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A new approach to modeling the effects of temperature fluctuations on monthly electricity demand[☆]

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A B S T R A C T

We propose a novel approach to measure and analyze the short-run effect of temperature on monthly sectoral electricity demand. This effect is specified as a function of the density of temperatures observed at a high frequency with a functional coefficient, in contrast to conventional methods using a function of monthly heating and cooling degree days. Our approach also allows non-climate variables to influence the short-run demand response to temperature changes. Our methodology is demonstrated using Korean electricity demand data for residential and commercial sectors. In the residential sector, we do not find evidence that the non-climate variables affect the demand response to temperature. In contrast, we show conclusive evidence that the non-climate variables influence the demand response in the commercial sector. In particular, commercial consumers are less responsive to cold temperatures when controlling for the electricity price relative to city gas. They are more responsive to the price when temperatures are cold. The estimated effect of the time trend suggests that seasonality of commercial demand has increased in the winter but decreased in the summer.

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1. Introduction

In households and firms in modern economies, electricity is one of the most essential goods consumed. It is certainly no surprise that there is an extensive literature that seeks to explain the variability of electricity demand across markets or in a given market over time. There is a long tradition in this literature, going back at least to Engle et al. (1989), of modeling the long-run and short-run effects of economic covariates, such as price and income, using an error-correction model. See also Silk and Joutz (1997) and Beenstock et al. (1999), *inter alia*.

Because of the obvious effects of temperature on the demand for electricity in heating and cooling, these studies typically employ some temperature-based metric to control for short-run temperature-induced fluctuations in demand, which occur at seasonal and higher frequencies. Controlling instead for long-run influences on electricity demand, we focus on modeling these short-run (SR) demand fluctuations, which we may think of as the SR component of electricity demand. We may view the response of the SR demand component to temperature as a *temperature response function* (TRF).[1]

In modeling temperature effects, researchers have long recognized the inadequacy of temporally aggregated measures of temperature, such as a monthly average. A linear TRF based on a monthly average temperature suffers from at least two major well-known deficiencies: linearity fails to capture increased demand at both very high and very low temperatures, and the average over a month may not adequately reflect usage during periods of temperature extremes in a given month.

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[1] Our approach does not explicitly model a demand response from temperature fluctuations at periodicities longer than seasonal, because we do not differentiate between the distribution of temperatures in January of one year from that in January of another year.

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The standard method for handling these deficiencies has been to employ heating degree days (HDD) and cooling degree days (CDD), which measure the number of degrees that the daily average temperatures in a given period – say, a month – fall below (for HDD) or rise above (for CDD) a threshold value, usually 18°C or 65°F (see, e.g., Gupta and Yamada, 1972; Al-Zayer and Al-Ibrahim, 1996; Sailor and Muñoz, 1997; Fan and Hyndman, 2011). Using these metrics in an otherwise linear model replaces a linear TRF with a piecewise linear TRF with a break point at the threshold temperature, addressing the first deficiency, while indirectly employing intra-monthly data (daily averages), addressing the second deficiency.

Of course, piecewise linearity of the TRF and an arbitrary specification of the threshold may still be inadequate, and there are a number of studies aimed at improving the functional form by way of more sophisticated nonlinear parametric methods or even nonparametric methods, including Engle et al. (1986), Filippini (1995), Pagá and Gürer (1996), Henley and Peirson (1998), Valor et al. (2001), Pardo et al. (2002), and Moral-Carcedo and Vicéns-Otero (2005).

The second deficiency, using a temporal aggregate, seems to have received less attention. Perhaps the indirect use of daily data by way of the HDD and CDD (H/CDD) metrics is viewed as adequate to capture intra-monthly fluctuations, and perhaps the lack of econometric methods to deal with data observed at different sampling frequencies has been an obstacle to using intra-monthly temperature data. Nonetheless, the fact that temporal aggregation may have a deleterious effect on inference is well known.

Two examples illustrate the inadequacy of using H/CDD data. First, suppose that two months have the same number of CDDs (20), but that one has 20 days on which the average temperature is 19°C with the remaining days at or below 18°C, but the other has one day on which the average temperature is 38°C but with the remaining days at or below 18°C. A deviation from the threshold of a single degree would not likely increase electricity usage much if at all, while a deviation of 20°C would very likely induce a massive increase in cooling. Introducing piecewise linearity into the TRF by way of CDDs cannot adequately capture this difference, because the number of CDDs is the same in both months.

As a second example, suppose that temperature fluctuations within a day are substantial, as may be the case in continental climates, such as the Midwestern US. On a given day, the average may show 18°C, while the fluctuation over the course of that day may be ±8°C.[2] Monthly measures of HDD and CDD would not count that day, even though automated thermostats may switch on the heat, the air conditioning, or even both during the course of that day.

There is a third – perhaps more subtle – deficiency of standard temperature response functions. A TRF based only on temperature does not take into account economic or other non-climate covariates, such as the price of electricity. The subtlety lies in the fact that demand models typically *do* include these covariates. However, controlling for short-run temperature fluctuations separately from these covariates means that the impact of cold weather, for example, must be the same regardless of the price of electricity. Since the price of electricity relative to an alternate heating source, such as city gas, may influence an economic agent's use of electricity at a given cold temperature, we should not expect the TRF to be stable as relevant economic covariates evolve.

Further, the effect of price in such models must be the same regardless of season. Nevertheless, if the electricity price is less expensive relative to rival fuels, demand for electricity in heating may increase during the winter time, even though the effect of changes in price may be negligible during the spring and summer time when there is little demand for heating. Fan and Hyndman (2011) find differences in price elasticities between winter and summer.

In related research (Chang et al., 2014) focusing on time-varying coefficients in an error-correction model, we employ a semiparametric functional coefficient approach to the temperature response function that maps hourly and geographically disaggregated temperature observations onto a monthly measure of the seasonal component of electricity demand. This mixed sampling frequency functional coefficient approach easily addresses the first two deficiencies of the standard H/CDD approach mentioned above: the semiparametric specification allows for nonlinearity in the spirit of Engle et al. (1986), *inter alia*, while the functional coefficient explicitly utilizes intra-monthly temperature data.

In this paper, we focus only on the SR component of demand, and our main aim is to address the third deficiency in addition to the first two. In place of a TRF, we introduce a new concept: the cross-temperature response function (CTRF). The CTRF employs economic covariates directly in the component temperature response functions, both allowing the seasonal demand component to respond to non-climate variables and allowing the effects of non-climate variables to affect the response of the SR component of demand to temperature.

We decompose the effect of temperature on the SR component of electricity demand into three different components: a pure temperature effect, a price–temperature effect, and a time–temperature effect. We investigate the effect of temperature conditional on price and other factors proxied by time, so that the pure temperature effect can be identified.

We apply our model to Korean residential and commercial electricity demand, finding that non-climate variables have particularly substantial effects on changes in the temperature response function of the commercial sector.

The rest of the paper is organized as follows. In the next section, we introduce the TRF and CTRF, novel measures of seasonality using the entire intra-monthly temperature distribution for each month, and we show how they generalize extant measures of seasonality, average temperature and H/CDD data. We discuss data for our application to Korean electricity demand in Section 3 and our estimation results in Section 4. Section 5 concludes. An appendix contains some technical details of the derivations of the regression models in Section 2.

2. Measurement of the temperature effect

2.1. Temperature response function

The temperature response function was used by subsets of the present authors in previous work (Chang and Martinez-Chombo, 2003, and Chang et al., 2014). Because this concept is critical in developing our analysis, we provide here all of the details for the reader's convenience and in fact a more extensive discussion that supersedes the discussions of the temperature response function in those papers.

Consider a hypothetical measure y of the SR component of electricity demand. Such a SR measure abstracts from demand changes directly due to slowly evolving economic covariates, such as long-run income changes. We will refer to this component of demand simply as the *SR component*. Our main purpose is to estimate the mean of y conditional on temperature and economic covariates that may fluctuate frequently. Setting aside the possibility of economic covariates for now, we define the *temperature response function* (TRF) g to be a possibly nonlinear function that maps the temperature distribution (a distribution of stock variables observed over some period of

[2] According to the US National Weather Service, http://www.srh.noaa.gov/ama/?n=50ranges, accessed October 10, 2014, average fluctuations of 30° F (16.68 °C, or roughly ±8 °C) are common for some parts of the Midwest (High Plains region) in March.

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