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Can the market forecast the weather better than meteorologists?

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Can the market forecast the weather better than meteorologists?*

Matthias Ritter[ab]

Abstract. Many companies depend on weather conditions, so they require reliable weather forecasts for production planning or risk hedging. In this article, we propose a new way of gaining weather forecasts by exploiting the forward-looking information included in the market prices of weather derivatives traded at the Chicago Mercantile Exchange (CME). For this purpose, the CME futures prices of two monthly temperature indices relevant for the energy sector are compared with index forecasts derived from meteorological temperature forecasts. It turns out that the market prices generally outperform the meteorological forecasts in predicting the outcome of the monthly index. Hence, companies whose profit strongly depends on these indices, such as energy companies, can profit from this additional information source about future weather.

Keywords: *Weather derivatives, weather forecasts, CME, energy sector*

JEL classification: *G15, G17, Q41, Q47*

1 Introduction

Weather risk plays an important role in many economic sectors. For example, the beverage industry sells less drinks if a summer is colder and wetter than expected,

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whereas farmers get less profit in a hot and dry summer. One of the most weather sensitive sectors is the energy sector as energy demand strongly depends on weather conditions. Consequently, reliable meteorological weather forecasts are necessary for production planning and risk hedging.

Weather derivatives based on different temperature indices are traded at the CME (Chicago Mercantile Exchange) and offered for 24 cities in the USA. If the traded asset is somehow weather related, its price depends on meteorological weather forecasts because all market participants are aware of this information and use it to adjust the bid and ask prices to the expected weather outcome. Roll (1984) has found a strong correlation between futures prices of frozen orange juice and weather forecasts; Dorfleitner and Wimmer (2010) and Ritter et al. (2011) demonstrate that the prices of temperature futures are clearly influenced by meteorological weather forecasts. From historical data for Chicago and New York, Kulkarni (2003) has discovered a linear dependence between natural gas consumption in winter and the monthly Heating Degree Day (HDD) index and has shown that the market prices of HDD futures can be used for forecasting gas consumption in winter. He neglects, however, if this result really comes from the weather forecasting ability of the market prices or from the natural seasonality of temperature, which is reflected in the HDD futures price as well. It is not verified if similar results could be obtained with historical averages of the temperature or with meteorological temperature forecasts.

In this study, it is analyzed if the market price of weather futures really contains more information about the future weather than usual meteorological forecasts from an atmospheric model and can thus be used as a weather forecast itself. For this purpose, the CME futures prices of two temperature indices relevant for the energy sector, namely, monthly HDD and CDD (Cooling Degree Day), are compared with an index forecast derived from meteorological temperature forecasts up to 14 days before the accumulation period ends. The results show that in most cases, the HDD/CDD market prices significantly outperform the HDD/CDD forecasts derived from meteorological forecasts in predicting the index outcome at the end of the month. Hence, companies whose profit strongly depends on the HDD/CDD index evolution, such as energy companies, can exploit this additional information for forecasting the short-term energy demand.

The paper is organized as follows: In the next section, it is explained in detail how the market prices are compared with the meteorological temperature forecasts. Furthermore, a benchmark model based on historical data, as well as the market price data and the meteorological forecast data, are introduced. In Section 3, the performance of the different approaches in predicting the index outcome is compared. Further discussion on the applicability of the results and conclusions are provided in the last section.

2 Methods and data

2.1 Definitions

The two indices traded at the CME and used in this study are both based on the Daily Average Temperature (DAT) T_t, which is defined as the average of the minimal and the maximal temperature on day t. From the DAT, the indices are derived as follows: The (cumulative) HDD index over a period $[\tau_1, \tau_2]$, $\tau_1, \tau_2 \in \mathbb{N}$, $\tau_1 \leq \tau_2$, with threshold K (usually 18 °C/65 °F) is defined as the sum of the daily heating degree days in the period, i. e.,

$$\mathrm{HDD}(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} \mathrm{HDD}_t = \sum_{t=\tau_1}^{\tau_2} \max(0, K - T_t). \qquad (1)$$

Hence, the HDD index measures the difference of the temperature to 65 °F if the temperature is lower than 65 °F and heating is needed. The CDD index, however, measures the difference of the temperature to 65 °F if the temperature is higher than 65 °F and cooling is needed. The (cumulative) CDD index over a period $[\tau_1, \tau_2]$, $\tau_1, \tau_2 \in \mathbb{N}$, $\tau_1 \leq \tau_2$, with threshold K (usually 18 °C/65 °F) is defined as the sum of the daily cooling degree days in the period, i. e.

$$\text{CDD}(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} \text{CDD}_t = \sum_{t=\tau_1}^{\tau_2} \max(0, T_t - K). \tag{2}$$

HDD and CDD contracts are offered on a monthly and seasonal basis at the CME, but for the most traded contracts, the accumulation period $[\tau_1, \tau_2]$ is one calendar month. The prices are reported in index points and after the end of the contract, the tick size (20 \$ per index point for US cities) converts the index outcome into a monetary amount.

2.2 Approaches

In this article, we compare three different ways of predicting the actual index outcome I_i of an HDD/CDD futures contract i with accumulation period $[\tau_1^i, \tau_2^i]$ (one calendar month). The prediction of I_i takes place k days before the end of the contract and is denoted by $\hat{I}_{k,i}$. Here, k describes the number of missing days that have to be predicted and ranges from 1 to 14 in this study.

The first approach is using the current market price of weather futures, which is reported at the CME. As it contains the payoff expectation of all traders, it can be seen as a prediction of the index outcome. The predicted payoff for contract i with accumulation period $[\tau_1^i, \tau_2^i]$ and k missing days to be predicted is given by the market price at time $t = \tau_2^i - k + 1$ (see Fig. 1):

$$\hat{I}_{k,i}^{\text{Market}} = F(\tau_2^i - k + 1; \tau_1^i, \tau_2^i), \tag{3}$$

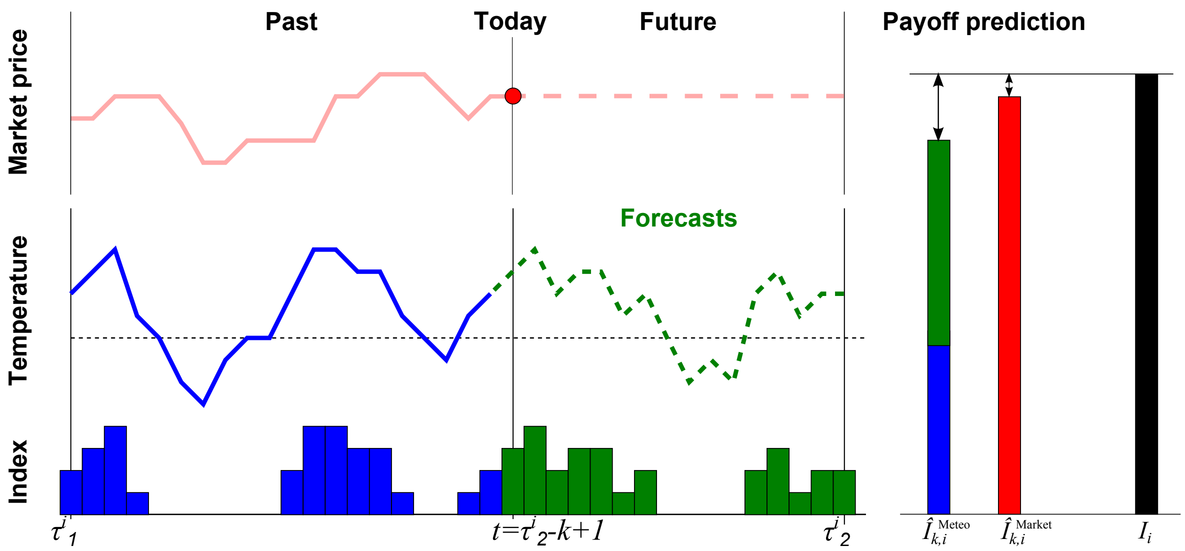

Figure 1: Payoff prediction k days before the end of the contract by the market and the meteorological forecasts approach

with $F(t;\tau_1,\tau_2)$ indicating the market price at time t of a contract with accumulation period $[\tau_1,\tau_2]$.

The second approach is based on meteorological temperature forecasts. As they are usually not available one month in advance, we compare the approaches only on those days where meteorological forecasts are available for the rest of the accumulation period. The first part of the accumulation period until the previous day is already observed, leading to a certain HDD/CDD index value (see Fig. 1). Then, the HDD/CDD forecast derived from the temperature forecast for the rest of the period is added to the already observed value. This results in one value which is the predicted index outcome for the calendar month. The closer to the end of the contract, the lower the portion of predicted, unobserved values.

$$\hat{I}^{\text{Meteo}}_{k,i} = \text{HDD}(\tau^i_1, \tau^i_2 - k) + \sum_{t=\tau^i_2-k+1}^{\tau^i_2} \max(0, K - \hat{T}^{\text{Meteo}}_t) \tag{4}$$

The prediction for a CDD contract is calculated analogously.

The third approach used as a benchmark is based on the historical temperature evolution. Here, the missing future index values are derived from the historical average temperatures $\bar{T}_t^{\text{Hist}}$. Consequently, this approach does not consider any forward-looking information, but considers the typical long-term behaviour of the temperature.

$$\hat{I}_{k,i}^{\text{Hist}} = \text{HDD}(\tau_1^i, \tau_2^i - k) + \sum_{t=\tau_2^i-k+1}^{\tau_2^i} \max(0, K - \bar{T}_t^{\text{Hist}}) \qquad (5)$$

The prediction for a CDD contract is calculated analogously.

To keep the approaches comparable, they are all based on the same day's data. If the market price is reported on day t, historical temperature data, and thereby historical HDD/CDD index values, are observed until day $t-1$. Hence, the meteorological forecasts calculated on day t predict the temperature (index) for day t and the subsequent days. The historical approach predicts the index on the missing days t, $t+1$, ... by averaging the historical temperatures on these days in the previous years and calculating the index.

The accuracy of the prediction is evaluated for each approach through the Root Mean Squared Error (RMSE), defined as:

$$\text{RMSE}(k) = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(\hat{I}_{k,i} - I_i\right)^2}$$

where k describes the forecast horizon, i. e., how many days before the end of the contract the index outcome is predicted. $\hat{I}_{k,i}$ is the predicted index outcome of the ith contract k days before the end of the contract, whereas I_i is the actual index outcome. The quadratic deviation of the predicted index outcome from the actual one is averaged for all N contracts.

City	Type	Months	Number	Total volume
New York City	HDD/CDD	Jan09–Mar12	40	77 431
Minneapolis	HDD/CDD	Jan09–Mar12	39	15 970
Cincinnati	HDD/CDD	Jan09–Mar12	41	12 517
Houston	HDD/CDD	Jan09–Mar12	40	11 557
Kansas City	HDD/CDD	Jan09–Mar12	39	11 950
Portland	HDD/CDD	Feb10–Mar12	24	800

Table 1: Decription of the monthly contracts used in this study

2.3 Data

This study is based on the monthly HDD/CDD contracts from January 2009 to March 2012, i. e., around 40 contracts for each city. The considered reference stations are New York City (LaGuardia Airport), Minneapolis (Saint Paul International Airport), Cincinnati (Northern Kentucky International Airport), Houston (Bush Intercontinental Airport), Kansas City (International Airport) and Portland (International Airport). The HDD contracts are offered in the winter months, October–March, whereas the CDD contracts, April–September. For some cities, both HDD and CDD contracts are offered for April and October. Details about the contracts for the six cities used in this study are depicted in Table 1.

For all these contracts, CME market prices are available for every weekday in the trading period. They are obtained from Bloomberg via the Research Data Center (RDC) of the Collaborative Research Center (CRC) 649 ‘Economic Risk’.

Furthermore, meteorological point forecasts derived from WeatherOnline[1] for the period January 2009–March 2012 for all cities except Portland are used. The forecast data for Portland start from February, 2010, so that the analysis for this city starts with the HDD contract February 2010. The dataset consists of forecasted minimum and maximum temperatures from 0 to 13 days in advance, that is, 14 days. Please note that only

[1]The author cordially thanks H. Werner and U. Römer from WeatherOnline for providing meteorological forecast data.

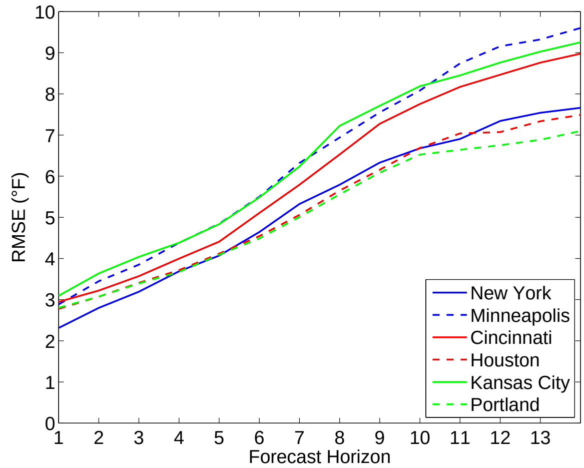

Figure 2: RMSE of the meteorological forecasts compared with the realized temperatures in dependence of the forecast horizon, data 01/01/2009–31/03/2012

the forecasts calculated on the last 14 days of each month are needed in this study. For the benchmark approach, historical temperature data are provided for each city since 1997 by the CME. To avoid bias in the analysis, all missing days in the datasets are linearly interpolated.

3 Results

3.1 Meteorological forecasts

At first, we analyze the quality of the meteorological forecast data. Therefore, the meteorological forecast data for the daily average temperature are compared with the realized temperatures from 01/01/2009[2] to 31/03/2012. Fig. 2 shows similar and unsurprising results for all six cities: The further the forecast horizon, the less reliable the meteorological forecasts. This emphasizes the difficulty of obtaining good mid-term forecast data.

[2]For Portland, the forecast data starts on 13/02/2010.

3.2 Payoff prediction

In this section, we investigate if the market price includes more information about the future weather than the meteorological forecast and the historical forecast. For each city and each contract, the difference between the realized outcome of the HDD/CDD index and the outcome forecasted up to 14 days before the end of the contract is calculated. For forecasting the outcome, the three approaches from Section 2.2 are used: historical forecast, meteorological forecast and market forecast. Then, the RMSE for all contracts is calculated separately for each city and each forecast horizon. Hence, each value of the RMSE is based on around 40 values (the number of contracts), and the calculation is repeated for the three approaches, the six cities and the 14 different forecast horizons.

The results in Fig. 3 depict a similar behaviour for all six cities: First, the RMSE for all forecast approaches decreases with decreasing forecast horizon. This is not surprising as with approaching the end of the contract, more and more days are already observed and the uncertainty reduces. Second, the approach based on historical data is always outperformed by the other two approaches, including forward-looking information.

Third, the market forecast approach always outperforms the meteorological forecast approach for a longer forecast horizon: If the end of the contract is at least eight days away, the RMSE for the market forecast is the lowest for all six cities. This difference, however, vanishes if the forecast horizon decreases. This is in accordance with the findings from Section 3.1, that the meteorological forecasts improve for a shorter forecast horizon.

Table 2 shows the results of a one-tailed two-sample t-test with unequal variances to find out if the deviations of the meteorological forecast approach and the market forecast approach are significantly different. At the 5 % significance level, the difference is significant in 31/48 cases (65%) for a forecast horizon of at least seven days. At the 10 %

p-values	14	13	12	11	10	9	8	7	6	5	4	3	2	1
New York	0.01	0.01	0.01	0.00	0.01	0.00	0.02	0.03	0.06	0.10	0.05	0.11	0.35	0.74
Minneapolis	0.13	0.14	0.25	0.09	0.05	0.07	0.03	0.03	0.08	0.25	0.26	0.33	0.61	0.89
Cincinnati	0.06	0.20	0.24	0.01	0.02	0.01	0.01	0.01	0.02	0.04	0.15	0.07	0.15	0.64
Houston	0.02	0.04	0.03	0.08	0.10	0.11	0.06	0.07	0.04	0.14	0.13	0.48	0.98	1.00
Kansas	0.16	0.13	0.03	0.02	0.03	0.02	0.41	0.79	0.26	0.43	0.23	0.18	0.36	0.67
Portland	0.05	0.02	0.03	0.05	0.02	0.03	0.03	0.04	0.61	0.11	0.38	0.56	0.62	0.88

Table 2: p-values of a one-tailed two-sample t-test for significant deviations

significance level, this number increases to 38/48 cases (79%). Hence, the market price clearly includes better forward-looking information than the meteorological forecasts.

4 Discussion and conclusion

In this article, the performance of different approaches in predicting the outcome or payoff of certain temperature indices was compared. The historical forecast approach performed poorly for all cities, so that one could think of applying a more sophisticated time series model based on historical temperatures such as the ARMA-GARCH model by Campbell and Diebold (2005). This article, however, focusses on a comparison of the market forecast and the meteorological forecast, so that the benchmark model is kept as simple as possible.

For the other approaches, it turned out that the market price generally includes better forward-looking information than meteorological weather forecasts. As market participants have access to meteorological forecasts provided by many different meteorological services, they are all incorporated in the market price. Hence, the market price is a mixture of all forward-looking information and thus can outperform meteorological forecasts derived from a single weather service.

Naturally, this result is restricted to the specific indices and cannot be used to forecast the temperature on single days. If a company's profit, however, has a strong relation with an index traded at the CME, the CME market price can be used as a forecast for

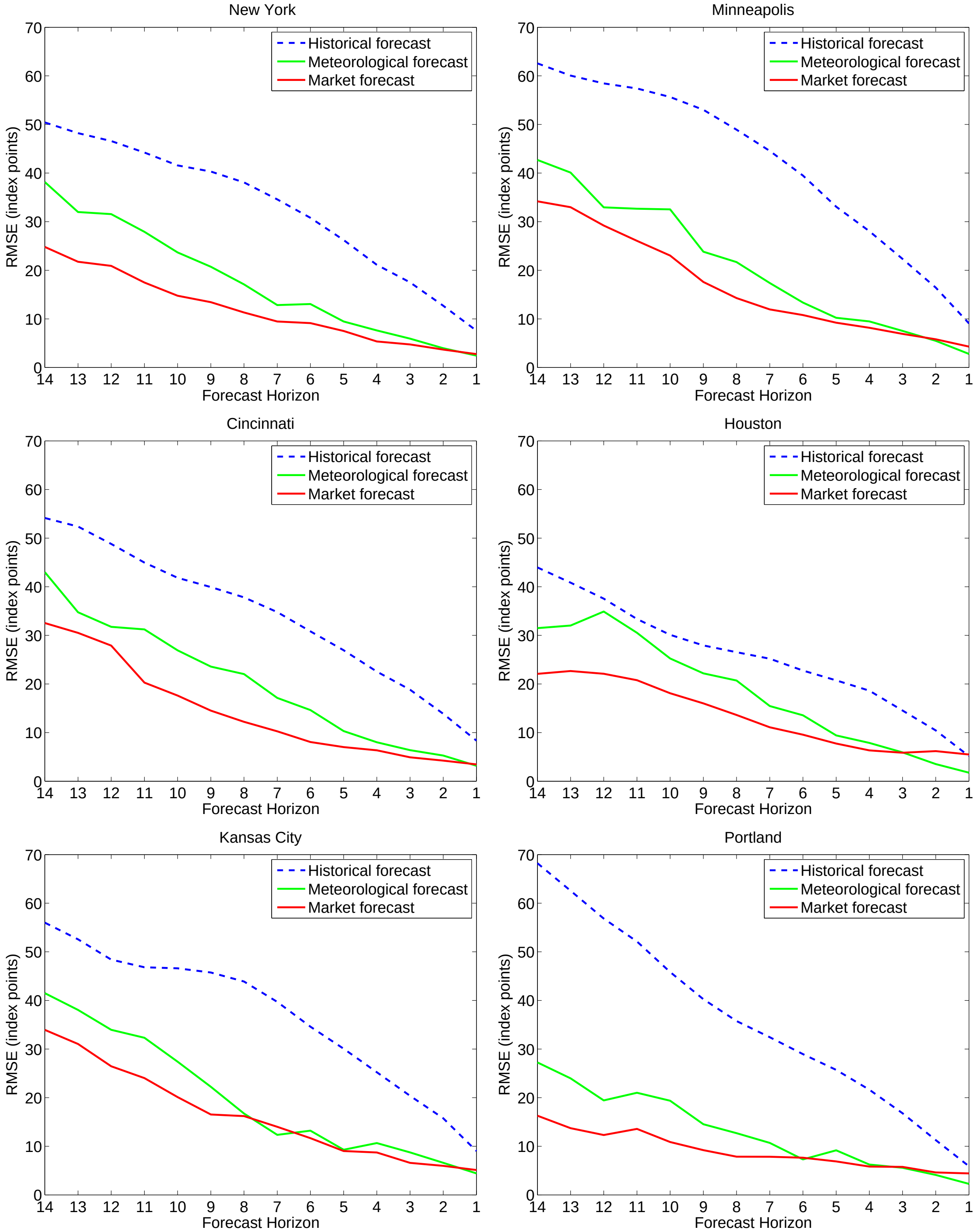

Figure 3: RMSE of the predicted index outcome compared to the real outcome, HDD/CDD contracts 01/2009–03/2012

the index outcome. Energy demand, for example, strongly depends on temperature, or derived temperature indices, such as the monthly HDD and CDD indices, traded at the CME (Fischer, 2010; Pardo et al., 2002; Sailor and Muñoz, 1997). Kulkarni (2003), for example, showed that a linear function of the monthly HDD index is a good approximation of the natural gas consumption in winter. Those indices are especially designed for the energy sector as energy demand increases if temperatures are low (heating) or high (cooling) (Mirasgedis et al., 2006; Svec and Stevenson, 2007). Hence, the forward-looking information included in the monthly HDD/CDD market prices can be exploited by energy companies, that require short-term and mid-term load forecasts, and therefore, weather forecasts to manage production, transmission and distribution of electricity (Soares and Medeiros, 2008).

The maximal forecast horizon was 14 days in this study because of the length of the meteorological forecast data. Further studies are needed to find out if the results can be generalized to longer forecast horizons. Moreover, the analysis should be repeated for other contracts traded at the CME, especially for CAT (Cumulated Average Temperature) and weekly contracts, to find out if they also include usable information about future weather.

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