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

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Abstract

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 16.5% 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.

Keywords: Environmental Standards, Quality Standards, LEED.

JEL Codes: L15, L85, Q52.

1 Introduction

Consumers often value aspects of a product that are not directly apparent from its consumption. To overcome this problem, credible third parties can certify hard-to-observe product attributes such as environmentally conscious production, high labor standards or safety. The last several years have seen a proliferation of voluntary certification programs that provide information about corporate social or environmental performance, often organized by industry-led not-for-profit organizations. This rapid increase in opportunities for voluntary certification has stimulated debate about the design of these programs, and the determinants of their adoption.[1]

Certification programs typically recognize products for passing some level of investment or performance, and an important design question is how many levels or tiers of recognition to offer. This paper studies 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. The LEED approach contrasts with the approach of other certification programs, such as ENERGY STAR, a government program that offers only one level of certification of environmental investment.[2] Using four levels of certification rather than one provides consumers with a more accurate signal of underlying investment, but may also be important because multiple certification levels provide more opportunities for builders to differentiate their product.

It is natural to think of builders investing in higher quality as a way to distinguish themselves from rivals. 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." Rivalry may also lead building owners to choose a lower certification level rather than a higher one. 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, multi-level certification, and environmental investments is ambiguous: it depends on characteristics of the

[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 (2016) on multi-tier certification systems or Kok et al. (2011) on the diffusion of environmental standards.

[2] A similar example is the contrast between the Marine Stewardship Council, which certifies seafood as sustainably caught, and the Environmental Defense Fund, which has labels for three categories: Best Choice, Good Alternative or Avoid. 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).

local market, what others have chosen, and also the opportunities for differentiation afforded by the design of the underlying standard.

Indeed, the four levels of certification in LEED appear to be important for builder choices. Investment in green buildings could lead to economic benefits in several ways, such as decreased operating costs, improved employee productivity, and through higher rents due to signalling superior social responsibility. Eicholtz et al. (2010) discuss these factors, and also find that buildings with ratings command measurably higher returns.[3] However, higher levels of investment are more costly.[4] In addition, there appears to be a competitive effect to local building choices.[5]

Our paper has two main goals. First, we evaluate the extent to which building owners use LEED as a source of differentiation. Positioning relative to rivals is a classic question in strategic management, and the novel feature of our study is the focus on vertical differentiation *within* a third-party environmental certification program. Our second goal is to study how the role of differentiation interacts with the design of the LEED standard. In particular, we study how outcomes might change if LEED used fewer levels of certification, and how to choose the threshold between tiers given a restricted number of certification levels. 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.[6]

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, which we take as evidence of unobserved market characteristics. Certification levels are also correlated

[3] They find "buildings with a green rating command rental rates that are roughly 3 percent higher per square foot than otherwise identical buildings,... and selling prices of green buildings are higher by about 16 percent." Other studies also find the price or rent premium for LEED certified buildings, see Wiley et al. (2010); Reichardt (2014). Fuerst and McAllister (2011) find that higher levels of certification achieve higher premia.

[4] Tatari and Kucukvar (2011) find that, compared to non-LEED buildings, the cost premiums to achieve LEED *Certified, Silver, Gold* and *Platinum* are 0.66%, 2.1%, 4.4% and 6.5% respectively. The results are based on an early study by Kats et al. (2003).

[5] Chegut et al. (2014) find that the marginal benefits of certification relative to non-green buildings in the neighbourhood decreases as the number of certified buildings increases.

[6] 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.

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 choice to show that mean reversion cannot fully explain our results. Overall, our estimates imply that building owners' differentiation strategies explain 16.5% of variation due to observable 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. Specifically, 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, the overall level of investment in achieving LEED points 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 counterfactual simulation: 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

An important early model of vertical differentiation is Shaked and Sutton (1982). 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 (2014) review the emerging theoretical literature on eco-labels, and also develop the only model (Fischer and Lyon, 2016) of multi-tier environmental standards, such as LEED, that allow for differentiation among adopters.[7] 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. Houde (2017) considers how consumers evaluate a continuous and binary indicator of environmental efficiency in the context of U.S. refrigerators.

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.

[7]As explained by Fischer and Lyon (2014), environmental certification programs are typically non-profit organizations that differ in important ways from the for-profit information intermediaries studied by Lizzeri (1999).

As for environmental product differentiation, Reinhardt (1998) discusses firms' strategy of differentiating products along environmental lines, and points out that producing goods in ways that are less environmentally burdensome raises costs, but can also enable businesses to command a price premium, or to capture additional market share. Delmas et al. (2007) study firms' strategies in response to deregulation, and find evidence of environmental differentiation.

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. Thus, our paper differs because we focus on the use of a mutli-level certification program as a source of differentiation among adopters, and we emphasize the design of a multi-tier certification scheme. Our techniques for identifying differentiation are also quite different.

Our paper also contributes to the 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. 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. There is an extensive literature investigating the cost premium associated with the green building.[8] Dwaikat and Ali (2016) conduct a literature survey and find that "more than 90% of the reported green cost premiums through empirical investigations fall within a range from -0.4% to 21%.Sandoval and Prakash (2016) conduct interviews with builders/owners, and find that if the leasing time frames are usually short and a high rental can not be secured in the long run, they would prefer a lower certification level, say *Certified*. 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

[8]See Kats et al. (2003); Houghton et al. (2009); Mapp et al. (2011); Tatari and Kucukvar (2011).

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.[9] 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.[10]

LEED certification involves several steps. The process begins with the 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. While 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 USGBC has consistently set the point-gap between Gold and Platinum to be twice as large as the gap between Certified and Silver or between Silver and Gold.

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

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

[10] See for example, Eicholtz et al. (2010) or "Financing and Encouraging Green Building in Your Community."

range from relatively cheap (such as installing bicycle racks and showers) 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).[11]

An important issue is that LEED standards change over time. That is, the USGBC periodically adjusts the number of points associated with different investments, as well as the exact point cutoffs for different levels of certification. We account for this issue with time dummies in our empirical model, and in a robustness check, we use time dummies interacted with building type to control for the fact that different LEED versions (such as New Construction and Existing Buildings) are adjusted separately and at different times. Buildings do not lose their certification even if they would no longer obtain that level under a recently adjusted standard. A maintained assumption throughout our paper is that owners respond to the certification level of their rivals, not the underlying investment of their rivals. Thus, the presence of a Gold building has the same affect on rivals whether that building achieved its certification under the current standard or under some previous (probably less demanding) standard. We believe this accurately describes the market, and it is difficult for us to relax in our framework. Furthermore, we provide evidence below that building owners typically accumulate just enough points to achieve a given certification level and rarely many more, which suggests the importance of the certification level relative to the underlying investment.

Much of the paper focuses on differentiation and its converse, agglomeration, so it is worth discussing what we mean by this. Observationally, agglomeration will mean seeing buildings within a locale grouped onto one or a few certification levels, more so than would be predicted by independent random choice by each owner. Similarly, we will conclude the data is characterized by differentiation if buildings spread more evenly across certification levels than independent random choice would predict. What we mean by independent random choice depends on exactly what explanatory variables we are conditioning on, and we explore several models throughout the paper.

We can think of several explanations for agglomeration. Some of these explanations are causal. For example, the choice of one building owner could lead other local owners to make the same choice. Causality could also arise from learning and supply development, for instance, if the certification level of one building causes local LEED professionals to develop skills in certain

[11] 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).

features and makes contractors more familiar with certain building attributes. In contrast, rather than a causal explanation, agglomeration could appear because of local unobserved heterogeneity. Sources of heterogeneity might be unobserved market-level demand-side factors such as local preference for a particular green level, local energy prices, or features of the local construction market. In contrast, the appearance of differentiation is more likely to be driven by causal effects, whereby building owners want to differentiate their products from each other. It is difficult to develop narratives of unobserved heterogeneity that lead to the appearance of differentiation.

In our integrated empirical model, we generate agglomeration with unobserved market heterogeneity and find that the causal effect of the choice of one owner on the other leads to differentiation. We do not rule out there may be some agglomerative causal effects. Rather, we estimate only the total (net) causal effect, which we find to favor differentiation. Thus, it may be that causal effects generate both agglomeration and differentiation, but we find that the effect of differentiation is larger. Disentangling these effects is not a goal of the paper. Rather, our focus is on separately identifying the overall causal effect and the extent of unobserved market heterogeneity.

2.1 Data

We use data published by USGBC to study LEED certification-level choices of U.S. buildings between 2000 and June, 2014.[12] For most of our results, we restrict our sample to commercial buildings, where we expect incentives for differentiation to be the highest. There are 6,834 commercial buildings in the data, which account for about 46% of all observations.[13] The data set contains information about each building's registration date, certification date, certification level, and characteristics including ownership type, rating system and address.[14] Ownership type has several values: for-profit, education, government and non-profit. Restricting our sample to commercial buildings increases the portion of for-profit buildings in our sample, but some of the other types rent space on the commercial market and are thus in the commercial category.

Figure 1 illustrates the number of observations by certification-year, and shows that LEED certification accelerated sharply between 2007 and 2010. Over the entire period, 18 percent

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

[13] We use the "Project Types" field in the LEED certification data set to classify building types into commercial (46%), public (34%), retail (19%), residential (7%), industrial (6%) and other (4%) categories. The commercial category includes all projects types matching the string "Commercial Office" or "Office:" or "Financial".

[14] 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.

of the buildings in our data chose the lowest level of Certified, 33 percent achieve Silver, 42 percent achieve Gold and just 7 percent achieve the highest level of Platinum.[15]

To provide some evidence that achieving a higher tiers is costly, Figure 2 shows the underlying distribution of LEED Credits for 849 commercial buildings certified under version 3 of the LEED for New Construction standard (also called LEED NC-v2009). The vertical lines in this figure correspond to cutoffs between certification levels.[16] 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. 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

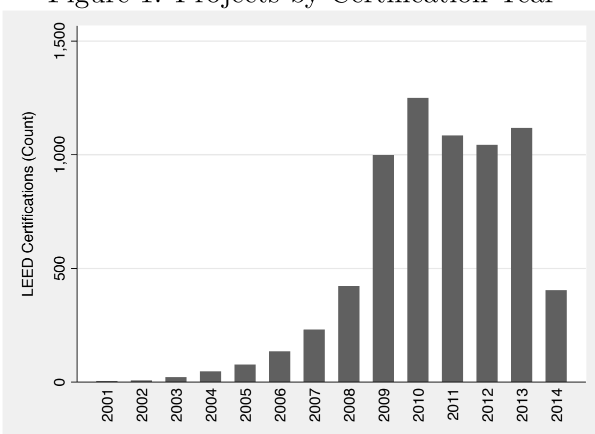
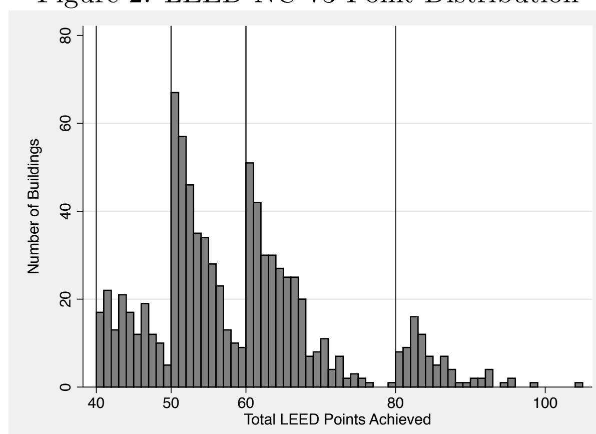


Figure 2: LEED-NC v3 Point Distribution



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.[17] This market definition leads to an estimation sample of 6,834 certified projects located in 625 markets. The distribution of projects per market is quite skewed (see Figure A-2).

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

[16]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).

[17]There are about 900 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).

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. For example, building owners may care about national product market competitors when making their decisions, rather than local building owners. That would lead our measure of rival choices to be mismeasured. Assuming the mis-measurement is orthogonal to the explanatory variables, we can view our coefficient on the choices of local buildings as a lower bound for the true role of differentiation, which makes a statistically significant result particularly compelling. In practice, the commercial buildings in our sample are mainly used for offices, and designed to attract local customers. Previous studies also make the implicit assumption that commercial buildings are competing for financial benefits locally. For example, Eicholtz et al. (2010) examine the market benefits (such as the rents and the selling prices) of certified green office buildings by comparing the certified and non-certified buildings in the same geographic market.

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.

Table 1: Demographic Variables

		Mean	**Std. Dev.**	**Min**	**Max**
Population	Total population(1000)	394.52	372.37	3.68	2,878.55
Income	Median HH income(1000)	41.63	11.11	20.45	108.54
Housing	Housing units(1000)	161.33	144.94	1.47	1,146.99
Median Rent	Median gross rent (% of HHI)	0.25	0.02	0.13	0.34
Vacancies	Vacant housing units (%)	0.10	0.06	0.01	0.47
Rental Rate	Renter occupied housing (%)	0.30	0.11	0.10	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=625				

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, setting aside any control variables for now. Our approach is to compute the unconditional probability of choosing each certification level from national data, and we take independent random choice to mean owners choosing their certification level with these probabilities. Seeing buildings within locales grouped on a relatively small number of certification levels will lead us to characterize the data as agglomerated, whereas seeing buildings spread across certification levels (that is, adhering to these probabilities within each market more than independent random choice would predict) will classify the data as differentiated.

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.[18]

Table 2 shows results from MTAD for commercial buildings. 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 cut-off 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 the first three rows, we find that the expected likelihood is significantly higher than the observed likelihood, which indicates that the data are characterized by agglomeration. The fourth row shows there is no significant evidence for agglomeration or dispersion. This might be because, on average, we observe less than one Platinum certified building per market, and this number is too small to show any significant pattern.

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.

[18] 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	-3.59	-3.19	0.032	12.58	Agglomeration
Certified vs. Higher	-1.39	-1.14	0.026	9.67	Agglomeration
Silver and Below vs. Above	-1.70	-1.43	0.021	12.96	Agglomeration
Below Platinum vs. Above	-0.84	-0.80	0.028	1.26	

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.[19]

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. 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 2014, 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.

[19] 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 conduct a robustness check below assuming that buildings also account for expectations of future choices. Please see Appendix C for more details.

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 $E[\varepsilon_{jm}|X_{jm}, N_{jm}, t] = 0$ and $Y_{jm} = Y^*_{jm}$. Thus, this model treats the outcome as a cardinal variable, so Gold (3) is preferred to Silver (2) by the same amount that Silver is preferred to Certified (1). The ordered probit model relaxes this assumption, treating Y_{jm} 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.[20] 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 because 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.[21]

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 unobserved market-level effects. We also find evidence of a higher mean certification-level for buildings with non-profit owners, and that are located in markets with relatively high 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.[22] 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.[23] 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

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

[21]Please see Appendix C for more details.

[22]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.

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

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})	0.287***	0.221***	-0.678***	-0.242***
	(0.043)	(0.032)	(0.056)	(0.017)
Log(Gross Square Feet)	0.061***	0.05***	0.078***	0.029***
	(0.015)	(0.012)	(0.018)	(0.007)
OwnerType: Profit	-0.034	-0.027	-0.086	-0.031
	(0.064)	(0.049)	(0.069)	(0.026)
OwnerType: Education	0.244	0.193*	0.113	0.045
	(0.153)	(0.117)	(0.177)	(0.067)
OwnerType: Government	0.077	0.061	-0.039	-0.015
	(0.084)	(0.065)	(0.088)	(0.033)
OwnerType: Non-profit	0.173**	0.13**	0.104	0.039
	(0.081)	(0.062)	(0.093)	(0.035)
System: CI(Commercial Interiors)	0.406**	0.325**	0.368	0.138
	(0.195)	(0.152)	(0.262)	(0.098)
System: CS(Core&Shell)	0.59***	0.465***	0.509**	0.191**
	(0.175)	(0.136)	(0.228)	(0.085)
System: EB(Existing Buildings)	0.33*	0.268*	0.281	0.108
	(0.186)	(0.144)	(0.232)	(0.086)
System: NC(New Construction)	0.509***	0.402***	0.398	0.151*
	(0.184)	(0.143)	(0.247)	(0.092)
Log(Population)	-0.175	-0.126	-0.222	-0.079
	(0.356)	(0.277)	(0.495)	(0.182)
Log(Income)	0.155	0.123	0.243	0.094
	(0.145)	(0.112)	(0.220)	(0.080)
Log(Housing)	0.201	0.146	0.342	0.122
	(0.355)	(0.277)	(0.496)	(0.182)
Rent	4.252***	3.259***	3.247*	1.158*
	(1.267)	(0.988)	(1.731)	(0.639)
Vacancies	-0.537	-0.373	-0.561	-0.177
	(0.916)	(0.700)	(1.125)	(0.404)
Rental rate	0.739**	0.582**	0.945**	0.353**
	(0.295)	(0.226)	(0.452)	(0.164)
High school	0.249	0.201	0.545	0.19
	(0.569)	(0.440)	(0.832)	(0.303)
College	0.27	0.205	0.536	0.19
	(0.345)	(0.268)	(0.586)	(0.217)
Log Pseudo-likelihood	-7450.3		-4065.8	
Pseudo R-squared	0.024	0.058	0.054	0.071
Observations	6204	6204	6204	6204

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 other type, and the omitted category of LEED system includes LEED ND(Neighborhood Development) and LEED for Schools.

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 market characteristics, or try to pick similarly to their rivals there will be a zero coefficient. Thus, 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.[24]

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 from their predecessors. To understand the size of this effect, consider the latent variable Y^*_{jm} in Equation 2.1 when $N_{jm} = 1$ (its lowest possible value, which implies that all previous buildings chose the *Certified* level). At the mean value of the variables X_{jm}, the expected value of Y^*_{jm} is 0.93. As N_{jm} rises to 3 (implying that previous buildings in the same market picked *Gold* certification on average) the expected value of Y^*_{jm} falls from 0.93 to -0.42. In the probit model, that change of N_{jm} implies that the probability of choosing above the previous mean falls from 0.83 to 0.34. Thus, changes in the previous mean imply substantial changes in the probability of choosing above the previous mean.

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.

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

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

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 more negative 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, and having the largest amount of mean reversion that is consistent with our data, could produce negative coefficients as large as the ones reported 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.[25] 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).[26] 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: 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})	0.287***	0.541***	4.33	-0.678***	-0.485***	2.53
	(0.043)	(0.040)		(0.056)	(0.052)	
Marginal Effect	0.039***	0.094***	5.98	-0.270***	-0.194***	2.50
	(0.006)	(0.007)		(0.022)	(0.021)	

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.

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

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

[26] 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.

2.3.2 Robustness checks

We have conducted several robustness checks for the results in Table 4. Here, we describe results for new construction, for an extended sample that includes non-commercial buildings, and for a recency-weighted version of the key variable N_{jm}.

New construction may provide more scope to choose among different certification levels than renovations of existing buildings. This is because builders start from a "clean slate" and are often working with particularly demanding customers. To test this idea, we examine the subsample of 2,343 commercial buildings in 574 markets that were certified using version LEED-NC (New Construction). The results are reported in Table 5.[27] The coefficients on "Previous Mean" for actual data are significantly different than the ones for simulated data, which indicates the presence of differentiation. Moreover, the differences in parameter estimates between true and simulated data are larger than for the full sample, suggesting that the incentive to differentiate is stronger for new construction.[28]

Table 5: Simulations: LEED-NC (New Construction) Sub-sample

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Previous Mean	0.157***	0.529***	5.48	-0.947***	-0.532***	4.84
	(0.048)	(0.048)		(0.065)	(0.056)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01,^{**} p < .05,^{*} p < .10$. Building characteristics, market characteristics and time dummies are not reported. 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. We make the above assumption throughout all the robustness checks.

As described above, we expect differentiation incentives to be larger for the sample of commercial buildings because of the local nature of demand. Academic and government buildings are more likely to be judged against faraway peers. Nevertheless, as a robustness check, we implement our tests for differentiation on the entire sample of LEED certified buildings, which includes commercial, residential, public, retail and industrial building types. This sample in-

[27] For all the robustness checks, we present only the main parameters. The full set of parameter estimates are available upon request.

[28] Results for the sub-sample of buildings certified under versinon LEED-EB (Existing Building) are presented in Appendix Table C-1.

cludes 15,761 certified buildings located in 778 markets. Results are presented by Table 6. In this sample, coefficients estimates are significantly different for the Ordered Probit, but not the Probit regression. Thus, although endogenous differentiation may be present for all building-types, the effect appears to be strongest for commercial projects.

Table 6: Simulations: All Certified Buildings

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Previous Mean	0.248***	0.474***	4.63	-0.680***	-0.567***	1.40
	(0.036)	(0.033)		(0.058)	(0.056)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. Building characteristics, market characteristics and time dummies are not reported.

Another concern is that competition, and thus differentiation, could be stronger for projects completed around the same time. This would lead to measurement error on the key explanatory variable N_{jm}. To address this concern, we construct a weighted average of previous choices, placing more weight on recently certified buildings. Specifically, for each building i, we order all of the previously certified buildings in the same market according to their certification date, and compute weights w_k for each previously certified building k, where $w_k = o_k / \sum_{n<i} o_n$, and o_k is the order of certification for building k. We then compute building i's weighted average of previous choices as $N_i = \sum_{k<i} w_k Y_k$, where Y_k is building k's choice of certification level.[29] Results using this weighted average instead of the previous mean are shown in Table 7. Once again, the coefficients on "Previous Weighted Mean" for the actual data are significantly different than the ones for simulated data, consistent with the presence of differentiation.

Appendix C describes a variety of additional robustness checks. Capturing rival adoption behavior with the mean of previous choices may generate misspecification, particularly if the four certification-levels do not have a cardinal interpretation. In Table C-2, we find similar results when we substitute the mean prior certification-level N_{jm} with several alternatives: the median, the maximum, the minimum and the mode of past choices. One might also imagine that builders have rational expectations about their rivals' future choices. We account for this by replacing the previous mean with a weighted average of other buildings' past and

[29] For example, suppose that building i is the third to get certified in a market where the first building chooses $Y_{1m} = 1$, and the second chooses $Y_{2m} = 2$. The weighted average of previous choices for building $i = 3$ is computed as: $N_{3m} = \frac{1}{(1+2)} \times 1 + \frac{2}{(1+2)} \times 2 = 1.6667$.

Table 7: Simulations: Recency-Weighted Previous Mean

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Previous Weighted Mean	0.267***	0.506***	4.02	-0.719***	-0.520***	2.58
	(0.044)	(0.040)		(0.057)	(0.052)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. Building characteristics, market characteristics and time dummies are not reported.

future certification-level choices. Table C-3 shows that our results are robust to this alternative measure of rival choice.

LEED standards change over time, and at different times for different versions. If LEED-NC is updated at a different time than LEED-EB, a single set of time dummies may fail to account for these changes. Table C-4 shows that our results are robust to including a separate set of time dummies for each standard. Differential trends in LEED adoption across states or regions might also influence our results. Table C-5 presents a robustness check with separate state time trends to address this concern. Finally, we consider counties as an alternative market definition (although Appendix C provides several reasons we prefer the 3 digit zip code). Table C-6 shows that we find broadly similar results using county-level markets.

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 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.[30] The parameter μ_m represents a market random effect. We assume μ_m is distributed normally with standard deviation σ_μ, 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 $\theta = \left\{\delta^X, \delta^N, \delta_t, \rho, \sigma_\mu\right\}$. Key parameters for our results are δ^N, which determines the importance of differentiation in the model, and σ_μ, which controls the level of unobserved market heterogeneity, and thus the extent of agglomeration, as well as the strength of mean-reversion in sequential choices.

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 σ_μ) in a single integrated model.

3.2 Estimation

Although we have fully specified the model, it is difficult to estimate via Maximum Likelihood, as 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 Monfort, 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 because 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,

[30] In practice, the cut-points in LEED have been adjusted over time. We assume that $\{\rho_1, \rho_2, \rho_3\}$ are constant over time, but we allow for year dummies in the determination of π_{jm}, which should capture this issue well.

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.[31] 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*, *Silver* and *Gold*) with representative element $n_i^* = \sum_j \sum_m \mathbb{1}\{Y_{jm} = i\}$.[32] 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 $\phi^s(\theta) = \Psi(Y^s(\theta), X^s(\theta), N^s(\theta))$.
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 must follow the algorithm again, starting from step 2. The GMM objective function has the form:

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

[31] 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 that using linear models augmented with the vector n^* works well.

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

with weighting matrix

$$W = \begin{pmatrix} X'X & 0 \\ 0 & I_3 \end{pmatrix}, \tag{3.3}$$

where variable matrix X consists of the explanatory variables from the reduced-form regressions using the real data, and I_3 is the identity matrix.[33]

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 $\hat{\theta}$.

We briefly discuss, at an intuitive level, identification of our parameters of interest. In particular, we are interested in separately identifying the differentiation parameter δ^N from the role of unobserved market heterogeneity μ_m, which is governed by the variance parameter σ_μ. The key point to recognize is how this approach addresses mean reversion. If the parameter on the previous mean in the auxiliary regressions was entirely generated by mean reversion, the indirect inference approach would match that by setting $\delta^N = 0$ and using σ_μ to generate mean reversion. In this case, the simulated data would have the same level of mean reversion as the true data, and thus the parameters from the auxiliary regressions in the true and simulated data would match. Thus, the intuition for identification in the indirect inference procedure follows from our argument for the importance of differentiation in Table 4 — the parameter on the previous mean in the auxiliary regression on the true data is too large to be matched by mean reversion alone, which leads us to find a significant value of δ^N.

3.3 Estimation Results

The results of estimating the integrated model are reported in Table 8. 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 their rivals. We also find that σ_μ is well-identified at 1.14, meaning that unobserved market heterogeneity is large as well.

[33] Previous studies used the inverse of the covariance matrix ($\sigma^2(X'X)^{-1}$) from the reduced-form regressions as the weighting matrix (see for example Collard-Wexler 2013). But we believe it is more suitable to use the inverse of $(X'X)^{-1}$ here as we have two auxiliary regressions and the magnitudes of σ^2 are different. As robustness checks, we also tried the form of inverse of the robust covariance matrix, and the identity matrix. The results are quite similar.

Table 8: Estimates from Indirect Inference

			Coeff.	S.E.
δ^N	N_{jm}	Previous Mean(N_{jm})	-0.1487	0.0505
δ^X	**Project's Characteristics**	Log(Gross Square Feet)	0.0714	0.0042
		OwnerType: Profit	-0.0852	0.0201
		OwnerType: Education	0.1740	0.0531
		OwnerType: Government	0.0001	0.1899
		OwnerType: Non-profit	0.1204	0.0293
		System: CI	0.4349	0.0508
		System: CS	0.6327	0.0533
		System: EB	0.3413	0.0502
		System: NC	0.5346	0.0535
δ^X	**Market's Characteristics**	Log(Population)	-0.0001	0.0010
		Log(Income)	0.2332	0.0180
		Log(Housing)	0.0011	0.0037
		Rent	5.7361	0.5792
		Vacancies	-0.0498	0.2897
		Rental rate	1.1871	0.1303
		High school	0.4852	0.1846
		College	0.2884	0.1424
δ_t	**Year Dummies**	Certified before 2004	0.2553	0.4564
		Certified in 2004	-0.6231	0.1375
		Certified in 2005	-0.4623	0.0767
		Certified in 2006	-0.4978	0.0527
		Certified in 2007	-0.3705	0.0387
		Certified in 2008	-0.2738	0.0299
		Certified in 2009	-0.0426	0.0251
		Certified in 2010	-0.0055	0.0202
		Certified in 2011	0.0775	0.0239
		Certified in 2012	-0.0039	0.0250
		Certified in 2013	-0.0469	0.0220
σ_μ		S.D. of market effect	1.1439	0.0799
ρ		Cutoff 1	5.3210	0.1853
		Cutoff 2	6.3384	0.2011
		Cutoff 3	7.8626	0.2245

The parameters δ^X for building j's size, ownership type and LEED system are also shown in the table. We find that larger buildings tend to adopt higher levels. Among all the ownership categories, Education and Non-profit projects adopt at higher LEED tiers while For-profit projects adopt at lower LEED tiers, after controlling for the differentiation strategy. Compared to the omitted LEED system category of LEED ND and LEED for Schools, LEED CI, CS, EB and NC tend to adopt higher levels.

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 large 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. Although this variable is based on rents in the residential market, we believe it proxies for related issues in the commercial market. The other results include that places with higher median income, more renter-occupied housing units and a larger share of high school and college educated 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 from 2004 till 2011, before leveling off and perhaps declining somewhat.[34] Relative to the standard deviation of 1 for the project idiosyncrasy, the variance of market-level unobserved effects is estimated to be 1.1439, significantly different from zero. Our results predict the overall adoption rates of each level almost perfectly, which is not surprising because we impose these adoption rates as moments to match.

3.3.1 Variance Decomposition

We observe significant heterogeneity in adoption of LEED, both across and within markets. We are interested in the determinants of this variation; for example, how important are market characteristics relative to building characteristics, and observed characteristics relative to unobserved characteristics. We are particularly interested in the importance of differentiation in determining outcomes relative to these other effects, as this speaks to our primary question of how important differentiation is in determining certification outcomes. Thus, 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 propor-

[34] The omitted year dummy is 2014.

tions of total variation attributable to these factors.[35]

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.

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

Thus, $1/V$ measures the proportions of total variation attributable to idiosyncratic (unobserved) project characteristics, $\hat{\sigma_\mu}^2/V$ is the proportion 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 proportion 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 proportion 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 proportion 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 Tables 9 and 10. Table 9 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 16.54% of variation due to observable characteristics. It is close in level to observed project characteristics (24.92%), and about a quarter as important observed market characteristics (58.54%). However, Table 10 shows that, as is common in cross-sectional and panel studies, 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 3.5% of the total variation. Differentiation accounts for 0.58% of the total variation, less than the 54.26% attributed to unobserved market effects, as suggested by the earlier MTAD results. Overall, it appears that differentiation plays an important role in determining outcomes, and makes up a substantial share of observable characteristics, although there is significant unobserved heterogeneity driving building adoption patterns.

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 the Partial Marginal Variance Decomposition of Feldman

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

Table 9: Sources of Variation (Observable Factors)

		Percent
Observed	Differentiation	16.54
	Observed building characteristics	24.92
	Observed market characteristics	58.54

Table 10: Sources of Variation (All Factors)

		Percent
Observed	Differentiation	0.58
	Observed building characteristics	0.87
	Observed market characteristics	2.05
Unobserved	Time variation	0.77
	Unobserved market effect	54.26
	Idiosyncratic building characteristics	41.47

(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. This choice is particularly complicated when differentiation is important, because 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.[36]

To perform out counterfactual, we simulate draws for Equation 3.1 and solve for the outcomes of buildings in our data set assuming that there are only two levels of certification. That is, we solve for the outcomes from Equation 3.1, but assuming that builders choose between only two levels, picking the high level if the simulated π_{jm} is above a cut-point. In the first simulation, we allow buildings to choose between levels 1 and 2, we set the cut-point equal to $\hat{\rho}_1$. Thus, the previous mean of choices is the mean of values of 1 and 2. Next, we set the cut-point to $\hat{\rho}_2$ and allow the buildings to choose 1 or 3. We also consider choices 1 and 4 with a cut-point of $\hat{\rho}_3$.

We contrast the outcome with what would happen if we used simulated π_{jm} from the case

[36]Because 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.

of four levels of certification to determine whether each building would choose high or low. That is, we contrast simply reassigning π_{jm} from the case of four certification levels to two certification levels with how buildings would choose π_{jm} when actually facing two certification levels. These two predictions differ only because the mean of previous choice changes, and thus they differ only to the extent that δ^N is large. We simulate 1000 times and compute the mean of numbers of adopters at each level. The results are shown in Table 11.

The maintained assumption in this exercise is that the parameters we estimate for Equation 3.1 do not change in our counterfactual exercise. In particular, the competitive effect of rival choices (δ^N) must not change. We find this to be reasonable for our exercises, but is of course difficult to verify, as perhaps consumer perceptions of these standards could change drastically under some policy intervention. At the very least, we believe our results so far are compelling that even under the counterfactual, higher levels of certification exert larger negative effects on profits from higher levels of rival certification, which is captured by the parameters we make use of here.

Table 11: Counterfactual Two-Level Standards

<table>
<tr><th>Cut-point</th><th></th><th colspan="2">ρ_1(L:1 H:2)</th><th colspan="2">ρ_2(L:1 H:3)</th><th colspan="2">ρ_3(L:1 H:4)</th></tr>
<tr><th></th><th>Actual</th><th>Baseline</th><th>Model</th><th>Baseline</th><th>Model</th><th>Baseline</th><th>Model</th></tr>
<tr><td>Certified(1)</td><td>1,217</td><td>1,217</td><td>1,111</td><td rowspan="2">3,475</td><td rowspan="2">3347</td><td rowspan="3">6,317</td><td rowspan="3">6,164</td></tr>
<tr><td>Silver(2)</td><td>2,258</td><td rowspan="3">5,617</td><td rowspan="3">5,723</td></tr>
<tr><td>Gold(3)</td><td>2,842</td><td rowspan="2">3,359</td><td rowspan="2">3487</td></tr>
<tr><td>Platinum(4)</td><td>517</td><td>517</td><td>670</td></tr>
<tr><td>Mean Level</td><td>2.39</td><td>1.82</td><td>1.84</td><td>1.98</td><td>2.02</td><td>1.23</td><td>1.29</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.

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 ($\hat{\rho}_1$), 106 of the 1,217 buildings in the Low certification level 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 128 (of 3,475), and 153 (of 6,317) 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 cut-off for Gold ($\hat{\rho}_2$), projects that chose the Platinum level under a four-tier standard most likely reduce their investment to the Gold level, and projects anywhere below Gold will reduce their investments to the minimum required for LEED certification (unless they decide to shift up).[37] 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 11 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 result 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.

We can use these results, however, to answer a different question: Given that LEED consists of two levels, where should USGBC locate the cut-point between them? The bottom row in Table 11 shows a concave, non-monotonic relationship between the location of the cut-point and the mean certification level (i.e. total investment). 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. We see in Table 11 that without differentiation, the mean certification level increases by 0.16 points (from a Baseline levels of 1.82 to 1.98) 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 0.18. Thus, differentiation

[37] 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).

accounts for roughly 11% 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 accounts for 16.5 percent of variation due to observable characteristics, 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 between the current Silver and Gold tiers, a level that is high enough to induce strong investment but not so high as to be irrelevant or out of reach.

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Appendix A

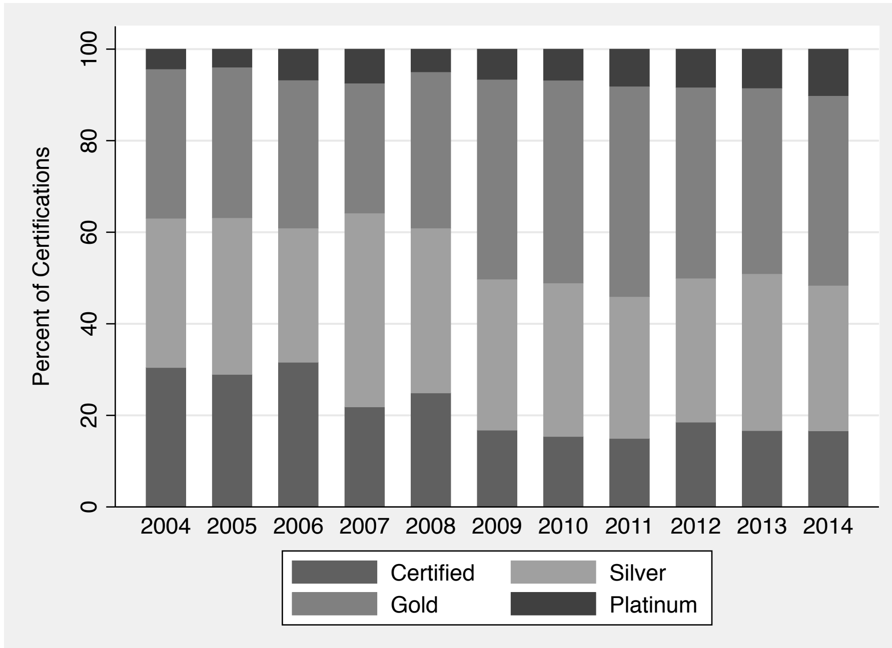

Figure A-1: Certification Levels by Year

Table A-1: Additional MTAD Results Stratified by Market Size

Sample	Observed Likelihood	Expected Likelihood	Standard Deviation	Z-Score	
Certified Projects $<$ 10	-2.39	-2.29	0.033	2.9	Agglomeration
10 $\leq$ Certified Buildings $<$ 20	-5.47	-4.94	0.112	4.8	Agglomeration
20 $\leq$ Certified Buildings $<$ 30	-6.68	-5.82	0.211	4.1	Agglomeration
30 $\leq$ Certified Buildings $<$ 40	-7.05	-6.22	0.371	2.2	Agglomeration
Certified Projects $\geq$ 40	-9.68	-7.52	0.184	11.7	Agglomeration

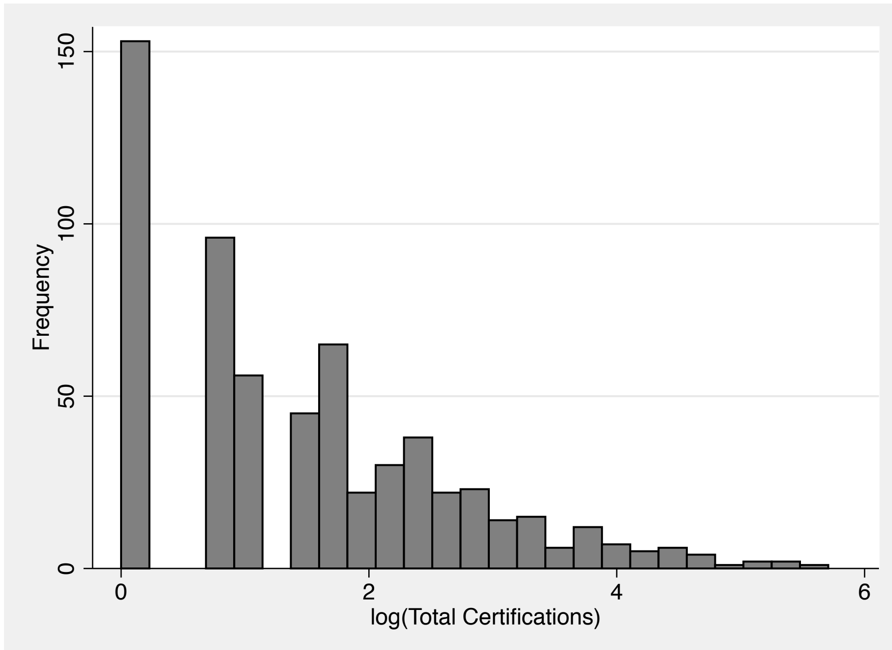

Figure A-2: Number of certifications in the market (log scale)

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})	**0.371*** **	**0.293*** **	**-0.496*** **	**-0.188*** **
	(0.042)	(0.032)	(0.056)	(0.020)
Log Pseudo-likelihood	-7561.6		-4208.6	
Pseudo R-squared	0.01	0.02	0.02	0.03
Observations	6204	6204	6204	6204

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	Probit	Simulated
	Level(1-4)		1[Level>Prev.Mean]	
	(1)	(2)	(3)	(4)
Previous Mean(N_{jm})	0.287***	0.541***	-0.678***	-0.485***
	(0.043)	(0.040)	(0.056)	(0.052)
Log(Gross Square Feet)	0.061***	0.067***	0.078***	0.073***
	(0.015)	(0.012)	(0.018)	(0.014)
OwnerType: Profit	-0.034	-0.101*	-0.086	-0.16**
	(0.064)	(0.060)	(0.069)	(0.073)
OwnerType: Education	0.244	0.189	0.113	0.169
	(0.153)	(0.145)	(0.177)	(0.196)
OwnerType: Government	0.077	-0.022	-0.039	-0.05
	(0.084)	(0.071)	(0.088)	(0.085)
OwnerType:non-profit	0.173**	0.046	0.104	0.042
	(0.081)	(0.087)	(0.093)	(0.108)
System: CI	0.406**	0.379**	0.368	0.348*
	(0.195)	(0.186)	(0.262)	(0.197)
System: CS	0.59***	0.479***	0.509**	0.416**
	(0.175)	(0.183)	(0.228)	(0.194)
System: EB	0.33*	0.237	0.281	0.184
	(0.186)	(0.183)	(0.232)	(0.194)
System: NC	0.509***	0.44**	0.398	0.351*
	(0.184)	(0.180)	(0.247)	(0.192)
Log(Population)	-0.175	0.104	-0.222	0.024
	(0.356)	(0.360)	(0.495)	(0.505)
Log(Income)	0.155	-0.105	0.243	-0.006
	(0.145)	(0.141)	(0.220)	(0.191)
Log(Housing)	0.201	-0.085	0.342	0.071
	(0.355)	(0.356)	(0.496)	(0.504)
Rent	4.252***	1.894	3.247*	2.274
	(1.267)	(1.290)	(1.731)	(1.808)
Vacancies	-0.537	-0.342	-0.561	-0.424
	(0.916)	(0.905)	(1.125)	(1.217)
Rental rate	0.739**	0.25	0.945**	0.307
	(0.295)	(0.300)	(0.452)	(0.449)
High school	0.249	0.019	0.545	0.159
	(0.569)	(0.634)	(0.832)	(0.882)
College	0.27	0.45	0.536	0.737
	(0.345)	(0.378)	(0.586)	(0.589)
Log Pseudo-likelihood	-7450.3	-7550.3	-4065.8	-4170.0
Pseudo R-squared	0.024	0.031	0.054	0.030
Observations	6204	6204	6204	6204

$^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. 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 $\begin{pmatrix} 4 \\ x \end{pmatrix}$, 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. $\begin{pmatrix} 4 \\ 0 \end{pmatrix} = \begin{pmatrix} 4 \\ 4 \end{pmatrix} = 1$. A most dispersed arrangement would be two projects choosing high and two choosing low, which maximizes the combinatoric expression, i.e. $\begin{pmatrix} 4 \\ 2 \end{pmatrix} = 6$. 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

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

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 .

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

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.

Appendix C

We conduct several robustness checks in this appendix.

In Section 2.3.2, we perform the robustness check on the subsample of commercial buildings with version LEED-NC (New Construction). Here we examine the subsample of commercial buildings with LEED-EB (Existing Buildings). There are 1,779 buildings under LEED-EB in 236 markets defined by three-digit zip code digits. Again, we perform the reduced-form regressions in Table 3, and simulation method as in Section 2.3.1. Table C-1 shows the main results. For the Ordered Probit regressions, the coefficients on "Previous Mean" for actual data are significantly smaller than the ones for simulated data, which indicates the presence of differentiation. But for the Probit regressions, the difference in coefficients is not statistically significant. Given the reduction in sample size, we do not place much weight on the loss of significance. And a comparison with Table 5 suggests that new buildings certified under LEED NC have stronger incentives or more opportunities to differentiate than the existing buildings certified under LEED EB.

Table C-1: Simulations: LEED-EB (Existing Buildings) Sub-sample

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Previous Mean	0.441***	0.704***	2.10	-0.503***	-0.324***	0.99
	(0.086)	(0.091)		(0.140)	(0.114)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01,^{**}p < .05,^{*}p < .10$. Building characteristics, market characteristics and time dummies are not reported.

One possible concern is that we have constructed the variable of interest as the mean of past choices - as if the indicator of choice was a cardinal variable. So we substitute the mean with several alternatives: the median, the maximum, the minimum and the mode of past choices. We then conduct the Ordered Probit and Probit regressions in Table 3, by using the actual and simulated data generated by the method in Section 2.3.1. The idea is the same as in Section 2.3.1: We want to compare the parameter on previous choices that would occur if the data were truly generated from independent random choice to the parameter that we actually find in data. The main results are reported by Table C-2, which show that buildings differentiate from each other.

In the paper we assume buildings respond only to previous choices. Another concern is

Table C-2: Simulations: Previous Median, Max, Min and Mode

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Median(Max,Min,Mode)]		
Data	Actual (1)	Simulated (2)	$Z_{(1)=(2)}$	Actual (3)	Simulated (4)	$Z_{(3)=(4)}$
Previous Median	0.196***	0.372***	4.08	-1.139***	-0.827***	5.58
	(0.031)	(0.030)		(0.039)	(0.040)	
Previous Max	0.141***	0.229***	2.11	-1.301***	-1.049***	3.63
	(0.029)	(0.030)		(0.052)	(0.046)	
Previous Min	0.098***	0.239***	2.85	-1.035***	-0.926***	1.73
	(0.034)	(0.036)		(0.045)	(0.044)	
Previous Mode	0.139***	0.287***	3.95	-1.114***	-0.898***	4.24
	(0.027)	(0.026)		(0.037)	(0.035)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. Building characteristics, market characteristics and time dummies are not reported.

that people might have rational expectations about future choices. So if one building wants to differentiate from others in the market, it may also take into account of expectations of future choices. To address this problem, we firstly construct a variable of "future weighted mean", which is the weighted average of future choices in the market in our sample. The weights are constructed similarly to that in Section 2.3.2, but this time we order each building according to its certification time descendingly.[38] We then construct the variable "weighted mean", which is the average of "future weighted mean" constructed just now, and "previous weighted mean" constructed in Section 2.3.2.[39] By using the new "weighted mean" instead of "previous mean", we conduct the Ordered Probit and Probit regressions, by using the actual and simulated data generated in Section 2.3.1 again. The main results are reported in Table C-3. The coefficients on "weighted mean" for actual data are significantly smaller than the ones for simulated data, which indicates differentiation.

The USGBC periodically updates the various LEED standards, leading to differences over time in the types of practices eligible for LEED credits, the cost of achiving a certain number of points, and the number of points required to achieve a particular certification level. As another

[38]For example, if we have building A, B, C, D enter the market sequentially, with level of 1, 2, 3 and 4 respectively. We assign order 4, 3, 2, 1 to building A, B, C, D. If we compute building B's future weighted mean, that will be: C's level×C's weight+D's level×D's weight$=3 \times \frac{2}{(2+1)} + 4 \times \frac{1}{(2+1)} = 3.33$.

[39]The weights for "future weighted mean" and "previous weighted mean" are simply 1/2, 1/2.

Table C-3: Simulations: Rational Expectations (Past and Future-Weighted Mean)

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Weighted Mean	0.439***	0.770***	3.69	-0.434***	-0.231***	2.02
	(0.071)	(0.055)		(0.071)	(0.071)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01,^{**} p < .05,^{*} p < .10$. Building characteristics, market characteristics and time dummies are not reported.

robustness check, we do the analysis by including the interactions of LEED system (such as LEED-NC and LEED-EB) and time dummies, to account for the fact that LEED for different types are adjusted separately and at different times. Similarly, we perform the reduced-form regressions in Table 3, and simulation method in Section 2.3.1. The results still hold and are reported in Table C-4.

Table C-4: Simulations: LEED System-by-Year Fixed Effects

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Previous Mean	0.284***	0.525***	4.01	-0.691***	-0.487***	2.76
	(0.044)	(0.041)		(0.057)	(0.047)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01,^{**} p < .05,^{*} p < .10$. Building characteristics, market characteristics, and the interactions of LEED system and time dummies are not reported.

Different states might have different time trends regarding LEED certification. Instead of using national year fixed effects, we consider state-specific time trends here.[40] By performing the reduced-form regressions and simulation method again, we get the similar results as reported by Table C-5. These results indicate the presence of differentiation.

Finally, in our paper, we define markets by the three-digit zip codes. In order to check if different geographical contexts would change our results, we consider to define markets alter-

[40]That is, the α_t in Equation 2.1 are state-specific time trends, instead of year fixed effects.

Table C-5: Simulations: State-level Time Trends

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Previous Mean	0.203***	0.433	4.01	-0.820***	-0.637***	2.64
	(0.038)	(0.043)		(0.052)	(0.046)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. Building characteristics, market characteristics, and state-specific time trends are not reported.

natively by county. However, we believe that the definition of three-digit zip codes is preferred to county, for the following reasons:

First, our original data don't have county information. So we roughly match zip code with county by using the HUD-USPS Crosswalk Files, provided by U.S. Department of Housing and Urban Development. About 6% of the commercial buildings have one zip code but multiple corresponding counties. So we picked the county with the most residential addresses with that zip code, which could cause some mismatches.

Second, using all counties is problematic in our data, because of the huge variation across counties regarding the number of LEED buildings in them.[41] There are 759 counties that have one or more LEED certified commercial buildings, but 329 (43%) counties have only one building in it. Among the counties with more than one building, the number of certified commercial buildings in each county has a mean of 15, and S.D. of 33. However, this variation is smaller if we define markets as three-digit zip codes: there are 625 markets with certified commercial buildings, and 153 (24%) markets have only 1 building in it. Among the markets with more than one building, the number of certified commercial buildings in each market has a mean of 14 and S.D. of 27.

With these caveats in mind, we perform the reduced-form regressions and simulation method in Section 2.3.1 again, with markets defined by county. Table C-6 reports the main results. We

[41] Previous studies also discuss this problem. Zhu et al. (2009) discuss markets defined by counties and pointed out "using all counties as markets is problematic because of extreme heterogeneity in their characteristics. In particular, population exhibits large variation across MSA and non-MSA counties, such that average MSA markets are more than ten times larger than non-MSA markets. Although large variation in population is not a problem in general, this variation is associated with heavy store presence in some cases." Hottman (2014) also mention about the limitation of using counties to define markets: "One concern with my price index is that some counties are very large, like Los Angeles County, and consumers may not actually shop far from where they live and work. To address this potential concern, I alternatively construct price indices using truncated (first 3-digits) zip code areas instead of counties. This breaks up Los Angeles County (and other counties) into smaller areas."

can see that the coefficients on “Previous Mean” for actual data are significantly smaller than the ones for simulated data. But we lose some statistical significance here, compared to the results from three-digit zip codes. It makes sense, considering we lose power because of more markets with a single building. In sum, by defining markets by county, we get similar results. And we believe the definition of three-digit zip codes is preferred.

Table C-6: Simulations: Markets Defined by County

Specification	Ordered Probit			Probit		
Outcome	Level(1-4)			1[Level>Prev.Mean]		
Data	Actual	Simulated	$Z_{(1)=(2)}$	Actual	Simulated	$Z_{(3)=(4)}$
	(1)	(2)		(3)	(4)	
Previous Mean	0.289***	0.514***	3.09	-0.568***	-0.424***	1.67
	(0.050)	(0.053)		(0.058)	(0.064)	

Robust standard errors (clustered on market) in parentheses. $^{***}p < .01, ^{**}p < .05, ^{*}p < .10$. Building characteristics, market characteristics and time dummies are not reported.