Differentiation in Adoption of Environmental Standards: LEED from 2000-2010*

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Abstract

Understanding how firms adopt voluntary quality or environmental standards is important for designing such programs and evaluating their success. We study the adoption of LEED (Leadership in Energy & Environmental Design), an internationally recognized environmental building certification system. LEED offers four levels of certification, corresponding to greater investments in green building technology. We find substantial heterogeneity in the choice of certification levels, even within relatively small markets. In order to explain this heterogeneity, we specify a model that encompasses market and building factors, as well as differentiation – choosing LEED levels that distinguish a building from its rivals. We estimate this model via indirect inference, and find that differentiation accounts for 34.1% of the variation due to observable variables. It is more important than observed project characteristics, almost as important as observed market characteristics, and 16.07% as important as unobserved market effects. We also use the model to evaluate a counterfactual LEED standard that provides only two certification levels, reducing opportunities for differentiation. Our model predicts that certification levels would increase under the counterfactual standard, though this need not produce improved environmental performance.

Keywords: Environmental Standards, Quality Standards, LEED.

JEL Codes: TBD.

1 Introduction

Over the last several years, many private not-for-profit organizations have developed voluntary certification programs aimed at revealing information about corporate social and environmental performance. The web site www.ecolabelindex.com, for example, maintains a registry of 448 different environmental certification programs. The rapid increase in opportunities for voluntary certification has stimulated a debate about the design of these programs and the determinants of their adoption.

We study the adoption of LEED (Leadership in Energy & Environmental Design), an internationally recognized environmental building certification system. LEED is developed by the non-profit U.S. Green Building Council (USGBC), and offers four levels of certification (Certified, Silver, Gold and Platinum) corresponding to greater investments in green building technology. The multi-tier nature of LEED produces opportunities for differentiation. This paper focuses on whether LEED adopters' certification-level choices reflect a desire to differentiate their buildings from other LEED certified projects. More generally, we are interested in explaining the heterogeneity of certification-level choices, and determining how much of that heterogeneity can be explained by various factors, such as building characteristics, market characteristics, and differentiation. We also ask how certification would be different if LEED was designed differently, for instance, to have only two certification levels instead of four.

By differentiation, we have in mind that building owners use LEED certification as a source of vertical product differentiation.[1] The following quote from Toffel and Sesia (2010)is an example of how building owners compare themselves to rivals:

> *"This building must be second to none. There's an enormous difference between being the best and not being the best. Let's see what we can do to achieve LEED Platinum." Henri Termeer, Genzyme CEO*

Similarly, rivalry might lead a building owner to choose a lower level of certification. For example, there are presumably only a limited number of potential clients to an office building that are willing to pay for LEED Platinum certification. If an office developer has the opportunity to be the first building with Platinum certification in the market, it may be attractive. But if there is already a Platinum-certified building nearby, the "Platinum market" is more competitive and perhaps the investment is no longer worth it. Note that whether this type of differentiation promotes environmental performance depends on what others have chosen, and can also depend on the opportunities for differentiation afforded by the design of the certification program.

[1] An important early model of vertical differentiation is Shaked and Sutton (1982).

We find that differentiation plays an important role in certification-level choices, as do market and building characteristics. In particular, LEED levels are positively correlated (i.e. agglomerated) across buildings within relatively small geographic markets, and also correlated with market and building-level observables in a manner that suggests builders respond to local demand for environmental performance. At the same time, certification-level choices within local markets are more dispersed than a model of random adoption would predict, suggesting that builders have an incentive to differentiate from one another. Intuitively, if the typical "LEED level" in a given market at a particular point in time is Gold, we find an increased probability that the next certificate will be either Platinum (higher) or Silver (lower). Our estimates suggest that differentiation explains roughly the same amount of variation in certification choices as observed market-level characteristics, such as income and education, but only 16-percent of the variation associated with unobserved market-level effects.

Our model requires us to distinguish the causal effect of one project on another from factors that generate correlation in choices, such as unobserved location heterogeneity. For identification, we exploit variation in the timing of certification-level choices, taking previous choices as exogenous to later choices. Although our approach could falsely find differentiation because of mean-reversion in the adoption process, we use a simulation of independent random choice to show that mean reversion cannot explain our results. We present separate regressions that show the importance of market unobservable terms and differentiation, and then integrate these factors into a single model that we estimate via indirect inference.[2]

We are interested in the design of certification standards, and in particular, how many certification levels they should offer. Whereas more levels allows for a finer signal of investment, it also allows for more differentiation, which itself may be good or bad. With this in mind, we use the model to simulate a counter-factual standard with only two certification levels: High and Low. The simulation suggests that 4 percent of LEED certified buildings would increase their certification level under this two-tier regime, though it is not possible to characterize the net environmental impact of such a change, since some buildings may reduce their environmental investments when there is no distinction between the highest levels of investment.

This paper makes several contributions to the literature on voluntary certification. To our knowledge, this is the first paper to empirically examine the role of differentiation in the adoption of environmental standards, and the first paper to use a model to simulate outcomes for a counterfactual quality standard. From a methodological perspective, we show how to exploit

[2]Our model is not "fully structural" because we do not solve for certification-level choices in a competitive equilibrium with forward-looking agents. Rather, we assume myopic agents who differentiate relative to the current "installed base" of LEED adopters. Below, we argue that there is little value to solving the full model over what we do.

variation in the timing of certification decisions to estimate a model that encompasses both agglomeration-producing locational heterogeneity, and within-market incentives for differentiation. Also, we present a new approach, based on simulating independent random choice, to addressing the issue of mean reversion that often arises in these contexts. Substantively, our results show that incentives to differentiate are quantitatively important. This has implications for the design of multi-tier certification schemes. In particular, adding tiers creates opportunities for differentiation, which may not promote environmental performance depending on the context. This paper also faces several limitations. For example, we observe only buildings that have adopted LEED, not those that have not, so our results are about the choice of certification level conditional on certification, not about the choice of whether to certify or not. Also, the fact that we do not solve a fully structural model limits the set of counterfactual calculations that we can perform.

Related Literature

Dranove and Jin (2010) review the literature on quality standards and certification, with particular emphasis on applications to health care, education and finance. They describe a large theoretical literature that offers explanations for the absence of private decentralized quality disclosure, as envisioned in the well-known "unraveling" models of Grossman (1981) or Milgrom (1981). For environmental certification programs such as LEED, unraveling may fail because the underlying investments are hard to observe or verify. Fischer and Lyon (2014a) review the emerging theoretical literature on eco-labels, and also develop the only model (Fischer and Lyon, 2014b) of "multi-tier" environmental standards, such as LEED, that allow for differentiation among adopters.[3]

While there is a substantial empirical literature linking information disclosure and certification to quality or firm performance (e.g. Jin and Leslie, 2003; Powers et al., 2011; García et al., 2007), relatively few empirical papers (and none in the environmental literature) examine strategic interactions among firms seeking certification. Jin (2005) examines the link between competition and information disclosure by Health Maintenance Organizations, and concludes that differentiation is an important factor in HMO decision-making. In a different setting, Augereau et al. (2006) show that ISPs chose to differentiate from their competitors in the adoption of an inter-operability standard for 56K modems. Bajari et al. (2010) also estimate a model of peer-effects in certification decisions, and find that equity analysts avoid differentiation by selecting recommendations close to their peers'. Unlike each of these prior papers,

[3] As explained by Fischer and Lyons, environmental certification programs are typically non-profit organizations that differ in important ways from the for-profit information intermediaries studied by Lizzeri (1999).

our model relies on dynamics – specifically the order of certification decisions – to identify the differentiation effect.

Our paper also contributes to an emerging literature on green buildings. Several papers in this literature examine the diffusion of green standards, and show that adoption is geographically concentrated (Kahn and Vaughn, 2009; Kok et al., 2011; Simcoe and Toffel, 2014). Eicholtz et al. (2010) use a matching model to show that green building certification is associated with higher rent and occupancy rates, conditional on local market and building characteristics. We build on some results in Matisoff et al. (2014), which show that the LEED point distribution bunches near the threshold for a particular certification level. This paper is the first study in the literature on green buildings to focus on incentives for differentiation. To the extent that differentiation through selective disclosure promotes "greenwashing" our results highlight a potential tension between designing multi-tier standards that allow for differentiation among adopters (e.g. to promote adoption) and single-tier programs that set a uniformly high bar for certification.[4]

Eicholtz et al. (2010) is notable for matching LEED data to local real estate data in order to be able to compare buildings that adopt LEED to those that do not. Because constructing the building-level data for non-adopters is costly, we do not engage with this in our paper, instead focusing on incentives to differentiate among those projects that do adopt LEED.

The remainder of the paper is structured as follows: Section 2 describes the LEED standard, discusses our data, and presents some reduced form evidence on the certification process. Section 3 specifies and estimates our semi-structural model, uses the estimation results to perform a variance decomposition and to simulate a counterfactual standard. Section 4 provides concluding remarks.

2 Background and Descriptive Evidence

LEED is a third-party green building certification system developed and administered by the U.S. Green Building Council. The standard aims to measure environmental sustainability in the building and construction industries. Since it was first introduced in 1998, LEED has been adapted to a wide variety of commercial and residential building types, including healthcare facilities, schools, homes and even entire neighborhoods.[5] For builders and owners, the private benefits of LEED certification include lower operating costs, tax rebates, regulatory incentives

[4]Lyon and Maxwell (2011) define greenwashing as "selective disclosure of positive information about a company's environmental or social performance, without full disclosure of negative information on these dimensions."

[5]We use the terms building, project and firm interchangeably in this paper.

and increased demand from tenants and buyers who prefer to own or occupy a green building.[6]

LEED certification involves several steps. The process begins with selection of a particular version of the rating system. This initial choice is generally dictated by the type of project. USGBC has developed versions of LEED that apply to New Construction (NC), Existing Buildings (EB), Commercial Interiors (CI), Schools, Homes and so on. The second step is to register a project with USGBC. Registration "serves as a declaration of intent to certify" the building, provides the developer access to LEED information and tools, and lists the project in the publicly available online LEED project database (Green Building Certification Institute, 2011). Once the construction or renovations are complete, the next step is to submit an application for certification.

Certification decisions are made by third-party auditors who apply a point system described in the standard. Buildings earn "LEED Credits" by adopting green building practices that fall into several categories, including sustainable sites, water efficiency, energy and atmosphere, materials and resources, indoor environmental quality and innovation. Most versions of LEED offer four certification levels – Certified, Silver Gold and Platinum – and buildings qualify for higher levels by earning more credits. The exact number of points required to reach a given certification level, and their distribution across categories, varies across different versions of the standard.

The cost of adopting the building practices necessary to obtain LEED certification varies with the location, type and scale of a project and with the desired certification level. A substantial share of these costs come from coordinating the required design elements and from using more expensive materials and technologies. The activities required to obtain LEED points range from relatively cheap (such as installing bike racks) to quite expensive (such as remediating a brownfield site). The administrative costs of LEED certification are small by comparison: roughly $450-600 to register a project with USGBC and a certification fee of $2,500. Estimates of the non-construction-and-materials marginal costs of LEED ("soft costs" that mainly comprise additional design and documentation) range from $0.41 to $0.80 per gross square foot, or roughly $30,000 for an 50,000 square foot building (the median project in our estimation sample).[7]

[6]See for example, Eicholtz et al. (2010) or "Financing and Encouraging Green Building in Your Community" (available at http://www.usgbc.org/sites/default/files/Docs6247.pdf, accessed December 6, 2014).

[7]Estimates of soft costs were obtained from the "LEED Cost Study" commissioned by the US General Services Administration (Contract No. GS-11P-99-MAD-0565, p. 187).

2.1 Data

We use data published by USGBC, covering 29,895 LEED registrations in the U.S. from 2000 to July, 2010. The data set contains information about the buildings' registration dates, certification dates, certification levels, and characteristics including ownership type, rating system and address. Most of our analysis is based on a sub-sample of 5,964 projects that were certified as of July 2010. Figure 1 illustrates the number of registered and certified projects by year of registration. Note that LEED registrations accelerated sharply in 2007 and many registered projects were not certified when our were collected.[8] We do not include registered but uncertified projects in our analysis because we do not have data on the certification-level choices of those buildings.

For buildings that do become certified during our sample period, 25 percent select the Certified level, 33 percent achieve Silver, 37 percent achieve Gold and just 5 percent achieve the highest level of Platinum. Figure 2 shows the underlying distribution of LEED Credits for 1,323 buildings certified under versions 2.1 or 2.2 of the LEED for New Construction standard. The vertical lines in this figure correspond to cutoffs between certification levels.[9] It is clear from the figure that projects typically earn exactly the number of points required to achieve a particular certification-level, or perhaps one or two additional credits. Very few projects come in one or two points below the cutoff for a higher level of certification. As discussed in Matisoff et al. (2014), this point distribution strongly suggests that buildings minimize their overall costs, subject to achieving a targeted certification level. It also suggests that users of the LEED standard focus on the four certification levels, even though more detailed information on credits is often available to the public.

Since our analysis is focused on differentiation in agents' certification level choices, we must define a reference group of buildings that will serve as the baseline for comparison. We use three-digit zip codes to define geographic markets and assume that agents interact only within these markets.[10] This leads us an estimation sample with 5,964 certified projects located in 631 distinct markets. The distribution of certified projects per market is quite skewed (see Figure A-3). Twenty-five percent of the markets have only one certified project, and 20 percent (114 markets) have just two certifications. In order to study how firms' decisions would be affected by their rivals within the market, we focus on the 474 markets with at least two certifications.

For each market, we obtain demographic information such as population, income, and the

[8] The median time from registration to certification in our data is two years.

[9] For this version of LEED, the certification levels were defined as: *Certified* (40-49 points), *Silver* (50-59 points), *Gold* (60-79 points) and *Platinum* (80+ points).

[10] There are 862 three-digit zip codes in the United States, and other studies have used three-digit zip codes to define retail markets (Khanna and Tice, 2000).

Figure 1: Projects by Registration Year

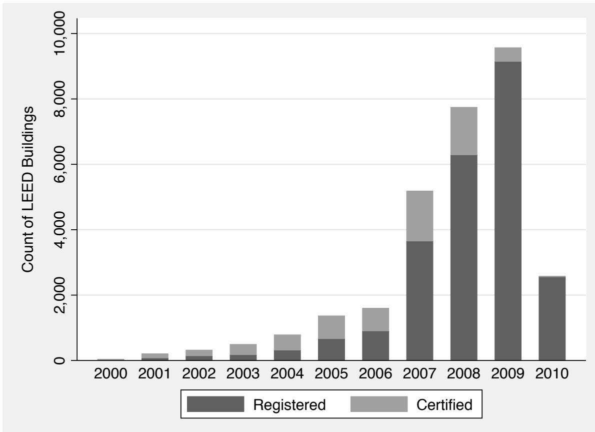
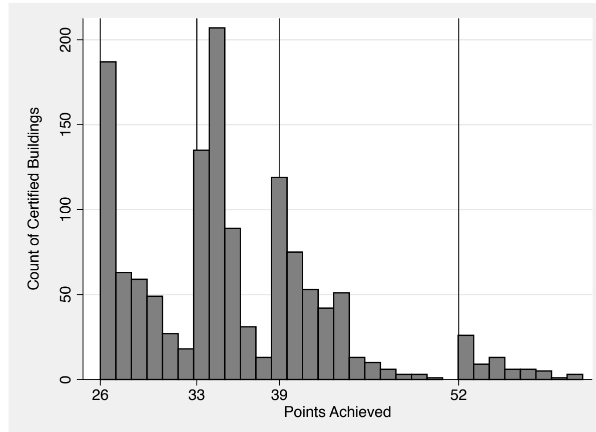


Figure 2: NCv2 Point Distribution



ratio of rent to income from the 2000 Census. By merging this dataset with our LEED data, we get 469 markets (which have at least two certifications) with 4,558 certified projects in them. Table 1 shows demographic summary statistics for the markets in our estimation sample.

Table 1: Demographic Variables

		Mean	**Std. Dev.**	**Min**	**Max**
Population	Total population(1000)	467.4	400.5	8.2	2,878
Income	Median HH income(1000)	43.9	11.3	24.0	108.5
Housing	Housing units(1000)	190.2	155.2	5.5	1,146
Median Rent	Median gross rent (% of HHI)	0.25	0.02	0.20	0.34
Vacancies	Vacant housing units (%)	0.09	0.06	0.02	0.47
Rental Rate	Renter occupied housing (%)	0.31	0.11	0.11	0.84
High School	High school or higher (%)	0.82	0.06	0.51	0.98
College	College or higher (%)	0.26	0.10	0.10	0.75
Source	U.S. Census 2000				
Markets	N=469				

2.2 Between-City Agglomeration

As an initial piece of descriptive evidence on the drivers of certification level decisions, we ask whether our data is consistent with independent random choice, or whether it is better characterized by agglomeration or dispersion. Projects may appear to agglomerate because they actually value being at the same level as others in the market, but more likely because unobserved market characteristics lead projects in the same market to choose similar certification levels. At the same time, projects may try to differentiate from each other when choosing certification levels, as a result of competition and product differentiation.

Our evidence is based on the Multinomial Test of Agglomeration and Dispersion (MTAD) developed by Rysman and Greenstein (2005). MTAD compares the national unconditional distribution of choices to the distribution of choices in individual markets. For instance, if we see nationally that projects choose each of the four levels 25% of the time, we wish to know whether the distribution of choices within markets is consistent with random choice at these percentages, or whether we see projects within markets group on a particular level (agglomeration) or disperse more evenly across levels than would be predicted (differentiation). The details of MTAD are described in Appendix A. But briefly, the test statistic is based on whether the likelihood function of the multinomial distribution is above or below what would be expected under independent random choice, with a higher-than-expected value indicating dispersion and a lower value indicating agglomeration. To compute the expected likelihood value and the confidence interval under independent random choice, MTAD uses simulation.

Table 2 shows results from MTAD. The first row assumes that firms choose between all four LEED levels (*Certified*, *Silver*, *Gold* and *Platinum*), while the next three rows assume a binary standard where all LEED levels above/below a particular cutoff are grouped together. We report the log-likelihood of the observed data from a multinomial distribution averaged over markets, as well as the expected log-likelihood and the standard deviation that would arise if the data were generated by independent random choices according to national averages. For all four rows, we find that the expected likelihood is significantly higher than the observed likelihood, which indicates that the data are characterized by agglomeration. In other words, buildings in the same market make certification level choices that are more similar than we would observe under independent random choice.

Table 2: Multinomial Tests of Agglomeration & Dispersion

Description	Observed Likelihood	Expected Likelihood	Standard Deviation	
All Four Levels	-3.843	-3.517	0.045	Agglomeration
Certified vs. Higher	-1.687	-1.401	0.028	Agglomeration
Silver & Below vs. Above	-1.753	-1.558	0.029	Agglomeration
Below Platinum vs. Abvove	-0.821	-0.761	0.032	Agglomeration

As a robustness check for these MTAD results, we also considered whether the evidence of agglomeration varies across markets with different numbers of certified projects. In general, we find strong evidence of agglomeration, even after controlling for market size.[11]

2.3 Within-City Dispersion

The results in Table 2 show that adoption exhibits agglomeration. In this sub-section, we ascribe that agglomeration to observed and unobserved characteristics. Further, we show that projects nevertheless recognize an incentive to differentiate from other projects in the same market, even though the role of market characteristics leads the MTAD test to conclude that agglomeration characterizes the data overall. That is, without this incentive to differentiate, there would be even more agglomeration.

In order to measure the role of differentiation, we rely on the fact that we observe the order of certification-level decisions in a market. It is often difficult to identify neighborhood effects or social spillovers because in cross-sectional data, we cannot tell which agents responded to which, or whether market-level features determine the outcome. We circumvent this problem by studying a project's certification-level choice as a function of all previous choices.[12]

To motivate our empirical tests, consider project j in market m at time t. We assume that j is ordered by the timing of choice, so $j < j'$ implies that j chooses before j'. We wish to model the certification-level choice Y_{jm}: an integer from 1 to 4, where *Certified* is 1, *Silver* is 2, *Gold* is 3 and *Platinum* is 4. Each project $\{j, m\}$ is assigned a year t based on its registration date. Let N_{jm} denote the mean certification-level in market m before j. That is, $N_{jm} = \frac{1}{j-1} \sum_{k<j} Y_{km}$. Our analysis will focus on the relationship between Y_{jm} and the prior mean N_{jm} (dropping observations for $j = 1$). Specifically, we estimate the following model:

$$Y^*_{jm} = \alpha_0 + \alpha^N N_{jm} + X_{jm}\alpha^X + \alpha_t + \varepsilon_{jm}. \tag{2.1}$$

where $X_{jm} = [X_j, X_m]$ represents observed project and market-level characteristics, the α_t are year dummies from 2000 to 2009, and ε_{jm} is the econometric error term. Observing $\alpha_N > 0$ is consistent with agglomeration, driven either by unobserved market characteristics or by the choices of early projects directly affecting the choices of later projects. Observing $\alpha^N < 0$ is consistent with differentiation.

We estimate a linear version of equation 2.1 by OLS, and an ordered probit version by maximum likelihood. For the linear model, we assume $Y^*_{jm} = Y_{jm}$ and treat the outcome as

[11] These results are summarized in Figure A-4.

[12] We are using reduced-form estimation, and do not provide a full model of how projects make choices. Naturally, our equations are consistent with a model in which projects choose myopically, responding only to projects that came before and ignoring the implications for future projects. We believe our approach is also consistent with any model where projects respond more strongly to previous choices than to the strategic implications of future projects.

a cardinal variable, so Gold (4) is preferred to Silver (3) by the same amount that Silver is preferred to Certified (2). The ordered probit model relaxes this assumption, treating Y_{jm} only as an ordinal variable. For the ordered probit model, we assume that $\varepsilon_{jm} \sim \mathcal{N}(0,1)$ and Y_{jm} indicates if the latent variable Y^*_{jm} falls between the appropriate pair of cutoff values.[13] Note that although the ordered probit model treats the dependent variable as an ordinal variable, there is a sense in which Y_{jm} is still treated as cardinal since N_{jm} is computed as a mean across values of Y_{jm}. Computing N_{jm} this way provides a convenient tool for summarizing previous choices, but we implement some robustness checks along this dimension below.

Results appear in columns (1) and (2) of Table 3. From the ordered probit and OLS regressions, we find a positive and significant coefficient on N_{jm}. Projects are more likely to choose higher levels if the previous mean is higher. This result is quite consistent with the result from MTAD, and indicates agglomeration either because of endogenous or market-level effects. We also find evidence of a higher mean certification-level for buildings with individual and non-profit owners, and that are located in markets with relatively high incomes and rental prices.

Our second set of regressions is designed to separate unobserved market-level characteristics from a differentiation effect. A common strategy for modeling unobserved market-level characteristics is to include location fixed effects. However, that will not work in our context, since the fixed effects would guarantee a negative estimate of α^N, regardless of the underlying choice process.[14] So, instead of using fixed effects, we define a new outcome variable Y'_{jm} to indicate whether a project chooses a higher or lower level of certification than the average of what came before. Specifically, $Y'_{jm} = \mathbb{1}\{Y_{jm} > N_{jm}\}$, where $\mathbb{1}$ is the indicator function.[15] For these tests, we estimate a probit model of the the probability that $Y'_{jm} = 1$ as a function of the explanatory variables in Equation 2.1, via Maximum Likelihood. We also consider linear probability models, estimated via OLS.

This regression uses the dynamics of choices within a market to identify the differentiation effect. A negative coefficient ($\alpha^N < 0$) arises if buildings try to pick low when rivals pick high, and pick high when rivals pick low. If buildings try to pick near their rivals, or always want to pick just above or just below rivals, there will be a zero coefficient, since whether buildings pick above or below rivals does not depend on rival choices. Since $\alpha^N = 0$ is also consistent with no

[13]Specifically, there are three cutoff values $\{\tau_1, \tau_2, \tau_3\}$. We observe $Y_{jm} = 1$ if $Y^*_{jm} < \tau_1$, $Y_{jm} = 2$ if $\tau_1 \leq Y^*_{jm} < \tau_2$ etc. We estimate the parameters τ along with $\{\alpha^N, \alpha^X, \alpha_t\}$.

[14]To get intuition on this, consider a regression with market level fixed effects and only two projects. The fixed effect would be set equal to the average of the choices of the two projects. For the second project, if the first one chose above average than the second must choose below average by construction, and if the first chose below average than the second must be above. Thus, the effect of the first on the second appears to be negative.

[15]Defining $Y'_{jm} = \mathbb{1}\{Y_{jm} \geq N_{jm}\}$ does not alter our results.

Table 3: Reduced-form Regressions

Specification	Ord. Probit	OLS	Probit	OLS
Outcome	Level (1-4)		1[Level > Prev. Mean]	
	(1)	(2)	(3)	(4)
Mean of previous certification levels in the market	**0.230*** **	**0.175*** **	**-0.724*** **	**-0.246*** **
	(0.040)	(0.030)	(0.058)	(0.016)
Indicator: for-profit	-0.019	-0.01	-0.048	-0.016
	(0.067)	(0.051)	(0.08)	(0.029)
Indicator: nonprofit	0.229***	0.178***	0.160*	0.059*
	(0.077)	(0.059)	(0.092)	(0.034)
Indicator: government	0.030	0.029	-0.0003	0.001
	(0.081)	(0.063)	(0.100)	(0.036)
Indicator: individual	0.228**	0.179**	0.174	0.066
	(0.114)	(0.088)	(0.126)	(0.046)
Indicator: Commercial Interiors rating system	-0.206	-0.162	-0.233	-0.087
	(0.136)	(0.106)	(0.172)	(0.064)
Indicator: Core&Shell rating system	0.083	0.069	0.061	0.020
	(0.145)	(0.114)	(0.180)	(0.067)
Indicator: New Construction rating system	-0.079	-0.063	-0.094	-0.036
	(0.131)	(0.103)	(0.166)	(0.062)
Indicator: Existing Building rating system	-0.202	-0.160	-0.210	-0.080
	(0.154)	(0.120)	(0.189)	(0.070)
Indicator: Neighborhood Development rating system	-0.371	-0.282	-0.277	-0.096
	(0.259)	(0.201)	(0.311)	(0.114)
Log of total population	-0.253	-0.233	-0.850	-0.279
	(0.404)	(0.308)	(0.567)	(0.203)
Log of median household income	0.334**	0.259**	0.177	0.055
	(0.170)	(0.129)	(0.235)	(0.082)
Log of number of housing units	0.268	0.245	0.922	0.303
	(0.405)	(0.309)	(0.573)	(0.205)
Median gross rent as a percentage of household income	4.007***	3.162***	6.43***	2.149***
	(1.391)	(1.078)	(1.880)	(0.678)
Percentage of vacant housing units	0.563	0.377	-1.055	-0.354
	(0.971)	(0.741)	(1.216)	(0.424)
Percentage of renter occupied housing units	0.831***	0.613***	0.396	0.150
	(0.275)	(0.212)	(0.430)	(0.152)
Percentage of high school graduates or higher	0.793	0.558	0.387	0.142
	(0.681)	(0.522)	(0.976)	(0.345)
Percentage of college graduates or higher	0.229	0.189	0.846	0.299
	(0.370)	(0.287)	(0.575)	(0.203)
Log Pseudo-likelihood	-4850.5		-2602.3	
Pseudo R-squared	0.033	0.079	0.078	0.099
Observations	4,077	4,077	4,077	4,077

Robust standard errors are clustered at the market level and are in parentheses. $^{***}p < .01,^{**}p < .05,^{*}p < .10$. Time dummies are not reported.

interaction of choices, we consider finding α_N different than zero to be stronger evidence for differentiation than finding $\alpha^N = 0$ is evidence for endogeneous agglomeration.

Note that $\alpha_N < 0$ can also be generated by mean reversion. That is, if there is no interaction between projects and the first one happens to pick high, it is likely the next one will pick below its market average. We present a method for addressing this issue below.

Columns (3) and (4) in Table 3 display the estimation results. For both the probit and OLS regressions, we see a negative and significant coefficient on N_{jm}, which indicates that projects choose certification levels to be different than existing projects. To see the size of this effect, consider the value of the index function in Equation 2.1 if $N_{jm} = 1$, its lowest possible value. At the mean value of the variables X_{jm}, the right-hand side of Equation 2.1 is 0.798. In the probit model, that implies a probability of choosing above one of 0.788. As N_{jm} rises to 3, this index falls to -0.651, implying a probability of 0.258. At the maximum of $N_{jm} = 4$, the probability we would compute based on our model is 0.084 (although in fact, there is no way to pick a number greater than 4).

Note that it is possible that there are some forces that lead projects to choose the same levels, but others that lead them to choose differently. For instance, a causal effect towards positive correlation might be that when one project picks a certification level, it leads local LEED professionals to develop skills in the features that lead to that level, which makes it cheaper or easier for the next project to pick the same level. At the same time, product differentiation may generate a causal effect towards negative correlation. Our result here is reduced-form in the sense that we estimate the sum of these causal effects, and find that they are overall negative. Our approach allows us to separate the effects of market heterogeneity from causal effects, but does not allow us to decompose the causal effect into its various sources.

We also explore some robustness issues. The independent variable of interest, the mean of past choices, is treated as cardinal, which might raise concerns. However, we find that the results in Table 3 are robust to alternative specifications. In particular, we have substituted the mean with several alternatives: the minimum, the maximum, the mode and the median of past choices. In unreported results, all lead to very similar results.

Another concern is that government and non-profit developers have different objective functions that private commercial developers, and thus might not be engaged in strategic interactions. Such agencies are heterogeneous and it is difficult to say the extent to which they should be evaluated differently, but we would be concerned if our results were driven entirely by such developers. However, we run the regressions in Table 3 on commercial buildings only, while still computing the previous mean as the mean over all buildings, and we find similar (unreported) results.

2.3.1 Mean reversion

A natural concern is that the negative coefficient in columns (3) and (4) of Table 3 is driven by mean reversion. Even if there is no differentiation between projects, predicting whether a choice is above or below the previous mean should mechanically generate a negative coefficient. Suppose the first several choices were, by coincidence, above the mean. Then it is likely that the next choice will be below the first choices not because of differentiation but because every choice is likely to be near the mean. This phenomena leads to a negative coefficient on previous choice. If the first several choices were randomly below the mean, the next choice is likely to be above the previous choices, again generating a negative coefficient. Any bias from mean reversion should decline as the number of previous choices increases, but many of the markets in our sample have only a handful of certifications.

To address this, we extend the ideas in MTAD to a regression framework. Our idea is that we want to look at the parameter on N_{jm} that we would find if the data were really generated from independent choice, and compare it to the parameter we find in data. While independent random choice will lead us to find a negative coefficient via mean reversion, if our negative coefficient is bigger than what could have been generated from independent random choice, then we conclude that mean reversion alone cannot explain our result and differentiation must play a role. In generating the outcome from independent random choice, we include location fixed effects, which maximizes the role of mean reversion in generating the data.

To develop our model of how projects make choices under independent random choice, consider the following model of choice:

$$Y_{jm} = \gamma_0 + X_j\gamma_1 + \gamma_t + \gamma'_m + u_{jm}. \tag{2.2}$$

Here, the variables are defined as above. Now, γ_t are the time fixed effect. The new variable is γ'_m, the location fixed effect. The variable u_{jm} is the econometric error term. We assume $E[u_{jm}|X_j, t, m] = 0$. Note that N_{jm} is not an explanatory variable.

Our evaluation of mean reversion takes the following steps:

1. Estimate Equation 2.2 via OLS.

2. Simulate a new data set from the results of this estimation. For these purposes, we assume that $u_{jm} \sim \mathcal{N}(0, \sigma_u)$ where σ_u is estimated from the regression in step 1. We round the predicted variable to an integer from 1 to 4.

3. Estimate the models in Table 3 on the simulated data from step 2.

4. Test whether the coefficient on N_{jm} from the regression in step 3 is as big as the analogous

parameter in Table 3.

The inclusion of market fixed effects in step 1 is intended to maximize the size of the negative coefficient in step 3. That is, we want to see if a model with no differentiation but the largest amount of mean reversion that is consistent with our data set could lead to a negative coefficient that is as large as we found in Table 3.

For the reported results, we draw one version of the simulated data set, although the results are robust to doing many simulations. Table 4 presents the results. Column (2) shows the results of the ordered probit model estimated on the simulated data, and column (4) shows the results of probit regression on simulated data. Columns (1) and (3) repeat the results from Table 3. By comparing regressions (1) and (2), we see the coefficient on N_{jm} in Column (2) is significantly greater than that in Column (1).[16]That is, the simulated data exhibits significantly more agglomeration than the actual data. This is consistent with the hypothesis that projects differentiate from each other.

Table 4: Results from Simulation

Specification	Ordered Probit	Simulated O-Probit	Probit	Simulated Probit
Outcome	Level (1-4)		1[Level > Prev. Mean]	
	(1)	(2)	(3)	(4)
Market Mean	0.230***	0.472***	-0.724***	-0.560***
	(0.040)	(0.043)	(0.058)	(0.054)

Robust standard errors clustered at the market level and are in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. Actual and simulated estimates for all other variables are presented in Table A-1.

The results in Column (3) and (4) tell a similar story. We see a significant and negative coefficient on N_{jm} in Column (4), as a result of mean-reversion. But that coefficient is significantly smaller than what is in Column (3). Thus, mean reversion alone cannot generate the outcome in Table 3.

[16]We assume the parameters from the two regressions are independent. In the classical linear regression model, if $\hat{\alpha}$ and $\hat{\beta}$ are OLS estimators, and the quantity s.e. $\hat{\alpha}$ (or s.e. $\hat{\beta}$) correctly estimates the asymptotic variance of these parameters, then $\left(\hat{\alpha}-\hat{\beta}\right)/\sqrt{(s.e.\,(\hat{\alpha}))^2+\left(s.e.\left(\hat{\beta}\right)\right)^2}$ is asymptotically standard normal distributed. The Z value here is 4.12, which is significantly different from zero at conventional levels of significance, and rejects the null hypothesis $\alpha^0=\beta^0$, where α^0 and β^0 are the population parameters.

3 Integrated Model

The previous section establishes that both differentiation and market heterogeneity play a role in determining the adoption patterns of LEED. In this section, we embed both forces in an integrated model so we can compare their relative sizes. The first subsection presents the model and the second presents our estimation method.

3.1 Model

In the model, there are M markets, indexed by $m = 1, ..., M$. Each market has J_m projects that sequentially choose Y_{jm}, the level of certification. The sequence of projects is given exogenously. Choices are irreversible. Projects are characterized by X_{jm}, which are observed market and building characteristics. Let N_{jm} capture the choices of buildings previous to j. Profit to project j is:

$$\pi_{jm} = X_{jm}\delta^X + \delta^N N_{jm} + \mu_m + \delta_t + \epsilon_{jm}. \tag{3.1}$$

There are three cutoffs ρ_i, $i \in \{1, 2, 3\}$. If $\pi_{jm} < \rho_1$, then j chooses *Certified.* If $\rho_1 \leq \pi_{jm} < \rho_2$, then j chooses *Silver.* If $\rho_2 \leq \pi_{jm} < \rho_3$, then j chooses *Gold.* If $\rho_3 \leq \pi_{jm}$, then j chooses *Platinum.* The parameter μ_m represents a market random effect. We assume μ_m is distributed normally with standard deviation σ_m, and is orthogonal to X_{jm}. The unobserved term ϵ_{jm} is distributed *iid* according to the standard normal. We wish to estimate the parameters $\theta = \left\{\delta^X, \delta^N, \delta_t, \rho, \sigma_m\right\}$.

Note that we have not developed a fully structural model in the sense that we have not allowed projects to be forward looking in their decision-making. We believe that estimating the fully-structural model of dynamic decision-making and equilibrium play in this context would be challenging and would add little new insight to our analysis. Presumably, a fully structural model that calculated expectations of future adoption would still rely on previous adoption to shift those expectations, and provide variation across different observations. Instead, we have specified a reduced-form model that allows for both the effects of differentiation (measured by δ^N) and market heterogeneity (measured by δ^X and μ_m) in a single integrated model.

3.2 Estimation

To estimate this model, we use the technique of indirect inference (Gourieroux et al., 1993), which has been used widely (see for example Collard-Wexler, 2013). This method is quite practical here, since it is relatively simple to estimate, and we have already explored reduced-form regressions that capture choices.

Under indirect inference, the researcher simulates data from a model that is a function of parameters of interest. The researcher also specifies a set of *auxiliary regressons.* The researcher estimates the auxiliary regressions on the actual data and the simulated data, and uses the differences between the parameters in the two auxiliary regressions to form moments. The researcher picks the parameters of interest to set the difference between the parameters from the auxiliary regressions as small as possible.

Formally, we specify an auxiliary regression $\Psi(Y, X, N)$ that generates parameters ϕ. Let ϕ^* be the parameters from performing the auxiliary regression on the observed data, so $\phi^* = \Psi(Y, X, N)$. In practice, we use the two linear models in Table 3 as the auxiliary regressions in this paper. We also want the model to match the overall number of adopters at each level of certification. That is, we let n^* be the 3×1 vector of the total number of adopters of each level (*Certify*, *Silver* and *Gold*) with representative element $n_i^* = \sum_j \sum_m \mathbb{1}\{Y_{jm} = i\}$. Note that it is not necessary to include a count of *Platinum* projects since that is implied by the other three.[17] Thus, ϕ^* is the stacked vector of three sets of parameters, the parameters from Column (2) of Table 3, the parameters from Column (4) of Table 3, and n^*.

Our algorithm is as follows:

1. Draw random variables u_m^s, $s = 1, ..., MS$ from the standardnormal, where M is the number of markets (469 markets in the paper), and S is the number of simulation (set to 1000 in the paper). Draw ϵ_{jm}^s from the standard normal, the project idiosyncratic effects.

2. Guess a value of θ, called θ^0 .

3. Sequentially compute choices for buildings according to Equation 3.1, on each path s, sequentially computing N_{jm}^s as we go.

4. Term the new data set $Y^s(\theta)$ and $X^s(\theta)$.

5. Perform the pseudo-regression on each sample s. That is, let $\phi^s(\theta) = \Psi(Y^s(\theta), X^s(\theta), N^s(\theta))$.

6. Let $\hat{\phi}(\theta)$ be the mean of $\phi^s(\theta)$.

7. Form moments $h(\theta) = \left[\hat{\phi}(\theta) - \phi^*\right]$

We form the moments $h(\theta)$ into a GMM objective function, and search for the parameters θ that minimize the objective function. For each guess of the parameters that we evaluate, we

[17] One might prefer to use the probit versions of the models in Table 3 as auxiliary regressions. However, we must estimate the auxiliary regressions many times and using non-linear models for auxiliary regressions greatly slows down our estimation. We found the using linear models augmented with the vector n^* works well.

must follow the algorithm again, starting from step 2. The GMM objective function has the form::

$$Q(\theta) = h(\theta)' W h(\theta), \tag{3.2}$$

Let weight matrix

$$W = \begin{pmatrix} Var[\phi^*]^{-1} & 0 \\ 0 & I_3 \end{pmatrix}, \tag{3.3}$$

where $Var[\phi^*]^{-1}$ is the inverse of the covariance matrix from the reduced-form regressions using the real data, and I_3 is the identity matrix.

The Indirect-Inference estimator $\hat{\theta}$ is consistent and $\sqrt{S}\left(\hat{\theta} - \theta_0\right)$ is asymptotically normally distributed with mean zero and covariance matrix

$$\left(G_0' W G_0\right)^{-1} \left(G_0' W S_0 W G_0\right) \left(G_0' W G_0\right)^{-1}, \tag{3.4}$$

where $G_0 = E\left[\frac{\partial \mathrm{h}}{\partial \theta}|_{\theta_0}\right]$ and $S_0 = E\left[hh'|_{\theta_0}\right]$. Estimates of the standard errors are obtained by replacing the terms with $\hat{\theta}$.

3.3 Estimation Results

The results of estimating the integrated model are reported in Table 5. The parameters of primary interest include the parameter for N_{jm}, which shows how firms respond to previous certification levels. We find it is significantly negative, meaning that firms try to distinguish themselves from their rivals.

The parameters δ^X for building j's ownership type and rating systems are also shown in the table. We find nonprofit, government, and individual projects tend to adopt higher levels, but we don't see a significant effect of ownership type *for-profit* on adoption decisions. Compared to the rating system of School[18], we see projects that belong to Core&Shell are slightly more likely to adopt higher levels, but the others tend to adopt lower levels, especially projects of type Neighborhood Development.

The parameters δ^X include the parameters from observed market characteristics, such as population, income and rent. Note that the effect of *Rent*, which is the median gross rent as a percentage of household income, has a huge effect on the adoption choice. The places with relatively higher ratio of rent to income, are more likely to adopt higher levels. This makes sense, since rent is a great incentive for firms to adopt higher levels and to attract more tenants. It also may proxy for a sort of urban professionalism that leads to high certification.

[18] The excluded rating system is School.

Table 5: Estimates from Indirect Inference

			Coeff.	S.E.
δ^N	N_{jm}	Mean of previous certification in the market	-0.415	0.011
δ^X	**Project's Characteristics**	Indicator: for-profit	-0.003	0.003
		Indicator: nonprofit	0.266	0.003
		Indicator: government	0.051	0.003
		Indicator: individual	0.260	0.005
		Indicator: Commercial Interiors rating system	-0.280	0.006
		Indicator: Core&Shell rating system	0.040	0.007
		Indicator: New Construction rating system	-0.126	0.006
		Indicator: Existing Building rating system	-0.253	0.007
		Indicator: Neighborhood Development rating system	-0.450	0.012
δ^X	**Market's Characteristics**	Log of total population	-0.704	0.011
		Log of median household income	0.605	0.011
		Log of number of housing units	0.600	0.013
		Median gross rent as a percentage of household income	7.714	0.042
		Percentage of vacant housing units	0.219	0.029
		Percentage of renter occupied housing units	0.937	0.019
		Percentage of high school graduates or higher	0.322	0.030
		Percentage of college graduates or higher	0.319	0.026
δ_t	**Year Dummies**	Dummy whether it's registered in 2000	0.607	0.031
		Dummy whether it's registered in 2001	0.341	0.017
		Dummy whether it's registered in 2002	0.582	0.017
		Dummy whether it's registered in 2003	0.384	0.017
		Dummy whether it's registered in 2004	0.511	0.015
		Dummy whether it's registered in 2005	0.929	0.016
		Dummy whether it's registered in 2006	1.104	0.016
		Dummy whether it's registered in 2007	1.186	0.016
		Dummy whether it's registered in 2008	1.070	0.016
		Dummy whether it's registered in 2009	0.827	0.015
σ_m		Variance of market effect	0.540	0.008
ρ		Cutoff 1	6.600	0.012
		Cutoff 2	7.637	0.012
		Cutoff 3	9.267	0.013
	GMM Criterion		37.424	

The other results include that places with less population, higher income, more total housing units, more vacant housing units, more renter-occupied housing units and more students with higher education, tend to adopt higher certification levels.

The parameters δ_t represent the time variation of adoption. From the results, we see the certification levels generally climb over time. Relative to the standard deviation of 1 for the project idiosyncrasy, the variance of market-level unobserved effects is estimated to be 0.54, significantly different from zero. We further explore the relative size of these parameters in the next sections. Our results predict the overall adoption rates of each level almost perfectly. This is not surprising since we impose these adoption rates as moments to match.

3.3.1 Variance Decomposition

In this section, we decompose the total variance of the latent variable into its constituent parts. Let V be the variance of π_{jm} where π_{jm} is defined in Equation 3.1. Sources of variation are observed project characteristics, observed market characteristics, idiosyncratic (unobserved) project characteristics, unobserved market effects (assumed fixed over time), time variation and differentiation. We use variance partition coefficients (VPCs) to measure proportions of total variation attributable to these factors.[19] For example, the proportion of variance that can be explained by unobserved market effects is $\frac{\hat{\sigma}_m^2}{V}$. For these purposes, we divide up x_{jm} into $x_{jm} = \{x'_{jm}, x''_m\}$ where x' are project characteristics and x'' are market characteristics. We divide $\delta^X = \{\delta^{X\prime}, \delta^{X\prime\prime}\}$ similarly. We let $\overline{x}$ refer to the mean of x over the entire data set. Variance V can be decomposed as follows:

$$\begin{aligned} V = \;& 1 + \hat{\sigma_m}^2 + \frac{1}{J}\sum_{j,m}\left(\left(x'_{jm} - \overline{x'}\right)\delta^{X\prime}\right)^2 + \frac{1}{J}\sum_{j,m}\left(\left(x''_m - \overline{x''}\right)\delta^{X\prime\prime}\right)^2 \\ & + \frac{1}{J}\sum_{j,m}\left(\left(N_{jm} - \overline{N}\right)\delta^N\right)^2 + \frac{1}{J}\sum_{j,m}\left(\left(t_j - \overline{t}\right)\delta_{t_j}\right)^2. \end{aligned} \tag{3.5}$$

Thus, $1/V$ measures the proportions of total variation attributable to idiosyncratic (unobserved) project characteristics, $\hat{\sigma_m}^2/V$ is the proportions of total variation attributable to unobserved market effects, $\frac{1}{J}\sum_{j,m}\left(\left(x'_{jm} - \overline{x'}\right)\delta^{X\prime}\right)^2/V$ is the proportions of total variation attributable to observed project characteristics, $\frac{1}{J}\sum_{j,m}\left(\left(x''_m - \overline{x''}\right)\delta^{X\prime\prime}\right)^2/V$ is the proportions of total variation attributable to observed market characteristics, $\frac{1}{J}\sum_{j,m}\left(\left(N_{jm} - \overline{N}\right)\delta^N\right)^2/V$ is the proportions of total variation attributable to differentiation, and $\frac{1}{J}\sum_{j,m}\left(\left(t_j - \overline{t}\right)\delta_{t_j}\right)^2/V$ measures the time variation.

Results are reported in Table 6 and Table 7. Table 6 shows the variation attributable to observable variables, which are made up of observable market characteristics, observable project

[19] The term Variance Partition Coefficient is introduced in Goldstein et al. (2002).

characteristics, and differentiation. We find that differentiation is important in determining adoption choices. Differentiation accounts for 34.1% of variation due to observable characteristics. It is more important than observed project characteristics, almost as important as observed market characteristics. However, as is common, unobservable factors explain a great deal of variation. Unobservable factors are made up of unobserved market characteristics, time effects and project idiosyncratic effects. Observable factors explain 9.09% of the total variation. Thus, differentiation accounts for 3.10% of the total variation, and are 16.07% $\left(\frac{3.10}{19.37}\right)$ as important as unobserved market effects. We find that 5.57% $\left(\frac{5.06}{5.06+19.37+66.48}\right)$ variation caused by unobservable factors comes from time variation, 21.3% from unobserved market effect, with the remaining coming from the idiosyncratic term.

Table 6: Sources of Variation (Observable Factors)

		Percent
Observed	differentiation	34.1
	observed building characteristics	15.62
	observed market characteristics	50.28

Table 7: Sources of Variation

		Percent
Observed	differentiation	3.1
	observed building characteristics	1.42
	observed market characteristics	4.57
Unobserved	time variation	5.06
	unobserved market effect	19.37
	idiosyncratic building characteristics	66.48

3.3.2 Counterfactuals

A natural question when designing a certification standard is whether to use multiple levels or not. This is particularly complicated when differentiation is important, since the use of multiple levels determines the extent to which firms can differentiate in this dimension. In this section, we ask how adoption would be different under a different set of certification levels. We assume the relationship between the score and the explanatory variables stays the same. That is, we compare what would happen if we simply reassigned projects to the new levels based on the latent variable (π_{jm} from Equation 3.1) to what happens when projects respond to the choices of competitors. That is, we compute a new value of π_{jm}, which differs from the observed one only through δ^N because rivals make different choices. We assume there are only two levels (Low and High) for the buildings to choose, which limits the ability of buildings to differentiate from each other. We use $\hat{\rho}_1$, $\hat{\rho}_2$ and $\hat{\rho}_3$ respectively to design the two-tier regime, and we study how buildings would behave when offered with less choices.

We assume buildings would choose the lowest level to get the rating. This is rational for a cost minimizer, and consistent with what we observe in reality (see Figure 2). Specifically, in the two-tier regime with $\hat{\rho}_2$ as the cutoff, building j would choose level 1 if $\pi_{jm} < \hat{\rho}_2$, and level 3 if $\pi_{jm} \geq \hat{\rho}_2$. We simulate 1000 times and get the mean of numbers of adopters for each level. Results are shown in Table 8.

Compared to the real data, we find buildings would shift up in all the three cases. The two-tier regimes with $\hat{\rho}_1$, $\hat{\rho}_2$ and $\hat{\rho}_3$ as the cutoffs, make 181, 186, and 195 of the 4558 buildings to shift up respectively. However, it's hard to conclude if we have net environmental gains from these changes, since buildings would agglomerate at the lowest levels within each category (Low or High).

Table 8: Experiment I

<table>
<tr><th>Certification Level</th><th colspan="2">Real Data</th><th>ρ_1
L:1 H:2</th><th>Real Data</th><th>ρ_2
L:1 H:3</th><th>Real Data</th><th>ρ_3
L:1 H:4</th></tr>
<tr><td>Certified(1)</td><td>1,122</td><td>1,122</td><td>941</td><td rowspan="2">2650</td><td rowspan="2">2464</td><td rowspan="3">4,307</td><td rowspan="3">4,112</td></tr>
<tr><td>Silver(2)</td><td>1,528</td><td rowspan="3">3,436</td><td rowspan="3">3,617</td></tr>
<tr><td>Gold(3)</td><td>1,657</td><td rowspan="2">1908</td><td rowspan="2">2094</td></tr>
<tr><td>Platinum(4)</td><td>251</td><td>251</td><td>446</td></tr>
<tr><td>No. of Certifications</td><td>4,558</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

4 Conclusion

Quality standards and certification programs vary widely in how they report information. For example, the Marine Stewardship Council certifies seafood as sustainably caught, while the Environmental Defense Fund has labels for three categories: Best Choice, Good Alternative or Avoid. For movies, Siskel and Ebert famously gave films a "thumbs up" or "thumbs down" review, NetFlix has a five star rating scheme, and the web site Rotten Tomatoes reports 100 different rating levels.[20] Recognizing that firms use certification programs as a tool for product

[20]In a more familiar setting, some schools report a student's numerical grade on their transcript, others report a letter grade, and still others report a handful of categories (e.g. Harvard Business School uses three categories and a forced curve).

differentiation leads to important questions about the adoption of quality standards, and how those standards should be designed.

This paper studies the initial adoption of LEED, a standard for measuring the environmental performance of buildings that offers four levels of certification. We find substantial variation in certification-level choices across projects and geographic markets. Several descriptive statistics and reduced-form regressions show that certification decisions tend to be agglomerated within markets relative to the national average, suggesting the market features are important in determining certification levels. However, we also find that new projects tend to differentiate from already-certified buildings in the same market by choosing a higher or lower certification level. Our identification of this differentiation effect relies on the timing of decisions, taking previous choices as exogenous. While this approach is susceptible to misspecification due to mean reversion, we provide a new method for evaluating the impact of mean reversion based on simulating independent random choice, and find that mean reversion cannot explain our results.

In order to compare the relative importance of the location effects and differentiation, we integrate the two effects into a single model that we estimate via indirect inference. Our results suggest that differentiation is about as important as market observable effects, such as education and income, for explaining certification choices. However, market and building unobservable effects are substantially more important. Finally, we simulate a counterfactual world in which LEED offered only two levels of certification. In this simulation, a substantial number of firms would raise their level of investment in order to reach a higher certification level, although presumably, firms that do not switch up reduce their investment when their current level becomes less demanding.

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Appendix A

MTAD (*Rysman and Greenstein (2005)*) relies on the likelihood function of the multinomial distribution. MTAD recognizes that if the choices are more agglomerated than would be predicted by independent random choice, than the likelihood of the data will be low, whereas if the choices are dispersed, the likelihood will be higher. For example, suppose that there are only two levels to choose and suppose we observe many markets, each with 4 projects. Suppose that across all markets, we see projects pick the high level with probability of 50%. The key element of the binomial likelihood is the combinatoric expression $\binom{4}{x}$, where x is the number of projects that get the high level. A highly agglomerated arrangement would have all projects choosing the high level or the low level, which leads to the lowest possible outcome for the combinatoric expression, i.e. $\binom{4}{0} = \binom{4}{4} = 1$. A most dispersed arrangement would be two projects choosing high and two choosing low, which maximizes the combinatoric expression, i.e. $\binom{4}{2} = 6$. The expression has an expected value under independent choice that falls between these two values: for a choice probability of 50%, it is 4.37. Thus, by comparing the combinatoric expression across markets, or more specifically, the binomial likelihood to this expected value of the binomial likelihood under independent random choice, we can characterize whether the data is agglomerated or dispersed. In practice, it is difficult to compute the expected value of the binomial likelihood, particularly when different markets have different numbers of projects. We also need to compute the confidence interval around the expected value. As a result, we use simulation to do these computations.

Suppose there are M markets each populated by n_m agents ($\underline{n} < n_m < \overline{n}$). The variable n_m is distributed as a discrete distribution $f(n_m)$. In each market, the agents can choose from C options, and the unconditional probability of observing option c is p_c . The number of agents choosing option c is denoted by variable x_m^c. If the agents make choices independently, the average log-likelihood of observing the outcome $x_m^1, ..., x_m^c$ in for M markets is

$$l(X, n, P) = \frac{1}{M} \sum_{m=1}^{M} ln \left(\binom{n_m}{x_m^1, ..., x_m^c} \right) + x_m^1 ln(p_1) + ... + x_m^c ln(p_c)$$

Consider the likelihood value if the data were actually generated by independent random choice. Let the random variable $l(f, p)$ be distributed according to the distribution $l(X, n, p)$ if X was actually drawn from a multinomial distribution and n_m was drawn from f .

$$E[l(f, p)] = \sum_{n=\underline{n}}^{\overline{n}} \sum_{z \in \Sigma(n_m)} \left(ln \left(\binom{n_m}{z^1, ..., z^c} \right) + z^1 ln(p_1) + ... + z^c ln(p_c) \right) L(z, n_m, p) f(n_m),$$

where $\Sigma(n_m)$ is the set of all possible choice configurations of n_m agents.

Then the statistic, $t(X, n, p) = l(X, n, p) - E[l(f, p)]$ is distributed asymptotically normal.

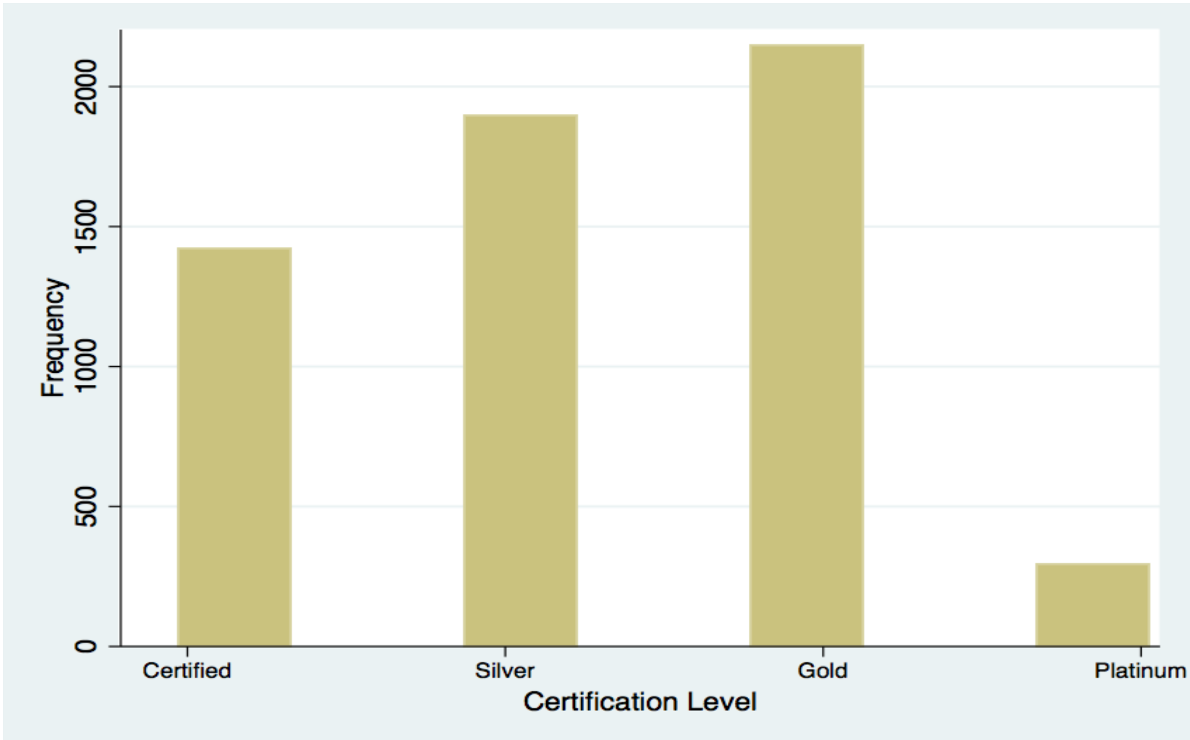

Figure A-1: Certification Levels

Table A-1: Results from Simulation

Specification	Ordered	Simulated	Probit	Simulated
Outcome	Probit	O-Probit		Probit
	Level (1-4)		$1[\text{Level}> N_{jm}]$	
Mean of previous certification levels in the market	**0.230***** (0.040)	**0.472***** (0.043)	**-0.724***** (0.058)	**-0.560***** (0.054)
Indicator: for-profit	-0.019 (0.067)	-0.03 (0.066)	-0.048 (0.08)	-0.028 (0.070)
Indicator: nonprofit	0.229*** (0.077)	0.304*** (0.072)	0.160* (0.092)	0.270*** (0.083)
Indicator: government	0.030 (0.081)	0.014 (0.073)	-0.0003 (0.100)	-0.057 (0.084)
Indicator: individual	0.228** (0.114)	0.241** (0.098)	0.174 (0.126)	0.341*** (0.126)
Indicator: Commercial Interiors rating system	-0.206 (0.136)	0.197 (0.154)	-0.233 (0.172)	0.113 (0.189)
Indicator: Core&Shell rating system	0.083 (0.145)	0.469*** (0.164)	0.061 (0.180)	0.378* (0.203)
Indicator: New Construction rating system	-0.079 (0.131)	0.329** (0.151)	-0.094 (0.166)	0.223 (0.184)
Indicator: Existing Building rating system	-0.202 (0.154)	0.276* (0.164)	-0.210 (0.189)	0.165 (0.199)
Indicator: Neighborhood Development rating system	-0.371 (0.259)	0.353 (0.230)	-0.277 (0.311)	0.191 (0.286)
Log of total population	-0.253 (0.404)	0.331 (0.383)	-0.850 (0.567)	0.111 (0.439)
Log of median household income	0.334** (0.170)	0.134 (0.155)	0.177 (0.235)	-0.038 (0.195)
Log of number of housing units	0.268 (0.405)	-0.321 (0.381)	0.922 (0.573)	-0.025 (0.433)
Median gross rent as a percentage of household income	4.007*** (1.391)	0.659 (1.460)	6.430*** (1.880)	2.204 (1.937)
Percentage of vacant housing units	0.563 (0.971)	1.189 (0.866)	-1.055 (1.216)	0.207 (0.991)
Percentage of renter occupied housing units	0.831*** (0.275)	0.784** (0.313)	0.396 (0.430)	0.537 (0.453)
Percentage of high school graduates or higher	0.793 (0.681)	0.769 (0.683)	0.387 (0.976)	0.964 (0.924)
Percentage of college graduates or higher	0.229 (0.370)	0.217 (0.398)	0.846 (0.575)	0.490 (0.563)
Log pseudolikelihood	-4850.529	-4946.657	-2602.322	-2668.503
(pseudo) R-square	0.033	0.038	0.078	0.055
Num of obs.	4077	4077	4077	4077

$^{***}p < .01,^{**} p < .05,^{*} p < .10$. Time dummies are not reported.

Figure A-2: Certification Levels by Registration Year

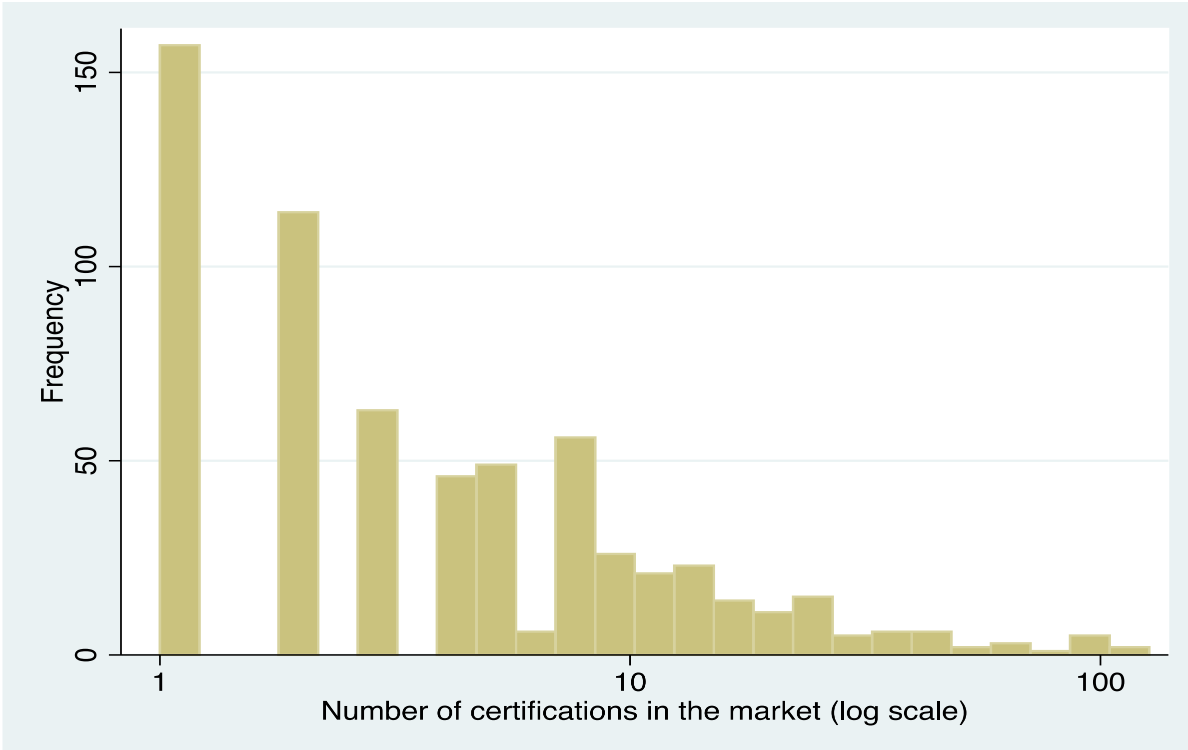

Figure A-3: Number of certifications in the market (log scale)

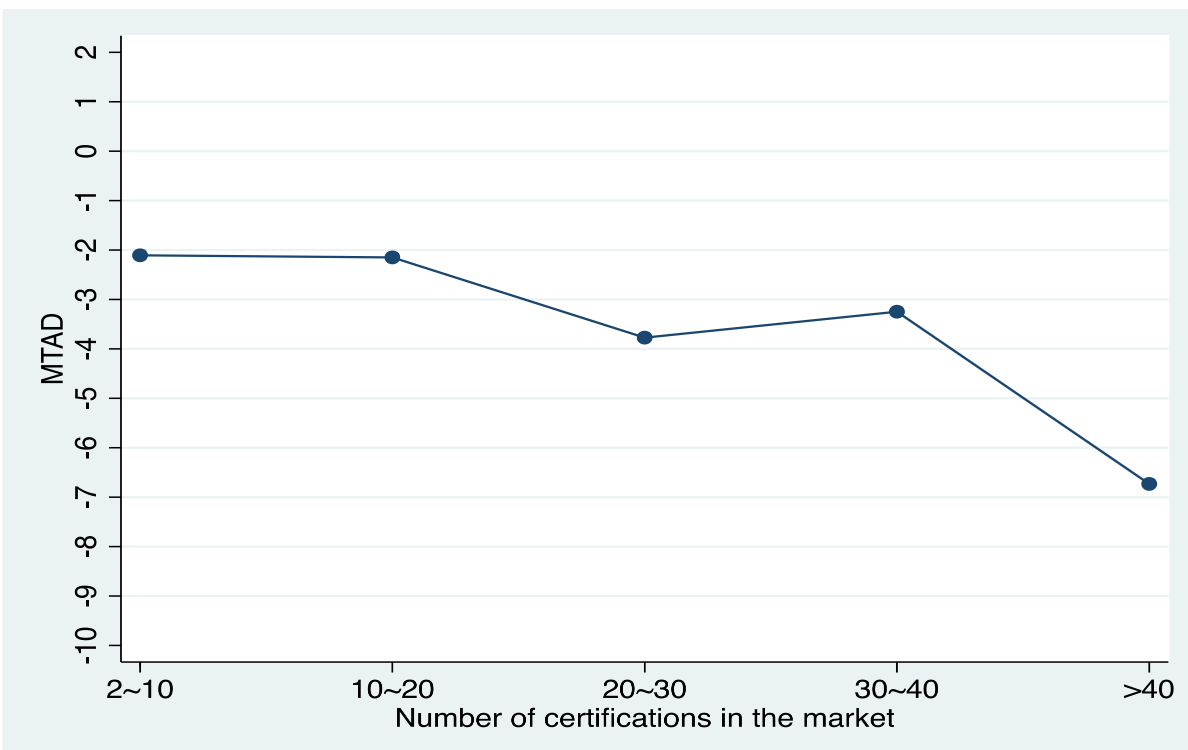

Figure A-4: MTAD Values