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Differentiation Strategies in the Adoption of Environmental Standards: LEED from 2000-2014

(Authors' names blinded for peer review)

We study the role of vertical differentiation in the adoption of LEED (Leadership in Energy & Environmental Design), a multi-tier environmental building certification system. Our identification strategy relies on the timing of adoption, and shows that builders seek to differentiate from each other when choosing a certification level. We estimate a model that incorporates both differentiation incentives and correlated market-level unobservables, and find that differentiation accounts for 28% of the variation due to observed factors. Finally, we use our estimates to simulate the impact of reducing the number of LEED tiers from four to two, and find that the impact on environmental investments depends upon the location of the threshold between levels.

Key words: Environmental Standards, Quality Certification, Green Building, LEED

1. Introduction

For firms to differentiate based on investments in public goods, consumers must be able to observe and understand the relevant outcomes. Thus, over the last several years, many private not-for-profit organizations have developed voluntary certification programs that provide information about corporate social or environmental performance. The rapid increase in opportunities for voluntary certification has stimulated debate about the design of these programs and the determinants of their adoption.[1] This paper studies the link between the design and the adoption of LEED (Leadership in Energy & Environmental Design), an internationally recognized environmental building certification system.

The LEED standard offers four levels or "tiers" of certification (Certified, Silver, Gold and Platinum) corresponding to greater investments in green building technology. We estimate a model of certification level choice, and find evidence that building owners seek to differentiate themselves

[1] For some examples, see the web site www.ecolabelindex.com, which maintains a registry of 448 different environmental certification programs. For an overview of the debate about how these labels are used, see Chatterji et al. (2009) on measurement validity; Lyon and Maxwell (2011) on "greenwashing"; Fischer and Lyon (2014b) on multi-tier certification systems or Kok et al. (2011) on the diffusion of environmental standards.

from other LEED projects in the same local market through their choice of certification level. We then use our model to simulate the response to a counter-factual two-tier LEED standard, holding differentiation incentives constant.

Our empirical model is based on the idea that building owners use LEED certification as a source of vertical product differentiation.[2] For example, in a case study of LEED adoption at Genzyme (Toffel and Sesia 2010), CEO Henri Termeer was quoted on the importance of achieving a high *relative* certification level, "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." At the same time, rivalry may lead building owners to choose a lower certification level. For example, if only a few tenants in a given market are willing to pay for LEED Platinum certification, the marginal benefits of top-tier certification will fall as the stock of Platinum buildings grows, and at some point the necessary investments will no longer be worthwhile. Thus, the overall link between vertical differentiation and environmental investments is ambiguous: it depends on characteristics of the local market, what others have chosen, and also the opportunities for differentiation afforded by the design of the underlying standard.

The main empirical challenge we face in using certification level choices to infer differentiation strategies is to separate the causal impact of rival builders' actions from other factors that produce correlated choices, such as unobserved heterogeneity across local markets. For identification, we exploit variation in the timing of certification-level choices within a local market, taking previous choices as exogenous to later ones. 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.[3]

We find that differentiation plays an important role in certification-level choices, as do market and building characteristics. In particular, LEED certification levels are positively correlated (i.e. agglomerated) across buildings within relatively small geographic markets, and are also correlated with market and building-level observable characteristics in a manner that suggests builders respond to local demand for environmental performance. At the same time, certification-level choices (conditional on previous choices) are more dispersed than a model of random adoption with unobserved market-level effects would predict, suggesting that builders have an incentive to differentiate from one another. Although our empirical approach could falsely find differentiation because of mean-reversion in the adoption process, we use a simulation of independent random

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

[3] 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.

choice to show that mean reversion cannot fully explain our results. Overall, our estimates imply that building owners' differentiation strategies explain as much variation in certification choices as observed market characteristics, though unobserved market-level heterogeneity explains more.

After providing evidence that differentiation strategies play a role in the adoption of LEED, we use our model of certification-level choice to explore the design of multi-tier labels. One important question for a standard setting organization is how many certification levels to offer. More levels allows for a finer signal of investment, and also more differentiation, which itself may be good or bad. With this in mind, we use our empirical model to simulate a counter-factual LEED standard with only two tiers: High and Low. The simulation suggests that some lower-tier buildings would increase their investments to achieve more points and a higher LEED certification level under a two-tier regime. However, because infra-marginal buildings typically acquire the minimum number of points needed to reach a given certification level, overall investments in LEED would decline when switching from four tiers to two.

While our simulation results suggest that increasing the number of certification levels can promote investments in quality, in practice most standards offer at most a handful of tiers. Presumably, standards bodies are responding to issues of consumer confusion and information processing, which leads to our second important question: Given that a standard will offer relatively few certification levels, where should the cut-points be set? We vary the location of the High/Low threshold in our simulated two-tier LEED standard, and find that investments are maximized when the cut point is located at the margin between Silver and Gold in the actual LEED standard. Intuitively, Gold is a relatively demanding level that is still relevant to many projects, whereas Platinum is sufficiently more demanding that it affects very few buildings. And although Silver is achievable by many more firms, setting the threshold that low reduces investments by many firms that would have gone for Gold.

Overall, this paper makes several contributions to the literature on differentiation through voluntary environmental certification. To our knowledge, it is among the first to empirically examine the role of differentiation in the adoption of environmental standards, and to use a model to simulate outcomes for a counterfactual quality standard. From a methodological perspective, we show how to exploit 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 address 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 or may not promote environmental performance depending on the context.

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.[4] Other recent theoretical models of environmental certification include Heyes and Martin (2016), who study competition between labels under free entry, and Harbaugh et al. (2011), who develop a model where consumer beliefs about products and labels are simultaneously determined.

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

Perhaps the closest paper to ours is Houde (2014), who studies the adoption of ENERGY STAR ratings by refrigerator manufacturers. He structurally estimates demand and pricing, along with the strategic adoption of the environmental standard, and uses those estimates to compute market outcomes if the ratings system were not in place. Relative to our paper, Houde studies a standard with only a single certification level, and so does not address either differentiation among adopters or the design of a multi-tier certification scheme.

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

[4] 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).

rent and occupancy rates, conditional on local market and building characteristics. Their paper is notable for matching LEED data to local real estate data in order to compare buildings that adopt LEED with non-adopters. 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. Finally, we replicate some findings of Matisoff et al. (2014), showing that the LEED point distribution bunches near the threshold for a particular certification level, and use this result to motivate a key assumption for our counterfactual simulations.

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 (USGBC). 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 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

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

[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).

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 range from $0.41 to $0.80 per gross square foot, or roughly $30,000 for a 50,000 square foot building (the median project in our sample).[7]

2.1. Data

We use data published by USGBC, covering 15,947 LEED certifications in the U.S. between 2000 and June, 2014.[8] The data set contains information about the buildings' registration dates, certification dates, certification levels, and characteristics including ownership type, rating system and address.[9] Figure 1 illustrates the number of observations by certification-year, and shows that LEED certification accelerated sharply between 2007 and 2010. Twenty-percent of the buildings in our data chose the lowest level of Certified, 33 percent achieve Silver, 38 percent achieve Gold and just 6 percent achieve the highest level of Platinum.[10]

To provide some evidence that achieving a higher tiers is costly, Figure 2 shows the underlying distribution of LEED Credits for 6,369 buildings certified under version 2 of the LEED for New Construction standard. The vertical lines in this figure correspond to cutoffs between certification levels.[11] 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 builders view LEED investments as a serious concern, and minimize their overall costs, subject to achieving a targeted certification level.

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

[8] An earlier draft obtained similar results from a smaller data set based on certifications as of July 2010.

[9] 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. The median time from registration to certification for certified buildings is two years.

[10] Figure A-1 in the appendix shows the share of each LEED tier by certification year.

[11] For this version of LEED, the certification levels were defined as: *Certified* (26-32 points), *Silver* (33-38 points), *Gold* (39-51 points) and *Platinum* (52+ points).

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.

Figure 1 Projects by Certification Year

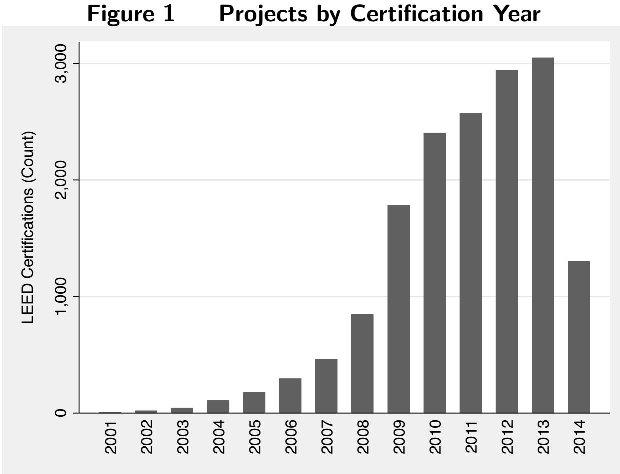
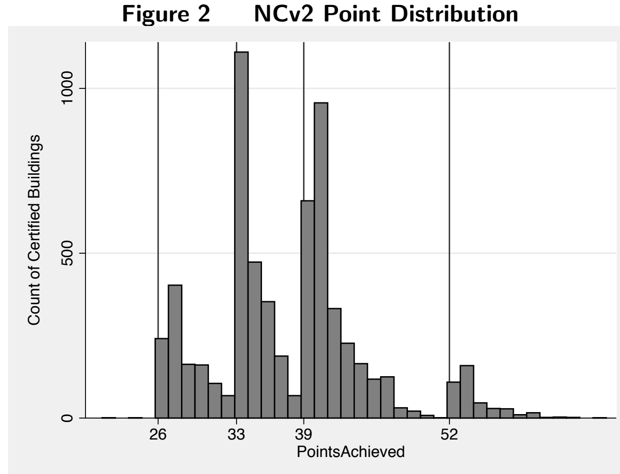


Figure 2 NCv2 Point Distribution



Because 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 local real estate markets.[12] If projects actually condition their choices on the certification-level decisions of some other unmeasured reference group, we expect the resulting measurement error to produce a downward bias in our estimates of the impact of differentiation.

The distribution of certified projects per market is quite skewed (see Figure A-2). Eleven percent of the markets have only one certified project. In order to study how firms' decisions are affected by their rivals within a market, we focus on markets with two or more certifications. This leads to an estimation sample with 15,861 certified projects located in 692 distinct markets. For each market, we obtain demographic information such as population, income, and the ratio of rent to income from the 2000 Census. Table 1 shows demographic summary statistics for the markets in our estimation sample.

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

[12] 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).

Table 1 Demographic Variables

		Mean	Std. Dev.	Min	Max
Population	Total population(1000)	378.49	360.44	0.06	2,878
Income	Median HH income(1000)	41.41	10.90	20.45	108.54
Housing	Housing units(1000)	155.09	140.26	0.04	1,146
Median Rent	Median gross rent (% of HHI)	0.25	0.02	0.11	0.34
Vacancies	Vacant housing units (%)	0.10	0.07	0.02	0.47
Rental Rate	Renter occupied housing (%)	0.29	0.11	0.11	0.92
High School	High school or higher (%)	0.81	0.07	0.49	0.98
College	College or higher (%)	0.24	0.10	0.09	0.75
Source	U.S. Census 2000				
Markets	N=692				

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 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-than-expected value indicating agglomeration. To compute the expected likelihood value and the confidence interval under independent random choice, MTAD uses simulation.[13]

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.

[13] Additional details on MTAD are described in Appendix B.

Table 2 Multinomial Tests of Agglomeration and Dispersion

Description	Observed Likelihood	Expected Likelihood	Standard Deviation	Z-stat	
All Four Levels	-4.94	-4.24	0.035	20.0	Agglomeration
Certified vs. Higher	-2.01	-1.60	0.021	19.5	Agglomeration
Silver and Below vs. Above	-2.25	-1.80	0.024	18.8	Agglomeration
Below Platinum vs. Above	-1.14	-1.04	0.023	4.3	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 (see Table A-1). In general, we find strong evidence of agglomeration, even after controlling for market size.

2.3. Within-City Dispersion

The results in Table 2 show that LEED certification-level choices exhibit 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. Without this incentive to differentiate, we would observe even more agglomeration.

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 (Manski 1993). We circumvent this problem by studying a project's certification-level choice as a function of all previous choices.[14]

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 certification 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:

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

[14] 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 in which projects respond to previous choices, even project also account for expectations of future behavior.

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 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.[15] 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 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. The latter results on project and market-level observables suggest that buildings choose a higher certification tier when the owner or prospective tenants have a stronger taste for environmental amenities.

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. Because N_{jm} contains lagged outcomes, the strict exogeneity assumption is violated by construction, and including fixed effects would also guarantee a negative estimate of α^N regardless of the underlying choice process.[16] So, instead of using fixed effects, we define a new outcome variable Y'_{jm} to indicate whether a project

[15] 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 $\{\alpha^N, \alpha^X, \alpha_t\}$.

[16] To get intuition for why fixed effects will always produce a negative coefficient, 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.

Table 3 Reduced Form Evidence of Agglomeration and Differentiation

Specification	Ord.Probit	OLS	Probit	OLS
	Level(1-4)		1[Level>Prev.Mean]	
	(1)	(2)	(3)	(4)
Previous Mean (N_{jm})	0.484***	0.360***	-0.571***	-0.199***
	(0.024)	(0.018)	(0.050)	(0.015)
Log(Gross Square Feet)	0.069***	0.055***	0.078***	0.029***
	(0.008)	(0.006)	(0.009)	(0.003)
Indicator: Government	-0.093	-0.068	-0.073	-0.028
	(0.062)	(0.047)	(0.071)	(0.027)
Indicator: Non-profit	-0.069	-0.056	-0.089	-0.034
	(0.071)	(0.054)	(0.080)	(0.031)
Indicator: For-profit	-0.456***	-0.349***	-0.408***	-0.154***
	(0.065)	(0.049)	(0.073)	(0.028)
Indicator: Other	-0.195***	-0.147***	-0.183**	-0.070**
	(0.073)	(0.056)	(0.085)	(0.032)
Log(Population)	0.114	0.085	-0.282	-0.113
	(0.190)	(0.146)	(0.324)	(0.117)
Log(Income)	0.196**	0.151**	0.287*	0.111*
	(0.094)	(0.072)	(0.159)	(0.057)
Log(Housing)	-0.088	-0.066	0.382	0.148
	(0.193)	(0.149)	(0.330)	(0.120)
Rent	3.467***	2.646***	5.970***	2.132***
	(0.672)	(0.512)	(1.148)	(0.419)
Vacancies	0.822**	0.645**	0.430	0.142
	(0.385)	(0.292)	(0.621)	(0.221)
Rental rate	0.892***	0.683***	0.932***	0.343***
	(0.168)	(0.128)	(0.273)	(0.098)
High school	0.541*	0.403	0.636	0.210
	(0.322)	(0.247)	(0.571)	(0.207)
College	0.288	0.225	0.808**	0.282**
	(0.204)	(0.156)	(0.382)	(0.139)
Log Pseudo-likelihood	-17888.8		-9887.1	
Pseudo R-squared	0.045	0.107	0.058	0.075
Observations	15156	15156	15156	15156

Robust standard errors are clustered at the market level and are in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. Time dummies are not reported. The omitted category of owner-types is Education.

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.[17] 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 ignore rivals and pick based on some other criteria, such as

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

market characteristics, or try to pick similarly to their rivals there will be a zero coefficient. So, finding $\alpha^N = 0$ is consistent with either no interaction of choices or agglomeration, whereas $\alpha_N < 0$ indicates differentiation. However, note that $\alpha_N < 0$ can occur if there is any tendency to 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 the first one. We describe a method for addressing this issue below.[18]

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 it is 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.

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 0.65. In the probit model, that implies a probability of choosing above one of 0.788. As N_{jm} rises to 3, the index falls to -0.49, implying a probability of 0.32. At the maximum of $N_{jm} = 4$, the probability we would compute based on our model is 0.16 (although in fact, there is no way to pick a number greater than 4).

We also explore some robustness issues. First, the intuition that the coefficient on the previous mean of choices can be interpreted to measure whether there is agglomeration or differentiation among certification choices could be undone if the previous mean is correlated with our other explanatory variables. For instance, it could be that agglomeration characterizes the data, but because of particular correlation between our regressors, we find a negative coefficient on the previous mean. As a robustness check, we re-estimate the model in Table 3 with only the previous mean as an explanatory variable and no other explanatory variables. The results in Table A-2 show that the parameters on the previous mean change very little when other covariates are dropped, suggesting that this issue is not a concern.

[18] The intuition behind our method is to measure "accelerated" mean reversion relative to what we would observe under a model of independent random choice.

Another potential concern is that we have constructed the explanatory variable of interest – the mean of past choices – as if the indicator of choice was a cardinal variable. 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.

A third possible issue is that there could be too much heterogeneity among markets. As a robustness check, we trim all markets with observations in the top or bottom 3% in any census variable, which eliminates more than 25% of our observations, and re-estimate the models in Table 3. In unreported results, we find similar qualitative and quantitative results.

A final concern is that government and non-profit developers may have different objective functions from private commercial developers, and thus might not be engaged in strategic interactions. These agents are heterogeneous, and it is difficult to say *a priori* whether they should be treated differently from private developers. However, we would be concerned if our results were driven entirely by non-profit developers. As a robustness check, we estimated the regressions in Table 3 using commercial buildings only, while still computing the previous mean as the mean over all buildings, and find similar 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 to compare the parameter on N_{jm} that would occur if the data were truly generated from independent random choice to the parameter that we actually find in data. Independent random choice will lead to a negative coefficient via mean reversion. However, if the negative coefficient in the actual data is larger than what could have been generated from independent random choice, then we conclude that mean reversion alone cannot explain our result – differentiation must also 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 independent random certification level choices, consider the following specification:

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

Here, the variables are defined as above. Now, γ_t are the time fixed effects. 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 main results.[19] 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).[20] 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.

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 higher than what is in Column (3). In other words, mean reversion alone cannot generate the outcome in Table 3. The table displays marginal effects as well as parameter coefficients. Naturally, the

[19] See Table A-3 for the full set of parameter estimates.

[20] We assume that the estimates from the two regressions $\hat{\alpha}$ and $\hat{\beta}$ are uncorrelated, and that the quantities $s.e.(\hat{\alpha})$ and $s.e.(\hat{\beta})$ consistently estimate the asymptotic standard errors of these parameters, so that $Z = (\hat{\alpha} - \hat{\beta})/[(s.e.(\hat{\alpha}))^2 + (s.e.(\hat{\beta}))^2]^{1/2}$ is asymptotically standard normally distributed.

Table 4 Simulations of Mean Reversion

Specification	Ordered Probit			Probit		
Outcome	Level (1-4)			1[Level > Prev. Mean]		
Data	Actual (1)	Simulated (2)	$Z_{(1)=(2)}$	Actual (3)	Simulated (4)	$Z_{(3)=(4)}$
Previous Mean (N_{jm})	0.484***	0.647***	3.99	-0.571***	-0.438***	1.96
	(0.024)	(0.033)		(0.050)	(0.046)	
Marginal Effect	0.051***	0.089***	6.52	-0.228***	-0.174***	2.07
	(0.003)	(0.005)		(0.019)	(0.018)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01,^{**} p < .05,^{*} p < .10$. We assume that the estimates from the actual and simulated data regressions ($\hat{\alpha}$ and $\hat{\beta}$ respectively) are uncorrelated, and that the quantities $s.e.(\hat{\alpha})$ and $s.e.(\hat{\beta})$ consistently estimate the asymptotic standard errors of these parameters, so that $Z = (\hat{\alpha} - \hat{\beta})/[(s.e.(\hat{\alpha}))^2 + (s.e.(\hat{\beta}))^2]^{1/2}$ is asymptotically standard normally distributed.

marginal effects are closer to each other than the coefficients, but a statistical test of the equality of the marginal effects still fails.[21]

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. This model allows us to compare the relative size of these forces, and to perform counterfactual analysis. The first subsection presents the model, the second discusses our estimation method, and the third describes the results and counterfactual analysis.

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. The desired number of LEED points for 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 $\rho_i,\ i \in \{1, 2, 3\}$. If $\pi_{jm} < \rho_1$, then j chooses Certified. If $\rho_1 \le \pi_{jm} < \rho_2$, then j chooses Silver. If $\rho_2 \le \pi_{jm} < \rho_3$, then j chooses Gold. If $\rho_3 \le \pi_{jm}$, then j chooses Platinum.

[21] A potential concern with robustness is that LEED professionals consider the "New Construction" category to be the most important application of the certification program, and perhaps not easily compared with the other categories. In unreported results, we estimated the regressions in Table 3 and Table 4, restricting our sample to new constructions only, even for computing the previous mean of choices. We find similar results to those for the full sample.

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 $\theta = \{\delta^X, \delta^N, \delta_t, \rho, \sigma_m\}$.

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

Although we have fully specified the model, it is difficult to estimate via Maximum Likelihood, since the market unobserved effect creates a challenging integral. While simulated maximum likelihood is a possibility, there is still an issue with the consistency of simulated ML for fixed numbers of draws (see for instance Pakes and Pollard 1989, Gourieroux and Montfort 1996), as well as computational complexity. 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 regressions*. The researcher estimates the auxiliary regressions on both the actual data and the simulated data, and uses the differences between the parameters obtained 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.[22] 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 (*Certified*,

[22] 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.

Silver and *Gold*) with representative element $n_i^* = \sum_j \sum_m \mathbb{1}\{Y_{jm} = i\}$.[23] 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 standard normal, where M is the number of markets, and S is the number of simulations (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, updating 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 $\phi^s(\theta) = \Psi\left(Y^s(\theta), X^s(\theta), N^s(\theta)\right)$.
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 must follow the algorithm again, starting from step 2. The GMM objective function has the form:

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

with 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 differentiate themselves from

Table 5 Estimates from Indirect Inference

			Coeff.	S.E.
δ^N	N_{jm}	**Previous Mean** (N_{jm})	-0.532	0.057
δ^X	**Project's Characteristics**	**Log(Gross Square Feet)**	0.087	0.010
		Indicator: Government	-0.089	0.064
		Indicator: Non-profit	-0.102	0.099
		Indicator: For-profit	-0.487	0.105
		Indicator: Other	-0.215	0.098
δ^X	**Market's Characteristics**	**Log(Population)**	0.024	0.120
		Log(Income)	0.168	0.073
		Log(Housing)	-0.107	0.180
		Rent	8.936	0.542
		Vacancies	1.226	0.566
		Rental rate	1.526	0.287
		High School	0.412	0.323
		College	0.196	0.094
δ_t	**Year Dummies**	Certified in 2004	-0.404	0.361
		Certified in 2005	-0.194	0.050
		Certified in 2006	-0.252	0.109
		Certified in 2007	0.032	0.016
		Certified in 2008	0.001	0.0003
		Certified in 2009	0.147	0.035
		Certified in 2010	0.196	0.072
		Certified in 2011	0.030	0.011
		Certified in 2012	0.169	0.043
		Certified in 2013	0.044	0.020
		Certified in 2014	-0.087	0.031
σ_m		S.D. of market effect	0.585	0.142
ρ		Cutoff 1	2.737	0.209
		Cutoff 2	3.786	0.236
		Cutoff 3	5.440	0.322
	GMM Criterion		40.935	

their rivals. We also find that σ_m is well-identified at 0.59, meaning that unobserved market heterogeneity is large as well.

The parameters δ^X for building j's size and ownership type are also shown in the table. We that find larger buildings tend to adopt higher levels. Compared to the omitted ownership category of Schools, For-profit projects adopt at lower LEED tiers.

[23] It is not necessary to include a count of *Platinum* projects, since that is implied by the other three.

The parameters δ^X also include the coefficients for observed market characteristics, such as population, income and rent. The variable Rent, which measures the median gross rent as a percentage of household income, has a huge effect on the certification level choice – places with a higher ratio of rent to income are more likely to adopt higher LEED levels. This variable may proxy for the profit margins that a building developer obtains from LEED certification, or for a sort of urban professionalism that leads to higher certification levels. The other results include that places with higher median income, more renter-occupied housing units and a larger share of college-education persons tend to choose 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 until 2010, before .leveling off and perhaps declining somewhat Relative to the standard deviation of 1 for the project idiosyncrasy, the variance of market-level unobserved effects is estimated to be 0.59, 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, which 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. 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.[24]

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. Under the VPC approach, we let V be the sum of the variance of each of these elements.

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

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

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

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 $\frac{1}{J}\sum_{j,m}\left(\left(t_{j}-\bar{t}\right)\delta_{t_{j}}\right)^{2}/V$ measures the time variation.[25]

Results are reported in Tables 6 and 7. Table 6 shows the variation attributable to observable variables, which are made up of observable market characteristics, observable project characteristics, and differentiation. We find that differentiation is important in determining adoption choices. Differentiation accounts for 28% of variation due to observable characteristics. It is just as important as observed project characteristics, and somewhat less important than observed market characteristics. However, Table 7 shows that, 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 just 12% of the total variation. Differentiation accounts for 3.4% of the total variation, less than the 22% attributed to unobserved market effects, as suggested by the earlier MTAD results.

Table 6 Sources of Variation (Observable Factors)

		Percent
Observed	Differentiation	28.33
	Observed building characteristics	30.08
	Observed market characteristics	41.58

Table 7 Sources of Variation (All Factors)

		Percent
Observed	Differentiation	3.40
	Observed building characteristics	3.61
	Observed market characteristics	4.99
Unobserved	Time variation	0.76
	Unobserved market effect	22.23
	Idiosyncratic building characteristics	65.01

An issue is that V as defined in Equation 3.5 does not account for correlation between explanatory variables. The variance of π will equal V only if those correlation terms are equal to zero. Assigning variance from correlation between explanatory variables to one variable or the other is necessarily somewhat arbitrary. Grömping (2007) discusses several methods for doing so. We have implemented

[25] Note that variance due to differentiation should be interpreted as a measure of how much the mean of previous choices affects current choices, conditional on the choices we observe. As can be seen in Equation 3.5, large values of δ^{N} increase the variance due to variation. However, an alternative way to think about this concept would be to imagine simulating market outcomes from the start of time with alternative values of δ^{N}. In this case, large values of δ^{N} *reduce* the overall variance of choices, since differentiation causes accelerated mean reversion in our set-up.

the Partial Marginal Variance Decomposition of Feldman (2005) and found similar results to those reported here.

3.3.2. Counterfactual analysis A natural question when designing a certification standard is whether to use multiple levels. 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.[26] This choice 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 LEED adoption would differ if the standard offered only two certification levels (Low and High) for buildings to choose from.[27]

Our counterfactual analysis assumes that the relationship between the score and the explanatory variables stays the same, and uses $\hat{\rho}_1$, $\hat{\rho}_2$ and $\hat{\rho}_3$ respectively to design the two-tier regime. 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 in our model when projects respond to the choices of competitors. To account for differentiation under the hypothetical two-tier standard, 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 throughout that buildings choose the lowest level of investment necessary to achieve a given certification level. 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 compute the mean of numbers of adopters at each level. The results are shown in Table 8.

In all three counter-factual scenarios, reducing opportunities for differentiation leads more buildings to choose a higher certification level than we observe in the data. For instance, in a two-tier regime where the High/Low margin is set between Certified and Silver ($\hat{\rho}_1$), 824 of the 3,547 buildings in the Low certification level to shift up to the High level. When the cut-off is set between Silver and Gold ($\hat{\rho}_2$) or Gold and Platinum ($\hat{\rho}_3$), the number of buildings shifting up is 838 (of 8,868), and 1,013 (of 14,963) respectively.

Although some buildings increase their certification-level when opportunities for differentiation are reduced, many others choose not to. Thus, the effect on overall investment is a concern. For example, if the two-tier cut-off is set at the Silver-Gold margin ($\hat{\rho}_2$), projects located near the

[26] 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. pass/fail).

[27] Since we have not claimed that we have a true structural model, it is possible that our parameters are not robust to the policy change that we implement. In this case, our experiments are better thought of as a way to evaluate how large the parameters are, rather than a true counterfactual exercise.

Table 8 Counterfactual Two-Level Standards

<table>
<tr><td>Cut-point</td><td></td><td colspan="2">ρ_1 (L:1 H:2)</td><td colspan="2">ρ_2 (L:1 H:3)</td><td colspan="2">ρ_3 (L:1 H:4)</td></tr>
<tr><td></td><td>Actual</td><td>Baseline</td><td>Model</td><td>Baseline</td><td>Model</td><td>Baseline</td><td>Model</td></tr>
<tr><td>Certified(1)</td><td>3,547</td><td>3,547</td><td>2,723</td><td rowspan="2">8,868</td><td rowspan="2">8,030</td><td rowspan="3">14,963</td><td rowspan="3">13,950</td></tr>
<tr><td>Silver(2)</td><td>5,321</td><td rowspan="3">12,387</td><td rowspan="3">13,211</td></tr>
<tr><td>Gold(3)</td><td>6,095</td><td rowspan="2">7,066</td><td rowspan="2">7,904</td></tr>
<tr><td>Platinum(4)</td><td>971</td><td>971</td><td>1,984</td></tr>
<tr><td>Mean Level</td><td>2.28</td><td>1.78</td><td>1.83</td><td>1.89</td><td>1.99</td><td>1.18</td><td>1.37</td></tr>
</table>

This table shows project counts by certification-level for three counterfactual two-tier standards, with the cut-point for a "High" certification-level set at ρ_1, ρ_2 or ρ_3. The column labelled "Actual" displays project counts in our four-tier estimation sample. For each hypothetical two-tier standard, the column labelled "Baseline" assumes no differentiation and simply aggregates counts from the "Actual" column, while the column labelled "Model" uses our integrated model to simulate project choices under differentiation. The final row shows the mean LEED certification level, assuming that projects minimize costs within a tier, as described in the text.

Certified-Silver margin ($\hat{\rho}_1$) under a four-tier standard will reduce their investments to the minimum required for LEED certification (unless they decide to shift up). While we lack data to evaluate the environmental impacts of any change in overall investment, we can evaluate the effect of these counterfactuals on total investment relative to the existing four-tier standard.

Table 8 contains a row titled "Mean Level," which reports the mean certification level, assigning values of 1, 2, 3, and 4 to the four levels. In column 1, where only Certified and Silver are available, we assign values of 1 and 2. In column 2, which has the High level set to Gold, we assign 1 and 3, and we assign 1 and 4 for column 3. Thus, this calculation assumes that any building will choose the minimum level of investment to achieve its level of certification.

In each case, eliminating options reduces total investment relative to the four-tier standard. This is not surprising: even firms that might be inclined to invest more will not do so if there is no public recognition. While this suggests that USGBC should increase the number of tiers, or just report the underlying number of LEED points, most certification programs seem to offer fewer levels, presumably because of the impact on consumer understanding.

The more interesting result to draw from the bottom row in Table 8 is the concave relationship between the location of the cut-point and the mean certification level (i.e. total investment) conditional on using a two-tier standard. This result gives insight into where a standard setting body should set certification requirements, given that it will use a limited number of tiers. Column 2, in which buildings choose between Certified and Gold, yields the most total LEED points because there are many buildings at Gold, and because Gold is relatively high. This result emphasizes the usefulness of having certification levels with relatively high cut-off investments, but not so high that most firms ignore it, as in the case where the cut-off is at the Gold-Platinum margin.

Finally, we note that differentiation plays an important role in determining the optimal cut-point under a counterfactual two-tier standard. Without differentiation, the mean certification level increases by 0.11 points (from a Baseline levels of 1.78 to 1.89) when the cut-point is switched from ρ_1 to ρ_2. With differentiation, the same change in the cut-point for a two-tier standard produces a marginal increase in investment of 0.16. Thus, differentiation accounts for roughly one-third of the improvement from setting the High certification level to Gold rather than Silver.

4. Conclusion

Recognizing that firms use certification programs as a tool for product differentiation leads to important questions about the adoption of quality standards, and how those standards should be designed. This paper studies the adoption of LEED, a standard for measuring the environmental performance of buildings that offers four tiers 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 that 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 unobservable effects are substantially more important, leading to an overall characterization of agglomeration. 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. However, overall investment falls. We find that the loss from coarsening the number of certification levels is minimized when the remaining level is set moderately high, high enough to induce strong investment but not so high as to be irrelevant or out of reach.

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Appendix A

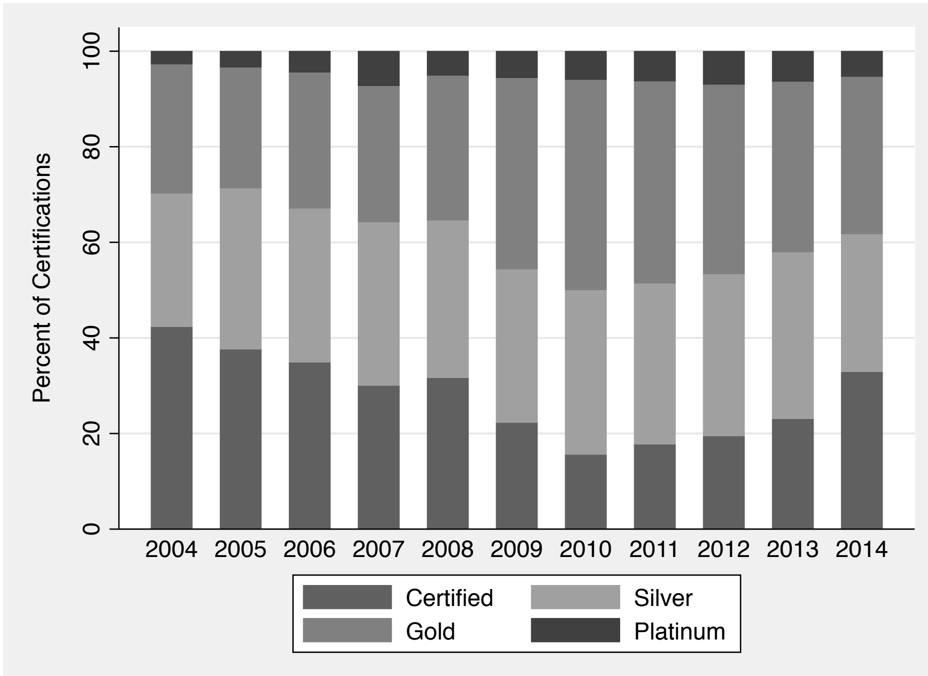

Figure A-1 Certification Levels by Year

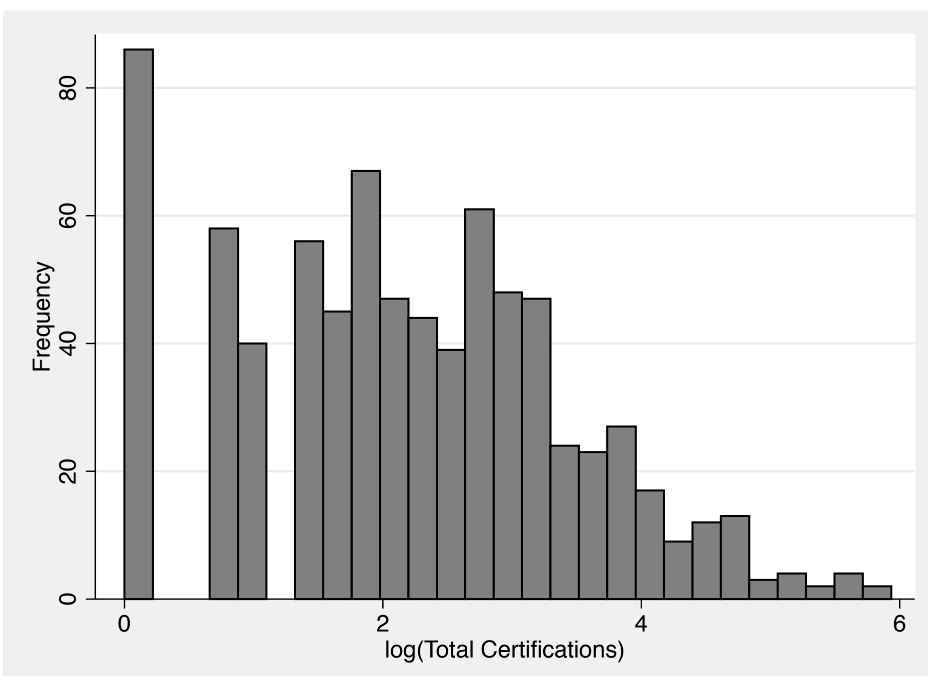

Figure A-2 Number of certifications in the market (log scale)

Table A-1 Additional MTAD Results Stratified by Market Size

Sample	Observed Likelihood	Expected Likelihood	Standard Deviation	Z-Score	
Certified Projects < 10	-2.77	-2.65	0.042	2.9	Agglomeration
$10 \leq$ Certified Buildings < 20	-5.19	-4.76	0.078	5.5	Agglomeration
$20 \leq$ Certified Buildings < 30	-6.75	-5.76	0.125	7.9	Agglomeration
$30 \leq$ Certified Buildings < 40	-7.45	-6.13	0.213	6.2	Agglomeration
Certified Projects ≥ 40	-10.07	-7.56	0.121	20.7	Agglomeration

Table A-2 Reduced Form Regressions Omitting Controls

Specification	Ord. Probit	OLS	Probit	OLS
Outcome	Level (1-4)		1[Level > Prev. Mean]	
	(1)	(2)	(3)	(4)
Previous Mean (N_{jm})	**0.575*** **	**0.446*** **	**-0.310*** **	**-0.121*** **
	(0.026)	(0.020)	(0.047)	(0.018)
Log Pseudo-likelihood	-18,373		-10,420	
Pseudo R-squared	0.02	0.05	0.01	0.01
Observations	15,169	15,169	15,169	15,169

Explanatory variables include only the mean of previous certification. Robust standard errors are clustered at the market level and are in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$.

Table A-3 Full Results for Simulation (Table 4)

Specification	Ord.Probit	Simulated O-Probit	Probit	Simulated Probit
Outcome	Level(1-4)		1[Level>Prev.Mean]	
	(1)	(2)	(3)	(4)
Previous Mean (N_{jm})	0.484***	0.647***	-0.571***	-0.438***
	(0.024)	(0.033)	(0.050)	(0.046)
Log(Gross Square Feet)	0.069***	0.068***	0.078***	0.064***
	(0.008)	(0.006)	(0.009)	(0.007)
Indicator: Government	-0.093	-0.188***	-0.073	-0.151***
	(0.062)	(0.047)	(0.071)	(0.058)
Indicator: Non-profit	-0.069	-0.093	-0.089	-0.047
	(0.071)	(0.050)	(0.080)	(0.065)
Indicator: For-profit	-0.456***	-0.455***	-0.408***	-0.389***
	(0.065)	(0.045)	(0.073)	(0.058)
Indicator: Other	-0.195***	-0.272***	-0.183**	-0.205***
	(0.073)	(0.056)	(0.085)	(0.069)
Log(Population)	0.114	0.278	-0.282	0.074
	(0.190)	(0.237)	(0.324)	(0.319)
Log(Income)	0.196**	0.107	0.287*	0.214
	(0.094)	(0.116)	(0.159)	(0.152)
Log(Housing)	-0.088	-0.256	0.382	-0.032
	(0.193)	(0.238)	(0.330)	(0.320)
Rent	3.467***	2.801***	5.970***	3.757***
	(0.672)	(0.872)	(1.148)	(1.195)
Vacancies	0.822**	0.895*	0.430	0.601
	(0.385)	(0.493)	(0.621)	(0.636)
Rental rate	0.892***	0.659***	0.932***	0.918***
	(0.168)	(0.190)	(0.273)	(0.241)
High School	0.541*	0.617	0.636	0.905
	(0.322)	(0.392)	(0.571)	(0.576)
College	0.288	0.466*	0.808**	0.314
	(0.204)	(0.261)	(0.382)	(0.373)
Log Pseudo-likelihood	-17888.8	-18098.0	-9887.1	-10102.1
Pseudo R-squared	0.045	0.052	0.058	0.036
Observations	15156	15156	15156	15156

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

Appendix B

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.