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Do Pilot and Demonstration Projects Work?

Abstract

Pilot and demonstration (P&D) projects are commonly deployed to catalyze early adoption of technology, but are poorly understood in terms of mechanism and impact. We conceptually distinguish unique functions of pilots and demonstrations, then examine whether they accelerate green building adoption. To identify effects of P&Ds on adoption, we develop a difference-in-difference-in-differences strategy, exploiting variation in location, technologies, and timing of P&D projects. Results indicate a 12% increase in adoption rates within markets affected by P&D projects. Further analyses examine mechanisms driving this effect. Subsequent results suggest green building demonstration projects create learning externalities, proliferating technology diffusion under certain conditions.

JEL-Codes: O330, Q550, D830.

Keywords: information spillovers, peer effects, social learning, pilot and demonstration projects, technology adoption, diffusion, policy evaluation, green building.

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1 Introduction

Investment in new technologies may have substantial benefits for firms, their stakeholders, and the environment, but is hindered by uncertainty about the performance of the emergent technology (Bass 1969). For durable technologies, resolving uncertainties may be an important strategy to foster market uptake (Doraszelski 2001; Farzin, Huisman, and Kort 1998; Jensen 1982). Traditional policy interventions to catalyze adoption often leverage regulatory mandates or provide financial incentives (Stoneman and Diederen 1994). Alternatively, policymakers may implement pilot and demonstration (P&D) programs, deploying the technology at reduced scale to remediate uncertainty about the reliability and performance of new technology (Nemet, Zipperer, and Kraus 2018).

P&D programs may serve a critical role in the successful early deployment of emerging technologies. Technology pilots are experimental implementations designed to verify feasibility and assess private benefits of adoption (Kotchen 2017). Demonstration projects are technology showcases that may create information or learning spillovers, mitigating uncertainty about how well a technology aligns with private interests (Bollinger 2015). Despite the use of P&D programs by a wide variety of private firms and public agencies, little work has verified and evaluated their efficacy in increasing technology adoption.[1] This gap is particularly prominent in comparison to the breadth of analysis on research and development stages, where analysis typically identifies conditions of innovation and outcomes of research programs.

We first seek to identify whether P&D programs work. Using data on adoption of green building technologies, we investigate the impacts of a suite of green building P&Ds on subsequent local market adoption rates. Our primary identification strategy leverages a *difference-in-difference-in-differences* (DDD) estimation framework to identify the average effect of a P&D project on market uptake of green building technology by exploiting quasi-experimental variation across time, geography, and building typologies. Results suggest that, on average, local adoption rates increase between 5% and 12% following the completion of a P&D project. This finding is robust to a variety of alternative assumptions and specifications.

Successful P&D programs remediate uncertainties about the performance and/or feasi-

[1] Agencies around the world operate demonstration programs explicitly linked to information-based market failures. These include (i) the World Health Organization's efforts to increase adoption of public health technologies in developing countries (http://www.who.int/phi/implementation/phi_cewg_meeting/en/); (ii) the US General Services Administrations program to increase the use of efficient building technologies in government offices (https://www.gsa.gov/about-us/organization/office-of-governmentwide-policy/office-of-federal-highperformance-buildings/projects-and-research/demonstration-projects); and (iii) the European Space Agency's initiative to increase applications of space technologies to broader markets (https://business.esa.int/funding/direct-negotiation-call-for-proposals/demonstration-projects), to name a few.

bility of an emerging technology. While the results identified in the DDD model may be driven by social learning in which information spillovers resolve these uncertainties, herding behavior may also explain the uptick in adoption. Because herding may inadvertently create lock-in around a technology chosen by policymakers, rather than market processes, learning is the preferred P&D outcome which generates the greatest social value. Moreover, while the DDD estimates suggest effects of the project on surrounding markets, it does not capture effects of participant firm experience that that may further drive adoption. We perform subsequent analysis to explore how P&D projects work and unpack some of these channels of effectiveness.

A series of empirical tests collectively informs our understanding of the roles that learning and herding play in the outcomes of P&D programs. First, projects occurring at a later date and deploying more certain technology have a more significant effect on adoption rates when compared to the effects of earlier, more experimental P&D projects. This result suggests potential adopters may be updating their private beliefs in response to the demonstrated performance of the new technology, rather than simply imitating the behavior of early adopters. Second, we find the required implementation time is 9-12% lower for organizations local to a P&D project. As the industry is sensitive to costly project delays, we interpret this reduced implementation time as evidence that stakeholders learn from P&D participation, and may socially influence non-participant neighbors.

This paper contributes to the existing literature in at least three ways. Foremost, we provide empirical strategies to evaluate the extent to which P&D programs foster technology diffusion. Our DDD identification strategy compares variation in the adoption rates before and after market exposure to P&D projects to adoption trends in untreated markets, and does so for a suite of building typologies. The results estimate the causal effect of a P&D project on the diffusion of green building technologies and practices. By comparison, past P&D literature typically addresses this question qualitatively or evaluates the effects of an individual project on the performance of a technology. For example, Mah et al. (2013) describe the opportunities and challenges of smart grid P&D projects within regulatory and business-oriented schemas in Japan. Hendry, Harborne, and J. Brown (2010) present dozens of case studies highlighting innovation lessons from solar photovoltaic and wind energy P&D projects in the United States, Japan, and Europe. Hendry and Harborne (2011) examine qualitative evidence from wind developments in Denmark to show how P&D projects enhance the overall innovation process. Rather than taking a qualitative approach or assessing P&D effects on private performance, we investigate the role of P&D projects on market adoption of emerging technologies.

Second, we contribute to an burgeoning dialogue on information spillovers from environmental programs. Green technologies often have multiple positive externalities, leading private costs to be less than social benefits and inhibiting optimal levels of adoption. For durable technologies that provide returns over a long-time horizon, discounting slows investments in emerging technologies (Stoneman and Diederen 1994). Information provision appears to be an effective policy intervention that generates positive regional learning externalities for these technologies, such as lighting (DeCanio and Watkins 1998) and garment cleaning (Bollinger 2015). Pollution prevention programs have been shown to be effective when leveraging information spillovers, even absent stringent regulatory measures (Bui and Kapon 2012; Lange 2009). We complement these findings by examining how well P&D programs impact adoption, drawing on evidence suggesting an information spillovers mechanism.

Finally, our results give insight on the role of early adopters in the long-run diffusion of a technology (Catalini and Tucker 2017). If the lead organization responsible for the P&D project has establishments in multiple locations, organizational learning lowers costs of adoption in subsequent locations (Attewell 1992). Further, if P&D project stakeholders are highly visible and transparent regarding their experiences with the project, adoption may be seeded in local and new markets through peer effects (Aral and Walker 2012; Bollinger and Gillingham 2012; De Grip and Sauermann 2012; Zimmerman 2003) or social learning (Bandiera and Rasul 2006; Conley and Udry 2010). Section 7 discusses opportunities to strategically manage this outcome of P&D programs based on the evidence we provide.

To evaluate whether P&D projects increase adoption of green building technologies and practices, we organize the paper in 7 sections. In section 2, we distinguish the characteristics of pilot and demonstration projects, and their roles in fostering market uptake of emerging technologies. We identify potential mechanisms driving the success of P&D projects. Section 3 describes the empirical context and data used in the analysis. We utilize data on P&D projects for the Leadership in Energy and Environmental Design (LEED) green building standard, and here introduce the institutional characteristics of LEED that are crucial for our analysis. We present the main empirical strategy, including our identifying assumptions, in Section 4. Section 5 presents the main results of the study and presents several robustness checks to test our estimates against alternative assumptions and model specifications. Our main results suggest P&D projects contribute to a 5-12% increase in quarterly adoption rates of the LEED standard in regions with a completed P&D project. In section 6, we explore whether this effect is driven by learning externalities or herding behavior. We present evidence supporting the claim that learning externalities from P&D projects drive adoption of the LEED standard. Lastly, we conclude and provide additional policy implications in section 7.

2 Conceptual Framework

As new ideas and technologies emerge from basic and applied research, numerous uncertainties inhibit new innovations from reaching market maturity. Unproven technical reliability, uncertain market and institutional receptiveness, and limited organizational and managerial expertise characterize this intermediate stage of the technology lifecycle. Because these uncertainties may limit early investment in emerging technologies (Hendry, Harborne, and J. Brown 2010), this stage is sometimes referred to as the technological "valley of death," in which socially beneficial technologies fail to diffuse. In this stage, successful market deployment requires a balance of periods of experimentation and market development (Nemet, Zipperer, and Kraus 2018). Market interventions designed to bridge the valley of death spark diffusion of new technologies by remediating these technical, organizational, market, and institutional uncertainties.

Common interventions promoting new technologies in this stage of development include P&D projects, which implement new technologies at small scale with the goal of reaching broader implementation (market maturity). Pilot projects adopt new technology in experimental fashion, with the intent to learn from the implementation process and refine the technology or verify its best management practices (Kotchen 2017). Due to their experimental nature, pilots often occur within narrow divisions of an organization, such as one department or establishment. Demonstration projects showcase technical feasibility and reliability to broad sets of market actors, often engaging numerous stakeholders to reduce technical and management uncertainties (Bollinger 2015; M. Brown et al. 1993). P&D programs often leverage elements of both pilots and demonstrations, because both interventions aim at inducing learning or reduce uncertainties that otherwise inhibit adoption. However, other mechanisms are possible, and few econometric evaluations of P&D performance have been conducted. To frame our analysis, we first describe the mechanisms by which P&D projects may achieve this goal.

2.1 Demonstration projects and social learning

To conduct a demonstration project, a mix of private and public sector actors must coordinate on key project features and execution. Managing the production and dissemination of knowledge within this network is considered essential for the success of demonstrations (Nemet, Zipperer, and Kraus 2018): demonstrations that contribute to the formation of social and business relationships among members of the project's development team can subsume costs of learning-by-searching for future adopters. The social and business ties established during the demonstration project reduce search and matching frictions by brokering and screening interactions between future adopters, project stakeholders, and input suppliers (Boudreau et al. 2017; Cassi and Plunket 2014; Fafchamps, Leij, and Goyal 2010; Jackson and Yariv 2007). The development of a robust knowledge-sharing network facilitates the diffusion of information on product reliability and performance (Reiner 2016), including diffusion to actors not participating in the demonstration.

2.2 Social learning versus herding

Even if P&Ds fail to induce learning, an effect on adoption is still plausible. When information fails to diffuse, or when the information is not meaningfully incorporated into the decision making process, herd behavior drives investment in the emerging technology if managers assume that those promoting or involved in the demonstration have better information guiding the decision to adopt (Banerjee 1992; Scharfstein and Stein 1990).This is especially viable when demonstrations actively seek to engage key stakeholders such as market leaders and high-status firms (Nemet, Zipperer, and Kraus 2018). Importantly, while mimicry drives the diffusion of the technology, herding may lead to lock-in on underperforming technologies. Technology diffusion via learning is the preferred policy outcome as it reveals information that otherwise hinders deployment, thus reducing market barriers for the most efficient available technologies.

2.3 Pilot projects and organizational learning

From the outset of a pilot project, those implementing the new technology engage with learning-by-searching and learning-by-doing (Kamp, Smits, and Andriesse 2004). As early adopters, organizations actively search for resources useful for technical implementation, and for information regarding likely performance that will later guide project evaluation. This evaluation primes learning-by-doing that enables efficient deployment for later adoption (Arrow 1962). Thus, organizations learning from participation in a pilot program may have fewer barriers to adoption in other parts of the organization.

At this point, learning-by-interacting may enable additional organizations and stakeholders sharing feedback to diffuse the practice (Kamp, Smits, and Andriesse 2004; Von Hippel 1978; 1986; 2010), amplifying the effect of the original project through networks of users and stakeholders (Hellsmark et al. 2016). After learning from a pilot, a repeat adopter implementing the piloted technology at a different establishment may effectively demonstrate that technology to a new set of stakeholders. In this sense, pilots and demonstrations are conceptually and pragmatically distinct, but are not mutually exclusive when iterated. Our analysis presents evidence from P&Ds in one industry, in terms of social learning, social herding, and organizational learning.

3 Empirical Context

The United States Green Building Council (USGBC) certifies buildings that meet its standard for Leadership in Energy and Environmental Design (LEED). The LEED certification system identifies baseline design and performance norms in the construction and real estate industry, and recognizes achievement beyond those norms. Certification is based on improvements to the entire building footprint (including energy, water, materials, land use, and indoor environment) rather than a single characteristic. To attain certification, builders must register, implement high environmental performance technologies, and provide sufficient evidence of these improvements. The certification standard may be flexibly adapted to the particular needs of specific buildings. Though the technologies and practices implemented may vary across buildings, all buildings meet the minimum baseline for each monitored category of environmental technology, and most use advanced planning processes recommended by the USGBC. These best practices are reinforced by a community of professionals trained on the LEED certification process and familiar with how it may be implemented.

3.1 LEED Building Standards and Pilot Programs

The USGBC offers separate certification standards for major building categories to recognize the heterogeneous technology demands of different building typologies. For example, the USGBC distinguishes the functional design and practices required by newly constructed buildings from renovations to existing building structures. Standards are further distinguished for several major building uses, namely commercial office, retail, schools, and residential dwellings. These distinct standards are designed to meet the particular needs of each sector of the real estate market and are periodically updated as advances are made in green building technology and practices.

Before introducing a new building standard, the USGBC experiments with different forms of the standard to determine the standard's market viability and to demonstrate the value of the technologies and practices embedded in the standard. After gaining stakeholder support for a version of the standard that appears feasible, the USGBC recruits a limited number of firms that volunteer as early adopters. The LEED-Pilot program constitutes a set of demonstration projects, in that they are attained by the initial adopters of the new building technology, and the USGBC provides coordination assistance to engage stakeholders in completing the project, with the aim of spreading the standard to others in the building market.

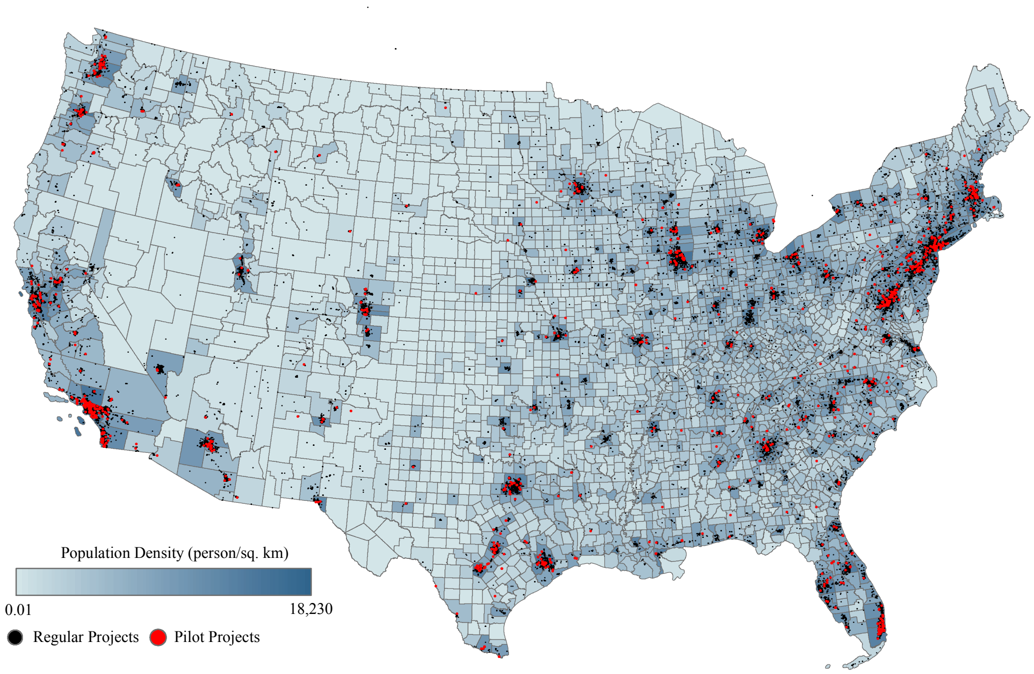


Figure 1: Spatial distribution of LEED buildings in the contiguous United States.

These experimental standards are also pilots for the participating firms, who are often interested in adopting the standard at larger scale. Moreover, the name "LEED-Pilot" refers to the USGBCs experimentation with the standard itself, with the final form of the new LEED standard informed by feedback from early adopters of the piloted standard. In this paper, we leverage data on LEED-Pilots, and subsequent LEED registrations in the United States to evaluate the effect of P&D projects fostering adoption of emerging technologies and practices for greener buildings.

3.2 Location and Timing of LEED Pilots and Certifications

Adoption of the LEED standard varies over space and time. In Figure 1 we show the spatial distribution of LEED certified buildings and LEED-Pilot projects in the contiguous United States. The distribution of registered buildings (black circles) and, notably, LEED-Pilot projects (red circles) in the map is consistent with previous research aligning the location of green building activity with environmental preferences and natural resource demands (Cidell 2009; Kahn and Vaughn 2009). Additionally, the frequency and location of green building adoption may closely track regional trends in population growth and urbanization, as illustrated by the clustering of registrations in densely populated areas.

Temporal variation in LEED registrations and LEED-Pilot projects are displayed in

Figure 2, where we plot the frequency of registrations across years. Examining the figure reveals a close correlation between the completion of LEED-Pilots and registrations for the corresponding building standard. The initial LEED-Pilot program (for New Construction) ran just 8 projects to test and verify the standard. However, subsequent standards have been tested and verified more extensively, with more recent programs (Retail-Commercial Interiors and Retail-New Construction) associated with more than 150 projects each.

3.3 Data and Summary Statistics

The primary source of data used in this analysis is collected, maintained, and publicly distributed by the USGBC's Green Building Information Gateway. This database contains information on all buildings registered since 2000. The time horizon of our study covers the period 2000-2015, after which the majority of certifications occur in the more recent versions of the standards. Our analysis covers the 44,330 buildings registered within the United States and the six building standards for which pilot program data is available. These ratings systems are Existing Buildings (EB), Commercial Interiors (CI), Core and Shell (CS), New Construction (NC), Retail-New Construction (RNC), and Retail-Commercial Interiors (RCI).

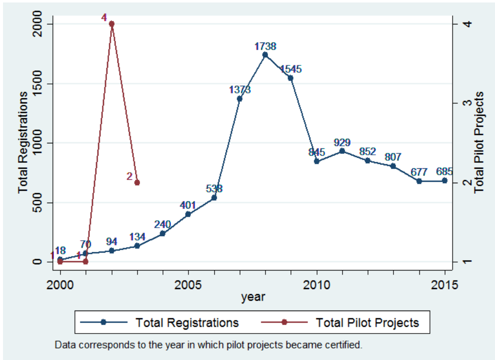
Table 1 presents the summary statistics for the central data used in the analysis. Panel A presents the panel summary statistics, corresponding to the typical LEED standard, local markets (measured as 5-digit ZIP code), and quarter. Panel B aggregates the data to present cumulative adoption statistics for the typical LEED standard and local market. Columns (I) and (II) present summary statistics for registrations and building stocks for local markets with and without LEED-Pilot projects, respectively. Column (III) summarizes the key adoption statistics for the entire dataset. Lastly, Column (IV) presents the results of an unequal variances t-test for difference-in-means between Column (I) and Column (II). A quick inspection of Column (IV) reveals registrations are typically higher in local markets with LEED-Pilots.

A naïve interpretation of Column (IV) in Table 1 may note the statistically significant increase of green building adoption in local markets with LEED-Pilots as a sign that learning externalities from P&D projects induce greater adoption. However, it is important to note that LEED-Pilots are not randomly assigned across space (see Figure 1). Rather, those volunteering to pilot a new version of LEED may self-select based on both internal motivations and external pressures to adopt. As early adopters, LEED-Pilot participants may be critical for shaping the course of future adoption and systematically differ from later adopters (Aral and Walker 2012; Catalini and Tucker 2017; Läpple and Rensburg 2011). Moreover,

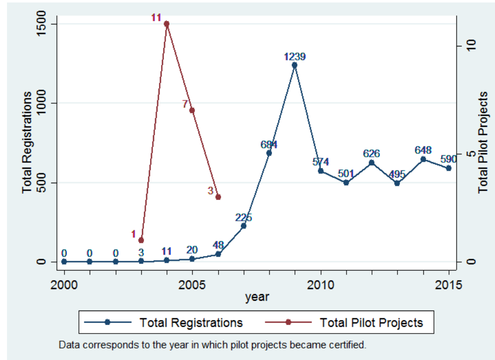
Table 1: Adoption statistics for ZIP Codes with and without LEED-Pilot projects

Panel A: Panel Summary Statistics	(I) LEED-Pilot (mean/sd)	(II) No LEED-Pilot (mean/sd)	(III) All (mean/sd	(IV) Difference (diff/t-stat)
Privately-owned building registrations (R_{zsq})	0.019	0.008	0.008	0.011***
	(0.178)	(0.113)	(0.114)	(13.986)
Local firm building registrations (R^{local}_{zsq})	0.008	0.004	0.004	0.004***
	(0.111)	(0.075)	(0.076)	(8.444)
Multiregional firm registrations (R^{multi}_{zsq})	0.010	0.004	0.004	0.007***
	(0.120)	(0.079)	(0.080)	(12.92)
Publicly-owned building registrations (R^{pub}_{zsq})	0.002	0.004	0.004	-0.002***
	(0.086)	(0.104)	(0.104)	(-4.974)
Certified private and public building stock (M_{zsq})	0.180	0.089	0.091	0.091***
	(1.378)	(0.595)	(0.617)	(15.406)
Local firm certified building stock (M^{local}_{zsq})	0.074	0.0326	0.033	0.042***
	(0.633)	(0.271)	(0.281)	(15.404)
Multiregional firm certified building stock (M^{multi}_{zsq})	0.092	0.032	0.033	0.060***
	(0.785)	(0.323)	(0.281)	(17.931)
Publicly-owned certified building stock	0.014	0.025	0.025	-0.011***
	(0.170)	(0.268)	(0.266)	(-15.012)
Observations (ZIP Codes x Standards x Quarters)	55,104	3,071,040	3,126,144	3,126,144
Panel B: Cumulative Summary Statistics (by 2015)				
Total privately-owned building registrations	8.120	2.598	3.144	5.52***
	(16.860)	(4.804)	(7.182)	(9.25)
Total local firm building registrations	4.015	1.424	1.680	2.59***
	(8.040)	(2.586)	(3.607)	(9.09)
Total multiregional firm registrations	4.106	1.174	1.464	2.93***
	(9.466)	(2.769)	(4.065)	(8.74)
Total publicly-owned building registrations	1.615	1.319	1.348	0.30***
	(3.270)	(3.484)	(3.465)	(2.42)
Total certified private and public building stock	5.086	1.938	2.249	3.15***
	(10.150)	(3.266)	(4.546)	(8.75)
Total local firm certified building stock	1.852	0.621	0.743	1.23***
	(4.260)	(1.434)	(1.945)	(8.15)
Total multiregional firm certified building stock	2.406	0.718	0.885	1.69***
	(5.778)	(1.730)	(2.500)	(8.25)
Total publicly-owned certified building stock	0.827	0.599	0.622	0.23***
	(1.836)	(1.544)	(1.577)	(3.39)
Observations (ZIP Codes)	805	7,336	8,141	8,141

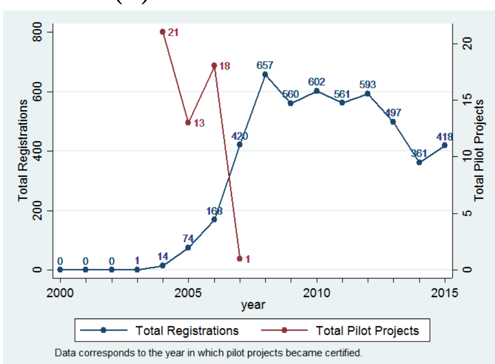
Notes: Summary statistics are reported for registrations and building stock aggregated to the 5-Digit ZIP code level. Columns (I) – (III) present means in the top row and standard deviation in parentheses. Column (IV) presents the results of Welch's unequal variance t-test for difference in means between Columns (I) and (II). A local firm corresponds to a firm or organization with buildings registered in a single ZIP code. A multiregional firm corresponds to a firm or organization with buildings registered in multiple ZIP codes. Publicly-owned buildings account for municipal, state, and federal buildings.



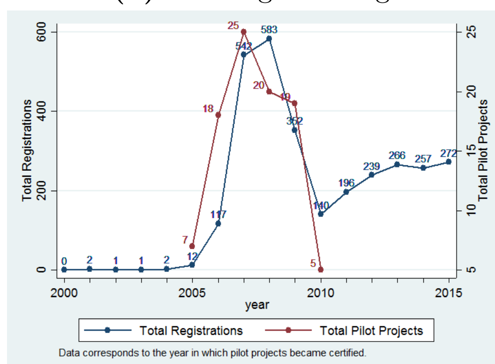
(a) New Construction



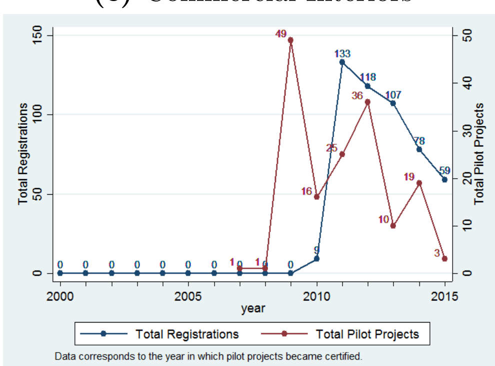
(b) Existing Buildings



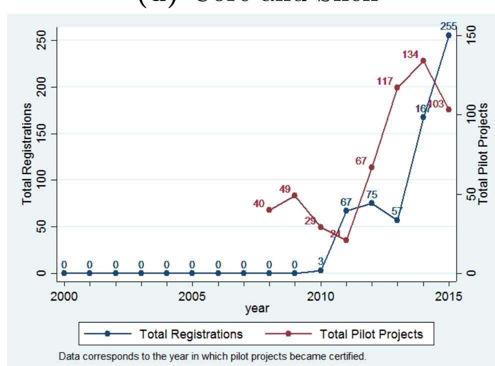
(c) Commercial Interiors



(d) Core-and-Shell



(e) Retail-New Construction



(f) Retail-Commercial Interior

Figure 2: This figure displays total annual registered buildings and pilot projects for each LEED standard. The blue markers correspond to the annual number of buildings registered for a LEED standard in the United States. Values for total registrations are plotted on the primary y-axis. The red markers represent the annual number of *certified* LEED-Pilot projects for a standard in a given year. These values are plotted on the secondary y-axis. Panels are sorted based on the order in which standards were introduced.

the USGBC actively recruited specific firms as early adopters, in hopes of maximizing feedback about the process. Our analysis assumes that P&D programs follow best practices by selecting suitable participants (Nemet, Zipperer, and Kraus 2018).

4 Empirical Strategy

To investigate average effects of a well-designed P&D program across regional markets, market sectors, and time periods, we develop a reduced-form empirical model to measure the impact of a LEED-Pilot on adoption of the LEED standard.

4.1 Identifying Assumption

A simple strategy to estimate the effects of a LEED-Pilot on green building adoption could be to measure the change in adoption rates in markets before and after the completion of a LEED-Pilot, and compare these changes with the change in adoption rates in markets without a LEED-Pilot. This comparison yields the well-known *difference-in-differences* (DD) estimator (Ashenfelter and Card 1985). Define R as the number of private sector LEED building registrations. In a simplified, conceptual model with two regions (z, z'), and two time periods $(pre, post)$, consider the treated region (the region with a LEED-Pilot project) to be z and the control region as z' (the region without a LEED-Pilot project). The DD estimator can be written as

$$\hat{\beta}^{DD} = \left(\bar{R}_z^{post} - \bar{R}_z^{pre}\right) - \left(\bar{R}_{z'}^{post} - \bar{R}_{z'}^{pre}\right) \tag{1}$$

This estimator does not account for the possibility that changes in adoption rates may be driven by idiosyncratic shocks to local markets for green building technologies rather than completion of a LEED-Pilot. For example, Simcoe and Toffel (2014) provide evidence that municipal green building policies increase private-sector demand for green building technologies. Specifically, they show that cities with municipal green building policies experience an overall increase in LEED registrations than cities without these procurement policies. If municipal green building policies are implemented around the same time a LEED-Pilot is completed, then the DD estimate erroneously attributes variation in adoption rates to the LEED-Pilot and is biased.

We account for this possibility, as well as any other idiosyncratic shock that raises overall demand for green building technologies, by introducing a third source of variation in the model. Because LEED-Pilot projects constitute the first application of a set of technologies and practices to a particular building typology, we exploit variation in adoption rates within a particular LEED standard (s) as a third source of variation. Our identifying assumption is that, for one particular standard, market location, and time, only a LEED-Pilot project within a particular standard, location, and time is affecting the rate of adoption of a LEED standard. Under this assumption, only the interaction of the three sources of variation (location, building standard, and time) can be interpreted as plausibly exogenous. Given this assumption holds, we can thus exploit quasi-experimental variation in the location, building standard, and timing of LEED-Pilot projects to estimate a causal effect of P&D projects on adoption.

Our empirical strategy boils down to a *difference-in-difference-in-differences* (DDD) estimation that controls for a variety of confounding factors that would otherwise limit our ability to interpret our estimates as causal. For instance, we control for all time-invariant heterogeneity across both geography and building standards, including interactions between them. Additionally, our approach controls for the impact of real estate trends across the United States, within building typologies, and within regional markets that may have affected demand for green building technologies and practices.

Using the notation from equation 1, consider a LEED-Pilot project is conducted in region z for some standard s. We denote untreated standards as s', and, as before, untreated regions as z'. Thus, the DDD estimator is written as

$$\begin{aligned}\hat{\beta} &= \left(\bar{R}^{post}_{z,s} - \bar{R}^{pre}_{z,s}\right) - \left(\bar{R}^{post}_{z',s} - \bar{R}^{pre}_{z',s}\right) - \left(\bar{R}^{post}_{z,s'} - \bar{R}^{pre}_{z,s'}\right) - \left(\bar{R}^{post}_{z',s'} - \bar{R}^{pre}_{z',s'}\right) \\ &= \hat{\beta}^{DD}_{s} - \hat{\beta}^{DD}_{s'} \end{aligned} \tag{2}$$

where the parameter $\hat{\beta}^{DD}_{s'}$ represents the DD estimator given in equation 1 for untreated (existing) standards. Equation 2 measures the extent to which changes in local adoption rates differ from adoption rates in existing standards, following the completion of a LEED-Pilot, relative to the same change in untreated regions. If contemporaneous shocks drove adoption of green building technologies and practices across all building types, then the DDD estimator $\hat{\beta}$ in equation 2 would net-out the impact of these shocks. Our identification strategy rests on the assumption that the remaining variation in adoption rates is thus attributable to the effects of the LEED-Pilot project itself.

4.2 Estimating Equation

We estimate the effect of LEED-Pilots on local adoption of the LEED standard using the reduced-form equation

$$\tilde{R}_{zsq} = V_{zsq} + \beta P_{zsq} + \varepsilon_{zsq} \tag{3}$$

where the index z corresponds to the 5-digit ZIP codes with at least one LEED registered building to date. The subscript s indexes the LEED standard. Lastly, the index q corresponds to the quarter and year of registrations.

The behavioral outcome of interest in equation 3 is adoption of a LEED standard within a 5-digit ZIP code R_{zsq}. For the analysis, we use the number of privately-owned registrations of a LEED standard as a proxy for building adoption. Due to a preponderance of zero registrations in the data, the LHS variable $\tilde{R}_{zsq}$ corresponds to the Inverse Hyperbolic Sine (IHS) transformation of quarterly registrations (Burbidge, Magee, and Robb 1988; Pence 2006).[2]

In the main analysis, we treat the LEED-Pilot variable P_{zsq} as a binary variable taking values

$$P_{zsq} = \begin{cases} 0 & \text{if } q < \tau_{zs}^{cert} \\ 1 & \text{if } q \geq \tau_{zs}^{cert} \end{cases} \tag{4}$$

where τ_{zs}^{cert} represents the date a pilot project achieved certification. In locations with multiple LEED-Pilots in the same standard, the variable P_{zsq} represents the completion date of the *first* LEED-Pilot to be certified in a 5-digit ZIP code.

We use $V_{zsq} = \lambda_q + \delta_z + \gamma_s + \xi_{sq} + \alpha_{zs} + \pi_{zq}$ as shorthand to represent the fixed effects terms in the model. We include a full set of fixed effect and interaction terms to control for confounding factors in the analysis. Time period fixed effects λ_q control for time-varying secular patterns in the United States that may have influenced private sector investment in green building technologies, such as fluctuations in real interest rates or federal building standards. We include ZIP code fixed effects δ_z to control for unobserved, time invariant factors that may have influenced adoption of the LEED standard in a particular location, such as local geographic conditions. LEED standard fixed effects γ control for time-invariant heterogeneity across standards or building types.

A full set of dummy variables are included to capture interactions between these three sets of fixed effects. Time-varying shocks within LEED standards are controlled for by ξ_{sq} in equation 3. These account for the impact of variations within a LEED standard on adoption across the United States, such as price variations in underlying technologies, aggregate learning-by-doing, or broader awareness of the standard that is exogenous to the LEED Pilots. The term α_{zs} accounts for time-invariant interactions between regional markets

[2]The IHS transformation of quarterly registrations is calculated using the following relation

$$\tilde{R}_{zsq} = \ln\left(R_{zsq} + \left(R_{szq}^2 + 1\right)^{1/2}\right)$$

and standards. For instance, regional markets with an initial building stock mainly comprised of old, commercial buildings may naturally experience more registrations in the Existing Building standard given the larger initial stock of this building type. We account for time-varying shocks within regional markets with the term π_{zq} in equation 3. These interacting dummies control for time-varying factors that influence the propensity for green building adoption within a particular regional market. These time-varying factors include but are not limited to changes in municipal green building policy, variations in environmental preferences, or fluctuations in local real estate market conditions.

The parameter of interest in equation 3 is β, which measures the average effect of LEED-Pilots on local adoption of a LEED building standard. Our identification of this effect relies on the assumption that, other than what we have already controlled for in equation 3, there are no other idiosyncratic shocks occurring around the completion of a LEED-Pilot project that influence local demand for a particular LEED building standard. If this assumption holds, the parameter β is equivalent to the DDD estimator $\hat{\beta}$ given in equation 2 and is identified from within ZIP-standard comparisons over time. For P&D projects to successfully induce widespread adoption in local green building markets, LEED-Pilots must have positive and significant effect on registrations within a LEED building standard ($\hat{\beta} > 0$ after estimation).

5 Results

5.1 Baseline Results

We estimate equation 3 using Ordinary Least Squares (OLS); the estimates of the impact of LEED-Pilots on local registrations are reported in Table 2. The results are reported for 5-digit ZIP codes. Table 2 presents the results from estimating a pooled regression, a *difference-in-differences* (DD) model, and a *difference-in-difference-in-differences* (DDD) model. Each estimation accounts for different sources of variation to delineate the contributions of each source of variations impact on adoption.

To measure the impact of LEED-Pilot projects on adoption of green building technology, we compare the point estimates given in Table 2 to the change in average LEED adoption rates in treated areas. The average change in adoption rates is calculated by comparing the average number of registrations in treated ZIP codes after a LEED-Pilot project is certified to the average number of registrations before the LEED-Pilot project is completed. For 5-digit ZIP codes, we calculate this change without accounting for within-standard variation

Table 2: Local impact of LEED-Pilot on adoption

	Pooled	DD	DDD
LEED-Pilot Project (β)	0.0367***	0.0219***	0.00747**
	(0.00867)	(0.00498)	(0.00303)
Observations	3,125,760	3,125,760	3,125,760
Adj. R^2	0.001	0.066	0.082
No. of Clusters	1,567	1,567	1,567

Notes: The dependent variable is the IHS transformation of quarterly, privately-owned building registrations. Clustered standard errors reported in parentheses. Standard errors for 5-Digit ZIP code estimates are clustered by county. Estimated coefficients are rounded to the third significant digit for comparison across models. Significance stars in the table correspond to the following levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

as 0.052 and accounting for within-standard variation as 0.062.[3]

We compare the point estimates from the pooled and DD regressions to the average change in adoption rates without accounting for within-standard variation, i.e. 0.052. From the pooled estimation results, we estimate that LEED-Pilots account for 70.6% (=100% $\times$ 0.0367/0.052) of the change in adoption rates. The pooled estimate is statistically significant at the 1% level. These results, however, cannot be interpreted as causal as they can be driven by location and standard characteristics that can be confounded with the location and timing of the LEED project. Because LEED-Pilot locations where not chosen randomly, we need to account for location-specific time-invariant characteristics. After accounting for within ZIP-standard and quarterly variation in the DD estimation, we find LEED-Pilots account for 42.1% of the change in adoption rates. This implies that 28% of the change in adoption rates is statistically indistinguishable from time-invariant heterogeneity within ZIP code and standards and aggregate trends.

There is still variation in the location and timing of LEED-Pilots that can be attributed to standard specific characteristics. Hence, in our next step, we exploit within-standard variation to control for contemporaneous shocks that raise demand for green buildings across each building standard. Exploiting this variation in the DDD estimation, we find LEED-Pilot projects account for a smaller percentage of the change in adoption rates within treated ZIP codes. Specifically, we estimate LEED-Pilot projects account for 12.0% (=100% $\times$ 0.00747/0.062) of the change in adoption rates in treated areas. The point estimate is significant at the 5% level.

[3]These averages are calculated using the IHS transformed dependent variable to ensure these averages are in the same units as the coefficients in the estimated regression models.

Altogether, our results suggest that the LEED-Pilot program is an example of P&D projects that lead to increased adoption of the technology, in this case an increase in LEED building registrations. We next present additional results to test our identifying assumption while providing initial evidence of learning from LEED projects. We examine the role of market size and firm experience in inducing changes in adoption rates before presenting other robustness checks to illustrate the validity of our specifications and results.

5.1.1 Market size and firm experience

Our identification strategy relies on the assumption that no other factors affect adoption for a given standard, in a given ZIP code at a particular time. To further test the validity of our identifying assumption, we account for two other factors that could affect adoption within a LEED standard. Specifically, we extend the DDD model in equation 3 to account for market size and firm experience. The new estimating equation is given by

$$\tilde{R}_{zsq} = V_{zsq} + \beta P_{zsq} + \theta M_{zsq} + \psi B_{zsq} + \varepsilon_{zsq} \tag{5}$$

where, as before, V_{zsq} is shorthand for the fixed effect terms and P_{zsq} is the binary treatment indicator for when a LEED-Pilot was completed. The variable M_{zsq} measures the size of the local green building market for a particular standard. We measure this as the installed-base of LEED certified buildings within a building standard. The installed-base of a technology is often used to approximate peer effects in models of technology diffusion, e.g., see Bollinger and Gillingham (2012). In our setting, the installed-base of LEED buildings may also capture the maturity of a local green building market. Because of this, we interpret the coefficient θ on the market size term as measuring the extent to which green buildings act as strategic substitutes or complements. The variable B_{zsq} measures the installed-base of certified buildings owned by firms (or organizations) that register a building in a ZIP code, standard, and quarter. In this sense, we are measuring the impact of certified buildings in other markets on local registrations. The coefficient ψ on the firm experience term measures how organizational learning affects adoption. We expect firm experience to have a positive effect on adoption, i.e. we hypothesize that $\hat{\psi} > 0$.

Table 3 reports the results of estimating equation 5 using OLS. The results are reported in different columns to illustrate the impact of omitting market size and firm experience on the point estimate for LEED-Pilot projects. For ease of comparison, Column (I) reports the results of the baseline DDD estimate from Table 2.

Column (II) reports the estimates for the effect of demonstration projects and market size on green building adoption. By including market size, we find our estimate of the treatment

Table 3: Impact of LEED-Pilot projects, market size, and firm experience on LEED adoption

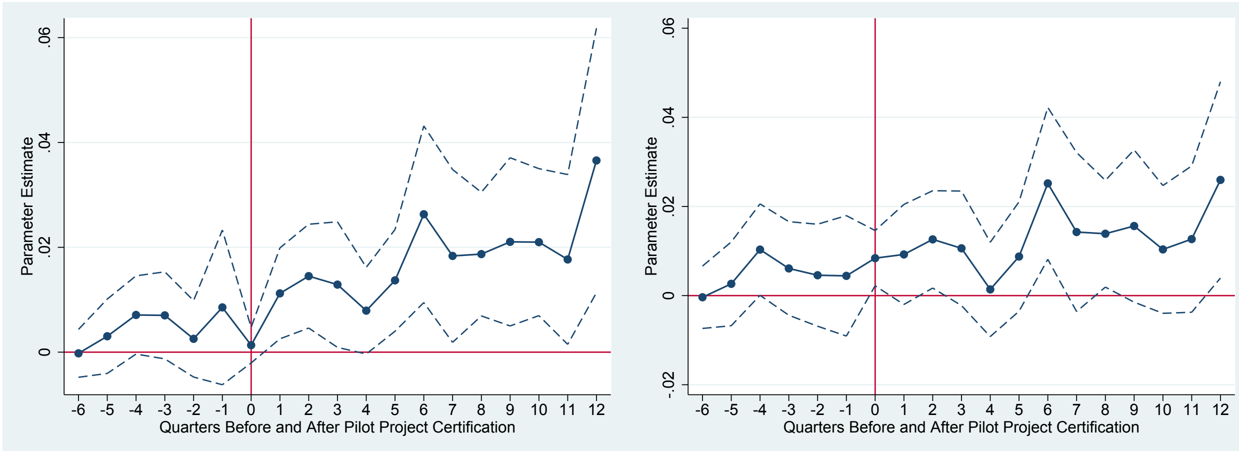
	(I)	(I)	(III)	(IV)
LEED-Pilot Project (β)	0.00747**	0.00786***	0.00701**	0.00735**
	(0.00303)	(0.00285)	(0.00304)	(0.00287)
Local Market Size (θ)		0.00550***		0.00480***
		(0.00186)		(0.00185)
Firm Experience (ψ)			0.00496***	0.00495***
			(0.000122)	(0.000120)
Observations	3,125,760	3,125,760	3,125,760	3,125,760
Adj. R^2	0.082	0.083	0.120	0.121
No. of Clusters	1,567	1,567	1,567	1,567

Notes: Reported coefficients are estimated using the DDD model. The dependent variable in each model is the IHS transformation of quarterly, privately-owned registrations. Clustered standard errors reported in parentheses and are clustered by counties. Estimated coefficients are rounded to the third significant digit for comparison across models. Significance stars in the table correspond to the following levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

effect $\hat{\beta} = 0.00786$ is statistically indistinguishable from the baseline model without market size, implying investment responses to LEED-Pilots are independent of market size. Yet, the point estimate does increase slightly in magnitude, and this increase suggests an underlying negative association between market size and LEED-Pilots.

We estimate an additional, certified green building in a local market contributes to a 0.55% increase in local adoption rates. This effect is significant at the 1% level. The positive, reduced-form parameter on market size $\hat{\theta} = 0.0055$ indicates green buildings may serve as strategic complements, indicating additional buildings might reduce overall investment costs in local markets. This effect could be driven by peer-to-peer interactions or general equilibrium effects, e.g. reduced input prices driven by entry of input-suppliers or specialized contractors in local markets.

We also estimate the model including firm experience B_{zsq} in Column (III). Again, we find the estimated parameter for a LEED-Pilot project $\hat{\beta} = 0.00701$ is not changed by including additional covariates in the model. Conforming with our expectations, we find that as firms gain more experience with green building construction, local adoption rates increase. Specifically, we estimate that an additional certified building *in another ZIP code* increases local adoption rates by 0.50%. Additionally, the estimated parameter on firm experience $\hat{\psi} = 0.00496$ suggests organizational learning is an important driver of adoption.



(a) Difference-in-differences **(b)** Difference-in-difference-in-differences

Figure 3: These figures visually inspect the parallel trend assumption for the difference-in-differences (DD) and the difference-in-difference-differences (DDD) estimation for 5-Digit ZIP codes, respectively. The solid line represents the point estimates for each quarter obtained from the DD estimation; whereas, the dotted lines correspond to the 95% confidence intervals of these point estimates.

Lastly, in Column (IV), we report the estimates including all covariates in the model. Importantly, we find the estimated effect of LEED-Pilot projects on adoption rates $\hat{\beta} = 0.00735$ is robust to the addition of both market size and firm experience in the model. The positive, statistically coefficients $\hat{\theta}$ and $\hat{\psi}$ may suggest both social and organizational learning, respectively. While consistent with our conceptualization of LEED-Pilots and other P&D programs as dual demonstration and pilot initiatives, we caution against interpretation on this evidence alone, and provide further analysis of a learning mechanism in Section 6.

5.2 Robustness

5.2.1 Parallel Trend Assumption

For the DD estimates and DDD estimates presented in Table 2 to be valid estimates of the causal effect of LEED-Pilot projects on adoption, the trend in adoption rates between treated and control groups must be similar before LEED-Pilot projects were introduced, conditional on observable characteristics. This parallel trend assumption ensures the control group represents a valid counterfactual baseline to evaluate the outcomes of the treatment group in the absence of a LEED-Pilot project.

We evaluate the validity of this assumption in the context of our estimation framework.

To do this, we estimate the following specification:

$$\tilde{R}_{zsq} = V_{zsq} + \sum_{k} \beta_k P_{zsq} + \varepsilon_{zsq} \tag{6}$$

In the specification above, we center the time period a LEED-Pilot is completed at $k = 0$ and evaluate the impact of LEED-Pilots from $k = -6$ quarters before and $k = 12$ quarters following this certification date. We then compare the trend across treated and control groups, before and after completion. Figure 3 plots the coefficients $\hat{\beta}_k$ for the DD and DDD model. The horizontal axis measures the number of quarters preceding and following the certification date of a LEED-Pilot. The vertical line centered at $k = 0$ corresponds to the normalized time period a LEED-Pilot was completed. The vertical axis is the value of the estimated parameter. The solid line corresponds to the point estimates for $\hat{\beta}_k$k and the dotted lines represent the 95% confidence intervals of these estimates.

Figure 3a plots the estimates from the DD model. For $k \leq 0$, the estimates are not statistically distinguishable from 0. The panel suggests that there is not a statistical difference in pre-treatment adoption trends between treated and control regions under a 95% confidence level. Further, in the step from $k = 0$ to $k = 1$, we find a statistically significant increase in adoption rates in treated regions, suggesting the completion of LEED-Pilot projects do have a positive impact on adoption decisions. Similarly, Figure 3b shows for the DDD model that adoption rates were not statistically different between treated and control groups in the pre-treatment period. At $k = 0$, we observe a statistically significant increase in adoption rates in the treated group, again suggesting the presence of a LEED-Pilot project increases local adoption.

5.2.2 3-digit ZIP code analysis

We have so far assumed the appropriate boundaries of regional real estate markets are best approximated by 5-digit ZIP codes. In this section, we test the robustness of our main results by re-defining the boundary of a regional real estate market. This robustness test also helps us to re-examine the geographic scope of spillovers from LEED-Pilots. To this end, we estimate the DDD model using 3-digit ZIP codes to approximate the boundaries of regional real estate markets. We find re-defining geographic boundaries changes the estimated impact of LEED-Pilots, in terms of the contribution of a LEED-Pilot project to the change in local adoption rates, but the overall effect is still positive and statistically significant.

Similar to the presentation of the main results in section 5.1, we compare the point estimates for the treatment effect to the change in average adoption rates when a LEED-Pilot is introduced in treated locations. After accounting for within-standard variation,

Table 4: Impact of LEED-Pilot projects in 3-Digit ZIP Codes

	(I)	(II)	(III)	(IV)
LEED-Pilot Project (β)	0.0163***	0.0303***	0.0165*	0.0298***
	(0.00919)	(0.00927)	(0.00905)	(0.00906)
Market Size (θ)		0.00622***		0.00590***
		(0.000892)		(0.000889)
Firm Experience (ψ)			0.00384***	0.00382***
			(0.000196)	(0.000196)
Observations	319,104	319,104	319,104	319,104
Adj. R^2	0.374	0.378	0.402	0.406
No. of Clusters	831	831	831	831

Notes: The dependent variable is the IHS transformation of quarterly, privately-owned building registrations. Clustered standard errors reported in parentheses. Standard errors for 3-Digit ZIP code estimates are clustered by 3-Digit ZIP codes. Estimated coefficients are rounded to the third significant digit for comparison across models. Significance stars in the table correspond to the following levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the average change in adoption rates is 0.326. Column (I) presents the results from the DDD estimation using only the LEED-Pilot indicator. We estimate LEED-Pilots account for around 5% (=100% 0.0163/0.326) of the average change in adoption rates in treated 3-digit ZIP codes.

Column (II) reports the results of the estimation when including only market size. By including market size, we find the point estimate for the treatment effect approximately doubles from the estimate presented in Column (I), again indicating a negative association between market size and P&D projects; however, the estimate is statistically indistinguishable from the estimate in Column (I) at the 5% level. We estimate market size has a positive, statistically significant impact $\hat{\theta} = 0.00622$ on adoption rates, suggesting as before that green building investments are complementary. All else constant, we find an additional certified building is expected to increase local adoption rates by 0.6%.

Column (III) reports the estimation results when including firm experience. The estimated treatment effect $\hat{\beta} = 0.0165$ is unaffected by including firm experience, and, again, we estimate firm experience $\hat{\psi} = 0.00384$ is expected to increase adoption rates. Lastly, Column (IV) reports the results of the full-specification. After including market size and firm experience, we estimate LEED-Pilot projects account for approximately 9.1% of the increase in adoption rates in treated areas. Further, the point estimates for market size and firm experience remain positive and statistically significant at the 1% level.

Table 5: Robustness check using the quarters after a LEED-Pilot is certified

	(I)	(II)	(III)	(IV)
Quarters After (β)	0.000636***	0.000529***	0.000594**	0.000501**
	(0.000240)	(0.000205)	(0.000236)	(0.000203)
Market Size (θ)		0.00544***		0.00474***
		(0.00185)		(0.00184)
Firm Experience (ψ)			0.00496***	0.00495***
			(0.000122)	(0.000120)
Observations	3,125,760	3,125,760	3,125,760	3,125,7604
Adj. R^2	0.082	0.083	0.120	0.121
No. of Clusters	1,567	1,567	1,567	1,567

Notes: The dependent variable is the IHS transformation of quarterly, privately-owned building registrations. The treatment variable measures the number of quarters since a pilot project received certification. All specifications are estimated using the DDD model. Clustered standard errors reported in parentheses. The average number of quarters after a pilot project receives certification is 14.34 for 5-Digit ZIP codes. Standard errors for 5-Digit ZIP code estimates are clustered by county. Estimated coefficients are rounded to the third significant digit for comparison across models. Significance stars in the table correspond to the following levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.3 Continuous Treatment

The main results of this paper are presented as a step change in adoption rates because the treatment covariate is coded as a binary variable. In contrast, we can also account for trend changes in adoption rates using a continuous measure of treatment. In this subsection, we test for trend changes in the rate of adoption by measuring the treatment variable as the number of quarters since a completion of a LEED-Pilot. Formally, we estimate the following model

$$\tilde{R}_{zsq} = V_{zsq} + \beta \sum_{\tau \leq q} P_{zs\tau} + \theta M_{zsq} + \psi B_{zsq} + \varepsilon_{zsq} \tag{7}$$

The results of the estimation are reported in Table 5. As before, we present the results in different columns, where each column includes a different set of covariates. Further, the results are only reported for 5-digit ZIP codes. Column (I) presents the results using only the continuous measure of treatment. Subsequent columns introduce additional covariates in the model, namely market size and firm experience. Point estimates related to these covariates are nearly identical to the estimates presented in section 5.2.2; we focus our discussion of this robustness test exclusively on the treatment effect.

The estimates of the treatment effect ranges from $\hat{\beta} = 0.000501$ to $\hat{\beta} = 0.000636$, implying adoption rates increase by these magnitudes at a quarterly frequency. The average number of quarters since a completion of a LEED-Pilot is approximately 14 quarters. Evaluating the treatment effect at this average, implies the effect of LEED-Pilots projects on local adoption ranges from 0.00701 to 0.00890. Again, by comparing these point estimates to the average change in adoption rates (0.062), we find LEED-Pilot projects contribute to an additional 11-14% in adoption rates. Overall, these estimates are consistent with the 12% baseline effect from the main specification.

5.2.4 Alternative transformations of dependent variable

The baseline specification uses the IHS transformation of privately-owned building registrations. In this section, we test for the impact of LEED-Pilot projects using alternative transformations of the dependent variable. Table 6 presents the results of estimating the DDD model using different transformations of the dependent variable.

Table 6: Estimated impact of LEED-Pilot projects with alternative transformations

	IHS(R_{zsq})	R_{zsq}	$\ln(R_{zsq}+1)$
LEED-Pilot Project (β)	0.00735**	0.00891**	0.00573**
	(0.00287)	(0.00398)	(0.00222)
Observations	3,125,760	3,125,760	3,125,760
Adj. R^2	0.121	0.1103	0.121
No. of Clusters	1,567	1,567	1,567

Notes: Clustered standard errors reported in parentheses. Standard errors for 5-Digit ZIP code estimates are clustered by county. Estimated coefficients are rounded to the third significant digit for comparison across models. Each model includes the market size and firm experience covariates. Significance stars in the table correspond to the following levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Each estimation includes the market size M_{zsq} and firm experience B_{zsq} covariates, and the estimated coefficients for these variables are consistent with the results presented in 3. Hence, we only present the results for the treatment effect. We estimate two additional models using the level of privately-owned building registrations R_{zsq} and an alternative log-transformation. These estimates are presented in the second and third columns of Table 6, respectively. We follow the same procedure from earlier sections and compare the point estimates to the average change in adoption rates for treated markets. We calculate the average change in adoption rates as 0.080 for the level variable and 0.048 for alternative log-transformed variable.

We find the point estimates for the effect of LEED-Pilot projects on adoption using alternative transformations of privately-owned builindg registrations are consistent with the main results. Specifically, comparing the point estimates to the average change in adoption rates in treated markets, we find LEED-Pilot projects are estimated to increase adoption rates by 11.1% using the level of building registrations. Similarly, we find adoption rates increase by 12.0% using the alternative log-transformation in the third column. Overall, both results are consistent with the baseline treatment effect of 12% discussed in section 5.1.

6 Is adoption driven by learning or herding?

The main results presented in Table 2 suggest LEED-Pilots have the effect of increasing adoption of green building technologies and practices. In this sense, the results are consistent with our hypothesis that P&D projects induce social and organizational learning to affect local demand for green building technologies and practices. However, the results presented above do not provide evidence for the mechanism of this effect. Following the conceptual framework presented in Section 2, we investigate the possibility that this effect is due to herding, rather than learning. The analysis that follows attempts to disentangle these mechanisms driving the main results, and collectively informs our understanding of the effectiveness of P&D programs.

Consider the possibility that the estimated increase in adoption may be driven by herding behavior rather than learning or knowledge spillovers. If observed increased uptake is due to herding, building owners may determine that P&D project stakeholders know more about the performance value of green building adoption and, consequently, imitate or conform to the actions taken by P&D stakeholders (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992).

In the herding model, subsequent adopters react to the presence of new certifications and mimic this behavior, regardless of the performance characteristics of the P&D project. An extreme case may result in lock-in on sub-optimal technologies, rather than the iterative improvement of practices achieved through learning. By comparison, if the project generates knowledge spillovers, impacted market players integrate new information in the decision to invest in the new technology (Kotchen 2017), and in some cases are able to adopt at lower costs. Reductions in costs may arise from, for example, the creation of new value chains in local markets, where new social and business ties between building owners, developers, and contractors reduce transaction costs for subsequent adopters.

6.1 Evidence of Iterative Learning

During the deployment phase, dozens of P&D projects may be built. Nemet, Zipperer, and Kraus (2018) suggests that sequentially executing P&D projects allows innovators to build from the successes and failures of previous projects, and thus improving the technology's value in each iteration. Consistent with this perspective, we assume that later LEED-Pilot projects are more refined than the earlier projects and have improved performance characteristics. Leveraging the difference between the registrations of the early versus later LEED-Pilots, we attempt to identify a learning effect that drives the subsequent uptake of LEED buildings.

We use the sequential timing of LEED-Pilots to determine if adoption is driven by herding or learning about performance. If adoption is driven by herding behavior, then the value or performance characteristics of later projects should have very little impact on adoption. Herding would produce no difference between the effect of earlier versus later LEED-Pilots on adoption rates. In contrast, if adoption is driven by knowledge spillovers and learning about the performance of the technology, we should observe that later LEED-Pilots increase adoption rates more than earlier projects. In both cases, we assume that the performance of technologies and practices used in LEED-Pilots improves with each iteration. We argue that rival interpretations of trends are addressed through our DDD framework in the interpretation of these results.

To test these hypotheses, we divide the LEED-Pilots into 5 bins based on the day the project registered with the USGBC. The registration date of the LEED-Pilot project corresponds to when a project registered with the USGBC and is the appropriate measure to use when trying to measure the time when a LEED-Pilot enters the program. The first bin corresponds to the first 20% of registered LEED-Pilots, with each subsequent bin representing the next quintile. We segment the bins based on percentages instead of total projects to make estimates comparable across standards that have different numbers of projects. Utilizing the empirical strategy as before, we examine differences in the trajectory of uptake of a particular LEED standard at the ZIP code level, based on the timing of the LEED-Pilots. We then estimate the following model using both the DD and DDD framework

$$\tilde{R}_{zsq} = V_{zsq} + \sum_{i=1}^{5} \beta_i P_{izsq} + \varepsilon_{zsq} \tag{8}$$

where the subscript i corresponds to the bins used for segmenting the timing of the LEED-Pilot projects, and P_{izsq} is a dummy variable equal to 1 if a LEED- Pilot project is in the ith bin and has registered by quarter q.

Figure 4 presents the estimated coefficients from the model using the registration date

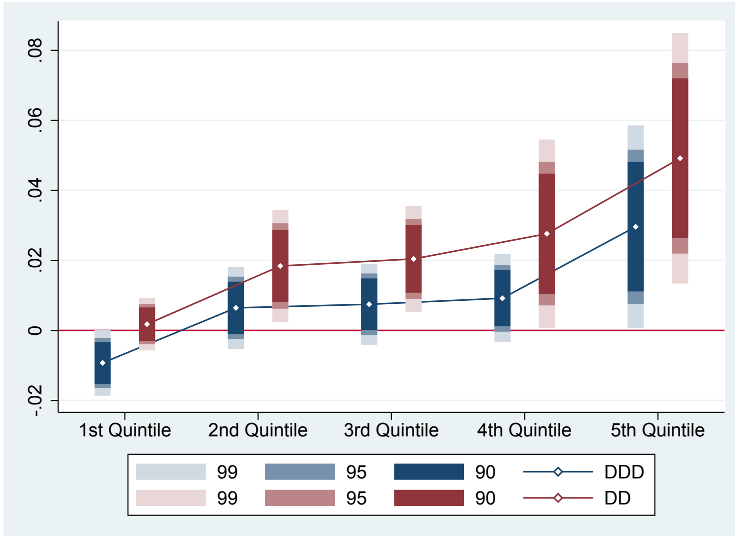


Figure 4: Effect of LEED-Pilot timing on adoption

of the LEED-Pilot projects. We present the estimated coefficients for each of the bins with their respective 90%, 95%, and 99% confidence intervals. For the purpose of comparison, we also estimate the same model using the DD framework. In both the DD and DDD estimations, there appears to be an increase in the point estimates for each iteration of LEED-Pilot projects. For the DDD estimation, we estimate that regions with the earliest registered LEED-Pilot projects experienced a statistically significant decline $\hat{\beta} = -0.00926$ in adoption rates relative to control regions, significant at the 5% level.

However, in subsequent iterations, we estimate a positive and statistically significant effect of LEED-Pilots on adoption. Notably, for the third and fourth bins, we estimate regions with these projects experienced an increase in adoption rates $\hat{\beta}_3 = 0.00748$ and $\hat{\beta}_4 = 0.00921$, both estimates being significant at the 10% level. The largest estimated impact, however, is associated with the final 20% of LEED-Pilot projects registering within a standard. We estimate these projects have the largest effect on adoption $\hat{\beta}_5 = 0.0296$, significant at the 1% level.

Although we cannot conclude that these estimates are statistically different from each other, the results of this estimation seem to suggest a process where building owners are learning about the performance characteristics of the LEED standard from LEED-Pilots. Later LEED-Pilot projects appear to have more impact on local adoption of new standards than do earlier projects. The strongest evidence in support of this conclusion comes from the estimated effects of the earliest $\hat{\beta}_1 = -0.00926$ and the latest $\hat{\beta}_5 = 0.0296$ projects. The negative point estimate for the first iteration of projects suggests these projects had little effect on resolving the technical uncertainty of LEED certification and may have actually stalled diffusion of the standard in these areas. That is, the earliest LEED-Pilot projects (which may face implementation challenges) have the smallest effect on subsequent adoption and may have inhibited future uptake of the new standard. In contrast, the large point estimate for the last quintile of projects suggests that the iterative improvements within the LEED-Pilot program led to technical improvements to the new LEED standards. These more refined projects with improved performance characteristics increased local adoption by the largest magnitudes.

An alternative explanation for these results may be that market momentum is driving the increasing impact of LEED-Pilot projects rather than learning externalities. Recall that our DDD estimation controls for time-varying fluctuations within standards, such as changes in the prices of component technologies or general advertising and promotion of the new standard by the USGBC. To the extent market momentum is driven by these effects, the DDD estimation should control for these changes. On the other hand, momentum may vary at the regional level, and the estimates from the DDD model would be picking up these effects. However, this would require that the momentum behind a new standard differs substantially between treated and control regions. Because of this, we conduct additional tests to determine whether the change in adoption is driven by herding or learning externalities.

6.2 Evidence of Reduced Adoption Costs

In this section, we provide additional evidence supporting the claim that the change in local adoption rates following the completion of a P&D project is driven by learning rather than herding behavior. Specifically, we evaluate the impact of LEED-Pilots on the costs of achieving LEED certification to directly test this claim. If adoption is the direct result of herding behavior, and public opinion is valued more than private beliefs, then we would expect LEED-Pilots to have no effect on the costs of LEED certification. In contrast, if P&D projects increase adoption through a learning process, then we should observe a reduction in the costs of achieving LEED certification following the completion of a LEED-Pilot project.

However, because we do not directly observe the financial costs of certification, we need a suitable proxy for these costs to test our claim above. To this end, we use the number of days $\mathcal{D}$ elapsed between the day a building is registered with the USGBC and the day the building is awarded certification. Longer project completion times may proxy higher rental costs of capital equipment, labor costs of workers and contractors, as well as construction permitting costs.

Conducting this analysis requires a change in the unit of analysis. Rather than evaluating the aggregate adoption rates in a geographic region, we observe a building b managed by an organization o. As before, we differentiate buildings by LEED standard s and the quarter-year q the building was registered with the USGBC. To measure project implementation time, we must limit the sample to projects that reach certification, and then calculate the number of days between registration, or intent to implement the new technology, and certification, or completed adoption. We also restrict the sample to include organizations which have at least 5 buildings that have achieved certification. Lastly, we only consider organizations that have at least 1 project before exposure to treatment. That is, if an organization does not register buildings over the "pre" period, adoption times for those organizations cannot be compared before and after the treatment. Overall, there are 329 organizations and 5,272 buildings in the restricted sample.

We estimate the following model using OLS

$$\mathcal{D}_{bosq} = \Psi_{osq} + \beta E_{osq} + \eta B_{oq} + \mathbf{X}_b^{'}\boldsymbol{\theta} + \upsilon_{bosq} \tag{9}$$

where $\Psi_{osq} = \zeta_o + \kappa_s + \tau_q + \omega_{os} + \rho_{sq}$ is shorthand notation for the fixed effect terms in the model. The treatment dummy E_{osq} measures whether an organization o is exposed to a LEED-Pilot by time q. We assume an organization is exposed to a LEED-Pilot project if the organization registers a building in the same 5-digit ZIP code in which a LEED-Pilot project is completed. As before, we differentiate this exposure at the level of a particular LEED standard s, meaning exposure (treatment) is defined within a standard. The treatment dummy E_{osq} is equal to 0 if an organization has not registered a building in the same 5-digit ZIP code as a LEED-Pilot and equal to 1 after a building is registered in the same 5-digit ZIP code of a completed LEED-Pilot.

Equation 9 also controls for other factors that may have influenced the costs of the LEED certification process. For instance, organizational learning may have contributed to reduced certification costs if organizations are capable of utilizing previous building experience into new projects. We measure a firm's previous building experience using the installed-base B_{oq} of an organization's buildings that have achieved LEED certification. The parameter η captures the effect of this experience on the costs of achieving LEED certification. We also include building level controls $\mathbf{X}_b^{'}$ to account for building-specific heterogeneity that may impact project delays. The vector $\mathbf{X}_b^{'}$ includes controls for the number of credits (Points Achieved) awarded to a building and the gross square footage (Square Footage) of the building. Based on the specification in equation 9, the main parameter of interest β corresponds to the DD estimator, similar to the estimator described in equation 1.[4] Table 7 codifies the results of the estimation. Column (I) corresponds to the estimation that only includes the

[4]Using the same notation as before, where o is a treated organization and o' is a control organization,

treatment dummy, Column (II) includes organizational experience, Column (III) includes building level controls, and Column (IV) includes variation from all controls.

Table 7: Effect of LEED-Pilot on Building Construction Time

	(I)	(II)	(III)	(IV)
Exposed to LEED-Pilot	-0.117**	-0.0995**	-0.112**	-0.0942*
	(0.0492)	(0.0502)	(0.0499)	(0.0504)
Points Achieved		0.00613**		0.00575**
		(0.00250)		(0.00232)
Square Footage (Log)		0.0526**		0.0553***
		(0.0208)		(0.0206)
Firm Experience			-0.00391**	-0.00383**
			(0.00186)	(0.00179)
No. of Observations	5,272	5,265	5,272	5,265
Adjusted R^2	0.714	0.719	0.715	0.721

Notes: Cluster-robust standard errors are reported in parentheses. Standard errors are clustered on organizations with 329 clusters. The dependent variable is the natural logarithm of project completion time. Project completion times are measured as the number of days between the registration and certification date of an individual building. The average project completion time in the sample is 596.85 days and the median completion time is 477 days. In Column (II) and (IV), 7 observations are dropped because of missing building size data. Significance stars in the table correspond to the following levels: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

In Column (I), we estimate a negative and statistically significant effect of exposure to a LEED-Pilot project. We estimate that exposure induces an 11% reduction in the number of days required to certify a building with the USGBC. This estimate is robust to inclusion of the organizational experience variable in Column (II). We find organizational experience plays an important role in driving adoption, particularly through the cost channel. In particular, we estimate an additional certified building reduces the number of days to achieve certification by around 0.3%.

Column (III) includes building-level controls. We find the point estimate for exposure decreases slightly but remains negative and statistically significant at the 5% level. Further, we find the amount of technologies and practices implemented in a building, as measured by the number of credits, increases the time to achieve certification. Specifically, an additional

the β in the equation above is similar to

$$\beta = \left(\bar{\mathcal{D}}_{os,post} - \bar{\mathcal{D}}_{os,pre}\right) - \left(\bar{\mathcal{D}}_{o's,post} - \bar{\mathcal{D}}_{o's,pre}\right) \tag{10}$$

10 credits is associated with an increase of 6% in the certification timeframe. Lastly, we find that larger buildings require more time, on average, to achieve certification. Column (IV) includes all covariates in the model. We find the estimated effect of exposure to P&D projects retains its sign and statistical significance.

These results suggest that P&Ds reduce local costs of adoption, consistent with the expectation that demonstrations foster formation of supplier and knowledge sharing networks. This, combined with results in Section 6.1, suggest learning occurs from P&Ds, and the observed effect is not purely the result of herding behavior. Notably, these estimates are conservative with respect to a key assumption: that effects are highly localized. Though there is some evidence that this is true (see Section 5.2.3), organizational learning from participating in LEED-Pilots may facilitate adoption at other (non-local) establishments.

7 Conclusion

Pilot and demonstration (P&D) programs aim to catalyze early diffusion of new technologies. In this paper, we define pilot projects as those seeking to provide internal learning, while demonstration projects diffuse knowledge outwards to external parties. Using data on adoption of green building technologies provided by the USGBC's LEED-Pilot program, we empirically test for the impact of P&D projects in the process of technology deployment. Using a difference-in-differences-in-differences empirical strategy that exploits quasi-experimental variation across time, geography, and certification typologies, we find that local adoption rates of the LEED green building standard increases between 5% and 12% following the completion of a LEED-Pilot project, controlling for other temporal, spatial, and industry trends.

These findings are important in understanding the promotion of beneficial technologies and market transformation. Due to a variety of market failures and barriers, the adoption of potentially effective and efficient technologies is not guaranteed. P&D projects can help lower search costs, procurement costs, and other transaction costs associated with the adoption of new technologies, as well as help promote improved understanding of the benefits and costs of new technologies. Using a quasi-experimental design, our evidence identifies an aggregate causal effect of P&D projects on the adoption of innovative energy and environmental technologies. By extending this research, we are able to examine evidence of mechanisms driving these effects to deduce lessons for policy design.

We find support for several mechanisms driving the adoption of energy and environmental technologies. First, and most prominently, we find evidence for learning driving the observed increase uptake of green building strategies and technologies. This evidence comes from several sources: we find evidence for increased adoption based on past firm experience with green building technologies; we find evidence for decreased construction times if a firm has been exposed to a P&D project. Together, these findings provide strong support for learning outcomes. These findings, in addition to evidence that exposure to a P&D project increases adoption in local markets, do not preclude the possibility that some increased uptake is due to herding behavior or mimicry. Rather, elements of our results suggest that firms differentiate successful experiments from unsuccessful ones, learning from those more effectively implemented. We find that earlier, more experimental P&D projects have less impact than later, more mature, projects. Moreover, as the number of LEED-Pilot projects increases in a market, the faster the completion time is between registration and certification of a building; suggesting a mechanism where learning spillovers to non-participant projects. We also identify a within firm learning channel, where firms with establishments exposed to LEED-Pilot projects, later implement projects in different locations, expanding the reach of LEED-Pilots beyond localized markets.

Our estimates are robust to a large number of threats to validity. The DDD estimates provide a robust causal identification strategy that controls for multiple sources of exogenous variation, including secular trends, geographic and market trends, and unobservable differences in geographic suitability for different certification vintages. Our DDD strategy addresses a challenge of identification that is persistent through much of the literature on information, technology, and policy spillovers, where adoption decisions cannot be distinctly or separately identified from other concurrent trends or influences. The finely grained data that involved individual building locations, as well as rich information about building construction date, construction duration, and certification vintages allowed for a sophisticated identification strategy and unique research context that lent itself to a robust identification strategy and a variety of research extensions that help shed light on the causal pathways for our findings.

The success of P&D programs in the LEED context may reflect on specific strategic choices made by the USGBC when designing and implementing the LEED program. First, USGBC identifies and works with market leaders willing to undertake financial risks in exchange for marketing benefits. The market premium provided by being an early adopter of LEED exceeds the risks for some companies. This market premium accrues by signaling employees, customers, investors, and the community that the firm is innovative and embodies values of sustainability. USGBC coordinates with firms engaging in P&D projects throughout the process, essentially providing technical assistance in exchange for undertaking a risky pilot project. By pursuing numerous P&D projects, USGBC ensures the adequate development of new standards and spurs the dissemination of the new standard across industry.

Together, these efforts highlight ways to incentivize the voluntary undertaking of risky P&D projects to help seed market transformation.

The LEED-Pilot program highlights a set of best practices that lead to increased uptake of energy and environmental technologies, and suggests a set of principles that can be leveraged to help disseminate the adoption of advanced technology. By providing some technical assistance and a marketing benefit in exchange for taking on a risky P&D project, USGBC encourages the early adoption of technologies and the sharing of knowledge associated with these experiments. Together, these reduce the costs for future adopters to pursue advanced energy and environmental technologies by promoting learning about the costs and benefits of emergent technologies and reducing the costs associated with procuring and implementing new energy and environmental technologies. Moreover, the USGBC may be able to strategically select or recruit early adopters, favoring those with high market status or visibility, in order to facilitate the broadest impact on subsequent adoption. In a world where the rapid diffusion of advanced technologies may be vital to reducing environmental impact, this study highlights the potential role of information programs in spurring investment that can promote broader market transformation.

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