Estimating Office and Multifamily Building Energy Retrofit Hurdle Rates and Risk Arbitrage in Energy Efficiency Investments

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Abstract

Despite extensive empirical evidence of the economic and financial benefits of green buildings, the adoption of energy retrofit investments in existing buildings has been limited. The global push to increase the efficiency of the building sector, including city-level policies requiring energy use disclosure and mandatory energy audits, continues to face barriers caused by information asymmetries, insufficient pricing signals, principal-agent challenges, and uncertainty in the risk and return of energy retrofit investments. This paper develops a substantial, large-scale database of building energy use, energy audit reports, land use, and financial characteristics in New York City to empirically model the hurdle rate for energy retrofit investments, using actual audit data and permitted renovation work. By modeling the estimated rate of return for energy retrofit investments for different property types and building characteristics, we generate a more comprehensive understanding of the perceived risk of these investments and the market and regulatory mechanisms that can overcome financial and informational barriers to the adoption of energy conservation measures (ECMs). Median internal rate of return (IRR) for adopted ECMs is found to be 20% for Multifamily and 24% for Office, which is consistent with the estimated return of a bundle of NPV-postive ECMs. Adoption rates are higher for Office buildings than Multifamily, and in both cases adopter buildings tend to be larger, higher value, and less efficient at time of adoption. Based on our methodology, we propose the development of a National Retrofit Investment and Performance (NRPI) database. This database would track building-level energy audits, implemented energy conservation measures and retrofit investments and their financial and energy performance metrics, and pre/post energy use profiles.

1. Introduction

There is an extensive body of research on the opportunity for retrofitting existing commercial buildings to reduce national energy use and carbon emissions (Chidiac et al., 2011; Koomey et al., 1998; Ma et al., 2012; Papadopoulos & Kontokosta, 2019). Despite the potential positive impacts of such a reduction, the pace of adoption of energy efficient practices and technologies has been slow, and significant barriers–both perceived and actual–persist (Ardente et al., 2011; Eichholtz et al., 2010; Fuerst & McAllister, 2009; Koomey et al., 2001). These barriers include information asymmetries between stakeholders, uncertainty over future savings, lack of knowledge about energy technologies, first-cost capital constraints, economic dis-incentives including the split-incentive problem, and the decreasing cost of fuel (Fuerst et al., 2014; Mills et al., 2006; Palmer & Walls, 2015). To overcome these obstacles, the recent proliferation of energy disclosure policies in U.S. cities has generated significant new streams of data on energy use in buildings to benchmark performance, led by New York Citys (NYC) Local Law 84 (LL84) (Hsu, 2014; Kontokosta, 2013, 2015).

New energy disclosure, audit, and retro-commissioning requirements create detailed inventories of building energy use, systems, and potential energy conservation measures (ECMs) (Mathew et al., 2015). Energy audit and retro-commissioning requirements have also begun to emerge alongside disclosure mandates, providing owners, tenants, and policymakers with detailed accounting of building systems and energy end-use, as well as the energy savings and cost savings potential of the implementation of specific ECMs. NYC Local Law 87 (LL87) is the first city-wide building energy audit mandate in the U.S. (Marasco & Kontokosta, 2016). Early studies indicate that energy disclosure is driving meaningful reductions in building energy use in U.S. cities (Meng et al., 2017; Palmer & Walls, 2015; Papadopoulos et al., 2018). Yet few studies have examined the impact of audits on energy use reductions and retrofit investment decisions in large office and multifamily buildings. This is an important omission; mandatory audits implicitly provide a natural experiment for the measurement of the hurdle rates of return on investment that must be exceeded before energy efficient investment is deemed profitable in the private sector. Such insights can subsequently guide education, regulations, or subsidy policies.

In addition to these informational regulations, cities are beginning to introduce carbon reduction and energy efficiency mandates. In NYC, the Climate Mobilization Act requires buildings over 25,000 square feet to reduce carbon emissions by 40% from 2005 levels by 2030 and 80% by 2050. Given regulatory and market pressures to improve energy efficiency, building owners, investors, and policymakers need to understand the financial implications of the various pathways to energy use reductions through building retrofits. Previous research has shown that the most significant barriers to retrofit adoption are perceived or expected long payback periods on ECM investments and a lack of access to capital to fund implementation costs (Amstalden et al., 2007; Jackson, 2010; Kontokosta, 2016). However, despite these survey-reported findings, there is little understanding of the potential return on investment of retrofit measures, how returns vary with individual ECMs and packages of ECMs, and the hurdle rate required by owners to invest in retrofits in practice.

This paper examines a critical, and previously unexplored, question about the link between building energy retrofits and financial performance. Using a unique, large-scale database of building-specific energy use, systems, financial metrics, construction permit records, and energy audit data, we estimate the hurdle rate for energy retrofit investments, using actual audit data and permitted renovation work. By modeling the internal rate of return (IRR) and net present value (NPV) for energy retrofit investments for different property types and building characteristics, we model the perceived risk of these investments and discuss incentive and regulatory mechanisms that can overcome financial and informational barriers to the adoption of energy efficiency measures. Ultimately, this study presents a detailed analysis of the potential return profiles for building retrofits across building types and characteristics, and what ECMs are most likely to be adopted and in what circumstances.

2. Data

2.1. Building Audits (LL87)

The comprehensive energy data ecosystem in NYC provides an unprecedented opportunity to examine the relationship between energy performance, retrofit energy savings potential, and financial performance in commercial and residential buildings. The City has recently introduced several policy innovations to drive energy efficiency market transformation. In 2010, Local Law 84 was launched, mandating all properties larger than 50,000 sq.ft. to annually report their energy consumption. In 2013, Local Law 87 required a randomly-identified subset of LL84-covered properties each year to undertake an energy audit and report its results. The data collected under LL87 include information about a building's physical characteristics, energy systems, as well as ECM recommendations with their associated implementation costs and energy/cost savings potential. These mandatory audits, known as Energy Efficiency Reports, must be conducted by a certified design professional to American Society of Heating, Refrigerating, and Air-conditioning Engineers (ASHRAE) Level 2 standards.[1]

We analyze data from approximately 4,000 building audits reported through LL87 between 2013 and 2016. The NYC Mayor's Office of Sustainability (MOS) identifies buildings that have to comply with LL87 by matching the last digit of the reporting year and the last digit of Borough-Block-Lot (BBL) 10-digit unique property identifier (NYC Mayor's Office of Sustainability, 2019). For the year 2015, as an example, MOS selected all properties with 5 as the last digit of their respective BBLs. Therefore, each audit is associated with a unique building identifier that can be used to join the audit data to energy performance (LL84), zoning and tax information (PLUTO), and building permit records. We constrain our analysis to the main two building typologies encountered in the data, namely multifamily residential buildings and office buildings. Although LL87 are reported by certified energy professionals, we encounter several misreported or erroneous entries that need to be treated before analysis. Data pre-processing proceeds in the following steps: First, we standardize BBLs and remove erroneously reported entries. Second, we identify properties where no ECMs were recommended. After merging audit records in different years based on BBL-BIN (Building Identification Number) pairs, we parse Gross Floor Area (GFA) and Energy Use Intensity (EUI) values into regular expressions (e.g. "400,392.923 square feet" becomes "400392"). We then extract the ECM recommendations and remove those that are missing one of the following fields: category, implementation cost, annual cost savings, annual energy savings. Finally, we exclude from our analysis ECMs with payback periods longer than 50 years and less than 0.5 years, as we identify these as outliers based on the sample distribution.

2.2. Building Construction and Renovation Permits

Several major cities in the U.S., including NYC, have digitized the construction and renovation permit application process. In NYC, the Department of Buildings (DOB) maintains building permit records that includes BIN, BBL, building type, permit type, job type, filing date, job description, and owner's information (New York City Department of Buildings, 2015). The permit type is a series of codes describing the proposed work in the property based on the nature of the application, such as major alteration (i.e. alteration that will change the use, egress, or occupancy of the building), minor alteration (i.e. multiple types of work that do not affect the use, egress, or occupancy of the building), and minor work (i.e. typically repair work that does not affect the use, egress, or occupancy of the building). Table 1 is a summary of building alteration permits from 2013 to 2017. NYC recorded a total of 188,051 alteration permits with the majority (75%) classified as minor

[1] For more information: Local Laws of the City of New York, No. 78.`http://www.nyc.gov/html/planyc2030/downloads/pdf/ll87of2009_audits_and_retro-commissioning.pdf`

alterations. Of these, approximately 12.39% (n=23,306) of the total permits occurred in buildings that comply with LL87. By matching permit data and audit records by BBL and comparing the audit date and permit filing date, we identify 6,111 permits related to post-audit actions, which includes 21 major alterations, 5,182 minor alterations, and 908 minor work projects. We note that a building can have multiple permits attributed to it in the post-audit period.

Table 1: **Building alteration works by permit type and critical components**

Sample size 2013-2017 / Permit type	All permits	All permits in buildings comply with LL87	Post-audit permits
Major Alteration (A1)	6313	87	21
Minor Alteration (A2)	140689	20078	5182
Minor Work (A3)	41049	3141	908
Total	188051	23306	6111

In addition to permit typology, NYC DOB's permitting system provides multiple check-boxes for common alteration actions (e.g., boiler, mechanical, HVAC[2]) (DOB, 2016). As Table 2 shows, building enlargement is not common due to the building types that are covered by LL87 and zoning regulations that constrain building expansion. Although about 65.5% of minor work permits checked equipment, the relatively low percentages indicate that these check-box information fields do not capture the full extent of renovation work. Therefore, the current binary variables in a permit application provide limited information describing the proposed work. Therefore, extracting information from the user-generated text input field for the scope of work description is necessary to understand the nature and extent of permitted work. The DOB permit filing system requires that applicants (e.g., a licensed architect or engineer) provide a text description to summarize the proposed work, including major actions (e.g., replace, remodel, renovate), building systems affected (e.g., boiler, wall, fixture), and locations of work within the building (e.g., kitchen, bathroom, bedroom) (Table 3). We use natural language processing and text mining to standardize and extract the information contained in these text fields.

Table 2: **Post-audit alteration works by permit type and critical components**

Component / Permit	Plumbing	Mechanical	Boiler	Equipment	Horizontal Enlarg.	Vertical Enlarg.
Major Alteration (n=21)	17.4%	8.7%	0.0%	0.0%	0.0%	4.3%
Minor Alteration (n=5182)	23.3%	11.7%	1.2%	1.5%	0.0%	0.0%
Minor Work (n=908)	0.0%	0.0%	0.0%	65.5%	0.0%	0.0%

[2]Heating, ventilation, and air conditioning.

Table 3: **Sample post-audit building alteration permits**

BIN #	BBL	Permit Type	Time	Full Description
1025xxx	1010360xxx	Major Alteration	2015-08-20	Filing to convert a portion of the existing storage area to a tenant's only laundry room. New non-load partitions, doors, ceiling and finishes. Installation of dryer duct ventilation system. Plumbing work for new laundry equipment as shown on drawings filed herewith.
1037xxx	1013150xxx	Minor Alteration	2015-04-17	Cooling tower replacement on the 19th floor roof as per plans filed herewith. No change in use egress or occupancy.
1042xxx	1013990xxx	Minor Work	2015-05-11	Hereby filing for installation of new steel and laminated glass marquee.

NOTES: This table illustrates partial key information and does not include full permit data attributes.

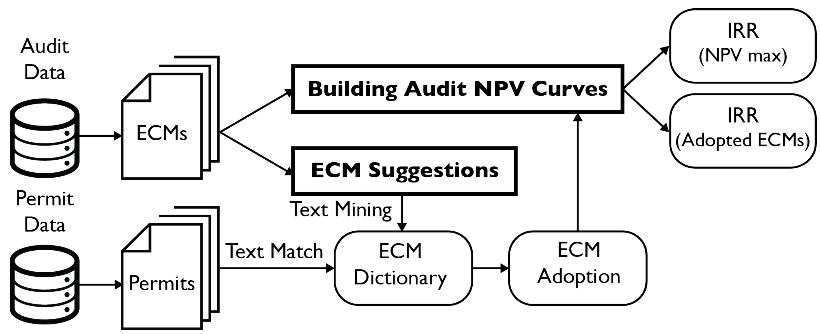

Figure 1: Data integration and analysis workflow.

3. Methodology

Figure 1 summarizes our overall data integration and analysis approach. Using four years of energy audit reports and five years of permit records, we first extract detailed descriptions and metrics for each ECM recommendation by building. We then conduct text mining to generate a dictionary of recommended upgrades for each individual ECM category derived from the full audit sample. We then match audit recommendations with DOB building permit scope of work data to identify ECM adoption based on actual renovation activity subsequent to an audit. For all buildings, we estimate NPV and IRR for three scenarios representing return-maximizing, energy savings-maximizing, and balanced packages of ECMs. For buildings where audit recommendations were adopted, we calculate the IRR based on the bundle of adopted ECMs, and compare these values to the three potential adoption scenarios described above.

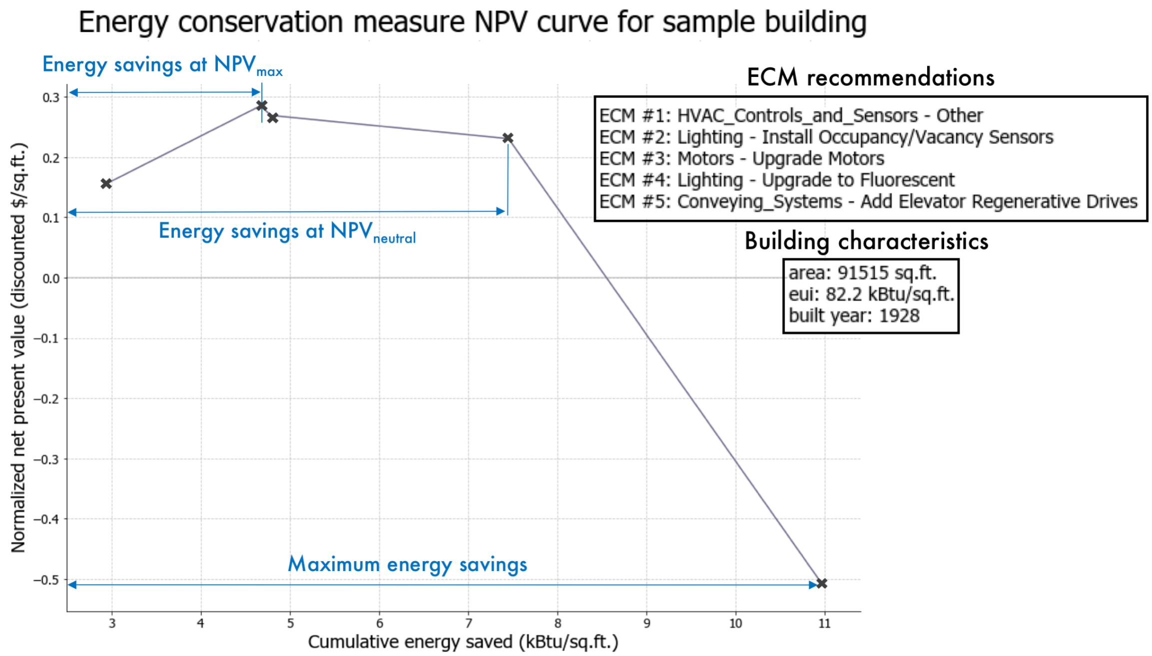

Figure 2: Sample building NPV curve.

3.1. Building Audit NPV Curves

Using the implementation cost, energy savings, and annual cost savings data for individual ECM recommendations provided in the audit report, we compute the NPV for each as follows:

$$NPV = \sum_{t=0}^{n} \frac{R_t}{(1+i)^t} \tag{1}$$

where n is the number of time periods of the investment, R_t is the net cash flow at period t, and i is the discount rate. For the purpose of this study, we assume $n = 15$ years and $i = 0.1$. After calculating the NPV for individual ECMs, we are able to compute the cumulative NPV for all ECM recommendations for each building and plot the calculated values by cumulative energy savings. Figure 2 shows the NPV/energy savings curve for a sample building in the data, with each point indicated on the curve associated with a specific ECM. Note that we normalize both NPV and energy savings by the building area to allow for comparison across building types and characteristics. The curve presented in 2 is one of three commonly-identified NPV profiles, with the other two being a linear positive slope and the other a linear negative slope.

In this particular example, we see that the NPV curve peaks after two ECMs (specifically, HVAC controls and occupancy sensors for the lighting system), and the remaining ECMs are NPV negative. However, only the last recommendation for conveying systems causes the building's cumulative

NPV to drop below zero. Calculating cumulative NPV/energy savings curves for each building in the data allows us to study inflection points in the curves, draw a more nuanced picture of the proposed ECMs' economic feasibility, focus on certain subsets of ECMs, and compute additional financial metrics. We calculate a NPV curve by plotting cumulative NPV (normalized per square foot) against energy savings per square foot, with each point on the curve represented by a single ECM. Based on these points, we define three bundles of ECMs or retrofit scenarios: NPV_{max}: the set of ECMs that maximize NPV, $NPV_{neutral}$: the set of ECMs yielding cumulative NPV close to zero, and $EnergySavings_{max}$: all ECMs that would result in the greatest possible energy savings. For each scenario, we calculate the IRR for the identified ECMs that comprise each scenario. Moreover, based on the building's physical characteristics (age, area, EUI), we subset the data and study the aforementioned metrics by building sub-categories.

3.2. Text Mining and Audit-to-Permit Matching

We first identify buildings with alteration work subsequent to the date the audit was performed on the building, according to the filing dates of both audits and permits (if any). If a building has no post-audit permit record, we assume no renovation activity occurred in the building and thus no audit recommendations were adopted. It is possible, however, that the implementation of a particular ECM would not require the filing of a building permit; we discuss this scenario in more detail below. In the LL87 audit data, each ECM recommendation has a category-suggestion structure. Based on all recommendations, we generate ECM category-specific dictionaries by extracting text from auditors' recommended improvement (e.g. upgrade to LED). We use part-of-speech (POS) tagging to clean the raw permit descriptions by dropping conjunctions, determiners, pronouns, and punctuation. For each word, we calculate its frequency based on its total appearance divided by total appearance of all vocabulary. Therefore, a final dictionary contains all unique words and their frequency, which are objectively quantified based on empirical audit records. Figure 3 are word-clouds that visualize the top 30 words for each ECM category. Using these dictionaries, we estimate the adoption likelihood for each ECM recommendation, according to its identified post-audit building permit descriptions.

For building permit descriptions, we clean input text for the scope of work using a similar POS tagging process. To compare the content between a permit description and a specific ECM recommendation, a word-matching algorithm proceeds in the following three steps: First, according to the ECM category, it associates the scope of work description with the dictionary mentioned above. Then, based on this dictionary, it identifies the words that appear in the permit description. Finally, it returns two new variables: (1) the total number of matched words and (2) a list of matched words. This approach quantifies the relationship between post-audit building permit descriptions and each ECM recommendation category as an estimate of the likelihood of ECM adoption.

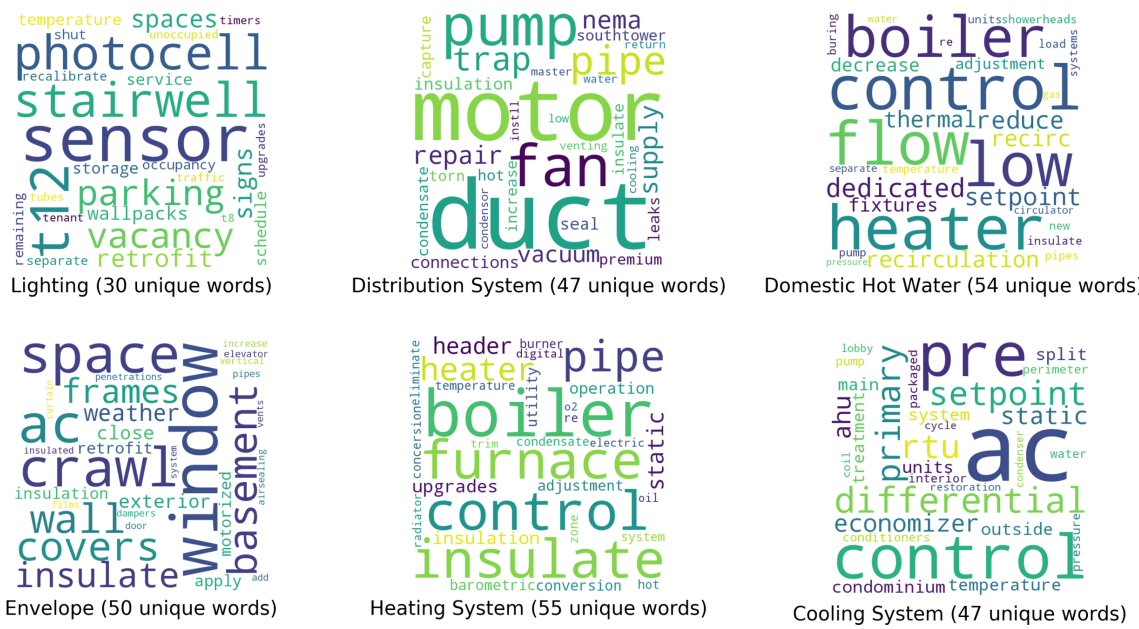

Figure 3: Word-cloud of dictionary for each ECM category.

4. Results

4.1. Data summary and matching results

The final dataset contains a total of 22,230 ECM recommendations extracted from 3,632 audits (Table 4).

Table 4: **Building audit (LL87) data summary**

Audits	**ECMs**	**Period**	**Audits with post-audit alteration**		
			Audits	ECMs	Post-audit alterations
3632	22230	2013-2016	1385	6545	6111

Figure 4 compares the proportion of each ECM category recommended for office and multifamily buildings, respectively, together with the percentage adopted. Several categories, such as lighting, HVAC control and sensors, distribution system, and heating system improvements, have a similar prevalence across the two building types. In contrast, office buildings have a much higher percentage of recommendations for motors, cooling system, and ventilation retrofits, while multifamily buildings are more likely to have envelope and domestic hot water ECM recommendations. As expected, lighting improvements constitute the largest share of recommended and adopted ECMs.

Figure 5 presents a box-plot of the calculated simple payback period by ECM category. The distribution of payback periods within each category are a result, in part, of the range of specific

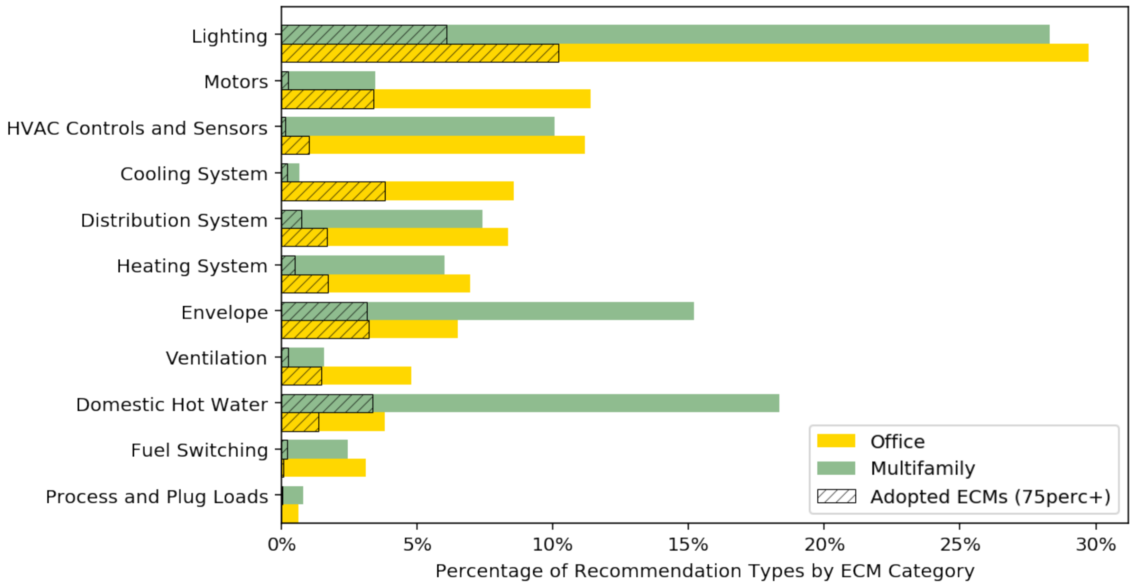

Figure 4: Percentage of recommendation types by ECM category.

recommendations contained within each of the higher-order ECM categories (e.g., envelope, conveying system) and the variance in auditor estimations. Outliers reflect erroneous entries (indicated by the diamond points), most likely caused by data entry error or incorrect assumptions or reference data used by the auditor.

For all buildings, we estimate the IRR for the NPV_max, $\text{NPV}_neutral$, and EnergySavings_max scenarios. Table 4.1 presents descriptive statistics for the return-maximizing and energy savings-maximizing cases, by building type, age, and size (quartiles). Newer and larger office buildings are found to have higher mean IRR in both retrofit scenarios, while this pattern tends to be reversed in the case of multifamily buildings. Overall, however, we find relatively consistent expected IRRs across observed building characteristics.

4.2. Comparing adopters and non-adopters

After matching LL87 audit data and DOB building permits by BBL, we identify 1,385 buildings with an audit and at least one building permit filed after the date of the audit. We define this as a post-audit alteration. There are a total of 6,111 post-audit alterations since one building may file multiple alteration applications. For buildings with post-audit alterations, a total of 6,545 ECMs are matched between audit and permit, including lighting (n=2,028), domestic hot water (n=934), envelope (n=856), HVAC controls and sensors (n=634), distribution system (n=537), heating system (n=427), motors (n=234), fuel switching (n=175), cooling system (n=168), ventilation(n=160), on-

Table 5: **Summary of ECMs by category.**

Office											
ECM Category	# of Times Recommended	% of Audits	Implementation Cost ($/sq.ft.) median	mean	std	Energy Savings (KbtU/sq.ft.) median	mean	std	Median Payback	Median IRR	Median NPV
Lighting	574	87.6%	0.06	0.09	0.08	0.31	0.47	0.42	3.3	0.29	0.06
Domestic Hot Water	73	16.4%	0.06	0.12	0.12	0.62	1.23	1.39	3.6	0.30	0.03
Envelope	125	21.9%	0.34	0.80	0.97	0.99	2.40	2.72	7.8	0.09	-0.01
HVAC Controls & Sensors	216	39.6%	0.16	0.19	0.16	1.30	1.65	1.30	3.8	0.25	0.06
Distribution System	161	30.4%	0.03	0.07	0.20	0.36	0.56	0.59	4.1	0.23	0.01
Heating System	134	28.1%	0.19	0.41	0.55	1.66	2.18	2.02	4.4	0.21	0.03
Motors	220	33.3%	0.12	0.14	0.10	0.55	0.73	0.61	4.0	0.24	0.07
On Site Generation	35	8.5%	1.08	1.21	0.85	1.73	2.60	3.02	11.3	0.03	-0.28
Fuel Switching	60	14.7%	1.23	1.47	0.76	1.29	1.46	1.14	4.3	0.22	0.59
Ventilation	92	14.9%	0.17	0.22	0.19	0.95	1.51	1.62	4.5	0.20	0.04
Cooling System	165	28.1%	0.29	0.63	0.78	0.92	1.81	2.22	6.3	0.13	0.01
Conveying Systems	42	10.2%	0.51	0.79	0.64	1.33	1.36	0.90	8.1	0.08	-0.02
Process and Plug Loads	12	3.0%	0.09	0.10	0.10	0.32	0.45	0.54	5.2	0.17	0.01
Other	21	5.0%	0.08	0.20	0.29	0.59	0.91	0.94	3.30	0.29	0.03
Multifamily											
ECM Category	# of Times Recommended	% of Audits	Implementation Cost ($/sq.ft.) median	mean	std	Energy Savings (KbtU/sq.ft.) median	mean	std	Median Payback	Median IRR	Median NPV
Lighting	5028	87.5%	0.03	0.05	0.05	0.14	0.23	0.23	3.2	0.30	0.03
Domestic Hot Water	3259	63.4%	0.09	0.17	0.16	1.70	2.25	1.85	4.6	0.20	0.03
Envelope	2697	42.8%	0.36	0.80	0.96	1.86	3.15	2.97	16.7	-0.02	-0.20
HVAC Controls & Sensors	1788	43.6%	0.25	0.26	0.13	3.56	3.86	1.75	4.8	0.19	0.09
Distribution System	1312	35.3%	0.02	0.04	0.04	0.52	0.83	0.82	3.7	0.26	0.02
Heating System	1063	28.8%	0.10	0.39	0.57	2.15	2.82	2.30	4.9	0.19	0.02
Motors	613	15.8%	0.07	0.09	0.06	0.32	0.45	0.38	4.1	0.23	0.04
On Site Generation	735	22.2%	1.30	1.47	0.78	2.82	3.20	2.11	9.9	0.05	-0.33
Fuel Switching	432	13.3%	1.67	1.88	0.82	1.90	1.84	1.42	4.2	0.23	1.47
Ventilation	275	7.5%	0.11	0.23	0.24	1.44	2.26	2.34	5.0	0.18	0.02
Cooling System	113	3.2%	0.15	0.40	0.60	0.36	1.33	2.97	7.3	0.10	0.00
Conveying Systems	118	3.7%	0.67	0.88	0.65	0.78	0.89	0.39	10.6	0.05	-0.11
Process and Plug Loads	141	4.1%	0.08	0.15	0.14	0.49	0.55	0.40	6.7	0.12	0.00
Other	113	3.2%	0.09	0.20	0.21	0.27	0.48	0.68	7.3	0.1	0.00
Submetering	78	2.4%	0.35	0.42	0.28	1.68	1.83	1.12	2.7	0.36	0.28

NOTES: Median, mean and standard deviation are reported within 10th - 90th percentile range.

site generation (n=147), conveying systems (n=77), process and plug loads (n=40), and sub-metering (n=33).

For each ECM suggestion, our text-matching algorithm retrieves associated permit descriptions and identifies matched words based on previously collected ECM-category dictionary. Based on the distribution of total matched words, we define three different matching criteria. We use a 90 percentile threshold (matched words >= 6) as a conservative matching scenario (labeled as '90th pec' in result summary) and 75th percentile (matched words >= 3) as our base matching scenario (labeled as '75th pec'). Furthermore, most building permit descriptions do not report lighting improvements (e.g., upgrade to LED, install timers) since these actions typically do not involve building structural, mechanical, or other work defined by the DOB as requiring a permit. Therefore, using the 75th percentile matching results, we define the third scenario by assuming the building also implemented lighting ECMs that would not require a permit (labeled as '75th perc+'). In this

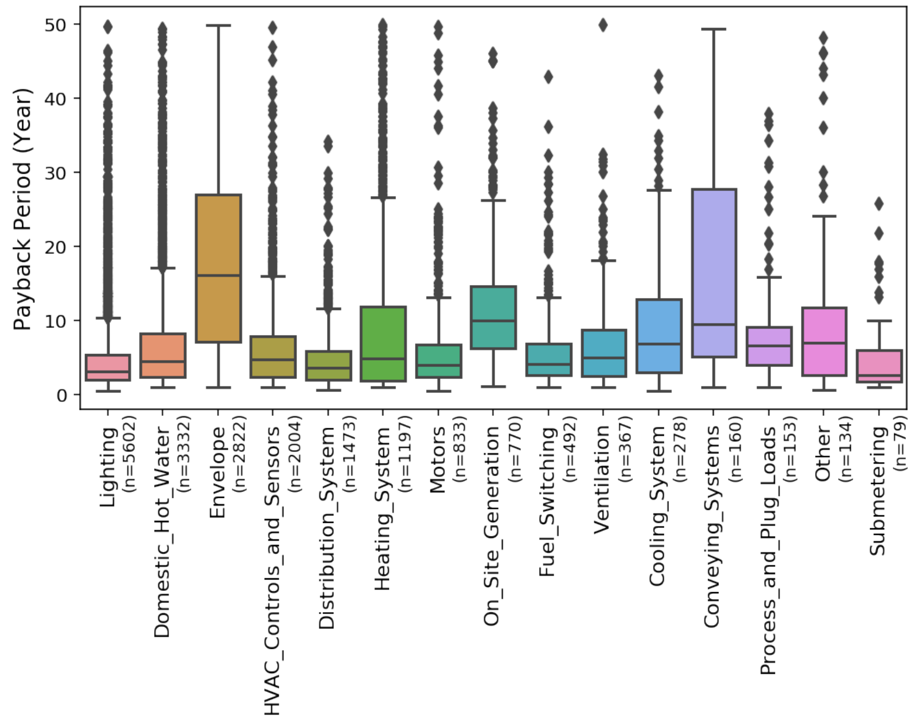

Figure 5: Box-plot of estimated payback period distributions by ECM category sorted by total number of suggestions.

Table 6: **IRR distributions for NPV$_{max}$ and max energy saving scenarios by building type, age, and size.**

Groups by Quartile		Count	IRR (NPV max scenario)			IRR (Max energy saving scenario)		
			median	mean	std	median	mean	std
Office								
Age by Built Year	1850-1913	103	0.32	0.36	0.18	0.19	0.21	0.18
	1913-1928	97	0.30	0.36	0.20	0.20	0.24	0.20
	1928-1965	89	0.34	0.45	0.42	0.20	0.25	0.23
	1965-2015	96	0.33	0.43	0.31	0.20	0.28	0.28
Built Area (sq. ft.)	50000-83750	97	0.30	0.39	0.24	0.16	0.23	0.23
	83750-163000	96	0.31	0.36	0.19	0.19	0.22	0.20
	163000-368898	96	0.34	0.43	0.40	0.22	0.26	0.20
	368898-3018588	96	0.33	0.41	0.29	0.21	0.26	0.26
Multifamily								
Age by Built Year	1853-1928	881	0.35	0.44	0.36	0.18	0.22	0.32
	1928-1941	674	0.34	0.43	0.28	0.17	0.21	0.21
	1941-1963	782	0.32	0.40	0.26	0.17	0.21	0.21
	1963-2015	760	0.34	0.42	0.30	0.18	0.23	0.23
Built Area (sq. ft.)	19464-64650	775	0.36	0.45	0.38	0.15	0.22	0.34
	64650-83844	774	0.32	0.42	0.26	0.16	0.20	0.19
	83844-134674	774	0.34	0.43	0.43	0.18	0.22	0.22
	134674-7842590	774	0.32	0.40	0.40	0.20	0.24	0.24

study, we consider a building to be an "adopter" if there is at least one ECM match between the audit recommendations and permit description.

We compare the number of audits and total number of ECMs recommended for office and multifamily buildings grouped by non-adopters and adopters based on the '75th perc +' matching criteria (Table 7). Office buildings have a higher adoption rate (32%) compared to multifamily buildings (19%). We also compare building characteristics, including built year, residential property ownership (condominium vs. co-operative), built area, and assessed value (per square foot) by merging with NYC Primary Land Use Tax Lot Output (PLUTO) data. Results show the adoption rate in co-operatives (18%) is lower than condominiums (23%), possibly due to additional board approval requirement for building improvements in co-operative properties. Two-sample t-tests indicate statistically significant differences in building area, energy use intensity (EUI), and median assessed value per square foot. For both office and multifamily, buildings that adopt ECM recommendations are found to be larger, higher value, and have higher potential energy savings (for office buildings only) based on the ECMs identified in the NPV$_{max}$ scenario. Although buildings that adopt tend to be newer, there is no statistically significant difference in built year.

Table 7: **Summary of audits, ECM suggestions, and building characteristics comparison between non-adopters and adopters.**

Building Type	**Office**		**Multifamily**	
Total Audits	402		3209	
Total ECM Suggestions	1960		17786	
	Non-Adopters	**Adopters**	**Non-Adopters**	**Adopters**
Number of Audits	174 (68%)	128 (32%)	2588 (81%) Condo=314, Co-op=2274	621 (19%) Condo=95, Co-op=526
Number of ECMs	1250 (64%)	710 (36%)	14248 (80%)	3538 (20%)
Median Built Year	1926	1930	1941	1943
Median Building Area (sq.ft.)*	156690	199839	81045	103130
Median Site EUI (kBtu/sq.ft.)*	79	88	82	81
Median Value ($/sq.ft.)*	110	120	33	47
Median Energy Savings NPV max (kBtu/sq.ft.)*	3.46	4.21	6.79	5.43

NOTES: This table report results based on '75th perc +' scenario; * = Two-sample T-test significant at 95% ($p \leq 0.05$).

Energy intensity, measured as site EUI, is higher for adopter buildings than non-adopters in 2013, but decreases over the study period. Between 2013 and 2017, EUI for adopter buildings decreased by approximately 3.5% for office and 1% for multifamily buildings, as shown in Figure 6. Non-adopter buildings, on the other hand, reported increasing EUI, up by as much as 5.7% over the five-year time period. For a more detailed analysis of this relationship, please see Papadopoulos et al. (2018).

Figure 7 compares the calculated IRR based on ECMs included in (1) the NPV$_{max}$ scenario, (2) the NPV$_{n}eutral$ scenario, and (3) actually adopted. Median IRR for adopted ECMs are found to be 20% for multifamily and 24% for office (using the '75th perc +' matching threshold). For office, the IRR of adopted ECMs outperforms the return for the NPV$_{neutral}$ scenario of non-adopters,

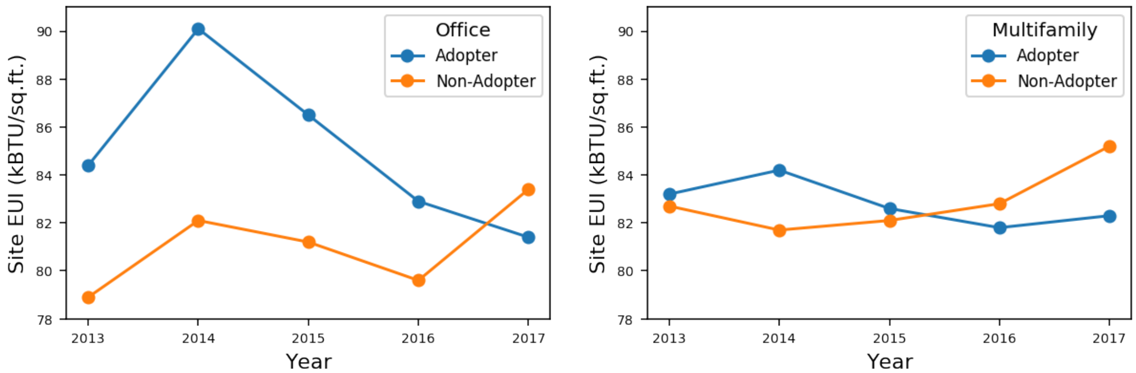

Figure 6: Median energy performance (site EUI) over time (2013-2017).

indicating that adopter buildings may be choosing alternatives that maximize energy savings with net positive return on investment. From Table 4.2, the median cost for the adopted ECMs is \$0.64 per square foot, which falls between the NPV$_{max}$ and NPV$_{neutral}$ scenarios. Expected energy savings of 3.69 kbtu per square foot is less than the expected savings from the NPV$_{max}$ scenario. This is consistent with the assumption that building owners are motivated to initiate energy improvements by the need for repair or replacement of existing systems, but may also reflect false positives in the ECM matching process.

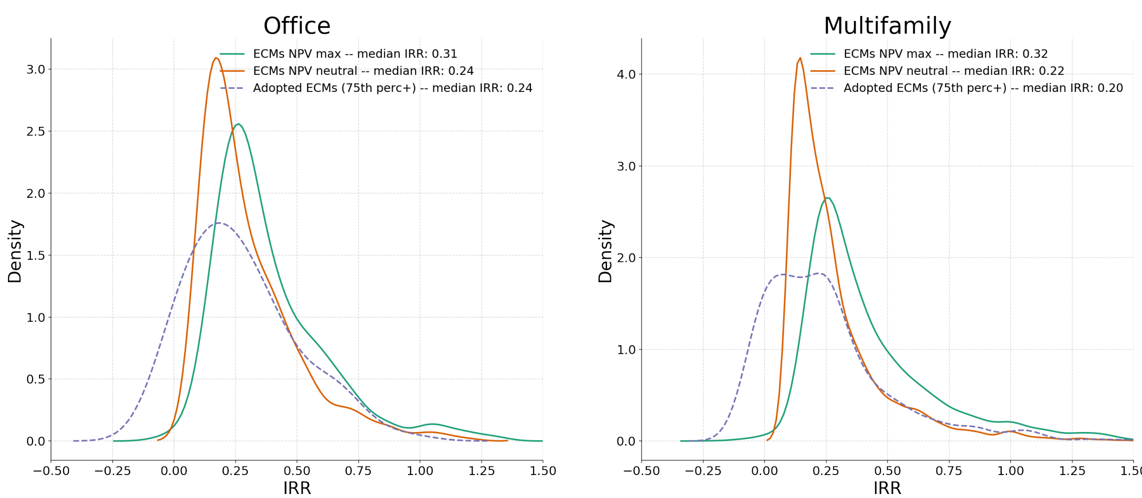

Figure 7: Internal rate of return (IRR) of office and multifamily buildings.

Multifamily buildings exhibit a similar pattern, with an estimated IRR for adopted ECMs of 0.20, slightly below the IRR of the NPV$_{neutral}$ scenario of 0.22. First costs of adopted ECMs are approximately \$0.14 higher than the NPV$_{max}$ scenario, but less than the NPV$_{neutral}$ ECM package.

Table 8: **Comparison between non-adopters and adopters.**

IRR										
		NPV max scenario			NPV neutral scenario			Adopted ECMs		
		median	mean	std	median	mean	std	median	mean	std
Office	Non-adopter	0.31	0.38	0.23	0.23	0.29	0.19	–	–	–
	Adopter	0.31	0.41	0.38	0.24	0.30	0.18	0.24	0.27	0.22
Multifamily	Non-adopter	0.34	0.43	0.31	0.22	0.28	0.24	–	–	–
	Adopter	0.32	0.41	0.27	0.22	0.29	0.22	0.20	0.25	0.27
Energy Savings (kBtu/sq.ft.)										
		NPV max scenario			NPV neutral scenario			Adopted ECMs		
		median	mean	std	median	mean	std	median	mean	std
Office	Non-adopter	3.46	6.96	14.87	4.15	7.16	8.71	–	–	–
	Adopter	4.13	6.58	8.00	5.21	8.00	9.70	3.69	6.04	6.19
Multifamily	Non-adopter	6.79	9.35	9.34	8.79	11.75	11.19	–	–	–
	Adopter	5.28	7.88	8.00	7.33	10.57	10.98	4.19	6.52	6.92

Median First Cost ($/sq.ft.)					
		NPV max scenario	NPV neutral scenario	Adopted ECMs	Max savings scenario
Office	Non-adopter	0.44	0.66	–	1.23
	Adopter	0.54	0.75	0.64	1.29
Multifamily	Non-adopter	0.34	0.76	–	1.22
	Adopter	0.39	0.74	0.53	1.47

Expected energy savings are lower than those in the NPV$_{max}$ and NPV$_{neutral}$ alternatives.

For both building types, there is not a clear relationship between the variability in estimated payback period (as a proxy for uncertainty in projected cost and savings) and the adoption of each ECM category. Figure 8 presents the adoption rate for ECM categories plotted against the range in projected payback period, measured by the difference (in years) between the 95th percentile and 5th percentile estimate for each ECM. While the majority of ECM adoption rates are in the expected range, such as lighting, ventilation, and domestic hot water, the high adoption rate of the envelope ECM category indicates a potential false positive match between audit and permit descriptions. Given the high implementation cost of envelope retrofits, and the relatively long payback period, envelope work is typically driven by other factors than energy efficiency. The potential over-matching of the envelope ECM category may be impacting the IRR and NPV estimates for adopter buildings, given the low return and negative NPV associated with this measure.

We also examine the extent to which additional ECMs, beyond those adopted, would have improved expected return. Table 4.2 presents the "next-best" ECM for office and multifamily adopter buildings, respectively. The next-best ECM is defined as the ECM with the highest NPV that was not implemented as part of the bundle of ECMs matched to the building's renovation permit. We find that the IRR for office buildings would fall by 1% and would increase by 2% for multifamily properties. The most commonly identified next-best ECM for office buildings is fuel switching, a relatively high-cost investment that is dependent on infrastructure access to alternate fuel sources (e.g. natural gas) and on the prices variability of different fuels. For Multifamily

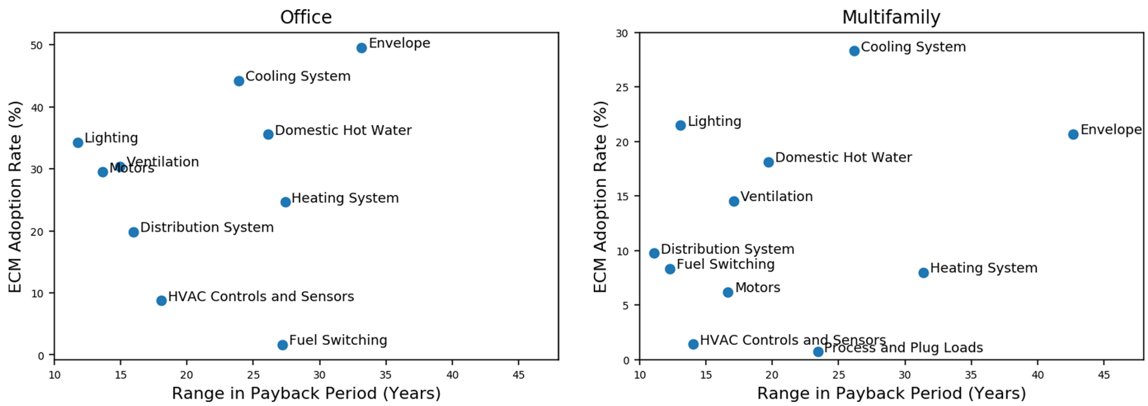

Figure 8: The payback period range between the 5th and 95th percentiles versus the rate of adoption for each ECM category.

Table 9: **Summary of next best ECMs.**

Next Best ECM to Adopt			
Office		**Multifamily**	
Category	**Number**	**Category**	**Number**
Fuel Switching	11	Distribution System	80
Distribution System	8	Fuel Switching	68
Motors	7	Heating System	46
Conveying Systems	5	Motors	22
Other	4	On Site Generation	20
Ventilation	3	Ventilation	16
Process and Plug Loads	2	Submetering	12
On Site Generation	2	Other	10
Heating System	2	Process and Plug Loads	9
Submetering	1	Cooling System	3
General Lighting	1	Conveying Systems	1
Chiller Plant	1	Apartment AC Units	1
Two Scenarios Comparison			
Metric	**Scenario**	**Office**	**Multifamily**
Median IRR	ECM Adoption	0.23	0.17
	ECM Adoption +	0.22	0.20
Median NPV	ECM Adoption	0.26	0.11
	ECM Adoption +	0.47	0.41

buildings, distribution system improvements and fuel switching are found to be the among the next-best ECM alternatives based on NPV.

5. Discussion and Conclusion

The primary contributions of this study are twofold: First, we develop a new method to extract data from energy audit reports and building permit records to match ECM recommendations to permitted renovation activity. Second, we introduce an approach to identify building- and ECM-specific energy retrofit adoption and to estimate the IRR and other financial metrics for these energy efficiency investments. To the best of our knowledge, there is currently no data repository that maintains detailed energy retrofit upgrades for individual buildings following mandatory energy audits in the commercial building sector. This study provides the methodological foundation for a large-scale, nation-wide study of building energy retrofit activity and provides new insight into the return on investment for actual energy improvements put-in-place.

Our results demonstrate a 20% median IRR for adopted ECMs for multifamily buildings and 24% for office buildings, which are lower than IRRs for retrofit scenarios yielding the highest NPV, but consistent with $\text{NPV}_{neutral}$ scenarios that balance investment return with energy savings potential. The magnitude of the IRR reflects the uncertainty in future energy savings, particularly given the significant variation in estimated payback periods for individual ECMs based on auditor cost and savings data. These investments are associated with energy efficiency gains of approximately 5% and 10% for office and multifamily, respectively, in overall site EUI. We also find that the "next-best" ECM would decrease the IRR of the aggregate retrofit investment by 1% for office, but increase the return by 2%, on average, for multifamily buildings. The next-best ECM is determined to be fuel switching in office buildings, which has high implementation costs and variable energy savings based on energy price fluctuations and the availability of alternate fuel source infrastructure. For multifamily properties, the next-best ECM is the distribution systems category, which can present challenges given constraints on access to individual apartments to do recommended work. The technical challenges and financial implications of the next-best ECM suggest that owners are balancing return and energy savings in the decision process.

We acknowledge that our approach has several limitations, primarily due to data sparsity and audit quality. A number of assumptions are made to estimate NPV of the various ECM scenarios, including discount rate and useful life of the installed system or improvement. Thus, future analysis will include uncertainties based on distributions of input parameters. Different reporting systems (audit vs. permit) and data entry standards (auditor vs. contractor) create uncertainties in text matching. Building permit work descriptions are often vague and may not capture all ECM categories since several ECMs may not constitute work requiring a building permit. For example, a building owner often does not need to file a permit application to DOB for lighting improvements. This missing information may cause an underestimation of lighting ECM adoptions, although we account for this in our model. Data quality is also a significant concern for both energy audit reports and permit scope of work descriptions. We find inconsistent input formats, naming conventions, and misreported or erroneous savings and cost projections. A data standardization effort for energy audit reports is underway in NYC; however, this does not address the underlying issue of the reference data and metrics used by auditors to estimate future savings.

Although multiple agencies and organizations collect data related to building energy performance,

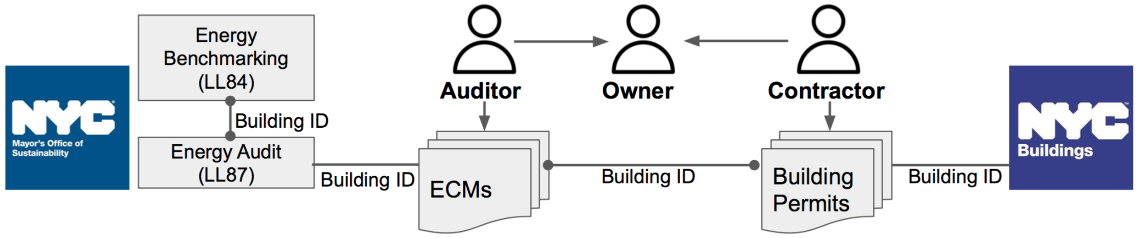

Figure 9: A schematic illustration of future integrated building information system.

energy audits, and renovation work, these efforts are largely siloed and constrained by sparse datasets representing single building types, regions, or portfolios. Our methodology can be used to better integrate audit data, building characteristics, and permit scope of work information. Figure 9 presents a schematic illustration of how audit data (LL87) and energy benchmarking data (LL84) can be linked with renovation permit data to create an integrated information system based on a single unique building identifier. To improve data reliability, consistency, and geographic coverage, we propose to develop a National Retrofit Investment and Performance (NRPI) database. This database would track building-level energy audits, implemented energy conservation measures and retrofit investments and their financial and energy performance metrics, and pre/post energy use profiles. The NRPI would integrate directly with U.S. Department of Energy's Building Performance Database and other federal resources (such as EPA's Portfolio Manager), and provide a detailed repository for actual building audits and retrofit measures.

Additional future work will study the difference between ECM implementation costs and savings for individual buildings with the observed (predicted) price premium for Energy Star labeled buildings of that property type. This will allow us to determine whether observed premia for green certifications are derived from the cost savings associated with energy efficiency or other factors, such as marketing or public relations benefits. We will further identify patterns in the variance between the premium and retrofit cost by building type. physical characteristics (building age, size, etc.), and investor class and ownership type.

As cities introduce more expansive regulations on building energy efficiency and carbon emissions reductions, a complete understanding of the financial implications of retrofit investments is needed to evaluate viable pathways toward near- and long-term sustainability goals. For building owners, our IRR and NPV models provide greater insight into the financial returns to individual ECMs and packages of ECMs. For policymakers, the analysis can be used to assess the economic feasibility of new and existing regulations, and determine where incentives can help overcome barriers to adoption. By identifying buildings that adopted energy efficiency investments, and quantifying the return on those investments, we are able to measure a critical component of the perceived barriers to greater energy efficiency in existing buildings.

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Appendix

Table 10: **Major suggestions in each ECM Category**

ECM Category	**Suggestions (%)**
Lighting	Upgrade to LED (58%), Other (11%), Install Occupancy/Vacancy Sensors (7%), Upgrade to Fluorescent (7%), Upgrade Exterior Lighting (6%)
Domestic Hot Water	Separate DHW from Heating (38%), Install Low-Flow Aerators (25%), Other (9%), Insulate DHW Piping (7%), Install Low-Flow Showerheads (6%)
Envelope	Increase insulation - Roof (20%), Replace Windows (16%), Sealing - Door (16%), Increase insulation - Wall (14%), Add Window Films (9%)
HVAC Controls and Sensors	Install or Upgrade EMS/BMS (43%), Install TRVs(28%), Change Set Points / Setbacks - Heating (9%), Install Indoor Sensors (6%), Other (5%)
Distribution System	Insulate Pipes (73%), Other (7%), Install or Upgrade Master Venting (7%), Replace or repair Steam Traps (5%), Upgrade Pumps (2%)
Heating System	Other (24%), Clean & Tune Boiler/Furnace (19%), Replace Boiler (15%), Upgrade Burner (13%), Upgrade Boiler (10%)
Motors	Install VFDs (55%), Upgrade Motors (38%), Other (4%), Remove Motors (3%), Install or Upgrade EMS/BMS (0.2%)
On Site Generation	Install Solar/Photovoltaic (57%), Install Cogeneration Plant (28%), Solar (13%), Other (0.4%), Low Flow Fixtures (0.3%)
Fuel Switching	#6 oil or #4 oil to natural gas (58%), #2 oil to natural gas (27%), #6 to dual fuel (5%), District steam to on-site generation (3%), District steam to on-site generation (3%), Utility steam to on-site generation (3%)
Ventilation	Other (31%), Install Demand Control Ventilation (20%), Install CAR Dampers (17%), Install Exhaust Fan Timers (16%), Upgrade Fan/Air Handlers (8%)
Cooling System	Other (34%), Replace packaged units (13%), Replace Chiller (12%), Upgrade packaged units (11%), Upgrade Chiller (9%)
Conveying Systems	Other (41%), Upgrade Motors (31%), Add Elevator Regenerative Drives (14%), Upgrade Controls (13%), Regenerative Drive for Elevators (1%)
Process and Plug Loads	Other (54%), Replace Washing Machines (39%), Replace Clothes Dryers (3%), Automatic Shutdown / Sleep Mode for Computers 2%), Install Solar/Photovoltaic (1%)
Other	Other (82%), Low Flow Fixtures (13%), Install Solar PV System (1%), LBS Smart Meters (1%), Insulate piping (1%)
Submetering	Install Submetering (73%), LBS Smart Meters (22%), Sub-Metering (1%), Other (1%), Low Flow Fixtures (1%)

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