Ecological Economics 69 (2010) 1324–1329

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

Energy savings from tree shade

Ram Pandit [a], David N. Laband [b,*]

[a] School of Agricultural and Resource Economics, University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia
[b] School of Forestry & Wildlife Sciences, Auburn University, 602 Duncan Drive, Auburn, AL 36849, USA

ARTICLE INFO

Article history:
Received 15 October 2009
Received in revised form 19 January 2010
Accepted 31 January 2010
Available online 22 February 2010

Keywords:
Tree shade
Enery conservation
Electricity use
Natural air conditioning

ABSTRACT

Trees cast shade on homes and buildings, lowering the inside temperatures and thus reducing demand for power to cool these buildings during hot times of the year. Drawing from a large sample of residences in Auburn, Alabama, we develop a statistical model that produces specific estimates of the electricity savings generated by shade-producing trees in a suburban environment. This empirical model links residential energy consumption during peak summer (winter) months to average energy consumption during non-summer/non-winter months, behaviors of the occupants, and the extent, density, and timing of shade cast on the structures. Our estimates reveal that tree shade generally is associated with reduced (increased) electricity consumption in the summertime (wintertime). In summertime, energy savings are maximized by having dense shade. In wintertime, energy consumption increases as shade percentage in the morning, when outdoor temperatures are at their lowest, increases.

© 2010 Elsevier B.V. All rights reserved.

1. Introduction

Public discussion and policy initiatives related to energy tend to focus on supply-side aspects such as generation from non-fossil fuel sources (e.g., wind, solar, geothermal, tidal, and nuclear). Yet more effective management of demand potentially would generate sizable benefits in the form of reduced energy consumption. One significant demand-side management option is the natural air conditioning provided by tree shade. Trees cast shade on homes and buildings, lowering the inside temperatures and thus reducing the demand for power to cool these buildings during hot times of the year. The savings may be sizable — electricity usage for cooling houses in summer months is especially costly for those who live in hot climates as the energy used for air conditioning makes up a large fraction of the peak electrical utility loads during the warmest period of summer (Rudie and Dewers, 1984).

Without knowing how valuable the natural air conditioning provided by tree shade is, individuals have little incentive to use trees strategically to reduce their electricity use during the hot summer months. Thus, a *sine qua non* for encouraging individuals to adopt management strategies that help conserve energy is to give them scientific data identifying the financial savings they personally can enjoy that result from strategic development/management of tree shade on their residential lots.

A simple way of thinking about how to assign a monetary value to the cooling services provided by tree shade is to think in terms of replacement cost. In the absence of the natural air conditioning provided by tree shade, we artificially cool our dwellings and commercial buildings and we can identify the costs of doing so. Thus, we can estimate the value of natural air conditioning provided by tree shade by calculating homeowners' savings from not having to provide the equivalent level of mechanical cooling.

2. Literature Review

Most of the available analyses of empirical link between tree shade and residential energy usage are based on simulation exercises. For example, the simulation results of Simpson and McPherson (1996) indicated that two trees shading the west-facing exposure of a house and one tree shading the east-facing exposure reduced annual energy use for cooling by 10 to 50% and peak electrical use up to 23%. Huang et al. (1987) conducted a simulation study of the potential role of vegetation in reducing summer cooling energy in residential houses across 4 U.S. cities. Their results suggested that an additional 25% increase in tree cover would reduce annual cooling energy use by 40%, 25%, and 25% for an average house in Sacramento, Phoenix, and Lake Charles, respectively. However, the fourth city, Los Angeles, had minimal calculated savings. Similarly, another simulation study by McPherson et al. (1997) in Chicago indicated that three 7.6 m tall trees around a well-insulated new house would reduce annual heating and cooling costs by 8% as compared to otherwise identical houses without trees. However, conclusions drawn from these tightly controlled simulation exercises may not accurately reflect the savings realized by consumers, who lead lives that are considerably more complicated, in terms of energy consumption, than simulation exercises admit.

* Corresponding author.
E-mail addresses: ram.pandit@uwa.edu.au (R. Pandit), labandn@auburn.edu (D.N. Laband).

0921-8009/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.ecolecon.2010.01.009

There are a few empirical studies of shade trees and residential energy consumption based on real-world data, but the usefulness of the findings generated by these studies (Akbari et al., 1992; Akbari et al., 1997; Carver et al., 2004) is limited due to small samples or the absence of rigorous controls for confounding effects (Clark and Berry, 1995; Laverne and Lewis, 1996). For example, Akbari et al. (1997) analyzed the impact of shade trees on peak power and cooling energy use in 2 houses in Sacramento, CA and found a 30% reduction in energy use and 0.6 to 0.8 kW peak demand savings due to shade trees. In their tightly controlled experiment, Laband and Sophocleus (2009) found that the amount of electricity used exclusively to cool 2 buildings located in Beauregard, Alabama to 72 °F during April–September 2008 was 2.6 times greater for the building situated in full sun as compared to an otherwise identical building situated in dense shade.

There have been several large-scale empirical analyses of the linkage between tree shade and energy consumption in a residential context. Rudie and Dewers (1984) examined the impact of shade cast in different coverage categories on energy consumption by 113 residents in College Station, TX. Rudie and Dewers evaluated tree shade on roofs for 3 years (1977–1979) from June to September, using measured tree height to estimate the amount of shade cast based on hourly solar position on the 21st day of each month. They developed a shade score for each home ranging from 1 to 4 based on the shaded roof perimeter and wall space, and classified each homes into one of 4 shade categories (category 1 with 15 ft or greater depth of shade and category 4 homes with no shade/trees) to analyze energy savings as a result of tree shade. Their findings for different shade categories indicated that the amount of shade, roof color, and wall color were significant determinants of residential energy consumption.

Jensen et al. (2003) used remote sensing to measure Leaf Area Index (LAI) at 118 randomly selected points in Terre Haute, IN and regressed residential energy consumption against LAI values. The regression estimation produced statistically insignificant results, contradicting the strong and significant role of shade trees on residential energy consumption revealed by other studies.

Donovan and Butry (2009) estimated the effect of shade trees on the summertime electricity use of 460 single-family homes in Sacramento, California. Controlling for a modest number of structural characteristics (e.g., house age, square footage, and the presence of a swimming pool), they conclude that tree shade on the west and south sides of a house reduces summertime electricity use. By contrast, tree shade on the north side of a house *increases summertime electricity use*.

3. Methods and Data

Drawing from a sample of 160 residences in Auburn, Alabama, we developed a statistical model that produces specific estimates of the electricity savings generated by shade-producing trees in a suburban environment. This empirical model links residential energy consumption during peak summer (winter) months to average energy consumption during non-summer/non-winter months, behaviors of the occupants, and the extent, density, and timing of shade cast on the structures.

3.1. Empirical Models

Our empirical models analyze the impacts of tree shade and shade density on daily electricity consumption for three summer months (July, August, and September) and three winter months (January, February, and March). Eqs. (1) and (2) are the respective specific functional forms of the models we estimated for summer and winter months.

$$\mathrm{DECS}_{ijk} = \alpha_0 + \alpha_1 \mathrm{BaseKwh}_{ij} + \alpha_2 \mathrm{PercentShade}_{ijk} + \alpha_3 \mathrm{ShadeDensity}_{ijk} + \alpha_4 \mathrm{Pool}_{ij} + \alpha_5 \mathrm{Tempdiff}_{ij} + \varepsilon_{ijk} \quad (1)$$

$$\mathrm{DECW}_{ijk} = \beta_0 + \beta_1 \mathrm{BaseKwh}_{ij} + \beta_2 \mathrm{PercentShade}_{ijk} + \beta_3 \mathrm{ShadeDensity}_{ijk} + \beta_4 \mathrm{Tempdiff}_{ij} + v_{ijk} \quad (2)$$

where

DECS average daily electricity consumption (kilowatt hours) at an individual house in a summer month (July, August, and September)
DECW average daily electricity consumption (kilowatt hours) at an individual house in a winter month (January, February, and March)
BaseKwh average daily electricity consumption (kilowatt hours) at an individual house during April, May, June, October, November, and December
Pool whether the house has a swimming pool
Tempdiff the average daytime outside temperature minus the daytime thermostat setting for a given month (positive for summer months and negative for winter months)
PercentShade the extent of the roof area covered by tree shade, in decile percentages
ShadeDensity the intensity of tree shade cast on the dwelling, assigned one of four categories — no shade, light, moderate, or heavy[1]
ε_{ijk} model error term for summer months, assumed to be normally distributed
v_{ijk} model error term for winter months, assumed to be normally distributed
i sample households ($i = 1$ to 160)
j electricity consumption period for each i (for summer (S), j = July, August, and September; for winter (W), j = January, February, and March)
k shade monitoring times in a day per month ($k = 1$ to 3; 1 for late a.m., 2 for early p.m., and 3 for late p.m.)

The information we needed came from two sources — (1) the residents themselves, in response to a survey questionnaire and through submission of monthly electric bills, and (2) direct observation of shade conditions on the properties in our sample. Participants were identified using a stratified random sample design. We deliberately selected specific neighborhoods for inclusion in our sample, to ensure substantial variation in tree shade conditions. However, within each neighborhood, the distribution of invitations was random — every other home was contacted. In the invitation letter we explained the nature and scope of the study and provided relevant information for respondents to use to indicate their willingness to participate.[2] Our final sample of homeowners reflects a complete range of shade conditions, in terms of both extent and density, on properties as well as the other explanatory variables in our model.

We recorded monthly electricity usage data from each participating household from August 2007–August 2008. Specifically, we

[1] Our categorization of shade as light, moderate, or heavy was subjective, as we did not have an instrumentation measuring light conditions (e.g., PAR values) on each structure. Heavy shade density was recorded for shade with little or no light reaching the structure. Light shade density was recorded for shade with a lot of light still reaching the structure. Moderate shade, then, was recorded when there was substantial shade, but also substantial light, reaching the structure.

[2] Our invitation to participate was distributed to 2000 homes in Auburn, AL. We received responses from 165 individuals who agreed to participate (just over 8%). Although this response rate may seem low, we are quite impressed and pleased with this level of participation, for 3 reasons. First, the initial questionnaire was quite lengthy and asked a number of questions about the respondents' family, aspects of their dwelling, household behaviors, and electricity usage. Second, not only did we ask respondents to complete the up-front questionnaire, we requested continuing involvement for a full year, in terms of supplying us with their monthly power bill. Third, we requested access to their property each month, to assess shade conditions on the residential structure. During the course of our study, 5 participants dropped out because they moved.

collected information on dates of current service, number of days in service period, and the amount of electricity consumed during the specified period. Because not all residences are on the same billing cycle, we divided kW h used per billing cycle by the number of days in the billing cycle. This standardized our variable of interest, kW h used per day, across participating households.

Although there is considerable variation across residences with respect to building characteristics (e.g., age of house, living space, number of stories, type of cooling system, exterior construction materials, and presence of an additional freezer) and occupant characteristics (e.g., number of family members by age and gender, and average number of laundry loads run per week), these characteristics are essentially time-invariant with respect to electricity usage. By including a variable reflecting average daily electricity usage during non-winter, non-summer months (April, May, June, October, November, and December), we control for residence-specific, but (for the most part) time-invariant influences. This is similar to the methodology employed by Donovan and Butry (2009). In our model of average daily electricity usage during summer months, we did include a dummy variable for the presence/absence of a swimming pool. Although some pool owners run the pump year-round, others (one of the authors included) do not. This means that the marginal electricity used in conjunction with the pool arguably is time-sensitive to summer months. In addition, we collected information on the daytime and nighttime inside house temperature maintained by the residents both in summer and winter months. In conjunction with information about exterior temperatures, this permitted us to construct a measure of the intensity of the cooling (heating) regime at each residence across different seasons and months.

Monthly data on the extent and density of tree-cast shade was recorded through field visits conducted three different times on a sunny day as close as possible to the middle of each month. The extent of shade estimated in decile percentages three times a day — morning (9:00–11:00 a.m.), early afternoon (noon–2:00 p.m.), and late afternoon (3:00–5:00 p.m.) — was averaged to obtain a mean percentage of shade on each house. Shade density was recorded in one of four categories — heavy, moderate, light, and none. Heavy shade density refers to shade characterized by few-to-no patches of sunlight, light shade density refers to shade that allows most of the sunlight shine onto the structure, and moderate shade density is characterized by roughly equal amount of sunlight and shade hitting the dwelling. A single measure of shade density was constructed from the three density observations taken at different times of the day, using a weighted scheme reflecting the extent and density of shade. For example, if a house received 15% heavy shade in the late morning, 5% moderate shade in early afternoon, and 55% heavy shade in the late afternoon, then the mean shade extent for this house was assigned at 25% and shade density assigned was heavy. The same researcher monitored the extent and density of shade cast on each house every time to ensure consistency and uniformity with respect to the data.

We split our sample in two: the 3 hottest summer months, consisting of July, August, and September, and the 3 coldest winter months, comprised of January, February, and March. During the summer (winter) electricity use per day peaks in August (February) which coincides exactly with the maximum difference between the residents' desired thermostat setting and outdoor temperature, measured either as average daily temperature or average daily high/low temperature — see Fig. 1.

Descriptive statistics for time-variant attributes in the summer (winter) months are presented in Table 1a (Table 1b). We employed a mixed-modeling approach with restricted maximum likelihood estimation technique to estimate Eqs. (1) and (2) for two reasons: i) the data were collected from the same observational units over time, and ii) we included both time-invariant (e.g., base daily electricity usage during non-summer and non-winter months) as well as time-variant (shade conditions and intensity of cooling/heating effort) explanatory variables in the models. In particular, we used a random intercept model that allows the intercept term to vary among residences around a fixed mean to capture some unobserved variations in daily electricity consumption at each residence[3].

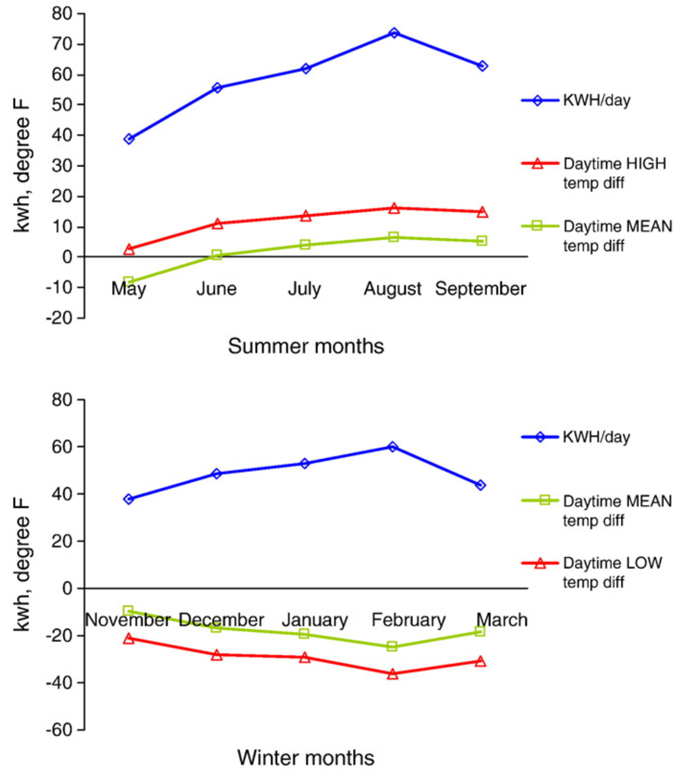

Fig. 1. In summer (winter) months, electricity usage per day increases with the intensity of cooling (heating) effort, whether measured as average high (low) temperature minus desired thermostat setting or average temperature minus desired thermostat setting.

4. Empirical Results

Although we had only 160 participating homeowners, our shade and electricity usage sampling was monthly and each power bill gave us electricity usage for the current billing cycle and for the equivalent billing cycle one year previously. So for each 3-month period, we started with $160 \times 3 \times 2 = 960$ observations. We lost a number of observations because individual participants occasionally failed to provide their monthly electric bill. We present our estimation results for summer (winter) months in Table 2 (Table 3).

Electricity consumption is affected strongly by the intensity of the cooling/heating effort in a residence. This effort is determined by the occupants' thermostat setting; as the distance between the desired temperature and the actual temperature increases, so does the intensity of the cooling/heating effort, depending on season.

[3] To explore the sensitivity of our results, we further estimated Eqs. (1) and (2) with the Percent Shade explanatory variable included. In this additional work, we permitted both a random intercept and random slope in the same model. The fixed-effect results for these models are similar to the results from models estimated with a random intercept only. While the covariance parameter estimate for the intercept term is highly significant for all models in both the cases (random effect of intercept versus random intercept and slope of PercentShade), the covariance parameter estimate for the PercentShade variable is not significant for any models. Also, the Akaike Information Criteria (AIC) for model selection indicates lower values for the random intercept models than for the random intercept plus random slope models. Therefore, only random intercept model based estimates are presented here, detailed results are available from the authors.

Table 1a
Sample statistics for time-variant attributes: summer months ($n=906$).

Attributes	Mean	Std. Dev.	Min.	Max.
kW h/day	66.04	27.04	0.02	192.97
Daytime inside temp °F (°C)	76.35 (24.64)	2.73	70.00 (21.11)	85.00 (29.44)
Nighttime inside temp °F (°C)	75.66 (24.26)	3.15	65.00 (18.33)	85.00 (29.44)
Outside high temp °F (°C)	91.21 (32.89)	2.31	86.35 (30.19)	95.61 (35.34)
Outside mean temp °F (°C)	81.44 (27.47)	1.81	77.57 (25.37)	85.03 (29.46)
Outside min. temp °F (°C)	71.18 (21.77)	1.52	68.20 (20.11)	73.94 (23.30)
Daytime mean temp diff (°F)	5.09	3.30	−7.34	15.03
Nighttime mean temp diff (°F)	5.78	3.66	−5.40	18.79
Percentage of house area under tree shade	19.30	21.10	0.00	88.00
Late a.m. (9–11 a.m.) percent house area under tree shade	22.88	27.08	0.00	100.00
Early p.m. (12–2 p.m.) percent house area under tree shade	11.84	16.77	0.00	90.00
Late p.m. (3–5 p.m.) percent house area under tree shade	32.04	33.06	0.00	100.00

Table 1b
Sample statistics for time-variant attributes: winter months ($n=904$).

Attributes	Mean	Std. Dev.	Min.	Max.
kW h/day	53.82	29.24	11.11	199.14
Daytime inside temp °F (°C)	70.16 (21.20)	3.13	60.00 (15.55)	80.00 (26.67)
Nighttime inside temp °F (°C)	68.23 (20.13)	3.91	55.00 (12.78)	78.00 (25.56)
Outside high temp °F (°C)	59.71 (15.39)	4.37	50.91 (10.51)	67.89 (19.94)
Outside mean temp °F (°C)	49.18 (9.54)	3.97	40.87 (4.93)	56.00 (13.33)
Outside min. temp °F (°C)	38.14 (3.41)	3.90	29.55 (−1.36)	44.90 (7.17)
Daytime mean temp diff (°F)	−20.98	5.17	−36.78	−4.94
Nighttime mean temp diff (°F)	−19.05	5.60	−35.10	0.06
Percentage of house area under tree shade	18.97	19.90	0.00	78.00
Late a.m. (9–11 a.m.) percent house area under tree shade	23.29	25.43	0.00	100.00
Early p.m. (12–2 p.m.) percent house area under tree shade	12.09	15.78	0.00	70.00
Late p.m. (3–5 p.m.) percent house area under tree shade	29.76	29.62	0.00	100.00

Shade conditions on a property have a significant effect on energy consumption throughout the year, with strong seasonal and density components. During the 3 hottest summer months (July, August, and September), the mean shade coverage in our sample was 19.3%. As compared to a house with no shade, electricity use at an otherwise similar residence characterized by mean shade conditions was an estimated 3.8% lower.[4] Every 10% of shade coverage on average reduces electricity consumption by 1.29 kW h/day (2% of the sample mean). However, not all shade is created equal; dense shade provides significantly more cooling in the summer than does moderate or light shade. At a 'typical' house with mean shade coverage of 19.3% during the summer months, dense shade reduces daily electricity consumption by an estimated 9.3%.[5] Electricity consumption at a house characterized by dense shade covering an average of 50% of the structure throughout the day is more than 14% lower than an otherwise identical house situated in full sun. Although Donovan and Butry (2009) report that shade cast on the west and south sides of a residence reduces summertime electricity usage, presumably because it falls on the structures during the hottest times of the day, we find no evidence of significant time-of-day effects.

In winter, the additional darkness in conjunction with the added shade increases residential energy used for two reasons: (1) natural warming from the sun is reduced, and (2) there is increased need for lighting inside the structure. Nonetheless, in Auburn, Alabama average daily electricity consumption was lower in winter (53.82 kW h) than in summer (66.04 kW h), because winter is relatively mild whereas summer is relatively hot, as compared to locations further north.

A one percentage point increase in average shade falling on a residential structure during the winter months is associated with an increase in electricity consumption of 0.1739 kW h/day. Average daily electricity usage at a house characterized by the mean shade coverage of 18.97% in the winter is an estimated 6.3% higher per month than a house with no shade. Again, we find evidence that density of tree shade matters; not surprisingly, heavy shade is associated with higher electricity usage, presumably because it more effectively prevents even minimal solar warming during the daytime. Finally, we observe in model 4 that the timing of shade also is important — specifically, we find that shade in the morning, when winter temperatures are coldest, is associated with significantly higher electricity usage. Presumably, this reflects the substitution of man-produced heat for the naturally-produced heat that would warm a structure in the absence of shade (Table 4).

5. Discussion/Conclusions

In terms of reliance on real-world data drawn from sizable samples of residential homes, our empirical methodology most closely resembles the analyses conducted by Rudie and Dewers (1984), Donovan and Butry (2009), and Pandit and Laband (forthcoming). Our findings with respect to the impact of tree shade on summertime energy use at least partially reinforce findings from these studies. For example, our finding that increasing the overall amount of tree shade reduces energy used for cooling is consistent with all 3 studies. However, unlike Donovan and Butry, we (surprisingly) fail to observe that late afternoon shade, typically cast from trees on the west and south sides of a property in the summertime, reduces energy consumption more than morning or early afternoon shade. On the other hand, we do find that morning shade in the winter is associated

[4] From Model 1, each percent of tree shade reduced daily electricity consumption by an estimated 0.1294 kW h. So a residence with the mean tree shade coverage of 19.3% used an estimated $19.3\times0.1294=2.5$ kW h *less* electricity per day than a residence with no tree shade. Compared to the average summertime consumption (66.04 kW h/day), this is a 3.8% reduction.

[5] From Model 3, each percent of tree shade reduced daily electricity consumption by an estimated 0.1034 kW h. In addition, there is a fixed effect of dense shade of an estimated 4.1399 kW h/day reduction in electricity use. So a residence with 19.3% dense tree shade used an estimated $19.3\times0.1034=2.0+4.1399=6.1399$ kW h *less* electricity per day than a residence with no tree shade. Compared to the average summertime consumption (66.04 kW h/day), this is a 9.3% reduction.

Table 2
Estimated regression coefficients (standard errors) for the impact of shade on daily electricity usage (kW h) — summer, mean kW h/day = 66.04.

	Model 1	Model 2	Model 3	Model 4
Intercept	23.0714*** (4.8150)	24.2395*** (4.9057)	24.7167*** (4.8683)	23.0554*** (4.8303)
Base daily kW h used	0.8874*** (0.0513)	0.9010*** (0.0514)	0.8896*** (0.0513)	0.8900*** (0.0513)
Temperature difference (cooling intensity)	2.7055*** (0.1722)	2.5292*** (0.1722)	2.6040*** (0.1753)	2.6936*** (0.1929)
Swimming pool	7.7045** (3.9486)	7.8895** (3.9845)	7.5810** (3.9482)	7.8077** (3.9597)
Percent shade mean = 19.30	−0.1294*** (0.0385)		−0.1034** (0.0447)	
Light density shade		− 4.3530*** (1.5816)	−3.1137* (1.6621)	
Moderate density shade		−3.3514** (1.6146)	−1.1885 (1.8568)	
Heavy density shade		−6.2448*** (1.7288)	−4.1399** (1.9482)	
Late morning shade % mean = 22.88				− 0.0360 (0.0315)
Early afternoon shade % mean = 11.84				−0.0489 (0.0459)
Late afternoon shade % mean = 32.04				−0.0322 (0.0259)
−2 log-likelihood	7114.6	7098.0	7097.0	7126.8
Degrees of freedom				
Intercept	158	158	158	158
Explanatory variables	742	740	739	740

*** (**)[*] Coefficient estimate statistically significant at 0.01 (0.05) [0.10] levels.

Table 3
Estimated regression coefficients (standard errors) for the impact of shade on daily electricity usage (kW h) — winter, mean kW h/day = 53.82.

	Model 1	Model 2	Model 3	Model 4
Intercept	30.0298*** (3.8833)	27.7446*** (4.0968)	29.2172*** (4.1040)	31.0833*** (3.9248)
Base daily kW h used	1.0030*** (0.0648)	0.9998*** (0.0652)	1.0069*** (0.0649)	0.9986*** (0.0649)
Temperature difference (heating intensity)	1.6875*** (0.1020)	1.6875*** (0.1028)	1.7035*** (0.1024)	1.6964*** (0.1019)
Percent shade mean = 18.97	0.1739*** (0.0433)		0.1541*** (0.0483)	
Light density shade		0.3536 (2.3919)	−1.9818 (2.4907)	
Moderate density shade		3.3883 (2.6531)	−0.3792 (2.8928)	
Heavy density shade		12.6936*** (4.4073)	7.2552 (4.7051)	
Late morning shade % mean = 23.29				0.1086*** (0.0440)
Early afternoon shade % mean = 12.09				0.0255 (0.0636)
Late afternoon shade % mean = 29.76				0.0510 (0.0376)
−2 log-likelihood	7494.9	7483.7	7477.8	7498.6
Degrees of freedom				
Intercept	156	156	156	156
Explanatory variables	744	742	741	742

***coefficient estimate statistically significant at 0.01 level.

with higher average daily electricity consumption, which clearly indicates that the timing of tree shade matters under certain conditions. In both this analysis as well as Pandit and Laband (2010) we make a new contribution to this literature by demonstrating that not all shade is created equal — specifically, in addition to the extent of shade coverage, it is dense shade, rather than light or moderate shade, that yields a statistically significant reduction in summertime residential energy consumption, as compared to no shade. This finding has implications for the tree species that homeowners plant in hopes of realizing energy savings in the future — such savings will be maximized by tree species with dense leaf canopies during the hot summer months. The current analysis is considerably more extensive than Pandit and Laband (2010), as the latter focuses only on the impact of tree shade on summertime electricity consumption whereas the current analysis encompasses winter months.

Table 4
Estimated percentage reduction (increase) in average daily electricity consumption due to tree shade in summer (winter).

	Summer		Winter	
	% change	kW h/day	% change	kW h/day
Mean tree shade %	−3.78	−2.50	6.13	3.30
50% tree shade	−9.80	−6.47	16.15	8.69
Mean tree shade — dense	−9.29	−6.14		
50% tree shade — dense	−14.10	−9.31		
Mean morning shade%			4.70	2.53
50% morning shade%			10.09	5.43

The native tree species that are most common in our study area are sweetgum (*Liquidambar styraciflua*), loblolly and slash pine (*Pinus teada*, *Pinus elliottii*), tulip poplar (*Liriodendron tulipifera*), water oak (*Quercus nigra*), black oak (*Quercus velutina*), pin oak (*Quercus palustris*), dogwood (*Cornus florida*), red maple (*Acer rubrum*), Eastern Red Cedar (*Juniperus virginianus*), and southern shagbark hickory (*Carya carolinae septentrionalis*). Most of these species lose their leaves during the winter months, thus homeowners enjoy the benefits of reduced cooling costs due to relatively dense shade during the summer while suffering only a small offset from higher heating costs due to winter shade, which tends to be light, not dense.

A potentially important caveat regarding our findings was suggested by an anonymous reviewer: “A potential endogeneity problem is that more environmentally aware households may have a preference for 1) trees and 2) minimizing energy consumption.” If true, this would mitigate the conclusion that tree shade directly reduces energy used for cooling (Akbari et al., 2001). We are not able to explore this issue with our current data.

Human behavior is influenced strongly by personal incentives. In the absence of specific information about the personally-relevant economic benefits from tree shade, homeowners have little direct incentive to plant trees and/or leave trees near their homes. By extension, home builders have correspondingly little financial incentive to design and build homes that leave mature trees intact. Unless and until these directly-affected parties can be ‘shown the money’ they will continue to make completely rational and predictable decisions that, for the most part, ignore the energy conservation benefits from shade trees.

But sizable amounts of money are at stake. At the current Alabama Power Company charge per kilowatt hour, we estimate that having dense shade at the sample mean (an average during the day of 19.30% of the residential structure) would save a home owner $21.22/month (9.3%) in electricity costs during the summer months, as compared to a home owner with no shade falling on the residence. Why, then, don't more home owners take advantage of the benefits provided by shade trees? We suspect that, in part, homeowners simply have not been made aware of the potential benefits. Then again, even in the relatively hot Southeastern U.S., these benefits will only accrue for perhaps 5 months each year, so aggregate annual savings may only be in the neighborhood of $106. Of course, the expected benefits rise as the amount of shade increases. A homeowner at the sample means of the other variables in our model whose property receives dense shade covering, on average, 50% of the residence during the day would save an estimated $32.2/month (14.4%) during the summer. But even this sum may not be sufficient to motivate owners of private residences to strategically manage trees on their lots, especially if they perceive there to be sizable costs associated with having those trees (including the foregone benefits from alternative landscaping). We did not question our survey respondents about their motivations for having trees in their yards or their perceptions of costs and benefits. But such work in the future surely would improve our understanding of what might be perceived as a persistent market failure.

Going even further, Akbari et al. (2001) and Akbari (2002) argue convincingly that urban trees provide social benefits by lowering ambient air temperatures in cities (thus reducing the amount of energy needed to cool buildings artificially) and sequestering carbon and other airborne pollutants. Because homeowners with trees cannot capture any part of the value of these positive externalities, there is a strong incentive to free-ride on the tree-growing proclivities of others (Mueller, 2003). The combination of demonstrable social benefits and free-rider behavior provides some rationale in favor of public regulation of tree-cutting on private property, and public subsidies for tree planting and maintenance, in urban areas. But more to the point, Akbari's findings underscore the importance of encouraging private homeowners in urban areas to plant and retain shade-producing trees on their lots.

Acknowledgments

This research was supported by grant #07-DG-11420004-027 provided by the National Urban and Community Forestry Advisory Council (NUCFAC). We appreciate the helpful comments received from 3 reviewers. The usual caveat applies.

References

Akbari, H., 2002. Shade trees reduce building energy use and CO_2 emissions from power plants. Environmental Pollution 116 (supp. 1), S119–S126.
Akbari, H., S. Davis, J. Huang, S. Dorsano, and S. Winnett. 1992. Cooling our communities: A guidebook on tree planting and light-colored surfacing. Washington D.C.: US Environmental Protection Agency, Office of Policy Analysis, Climate Change Division.
Akbari, Hashem, Kurn, Dan M., Bretz, Sarah E., Hanford, James W., 1997. Peak power and cooling energy savings of shade trees. Energy and Buildings 25 (2), 139–148.
Akbari, H., Pomerantz, M., Taha, H., 2001. Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. Solar Energy 70 (3), 295–310.
Carver, Andrew D., Unger, Daniel R., Parks, Courtney L., 2004. Modeling energy savings from urban shade trees: an assessment of the CITYgreen® Energy Conservation Module. Environmental Management 34 (5), 650–655.
Clark, Kim E., Berry, David, 1995. House characteristics and the effectiveness of energy conservation measures. Journal of the American Planning Association 61 (3), 386.
Donovan, G.H., Butry, D.T., 2009. The value of shade: estimating the effect of urban trees on summertime electricity use. Energy and Buildings 41, 662–668.
Huang, Y.J., Akbari, H., Taha, H., Rosenfeld, A.H., 1987. The potential of vegetation in reducing summer cooling loads in residential buildings. Journal of Applied Meteorology 26 (9), 1103–1116.
Jensen, R.R., Boulton, J.R., Harper, B.T., 2003. The relationship between urban leaf area and household energy usage in Terre Haute, Indiana, U.S. Journal of Arboriculture 29 (4), 226–230.
Laband, David N., Sophocleus, John P., 2009. An experimental analysis of the impact of tree shade on electricity consumption. Arboriculture and Urban Forestry 35 (4), 197–202.
Laverne, R.J., Lewis, G.M.D., 1996. The effect of vegetation on residential energy use in Ann Arbor, Michigan. Journal of Arboriculture 22, 234–243.
McPherson, E.G., Nowak, D., Heisler, G., Grimmond, S., Souch, C., Grant, R., Rowntree, R., 1997. Quantifying urban forest structure, function, and value: the Chicago Urban Forest Climate Project. Urban Ecosystems 1, 49.
Mueller, D.C., 2003. Public Choice III. Cambridge University Press, Cambridge.
Pandit, R., Laband, D.N., 2010. A hedonic analysis of the impact of tree shade on summertime residential energy consumption. Arboriculture and Urban Forestry 36 (3), 73–79.
Rudie, R.J., Dewers, R.S., 1984. Effects of tree shade on home cooling requirements. Journal of Arboriculture 10 (12), 320–322.
Simpson, J.R., McPherson, E.G., 1996. Potential of tree shade for reducing residential energy use in California. Journal of Arboriculture 22, 10–18.