Explaining the Adoption of Energy-Efficient Technologies in U.S. Commercial Buildings

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Abstract

This paper investigates factors explaining the adoption of energy-efficient heating, cooling, window, and lighting technologies in U.S. commercial buildings. It presents multinomial logit models of technology adoption using the 2003 Commercial Buildings Energy Consumption Survey microdata set, examining, first, fundamental building components, and, second, energy-efficient adaptations. Key findings are that the choice of fundamental building components is strongly influenced by locational factors, the activities that are expected to take place in the building, and building-specific characteristics. Lighting technologies are an exception, and are poorly explained by these factors. By contrast, energy-efficient heating, cooling, window, lighting, and control adaptations appear to share common drivers, and are more likely to be adopted in newer, larger, more energy-intensive, owner-occupied buildings. These are the buildings that can best afford the up-front costs of innovation, which is often a design-intensive process. Absent policy interventions, the energy-efficient adaptations are unlikely to diffuse rapidly to the rest of the commercial building stock.

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Introduction

Commercial buildings are complex assemblages of architectural, structural, mechanical, electrical and other elements that form distinct systems within integrated building designs. Indeed, the assembly of discrete technological components into systems is the key feature of the design process. The technological options change over time, and the adoption of new technologies is possible every time a building is built or renovated. Why do designers preferentially adopt certain technologies?

Explaining technology adoption in this context requires an appreciation of building design and innovation diffusion processes. The process of building design is project-specific, and it considers factors such as the activities and purposes of the occupants, ownership arrangements, climate, and utility costs. The process of innovation diffusion is economy-wide, and it involves both micro-level adoption choices and macro-level market transformations.

This paper examines the adoption of so-called energy-saving technologies within the U.S. commercial building stock. It does so by analyzing the 2003 Commercial Buildings Energy Consumption Survey (CBECS) microdata files and supplementary data for evidence explaining the presence of specific technologies.

Commercial Building Design

Vitruvius offers timeless architectural design principles that have been variously translated as “firmness, commodity and delight” (Wotten 1624), and “construction, convenience and beauty” (Hamlin 1940). Durable, useful, and beautiful buildings remain our ideal, with variations: modern architects pursue an aesthetic of functionality (Sullivan 1896), whereas postmodernists are willing to separate form and function (Venturi, Scott Brown & Izenour 1972). More recently, an ethical consideration of sustainability has also entered the design lexicon (Vale & Vale 2000).

The engineering design tradition also pursues beauty and utility, form and function. It applies scientific principles and knowledge to solve problems, typically framing the design task as a search for an optimal solution given a set of binding constraints. Design emphases vary, so that engineers may seek to expand the range of solutions considered, make the search process more efficient, or identify more elegant solutions.

Commercial building design shares much in common with the engineering approach of optimizing performance within constraints. Many U.S. commercial building projects are treated as investments that should earn a good rate of return without imposing undue financial risks. The design process is thus subject to a rigorous financial discipline that attempts to ensure adequate performance at the lowest possible construction cost.

Some U.S. commercial building designs instead pursue high performance and tolerate slightly higher initial construction costs (Crosbie 2000). Higher performance takes the form of a better occupant experience and lower operating costs, both of which add value from a life-cycle cost perspective. Technologies intended to deliver higher performance are a particular focus of this study.

Technology Adoption

Innovations diffuse to new users in a manner that typically follows an S-curve pattern over time, proceeding from low initial rates of adoption, to accelerating adoption rates, saturation, and eventually, displacement by subsequent innovations. Explanations of this pattern variously view diffusion as analogous to an epidemic with information spillovers to non-users; a discrete choice driven by users' wealth, expectations, search and learning costs, and switching and opportunity costs; or an information cascade involving an early adopter's stochastic and personally-risky initial choice, followed by a more deterministic lock-in and legitimation of the innovation, and then by a bandwagon effect that sweeps the rest of the market along (Geroski 2000).

Rogers (1995) identifies the key attributes that determine the rate and extent of diffusion: these include the innovation's advantage over existing means, its compatibility with existing systems, its absolute complexity, its trialability by potential users, and its observability by potential users. These factors provide a starting point for developing explanations of technology adoption within commercial buildings.

Technologies adopted in commercial buildings presumably have to demonstrate some relative advantage by being less costly or delivering higher performance. They probably need to be compatible with existing construction practices and not run afoul of building codes or union rules. They probably need to be simple to install and operate. It should be possible to try out the technology without making a major investment relative to the user's total financial assets. Examples of these innovations probably need to be visible near potential users to demystify the technologies. The commercial building technologies studied here have all passed the early-adoption threshold and can now be considered mature, legitimated technologies that have diffused successfully.

The primary objective of this paper is to identify the key factors associated with the adoption of high-performance heating-ventilating-air-conditioning (HVAC), window, lighting, and control technologies within U.S. commercial buildings. The secondary objective is to compare the drivers of adoption for fundamental building technologies to these high-performance adaptations. Expectations are that these explanatory factors include the locational context, the principal activities of the presumed occupants, and the characteristics of the building itself. Locations have varied climates and energy prices that are likely to influence which technological solutions are optimal in each context. Occupant activities govern the basic building program and determine such characteristics as owner occupancy, operating hours and building floor area. Buildings vary in age and construction characteristics.

Methodology

This section introduces the data set and analysis method used to meet the paper's objective. It relies on the CBECS 2003 microdata files and multinomial logistic regression analysis.

CBECS

Every four years, the U.S. Department of Energy conducts the Commercial Building Energy Consumption Survey (CBECS) on a stratified national sample of commercial buildings. Survey questions cover energy-related building characteristics, and reported energy consumption and expenditures. The most recent survey, conducted in

2003 received usable responses for 5,215 buildings. The survey defines commercial buildings as those that do not serve primarily residential, manufacturing/industrial, or agricultural purposes. The publicly available microdata file consists of individual survey responses stripped of identifiers (EIA 2006).

Principal building activities included in the CBECS data set include office, laboratory, nonrefrigerated warehouse, food sales, public order and safety, outpatient health care, refrigerated warehouse, religious worship, public assembly, education, food service, inpatient health care, nursing, lodging, strip shopping mall, enclosed mall, retail other than mall, service, other, and vacant buildings. The most energy intensive activities are food service, inpatient health care, and food sales (EIA 2006: Table C3), but more floor area is devoted to office, mercantile, warehouse and storage, and education than to other activities (EIA 2006: Table A1).

CBECS includes several data fields that are useful for the current study. In addition to descriptors such as building age, region, size, and principal activity, the survey also indicates whether buildings incorporate specific technologies. Emerging technologies such as solar panels are not considered here because their penetration into the commercial building stock is so low. Eight categories of innovations are analyzed in this paper. See EIA (2006) for detailed descriptions of these design alternatives. The first four are basic building components, and the last four are related features designed to improve energy efficiency. In the list below, their current penetration into the U.S. commercial building stock on a percent-of-floor-area basis is shown in parenthesis. Note that the percentages add up to more than 100% because some buildings use more than one technology. Basic building components include the following:

- Heating equipment types include furnaces (32%), boilers (36%), packaged heating units (29%), individual space heaters (20%), heat pumps (15%), district steam or hot water (9%), and other heating equipment (5%).
- Cooling equipment types include residential-type central air conditioners (17%), heat pumps (18%), individual room air conditioners (18%), district chilled water (6%), central chillers (25%), packaged air conditioning units (52%), swamp coolers (3%), and other (2%).
- Window types include single-layer glass (32%), multi-layer glass (37%), a combination of both (17%), or no windows (4%).
- Lighting types include incandescent (54%), standard fluorescent (83%), compact fluorescent (38%), high-intensity discharge (29%), halogen (25%), and other (~0%).

Features intended to promote energy efficiency include the following:

- Heating-Ventilating-Air-Conditioning (HVAC) efficiency features tracked in CBECS include variable-air-volume (VAV) systems (39%), economizer cycles (42%), preventative HVAC maintenance (87%), and energy management and control systems (EMCS)(31%).
- HVAC control strategies include time-clock thermostats (20%), manually-reset thermostats (25%), and as part of an EMCS (31%).
- Window treatments include tinted window glass (42%), reflective window glass (12%), external overhangs or awnings (24%), and skylights or atriums (18%).
- Lighting efficiency features include daylighting (13%), daylighting sensors (4%), specular reflectors (36%), electronic ballasts (65%), and control systems for lighting (7%).

Together, these items provide a broad basis for examining the penetration of innovative technologies within the U.S. commercial building market.

Multinomial Logistic Regression Analysis

This paper shares inferential analysis of the CBECS 2003 data file developed using spreadsheet manipulations and the statistical package SPSS 16. The analysis seeks to answer the following question:

- What are the factors that explain the adoption of specific energy-efficient technologies within U.S. commercial buildings?

We use multinomial logistic regression analysis to predict technology adoptions. A cross-sectional analysis of current U.S. commercial buildings can identify the correlates of specific technology adoptions. The data set indicates whether or not each technology has been adopted in each sample building. We turn to multinomial logistic regression to understand the factors leading to the adoption of specific technologies because it can handle categorical dependent variables.

The dependent variable *y* in a binary logistic regression is dichotomous, that is, it can take the value 1 with a probability *p*, or the value 0 with probability 1-*p*. The explanatory variables *x* in a logistic regression analysis can take any form because logistic regression makes no assumption about their distribution. They can include a mix of continuous and categorical variables. The relationship between the explanatory and dependent variables is not a linear function as in the case of ordinary least squares regression, instead, a logistic regression function uses the logit transformation of *p*. Logistic regression uses maximum likelihood estimation instead of minimizing least square differences.

Multinomial logistic regression allows the user to have a dependent variable with three or more categories. Computationally, it maximizes both the model's fit overall, and for each category of the dependent variable. Key diagnostic statistics include Chi^2 tests of overall model significance and of the significance of each explanatory factor, plus tests of the significance of coefficients within the submodel for each category of the dependent variable. A Nagelkerke Pseudo R^2 value is reported to give readers a quick, if imprecise, feel for the overall explanatory power of the model. Illustrative multinomial logistic regression results are shown in Tables 1 and 2.

The tables include a great deal of information and their layout needs explanation. Each column in the table reports results for a different groups of technologies (space heating, space cooling, etc.). The top portion of each column describes the performance of the overall model for that group of technologies. The bottom portion of each column shows the category submodels that use the standard set of explanatory variables to predict the adoption of specific technologies (furnaces, boilers, etc.). One specific technology becomes the reference case, and the coefficients in the category submodels then show the divergence from the reference case.

To assess the predictive power of the overall model, the top portion of each column shows the Nagelkerke Pseudo R^2 value, which has a range of nearly 0 to 1 and is a measure of the improvement in prediction gained from the null model (predicting the dependent variable without any explanatory variables) to the fitted model (Long 1997). The greater the improvement, the higher the pseudo R-squared. It is meant to be analogous to a standard R^2 value used in ordinary least squares regression (and which is unavailable in discrete choice models).

A measure of the overall model's goodness of fit is the Likelihood Ratio Chi-Square test (abbreviated as Chi^2 test of –2LL (DF)) that at least one of the explanatory variables' regression coefficient is not equal to zero in the model. The Likelihood Ratio Chi-Square statistic can be calculated by -2*L(null model) - (-2*L(fitted model)), where L(null model) is the log likelihood without explanatory variables in the model and L(fitted model) is the log likelihood from the final iteration with all the explanatory variables (UCLA 2008). For a given number of variables and the model's corresponding degrees of freedom (DF), a significant Chi-Square value (marked by asterisks) provides the basis for rejecting the null hypothesis that all of the regression coefficients in the model are equal to zero. This measure is used to test both overall fit and respective fit of each of the nested submodels.

The lower portion of each column in the tables that summarizes the category submodels shows the regression coefficients and associated standard errors (S.E.). Since these are estimated multinomial logistic regression coefficients, they are relative to the referent group. The standard interpretation of the multinomial logit is that for a unit change in the explanatory variable, the logit of outcome *m* relative to the referent group is expected to change by its respective coefficient estimate (which is in log-odds units) assuming that the other variables in the model are held constant (UCLA 2008). For significant coefficients (marked with asterisks), we reject the null hypothesis that a particular explanatory variable's regression coefficient is zero given that the rest of the predictors are in the submodel.

Explanatory Variables

Descriptive analysis of the CBECS data sets (XXXX 2008) makes it clear that new technologies are displacing old ones, and that their levels and rates of penetration vary substantially. This begs the following question: What are the factors associated with the adoption of specific technologies?

The location of a building dictates the price it pays for energy, the climatic conditions it endures, and its regulatory and cultural context. The CBECS data set indicates in which of nine U.S. Census Divisions a building is located, which roughly discriminates on energy prices and climate, but not on regulatory context. CBECS also directly reports on energy consumption and expenditures, from which we derive average prices. Additionally, CBECS directly reports the number of heating and cooling degree days in the local climate. In the regression analyses that follow, we use energy prices, heating degree days, and cooling degree days as proxies for location. Each of these variables supports a finding of systematic differences among Census Divisions at the $p < 0.001$ level of significance in one-way analysis-of-variance tests, not shown. A multinomial logistic regression analysis (not shown) predicting Census Division using these three variables confirms their explanatory power at the $p < 0.001$ level of significance for the overall model and individual parameter estimates. Thus, rather than make subsequent analyses unwieldy by having too many variables, we rely solely on the variables of energy price, heating degree days, and cooling degree days to operationalize the concept of location.

The activities expected to take place within a building should strongly influence its design and associated technology choices. The CBECS data set assigns buildings to one of eighteen principal activity categories, such as “office” or “inpatient healthcare.” CBECS also directly reports variables that function well as proxies for activity, including building size (floor area), energy intensity (calculated by dividing energy consumption by floor area), and owner-occupant relationship (represented here by a binary variable that selects for the problematic yet ubiquitous privately-owned rental building that suffers from the split incentive of having different parties own the building and pay the utility bills). These proxies relate intuitively to activity categories. Illustratively, educational activities require a significant amount of floor area, are not very energy-intensive, and are almost never in rented buildings. By contrast, food service requires only a small footprint, is very energy intensive, and often occupies rented space. Each of these variables supports a finding of systematic differences among principal activities at the $p < 0.001$ level of significance in one-way analysis-of-variance tests, not shown. A multinomial logistic regression analysis (not shown) predicting principal activity using these three variables confirms their explanatory power at the $p < 0.001$ level of significance for the overall model and individual parameter estimates. Again, rather than make subsequent analyses unwieldy, we rely solely on the variables of floor area, energy intensity, and private rental to operationalize the concept of principal activity.

Characteristics of the building itself should also strongly influence technology adoption. Most obviously, the year of construction affects the architectural style, relative factor prices (costs of labor, materials, and energy), and universe of available technologies. Also important for influencing energy use is the amount of glazing in the building envelope (measured as percent that is glass). Glazing also correlates with a Modernist architectural style and its associated construction techniques. These two variables serve to operationalize the concept of building-specific characteristics.

Finally, characteristics of the technology to be adopted should be influential. We focus here on its installed cost, measured as an ordinal variable with low, medium, and high values.

Results

The multinomial logistic regression models shown in Tables 1 and 2 predict the adoption of fundamental energy technologies and energy efficiency improvements, respectively, within U.S. commercial buildings. A common set of explanatory variables is used in all of the models to facilitate comparisons across technologies of the factors driving technology adoption. The following discussion highlights only the key empirical findings and is not exhaustive.

Adoption of Fundamental Building Technologies

Table 1 summarizes models of technology choice for space heating, space cooling, windows, lights. As mentioned in the methodology section, each column in the table is a discrete choice (multinomial logit regression) model for a different group of technologies. The top part of each column summarizes the performance of the overall model, and the bottom part of each column provides details on the associated submodels. The submodels show how important the explanatory variables are in predicting the adoption of specific technologies. An overall model that performs well will have a high Nagelkerke Pseudo R^2 and strongly significant Likelihood Ratio Chi-Square tests. Explanatory variables that do not have strongly significant Likelihood Ratio Chi-Square tests do not contribute to the overall model's predictive power. Within the category submodels, regression coefficients with significant explanatory power are marked with asterisks. Coefficients are measured relative to the reference category.

The model of space heating technology choice shown in Column 3 of Table 1 asks: What factors explain whether space heating is accomplished with packaged units, furnaces, boilers, or other technology? Based on the pseudo R^2 and Likelihood Ratio Chi-Square tests, the model performs well enough to reject the null hypothesis overall and for each explanatory factor except the installation cost of the technology. Recall that the null hypothesis is that there is no systematic relationship among the explanatory and dependent variables. Based on the signs of the significant regression coefficients in the lower part of Column 3, packaged heating units, the reference category, are found nationwide, especially in newer buildings in warmer climates. Relative to packaged units, furnaces are more prevalent in locations with lower energy prices and colder climates, with principal activities that require a smaller floor area and lower energy intensity, in buildings that are older. Boilers are also more common in locations with lower energy prices and colder climates, but with principal activities requiring more floor area, not rented for profit, in buildings that are older but with more glass. Other space heating technologies include individual space heaters, heat pumps, district heat, and other heating equipment. In additional analyses not shown, individual space heaters appear more often in older, less energy-intensive, rental buildings. Heat pumps, a relatively recent innovation, are found nationwide where principal activities require less floor area and energy intensity, are not rented, and are in newer buildings with more glass. District steam and hot water systems are used in locations with lower energy prices, where principal activities demand a larger floor area, greater energy intensity, and owner-occupancy, in buildings that are older but with much glass.

Column 4 of Table 1 shows a robust model of space cooling technology choice. It asks: What factors explain whether space cooling is accomplished with packaged units, residential-type central air-conditioning systems or room air conditioners, central chillers or district chilled water systems, or other technology such as heat pumps or swamp coolers? The overall model has a relatively high pseudo R^2 and passes the Chi-Square significance test except for the installed cost variable. Based on the signs of the significant coefficients in the bottom part of Column 4, packaged air-conditioning units, the reference category, are most common in mid-sized, rented buildings. Residential-type central air-conditioning systems and individual room air conditioners are more prevalent in locations with more extreme, inland climates, with principal activities requiring a smaller floor area and lower electricity intensity, in older buildings with a substantial amount of glass. Central chillers and district chilled water systems appear in locations with lower electricity prices and heating loads, with non-rental uses that require more floor space and higher electricity intensity, in buildings that are older and have much glass. Heat pumps and other space cooling technologies appear in locations with lower electricity prices and less extreme climates, with principal activities that require less floor area are less electricity intensive.

Column 5 of Table 1 shows a model that answers this question: What factors explain the choice between single-layer, multi-layer, or a combination of single- and multi-layer windows? Based on a modest pseudo R^2 value and Chi-Square tests, the model predicts the adoption of window types performs well enough to reject the null hypothesis overall and for most of the explanatory factors except cooling degree days, percent glass, and installation cost. Based on the signs of the significant regression coefficients in the lower part of Column 5, the model indicates that single-layer glass, the reference category, is more common in older, smaller, rental buildings in warmer climates. Multi-layer glass, or a combination of both single- and multi-layer glass, is an innovation that has been adopted especially in locations with lower energy prices and colder winters, with uses requiring more floor area and higher energy intensities, not rented, in newer buildings. The only part of this pattern that does not make economic sense, and agree with a theory of adoption as being driven by relative advantage, is the correlation with lower energy prices, a result most likely due to unobserved regional factors such as local building codes.

Column 6 of Table 1 shows a model of lighting technology adoption that asks: What factors explain whether incandescent, fluorescent or more advanced types of lights are chosen? Based on the pseudo R^2 and Chi-Square statistics, this model has very little explanatory power. This is due to the preeminence of fluorescent lighting in commercial buildings. Alternatives, such as old-fashioned incandescent bulbs, or new, advanced halogen and high-intensity discharge bulbs are still relatively rare. Based on the signs of the significant regression coefficients in the bottom part of Column 6, some first-cost-conscious users choose incandescents, whereas some of those with larger capital budgets may choose more advanced technologies. Lighting technology is easy to retrofit into existing buildings, hence it does not closely track location-, use-, or building-specific variables.

Adoption of Energy-Efficiency Technologies

Table 2 summarizes models explaining adoption of energy-efficiency technologies including HVAC features, control system types, window treatments, and lighting technologies. As in Table 1, each column in the table is a discrete choice model for a different group of technologies. The top part of each column summarizes the performance of the overall model, and the bottom part of each column provides details on the associated submodels.

Column 3 of Table 2 shows a model that asks: What factors explain whether buildings contain none, one, two, or three or more HVAC efficiency technologies? Specifically, it shows results for a suite of HVAC efficiency technologies including variable-air-volume systems, economizer cycles, preventative maintenance, and energy management and control systems, represented as a categorical index of none, one, two, or three or more of these technologies adopted. Based on a modest pseudo R^2 and significant Chi-Square tests, the overall model is robust enough to generate insights. Both the Chi-Square tests and the submodels' regression coefficients show that locational factors (energy price, heating and cooling degree days) lack explanatory power in this model. The significant regression coefficients in the bottom part of Column 3 show that greater adoption of these technologies is associated with activities requiring a larger floor area and higher energy intensity, in newer buildings that have much glass and are not rented. Recall that percent glass is important partly as an indicator of architectural style.

Column 4 of Table shows a model of HVAC control system choices, asking: What factors explain whether manual thermostats, time-clock thermostats, or advanced energy management and control systems are adopted in buildings? The overall model is robust, with a respectable pseudo R^2 and significant Chi-Square tests. The signs and significance of the regression coefficients in the lower part of Column 4 demonstrate that locational factors again have a relatively weak influence. Relative to manual thermostatic control, more advanced time-clock thermostats appear more often with principal activities that are more electricity intensive, in buildings that are newer and have more glass. Highly-advanced energy management and control systems appear in larger, more electricity-intensive, owner-occupied buildings that are newer and have more glass.

Column 5 of Table 2 shows a model that asks: What factors explain buildings use none, one, two, or three or more energy-efficient window treatments? With a low pseudo R^2 and several explanatory variables not passing the Chi-Square significance test, this is a relatively weak model that attempts to explain the choice of energy-efficient window treatments including tinted glass, reflective glass, awnings or louvers, and skylights or atriums. These items are represented as a categorical index of none, one, two, or three or more of these treatments adopted. Again, locational factors do not play much of a role, with only heating degree days showing significance. Based on the signs of the significant regression coefficients in the lower part of Column 5, a greater number of window treatments appear in larger, newer, more energy-intensive buildings with much glass.

Lighting efficiency choices are the subject of a final model, shown in Column 6 of Table 2. It asks: What factors explain whether buildings use none, one, two, or three or more lighting efficiency technologies? These include specular reflectors, electronic ballasts, auto sensors, and energy management and control systems for lighting, represented as a categorical index of none, one, two, or three or more of these technologies adopted. Based on a modest pseudo R^2 and mostly significant Chi-Square tests, the overall model performs well enough to provide insights. Again, based on the signs and significance of the regression coefficients in the lower part of Column 6, locational factors do not play a strong role. Principal building activity has more explanatory power, with greater floor area, higher energy intensity, and owner-occupancy correlating with more lighting efficiency technologies adopted. Newer buildings with more glass are also more likely to adopt these technologies. Daylighting, or reliance on natural light, is an alternative lighting efficiency strategy not included above because it has such different correlates, and it is more often found in older, smaller, less electricity-intensive buildings with large amounts of glass.

Comparing Fundamental Components and Energy-Efficiency Choices

In summary, the adoption of fundamental heating, cooling, and window technologies in U.S. commercial buildings is very much a function of locational factors, principal building activity, and building-specific characteristics. Different technologies have acquired specific niches, and no technology dominates across locations and uses. There are a few pronounced regional differences identified by the authors' inspection of the data behind the models summarized here; for example, energy management and control systems are especially common in the Pacific region, and economizer cycles are more prevalent in the New England and Pacific areas. Regular HVAC maintenance is now a ubiquitous practice.

Lighting technologies are different story. Fluorescent bulbs have captured most of the U.S. commercial building market and have dominated that market for decades. New technologies are penetrating that market only at the margins, mostly in newer, higher-end buildings.

Energy-efficiency technologies for heating, cooling, windows, lighting, and controls are entering widespread use, but their adoption patterns differ from the fundamental building components discussed above. Locational factors typically play a smaller role. Principal building activity and building characteristics retain explanatory power. More of these technologies are present in buildings that are newer, larger, more energy-intensive, have more glass on the exterior, and are owner-occupied. By contrast, these innovations are less likely to be present in smaller, older, ordinary, rented commercial buildings.

Conclusions

This research has shown that numerous technologies have penetrated the U.S. commercial building sector; but only a few, such as fluorescent light bulbs, have become dominant (see also XXXX 2008).

What are the factors associated with the adoption of specific basic building technologies? Analysis of this question supports the compatibility tenet of diffusion theory. This research confirms that submarkets are defined by locational factors (energy prices, climatic conditions), principal activity (floor area, energy intensity of use, occupant status), and building factors (vintage, envelope design). Rational attention to technologies that bestow a relative advantage on the owner is also evident, but this does not always lead to outcomes that reduce life-cycle costs, especially when the occupants rent the building.

By contrast, energy-efficient adaptations most often appear in newer, larger, more energy-intensive, owner-occupied buildings. These are the buildings that can best afford the up-front costs of innovation, which is often a design-intensive process. This finding matches a discrete-choice model of innovation diffusion driven by the users' wealth, expectations, ability to absorb search and learning costs, and a situation with low switching and opportunity costs. These energy-efficient technologies therefore are unlikely to diffuse very rapidly beyond the current group of adopters.

There are several implications of this research for building practice and public policy, as follows:

- Much so-called energy-efficiency investment is taking place in higher-end buildings, and only partly compensating for these buildings' overall higher energy intensities. If energy efficiency is an important public objective, then the minimum threshold for acceptable efficient performance has to be raised substantially by regulation or other means to ensure that most commercial buildings become adopters of these technologies.
- The renter's split-incentive dilemma is real, because rental buildings are indeed less likely to adopt energy-efficient features in comparison to owner-occupied buildings.

- The design of fundamental building components is appropriately place- and use-specific. Building performance rating systems, such as the U.S. Green Building Council's Leadership in Energy and Environmental Design (LEED), should rely on performance measures rather than technology specifications in recognition of the desirability of tailoring designs to specific contexts.
- The large stock of existing buildings is both a persistent problem and an opportunity. To date, they contain few innovations, yet they represent an unexploited opportunity to achieve better performance in the nation's commercial building inventory if energy-efficient adaptations such as those discussed here become mandatory, or more cost-effective.

Future research should investigate how the adoption of individual innovative technologies relates to the construction of innovative, high-performance buildings. Further examination of the energy efficiency – energy intensity link is also needed.

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Table 1: Factors Explaining Fundamental Energy Technology Choices in U.S. Commercial Buildings

Multinomial Logit Model		**Space Heating**[1]	**Space Cooling**[2]	**Windows**[3]	**Lights**[4]
Nagelkerke Pseudo R^2		0.47	0.44	0.25	0.14
Model Fit	**Factor Type**	**Chi^2 test of -2LL (DF)**	**Chi^2 test of -2LL (DF)**	**Chi^2 test of -2LL (DF)**	**Chi^2 test of -2LL (DF)**
Overall model		2085 (54)***	1630 (27)***	933 (18)***	387 (18)***
Explanatory factors:					
Constant		168 (6)***	94 (3)***	446 (2)***	14 (2)***
Energy price	Location	130 (6)***	36 (3)***	30 (2)***	5 (2)
Heating degree days	Location	44 (6)***	74 (3)***	139 (2)***	1 (2)
Cooling degree days	Location	53 (6)***	30 (3)***	1 (2)	2 (2)
Floor area	Activity	337 (6)***	682 (3)***	17 (2)***	1 (2)
Energy intensity	Activity	304 (6)***	240 (3)***	15 (2)***	3 (2)
Rental	Activity	180 (6)***	72 (3)***	11 (2)**	<1 (2)
Year built	Building	174 (6)***	81 (3)***	424 (2)***	4 (2)
Percent glass	Building	91 (6)***	24 (3)***	6 (2)	1 (2)
Installed cost	Technology	3 (6)	<1 (3)	<1 (2)	374 (2)***
Category Submodels	**Factor Type**	**Coefficient (S.E.)**	**Coefficient (S.E.)**	**Coefficient (S.E.)**	**Coefficient (S.E.)**
Reference category		Packaged unit (reference category, n=737)	Packaged unit (reference category, n=1280)	Single-layer glass (n=1450)	Fluorescent bulbs (n=3130)
Category 1		Furnace (n=1001)	Residential or Individual unit (n=843)	Multi-layer glass (n=1639)	Incandescent bulbs (n=338)
Constant		26.951 (4.540)***	28.996 (3.538)***	-65.150 (3.581)***	1.899 (4.456)
Energy price	Location	-0.010 (0.002)***	0.149 (0.147)	-0.006 (0.002)***	0.330 (0.180)
Heating degree days	Location	0.279 (0.073)***	0.293 (0.063)***	0.637 (0.057)***	0.080 (0.079
Cooling	Location	-0.573	0.498	0.128 (0.112)	0.200 (0.169)

degree days		(0.161)***	(0.135)***		
Floor area	Activity	-0.051 (0.008)***	-0.328 (0.035)***	0.007 (0.002)**	0.003 (0.003)
Energy intensity	Activity	-0.340 (0.062)***	-0.384 (0.054)***	0.158 (0.045)***	0.001 (0.061)
Rental	Activity	-0.092 (0.107)	0.015 (0.098)	-0.130 (0.085)	0.001 (0.131)
Year built	Building	-12.190 (2.298)***	-12.984 (1.790)***	31.971 (1.807)***	-0.347 (2.258)
Percent glass	Building	-0.126 (0.058)*	0.163 (0.052)**	0.079 (0.042)	-0.059 (0.065)
Installed cost	Technology	-0.106 (0.097)	0.003 (0.072)	0.007 (0.044)	-1.367 (0.144)***
Category 2		Boiler (n=860)	Central chiller or district ch. water (n=580)	Combination of both (n=722)	Advanced bulbs (n=338)
Constant		46.351 (4.779)***	0.179 (5.311)	-12.859 (3.199)***	-16.012 (4.557)***
Energy price	Location	-0.030 (0.003)***	-0.836 (0.199)***	-0.010 (0.002)***	0.207 (0.173)
Heating degree days	Location	0.000 (0.084)	-0.392 (0.090)***	0.508 (0.070)***	-0.001 (0.076)
Cooling degree days	Location	-1.093 (0.198)***	0.152 (0.182)	0.090 (0.149)	-0.084 (0.175)
Floor area	Activity	0.039 (0.005)***	0.891 (0.052)***	0.010 (0.003)***	0.000 (0.003)
Energy intensity	Activity	0.219 (0.075)**	1.001 (0.094)***	0.148 (0.056)**	0.097 (0.060)
Rental	Activity	-0.949 (0.131)***	-1.241 (0.158)***	-0.355 (0.109)***	-0.037 (0.128)
Year built	Building	-23.190 (2.431)***	-8.805 (2.698)***	5.304 (1.626)***	4.530 (2.306)*
Percent glass	Building	0.374 (0.059)***	0.260 (0.061)***	0.109 (0.050)*	-0.040 (0.063)
Installed cost	Technology	0.020 (0.108)	0.075 (0.099)	0.031 (0.053)	1.890 (0.138)***
Category 3		Other (n=849)	Other (n=398)		
Constant		22.946 (6.310)***	-9.631 (5.473)		
Energy price	Location	-0.005 (0.003)	-0.717 (0.185)***		

Heating degree days	Location	0.232 (0.105)*	-0.304 (0.079)***		
Cooling degree days	Location	0.047 (0.209)	-0.435 (0.164)**		
Floor area	Activity	-0.017 (0.011)	-0.173 (0.043)***		
Energy intensity	Activity	-0.634 (0.087)***	-0.306 (0.067)***		
Rental	Activity	0.448 (0.154)**	-0.162 (0.124)		
Year built	Building	-10.640 (3.193)***	5.505 (2.772)*		
Percent glass	Building	0.056 (0.084)	0.144 (0.062)*		
Installed cost	Technology	-0.089 (0.143)	-0.037 (0.090)		

Notes:

1. Energy price and energy intensity refer to multi-fuel energy (electricity, natural gas, fuel oil, other). Other category includes individual space heaters, heat pumps, district heat, and other heating equipment.
2. Energy price and energy intensity refer to electricity only, because most cooling technologies do not use anything else. Other category includes heat pumps, evaporative coolers, and other cooling equipment.
3. Energy price and energy intensity refer to multi-fuel energy (electricity, natural gas, fuel oil, other).
4. Energy price and energy intensity refer to electricity only, because most lighting technologies do not use anything else. Cases are placed into categories based on the predominant lighting technology used, by percent of floor area. Advanced lamps include compact fluorescents, high-intensity discharge, halogen, and other technologies.

Multinomial logistic regression analysis. Predicts choice among categories based on explanatory factors.

In the analyses, floor area, energy price, and energy intensity are subjected to a log transformation to improve normality.

In the analyses, heating degree-days, cooling degree-days, and year constructed are divided by 1000 to reduce the number of decimal places in the regression coefficients.

*** Significant at 0.001 level
** Significant at 0.01 level
* Significant at 0.05 level

Table 2: Factors Explaining Energy-Efficiency Choices in U.S. Commercial Buildings

Multinomial Logit Model		**HVAC**[1]	**Controls**[2]	**Windows**[3]	**Lights**[4]
Nagelkerke Pseudo R^2		0.20	0.33	0.15	0.21
Model Fit	**Factor Type**	**Chi^2 test of -2LL (DF)**	**Chi^2 test of -2LL (DF)**	**Chi^2 test of -2LL (DF)**	**Chi^2 test of -2LL (DF)**
Overall model		774 (27)***	608 (18)***	542 (27)***	621 (27)***
Explanatory factors:					
Constant		111 (3)***	56 (2)***	135 (3)***	42 (3)***
Energy price	Location	6 (3)	41 (2)***	6 (3)	32 (3)***
Heating degree days	Location	7 (3)	4 (2)	22 (3)***	3 (3)
Cooling degree days	Location	2 (3)	11 (2)**	4 (3)	15 (3)**
Floor area	Activity	256 (3)***	187 (2)***	144 (3)***	155 (3)***
Energy intensity	Activity	65 (3)***	55 (2)***	24 (3)***	38 (3)***
Rental	Activity	55 (3)***	34 (2)***	4 (3)	78 (3)***
Year built	Building	92 (3)***	50 (2)***	125 (3)***	26 (3)***
Percent glass	Building	61 (3)***	28 (2)***	45 (3)***	48 (3)***
Installed cost	Technology	5 (3)	1 (2)	2 (3)	3 (3)
Category Submodels	**Factor Type**	**Coefficient (S.E.)**	**Coefficient (S.E.)**	**Coefficient (S.E.)**	**Coefficient (S.E.)**
Reference Category		None adopted (n=1708)	Manual thermostat (n=763)	None adopted (n=1201)	None adopted (n=2955)
Category 1		One technology adopted (n=826)	Time-clock thermostat (n=470)	One treatment adopted (n=1477)	One technology adopted (n=224)
Constant		-8.543 (3.063)**	-28.198 (4.912)***	-18.0391 (2.851)***	-8.472 (5.496)
Energy price	Location	-0.153 (0.125)	-1.066 (1.786)	-0.056 (0.116)	-0.847 (0.210)***
Heating degree days	Location	-0.107 (0.058)	-0.074 (0.080)	-0.250 (0.055)***	-0.105 (0.100)
Cooling degree days	Location	0.152 (0.120)	-0.614 (0.186)***	-0.215 (0.116)	0.193 (0.201)
Floor area	Activity	-0.051 (0.007)***	0.014 (0.009)	0.025 (0.004)***	0.017 (0.003)***

Energy intensity	Activity	0.025 (0.046)	0.213 (0.069)**	0.068 (0.044)	0.306 (0.085)***
Rental	Activity	-0.172 (0.092)	-0.095 (0.129)	0.159 (0.087)	-1.216 (0.200)***
Year built	Building	4.230 (1.556)**	13.506 (2.439)***	9.557 (1.452)***	0.749 (2.798)
Percent glass	Building	0.165 (0.048)***	0.197 (0.065)**	0.159 (0.045)***	0.248 (0.069)***
Installed cost	Technology	0.076 (0.037)*	0.037 (0.071)	-0.022 (0.035)	-0.031 (0.079)
Category 2		Two technologies adopted (n=443)	Energy Mgmt Control System (n=528)	Two treatments adopted (n=685)	Two technologies adopted (n=308)
Constant		-21.329 (4.356)***	-33.322 (5.625)***	-30.217 (3.950)***	-18.307 (5.229)***
Energy price	Location	0.136 (0.159)	-14.271 (2.419)***	-0.067 (0.147)	-0.823 (0.187)***
Heating degree days	Location	-0.172 (0.073)*	-0.193 (0.095)*	-0.174 (0.068)**	-0.050 (0.087)
Cooling degree days	Location	0.082 (0.147)	-0.294 (0.199)	-0.195 (0.144)	0.069 (0.185)
Floor area	Activity	-0.003 (0.005)	0.075 (0.008)***	0.034 (0.004)***	0.023 (0.003)***
Energy intensity	Activity	0.273 (0.062)***	0.586 (0.082)***	0.222 (0.058)***	0.355 (0.075)***
Rental	Activity	-0.282 (0.117)*	-0.856 (0.155)***	0.052 (0.109)	-0.942 (0.162)***
Year built	Building	9.178 (2.211)***	15.217 (2.794)***	14.427 (2.012)***	5.622 (2.657)*
Percent glass	Building	0.234 (0.056)***	0.354 (0.069)***	0.316 (0.052)***	0.327 (0.059)***
Installed cost	Technology	-0.006 (0.046)	-0.041 (0.080)	0.022 (0.044)	-0.101 (0.070)
Category 3		Three or more adopted (n=736)		Three or more adopted (n=296)	Three or more adopted (n=160)
Constant		-39.407 (4.227)***		-59.330 (6.851)***	-43.680 (8.582)***
Energy price	Location	-0.244 (0.143)		-0.496 (0.208)*	-0.448 (0.259)
Heating	Location	-0.073		-0.232	-0.166

degree days		(0.066)		(0.095)*	(0.109)
Cooling degree days	Location	-0.043 (0.142)		-0.145 (0.195)	-0.989 (0.291)***
Floor area	Activity	0.024 (0.003)***		0.043 (0.005)***	0.033 (0.003)***
Energy intensity	Activity	0.420 (0.059)***		0.325 (0.084)***	0.311 (0.103)**
Rental	Activity	-0.813 (0.113)***		-0.012 (0.153)	-0.433 (0.201)*
Year built	Building	18.591 (2.150)***		29.237 (3.480)***	19.094 (4.342)***
Percent glass	Building	0.360 (0.048)***		0.333 (0.068)***	0.353 (0.079)***
Installed cost	Technology	0.009 (0.042)		0.059 (0.061)	-0.121 (0.097)

Notes:

1. Energy price and energy intensity refer to multi-fuel energy (electricity, natural gas, fuel oil, other). HVAC efficiency technologies include variable-air-volume systems, economizer cycles, preventative maintenance, and energy management and controls systems.
2. Energy price and energy intensity refer to electricity only, because most HVAC technologies controlled by these systems do not use anything else.
3. Energy price and energy intensity refer to multi-fuel energy (electricity, natural gas, fuel oil, other). Window treatments include tinted glass, reflective glass, awnings or louvers, and skylights or atriums.
4. Energy price and energy intensity refer to electricity only, because most lighting technologies do not use anything else. Lighting efficiency technologies include specular reflectors, electronic ballasts, auto sensors, and energy management and controls systems for lighting.

Multinomial logistic regression analysis. Predicts choice among categories based on explanatory factors.

In the analyses, floor area, energy price, and energy intensity are subjected to a log transformation to improve normality.

In the analyses, heating degree-days, cooling degree-days, and year constructed are divided by 1000 to reduce the number of decimal places in the regression coefficients.

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