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Time effects of green buildings on energy use for low-income households: A longitudinal study in the United States

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ABSTRACT

The U.S. government has included green building policy in affordable housing programs for years. However, little to no evidence is available to elucidate this policy's efficacy in the context of energy performance and financial savings. This paper reports a longitudinal study that investigates time effects of such policy on the energy performance in low-income housing units. The researchers collected monthly energy use data over three years from 310 residential units and conducted profile analysis and MANOVA. Results indicate that (1) green buildings' energy performance is consistent across years; (2) construction type, technology level, and apartment size significantly and consistently affect energy use; and (3) occupant type inconsistently affects energy use. Results suggest financial savings of $648 per year due to reduced energy usage in green buildings. The savings equate to 9.3%, 5.6%, and 3.5% of annual income for extremely low-income, very low-income, and low-income families, respectively. Savings represent a 26.6%–37.5% reduction of energy expenditure for low-income households. Findings strongly suggest that green building incentives and the diffusion of green building practice is resulting in affordable housing systems.

1. Introduction

Affordable housing has long been a national effort in the United States. In the early decades of the implementation of the Housing Act of 1937 (Mo, Zhao, McCoy, Du, & Agee, 2017; Vale, 2007), the federal government's involvement was directly funding affordable housing development including construction costs; while state and local public housing authorities (PHA) covered the operational and maintenance costs. In return, PHAs owned the properties and controlled the design, construction, and tenant selection. Beginning in the 1960s, the U.S. Department of Housing and Urban Development (HUD) started to prioritize public-private partnerships that encouraged private developers to develop affordable housing by offering subsidies and vouchers to offset development and construction costs. To date, the Low Income Housing Tax Credit (LIHTC) program has become the largest and most significant federal program for the production and preservation of affordable housing for low-income families in the nation (Collinson, Ellen, & Ludwig, 2015). Eligible LIHTC-assisted projects require that 20% or greater of residents have incomes below 50% of the area median income (AMI) and 40% or greater of residents have incomes below 60% of AMI. The federal government annually earmarks $6 billion to the LIHTC program which has supported more than 2 million residential units and retained a large tax credit portfolio (Khadduri, Climaco, Burnett, Gould, & Elving, 2012).

Over the same 40–50 years, building energy use reduction has also been a national effort. In the U.S. residential buildings account for at least 21% of energy consumption and carbon emissions based on the U.S. EIA (2016). This usage represents 20 quadrillion British thermal units (BTU) and US$218 billion in energy expenditure. Many low-income families are involved in energy poverty since they must allocate significantly more of their household income to energy expenditures than other households (Bird & Hernandez, 2012). Low-income households often live in homes that are not energy efficient and they are unable to afford energy-saving measures (Guerra Santin, 2011; Langevin, Gurian, & Wen, 2013). The broad concept of green building can be defined as aspects of energy efficiency, sustainability, and environmentally friendly products (Adomatis, 2012; Hodges, 2005; Tucker, Pearce, Bruce, McCoy, & Mills, 2012). In this research, the authors focus on human-centered energy efficiency to measure the performance of green building (McCoy, Zhao, Ladipo, Agee, & Mo, 2018). The focus on energy performance is consistent with LIHTC policy.

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To improve building energy efficiency, the architecture, engineering, and construction (AEC) industry has engaged in R&D for building technologies. These technologies range from enclosure systems advancements (e.g. spray-applied insulation and weather resistant barriers, air sealing techniques, and high-performance glazing systems) to sub-system advancements (e.g. inverter-driven heat pumps, efficient lighting and appliances, and low-flow water fixtures). Green buildings also provide a healthier built environment, addressing indoor environmental quality (IEQ) and occupant quality of life (Amiri, Mottahedi, & Asadi, 2015; Baughman & Arens, 1996; Hoskins, 2003; Singh, Syal, Grady, & Korkmaz, 2010; Singh, Syal, Korkmaz, & Grady, 2010; Spengler & Sexton, 1983). The U.S. Department of Energy (DOE) has set long-term goals toward 50% energy reduction in buildings and committed to catalyzing green buildings at a national level through model building codes and supporting third-party green rating systems (e.g. LEED, Energy Star, and EarthCraft).

As a part of this national effort, HUD and local housing finance agencies (HFAs) have integrated green building rating systems into state-led LIHTC programs. Financial support from the LIHTC programs address essential barriers to green building implementation, including higher initial costs of design and construction (Beheiry, Chong, & Haas, 2006; Lee, Chin, & Marden, 1995; Zhao, McCoy, & Smoke, 2015). At the federal level, the LIHTC program does not mandate green building rating programs for apartment development; however, the U.S. Internal Revenue Service (IRS) specifies that energy efficiency shall be considered in state-level requirements for LIHTC development. In practice, HFAs provide financing for affordable housing and are the agencies that award the IRS credits. The IRS credits are distributed to developers based on the Qualified Allocation Plan (QAP).

To date, all state PHAs have incorporated some form of green building policy (e.g. discrete green building measures and/or green building rating systems) into their QAPs. As listed in Table 1, the QAP either requires LIHTC applicants (e.g., the developer or builder) to participate in a green building rating system or encourages them to achieve green building certification by offering additional scoring points.

LIHTC is an ideal platform to gauge home energy efficiency; however, little to no research has fully utilized this platform to investigate green homes' energy performance and economic impact. This knowledge gap prevents policymakers from a better understanding of green building efficacy, particularly for low-income households. To address part of this gap, as shown in Fig.1, this study has two objectives: (1) to identify energy performance of LIHTC-assisted green buildings over time, and (2) to determine economic impacts on low-income households as a result of these green buildings. In reaching the objectives, the authors have conducted a longitudinal study on energy consumption of LIHTC-assisted green buildings over 36 consecutive months from 2013 to 2016. Unlike cross-sectional studies that only reveal static homogeneity and heterogeneity, longitudinal study uncovers dynamic trends of energy use and time effects of energy efficiency (Diggle, 2002). In other words, this study focuses on whether or not energy performance is stable, durable, and consistent over time in these green buildings. Energy use trends and time effects unveiled from this study contribute to the robust long-term decision-making for both energy and housing policymakers. In this regard, the authors also discuss data-driven policy implications based on analytical results.

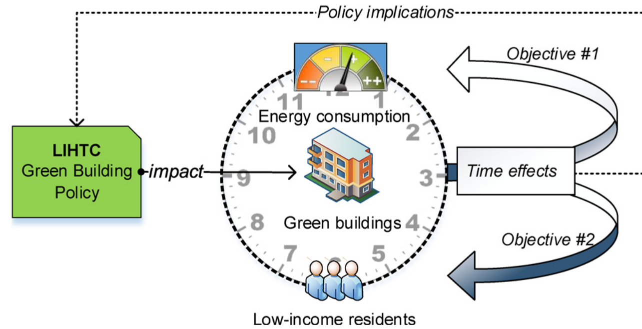

Fig. 1. Diagram of research design and objectives.

2. Materials and methods

2.1. Data

Fig. 2 displays the 310 residential units across 16 developments in the state of Virginia from which energy use data were collected. Apartment-level electricity data were collected on a monthly basis from May 2013 to April 2016 using an online benchmarking software. The authors applied a method of geographic cluster sampling (or termed area cluster sampling). The cluster sampling technique has been widely used in research by many statistic agencies including the World Bank (Himelein, Eckman, & Murray, 2013) and U.S. Department of Agriculture (2016). In this research, the geographic clusters are based on the metropolitan statistical area (MSA), a geographical region with a relatively high population density at its core and close economic ties throughout the area (U.S. Census Bureau, 2016). MSA is a result of national standards for statistical purposes and has been adopted by many federal agencies including the Census Bureau and HUD. The sampling strategy aligns with the referenced national standards and, therefore, allows for representing a larger population in each statistical area and producing more accurate analytical results (Himelein et al., 2013). To minimize the disturbance from missing data (Everitt, 1998; Molenberghs & Verbeke, 2000), the study used longitudinal data with complete records during the whole 3-year period.

Virginia is selected for data collection because it contains a large number of LIHTC-assisted green apartments with considerable quality. Since 2007, the Virginia Housing Development Authority has integrated

Table 1
Summary of state-level LIHTC green building programs in the United States.

Certification	Require Certification by State	Encourage by State
• LEED for Homes • Home Energy Rating System • EarthCraft House • Enterprise Green Communities Criteria • National Green Building Standard • ENERGY STAR appliances • Green Point Rated Multifamily Guidelines • Green Globes • LEED for Neighborhood Development	Alaska, Arkansas, Arizona, California, Colorado, Connecticut, District of Columbia, Delaware, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Nebraska, North Carolina, Louisiana, Massachusetts, Maryland, Michigan, Minnesota, Missouri, Mississippi, Montana, New Hampshire, New Jersey, Nevada, New York, Ohio, Oklahoma, Oregon, Rhode Island, South Dakota, Tennessee, Texas, Utah, Virginia, Washington	Hawaii, North Dakota, New Mexico, Pennsylvania, South Carolina, Vermont, Wisconsin, West Virginia, Wyoming

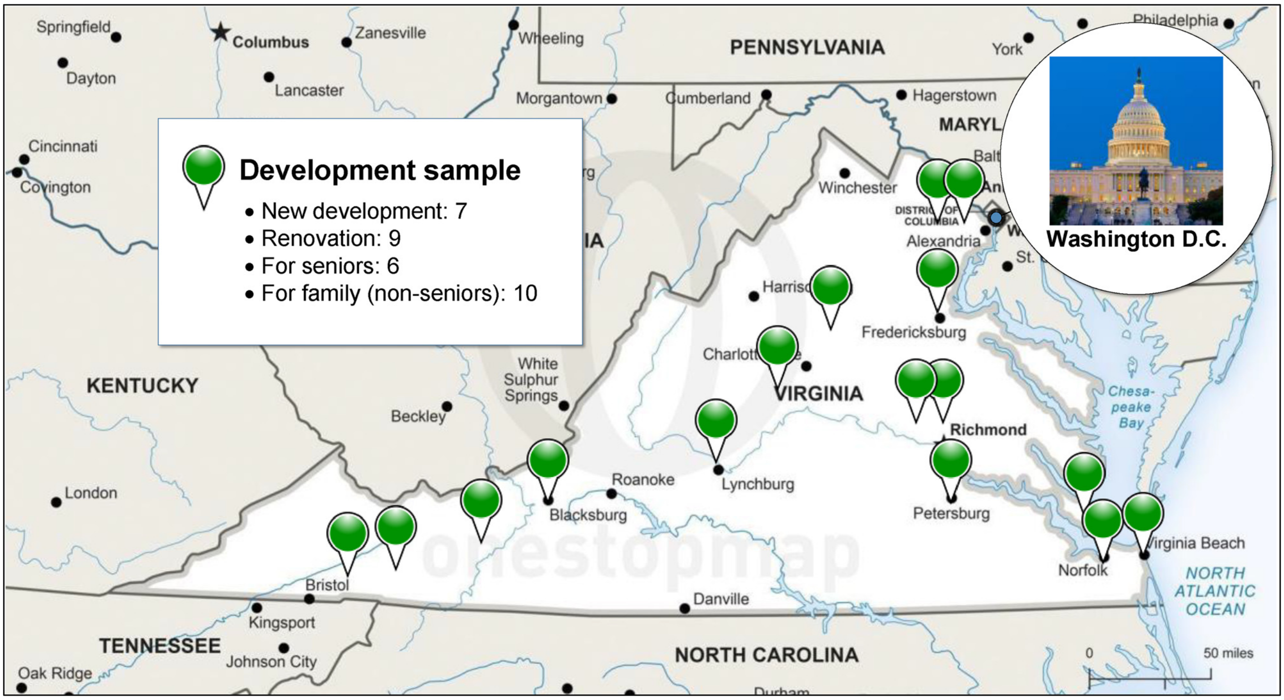

Fig. 2. Geographical display of sampled residential developments.

Table 2
Longitudinal analysis periods.

Time Separation	Period	Month	Duration	Dominant Seasonal Load
Annual	Y_1	May 2013–Apr. 2014	12 months	Cooling/heating
	Y_2	May 2014–Apr. 2015	12 months	Cooling/heating
	Y_3	May 2015–Apr. 2016	12 months	Cooling/heating
Semiannual	T_1	May 2013–Oct. 2013	6 months	Cooling
	T_2	Nov. 2013–Apr. 2014	6 months	Heating
	T_3	May 2014–Oct. 2014	6 months	Cooling
	T_4	Nov. 2014–Apr. 2015	6 months	Heating
	T_5	May 2015–Oct. 2015	6 months	Cooling
	T_6	Nov. 2015–Apr. 2016	6 months	Heating

green building rating systems as an incentive for the state QAP (McCoy et al., 2018). Virginia ranks in the top 10 in the nation and the first in the southeastern region on recent LIHTC production: building more than 2000 residential units per year. All of the sample developments were built or renovated after 2009, making current green building technologies available in the design and construction. Further, all buildings sampled for this research were certified by the EarthCraft green building rating system. The authors acknowledge that there are other green building rating systems (e.g. LEED, Enterprise Green Communities) available to policymakers and developers. The analysis represented in this paper focuses only on EarthCraft certified developments in Virginia because (1) the EarthCraft program in Virginia's QAP represents the only accessible database with the detailed technical information of design and construction available for this type of analysis and (2) 100% of the Virginia LIHTC project since 2007 elected to pursue EarthCraft certification.

Data for energy analysis included monthly electricity use (kWh), construction type (i.e., new or renovated), occupant type (i.e., family or senior), technology level, climate, and conditioned floor area data. Residential units were 100% electric in fuel source. Monthly electricity use was sourced with residents' consent and with help from property managers. In 2013, the authors invited residents to an onsite educational meeting in the form of a "pizza party" at every development. As part of the meeting, the study goals were introduced to residents, the energy efficiency of apartments where they lived, and energy efficiency technologies placed within the apartments. The research team provided a $25 gift certificate (financial incentive) to participants who filled out a utility release form, a behavior survey, and agreed to provide access to their unit's electricity utility account. Meanwhile, the authors partnered with developers and property managers to collect data from the development's green building certification. Particularly, the certification provides housing unit design specifications and a Housing Energy Rating Certificate (HERC) document to measure the level of green building technology and simulated energy performance (Zhao, McCoy, & Du, 2016). The HERC is based on a score (termed HERS) that is a nationally recognized asset scoring system in the U.S., of which 100 indicates an apartment built to current model code standards and lower scores indicate higher energy efficiency. Other data for economic impact analysis (e.g., local AMI values and electricity prices) were derived from national census databases: the 2012–2016 American Community Survey (ACS) and American Housing Survey (AHS).

Table 2 summarizes time separation and periods on an annual or semiannual basis. For the annual-based separation, the authors aggregated monthly energy data into 3 periods (i.e., Y_1, Y_2, and Y_3) with a duration of 12 months for each period. This time scale demonstrates electricity use trends across the first, second, and third year. For the semiannual-based separation, the authors aggregated energy data into 6 periods (i.e., T_1, T_2, …, T_6) with a duration of 6 months for each period.

Measurements at this time scale avoid bias due to discrepancies of energy use between heating and cooling-intensive seasons. For example, annual energy use may not change when a home has higher consumption for cooling and lower consumption for heating. Virginia's heating season (climate zone 4A), often starts in November and ends in April. Therefore, the two sets of time separation allowed this longitudinal study to analyze yearly and seasonal time effects.

2.2. Methods

Through longitudinal study, the authors performed three analytical analyses: (1) profile analysis, (2) multivariate analysis of variance (MANOVA) and (3) economic impact analysis. The authors separated the 3-year duration into 12-month and 6-month periods to track longitudinal trends and utilized SAS v12 software for all analysis.

Profile analysis is a sequence comparison method that identifies patterns between cohorts across time points. Mathematically, it is the multivariate equivalent of repeated measures. Profile analysis can visualize patterns through graphs of data (e.g., plots and curves) and thus is more informative when comparing the same dependent variables between cohorts over multiple time points (Srivastava, 1987). Typical to profile analysis, this work tested the pattern's parallelism, level, and flatness. The parallelism test seeks whether or not profiles have the same trend across time points, which is reflected in the curve's shape or slope change. The level test checks if profiles have equal levels on average (i.e., average energy use) across time points. The flatness test identifies a profile's time effect assuming its curve's slope is 0. As a supplement, matched-pairs *t*-tests were performed to confirm the observed patterns.

The authors used profile analysis to visualize cohort effects of energy use across three years. Specifically, two sorts of cohort effects were analyzed. One cohort sort is based on construction type and has two cohorts: newly constructed buildings (hereafter termed New) and renovated buildings (hereafter termed Renovation). The other cohort sort is based on occupant type and has two cohorts: units designed for senior residents (hereafter termed Senior) and non-senior family residents (hereafter termed Family). Based on HUD regulations (2013), senior housing refers to facilities and communities for persons age 55 and older. All cohorts under study were fixed and thus changes in time were not confounded by cohort differences (Fitzmaurice, Davidian, Verbeke, & Molenberghs, 2008). Therefore, results from profile analysis enabled researchers to delineate the differences of energy use trends between New and Renovation and between Senior and Family apartments and occupants.

MANOVA analysis simultaneously analyzes the responses of many correlated dependent variables. We use MANOVA to explore how various factors affect energy use and whether or not such effects change over time. Specifically, the between-subject effect and within-subject effect over time were tested (Fitzmaurice et al., 2008; West, Galecki, & Welch, 2014). The between-subject effect represents a factor's effect across all building units, and the within-subjects effect represents a factor's repeated effect over time. Mathematically, the between-subject effect was modeled by fitting the sum of the repeated measures to the model effect; and the within-subject effect was modeled with a function that fits differences in the repeated measures. In this study, the profile function was employed to perform MANOVA on energy data over time Y_1-Y_3, and the compound function was employed on data over time T_1–T_6 (Scheiner & Gurevitch, 2001).

The MANOVA analysis considers five specific effects (i.e., construction type, occupant type, building technology level, climate, and conditioned floor area). Eq. (1) expresses the multivariate regression formula that models these effects. The five effects correspond to five critical factors that directly and significantly affect home energy consumption, which the literature refers to as: building, user, operation systems, climate, and space (Anderson et al., 2017; Yu, Fung, Haghighat, Yoshino, & Morofsky, 2011). In addition, the number of occupants were very similar across the sample and thus not included in the analysis. The factor of climate is represented using the 10-year average ratio of heating degree days (HDD) and cooling degree days (CDD). The research team sourced HDD/CDD data from the U.S. NOAA (2016) database. Other factor data were sourced from HERC documents during data collection.

$$\boldsymbol{E}_{it} = \begin{bmatrix} E_{i1} \\ E_{i2} \\ \vdots \\ E_{iT} \end{bmatrix} = \beta_0 + \beta_1 CT + \beta_2 OT + \beta_3 BT + \beta_4 WT + \beta_5 HS + \varepsilon_{it}, \quad \forall\ t = 1,\ 2,\ \ldots, T \tag{1}$$

where:

$\boldsymbol{E_{it}}$ = the electricity use at the *i*th residential unit during time period *t*;

CT = the effect for construction type (i.e., New versus Renovation);

OT = the effect for occupant type (i.e., Senior versus Family);

BT = the effect for building technology level (i.e., HERS score);

WT = the effect of weather (i.e., the ratio of HDD/CDD);

HS = the effect for apartment size (i.e., the conditioned floor area).

Economic impact analysis is used to identify financial benefits from energy savings. Energy savings were calculated by comparing observed energy use for the sample to Virginia statewide average energy use. To provide a holistic view, the researchers compared the energy savings to the average of Virginia low-income households and to the average of all Virginia households (U.S. EIA, 2016). The financial benefit is represented in monetary value V with a rate of income R. The team then converted benefits and prices into a 2014 dollar value ($) to mitigate for inflation influence. V and R are measured using the following Eqs. (2) and (3), respectively.

$$V = (E_0 \times P_0) - \frac{\sum_{i=1}^{n} \sum_{j=1}^{12} (E_{ij} \times P_{ij})}{n} \tag{2}$$

$$R = \frac{V \times n}{\sum_{i=1}^{n} I_i} \tag{3}$$

where:

V = the annual financial benefit value (in $);

R = the annual financial benefit rate (in %);

E_{ij} = the observed annual energy use in the *i*th residential unit in month j (in kWh);

E_O = the average residential energy use (in kWh);

P_{ij} = the local utility price for the *i*th residential unit in month j (in $/kWh);

P_O = the average utility price (in $/kWh); and

I_i = the local low-income threshold (in $).

3. Results

3.1. Descriptive analysis

Table 3 summarizes electricity use over time, based on annual and semiannual delineations. 3-year overall electricity use is 533 kWh per month and its standard deviation is 269. Electricity uses during Y_1, Y_2, and Y_3 were 514, 558, and 525 kWh, respectively, close to the 3-year overall use. The energy usage for the observed period was tested against climate factor (i.e., HDD and CDD) and no significant difference of energy usage was found across the three years Y_1, Y_2, and Y_3 ($F = 1.72$, $p = 0.18$). Results indicate high-performance buildings' stable and consistent energy performance across three years. Semi-annual electricity uses over T_1, T_3, and T_5 were 419.32, 466.54, and 471.33 kWh, respectively. Semi-annual electricity use is lower than the 3-year overall electricity use and each is significantly different from each other statistically ($F = 5.04, p < 0.01$). Similarly, electricity uses during T_2, T_4, and T_6 were 640.30, 664.53, and 577.30 kWh, respectively. Each time

Table 3
Summary of energy use over time (kWh/month).

Separation	Period	Mean	Std. Dev.	Lower CL	Upper CL	Min.	Max.
Overall	3-year	532.66	268.66	523.92	553.30	40.00	1906.33
Annual	Y_1	514.38	206.53	483.11	545.65	60.58	1704.67
	Y_2	558.46	233.05	523.18	593.75	48.76	1721.22
	Y_3	525.17	244.16	488.20	562.13	64.00	1608.42
Semiannual	T_1	397.89	198.68	386.20	452.45	70.00	1503.00
	T_2	630.86	247.27	607.82	672.78	51.17	1906.33
	T_3	457.55	230.98	434.60	498.47	57.49	1660.84
	T_4	659.32	276.76	630.63	698.42	40.00	1781.67
	T_5	471.66	249.74	436.35	506.31	56.33	1668.00
	T_6	578.67	269.74	540.45	614.39	71.67	1756.67

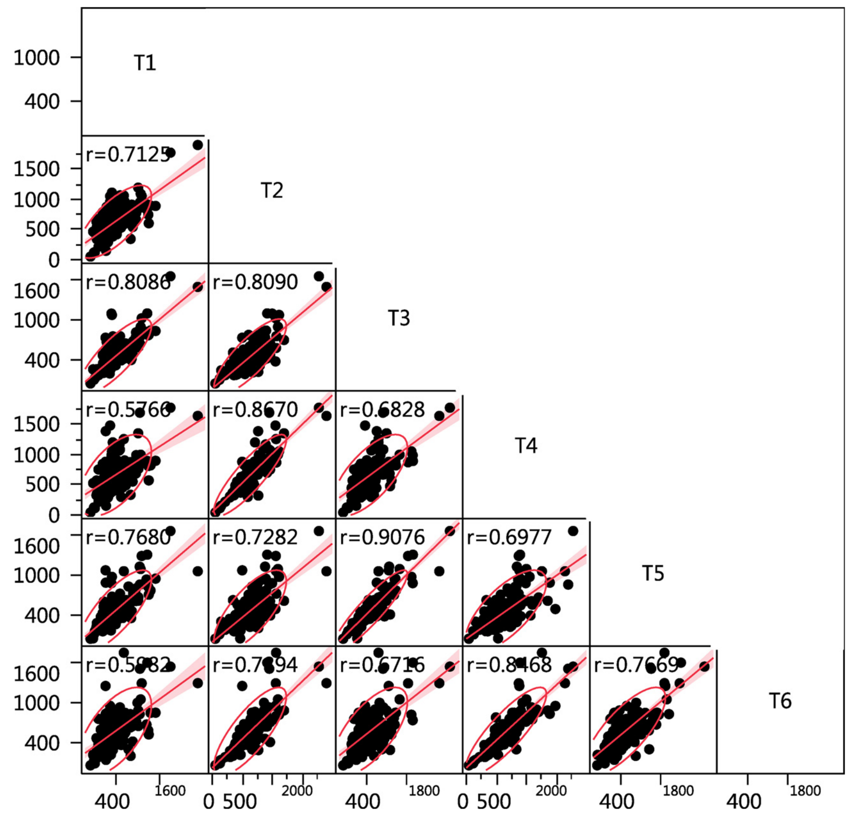

Fig. 3. Scatter plots of energy use over time showing correlations.

period was slightly higher than the 3-year overall use and significantly different statistically as well ($F = 4.05$, $p = 0.02$). The differences indicate that units use more energy in heating seasons than cooling seasons and results confirm that electricity use fluctuates by season. In the next section, the correlation analysis explores these fluctuations.

Fig. 3 displays an array of scatter plots showing the correlation of electricity use across seasons. The plots show that electricity uses during T_1, T_3, and T_5 were closely correlated, and electricity uses during T_2, T_4, and T_6 were closely correlated. For example, the correlation between T_1 and T_3 was stronger than between T_1 and T_2. Specifically, the highest correlation of electricity use ($r = 0.908$) occurred between T_3 and T_5, indicating a strong linear association. Results confirm previously-identified fluctuations and quantify the trend. Scatter plots also indicate a slight decrease in correlation due to increasing durations between the observation periods. For electricity use one year apart (i.e., across two time periods), the correlation between T_1 and T_4 ($r = 0.577$, longer duration) was weaker than that between T_1 and T_2 ($r = 0.712$, shorter duration); or the correlation between T_2 and T_5 ($r = 0.728$, longer duration) was weaker than that between T_2 and T_3 ($r = 0.809$, shorter duration). The resulting variability suggests the effect of external factors on electricity use, such as weather or occupant behavior across years. In addition, most off-diagonal values in the plots were lower than 0.9, indicating little multicollinearity and therefore a stable model for MANOVA. In other words, the predictive power and reliability of the model as a whole were satisfied (Hill & Lewicki, 2006).

3.2. Profile analysis

Fig. 4 illustrates the profile analysis results showing the cohort effects of energy use on an annual basis. In Fig. 4a, the profile analysis results are separated by construction type and present parallelism, level effects, and an absence of flatness. Parallelism indicates differences by type (comparing slopes), level effects indicate differences by electricity use (y-axis), and flatness (or absence thereof) indicates differences (up or down) over time (x-axis).

The two slopes are nearly parallel, indicating similar electricity use patterns between New and Renovated apartments. The slope of the new (mean = 576.57 kWh) units are uniformly higher than of the

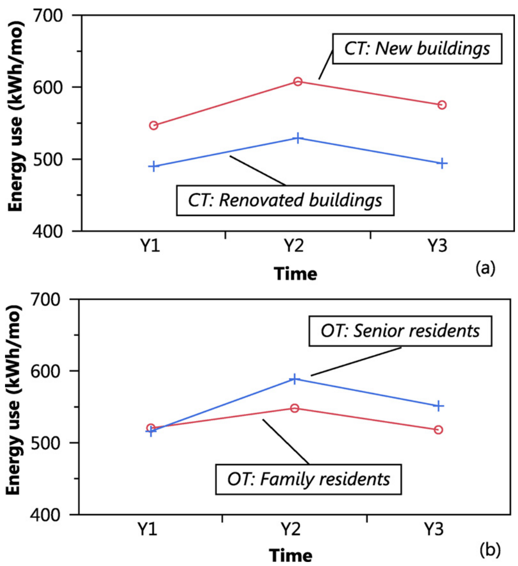

Fig. 4. Energy use trends across Y_1–Y_3 by (a) construction type and (b) occupant type.

Renovated (mean = 504.42 kWh) units, indicating a consistent level difference. The difference of 72.15 kWh is statistically significant confirmed by the matched pairs *t*-test ($t9.39, p = 0.01$). The slopes indicate an absence of flatness (i.e., slope ≠ 0) or a change in energy use over time. Therefore, combined results suggest that the Renovated units sampled used 12.5% less electricity than the New units. In Fig. 4b, the profile analysis delineates absence of parallelism, level effects, and flatness by occupant type. The two slopes diverge, indicating different energy use patterns between Senior and Family occupants. The slopes' level effects become moot due to a lack of parallelism. The matched pairs *t*-test confirms no significant level difference ($t = 1.66, p = 0.24$) statistically across the sample by occupant type. The slopes are not flat (i.e., slope ≠ 0), indicating an effect of time on energy use. Therefore, results suggest that Senior occupants may not have consistently used more energy than Family occupants (i.e., non-seniors) in the sample. For example, seniors typically prefer higher set points, which leads to more consumption during heating but less during cooling – thus canceling each other out over a full year. The further analysis below separates for the heating and cooling periods T_1–T_6 to test this idea of seasonal changes.

Similarly, Fig. 5 illustrates the results of profile analysis showing cohort effects of electricity use on a semi-annual base. The profile slopes

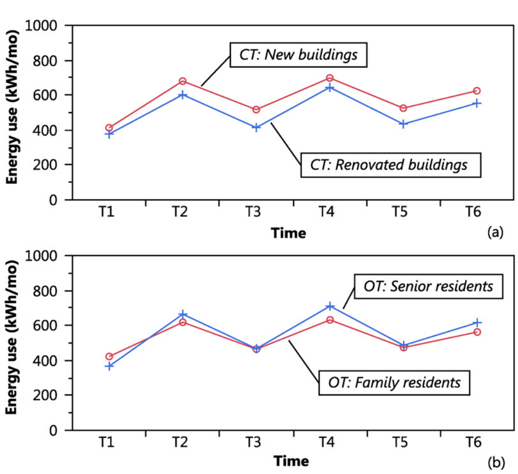

Fig. 5. Energy use trends across T_1–T_6 by (a) construction type and (b) occupant type.

indicate a pattern of fluctuation. In Fig. 5a, the profile analysis by construction type depicts parallelism, level effect, and an absence of flatness. The two slopes are nearly parallel, indicating similar energy use patterns between New and Renovated units. The slope of the New unit sample is consistently higher than that of the Renovation unit sample, indicating a consistent level difference. The difference is also statistically significant based on the matched pairs *t*-test ($t = 7.23$, $p < 0.01$). The slopes show no flatness (i.e., slope ≠ 0), indicating a change in energy use over time. Therefore, results confirm previously identified consistent electricity use differences between new and renovated housing units. Fig. 5b indicates an absence of all three, though: parallelism, level effect, and flatness. Similar to Fig. 4b, the energy use slopes intertwine with each other early, indicating different energy use patterns between family and senior residents. The slopes are nearly overlapping, indicating a moot level difference. The matched pairs *t*-test identifies the level difference is not statistically significant ($t = 1.20$, $p = 0.24$). The slopes are not flat (i.e., slope ≠ 0), indicating an effect of time on energy use. Additional matched pairs *t*-tests on energy use indicate no statistically significant difference ($t = -0.63, p = 0.60$) for cooling-intensive periods (T_1, T_3, and T_5) but a statistically significant difference of 59.61 kWh ($t = 6.02$, $p = 0.03$) for heating-intensive periods (T_2, T_4, and T_6). These results strongly suggest that the senior residents used 9.9% more electricity for heating than family residents (i.e., non-seniors). Such a finding is noteworthy and needs to be fully considered by architects, engineers, builders, and energy raters for the design and construction of units.

3.3. MANOVA analysis

Table 4 shows results of the MANOVA analysis of energy use across Y_1-Y_3. The between-subjects effects from CT, BT, and HS are statistically significant while that from OT and WT are not significant. The results are consistent with the literature, indicating that the construction type ($F = 4.3$, $p = 0.04$), building technology ($F = 10.67$, $p = 0.01$), and floor area ($F = 41.55, p = 0.01$) significantly affect electricity use. The results show that the two occupant types in this sample are not a significant factor, indicating that electricity use is stable regardless of senior residents or families and similar to the parallelism, level effect, and flatness findings. Unlike literature that asserts weather as an impact factor on energy use, the results do not produce a similar observation and we speculate the difference as a result of the sample's close geographic distance: because the sampled units were located in the same state and climate zone, the effect of weather was minimal. Moreover, the within-subject effect from WT is statistically significant ($F = 4.05$, $p = 0.02$) and that from CT, OT, BT, and HS are not significant. This finding indicates weather effect changes across Y_1, Y_2, and Y_3 while other effects do not. In other words, except the weather, no interaction effect between time and other factors were found. It is noteworthy that

Table 4
MANOVA results of energy use across Y_1-Y_3.

Statistic	Value	*F*	Num. df	Den. df	*p*
Between-subjects					
CT	0.027^{*}	4.37	1	164	0.04
OT	0.002	0.39	1	164	0.53
BT	0.065^{**}	10.69	1	164	< 0.01
WT	0.013	2.06	1	164	0.15
HS	0.253^{**}	41.55	1	164	< 0.01
Within-subject					
Time (Year)	0.033	2.65	2	163	0.07
CT × Year	0.010	0.81	2	163	0.45
OT × Year	0.036	2.95	2	163	0.06
BT × Year	0.015	1.24	2	163	0.29
WT × Year	0.050^{*}	4.05	2	163	0.02
HS × Year	0.009	0.69	2	163	0.50

Note: * = significant at 95%, ** = significant at 99%.

Table 5
MANOVA results of energy use across T_1–T_6.

Statistic	Value	F	Num. df	Den. df	p
Between-subjects					
CT	0.027*	4.37	1	164	0.04
OT	0.002	0.39	1	164	0.53
BT	0.065**	10.69	1	164	< 0.01
WT	0.013	2.06	1	164	0.15
HS	0.253**	41.55	1	164	< 0.01
Within-subject					
CT × Year	0.010	0.81	2	163	0.45
OT × Year	0.036	2.95	2	163	0.06
BT × Year	0.015	1.24	2	163	0.29
WT × Year	0.050*	4.05	2	163	0.02
HS × Year	0.008	0.69	2	163	0.50
CT × Season	0.001	0.11	1	164	0.75
OT × Season	0.037*	6.03	1	164	0.02
BT × Season	0.017	2.83	1	164	0.09
WT × Season	0.044**	7.24	1	164	0.01
HS × Season	0.004	0.72	1	164	0.40

Note: * = significant at 95%, ** = significant at 99%.

the effect of Time (year) is not statistically significant, indicating a consistent energy use trend across three years. Findings suggest that the effects of construction, occupant, technology level, and apartment size are consistent over years and do not contain more of one effect during one time period.

Table 5 shows results of the MANOVA analysis of energy use across T_1–T_6. The between-subjects effects from *CT*, *BT*, and *HS* are statistically significant while OT and WT are not. Such results are consistent with previous findings of MANOVA over Y_1–Y_3 (Table 4). Based on the within-subject effect, MANOVA identifies three significant interaction effects: WT × Year, WT × Season, and OT × Season. Similar to the previous MANOVA analysis (Table 4), this finding indicates that the effect of weather was not consistent, changing over times T_1-T_6 and makes sense as weather contains uncertainty and varies over time. Unlike the previous MANOVA (Table 4), the statistically significant interaction effect of OT × Season ($F = 6.03$, $p = 0.02$) indicates that occupant behavior varies between heating-intensive and cooling-intensive seasons. This finding explains the assertion from profile analysis that Senior residents consumed more energy for heating and possibly less energy for cooling than Family occupants.

In summary, the MANOVA analysis revealed three important findings: (1) high performance buildings' energy performance remains consistent over multiple years; (2) construction type, technology level, and home size have significant impacts on energy use and such impacts are consistent over time; and (3) the two occupant types do not have a significant impact on energy use long-term while this lack of impact is inconsistent over shorter periods of time. Shapiro-Wilk tests were performed to test the model's normality. Results show that error terms of the MANOVA model are statistically normally distributed at a 95% confidence and suggest valid conditions of regression (Hill & Lewicki, 2006).

3.4. Economic impact analysis

Due to economic factors, it is assumed that low-income households use less energy; however, low-income does not imply low energy consumption. In fact, the energy use from low-income households has a considerable variation and it can be 26% higher than that from higher-income households (Berelson, 2014). A Tetra Tech (2012) report highlighted the fact that low-income residents often consumed more than higher-income residents because they were generally less aware of energy literature or in housing without EE systems and technologies. Therefore, this study used the average energy use of the Virginia population as the baseline to analyze economic impacts and financial benefits.

According to the U.S. EIA (2016), residential electricity consumption in Virginia was 1117 kWh/month on average; the electricity price (per kWh) varied between \$0.1066 and \$0.1204 monthly and its average was \$0.1167/kWh. Based on HUD income limits, thresholds for low-income, very low-income, and extremely low-income families are 80% AMI, 50% AMI, and 30% AMI respectively. Virginia's AMIs from 2013 to 2016 were \$76,900, \$77,500, \$78,400, and \$77,500, respectively. The research team used these economic data as inputs in Eqs. (2) and (3) to calculate economic impact.

As a result, the financial benefit value (V) due to energy efficiency in LIHTC-assisted high-performance buildings equates to \$648 per year (i.e., \$54 per month). The financial benefit rates (R) equate to 9.3% for extremely low-income households, 5.6% for very low-income households, and 3.5% for low-income households. The average energy expenditures for low-income households with income thresholds of less than \$20,000, \$20,000–\$39,999, and \$40,000–\$59,999 were \$1719, \$1940, and \$2433, respectively. Therefore, the financial benefits due to energy efficiency as a product of LIHTC developments can reduce 26.6%–37.5% of energy cost for low-income households.

4. Discussion

4.1. Energy efficiency

This longitudinal study showed consistent energy performance across three years and confirmed the reliability of green-rated developments that have energy efficient systems and technology. Findings from data analysis strongly support the implementation of green building systems into future policies and finance mechanisms. Energy efficient housing is critical when considering overall energy demand and the cost of infrastructure and consumption, as the impacts are complex and far-reaching. In addition to environmental and economic implications, the fiscal health of a household can be closely tied to the cost burden of energy expenditure.

Prior literature and governmental reports have outlined the importance and impacts of energy efficiency in the residential housing sector (Dakwale, Ralegaonkar, & Mandavgane, 2011; Gillingham, Newell, & Palmer, 2009); however, energy-efficient houses are not necessarily easy to embrace. Historically, one of the primary barriers in the market is the developer's perception of higher initial costs associated with these homes and lower economic benefits (reportedly due to added personnel hours and use of innovative materials and technologies) (Konchar & Sanvido, 1998). In reality, residential units are constructed as inexpensively as permissible by market type to meet minimum requirements for current local codes and certification standards. This "low-bid" mentality is meant to keep first costs low, thus ensuring financial accessibility of clients and maximizing profitability for developers and homebuyers alike. In the past, little consideration was given toward energy efficiency and the additional expense of operation (primarily air conditioning cost) that result from building to minimum standards (Hayles & Dean, 2015; Ruparathna, Hewage, & Sadiq, 2016). Such practices have been found to be common when attempting to create housing accessible to low-income households. As a result, housing built to target a cost point with short-term financial motives and to minimum standards is often not as energy efficient as it could be. This lack of energy efficiency creates higher operating costs when compared to buildings where high-performance construction methods and materials are employed. The longer-term returns to developers who build and maintain high-performance building projects can be a remedy to this problem through improved maintenance costs and utility costs (Beheiry et al., 2006). This work provides concrete and durable evidence to support these decisions.

4.2. Affordable housing

Data analysis indicates consistent cost savings in LIHTC multifamily green buildings. As previously mentioned, the economic impact owing to energy efficiency in green buildings is highly beneficial for low-income residents by reducing up to 25% of total household expenditure. Findings could have important economic and social implications that extend beyond energy efficiency to the development itself (Freedman & McGavock, 2015). Low-income housing developments affect the mix of residents within neighborhoods not only by increasing the availability of certain forms of affordable housing but also by potentially influencing the attractiveness of communities to different types of households and income levels. For example, LIHTC programs have provided funding for about one-third of all new units in multifamily housing built in the United States since the late 1980s (Khadduri et al., 2012). The housing investment under LIHTC has measurable effects on the distribution of income within and across communities and provides potential to leverage economic benefits through both affordable communities and energy savings.

Nevertheless, home energy expenditure posits a heavier weight in the low-income household's equation. Utility costs incurred from household operation hold the potential to create a financial hardship. The global trend of increasing energy consumption and cost will only further the financial burden placed on these households. While this is true for all households, irrespective of income level, it holds especially true in the case of low-income households. For these households, the cost of housing alone can constitute a significant portion of their gross income. Since it is widely accepted that housing cost should ideally not be more than 30% of one's gross income (Schwartz, 2014), this study illustrates how easily low-income households could spend more than 30% of their gross income on housing and associated operating costs. Additional hardships could also be realized as month-to-month and year-to-year energy costs are often not constant. As household energy demands fluctuate, dependent on climate conditions, so do monthly energy costs. This erratic monthly variance in the percentage of income allotted for housing is destabilizing to household finances. All households are affected by energy expenditure and rising energy costs could result in fewer households with the financial means to pay for increasing future energy expenditure. Economically, households with the lowest incomes are burdened the most by inflation. Therefore the ability, resulting from adopting energy efficient technologies, to save these operational costs contributes to stability in the household and the community.

4.3. Energy retrofitting

Findings indicate that renovated buildings consistently demonstrate improved energy performance compared to new buildings. This improvement can be 12.5% and does not change over time. The authors speculate that this observation could be due to (1) the renovation projects in the sample do not have mechanical fresh air systems like the new construction projects in the sample; and (2) new construction units have more permanent light fixtures and wall outlets than the renovation projects, thus there is more opportunity for miscellaneous electric loads (MELs). Another possible explanation for the increased energy use in the new construction sample could be due to the Jevon's Paradox, used in environmental economics to suggest that the increased efficiency due to technological progress raises consumption (Polimeni, Mayumi, Giampietro, & Alcott, 2015). This paradox is difficult to measure empirically but makes sense for an interesting theoretical argument. Jevon's Paradox suggests occupants in a new housing unit might feel that they can use more energy because the unit is efficient, while those in a renovated unit might not see it as new. Other possibilities include the differences in technologies included in the unit or other variability unable to be studied in this work, a limitation, but the researchers are currently measuring a small subset of the sample using circuit-level energy monitors. Results also suggest the necessity of energy auditing and retrofitting to update the existing stock since it is not always economically feasible to build new construction developments.

4.4. Occupant behavior

The industry has an energy efficiency information gap – a lack of verified energy performance standards, real-time data, and post-occupancy feedback for residential projects. Human factors researchers have reported that people are generally poor at managing systems with lags in information and delayed feedback loops (Brehmer, 1992; Sterman, 1989). In the context of this research, the human-building socio-technical system is ripe for reducing the information gap and lag to occupants. Nahmens, Joukar, and Cantrell (2015) found that the top five behavioral factors that have a significant impact on the energy bills of low-income occupants are the following (in order of importance): (1) cooling setpoint during summer; (2) energy-saving practices/behaviors of households; (3) occupant behavior with respect to indoor environment quality; (4) occupant behavior with respect to lighting and electrical appliances; and (5) heating setpoint during winter. Zhao, McCoy, Du, Agee, and Lu (2017) identified four direct correlates between resident behavior and home energy use: temperature settings (winter/summer), use of a washer and dryer, and knowledge about building systems. Zhao et al. (2017) also identified two indirect correlates (increasing the effect) between technology and behavior: temperature settings specifically during winter and knowledge about building systems. This study suggests that occupant type does not have a significant impact on energy use while this lack of impact is inconsistent over time. Behavior remains critical to understanding the progress in energy efficiency and this variance highlights the potential.

Findings suggest that the senior occupants' seasonal energy use behavior present an opportunity for designers and engineers to improve building technologies that can accommodate senior occupants. Future investigations could focus on this subset of the population through purposeful design and construction to reduce this usage. Senior housing demand is increasing rapidly, as the U.S. 55+ population will reach 98.2 million by 2020 (Nyberg & Liu, 2009; U.S. Census Bureau, 2015; HUD, 2013) and the senior housing construction market is estimated to be between $250-270 billion (CBRE, 2015; Worzala, Karofsky, & Davis, 2009).

5. Conclusion

This empirical study investigates time effects of energy efficient technologies and resident behaviors in green buildings for low-income residents from 310 residential units across many years (2013–2016). Results indicate high-performance buildings' stable and consistent energy efficiency across these years; units use more energy in heating seasons than cooling seasons; and results confirm that energy use fluctuates by season. Results also indicate similar energy use patterns for different construction types, while new units have significantly higher energy usage levels than renovated units. There are different energy use patterns based on occupant type as well, yet no statistically significant level difference ($t = 1.66$, $p = 0.24$) while senior residents used 9.9% more energy on average in heating than family residents (i.e., non-seniors). Senior occupants are not consistently using more energy than Family occupants over longer periods of time though. MANOVA analysis reveals three important findings: (1) high performance buildings' energy performance remains consistent over multiple years; (2) construction type, technology level, and home size have significant impacts on energy use and such impacts are consistent over time; and (3) occupant types do not have a significant impact on energy use over long periods of time while this lack of impact is inconsistent over short periods of time. The financial benefit value due to energy efficiency in LIHTC-assisted high-performance buildings equates to $648 per year (i.e., $54 per month). The financial benefit rates equate to 9.3% for extremely low-income households, 5.6% for very low-income households, and 3.5% for low-income households. The financial benefits due to energy efficiency reduce energy expenditure by 26.6%–37.5% for low-income households.

This work contributes to the body of knowledge pertaining to human-environment interactions toward home energy efficiency since humans spend roughly 90% of their lives in buildings. First, these findings advance the understanding of human factors in the early design and construction phases, which reinforces current thinking of scientists and engineers to maximize the effect of technology investments. Second, these findings improve the understanding of the complex sociotechnical system for low-income groups, which represents the linkage of society, occupants, and the environment. These findings have implications for policymakers on the integration of green building policy into affordable and public housing systems. Results strongly suggest the success of governmental support in overcoming barriers, building public recognition of green buildings, and attracting industry-driven investments on green buildings.

It is important to recognize the limitations of this work. First, number of occupants was excluded in the model since the sample provided little variance and correlation. Second, energy use analysis focuses on electricity use only and energy costs in terms of $/kWh. The analysis excludes utility taxes, tariffs, and services fees since the variability in utility fee and municipal tax structures across the state distort the energy use analysis. Third, although the findings are very likely to be applicable for other regions, they are not tested against differing geographic zones in this study.

This work provides an opportunity for future work. First, the samples in this study are green buildings certified by the EarthCraft rating, one of the only datasets currently available that allow for this type of inquiry. Other potential benefits of 3rd party rating systems may be analyzed. Another future study can explore tailor-made green technologies to specific occupants (e.g., senior resident) in ways that green buildings' energy saving potentials can be maximized. For future work, data collection can continue across a longer period of time and diverse geography, which may enhance findings of the time effects and climate.

Declarations of interest

None.

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