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Spatial Energy Efficiency Patterns in New York and Implications for Energy Demand and the Rebound Effect

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Abstract
This study uses a spatial Durbin error model (SDEM) approach to analyze adoption trends for residential energy-efficiency measures (EEMs) in New York state. Model results are based on socioeconomic, building, and house-hold demographic characteristics during the 2012–2016 period. Our study's results confirm that a positive correlation exists between EEM uptake and multifamily buildings, gas-heated homes, education effects, and spatial spil-lover effects among neighboring ZIP codes. The results show that building attributes hold a relatively high explanatory power over EEM adoption compared with socioeconomic characteristics. Our results show that energy-efficiency policies can create positive and significant neighborly effects in promoting EEM adoption. The developed SDEM methodological framework provides useful insights in identifying energy-efficiency opportu-nities that exist in rural, suburban, and urban communities, highlighting the need to review policy incentives periodically to address underlying changes in the built environment and spatial disparities in energy-efficiency investments.

Keywords
Energy efficiency, spatial spillover effects, spatial Durbin modeling, neighborly emulation, rebound effects, New York, energy-efficiency measures

Introduction

Climate change and the confluence of forecasted long-term increases in fossil fuel prices with greater opportunities for deploying low-carbon technologies have made the expeditious transition to an energy-efficient future an at tractive ch oice (G raziano, F iaschetti, an d At kinson-Palombo 2019; Kanger et al. 2019; Nyangon 2021). New investments in cities have focused on designing smart, polycentric energy frameworks (Nyangon 2021), including transportation-as-a-service and associated business model innovations that promote electric vehicles (EVs), car-sharing, ride-sharing, and using the urban fabric for "solar city" development (Byrne and Taminiau 2018). In the residential building sector, which consumes nearly 39% of electricity in the United States (EIA 2020), growth in energy retrofits and r apid a doption o f energy-efficient household app liances are ris ing to red uce energy demand and achieve climate-related goals (Douthat et al. 2020). However, most studies to date that have considered links between climate change, energy prices, and low-carbon technologies have focused on either adoption rates based on expectations of future electricity demand changes, or socially incremental choices that are driving the energy transition process, often in terms of consumer behavior or energy consumption patterns (Heijden 2017). An overlooked critical area is how and where these technologies diffuse across s pace b ased o n t he p erformance o f e nergy efficiency (EE) policies or complementarities across policy mixes to achieve direct, measurable benefits (Trencher and van der Heijden 2019). Spatial sensitivity is an essential variable in analyzing technology- or sector-specific EE policies to promote efficient buildings. The National Renewable Energy Laboratory, under the U.S. Department of Energy's Office of Energy Efficiency & Renewable Energy, agrees with this view (Wilson et al. 2017). To address the neglected role of spatial sensitivity, we developed a model that includes standard explanatory variables – including socioeconomic characteristics, building attributes, dwellings' characteristics, and households' attitudes and behavior (Bertoldi and Mosconi 2020; Douthat et al. 2020) – that influence the adoption and diffusion of these energy-efficiency measures (EEMs) in existing households (Spyridaki et al. 2020).

For New York state, which has the fourth-highest share of residential electricity consumption in the United States – nearly 3.9%, behind only Texas (10.8%), California (6.9), and Florida (6.3%) – identifying local spatial conditions' influence on the uptake of energy-efficient technologies by homeowners can support the diffusion of EEMs, particularly in lower-income households (i.e., technology diffusion) (EIA 2020). Applying a spatial perspective approach provides geographically rich insights for understanding changing socio-technical factors and the preferences for technology adoption that underlie these shifts. Whether electricity-powered appliances, space heating, and cooling appliances, or domestic water heaters, innovation and investment in energy-efficient technologies reduce energy use and carbon emissions. Energy consumption differs across building stocks and locations, and accounting for these geographical variations is vital to formulating effective EE policies to improve building energy performance measurement (Papadopoulos and Kontokosta 2019) and scale up deep energy retrofits that holistically address a combination of heating, cooling, and the building envelope.

Herein lies the growing strategic challenge for utility program facilitators and policymakers: Why does EEM adoption happen in one location or dwelling type and not another? Do geographical or local differences in socioeconomic and building characteristics matter in explaining the scale, pace, and outcome of EE diffusion? If so, which ones exert the most explanatory power? Pang et al. (2020), Wilson et al. (2019), Nyangon (2017), and Granade et al. (2009) go further by examining EE opportunities' huge, untapped potential in the residential sector, as well as available policy support programs, to foster the uptake of EE technologies. Such measures include regulations such as minimum energy performance requirements, building codes and standards, information programs (e.g., energy labeling), and financial support for EE programs, such as subsidies, tax rebates for replacing less-efficient appliances, etc. (Douthat et al. 2020; Safarzadeh and Rasti-Barzoki 2019; Spyridaki et al. 2020). Characterizing the geographical elements of the scale, pace, and patterns in the adoption of these EEMs requires a detailed spatial accounting of the building envelope and the dwellings' characteristics. For example, using spatially distributed energy demand information, homeowners can access the right financial and business models for EE retrofits, leading to improved project bankability (i.e., the ability to access project financing from banking institutions) and EE investment decisions. Statistically, decomposing the ZIP-code-level dataset to demonstrate EE programs' adoption trends is one of the best methods with which to create and evaluate a spatially resolved set of variables and encourage energy consumers to double down on all EEMs' adoption, diffusion, and innovation progress.

However, considering the aforementioned aspects, EE upgrades of conventional appliances and existing households through adoption of energy-efficient systems not only result in reduced energy demand, but also might elicit undesirable effects, thereby reducing the benefits from the efficiency improvements (Safarzadeh and Rasti-Barzoki 2019). Furthermore, these effects could elicit "rebound effects," (Seebauer 2018). Typically, the energy rebound encourages homeowners to use more energy and generally is divided into direct and indirect effects. Furthermore, these effects can be investigated from the consumer side (i.e., technological efficiency improvements associated with new electrical appliances) or producer side (i.e., the backfire or "Jevons paradox" effect resulting from technological efficiency improvements made to production processes) (Sorrell 2009). The energy rebound, as a behavioral reaction discussed in this article, considers the consumer side of household energy consumption.

This study uses a spatial Durbin error model (SDEM) approach to test how local residential EE-relevant indicators – including households' socioeconomic characteristics, buildings' characteristics, households' attitudes, consumer behavior, and knowledge about consumers' energy use

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and spending that influence the adoption of EE technologies – can help policymakers understand the spatial diffusion of EEMs, energy demand, and rebound effects. Our study analyzes geographical variations in EE development in New York state during the 2012–2016 period to determine which factors exerted the most impact on spatial diffusion of New York's Energy Efficiency Portfolio Standard (EEPS) policy. We developed a spatial regression model to analyze the identified indicators to understand their statistical significance in predicting observed spatial variation in EEPS policy diffusion. In doing so, this study aims to complement other results that demonstrate how spatial processes influence energy-efficiency policy performance. The article is organized as follows: Section 2 introduces EE policies' spatial proximity perspectives and contrasts them with other mainstream approaches. Section 3 reviews the EEPS policy directive and discusses in detail the methodology and performance indicators employed in this spatial analysis. Section 4 presents the study's results and a discussion of our key findings. Finally, Section 5 offers a perspective on the policy implications and significance of spatial heterogeneity in relation to energy demand and energy rebound in relation to EEM diffusion.

2. Background and literature review

2.1. Spatial perspectives on energy-efficiency policy implementation

This article draws from extensive extant literature on adoption and diffusion of EEMs and EE technologies that consider energy policies and just transitions (Day, Walker, and Simcock 2016; Lele et al. 2019; Meyers and Hu 2001); interlinkages between building regulations, economic structures, and business model innovations (Dormady et al. 2019; Nyangon and Byrne 2018; Zabaloy, Recalde, and Guzowski 2019); and minimum energy performance standards and building codes (Chung 2011; Geels et al. 2018; Li et al. 2019; Papadopoulos, Bonczak, and Kontokosta 2018; Zou, Wagle, and Alam 2019). However, this is one of only a few papers that accounts for spatial dimensions at the ZIP-code level from the perspective of EEM adoption and EE policy diffusion. One of the earliest reviews of building energy performance found that benchmarking results can be used to foster uptake of EEM opportunities (Chung 2011). A more recent study that examined impacts from information asymmetry found that lack of information, as well as households' knowledge about energy consumption and adoption decisions, can limit uptake of EEMs (Liu, Yao, and Wei 2019). However, what these studies lack is geographically resolved ZIP-code-level data on EEM adoption that captures impacts from socioeconomic characteristics and the built environment. Graziano, Fiaschetti, and Atkinson-Palombo (2019) noted that the lack of a rich data set that accounts for the built environment's impact at multiple levels is a recurring problem in the EE marketplace, including the building of energy management and automation systems.

More recently, attempts to account for geographical insights relevant to EE technology diffusion and EEM adoption in the residential sector have focused on identifying and quantifying sustainability metrics on local conditions. Using statistically decomposed ZIP-code-level electricity and fuel consumption data from the New York City Mayor's Office of Long-Term Planning and Sustainability, Howard et al. (2012) estimated end-use energy consumption in New York City. However, this study did not demonstrate how trends in energy consumption can be linked to specific EEM or EE retrofit options and physical processes in a residential building. Bridge et al. (2013) showed that energy infrastructure systems are situated spatially (e.g., space heaters and coolers, domestic water heaters, and electricity-powered applications are embedded in a particular geographical setting). Thus, geographical processes (e.g., landscape, location, spatial differentiation, scaling, spatial embeddedness, and territoriality) can impact ongoing sustainability transition trajectories. Graziano and Gillingham (2015) showed that solar photovoltaic (PV) technologies' diffusion patterns are mediated by spatial and socioeconomic factors in the built environment, with the spatial neighborly effect from nearby systems diminishing with distance and time.

The benefits from explicitly (and spatially) accounting for the built environment and its different asset classes are underscored further by Urquizo, Calderón, and James (2018). Using more recent results, they showed that district heating (decentralized energy supply) and group heating networks make a considerable impact on spatial patterns of energy consumption. Common benefits from a spatially detailed approach include appropriately capturing and comparing local contexts, as well as linking observed trends in EEM patterns to specific retrofit options and physical processes in the building. For example, spatial differences reflect geographical variations in energy systems – such as energy generation, distribution, and demand patterns – as well as forms of EE upgrades and technologies. Papadopoulos and Kontokosta (2019), Papadopoulos, Bonczak, and Kontokosta (2018), and Graziano, Fiaschetti, and Atkinson-Palombo (2019) offered a similar perspective, noting that due to the built environment's spatial heterogeneity and demographic information, authorities should prioritize using local data on building characteristics and energy consumption patterns to evaluate unique local conditions with more spatially detailed outputs.

Additionally, by using artificial neural network algorithms to model geographical variations in occupancy patterns and habitual energy-use behavior, Wang et al. (2017) showed that spatially detailed outputs foster an accurate and more granular determination of occupancy detection in building energy management and adoption of EEM technologies. Policymakers designing policy support schemes to foster uptake of smart EE features could use insights from these detailed trends to upgrade local energy building codes and other regulations governing the built environment. However, analysis of the literature reveals some limitations. First, to date, most of these research efforts often are "geographically coarse" (Wilson et al. 2019) because they use data at an aggregated, large-area level, either on a national or regional scale, and few models have been employed to study ZIP-code-level data (Nemet et al. 2017). Considering that these studies often inform policymaking efforts, this limitation could lead to sub-optimal investments, as differences in building types between rural, suburban, and urban neighborhoods (e.g., electricity use in urban areas), as well as varying socioeconomic contexts, exert a large impact on policy diffusion. Second, these studies are based primarily on historical energy-savings data (Barbose et al. 2013; Bilgen and Sarıkaya 2016; Wilson et al. 2019). With recent innovations in EE technologies, policies, markets, and building design continuing to reshape the residential building sector, basing future trends in EE growth on only historical energy-savings is inherently inadequate and problematic.[1] Anderson et al. (2013) investigated opportunities for integrating EE technologies and solar PV systems in buildings, and found that as minimum energy codes continue to improve for new homes, and residential PV systems "begin to break the 3 USD/kW barrier that represents rough parity with the retail cost of residential electricity in many areas of the United States," zero-net energy communities will increase over time nationwide. Achieving this target requires bridging the gap between consumer choices and EE investment in research and development (R&D) (Michas et al. 2019).

2.2. Factors affecting residential EEMs and energy-saving behaviors

Socioeconomic, demographic, and dwelling characteristics influence residential end-users' adoption of EEMs (Bertoldi and Mosconi 2020; Douthat et al. 2020). Typical classification of these factors distinguishes between (1) households' socioeconomic contexts (e.g., age, employment, education, households' dwellers' knowledge about their energy spending and use, etc.); (2) building characteristics (e.g., type, age, tenure, size, etc.) and local environmental conditions (Chokhachian et al. 2020; Douthat et al. 2020; Papadopoulos, Bonczak, and Kontokosta 2018; Zabaloy, Recalde, and Guzowski

[1]These innovations include urban infrastructure development and land-use planning, EE policy and program design, improvement in market and regulatory environment, etc. For example, implementation of city-scale urban sustainability, should prioritize innovations targeting low-income households in driving EE investments, such as modal shifts that promote cost-effective EE technologies, on-site distributed electricity generation, subsidies supporting EE upgrades, improving building codes and standards, EE business model innovation, and strengthening partnership and collaboration with the building construction industry (Bertoldi and Mosconi 2020; Taminiau and Byrne 2020).

2019); (3) economic factors (e.g., high energy prices or constrained energy supply) (Matosović and Tomšić 2018; Nyangon, Byrne, and Taminiau 2017; Tsemekidi Tzeiranaki et al. 2019); and (4) policy and program design parameters (e.g., taxes and subsidies) (Seebauer 2018; Trencher and van der Heijden 2019).

Typical tools for promoting residential EE upgrades through the diffusion of EEMs include household equipment and appliance configurations, taxation, regulations, monetary incentive schemes, and information and education programs to raise awareness (Bertoldi and Mosconi 2020; Spyridaki et al. 2020; Trencher and van der Heijden 2019). Besides occupants' age and family profiles, living arrangements – such as single-family and/or married family with or without children – and household size variables often are considered. Katircioğlu (2014) assessed the relationship between energy consumption and household education levels, and found that awareness of energy use and knowledge about energy-saving opportunities were higher among college-educated households. Lundberg, Tang, and Attari (2019) reported similar findings by showing that support for EE standards and other factors – such as information awareness about a household's spending and energy consumption, building-labeling schemes, and energy audits and assessments – were correlated positively to education level.

The American Community Survey ACS (2020) and the American Housing Survey (AHS) classify dwelling types as detached, attached, duplex, or multifamily building stock. Seebauer (2018) found that those living in low-income and energy-poor single-family detached or terraced houses were more liable to practice energy-efficiency rebound behaviors, noting that habitual heating practices increase energy rebound. Papadopoulos, Bonczak, and Kontokosta (2018) similarly analyzed buildings with similar temporal energy performance patterns in New York City and found that large multifamily buildings had higher energy-use intensity, while those with higher unit density showed improved performance over time. However, residential buildings using fuel oil boilers had increasing energy-use intensity over time, further highlighting the education effect and need to address the inertia from deferred maintenance and replacement delays. With respect to tenure status and dwelling size, several features, including ownership patterns (e.g., owned outright and owned with mortgage status) and occupancy-related parameters (e.g., number of rooms, number of residents, and number of bedrooms) are employed often to evaluate the link between building characteristics and energy consumption, respectively (Chokhachian et al. 2020; Matosović and Tomšić 2018; Seebauer, Friesenecker, and Eisfeld 2019). Urquizo, Calderón, and James (2018) found that a dwelling characteristic, such as tenure, correlates strongly with the type of heating system used, with owner-occupied and social housing stock being the predominant tenures. Assessment of dwelling tenure typically focusses on market failures in EE investments, such as fragmented market structure, and split-incentive problems between a building's owner (who invests in an energy-efficient upgrade) and a tenant (who benefits from lower energy costs). Bednar, Reames, and Keoleian (2017) noted a statistically significant correlation between dwelling tenure and heating energy consumption. However, heating energy consumption was correlated negatively with the number of energy-burdened households experiencing economic poverty (Bohr and McCreery 2019). The number of bedrooms generally has a significant positive correlation with energy consumption and increases monotonically (Douthat et al. 2020), indicating that larger single-family households tend to consume more electricity. Moreover, the number of occupants is related to the number of rooms and, thus, square feet and energy consumption rate.

Besides socioeconomic and building characteristics, households' demographics (e.g., income levels, energy rates and policy factors (e.g., energy tax credits and subsidies) also are considered typically because (1) low energy prices may impact EE improvement rates negatively, and (2) higher-income households are associated with the propensity to invest in EEMs (Spyridaki et al. 2020). This phenomenon refers to "demand effect," as high-income households tend to have higher energy consumption and are more likely to invest in high-cost EE retrofit measures. Zabaloy, Recalde, and Guzowski (2019) found that EEM adoption varies regionally across residential households because it depends on income levels, energy prices, building characteristics, location, weather, energy access, energy resources' availability (e.g., natural gas, electric, oil, and kerosene central heating), equipment characteristics, and existing EE policies. Similarly, according to Fell, Li, and Paul (2014) personal incomes and residential electricity demand display relatively strong correlation coefficients, but price elasticity varies across different U.S. regions, with the Northeast being the least price-elastic region and the South displaying the most price elasticity. In contrast, a regression analysis by Yalcintas and Kaya (2017) found that electricity demand in Hawaii increased while electricity prices rose, provided that personal income grew at the same rate or higher.

2.3. The energy-efficiency portfolio standard

To examine spatial variability in EEM adoption, we selected the New York Energy Efficiency Portfolio Standard (EEPS) as a case study. EEPS energy-efficiency programs only recently have been adopted in the U.S., and New York, through the New York Public Service Commission (NYPSC), was one of the first states to implement it in June 2008 (NYPSC 2008). Our model (described in more detail below) shows how we can measure the spatial factors that influence statewide EEM diffusion and adoption. The EEPS pilot program's objective was to reduce the state's energy consumption by 15% by the year 2015, its end date (i.e., "15 x 15"), and specified both electric and natural gas consumption. The June 2008 order also required the state's utilities, the New York State Energy Research and Development Authority (NYSERDA), and other interested parties to submit all their energy-efficiency programs to the NYPSC for approval.

The EEPS' performance metrics increased across all electric and gas savings categories except for total net gas savings for electric programs, which fell sharply, nearly 109% from 2012 to 2013 (Table 1). The EEPS program addresses several foundational issues, including creating a three-year cycle target for energy savings and forecasting potential EE reductions for achieving the 15 × 15 directive. It also fast-tracks approval of EE programs for immediate implementation and directs investor-owned utilities (IOUs) in New York to develop a mechanism for collecting system benefits charges (SBCs)[2] from ratepayers to fund EEPS programs (NYPSC 2008). Berg et al. (2018) discussed the vision for New York's EE and clean energy development initiatives to include: (a) EmPOWER New York, a program administered by NYSERDA to support EE upgrades for low-income households (such as energy audits and replacing old appliances with newer and more efficient ones); (b) investing nearly 234.5 USD million from the Clean Energy Fund (CEF) in residential retrofits and low-income EE programs over the first three years of the CEF; and (c) reducing the energy burden for low-income households to no more than approximately 6% of household income. The historical and future efficiency savings in New York and EEPS progress, as a share of the 2015 target, are shown in Figure 1.

Table 1. EEPS cumulative electricity and gas savings and expenditures in New York, 2012–2016.

	Total electric savings acquired and committed		Total net gas savings acquired and committed		Total expenditures and encumbrances	
Year	for electric programs (TWh)	for gas programs (Billion BTU)	for Electric Programs (TWh)	for gas programs (Billion BTU)	for electric programs (Billion US$)	for gas programs (Billion US$)
2012[a]	4,226	11	663	8,124	0.829	0.252
2013[b]	5,504	16	(57)	12,997	0.827	0.295
2014[c]	7,083	26	(620)	17,594	1.467	0.558
2015[d]	8,110	32	(1,312)	20,324	1.716	0.670
2016[e]	8,119	33	(989)	19,886	1.716	0.677

Note: [a]12 gas programs reported ancillary electric savings while 14 electric programs reported ancillary gas savings in 2012; [b]13 gas programs reported ancillary electric savings while 14 electric programs reported ancillary gas savings in 2013; [c, d, e]14 gas programs reported ancillary electric savings while 15 electric programs reported ancillary gas savings in 2014, 2015, and 2016, respectively. All the reports did not include evaluation for the expenditures and encumbrances. Data Source: (NYPSC 2020b).

[2]The New York state's SBC programs are administered by NYSERDA, and collectively fall under New York Energy $mart[SM] public benefits program. The New York Energy $mart[SM] programs support an accelerated market penetration of energy-efficient technologies.

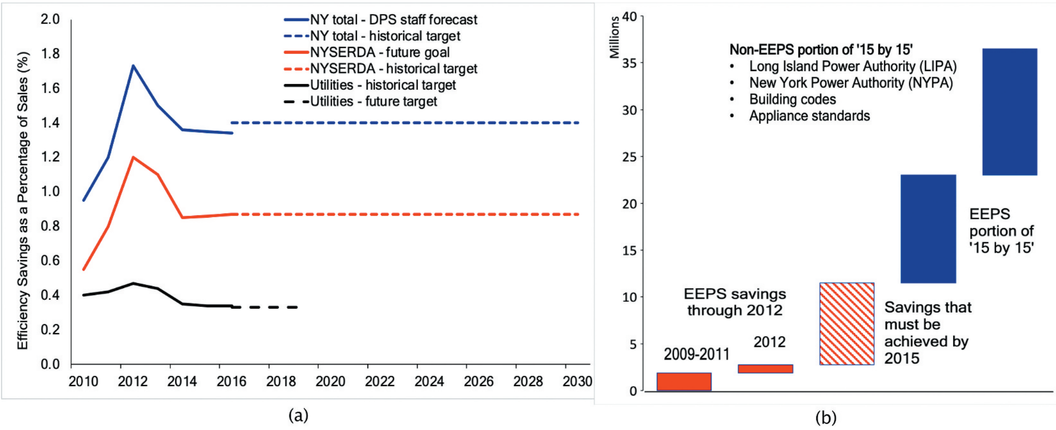

Figure 1. (a) Trends in New York energy-efficiency savings: historical targets and staff forecast. (b) EEPS progress as a share of the 2015 target. Sources: Woolf et al. (2016); Morris and Stutt (2013)

The research presented here focusses on EEM adoption during the EEPS policy implementation period from 2012 to 2016. Instead of renewing the targets when EEPS ended in 2015, NYPSC published a new framework under New York's Reforming Energy Vision (REV), which supported utility EE programs under EEPS to deliver more transformational EEM programs, with an emphasis on low- and moderate-income households. For this reason, this research covers utility EE programs under the EEPS 2008–2015 pilot period, which focused on "acquiring energy savings as a resource," and the first year under REV in 2016, which concentrated on "market transformation of energy-efficient" opportunities (Woolf et al. 2016). The implementation process of EEPS policy comprises four stages, shown in Table 2. This process addresses market barriers to EE development, such as access to capital, information asymmetry, high transaction costs, and institutional and regulatory impediments.

The NYPSC is required to establish a framework for conducting technical assessments and estimates of costs and energy-savings opportunities. For example, following the evaluation, the program administrator selects a balanced energy-efficiency portfolio for approval based on a set of measurement and verification metrics that result in the greatest savings during the relevant period. Expectations are that higher transparency around the approval process––anchored on the merits of the EE programs, not the proposing entity's identity––might spur investments in retrofitting and stimulate market demand for EEMs. In other words, energy auditing and retro-commissioning

Table 2. A programmatic perspective of the EEPS process.

1. Energy Efficiency Portfolio Standard Assessment
EEPS allocates (initial) energy efficiency target to jurisdictional service territories based upon sales. The EEM deemed most likely to be successful in individual service territories are assessed. NYPSC assesses if certain service territories can benefit more from the EE opportunities and, if so, the initial territorial assignments are altered to reflect those benefits.
2. Approval and Recommendation of EE Programs by NYPSC
NYPSC approves portfolio of proposed utility, NYSERDA, and other energy efficiency programs for each service territory based upon its assessment of each proposal measured by the measurement and verification protocol adopted by the Commission. The selected programs include "fast-track" Programs.
3. Energy Efficiency Portfolio Standard Selection Plan
For each program, EEPS efficiency targets are scrutinized based on: the total resource cost test's benefit-cost ratio, electric rate impact, electric rate impact per MWh saved, peak coincidence factor of MWh saved in 2015, number of participants as a percentage of the number of customers in the class as of 2015, and gas rate impact, gas rate impact per MBTU saved (levelized over the years through 2015).
4. Installation and Repayment
Certified utility installers undertake energy efficiency retrofits on a customer's premises and the customer pays its share of costs for the improvements through its utility bills, which are no higher than before the installation since the energy savings offset the capital costs. *EmPower NY* targets payment-troubled customers and help them to pay their utility bills.

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requirements are handled separately from installation, and program administrators do not influence funding allocations for energy-efficiency programs.

Our research uses EEPS assessments as a proxy for EEM adoption, i.e., initial EEPS savings achieved from the program's October 2008 inception through year-end 2011 ("EEPS 1") and 2012–2015 ("EEPS II"). Morris and Stutt (2012) evaluated EEPS 1 performance based on projected benefits that would be realized from its successful implementation and found that EEM adoption was slower than expected (see Table 3). Administrative delays in approval of EE proposals, competition for EE opportunities in the same market segments between NYSERDA and the IOUs, and a flawed approach to cost-effectiveness screening of EE projects contributed to this shortfall. Using data from the NYPSC's EEPS Electric Performance Summary website, Woolf et al. (2016) estimated the cost of electricity savings for the EEPS II programs at approximately 3.4 cents/kWh (i.e., levelized total cost of 3.4 cents per lifetime kWh saved). During the lifetime of the EEPS, nearly 9,870 assessments (electric and natural gas) were completed in New York state, covering 7,226,693 commercial, multifamily, and residential sectors. This equates to roughly 88% of the total building stock over the study period. Figure 2 shows the levelized cost of EE programs for different market segments and customer types.

Table 3. Estimated projected and actual electric savings and foregone benefits not realized by missing EEPS targets.

Benefits	Projected savings and associated benefits of EEPS 1	Actual savings and associated benefits of EEPS 1	Lost energy-saving opportunities
Electric savings	3,424,379 MWh	2,132,093 MWh	1,292,286 MWh
Directly avoided energy payments	$2.914 billion	$1.814 billion	$1.1 billion
Demand-Reduction-Induced Price Effect Savings (DRIPE) due to decreased statewide electricity demand	$897 million	$558 million	$338 million
Avoided capacity charges	$1.345 billion	$837 million	$508 million
Total energy savings ($)	$5.16 billion	$3.21 billion	$1.95 Billion
Jobs created	16,586	10,327	6,260

Data sources: NYPSC (2020a); Woolf et al. (2016)

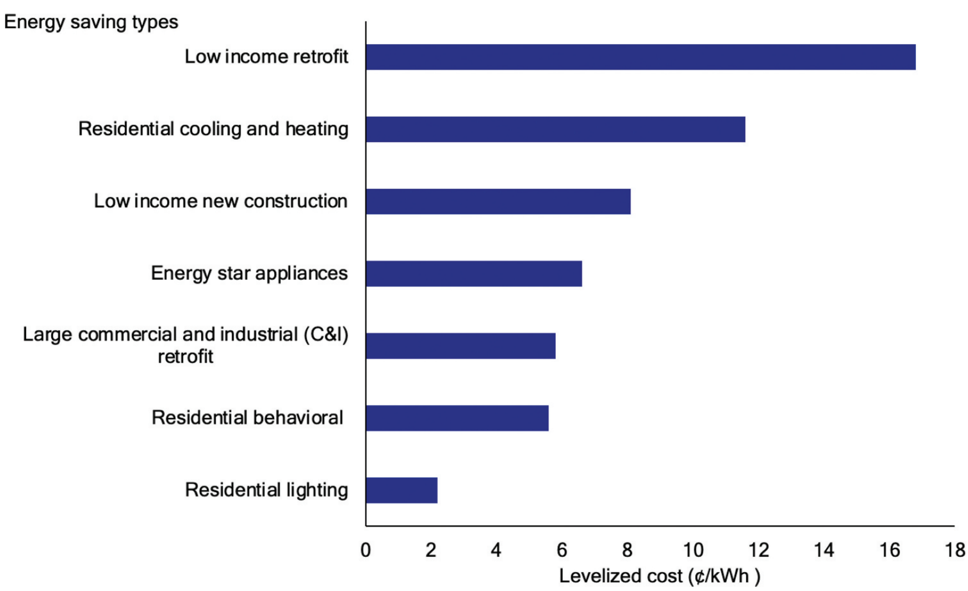

Figure 2. Levelized costs (c/kWh) of efficiency programs. Data source: (Woolf et al. 2016).

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3. Methods and data

3.1. Hypothesis and rationale for spatial diffusion of energy-efficiency variables

This study evaluates the spatial patterns of residential EEM diffusion and adoption in New York, focusing on five explanatory parameters: socioeconomic characteristics; building attributes and differences in their explanatory power of energy-saving opportunities; education effects; building heating types; and spatial spillover effects.

Our core hypothesis concerns:

- Spatial spillover effects: The diffusion of EEPS policy (and EEM adoption) in New York exhibits positive effects and "neighborly emulation" factors, implying that the uptake of energy efficiency retrofits in a particular local ZIP code is associated positively with rates observed in neighboring ZIP codes after accounting for technologies, policies, economics, socioeconomic contexts, and building stock.

3.2. Data sources

This article uses a highly geographically resolved, household-level data set from multiple sources. EEPS data were obtained from NYPSC and include monthly reports, program sectors (e.g., commercial, multifamily, and residential buildings), program types (monthly electricity and natural gas consumption), and program status (i.e., open or closed) (NYPSC, 2020a). These data were gathered from NYSERDA and major IOUs in New York, including ConEdison, Central Hudson Gas & Electric, Cascade Natural Gas, National Fuel, National Grid, New York State Electric & Gas, Orange and Rockland Utilities, and Rochester Gas & Electric. This data set covers a total of 9,870 EEPS 1 and EEPS II assessments from February 2010 to December 2015. This spatially explicit data set covers 1,483 ZIP codes, which equates to approximately 69% of the state's total ZIP codes. We also obtained data from building and socioeconomic variables covering New York State ZIP codes (NYSZCs) from the ACS database covering the period from January 2012 to December 2016 (ACS 2020; PolicyMap 2020). This data set contains the number of EEPS assessments, socioeconomic characteristics, building and dwelling characteristics, and EEM types, as detailed in Table 4. We processed and spatially joined this data set in PolicyMap to create a geo-referenced shapefile that contains detailed, geographically rich, ZIP-code-level energy consumption data (PolicyMap 2020).

3.3. Spatial analysis

Typically, the literature acknowledges three main methods that can be applied to examine energy consumption and EEM adoption patterns in buildings: regression analysis; neural networks; and decision trees (Tso and Yau 2007). However, while neural networks and decision trees perform better in different local settings, the three methods are not significantly different from each other. Thus, we used a multiple linear regression (MLR) approach, as applied in Howard et al. (2012), to study the uptake of energy-efficiency upgrades considered in this article. The Residential Energy Consumption Survey (RECS) has identified fuel types and end-uses, structural and geographic characteristics, appliances, electronics, lighting, space heating, air conditioning, water heating, household demographics, building unit size, and household energy insecurity as making a large impact on energy consumption (EIA 2020). In addition, we used various software tools to produce our statistical outputs, including Tableau for data visualization, GeoDa for analyzing spatial variance and autocorrelation and spatial weight construction (Anselin 1995), and the *GeoDa Regress* functionality (Anselin, Syabri, and Kho 2006) for spatial regression analysis.

Table 4. Descriptive statistics of variables related to socioeconomic, education, income, building, and energy-efficiency characteristics employed in our analysis (n = 1483).

Variables | *EEMs Adoptions*	Mean	S.D.	Min.	Max.
EEPS 1 and EEPS II (per 1000 household)[a]	4.87	6.87	0.038	42.78
Socioeconomic characteristics				
Family with children (%)[b]	40.27	9.13	7.87	95.69
Family without children (%)[b]	59.73	9.13	4.31	92.13
Married family with children (%)[b]	27.47	8.97	2.25	88.79
Single-headed family with children (%)[b]	12.80	7.81	0.77	54.17
Single female-headed family with children (%)[b]	9.21	6.77	0.00	48.82
3-person households (%)[b]	15.79	4.94	1.95	60.49
4-or-more person households (%)[b]	22.18	8.55	0.66	61.96
Education level				
No qualifications 25 years and over (%)[b]	3.97	3.79	0.00	28.11
High school diploma 25 years and over (%)[b]	89.11	6.80	51.17	100.00
Associate's degree 25 years and over (%)[b]	27.99	6.86	3.57	60.28
Bachelor's degree 25 years and over (%)[b]	16.58	8.24	0.97	53.78
Postgraduate degree 25 years and over (%)[b]	13.39	9.16	0.36	52.40
Doctorate 25 years and over (%)[b]	1.29	1.68	0.00	21.97
Energy tax credit				
Residential energy tax credit (%)[b]	1.68	1.39	0.00	5.83
Income level				
Median personal income ('000 $)[c]	79.30	34.38	20.96	250.00
Economic				
Family in poverty (%)[c]	9.00	7.72	0.00	49.44
Families with single female poverty (%)[c]	31.92	22.24	0.00	100.00
Families with one parent poverty (%)[c]	28.06	20.08	0.00	100.00
Building/dwelling characteristics				
Detached house (%)[c]	68.21	23.97	0.00	100.00
Attached house (%)[c]	3.18	5.51	0.00	73.91
Multifamily house (%)[c]	17.69	23.71	0.00	100.00
Duplexes (%)[c]	6.78	8.17	0.00	59.69
Tenure parameters				
Owned-outright (%)[c]	40.89	10.94	0.00	100.00
Number of owned mortgage [c]	1634.76	2056.79	0.00	15,649.00
Rent cost as percentage of income (%)[c]	31.22	7.88	10.00	50.00
Dwelling size				
Mean number of rooms[c]	2266.35	4807.62	0.00	32,060.00
Mean number of homeowners [c]	2606.67	3135.11	0.00	23,008.00
Mean number of bedrooms (3 bd and more)[c]	475.33	940.22	0.00	7366.00
Energy efficiency heating types				
Gas central heating (%)[a]	37.93	30.64	0.00	100.00
Electric central heating (%)[a]	10.38	9.48	0.00	83.95
Oil and kerosene central heating (%)[c]	30.86	22.62	0.00	95.13
Households using other energy heating sources[c]	160.67	183.94	0.00	2884.00
No central heating (%)[c]	0.42	0.79	0.00	7.04

[a]NYPSC (2020a)
[b]ACS (2020)
[c]PolicyMap (2020)

3.4. Spatial weights and autocorrelation

To evaluate the geographical patterns of EEM uptake distribution and statistically model their relationship to the underlying data sets, we applied a three-step spatial analysis. First, we examined spatial heterogeneity in EEPS adoption in New York by creating a series of choropleth maps to assess spatial resolution of EEPS uptake across NYSZCs between January 2012 and December 2015 (the full monthly data for EEPS 1 and EEPS 11 implementation periods) and 2016 – the first full year under the REV process. Following Haining (2010), we specified a spatial weight matrix to classify the NYSZCs (georeferenced data) based on their degree of connectivity with one another. Equation (1) shows the structural form of the standardized local spatial weight matrix, W, in which the elements W_{ij} of the matrix are the spatial weights. In addition, using

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the first-order queen contiguity approach, we defined the geographical units as neighbors (i.e., neighboring ZIP codes that share a point or line boundary) in the manner specified by Yang and Jensen (2015). Using the results from this stage, we calculated a spatially lagged variable of EEPS adoption across the 1,483 NYSZCs:

$$\mathrm{W} = \begin{bmatrix} \mathrm{W}_{11} & \mathrm{W}_{12} & \cdots & \mathrm{W}_{1\mathrm{n}} \\ \mathrm{W}_{21} & \mathrm{W}_{22} & \cdots & \mathrm{W}_{2\mathrm{n}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{W}_{\mathrm{n}1} & \mathrm{W}_{\mathrm{n}2} & \cdots & \mathrm{W}_{\mathrm{nn}} \end{bmatrix} = W_{ij} : i, j = 1, \ldots, n$$

$$\mathrm{W}_{\mathrm{ij}} = \begin{cases} 1, \text{ if spatial unit j and i are neighbors} \\ 0, \text{ if spatial unit j and i are not neighbors} \end{cases} \tag{1}$$

We then applied georeferenced spatial analysis, often referred to as spatial autocorrelation analysis, to analyze neighborly relationships between the observed values of various data sets across NYSZCs (Geels 2012; Getis and Ord 1992). This type of analysis is categorized by methods that focus on global or local effects. The local context investigates spatial autocorrelation for singular geographical units, while the global perspective considers all geographical units within a given region. To depict local and global locations of EEPS uptake clusters clearly, we applied two well-known spatial techniques: Anselin's cluster and outlier analysis, and an optimized Getis-Ord method (Anselin 1995; Getis and Ord 1992; Ord and Getis 1995). These methods have found extensive applications in various fields, e.g., evaluating distributed solar PV adoption (Graziano and Gillingham 2015), electric vehicles' demand (Morton et al. 2018), distribution of urban heat island effects (Shaker et al. 2019), and adoption of building EE policies (Kontokosta 2011). Having summarized the spatial structure in a spatial weight matrix, we used Moran's I to define the global spatial autocorrelation (Moran 1948).

The structural form of Moran's I is summarized in Equation (2), in which n is the number of points or spatial units, x is the observed values of the variable of interest (e.g., EEPS uptake per 1,000 households) in geographical units i and j, $\bar{x}$ is the mean of x, and w_{ij} is the spatial weight describing the adjacency, or distance, between the i-th and j-th point:

$$I = \left. \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \right) \left(\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=j}^{n}\left(x_i - \bar{x}\right)^2} \right) \tag{2}$$

When there is no spatial correlation, the expected value of Moran's I is given as

$$E(I) = \frac{1}{n-1} \tag{3}$$

The significance of Moran's I can be determined by calculating the variance of I and comparing the statistic with the standard normal distribution.

$$Z = \frac{I - E(I)}{Var\ (I)} \tag{4}$$

Assuming that the observed distribution of points is just one of the many possible patterns of n points, the variable is expressed as

$$var(I) = \left. \frac{nS_4 - S_3S_5}{(n-1)(n-2)(n-3)\ \left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2} \right) \tag{5}$$

in which

$$S_1 = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(w_{ij}+w_{ji}\right)^2}{2}\Bigg)$$

$$S_2 = \sum_{i=1}^{n}\ \sum_{i=1}^{n} w_{ij} + \sum_{j=1}^{n} w_{ji}\Bigg)^2$$

$$S_3 = \frac{n^{-1}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^4}{\left(n^{-1}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2\right)^2}$$

$$S_4 = \left(n^2-3n+3\right)S_1 - nS_2 + 3\Big(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\Big)^2$$

and

$$S_5 = S_1 - 2nS_1 = 6\Big(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\Big)^2$$

In practice, $Z \geq 2.0$ or $Z \leq -2.0$ (p-values $\leq$ 0.05) indicates significant spatial autocorrelation.

Following Anselin (1995), we developed local indicators of spatial association (LISA) by decomposing global statistics (e.g., Moran's I) in Equation (2) to create local Moran's I, which identifies the occurrence of local patterns. LISAs are useful in identifying spatial regimes, which may indicate the presence of spatial heterogeneity. They also can be applied to identify spatial clusters of values of a variable in each geographical area. We also examined the relationships between EEPS and EEM adoption, socioeconomic characteristics, and building stock. Finally, we specified the MLR models. The natural logarithms from both the dependent and explanatory variables were calculated for each MLR. For the final analysis, we specified an ordinary least squares (OLS) regression model as follows:

$$EEPS_{uptake} = \alpha + \beta_1 \mathrm{x}_1 + \beta_2 \mathrm{x}_2 + \varepsilon \tag{6}$$

For the uptake of EEMs and EEPS for a given ZIP code, α is a constant factor, β_1 are the coefficients associated with socioeconomic variables, x_1 are the observations of socioeconomic variables, β_2 are the coefficients associated with the building's explanatory variables, x_2 are the observations of building explanatory variables, and ε is the model residual. To obtain a more robust estimation, we eliminated the NYSZCs with incomplete data sets.

3.5. Spatial regression

To account for local or spatial spillover effects from neighboring NYSZCs, we introduced an endogenous spatial interaction effect by integrating spatially lagged variables into Equation (6) (Lesage and Pace 2009). The endogenous spatial interaction effect allows for examination of whether EEPS and EEM adoption in each ZIP code can be associated with the uptake of energy-efficiency measures observed in a neighboring ZIP code (Brännström, Trolldal, and Menke 2016). The estimated spatial model is reported in Equation (7):

$$EEPS_{uake} = \alpha + \beta \mathrm{x} + \rho W_{\mathrm{y}} + \theta W_x + \varepsilon \tag{7}$$

in which α is a constant factor, β is the coefficient for the explanatory variables, x is the observation of the explanatory variables, ρ represents a spatial interaction coefficient for the spatially lagged dependent variable, W_{y} represents observations of the spatially lagged dependent variable, W_x is a vector set of observations of the spatially lagged explanatory variables, θ is a vector of coefficients of the spatially lagged model explanatory variables, and ε is the model residual. Finally, although Zhou, Wang, and Cadenasso (2017) and Bell and Bockstael (2000) cautioned that spatial autocorrelation analysis may be less sensitive to the choice of the neighboring matrix, resulting in spurious inferential findings, few studies have attempted to correct the associated errors during parametric tests. Furthermore, this problem lies beyond this study's scope, so we followed the common practice of using spatially lagged analysis to examine the correlation between neighboring geographical units.

4. Results and Discussion

4.1. Spatial variation in EEPS adoption

Figure 3 illustrates the spatial dynamics of EEPS adoptions across NYSZCs between January 2012 and December 2016. A significant degree of geographical variability in EEPS/EEM diffusion was observed. The ZIP codes located in major cities contain a relatively high level of EEM adoption. Nearly 67% of the ZIP codes display the lowest level of EEM uptake, at 9.1 per 1000 households in December 2016. New York City, Buffalo, and Rochester have the highest rate of EEM adoption, at 36.4–45.5 per 1,000 households. As the implementation of EEPS policy progresses, the ZIP codes located in downstate regions (e.g., Hudson Valley, New York City, and Long Island), contain relatively higher adoption rates, especially those surrounding some of the large boroughs and counties (e.g., Kings, Queens, New York, Bronx, and Richmond) and counties (e.g., Erie, Monroe, Westchester, and Onondaga).

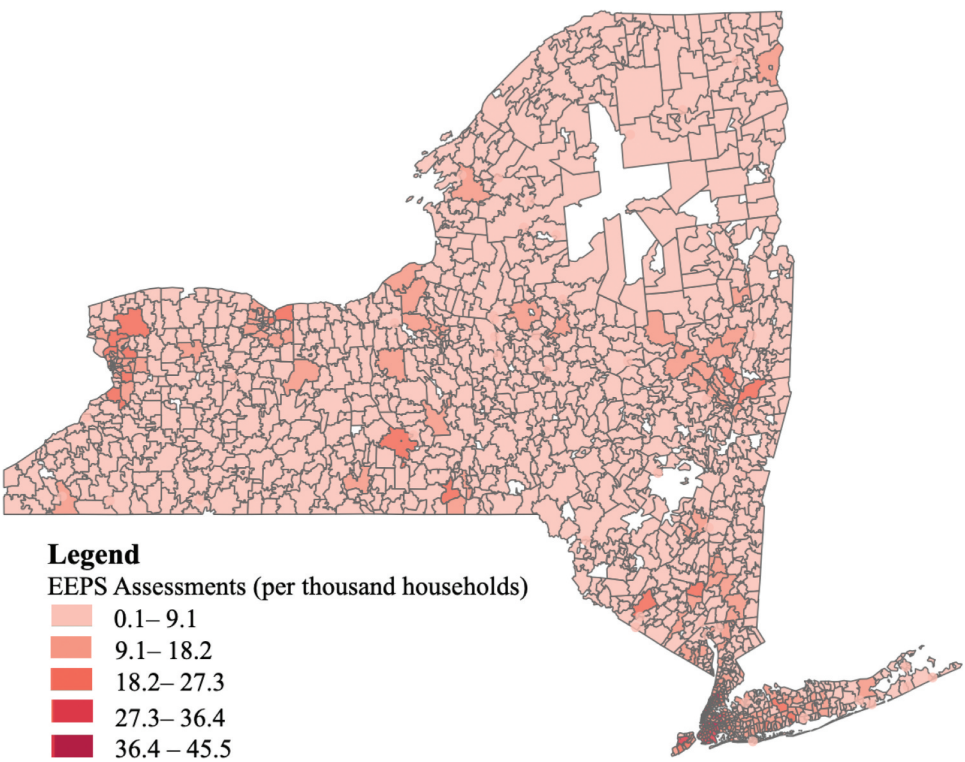

Figure 3. Classified choropleth map of EEMs/EEPS uptake per 1000 household across the geographical units (ZIP codes) of New York state.

4.2. Spatial Autocorrelation Analysis

A significant degree of spatial variation in EEPS and EEM uptake is evident in Figure 4, but it is difficult to deduce whether this variation is random only by visually inspecting the spatial map. Therefore, we conducted further spatial autocorrelation analysis to examine whether EEM adoption across the NYSZCs has a degree of spatial dependence. Figure 4's legend contains five codes for corresponding spatial association: pink (not significant); coral pink for high-high; light red (salmon) for low-low; vermilion for low-high; and maroon for high-low. High-high means the ZIP codes with high EEM adoption rates are clustered with similar areas that also have large EEM uptake values. Conversely, low-low means the NYSZCs with low EEM uptake are clustered together. High-low indicates ZIP codes with high-EEM adoption that are surrounded by ZIP codes with low EEM uptake. Similar descriptions were applied to low-high and high-low codes (i.e., low surrounded by high and high surrounded by low, respectively). The high-high areas are mainly in the Central New York, North Country, Mohawk Valley, and Capital District regions of New York. A few areas in the Finger Lakes and Southern Tier regions also have a clustering tendency with high-EEM diffusion. New York City, Buffalo, and Rochester have high-low clustering, i.e., high EEPS adoptions surrounded by neighboring ZIP codes with low EEM uptake.

The results from Moran's I test of global spatial autocorrelation yield 0.658 (p-value < 0.05). This signifies that the spatial correlation of EEPS uptake is moderate, i.e., with ZIP codes 269, 168, and 113 being statistically significant at 0.05, 0.01, and 0.001, respectively. Figure 4 illustrates the LISA analysis of EEM uptake clustered in specific territories of New York. Regions highlighted in pink (0.1–9.1 EEM adoption) represent clusters of ZIP codes with low EEM uptake (i.e., cold spots). These regions cover a large part of the state, suggesting that with relevant policymaking and EE program administration, these locations could offer potential energy-saving opportunities in the future. A visual inspection of the LISA map illustrates again that regions with the highest levels of EEPS adoption (highlighted in

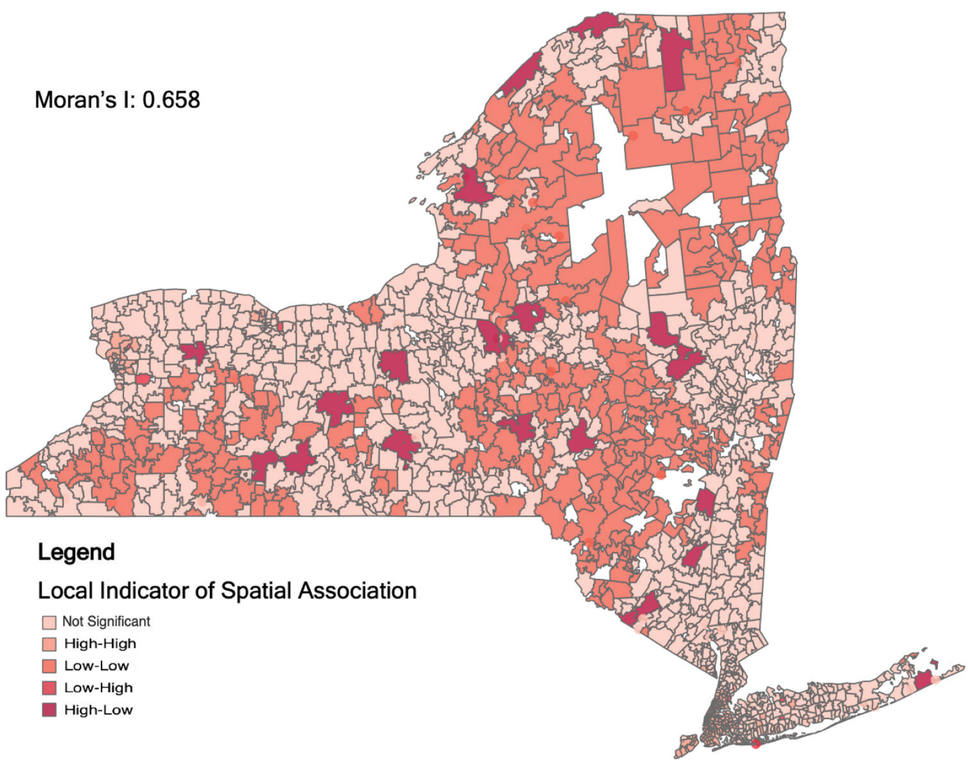

Figure 4. LISA of EEMs adoption across ZIP codes from 2012 to 2016.

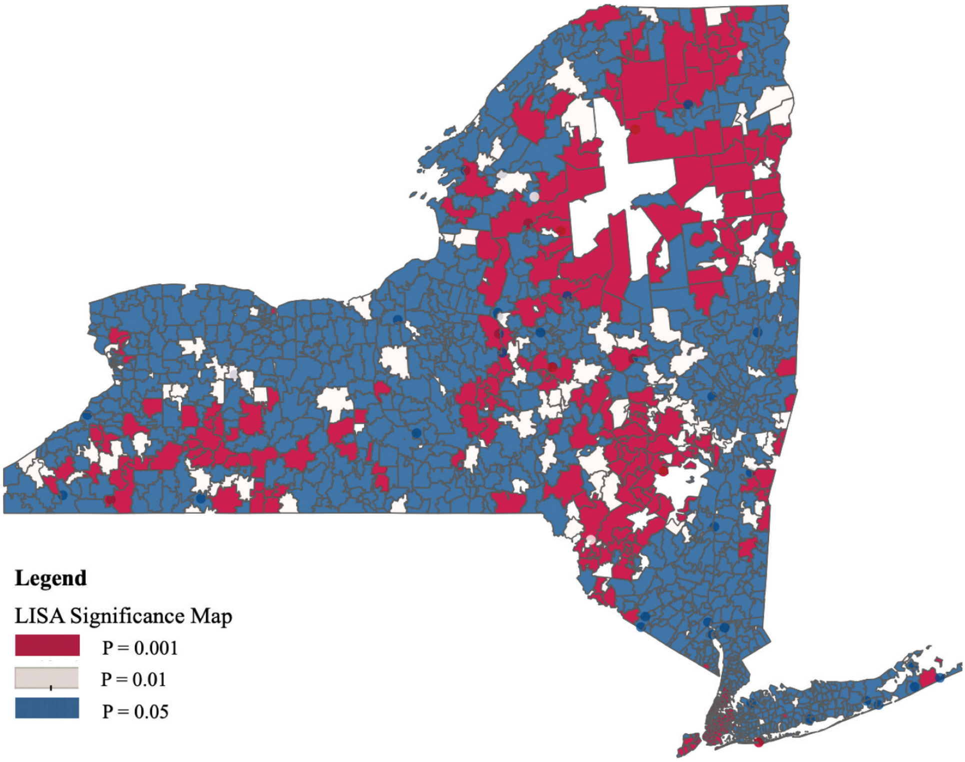

Figure 5. Moran's 1 test – LISA significance map of EEPS adoption across ZIP codes of New York state.

maroon color) – represented by New York City, Buffalo, and Rochester – contain a cluster of ZIP codes with relatively high rates of EEM adoption (see also Figure 5).

4.3. Correlation Analysis

Table 5 presents correlation analyses between EEM adoption and households' socioeconomic characteristics. We employed Spearman's rank-order approach and grouped the parameters into two main categories: socioeconomic and building stock characteristics. The results indicate a substantial degree of correlation, with EEM uptake displaying moderate (coefficient between 0.1 and 0.4) positive correlation with three-person family households (r_s: 0.10), households with children (r_s: 0.24), 25-years-and-older family households with a bachelor's degree (rs: 0.41), median-income family households (r_s: 0.19), and households with a graduate or professional degree (r_s: 0.30). A series of less-moderate negative correlations also was observed with no-children households (r_s: −0.24), high school education (rs: −0.079), and those 25 years and older and with associate's degrees (rs: −0.30). Generally, the correlation between socioeconomic factors and the adoption of EE retrofits is inherently weak to moderate.

Similarly, Table 6 presents the correlation between EEPS and EEM adoption and building stock parameters. Unlike the socioeconomic variables, a higher degree of interaction is observed with energy-related building stock, with the correlations between EEM adoption and the building parameters showing a moderate-to-strong relationship. In terms of positive correlations, EEM uptake is correlated significantly with multifamily households (r_s: 0.69), duplexes (r_s: 0.42), and homeowners with mortgages (r_s: 0.94). In addition, a significant positive relationship is identified between uptake of energy-saving measures and natural gas central heating (r_s: 0.61), electric heating (r_s: 0.15), and

Table 5. Spearman's correlation analysis between EEM adoption and socioeconomic parameters.

Variable	Coefficient	Variable	Coefficient
Family with children	0.24**	Associate's degree (≥ 25 years)	−0.30**
Family without children	−0.24**	Bachelor's degree (≥ 25 years)	0.41**
Married family with children	0.14**	Postgraduate degree (≥ 25 years)	0.30*
Single-headed family with children	0.03	Doctorate (≥ 25 years)	0.33**
Single female-headed family with children	0.08**	Median personal income	0.19**
3-person households	0.10**	Family in poverty	0.084*
4-or-more person households	0.14**	Families with single female in poverty	0.002
No qualifications (≥ 25 years)	0.28**	Families with one parent in poverty	0.01
High school diploma (≥ 25 years)	−0.079**		

*: *p*-value <0.05
**: *p*-value <0.01

Table 6. Spearman's correlation analysis between EEM adoption and building stock.

Building stock parameter	Coefficient	Building stock parameter	Coefficient
Detached house	−0.46	Mean number of homeowners	0.94*
Attached house	0.57**	Mean number of bedrooms (≥ 2)	0.92*
Multifamily house	0.69**	Mean number of bedrooms (≥3)	0.91*
Duplexes	0.42	Gas central heating	0.61
Owned-outright	−0.3	Electric central heating	0.15**
No. of owned mortgages	0.94	Oil and kerosene central heating	−0.30
Rent cost as % of income	0.15**	Households using coal, wood, solar heating	0.26
Mean number of rooms	0.95	No central heating	0.54**

*: *p*-value <0.05
**: *p*-value <0.01

buildings without central heating (r_s: 0.54). With respect to negative correlations, energy-efficiency diffusion is correlated significantly with detached building stock (r_s:−0.46), owned-outright buildings (r_s:−0.30), and buildings that use oil and kerosene central heating systems (r_s:−0.3). The findings indicate a stronger degree of explanatory power between EEM uptake and building characteristics (dwelling type, building size, heating fuel, etc.) compared with socioeconomic factors (see also Table A1).

4.4. Regression analysis

Table 7 presents the results of the benchmark OLS regression model. The dependent and explanatory variables employed in the analysis were transformed into their natural logarithm. These variables were selected based on the preceding insights and the specific questions outlined in this study. To ensure that the chosen variables were unbiased, we conducted a multicollinearity test to exclude redundant explanatory variables and only utilized dominant variables by calculating the variance inflation factor (VIF) for each of the specified MLR models. The highest VIF observed is 7.779, while the mean VIF is 2.917, which is within the threshold tolerance level of 10 (Salmerón, García, and García 2018). Different groups of explanatory variables were considered separately for model specification by employing staged-entry procedures. For instance, Model 1 includes only explanatory variables related to socioeconomic characteristics, while Model 2 contains building stock parameters. Model 3 (final stage) incorporates explanatory variables from Models 1 and 2 into one integrated model.

The results show that building stock variables demonstrate relatively high explanatory power over energy-efficiency adoption (Model 2 R^2: 0.69) compared with socioeconomic characteristics (Model 1 R^2: 0.37). Model 3, which integrates both socioeconomic and building stock parameters, displays the highest level of explanatory power (Model 2 R^2: 0.751), explaining three-quarters of the variance observed in energy-efficiency adoption in New York. Model 3 also returns the lowest value for the Akaike information criterion (AIC). The AIC model fit performance metric indicates that Model 3's

Table 7. Benchmark log-log ordinary least squares regression models with EEPS assessments as the dependent variable.

	OLS: Model 1		OLS: Model 2		OLS: Model 3	
Variable	Beta	Std. Err.	Beta	Std. Err.	Beta	Std. Err.
Constant	0.57*	3.10	−0.78**	0.64	1.291**	3.42
Socioeconomic Characteristics						
% Family with children (ln)	3.53**	0.28			0.62**	0.34
% Family without children (ln)	3.20**	0.33			0.71**	0.39
% Married family with children (ln)	−0.65*	0.13			−0.37*	0.12
% 3-person households (ln)	0.31	0.09			0.11	0.12
% 4-or-more person households (ln)	0.20*	0.09			0.25*	0.10
% University education (ln)	1.51*	0.07			0.91*	0.07
% High school diploma 25 years and over (ln)	−6.73	0.46			−2.38	0.42
Building Attributes						
% Duplexes			0.03*	0.02	0.09*	0.02
% Multifamily house			0.55*	0.03	0.38*	0.03
% Owned-outright			−0.73	0.11	−0.56	0.11
% Rent cost as percentage of income (ln)			0.45*	0.13	0.49*	0.12
% Gas central heating			0.28	0.03	0.21	0.03
% Electric central heating (ln)			−0.25**	0.04	−0.18**	0.04
% Oil and kerosene central heating (ln)			0.02	0.03	−0.05	0.03
Number of households using coal, wood, solar and other heating (ln)			0.29	0.02	0.36	0.02
% No central heating (ln)			−0.12	0.03	−0.14	0.03
Model fit						
R2 (adjusted)	0.37		0.69		0.751	
AIC	1721.61		1293.82		1159.28	
Spatial diagnostics						
Robust Lagrange-Multiplier (lag)	40.14*		33.61*		22.44*	
Robust Lagrange-Multiplier (error)	0.0006		16.08*		21.08	

*: *p*-value <0.05
**: *p*-value <0.01

specification has a higher degree of explanatory power, thereby providing more accurate estimates of the EEMs under consideration. Following Anselin et al. (1996), we calculated the robust Lagrange Multiplier (LM) spatial diagnostic tests for each of the models specified to identify whether there were any misspecification cases, often attributed to spatial autocorrelation in the model error or omission of a spatially lagged dependent variable. In the case of our integrated model (Model 3), the robust LM tests indicate that the benchmark OLM model fit can be improved by introducing a spatially lagged dependent variable. Consequently, following Anselin, Syabri, and Kho (2006), we specified SDEM to examine the relationships between EEM adoption and a set of independent or explanatory variables. The SDEM employs a two-stage approach to address both the spatial autocorrelation in the error term and the spatially lagged independent variables (Lesage and Pace 2009). The results are reported in Table 8.

The results from the SDEM show that model fit is enhanced in relation to the OLS model. Furthermore, the existence of direct effects, i.e., effects derived from within the ZIP code boundary, is very apparent. Significant and positive direct effects are established for variables that measure the proportion of households with children (β: 0.725), without children (β: 0.715), college-educated (β: 0.731), duplex houses (β: 0.111), multifamily homes (β: 0.300), rent-income ratios (β: 0.438), and natural gas heating systems (β: 0.180). The positive direct effects for the coefficient of the proportion of college-educated households are relatively high, suggesting that increased awareness of energy use and knowledge about specific energy-saving opportunities facilitate the pursuit of energy-saving technologies. The rate of EEM adoption in multifamily buildings exerts a higher direct positive effect relative to duplexes, further indicating that multifamily residential households have higher adoption of EE retrofits, potentially offsetting their relatively high monthly utility bills.

Table 8. SDEM results estimating direct and indirect effects, with EEPS as the dependent variable.

	Direct		Indirect	
Variables	Mean	Z-Value	Mean	Z-Value
Socioeconomic characteristics				
% Family with children (ln)	0.725**	0.322	0.636	2.088
% Family without children (ln)	0.715**	2.027	0.695	2.072
% Married family with children (ln)	−0.319*	−2.928	−0.250*	−2.111
% 3-person households (ln)	0.019	0.173	0.187	1.794
% 4-or-more person households (ln)	0.244*	2.756	0.233*	2.604
% University education (ln)	0.731*	10.607	0.787*	10.613
% High school diploma 25 years & over (ln)	−1.650*	−4.269	−2.013	−4.935
Building characteristics				
% Duplexes	0.111*	5.044	0.143	5.834
% Multifamily house	0.300*	9.533	0.305*	9.830
% Owned-outright	−0.406*	−4.185	−0.359	−3.422
% Rent cost as percentage of income (ln)	0.438*	3.887	0.325	2.908
% Gas central heating	0.180*	6.757	0.190*	7.004
% Electric central heating (ln)	−0.092**	−2.458	−0.096	−2.444
% Oil and kerosene central heating (ln)	−0.042**	−1.785	−0.090	−3.020
Number of households using coal, wood, solar and other heating (ln)	0.370	17.632	0.408	18.732
% No central heating (ln)	−0.172*	−6.369	−0.109**	−4.114
Spatial Interaction				
Spatial lag of EEPS (ln) – ρ	0.273*	10.538		
Model fit				
AIC	1064.710			

*: p-value <0.05
**: p-value <0.01

Significant and negative direct effects were reported for high-school-educated households (β: −1.650), indicating that situations in which a lack of awareness or knowledge about specific energy-saving incentives and financing, or end-user inertia, could block the pursuit of an opportunity to upgrade to more energy-efficient technologies. Besides a lack of public awareness of the magnitude of available net present value (NPV)-positive EEM opportunities available to residential homeowners, geographical and financial barriers to EE development may combine to create an "energy efficiency gap" or "energy efficiency paradox," i.e., "the slow rate of uptake of energy-efficiency products and services even when they are economically beneficial" (MacDonald et al. 2019). Similarly, outright-homeownership status (β: −0.406) and electric central heating households (β: −0.092) exert significant and negative effects, implying that EEM adoption is less popular with homeownership, as well as households using electric heating systems. This result could be attributed to the high property taxes in New York, especially in Manhattan and surrounding boroughs of Queens, Brooklyn, Staten Island, and the Bronx.

Four significant and positive indirect attributes, i.e., effects exercised by neighboring (contiguous) ZIP codes, have been observed in the model, with four-or-more-person households (θ: 0.233), college-educated households (θ: 0.787), multifamily buildings (θ: 0.305), and buildings that use natural gas heating systems (θ: 0.190) associated with EEM diffusion. Most of the energy-efficiency retrofits are implemented in four-or-more-person multifamily residential and college-educated households using natural gas heating systems. The positive correlation between EEM adoption and education level is well-documented in relevant related studies in the field (Ma and Cheng 2016; Mills and Schleich 2012, 2010).

The presence of less-efficient gas-heating systems is more likely to encourage investment in EE retrofits (relative to electricity or oil) because homeowners opt for highly energy-efficient natural gas systems with a higher seasonal energy-efficiency ratio (SEER). A higher SEER number indicates a more efficient natural gas system. According to Prabatha et al. (2020), retrofitting electrically heated buildings, especially in areas with high grid emissions, yields insignificant environmental benefits, while in locations "with greener electricity grids, upgrading houses heated with [old, less-efficient] natural gas [equipment] results in better environmental performance improvements, although it is economically unattractive" (p. 15). There is already a literature consensus acknowledging that a decision on whether to adopt a specific EE retrofitting strategy (e.g., electricity, liquid/solid fuels, etc.) often changes based on the homeowner's priorities, cost implications, and local conditions (Nyangon 2021; Pasichnyi, Wallin, and Kordas 2019; Polzin, von Flotow, and Nolden 2016; Seebauer, Friesenecker, and Eisfeld 2019). However, regarding the influence of heating fuel chosen (e.g., electricity, oil, or natural gas systems), a breakdown of households using different heating fuels to enable estimations of fuel options by dwelling type could not be provided due to data limitations.

Furthermore, these statistically significant and positive indirect factors confirm that EEM adoption and diffusion generate neighborhood effects, which should be accounted for together with other geographically tagged dimensions. Significant and negative indirect effects were found for married-family-with-children households (θ:−0.250) and building stock without central heating systems (θ: −0.109). Meanwhile, the spatial lag of EEPS adoption exhibits a significant positive effect (ρ: 0.273), implying that the diffusion of EEM in New York displays spillover effects. This indicates that the rate of uptake of EEMs in a given ZIP code is associated positively with those observed in the neighboring ZIP codes after accounting for the effects of socioeconomic and building stock parameters. This also could imply potential "neighborly emulation"[3] effects, indicating shared peer relationships through which networks exchange policy-relevant information––an important predictor of energy policy diffusion (Carley and Nicholson-Crotty 2018). Figure 6 illustrates local information flows in distribution channels that are driving EE investment and efficiency gains in New York state. Geo-localization of local information flows, i.e., the association of such data to ZIP code blocks, was implemented in GeoDa^{TM} by creating one geo-database for deep EE retrofits at the ZIP code level.

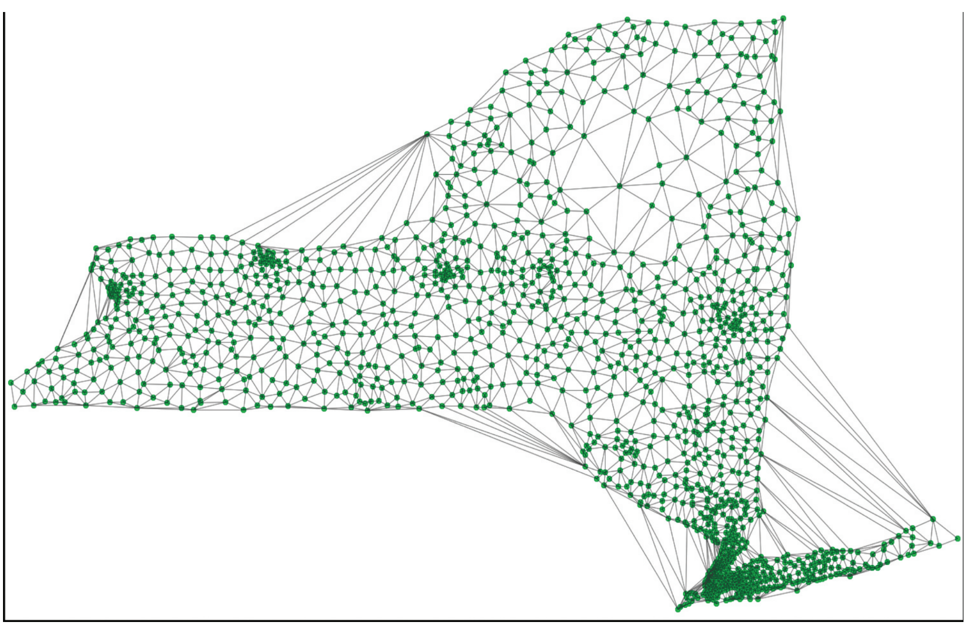

Figure 6. Local information channels for EEPS adoption and diffusion.

[3]Neighborly emulation is driven by shared energy markets, extent of connections with neighboring parameters in the built environment, norms and governance, the influence of residents' groups, and existing local economic configurations.

Table 9. Summary of EE policy implications to foster EEMs adoption.

Policy implication	Explanation
EE policy design and regulatory innovation	• Strengthen EE policy design and regulatory frameworks • Improve EE permitting processes, building code design, appliance and equipment standards, and energy labeling. • Consistent adoption of cost-effective EE technologies that surpasses the sum of the parts to achieve synergistic policy and regulatory benefits • Improve building energy performance measurement, benchmarking, energy audits, and household readiness for uptake of smart EE features.
Technology and R&D innovation	• Improve investment in cost-effective R&D for new EE technologies (e.g., lighting, refrigeration, air conditioning, heat pumps, building design and control, etc.)
Reduce energy-burden for low- income groups	• Design socially equitable products to address economic and financial barriers to EE opportunities for low-income households by addressing conditions which constrain EE uptake across spatial contexts. • Address the split-incentive problem between landlords and tenants (e.g., through on-bill financing schemes, provision of landlord incentives, and promote mutual cooperation from landlord and tenant to conserve energy), expand EE programs to low-income households residing in rural areas. • Better matching of subsidy support programs for vulnerable consumers with the households' adoption of EEMs.
Administration of EE information and education programs to raise awareness	• Targeted application of EE tax incentives, including energy savings performance contracts, property-assessed clean energy (PACE) loans, and energy-focused loans from national lenders. • Invest in education and peer-pressure programs to raise public awareness of EE opportunities and motivate EE actions.
Building grading and disclosure of EE footprint	• Integrate energy performance into building auditing, retrocommissioning, locational decisions, etc. • Encourage competition among building owners by, e.g., disclosing building energy footprint. • Allow tenants to account for building energy performance and other energy-related risks when making their leasing decisions.
Develop new technical, financing and business models for the EE sector	• Support design of new utility EE programs, demand response, mandatory standards, eco-labeling, and energy use behavior, etc.

5. Conclusions and policy implications

This article empirically examines the spatial patterns from the diffusion and adoption of residential EEMs using a set of socioeconomic and building stock explanatory variables. Besides the more commonly studied factors in relevant extant literature––such as socioeconomic, building stock/dwelling, and demographic characteristics––this article's novelty lies in adopting the spatially resolved range of the data set, which this study uses to analyze the policy effects from EEPS, revealing detailed trends in the diffusion and uptake of EEMs and ensuring that a geographically rich local context and scenarios are captured appropriately in the analysis to inform cost-effective policy design and planning of EE investment opportunities. To examine the diffusion of EEMs during the EEPS policy implementation period, we applied SDEM to a highly geographically resolved, household-level, statistical data set in New York state from the 2012–2016 period to understand households' behavioral features, such as their energy conservation behavior, education effects, the influence from households' building stock/dwelling characteristics, and the role of neighborly emulation and spillover effects in the uptake of EEMs, as well as to reflect on future adoption trends. Public policy is fundamentally about changing behavior. Hood (1986) grouped instruments for detecting and implementing new policies into four categories: nodality; authority; treasure; and organization (NATO) tools. In network governance, nodality instruments are information-based policy tools that influence people through knowledge transfer to achieve a policy result. Treasure tools denote either incentives to encourage certain behaviors or disincentives (e.g., taxes or fines) designed to discourage certain behaviors. Authority tools refer to laws and regulations that support sustainability transitions. For instance, New York has several laws that govern appliance standards, building codes, public benefit funds, and rebate programs, and the state is leading by example through the REV process. Finally, organization tools represent institutional choices––such as NYSERDA, NYPSC, etc.––that the state uses to deliver public services. Our findings confirmed a more complex picture of EE development in New York state across its different counties, cities, and ZIP codes. These results are consistent with other studies on spatial diffusion of low-carbon energy technologies (Brännström, Trolldal, and Menke 2016; Graziano, Fiaschetti, and Atkinson-Palombo 2019; Kanger et al. 2019; Zabaloy, Recalde, and Guzowski 2019).

Our results confirmed relatively strong positive correlation coefficients for college-educated households, indicating that with information and education, awareness of energy consumption patterns and knowledge about specific energy-saving opportunities can be increased to enable end-users to act more swiftly in their financial interests, thereby addressing the energy-efficiency gap issue. The results also could hold implications for energy demand, design of appliance standards, building code development, fuel economy standards, and rebound effects. With the growing investment in weatherization initiatives, the cost per kilowatt-hour of heating and cooling decreases, and this cost savings attribute motivates consumers to increase utilization of these energy services, i.e., a direct rebound effect on energy demand. Therefore, understanding residential energy-efficiency patterns (spatially) for ranges of building stock and socioeconomic aspects offers multiple opportunities to support policy and program designs that mitigate the rebound effect, such as stronger statewide environmental efficiency standards.

Furthermore, policymakers seeking to expand energy-efficiency programs and mitigate the rebound effect at different levels could use these findings to develop solutions to address rebound effects from both energy-efficiency improvement and energy demand perspectives (Fournier et al. 2019; Toroghi and Oliver 2019; Wei, Zhou, and Zhang 2019) as well as direct impacts from the rebound effect on energy demand if the efficiency is associated with energy intensity (kWh/square foot) instead of energy-augmented technology (Fan, Luo, and Zhang 2016; Shao, Huang, and Yang 2014). When designing policies and practices for promoting policy diffusion, e.g., uptake of EEMs and other utility-sponsored programs for low-income households, emulation theorists, among others, argue that policymakers and utility program implementers would benefit from policy information networks and best practices that promote a low-cost approach to policymaking, such as copying from peers, i.e., mimicking possible outcomes due to common geographic proximity or socioeconomic characteristics (Brinks and Coppedge 2006; Zhou et al. 2019). Such efforts may include programs under the U.S. Department of Energy, e.g., the Weatherization Assistance Program (WAP), which provides states with funds to implement deep retrofits, building envelopes, lighting upgrades, replacements of HVAC equipment, domestic water heating, plug-loads, and operation and maintenance.

Moreover, extant research has indicated that information asymmetry between governments (e.g., due to incomplete and imperfect information on minimum possible energy-savings opportunities that consumers could realize in reference cases) and businesses (e.g., due to the maximum technical potential of energy-efficiency improvement that firms can achieve realistically) can lead to sub-optimal energy-efficiency investments (Gillingham, Jenn, and Azevedo 2015). Such an asymmetric response would exacerbate peak electricity demand issues (Taminiau and Byrne 2020) and the rebound effect (Seebauer 2018; Wei, Zhou, and Zhang 2019). Marketing efficiency-upgrade schemes, audits and other assessments, and awareness campaigns in these low- and moderate-income communities, as well as addressing the barriers to energy-efficiency deployment––especially information asymmetry, high project development costs, split incentives between landlords and tenants, and lack of standardized measurement and verification (M&V) practices––would improve social welfare and equity effects (Labanca et al. 2015; Maiorano 2019). According to our results, building characteristics have relatively high explanatory power over energy-efficiency adoption relative to socioeconomic characteristics, accounting for nearly 75% of the variance. Thus, it would be beneficial to understand residential energy-efficiency potential for ranges of building stock to support policy and program design, as well as address direct rebound effects, as proposed by Toroghi and Oliver (2019) and Safarzadeh and Rasti-Barzoki (2019). The results also indicate that the rent-to-income ratio exerts a significant positive direct effect on energy-saving opportunities. For example, targeting retrofit programs, creative financing vehicles (such as on-bill financing), and offering monetary incentives to households with higher rent-to-income ratios could increase EEM uptake within this group, as swift actions likely would be taken to reduce monthly utility bills.

The extension of the benchmark OLS model to the spatial Durbin model yields an improved model specification, with direct effects from the model's explanatory variables dominating. Furthermore, a significant spatial autocorrelation coefficient in the model (ρ: 0.273) indicates the presence of neighborly effects. This suggests consumers' willingness to pay for, or the state to subsidize, a variety of EEMs and EE savings opportunities at the neighborhood level. Furthermore, investing in high-potential retrofitting options in once-flourishing cities like Buffalo and Rochester––e.g., automated heating control, pre-programmed default temperature profiles, and eco-design product standards––also could offset household-level rebound effects (Seebauer 2018). Additionally, propane, oil, and electric resistance heating varieties are used mostly in rural areas, but these forms of heating are often more expensive compared with natural gas or electric heat pumps (which are used primarily in urban settings). As a result, policymakers and utility program managers should consider tailoring EEM opportunities to regions with the greatest potential for rapid adoption. Results from the influence of the built environment and jurisdictional boundaries, as reported in the choropleth and LISA maps, show that transition capacities are unlikely to be uniform spatially.

Consequently, when designing solutions to address the barriers that impede cost-effective adoption of EEM opportunities, authorities should consider additional metrics that factor in these spatial nonuniformities, such as area median income and federal poverty levels, which currently are used to determine which households are eligible for WAP, the U.S. Department of Housing and Urban Development assistance programs, and the U.S. federal Low Income Home Energy Assistance Program (LIHEAP). Designing these programs and policy objectives also requires accurate, granular, and reliable spatial data on the drivers of and barriers to energy-efficiency management at the city level, particularly geographical units with heterogeneous characteristics. Finally, without making specific recommendations, Table 9 summarizes policy implications that this study could guide to reduce energy demand and potential energy rebound effects.

In conclusion, this work dealt with the limitations of using EEPS assessments as a proxy for EEM adoption. At its core, the EEPS analytical approach's efficacy is contingent on accurate reporting and disclosure on EEM opportunities at the granular level, such as income levels, building profiles, and geographical insights. Due to the well-documented "aggregation" barrier (Anselin 2002), the findings from EEM adoption trends discussed in this article only apply to the New York context and may not be generalized to other regions or states with similar EEPS policies. This issue is also sometimes referred to as the ecological fallacy problem (Winzar 2015), i.e., drawing inferences about a large geographical unit, such as a region or country, concerning its residents' behavior could be misleading. Furthermore, the use of ZIP codes and ZIP code tabulation areas for the spatial analysis of EE opportunities presents a unique "modifiable areal unit problem" (Xu, Huang, and Dong 2018), i.e., these geographical units' layouts were designed for postal delivery purposes and may fail to capture some aspects of dynamic energy policy design fully, such as EEM adoption.

Greater policymaking processes and program design administration of energy consumption for the local context could mitigate potential administrative burdens, and perhaps even disparities in local energy-efficiency management. As for future research, we call for studies on the policy efficacy of EERS on energy-efficiency uptake in low-income households and the rebound effect. Also, disparities in access to local energy-efficiency incentives and information, as well as education on savings opportunities in low-income households, can be factored into the rebound effect calculation.

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Declaration of competing interest

The authors declare no competing interests.

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