A Case Study on the Informational Role of Futures Markets: Can Weather Futures Forecast Electricity Consumption?

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Abstract

This paper provides a case study on the informational role of futures markets by investigating the ability of Cooling Degree Day (CDD) futures prices to forecast electricity consumption for New York State. I develop a cross-sectional model relating electricity consumption with the cumulative CDDs in a month for New York City and utilize the 30-day and 20-day ahead settlement prices of the New York CDD futures contracts within the model to forecast electricity consumption. The forecasts derived explain up to 94.68% of the variation in actual electricity consumption, suggesting that the CDD futures prices contain useful forward-looking information about electricity consumption.

I. Introduction

Futures markets are well-known as a mechanism for reallocating risk pertaining to the prices of commodities or financial assets. The Keynes (1936) theory of commodity futures markets postulate that such markets exist to enable risk-averse speculators to insure other risk-averse traders with inverse risk profiles. A lesser known role of futures markets pertains to its ability to provide forward-looking information about the prices of assets traded on the market. Grossman (1977) proposed that future markets exist as a site for information exchange and enable people who gather information to make predictions about the future states of the market to profit from doing so. The markets enable such investors to trade based on their knowledge and reap private gains from their investments. As a consequence of their actions, futures prices reflect the information that these informed investors have about the future state of the market.

The forecasting ability of futures markets have been investigated in the context of end-of-the-day returns of stock index futures (Herbst and Maberly, 1992) and Treasury bill futures (Hegde and McDonald, 1986). The studies utilize futures prices to predict the spot price of the underlying instrument at a fixed point of time in the future and find that futures prices do indeed contain useful information about the future spot prices. These successes induce an investigation of other futures markets where forward-looking information could be of use.

The recent securitization of weather opens up the exciting prospect of gaining forward-looking information about weather from the weather futures market. Weather futures are derivative contracts written on weather indexes such as temperature, precipitation and rainfall. Since its inception in 1997, the notional value of weather derivatives traded annually in the market has grown from $4 billion to $45 billion (Pizzani, 2006). Of this, the notional value of weather contracts traded annually on the Chicago Mercantile Exchange (CME), has grown from less than $5 billion in 2003 to $22 billion in 2005. Currently, the exchange facilitates trading of futures and option contracts on temperature for 18 United States (US) cities, 9 European cities and 2 Japanese cities, on snowfall for New York and Boston and on frost days for Amsterdam[1]. Of these, temperature contracts are the most highly traded and therefore form the focus of this study. Temperature contracts are divided into Heating Degree Day (HDD) contracts traded in the winter season and Cooling Degree Day (CDD) contracts traded in the summer season. The nominal value of a monthly HDD or CDD contract is determined by the cumulative HDDs or CDDs in a month, multiplied by $20 (see Appendix 1 for an explanation of the calculation techniques).

While transactions in weather derivatives used to involve only economic producers who wished to hedge against volumetric risk posed by weather changes[2] and market makers such as insurance firms who write those derivatives, the presence of the CME has decreased the counterparty credit risk associated with over-the-counter (OTC) trading of the contract and greatly increased its liquidity (Kulkarni, 2003). Several studies have also found the performance of weather derivatives to be highly uncorrelated with other asset classes such as stocks, bonds, commodities and real estate (Jewson and Brix, 2001; Cao, Li and Wei, 2003; Lennep, Oetomo, Stevenson and de Vries, 2004), enhancing the case for investing in such instruments. Gradually, the market has been attracting speculators armed with proprietary technology in weather forecasting (Kulkarni, 2003). In line with Grossman's assertion, the

[1] The specifications of each contract are readily available on the Internet. See www.cme.com.
[2] Volumetric risk refers to risk associated with an increase or decrease in consumption volume due to weather changes, as opposed to price risk which refers to risk associated with price changes of the product in the market.

participation of such investors in the weather market should reveal valuable information about the future state of the weather indexes on which contracts are written.

The forward-looking weather information supplied by these markets could be useful to a variety of industries. While speculators in temperature futures have the economic incentive to invest in proprietary weather forecasting technology, companies that are in the business of producing economic goods do not have such motivation, resources or expertise to do so. If the futures market for CDD contracts reveals information about future temperature trends, companies whose businesses are directly affected by the weather could benefit from watching the market.

In particular, electricity consumption is highly dependent on temperature trends and energy producers often rely on temperature forecasts provided by the government and private meteorologists to determine how much electricity to produce and whether to buy or sell energy on the world market. Errors in forecast are costly; a three-degree Fahrenheit difference between forecasted and actual temperature for the Tennessee Valley Authority (TVA), one of the largest public energy producers, could result in a 1,350-megawatt difference in demand. Older, more expensive power plants are often used to match excessive demand and unnecessary usage of these facilities could cost up to $600,000 per day (IBM, 2006). Failure to predict high electricity loads could also lead to outages that cause severe economic damage. The intense heat in the summer of 2006 caused electricity demand in the New England region to peak at a record-high of 28,021 megawatts, nearly straining the distribution grid to its limit. California, Missouri and New York City each experienced blackouts due the high electricity demand for cooling needs that caused the distribution equipment to fail (Trafton, 2006). Given these consequences, reliable forecasts of monthly temperatures would enable energy producers and grid operators alike to make better production decisions and plan against such outages.

The quality of information contained in the prices of weather futures has been examined by Kulkarni (2003), who uses HDD futures prices to forecast monthly natural gas consumption. Kulkarni's study underscores the pivotal role of temperature in determining the type of energy consumption. During winter months, low temperatures lead to increased consumption of natural gas for heating needs while in the summer, high temperatures lead to increased consumption of electricity for cooling needs. To date, no attempt has been made to examine the effectiveness of CDD futures prices as a forecasting tool for electricity consumption. This paper analyzes the issue by building a model relating the CDD index of a US city to electricity consumption, and then using 30-day and 20-day ahead futures prices of the CDD futures contract written on the city in the model to forecast electricity consumption. After comparing the forecasts with figures for actual electricity consumption, I find that they explain a large percentage of the variation in actual electricity consumption. Therefore in the 20 and 30-day forward-looking period, the CDD futures market reflects valuable forward-looking information about summer temperatures that aid in forecasting electricity consumption.

Section II of the paper reviews the relevant literature on the informational role of futures prices and studies that relate temperature to electricity consumption. Section III establishes the theoretical justification for the paper's methodology and use of certain variables in the model relating CDDs to electricity consumption. Section IV summarizes the data used in this study. Section V discusses the empirical specifications of the model and collates the forecasted electricity consumption based on CDD futures prices. Section VI summarizes the findings, discusses the implications of this research and suggests areas for improvement.

II. Literature Review

Because the study attempts to connect two distinct topics, the literature pertaining to my study is divided into two bodies. The first deals with the role of the futures markets in information transmission between investors. The second deals with empirical models developed relating electricity consumption to temperature. Discussing the former places the study in the context of past applications of the idea and examining the latter lays the groundwork for the construction of a model relating electricity consumption and temperature.

The Informational Role of Futures Markets

Several key theoretical papers broach the concept that futures markets exist as a site of information exchange and many empirical papers have attempted to assess the validity of the proposed concept. Several studies have also attempted to assess the quality of the pricing information revealed in the futures market in terms of its ability to predict the future spot price. The application of this concept to weather futures is, however, new and there has only been one paper written on it. Moreover, the paper is the only one that has assessed the quality of the pricing information revealed in the futures market in term of its ability to predict other economic quantities related to the spot price of the asset on which the futures are traded.

Grossman (1977) was the first to suggest that apart from providing a mechanism for the reallocation of risk, futures markets also serve as a site of information exchange where the actions of “informed traders” influence prices and reveal information about their forecasts of the future states of that market to “uninformed traders”. Informed traders are market participants that invest time and effort into assessing and predicting future states of the market and certain conditions that exist in the futures market allow them to make an economic return on their efforts. Grossman’s model suggests that the degree of predictability of a future spot price from a current spot price determines the private incentives for futures trading in an asset which has no futures market. Given the difficulty in predicting the weather, his result suggests that private incentives exist for the trading of weather futures. In the context of CDD futures, the “spot price” is the value of the CDD index at the current point in time. Our ability to develop a forward looking estimate of the CDD index based on its current value is limited and thus traders with proprietary weather models find an economic incentive to trade based on their exclusive information.

Brannen and Ulveling (1984) tested Grossman’s hypothesis on several markets and found that private incentives for research and forecasting existed within the futures market for pork bellies, lard, wool and frozen concentrate orange juice (FCOJ) because the current spot price in those markets conveyed little information about future spot prices. Furthermore, the authors showed that the establishment of a futures market for each of these commodities reduced the expected price deviations among traders, illustrating that the futures price has provided information that is factored into market participant’s expectation of prices. However, while Brannen and Ulveling provide evidence that helps confirm Grossman’s hypothesis, they do not assess the quality of the information contributed by futures markets. Having a measure of this quality is however, useful if we intend to utilize the forward looking information contained in the price levels of futures markets. In particular, knowing the future price of one commodity could help us evaluate changes in the quantity demanded of substitute or complementary goods.

Subsequently, Hegde and McDonald (1986) investigate the quality of information contained in Treasury bill futures and find that from the second quarter of 1976 to the third quarter of 1983, the futures contract provides better forecasts of the future spot rate on a thirteen week Treasury bill compared to the Martingale forecast[3], for up to four weeks prior to the delivery of the futures contract. This study provides an example of an application of Grossman's theory and illustrates that the futures rate give by Treasury bills does have some predictive power over the future spot rate. For my paper, I take this application a step further and assess the predictive ability of weather futures on another economic variable significantly affected by weather, namely electricity consumption.

Kulkarni's (2003) paper is the sole study dealing with the information content of weather derivatives. Specifically, he uses the futures prices for Heating Degree Day (HDD) futures to forecast net natural gas withdrawals during winter months in the US. He finds that the 20-day-ahead HDD futures price for a HDD contract written on the Chicago O'Hare weather station can account for 78.81% of the variation in *national* monthly natural gas withdrawals. This is a rather strong result, considering that national natural gas consumption should be affected by overall temperature trends in the US, rather than just the temperatures trends in Chicago. When Kulkarni focuses on the forecast for natural gas withdrawals in New York (NY) state using HDDs written on the New York La Guardia airport, the 20-day-ahead forecast explains 86.67% of the variation in state monthly natural gas consumption. These results suggest that the price level of temperature futures hold large potential in forecasting

[3] The martingale forecast assumes that the current spot rate is the best forecast of the future spot rate. This is considered a rather naïve forecast (Hegde and Mcdonald, 1986)

actual temperatures and economic variables significantly affected by temperature. However, the model used by Kulkarni to relate monthly natural gas withdrawals to the HDD level is a rather simplistic one factor model, and thus might not account for several other factors that could affect monthly natural gas usage, such as the price of natural gas. Furthermore, Kulkarni ignores the possible presence of a risk premium in the futures prices that could accrue from the insurance function of the futures market. Lastly, Kulkarni writes this paper under the sponsorship of the CME, who profits from selling data on weather futures. My paper aims to improve Kulkarni's methodology by creating a more elaborate model, correct the futures prices for the risk premium and verify these results from an objective perspective.

Relating Electricity Consumption and Temperature

Many studies have been conducted to investigate how electricity consumption varies with temperature. These studies suggest useful physical factors apart from temperature that could affect electricity consumption as well as depict the nature of the relationship between the variables. The literature tends to originate from the disciplines of environmental science and engineering rather than economics. Nevertheless, the expertises provided by these disciplines allow us to accurately determine the relationship and the ensuing model can be easily adjusted to account for economic factors.

Le Comte and Warren (1980) first suggested that a measure of temperature could be represented by CDDs and HDDs, and that a very close relationship between national CDDs and electricity consumption can be found. A simple linear regression model relating both variables explained at least 91% of the variance in weekly national electric output in 1977 to 1979, while a combined multiple regression equation with additional variables for holidays, preceding temperatures and annual changes in base electricity consumption accounted for 96% of the variance. However, the authors model electricity consumption on a weekly basis while our timeframe of interest is that of a month, given the duration of a typical CDD futures contract. This allows us to do away with factors such as preceding holidays as such factors are sensitive to weekly cumulative temperatures , but less so for monthly ones. The author's inclusion of temperatures in the previous period as a determinant of electricity consumption stems from the fact that cooling requirements are affected by previous heat buildup as well as current outside temperatures. While this might be true on a weekly basis, it is probably less significant on a monthly basis. However, to account for the heat effects of buildup and also for the possibility of consumers basing current electricity consumptions levels on past temperatures, my paper will include previous period CDDs as a variable in the multi-factor model. The authors also use the method of "population-weighted CDDs" rather than adjusting for per capita electricity consumption. My paper aims to use the second method as it facilitates investigation on a state scale.

Sailor (2001) carries out the same investigation on a regional basis, stressing on the climate-related parameters that affect electricity consumption. He finds that there is a linear relationship between electricity consumptions, CDD level and humidity. Humidity is measured by enthalpy latent days (ELDs) and account for the possible humidity effects on summer air conditioning demand. However, the resulting coefficient for ELD was statistically significant for only the state of Louisiana. A major criticism of his paper is the narrow focus on climatic variables. He acknowledges that "the models used in this study are static in that they do not contain variable socio-economic data". I will address this shortcoming by including economic variables such as price and income in my model.

In summary, my study contributes to the existing literature by testing Grossman's hypothesis in a new type of futures market, namely that for CDD futures. I also improve current models that relate CDD levels to electricity consumption by taking into account both the climate and economic determinants of the latter and correct for the risk premium in the futures prices.

III. Theoretical Framework

Relation between the CDD Index and CDD Futures

The relation between the CDD index and the CDD futures price can be inferred from the relation between the futures price and spot price of a typical commodity. A futures contract comprises of an obligation to buy or sell an underlying asset at a fixed time in the future, at a price specified when the contract is created. Such a price is known as the *futures price* of the contract. For every party wishing to purchase a futures contract, there must be a party that wishes to sell the contract. The fair price of the contract - the futures price - at any point in time is thus determined by the interplay of supply and demand for the futures contract. An investor who takes a long position in a futures contract will gain if the spot price of the asset rises above the initial futures price on which the contract is written. Likewise, an investor who takes a short position in a futures contract will gain if the spot price of the asset falls below the initial futures price on which the contract is written. The futures price that an investor is willing to pay for a contract depends on whether the investor is bullish or bearish on the future spot price of the underlying asset and thus reflects the investor's belief of the future spot price.

However, there might be other factors that could affect the futures price other than the investor's belief of the future spot price. Futures markets have two main classes of participants: hedgers and speculators. Hedgers use futures markets to avoid risk by locking in the prices of raw materials or finished goods in advance of the sale date while speculators assume the other side of the transaction. Both Keynes (1930) and Hicks (1946) proposed that because the mitigation of risk is valuable to hedgers, they should pay a premium to speculators for assuming that risk. If that is the case, the futures price will be a biased estimator of the expected future spot price.

This scenario is highly relevant in the case of weather futures as, unlike conventional futures written on assets such as stocks, bonds or commodities, weather is not a tradable asset. Speculators cannot hedge away the risk on a weather future by purchasing a "weather asset" in the "spot market" as such a market does not exist. Notably, the risk premium is a factor that Kulkarni has overlooked when he asserts that "by observing the traded levels of CME weather futures, all players have valuable and quick access to the best available forward looking weather information" (Kulkarni, 2003). For this study, I utilize a formula derived by Cao and Wei (2004) that correct the futures prices of CDD contracts for the risk premium before utilizing those prices in a predictive capacity.

Cao and Wei (2004) utilize an extension of the CAPM model of market risk, the Lucas equilibrium asset-pricing model (1978), to estimate the futures price of a temperature futures contract. In their analysis, a generic benchmark known as the "aggregate dividend" is used instead of the returns on the market portfolio (as in the case of CAPM). Gross Domestic Product (GDP) is used as a proxy for aggregate dividend[4] and is denoted by δ_t. The following

[4] This makes intuitive sense as temperature levels have an effect on the economy as well as the stock market. In fact, the United States (U.S.) Department of Commerce estimates that nearly a third of the U.S. economy is

formula relates the futures price and expected spot price for a CDD contract for an investor with constant relative risk aversion[5]:

$$F_{CDD}(t,T) = E(S_{CDD}(T)) + \frac{Cov(\delta_t, S_{CDD}(t))}{E(\delta_t)} \quad (1)$$

where $F_{CDD}(t,T)$ denotes the futures price at time t of a contract expiring at time T, $E(S_{CDD}(T))$ denotes the expected "spot price" of the CDD contract at expiry time T, $Cov(\delta_t, S_{CDD}(t))$ denotes the covariance between the "spot price" of the CDD contract and the aggregate output up to time t and $E(\delta_t)$ denotes the expected value of GDP at time t.

The latter portion on the equation's right-hand side represents the risk premium of a temperature futures contract. Using this formula, we can find the expected future "spot price" for the CDD contract by subtracting that quantity from the futures price of the CDD contract. Since the "spot price" of the contract is simply the value of the CDD index, the expected "spot price" of a CDD contract reflects the expected value of the CDD index at the time of expiry. In essence, the risk-adjusted futures price of a monthly contract can give us a forward-looking estimate of cumulative CDDs for that month, and thus an idea of the temperature levels that will prevail during the contract month.

General Approach to Utilizing Weather Futures Information

To forecast electricity consumption, there must be a way quantitatively relate CDD futures prices to electricity consumption. Kulkarni (2003) suggests a two step methodology

directly affected by weather (Brockett et al, 2005) and a New York Times article (June 27, 1999) reported that U.S. businesses whose cash flows and earnings are significantly affected by weather have more than $1 trillion in yearly revenues. Not all of these companies are publicly-traded and hence not accounted for in the market portfolio.

[5] According to Cao and Wei (2004), convention in the literature assumes the representative investor to have constant relative risk aversion.

that I utilize in this paper. First, formulate a quantitative estimate of weather dependency for electricity consumption. This can be achieved by deriving an econometric model relating electricity consumption and the CDD index, based on historical data. Note that the levels of electricity usage must correspond to the level of the CDD index *at the same point in time*. This allows us to find the estimated level of electricity consumption given a particular temperature level. As mentioned in the literature review, factors other than the CDD index could affect electricity consumption and be related to the CDD index. Including more of such factors in the model allows us to mitigate the possibility of omitted variable bias.

Second, given that we have derived a cross-sectional relation for electricity consumption, the CDD index and other variables, we can use the risk-adjusted CDD futures prices a chosen number of days before expiry in the model together with non-forward looking information about the other variables to produce a cross-sectional view of electricity consumption at the time of the contract's expiry. With this value, we can deduce the additional electricity consumption during the month. Note that for a fully-accurate forward looking cross-sectional estimate of electricity consumption, forward-looking quantities for other variables in the model should be used. However, our purpose is to isolate the effect of using forward-looking estimates of just the CDD index (i.e the CDD futures prices) and having forward-looking estimates of other quantities could cloud the results of our experiment.

Modeling Electricity Consumption and the CDD Index

When ascertaining the relationship between electricity consumption and the CDD index, one must necessarily ask two questions. Firstly, what are the other variables that could affect electricity consumption and are they correlated strongly to the CDD index? If so, leaving them out could lead to the problem of omitted variable bias when we estimate the effect of the CDD index on electricity consumption. Secondly, what form does the relationship between electricity consumption and these independent variables take? Both Le Comte and Warren (1981), and Sailor (2001) suggest that these quantities are linked by a simple linear relationship. Given that we are investigating only summer time temperatures and electricity consumption, this is a plausible form to take as we have reduced the seasonality inherent in electricity consumption, compared to the scenario that would prevail were we to investigate the relation for the entire year.

The variables affecting electricity consumption can be separated into climate factors and economic factors. Climate factors include temperature and humidity while economic factors include electricity price and average income, as suggested by Harris and Liu (1993).

Climate Factors

Cooling degree days serve as a measurement for temperature trends within a month. As mentioned in the introduction, cooling degree days measure the magnitude of deviation of the average daily temperature above 65 degrees Fahrenheit. (Refer to Appendix 2 for the method of calculating the CDD index) This measure is known as a cooling degree day as temperatures above 65 degrees Fahrenheit necessitate cooling the environment to keep it bearable. We are primarily interested in the cumulative CDDs in a month as this gives us an indication of the demand for cooling during that month. Given that air conditioning is the main way to keep the environment cool when temperatures are high, we would expect increased use of such devices when the CDD index is high and electricity consumption to rise correspondingly.

Le Comte and Warren (1981) also find that the CDD index in the previous period also contributes to electricity consumption in the current period. Cooling requirements are affected by heat buildup in previous periods as well as current temperatures. The heat buildup affects both the CDD index as well as electricity usage in the current month. Although the authors have made this observation in the context of measuring the weekly CDD index, this is likely to be relevant on a monthly scale. Thus the previous month's CDD index is another relevant variable to be considered. *Ceteris paribus*, we would expect electricity consumption to increase with a higher CDD index for the previous period.

Humidity also has an effect on summer air conditioning demand as increased humidity leads to a greater desire to be in a cool and dry environment. Humidity is measured by enthalpy latent days (ELDs), which represents the amount of energy required to lower the humidity to the comfort level established by the American Society of Heating, Refrigerating and Air-Conditioning Engineers without reducing air temperature. However, Sailor (2000) finds that the coefficient for ELDs was significant for only the state of Louisiana, using data up to 2001. He further states that such a result was expected, given high humidity levels in Louisiana during the summer. Thus in our analysis, I will not consider the effects of ELDs for states that are considered to have low humidity levels during the summer.

Economic Factors

Harris and Liu (1993) assert that price plays a major role in explaining conservation behavior by electricity consumers and suggest that a higher price of electricity results in a lower level of electricity consumption. This is in line with conventional economic theory that a higher price of a commodity decreases the demand for it. Moreover, price could be indirectly related to the CDD index, given that a higher CDD index can increase the demand for electricity and in turn increase electricity prices. To avoid the problem of omitted variable bias, price should be a factor in our model.

Harris and Liu (1993) also argue that as household income rise, electricity consumption should also go up. When their incomes go up, consumers purchase more and larger appliances beyond basic necessity, such as larger homes and refrigerators with larger storage capacities. Moreover, rising incomes enable households to substitute labor for leisure by purchasing labor saving devices such as dishwashers and recreational facilities such as bathroom Jacuzzis, both of which increase electricity consumption. Thus we would expect electricity consumption to increase as average income increases. Household income could also be related to the CDD index through the effects of warm weather on the economy, thus making it a potential cause of omitted variable bias if excluded.

Other Factors

The localized nature of CDD contracts poses a challenge to the validity of the model relating electricity consumption to the CDD index. Weather stations and outposts containing thermometers are the physical measurement points for CDDs. For example, the representative station for New York City is situated at LaGuardia Airport. Temperature conditions change as the distance from LaGuardia Airport grows and thus the measurement point might not give an accurate representation of the CDD index pertaining to the entire state of New York. Given that electricity consumption for the state is affected by state-wide

CDD conditions, any forecast based on just the LaGuardia Airport measurement point is likely to be unreliable.

One might circumvent the problem by conducting individual forecasts for each city using the various measurement points throughout the state. This approach is, however, limited by the types of CDD futures contracts traded on the exchange. The contracts are only written on one major city or less per state, using one designated measurement point near the city. Thus, forward-looking information about measurement points other than the one on which the contract is written on is not available.

However, we could include a factor in the model that accounts for the variability of the CDD index throughout the state, relative to the designated measurement point. A simple method is to collect monthly information on the cumulative CDD index for all measurement points in the state and compute the average difference in the CDD index of those stations with the CDD index at the designated measurement point. Thus, a measure of variability could take on the following form:

$$AvgCDDVariability = \frac{1}{n}\sum_{i=1}^{n}\left(CDD_D - CDD_i\right) \tag{2}$$

where i = 1,…, n refers to the individual measurement points within the state and D refers to the designated measurement point in the state.

Model

For the model, a log-linear relationship between the dependent variable serves to better elucidate the effect of each variable on electricity consumption by allowing us to interpret the changes in percentage terms. Similarly, a log-log relationship is used for the dependent variable and average monthly price. Combining the discussed climatic and economic factors, a linear model that relates periodic electricity consumption and the periodic CDD index takes the following form:

$$
\begin{aligned}
& Ln(ElectricityConsumptionPerCapita_m) = \\
& \beta_0 + \beta_1 CDD_m + \beta_2 CDD_{m-1} + \beta_3 Ln(AvgElectricity\,\mathrm{Pr}\,ice_m) + \\
& \beta_4 MedHouseholdIncome_m + \beta_5 AvgCDDVariability_m + \varepsilon
\end{aligned}
\tag{3}
$$

In the context of this study, I will investigate monthly statewide electricity consumption for the state of New York (NY). All the variables in the proposed model will be computed on a monthly basis and the subscript m refers to the month. In Section V, I run a regression on these factors to ascertain the magnitudes and signs of each of the coefficients in the model and apply the risk-adjusted CDD futures prices in the model to forecast electricity consumption.

IV. Data

Two different sets of data are needed; one set for formulating the model and another set for forecasting electricity consumption based on the model. Table 1 provides summaries of the data needed for each variable in the model. Table 2 summarizes the additional data required when the model is used to forecast electricity consumption. Subsequent paragraphs discuss the source, and applicability of the data.

Variable	Description	Data Needed
$ElectricityConsumptionPerCapita_m$	Monthly per capita electricity consumption for the state	• Total monthly electricity consumption for NY in the months of May through September • Total monthly population figures for NY in the months of May through September
CDD_m, CDD_{m-1}	Monthly CDD Index and Previous month's CDD Index for the designated measurement point in the state	• Monthly CDD index for LaGuardia Airport in the months of April through September
$AvgElectricityPrice_m$	Average monthly electricity price charged to state consumers	• Average monthly electricity price charged to state consumers in the months of May through September
$MedHouseholdIncome_m$	Median monthly household income of state	• Median monthly household income of state in the months of May through September
$AvgCDDVariability_m$	Average variability of CDD index throughout state relative to designated measurement point	• CDD Index for designated measurement point • CDD Index for all other weather stations in state

Table 1: Variables and Data for Model

Variable	Description	Data Needed
$F_{CDD}(t,T)$	CDD futures prices for monthly CDD contracts on LaGuardia Airport	• 30-day ahead CDD futures prices for May, June, July, August and September CDD contracts on LaGuardia Airport • 20-day ahead CDD futures prices for May, June, July, August and September CDD contracts on LaGuardia Airport
$SCDD(t)$	Monthly "spot price" for CDD "asset"	• Monthly CDD index for LaGuardia Airport in the months of April through September
δ_t	Monthly aggregate dividend paid out by the economy	• Quarterly Gross Domestic Product (GDP) for the US economy for the second and third quarter of each year
$E(\delta_t)$	Expected value of aggregate dividend paid out by the economy	• Forecasted GDP of the US economy for the subsequent year

Table 2: Variables and Data for Forecasts

Electricity Consumption Per Capita

As described in Table 1, the two components of data for the electricity consumption per capita are the total monthly electricity consumption and the total monthly population for the state of NY. For the first component, the study uses the electric utility sales and revenue data compiled by the Energy Information Administration (EIA) from Form EIA-826. This data is available to the public on the EIA website[6]. The database contains information on the total electricity sales by month from 1990 to 2006 for all the states in the US. The figures for total monthly electricity sales are the sum of electricity sales from the residential, commercial,

[6] http://www.eia.doe.gov/cneaf/electricity/page/eia826.html

industrial and "other" [7] sectors. The data is collected monthly from a statistically chosen sample of electricity utilities in the US, and then extrapolated to reflect total state consumption.

This study uses only data for NY State, for the months of May through September, between the years of 1997 through 2006. The months of May through September are chosen because the study is concerned only with investigating electricity consumption in the summer months. Furthermore, monthly CDD contracts are typically written only for the months of May through September each year. The 10 year time period of 1997 to 2006 is chosen to be consistent with the available timeframe of CDD data for the state of NY.

Population figures for NY State were collected from the US Census Bureau website[8]. Due to a lack of data available on a monthly basis, I assumed that the state population remained constant for certain months of the year. Moreover, census data was available for only 1990 and the population figures given for 2000 to 2005 and 2010 were estimates. For simplicity, I also assumed that population grew at a constant rate each year between 1990 and 2000 and used a linear relation to derive the state population figures for the years of 1997 through 1999 and that for 2006. The figures for monthly electricity consumption per capita were obtained after dividing monthly electricity sales by total state population for that month. Over the ten year time period, there were a total of 50 observations for the dependent variable.

The lack of accurate population figures might constitute one weakness of the data used. However, the population for the state of NY has changed only 5% between 1990, when the first reliable census figures are available and 2000, when the first estimates for state

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[7] Electricity sales in the "other" category include activities such as public street highway lighting, usage by the public sector, and sales to railroads and railways.
[8] http://quickfacts.census.gov/qfd/states/36000lk.html

population are made by the bureau. Given the small magnitude of the change over the years, the lack of accurate data between the years of 1990 and 2000 should not affect the figure for per capita electricity consumption in a serious manner. Posing a more serious problem, the population figures for the state do not include only residents of NY State and omit people who live in neighboring states and commute to NY for work and other purposes. These individuals should rightly be accounted for, given that they consume electricity in NY State as well. This might cause the figure for electricity consumption per capita to be overestimated.

Monthly CDD Index

The monthly CDD index figures were obtained from the database maintained by the National Centers for Environmental Protection (NCEP), a sub-agency of the National Oceanic and Atmospheric Administration (NOAA)[9]. The database contains information about the monthly cumulative number of CDDs for various weather stations around the US, from May 1997 to March 2007. The cumulative number of CDDs is calculated by the method outlined in Appendix 2 and thus represents the total number of degrees in a month where the temperature has risen above 65 degrees Fahrenheit. For the variable denoting monthly CDD index, I have used the monthly cumulative CDDs for May through September for the years of 1997 through 2006. For the variable denoting the previous month's CDD index, I have used the monthly cumulative CDDs for April through August for the same years.

The LaGuardia Airport (LGA) weather station was chosen as the primary measurement point for the CDD index in this study. Exchange-traded CDD weather futures contracts pertaining to NY State are written only on LGA and not other weather stations in

[9] ftp://ftp.cpc.ncep.noaa.gov/htdocs/products/analysis_monitoring/cdus/degree_days/archives/

the state. Contracts written on other weather stations in NY State are traded OTC and are not the focus of this study. Moreover, using the pure CDD index for a single weather station provides an advantage over the population-weighted CDDs that have been utilized in previous studies as it allows us to single out the CDD trend without interference by population changes, and relate it to the CDD futures prices which also do not account for population changes.

Figure 1 depicts the typical trend for electricity consumption per capita within a summer season and the CDD index for that season. Both the CDD index and electricity consumption per capita increase between the month of May and August, after which they peak and decrease. The trend for the CDD index corresponds to the rising temperatures experiences in the summer months of May, June, July and August and the cooler temperatures when fall begins after August. The similar trend followed by electricity consumption per capita suggests that the CDD index is highly correlated with electricity consumption, a result that agrees with previous studies by Le Comte and Warren (1980).

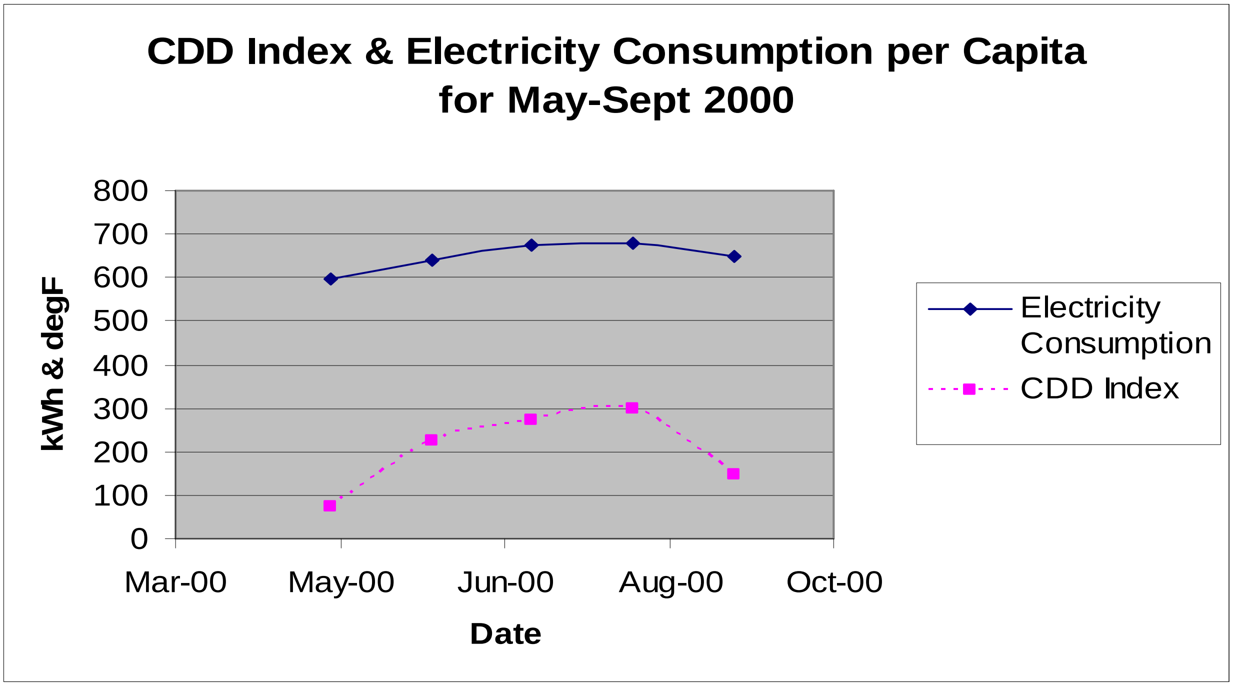

Figure 1: CDD Index & Electricity Consumption per Capita for May-Sept 2000

Average Monthly Electricity Price

Data for the average monthly electricity prices were obtained from Form EIA-826 on the EIA website. The price figure used represents the average price across the residential, commercial, industrial and "other" sector[10]. The price figures for each sector in turn represent the average electricity price charged within the month. This study uses prices figures for the months of May through September each year from 1997 through 2006. There are a total of 50 observations from the data. The prices are also adjusted for inflation using the GDP deflator index on EconStats.com[11] and 2000 as the base year. As outlined in the model in Section III, the logarithm of the inflation-adjusted average monthly electricity price is used.

[10] See Footnote 9

[11] http://www.econstats.com/weo/C172V021.htm. The formula for calculating the inflation-adjusted price is given by: Current price x (GDP Index in Current Year)/(GDP Index in 2000)

Figure 2 depicts the typical trend for the log of average monthly electricity price. The price increases in May, peaks in July and decreases thereafter. This trend could be a result of greater demand for electricity during the summer months of July, leading to increased prices.

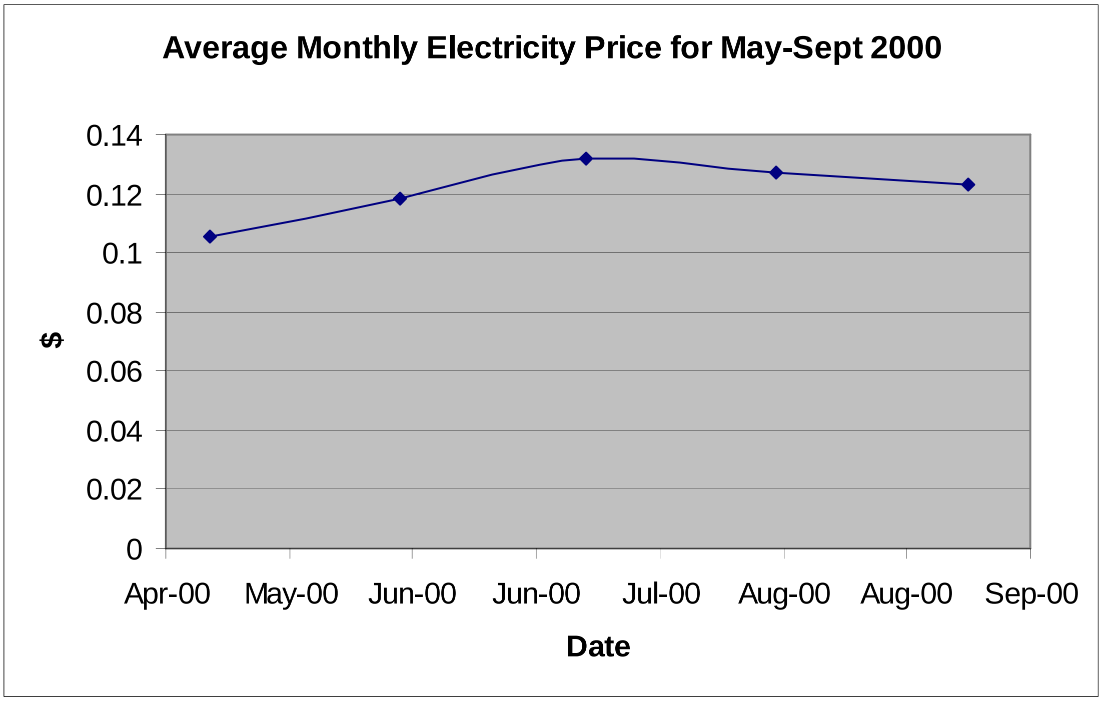

Figure 2: Average Monthly Electricity Price for May-Sept 2000

Median Household Income

The median for household income in NY State was used instead of the mean as data for the former was more readily available than the latter. The figures for 1997 to 2006 were obtained from the US Census Bureau's website[12]. Due to a lack of availability of monthly data, I assumed that the median household income for the state remained constant throughout the months of May through September each year. The figures were also adjusted for inflation

[12] http://www.census.gov/hhes/www/income/histinc/h08.html

using the GDP deflator index on EconStats.com[13] and 2000 as the base year. In total, there were 50 observations for median household income. While the lack of accurate monthly data for median household income might come across as a weakness, it should not have large implications for this study. Electricity is a basic necessity and should be relatively inelastic to income changes.

Average CDD Variability

Other than the LGA weather station, the monthly CDD index was taken for nine other weather stations located around NY State. The locations of these weather stations are illustrated in Appendix 3. The stations were chosen to be spread out in different locations throughout the state, so as to give a more accurate picture of the variability in CDDs within the state. The CDD indexes for the nine other weather stations were obtained from the same source as the CDD index for LGA station and over the same period of time, with the same frequency. The figure for average CDD variability was then computed using equation (2).

Note that throughout the data, the CDD index for LGA always appears higher than the CDD indexes for the nine other weather stations. This was surprising initially as one would expect the temperature at different locations in NY State to be both higher and lower than that at LGA. However, this could be explained by the fact that the area surrounding LGA is more built-up than other locations as New York City is the largest city in the state. This causes the measurement point to heat up faster and retain heat longer than the other weather stations.

Figure 3 depicts the trend of average CDD variability with time for each summer season from 1997 to 2006. The graph shows that the variability increases up to the middle of

[13] See Footnote 12.

summer, after which it decreases. Again, the built up surroundings of LGA might be responsible for this. June, July and August are typically the hottest months of the summer and the built up area around LGA causes heat to dissipate more slowly compared to other weather stations. This effect is accentuated during hot months, thus increasing the difference in CDD index between LGA and the other weather stations during June, July and August.

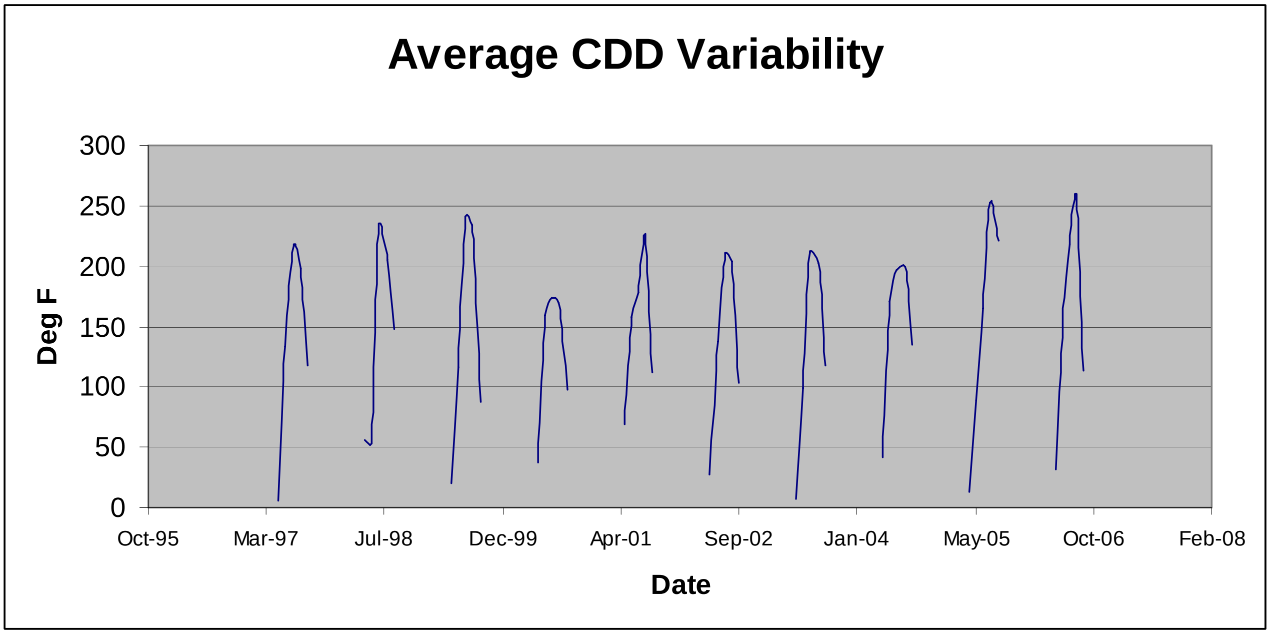

Figure 3: Average CDD Variability from 1997 - 2006

Gross Domestic Product

The Gross Domestic Product (GDP) for the US economy is used as a proxy for the aggregate dividend, δ_t, outlined in (1). The data for the second and third quarter GDP figures between the years of 1997 through 2006 was obtained from historical records on the US Bureau of Economic Analysis website[14]. Although monthly GDP figures would have been ideal, quarterly figures were used due to lack of availability of the former. Second and third

[14] http://www.bea.gov/national/index.htm#gdp

quarter figures were used as they corresponded to the CDD index recorded for the months of May through September and a total of 20 observations were recorded for the time period considered. Figures in the database were also pre-adjusted for inflation with 2000 as the base year, making this consistent with the inflation adjustments in my other data sets.

For the expected value of US GDP, I used the forecast for 2004, 2005 and 2006 GDP provided in the annual budget and economy report authored by the Congressional Budget Office[15]. As the forecasts are provided on a yearly basis, I assume that the expected value of GDP remains constants for the months of May through September within each year. In contrast, Cao and Wei (2004) use a mean reverting time-series model to produce these forecasts on a monthly basis. My method thus constitutes a simplifying measure for the calculation of those figures.

CDD Futures Prices

Pricing data on CDD futures were obtained from the end-of-day pricing (EOD) records of the CME. These records were purchased and retrieved using the CME Datamine service, yielding a data series that ranged from April 2004 to October 2006. Within the EOD records, the daily settlement price of the contract was taken to represent the price of the futures for that corresponding day. The settlement price is the official daily closing price of the futures contract and is determined by the range of bids and offers received by the exchange for the contract in the final 30 seconds of trading for the day.

Settlement prices for the CDD futures contract on LGA were retrieved from the record with the ticker symbol K4. Within the record, the trade date, contract year, delivery month and settlement price were noted. The trade date denotes the day of trading for which

[15] http://permanent.access.gpo.gov/lps755/

the settlement price pertains to. The contract year and delivery month refers to the year and month to which the contract is designated. This is important as contracts typically expire three to six days after the end of their delivery month[16]. Therefore, the value of the contract denotes the cumulative CDDs one would expect within the delivery month. As mentioned in Table 2, the 30-day ahead and 20-day ahead settlement prices for each monthly contract were extracted for the study. This is done by taking the settlement price of the contract on a trade date approximately 30 and 20 days ahead of the expiration date specified by the exchange. Due to the presence of weekends and holidays, trades dates that were slightly over 30 days and 20 days before expiry were used for some contracts. In total, there were 14 observations for the 30-day ahead futures prices and 15 observations for the 20-day ahead futures prices. The missing observation for the 30-day ahead futures prices is due to the absence of trading for the May 2005 contract 30 days or more before its expiry.

Figure 4 depicts a comparison of the 30-day ahead futures price with the actual CDD index for the corresponding delivery month. the futures prices are observed to mirror closely the actual CDD index, suggesting that the futures prices have strong predictability on actual CDD conditions. Regressing the actual CDD index on the futures prices yields an adjusted R-squared of 0.91, confirming our observations about the predictive ability of futures prices.

The primary weakness of using pricing data lies in the short span of data available for analysis. As such contracts only begun trading on exchanges in 2000 and recorded data for NY State is only available from 2004 onwards, the series represents only three years of prices and thus might turn out to be too short a time span to capture all possible pricing trends in the temperature futures market. This is a limitation that can be only overcome with time.

[16] The exact expiration dates of the contracts used were retrieved online from http://www.cme.com/clearing/clr/list/contract_listings_cl.html?product=K4

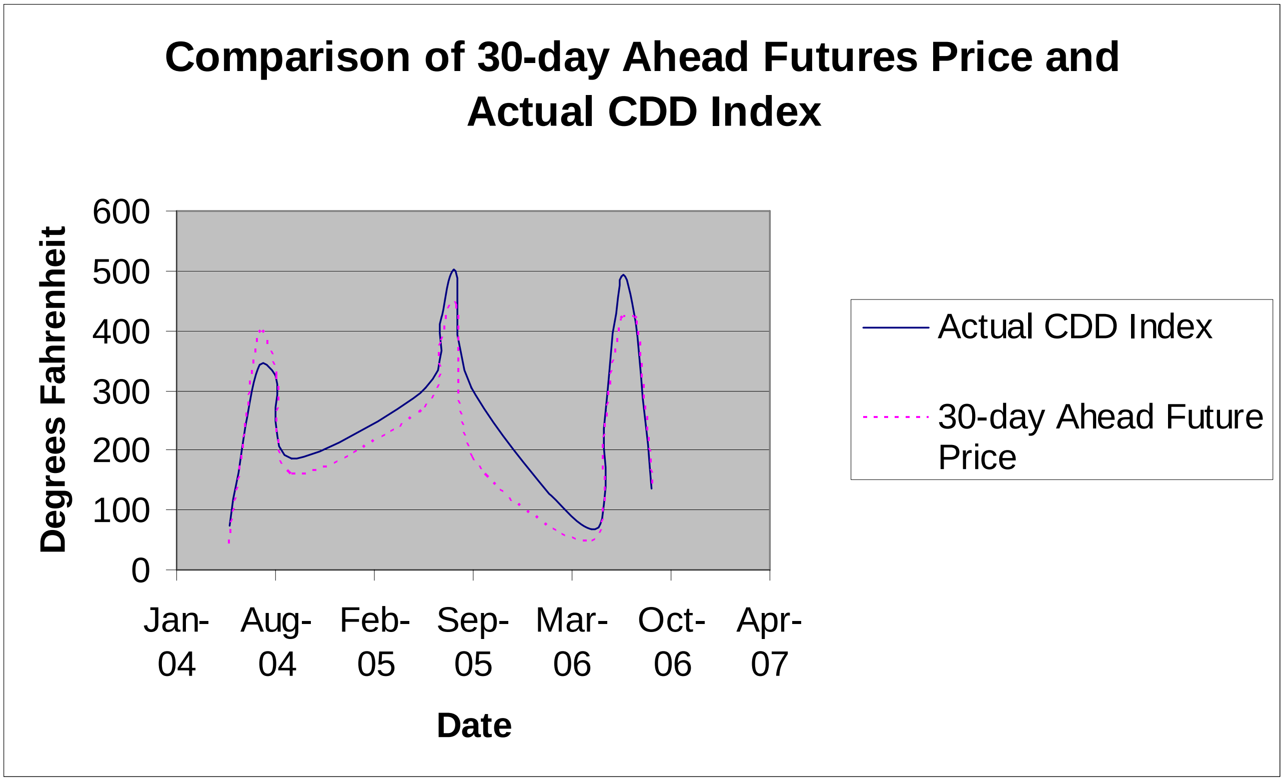

Figure 4; Comparison of 30-day Ahead Futures Price and Actual CDD Index

V. Findings

Specifications of the Model

As outlined in Section III, the model investigating the effect of the monthly CDD index on electricity consumption per capita was estimated using the following equation:

(3)

$$Ln(ElectricityConsumptionPerCapita_m) =$$

$$\beta_0 + \beta_1 CDD_m + \beta_2 CDD_{m-1} + \beta_3 Ln(AvgElectricity\Pr ice_m) +$$

$$\beta_4 MedHouseholdIncome_m + \beta_5 AvgCDDVariability_m + \varepsilon$$

The results of the regression obtained from an Ordinary Least Square (OLS) procedure with robust standard errors are shown in Table 3. Although there are only 50 observations in the sample, the adjusted R-squared is high at 0.8843. With the exception of *Ln* $(AvgElectricityPrice_m)$ and $AvgCDDVariability_m$, the coefficients on all other variables were statistically significant at the 1% level. *Ln* $(AvgElectricityPrice_m)$ and $AvgCDDVariability_m$ were not statistically significant at the 10% level.

Some of the results from the regression were well in line with my expectations. Firstly, the coefficient on CDD_m, tells us that a one degree day increase in the CDD index for LGA weather station leads to a 0.04% increase in electricity consumption for that month. Suppose the temperature for the month stayed above 65 degrees Fahrenheit for the entire month and increased by 1 degree Fahrenheit everyday. This translates to a 30 degree day increase in the CDD index for the month and a 1.2% increase in electricity consumption for the month. This figure is a reasonable figure and agrees with results found in the literature. Secondly, the coefficient on CDD_{m-1} reveals that a one degree day increase in the CDD index for LGA weather station in the previous month leads to a 0.02% increase in electricity consumption for that month. The sign of the coefficient falls within my expectation and the magnitude is less than that of CDD_m, , which is a reasonable result. One would expect the current CDD index to affect electricity consumption more than the previous month's CDD Index. Lastly, the coefficient on $MedHouseholdIncome_m$ shows that every dollar increase in the median household income leads to a 0.0003% increase in electricity consumption. The small magnitude of the coefficient is also in line with my expectations, given that electricity consumption is a basic economic good and is likely to be insensitive to changes in income.

However, the coefficient on *Ln (AvgElectricityPrice$_m$)* was positive instead of negative and had a large effect on electricity consumption. The former runs counter to our expectations and findings in the literature, given that a higher price of electricity should result in lowered consumption, not vice versa. This might be due to the fact that the figures used for the dependent variable relate to finalized sales of electricity, not the quantity of electricity demanded. Essentially, the relation takes the form of *equilibrium* quantities of electricity versus price. Therefore, it is difficult to judge if the relation should represent that of a downward sloping demand curve for electricity.

Overview	Number of Observations Adjusted R-Squared	50 0.8843
Independent Variable	Coefficient Estimate (Standard Error)	P-Value
Intercept	6.381*** (0.2175)	0.000
CDD_{m},	0.0004093*** (0.000092)	0.000
CDD_{m-1}	0.0002651*** (0.0000348)	0.000
Ln (AvgElectricityPrice$_m$)	.08883 (0.0931)	0.345
$MedHouseholdIncome_m$	0.00000315*** (0.000000735)	0.000
$AvgCDDVariability_m$	-0.0001028 (0.000178)	0.567
*Coefficient estimate is significant at the 10% level. **Coefficient estimate is significant at the 5% level. ***Coefficient estimate is significant at the 1% level.		

Table 3: Results of OLS Regression for Model

Risk-Adjusted Futures Prices

Table 4 shows the results of some calculations relating to the risk premium. The correlation estimate of 0.14 is relatively close to that of 0.22 which Cao and Wei (2004) obtain using data from 1979 to 1998. This figure was obtained by finding the correlation between CDD indexes and quarterly GDP, using data from 1997 through 2006. After dividing the covariance value with expected GDP for each period, the risk premiums for the contracts were determined. On average, the risk premium was found to be 3.305 degree days and this translates into a monetary value of $66.10[17].

Quantity	Estimate
$Cov(\delta_t, S_{CDD}(t))$	4.02575E+13
$Corr(\delta_t, S_{CDD}(t))$	0.14
Average Risk Premium	3.305 degree days

Table 4: Calculations Relating to Risk Premium

Forecasts of Monthly Electricity Consumption per Capita

Three methods of forecasting monthly electricity consumption per capita were used in the study to illustrate the forecasting ability of temperature futures. Firstly, I predict monthly electricity consumption using a martingale forecast method for the CDD index variable within the model. As defined by Hedge and McDonald (1986), the martingale forecast assumes that the current CDD index is the best predictor of the CDD index in the future. Hence for the martingale forecast, the CDD index for the delivery month is assumed to be the

[17] Recall the future contracts traded on the CME hold a value of $20 per degree day.

same as the CDD index for the prior month. Secondly, I predict monthly electricity consumption using the CDD index for the same month in the *previous* year. This method reflects a belief in the seasonality of temperature trends and that the CDD index for the summer months this year will be just like the index for the corresponding months last year. Thirdly, I utilize the 30-day ahead and 20-day ahead CDD futures prices as values representing the CDD index for the month.

For all three methods, the quantities of variables other than the CDD index and the previous month's CDD index are assumed to take on the values of the prior month. The quantities used for the previous month's CDD index are those of the current month.
For example, if we were forecasting electricity consumption for the month of May, the average price of electricity for the month of April would be used as a best guess for the average price of electricity for the month of May. However, the CDD index for April instead of March would be used for the variable relating to the previous month's CDD index.

With these quantities, I use the model to predict electricity consumption and compare that to the actual electricity consumption for the month. As the CDD futures prices are available only for the summers of 2004, 2005 and 2006, the process is done only for May through September in each of those years. The observations for each method thus numbers only 15 (14 in the case of the 30-day ahead forecast). For each method of forecast, an OLS regression is run with the actual electricity consumption as the dependent variable and the predicted electricity consumption as the independent variable. By observing the adjusted R-squared of these regressions, we can then deduce the percentage of variability in actual electricity consumption that is explained by the forecasts.

Table 5 depicts the results of the analysis. Using the 30-day ahead and 20-day ahead futures prices in the model produce forecasts that explain a greater percentage of variation in actual electricity consumption compared to forecasts obtained from the martingale and seasonal methods. The standard error for predicted electricity consumption are 20.61 kilowatts per hour (kWh) and 17.03 kWh for the 30-day ahead and 20-day ahead forecasts respectively, both of which are lower than the standard errors for the martingale and seasonal forecasts. Moreover, the 20-day ahead forecasts display greater explanatory power and a smaller standard error compared to the 30-day ahead forecasts. This fits in with our expectations that forecasting is more accurate over a shorter time period.

Method of Forecasting	Adjusted R-Squared	Standard Error for Predicted Electricity Consumption
Martingale	0.6585	50.03
Seasonal	0.7682	34.19
30-Day Ahead	0.9100	20.61
20-Day Ahead	0.9467	17.03

Table 5: Comparison of Forecasting Methods for Electricity Consumption per Capita

The results suggest that the CDD futures prices are valuable in predicting monthly electricity consumption. Comparing with previous studies, Kulkarni (2003) found that the 30-day and 20-day ahead prices for HDD futures contracts produced forecasts for monthly statewide national gas consumption n with adjusted R-squares of 0.5867 and 0.8667 respectively. This study shows that the corresponding prices for CDD futures contracts produce R-squares of an even higher magnitude. This is probably because the model relating monthly electricity consumption per capita with the CDD index contains more independent variables that are related to monthly electricity consumption per capita. As mentioned in Section II, Kulkarni's uses a simple model with only one independent variable.

VI. Conclusion

This study set out to examine the ability of Cooling Degree Day (CDD) futures prices to forecast electricity consumption for the state of NY. In doing so, a model relating monthly electricity consumption and the monthly CDD index was constructed and the 30-day and 20-day ahead futures prices of the CDD futures contracts used within that model to forecast electricity consumption. In the process, the futures prices were also corrected for a risk premium. The forecasts using 30-day and 20-day head CDD futures prices were found to explain 91.00% and 94.67% of the variation in actual electricity consumption respectively. This is an exceptionally high figure, suggesting that CDD futures prices contain useful information about monthly electricity consumption. The average risk premium was found to be 3.305 degree days, translating into a monetary value of $66.10.

The results suggest that movements in the CDD futures markets should be watched by energy producers and policy makers alike. Information contained in the futures prices can help these parties make useful decisions about energy production and distribution grid capacities, thus lowering costs associated with faulty weather forecasts and unexpectedly high electricity loads.

The first limitation of this study relate to the lack of futures pricing data to derive forecasts for electricity consumption. As data was available for only the summer seasons of 2004 to 2006, there were only 15 observations for comparing predicted and actual electricity consumption. Having more data points will allow us to confirm the high adjusted R-squares obtained from the comparison. The second limitation of the study relates to the method used to estimate the expected value of the aggregate dividend. For simplifying measures, the yearly estimates produced by the Congressional Budget Office were used. This resulted in the same expected value for GDP for all months in the same year. One could obtain monthly estimates by constructing a time series model that forecasts GDP on a monthly basis. This would lead to more accurate calculations for the risk premium of each CDD futures contract. The third limitation of the study relates to quantities used for the variables in the model other than the current CDD index and the previous month CDD index. Notably, I assumed that the average electricity price and average CDD variability for the coming month would be the same as that for the current month. This could be corrected by incorporating forward-looking information about electricity prices and CDD variability. For the former, electricity futures prices could be used to represent forward-looking information about electricity prices. For the latter, the prices of futures contracts on the temperature spread between LGA and other weather stations in NY State could be utilized. This would enable the model to produce an even better forecast of electricity consumption.

Nevertheless, this study has tested the methodology first proposed by Kulkarni (2003) in using HDD futures prices to predict natural gas consumption and verified its usefulness. The same methodology could come in useful when investigating the informational content of other futures contract prices.

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Appendix 1 – Calculation of HDD and CDD Index

HDD and CDD values represent the number of degrees the day's average temperature is lower and higher than 65 degrees Fahrenheit respectively. The average daily temperature is calculated by taking the average of the daily highest and lowest temperatures:

$$Average\ Daily\ Temp = (Highest\ Daily\ Temp + Lowest\ Daily\ Temp)/2 \tag{4}$$

HDD or CDD values are then obtained by taking the difference of the average daily temperature from 65:

$$\text{CDD}_t = \max[\text{average daily temperature} - 65, 0] \tag{5a}$$

$$\text{HDD}_t = \max[65 - \text{average daily temperature}, 0] \tag{5b}$$

where t denotes the day of the month.

For example, a daily highest temperature of 60 ° and a daily lowest temperature of 30° would yield average daily temperature of 45 °. The HDD value for that day would then be 65 – 45 = 20. If the temperature exceeded 65 °, the value of the HDD would be zero. Suppose the daily average temperature was 75 °instead. Then the CDD value for that day would be 75 – 65 = 10. If the daily average temperature was below 65 °, the CDD value would be zero.

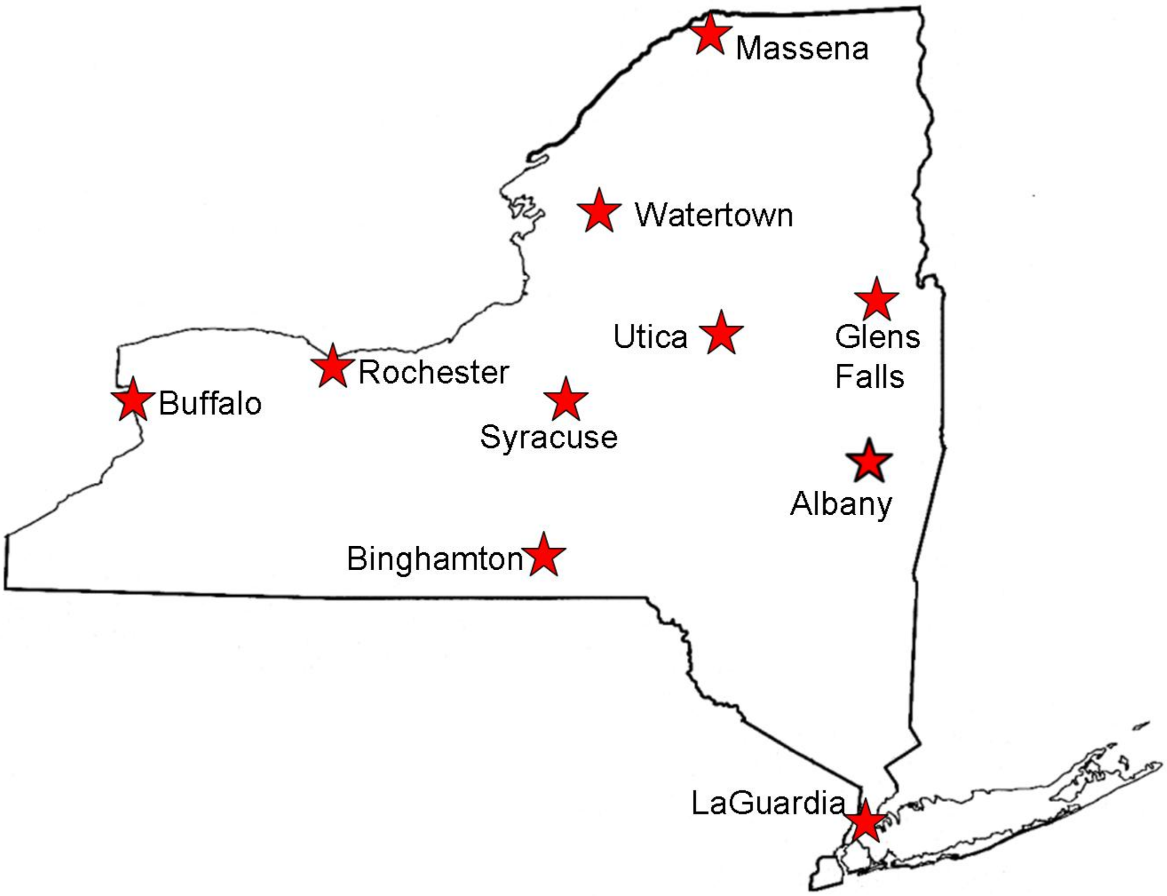
The monthly HDD or CDD index value is the sum of daily HDDs or CDDs during that given month:

$$\text{CDD}_m = \sum_{t=1}^{n} CDD_t \tag{6}$$

where m denotes the month and n denotes the number of days in the month.
The standardized contract size per index point (tick) is $20. Thus the value of a CME weather futures contract for a given month is $20 multiplied by the monthly HDD or CDD index value. For example, if the HDD index for October was 400, the value of the October

HDD contract would be 20 x 400 = $8,000.

Appendix 2 – Location of Weather Stations in NY State



Source: This schematic was created with reference to Mapquest