



# Empirically Modeling the Energy Implications of Cool Roof Retrofits

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The energy effects of roofs have primarily been studied using theoretical models. However, empirical methods are needed for validation or when not all drivers of energy change can be observed. This study used mixed empirical techniques to estimate the impact of whitening existing roofs. Two years of hourly site cooling energy use were collected for 114 homes in Austin, TX. Seven properties selected to have their roofs coated white at no charge, imitating incentive policies. The empirical results are mixed, primarily limited by the small treated sample size. Individual household comparisons generally demonstrate statistically significant impacts of whitening, ranging from 14% to 49.2% reductions in daytime site cooling energy use and a 9.7% increase to a 40.3% decrease in nighttime site cooling energy use. Ordinary least squares regression estimates statistically significant mean daytime reductions of 9.7% but no significant nighttime effects. However, clustering the standard errors by household substantially reduces the significance level. Tweedie regression, which better accommodates slightly inflated zeros in the sample, demonstrates significant daytime and nighttime reductions of 14.3% and 5.5%, respectively. A life-cycle costs analysis using a mix of primary and secondary data explored the secondary benefit of delaying roof replacement resulting from the added protection of the coating material. Absent this delay, whitening would pay for itself in only 41% of simulations with a median net cost of \$310 and simple payback of 22 years. Including a benefit to delay roof replacement, the median payback period is 1 year and the median net benefit is \$310 across a range of assumptions. However, the benefits of whitening are only robust for older roofs and longer service lives for the coating. For roofs older than 10 years of age, most simulations reflect net benefits if the coating lasts at least 5 years.

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## INTRODUCTION

Almost 90% of United States homes now use space cooling (Doe (U.S. Department of Energy), 2017b). Thus, cost-effective strategies to reduce energy consumed for cooling are critical to improving the performance of the U.S. energy system.

In warm climates, a significant passive heat load may enter the building through the roof (Nahar et al., 2003). Passive design strategies can mitigate excess heat loads using either natural ventilation, thermal insulation, orientation, evaporation, or solar reflectance (Hernández-Pérez et al., 2014). All else equal, white roofs will reflect more sunlight than dark roofs, reducing a building's heat gain.

In addition to albedo, a roof's thermal emittance, or its propensity to emit thermal radiation, can also impact thermal performance. Highly emissive roofing materials, such as most asphalt shingles, will radiate more stored heat away from the building than lower emissivity materials, such as bare metal roofs. However, most research indicates that roof albedo dominates a roof's effect on building cooling (Akbari and Konopacki, 1998; de Brito Filho et al., 2011; Al-Obaidi et al., 2014; Brito Filho and Santos, 2014). In cooler climates, however, less emissive materials can beneficially store and indirectly transfer heat into buildings during the heating season.

The thermal effects of building albedo change are relatively well understood. Hernández-Pérez et al. (2014) review several decades of building albedo research, identifying 42 studies applying theoretical models of building albedo, 18 field trials, 10 studies of albedo change on existing buildings, and 8 studies using calibrated theoretical models. Collectively, these studies produce a high pedigree of confidence that higher albedo building surfaces reduce building cooling site energy use, with the magnitude of any given reduction being influenced by the degree of albedo change, building-level characteristics, and climate.

Studies also indicate that site heating energy use increases with increasing albedo, typically referred to as the "heating penalty." However, studies find few contexts in which the heating penalty outweighs the environmental or monetary benefits of cool roofs (Akbari and Konopacki, 1998; Hosseini and Akbari, 2014). For example, Synnefa et al. (2007) use theoretical building energy demand models to explore global variation in site cooling energy use in homes retrofitted with a cool roof coating. For a solar reflectance change to 0.85 from 0.20, they estimate reductions in end use consumption for cooling exceeding any increases in heating site energy use for 26 of 27 global cities, with the heating penalty in Mexico City being slightly larger than the reduction in site cooling energy use. If losses in electric power generation and transmission were included, the results would likely show primary energy savings for all locations.

Growing awareness of cool roof performance has prompted research estimating outcomes from widespread cool roof adoption and respective implications for policy. Levinson and Akbari (2010) estimate that retrofitting 80% of U.S. commercial buildings with a white roof would reduce cooling site energy use by 37 PJ per year and provide HVAC energy cost savings of \$735 million per year. State estimates of site cooling energy reductions vary from 12 to 28 MJ per year per m<sup>2</sup> of roof (mean of 18), and site heating energy penalties range from 0.32 to 15 MJ per year per m<sup>2</sup> of roof (mean of 6.9). Coupling their results with state energy prices and regional power grid emissions, Levinson and Akbari (2010) estimate net monetary savings and reductions in CO<sub>2</sub>, NO<sub>x</sub>, SO<sub>2</sub>, and Hg for all U.S. states, even when including a heating penalty.

Sproul et al. (2014) perform a similar techno-economic assessment of traditional black, white, and green roof alternatives using literature estimates and data from 22 roof projects in diverse U.S. cities. Including installation and maintenance costs, electricity grid emissions, equipment downsizing for stormwater

and cooling, and avoided storm water fees, they estimate that white roofs outperform black roofs for all 22 projects and outperform green roofs in 21 projects, with a representative white roofs lifetime savings of \$96 per m<sup>2</sup> and \$26 per m<sup>2</sup> relative to green and black roofs, respectively.

By reducing the thermal extremes to which roofs are exposed, white roof coatings may also increase the useful roof service life over and above darker materials, and such benefits are often cited by policy makers (Doe (U.S. Department of Energy), 2017a). Industry estimates suggest that coatings can increase the service life of conventional commercial roofs by 5–15 years for a diverse type of roof materials (APOC, 2017). However, I identified no empirical information describing the observed increase in roof service life from coatings.

Policy makers have responded to the opportunities of cool roofs by encouraging adoption using a mix of financial incentives, standards, and labeling schemes. The Cool Roof Rating Council (2017) indicates that 17 municipalities (across 13 states), 7 states, and the U.S. Internal Revenue Service offer rebates for cool roofs. The U.S. Energy Star program promulgated its first consumer label for cool roof products in 1999, which has since been revised twice (Energy Star, 2017). Researchers have previously recommended changes to California's building energy code on the basis of theoretical energy reductions from cool roofs (Levinson et al., 2005; Rosado and Levinson, 2019).

Measuring the performance of cool roofs adopted in response to current policies requires methods different from those theoretical techniques profiled above. Theoretical models and field trials can treat influential parameters (e.g., envelope insulation) parametrically when estimating performance. However, such influential variables are unobserved in the context of current policies aiming to influence consumer choices. Policy makers simply offer an incentive or provide a label but do not get to prescribe the occupancy or building characteristics associated with affected retrofits. As a result, methods that accommodate unobserved participant heterogeneity or selection bias are needed to estimate roof performance in the context of current adoption policies. For example, occupant behavior, which is not integrated into current theoretical models, has been shown to significantly affect roof performance (Pisello et al., 2015).

The difference-in-differences (DiD) method is a quasi-experimental technique that utilizes longitudinal data to "difference out" group effects that could otherwise influence measured outcomes. Equation 1 presents the basic DiD model.

$$Y_{i,t} = \beta_0 + \beta_1 treat_i + \beta_2 post_t + D(treat_i \times post_t) + \varepsilon_{i,t} \quad (1)$$

where  $Y_{i,t}$  = outcome for unit  $i$  at time  $t$

$treat_i$  = group indicator distinguishing for treated units (0 = control; 1 = treated)

$post_t$  = indicator for the treatment period (0 = prior to treatment; 1 = post treatment)

$\beta_0, \beta_1, \beta_2$  = estimated model coefficients

$D$  = difference-in-differences estimate or the effect of the treatment

$\varepsilon_{i,t}$  = error term.

Consider comparing expected values ( $E[Y]$ ) for two groups (a treated and a control) with one common treatment period (treat = 0 before treatment and treat = 1 after treatment).

$$\begin{aligned} E[Y_{treat=1,post=0}] &= \beta_0 + \beta_1 = \text{before treatment, treated group} \\ E[Y_{treat=1,post=1}] &= \beta_0 + \beta_1 + \beta_2 + D = \text{after treatment, treated group} \\ E[Y_{treat=1,post=0}] - E[Y_{treat=1,post=1}] &= \beta_2 + D = \text{average effect of treatment on treated group.} \end{aligned}$$

By modeling differences in the outcome,  $Y$ , within a treated group over time, the group-level term,  $\beta_1$ , has been “differenced out.” Controlling for group effects is important if the treatment group demonstrates tendencies that influence  $Y$  that are otherwise unrelated to the treatment. For example, homeowners choosing a white roof might also have higher site cooling energy use as a result of poor insulation. Without a group effect that controls for this, the effect of attic insulation could be improperly attributed to whitening. This first difference,  $D + \beta_2$ , represents the average effect of the treatment comparing the treated group before and after treatment, which includes both the outcome of interest,  $D$ , and a time effect,  $\beta_2$ . The parameter  $\beta_2$  represents any impacts to energy use that occurred in the treatment period unrelated to the treatment itself. By modeling a second “difference” across control and treatment groups, one can find this time effect as follows.

$$\begin{aligned} E[Y_{treat=0,post=0}] &= \beta_0 = \text{outcome before treatment, control group} \\ E[Y_{treat=0,post=1}] &= \beta_0 + \beta_2 = \text{outcome after treatment, control group} \\ E[Y_{treat=0,post=0}] - E[Y_{treat=0,post=1}] &= \beta_2 = \text{fixed effect for treatment period.} \end{aligned}$$

The second difference,  $E[Y_{treat=0,post=0}] - E[Y_{treat=0,post=1}]$  or  $\beta_2$  is the average difference for the control group before and after the treatment period. This difference should represent any time effects unrelated to the treatment. A final “difference-in-differences” produces the estimate of interest,  $D$ .

$$\begin{aligned} \beta_2 + D - \beta_2 = D &= \underbrace{E[Y_{treat=1,post=0}] - E[Y_{treat=1,post=1}]}_{\text{Average difference in treated group before and after treatment}} \\ &\quad - \underbrace{E[Y_{treat=0,post=0}] - E[Y_{treat=0,post=1}]}_{\text{Average difference for control group before and after treatment period}} \end{aligned}$$

This second difference removes any confounding time effects,  $\beta_2$ , assuming such affects are similar for the treated and control units. This assumption is known as the “parallel trend” assumption for DiD models. DiD methods have been applied to other energy efficiency retrofits (Adan and Fuerst, 2016; Datta and Filippini, 2016; Adland et al., 2018).

Similar to existing cool roof monetary incentives encouraging adoption, residents in Austin, TX were invited to participate in an experiment in which their roofs would be coated white at no charge. Space cooling branch circuits were separately monitored on an hourly basis for both the treated homes (those choosing to whiten their roof) and a control sample. Varied empirical methods, including individual within-household comparisons and regression, were used to estimate whitening’s impact.

A life-cycle costs analysis was also conducted to gauge the secondary benefit of delaying roof replacement as a result of the added protection afforded the roof membrane by the coating materials. In addition to the benefit from delaying replacement, the life-cycle cost analysis included the costs of roof whitening (materials and labor), a heating penalty, and site cooling energy reductions estimated from the DiD model. The methods profiled herein can be generally applied to measure the performance of roof retrofits where unobserved effects influence selection or energy consumption.

## MATERIALS AND METHODS

### Sample Preparation

Approximately 120 households across 25 ZIP codes in Austin, TX, United States were invited to participate in an experiment in which their roofs would be coated white at no charge and the effect on space cooling would be estimated. A total of seven homes were recruited.

Roofs on the treated homes (also referred to as the “coated” or “whitened” homes) were all conventional asphalt shingles that were either light gray, dark gray, or brown in color. Six of the treated homes were one story and one was three stories. The distribution of roofs slopes (rise to run) for the treated homes is 4 over 12 ( $n = 4$ ), 3.5 over 12 ( $n = 1$ ), 2.5 over 12 ( $n = 1$ ), and a mixed slope ( $n = 1$ ).

Two homes were coated in fall 2015, and the remaining five were coated in the summer and fall of 2016. Photographs of the coating used, Behr’s Multi-Surface Roof Paint (color White Reflective No. 65), are included in the **Supplementary Information**. Each home received two coats, the second within a week of the initial coat. The roof coating schedule is provided in the **Supplementary Information**. In preparing the sample for analyses, homes were indicated as coated on the date of the initial coat. Recruitment, project scheduling, and white roof coating (BEHR, 2020) were managed by the White Roof Research Project. Photographs of two coated homes are included in the **Supplementary Information**.

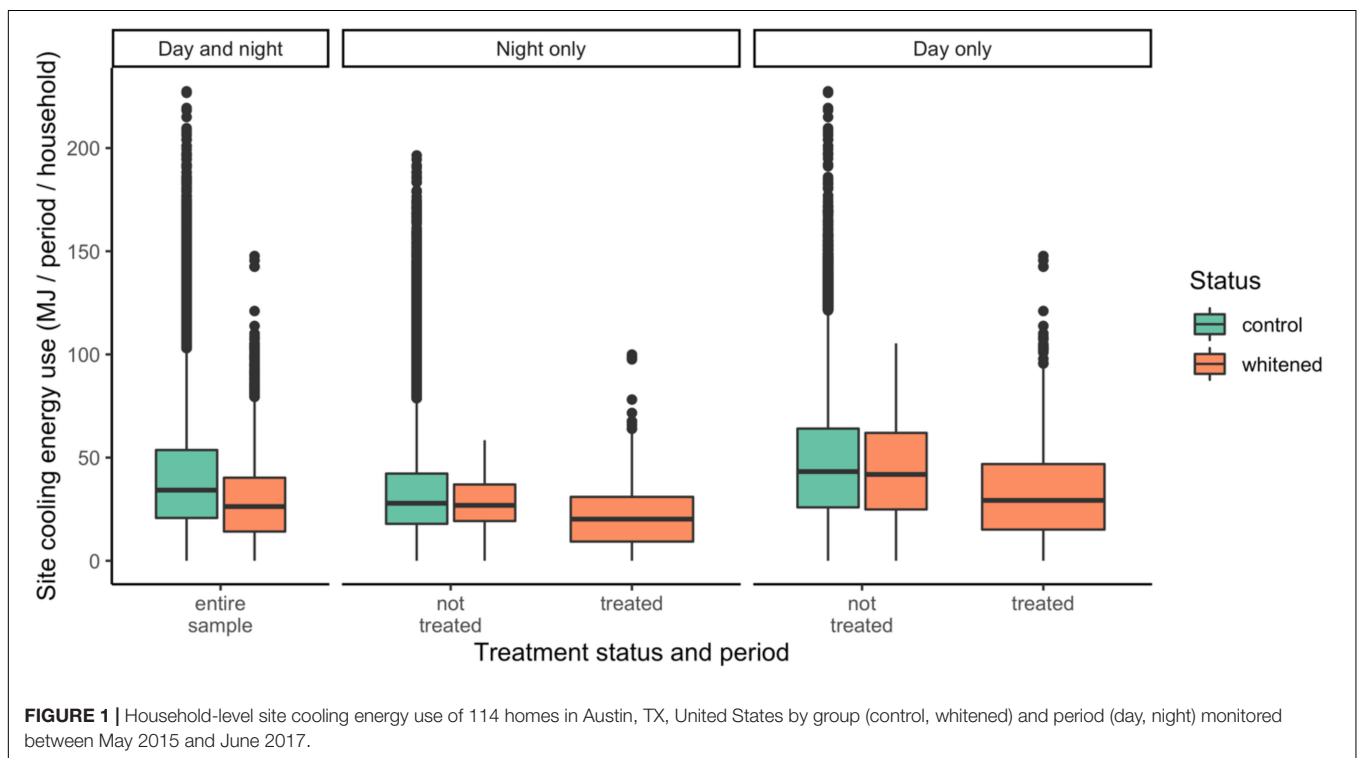
The Pecan Street Research Institute (2017) provided household characteristics data (floor space and number of floors) and metered hourly site cooling electricity use from May 2015 and October 2017. All data management, visualizations, and modeling were completed using the R language and compatible packages (Wickham, 2016; R Core Team, 2020; Wickham et al., 2020).

In an effort to reduce inflated zeros and remove observations of electricity used by heat pumps for heating, heating days were

**TABLE 1** | Household-level summary statistics (mean and standard deviation) of site cooling energy use and cooling degree hours per period for 114 homes in Austin, TX, United States monitored between May 2015 and June 2017.

Group	Status	Period	Observations (household * period)	Site cooling energy use per period (MJ per home)		Cooling degree hours per period	
All	–	Day and night	71,522	39.6	(26.5)	59.1	(53.2)
Control	Untreated	Day	34,288	47.3	(28.7)	101.6	(42.5)
Control	Untreated	Night	34,288	32.6	(22)	16.5	(14.8)
Treated	Before treatment	Day and night	826	36.1	(21.8)	65.0	(56.1)
Treated	Treated	Day	1060	33.6	(24.5)	101.6	(43.4)
Treated	Treated	Night	1060	22.1	(14.9)	17.1	(15.3)

The data reflect only the cooling season as described in the narrative. A “period” refers to either a full day, daytime, or nighttime as indicated by the row. Cooling degree hours were estimated as the sum over the hourly differences between the outdoor temperature and the median cooling setpoint of 25.6°C (78°F).



**FIGURE 1** | Household-level site cooling energy use of 114 homes in Austin, TX, United States by group (control, whitened) and period (day, night) monitored between May 2015 and June 2017.

estimated and removed by comparing thermostat set points to historical temperature records. Inflated zeros can cause the distribution of observations to deviate from normality, making it harder to fit data to related statistical models. Pecan Street publishes thermostat set point data for a broader sample of homes ( $n = 341$ ) than those for which cooling is monitored. The median heating (21.1°C or 70°F) and cooling (25.6°C or 78°F) thermostat set points were used as the basis for defining heating and cooling days. Only days where the mean outdoor temperature is above the median thermostat set point for heating were included in the analysis. These criteria identified 126, 128, and 123 cooling days in years 2015, 2016, and 2017, respectively, between May 2015 and October 2017. The distribution of the resulting air conditioning data still has a small amount of inflated point mass (0.3% of observations) at zero.

It was assumed that household occupants traveled during periods when at least two consecutive days during the cooling

season recorded no site cooling energy use, and these periods were dropped from the analysis.

The final sample, summarized in **Table 1**, consists of unbalanced observations of site cooling energy use for 114 homes (7 treated and 107 controls) by date, daytime, and nighttime, where daytime and nighttime periods were distinguished by local sunrise and sunset data (U.S. Navy, 2017). The Pecan Street data identifiers used in this analysis are included in the **Supplementary Information** for those interested in further studying this sample.

**Figure 1** shows distributions of site cooling energy use by treatment status, experimental group, and period (day or night). Visually, whitening appears to reduce site cooling energy use, which is most apparent during daytime. During the day, the distributions for each experimental group are nearly identical when untreated, whereas consumption for the treated group appears to decrease after whitening.

## Within-Household Comparisons

Site cooling energy use was compared before and after treatment for individual households using descriptive statistics and *t*-tests. Separate comparisons were made for day and night on the basis of sunrise and sunset.

## Model of Site Cooling Energy Use

Individual household comparisons may be misleading for two reasons. First, factors other than whitening—both technical and behavioral—can impact whitening’s performance. If these factors correlate with whitening, their effect on site cooling energy use could be improperly associated with whitening. Second, these same factors may influence whitening’s impact. An example of this is demonstrated by showing graphically the impact of observed attic insulation on whitening’s impact in the “Results” section.

Statistical approaches are needed to estimate whitening’s impact while controlling for other influences on site cooling energy use. Equation 2 presents a two-way fixed effects model of site cooling energy use.

$$ac_{i,t} = \beta_0 + \beta_{post} \times post_{i,t} + \beta_w \times w + \beta_h \times h + \varepsilon_{i,t} \quad (2)$$

where  $ac_{i,t}$  = site cooling energy use in units of MJ per period for household *i* at time *t*

$post_{i,t}$  = household *i* whitened at time *t* (0 = not whitened; 1 = whitened)

$w$  = day fixed effect

$h$  = household fixed effect.

Equation 2 is a more generalized version of the two-period DiD model presented in Eq. 1. Equation 1 includes only one, uniform treatment period and controls for household-level variation by group. In contrast, Eq. 2 controls for individual-level household and temporal variation with fixed effects or “dummy variables,” *h* and *w*. Equation 2 is more robust than Eq. 1 and also reduces potential confounding temporal effects characteristic of DiD methods (the parallel trend assumption).

Ordinary least squares (OLS) solutions to DiD models are often prone to serial correlation (Bertrand et al., 2004). Serial correlation would imply errors are correlated by household over time. Serial correlation biases the standard errors (and thus *p* values) for estimated coefficients. Standard errors are clustered by household to reduce serial correlation.

In an effort to better represent the observed frequency of zero site cooling energy use, Tweedie regression was applied in addition to OLS estimators. The Tweedie distribution better accommodates the slight observed probability mass spike at zero.

The performance of reflective roofs changes at night. Differences in roof temperatures between light and dark roofs have also been observed to sustain past sunset (Parker and Barkaszi, 1997). As such, separate daytime and nighttime models have been prepared, where periods are differentiated by sunset and sunrise (U.S. Navy, 2017).

The coefficient  $\beta_{post}$  in Eq. 2 represents the average effect of whitening for the treated homes compared to two control

groups: those untreated throughout the experiment and those not yet treated (Goodman-Bacon, 2018). The average effect is often of most interest to policy makers, where policies aimed at encouraging retrofits do not get to control for influential household-level variation and behavioral change may influence outcomes.

## Description of Life-Cycle Cost Analysis

The subset of homes ( $n = 89$ ) for which floor space and the number of floors are published (Pecan Street Research Institute, 2017) were used. The roof area for these homes was estimated as the floor space divided by the number of floors. The cost estimate sample consists of 89 homes with distributions of roof areas and air conditional site cooling energy use as described in **Table 2**.

Site cooling energy use reductions were estimated by applying Eq. 2 to these 89 homes. The regression results for  $\beta_{post}$  include the only mean effect of whitening, whereas whitening’s effect is expected to vary by household. It is assumed that the distribution of  $\beta_{post}$  estimated by regression is a reasonable proxy for household-level variation in whitening’s effect. To simulate this household-level variation, 100 random samples were drawn from the distribution of  $\beta_{post}$  for each household, producing 100 different records of daily energy reductions for each household. Importantly, the assumed  $\beta_{post}$  does not change within a simulated household record, as opposed to allowing  $\beta_{post}$  to vary across days. In other words, for any given simulation, the  $\beta_{post}$  assumed for a given household is constant. Daily simulations were then aggregated by household and month, and then a representative year for each household was constructed by randomly sampling months in the observation period to moderate across the different weather patterns experienced during the experiment. The net effect of sampling produced a synthetic record of monthly cooling consumption of 4450 household\*months.

In estimating the monetary savings from site cooling energy reductions, total electricity demand (Pecan Street Research Institute, 2017) was used in order to account for Austin’s tiered pricing schedule (Austin Energy, 2013). The remaining cost assumptions and references—including those used to estimate roof whitening costs, heating penalties, and delayed replacement benefits—are summarized in **Table 2**. Perhaps the most difficult of these assumptions is the expected heating penalty, modeled as a percent reduction. Previous works estimate ranges in heating penalties around 2% to 14% (Rosado and Levinson, 2019) and 10% to 30% (New et al., 2016). The latter estimated a cool roof heating penalty intensity of 1.8 MJ per m<sup>2</sup> of roof area. Applying this intensity to the 99 homes for which roof area is available would correspond to a 10% (first quartile) to 30% (third quartile) increase in site heating energy use, assuming baseline heating intensities are consistent with U.S. Department of Energy surveys (Doe (U.S. Department of Energy), 2012).

As summarized in Eq. 3 and **Table 3**, the life-cycle cost analysis includes a benefit for delaying roof replacement, electricity savings, the initial cost of whitening, and an annual heating penalty. Life-cycle costs are presented on a net present value basis using standard discounting. Social benefits, such as reduction in

**TABLE 2** | Assumptions used for the cost analysis.

Variable	Units	Assumed distribution	Empirical assumption
<b>Assumptions for uncertainty and variability modeling</b>			
Coating material (Clark, 2017, personal communication; homewyse.com, 2017)	\$ per m <sup>2</sup> of roof	Uniform	\$1.72/m <sup>2</sup> to \$2.26/m <sup>2</sup>
Labor cost (Clark, 2017, personal communication; homeadvisor.com, 2017; homewyse.com, 2017)	\$ per m <sup>2</sup> of roof	Normal	\$1.94/m <sup>2</sup> to \$4.52/m <sup>2</sup>
Roof space, floor space (Pecan Street Research Institute, 2017)	m <sup>2</sup>	Discrete	89 homes in the control sample with a mean (standard deviation) roof area of 130 m <sup>2</sup> (45) and floor space 190 m <sup>2</sup> (70)
Whitening cooling savings	MJ	Discrete, normal	Estimated from simulation using regression results (Eq. 2) in which values for regression model coefficients were randomly drawn assuming a normal distribution (see <b>Table 3</b> ). Simulations were aggregated by month, and then months were randomly sampled into a yearly record for each household.
Annual space heating site energy use per unit floor area	MJ per m <sup>2</sup>	Normal	The mean and standard deviation of 1.3 and 1.0 MJ per m <sup>2</sup> , respectively, were taken from a pooled sample of 784 of single family detached urban homes in Texas [ <i>n</i> = 541 from Doe (U.S. Department of Energy) (2012)] and Census Division West South Central [ <i>n</i> = 243 from Doe (U.S. Department of Energy) (2017b)]. These data were taken from microdata associated with Residential Energy Consumption Survey using fields TOTALBTUSPH and TOTHSQFT.
Heating penalty (Levinson et al., 2019; Rosado and Levinson, 2019)	% increase	Uniform	2%–5%. Estimated using theoretical models for homes of varied vintages (pre-1980, 1989, and 2012) and orientations (East–West and North–South) located in Houston, TX, United States assuming a modified albedo of 0.6. The lower (2%) and upper (5%) estimates aligns with two- and one-story homes, respectively.
Roof replacement (homeadvisor.com, 2017)	\$ per m <sup>2</sup>	Normal	Mean and standard deviation of \$34.40 and \$4.30 per m <sup>2</sup>
Roof service life	Years	Uniform	15–25 years
Coating service life (APOC, 2017)	Years	Uniform	10–15 years
<b>Assumptions for deterministic values</b>			
Price natural gas (Doe (U.S. Department of Energy), 2017c)	\$ per MJ	NA	\$0.0107
Cost of electricity (Austin Energy, 2013)	\$ per MJ	NA	Tiered charges of 0–1800 MJ \$0.0078 per MJ 1801–3600 MJ \$0.0016 per MJ 3601–5400 MJ \$0.022 per MJ 5401–9000 MJ \$0.026 per MJ >9000 MJ \$0.03 per MJ Fixed charges of \$0.0131/MJ in summer \$0.0129/MJ in non-summer
<b>Assumptions for switchover analysis</b>			
Roof age	Years	Discrete	{5, 10, 15, 20 years}
Years replacement delayed from whitening (APOC, 2017)	Years	Discrete	{1, 5, 10 years}
Discount rate. The 2019 10-year bond return was 7.2% (Damodaran, 2017)	–	Discrete	{3%, 5%, 7%}

Normally distributed variables were truncated at zero to avoid negative values.

**TABLE 3** | Summary of the cash flow discounting used in the life-cycle cost analysis.

Cash flow category	Discount factor, where <i>d</i> refers to the discount rate	Relevant cash flows	<i>n</i> (years)
Future values discounted to the present	$(1 + d)^{-n}$	Replacement cost without whitening	Roof service life minus roof age
		Replacement cost with whitening	Roof service life minus roof age minus years delayed
Future annuities discounted to present	$\left[ \frac{(1+d)^n - 1}{d(1+d)^n} \right]$	Electricity savings	Service life of coating
		Heating penalty	Service life of coating
Initial cost	–	Initial cost of whitening = $\frac{\text{Floor space}}{\text{Number of floors}} [\text{Unit price paint} + \text{Unit price labor}]$	–

greenhouse gases, are not included in this analysis.

$$NPV = \underbrace{\frac{\text{Replacement cost without whitening}}{\text{Benefit of delayed replacement}} - \frac{\text{Replacement cost with whitening}}{\text{Benefit of delayed replacement}}}_{\text{Benefit of delayed replacement}} + \frac{\text{Electricity Savings}}{\text{Savings}} - \frac{\text{Initial Cost of Whitening}}{\text{of Whitening}} - \frac{\text{Heating Penalty}}{\text{Penalty}}$$

## RESULTS

**Table 4** summarizes the household-level comparisons before and after treatment. **Table 4** indicates significant reductions at the 1% confidence level for all within-household comparisons except for daytime consumption for household 9654 and nighttime consumption for household 2158. Statistically significant percent reductions range from 14% to 49.2% during the day, and a 9.7% increase to a 40.3% decrease during nighttime.

Unobserved variation in multiple technical and behavioral factors is expected to drive the observed differences in whitening performance across households. As a demonstration, **Figure 2** shows variation in site cooling energy use by the amount of attic insulation before and after whitening. Theory suggests that whitening would have a lower impact with increasing attic insulation, which is demonstrated by the two linear trends approaching each other in **Figure 2**. At high *R* values in **Figure 3**, the 95% confidence intervals in the trend lines nearly approach each other, suggesting that whitening may not have detectable effects for *R* values beyond 35.

There are dozens of household and occupant factors expected to influence air conditioning consumption and the impact of white roofs. Since few, if any, of these factors can be measured in a realistic policy setting, regression is needed to estimate the mean effects, controlling for confounding variation where possible. **Table 5** summarizes the two-way fixed effects regression. Both day and night regresses suggest that whitening reduces

electricity consumption ( $\beta_{post} < 0$ ). While OLS estimates of  $\beta_{post}$  demonstrate statistical significance, clustering errors by household to moderate serial correlation increases the standard error of the coefficients to ranges normally not considered significant. The clustered errors should be contextualized given the small, unbalanced sample (MacKinnon and Webb, 2017). Using OLS estimators, the mean reductions in daytime and nighttime site cooling energy use are 7.6% and 1.8%, respectively. These reductions are considerably smaller than the household-level analysis presented in **Table 4** because Eq. 2 controls for other sources of variability that might either be improperly attributed to whitening or influence whitening’s impact, such as the example presented with insulation.

Relative to OLS estimates, using Tweedie estimators that better accommodate inflated zeros slightly worsens model fit for daytime periods (from a coefficient of determination or  $R^2$  of 0.76 to 0.69) but improves model fit for nighttime considerably (from an  $R^2$  of 0.51 to 0.68). This is likely because more homes have more inactive air conditioning periods at night. The Tweedie estimators also increase the impact of whitening from a mean reduction of 7.6% (OLS) to 14.3% (Tweedie) for daytime periods and 1.8% to 5.5% for nighttime site cooling energy use. Tweedie estimates decrease the *p* values for models of nighttime period from those well above thresholds considered significant ( $p = 0.38$  for OLS estimators) to a *p* value of 0.01 using Tweedie regression.

Site cooling energy reduction estimates were drawn equally from estimated coefficients ( $\beta_{post}$ ) using both the OLS and Tweedie estimators. Only daytime reductions were assumed, producing a conservatively low estimate of reductions in site cooling energy use.

**Figure 3** shows the results for each category of life-cycle costs, including decreased costs for cooling, increased heating costs (the heating penalty), the cost of roof whitening (labor and materials), and the savings from delaying replacement. See **Table 2** for assumptions used in the life-cycle cost analysis. Life-cycle results indicate that the savings from delaying replacement are on par with or greater than the other cash flows. Even for relatively

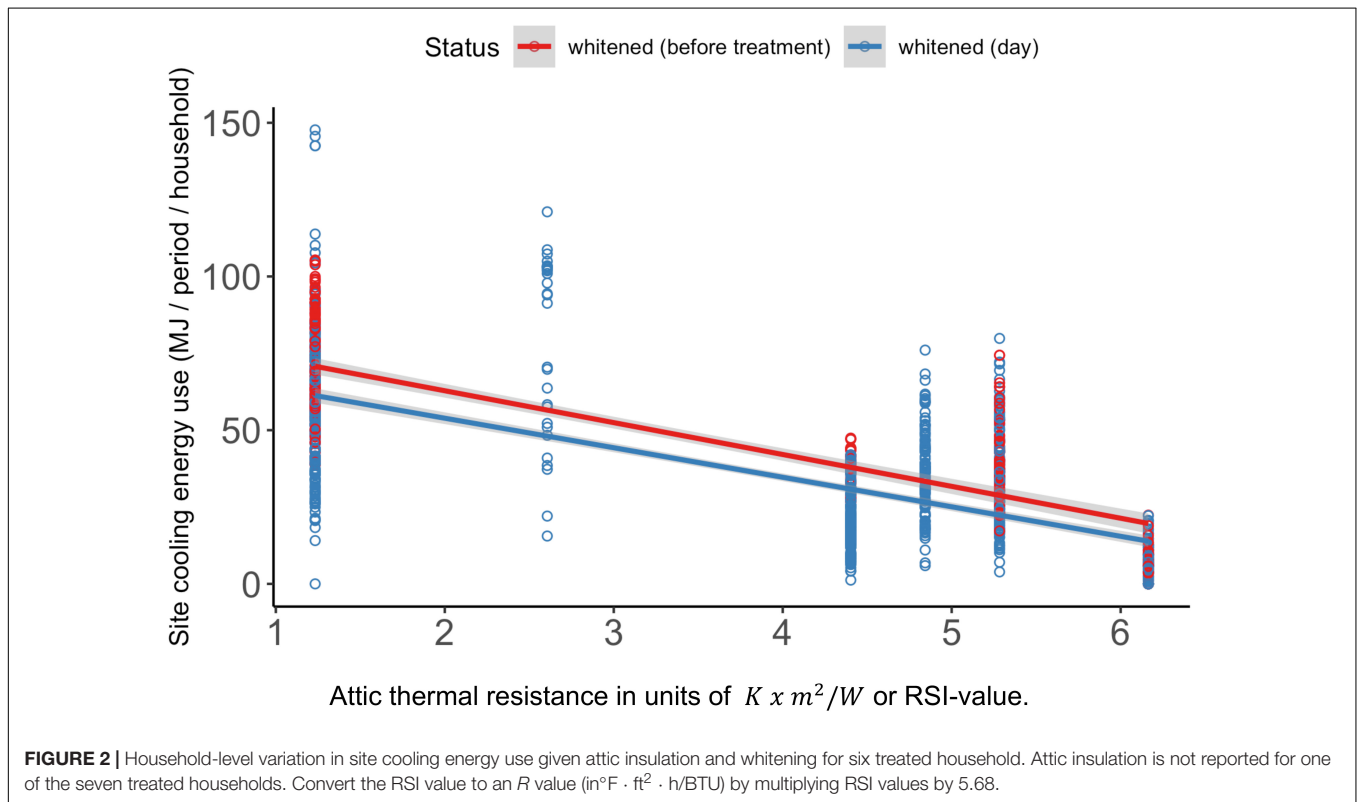
**TABLE 4** | Household-level comparisons for the treated sample.

Period	Household*	Mean (standard deviation) of site cooling energy use in MJ		Mean reduction (MJ)	Reduction	<i>p</i>
		Before whitening	After whitening			
Day	2158	252 (60.5)	212.4 (83.4)	39.6	15.7%	<0.01
Day	621	32.5 (15.3)	24.5 (17.5)	8.0	24.6%	<0.01
Day	8198	136.3 (22.3)	69.2 (30.1)	67.1	49.2%	<0.01
Day	930	147.2 (50.5)	126.5 (53.4)	20.7	14.0%	0.020
Day	9654	127.8 (64.5)	121 (60.9)	6.8	5.3%	0.38
Day	All	162.2 (90.2)	114.7 (87.2)	47.6	29.3%	<0.01
Night	2158	121 (33.3)	132.7 (57.5)	-11.7	-9.7%	0.018
Night	621	25.1 (8.5)	20.7 (9)	4.4	17.7%	<0.01
Night	8198	78.7 (14)	47 (23.6)	31.7	40.3%	<0.01
Night	930	108.1 (25.3)	92.6 (27.2)	15.5	14.3%	<0.01
Night	9654	100.8 (47.9)	79.6 (39.2)	21.2	21.0%	<0.01
Night	All	97.7 (45.5)	76.4 (54.8)	21.3	21.8%	<0.01

\*Only five treated homes are included because two homes were treated before electricity monitoring started.

**TABLE 5** | Regression results for applying Eq. 2 to the sample.

Estimator	Transformation of dependent variable	Period	$\beta_{post}$	No clustering		Clustered errors		$R^2$	Mean site cooling energy use (MJ)	Mean reduction
				Std error	$p$	Std error	$P$			
OLS	None	Daytime	-3.59	0.92	~0	3.48	0.30	0.76	47.0	7.6%
OLS	None	Nighttime	-0.58	0.66	0.38	1.84	0.75	0.51	32.2	1.8%
Tweedie	Log	Daytime	-0.15	0.002	~0	-	-	0.69	47.0	14.3%
Tweedie	Log	Nighttime	-0.057	0.021	0.01	-	-	0.68	32.2	5.5%



new roofs, the benefit from delaying replacement is, on average, more than half of the savings from reduced cooling. For older roofs, the benefit for delaying replacement is similar to that of the cooling savings. Uncertainty in the estimated cooling savings is high because the savings were estimated by drawing from two distributions estimated for the regression coefficient for  $\beta_{post}$ : one using basic OLS and Tweedie regression.

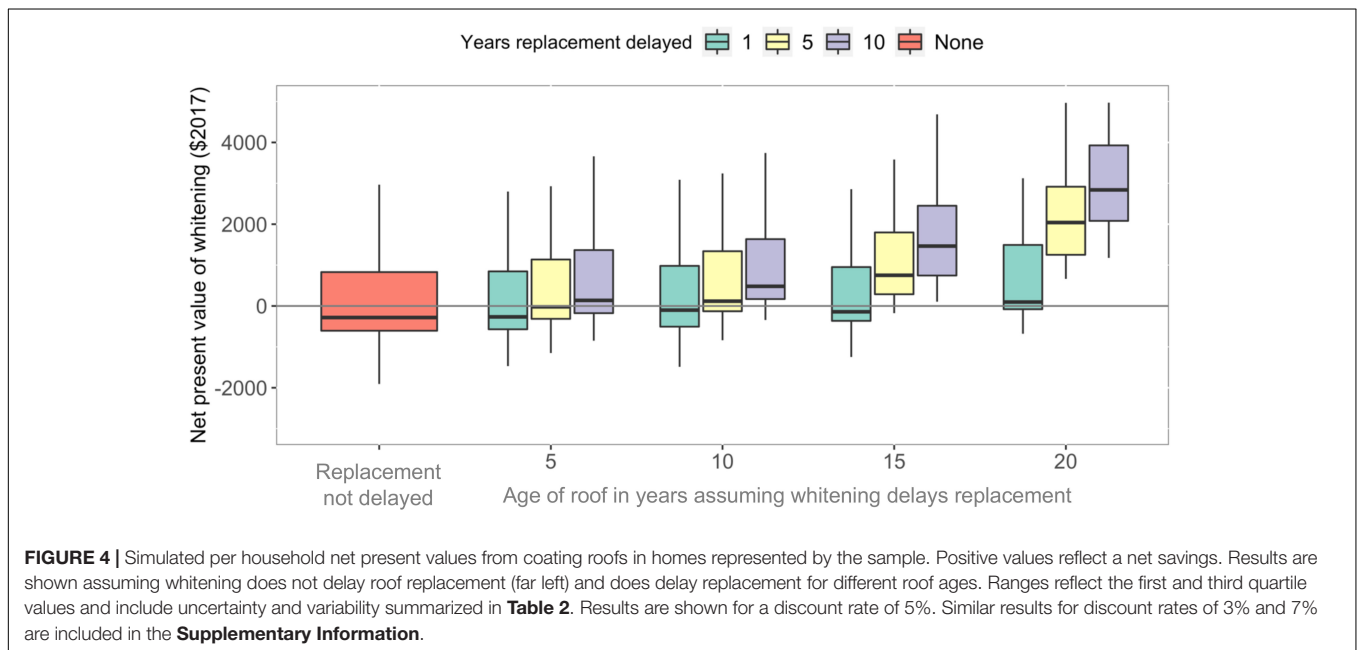
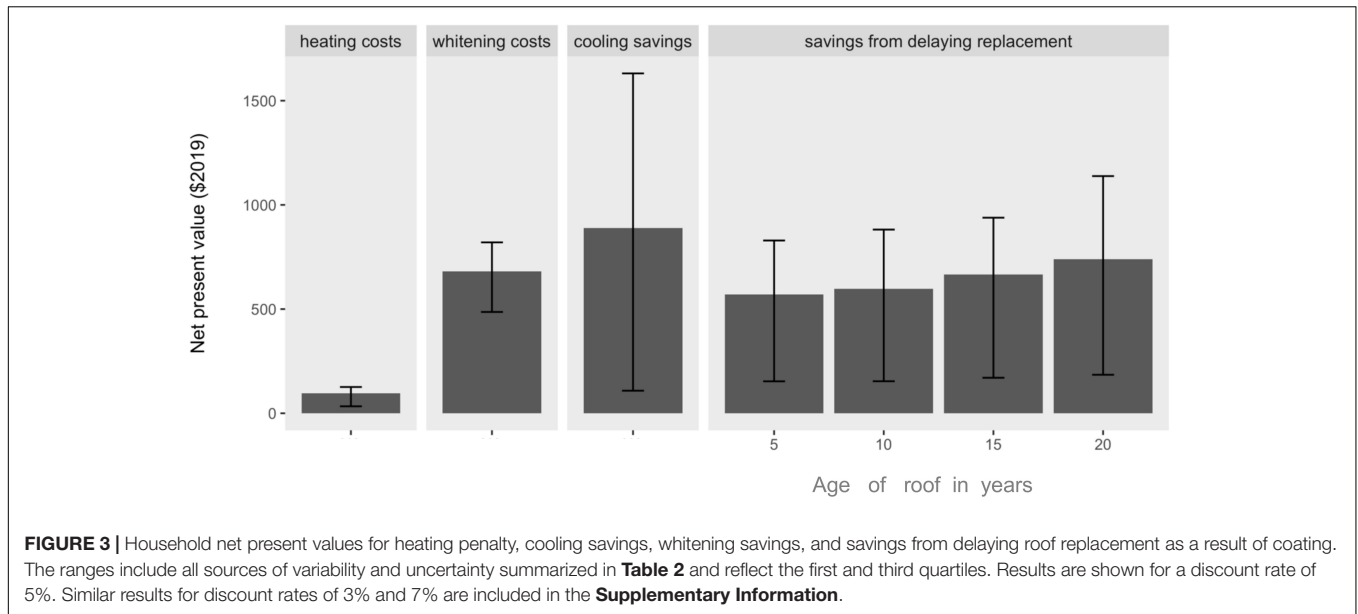
Figure 4 shows the overall net present value for different assumed roof ages and years of extended roof life (“years replacement delayed”). When adding costs and benefits, costs have been assigned a negative value and benefits have been assigned a positive value such that positive net present values represent a net savings. Absent increasing the service life, whitening would pay for itself in roughly 41% of simulations over the lifetime of the coating with a median cost of \$310 and a simple payback period of 22 years. However, including a benefit of delaying roof replacement significantly alters the benefit–cost implications. Across all simulations that assume some increased

service life, the median simple payback period and net benefit are 1 year and \$310, respectively. The positive benefits of whitening are only robust for older roofs and longer service lives from coating. For example, for roofs older than 10 years of age, most simulations reflect net savings if the coating lasts at least 5 years. This is despite the broad uncertainty in the empirically estimated impact of cooling.

## DISCUSSION

The potential energy benefits of cool roofs have spurred policies that encourage cool roof choices through incentives and labels. Properly measuring policy performance therefore must extend beyond theoretical models to accommodate unobserved occupant and household heterogeneity that also affects energy consumption. The empirically estimated average reduction in site cooling energy use from roof whitening—ranging from





7.8% to 14.3%—are on par with theoretical results profiled in the section “Introduction.” In particular, these results conform to a recent study that estimates cool roof savings for areas throughout the United States using applied theoretical models (Rosado and Levinson, 2019). Simulations for homes in Houston, TX, United States assuming varied vintages (pre-1980, 1989, and 2012) and orientations (East–West and North–South) estimate mean site cooling energy reductions for two-story homes of 4.7%, which would roughly correspond to 9.4% for a one-story home. While these consistencies between theory and empirical estimates are helpful, more robust empirical evidence than demonstrated here—derived through larger and more diverse samples—is needed to build widespread confidence in whitening’s impact.

The empirical evidence indicating whitening’s effect is limited by the small sample size of treated homes ( $n = 7$ ). Despite this limitation, the study is demonstrative of empirical methods that can measure cool roof performance in the future, providing an approach that differentiates between daytime and nighttime performance, distinguishing between heating and cooling seasons, modeling of zero inflated data expected of site cooling energy use, and reflecting the potential benefit of delaying roof replacement. The examples provided herein can improve future research and policy making. For example, primary heating data could readily be incorporated into the DiD framework to incorporate the heating penalty in the regression framework. Also, the DiD analysis can flexibly include other covariates, such

as geographic factors or orientation, which could be used to study roof performance for a sample that reflect more diverse climates or diverse homes. The methods outlined here would also be beneficial to document expected long-term decline of whitening's performance.

Future studies could make better use of diurnal variation in cool roofs' performance, where the treatment effect becomes muted at some point each night. This has the effect of increasing variation in the treatment effect, which both improves statistical rigor and would allow for more explicit testing of the "parallel trend" assumption inherent in DiD. This assumption assumes homogeneous time effects between the treated and control groups outside of the treatment itself (e.g.,  $\beta_2$  in Eq. 1 is the same for both treated and control groups). Experiments that couple monitoring energy consumption alongside roof surface temperatures for treated and control samples would help identify periods in which the treatment effect is muted at night.

The protective nature of cool coating materials is expected to increase the service life of roofs, but the amount of extended service life is uncertain and likely voids any remaining manufacturer warranties. Also, homeowners do not often know when their roof will fail. So, the delayed-replacement benefit of coating acts like a premium to insure against the future risk of failure. It is not clear how homeowners would weigh the potential benefits of delaying replacement given these uncertainties, suggesting an opportunity for future social science research.

## CONCLUSION

The empirical evidence for whitening's impact on cooling is mixed, with insight primarily constrained by a small treated sample. Most individual household-level comparisons of consumption before and after whitening demonstrate statistically significant ( $p < 0.01$ ) reductions from 14% to 49.2% during the day. During the nighttime, one house demonstrated a 9.7% increase in site cooling energy use ( $p = 0.018$ ) with the remaining treated households demonstrating statistically significant ( $p < 0.01$ ) nighttime reductions ranging from 14% to 40.3%. These results suggest the benefits of cooling extent past sunset, consistent with other observations (Parker and Barkaszi, 1997). Regressions results estimating the mean group effect are also mixed. OLS estimates demonstrate a statistically significant mean daytime reduction of 7.6% but no significant mean nighttime reductions. However, clustering the errors by

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household to moderate serial correlation increases  $p$  values to levels usually considered insignificant. Tweedie regressions, which better fit the slight zero inflation demonstrated in the sample, improve the model fit for nighttime consumption and produce statistically significant air conditioning reductions of 14.3% and 5.5% during the day and night, respectively.

The benefit for delaying roof replacement was found to be on par with or greater than other more conventionally estimated costs and benefits. A 5-year delay in roof replacement sways the average benefits of whitening to nearly negligible to quite favorable for roofs older than 10 years of age, results generally robust to a range of assumptions.

## DATA AVAILABILITY STATEMENT

Pecan Street Inc. provides to researchers the raw data supporting the conclusions of this article.

## AUTHOR CONTRIBUTIONS

MB performed all of the analysis and wrote the manuscript independently.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fbuil.2020.571429/full#supplementary-material>

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**Conflict of Interest:** The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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