Do Pilot and Demonstration Projects Work? Evidence from a Green Building Program

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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 adoption in the case of green building technology. To identify effects on adoption, we develop a *difference-in-difference-in-differences* strategy, exploiting variation in timing, location, and technologies of green building P&Ds. Results indicate local quarterly green building adoption rates double following completion of a P&D project. Further analyses examine mechanisms driving this effect. The results suggest green building demonstration projects create learning externalities, proliferating technology diffusion in local markets and through building owner networks. Together, these results suggest that investments in P&D projects by public and private actors can lower costs for subsequent adoption.

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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, & Kort, 1998; Jensen, 1982). Traditional policy interventions to catalyze adoption often leverage regulatory mandates or provide financial incentives (Stoneman & Diederen, 1994; Tang & Popp, 2016). Alternatively, various market actors are recruited via pilot and demonstration (P&D) programs to experiment with, verify, and showcase the performance of emerging technologies.

This paper is the first to undertake a systematic empirical assessment of whether P&D projects lead to broader proliferation of emerging technologies. We exploit variation from the United States Green Building Council's Leadership in Energy and Environmental Design (LEED)-Pilot program to evaluate whether P&D programs foster technology adoption. Our results indicate spillovers from the LEED-Pilot program doubled the local adoption of privately-owned LEED certified buildings per quarter (within ZIP codes). Aggregating this effect over time, we find local spillovers from LEED-Pilot projects increase adoption by at least 0.5 to 1.4 percent (nationwide). Additional analyses suggest this estimate may be a lower bound for the contribution of the LEED-pilot program to proliferation of the standard. In particular, we find evidence that local knowledge spillovers from P&D projects may reduce implementation costs for non-participating organizations by around 9 percent, corresponding to an average reduction in implementation timeframes of 2.5 months. Since some of these organizations own buildings in multiple locations, lower implementation costs may have stoked broader geographic diffusion of the LEED standard beyond markets local to a P&D project.

P&D programs may serve a critical role in the successful early deployment of breakthrough innovations. Technology pilots are experimental implementations designed to verify feasibility and assess private benefits of adoption (Kotchen & Costello, 2018). 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). Conceptually, the pilot and demonstration components of a P&D program can be distinguished based on the objectives of each stage. When combined into a unified policy program, the overarching policy objective for both projects becomes the broader diffusion of emergent technologies and practices. While pilot projects in isolation may exacerbate information asymmetries without coordinated demonstration of results (Reiner, 2016), a P&D program can effectively be coordinated such that knowledge acquired during the piloting stage can be readily demonstrated to other market participants.

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. 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. Yet without the transfer of knowledge between innovators, early adopters, and subsequent adopters, these innovations often fail to diffuse. More effective policy instruments must provide mechanisms to manage this knowledge transfer.

In this paper, we seek to identify whether P&D programs work by investigating the impacts of a suite of green building P&Ds on subsequent local market adoption rates of green building technologies and practices. P&D projects are not randomly assigned across time, location, and technology vintage, complicating causal identification of the effect of P&D projects on technology adoption. For example, P&D program managers may selectively recruit well-established firms or organizations who possess the necessary capital and labor resources to successfully carry out these experimental projects. At the same time, participating organizations can benefit from undertaking these risky projects by marketing their involvement to customers. In most cases, underlying heterogeneity among P&D participants could be driving the variation in technology adoption following the implementation of a P&D project, rendering causal identification difficult if not impossible.

To address potential selection bias, we investigate the spillover effect from P&D projects into the general population of potential green building adopters by measuring the impact of P&D projects on green building adoption by *non-participating* organizations, i.e. organizations that did not participate in the P&D program, but own building assets located near a P&D project. Our primary estimation leverages a *difference-in-difference-in-differences* (DDD) estimation framework to identify the average effect of a green building P&D project on market uptake of green building technology by exploiting variation across time, location, and technology vintage. By exploiting variation across these dimensions, our identification strategy controls for a large number of threats to causally inferring the spillover effect of P&D projects on local adoption rates.

Our baseline results suggest that, on average, local quarterly green building adoption rates approximately double following the completion of a P&D project. On an aggregate basis, this corresponds to 0.5 percent increase in the stock of green buildings within the United States. This finding is robust to a variety of alternative assumptions and specifications. Although we find evidence of a positive spillover effect of P&D projects on adoption, these results do not provide practical policy guidance for deploying P&D projects as a class of policy instruments. Recognizing this, we conduct subsequent analyses to further unpack the channels driving the positive spillover effect from P&D projects on local adoption of green buildings.

Successful P&D programs remediate uncertainties about the performance or feasibility of an emerging technology. While the results identified in the DDD model may be driven by learning externalities 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 produces greater 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 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, we examine whether the iterative deployment of LEED-Pilot projects led to improvements in the technologies and practices embedded within a LEED standard. We find LEED-Pilots deployed in later implementation stages exhibit shorter certification timeframes, suggesting knowledge gained from previous implementation stages led to subsequent refinements to a LEED standard. Second, we find the typical organization's certification timeframe for future projects decreases by 9-12 percent after certifying a building near a green building P&D project. This result suggests spillovers from P&D projects may reduce adoption costs for future adopters and, importantly, within organization knowledge transfer enables these spillovers to cut across geographies.

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 green building 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 technologies. The results estimate the causal effect of a P&D project on the diffusion of green building technologies. 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 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 a burgeoning dialogue on information spillovers from environmental programs. Green technologies often have multiple positive externalities, leading private returns to be less than social benefits and inhibiting socially optimal levels of adoption. Information provision appears to be an effective policy intervention that generates positive regional learning externalities for these technologies, such as lighting (DeCanio & 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 (Henriques, Husted, & Montiel, 2013; Nemet, 2012; Tang & Popp, 2016). We complement these findings by examining how well P&D programs impact adoption in the construction industry, providing evidence of an information spillover mechanism.

Finally, our results give insight on the role of early adopters in the long-run diffusion of a technology (Catalini & Tucker, 2017). If the lead organization responsible for the P&D project has establishments in multiple locations, organizational learning costs of adoption in other 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 & Walker, 2012; Bollinger & Gillingham, 2012; De Grip & Sauermann, 2012;

Zimmerman, 2003) or social learning (Bandiera & Rasul, 2006; Conley & 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 P&D 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 LEED certification, a green building program thought to reduce impacts on climate, habitat, resource use, and health. Specifically, we focus on LEED pilot projects (LEED-Pilot), and introduce the institutional characteristics of the program 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 LEED-Pilot projects contribute to a doubling of quarterly adoption rates in regions with a completed P&D project. In section 6, we conduct additional analyses to parse out whether learning and knowledge transfer can potentially explain why P&D programs work. 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 barriers inhibit new innovations from reaching market maturity. Unproven technical reliability, uncertain market and institutional receptiveness, underdeveloped supply and distribution channels, and limited organizational and managerial expertise characterize this intermediate stage of the technology lifecycle. Because these barriers may limit early investment in emerging technologies (Hendry, Harborne, & 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, & Kraus, 2018). P&D programs are a class of policy instruments that can potentially strike this balance. P&D programs, when effective, foster learning and knowledge spillovers (Nemet, 2012) that could reduce these barriers.

To encourage learning, knowledge spillovers, and market development at this stage of the technology lifecycle, common interventions promoting new technologies include subsidies (Nemet, 2012; Tang & Popp, 2016), voluntary programs (Lyon & Maxwell, 2007), and P&D programs. Pilot projects and technology demonstrations represent two mutually beneficial policy instruments for scaling up new technologies to broader implementation (market maturity), despite the fact that the objectives of pilot versus demonstration projects tend to differ in non-trivial ways. For instance, pilot projects adopt, develop, and customize new technology in an experimental fashion, with the intent to learn from the implementation process and refine the technology or verify its best management practices (Kotchen & Costello, 2018). Pilot projects precede demonstration projects in the technology lifecycle, creating verifiable results and knowledge for external dissemination. Moreover, pilot projects also seed initial market development, including the creation of specialized labor and input markets. Demonstration projects, in comparison, aim to diffuse knowledge of refined, yet emergent technologies outward to lessen frictions created by barriers to deployment.

Due to their experimental nature, pilot projects often occur within narrow divisions of an organization, such as one department or establishment. Demonstration projects, by contrast, showcase technical feasibility and reliability to broad sets of market actors, often engaging numerous stakeholders to reduce technical and managerial uncertainties (Bollinger, 2015; Brown et al., 1993). Because P&D programs often leverage elements of both pilots and demonstrations, we do not separately identify the causal effects of pilot versus demonstration projects on adoption. Both interventions aim at inducing learning or reducing uncertainties that otherwise inhibit adoption. Instead, our analysis allows us to evaluate some of the channels in which P&D programs may work, specifically through learning and knowledge spillovers. Few econometric evaluations of P&D performance have been conducted, and our work is unique in its ability to distinguish the impact of a P&D program from other policies that may drive observed outcomes. To frame our analysis, we first describe the mechanisms by which P&D projects may increase adoption of emerging technology.

2.1 Pilot Projects, Learning-by-Searching, and Learning-by-Doing

Pilot projects may have a number of impacts on the supply of emergent technologies. New technologies are often subject to substantial transaction costs. These transaction costs include the cost of acquiring relevant information for technical implementation and customization costs. Customization costs, in turn, include search costs, procurement costs, design costs, and other process related transaction costs. These costs are higher for emergent technologies due to fewer suppliers in the market, the need to design unique or customized solutions, and the need to develop new processes and supply chains.

From the outset of a pilot project, those implementing the new technology engage with learning-by-searching and learning-by-doing (Kamp, Smits, & Andriesse, 2004). As early adopters, organizations actively search for resources useful for technical implementation. Discovery of new resources for implementation, such as low cost input supply chains or specialized labor resources, reduces the transaction costs associated with the emergent technology for the organization. Piloting organizations may also uncover useful information regarding likely performance that will later guide project evaluation during the learning-by-searching process. This evaluation criterion primes learning-by-doing that enables efficient deployment for later adoption (Arrow, 1962). As organizations gain experience with a technology, process related transaction costs may decline and spur additional adoption.

When knowledge is retained internally, information asymmetries are exacerbated, and these asymmetries limit the piloting stage's impact on reducing transaction costs (Reiner, 2016). One strategy for eliminating information asymmetries is to establish a knowledge sharing network consisting of the various piloting organizations, where the search costs of acquiring new information may be substantially reduced. Coordinating the production and dissemination of knowledge within this network is considered essential for success: policy programs that contribute to the formation of knowledge sharing networks can reduce costs of learning-by-searching for future iterations of a piloted technology (Nemet, Zipperer, & Kraus, 2018).

With knowledge sharing networks in place, investments made by early adopters, i.e. those piloting the technology from the outset, reduce transaction costs for other piloting organizations, enabling subsequent generations of pilot projects to build on the successes and failures of previous pilot projects, further driving down transaction costs. Moreover, when the innovating organization is also a member of this network, learning from early adopter feedback can enable iterative improvements in product design and delivery (Von Hippel, 1986; Von Hippel, 2010). Improvements in product delivery, such as streamlined administrative processes, could further reduce user costs for subsequent adopters. Learning and knowledge transfer are implicitly at work behind the scenes when transaction costs are reduced and technologies are improved through the iterative piloting process. However, establishing knowledge sharing networks consisting only of pilot stakeholders is not sufficient for pulling emergent technologies across the valley of death.

2.2 Demonstration Projects and Learning-by-Interacting

While pilot projects seek to verify value and reduce uncertainty through the discovery of best practices surrounding implementation and operation, demonstration projects are intended to spark diffusion of verified technology by showcasing value and best practices to inexperienced users (Bollinger, 2015). Many technologies may be considered experience goods, where the technology's value cannot be assessed or is highly uncertain prior to use. This feature of an experience good is even greater during the early stages of the product lifecycle.

Opening knowledge sharing networks beyond the pilot stakeholders can facilitate knowledge spillovers to a broader set of market participants. This permits subsequent adopters to leverage the experience of early adopters to guide adoption decisions. For example, the social and business ties established during the piloting stage may reduce search and matching frictions for future adopters by brokering and screening interactions between these future adopters, project stakeholders, and input suppliers (Boudreau et al., 2017; Cassi & Plunket, 2014; Fafchamps, van der Leij, & Goyal, 2010; Jackson & Yariv, 2007). The brokering and screening process is a key feature of demonstration projects, where experienced users of a new technology demonstrate value and facilitate deployment on a broader scale (Bollinger, 2015).

The development of a robust knowledge sharing network facilitates the diffusion of information on product reliability, performance, sourcing, and operational best practices (Reiner, 2016), including diffusion to actors not participating in the piloting process. By opening knowledge sharing networks to prospective adopters, learning-by-interacting may enable the piloting organizations of a new technology to demonstrate their experiences to a broader set of market participants (Kamp, Smits, & Andriesse, 2004; Von Hippel, 1978; Von Hippel, 1986; Von Hippel, 2010). Policy programs of this nature, i.e. those designed to share the lessons from early investments to facilitate spillovers to other market participants, may be thought of as demonstration projects. In this sense, pilots and demonstration projects are conceptually and pragmatically distinct, but are not mutually exclusive when knowledge developed during the piloting process is disseminated outward.

Even without direct policy guidance, pilot projects may also inadvertently serve as demonstration projects when value is demonstrated and best practices are disseminated to subsequent adopters through word-of-mouth communication, shared suppliers, visual signals, and peer effects.

2.3 P&D Programs and Knowledge Spillovers

Technology diffusion programs often bundle multiple mechanisms to increase potential impact (Tang & Popp, 2016). Pilot and demonstration projects create complementary opportunities for increased technology uptake through learning and knowledge transfer. As policy instruments, these projects are often bundled into programs that jointly experiment with an emerging technology as a pilot (Kamp, Smits, & Andriesse, 2004), and seek to generate knowledge spillovers as a demonstration (Bollinger, 2015; Reiner, 2016). For example, solar and wind energy demonstrations often create innovation lessons for participating firms that pilot the technology (Hendry, Harborne, & Brown, 2010). P&D programs integrate these mechanisms, contextualizing the information revealed within a broader community of practice that can integrate knowledge spillovers.

Not all P&Ds are successful. In some cases, the technology undergoing experimental adoption may fail, such that subsequent adoption is contingent on iterative improvements (Nemet, Zipperer, & Kraus, 2018) and learning from failure (Cannon & Edmondson, 2005; Storey & Barnett, 2000). Alternatively, the piloted technology is implemented, and copied among other adopters, without meaningfully integrating the information revealed by the P&D. This “herding” 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 & Stein, 1990). Herding is especially plausible when demonstrations actively seek to engage key stakeholders such as market leaders and high-status firms (Nemet, Zipperer, & Kraus, 2018), a design feature preferred in related voluntary policy instruments (Henriques, Husted, & Montiel, 2013). By mimicking the P&D participants, later adopters may avoid some search and transaction costs, but fail to exploit iterative learning opportunities, so that they are unlikely to adopt more efficiently compared to earlier adopters. Importantly, while herding can drive technology diffusion, it may lead to lock-in on under-performing technologies. For P&Ds to truly be effective, these policy tools must drive learning and knowledge spillovers, as evidenced by iterative improvements in technology implementation and reduced adoption costs for subsequent adopters.

Well-designed P&D programs spur the diffusion of emergent technologies through learning and knowledge spillovers. The framework presented in this section provides several useful predictions for evaluating how P&D programs can be successful and thus can aid in developing effective P&D policy programs. First, during the pilot stage of a new technology, early iterations of experimental implementations can reduce transaction costs for subsequent iterations. This effect is predicated on a process of learning and knowledge transfer. Second, as a technology is gradually refined, knowledge spillovers from piloting organizations into a broader community of actors can enable diffusion on a larger scale. Knowledge spillovers may take a variety of forms, ranging from the demonstration of value that reduces uncertainty for later adopters to the development of a more robust local knowledge stock or material supply chains. In section 6, we use these predictions to guide our analysis of the mechanisms underlying the success of green building P&D projects.

3. Empirical Context

This paper exploits variation from the United States Green Building Council's (USGBC) Leadership in Energy and Environmental Design (LEED) green building pilot program. The USGBC's LEED pilot program offers a unique opportunity to investigate whether P&D programs work and to understand the mechanisms underlying their success. Section 2 discusses the important role for knowledge sharing networks during the piloting and demonstration components of a P&D program. In particular, we argue that, when these networks are in place, learning from the experimentation phase enables iterative improvements of the technology throughout the piloting phase as well as broader market development as piloting organizations may share their lessons with prospective adopters.

The USGBC encourages collaboration and knowledge spillovers across the community of LEED professionals and organizations. The USGBC's collaborative culture is evidenced through the maintenance and promotion of their network of professional organizations, LEED certified professionals, and their directory of previous projects.[2] Knowledge spillovers are actively encouraged and form a core feature of the USGBC's LEED community. In particular, the network of LEED professionals contributes "a wealth of knowledge to *benefit everyone* who shares USGBC's vision of green buildings" (emphasis added) and prospective organizations are encouraged to consult previous LEED projects to glean "best practices to guide the success" of future implementations of the standard (USGBC, 2019).

The USGBC certifies buildings that meet its LEED standard for green building best practices. The LEED certification system identifies baseline design and performance norms in the construction and real estate industry, and recognizes achievement beyond those norms. Certification serves to induce private actors to provide public goods by providing a marketing benefit to organizations that supply these public goods. In the construction market, certification systems, such as LEED, reward organizations for investing private resources for the provision of public goods such as improved storm water management, the provision of renewable energy, and the use of sustainably-sourced materials (Kotchen, 2006).

[2] At the time this paper was written, the USGBC maintained a network of more than 12,000 professional organizations, 200,000 volunteers and professionals, and 125,000 LEED building projects. Access to the directories can be found on the USGBC's website at https://www.usgbc.org/profile

LEED certification is based on improvements to the entire building footprint (including energy, water, materials, land use, and indoor environment) rather than a single characteristic (Matisoff, Noonan, & Flowers, 2016). To attain certification, builders must register, implement high environmental performance technologies, and provide sufficient evidence of these improvements. Certification has been demonstrated to cause an increase in the investment in energy and environmental technologies as well as improve the energy footprint of the building (Matisoff, Noonan, & Mazzolini, 2014). 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. Recent research has demonstrated the importance of these environmental entrepreneurs in promoting the adoption of new energy and environmental practices in green building. P&D projects may play an important role in overcoming psychological and social barriers that have inhibited the uptake of these new technologies (York, Vedula, & Lenox, 2018).

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 real estate developers, private organizations, and public agencies that volunteer as early adopters. While an organization's decision to volunteer for the pilot program is not random, the location of the eventual LEED-Pilot is independent of the USGBC's recruitment process, as the location decision is determined by the participating organization rather than the USGBC. Even when these locations may coincide, our strategy focuses on the spillover effect on potential adopters implying the location of the LEED-Pilot is effectively exogenous to potential adopters of the standard.

The LEED-Pilot program constitutes a set of demonstration projects, in that they are conducted 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. 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 USGBC's 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 on 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. Registered buildings (black circles) and, notably, LEED-Pilot projects (white circles) in the map appear to cluster in locations with high natural resource demands and stronger environmental preferences, consistent with previous research (Kahn & Vaughn, 2009; Cidell, 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.

[Figure 1 Goes Here]

Figure 1: Spatial Distribution of LEED Buildings in the Contiguous United States.

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, where approximately

[Figure 2a Goes Here]

(a) New Construction

[Figure 2b Goes Here]

(b) Existing Buildings

[Figure 2c Goes Here]

(c) Commercial Interiors

[Figure 2d Goes Here]

(d) Core-and-Shell

[Figure 3e Goes Here]

(e) Retail-New Construction

[Figure 3f Goes Here]

(f) Retail-Commercial Interior

Figure 2: This figure displays total annual registered buildings and certified pilot projects for each LEED standard. The upper portion of each panel corresponds to the annual number of buildings *registered* for a LEED standard in the United States. The lower portion of each panel represent the annual number of *certified* LEED-Pilot projects. Panels are sorted based on the order in which standards were introduced.

Table 1: Adoption Statistics by ZIP Code from 2000-2015

[Table 1 Goes Here]

half of these correspond to privately-owned buildings. 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). In total, our data includes 874 unique LEED-Pilots across these six building standards.

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. The summary statistics in this panel account for within-standard variation to give a sense of the average adoption rate within a typical ZIP code and LEED standard.

Panel B aggregates the data to present cumulative adoption statistics for the typical LEED standard and local market.[3] 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, this correlation may arise from various mechanisms, including location- or technology-specific characteristics, or exogenous trends within markets impacted by a LEED-Pilot. As seen in Figure 1, both LEED-Pilots and LEED registrations cluster in major cities, where private organizations may face greater competitive pressures to differentiate. As early market leaders, LEED-Pilot participants may self-select based on unobservable, organizational characteristics, internal motivations, or external recruitment from the USGBC to gain first-mover advantages. Moreover, the selection of particular organizations into the LEED-Pilot program may impact feedback that informs the USGBC's refinement of LEED standards, and may shape adoption trends (Catalini & Tucker, 2017; Läpple & Rensburg, 2011; Aral and Walker, 2012). Thus, the participant selection plays critical roles for both the pilot and demonstration goals of the LEED-Pilot program. The USGBC actively recruited public and private actors into the LEED-Pilot program, consistent with best practices in the implementation of P&Ds

[3] One important feature to note is that 805 5-digit ZIP codes are treated with a LEED-Pilot in one standard or another. This implies each treated region receives an average of 1.08 LEED-Pilots. The most LEED-Pilots per ZIP code is 6, for which there are three ZIP codes in this category.

(Nemet, Zipperer, & Kraus, 2018). Our analysis acknowledges this selection as a critical strategy for successful implementation of P&D programs.

4 Empirical Strategy

To investigate average effects of a well-designed P&D program across regional markets, building standards, and time periods, we develop a reduced-form empirical model to measure the impact of a LEED-Pilot on adoption of the LEED standard. By acknowledging differences in building technologies in use under various LEED standards, our identification strategy goes beyond past work that treats all LEED building standards equivalently (Simcoe & Toffel, 2014; Rysman, Simcoe, & Wang, 2016). Each LEED standard uses building technology tailored to the unique needs of a real estate sub-sector, developed through its own P&D program.

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 & 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

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

where $\bar{R}_z^t$ is the average number of registrations in region z during period t. 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 mechanisms occurring on the interaction of location, building standards, and time can be interpreted as plausibly exogenous. Given this assumption holds, we can thus exploit 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

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

where the parameter $\hat{\beta}_{s'}^{DD}$ 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. This produces an estimate of the total effect of a LEED-Pilot on local adoption rates, and leaves the mechanisms driving the effect to our later analysis.

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 registered LEED 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 in a particular quarter, denoted as R_{zsq} . For the analysis, we use the number of privately-owned registrations of a LEED standard as a proxy for building adoption rates. This regional measure is independent of the selection process by which a LEED-Pilot is assigned to an individual firm within the region. A common approach for diminishing the influence of extreme values within Ordinary Least Squares (OLS) estimation is to log-transform the dependent variable, bringing extreme values closer to the average. However, due to a preponderance of zero registrations in the data, the standard log-transformation is inappropriate. Instead of the standard log-transformation, we use the Inverse Hyperbolic Sine (IHS) transformation of quarterly registrations, denoted as $\tilde{R}_{zsq}$.[4] The IHS transformation is commonly used in wealth data, where extreme values are common, and a preponderance of zeroes makes standard log-transformation inappropriate (Burbidge, Magee, & Robb, 1988; Pence, 2006). As discussed in the results, and detailed in Appendix A, the IHS transformation impacts how we interpret economic meaning from the estimates produced.[5]

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

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

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

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

[5] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgixbin/jhome/34787

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 potential 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_s control for time-invariant heterogeneity within 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 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. The parameter β is equivalent to the DDD estimator $\hat{\beta}$ given in equation 2, if our identifying assumption holds, 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 a positive and significant effect on registrations within a LEED building standard ($\hat{\beta} > 0$ after estimation).

A LEED-Pilot participant's decision to volunteer for the program is likely driven by unobserved organizational-level heterogeneity not captured by the fixed effects in the model. This unobserved heterogeneity could bias our estimate of the treatment effect if the location of LEED-Pilot projects is non-random and confounded with adoption propensity. To avoid the selection bias of the LEED-Pilot program, our analysis investigates the impact of LEED-Pilot projects on local adoption of the LEED standard by *non-participating* organizations of the LEED-Pilot program.

By measuring the spillover effects caused by the P&D program on non-participants, we leverage this exogenous relationship between the P&D location decisions and the location decisions by *non*-P&D participants in the LEED program. The assignment of LEED-Pilot projects across locations by a participating organization is independent of the propensity for non-participating organizations to adopt the LEED standard in the same location and building standard. If the USGBC had selected the location of LEED-Pilot projects, for example, they would have selected the most favorable locations for diffusion of the new standard, i.e. where non-participating organizations have stronger incentives to adopt the piloted LEED standard. Under this scenario, our estimate of the effect of LEED-Pilots on adoption would be biased upward.

However, the USGBC does not select the location of LEED-Pilot projects. Instead, the LEED-Pilot program is conducted on a voluntary basis, and the assignment of LEED-Pilot projects across locations is delegated to the volunteering organization. Because of this feature of the program, location decisions are determined by the idiosyncrasies of the participating organizations, and thus the location of LEED-Pilot projects reflects what is optimal for the piloting organizations, and is independent of non-participants' location preferences.

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 variation's impact on adoption.

Because our dependent variable $\tilde{R}_{zsq}$ is the IHS transformation of quarterly registrations, we need to convert the parameter estimates into an economically meaningful unit of analysis before interpreting the results. We adapt recent insight on interpreting IHS-transformed dependent variables from Bellemare and Wichman (2020) to our panel data analysis and interpret accordingly. A detailed account of this procedure is provided in a technical Appendix A.[6] Since our DD and DDD models include a variety of fixed effects, we compare the point estimate for the treatment effect $\hat{\beta}$ with the

[6] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgixbin/jhome/34787

pre-treatment average quarterly adoption rate in control regions, $\hat{\alpha}_0 = 0.00656$, calculated using the IHS-transformed data. This produces the expected change in quarterly LEED registrations within a ZIP code and standard, as caused by the completion of a LEED-Pilot project.

From the pooled estimation results, we estimate that LEED-Pilots increase by 0.0367 buildings per quarter within treated ZIP codes and standards. This pooled estimate suggests spillovers from LEED-Pilots contributed to an additional 605 registrations within treated ZIP codes from 2000 to 2015, or a 2.42 percent increase in total LEED adoption. Though the pooled estimate is statistically significant at the 1 percent level, we do not interpret this result as causal: idiosyncratic characteristics of the locations and standards could impact location and timing of LEED-Pilot projects, potentially biasing this pooled estimation.

Table 2: Impact of LEED-Pilot on Adoption
[Table 2 Goes Here]

Our DD estimation accounts for this non-random assignment of LEED-Pilot location and timing. Controlling for within ZIP-standard and quarterly variation, this DD result suggests that LEED-Pilots increase adoption by 0.0219 buildings per quarter within treated ZIP codes and standard. Aggregating this effect across the sample period, we find the DD estimate suggests spillovers from LEED-Pilots contributed to an additional 362 registrations, or a 1.43 percent increase in total adoption. The difference between the pooled and DD estimates is statistically explained by time-invariant heterogeneity within ZIP codes and standards and aggregate trends.

LEED-Pilots may also be assigned based on characteristics of a particular standard. In our next step, we exploit within-standard variation to control for localized, contemporaneous shocks π_{zq} that raise demand for green buildings across each building standard through a DDD estimation. We find LEED-Pilot projects increase adoption by 0.00747 buildings per quarter within treated ZIP codes and standards. Aggregated over the sample period, this DDD estimate suggests that LEED-Pilots induced an additional 123 registrations, representing a 0.48 percent increase in total adoption. This seemingly modest value, when compared to the pre-treatment average quarterly adoption rate, still suggests that local exposure to a LEED-Pilot project doubles quarterly adoption rate of a particular standard in a treated region ($\Delta R_{zsq}^{DDD} / \sinh(\hat{\alpha}_0) = 1.13$).

We perform post-hoc spatial autocorrelation tests to determine whether spatial correlation is a serious issue for the standard error estimates. We find some evidence of a weak, negative correlation among the errors within the DDD model (Moran's I = -0.08, $z = -8.23$). Based on this evidence, we adjust the standard errors for spatial and serial correlation (Conley, 1999; Hsiang, 2010), and we present the results of this adjustment alongside the clustered standard errors in Table 2. However, we find the spatially-adjusted standard errors are roughly half the estimates for the standard errors when the errors are clustered by county. We maintain the use of clustered standard errors for throughout the remainder of the paper as they provide a more conservative range for inference.

Altogether, our results suggest that the LEED-Pilot program is an example of P&D projects leading to increased adoption of the technology, in this case an increase in LEED building registrations. We next present additional results that test the validity of our identifying assumption. We examine the role of market size and firm experience in inducing changes in adoption rates, alongside other robustness checks that test our assumptions and measurement validity. This includes relaxing our assumed geographic boundaries for potential spillovers from LEED-Pilots: in section 5.2.3, we extend the geographic boundary for treatment to determine whether these baseline results conservatively estimate the impact of a LEED-Pilot project.

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 validate our identifying assumption, we account for two other factors that could affect adoption within a LEED standard: peer effects and organizational learning. Past literature suggests that peer effects from prior adoption fosters technology diffusion, and accounts for this by controlling for the baseline installed amount of the technology in the market (Bollinger & Gillingham, 2012).

Similarly, firms may utilize previous experiences with the LEED standard when adopting the standard in new markets. If this so-called organizational learning is present, we may inadvertently assign importance to LEED-Pilots when in fact multiregional firms are simply transferring knowledge within the organization, and this transfer of knowledge drives local adoption. Our next model incorporates measures of both peer effects (adoption by other firms, in the same market) and organizational learning (prior adoption by multiregional firms) to affirm that these do not affect our baseline estimates from 3. 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 cumulative adoption of the standard within the local market (5-digit ZIP code). M_{zsq} includes certified public and private buildings, and is used to account for peer effects. We note that, in our setting, M_{zsq} may also measure the maturity of a local green building market. We interpret the coefficient θ on the market size term as measuring the extent to which green buildings act as strategic substitutes or complements. This interpretation does not preclude peer effects from being present, but instead, generalizes the interpretation of θ to include a broader set of market forces. The variable B_{zsq} is used to account for organizational learning, and measures the prior adoptions of the LEED standard by the participant firm in other markets. We expect firm experience to have a positive effect on adoption, i.e. we hypothesize that $\hat{\psi} > 0$.

Table 3: Impact of LEED-Pilot Projects, Market size, and Firm Experience on Adoption

[Table 3 Goes Here]

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 LEED-Pilot projects and market size on green building adoption. By including market size, we find our estimate of the treatment 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.

To interpret the economic significance of our estimates for market size and firm experience, we compute semi-elasticities following the approach outlined in Appendix A.[7] The estimated semi-elasticities for market size and firm experience, denoted as $\hat{\epsilon}_M$ and $\hat{\epsilon}_B$ respectively, are interpreted as the percentage change in quarterly adoption rates from a one unit increase in the corresponding covariate. In column (II), for instance, we estimate $\hat{\epsilon}_M = 0.68$, implying an additional (local) certified building increased quarterly adoption rates by 68 percent. This effect is significant at the 1 percent level. The positive, reduced-form parameter on market size indicates green buildings may serve as strategic complements, such that additional buildings might reduce overall investment costs in local

[7] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgixbin/jhome/34787

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 62 percent ($\hat{\epsilon}_B = 0.62$). In other words, because some firms own building assets in multiple locations, we expect an additional LEED certified building to generate a positive spillover effect on adoption in other ZIP codes through the firm's building network. This effect suggests organizational learning is an important driver of broader geographic diffusion of the LEED standard.

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 significant coefficients $\hat{\theta}$ and $\hat{\psi}$ may suggest both social and organizational learning drive adoption, 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 test for "anticipatory effects" using a standard F-test. The null hypothesis of this test states that average adoption rates do not differ between treated and control groups before the completion of a LEED-Pilot project. That is, we test whether the lead estimates jointly differ from 0, i.e. the null hypothesis is given by $H_0: \hat{\beta}_{-6} = \hat{\beta}_{-5} = \cdots = \hat{\beta}_{-1} = 0$. Rejection of the null hypothesis would suggest that the parallel trend assumption is violated, and consequently, the estimated treatment effect from the baseline empirical tests cannot be interpreted as causal.

For both the DD and DDD models, we do not find sufficient statistical evidence to conclude the parallel trend assumption is violated. For the DD estimation, we do not find a statistical difference in pre-treatment adoption trends between treated and control regions ($F = 0.85$, $p = 0.53$) at conventional significance levels. Even more, after controlling for within-standard variation in the DDD model, we also do not find evidence that average adoption rates were statistically different between treated and control groups in the pretreatment period ($F = 1.15$, $p = 0.323$).

[Figure 3a Goes Here] **[Figure 3b Goes Here]**

(a) Difference-in-Differences (b) Difference-in-difference-indifferences

Figure 3: These figures report the results from the event study analysis for the difference-in-differences (DD) and the difference-in-difference-differences (DDD) estimation for 5-Digit ZIP codes, respectively, at an annual frequency. The solid points correspond to the point estimates; whereas, the bars correspond to the 95 percent confidence intervals of these point estimates.

5.2.2 Event Study Analysis

We also investigate whether LEED-Pilots have a temporary or permanent effect on green building adoption using the event study design given by equation 6.[8] The results of the estimation are graphically presented in Figure 3. In the figure, we plot the results from using both the registration and certification date as the binary treatment measure for robustness.[9] The estimated lead and lag coefficients using the certification (registration) date are colored in blue (red) and symbolized using triangles (squares), and the bars in the figure correspond to the 95 percent confidence intervals for each point estimate. Figure 3 suggests LEED-Pilot projects have more than a transitory impact on green building adoption. For both models, the impact of LEED-Pilots on adoption increases for several years after LEED-Pilot certification.

5.2.3 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

[8] To increase the power of the event study analysis, we extend the unit of analysis to an annual frequency. We also estimate the baseline DD and DDD models at an annual frequency and find the results are consistent with our baseline estimates at a quarterly frequency. For the DD model, the point estimate for the treatment effect is $\hat{\beta}$ = 0.0620 and statistically significant at the 1 percent level. Similarly, the point estimate for the treatment effect in the DDD model is $\hat{\beta}$ = 0.0192, which is significant at the 5 percent level.

[9] The average time to certify a LEED-Pilot is 3.67 quarters, implying an approximate 1 year average difference between the registration and certification date of a LEED-Pilot project.

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.

Table 4: Impact of LEED-Pilot Projects on Adoption in 3-Digit ZIP Codes
[Table 4 Goes Here]

The results in column (I) present the DDD estimation using only the LEED-Pilot indicator. In this estimation, LEED-Pilots increase local adoption by 0.0163 buildings per quarter within treated 3-digit ZIP codes and standards, without controlling for covariates introduced in other columns. This corresponds to an additional 198 registrations over the sample period as a result of local spillovers from the LEED-Pilot, or a 0.77 percent increase in total LEED registrations.

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 percent 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 77.9 percent ($\hat{\epsilon}_M$= 0.779). 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 quarterly adoption rates by 48.1 percent ($\hat{\epsilon}_B$= 0.481).

Lastly, Column (IV) reports the results of the full specification. After including market size and firm experience, we estimate LEED-Pilot projects increase adoption rates by 0.0298 buildings per quarter in treated 3-digit ZIP codes. This estimate implies local spillovers from the LEED-Pilot program contributed to an additional 362.74 building registrations over the course of the sample, increasing total LEED registrations by 1.44 percent. Hence, after accounting for possible localized geographic spillovers from LEED-Pilot projects, we find LEED-Pilots had a larger impact on adoption than our baseline estimates might suggest. In the following section, we explore additional mechanisms that might explain the success of the LEED-Pilot program. Importantly, these additional tests provide some evidence that evaluating the impacts of P&D programs on a purely geographical basis would likely result in conservative estimates of their overall impact.

6. Unpacking the Mechanisms of P&D Programs

The main results presented in Table 2 suggest LEED-Pilots have the effect of increasing adoption of green building technologies and practices. The results are consistent with our hypothesis that P&D projects affect local supply and demand for green building technologies and practices. However, multiple mechanisms may drive the outcomes of programs designed to diffuse technology (Tang & Popp, 2016). Though we show this effect is not endogenous to particular technologies, markets, or trends over time, we do not provide evidence for the mechanisms driving this effect.

Following the conceptual framework presented in section 2, we conduct a series of tests to determine the mechanisms driving the success of P&D programs. We argue that bundling pilot and demonstration projects when deployed into a unified policy framework may overcome information asymmetries inherent in experimental stages of new technologies, drive additional refinement, and spur commercialization. While mimicry can facilitate technology uptake, learning and knowledge transfer are the preferred outcomes of this bundled approach to the deployment of cutting-edge technologies. Learning-by-searching and learning-by-doing during the piloting phase of the program refine technologies along a variety of dimensions, but without the necessary incentives to coordinate, pilot project stakeholders may keep information private. In the absence of incentives to share the knowledge acquired during this stage can halt the refinement of the new technology (Reiner, 2016).

We argue that establishing knowledge sharing networks during the pilot stages of the P&D program can drive iterative refinement of emerging technologies and ignite momentum in the diffusion of an emerging technology. In section 3, we discussed how the USGBC places strong emphasis on collaboration and knowledge transfer among the LEED professional community. This provides a unique opportunity to evaluate the predictions of the conceptual framework in the context of the LEED pilot program. Our analysis proceeds in two steps. First, we test whether LEED-Pilot projects exhibit iterative refinement. As noted above, iterative refinement suggests the presence of learning and knowledge transfer, with knowledge sharing networks playing a crucial role in this process. Second, we test for the existence of knowledge spillovers into a broader community of actors. This test corresponds closely with LEED-Pilots serving a dual role of both pilot and demonstration project, where the latter disseminates knowledge acquired during the piloting process outward.

6.1 Evidence of Iterative Learning and Knowledge Transfer

Dozens of P&D projects may be built in succession as both innovators and adopters experiment in the early deployment stages of a new technology. Nemet, Zipperer, and Kraus (2018) suggest that sequentially executed P&D allow innovators to build from the successes and failures of previous projects, thus improving the technology's value in each iteration. Learning and knowledge transfer is implicit within this iterative process. The earliest P&D projects are the pioneers of emergent technologies, deploying new technologies with minimal upfront knowledge, and consequently, face the most substantial barriers to implementation. As discussed in section 2, stakeholders of pioneer P&D projects can overcome these barriers by acquiring the required knowledge through processes of learning-by-searching and learning-by-doing. This knowledge may then be transferred to subsequent generations of P&D stakeholders given the appropriate coordination and knowledge transfer mechanisms are in place (Reiner, 2016). In our context, the USGBC works to coordinate knowledge transfer between different generations of its LEED-Pilots. Iterative deployment of subsequent generations of LEED-Pilots can build from knowledge acquired during early stages and may implement similar technologies at a reduced cost.

The USGBC deployed numerous LEED-Pilots during the roll-out of experimental LEED standards (e.g. see Figure 2). While the individual LEED-Pilot projects were conducted by a mix of private and public actors, the USGBC maintained the central position of overseeing the development and deployment of the broader LEED-Pilot program. As the central authority guiding the LEED-Pilot program, the USGBC was in a unique position to coordinate knowledge transfer between subsequent generations of LEED-Pilot stakeholders. Although learning and knowledge transfer is not directly observable in our context, subsequent refinement of LEED-Pilots may reflect iterative learning and knowledge transfer within the LEED-Pilot program.

Because many of the attributes of LEED-Pilots that would reflect an iterative learning process, most notably construction and implementation costs, are not directly observable, we require a suitable proxy to test whether learning and knowledge transfer were present during the program. To this end, we use the number of days D elapsed between the day a LEED-Pilot registered with the USGBC and the day the LEED-Pilot is awarded certification. Longer project completion times proxy higher rental costs of equipment, labor costs of workers and contractors, permitting costs, and the amount of search effort required for procurement of materials, labor, and services. Refinement through learning may manifest in a variety of ways, such as more robustly developed material supply chains (learning-by-searching) a larger, local green building knowledge stock (learning-by-doing), or the implementation of best practices discovered in earlier projects conducted by peers (learning-by-interacting).

[Figure 4 Goes Here]

Figure 4: The Impact of Iteration on LEED-Pilot Implementation Times

Leveraging the difference between registrations of early versus later LEED-Pilots, we test for whether the timing of a LEED-Pilot project influenced the project's expected implementation time. If the earliest generation of LEED-Pilot projects exhibited longer implementation times, while later generations exhibit the shortest, the decline in implementation times across iterative generations of LEED-Pilots would indicate a refinement process occurred over the course of the program. Given the USGBC coordinated the execution of these projects, subsequent refinement may be indicative of learning and knowledge transfer.

To test for iterative refinement, we divide 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 measuring when a LEED-Pilot enters the program. The first bin corresponds to the first 20 percent 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.

The unit of analysis is a LEED-Pilot, which corresponds to an individual building b, for a particular building standard s. We estimate the following model to test for the impact of iteration on project implementation time

$$\ln(\mathcal{D}_{bs}) = v_s + \sum_{j=2}^{5} \delta_j P_{bsj} + \boldsymbol{X}'\boldsymbol{\gamma} + \varepsilon_{bs} \tag{7}$$

where v_s corresponds to standard fixed effects, P_{bsj} is an indicator variable equal to 1 when a LEED-Pilot's registration date falls in quintile j and 0 otherwise, $\boldsymbol{X}$ corresponds to a vector of building characteristics, and ε_{bs} is the idiosyncratic error term. For building characteristics $\boldsymbol{X}$, we control for the number of credits awarded to a LEED-Pilot and the square footage of the project, as both features are expected to increase implementation times.

We present the estimates for each δ_j in Figure 4 and tabulate the full results in Online Appendix D.[10] The y-axis corresponds to the estimated δ_j from the model, and the x-axis corresponds to the separate quintiles for project timing. The bars in the figure correspond to the 95 percent confidence intervals for the estimates. It should also be noted the 1st quintile is omitted from the estimation to avoid the OLS dummy variable trap, and thus each estimate is interpreted relative to this omitted category. To provide some context, the average time to complete a LEED-Pilot in this quintile is 388.93 days or approximately 388.93/30.42 = 12.78 months.

The point estimates of the model show a declining trend in implementation times across different generations of LEED-Pilots.[11] For instance, the 2nd quintile of LEED-Pilots take around 50 percent less time to implement relative to similar projects in the 1st quintile. To put this in context, this estimate implies LEED-Pilots in the 2nd quintile are completed around 6 months earlier than comparable projects in the 1st quintile. Similarly, the 5th quintile of LEED-Pilots, on average,

[10] The estimates presented in the figure correspond to the estimates presented in Column (II). We prefer these estimates because they omit LEED-Pilots with project implementation times coded as 0, implying the project achieves certification on the same day it is registered with USGBC. As this scenario is highly unlikely in practice, we suspect the entries are errors in data entry and not actually consistent with actual implementation times. Nevertheless, the results across the different models are consistent, and the interpretation of the results is unaffected.

[11] To relay the economic significance of the estimates, note the expected percentage change in $\mathcal{D}_{bs}$ relative to the omitted category given the model in equation 7 for some $\hat{\delta}_j$ is given by

$$E[\%\Delta\mathcal{D}_{bs}|j] = \frac{e^{\hat{\delta}_j + \hat{v}} - e^{\hat{v}}}{e^{\hat{v}}}$$

where $\hat{v}$ is average of the fixed effects in the model. For our preferred estimates, we estimate $\hat{v} = -0.0861$.

achieve certification in 80 percent less time than the earlier cohort required for certification. This corresponds to a reduction in certification time of nearly 10 months. Importantly, we find this declining trend in implementation time across cohorts is not only an artifact of sampling. First, the point estimates on their own provide ample support for a statistically significant difference between implementation times relative to the 1st quintile of LEED-Pilots, even after controlling for the building standard and building characteristics. Second, we conduct F-tests to determine whether the differences across cohorts is merely driven by sampling. We do not have sufficient evidence to rule out sampling drives the differences between the 3rd, 4th, and 5th quintiles. Nevertheless, we are able to claim that LEED-Pilots in these quintiles achieved certification faster than similar projects in the 2nd quintile at the 1 percent level.

Our results thus provide evidence that subsequent generations of LEED-Pilots improved with respect to implementation time. As noted above, shorter implementation times could proxy improved material supply chains, a larger green building knowledge stock, or the dissemination of best practices between generations of LEED-Pilot stakeholders. The results presented above provides some indication learning and knowledge transfer were behind the success of the LEED pilot program. In particular, as LEED-Pilots underwent different iterations, new standards were gradually refined and improved, enabling broader market implementation. In Appendix E, we provide additional evidence that later LEED-Pilots are associated with a larger increase in adoption rates following their completion.[12]

[12] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgixbin/jhome/34787

6.2 Evidence of Knowledge Spillovers from P&D Projects

In this section, we test for evidence of knowledge spillovers from P&D projects to evaluate the impact of the demonstration component of LEED-Pilot projects. In section 2, we argued that when knowledge sharing networks are opened to a broader community of actors, piloting organizations can act as intermediaries who broker and screen interactions between input suppliers and prospective adopters. This has the potential of reducing various transaction costs associated with the adoption of new technology, specifically the search costs required to screen for quality input suppliers. To directly test for this spillover effect, we evaluate the impact of LEED-Pilots on the costs of achieving LEED certification.

Because we do not directly observe the financial costs of certification, we need a suitable proxy for transaction costs to test our claim above. To this end, we again use the number of days D elapsed between the day a building is registered with the USGBC and the day the building is awarded certification. As discussed previously, 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 observation. 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 (as those who do not reach certification have unknown implementation times), and then calculate the number of days between registration and certification. For the purpose of comparison, we only consider organizations that have at least 1 project before they are exposed to a LEED-Pilot.

To assure sufficient variance in implementations before and after the LEED-Pilot treatment, we restrict the sample to organizations with several certified buildings; we present results from a selected threshold of five buildings in order to echo our results from the quintiles presented above. Results for more restrictive samples of organizations with more buildings have longer trends over time but exacerbate potential selection bias; and results from samples of organizations with fewer buildings avoid the potential selection bias but sacrifice our ability to estimate marginal effects of experience. Overall, there are 329 organizations and 5,272 buildings in the restricted sample.

We estimate the following model using OLS

$$\ln\left(\mathcal{D}_{bosq}\right) = \Psi_{osq} + \beta E_{osq} + \eta B_{oq} + \boldsymbol{X}_b'\boldsymbol{\theta} + v_{bosq} \tag{8}$$

where $\Psi_{osq} = \xi_o + \kappa_s + \tau_q + \omega_{os} + \rho_{sq}$ 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 8 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 in 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 $\boldsymbol{X}_b'$ to account for building-specific heterogeneity that may impact project delays. The vector $\boldsymbol{X}_b'$ includes controls for the number of credits (Points Achieved) awarded to a building based on how certification is obtained, and the building size (Square Footage) of the building. Based on the specification in equation 8, the main parameter of interest β corresponds to the DD estimator, similar to the estimator described in equation 1.[13] Table 5 reports the results of the estimation. Column (I) corresponds to the estimation that only includes the treatment dummy, Column (II) includes building level controls, column (III) includes organizational experience, and column (IV) includes variation from all controls.

Table 5: Effect of LEED-Pilot on Building Construction Time

[Table 5 Goes Here]

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 percent reduction in the number of days required to certify a building with the USGBC. Before exposure to a LEED-Pilot, the average number of days to certify a LEED building is 717.87 days, or 23 months. Our point estimate suggests exposure to a LEED-Pilot reduces future certification timeframes by an average of 78.97 days, or approximately 2.5 months. This estimate is robust to inclusion of building level controls in column (II). We find the point estimate for exposure decreases slightly but remains negative and statistically significant at the 5 percent level, implying the typical certification timeframe after exposure to a LEED-Pilot reduces by 9 percent, or slightly more than 2 months. 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 10 credits is associated with an increase of 6 percent, or 2.3 months, in the certification time frame. Lastly, we find that larger buildings require more time, on average, to achieve certification. Our point estimates suggest a 1

[13] Using the same notation as before, where o is a treated organization and o' is a control organization, the β in the equation above is similar to

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

percent increase in building square footage corresponds to a 5 percent, or approximately 1 month, increase in the certification timeframe. Column (III) controls for organizational experience. 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 percent. Evaluating this estimate at the average, organizational-level installed base of 13.88 buildings implies the average effect of organizational experience is a reduction in certification time of slightly more than 1 month. Column (IV) includes all covariates in the model. We find the estimated effect of exposure to LEED-Pilot projects retains its sign and is statistically significant at the 10 percent level, implying exposure to a LEED-Pilot reduces future certification timeframes by an average of 2 months.

These results suggest that LEED-Pilots 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 occurred, 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 stoke learning within adopting firms, 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 standards, we find that local adoption rates of the LEED green building standard approximately double following the completion of a LEED-Pilot project, controlling for other temporal, spatial, and industry trends.

This study advances our understanding of policy tools that promote market transformation or the diffusion of emerging and beneficial technologies. We uncover the potential role for P&D programs to help transform the built environment. The adoption of potentially effective and efficient technologies is not guaranteed in the presence of a variety of market failures (Henriques, Husted, & Montiel, 2013; Hoffman and Henn, 2008; Nemet, 2012), which are abundant in the real estate market. We have argued that 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. Our pooled estimates suggest that LEED-Pilots contributed to an additional 605 building registrations in treated regions. This captures the more holistic impacts on the green innovation ecosystem and emphasizes that P&D projects interact with prevailing economic and technological conditions to achieve broader market transformation. These findings support other recent research that highlight the role of early adopters in helping stimulate the uptake of new environmental technologies (York, Vedula, & Lenox, 2018). However, these initial results do not control for policy conditions, price changes, or technological progress over time.

Our quasi-experimental design provides evidence of an aggregate causal effect of LEED-Pilots on the adoption of innovative energy and environmental technologies. The DDD estimates are robust to a large number of threats to validity: the approach controls for multiple sources of exogenous variation, including secular trends over time, differences in geographically-defined real estate market preferences, and unobservable differences in geographic suitability for different certification vintages. In doing so, our identification strategy addresses a common challenge to empirical research on information, technology, and policy spillovers, where adoption decisions are concurrent with other trends and influences. In our study, we exploit rich data describing individual building locations, construction dates, construction durations, and certification vintages to implement a sophisticated identification strategy in a unique research context that arrive at robust findings about the causal effect size of P&D projects on technology diffusion. The variety of empirical extensions in section 6 help shed light on the causal mechanisms driving our findings.

We find support for several mechanisms driving the adoption of energy and environmental technologies. Most prominently, and consistent with past findings on technology subsidies (Nemet, 2012; Tang & Popp, 2016), we find evidence that P&Ds drive an increased uptake of green building technologies by fostering learning. This evidence comes from several sources, as discussed in section 6: we find evidence that later LEED-Pilot projects may be more refined than early LEED-Pilots; we find evidence for increased adoption based on past firm experience with green building technologies; we 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. Together, these findings provide strong support for learning as a mechanism by which P&Ds drive market transformation.

Our study is subject to two limitations. First, the findings 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. Second, some portions of our analysis do not partition which agents undergo learning. The reduced implementation times observed in section 6 plausibly arise from more efficient program administration at LEED, better coordinated or managed implementation teams within the real estate development firm, or more informed approaches to design among architects and engineers involved in LEED projects. The mechanisms discussed in section 2 suggest each is a plausible learning outcome, which all reduce the costs and time required to certify a LEED building. This ambiguity does not threaten our overall finding that P&Ds accelerate technology diffusion through at least some learning, but rather creates opportunity for future research on how information management within complex project teams creates opportunities for learning and knowledge spillovers.

Pragmatically, our research suggests that programs like LEED and LEED-Pilots can help accelerate the uptake of environmentally-friendly technologies in the built environment. As urban populations in cities expand worldwide, mitigating the impacts of buildings on the natural environment is critical to sustainable development. Greener building designs use fewer resources, mitigate urban heat islands, protect habitat, and provide healthier spaces for people to thrive. Past studies demonstrate the improved environmental performance of LEED-certified buildings (Asensio and Delmas, 2017), an important step in decarbonization for climate change mitigation.

Deeper decarbonization requires rapid transformation through a wide array of policy instruments (Blackburn, Harding, & Moreno-Cruz, 2017), including pilots and demonstrations. In practice, it seems essential to use P&D projects as one policy tool in a suite of instruments to transform the built environment. For example, P&Ds may complement the transformative effects of public procurement policies (May & Koski, 2007; Simcoe & Toffel, 2014), or building codes and green building policies (Kontokosta, 2011), to limit the built environment's dependency on fossil fuel energy systems. Our study contributes to the growing policy literatures on decarbonization and building-sector energy use.

The success of the LEED-Pilots may suggest best practices for P&D implementation in other contexts. We note at least three features of the LEED-Pilot program which can inform future program design. 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, particularly those with strong market positioning. This market premium accrues by signaling employees, customers, investors, and the community that the firm is innovative and embodies values of sustainability (Henriques, Husted, & Montiel, 2013).

Second, the USGBC coordinates with firms engaging in LEED-Pilot projects throughout the process, essentially providing technical assistance in exchange for undertaking a risky pilot project. This creates opportunities to refine the LEED standard while also fostering learning among the team implementing the standard. Third, by pursuing numerous LEED-Pilots, the 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 participation in and learning from P&D projects that reduce costs for future adopters, and provide clearer understanding of the cost-effectiveness of new technologies, seeding market transformation. 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 adoption of advanced energy and environmental technologies.

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Online Appendix

A Economic Interpretation with IHS Transformation

The expected change in quarterly LEED registrations within a ZIP code and standard caused by the completion of a LEED-Pilot project is given by the following expression modified from Bellemare and Wichman (2020)

$$\Delta R_{zsq} = \left[\sinh\left(\hat{\alpha}_0 + \hat{\beta}\right) - \sinh(\hat{\alpha}_0)\right] P_{zsq}$$

Using this expression, we can aggregate the impact of LEED-Pilots up to total LEED building registrations by summing ΔR_{zsq} across all ZIP codes, standards, and quarters where $P_{zsq} = 1$. Formally, we compute total LEED registrations caused by the LEED-Pilot program using the following

$$\Delta R = \sum_z \sum_s \sum_q \Delta R_{zsq} = \sum_z \sum_s \sum_q \left[\sinh\left(\hat{\alpha}_0 + \hat{\beta}\right) - \sinh(\hat{\alpha}_0)\right] P_{zsq}$$

Throughout the text, we present our main results in terms of both ΔR_{zsq} and ΔR to relay the economic significance of the LEED-Pilot program. In addition, we can interpret the corresponding percentage increase in total LEED registrations as $100 \times \Delta\hat{R}/(R - \Delta R)$, where R is the total number of registrations (given in Table 1), and $\Delta\hat{R}$ is the change in registrations from the estimation of interest.

The above calculation is sufficient for interpretation of the binary treatment effect, but further calculation is needed to understand elasticities of other covariates. To compute semi-elasticities (as used in section 3), we use the following formula adapted from Bellemare and Wichman (2020)

$$\hat{\epsilon}_x = \frac{\partial \hat{y}}{\partial x}\frac{1}{x} = \hat{\beta}\frac{(\bar{y}^2 + 1)^{\frac{1}{2}}}{\bar{y}}$$

Where we substitute the average quarterly adoption rate within 5-digit ZIP codes $\bar{R}_{zsq} = 0.008$ for $\bar{y}$ above and the appropriate parameters for $\hat{\beta}$. For analysis at the 3-digit ZIP code level, we substitute the average quarterly adoption rate among 3-digit ZIP codes $\bar{R}_{zsq} = 0.08$ for $\bar{y}$.

B Additional Robustness Tests

B.1 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

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

The results of the estimation are reported in Table 6. 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 $\hat{\beta} = 0.000636$. The smaller magnitude of these estimates compared to our main specifications is consistent with the change in units for the treatment effect, from binary to quarterly effects. After aggregation, we find LEED-Pilot projects contribute to additional local adoption of green building certification.

Table 6: Robustness Check using the Quarters after a LEED-Pilot is Certified

[Table 6 Goes Here]

B.2 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 2 presents the results of estimating the DDD model using different transformations of the dependent variable.

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 Table 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 7, respectively. Note that the units of these transformed dependent variables vary across estimations. We can use each column to confirm the statistical robustness of the main results, but comparison of the economic significance is not straightforward.

Table 7: Impact of LEED-Pilot Projects on Adoption with Alternative Transformations

[Table 7 Goes Here]

We find the point estimates for the effect of LEED-Pilot projects on adoption using alternative transformations of privately-owned building registrations are consistent with the main results. Specifically, each estimate is positive and statistically significant. Overall, both new results are consistent with the baseline treatment effect discussed in section 5.1.

C Intensity Effects in 3-digit ZIP codes

In section 3.3, we provide summary statistics for the data used in the analysis. Importantly, our data contains 874 LEED-Pilots distributed across 805 5-digit ZIP codes. This implies the typical ZIP code will only contain around one LEED-Pilot. Based on this, we defined our binary treatment variable, P_{zsq}, as the timing of the first LEED-Pilot certified in a ZIP code. This assumption has little bearing for interpreting the results of the main estimation results for 5-digit ZIP codes since each treated ZIP code is assigned a single LEED-Pilot.

However, after aggregating the data to the 3-digit ZIP codes, each ZIP code may contain several LEED-Pilots, and using binary treatment variable, might mask intensity effects of LEED-Pilots. To test for the existence of intensity effects, we compute the installed-base of certified, LEED-Pilots within a 3-digit ZIP code and building standard and use this as our new measure of treatment for 3-digit ZIP codes. The results are summarized below.

Table 8: Impact of Cumulative LEED-Pilots on Adoption

[Table 8 Goes Here]

The DDD estimate for the treatment effect without intensity effects is 0.0163, and the DDD estimate with intensity effects is 0.0165. This implies the impact with intensity effects is slightly higher than the estimate without intensity effects.

D Additional Estimation Results for Section 6.1

Table 9: Impact of LEED-Pilot Timing on Building Construction Time

[Table 9 Goes Here]

E The Impact of Iteration on Adoption

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 P&D projects affect local demand for green building technologies and practices. However, multiple mechanisms may drive the outcomes of programs designed to diffuse technologies. Though we show this effect is not endogenous to particular technologies, markets, or trends over time, we do not provide evidence for the mechanism driving this effect. Following the conceptual framework presented in section 2, we investigate the possibility that observed effects are due to herding rather than learning. The analyses that follow attempt to disentangle the mechanisms driving our main results, and collectively inform our understanding of the effectiveness of P&D programs.

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, as would be 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 & Costello, 2018), 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.

E.1 Additional Evidence of Iterative Learning

During the deployment phase, dozens of P&D projects may be built. 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 (Nemet, Zipperer, & Kraus, 2018). 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 additional 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 the 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 percent 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

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

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 i-th bin and has registered by quarter q.

[Figure 5 goes here]

Figure 5: Effect of LEED-Pilot Timing on Adoption

Figure 5 presents the estimated coefficients from the model using the registration date of the LEED-Pilot projects. We present the estimated coefficients for each of the bins with their respective 95 percent confidence interval. For the purpose of comparison, we also estimate the same model using the DD framework. The DD estimates are in the solid pattern line with square symbols, and the DDD estimates are presented using the dashed line and the diamond symbols. In both the DD and DDD estimations, there appears to be an increase in the point estimates for each iteration of the LEED-Pilot projects. For the DDD estimation, we estimate that regions with the earliest registered LEED-Pilot projects experienced a decline ($\hat{\beta}_1 = -\ 0.0033$) in adoption rates relative to control regions. However, the effect is not significant at conventional levels.

In subsequent iterations, we estimate a positive and statistically significant effect of LEED-Pilots on adoption. Notably, for the third bin, we estimate regions with these projects experienced an increase in adoption rates ($\hat{\beta}_3 = 0.0138$), with the estimate being significant at the 5 percent level. The largest estimated impact, however, is associated with the final 20 percent of LEED-Pilot projects registering within a standard. We estimate these projects have the largest effect on adoption ($\hat{\beta}_5 = 0.0302$), significant at the 5 percent 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 first $\hat{\beta}_1 = -\ 0.0033$ and the last $\hat{\beta}_5 = 0.0302$ 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 stalled diffusion of the standard in these areas. 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 potentially improved performance characteristics increased local adoption by the largest magnitude. Coupling these results with the evidence presented in section 6.1, improvements in the underlying technologies and practices in later LEED-Pilot projects appear to have influenced local adoption via a knowledge spillover channel.

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 controls for these sources. On the other hand, momentum may vary at the regional level (i.e., at the interaction of time, technology, and location), and the estimates from the DDD model includes these momentum effects. However, this requires that the momentum behind a new standard differs substantially between treated and control regions. Because of this, we conduct additional tests that decouple the analysis from spatial boundaries to determine whether the change in adoption is driven by herding or learning externalities.

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

	Pooled	DD	DDD
LEED-Pilot Project (β)	0.0367	0.0219	0.00747
	(0.00867)	(0.00498)	(0.00303)
	[0.00266]	[0.00177]	[0.00159]
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 and spatially-adjusted standard errors are reported in brackets. Clustered standard errors for 5-Digit ZIP code estimates are clustered by county. The spatially-adjusted standard errors are computed using a distance threshold of 50 km and 3 temporal lags. The pooled model does not contain any fixed effects, the DD model contains zip-standard and quarter-year fixed effects, and the DDD model includes zip, standard, quarter-year, zip-standard, zip-quarter-year, and standard-quarter-year fixed effects.

	(I)	(II)	(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 DDD model is estimated using zip, standard, quarter-year, zip-standard, zip-quarter-year, and standard-quarter-year fixed effects. 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.

	(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. The estimates are from the DDD model with zip, standard, quarter-year, zip-standard, zip-quarter-year, and standard-quarter-year fixed effects. 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.

	(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. The model is estimated using organization, standard, quarter-year, organization-standard, and standard-quarter fixed effects.

	(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	3,125,760
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 with zip, standard, quarter-year, zip-standard, zip-quarter-year, and standard-quarter- year fixed effects. 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.

	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

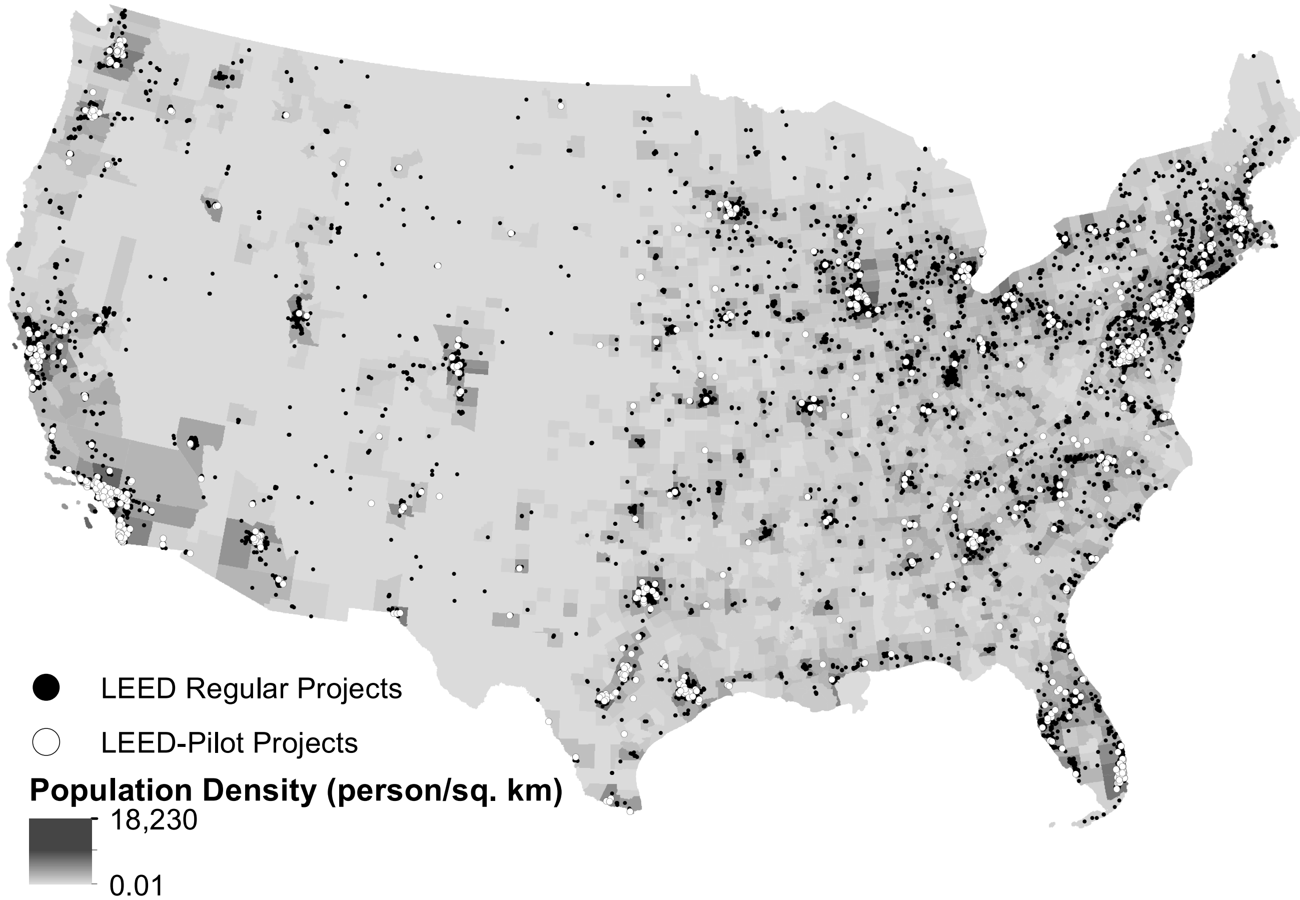
Notes: Clustered standard errors reported in parentheses. Standard errors for 5-Digit ZIP code estimates are clustered by county. Estimated coefficients are rounded to the third significant digit for comparison across models. Each model includes the market size and firm experience covariates, in addition to zip, standard, quarter-year, zip-standard, zip-quarter-year, and standard-quarter-year fixed effects.

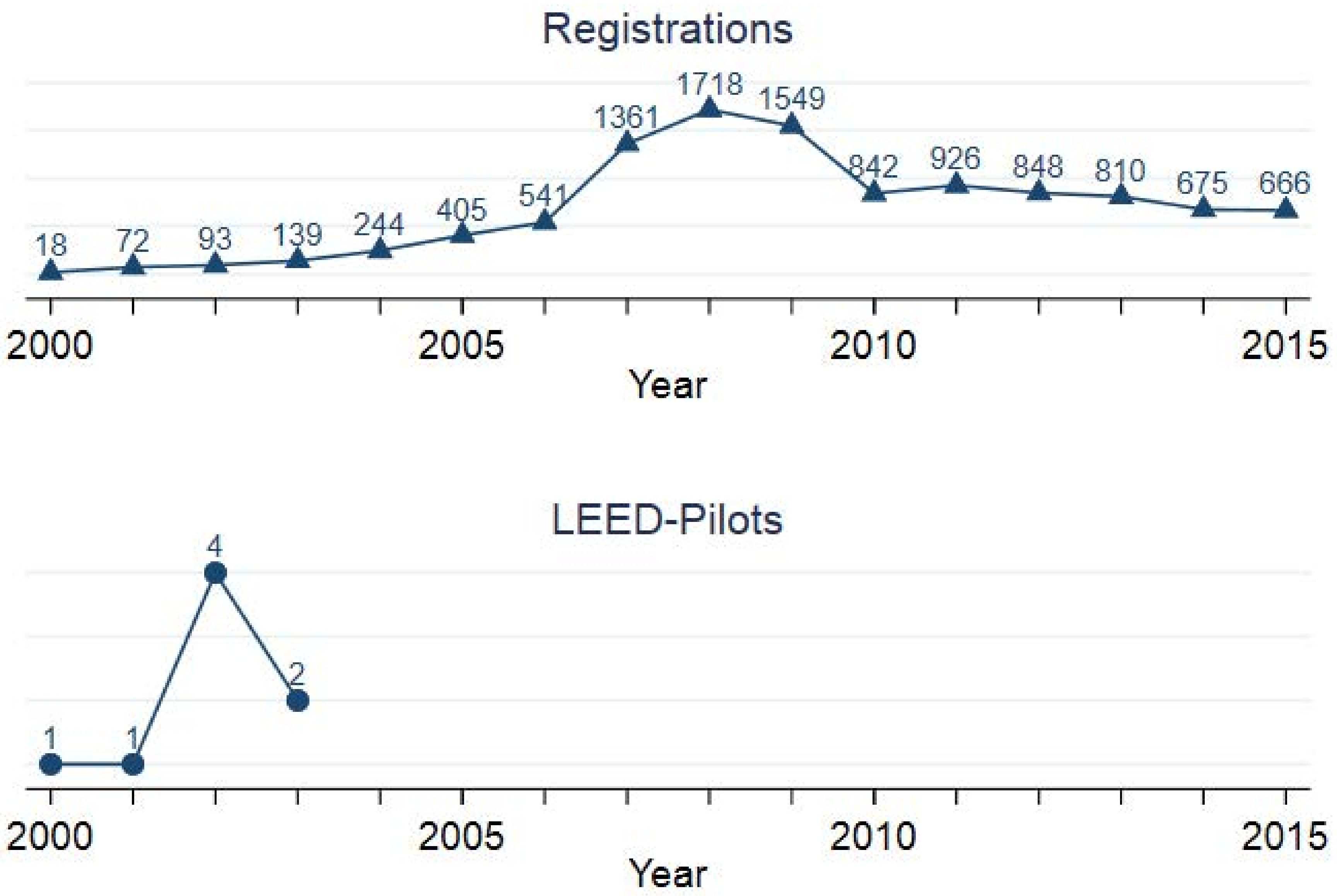
	Pooled	DD	DDD
Installed-Base of LEED-Pilots	0.104	0.0737	0.0165
	(0.0160)	(0.00890)	(0.00593)
Observations	319,104	319,104	319,104
Adj. R^2	0.023	0.285	0.374
No. of Clusters	831	831	831

Notes: The dependent variable is the IHS transformation of quarterly, privately-owned building registrations. Clustered standard errors reported in parentheses and are clustered by 3-digit ZIP code. The average of the installed- base of LEED-Pilots is 1.47. Estimated coefficients are rounded to the third significant digit for comparison across models. The pooled model does not contain any fixed effects, the DD model contains zip-standard and quarter-year fixed effects, and the DDD model includes zip, standard, quarter-year, zip- standard, zip-quarter-year, and standard-quarter-year fixed effects.

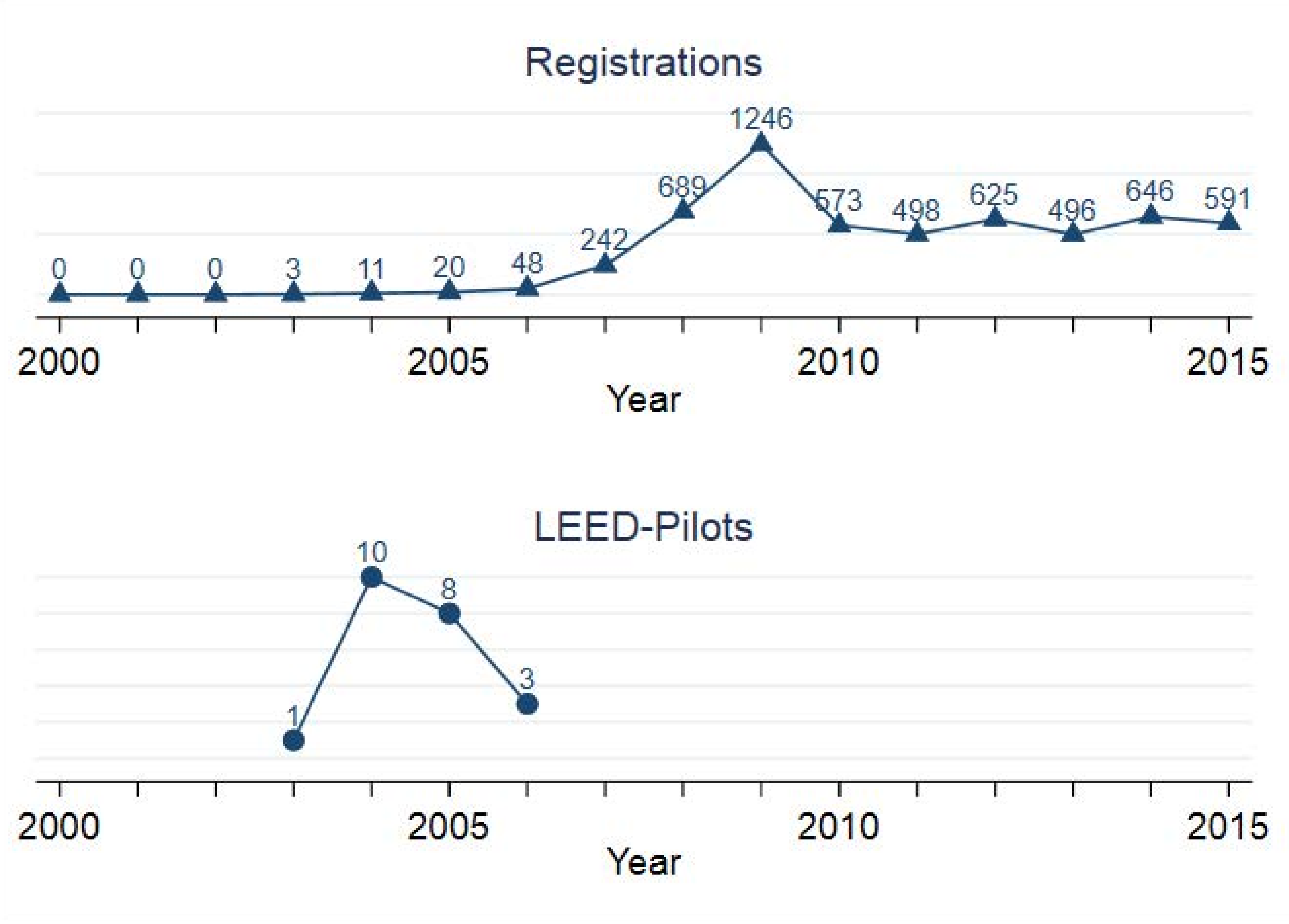
	(I)	(II)	(III)	(IV)
	ln(D)	ln(D)	IHS(D)	IHS(D)
2nd Quintile	-0.572	-0.704	-0.952	-1.105
	(0.183)	(0.174)	(0.274)	(0.268)
3rd Quintile	-1.469	-1.505	-1.655	-1.558
	(0.199)	(0.189)	(0.265)	(0.256)
4th Quintile	-1.517	-1.682	-1.466	-1.767
	(0.186)	(0.169)	(0.261)	(0.247)
5th Quintile	-1.493	-1.755	-1.323	-1.623
	(0.201)	(0.165)	(0.271)	(0.243)
Points Achieved		0.0525		0.0807
		(0.00434)		(0.00786)
Square Footage (Log/IHS)		0.062		-0.0144
		(0.0506)		(0.0352)
No. of Observations	623	600	874	874
Adjusted R^2	0.536	0.631	0.386	0.465

Notes: Robust standard errors are reported in parentheses. The number of observations between each model fluctuates based on whether implementation times, number of credits, or square footage are encoded as 0. The dependent variable is either the natural logarithm or the IHS transformation of implementation time. Square footage is also transformed, and the transformation corresponds to the transformation of the dependent variable. Each model controls includes standard fixed effects.

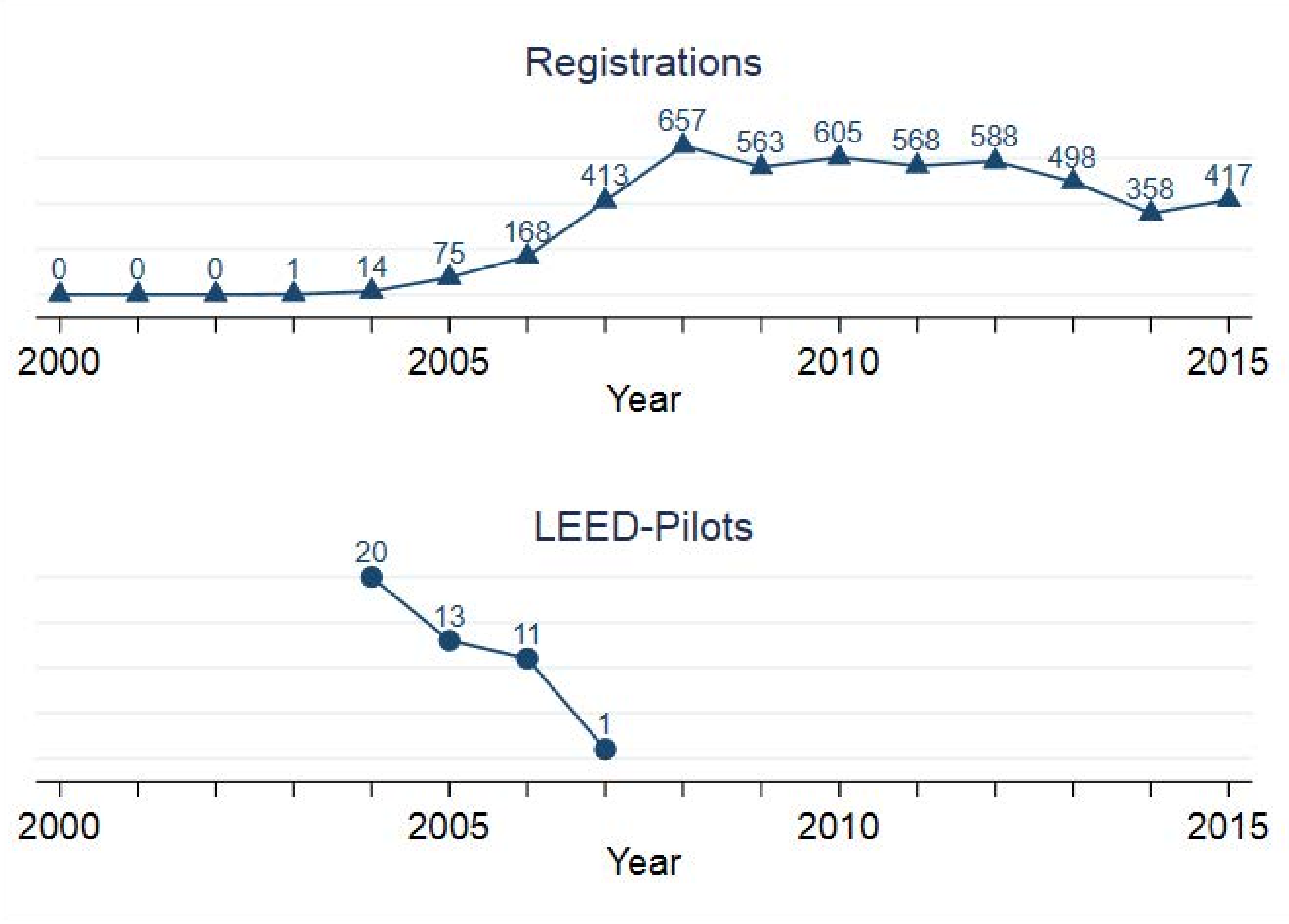

LEED Regular Projects
LEED-Pilot Projects
Population Density (person/sq. km)
18,230
0.01

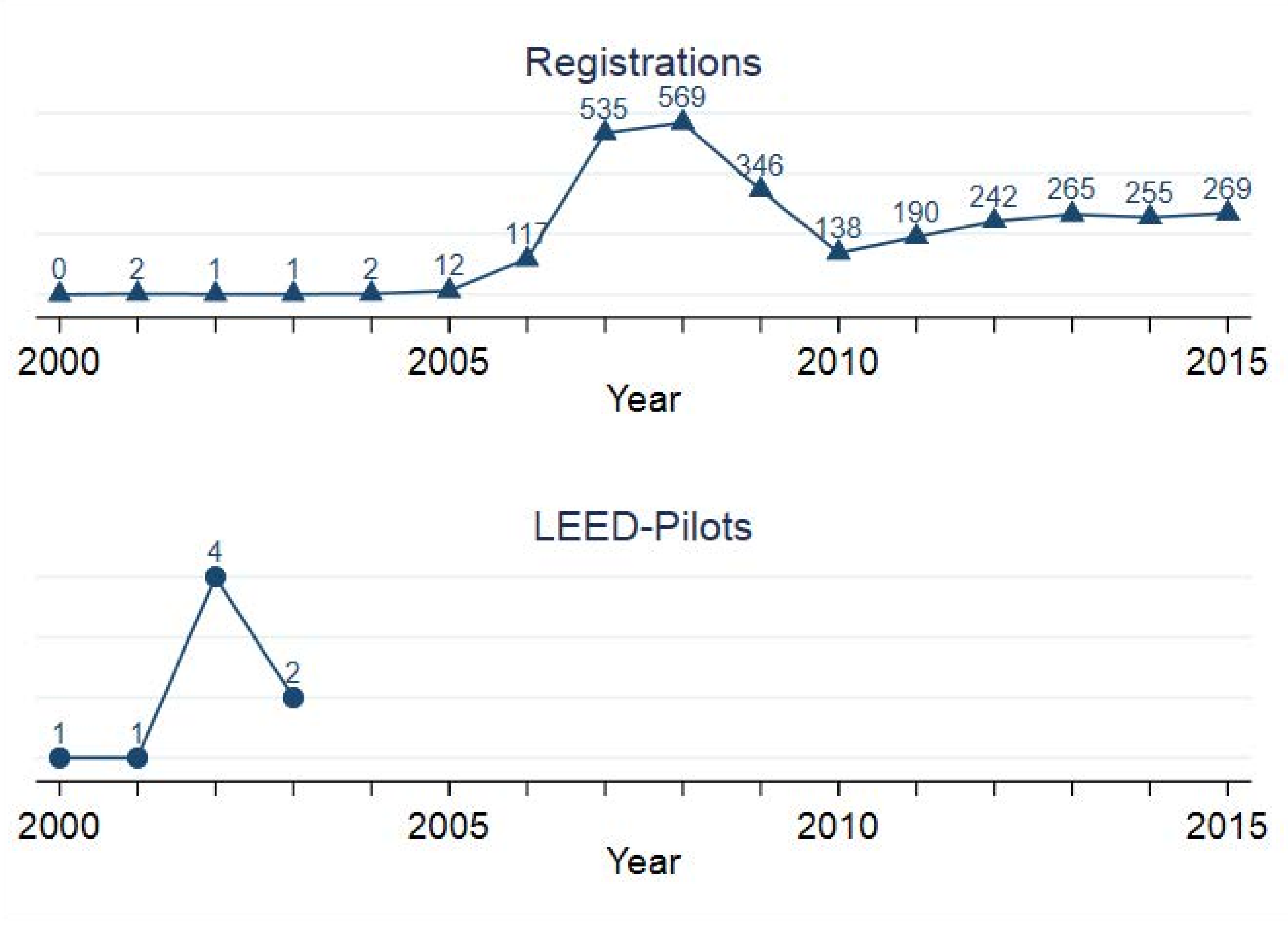


Registrations
18
72
93
139
244
405
541
1361
1718
1549
842
926
848
810
675
666
2000
2005
2010
2015
Year
LEED-Pilots
1
1
4
2
2000
2005
2010
2015
Year

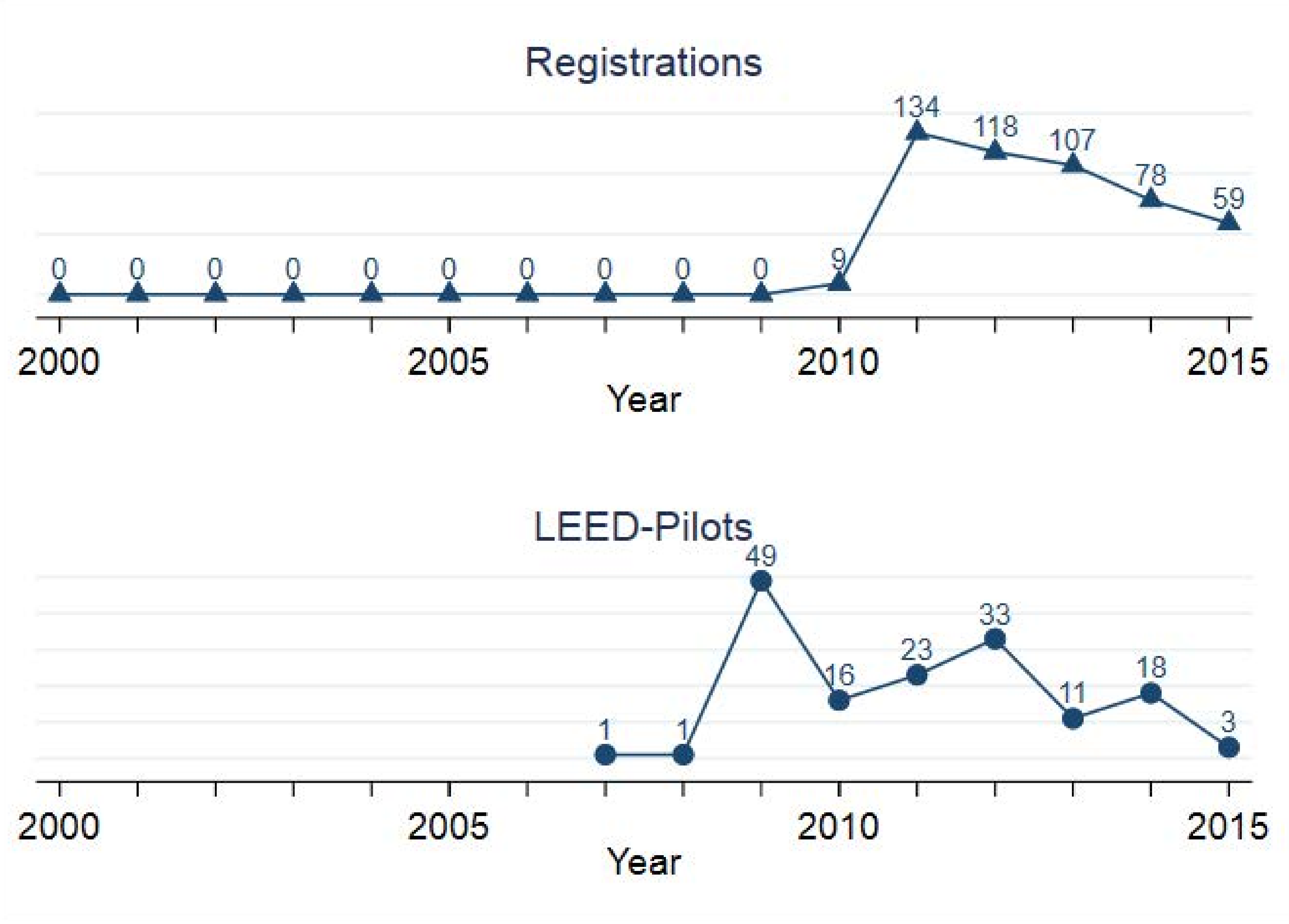


Registrations
0
0
0
3
11
20
48
242
689
1246
573
498
625
496
646
591
2000
2005
2010
2015
Year
LEED-Pilots
1
10
8
3
2000
2005
2010
2015
Year

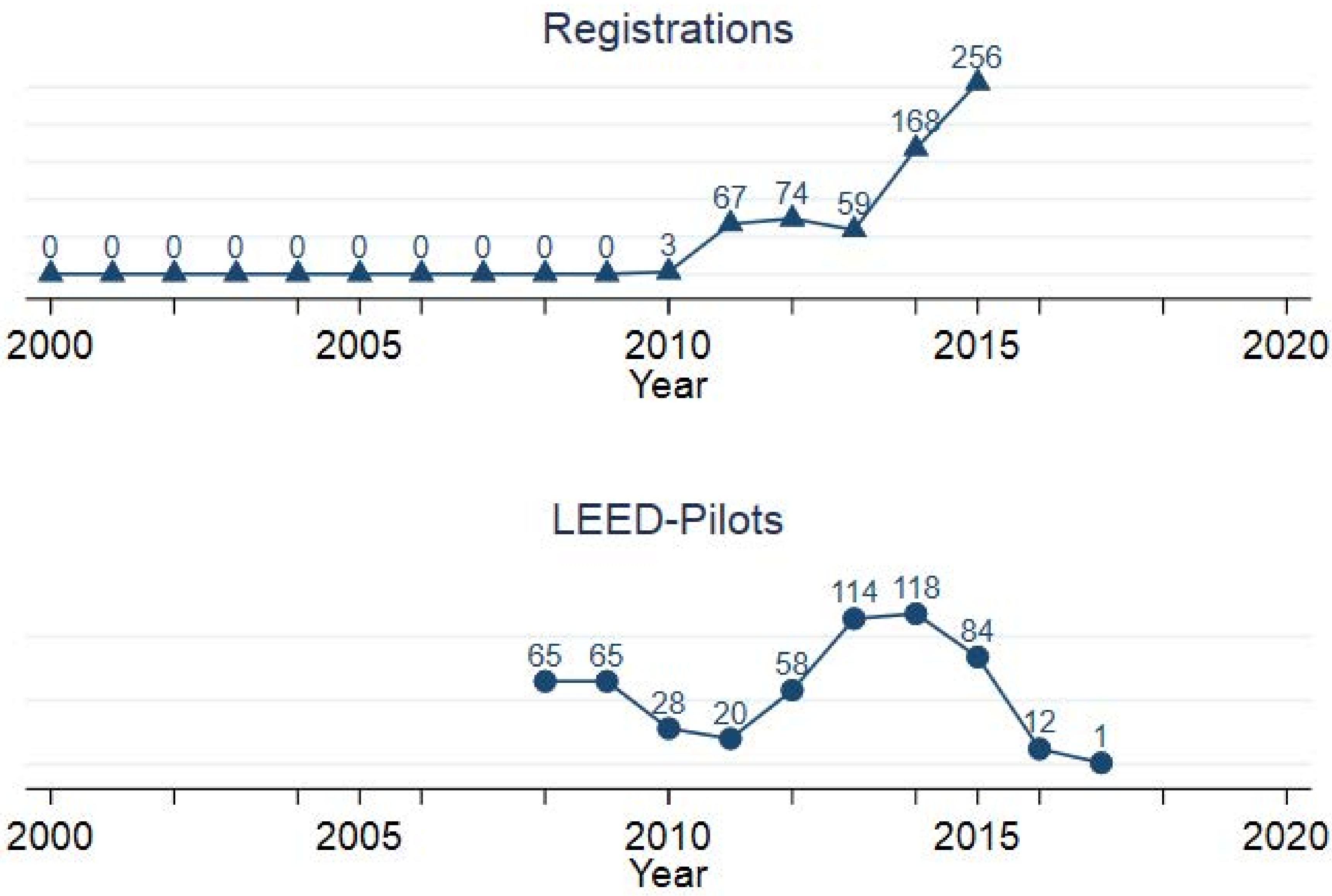

Registrations
0
0
0
1
14
75
168
413
657
563
605
568
588
498
358
417
2000
2005
2010
2015
Year
LEED-Pilots
20
13
11
1
2000
2005
2010
2015
Year

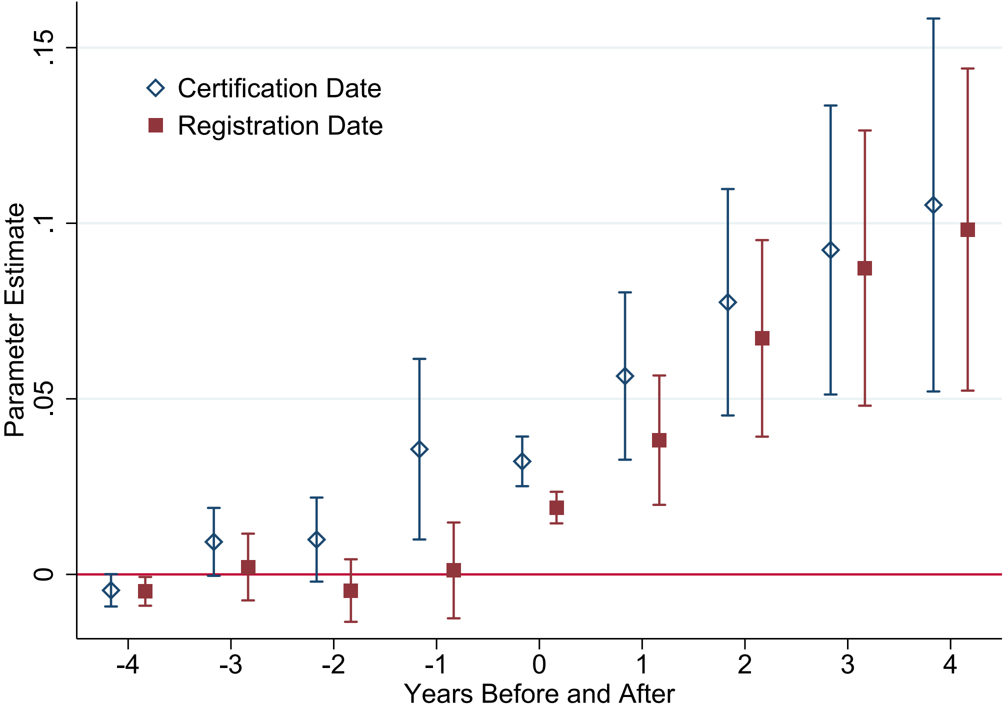


Registrations
0
2
1
1
2
12
117
535
569
346
138
190
242
265
255
269
2000
2005
2010
2015
Year
LEED-Pilots
1
1
4
2
2000
2005
2010
2015
Year

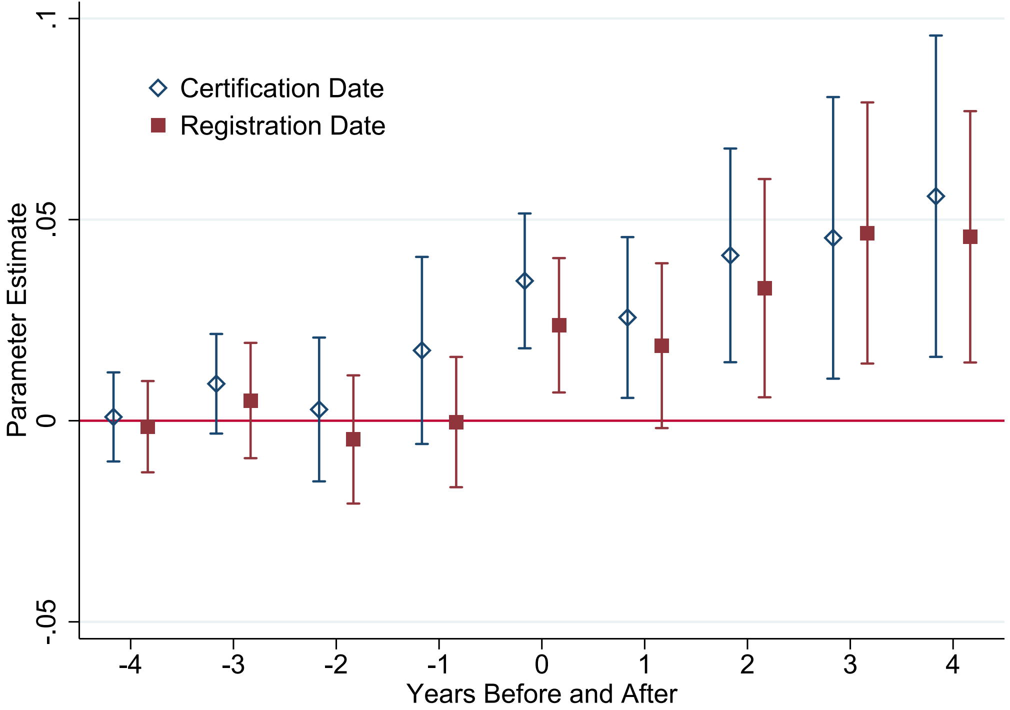


Registrations
134
118
107
78
59
0
0
0
0
0
0
0
0
0
0
9
2000
2005
2010
2015
Year
LEED-Pilots
49
33
23
16
18
11
1
1
3
2000
2005
2010
2015
Year

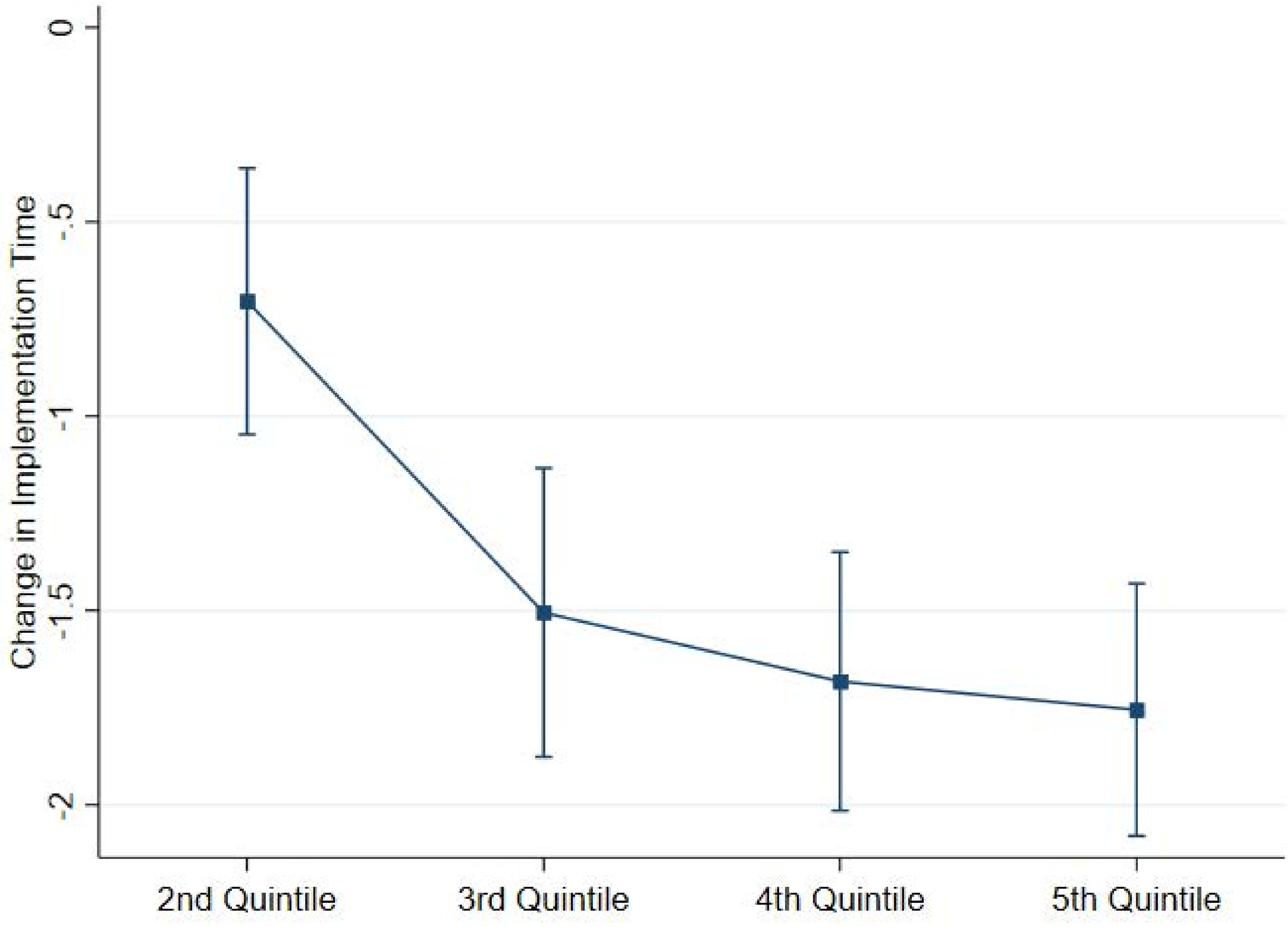

Registrations
0
0
0
0
0
0
0
0
0
0
3
67
74
59
168
256
2000
2005
2010
2015
2020
Year
LEED-Pilots
65
65
28
20
58
114
118
84
12
1
2000
2005
2010
2015
2020
Year

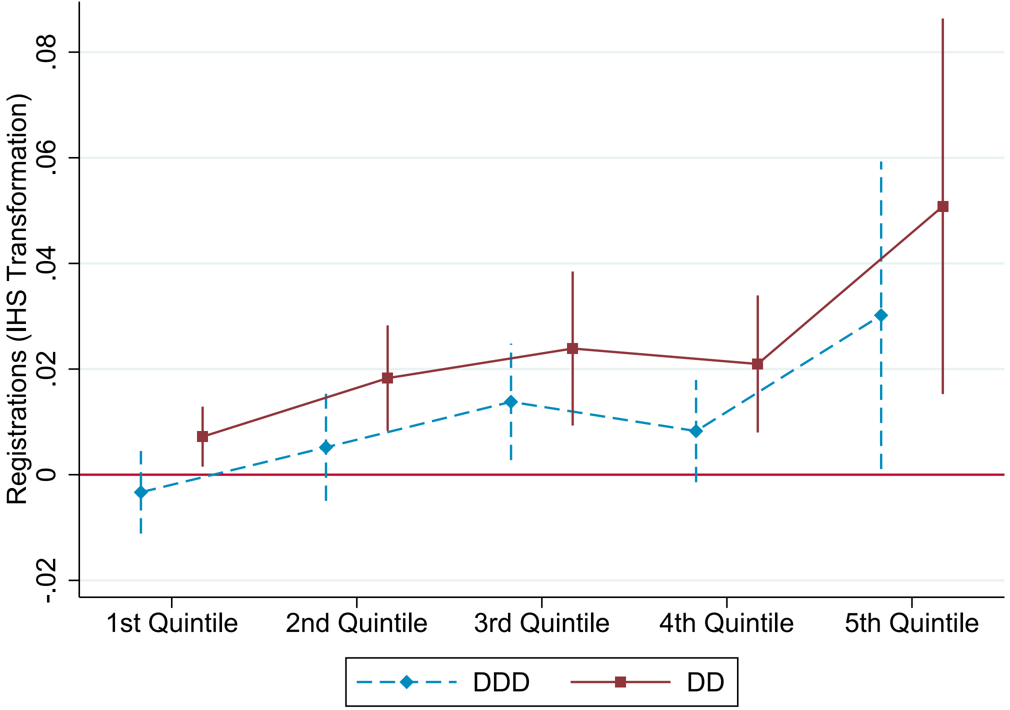


Certification Date
Registration Date
Parameter Estimate
.15
.1
.05
0
-4
-3
-2
-1
0
1
2
3
4
Years Before and After



Certification Date
Registration Date
Parameter Estimate
.1
.05
0
-.05
-4
-3
-2
-1
0
1
2
3
4
Years Before and After


0
-.5
-1
-1.5
-2
Change in Implementation Time
2nd Quintile
3rd Quintile
4th Quintile
5th Quintile


Registrations (IHS Transformation)
-.02
0
.02
.04
.06
.08
1st Quintile
2nd Quintile
3rd Quintile
4th Quintile
5th Quintile
DDD
DD