockpiling fuels, but are limited in their applicability. (Bhanot, 2002)

cost-of-carry arguments (Lucia and Schwartz, 2002). As such, finding alternate means of modeling electricity prices is an important and challenging endeavor.

2. The PJM Interconnection

The Pennsylvania- Maryland-New Jersey (PJM) Interconnection is a RTO responsible for ensuring electricity production and transmission within thirteen states, including the District of Columbia. Initially founded in 1927 as the PJM Pool, one of the world's first power pools, the PJM Interconnection was officially established in 1997, when it introduced bid-based market pricing and became the United States' first ISO under FERC's new deregulatory standards. ISOs function independently of their member companies, managing but not owning the transmission system. In 2001, PJM became the nation's first RTO, and now operates one of the largest wholesale power markets in the world. PJM is regulated by the Reliability First Corporation (RFC), itself a member of the North American Electric Reliability Corporation (NERC), as well as by FERC.

As an RTO, PJM operates wholesale electricity markets, balances supply and demand, coordinates and oversees generation and transmission and develops and implements short and long-term planning. Its goal is to ensure reliable electrical grid operation for the more than 50 million people who fall within its borders. PJM is comprised of over 700 member firms, though it exists as an independent entity, and oversees and regulates member conduct. Member firms include generation owners who own electric generating facilities, transmission owners who own high-voltage lines and deliver power to distributors, electric distributors who own local, low-voltage lines and deliver power to end users, power marketers, trading firms and large corporate end users

(PJM, 2011). All members participate in the wholesale markets, acting as both buyers and sellers of electricity.

PJM administrates two separate wholesale power markets- the real-time market, and the day-ahead market. The real-time market operates as a traditional spot market with participants buying and selling electricity for immediate delivery. The day-ahead market is a forward market in which participants buy and sell contracts to deliver power for a specific hour-block at a specific location the following day, and reports 24 market-clearing prices a day, one for each hour. The market-clearing prices in both the real-time and day-ahead markets are unique in that they are not solely dictated by the equilibrium of bids and offers, but instead are determined by locational marginal pricing. PJM introduced Locational Marginal Price (LMP) markets in 1998, to ensure that electricity prices reflected not only marginal production costs, but costs associated with line congestion and transmission constraints as well. LMP is defined to be "the marginal price for energy at the location where the energy is delivered or received," and is calculated as the sum of three components: the system price, congestion price and loss price. The system price is the price at which sellers offer to provide the next additional increment of electricity; the congestion price is the cost associated with delivering the additional increment of electricity along potentially congested transmission lines; and the loss price accounts for any gains or losses that occur as a result of changes in marginal production costs as generators across the system are asked to supply more or less power. As the name suggests, LMP is calculated on a location-by-location basis. These designated locations are called busses, and in the absence of any transmission constraints or marginal losses, LMP will be equal for all busses across the PJM network (PJM, 2010, 2011).

The PJM RTO is subdivided into eleven hubs, which are defined by the collection of busses that comprise them, and serve as central pricing points within the RTO. Hub LMPs (both real-time and day-ahead) are calculated as equally weighted averages of their component bus LMPs, and provide a more accessible and convenient measure of electricity prices across the system. PJM's Western Hub is a collection of 109 busses covering a region stretching roughly from Erie, PA to Washington, D.C., and includes parts of Pennsylvania, Maryland and Virginia (FERC 2010). It is one of the most liquid pricing points in the world and its real-time and day-ahead market LMPs provide the basis for many exchange-traded and OTC contracts. The high levels of liquidity and importance of Western Hub LMP in pricing financial products make it an attractive candidate for study.

3. Literature Review

The introduction of power industry deregulation and advent of electricity-based derivatives have inspired a growing literature that attempts to model and describe the behavior of power markets and related financial products. Prior to restructuring, electricity prices were controlled by regulatory agencies, and generally held at fixed levels. Emphasis was placed on demand forecasting and only in the past fifteen years, following deregulation, do we see research exploring the pricing of power and power derivatives.

The literature discussing electricity pricing can be broadly categorized based on forecasting model choice, with research divided between reduced-form models and equilibrium models. While these two models may sometimes be seen as competing, Bühler and Müller-Mehrbach (2009) remind us that they should be considered as complements to each other. The literature identifies several key characteristics of electricity prices that models of both forms attempt to capture. These include but are not limited to: daily, weekly and seasonal cycles, extreme price spikes, autocorrelation, mean-reversion, and volatility clustering

Equilibrium models attempt to model electricity supply and demand and estimate market prices based on the interaction between two. Reflecting the realities of electricity markets, such models can be extremely complex, and require an intimate understanding of the market and its participants. Such models must correctly identify market participants, who are numerous and varied, and often act as both buyers and sellers. They must account for the heterogeneous production of an indistinguishable end product, as electricity can be generated from natural gas, coal, nuclear hydro or wind (with many plants using a combination depending on load), and equilibrium models must also consider transmission constraints and congestion. Several notable papers that pursue equilibrium pricing models include Bessembinder and Lemmon (2006), Routledge, Seppi and Spatt (2001) and Bühler and Müller-Mehrbach (2009). Bühler and Müller-Mehrbach compare a generalized, dynamic form of Bessembinder and Lemmon's model to a basic ARMAX model of the sort proposed by Lucia and Schwartz (2002). They find that their model captures well many characteristics of power prices and that it predicts out of sample prices better than the reduced form model.

Lucia and Schwartz, in their oft-cited paper "Electricity Prices and Power Derivatives: Evidence from the Nordic Power Exchange," investigate spot, forward and futures markets at the Nordic Power Exchange. Observing autocorrelation and mean-reversion, they employ several variations of ARMAX type models using dummy variables to account for weekly and seasonal regularities in power markets. The model proposed by Lucia and Schwartz has served as the starting point and basis for comparison for subsequent research of the reduced-form variety. Wikens and Wimschulte (2007), applying the Lucia/Schwartz model to European Energy Exchange futures, find that while the model successfully accounts for spot market regularities, it is subject to biases when forecasting futures prices.

In 2000, California energy markets experienced extreme price fluctuations, shortages and forced blackouts. Using data from these markets for the periods preceding and following this crisis, Knittel and Roberts (2005) expand on the ARMAX model of Lucia and Schwartz. They propose several jump-diffusion and GARCH models, attempting to account for mean-reversion, price spikes and volatility clustering, and find an "inverse leverage effect," by which positive price shocks result in higher increases in volatility than do negative shocks.

Noting that jump-diffusion processes do not adequately account for non-normal market conditions (during price spikes occur), several papers have applied Markov regime-switching models (see Deng (1998); Ethier and Mount (1999) and Huisman and Mahieu (2003)). These models typically consist of a normal regime, modeled as a mean-reversion process, and a non-normal regime, modeled as a jump process, and dictate the process by which transition between regimes occurs. Mount, Ning and Cai (2006) modify this model by making regime switches dependant on reserve margin, and Huisman (2008), observing that reserve margin information is not readily available to all market participants, finds that temperature can be used as a proxy for reserve margin in dictating spike probability. Comparing the basic ARMAX model of the type used by Lucia and Schwartz to several regime-switching models, Kosater and Mosler (2005) find that regime-switching outperform ARMAX models with respect to long-run forecasting.

Various studies have noted that weather variables are an important consideration when constructing electricity demand and pricing models, including Huisman (2007), Knittel and Roberts (2005) and Taylor and Buizza (2002). The study of weather and its effect on commodities can be traced back to Richard Roll's seminal paper, "Orange Juice and Weather" (1984), which examines the effects of weather forecast on the price of frozen concentrated orange juice futures contracts, traded on the News York Cotton Exchange. He finds that temperature forecast errors, the percentage difference between forecasted and realized temperatures, have a statistically significant effect on orange juice futures, but that rainfall forecast errors do not. Importantly, he notes that orange production at the time of publishing was highly geographically concentrated, with 98% of production occurring in a relatively small region around Orlando. This regional concentration made orange production, and thus orange juice futures, susceptible to regionally specific influences, such as weather. This concept of a regional good can be applied to electricity as well.

Knittel and Roberts (2005) include realized hourly temperatures as variable when predicting hourly spot prices, and find that they have a statistically significant, but small explanatory power. They observe that below 50° the price-temperature relationship is negative, the result of electric heating, and that above 55 °, when commercial cooling begins, the relationship is positive. Taylor and Buizza make use of weather ensemble forecasts to predict short-term load (demand) in England and Wales. Ensemble forecasts consist of 51 probability-weighted predictions for a given variable, and while they have been found to be more accurate than single point estimates, they require a high level of meteorological expertise.

In "The Power of Weather" (2007), Huurman, Ravazzolo and Zhou reevaluate several of the previously mentioned reduced-form models for daily day-ahead prices in the Nordic Power Exchange. Using variations of ARMAX, and ARMAX-GARCH models, they test whether the addition of next day weather forecast variables (temperature, precipitation and wind) improve upon the model's predictive capabilities. They find that weather variables result in improved Akaike Information Criterion (AIC) for ARMAX and ARMAX-GARCH models and reduce the root mean square prediction error (RMSPE) and mean absolute percentage error (MAPE) measures of out of sample forecasting, for both ARMAX and ARMAX-GARCH models. Based on RMSPE, MAPE and AIC, they conclude that the ARMAX model modified to include weather forecast variables is the best at out of sample forecasting.

This paper will contribute to the literature in several ways. The author is unaware of any studies analyzing the PJM Western Hub Day-Ahead Power Market. While past research has touched upon PJM's Western Hub (Borenstein, Bushnell, Knittel, 1997; Mount, Ning and Cai, 2006), it has considered the period immediately following the introduction of market-based generation bidding, and used spot prices that predate the establishment of the Western Hub Day-Ahead Market.

Furthermore, while the literature repeatedly confirms the influence of weather on electricity pricing, and several papers have included realized weather data as explanatory variables in their calculations (Knittel and Roberts 2005; Huisman 2008; Longstaff and

Wang 2004), few have made use of weather forecasts to predict day-ahead prices. Today's forecast of tomorrow's weather (not today's realized weather) should be the best predictor of tomorrow's weather, and therefore should be preferred to other presently available weather information as an explanatory variable when estimating the price of a day-ahead contract with delivery tomorrow. Huurman, Ravazzolo and Zhou, in their examination of the Nordic Power Exchange, do so and find that forecasts of tomorrow's weather are significant predictors of day-ahead electricity prices. This paper follows their lead.

It is important to note that there exist many differences between the various international electricity markets, and even between domestic markets within the United States. These dissimilarities arise from, among other things, different regulatory schema and degrees of deregulation (if any), differences in generation technologies (while hydropower is predominant in Norway, coal is popular in the US), climatological variation and differences in end-users. Such inconsistencies limit the degree to which we can extrapolate results from one market and apply them to another. While, with careful consideration, we can note similarities and trends, it can be fruitful to evaluate each market separately.

4. Description of Data

This study uses data drawn from the PJM Western Hub's day-ahead market, which reports twenty four hourly settlement LMPs every day for each of its 108 busses, as well as hourly hub prices, which are calculated as equally weighted averages of the bus prices for the same period (PJM, 2011). All price data are available from PJM's website[2] and are updated on a daily basis. The data consists of prices for the seven-year period beginning January 1, 2001 and ending December 31, 2007 (2556 days), reported in US dollars per megawatt hour (MWh). Analysis was conducted using the arithmetic mean of the reported hourly prices (which will be referred to from this point forward as the daily price), and on the natural logarithm of the daily price.

Table 1 shows summary statistics for the daily price, and Figure 1 shows a plot of the time series of the daily price. Looking at this plot, several characteristics of power price behavior are apparent. Prices exhibit high levels of volatility, though they seem to be loosely anchored around a mean; extreme spikes in price are not uncommon; and prices seem to display a cyclical pattern, though the exact nature of that pattern is not immediately obvious. The sample has a maximum price of $232.57, minimum of $11.22 and mean of $43.63. Prices in the sample are leptokurtic and positively skewed; these non-normal distributive properties can be seen in the histogram[3]. The literature repeatedly reports autocorrelation as a defining quality of electricity prices, and these data confirm those findings. Graphing the autocorrelation function[4] (ACF) reveals that price is highly correlated with lagged values of itself, significantly so past 200 lags. Studying the graph, a weekly pattern in autocorrelation becomes apparent, and this finding is reinforced by the pattern visible in the plot of average price by day of week[5]. Prices appear to be highly correlated with prices immediately preceding them and those occurring seven days prior.

[2] www.PJM.com
[3] See Figure 2
[4] See Figure 3
[5] See Figure 4

As with all time series data, the question of stationarity must be addressed before proceeding with analysis. A time series is stationary if its probability distribution does not change over time. If a series is not stationary, then it must be transformed, generally through first-differentiation, to make it so (Stock and Watson, 2007). A Dickey-Fuller-Generalized Least Squares (DF-GLS) test rejects the null hypothesis of a unit autoregressive root through 29 lags at the 1% level, indicating that the price time series is stationary around a linear time trend.

Weather forecast data were obtained from the National Weather Service's (NWS) National Digital Forecast Database (NDFD)[6]. Next day forecasts of average, maximum and minimum temperature (in degrees Fahrenheit), precipitation in inches and wind speed in miles per hour, were collected from the Pittsburg and Washington, D.C. forecasting stations of the NWS. The geographic area corresponding to the PJM Western Hub is not precisely defined, and must be approximated. The Appalachian Mountains run through the middle of the area served by the Western Hub, forming in two distinct, though not entirely dissimilar climates, and thus single point forecasts cannot adequately account for weather across the region. Pittsburg and Washington are geographically and meteorologically representative of the area served by the Western Hub and the weather data are equally weighted averages of forecasts for these cities (Dello, 2011).

[6] PJM power market participants overwhelmingly use the meteorological services of Telvent, an information services company. Telvent's historical forecast data could not be obtained, but Telvent meteorologists, and most meteorologists in the United States, receive their weather data from the NWS weather satellites and models, refining said data to produce their own forecasts (Dello, 2011).

4. Model Specification

Within the literature it is customary to model electricity prices as consisting of two components, a deterministic term denoted X_t representing the predictable, regular aspects of prices (such as seasonal and weekly trends), and a stochastic term denoted Z_t describing a continuous diffusion process, that represents the random, mean-reverting behavior of prices (Wilkens et. al. 2007). Such formulations generally take the following form:

$$P_t = X_t + Z_t$$

$$Z_t = \theta Z_{t-1} + \varepsilon$$

in which ε is deemed a Gaussian white noise process, a type of random walk. This form describes exactly a model that is autoregressive in its error term, and can be represented as a moving average (MA) process of order one. We can rewrite the previous equation as:

$$P_t = X_t + \theta Z_{t-1} + \varepsilon$$

Noting that:

$$Z_{t-1} = P_{t-1} - X_{t-1}$$

We can rearrange terms and produce:

$$P_t = X_t + \theta(P_{t-1} - X_{t-1}) + \varepsilon$$

$$X_t = \alpha + \beta_D H_t + \sum_{i=2}^{12} \beta_i M_{it}$$

Where α is a constant term, H_t is binary variable taking a value of 1 for working days and 0 for weekends and holidays[7], and M_{it} a series of binary variables representing the months of the year. The model hopes to capture the weekly trend seen in prices via the holiday binary, and seasonal components via the monthly binaries.

This model, employed initially by Lucia and Schwartz (2002), is attractive in that it is easily applied and interpreted. It tells us that today's price is a function of conditions prevailing today- the time-dependent state variables described by X_t - yesterdays price, and yesterday's conditions. Despite its intuitive nature, in practice it does not explain price behavior particularly well. Nonetheless, it provides a good basis upon which to build a better model. Though analysis of Bayesian and Akaike Information Criteria (BIC and AIC)[8] at various autoregressive orders of price, with the goal of minimizing the information criteria, implied a very high-order lag was appropriate, a review of the literature suggests that fewer lags are sufficient (Huurman, et. al. 2007). Study of the ACF graph reveals a very high correlation of price with the previous day's price, and the price seven days prior. Preserving other aspects of the Lucia-Schwarz model and including price lagged one and seven days as regressors yields the following model:

$$P_t = X_t + \gamma_1 P_{t-1} + \gamma_2 P_{t-7} + Z_t$$

$$X_t = \alpha + \beta_D H_t + \sum_{i=2}^{12} \beta_i M_{it}$$

$$Z_t = \theta Z_{t-1} + \varepsilon$$

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[7] In PJM's electricity markets, Monday through Friday are considered "on-peak" and weekends and holidays (as defined by NERC) are considered "off-peak." Studying the plot of electricity prices against time, we see that prices tend to be higher for on-peak days and lower for off-peak days.

[8] $AIC_P=\ln(SSR_P/T)+(p+1)(2/T)$, $BIC_P=\ln(SSR_P/T)+(p+1)(\ln T/T)$, where p is the order of lags and T is the number of observations (Stock and Watson, 2007).

This model is of the ARMAX variety and can be expressed as an AR(1,7), MA(1) model, in which the AR term expresses the number of lags of the dependent variable P_t and the MA expresses lags of Z_t. In order to compare models, I employed several measures of fit and error in addition to comparing significance of coefficients, R^2 and root mean squared error (RMSE). These include the aforementioned AIC and BIC, and the Ljueng-Box white noise test, which examines the null hypothesis that the error term of the regression, ε, is a white noise process (Greene, 2008). Recall that this is an assumption of the initial theoretical model considered. If ε is a white noise process, it represents random, unpredictable movement in price, and the model successfully captures all of the predictable components of price. If the null is rejected the error terms exhibit autocorrelation and are predictable to a degree, indicating that the model can be improved (Greene, 2008). Of course none of the criteria described are a litmus test of whether the model is “good” or “bad” and must be examined with a critical eye.

Comparing the basic Lucia-Schwartz model to the modified expression of price, I found that, with minimal loss in significance of coefficients, the new model exhibited high levels of significance in the coefficients of the added variables, decreases in RMSE, AIC and BIC and an increase in R^2. While the Ljueng-Box test indicates that the error terms of both models are non-random, the second model is a clear improvement upon the first.

The results of the white noise test in mind, I reexamined the ACF graph and saw that there still appeared to be a high degree of autocorrelation between prices seven days apart, past the 28^{th} lag. This would seem to suggest that there exists a weekly pattern not accounted for by the seventh order lagging of price. Hoping to capture this weekly effect, I added binary variables to represent days of the week, such that the deterministic component of the model took the form:

$$X_t = \alpha + \beta_D H_t + \sum_{i=2}^{12} \beta_i M_{it} + \sum_{i=2}^{7} \delta_i D_{it}$$

Though regression results were promising, and the on-peak binary coefficient remained significant at the 1% level, increases in the standard error of the coefficient indicated some multicollinearity, which, upon examination, was logical, as each binary represented a different way of classifying days of the week. Comparing regression results between models including on-peak and day-of-week variables, I produced the basic model for the study:

$$P_t = X_t + \gamma_1 P_{t-1} + \gamma_2 P_{t-7} + Z_t$$

$$X_t = \alpha + \sum_{i=2}^{12} \beta_i M_{it} + \sum_{i=2}^{7} \delta_i D_{it}$$

$$Z_t = \theta Z_{t-1} + \varepsilon$$

Before incorporating weather variables, I studied scatter plots of forecasted temperature, precipitation and wind speed against price[9]. These plots reveal several interesting characteristics. Temperature and price have a nonlinear relationship, with price increases associated with extreme temperatures, both high and low. The relationship between wind and price is not obvious, though price spikes seem to occur at lower wind speeds, and precipitation and price have no observable relationship to speak of. Regression results produced by the basic model augmented by weather data seem to indicate that only wind

[9] See Figure 5 for temperature-price plot

speed has a significant relationship with price- temperature and precipitation coefficients are small and statistically insignificant. Hoping to capture the effect of extreme temperature on prices, I created a binary with a value of one when temperatures exceed 85° or drop below 32°, and zero when temperatures fall between the two. Replacing temperature with the temperature binary, retaining wind and removing precipitation as a variable delivered significant results and a model of the following form:

$$P_t = X_t + W_T + \gamma_1 P_{t-1} + \gamma_2 P_{t-7} + Z_t$$

$$X_t = \alpha + \sum_{i=2}^{12} \beta_i M_{it} + \sum_{i=2}^{7} \delta_i D_{it}$$

$$W_t = \omega_1 T_t + \omega_2 S_t$$

$$Z_t = \theta Z_{t-1} + \varepsilon$$

5. Empirical Results

Regression analysis of price and the natural logarithm of price was conducted using both the basic model and the weather variable-enhanced model. Results produced using price and the natural logarithm of price represented improvements over the standard Lucia-Schwartz model in RMSE, AIC and BIC[10]. Day-of-week variable coefficients were statistically significant at the 1% level, as were wind and temperature coefficients. The temperature binary indicates a positive relationship between electricity price and extreme temperatures, which is not surprising, but the negative coefficient for wind was, at first puzzling. Contrary to expectations, it indicates that wind chill does not

[10] See Table 2 for regression results from Lucia- Schwartz model, basic model and weather variable-enhanced model for price and natural logarithm of price

seem to exert much influence on electricity prices. The negative effect of wind on price can be explained by two factors. Though wind power accounts for only 2% of total generation for the PJM Interconnection (PJM, 2010), we would expect that on windy days, wind power represents more than 2% of generation (the opposite being true on windless days), and that this increased generation via wind would reduce prices. Second, 84% of heating in the area served by PJM uses natural gas or oil for heating (EIA, 2010), suggesting that cold temperatures and wind chill should not have a great effect on electricity prices. Air conditioning, however, relies almost exclusively on electricity, explaining in part the positive relationship between price and high temperatures. Increased wind on a hot day has a cooling effect, reducing the need for air conditioning and counteracting some of the positive effect temperature has on price.

Huurman et. al. (2007) find that precipitation levels have a significant effect on price, whereas this study found its impact to be negligible. In their study, Huurman et. al. analyze prices for Scandinavian countries, including Norway, where hydropower accounts for 95% of electricity generation, and therefore it is not surprising that precipitation would have greater effect on power prices. Generation for the PJM interconnection is primarily coal and natural gas-based, and much less sensitive to precipitation (PJM, 2010).

The effect individual months exert on price defy intuition and are not easily explained. Negative coefficients during traditionally cold or mild months can be partially accounted for by regional heating methods, when viewed through the prism of seasonal influences. However, positive coefficients for April and November, negative coefficients during summer months and the switching of signs of coefficients following the addition of weather variables, are unexpected and resist interpretation. Despite this, removal of month variables significantly increased prediction error measures with negligible effect on the coefficients for other variables, and thus they were kept in the model.

To test the hypothesis that inclusion of weather forecast variables improves the predictive power of electricity price forecasting models, I conducted out of sample analysis using data from the PJM Western Hub Day-Ahead Market for the period beginning January 1, 2009 and ending December 31, 2010[11]. When making predictions, I consider data through the period immediately preceding that being forecasted, which means the model considers actual values of P_{t-1} and P_{t-7} when calculating P_t, and not the predicted values produced by the model. Once forecasts were obtained using each model, I compared them to actual prices for the period and calculated the RMSE and MAPE for the predictions. When predicting prices, the model including weather variables had RMSE of 6.175 and MAPE of 0.9324, compared with 6.230 and 0.0938 for the basic model, and when predicting the natural log of prices, the model including weather variables had RMSE of 0.119 and MAPE of 0.0243, compared with 0.121 and 0.0245 for the basic model.

6. Conclusion

The literature regarding electricity price forecasting has repeatedly confirmed that predictable behavior in electricity prices is determined by regional and temporal influences, and the results of this study suggests that temperature can account for part of that regular behavior. Furthermore, this study suggests that day-ahead electricity market

[11] See Figure 6 for plot of Prices overlaid with predicted values

participants believe that weather plays a role in determining power prices, and that weather forecasts inform their bids and offers in the day-ahead market. The addition of weather variables produces improvement in out-of-sample forecasting power of both price and the natural logarithm of price. Results indicate that extreme temperature levels will have a positive effect on prices, and that prices tend to fall as wind speed increases. This study also suggests that while weather does influence electricity prices, regional variables such as methods of generation and manner of end-use determine how weather impacts prices, and what that impact will be.

While decreases in forecast RMSE and MAPE due to the addition of weather variables are small, this may be due to misspecification within the model, or perhaps to the unsuitability of ARMAX-type models to predicting electricity prices. The literature has shown that GARCH models and models incorporating regime-switching or jump-diffusion processes more accurately account for price spikes and can better forecast electricity prices.

This study is also hampered by the source and type of weather forecast data used. While Washington, D.C. and Pittsburgh can be considered representative of the general PJM Western Hub region, forecasts for every point within the region would be preferable. Again, incorporating such data in a study would prove challenging given the aggregate nature of hub prices. Using NWC station forecasts instead of private forecast data used by market participants also may have negatively impacted the results of the study. While most private forecasting firms make use of NOAA weather satellite models and data, they produce unique forecasts. Though NWC predictions are fairly accurate, they tend to err most during extreme weather events and conditions, times when we would expect power prices to spike, and electricity to be most sensitive to weather variables (Dello, 2011).

Electricity pricing models are constantly refined, and further investigation of the effects of weather and weather forecasts on electricity prices would prove fruitful to such research. Use of GARCH models or models incorporating regime-switching and jump processes could stand to benefit from the inclusion of weather variables. Alternatively, more complex weather forecast data, such as the ensemble forecasts used by Taylor and Buizza (2003), could improve model accuracy. Finally, exploration of other, less-studied electricity markets may help create a more complete understanding of the deregulated power industry.

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Table 1: Price Summary Statistics

Observation	2556
Mean	43.63397
Standard Deviation	19.18555
Variance	368.0853
Skewness	1.782198
Kurtosis	11.66632

Figure 1: Time Series of Price

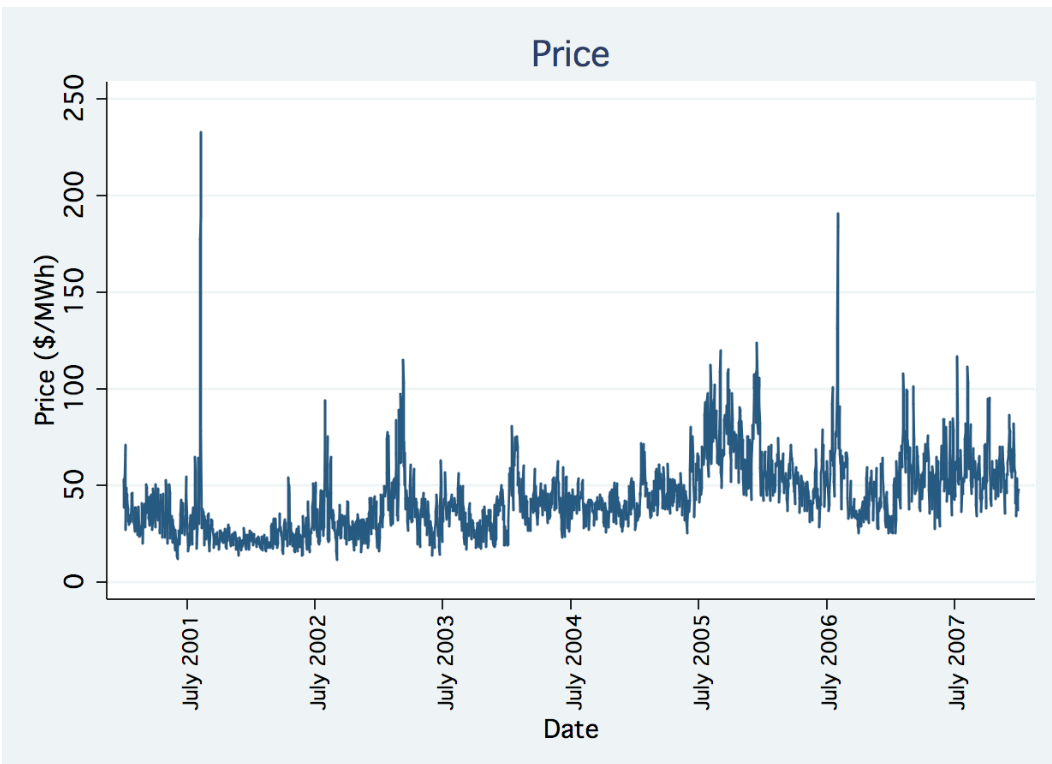

Figure 2: Histogram of Price

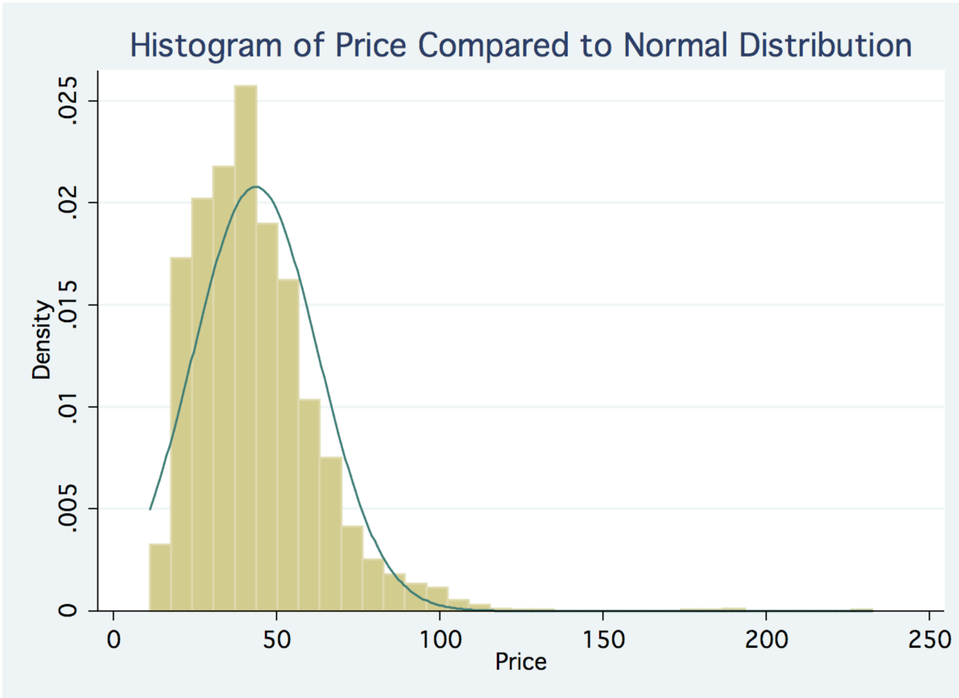

Figure 3: Autocorrelation Function of Price

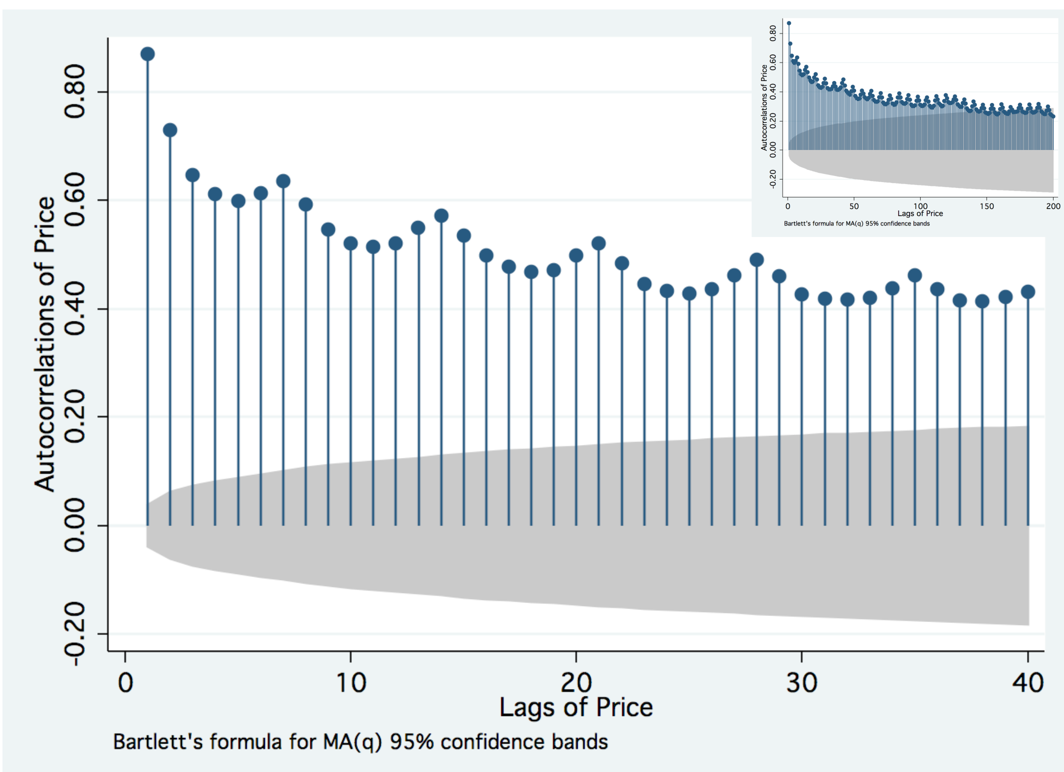

Figure 4: Average Price by Day of Week

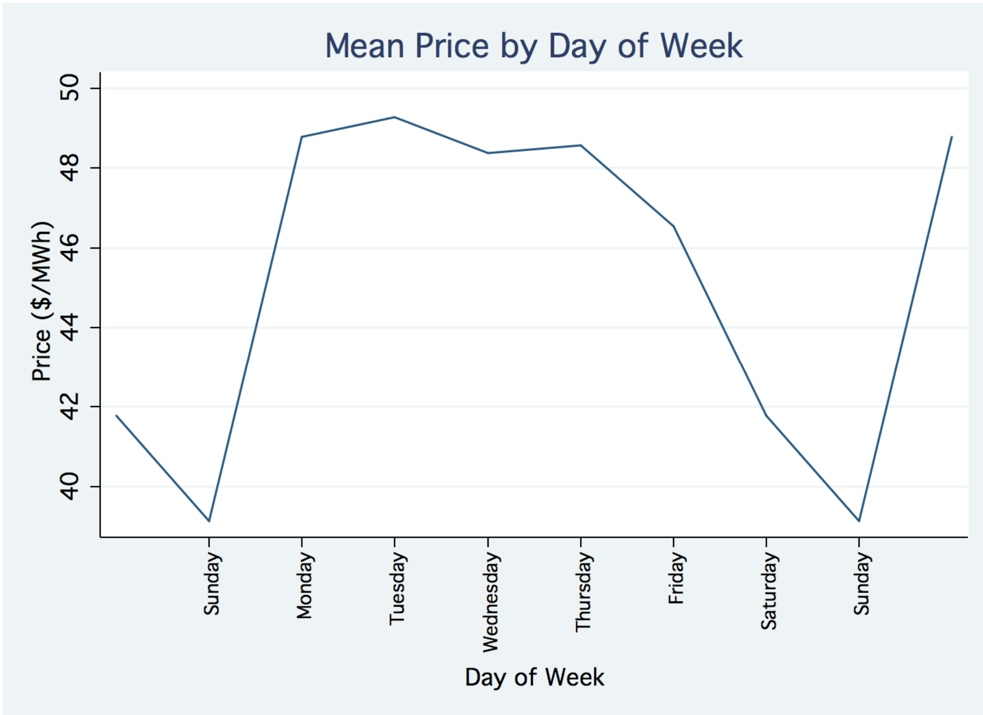

Figure 5: Scatter Plot of Temperature vs. Price

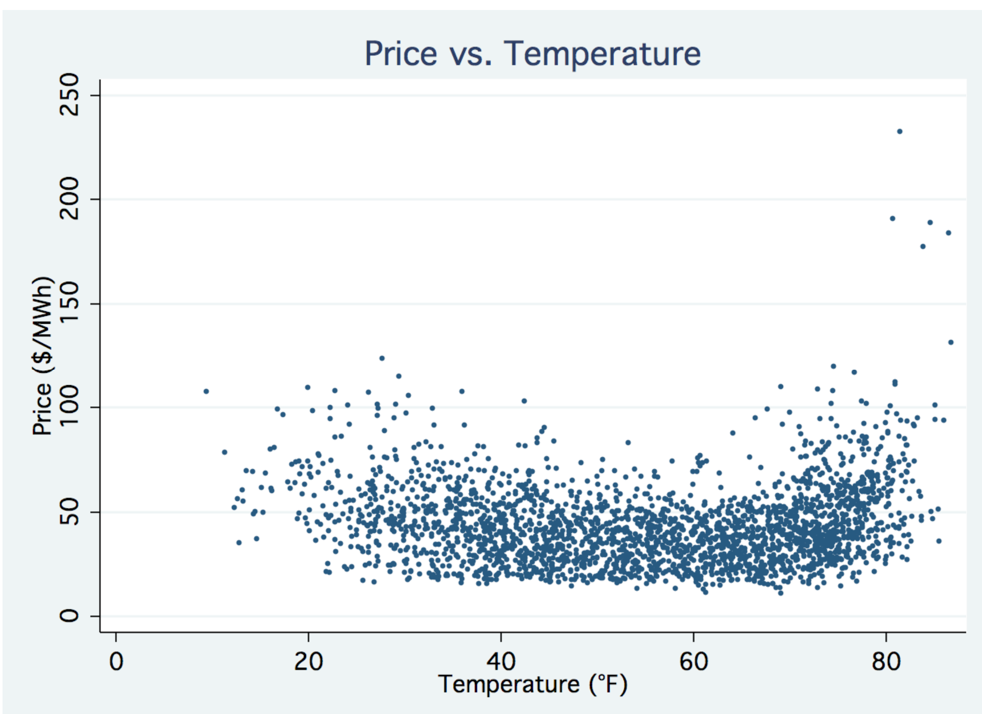

Table. 2: Standard Error in Parenthesis; ***p<0.01, **p<0.05, *p<0.1;LS denotes Lucia-Schwartz

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LS ln(Price)	LS ln(Price)	Price	Price	ln(Price)	ln(Price)
β_Δ	0.198***	0.198***				
	(0.0126)	(0.0125)				
β_2	-0.0943**	-0.0287	-0.635	-0.247	-0.0633	-0.0569
	(0.0411)	(0.0412)	(3.557)	(3.504)	(0.0759)	(0.0754)
β_3	-0.118***	-0.0707*	-2.777	-2.604	-0.0875	-0.0896
	(0.0400)	(0.0403)	(2.983)	(2.991)	(0.0632)	(0.0627)
β_4	-0.0186	-0.0132	2.307	1.790	0.0665	0.0507
	(0.0409)	(0.0399)	(1.985)	(1.965)	(0.0516)	(0.0508)
β_5	-0.00742	-0.0156	-3.422	-4.063*	-0.0990*	-0.114**
	(0.0447)	(0.0443)	(2.189)	(2.255)	(0.0530)	(0.0555)
β_6	0.0341	0.0624	-0.599	-0.636	-0.0445	-0.0474
	(0.0410)	(0.0400)	(3.296)	(3.434)	(0.0703)	(0.0741)
β_7	-0.00886	0.0497	-0.663	-0.358	-0.00231	0.00221
	(0.0379)	(0.0378)	(3.262)	(3.293)	(0.0758)	(0.0771)
β_8	-0.104***	-0.0414	-1.622	-1.066	0.00638	0.0173
	(0.0399)	(0.0394)	(3.224)	(3.203)	(0.0775)	(0.0778)
β_9	-0.0510	-0.0180	-0.762	-0.324	-0.0176	-0.00566
	(0.0430)	(0.0417)	(3.514)	(3.514)	(0.0850)	(0.0857)
β_{10}	0.0762*	0.0833**	-1.055	-0.813	-0.0182	-0.00917
	(0.0411)	(0.0398)	(4.066)	(4.040)	(0.0861)	(0.0856)
β_{11}	0.157***	0.169***	5.362	5.953	0.0800	0.0951
	(0.0431)	(0.0428)	(4.835)	(4.857)	(0.0908)	(0.0904)
β_{12}	-0.0973**	-0.0425	-0.790	-0.479	-0.117	-0.111
	(0.0424)	(0.0425)	(4.261)	(4.213)	(0.0856)	(0.0850)
δ_2			1.833***	1.747**	0.0416***	0.0396***
			(0.688)	(0.683)	(0.0132)	(0.0130)
δ_3			-5.246***	-5.300***	-0.131***	-0.132***
			(0.385)	(0.382)	(0.00861)	(0.00856)
δ_4			-8.327***	-8.394***	-0.220***	-0.222***
			(0.555)	(0.551)	(0.0116)	(0.0114)
δ_5			2.182***	2.275***	0.0366***	0.0388***
			(0.562)	(0.565)	(0.00869)	(0.00870)
δ_6			2.744***	2.648***	0.0548***	0.0526***
			(0.745)	(0.739)	(0.0133)	(0.0131)
δ_7			1.993***	2.025***	0.0411***	0.0420***
			(0.711)	(0.714)	(0.0120)	(0.0118)
ω_1		0.103***		2.557***		0.0620***
		(0.0141)		(0.640)		(0.0107)
ω_2		-0.00288		-0.135**		-0.00283***
		(0.00182)		(0.0523)		(0.00103)
γ_1			0.771***	0.766***	0.798***	0.793***
			(0.0616)	(0.0652)	(0.0201)	(0.0216)
γ_2			0.136***	0.143***	0.143***	0.151***
			(0.0422)	(0.0458)	(0.0180)	(0.0194)
θ_{t-1}	0.786***	0.771***	0.176***	0.159***	0.113***	0.0784**
	(0.00880)	(0.0102)	(0.0430)	(0.0461)	(0.0338)	(0.0388)
α	3.569***	3.516***	44.64***	44.40***	3.738***	3.730***
	(0.0296)	(0.0337)	(2.695)	(2.728)	(0.0738)	(0.0741)
RMSE	0.256***	0.253***	8.189***	8.132***	0.155***	0.153***
	(0.00361)	(0.00358)	(0.549)	(0.547)	(0.00368)	(0.00371)
R^2	0.6393153	0.71287751	0.8325687	0.83473167	0.86977316	0.87218369
AIC	325.0743	264.307	18049.19	18017.11	-2235.193	-2285.805
BIC	412.7673	363.6924	18177.8	18157.41	-2106.577	-2145.496

Figure 6: Price vs. Weather Variable-Enhanced Basic Model Predicted Values of Price

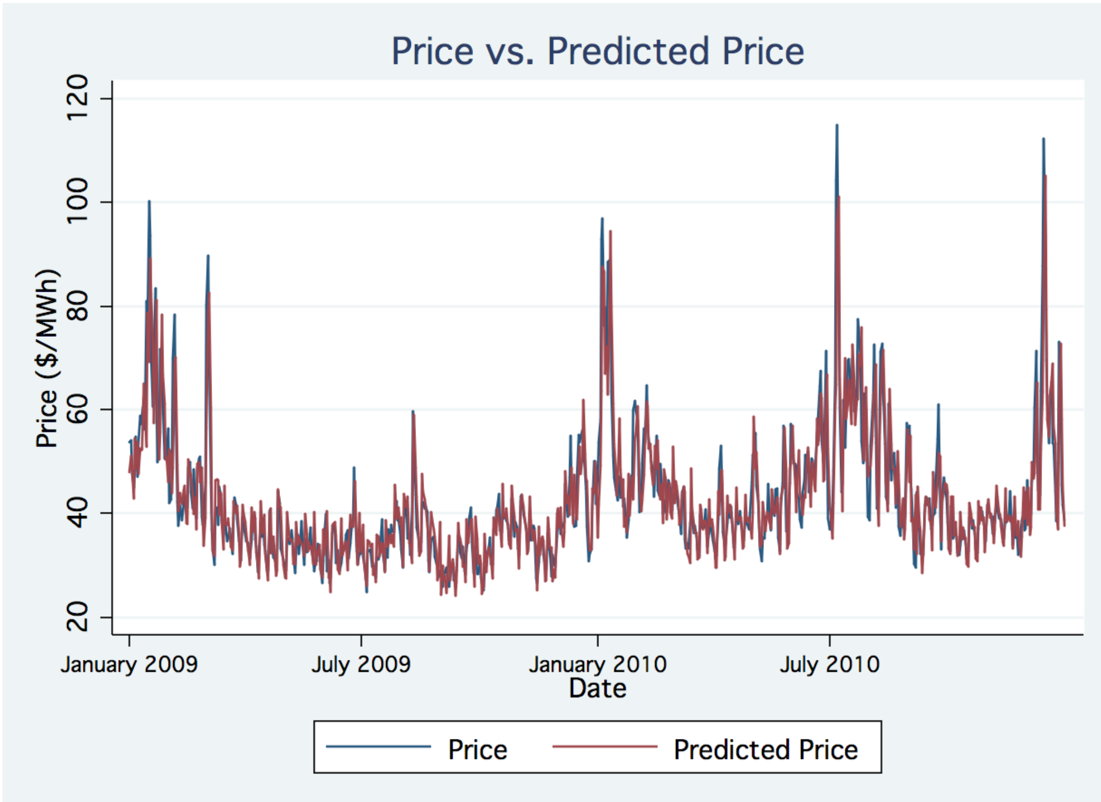

Table 3: Out-of-Sample Prediction Errors

Model	(3)	(4)	(5)	(6)
Variable	Price	Price	ln(Price)	ln(Price)
RMSE	6.2301509	6.1753073	0.12113216	0.11988953
MAPE	0.0937973	0.0932375	0.024459	0.0243151