

Feasibility of Zero Energy Multi-Family Low Income Housing Tax Credit (LIHTC) Developments

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Abstract

The residential sector in the United States is in need of comprehensive policy-making reforms that concurrently address housing affordability and environmental sustainability. This study investigates the feasibility of state-wide zero-energy affordable housing by analyzing historical data on climate, energy use, and solar system costs in the Commonwealth of Virginia. The hypothesis examined is that the net present cost of implementation of rooftop residential solar systems to achieve zero-energy Low-Income Housing Tax Credit (LIHTC) buildings is lower than the discounted present cost of energy of otherwise identical conventional buildings that run without renewable energy generation systems. The authors propose a generalizable framework for analyzing the feasibility of achieving region- or state-wide zero-energy LIHTC developments. To validate the framework, the authors employ a longitudinal sample of monthly energy use data from 2013-2016 obtained from 310 residential units of 15 LIHTC developments across the state. Based on statistical regression analysis, energy simulation, and simulation-based risk analysis, the authors find that the net present value of zero-energy LIHTC investments can be positive with a low risk. The investment value varies often depending on the zero-energy building definition, weather characteristics, retail price of electricity, and incentive rate. This study can help housing policymakers and industry professionals analyze and benchmark the feasibility of innovative zero-energy housing policies and projects.

Keywords: Affordable housing; Cost-benefit analysis; Monte Carlo simulation; Solar energy;

Highlights

- Presents a framework for analyzing the feasibility of zero-energy affordable housing.
- Shows energy-efficiency measures significantly reduce energy use and emissions.
- Finds zero-energy affordable housing is feasible from energy and financial standpoints.
- Suggests states have a critical role in enabling zero-energy low-income housing.
- Describes additional support the industry needs to bridge the gap to zero-energy.

1. Introduction

While renewable energy is rapidly growing in worldwide adoption, approximately 89 percent of the energy consumed in the US in 2019 still came from non-renewable sources like coal, gas, and nuclear power [1]. Of that energy produced, the residential sector accounted for approximately 21 percent of consumption. Simultaneously, almost half of all renter households are cost-burdened, often due to poverty and rapidly rising housing prices in large metro areas [2]. The residential sector in the US is clearly in need of comprehensive policy-making reforms that concurrently address affordability and environmental sustainability, reducing uncertainties around the national economy, energy security, declining natural resources, and climate change.

In 1986, the US Congress enacted the Low-Income Housing Tax Credit (LIHTC) program, which provides state LIHTC-allocating agencies with approximately \$8 billion per year to issue tax credits for the acquisition, rehabilitation, or new construction of rental housing for low-income households [3]. With more than 2.4 million active units [4], LIHTC is the principal federal housing production program, which incentivizes the production of a significant portion of below-market-rate multifamily rental units for extremely low-income to low-income households based on an indirect federal subsidy. Residents that qualify to live in a LIHTC unit benefit based on income and quality depending on their certified annual income and the maximum rent set by the project [5]. McClure (2019) describes the basics of the LIHTC program [6].

Energy-efficiency is increasingly considered important in LIHTC Qualified Allocation Plans (QAPs), which outline the criteria based on which state housing agencies allocate financial incentives in the form of tax credits to multi-family residential developers [7]. The basic federal criteria included in QAPs do not mandate specific energy-efficiency standards, but additional

criteria that support state housing policy goals often include energy-efficiency incentives. Previous studies show QAPs have significant impacts on the location and quality of LIHTC developments [8]. As a result, QAPs could either promote or inhibit the application of innovative designs and technologies in low-income developments. Existing literature on the LIHTC program suggests that, among other co-benefits, energy-efficient LIHTC properties have generated considerable financial savings for the occupants [9]. Despite its significance as an opportunity to drive innovative solutions to address environmental sustainability and economic development in low-income housing in the U.S., zero-energy buildings have received little attention in low-income housing literature, policy, and practice. If proved to be more cost-effective, zero-energy developments benefit residents and society as a whole by increasing affordability, environmental sustainability, and efficient distribution of federal financial incentives.

This article explores the existing gap to zero energy in the context of the LIHTC program: how much should state housing agencies raise energy efficiency and renewable energy requirements to bridge the gap to zero-energy LIHTC apartments?; how much does a zero-energy LIHTC building cost to developers at the present time?; is a zero-energy LIHTC building more cost-effective than a conventional building over its lifecycle?; and what types of additional support does the construction industry need to bridge the gap to zero-energy? The main hypothesis examined is that the net present cost of the implementation of rooftop residential solar systems to achieve zero-energy LIHTC buildings is lower than the discounted present cost of energy of otherwise identical conventional buildings that run without renewable energy generation systems. The authors propose a generalizable framework for analyzing the feasibility of achieving regional or state-wide zero energy in LIHTC developments. The framework is then validated using empirical data in a proof-of-concept case study focused on the rooftop grid-connected photovoltaic (PV) system as the only

source of harvesting renewable energy to offset 100 percent of a conventional multi-family residential building's annual energy demand in the Commonwealth of Virginia. This research addresses the knowledge gap in the literature and contributes to the body of knowledge through the examination of generalizable statistical energy load prediction methods and simulation-based risk analysis, which have essential applications in planning and policy analysis but are less explored in existing feasibility studies [10].

The following section sets forth a concise review of the literature on the need for energy-efficient low-income housing, the zero-energy building concept, and previous research on costs and benefits of zero-energy residential developments. Following the description of the analysis framework, the authors describe the study case, including the context, specifications, and related assumptions. Following steps are taken to test the research hypothesis and answer research questions: (1) Collecting data of LIHTC energy use, energy price, and state climatic divisions; (2) Predicting total energy load of the study case in the state climatic divisions; (3) Designing rooftop solar energy systems using simulation; (4) Estimating life-cycle cost analysis; (5) Deterministic and simulation-based feasibility analysis. Findings suggest that the net present value of zero-energy LIHTC apartments can be positive at a low risk. The investment value varies often depending on the zero-energy building definition, project location, the retail price of electricity, and the rate of incentives available for solar systems. The article concludes with a discussion on implications for the low-income housing literature, policy, and practice.

2. Literature Review

2.1. *Energy-efficient low-income housing*

In recent years, environmental concerns and the rising cost of energy have prompted a shift towards more energy-efficient homes regardless of end-users' finances. There are major reasons for decision-makers to consider energy-efficient housing for low-income residents. First, sustainable development requires a balanced integration of economic, environmental, and social goals. Nonetheless, environment and climate policy sectors alone are not capable of achieving all of the objectives and thus must work with traditionally siloed policy sectors, such as low-income housing [11,12]. Second, due to access to resources and information, public officials are increasingly responsible for taking the initiative to recognize and deploy innovative policies and programs, whether or not such utilities are expressed wants of all citizens [13].

Similarly, empirical evidence suggests that energy and water efficiency significantly reduce the total cost of living for low-income households throughout the building life-cycle [14,15]. Life-cycle thinking is particularly consistent with the way LIHTC developments are financed, and research suggests energy-efficient LIHTC units built to high-performance building standards (e.g., ASHRAE 90.1, ASHRAE 90.2) and rating systems (e.g., Energy Star for Homes, LEED, EarthCraft) can be more cost-effective than conventional units for stakeholders and the society as a whole in the long term [16,17]. LIHTC-financed housing units are charged a flat rent depending on the Area Median Income (AMI), typically close to 30 percent of household income for gross housing costs, including utilities. Therefore, if a LIHTC tenant's income decreases, they will be spending more than 30 percent on the monthly rent. Resident behavior and rising energy prices can increase utility costs, and the extra amount taken out of residents' monthly income and spent on utilities impacts housing affordability and economic well-being [18,19]. Some LIHTC projects

convert to market-rate units after the first 15-year compliance period due to lack of resources and funding to replace building systems in need of repair. Life-cycle savings from the adoption of durable energy-efficient building systems could help increase housing affordability, preserve the affordable units, and prevent the relocation of residents at the end of the compliance period [20]. Despite potential benefits, energy-efficient low-income housing units have positive externalities, meaning multiple factors, including split incentives, information lags, and asymmetries, risk aversion, skill shortages, and analytical failures. These externalities can lead to underinvestment in these units in the free market. Thus, government intervention is needed for the efficient distribution of social benefits [21,22]. Although the benefits of energy-efficient building for society as a whole are often larger than the average cost premium to obtain energy certifications, residential developers demand significant price premiums that are likely to affect affordability [23]. For instance, researchers have often reported up to 10 percent sales price premiums associated with energy-efficient single-family units with green building certifications in US cities [24,25]. Empirical studies suggest that financing initiatives highly affect (as much as 100 percent) the adoption of renewable energy generation systems in the residential sector [26]. Low-income housing legislation aimed at promoting sustainability and preserving housing affordability could balance energy-efficiency and renewable energy needs pending the careful assessment of the required levels of incentive and supportive financing mechanisms.

2.2. Zero-energy buildings

Built on low-energy building research which dates back to the 1940s, zero-energy buildings have received growing attention in recent years and are being incentivized and mandated in the housing sector to help developed countries, including the US, achieve carbon neutrality [27,28]. Zero-energy residential buildings use renewable sources of energy to generate enough energy to offset

the operation-phase energy demand, which normally includes heating, cooling, ventilation, domestic hot water, fixed lighting, plug loads, and elevators. An alternative and/or complementary to on-site renewable energy generation is a utility-scale renewable energy grid, which benefits from scale economies and equalizes local peaks.

In 2010, the European Union (EU) directive on the energy performance of buildings asserted that member states should ensure all new buildings are nearly zero-energy buildings by 31 December 2020 [29]. In 2008, California's long-term energy-efficiency strategic plan adopted energy efficiency goals stating all new residential construction in California will be zero-energy by 2020, which became a mandate in 2018 [30]. Past research concludes that energy use in the operation phase roughly accounts for 70–90 percent of a building's life cycle energy use, showing the significance of zero-energy buildings in mitigating greenhouse gas emissions. Considering the embodied energy of electricity grids, energy savings achieved in the operation of zero-energy buildings is considerably larger than the increase in embodied energy when switching from passive to zero-energy houses [31].

The US Department of Energy (DOE) recognizes builders for leadership in increasing energy efficiency, improving indoor air quality, and making homes zero-energy ready through the Zero Energy Ready Home program [32]. The DOE defines a zero-energy building as “an energy-efficient building where, on a source energy basis, the actual annual delivered energy is less than or equal to the on-site renewable exported energy” [33]. Accordingly, delivered energy refers to “any type of energy that could be bought or sold for use as building energy”, and exported energy is “on-site renewable energy supplied through the site boundary and used outside the site boundary” [33]. In the DOE's definition, the source energy is composed of the delivered energy, plus the energy consumed in the extraction, processing, and transport of primary fuels plus energy losses

in thermal combustion and in power generation plants plus energy losses in transmission and distribution to the building site [34]. An implicit assumption in this definition is that zero-energy buildings are not fully autonomous buildings and need to remain connected to existing energy grids that are able to exchange energy with the building. According to this definition, the embodied energy of building materials, construction, and recycling, may or may not be considered in zero-energy building calculations.

Zero-energy building balance is a condition in which the sum of all generated energy is equal to or higher than the sum of all building energy loads over a period, nominally a month or a year. Load matching refers to the temporal match between load and generation and represents the building's ability to work dynamically, in synergy with the grid. Salom et. al (2011) reviews various load matching indicators [35]. Equations (1) and (2) represent zero-energy building balance, where e and d stand for exported and delivered energy, g and l stand for generation and load, and w and i stand for weighting factor and energy carrier. E , D , G , and L stand for weighted exported energy, weighted delivered energy, weighted generation, and weighted load, respectively. Equation (3) represents load matching index, where F is the load matching index, t is the time interval used, e.g. hour, day or month, and N stands for the number of data samples (12 for monthly and 8760 for hourly time interval). For guidance and information on the grid interaction index equation, see Sartori et al. (2012) [36].

$$\sum_i e_i \times w_{e,i} - \sum_i d_i \times w_{d,i} = E - D \geq 0 \quad \text{Eq. 1}$$

$$\sum_i g_i \times w_{e,i} - \sum_i l_i \times w_{d,i} = G - L \geq 0 \quad \text{Eq. 2}$$

$$f_{load,i} = \frac{1}{N} \times \sum_{year} \min \left[1, \frac{g_i(t)}{l_i(t)} \right] \quad \text{Eq. 3}$$

To maximize a zero-energy building's operation at the balance condition over time, the demand should be reduced by the means of energy efficiency, and the supply should be increased by the means of renewable energy systems. Although zero-energy buildings are often designed to achieve energy balance on an annual basis, increasing the generation-load match in smaller time scales using optimized energy storage systems reduces zero-energy buildings' stress on the existing grid, particularly at the times of peak energy demand, and reduces energy waste and carbon-related emissions [37]. Past research has examined different equations and weights to define the zero-energy building balance, including balances of primary energy, site energy, carbon emissions, and energy cost for different energy systems [38,39]. Data from the International Energy Agency suggest that the percentage of source energy that reaches the final end-user, which describes the overall energy efficiency in the US supply sector, was 67.69 percent in 2010. The DOE definition of zero-energy buildings implies that these buildings should progress the restoration of the remaining 32.31 percent (loss) to the infrastructure system.

The surplus energy generation could be used as a basis to support asymmetric valuations of the energy exchanged between zero-energy buildings and energy grids, pricing the exported energy higher than that of the delivered energy. To export the equivalent of 32.31 percent of the annual load from multi-family buildings would require taking into account the need for large solar systems, installation of which may not currently be feasible based on design requirements and/or space availability in areas with low solar potential. For guidance and information on issues in zero-energy building, see D'Agostino & Mazzeella (2019) [34].

2.3. Cost-benefit analysis and simulation-based risk analysis

Researchers have examined the feasibility of utilizing renewable energy systems for residential and commercial purposes, while often in isolation [40,41]. The common approach is to evaluate

the integration of one or more renewable energy systems like solar systems, wind turbines, heat pumps, district heating and cooling into new or existing developments using simulations and calculating the energy payback period or levelized cost of energy in each scenario [42]. Amasyali & El-Gohary (2018) reviewed past research on data-driven building energy consumption prediction [43]. Some have used simulation software, such as EnergyPlus, HOMER, and TRNSYS, in conjunction with daily or monthly load profile data obtained from study cases. Most studies have focused on a single building and fewer studies have considered multiple developments with similarities and differences. Cost-benefit analyses include multiple non-financial criteria, such as the availability of technology, warranty period, ease of maintenance, required roof or ground area, avoided carbon emissions, and sensitivity analyses include the effect of changing key input variables for project outcomes, such as the effects of the cost of delivered energy, the value of exported energy, the introduction of a carbon tax, and the price of power generation technology. Fewer studies include an assessment of risk and uncertainty (e.g., the occurrence of alternative future events, into financial analysis) and most available studies rely on performing simple financial analyses [44].

As a powerful tool for evaluating the effects of policy decisions, cost-benefit analysis relies on estimates about variables that are not accurately predictable, e.g., future prices, weather patterns, occupant behavior [45]. To effectively contribute to rational decision making, an analysis (e.g., scenario analysis, sensitivity analysis, Monte Carlo simulation) of risks and uncertainties associated with observed data and modeling errors that could change the project outcome and identify the range of possible outcomes should be an integral part of any cost-benefit analysis [44,46–48]. A conundrum about cost-benefit analysis is the choice of discount rate for future costs and benefits of projects. The United States (US) Government recommends deterministic cost-

benefit models followed by sensitivity analyses and Monte Carlo simulations to perform a full risk analysis of costs and benefits of policy interventions. US Government guidelines for cost-benefit analysis of federal programs have required a discount rate of 7 percent, which is supported by more recent research suggesting discount rates in the range of 6-8 percent [49,50].

The National Renewable Energy Laboratory (NREL) benchmarks average U.S. solar photovoltaic (PV) system installed costs weighted by state installed capacities, accounting for all system and project development costs incurred from the perspective of the developer/installer, including profit in the cost of the hardware, along with the profit the installer/developer receives. According to NREL, residential rooftop systems, ranging from 3-10 kW in size, cost \$2.71 per watt DC (Wdc) or \$3.11 per watt AC (Wac) in the first quarter of the year 2018. [Figure 1](#) presents the NREL-estimated inflation-adjusted national average rooftop system costs in 2018 dollars. The gradual decrease in total cost has resulted from various drivers working simultaneously, including increases in module efficiency, labor productivity, small installer market share, and decreases in supply chain cost, permitting cost, and structural and electrical balance of system commodity pricing. According to the benchmarking analysis, the total cost of residential PV systems has decreased by 4.91 percent, from 2017-2018, and it can be expected that in 2019 and 2020, the total cost per watt DC (Wdc) has decreased to ~\$2.57 and ~\$2.45, respectively. Since on-site electricity storage systems significantly increase the total cost of installation, the most common approach to zero-energy building, particularly where full retail net metering is not available, is to simply rely on the electricity grid [51]. Additional data and information on residential solar photovoltaics with energy storage systems are available in NREL's installed cost benchmarks [52]. Information on major trends in the U.S. solar industry can be found in the Solar Energy Industries Association's (SEIA) solar market insight reports [53].

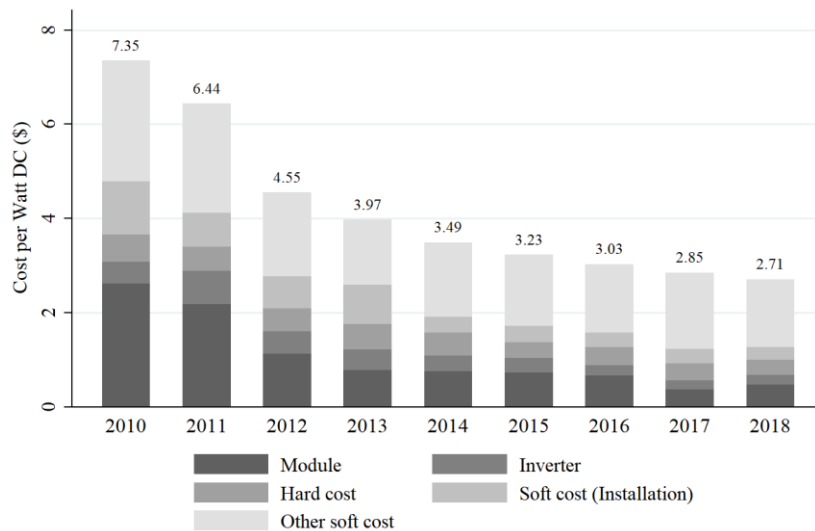


Figure 1 Inflation adjusted residential PV (6.2 kW) system cost from 2010–2018. [54]

3. Methodology

3.1. Analysis framework

Several US states, including Virginia, have enacted legislation demanding the production of 100 percent of electricity from carbon-free sources by 2050. The flowchart depicted in Figure 2 presents a generalizable framework for analyzing the feasibility of achieving region- or state-wide zero-energy in LIHTC developments. Since the future life-cycle values included in the feasibility analysis of any hypothesized study cases are unknown, the framework relies on values that have the greatest probability of occurring as suggested by historical data and provides reasonable estimates for modeling purposes. The authors apply and validate this framework using empirical data in a proof-of-concept case study to test the study hypothesis and answer the research questions.

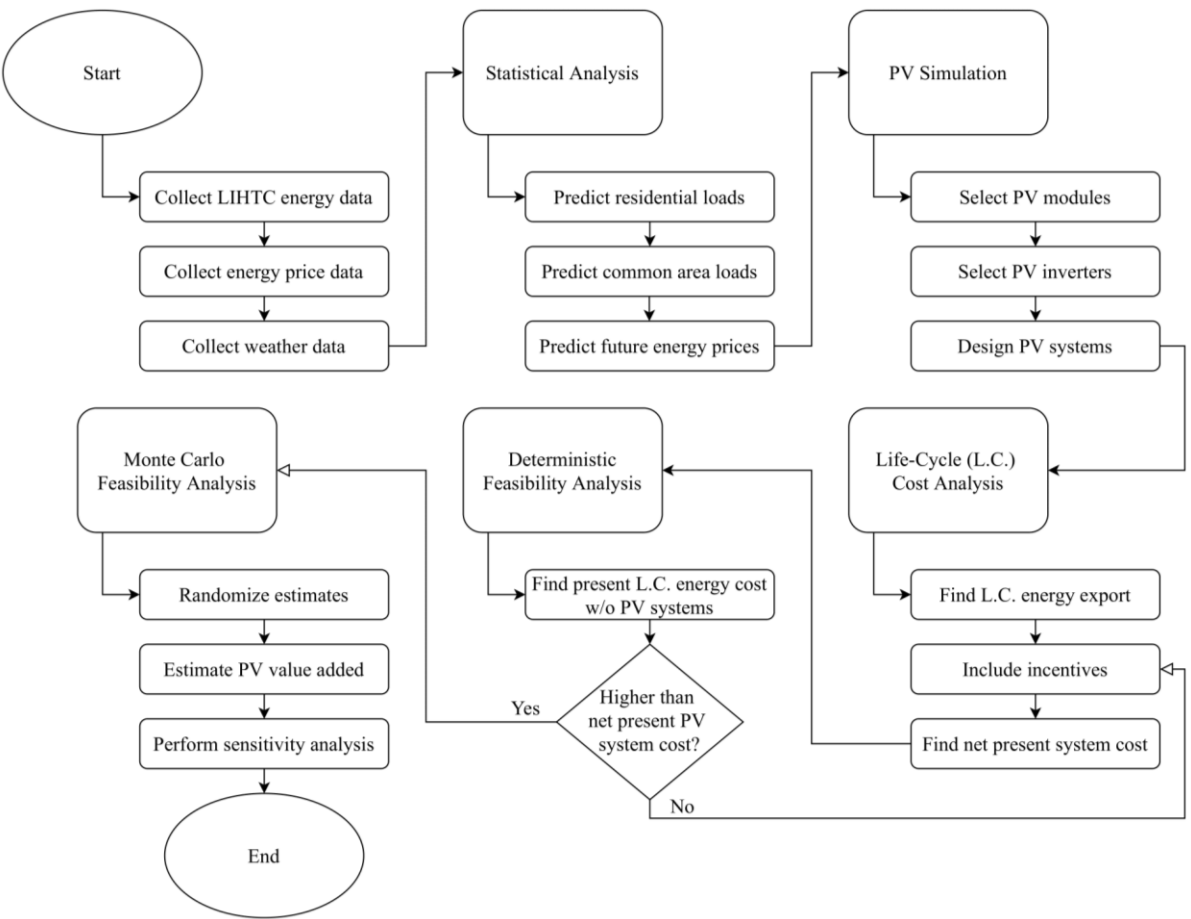


Figure 2 Zero-energy multi-family LIHTC development feasibility analysis framework (created in <https://app.diagrams.net>)

3.2. Data collection

From the LIHTC program’s inception in 1987 to 2017, 1,061 multi-family developments including 95,854 apartments have been placed into service in Virginia. On average, each development has 90.43 units (± 72.58 SD). The authors collected longitudinal, apartment-level energy use data on a monthly basis from May 2013 to April 2016 from 310 residential apartments across 15 LIHTC developments. The sample set was large enough to represent all LIHTC apartments built in Virginia with a 5 percent margin of error and a 95 percent confidence interval. Electricity is the only source of energy for all apartments in the sample, and the monthly electricity use data are obtained with residents’ consent, support from property managers, and in compliance with XXXX

institution's Institutional Review Board (IRB). The geographic clusters selected for random energy data sampling were the metropolitan statistical areas (MSAs) of Blacksburg-Christiansburg, Charlottesville, Hampton Roads, Harrisonburg, Kingsport–Bristol, Lynchburg, Richmond, and Washington-Arlington-Alexandria, which are nine of the eleven state MSAs and represent five of the six state climatic divisions defined by the National Oceanic and Atmospheric Administration (NOAA) (Figure 3). In addition to apartment-level monthly electricity use (kWh), the energy use dataset includes the apartments' conditioned floor area, type of construction (e.g., new or renovated), type of occupants (e.g., family or senior), and the apartments' energy-efficiency level as represented by the Home Energy Rating System (HERS) Index.

Developed and maintained by Residential Energy Services Network (RESNET), the HERS Index is the nationally recognized industry standard by which a residential unit's energy efficiency is calculated. A score of 100 is equal to the new construction standard of the current International Residential Code (IRC). A score of 150 means the modeled house is 50 percent less energy efficient than a standard new home. The IRC is upgraded on a three-year cycle, and the LIHTC developments from which energy use data are collected comply with the 2009 UBC, an amended version of the 2009 IRC/IBC. Typically, the amendment process creates a lag in adoption and enforcement. Therefore, when the sample apartments were being built from 2011-2013, the 2009 UBC was being enforced. Common areas (e.g., lobby, hallway, manager's office, gym, elevator) are excluded from the main analysis due to high levels of variability in space programming and energy use, which reduce generalizability. Common areas in the building can be treated as one large unit that is sub-metered and billed to the developer often based on commercial energy price rates. Common areas' energy information is available for benchmarking purposes at the Lawrence Berkeley National Lab's Building Performance Database (BPD) (<https://bpd.lbl.gov>), or online

energy benchmarking services (www.wegowise.com). The authors obtained data of the NOAA-defined climatic divisions from the National Solar Radiation Database (NSRDB) weather files (<https://nsrdb.nrel.gov>), and collected data of state-wide average retail price of electricity for residential and commercial use from the Energy Information Administration (EIA) website (www.eia.gov) of the US DOE.

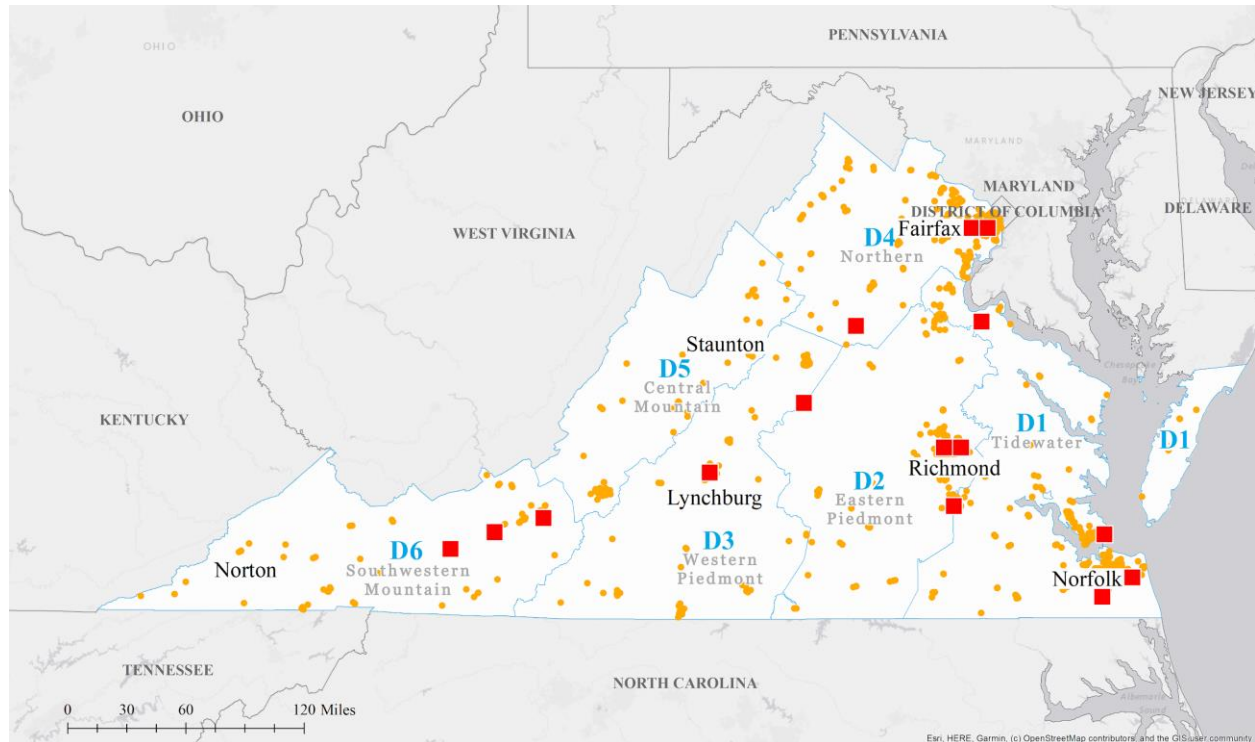


Figure 3 State climatic divisions and sampled (red squares) and existing (orange dots) LIHTC developments

3.2. Statistical analysis of loads

Using longitudinal data obtained from the geographical cluster sampling of LIHTC developments in Virginia, the authors estimate the energy load of residential apartments of the study case based on a multivariate regression model created in Stata 14.0 of StataCorp LLC (Eq. 4). The regression analysis provides the mean load for a residential apartment of a given size in a given climatic division, month, and year. The regression equation takes the basic form:

$$Sqrt(L_{ijkl}) = A_i\alpha + H_i\beta + R_i\gamma + S_i\delta + \sum_{j=1}^6 C_{i,j}\theta_{i,j} + \sum_{k=1}^{12} M_{i,k}\lambda_{i,k} + \sum_{l=1}^3 Y_{i,l}\mu_{i,l} + \varepsilon \quad \text{Eq. 4}$$

where $Sqrt(L_{ijkl})$ is the dependent variable, operationalized as the square root of energy load of LIHTC apartment i in climatic division j in month k in year l . The continuous variables A_i and H_i are the size (in square feet) and HERS score of apartment i , respectively. The binary variables R_i and S_i denote whether the apartment i belongs to a renovation or new construction development and whether the apartment i is occupied by senior or family households, respectively. The binary variables C_j , M_k , and Y_l denote the fixed effects of climatic division, month, and year of energy load. α , β , γ , and δ are unknown coefficients and $\theta_{i,j}$, $\lambda_{i,k}$, $\mu_{i,l}$ are vectors of unknown coefficients. The square-root transformation improves residual normality, reduces heteroskedasticity, and increases goodness-of-fit. The authors used Variance Inflation Factors (VIFs) to inspect for and avoid multicollinearity. Since margins obtained from the model represent conditional means of energy load, the total energy load of all apartments in a building is estimated by summing the predicted loads for all given apartment sizes multiplied by the number of apartments of those sizes in the building. Compared to conventional deterministic load forecasting based on a predefined set of load values, the adopted statistical approach can reduce uncertainty (e.g., variability whose distribution of values cannot be defined) using empirical data. The risk (e.g., variability whose distribution of values can be defined) is assessed using simulation-based risk analysis, also known as Monte Carlo analysis. Once residential loads in the reference location (Richmond, VA) are predicted, the energy use in kWh per degree day is used to estimate weather-normalized loads in other climatic divisions. The authors predict the annual average retail price of electricity based on a simple linear regression model. For guidance and more information on available electricity price forecasting methods, see Weron (2014) [55].

3.3. Study case and PV system simulation

The reference study case is a new LIHTC project in Richmond, VA, built to comply with the 2009 IRC building code, the same code version with which the sampled buildings comply. The average number of units per LIHTC application in the state from 2011-2020 is 67 (± 40 SD). The study case is a 60-unit residential building composed of equal numbers of small (693 sf), medium (910 sf), and large (1087 sf) units. The PV system is designed so that the energy exported to the existing utility grid during the first 30 years of operation simply exceeds the energy delivered to the building from the grid on an annual basis, without applying any weighting factors. Therefore, the analysis relaxes the need to fully offset the primary energy loss in the infrastructure in favor of minimizing the required rooftop area. The authors use the System Advisor Model (SAM) software to design, simulate, and estimate the energy performance of distributed photovoltaic systems for individual residential apartments in the study case.

The National Renewable Energy Laboratory (NREL) of the US DOE developed SAM as free techno-economic software to help project managers and engineers, policy analysts, technology developers, and researchers calculate performance and financial metrics of renewable energy projects. SAM is an open-source project, allowing researchers to access its publicly available codes, explore its algorithms, and add models and enhancements to all projects. Reference manuals describing the model algorithms are available at the NREL's website (<https://sam.nrel.gov>). Blair et al. (2018) provides a detailed description of SAM and Gilman et al. (2018) presents the photovoltaic performance model algorithm [56,57]. All the required weather information - hourly, or sub-hourly with up to one-minute time resolution - for the selected cities is obtained based on the closest weather station data available in the current version of the National Solar Radiation Database (NSRDB) and added to the software.

3.4. Feasibility analysis

The discounted cash flow (DCF) analysis tests whether the net present cost of the implementation of rooftop residential solar systems to achieve zero-energy LIHTC buildings would be lower than the discounted present energy cost of an otherwise identical building with no renewable energy generation systems. The first approach to feasibility analysis is to obtain the base case deterministic Net Present Value (NPV) of investment in a solar system that its generated energy exceeds the energy load of the reference building during its life-cycle. The NPV is obtained from subtracting the net present cost of the implementation of rooftop residential PV systems from the discounted present cost of the future cash flow of energy of the same building without renewable energy generation systems at a 7 percent discount rate (see the previous discussion on DOE discount). The authors examine cash flow periods of both 15 years and 30 years which reflect typical LIHTC construction loan periods. Since the values included in such an analysis can vary on a random basis, the authors perform a simulation-based risk analysis to account for risk and uncertainty. The Monte Carlo sampling method generates multiple probable outcomes for energy load, energy generation, and energy price based on historical data. Once the means and standard deviations of annual values of the three independent functions are predicted from statistical regression, the inverse cumulative distribution with random probabilities corresponding to the normal distribution of the predicted values is estimated and included in a single Monte Carlo simulation. The advantage of this method over the deterministic analysis is that it provides estimates of the NPV's mean, standard error, estimation error, and risk of loss (i.e., negative NPV). Iterations of the simulation are treated as a sample of all possible values of the real NPV, and the true mean can be estimated within a specific confidence interval and compared using the two-sample t-test to reject the null hypothesis (e.g., there is no statistically significant difference between life-cycle cost savings from the solar system

implementation and the life-cycle cost of energy of the project without the solar system). The current results are based on 15,000 iterations of the simulation, which ensures, on a gross estimation basis, that the obtained statistics' error margins are less than 2 percent.

4. Results

4.1. Load profiles

[Table 1](#) presents location, weather characteristics, and unit of measurement of six major cities, each located in one of the six NOAA-defined climatic divisions in Virginia. These major cities are selected for financial analysis to illustrate how benefits and costs of investment in zero-energy LIHTC projects vary across the state. Since degree days in each city can change each year, the mean values for 2013-16 corresponding to the years of sample data collection are chosen to predict energy loads. [Table 2](#) presents descriptive statistics of historical data for state-wide retail prices of electricity for residential use in Virginia from 1990 to 2018. City-specific mean retail prices of electricity are used for financial analysis. [Table 3](#) introduces descriptive statistics of the sample data.

[Table 1](#) Climatic division characteristics

	Division-1	Division-2	Division-3	Division-4	Division-5	Division-6	Unit
Selected city	Norfolk	Richmond	Lynchburg	Fairfax	Staunton	Norton	-
Latitude	36.8508	37.5407	37.4138	38.8462	38.1496	36.9334	°N
Longitude	-76.2859	-77.4360	-79.1422	-77.3064	-79.0717	-82.6290	°W
Global horizontal	4.50	4.08	4.44	4.27	4.44	4.28	kWh/m ² /day
Direct normal	5.01	4.36	4.88	4.54	4.84	4.51	kWh/m ² /day
Diffuse horizontal	1.60	1.60	1.63	1.69	1.71	1.75	kWh/m ² /day
Average temperature	14.50	14.90	12.80	11.80	11.10	10.80	°C
Average wind speed	3.60	0.80	0.10	1.90	0.30	0.10	m/s
2013 degree days	5201	5440	5509	5920	5958	5639	°F
2014 degree days	5235	5502	5625	6027	6102	5766	°F
2015 degree days	5063	5225	5254	5722	5617	5235	°F
2016 degree days	5296	5324	5313	5753	5683	5434	°F
Mean 2013-16 degree days	5198.75	5372.75	5425.25	5855.50	5840.00	5518.50	°F

[Table 2](#) Descriptive statistics of price of residential electricity

Variable	Description	Mean	Std. Dev.	Min	Max
Electricity price	Yearly average retail price of electricity (1990-2018)	8.976207	1.630367	7.25	11.73
Year	Year	2004	8.514693	1990	2018

Table 3 Descriptive statistics of energy use

Variable	Description	Mean	Std. Dev.	Min	Max	P ¹
Load	Monthly load of electricity in kWh	543.7161	303.7686	4	2930	
Sqrt. load	Square root of monthly load in kWh	22.48242	6.185601	2	54.12947	
Residential area	Residential unit floor area in square foot	899.788	232.0067	595	1774	0.3452***
HERS	HERS score of residential unit	68.05397	10.62989	15	98	0.0043
Rehabilitation	Rehabilitation (1) or new construction (0)	0.5807464	0.4934585	0	1	-0.1249***
Senior living	Senior living (1) or family living (0)	0.4095745	0.4917767	0	1	-0.0058
Climate id	National Weather Service climate division id	2.552407	1.684382	1	6	-0.1568****
Month	Month of electricity use	6.431897	3.429335	1	12	-0.1943***
Year	Year of electricity use	2014.297	0.9548647	2013	2016	0.1056***

1. P denotes uncontrolled Pearson Correlation Coefficient of dependent variables and electricity use

Table A1 presents the simple linear regression analysis of state-wide retail prices of electricity for residential use in Virginia. On average, the nominal retail price of residential electricity in Virginia has annually increased by 0.18 cents/kWh from 1990-2018 (**Fig A1**). When adjusting the price using the Consumer Price Index (CPI) of electricity for urban consumers in US cities, the real price of electricity has, on average across the US, decreased by 0.30 percent per year during the same period [58]. Whether this descending trend is going to remain in place is not quite clear, while an increasing trend in the price means PV system users would accrue more financial benefits than initially estimated. The US EIA has developed three different scenarios, suggesting that the national average price of 10.53 cents/kWh in 2018 can range anywhere from 9.7-11.6 cents/kWh in 2050 depending on economic growth, oil and gas resource prices, and renewable energy generating technology adoption rate [59]. These scenarios are considered in the current feasibility study.

Table 4 presents the conditional mean multivariate regression model of electricity use (the left-most column) and three quantile regression models from the same data and variables on the right, representing energy load at the first, second, and third quartiles. Nearly all the variables are statistically significant at $p < 0.01$ and, the main model represents about 41.4 percent of the

variability of energy load around the mean. The remaining unexplained variability can be attributed to the impacts of occupant behavior, variations in electrical appliances, and microclimatic factors, which have been extensively studied in the literature [60–63].

According to the conditional mean model and holding all other variables constant at the mean levels, each additional square foot of residential unit area increases energy load by ~0.048 kWh per month. The model suggests that residential units in rehabilitation developments have, on average, ~227.52 kWh per month less energy load than otherwise identical units in new construction developments. In addition, units occupied by senior households have, on average, ~1,288.57 kWh per month more energy load than otherwise identical units occupied by family households.

Table 4 Multivariate regression model of electricity use (Dependent variable: square root of electricity use)¹

Coef.	Std. Err.	P>t	25th Perc. Coef.	50th Perc. Coef.	75th Perc. Coef.

Residential area	0.0069323	0.0003169	0.000	0.0064999***	0.0060889***	0.0065996***
Rehabilitation	-0.4769924	0.1506556	0.002	1.4119500***	-0.3180811*	-1.3594700***
Senior living	1.135154	0.1968914	0.000	2.4538260***	1.3024960***	0.3886456
HERS	0.0679031	0.0053108	0.000	0.0305185***	0.0383766***	0.0797102***
Division_2	-2.887875	0.1665886	0.000	-2.8858520***	-2.9138500***	-2.6076770***
Division_3	0.7784545	0.281223	0.006	1.8117380***	0.6446663**	0.7666906*
Division_4	-5.08997	0.234813	0.000	-3.1304970***	-4.2182950***	-4.7952220***
Division_6	-2.119919	0.2131439	0.000	-0.3015351	-1.5618940***	-2.5685620***
Year_2014	0.7895158	0.1521175	0.000	0.5397313***	0.6422507***	0.9825435***
Year_2015	0.5985464	0.1565756	0.000	0.3706764**	0.5375932***	0.7723584***
Year_2016	-0.5726827	0.2345463	0.015	-1.2468680***	-0.6365490**	-0.1586213
Month_2	-0.7780375	0.2689897	0.004	-0.8079312**	-0.7477670***	-0.9516986**
Month_3	-3.267251	0.269671	0.000	-3.3230600***	-3.3488190***	-3.4724800***
Month_4	-7.298903	0.2697913	0.000	-7.2202860***	-7.4866920***	-7.9802690***
Month_5	-8.170684	0.2597029	0.000	-8.6665310***	-8.3186270***	-8.5421940***
Month_6	-7.294836	0.2751729	0.000	-8.1423060***	-7.5449440***	-7.4053190***
Month_7	-6.260478	0.2759217	0.000	-7.1655020***	-6.2866500***	-6.3571220***
Month_8	-6.804348	0.2768418	0.000	-7.5921900***	-6.9534360***	-6.9179430***
Month_9	-7.970385	0.2775862	0.000	-8.5779890***	-8.1719000***	-8.2824710***
Month_10	-7.916289	0.2778584	0.000	-8.2107210***	-8.0144990***	-8.5655400***
Month_11	-5.411357	0.2781303	0.000	-5.5206710***	-5.3851030***	-5.7131440***
Month_12	-2.514067	0.2783284	0.000	-2.7976880***	-2.3983750***	-2.5310830***
_cons	18.3616	0.6047202	0.000	16.7306100***	20.7209300***	21.4468200***
Obs	7,480			7,480	7,480	7,480
Pseudo R ²				0.2486	0.2624	0.2607
Adjusted R ²	0.4135					
Root MSE	4.6783					

1. Division_1, Month_1, and Year_2013, are default variables. No sample building is located in Division_5.

*** p<0.01, ** p<0.05, * p<0.1

Figure 4 depicts the predicted energy load (left) and residuals (right) for each observation.

Together, the regression models and the scatter plots suggest uncontrolled variables have large impacts on energy load in LIHTC apartments. Obtained from the conditional mean model, Figure 5 shows the predicted correlation of HERS score with monthly energy load with a 95 percent confidence interval, alluding to the practical significant role of energy-efficiency measures in reducing the operation phase energy use and carbon emissions. Holding all variables at the mean, each one-unit change in HERS score changes energy load by ~4.61 kWh per month.

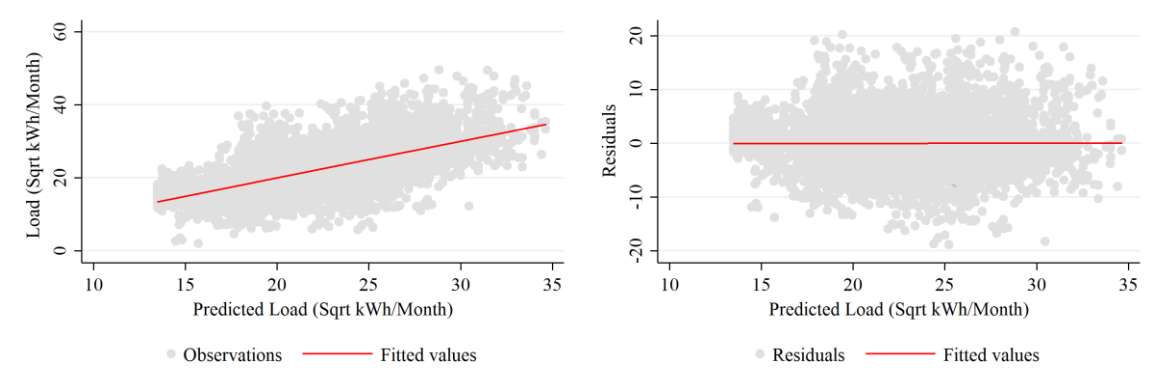


Figure 4 Post-estimated diagnostics of multivariate regression model

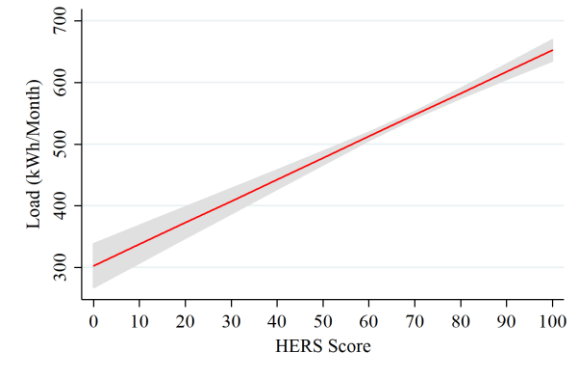


Figure 5 Predicted correlation of monthly load with HERS score with 95 percent confidence interval

Figure 6 illustrates impacts of HERS score, apartment size, and uncontrolled variables on annual energy load of apartments occupied by family households in new construction developments in the reference location, Richmond, VA. The low-, median-, and high-intensity categories refer to the predicted load values obtained from the three quantile regressions presented in Table 4. Similarly, HERS and unit size categories correspond to the first, second, and third quartiles of the corresponding variables. Table A2 presents the mean loads of new family-occupied apartments with median unit size (910 sf) and median HERS score (66) in the year 2013. The data suggest that the mean load of common areas in a 39-unit LIHTC building in the reference location is 113.71 kWh per month per unit.

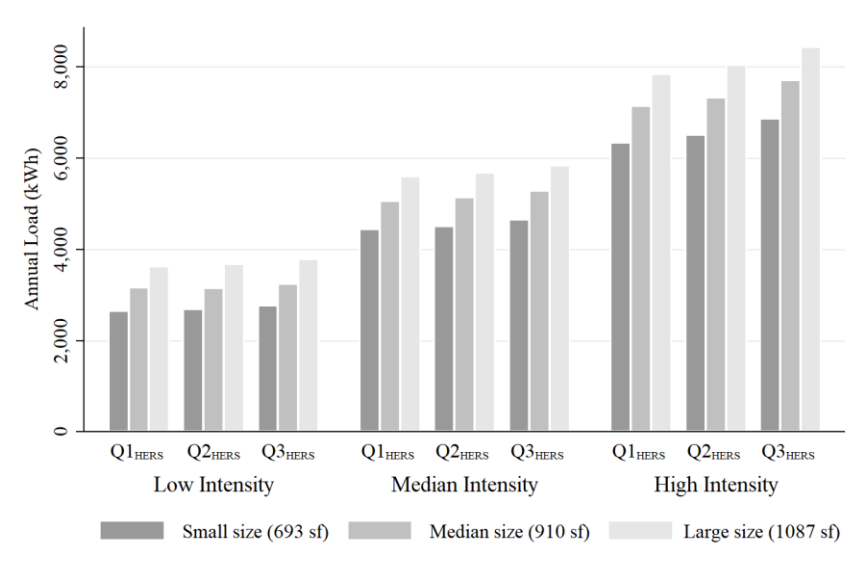


Figure 6 Estimated annual load based on the quartiles of load, unit size, and HERS score in Richmond, VA

4.2. PV system simulation

Table 5 and Table 6 present the selected PV module and inverter specifications currently available in the market and the design characteristics of the PV system at the reference location. The energy generated by the system exceeds the annual energy load of a new family-occupied apartment at the median unit size and the median HERS score during the first 30 years of operation. The annual balance partially restores energy loss in the infrastructure system, but to restore all the estimated energy loss (~32.31 percent) discussed previously, each apartment’s array size must increase from 6.5kW(dc) to 7 kW(dc), which increases each module area from 28 m² to 42 m². The 0.5 kW increase in capacity and 50 percent increase in area can increase the investment profit but may not be practical due to limited rooftop space on the 2-story multi-family building. Figure 7 shows a monthly pattern of energy generation and load in the reference location.

Table 5 Selected photovoltaic module and inverter characteristics for all climatic divisions in Virginia

PV module	Value	Unit	Inverter	Value	Unit
Company	LG Electronics	-	Company	Fronius USA	
Model	LG250N8K-G4	-	Model	Galvo 1.5-208-240	
Material	Mono-c-Si	-	Max AC power	2500	W(ac)
Bifacial	No	-	Max DC power	2619.470215	W(dc)
Standard testing conditions	250.217	W(dc)	Day power consumption	16.735605	W(dc)
Utility-scale testing conditions	231.9	W(dc)	Night power consumption	0.75	W(ac)
Max power	250.217	W(dc)	Nominal AC voltage	240	V(ac)
Voltage at max power	25.30	V(dc)	Max DC voltage	440	V(dc)
Current at max power	9.89	A(dc)	Max DC current	7.937789	A(dc)
Length	1.30	m	Min MPPT DC voltage	100	V(dc)
Width	0.98	m	Max MPPT DC voltage	440	V(dc)

Table 6 System characteristics in Richmond, VA

Parameter	Value	Unit	Parameter	Value	Unit
Number of inverters	2		Max DC voltage	440	V(dc)
Total number of modules	22		Min MPPT voltage	100	V(dc)
Total number of strings	2		Max MPPT voltage	440	V(dc)
Total module area	28	m ²	Average annual soiling loss	5	%
DC to AC ratio	1.10		Total DC power loss	4.44	%
Desired array size	6.5	kW(dc)	AC wiring loss	1	%
Nameplate DC capacity	5.505	kW(dc)	Annual DC degradation rate	0.5	%
Total AC capacity	5.0	kW(dc)	Tilt and azimuth	20, 180	Degree
Total inverter DC capacity	5.239	kW(dc)	Ground coverage ratio	0.3	GCR

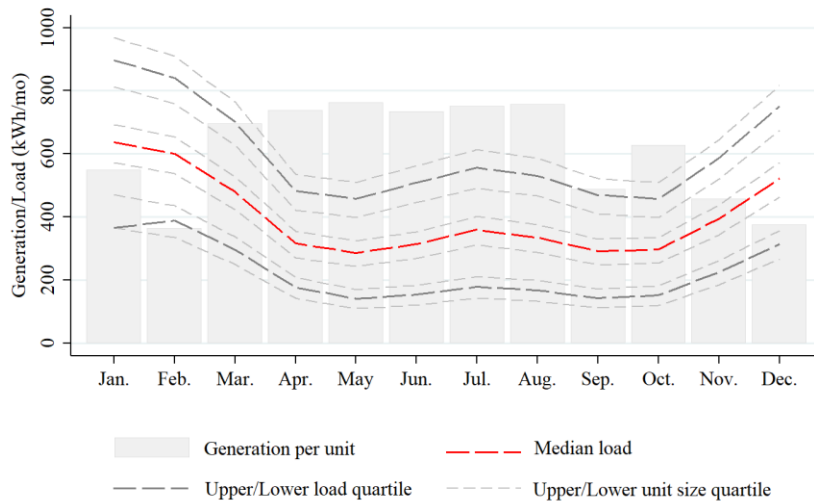
**Figure 7** Energy generation per unit and load quartiles in Richmond, VA

Figure 8 depicts the result of applying the same module, inverter, and design to the same median-size, median-HERS, median-load apartment in the state's six climatic divisions. The divisions 1-6 are ordered from left to right in each month and the values belong to the first year of operation. The red bars represent negative monthly balance, e.g., generation shortage to fully offset the energy load. **Table 7** presents the estimated cost of installation of the designated PV system in the year

2020. According to the NREL's benchmarking analysis, the national average cost of residential PV systems has decreased by 4.91%, from 2017-2018, and it can be expected that in the year 2020, the total cost per watt DC (Wdc) is approximately \$2.45. For the purpose of financial analysis, the total cost per watt DC of \$2.49 is uniformly applied to all climatic divisions.

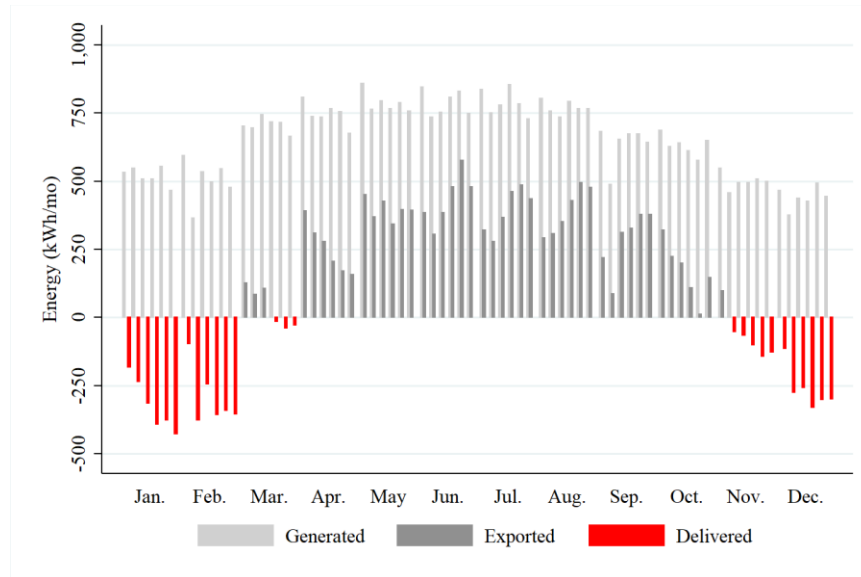


Figure 8 Estimated generated, exported, and delivered energy of median unit in six divisions

Table 7 Cost of system installation for one residential unit

Item	Unit Cost (\$/Wdc)	Total Cost (\$)
Direct capital costs		
Module	\$0.45	\$2,475.00
Inverter	\$0.14	\$700.00
Balance of system equipment	\$0.36	\$1,980.00
Installation labor	\$0.4	\$2,200.00
Installer margin and overhead	\$1	\$5,500.00
Total direct cost		\$12,855.00
Indirect Capital Costs		
Permitting and environmental studies		\$550.00
Sales tax (0.043 in VA)		\$276.38
Total indirect cost		\$826.38
Total installed cost	\$2.49	\$13,681.38

4.3. Discounted cash flow analysis

The study case is a two-story 60-unit LIHTC building comprising small (693 sf), medium (910 sf), and large (1087 sf) apartments in equal numbers. The total residential load is estimated from the sum of predicted loads for all given apartment sizes multiplied by the number of apartments of

each size (20) in the building. [Table 8](#) summarizes the assumptions and results of the 15-year and 30-year deterministic DCF analyses for Richmond, VA, including values from the stabilization year (2021) and the last year of cash flow periods. The year 2020 federal solar tax credit, which allows the owners to deduct 26 percent of the cost of installing a solar energy system from federal income taxes of that same year, is included in both analyses. State-, locality-, or LIHTC-related incentives are not considered. To simplify the calculations, the NPV of investment for the 3 individual apartment sizes (called sample) are first obtained and then multiplied by 20.

Table 8 Deterministic DCF analysis for Richmond, VA

Items / Assumptions		15-Year Cash Flow		30-Year Cash Flow	
Items					
Load (kWh/yr)	Year 2021	DPV	Year 2035	DPV	Year 2050
Small unit load (693 sf)	5,212.16		5,212.16		5,212.16
Median unit load (910 sf)	6,071.16		6,071.16		6,071.16
Large unit load (1087 sf)	6,771.83		6,771.83		6,771.83
Total load	18,055.15		18,055.15		18,055.15
Total cost of energy without PV ¹	(\$2,163.36)	(\$21,377.95)	(\$2,610.28)	(\$30,706.96)	(\$3,089.12)
PV system energy generation (kWh/yr)					
Generation per unit	7,303		6,802.24		6,303
Total generation	21,908.73		20,406.72		18,908.43
Total export	5,911.21		4,409.20		853.28
Total value of exported energy ²	\$461.73	\$3,791.27	\$339.97	\$4,642.35	\$145.99
PV system cost of financing and operating					
Debt balance per unit	\$10,040.80		\$0.00		\$0.00
Interest payment per unit	(\$688.80)	(\$3,418.53)	(\$49.04)	(\$5,080.33)	(\$31.58)
Principal payment per unit	(\$207.35)	(\$6,239.27)	(\$980.82)	(\$3,366.48)	(\$631.57)
Maintenance cost per unit	(\$110.00)	(\$1,161.28)	(\$155.43)	(\$1,770.87)	(\$225.10)
Insurance cost per unit	(\$69.00)	(\$728.44)	(\$97.50)	(\$1,110.82)	(\$141.20)
Total cost of financing and operating	(\$3,225.45)	(\$34,642.56)	(\$3,848.35)	(\$33,985.52)	(\$3,088.37)
Net present cost of PV system for sample (3 units) ³		(\$30,851.28)		(\$29,343.20)	
NPV of investment for sample (3 units) ⁴		(\$9,473.34)		\$1,363.76	
NPV of investment for project (60 units) ⁵		(\$189,466.80)		\$27,275.20	
Assumptions					
Inflation rate: 2.5%					
Discount rate: 7.00%					
Loan interest rate: 5.00%					
Federal incentive rate: 26.00%					
Price of electricity in 2021: \$11.98/kWh					
Value of export = Retail price of electricity					
Common areas are excluded					

Notes:

- (1) Total load multiplied by predicted price of energy
- (2) Total export multiplied by predicted price of energy
- (3) Total cost of financing and operating minus total value of exported energy
- (4) (3)-(1)
- (5) (4) multiplied by 20

The analysis suggests that with a long-term financing mechanism available, the net present cost of the zero-energy LIHTC apartments in Richmond, VA is lower than that of otherwise identical conventional apartments that have no renewable energy generation systems. Table 9 presents the results of the 30-year Monte Carlo cash-flow analysis of the six climatic divisions based on the same assumptions presented in Table 8 with randomized location-specific energy price, load, generation. Except for Norton, where the combination of low solar radiation, low ambient temperature, and low energy price reduces the value of investment, the NPV of investment in other cities is positive at zero or low risk of loss. Table A3 describes the two-way sensitivity of the

simulated NPVs to installation cost and price of exported energy in Richmond, VA and [Table 10](#) describes the sensitivity of the simulated NPVs to installation cost assuming equal prices for exported and delivered energy in all climatic divisions. The results suggest that achieving zero-energy LIHTC apartments, even with a 15 percent incentive, is feasible with low risk margins in many locations across the state. The presented sensitivity analysis can help the reader estimate impacts of further incentives from the state, locality, or the LIHTC program or potential reductions in technology costs in the next few years. At the 1.87 \$/Wdc installation rate (25 percent incentive), additional scenarios are examined to show the impacts of decreasing or increasing future price of energy by 10 percent by the year 2050 corresponding to the US DOE forecasts. The magnitude of effects of discount rates ranging from 6-8 percent on financial outcomes presented in the current sensitivity analysis seem negligible.

[Table 9](#) Monte Carlo financial analysis for all climatic divisions

	Norfolk	Richmond	Lynchburg	Fairfax	Staunton	Norton
Residential electricity rate 2020 (Cent/kWh)	11.81	11.81	10.71	11.81	11.81	10.13
Commercial electricity rate 2020 (Cent/kWh)	7.80	7.80	8.56	7.80	7.80	8.63
NPV of investment						
Mean	\$130,672	\$27,339	\$6,259	\$87,249	\$94,365	(\$55,057)
Standard deviation	\$26,405	\$23,644	\$22,379	\$25,408	\$25,690	\$20,651
Min	\$37,986	(\$55,612)	(\$87,724)	(\$26,934)	\$6,739	(\$130,664)
Max	\$319,740	\$469,866	\$96,945	\$370,786	\$307,244	\$101,252
Risk of loss	0.00%	12.01%	38.68%	0.04%	0.00%	99.58%

[Table A4](#) presents the results of a statistical two-sample t-test with equal variances for Richmond, VA at 26 percent incentive, suggesting that the NPV obtained from subtracting the net present cost of the implementation of the rooftop residential PV systems from the discounted present cost of energy of the same apartments without PV systems is statistically significant.

Table 10 Sensitivity of simulated NPVs to installation cost assuming equal prices for exported and delivered energy

Cost (\$/Wdc)		Norfolk	Richmond	Lynchburg	Fairfax	Staunton	Norton
2.12 (\$/Wdc)	Mean NPV	\$62,725	(\$40,799)	(\$61,371)	\$19,668	\$26,412	(\$122,984)
(2.49+15% incentive)	S.D.	\$26,577	\$23,209	\$22,774	\$25,113	\$25,290	\$20,444
	Risk of loss	1%	96%	100%	21%	15%	100%
1.99 (\$/Wdc)	Mean NPV	\$93,776	(\$9,226)	(\$30,740)	\$50,386	\$57,362	(\$92,188)
(2.49+20% incentive)	S.D.	\$26,747	\$23,508	\$22,683	\$25,343	\$25,635	\$20,707
	Risk of loss	0%	66%	91%	2%	1%	100%
1.87 (\$/Wdc)	Mean NPV	\$124,017	\$21,188	(\$247)	\$81,452	\$88,097	(\$61,219)
(2.49+25% incentive)	S.D.	\$26,442	\$23,066	\$22,445	\$25,675	\$25,470	\$20,379
	Risk of loss	0%	18%	51%	0%	0%	100%
1.87 (\$/Wdc)	Mean NPV	\$93,640	(\$5,341)	(\$25,607)	\$52,572	\$59,503	(\$84,566)
(2.49+25% incentive)	S.D.	\$25,720	\$22,951	\$21,845	\$24,465	\$24,538	\$19,913
(-10% energy price by 2050)	Risk of loss	0%	60%	88%	2%	1%	100%
1.87 (\$/Wdc)	Mean NPV	\$155,201	\$47,524	\$25,934	\$109,623	\$116,877	(\$37,723)
(2.49+25% incentive)	S.D.	\$27,915	\$24,127	\$24,443	\$25,972	\$26,570	\$21,289
(+10% energy price by 2050)	Risk of loss	0%	2%	13.68%	0%	0%	96%
1.74 (\$/Wdc)	Mean NPV	\$155,324	\$51,938	\$31,159	\$112,048	\$90,813	(\$30,365)
(2.49+30% incentive)	S.D.	\$26,724	\$23,208	\$22,583	\$25,522	\$26,935	\$20,694
	Risk of loss	0%	1%	8%	0%	0%	93%
1.62 (\$/Wdc)	Mean NPV	\$186,291	\$82,995	\$61,682	\$142,680	\$149,734	\$497
(2.49+35% incentive)	S.D.	\$27,014	\$23,165	\$22,571	\$25,264	\$25,488	\$20,485
	Risk of loss	0%	0%	0%	0%	0%	50%
1.49 (\$/Wdc)	Mean NPV	\$216,827	\$113,598	\$92,457	\$173,709	\$180,426	\$31,109
(2.49+40% incentive)	S.D.	\$26,613	\$23,438	\$22,347	\$25,239	\$25,499	\$20,566
	Risk of loss	0%	0%	0%	0%	0%	6.31%
1.37 (\$/Wdc)	Mean NPV	\$247,893	\$144,586	\$123,280	\$204,108	\$211,022	\$62,421
(2.49+45% incentive)	S.D.	\$26,756	\$23,318	\$22,590	\$25,804	\$25,459	\$21,032
	Risk of loss	0%	0%	0%	0%	0%	0%

5. Discussion

5.1. Key results and comparison with previous research

Based on the 30-year discounted cash-flow analysis, the net present cost of the implementation of rooftop residential solar systems to achieve zero-energy LIHTC apartments in Virginia can be lower than the discounted present cost of energy of otherwise identical apartments that have no renewable energy generation systems, and the value of cost savings can be statistically significant. The investment value often depends on the zero-energy building definition, weather characteristics,

retail price of electricity, and incentive rate. The DOE's definition of zero-energy building implies that these buildings should progress the restoration of the 32.31 percent loss (based on data from the 2010s) to the infrastructure system. A potential problem with this requirement in Virginia, where the solar potential is lower than that of states located in the South East, South West, and West regions, is not financial viability but the need for extra installation space. The analysis presented here relaxes this specification to minimize the required module area. According to the SAM analysis, each PV module should increase by 50% in size to fully restore the source energy loss, which equals to an increase from 1,680 sm (~18,083 sf) to 2,520 sm (~27,125.1 sf) in total solar array installation area, whereas the total usable rooftop area of the building is approximately 2500 sm (~26,900 sf) in the best-case scenario. Offsetting the total load of common areas, if included in the analysis, would require an additional 350 sm (~3,767 sf) rooftop space. In areas where the combination of high solar potential and price of energy exists, an increase in the array size can increase the investment's net present value. Therefore, it is feasible to fully offset the annual load of the entire building, but achieving the DOE definition of zero-energy building requires project designers to consider the spatial needs of solar PV systems at the conceptual design stage.

Although zero-energy LIHTC buildings can be more cost-effective than otherwise identical LIHTC buildings in the long run, the costs associated with PV systems are not evenly distributed in the state, leaving some areas like the Southeast more receptive to adoption of distributed generation systems than others like the Southwest. Differences in solar radiation, ambient temperature, energy prices, and diminishing prospects of the federal solar tax credit can affect consumers' willingness to invest in PV systems. Analyzing these variations and the significance of carbon emissions avoided as a result of renewable energy generation is a key to support the

construction industry in bridging the gap to zero-energy buildings, particularly in low-income housing.

Achieving annual balance of primary energy is a required step toward performance improvement, but zero-energy LIHTC design and upgrade considerations can include an optimized combination of power storage systems, mechanical and electrical operation control systems, and additional energy-efficiency measures that help buildings achieve balance in all individual months, reduce stress on existing power infrastructure, reduce greenhouse gas emissions, and increase the building's economic value [64,65]. The analysis of HERS score presented here suggests that further reductions in the embodied energy are achievable by applying construction methods, systems, and components that are more energy-efficient than conventional ones. Virginia's solar potential is not as abundant as that of other US states located at lower latitudes, and achieving a cost-effective balance that compensates for losses in primary to final energy conversion may not be widely implemented soon using distributed generation but the potential to reduce energy demand by improving design and construction standards exists.

5.2. Zero-energy LIHTC opportunities and barriers

Until recently, variability in net-metering agreements across utilities created barriers to the adoption of zero-energy LIHTC development. For example, a developer would have to analyze energy consumption rates (\$/kWh) and a different rate for producing and selling excess kWh to the local utilities. Utilities would charge \$0.11/kWh for consumption, and only pay \$0.05/kWh for excess generation. The difference between consumption and generation rates disincentivizes solar PV in housing and general market confusion. Following a 2015 change to Virginia law (Virginia Code §56-594) investor-owned utilities like Dominion and Appalachian Power and cooperatives compensate customers at one-to-one retail rate with a system size limit of 1,000 kW. In addition,

Many state codes (including Virginia Code § 58.1-3661) now allow localities to offer property tax exemption on solar energy equipment for a certain number of years. State, municipalities, utility companies, or other organizations willing to promote solar energy have offered limited-time rebates that can help significantly reduce installation costs. Other than direct federal, state, and local incentives, potential mechanisms to increase low-income citizens' access to renewable energy include loan loss reserve, on-bill financing or recovery, and revised underwriting criteria [66].

In 2019, the General Assembly of Virginia approved the Low-to-Moderate Income Solar Loan and Rebate Fund to provide a solar financing platform for solar installations or energy efficiency improvements specific to residents with household income at or below 80 percent of the state or regional median income. Other recent legislative developments in the state include House bill HB 572 Distributed renewable energy sales of electricity under third-party agreements and Senate bill SB 629 Shared solar programs, which promote the establishment of distributed renewable energy and allow customers to purchase electric power through a subscription in a shared solar facility. The Low-Income Energy Affordability Data (LEAD) Tool (www.energy.gov/eere/slsc/maps/lead-tool) and the Database of State Incentives for Renewables & Efficiency (DSIRE) (www.dsireusa.org) provide data and information on low- and moderate-income renewable energy policy in the US [67].

Despite significant decreases in total installation costs and increases in emerging opportunities for residential systems, barriers to zero-energy LIHTC deployment persist. Existing multifamily buildings have limited operating reserves, lack proper orientation or rooftop space to maximize energy generation, and are in need of roof repair and replacement, thus, making it difficult for owners and operators to allocate sufficient funding for direct financing and installation of solar

systems outside the already established 15-year operation and maintenance cash-flow schedules. Energy storage systems could increase the potential value of residential systems at the building level (e.g., through allowing for back-up power in the event of a grid outage and reducing residential demand charges through load shifting) and at the grid level (e.g., allowing for voltage and frequency regulation, deferred infrastructure investment, and resource adequacy) [52]. Nonetheless, PV-plus-storage systems are still expensive to purchase, the permitting process for installing and operating storage devices are complicated, and the interconnection and net metering is complex and costly. Finally, the lack of longitudinal performance data and regulatory nature of state QAPs creates uncertainty for developers and limits their willingness to test innovative technologies and approaches toward zero-energy LIHTC developments.

5.3. Recommendations

Beyond variability in consumption and generation rates, metering infrastructure, (e.g., sub or master-metered), impacts the value of investment in zero-energy LIHTC developments. In submetered developments each apartment's utility usage is measured individually and tenants pay through accounts they themselves establish with utility companies ([Figure 9a](#)). In master-metered developments ([Figure 9b](#)) the owner pays for all the utility costs and passes the costs on to individual tenants within their rent costs [65]. Within each LIHTC application, the developer identifies if the utilities will be master or sub-metered. There is little incentive to invest in energy-efficiency and renewable energy systems in master-metered developments since the developers cannot distribute additional costs on tenant rents due to the competitive nature of many rental assistance or housing production programs.

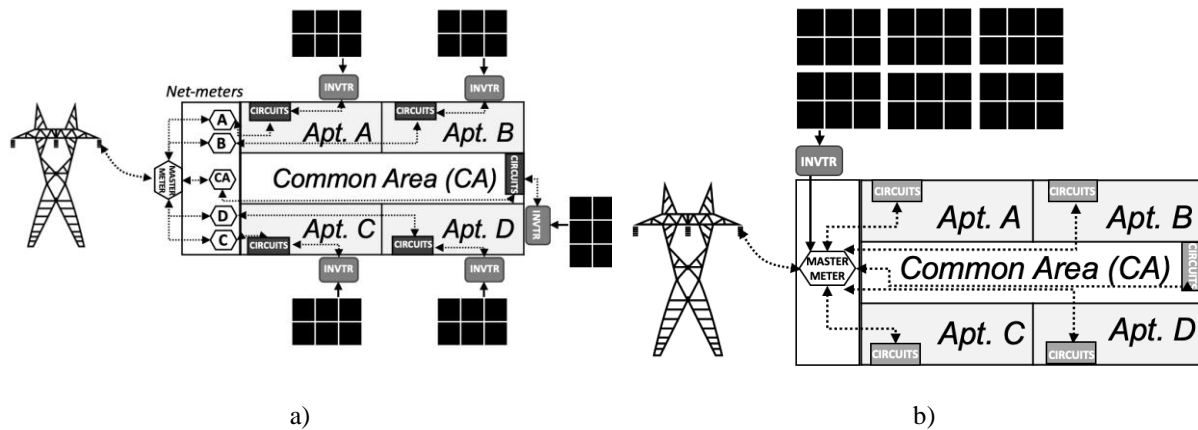


Figure 9 Common zero-energy LIHTC metering approaches a) sub-metered approach b) master metered approach

Submetering may to some extent address the so-called “split-incentive” problem in energy-efficiency transactions, at least by allowing individual residents to control the use of energy. In many cases, developers are allowed to sub-meter common areas at commercial rates, which helps reduce costs of operation and maintenance but decreases the value of investment in renewable energy systems for common areas. Therefore, variations in metering infrastructure and rates and the resulting effects should be considered in the financial analysis of individual zero-energy LIHTC buildings. In practice, housing programs have started to increase incentives where developers can demonstrate that tenants can benefit from energy-efficiency or renewable energy generation systems [65].

It is recommended that state housing finance agencies evaluate new methods for metering developments. For example, in addition to a single utility provided master meter, zero-energy LIHTC developments can employ Circuit-level Owner Metering (Figure 10) to better manage development performance. The approach provides real-time, high-resolution data on unit-level and circuit-level energy consumption, as well as solar system performance. Extant research suggests occupants are generally poor at managing systems with lags in information and delayed evaluation loops [68]. Current utility-provided metering technologies fail to provide customers with data that

is usable or timely in managing system performance, improving occupant experiences, or meeting zero-energy goals. With this approach, developers install metering hardware in each apartment's circuit panel and measure energy use in 1-second intervals. The accompanying software allows easy analysis of performance at circuit, unit, and development levels and could be leveraged for predictive analytics (e.g., identifying HVAC system maintenance issues before they occur). Circuit-level meters are commercially available starting at ~\$300 per system and have been employed in pilot zero-energy developments [69].

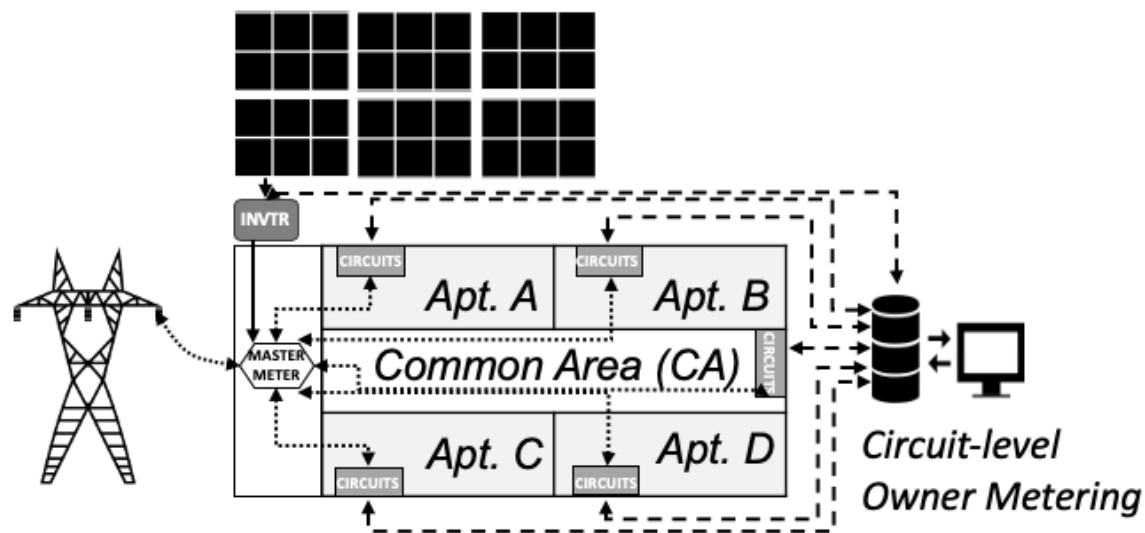


Figure 10 Circuit-level Owner Metering

The authors also recommend analyzing the net present values of incentivizing distributed generation using PV systems for specific stakeholders, such as private sector interests, the economy, and the government budget. Incentivizing PV systems should include an analysis of state-wide variations in solar radiation as QAP selection criteria and allocate additional scores for developments located in climatic divisions with less-than-average solar potential. Since the existing federal solar tax credit is expected to gradually decrease in the coming years, it is essential

for housing agencies to identify financing mechanisms that help fill the gap to maintain the feasibility of zero-energy LIHTC developments in the 2020s.

As evidenced by past research and the energy use data analysis presented here, a significant part of variability in energy consumption is attributable to human-building interaction. Since the extra spending on utilities impacts housing affordability and economic well-being of low-income residents, empowering final users to have an active role in reducing energy consumption, particularly for heating and cooling purposes, is becoming increasingly important [70]. Such activities can be included in the state's free energy efficiency and appliance testing and repair services that help create energy savings by reducing energy bills for qualified low-income, elderly, and disabled residents in rental and owner-occupied houses [71]. To further reduce energy demand, architects and engineers can design zero-energy LIHTC projects to maximize energy-efficiency and include monitoring and control technologies that reduce user-imposed inefficiencies and contribute to cost-effective operation of new or existing buildings [72,73].

6. Conclusion

This study investigated the feasibility of state-wide zero-energy affordable housing by analyzing historical data on climate, energy use, and energy system costs in the Commonwealth of Virginia, US. Addressing the knowledge gap in the literature on solar panel adoption in low-income housing, the study contributes to the body of knowledge through the examination of generalizable statistical energy load prediction methods and simulation-based risk analysis, which have essential applications in planning and policy analysis but are less explored in existing feasibility studies. The study suggests that, in most areas in Virginia, the net present life-cycle cost of the implementation of rooftop residential solar systems to achieve zero-energy LIHTC buildings is currently lower than the discounted present cost of energy of otherwise identical conventional

buildings that have no renewable energy generation systems, and the value of cost savings is statistically significant. The annual electricity generated using the PV system in the 60-unit zero-energy LIHTC study case is ~146,060 kWh/yr. The greenhouse gas emissions avoided by the PV system per year is equivalent to ~103 metric tons of carbon dioxide. This avoided carbon dioxide in 30 years amounts to nearly 348,600 gallons burnt of gasoline or 7,687,620 miles driven by an average passenger vehicle, suggesting the presence of great potentials for emission reductions, thus, contributing to economic, environmental, and equity effects in Virginia through promoting zero-energy LIHTC developments in the 2020s [74]. Based on the presented analysis, conventional LIHTC apartments built in the 2010s, which are more energy-efficient than those included in the study sample, can be converted to zero-energy with potentially higher than currently estimated investment rates of return. Since buildings represent nearly 40 percent of global energy use and 30 percent of global greenhouse gas emissions, investments in distributed renewable energy generation in buildings can significantly enhance environmental sustainability and climate change mitigation and, concurrently, address housing affordability and economic development.

Appendix

Table A1 Simple regression model of electricity price (Obs = 29, Adjusted R² = 0.8472, Root MSE = 0.63732)

	Coef.	Std. Err.	t	P>t	[95% C.I.]	[95% C.I.]
Year	0.1768079	.0141452	12.50	0.000	0.1477843	0.2058315
_cons	-345.3468	28.34729	-12.18	0.000	-403.5106	-287.1829

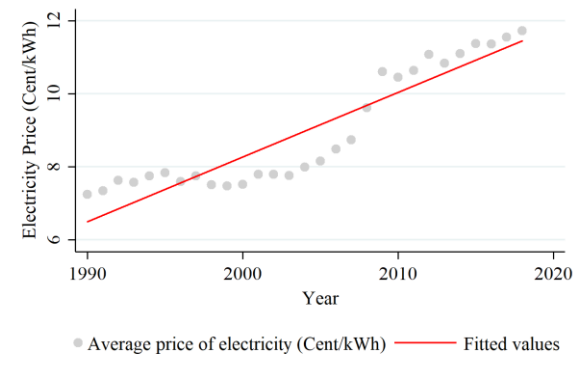


Figure A1 Average retail price of electricity for residential use in Virginia

Table A2 Predicted mean loads (kWh/Month)

Time	Richmond, VA	S.E.	Norfolk (D1)	Lynchburg (D3)	Fairfax (D4)	Staunton (D5)	Norton (D6)
January	784.37	15.74	716.24	822.99	901.54	931.70	894.59
February	741.40	15.75	692.20	778.87	855.24	885.69	832.99
March	612.04	15.77	577.28	637.27	733.31	755.20	692.89
April	428.81	15.78	416.24	456.37	559.72	584.85	519.60
May	393.46	14.28	408.97	368.13	422.93	392.95	362.44
June	428.98	14.58	461.29	367.54	327.77	252.84	267.40
July	472.89	14.60	515.78	413.15	394.52	299.29	293.97
August	449.54	14.61	511.54	383.82	363.94	270.93	288.46
September	401.45	14.63	463.90	343.02	345.25	295.29	265.85
October	403.62	14.62	366.13	441.58	504.06	564.24	503.14
November	510.55	14.60	449.84	559.66	596.18	652.10	626.66
December	649.87	14.60	580.72	695.04	757.63	795.24	743.75
Year (2013)	6276.97		6160.14	6267.45	6762.10	6680.31	6291.73

Table A3 Sensitivity of simulated project NPV to installation cost and price of exported energy in Richmond, VA

Cost (\$/Wdc)		Exported to Delivered Electricity Price Ratio					
		0%	20%	40%	60%	80%	100%
2.12 (2.49+15% incentive)	Mean NPV	(\$132,499)	(\$114,213)	(\$96,261)	(\$77,642)	(\$58,448)	(\$40,799)
	S.D.	\$191,374	\$152,437	\$116,473	\$78,414	\$43,808	\$23,209
	Risk of loss	75%	77%	79%	84%	91%	96%
1.99 (2.49+20% incentive)	Mean NPV	(\$103,656)	(\$82,006)	(\$66,450)	(\$47,615)	(\$28,267)	(\$9,226)
	S.D.	\$191,102	\$154,361	\$115,272	\$78,914	\$44,466	\$23,508
	Risk of loss	71%	71%	72%	73%	74%	66%
1.87 (2.49+25% incentive)	Mean NPV	(\$71,024)	(\$53,955)	(\$35,649)	(\$15,155)	\$2,279	\$21,188
	S.D.	\$190,222	\$154,821	\$114,549	\$78,962	\$43,783	\$23,066
	Risk of loss	65%	64%	62%	59%	49%	18%
1.74 (2.49+30% incentive)	Mean NPV	(\$41,370)	(\$21,838)	(\$4,083)	\$15,337	\$33,124	\$51,938
	S.D.	\$190,301	\$152,956	\$115,881	\$78,665	\$43,984	\$23,208
	Risk of loss	59%	56%	51%	42%	23%	1%
1.62 (2.49+35% incentive)	Mean NPV	(\$10,178)	\$9,108	\$25,688	\$45,307	\$64,358	\$82,995
	S.D.	\$189,545	\$153,202	\$115,841	\$78,288	\$43,912	\$23,165
	Risk of loss	53%	48%	42%	28%	7%	0%
1.49 (2.49+40% incentive)	Mean NPV	\$20,340	\$38,983	\$57,007	\$76,358	\$95,240	\$113,598
	S.D.	\$191,897	\$152,561	\$115,212	\$77,602	\$43,804	\$23,438
	Risk of loss	46%	39%	32%	17%	1%	0%
1.25 (2.49+45% incentive)	Mean NPV	\$51,865	\$70,815	\$88,607	\$106,372	\$125,677	\$144,586
	S.D.	\$189,706	\$152,961	\$113,422	\$78,565	\$44,123	\$23,318
	Risk of loss	39%	32%	22%	9%	0%	0%

Table A4 Two-sample t test with equal variances for Richmond, VA at 26 percent incentive

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
Conventional	15,000	30726.21	77.67104	9512.721	30573.97 30878.46
Zero Energy	15,000	29382.93	77.59321	9503.188	29230.83 29535.02
diff		1343.286	109.7884		1128.096 1558.476
Ho: diff = 0					t = 12.2352
Ha: diff != 0					df = 29998

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