Green Neighbors, Greener Neighborhoods: Peer Effects in Residential Green Investments*

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Abstract

Utilizing a nearest-neighbor research design, I find that households exposed to green neighbors within 0.1 miles are 1.6 times more likely to make their homes green within a year than the unexposed households. The exposure also increases the likelihood of multi-property owners greening their faraway secondary properties, indicating that information transmission, not local characteristics, drives the effect. While financial benefits of green homes—house prices, electricity savings, and regulatory incentives—strengthen the peer effects, pro-environmental household preferences do not. An information-cost-based theory model explains the findings and emphasizes that aligning green subsidies with peer effects can accelerate residential green investments.

JEL Classification: D12, D14, G51, Q54, R23, R31.

Keywords: Causal Neighborhood Peer Effects; Household Residential Green Investments; Nearest-Neighbor Design.

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Energy efficient homes deliver both environmental benefits, such as lower greenhouse gas (GHG) emissions, and potential financial gains, such as utility savings. Yet almost 98 percent of the single-family homes in the US remain non-certified for energy efficiency in 2022. With the residential sector contributing almost 20 percent of the annual GHG emissions (EPA, 2024), understanding the factors that facilitate or hinder households from investing in energy efficiency can help shape the global efforts towards sustainability and achieving the emission reduction goals (IEA, 2019).

This paper focuses on the decision of households to adopt green technologies for their homes. Investing in such green technologies is distinct from investing in other financial assets because the pro-environmental outcomes are direct and immediate (e.g., reduced GHG emissions), a topic of interest to policymakers aiming to accelerate the green transition. Moreover, while the financial assets come with well-developed advisory and intermediary markets and are often the focus of popular discourse, much less is discussed on how to invest in residential green technologies. These are lumpy and irreversible investments, often financed also through debt. The decision is highly idiosyncratic and informationally complex. It requires assessing the compatibility, geometry, and construction materials of the homes, microclimate, and local zoning and utility tariff structure (California Energy Commission, 2008). The benefits are often uncertain, complex to assess, spread over a long time horizon, and vary substantially across areas. Not surprisingly, informational unawareness is one of the key reasons that such investments are sparse.[1]

This paper is a step towards understanding how households overcome these informational challenges by utilizing peer networks. This is particularly relevant for residential green investments at least two reasons. First, peer network has been shown to be an important source of information for households in making complex financial decisions, such as mortgage refinancing and repayments (Maturana and Nickerson, 2019; W. B. McCartney and Shah, 2022; Gupta, 2019), property investment (Bayer et al., 2021; Bailey, Cao, Kuchler, and Stroebel, 2018), and consumption (Bailey et al., 2022). I ex-

[1] See Matisoff et al. (2016); Howarth and Andersson (1993); Ramos et al. (2015) and Giraudet (2020).

amine the role of neighbor peers on the decision of households to invest in residential green technologies, as households often rely on the real-life experiences and outcomes of their neighbors when information from other sources is scarce or unclear. Second, understanding the peer effect provides a promising tool for policymakers to enhance the effectiveness of policies promoting sustainable practices.

In this paper, I build a simple model of peer effect in which peers reduce the cost of information for households and empirically confirm the predictions in a causal manner using a nearest-neighbor research design applied to a nationwide novel data on green certifications of single-family homes. The empirical findings suggest that the peer effect is driven by information transmission among neighbors. Further analysis reveals that financial benefits are more important than green preferences in motivating households to seek information from neighbor peers about investing in residential green technologies. Finally, the distribution of regulatory incentives across counties is not in line with the pattern suggested by the first best.

In the theoretical model, the modal decision of the households is whether to adopt the costly but new green technologies for their homes. Households derive utility from installing the technologies, and paying cost of installation and information. As the number of neighboring peer households who have already adopted the technology increases, the cost of information reduces. Furthermore, in areas where green technology adoption is beneficial, households are incentivized to seek out localized information about the costs and benefits. Therefore, the presence of more adopting neighbors helps further reduce the uncertainty and assessment costs associated with these green investments. Utility maximization in this environment yields two testable implications. First, the larger the number of neighbors who have adopted green technologies in their homes, the more likely is a focal household to do so, henceforth referred to as the *green peer effect*. Second, this effect is heterogeneous across areas. The strength of peer effect is stronger in areas where green homes enjoy additional potential benefits. Adding to the model such households who have preference for green technologies (that is, those who gain additional utility from the adoption) suggests that adoptions are correlated with the number of such households, but the strength of the peer effect is not. The model also highlights that the level of adoption by households is not socially-optimum, because households do not account for the (positive) effect of their adoption decision on their neighbors. Such inefficiency could be reduced by subsidies targeted to areas where the green-peer effects are stronger.

A causal examination of the neighborhood peer effect faces two key challenges. First, the assignment of neighbor peers is rarely random; and second, the households within a neighborhood may be exposed to some common but unobservable shocks that confound the estimated effects (Manski, 1993). A nascent literature on causal neighborhood peer effect addresses these challenges using nearest-neighbor research design (Bayer et al., 2021, 2022; W. B. McCartney and Shah, 2022; Towe and Lawley, 2013; W. McCartney et al., 2023). I follow the research design of Bayer et al. (2021). The idea is to estimate the effect of green investment decisions by hyper-local neighbors (within 0.1 miles) on decisions of the focal households to do the same, while adjusting for the investments occurring within the slightly broader neighborhoods of 0.3 and 0.5 miles. It leverages two features of the single-family housing market. First, the thinness of the housing market in a small neighborhood of 0.3 and 0.5 miles restricts a household's ability to freely select a specific block within 0.1 miles, resulting in the quasi-randomly assigned neighbors. Second, household and property characteristics remain broadly similar across such small areas (of 0.1 and 0.5 miles), making it unlikely that the estimated difference in the investments are caused by some unobserved characteristics.

For the empirical analysis, I assemble a novel dataset on green certifications of single-family homes nationwide from Green Building Registry (GBR). A green certificate is an official recognition that a building or property meets specific environmental and sustainability standards. I define a house to be green certified if its score (or rating category) exceeds that of an average US home, and use the certification status as a proxy for investments in residential green technologies.[2] This is based on the idea that

[2] In section 6, I document that (i) the zipcode-level number of certifications is positively correlated with residential energy tax credits, which are claimable only for verified residential green improvements (Table B.1); (ii) green homes are more likely than non-green homes to have verified investments occurring within one year prior to the green certification date, where verified investments are proxied by building

green investments and certifications work in conjunction, with certification standards providing guided information for implementing green investments.

I measure green exposure of a focal household as the number of neighbors within d miles who green certified their homes for the first time in the past four quarters. Regressing certification status of a focal household on its green exposure within ($d =$) 0.1 miles, while controlling for that within 0.3 and 0.5 miles, yields the causal estimates of the effect of green peers. I find that one additional green neighbor within 0.1 miles raises the probability of a household also investing in residential green technologies by 1.6 times within the subsequent year. This effect is sizable relative to the reported peer effects of 8% for property investments (Bayer et al., 2021) and 3.3% for refinancing (W. B. McCartney and Shah, 2022). Also it is robust to the inclusion of granular fixed effects for spatial (zipcode), temporal (year-quarter), and a host of property and neighborhood controls. This finding is in line with the information-induced green peer effect predicted by the model.

I further examine the mechanism by focusing on the green investments by multi-property owners (MPOs) in their secondary properties located in faraway neighborhoods. I find that the number of green neighbors located close to MPOs' primary home (where they currently live) has a positive effect on MPOs' decision to invest in green technologies for their secondary properties. This suggests that MPOs receive information from their immediate green neighbors and adopt green technologies in their secondary properties. This pattern is also inconsistent with the alternative explanation that the positive effect of immediate green neighbors may have been driven by some unobserved characteristics of the neighborhood, such as contractor availability or marketing events.

Two additional findings lend support to the information channel. First, the focal households are more likely to choose the same green certificates, similar investment specifications, and the same lenders as their immediate neighbors (within 0.1 miles) compared to those slightly farther away (0.1 to 0.5 miles), shedding light on the *type* of

permits (Table B.2); and (iii) green investments as proxied by certifications are financially beneficial (Table B.3 and B.4).

information sought by the focal households. Second, the green-peer effect is stronger in areas with a higher strength of local community interactions, characterized by stronger social ties and fewer non-owner-occupied properties. These findings highlight the role of *ease* of information flow in driving the peer effect.

I also find that the green-peer effect is more pronounced in counties experiencing statistically significant premium for green home and also in areas that have above-median electricity savings potential (proxied by marginal retail electricity prices) and above-median number of regulatory financial incentives to invest in residential green technologies. At the same time, the effect is not statistically different across counties above and below the median share of households concerned about climate change or across counties above and below the median per household electric vehicles purchases. Moreover, the green-exposed households who invest in residential green technologies earn higher returns on housing transactions than the similarly-exposed households who do not invest. Collectively these findings emphasize that households' motivation to seek information from peers about investments in residential green technologies is largely shaped by financial motives than by green preferences, in line with the predictions of the model.

An important policy implication of the model is that in presence of peer effects, investments in residential green technologies would be lower than the first-best level and targeting the investment incentives to areas with stronger peer effects would deliver more bang for the buck. Analyzing the distribution of green incentives across counties reveals a disconnect. The number of regulatory incentives are not higher in areas characterized by stronger peer effects.

Several aspects of this paper are novel. It is one of the first studies documenting causal peer effects in household investments in residential green technologies. It is also the first to apply the nearest-neighbor design on a national scale, which is a computationally intensive task.[3] Furthermore, leveraging the unique features of housing

[3] Nearest-neighbor design in previous studies has been implemented on smaller geographies, such as one county (W. B. McCartney and Shah, 2022), a few metropolitan statistical areas, (Bayer et al., 2021) or one state (Bayer et al., 2022).

markets, it not only emphasizes the role of information transmission in peer effects but also is able to empirically document (in section 6) that the effects are unlikely to be solely driven by "keeping-up-with-the-Joneses" or conspicuous consumption preferences.

This paper contributes to the literature on information-induced peer effects in household financial decisions. Peer effects have been shown in stock market participation (Hong et al., 2004; Brown et al., 2008), property investment (Bayer et al., 2021; Bailey, Cao, Kuchler, and Stroebel, 2018), refinancing (Maturana and Nickerson, 2019; W. B. McCartney and Shah, 2022), repayments (Gupta, 2019), and consumption (Bailey et al., 2022). I add to this literature by showing that households use information from their neighbor peers to make informationally-complex decisions to invest innovative green technologies in their residential properties.[4] Peer effects have also been shown for solar panels (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Müller, 2021; Bigler and Janzen, 2023) and residential landscaping (Bollinger et al., 2020), both of which are applicable only to a subset of properties. My paper however examines the green technologies that are comprehensive and applicable to nearly all properties and differs significantly in terms of mechanism, empirical design and scope.[5] My paper also complements Qiu et al. (2016) who document spillovers in green certifications of institution-owned commercial buildings. Insights from my paper are significantly distinct since households are more likely to suffer from informational issues and financial constraints.

[4] My paper is also related to the literature on home improvement (Montgomery, 1992; H. Choi et al., 2014; Melzer, 2017) and specifically focuses on an environmentally-focused form of home improvement. Additionally, by using green certification as a measure, my paper provides a uniform way to quantify green investments, setting it apart from the more subjective assessments used in other paper.

[5] First, my paper focuses on how financial incentives influence peer effects in obtaining green certifications in housing markets, whereas other studies primarily examine the presence of spillovers in green practices without addressing housing market conditions or financial benefits. Second, my paper uses a nearest-neighbor design for causal estimates in local settings, as opposed to the OLS and IV methods in Bollinger and Gillingham (2012); Bigler and Janzen (2023); Bollinger et al. (2020). Third, my paper analyzes households' decisions to invest in residential green technologies—an extensive margin outcome of real property investments—while Bigler and Janzen (2023) focuses on electricity consumption, EV adoption, and PV installation. They do not distinguish whether electricity consumption reduces due to increased efficiency or due to cutting consumption. Similarly, they do not distinguish whether EV and PV adoption is caused by demand-side factors (such as financial motives and green preferences) or the supply-side factors (such as regulatory incentives and cheaper financing).

The paper also contributes to the literature on households' pro-environmental decisions. While environmental concerns have been shown to influence their decisions on retirement portfolio (Anderson and Robinson, 2019), investment portfolio (D. Choi et al., 2020; Fisman et al., 2023; Ilhan, 2020), and consumption (Gargano and Rossi, 2024), this paper focuses on their decisions to invest in residential green technologies that directly reduce GHG emissions. Literature has highlighted the debate between pro-environmental preferences and financial motives in driving households' sustainable investments (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019; Barber et al., 2021; Bauer et al., 2021; Giglio et al., 2023). I document that investments in residential green technologies is financially beneficial and financial motives play a larger role than green preferences in driving peer effects.

The rest of the paper is organized as follows. Section 1 presents the theoretical model. Section 2 describes the institutional background of residential green investments and certification, and Section 3 describes data and presents summary statistics. Section 4 illustrates the empirical strategy. Section 5 is centered on the results. Section 6 provides additional analyses, and section 7 concludes.

1 Theoretical Framework

To guide the empirical analysis, I build a theoretical model of peer effects following Boucher et al. (2024); Cornelissen et al. (2017) and Lee et al. (2021). In this model, the key choice a household faces is whether to adopt green technologies $g_i \in \{0, 1\}$ for his or her house, where $g_i = 1$ represents the adoption. The decision involves trading off the benefits and the costs of the adoptions in a utility maximization framework. The components of the model are described below.

A. Benefits

Adopting green technologies results in a utility gain for households from direct private benefits such as lower utility bills and increased comfort of green homes. As in Garbin (2021); Lambotte et al. (2023) and Lee et al. (2021), this gain is assumed to be linear in household- and neighborhood-level characteristics.[6] The payoff a household receives from adopting green technologies for his or her house is $\Pi_i(\cdot)$:

$$\text{Payoff}_i(g_i) = [\Pi_i(\cdot)]g_i, \text{ where } \Pi_i(\cdot) = \sum_{m=1}^{M} \beta_m x_i^m + u_i \,. \tag{1}$$

Here m indexes the household- and neighborhood-level characteristics, and u_i is unobservable (to the econometrician) characteristics of household i.

B. Costs

Households incur two types of cost to install green technologies. The first is an explicit private adoption cost $C_i^P(\cdot)$. It includes the costs such as the cost of material, labor, and maintenance. For simplicity and in line with Lambotte et al. (2023) and Cornelissen et al. (2017), this explicit private cost is assumed to be quadratic in the modal decision variable g_i:

$$C_i^P(g_i) = \frac{1}{2}\kappa g_i^2. \tag{2}$$

The second type of cost is an implicit information cost that arises because households cannot install the technologies in their homes without first gaining awareness about them and then assessing the potential private benefits and costs of the adoptions. Given that green technologies are new and not widespread, such information costs become especially relevant for households.

This information cost consists of two components. The first component C_i^1 is the cost of becoming aware about the existence of the technologies and acquiring general information about the benefits and costs of the technologies (Xiong et al., 2016), also known as awareness-knowledge (Rogers et al., 2014). Focal households incur cost F_1 to acquire such general information. Social interaction with their neighbor peers who have already adopted the technologies is a potential source of this information for focal households. Hence, the cost C_i^1 decreases as the number of peer adopters increases:

$$C_i^1(g_i, \boldsymbol{g}_{-i}) = F_1 g_i - \left(\nu_1 \sum_{j \neq i} g_j\right) g_i = F_1 g_i - (\nu_1 \tilde{g}_{-i}) g_i, \text{ where } \tilde{g}_{-i} = \sum_{j \neq i} g_j. \tag{3}$$

[6] This term is similar to the private utility in Lambotte et al. (2023), individual productivity in Lee et al. (2021), private deterministic component in Garbin (2021), and individual effects in Boucher and Bramoullé (2020).

The second component C_i^2 of the information cost results from the knowledge specific to the broader neighborhoods and specific to the homes that focal households need to acquire to estimate the net potential benefits of adopting the green technologies.[7] Accordingly, conditional on broader-neighborhood-level assessment revealing that adopting the technologies in these areas is potentially beneficial ($K_a = 1$), focal households further undertake home-specific assessments. These assessments are costly (F_2) and uncertain. The assessment accuracy improves with the number of neighbor peers who have already adopted the technologies, reducing the cost F_2 as follows:[8]

$$C_i^2(g_i, \boldsymbol{g}_{-i}) = K_a(F_2 - \nu_2 \tilde{g}_{-i})g_i. \tag{4}$$

Overall, the total cost of adopting green technologies for a household i is:

$$\begin{aligned}\text{Cost}_i(g_i, \boldsymbol{g}_{-i}) &= C_i^P(g_i) + C_i^1(g_i, \boldsymbol{g}_{-i}) + C_i^2(g_i, \boldsymbol{g}_{-i}) \\ &= \frac{1}{2}\kappa g_i^2 + F_1 g_i - (\nu_1 \tilde{g}_{-i})g_i + K_a(F_2 - \nu_2 \tilde{g}_{-i})g_i.\end{aligned} \tag{5}$$

C. Utility Maximization and Model Implications

The utility function of a household i is:

$$\begin{aligned}u_i(g_i, \mathbf{g}_{-i}) &= \text{Payoff}_i(g_i) \; - \; \text{Cost}_i(g_i, \boldsymbol{g}_{-i}) \\ &= \Pi_i(\cdot)g_i - \left[\frac{1}{2}\kappa g_i^2 + F_1 g_i - (\nu_1 \tilde{g}_{-i})g_i + K_a(F_2 - \nu_2 \tilde{g}_{-i})g_i\right] \\ &= \Pi_i(\cdot)g_i - \frac{1}{2}\kappa g_i^2 - F_1 g_i - K_a F_2 g_i + (\nu_1 \tilde{g}_{-i})g_i + (\nu_2 K_a \tilde{g}_{-i})g_i.\end{aligned} \tag{6}$$

This utility function of focal households to adopt green technologies is shaped by the neighbor peers who have adopted green technologies ($\tilde{g}_{-i}$) in two distinct ways. First, the peers act as a source of information by lowering the cost of becoming aware about the green technologies ($\nu_1 \tilde{g}_{-i}$). Second, conditional on being located in areas that have

[7] For example, the potential utility savings under HERS requires assessment of specific information about the broader neighborhood characteristics such as local climate (measured at city or zipcode level), ground reflectivity, building zone, and utility tariffs. Furthermore, the assessment is sensitive to the home characteristics such as materials used in and geometry of walls, floors, attics, and roofs; HVAC and water heating systems; and internal air circulation and leakages (California Energy Commission, 2008). In addition, the availability of the contractors and cost of installing the technologies vary across broader neighborhoods (Dorsey and Wolfson, 2024).

[8] Here the reduction in cost f_2 is understood as the certainty equivalent of the assessment process.

potential benefits of green technologies ($K_a = 1$), peers also lower the cost of learning the localized information ($\nu_2 K_a \tilde{g}_{-i}$).

The first-order condition (FOC) for maximization of this utility yields the following:

$$g_i = \frac{\Pi_i(\cdot) - F_1 - K_a F_2}{\kappa} + \frac{\nu_1 + \nu_2 K_a}{\kappa}\tilde{g}_{-i} = \frac{\Pi_i(\cdot)}{\kappa} + \frac{\nu_1}{\kappa}\tilde{g}_{-i} + \frac{\nu_2 K_a}{\kappa}\tilde{g}_{-i}.$$

Normalizing κ to one, the FOC becomes:

$$g_i = [\Pi_i(\cdot) - F_1 - K_a F_2] + \nu_1 \tilde{g}_{-i} + \nu_2 K_a \tilde{g}_{-i}. \tag{7}$$

Thus a utility-maximizing household i's decision to adopt green technologies is linked to the number of its green neighbor peers $\tilde{g}_{-i}$ through two sensitivity terms: ν_1 and $\nu_2 K_a$. This leads to the following testable implications:

IMPLICATION 1 (Peer Effects due to Information Transmission): *The decision of a focal household i to adopt the green technologies depends on its neighbor peers who have already adopted the technologies. The decision sensitivity of focal households to peers' decisions (the peer effect) is ν_1.*

IMPLICATION 2 (Heterogeneity in Peer Effects due to Financial Benefits): *In areas characterized by $K_a = 1$, the decision sensitivity of the focal household i to its peers g_{-i} to adopt green technologies increases from ν_1 to $(\nu_1 + \nu_2)$. Such areas are those where adopting green technologies delivers additional financial benefits relative to other areas.*

D. The Role of Green Preference in Adoption of Green Technologies

The model above accounts for the economic costs and benefits of adoption of green technologies, but omits the possibility that the adoption decisions of households could also be driven by non-financial objectives such as their preference for taking actions related to sustainability or preventing global warming. I extend the model below to account for such green preferences. The households with green preferences ($p_i = 1$) are modelled to receive additional utility δ from adopting green technologies. The utility function and the FOC (with κ normalized to one) are as follows:

$$\text{Utility: } u_i(g_i, \mathbf{g}_{-i}, p_i) = [\Pi_i(\cdot) - F_1 - K_a F_2]\, g_i - \frac{1}{2} g_i^2 + (\nu_1 \tilde{g}_{-i}) g_i + (\nu_2 K_a \tilde{g}_{-i}) g_i + (\delta p_i) g_i. \tag{8}$$

$$\text{FOC: } g_i = [\Pi_i(\cdot) - F_1 - K_a F_2] + \nu_1 \tilde{g}_{-i} + \nu_2 K_a \tilde{g}_{-i} + \delta p_i. \tag{9}$$

The FOC suggests that household i's decision to adopt green technologies is also linked to their green preference p_i through sensitivity term δ. This leads to the following implications:

IMPLICATION 3 (Green Adoption Decisions and Green Preferences): (i) *A focal household with green preference is more likely to adopt green technologies than a focal household without such preference.* (ii) *The decision sensitivity of focal households to peers' decisions* (*the peer effect*) *does not depend on their green preferences.*

E. Social Optimum and Policy Implications under Peer Effects

In the presence of peer effects, the decision function of individual households do not internalize the positive effect they have on the adoption decisions of other not-yet-adopting households. Thus the level of adoptions remains below the socially optimum level. To see this, consider a social planner who maximizes the sum of the utility of all households by choosing $\mathbf{g}$, the adoption decision $g_1, g_2, \ldots g_n$ of each household i with green preference p_i. The social planner maximizes $\mathcal{U}(\mathbf{g}, \mathbf{p})$ by choosing $\mathbf{g}$ as follows:

$$\max_{\mathbf{g}} \mathcal{U}(\mathbf{g}, \mathbf{p}) = \sum_i u_i(g_i, \mathbf{g}_{-i}, p_i), \tag{10}$$

where utility $u_i(g_i, \mathbf{g}_{-i}, p_i)$ is from (8). The FOC below gives the socially optimal level of adoptions:

$$g_i^o = [\Pi_i(\cdot) - F_1 - K_a F_2] + \nu_1 \tilde{g}_{-i} + \nu_2 K_a \tilde{g}_{-i} + \delta p_i + \underbrace{\left\{ (\nu_1 + \nu_2 K_a) \sum_j \left(g_j \frac{\partial \tilde{g}_{-i}}{\partial g_i} \right) \right\}}_{\text{non-internalized effect}}. \tag{11}$$

Comparing the FOC of the social planner with that of individuals from equation (9) shows that the aggregate level of adoptions without intervention by social planner will remain below the socially optimum level due to the non-internalized effect. This leads to the following implication:

IMPLICATION 4 (Policy Implications in Presence of Peer Effects): *The aggregate adoptions are inefficient and below the socially-optimum level when households optimize individually. This inefficiency is higher when peer effects are stronger, for example, when ν_1 is higher or when $K_a = 1$. Allocating more subsidies to such areas reduces the inefficiencies.*

2 Institutional Background

A green certificate, often referred to as a "green building certificate" or "sustainability certification," is an official recognition that a building or property meets specific environmental and sustainability standards and is typically issued by recognized organizations. Such certifications commonly assess elements such as site, water, energy, indoor air quality, materials, operation, and maintenance. For example, the Home Energy Rating System (HERS)—the most popular certification program in the US—evaluates various aspects of a home's energy efficiency, including insulation levels, air leakage, HVAC system performance, and overall energy consumption. The certification process involves comprehensive requirements and on-site inspections to ensure accurate energy efficiency assessments.[9] As a result, meeting these standards usually requires significant investment in green upgrades or remodeling, making green certification a valid proxy for residential green investment. Figure I provides sample green certification reports of HERS and HES programs, along with a word cloud of these reports.

This paper focuses on 15 residential green certification programs across the US, including both nationwide and local certifications. Residential green certification experienced notable growth starting from 2010, as shown in Panel A of Figure A.1. As of November 2022, these programs had certified about 1.5 million single-family properties. Panel B illustrates the spatial distribution of green certifications in terms of the proportion of green-certified single-family properties across counties in 2022. Counties in metropolitan areas exhibit a higher concentration of green-certified homes. Panel A of Figure A.2 provides the distribution of the residential green certification programs. HERS comprises approximately 94% of all certified homes. Panel B of Figure A.2 shows that utility savings are positively correlated with energy efficiency levels. Table I summarizes the programs by geographical coverage, attributes evaluated, and green contractors required. Among the 15 certification programs, six operate across the US and the remainder operate regionally. Programs also vary widely across the attributes they

[9] Figure A.3 provides examples of green certification technical standards; more technical details are available in California Energy Commission (2008) and The Department of Energy (2010).

evaluate: some focus exclusively on overall home energy efficiency (e.g., HERS and the Home Energy Score (HES)), while others adopt a more comprehensive approach by also focusing on environmental performance and building materials (e.g., Earth Advantage® Certifications).

Investments in residential green technologies are closely aligned with certification standards, which provide guided information for these investments. The certification process typically follows one of two pathways: using a green contractor or owner-directed. In the first, homeowners directly invest in a green renovation by hiring a green contractor affiliated with a certification organization. The contractor follows set guidelines during the remodeling and coordinates with a program rater to certify the property. In the second, homeowners customize their green renovations by specifying certification requirements in advance, allowing any contractor to complete the work according to these standards. Upon completion, homeowners independently hire a rater to assess and certify the home. Examples on the certification processes are provided in the Figure A.4.

3 Data, Sample Construction, and Summary Statistics

3.1 Data

The main empirical analysis utilizes two datasets: property, deed and mortgage data compiled by The Warren Group (n.d.) from county records offices and green certification data from the Green Building Registry (GBR) (Earth Advantage Inc., n.d.). The property data cover more than 155 million properties in the US and contain information on their geolocations, addresses, and property characteristics such as year built, living area, number of bedrooms, exterior materials, fuel type, heating system etc. The deed and mortgage data contain 104 million records of housing and mortgage transactions from 2018 to 2022. These include information such as the sale price, sale date, names of buyers and sellers, sale type, mortgage details (e.g., type, amount, term, interest rate), and the lender names. The GBR is the largest database of the green performance of residential and commercial properties in the US, containing over 2 million observations. From their website, I collected geolocations and addresses of the properties, as well as the associated historical records of certification type, certifying entity, certification date, and green rating. Using the geolocations and addresses, I match the property, deed, mortgage, and green certification data.

I also make use of the following datasets. To measure residential electricity pricing, I follow Borenstein and Bushnell (2022) and use data mainly from the Energy Information Administration's Form EIA-861 survey (EIA, n.d.) and the National Renewable Energy Laboratory's Utility Rate Database (URDB) (National Renewable Energy Laboratory, n.d.). To measure regulatory incentives for residential green investments, I use the Database of State Incentives for Renewables & Efficiency (DSIRE). For climate-related beliefs and green preferences of households, I use the Yale Climate Opinion Maps (Howe et al., 2015) and state EV registration data from the Atlas EV Hub. Home improvement loan data is obtained by matching records from housing and mortgage transactions with publicly data from the Home Mortgage Disclosure Act (HMDA). Building permit data is sourced from Buily Inc. (n.d.). I utilize community interaction measures from Bailey, Cao, Kuchler, Stroebel, and Wong (2018), Chetty et al. (2022), and Rupasingha et al. (2006, with updates), Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko et al. (2008) and Gyourko et al. (2021), and a range of socioeconomic and demographic data from the U.S. Census, IRS SOI, and HUD.

3.2 Sample Construction

I process the green certification data by first examining each of the 15 certification programs and their scores (or rating categories). I then create an indicator—Green—to uniformly represent the green certification status across these programs. This indicator takes the value of one when the score (or rating category) assigned to a given property under a given program exceeds that of an average US home.[10] Table I pro-

[10] Consider for example, the scores under the Home Energy Score (HES) Program. A score of 5 indicates energy efficiency equivalent to that of an average US home, 10 indicates the top ten percentile, and 1

vides thresholds for the scores (or rating categories) under each program. I define a property to be green certified when it crosses the threshold under any of the programs for the first time.

I broadly follow Bayer et al. (2021) to process the property transaction data. I categorize the property ownership into individuals, trusts, banks, business, government and nonprofit organizations, and focus on the properties owned by individuals (households). I then exclude the following records: (i) if a property was subdivided and resold; (ii) if the house was sold for less than \$1 or marked as a non-arms-length transaction; (iii) if a house changed hands more than once within a single day; or (iv) if there are potential data inconsistencies like a transaction year earlier than the year the house was built. These steps result in information on more than 73.8 million single-family properties and respective individual ownership tenures. I then utilize my university's cluster-computing infrastructure to perform the computationally intensive task of identifying neighboring properties within 0.1, 0.3 and 0.5 miles of these properties. Since the aim of this paper is to examine the peer effects of green neighbors, I remove those counties where none of the properties were ever green certified over the sample period from 2018 to 2022.

Having assembled the data on focal-neighbor property pairs and their green certification status, I count quarterly, for every individual-owned focal property, the number of neighboring properties (owned by individuals or otherwise) within 0.1, 0.3 and 0.5 miles that became green in the previous four quarters (inclusive of the current quarter). I stack these quarterly counts in a focal household × quarter panel, where a focal household is removed from the panel one quarter after it becomes green. The panel consists of 1,037,652,080 observations over the time period 2018–2022 about certification status and green exposures of focal households on 56,546,251 unique single-family properties located in 1632 counties.

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indicates the bottom 15 percentile (The Department of Energy, n.d.). I therefore assign properties rated under the HES program to be green certified (Green= 1) if their scores are higher than 5.

3.3 Summary Statistics

Table II reports the summary statistics for the main variables analyzed in this paper. The average probability of a household investing in residential green technologies in a given quarter is 0.004 percent. The average household has 0.09, 0.37 and 0.62 neighbors within a 0.1-, 0.3- and 0.5- mile ring respectively who became green within the last four quarters. Note that the mean of the variable Green (=10,000) reported for the property×year-quarter-level observations also has the interpretation of a quarterly hazard rate, meaning that 0.0747 percent of the households become green at a quarterly hazard rate of 0.004 percent. A typical single-family property in the sample was built in the year 1974, has a living area of 1855.41 square feet, and has 2.49 bedrooms. An average county has 3.68 green financial incentives offered by both county and state governments, and 53.87% of the adults are somewhat/very worried about global warming. The average housing density in a census tract is 2.06 residential properties per acre, and the average annual price growth in a census tract is 4.52%. At the zipcode level, the mean adjusted gross income per capita is $33,960.

4 Empirical Research Design

The main objective of this paper is to causally evaluate the effect of residential green investments in the immediate neighborhood on the likelihood of a household also investing in residential green technologies. Evaluating this is challenging due to two key endogeneity issues. First, households are not randomly assigned to specific neighborhoods, because they may sort into neighborhoods due to factors such as preferences, income, and social networks. Second, neighborhood-level shocks may cause households to simultaneously make similar decisions.

To deal with these issues, I employ a research design that has been used widely in the literature on causal neighborhood effects (Bayer et al., 2021; W. B. McCartney and Shah, 2022; Towe and Lawley, 2013; W. McCartney et al., 2023). Referred to as the nearest-neighbor research design, it estimates causal peer effects by focusing on the impact of decisions by hyper-local neighbors located within 0.1 miles, while controlling for the same decisions made by two sets of neighbors located just slightly away, within 0.3 and 0.5 miles respectively.

This research design relies on two crucial assumptions. First, the assignment of the immediate neighbors (within 0.1 miles) within slightly broader neighborhoods (within 0.3 or 0.5 miles) is quasi-random. The single-family housing market is suitable for employing this design, because while property characteristics can vary widely across broader neighborhoods, these tend to be remarkably similar within a small area, as demonstrated later. Also, while households are very likely to prefer specific neighborhoods, limited availability of properties for sale within such micro geographies diminishes their ability to select a given property. Second, neighborhood social interactions are more prevalent at hyper-local geographies (within 0.1 miles), since households tend to interact more with their next-door neighbors compared to those living slightly further away. This is an implicit condition for finding a non-zero effect, in the sense that if neighborhood interactions were not stronger at hyper-local geographies, the estimated effect would be zero.

The first assumption about spatial similarity in household characteristics—such as race, income, and price growth—have been argued to hold true within broader neighborhoods (within 0.5 miles) by several studies (Bayer et al., 2008, 2021; Towe and Lawley, 2013; W. B. McCartney and Shah, 2022; W. McCartney et al., 2023). Nonetheless, I verify whether property-level characteristics are similar within such neighborhoods to alleviate the concern that differences in these characteristics explain the (green investment) decisions of the neighbor peers. I calculate the proportional difference in a characteristic c of focal property i and its neighboring properties j located within a ring (donut) of d miles as follows:

$$\text{Proportional Diff}_{cid} = \frac{c_i - Avg(c_j)_{j \in [d-0.1:d]}}{c_i},\ d \in \{0.1, 0.2, \ldots 0.5\}. \tag{12}$$

For a given characteristic c, Panel A of Figure III plots *Proportional Diff* $_{cd}$, which is the average of *Proportional Diff* $_{cid}$ across all properties i. The four property characteristics are year built, living area (square feet), number of bedrooms, and building condition (measured on an ordinal scale from 1 to 6, 1 being excellent and 6 being unsound). The figure reveals that there are no jumps in the proportional difference with distance in any of the four characteristics of the neighboring properties and focal properties, corroborating the assumption that, within a small enough geographic scale, the nearest neighbors appear to be quasi-randomly assigned.

While neighboring properties are spatially similar to the focal properties in terms of the aforementioned characteristics, for the focal households to be influenced more by their closer neighbors than their slightly farther away neighbors (to make green investments), their exposure to green neighbors must increase substantially as their distance from the neighbors shrinks. To understand whether this pattern holds in the data, I plot in Panel B of Figure III the proportional difference in green exposure of green focal properties (G) and randomly selected non-green focal properties (NG) with distance.[11] We see that the proportional difference in green exposure remains stable as the distance from neighbors decreases from 0.5 miles to 0.2 miles, but it rises sharply as the distance decreases further to 0.1 miles. This suggests that households that invest in residential green technologies experienced many more green neighbors in their close neighborhoods than those who did not invest.

4.1 Regression Specification

Following the key specification of Bayer et al. (2021), I use the following regression specification for the nearest-neighbor research design:

$$Green_{it} = \alpha + \beta_1 \times N_G(\leq 0.1 \text{ mi}) + \beta_2 \times N_G(\leq 0.3 \text{ mi}) + \beta_3 \times N_G(\leq 0.5 \text{ mi}) + \theta_t + \theta_j + \epsilon_{it}, \quad (13)$$

[11] The green group G consists of all properties j which received green certification in year-quarter q. The non-green group NG consists of the sample of properties constructed by randomly drawing (with replacement) 50 non-green properties for every given property j that became green in year-quarter q. I re-index all properties in groups G and NG by i, and define the green exposure $Exposure_{id}$ of a property i over a ring of d miles as the total number of neighboring properties within the d-mile ring that became green during year-quarters $(q-3)$ and q. Here, q is the year-quarter a property i was assigned to its respective G or NG group, and a ring of d miles refers to a donut of $(d-0.1)$ to d miles, where $d \in \{0.1, 0.2, \ldots 0.5\}$. I calculate the proportional difference in green exposure for a d-mile ring as follows:

$$\text{Proportional Diff in Green Exposure}_d = \frac{Avg_{i \in G}(Exposure_{id}) - Avg_{i \in NG}(Exposure_{id})}{Avg_{i \in NG}(Exposure_{id})},$$

where Avg is the average across i calculated separately within group G and NG.

where $Green_{it}$ is an indicator that takes on a value of 10,000 if household i obtains the very first green certificate for their property in quarter t. The independent variable of interest is the exposure of focal household i to immediate green neighbors within 0.1 miles, denoted as $\mathrm{N}_G(\leq 0.1 \text{ mi})$. It is equal to the number of neighbors within 0.1 miles who obtained green certificates within quarters $t-3:t$. Similarly, the remaining two green exposure variables—$\mathrm{N}_G(\leq d \text{ mi})$, where $d \in \{0.3, 0.5\}$—control for green exposures at wider distance rings of $d = 0.3$ and 0.5 miles. The time subscripts for these exposure variables are omitted for brevity. Note that the three exposures are measured cumulatively, meaning that the outer rings are inclusive of the inner ring exposures. Thus, the coefficient β_1 measures the additional effect of the exposure occurring within the closest ring beyond the effect of exposures occurring in 0 to 0.5 miles. To account for spatial and temporal unobservable factors, this specification includes fixed effects represented by θ_t and θ_j, and specific choices for these are detailed in the respective estimations in Section 5. Additionally, to account for local characteristics, I modify Equation (13) by adding *Property controls*$_{it}$ and *Neighborhood controls*$_{it}$ as follows:

$$\begin{aligned} Green_{it} = \alpha + \beta_1 \times N_G(\leq 0.1 \text{ mi}) + \beta_2 \times N_G(\leq 0.3 \text{ mi}) + \beta_3 \times N_G(\leq 0.5 \text{ mi}) \\ + \delta_1 \text{Property controls}_{it} + \delta_2 \text{Neighborhood controls}_{it} + \theta_t + \theta_j + \epsilon_{it}, \end{aligned} \tag{14}$$

where property controls include property age, living area, # bedrooms, exterior materials, heat type and roof materials. Neighborhood controls include residential housing density and annual housing price growth at census tract level, adjusted gross income per person at zipcode level, number of regulatory green incentive programs and climate change concern at county level, and the proportion of green homes within a ring $d = 0.1$, 0.3 and 0.5 miles. Definitions of these variables are provided in Table II.

5 Results

5.1 Baseline Results

I begin the analysis by visually analyzing the effect of green neighbors on green investment decisions of households. I plot in Panel C of Figure III the average probability that households make green investments to their properties against the number of their green neighbors located at different distances who have become green in the last four quarters.[12] We see in the figure, moving from left to right, that the probability of green investments rises as the number of green neighbors located within a given distance increases. More importantly, we also see that the effect is substantially larger when the number of green neighbors spatially closer to the focal households (within 0.1 miles) increases than when the number spatially slightly farther away from the focal households (at 0.2, 0.3, 0.4, and 0.5 miles) increases. These patterns are consistent with the idea that spatially closer green neighbors influence the green investment decisions of households.

To understand the effect of green neighbors more rigorously, I use the regression specification for the nearest-neighbor research design from Equation (13) and report the results in Panel A of Table III. The coefficient on $N_G(\leq 0.1 \text{ mi})$ in column (1) is 0.69 and statistically significant, suggesting that the exposure to green neighbors within a 0.1-mile radius increases the likelihood of a household greening their property. The coefficient is easier to interpret in terms of the associated hazard ratio, which is equal to the ratio of the coefficient (β_1) to the intercept (α), that is, 0.692/0.318 = 2.18. It represents the change in the quarterly likelihood that households will invest in green technologies for their properties when the number of green neighbors within 0.1 miles increases by one compared to the households with no such green neighbors. In other words, the quarterly likelihood of green investments increases by 2.18 times. The hazard ratio is reported separately at the bottom of the table under *Marginal Effect to Hazard Ratio*.

In column (2) I employ the nearest-neighbor research design by incorporating green neighbors within 0.3 and 0.5 miles as additional controls following Equation

[12] Green neighbors located within d miles are defined as those who have become green in the past year, where d is [0, 0.1], (0.1, 0.2], (0.2, 0.3], (0.3, 0.4], and (0.4, 0.5]. The number of green neighbors is grouped in seven bins consisting of 0, 1, [2, 5], [6, 10], [11, 15], [16, 20], and greater than 20 neighbors. The average probability is calculated in quarter q for each bin and each distance ring d as the ratio of the number of properties that turn green for the first time in quarter q to the total number of properties (in the respective bin and ring) that did not become green until quarter $q-1$. The mean of these average probabilities across quarters is plotted in percentages on the y-axis. The neighbors across different rings are counted independent of those located in other rings.

(13). The coefficient on $N_G(\leq 0.1 \text{ mi})$ is statistically significant, and the associated hazard ratio is 1.58 (= 0.329/0.208). This ratio indicates that one additional green neighbor within 0.1 miles increases the likelihood that a focal household makes residential green investments in a given quarter by 1.58 times compared to a household with no green neighbors within 0.5 miles.[13] This can be understood as the effect of the exposure from one additional green neighbor within 0.1 miles *in excess of* the exposure from one additional green neighbor within 0.3 and 0.5 miles. The estimated magnitude of the green-peer effect is sizable compared to the peer effects documented in other similar settings, namely, 8% for housing investment decisions (Bayer et al., 2021) and 3.3% for refinancing decisions (W. B. McCartney and Shah, 2022). Column (3) incorporates year-quarter and zipcode fixed effects; and column (4), zipcode × year-quarter fixed effects. These specifications consistently yield similar coefficients and hazard ratios, indicating that the estimated effects are robust to the inclusion of granular spatial and temporal fixed effects. These findings are also in line with IMPLICATION 1 of the theory model.

I repeat these regressions following Equation (14) by adding controls for property and neighborhood characteristics and report the results in Panel B of Table III. These estimates reaffirm the conclusion that exposure to immediate green neighbors significantly raises the probability that households investing in residential green technologies within the next year.

To further validate the quasi-random neighbor assignment assumption, I test the baseline results in contexts where households have limited ability to self-select into preferred neighborhoods. I analyze the results in areas with varying levels of housing supply constraints, characterized by below- or above-median Wharton Residential Land Use Regulatory Index (WRLURI) (Gyourko et al., 2008, 2021). WRLURI mea-

[13] Note that these regression coefficients flexibly allow for estimating alternative hazard ratios which represent the effect of one additional green neighbor located at a given distance on the likelihood that a focal household makes residential green investments in a given quarter compared to a focal household with no green neighbors within 0.5 miles. For example, one additional green neighbor located at 0.4 miles increases the likelihood by 0.36 times ($\beta_3/\alpha = 0.075/0.208$), or equivalently, by 36%; one located at 0.2 miles increases it by 1.64 times ($(\beta_2+\beta_3)/\alpha = (0.266+0.075)/0.208 = 1.64$); and one located at 0.08 miles increases it by 3.22 times ($(\beta_1+\beta_2+\beta_3)/\alpha = (0.329+0.266+0.075)/0.208 = 3.22$).

sures the regulatory restrictiveness of the residential land use in a community. Higher WRLURI values indicate stricter regulations, leading to constrained housing supply. The results in Table B.5 consistently hold for properties in subsamples of both high and low housing supply constraints. These findings further strengthen the robustness of the causal interpretation of peer effects in green investments.

To ensure the robustness of the peer effect on residential green investments, I performed additional analyses. First, to strengthen the link between green certification and real investments, I estimate the baseline model for the subsample of green homes with verified investments occurring within one year prior to the green certification date, where verified investments are proxied by building permits. The results in Table B.6 show that the green-peer effect remains significantly positive, with a magnitude similar to the baseline results. Next, to address the possibility that the green-peer effects are merely symbolic gestures, I conduct a placebo test. This test estimates the baseline model in a sample of focal households whose green exposures arise exclusively from neighbors for whom the green certification processes revealed that their homes' efficiency were lower than that of an average home (inefficient green certificates). The results in Table B.7 show that exposure to neighbors who have obtained inefficient green certificates does not significantly affect the likelihood of also obtaining the inefficient green certificate. Additionally, to address concerns of builder-induced green clustering, I restricted the green homes to those certified more than two years after their first recorded sale. As shown in Table B.8, the green-peer effect persists with a reduced magnitude, indicating it is not solely a builder strategy. See Section 6 for more details.

The analyses in the rest of the paper are based on the specification in column (3) of Panel A. This specification does not include controls. This choice is motivated by the benefits and computational burden of including the granular fixed effects in this large panel data, the stable nature of the coefficients across different fixed effects specifications, and the reduction in the number of observations caused by the inclusion of controls for property and neighborhood characteristics.

5.2 Mechanism: Information Transmission

The baseline analysis in the previous section documents the peer effects of immediate green neighbors. These findings alone, however, do not pinpoint the mechanism that produces these effects. The extensive literature on peer effects commonly points to the mechanism based on information transmission, wherein neighbors serve as an additional source of information and potentially reduce the informational barriers in decision making (Maturana and Nickerson, 2019; Bayer et al., 2021; Bursztyn et al., 2014; Hong et al., 2004; Brown et al., 2008; Banerjee et al., 2013). In line with this literature, I explore the mechanism by studying several features of the residential green investment decisions of households. Specifically, I examine the decisions of MPOs to make their secondary properties green, which helps establish the information mechanism and rule out other alternatives. I also analyze commonalities in the choice of certificates, investment specifications and lenders among immediate neighbors to understand the type of information being transmitted. I conclude the section by also exploring heterogeneity in peer effects by the strength of local community interactions, reaffirming that the ease of information transmission facilitates the green-peer effect.

5.2.A Green Investment Decisions of Multi-Property Owners

In the information transmission mechanism, I hypothesize that focal households acquire knowledge from their neighbors about various aspects of green investments. The households could learn about associated upfront costs of installation and green renovation, potential benefits from utility savings and net metering, and important procedural details such as the adaptability of their houses, financing availability, technology suppliers, and the service quality of related providers. Such knowledge potentially raises their awareness, allowing them to update their beliefs about residential green investments, and facilitates improvements of their own homes.

Note that the increased probability of green investment among close neighbors (green-peer effect) could arise not only through the information transmission mechanism, but also through any within-neighborhood-level (within 0.1 miles) interactions or characteristics, which may not necessarily be observable to researchers. To isolate the information transmission mechanism from these other explanations, I design an empirical test where focal households get exposed to green neighbors in a different neighborhood located faraway from the property of interest. This test utilizes the green investment decisions of MPOs' secondary properties.[14] If the information transmission mechanism is at work, MPOs would likely acquire information from the immediate neighbors of their primary homes (where they reside) and apply it to decisions about their secondary properties, especially when the secondary properties resemble these neighbors. The prediction is that neighbors of the primary home would influence MPOs' decisions to make green investments to their secondary properties. In contrast, if MPOs' green investment decisions are driven solely by within-neighborhood-level characteristics, the primary home's neighbors would have no influence on probability of their secondary properties becoming green, and the effects of immediate neighbors of secondary properties would be uniform across all secondary properties, regardless of their similarity to the primary home's neighbors.

I next examine which of the two predictions discussed above holds by estimating Equation (13) for the properties of MPOs while including green exposures arising from neighbors located within 0.1, 0.3, and 0.5 miles around both their primary homes and their secondary properties. I denote these exposures by $N_G(\leq d\ mi)_{Primary\ Home}$ and $N_G(\leq d\ mi)_{Secondary\ Property}$, where $d \in \{0.1, 0.3, 0.5\}$. I focus on secondary properties in the top and bottom quartiles of similarity to their neighbors located within 0.1 miles of the primary homes. For highly similar properties, information flows seamlessly from primary homes' neighbors to secondary properties. Conversely, for less similar properties, the effectiveness of information transmission is likely to be limited.

Table IV reports the results. In columns (1) and (2), the sample includes secondary properties in the top quartile of property similarity, where the primary home is located respectively more than 20 and 50 miles away. We see that the effect of immediate green neighbors of primary home ($N_G(\leq 0.1\ mi)_{Primary\ Home}$) is statistically significant at about

[14] Chinco and Mayer (2016) also find that out-of-town second-house buyers affect the local housing market.

0.01 bps in both columns.[15] This suggests that information transmission from primary neighbors plays a key role for highly similar properties.

In columns (3) and (4), the sample includes the secondary properties in the bottom quartile of similarity. The effect of primary home's neighbors becomes insignificant, while the effect of secondary property's neighbors is marginally significant only in column (4) at 0.036 bps, much lower than the baseline results (Table III) and those in columns (1) and (2). These results suggest that information from primary neighbors becomes less applicable for very different houses, and the lack of clear reference for MPOs weakens the effects of both primary and secondary neighbors.

Overall, these findings support the information transmission mechanism and confirm IMPLICATION 1 of the theory model. They also rules out the explanation that the green-peer effect is solely a result of within-neighborhood-level interactions and characteristics, such as contractor availability or marketing events.

5.2.B Peer Commonalities in Green Certificates and Lenders

The information transmission mechanism can additionally be tested by examining the commonalities in the green investment decisions of the peers. The idea is that if households acquire information from neighbors, they are more likely to make similar choices to those of their neighbors, because the information acquisition minimizes the effort involved in researching available options. The richness of my data allows me to test for these predictions. Specifically, I examine whether households are more likely to choose the same green certificate, opt for similar investment specifications, and use the same

[15] Note that the coefficients on $N_G(\leq 0.1\ mi)_{Primary\ Home}$ are smaller than those on $N_G(\leq 0.1\ mi)_{Secondary\ Property}$. This pattern is consistent with the idea that MPOs learn from the immediate neighbors of their primary residence about general information on residential green technologies—akin to a necessary condition for considering green investments. However, because making these investment decisions also requires understanding localized costs and benefits, MPOs gather this localized information from the immediate neighbors of their secondary properties—akin to a sufficient condition. To elaborate, general information could include awareness about the green technologies, whereas localized information could pertain to the localized costs and benefits of green homes, suitability of their secondary property for green upgrades, the availability of local suppliers, the area's microclimate, etc. Such localized information is difficult to obtain from the primary residence neighbors, as it is highly area-dependent (Dorsey and Wolfson, 2024). Similarly, Chinco and Mayer (2016) find that out-of-town second-house buyers' decisions are influenced by factors from both their residence and the location of their purchases.

lenders as their immediate neighbors. This analysis highlights the specific types of information being transmitted among neighbor peers—particularly details about green technology specifications and localized cost-benefit analysis.

To test for commonality in certificates, I spatially match green neighbors within a 0.5-mile ring to create a panel at the "focal property certificate × neighboring property certificate" level and define the indicator $\mathbb{1}(\text{Same Cert.})$ to take the value of one when the certificates are the same for the focal household and the neighbor. I regress the same-certificate indicator on an indicator for immediate neighbors—$\mathbb{1}(\text{Dist.} \leq 0.1 \text{ mi})$—that takes the value of one when the neighbor is within 0.1 miles. Column (1) of Table V shows the result for all certificates, while column (2) shows the result after excluding HERS, the most common certification program. The coefficient indicates an increased likelihood of selecting the same certification by approximately 0.5 and 1.1 percentage points for immediate neighbor peers in columns (1) and (2) respectively.

Additionally, certification assessments and building permits provide insights into how immediate neighbors influence green investment decisions. When these documents show high similarity, it suggests that neighbors are likely adopting comparable green upgrades, such as using the same materials, HVAC systems, and making similar improvements like insulation or air sealing. I apply machine learning algorithms to compute textual cosine similarity of green certificates and building permits.[16] This approach helps assess the extent to which neighboring households are adopting similar green investments. The results in columns (3) and (4) show that the text similarities are higher for households within 0.1 miles, indicating that the transmission of specific technical details is more likely among immediate neighbors.

To test for commonality in lenders, I examine whether focal households opt for the same lenders after green certifying their properties as opted for by their immediate neighbors. If households receive information about localized costs and benefits of green investments from their neighbors, they may also learn about neighbors' lenders who are more likely to finance green investments due to existing relationships with

[16] Details of the data processing are described in Appendix C.

green-certified homes in the same neighborhood. I begin by selecting focal households who took out a mortgage within the 90 days before green certifying their properties. This selection ensures that the mortgages of focal households taken out within 90 days are presumably to finance the green investment. I then select their within-0.5-miles neighbors who took out a mortgage within one year after green certifying their properties. This selection ensures that neighbors' lenders are amenable to offering mortgages backed by green-certified properties. Finally, I select from the focal and neighboring households those pairs for which the mortgages of the focal households were taken out within one year after the mortgage dates of their neighbors. This selection ensures that the potential flow of value-relevant information about lenders and about financing green investments is pertinent and timely. Using these household pairs, I create a "focal household's mortgage $\times$ neighbor's mortgage" panel and define the indicator $\mathbb{1}$(Same Lender) to take the value of one when the mortgage lenders are the same for the focal household and the neighbor. I regress the same-lender indicator on the indicator for the neighbors located within 0.1 miles from the focal property. Column (5) shows the result for all lenders, while column (6) shows the result after excluding the top three lenders in a county-year based on the aggregate loan amount in mortgage applications received by lenders. The coefficients indicate that when focal households take out a mortgage just before making green investments to their properties, they are 13 to 14.1 percent more likely to use the same lender as used by their immediate neighbors compared to the slightly farther away neighbors. These findings and the associated magnitudes are similar to those in the context of property investing (Bayer et al., 2021) and refinancing (Maturana and Nickerson, 2019).

Taken together, the commonalities in the green investment decisions among close-neighbor peers corroborate the information transmission mechanism described in IMPLICATION 1 of the theory model, and indicate the specific types of information shared among neighbor peers.

5.2.C Heterogeneous Peer Effects: The Role of Local Community Interactions

Interactions within a community have been shown to be associated with transmission of valuable information (Chetty et al., 2022; Beaman, 2012; Laschever, 2013; Burchardi and Hassan, 2013). Therefore, if the green-peer effects are driven by information transmission, they are expected to be more pronounced in areas where local community interactions are stronger. I examine this prediction in a series of peer effect heterogeneity tests by exploiting the variations in the strength of local community interactions. I add to Equation (13) three new terms interacting the three variables for green neighbor exposures—$N_G(\leq d\ mi)$, $d \in \{0.1, 0.3, 0.5\}$—with the indicator $\mathbb{1}(\text{High }\mathbb{X})$, which equals one for above-median levels of the measure $\mathbb{X}$ of community interactions. The coefficient of interest is β_1 in the following equation:

$$
\begin{aligned}
Green_{it} = \alpha &+ \beta_1 \mathbb{1}(\text{High }\mathbb{X}) \times N_G(\leq 0.1\text{ mi}) \\
&+ \beta_2 \mathbb{1}(\text{High }\mathbb{X}) \times N_G(\leq 0.3\text{ mi}) + \beta_3 \mathbb{1}(\text{High }\mathbb{X}) \times N_G(\leq 0.5\text{ mi}) \\
&+ \beta_4 N_G(\leq 0.1\text{ mi}) + \beta_5 N_G(\leq 0.3\text{ mi}) + \beta_6 N_G(\leq 0.5\text{ mi}) + \delta \mathbb{1}(\text{High }\mathbb{X}) + \theta_t + \theta_j + \epsilon_{it}.
\end{aligned} \tag{15}
$$

The first set of community interaction measures is based on social ties: the zipcode-level social connectedness index, support ratio and county-level social capital (SK 2014).[17] The coefficient β_1 in columns (1) through (3) of Table VI consistently shows that the green-peer effect is stronger in areas with stronger social ties.[18]

I utilize another proxy for community interactions based on the idea that information is less likely to flow with ease in areas with a higher absence of owners—who hold the decision-making authority to implement changes in the property (W. B. McCartney

[17] The social connectedness index (within a zipcode) measures the strength of connectedness between two geographic areas using Facebook friendship ties, and support ratio is the proportion of within-zipcode friendships where the pair of friends share a third mutual friend within the same zipcode (Bailey, Cao, Kuchler, Stroebel, and Wong, 2018; Chetty et al., 2022). Social Capital (SK 2014) is a county-level measure of social capital in 2014, derived from principal component analysis using the number of social organizations, voter turnout, census response rates, and the number of non-profit organizations, excluding those with an international approach (Rupasingha et al., 2006, with updates).

[18] For the brevity of the presentation, Table VI reports results for three variables—the variable of interest $\mathbb{1}(\text{High }\mathbb{X}) \times N_G(\leq 0.1\text{ mi})$, $N_G(\leq 0.1\text{ mi})$, and $\mathbb{1}(\text{High }\mathbb{X})$. As shown in Equation (15), δ (the coefficient of $\mathbb{1}(\text{High }\mathbb{X})$) represents the effect of high local community interactions on the probability of investing in residential green technologies for households with no green neighbors within 0.1, 0.3, and 0.5 miles.

and Shah, 2022). To proxy for the absence of owners, I use the percentage of investment properties in a zipcode. The coefficient β_1 in columns (4) confirms the prediction that the green-peer effect is weaker in areas where the ease of information transmission is low.

In summary, all four heterogeneity tests utilizing the strength of local community interactions suggest that information transmission plays a role in the green-peer effect, reaffirming IMPLICATION 1 of the theory model.

5.3 Financial Benefits of Green Homes and the Green-Peer Effect

The results so far indicate that decisions of households to make green investments to their homes are shaped by the information available with their immediate neighbors. However, rational households would do so only if they find it to be financially beneficial. According to Equation (7), in areas where green investment is associated with higher financial benefits, the green-peer effects are expected to be stronger. I now investigate whether these decisions are influenced by the potential financial benefits of green homes (relative to non-green homes) in the housing markets. I therefore examine next: (i) whether the green-peer effect is stronger in areas where green homes fetch financial benefits; and (ii) whether the green-exposed households realize higher financial returns from investing in residential green technologies relative to the households that are similarly exposed but did not invest.

5.3.A Heterogeneous Peer Effects: The Role of Potential Financial Benefits

The features of the housing markets and regulatory programs targeted at green homes allow me to estimate the potential financial benefits of green investments in three ways—house prices, electricity savings, and regulatory monetary incentives. Using the following hedonic regression for house prices, I estimate the market-implied benefits of green homes relative to observationally equivalent non-green homes separately for each county and year:[19]

$$y_{it} = \alpha + \beta\, Green_{it} + \gamma\, Control_{it} + \theta_z + \epsilon_{it}. \tag{16}$$

The coefficient of interest is β. It estimates the difference in the outcome variable for a green home relative to a non-green home. The sample includes sales by individual buyers and sellers in county i and year t. To ensure the relevance of the green certification at the time of sale, I restrict the green homes to those that were sold within four years following their certification. The outcome variables are $ln(Price)$ for home-purchase transactions. Control variables for the house price regression include property age, living area, # bedrooms, exterior materials, heat type, roof materials, a 0/1 indicator of mortgage-financed purchase, mortgage term, and mortgage interest rate. All regressions include zipcode fixed effects.

Figure A.5 shows the counties where green homes fetch potential financial benefits for the sample period. The color intensity in Panel A represents the number of years (from 2018 to 2022) for which the coefficient β is statistically positive at the 10% level or below for house-price regressions and rate-spread regressions respectively. Panel B shows that 16% of county-year observations exhibit a statistically significant positive green premium. This result implies substantial regional variability in the economic benefits of residential green investments, consistent with the literature on the geographic disparities in the benefits of green technologies (Dauwalter and Harris, 2023). I then identify the county-year combinations where these potential benefits exist using the indicator $\mathbb{1}(\mathbb{B}\text{ exists})$, which equals one when the coefficient β is statistically positive at the 10% level or below.

[19] Note that here I do not attempt to estimate the benefits of the residential green investments in the absolute sense, as the data do not allow me to observe the relevant costs and benefits of such investments, making it infeasible to calculate net present value of such investments. As a compromise, I employ hedonic regression approach to infer the potential benefits of green properties relative to non-green properties as implied from the transactions in the housing markets. This approach is commonly used in the literature (Kahn and Kok, 2014; Aydin et al., 2020; Pigman et al., 2022; Muehlenbachs et al., 2015; Keiser and Shapiro, 2019; Avenancio-León and Howard, 2022). To further address the cost concerns and support the financial benefits of the green investments, I conduct additional analyses in Section 6 that examines the benefits and risks associated with purchasing a green home, as well as the returns on green upgrades.

Electricity savings that households may experience are measured using marginal retail electricity prices by each utility service territory for each year following Borenstein and Bushnell (2022).[20] Higher electricity prices make energy-efficient properties more attractive financially, as households can save significantly on utility bills through green technologies like solar panels or better insulation. As shown in Figure A.2b, households' utility savings are positively associated with the energy efficiency of the properties, thus motivating households in high-cost areas to make similar green investments. I thereby identify the utility service territory-year combinations where these electricity-savings benefits exist using the indicator $\mathbb{1}(\mathbb{B}$ exists$)$ which equals one for above-median levels of utility service territory-level electricity prices.

I measure regulatory monetary incentives for green homes as the sum of county- and state-level green incentives recorded in the DSIRE database under the Financial Incentive category calculated at the county $\times$ quarter level. Such incentives include a reduction in fees for solar panel installation and net metering benefits. Next, I identify the county-quarter combinations where these regulatory benefits exist using the indicator $\mathbb{1}(\mathbb{B}$ exists$)$ which equals one for above-median levels of county-level incentives.

Having identified the area-time combinations where green homes fetch the potential financial benefits, I examine whether the green-peer effect is stronger in these areas relative to the others using heterogeneity tests. In Equation (15), I replace the indicator $\mathbb{1}(\text{High } \mathbb{X})$ with the indicator for the three potential benefits, $\mathbb{1}(\mathbb{B}$ exists$)$. Table VII reports the results of the regressions. The coefficients on $\mathbb{1}(\mathbb{B}$ exists$) \times N_G(\leq 0.1\ mi)$ in column (1) through (3) suggest that the green-peer effect is stronger in the areas where the potential benefits are stronger.

In summary, the green-peer effect is not uniform. It is more pronounced where the potential financial benefits of green homes are higher, highlighting that financial

[20] I exclude Texas from the heterogeneity tests by electricity prices because the Texas Public Utilities Commission stopped updating the report cards on retail competition and summary of market share data since September 2017. As noted by Borenstein and Bushnell (2022), Texas utilities report bundled data in the EIA-861 survey without separating "energy" and "delivery" services. Consequently, the six local distribution companies do not contribute to this survey, making it difficult to conduct a comparable analysis of electricity savings with other states.

motives shape the peer effect in residential green investments, consistent with IMPLICATION 2 of the theory model.

5.3.B Housing Transaction Returns from Peer-induced Green Investments

Evidence so far indicate that households rely on information from immediate neighbors to learn about the residential green investments. In so far as residential green investments are capitalized in house prices, among the households exposed to green neighbors, I examine whether those who indeed greenify their homes experience higher returns on housing transactions than those who do not.

I create a sample of green-exposed households who green certified their homes and similarly-green-exposed households who did not certify their homes.[21] I then define an indicator $\mathbb{1}(Green)_i$ to take the value of one for the certifying households and 0 for the non-certifying households and estimate the following regression:

$$y_i = \alpha + \beta \ \mathbb{1}(Green)_i + \theta_{\text{buy year}} + \theta_{\text{sell year}} + \theta_{\text{green year}} + \epsilon_i. \tag{17}$$

The outcome variable y_i is the housing transaction returns measured in two ways: the annualized rate of return and sell residual. The residual is the observed price minus the predicted price ($r_{it} = p_{it} - \hat{p}_{it}$). The predicted price $\hat{p}_{it} = \hat{a}_i + \hat{\delta}_t$, where $\hat{a}_i$ and $\hat{\delta}_t$ represent respectively property and year-quarter fixed effects from the county-level standard repeat-sale regression of log price on the two fixed effects. The coefficient of interest β estimates the difference in housing return realized by households who made residential green investments during their ownership relative to those who did not. These regressions also include the three fixed effects corresponding to the years in which the property was bought, sold, and green certified.

[21] The detailed steps to construct the two samples are as follows. I begin with the households who bought and sold their properties during 2018 to 2022. I first create the sample C of green-exposed households who certified their houses. It consists of all households j who green certified their houses in a given year-quarter q during their ownership of the properties and had at least one green neighbor within a 0.1-mile distance in the past year at the time of certification. I then create the second sample NC of the similarly exposed never-certifying households (i.e., those who did not ever certify their houses during 2018 to 2022). The sample NC is constructed by randomly drawing (with replacement) 50 never-certifying households in year-quarter q—who had at least one green neighbor within a 0.1-mile distance in the past year—for every given certifying household j of year-quarter q from sample C.

Table VIII reports the results. The estimate in column (1) suggests that the green-exposed certifying households outperform their similarly exposed non-certifying counterparts by 13.2%. Similarly, the positive coefficient in column (2) indicates they sell their green-certified houses at a 7.7% higher price. Thus, conditional on being exposed to green neighbors, those who green certify their homes enjoy higher returns on housing transactions.

The findings in this section about the decisions of the MPOs, peer commonalities in certificates, investment specifications and lenders, effect heterogeneity by local community interactions and potential financial benefits of the green investments, and superior performance of certifying households point to the value-relevant information transmission mechanism, and highlight the role of financial motives in shaping the peer effect in residential green investments.

5.4 Green Preference and the Green-Peer Effect

In recent years, there is an ongoing debate on whether people also have ethical and social concerns when pricing the financial assets. Particularly, the beliefs of households about climate change and their green preferences are commonly used to explain a range of decisions such as stock investments (D. Choi et al., 2020; Fisman et al., 2023), mortgages, and EV purchase (Kahn, 2007). The question then arises: How do green preferences affect households' decisions to learn about and invest in green technologies? Model IMPLICATION 3 suggests that households with green preferences are more likely to adopt green technologies than those without such preferences. However, green preferences do not affect the likelihood of households learning about these investment opportunities from their neighbors. To shed some light on the previous question and test these predictions, I first investigate the association between the percentage of residential green-certified homes in an area and two proxies for green preference, and then examine whether the green-peer effect differs with the degree of green preference.

I utilize two proxies for the green preferences of households, *% Climate Worried* and *# EV/# Household*. The first proxy *% Climate Worried* equals the fraction of the adults in a county that is somewhat/very worried about global warming (Howe et al., 2015). The second proxy *# EV/# Household* equals the number of EVs per household at zipcode level, based on the idea that environmentalists are more likely to adopt green practices (Kahn, 2007).

I run the following regression to explore the relation between the ratio of the number of residential properties that are green certified in an area and the proxies for green preferences:

$$\%\ \text{Green Home}_{ct} = \alpha + \beta\,\text{Green Pref}_{ct} + \gamma\,\text{Controls}_{ct} + \theta_c + \theta_t + \epsilon_{ct}. \tag{18}$$

The controls include a series of area-level variables for housing market conditions and demographic characteristics: log amount of the residential energy tax credit, house price index, log number of new single-family homes, log population, per capita income, median age, and the percentage of people aged 25 and above with at least a college degree. In columns (1) and (2) of Table IX, we see that both the proxies for green preference are positively associated with the percentage of residential green-certified homes. This finding is in line with IMPLICATION 3 (i) of the theory model.

I now examine whether the green-peer effect varies with the degree of green preference as captured by the two proxies. To do this, I follow Equation (15), where $\mathbb{1}(\text{High}\,\mathbf{X})$ now represents an indicator that equals one for observations with county-level above-annual-median values of the two proxies X—*% Climate Worried* and *# EV/# Household*. Columns (3) and (4) show the regression results. The insignificant coefficients of the interaction term indicate that the strength of the green-peer effect is statistically not different across areas with different degrees of green preferences. This finding supports IMPLICATION 3 (ii) of the theory model. It also suggests that the effects are not solely driven by evolving green preferences.

5.5 Policy Implications

Understanding the patterns in residential green investments can help inform policies aimed at sustainable housing, environmental conservation efforts, and attaining the global emission mitigation targets (IEA, 2019). This is especially pertinent given the large scale of the regulatory programs, including policies on energy tax credits (IRS, n.d.), green mortgages (Freddie Mac, n.d.) and green mortgage-backed securities (Fannie Mae, 2020; Freddie Mac, 2021). Given the magnitude of these incentives, it is crucial for social planners—particularly those with constrained resources—to strategically target these resources to where each dollar of incentive yields the greatest increase in adoption rates. Otherwise, misdirected incentives can lead to inefficient fiscal spending and overlook opportunities to maximize the environmental and economic benefits of green technologies.

From IMPLICATION 4, we understand that regulatory incentives should be directed toward areas where green-peer effects are stronger, in order to minimize inefficiencies and achieve a social optimum. The results in Table X show that the distribution of incentives does not significantly correlate with areas experiencing strong green-peer effects proxied by the strength of local community interactions. This disconnect indicates a need for policy adjustments to better target and optimize the allocation of incentives.

6 Additional Analyses

In this section, I provide additional analyses that aid in interpretation of the main results and also help rule out other explanations.

A. Do residential green certifications represent real investments?

The implications of the residential green certifications are relevant for the environment only if they are accompanied by real improvements and investments in the houses. To understand whether the certifications are associated with real investments, I utilize the residential energy tax credits (RETCs) as a proxy for real green investments, relying on the idea that these tax credits are claimable only if households undertake verifiable green improvements and investments to their residences (IRS, n.d.). Hence I examine whether the percentage of homes that were newly green-certified in an area is positively associated with the amount of tax credits claimed by the households in the same area.

I regress a series of zipcode-level RETC-related variables on the zipcode-level percentage of residential properties that received new green certifications in a year as follows:

$$y_{zt} = \alpha + \beta \times \%\ \text{New Green Home}_{zt} + \gamma\ \text{Controls}_{zt} + \theta_z + \theta_t + \epsilon_{zt}. \tag{19}$$

The controls include a series of zipcode-level variables for housing market conditions and demographic characteristics: house price index, log number of new single-family homes, log population, per capita income, median age, and the percentage of people aged 25 and above with at least a college degree. The model includes fixed effects represented by θ_z and θ_t to account for zipcode- and year-level unobservable factors.

In column (1) of Table B.1, we see that a percentage point increase in the percentage of residential properties that were newly green-certified is associated with a 7% increase in the amount of RETCs, and column (2) suggests a $1.26 increase in the amount of RETCs per household. Column (3) shows that a percentage point increase in the percentage of residential properties that were newly green-certified leads to a 3.1% increase in the number of tax returns with RETCs, and column (4) indicates a 0.039 percentage point increase in the percentage of households filing for RETCs. Overall, these findings illustrate that green certifications are indeed associated with real investments.

To validate that green certification reflects real green investments, I use building permit data as a key indicator. Building permits are required for substantial home improvements, particularly those involving energy-efficient upgrades and the installation of green technologies such as solar panels, efficient HVAC systems, or insulation. This makes building permit data an ideal measure to validate the real investments associated with green certification. The results in Table B.2 show a positive relationship between green certification and completed building permits.[22] Specifically, columns (1) and (2) demonstrate that green-certified homes are significantly more likely than non-green homes to obtain building permit within the year preceding certification. Additionally, results in columns (3) through (6) indicate that green homes tend to secure more building permits and higher job values compared to non-green homes. This suggests that these households are undertaking multiple projects and making significant financial commitments to enhance the sustainability and energy efficiency of their properties before certification.

B. Is the green-peer effect merely a result of green clustering by builders?

A common concern regarding the observed green-peer effect is merely due to builders concentrating new green homes in certain areas rather than genuine peer influence among homeowners. Builders may anticipate market demands for green homes and build these spec homes in specific geographical patterns, creating an artificial appearance of peer influence.

To address this concern, I repeat my baseline analysis but only include those green properties that have a known purchase transaction occurring at least two years prior to becoming green. This time restriction ensures that the certification is more likely a result of homeowner choice influenced by their neighbors, rather than builder strategy. Table B.8 shows that with this restriction, the results still remain consistent with the baseline results in Table III. Therefore, green clustering by builders is unlikely to be the primary mechanism for the green-peer effect.

C. Are investments in green technologies financially beneficial?

While peer influence plays a role in the adoption of green technologies, it also raises questions about whether households are making financially sound decisions or following potentially misleading information. The concern is that households might view

[22] The sample for these regressions is constructed as follows. The green group G consists of all properties j that received green certification in year-quarter q between 2018 and 2022. The non-green group NG consists of the sample of properties selected by a random draw (with-replacement) of 50 non-green properties for every given property j that became green in year-quarter q (thus, non-green properties inherit the same value of q as the specific green property for which they were randomly drawn).

the green investments as beneficial based more on peer behavior than a thorough cost-benefit analysis, which could negatively affect individual financial health and lead to broader economic inefficiencies. While Section 5.3 shows that peer-induced green investments yield higher returns in housing transactions, this section aims to take a closer look at the overall benefits of green investments in the housing market.

The financial benefit one can easily think of is the increased resale value of green homes. Using the hedonic regression (16) for house prices, I estimate the nationwide market-implied benefits of green homes relative to observationally equivalent non-green homes. Column (1) of Table B.3 shows that green homes are associated with an average 2.4% increase in the sale value of a single-family property in the US. However, a potential concern is that the green premium may be just a reflection of the improvement costs incurred when households undertake green upgrades. By assuming tax appraisals account for all improvement costs, we can get the price premium for the green home when controlling for the assessed value. Given that my data on property assessed value is only available for Texas, I use the Texas data for this analysis. Column (2) reports a 7.2% premium in resale value for properties located in Texas. Controlling for the assessed improvement and land value, the green home status contributes a 4.9% green premium, as indicated in column (3). Column (4) examines the variability of house prices. The results show that the county-level standard deviation of house prices for green homes is significantly lower compared to non-green homes. This suggests that green homes not only potentially offer higher resale values but also present lower financial risk.

Another benefit comes from adopting green technologies for the property, or green upgrades. For this return analysis, I estimate additional returns on home improvement investments aimed at green certification. This analysis is important as it accounts for the investment costs, providing a clearer picture of the NPV of green upgrades. I start with all the home improvement loans during 2018 and 2022, and identify those specifically aimed at green certification. These loans are defined as those that were originated within one year before the certification date. By using the loan amount as a proxy for the investment cost, I calculate two returns: the return on the house transaction price (r_p) and the return on the property assessed value (r_v). I then examines whether investments in home improvements for green upgrades yield higher returns compared to non-green upgrades. Table B.4 shows that on average home improvements aimed at adopting green technologies are associated with significant additional returns of 36.9% on the home sale price and 32% on the property assessed value. Taken together, investing in a green home is on average financially beneficial.

D. Is the green-peer effect driven by social utility (or "keeping-up-with-the-Joneses" motive)? In addition to information transmission, a common alternative mechanism for peer effects proposed in the literature is referred to as social utility. It hypothesizes that one's utility from possessing a product depends directly on the possession of that product by neighbors (Bursztyn et al., 2014), resulting in a peer-mimicking behavior (Maturana and Nickerson, 2019). Such social utility often stems from peer pressure or the desire to "keep up with the Joneses" (Abel, 1990; Gali, 1994; Campbell and Cochrane, 1999; Hong et al., 2014; Heimer, 2016). In this context, households may choose to adopt green technologies because they observe their neighbors doing so, in an effort to align with social norms and avoid appearing less eco-friendly.

While social utility mechanism or keeping-up-with-the-Joneses motive can also explain some aspects of the green-peer effect, my paper provides evidence suggesting it is unlikely to be the primary mechanism. First, the social utility mechanism predicts that green-peer effect should be more pronounced when households are surrounded by more "Joneses". This would imply that the primary home's neighbors, who are more socially proximate and thus more likely to act as "Joneses", should have a stronger influence than the secondary property's neighbors. Additionally, the effects would not depend on the similarity between secondary properties and the primary home's neighbors, as social utility relies less on the relevance of information. However, Table IV show that the coefficient on $N_G(\leq d\ mi)_{Primary\ Home}$ is smaller than that of $N_G(\leq d\ mi)_{Secondary\ Property}$ for highly similar properties and becomes insignificant for dissimilar properties. These findings are inconsistent with what would be expected if social utility were the dominant mechanism.

Second, under the social utility mechanism, the decision to mimick the peers is not necessarily financially beneficial, whereas under information transmission mechanism, households follow their peers when the information is value-relevant (i.e., financially beneficial). Thus, if the green-peer effect I document in this paper were solely driven by social utility, then this effect would not vary with potential financial benefits of green investments. Moreover, the returns on housing transactions realized by exposed households who greenify their homes would not be higher than those who do not. However, the results in Tables VII and VIII show the opposite. Overall, I do not find evidence of keeping-up-with-the-Joneses motive or social utility playing a significant role in the green-peer effects documented in this paper.

E. Is the green-peer effect driven by conspicuous consumption utility (visual inference)?

The green-peer effect may also be driven by conspicuous consumption, where households infer the investment or consumption of their neighbors through visible observation, rather than direct interactions (Hopkins and Kornienko, 2004; Charles et al., 2009; Han et al., 2023). This channel is less likely in my setting as displaying the green certificate is not required by the programs. However, one might still argue that neighbors can observe all noticeable changes of the home improvements and interpret as indirect indicators of a household's participation in green certification programs, even without seeing an actual certificate.

To address this concern, I explore how the conspicuousness of green investments affects the green-peer effect. Solar panel is a highly visible form of green technology, more so than subtler improvements like advanced insulation, energy-efficient windows, or upgraded roofing materials. Such conspicuousness makes it easier for households to identify and infer green investments based solely on observing each other's properties. Therefore, if conspicuous consumption drives the effect, peer influence should be stronger in areas where solar panels are prevalent. However, if we do not find stronger peer effects in these areas, it seems unlikely that conspicuous consumption is affecting the green-peer effects.

I follow the similar strategy of Equation (15) to test this prediction, replacing $\mathbb{1}(\textit{High}\ \mathbb{X})$ with $\mathbb{X}$ which represents the degree of conspicuousness of green certifications within census tracts. To quantify the conspicuousness, I use three measures. In column (1), conspicuousness is an indicator equal to one for properties in census tracts with at least one solar building permit, and in column (2) is an indicator equal to one for census-tract-year level above-median percentage of properties with solar building permits. In column (3), I first calculate the percentage of green certifications from programs explicitly requiring photovoltaic (PV) solar generation in a census tract over the last four quarters, and construct an indicator variable that takes a value of one if the percentage for a given census tract-year is above the median.[23] Table B.9 show the regression results. The insignificant coefficients of the interaction term indicate that the strength of the green-peer effect is statistically not different across areas with varying degrees of conspicuousness of green investments. This finding suggests that the effects are not primarily driven by conspicuous consumption or visual inference.

7 Conclusion

Discussions on how to address climate change have gained significant attention in recent years, yet a gap remains in understanding how households make green investment decisions under uncertainties. This paper studies the role of green neighbors of households to invest in residential green technologies. I developed a theoretical model of peer effects and tested its predictions empirically using a nearest-neighbor research design that provides causal inferences. I construct a highly granular nationwide dataset of single-family property data combined with green certification records to serve as

[23] These programs are Built Green, Earth Advantage, Florida Green Building Coalition, Green Built Homes, GreenPoint Rated, Home Energy Score, LEED for Homes, National Green Building Standard, and Zero Energy Ready Home. Note that the HERS program (the most common certification program), despite considering PV solar generation in its certification criteria, is excluded from this index.

a proxy for green investments. Employing the nearest-neighbor research design to this nationwide dataset, I document causal evidence that green neighbors influence the decisions of the households. Specifically, a household is 1.6 times more likely to make green investments to their home when a neighbor within 0.1 miles has done so in the past year compared to a household with no such neighbor. These results are robust to the inclusion of granular spatial and temporal fixed effects and property- and neighborhood-specific controls. I further show that the peer effect of immediate green neighbors extends to secondary properties (located in faraway neighborhoods) of the focal green-exposed households, suggesting that the underlying mechanism is information transmission from close neighbors. I also find that peer effects are more pronounced in areas where residential green investments enjoy financial beneficial from higher house prices, electricity savings, and regulatory incentives. Furthermore, green-exposed households who green certify their homes perform better than similarly exposed counterparts who do not do so. In contrast, the peer effects remain similar across counties varying in green preferences. Finally, I find that the current distribution of regulatory incentives does not align with areas predicted by the model to most effectively promote adoption, namely those with strong green-peer effects.

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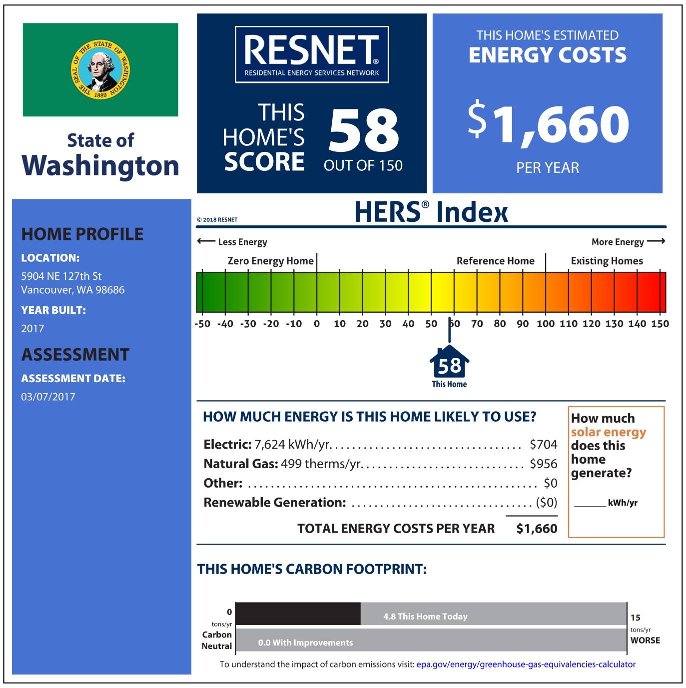
Figure I: Sample Green Certification Reports

This figure shows the certification reports issued by the two most common green certification programs in the US—HERS and HES—in Panel A and B respectively. The reports include information on property location, date of certification, and energy profile of the home. Panel C presents a word cloud generated from the 200 most frequently used words in the certification reports.

Panel A: HERS Program Homes



Panel B: HES Program

Panel C: Word Cloud of Certification Reports

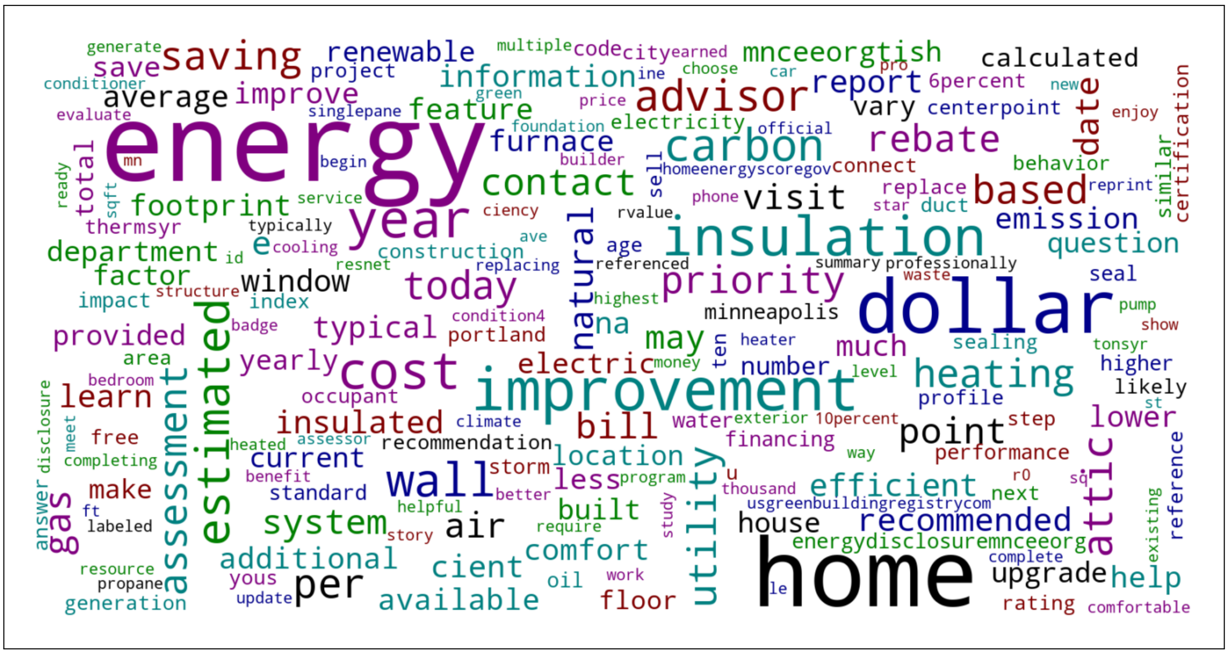
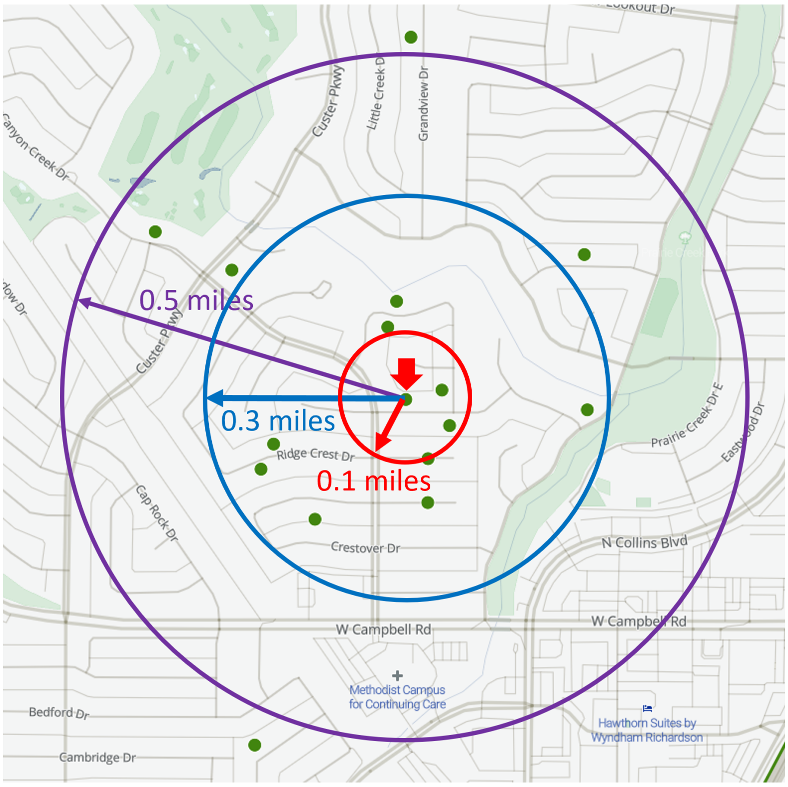


Figure II: Illustration of the Nearest-Neighbor Research Design

Panel A shows an example of a green focal property in Dallas (pointed to by the red arrow) and the number of its green neighbors within 0.1-, 0.3- and 0.5-mile rings (shown as green dots). Panel B shows an example of a non-green focal property in Dallas (pointed to by the red arrow) and the number of its green neighbors within 0.1-, 0.3- and 0.5-mile rings (shown as green dots).

Panel A: Green Neighbors around a Green Focal Property



Panel B: Green Neighbors around a Non-green Focal Property

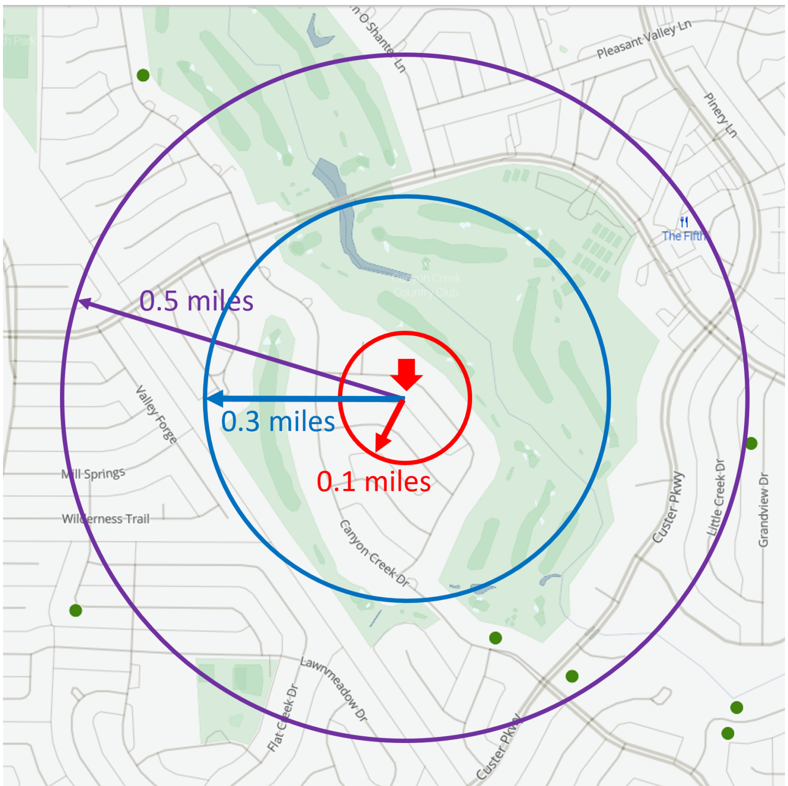
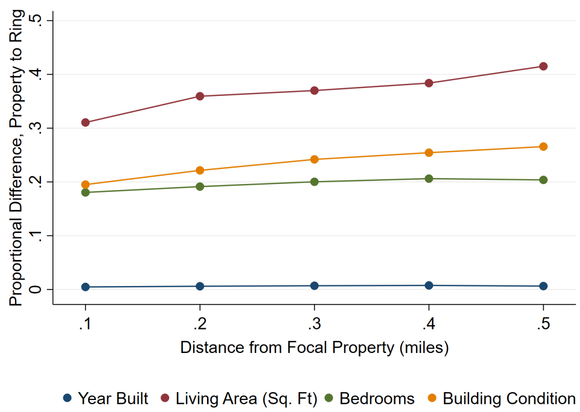


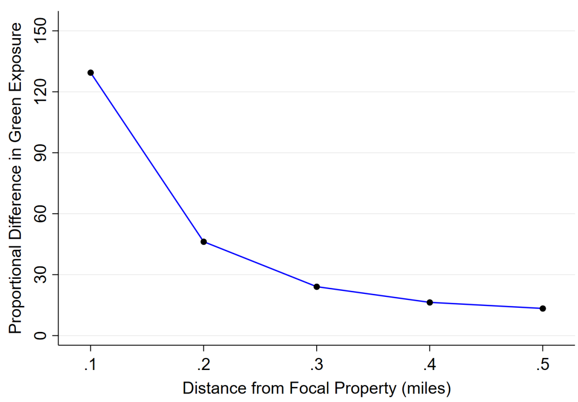
Figure III: Spatial Variation in Home Characteristics, Green Exposure, and Certification Probability

Panel A plots the characteristics of a focal property relative to the average across its neighboring properties within a ring (donut) of d miles, where $d \in \{0.1, 0.2, \ldots 0.5\}$. Panel B shows the average proportional difference in green exposure of green-certified properties (G) and non-green properties (NG). The green group G consists of all such properties j which received green certification in year-quarter q. The non-green group NG consists of the sample of properties constructed by randomly drawing (with replacement) 50 non-green properties for every given property j that became green in year-quarter q. Panel C plots on the y axis the average probability of a household green certifying the property against the number of neighbors located within d miles who have green certified their homes in the past year. The average probability is calculated in quarter q for each bin (of the number of green neighbors) and for each distance ring d as the ratio of the number of properties that are green-certified for the first time in quarter q to the total number of properties (in respective bin and ring) that have not become green until quarter $q-1$. The mean of these average probabilities across quarters is plotted in percentages on the y-axis.

Panel A: Characteristics of Focal and Neighboring Homes



Panel B: Green Exposure of Green and Non-Green Homes



Panel C: Probability of Green Certification and Green Exposure

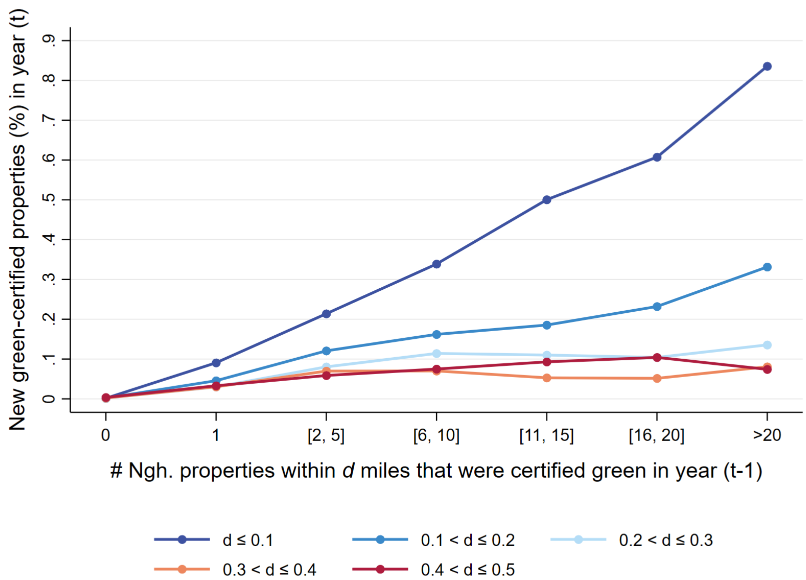


Table I: Green Certification Programs

This table reports the overview of 15 green certification programs. It includes their geographic coverage, attributes evaluated in their programs, whether they mandate the use of green contractors under the program. Column (4) reports the threshold scores (or rating categories) used in this paper to define whether a property is green certified (Green) under respective programs.

Program	Coverage	Attributes Evaluated	Green Contractors Required	Green Threshold
	(1)	(2)	(3)	(4)
Built Green	King County, WA Snohomish County, WA	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Single-family: $>$ 3-star Remodeling: $>$ 2-star, 20/20 Refit Challenge, Refit
ENERGY STAR Certified New Construction	National	Energy Efficiency	Yes	Certified
Earth Advantage® Certifications	Northwest	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
EarthCraft	Greater Atlanta Area	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
Florida Green Building Coalition	Florida	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
Florida Water Star	St Johns River Water Management District	Water	Not Necessary	Certified
Green Built Homes	North Carolina	Energy, Site, Water, Indoor Air Quality, Materials	Yes	Certified
GreenPoint Rated	California	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Not Necessary	$\geq$ 50 points
Home Energy Rating System	National	Energy Efficiency	Not Necessary	$<$ 100
Home Energy Score	National	Energy Efficiency	Not Necessary	$>$ 5
LEED for Homes	National	Energy, Site, Water, Indoor Air Quality, Materials	Yes	Certified
Missouri Home Energy Certification	Missouri	Energy Efficiency	Not Necessary	Certified
National Green Building Standard	National	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
TISH Energy Score	Minneapolis Bloomington	Energy Efficiency	Not Necessary	$>$ 85
Zero Energy Ready Home	National	Energy, Water, Indoor Air Quality	Yes	Certified

Table II: Summary Statistics

This table reports the summary statistics on key variables for the estimation samples. Each quarter, I observe whether households obtain a green certificate for their property (*Green*), the green adoption decision of their neighbors. Dummy variable *Green* is multiplied by 10,000 for readability. $N_G(\leq 0.1\ mi)$, $N_G(\leq d\ mi)$ measures how many neighbors of the household became green within d miles to the focal property in the last year, where $d \in \{0.1, 0.3, 0.5\}$. I also observe time invariant property characteristics *Year Built*, *Living Area* (*square feet*), *# Bedrooms*. *# Incentives* is the number of regulatory green incentives at both county and state-level. *% Climate Worried* measures the percentage of population in a county who are worried about climate change. *Annual Price Growth* is the annual change of the housing price index of a census tract. *Housing Density* is the number of residential properties per acre in a census tract. *AGI* (*$1,000*) *Per Capita* is the adjusted gross income (reported in thousands of dollars) per person at the zipcode level.

Variable	Obs.	Mean	Median	Std. Dev.
Green Status and Exposures (*Panel: Property×Year-Quarter*)				
Green (=10,000)	1,037,652,080	0.40	0	63.18
$N_G(\leq 0.1$ mi)	1,037,652,080	0.09	0	2.92
$N_G(\leq 0.3$ mi)	1,037,652,080	0.37	0	4.45
$N_G(\leq 0.5$ mi)	1,037,652,080	0.62	0	5.83
Property Characteristics (*Panel: Property level*)				
Green (=10,000)	56,546,251	7.47	0	273.12
Year Built	56,546,251	1,974.70	1,978	28.71
Living Area (square feet)	56,546,251	1,855.41	1,680	777.04
# Bedrooms	56,399,493	2.49	3	1.55
Neighborhood Characteristics (*Panel: Varies*)				
# Incentives	21,216	3.68	3	3.49
% Climate Worried	13,056	53.87	53	7.09
Housing Density	738,043	2.06	1	3.36
Annual Price Growth (%)	1,672,032	4.52	4	8.82
AGI ($1,000) Per Capita	227,336	33.96	28	29.46

Table III: Peer Effects of Green Neighbors on Residential Green Investments

Panel A reports the effect of green neighbors on the decision of a focal household to also invest in residential green technologies. The regression specification is from Equation (13). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. *Marginal Effect to Hazard Rate* is equal to the ratio of the associated coefficient to the intercept. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Baseline Results

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
$N_G(\leq 0.1$ mi)	0.69***	0.33***	0.37***	0.38***
	(0.06)	(0.05)	(0.05)	(0.05)
$N_G(\leq 0.3$ mi)		0.27***	0.23***	0.22***
		(0.02)	(0.02)	(0.02)
$N_G(\leq 0.5$ mi)		0.08***	0.06***	0.06***
		(0.01)	(0.01)	(0.01)
Constant	0.32***	0.21***	0.23***	0.23***
	(0.01)	(0.01)	(0.01)	(0.01)
Marginal Effect to Hazard Rate				
$N_G(\leq 0.1$ mi)	2.18***	1.58***	1.78***	1.82***
	(0.19)	(0.28)	(0.27)	(0.27)
Fixed effects	N	N	Zipcode, YQ	Zipcode × YQ
R^2 (Adj.)	0.0010	0.0014	0.0021	0.0033
Observations	1,037,652,080	1,037,652,080	1,037,652,076	1,037,641,505

Table III: Peer Effects of Green Neighbors on Residential Green Investments (contd.)

Panel B replicates column (3) of Panel A by adding property and neighborhood controls following Equation (14). The sample includes observations for which all control variables have non-missing values. The property controls include property age, living area, # bedrooms, exterior materials, heat type and roof materials. The neighborhood controls include residential housing density and annual housing price growth at census tract level, AGI ($1,000) per capita at zipcode level, number of regulatory green incentive programs, % climate worried at county level, and the proportion of green homes within a ring $d = 0.1$, 0.3 and 0.5 miles. The property and neighborhood controls are defined in Table II. All models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel B: Baseline Results - Including Controls

	Outcome: Green (=10000)			
	(1)	(2)	(3)	(4)
$N_G(\leq 0.1$ mi)	0.66***	0.66***	0.47***	0.47***
	(0.14)	(0.14)	(0.12)	(0.12)
$N_G(\leq 0.3$ mi)	0.17***	0.17***	0.17***	0.17***
	(0.02)	(0.02)	(0.03)	(0.03)
$N_G(\leq 0.5$ mi)	0.03***	0.03***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Property controls	N	Y	N	Y
Neighborhood controls	N	N	Y	Y
Fixed effects	Zipcode, YQ	Zipcode, YQ	Zipcode, YQ	Zipcode, YQ
R^2 (Adj.)	0.0026	0.0026	0.0028	0.0028
Observations	170,708,293	170,708,293	170,708,293	170,708,293

Table IV: Information Transmission: Peer Effects and Multi-Property Owners

This table reports green-peer effects observed from primary home of MPOs to their secondary properties. The sample in columns (1) and (2) includes the secondary properties in the top quartile of similarity to their neighbors located within 0.1 miles of the primary homes. This similarity is calculated using Gower's distance, based on property age, living area, exterior materials, heat type and roof materials; and in columns (3) and (4) includes those in the bottom quartile of the similarity. The regression specification follows Equation (13) and includes the green exposures from neighbors of both primary home ($N_G(\leq d\ mi)_{Primary\ Home}$) and secondary property ($N_G(\leq d\ mi)_{Secondary\ Property}$) for all three rings. In columns (1) and (3) the distance between the primary–secondary pairs is more than 20 miles, and in columns (2) and (4), 50 miles. All models include primary zipcode, secondary zipcode, owner and year-quarter fixed effects. Standard errors are clustered by primary residence zipcode × year-quarter and secondary property zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Secondary Property Green (=10,000)			
Secondary Property-Primary Nbrs Similarity:	[Top Quartile]		[Bottom Quartile]	
	(1)	(2)	(3)	(4)
Primary to Secondary Distance	>20 mi	>50 mi	>20 mi	>50 mi
$N_G(\leq 0.1\text{ mi})_{\text{Primary Home}}$	0.010**	0.010**	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
$N_G(\leq 0.1\text{ mi})_{\text{Secondary Property}}$	0.073*	0.080*	0.035	0.036*
	(0.04)	(0.05)	(0.02)	(0.02)
0.3- & 0.5-mi $N_{G,\text{ Primary Home}}$	Y	Y	Y	Y
0.3- & 0.5-mi $N_{G,\text{ Secondary Property}}$	Y	Y	Y	Y
Primary zipcode FE	Y	Y	Y	Y
Secondary zipcode FE	Y	Y	Y	Y
YQ FE	Y	Y	Y	Y
R^2 (Adj.)	0.1175	0.1154	0.1039	0.0989
Observations	16,228,739	15,335,946	24,882,976	24,660,686

Table V: Peer Commonalities in Green Certification Programs, Investment Specification, and Lenders

This table reports the results of regressing similarity measures of green investment decisions of focal household-neighbor pairs on an indicator for within-0.1-mile neighbors, where the omitted category is 0.1-to-0.5-mile neighbors. The outcome variable in columns (1) and (2) is one when a focal household × neighbor pair has the same green certificate ($\mathbb{1}$(Same Cert.)); in column (3) is textual cosine similarity of green certificates; in column (4) is textual cosine similarity of building permits; and in columns (5) and (6) is one when a focal household × neighbor pair has the same mortgage lender ($\mathbb{1}$(Same Lender)). The indicator $\mathbb{1}$(Dist. $\leq$ 0.1 mi) is one when the distance between focal household and neighbor is within 0.1 miles. The sample in column (1) includes all certificates; in column (2) excludes the most common certificate (HERS); in column (3) includes all such neighbor pairs whose green certificates are issued under the same program and downloadable from GBR website; in column (4) includes all building permits obtained by the green neighbor pairs within one year prior to their own green certification dates; in column (5) includes all lenders; and in column (6) excludes the top three lenders in terms of loan amount requested in mortgage applications in a county-year. All regressions include focal property's tenure and zipcode × year-quarter fixed effects. Standard errors are clustered by focal zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Program Similarity		Investment Similarity		Lender Similarity	
Outcome:	$\mathbb{1}$(Same Program)		Text Cosine Similarity		$\mathbb{1}$(Same Lender)	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	[All Prog]	[Ex Top Prog]	[Certificate]	[Bldg. Permit]	[All Lender]	[Ex Top 3 Lender]
$\mathbb{1}$(Dist. $\leq$ 0.1 mi)	0.005***	0.011***	0.020***	0.056**	0.130***	0.141***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
Focal tenure FE	Y	Y	Y	Y	Y	Y
Focal zipcode × YQ FE	Y	Y	Y	Y	Y	Y
R^2 (Adj.)	0.5227	0.5929	0.7093	0.2619	0.3473	0.3493
Observations	7,338,920	787,273	90,971	9,138,633	230,792	200,320

Table VI: Effect Heterogeneity by Strength of Local Community Interactions

This table reports the heterogeneous green-peer effects by the strength of local community interactions using Equation (15). The outcome variable *Green* (*=10,000*) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. The measure of the strength of local community interactions ($\mathbb{X}$) in the four columns are respectively: social connectedness, support ratio, social capital, and % investment properties. $\mathbb{1}$(High $\mathbb{X}$) is a 0/1 indicator for observations with above-median values of the respective characteristic $\mathbb{X}$. The bottom row in the column header denotes the level at which the median for respective characteristic $\mathbb{X}$ is calculated. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. All the models control for outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{1}$(High $\mathbb{X}$) $\times N_G(\leq d\ mi)$). All these variables are defined in Table II. All the models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode $\times$ year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
Characteristic $\mathbb{X}$:	Social Connectedness	Support Ratio	Social Capital	% Investment Properties
[Median of $\mathbb{X}$ calculated at:]	[zipcode]	[zipcode]	[county]	[zipcode $\times$ yq]
$\mathbb{1}$(High $\mathbb{X}$) $\times$ $N_G(\leq 0.1$ mi)	0.387*	0.401***	0.537***	-0.190*
	(0.22)	(0.13)	(0.11)	(0.11)
$N_G(\leq 0.1$ mi)	0.445***	0.438***	0.360***	0.554***
	(0.05)	(0.05)	(0.05)	(0.09)
$\mathbb{1}$(High $\mathbb{X}$)			-0.111**	0.074***
			(0.04)	(0.03)
Level: 0.3- & 0.5-mi N_G	Y	Y	Y	Y
Interaction: $\mathbb{1}$(High $\mathbb{X}$) $\times$ 0.3- & 0.5-mi N_G	Y	Y	Y	Y
FE: zipcode and YQ	Y	Y	Y	Y
R^2 (Adj.)	0.0024	0.0023	0.0021	0.0021
Observations	937,546,288	1,018,429,013	1,037,652,076	1,037,652,076

Table VII: Effect Heterogeneity by Green Home Benefits

This table reports the heterogeneous green-peer effects across counties with or without green home benefits. The outcome variable *Green* (=*10,000*) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. The indicator $\mathbb{1}(\mathbb{B}$ exists) in column (1) is a county × year variable taking the value of one when the coefficient on $Green_{it}$ in Equation (16) $y_{it} = \alpha + \beta\ Green_{it} + \gamma\ Control_{it} + \theta_z + \epsilon_{it}$ is statistically positive at the 10% level or below; in column (2) is a county × year indicator taking the value of one for above-median county-year-average HERS scores; and in column (3) is a county × year-quarter variable taking the value of one for above-median number of regulatory incentives. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring $d = 0.1$, 0.3 and 0.5 miles. All the models control for outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{1}(\mathbb{B}$ exists) × $N_G(\leq d\ mi)$). All these variables are defined in Table II. All the models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)		
	(1)	(2)	(3)
Benefit ($\mathbb{B}$) in terms of:	House Prices	Electricity Prices	Incentives
$\mathbb{1}(\mathbb{B}$ exists) × $N_G(\leq 0.1$ mi)	0.668***	0.339***	0.970***
	(0.24)	(0.10)	(0.10)
$N_G(\leq 0.1$ mi)	0.337***	0.123*	0.359***
	(0.04)	(0.06)	(0.06)
$\mathbb{1}(\mathbb{B}$ exists)	0.155***	-0.081***	-0.162***
	(0.06)	(0.03)	(0.04)
Level: 0.3- & 0.5-mi N_G	Y	Y	Y
Interaction: $\mathbb{1}(\mathbb{B}$ exists) × 0.3- & 0.5-mi N_G	Y	Y	Y
FE: zipcode and YQ	Y	Y	Y
R^2 (Adj.)	0.0022	0.0015	0.0023
Observations	303,576,068	874,272,556	983,212,581

Table VIII: Peer-induced Green Certifications and Housing Transaction Returns

This table reports the effect of the green certification decision on the housing market returns of the green-exposed households. The regression sample includes two sets of households. The first set consists of those who obtained green certificates and have at least one green neighbor within 0.1-mile distance in the past year at the time of certification. The second set includes randomly drawn (with replacement) non-green but similarly-exposed (i.e., at least one green neighbor within 0.1-mile distance in the past year) households following the procedure described in Figure IIIb. The outcome variable in column (1) is the annualized rate of return on properties observed to be sold by the peer-influenced households, trimming outliers greater than 200 percent. The outcome variable in column (2) is the implied residual at the time of sale relative to expected market rate as measured by a county-level quarterly price index. The variables of interest is an indicator ($\mathbb{1}$(Green)) taking the value of 1 for the households obtained a green certificate during their tenure at the property. All the models include year of purchase, sale, and green certification fixed effects. Standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)
Outcome:	Return	Sell Residual
$\mathbb{1}$(Green)	0.132***	0.077***
	(0.01)	(0.01)
Buy year FE	Y	Y
Sell year FE	Y	Y
Green year FE	Y	Y
R^2 (Adj.)	0.0624	0.0128
Observations	14,860	14,859

Table IX: Green Preference, Green Certifications, and Heterogeneous Peer Effects

Columns (1) and (2) of this table report the results of regressing the share of green homes on green preferences. Columns (3) and (4) report the heterogeneous green-peer effects across areas with different degrees of green preference. The outcome variable in columns (1) and (2) is the ratio of the number of residential properties that are green-certified in a year in an area (*% Green Home*); and in columns (3) and (4) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property (*Green (=10,000)*). *% Climate Worried* is the percentage of adults in a county who are worried about climate change. *# EV per HH* is the number of EV per household at zipcode level. Indicator $\mathbb{1}$(High $\mathbb{X}$) is one for above-median county × year values of the respective characteristic $\mathbb{X}$—*% Climate Worried* and *# EV per HH*. Columns (1) and (2) include *Housing mkt. & demog. controls*, which consists of the amount of the residential energy tax credit, house price index, number of new single-family homes, population, per capita income, median age, and the percentage of people aged 25 and above with at least a college degree. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring $d =$ 0.1, 0.3 and 0.5 miles. Columns (3) and (4) include controls for $\mathbb{1}$(High $\mathbb{X}$), outer ring green exposure ($N_G(\leq d\ mi)$), and the respective interaction terms ($\mathbb{1}$(High $\mathbb{X}$) × $N_G(\leq d\ mi)$). All these variables are defined in Table II. Standard errors are reported in parentheses, and the level of clustering is listed at the bottom of the table. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	% Green Home		Green (=10,000)	
	(1)	(2)	(3)	(4)
% Climate Worried	0.047***			
	(0.01)			
# EV per HH		1.314*		
		(0.69)		
$\mathbb{1}$(High % Climate Worried) × $N_G(\leq 0.1$ mi)			-0.018	
			(0.12)	
$\mathbb{1}$(High # EV per HH) × $N_G(\leq 0.1$ mi)				-0.108
				(0.14)
$N_G(\leq 0.1$ mi)			0.460***	0.773***
			(0.09)	(0.10)
Level: $\mathbb{1}$(High $\mathbb{X}$)	-	-	Y	Y
Level: 0.3- & 0.5-mi N_G	-	-	Y	Y
Interaction: $\mathbb{1}$(High $\mathbb{X}$) × 0.3- & 0.5-mi N_G	-	-	Y	Y
Housing mkt. & demog. controls	Y	Y	-	-
Fixed effects	County, Year	Zipcode, Year	Zipcode, YQ	Zipcode, YQ
Clustering level	County	Zipcode	Zipcode × YQ	Zipcode × YQ
Observation unit	County	Zipcode	Property	Property
R^2 (Adj.)	0.8247	0.7970	0.0020	0.0020
Observations	11,233	48,596	821,323,588	348,127,621

Table X: Policy Implications: Peer Effects and Provision of Regulatory Incentives

This table reports the results of Poisson pseudo-maximum-likelihood cross-sectional regression of the number of regulatory incentives on the strength of local community interactions. The outcome variable in columns (1) and (2) (columns (3) and (4)) is the mean (median) of the number of county- and state-level regulatory green incentives in a county over 2018 and 2022. Social connectedness and social capital are defined in Section 5.2.C. *Housing mkt. & demog. controls* are the mean (median) over 2018 and 2022 of house price index, population, per capita income, gdp growth, median age, and the percentage of people aged 25 and above with at least a college degree in columns (1) and (2) (columns (3) and (4)). All the models include state fixed effects. Standard errors are clustered by state and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	Mean # Incentives		Median # Incentives	
	(1)	(2)	(3)	(4)
Social Connectedness	0.007		0.009	
	(0.01)		(0.01)	
Social Capital		0.002		0.002
		(0.00)		(0.00)
Housing mkt. & demog. controls	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y
R^2	0.4330	0.4330	0.4254	0.4254
Observations	2,514	2,514	2,514	2,514

Online Appendix to

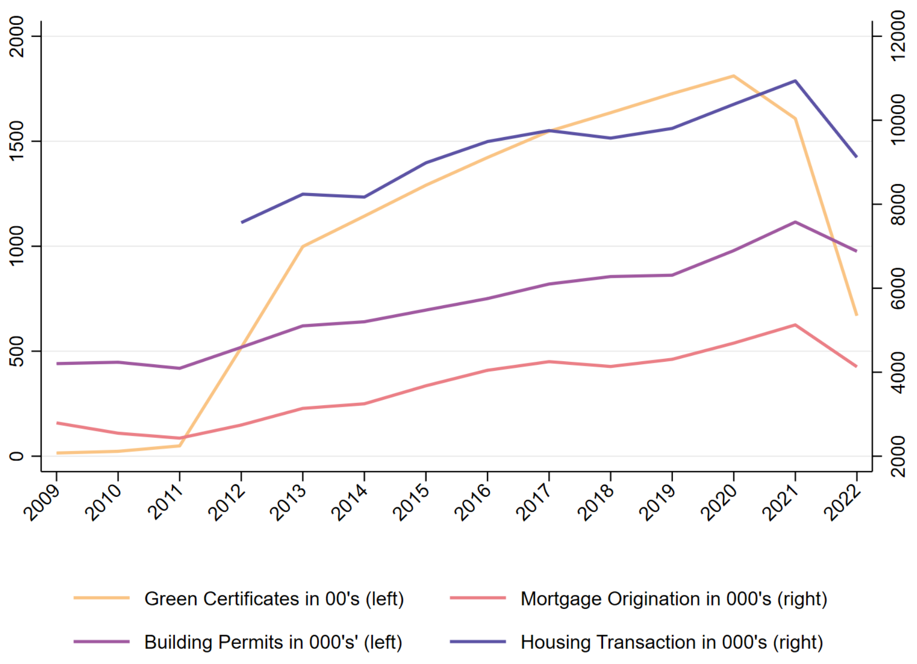
Green Neighbors, Greener Neighborhoods: Peer Effects in Residential Green Investments

A Online Appendix: Supplementary Figures

Figure A.1: Trends in Residential Green Certification in the US

Panel A plots the number of new green-certified single-family homes, new privately-owned single-family homes authorized in permit-issuing places, new home purchase mortgage origination and single-family home transactions in the United States from 2009 to 2022. Green certificates and building permits are represented on the left axis. Mortgage origination and housing transactions are plotted on the right axis. Panel B shows on the map of the contiguous US the percentage of single-family homes in the sample counties that are green certified as of 2022.

Panel A: Green Certifications and Housing Market over Time



Panel B: Spatial Distribution of Green-certified Single-family Homes

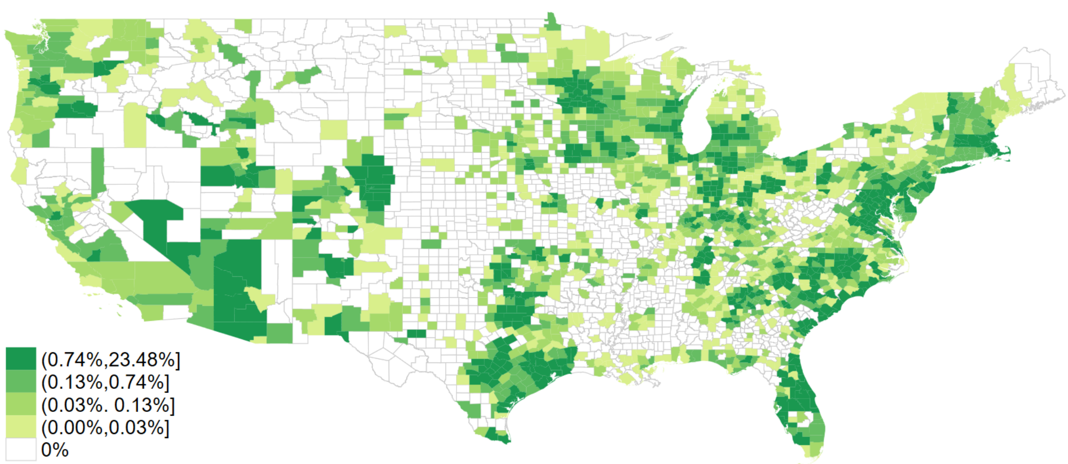
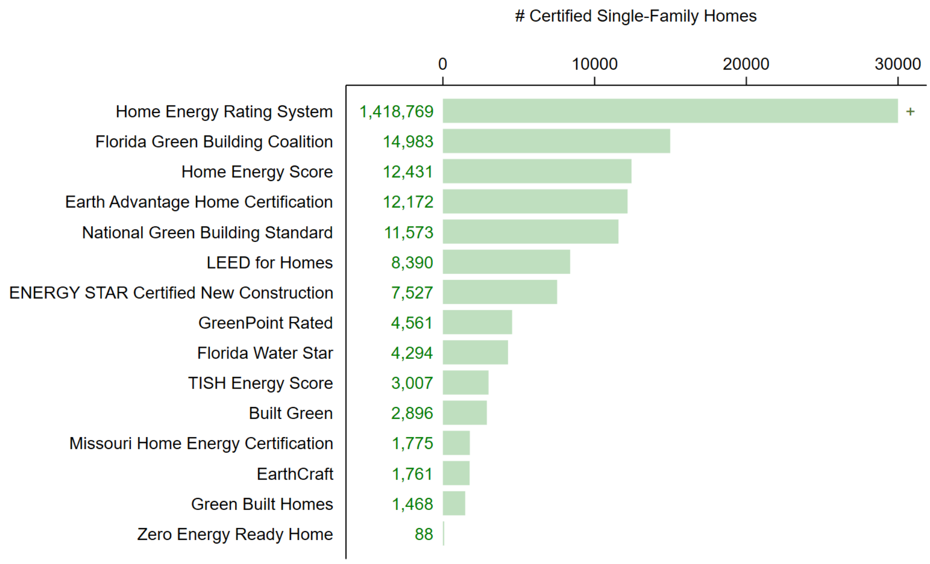


Figure A.2: Institutional Details of Residential Green Certification Programs

Panel A shows the number of single-family homes certified under major green certification programs as of 2022. Panel B plots the estimated annual energy savings for different Home Energy Rating System (HERS) scores. The data for this panel was extracted on August 17, 2024, from www.hersindex.com/hers-index/interactive-hersindex/interactive-hersindex-inside/.

Panel A: Distribution of Residential Green Certification Programs



Panel B: Utility Savings and HERS Scores

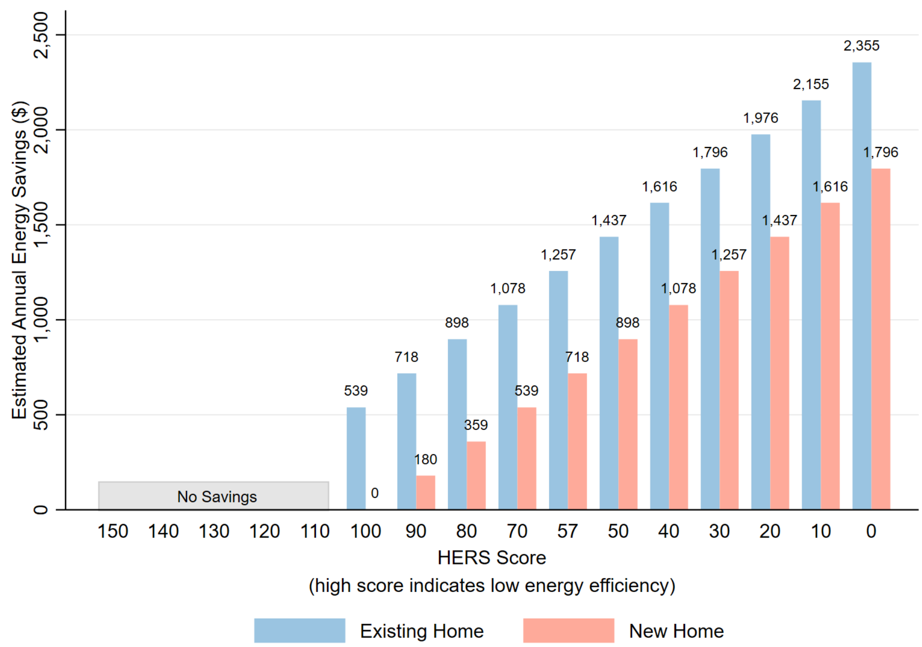
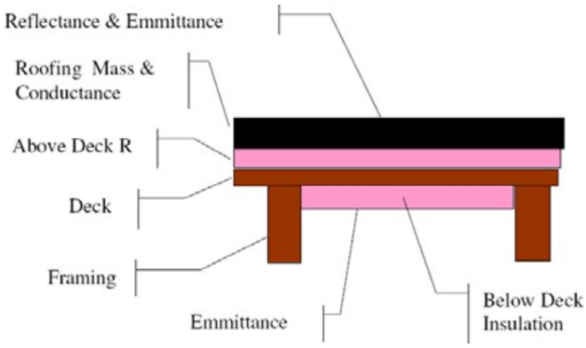


Figure A.3: Examples of Green Certification Technical Standards

This figure shows two examples of green certification technical standards. Panel A illustrates the specifications in inspecting the roof deck above the attic as part of the on-site inspection procedures for California HERS Ratings. Panel B displays an example of the blower door test inspection.

Panel A: Inspection Specifications for Roof Deck above Attic



Panel B: Illustration of Blower Door Test

Figure A.4: Examples of Green Certification Steps

Panel A shows an example of the steps a home contractor needs to follow to certify a home under Built Green program. Panel B shows an example of a post on an online forum by a homeowner sharing experience of green certification and energy rebates (link).

Panel A: Certification Steps for Contractors under Built Green Program

1 JOIN BUILT GREEN
Become a part of the local green building community and enjoy member benefits, including the ability to certify. Sign up.

2 ENROLL PROJECT
Let Built Green know you're working on a project. When you enroll, the project will receive a project ID number, which is required by some jurisdictions for incentives. Enroll your project now.

3 HIRE VERIFIER
Approved third-party verifiers will help you navigate certification requirements, bolster credibility, and assist with models and testing. See the list of verifiers.

4 With your verifier
TRACK GREEN FEATURES
Document green strategies and features on the Built Green checklist. Download checklists.

5 With your verifier
SAVE PERTINENT DOCUMENTATION
Back up your checklist claims with receipts, product specs, and an energy model. Your third-party verifier will help you with what you need.

6 With your verifier
PHOTOGRAPH PERTINENT ITEMS
Built Green pays attention to not only the final product, but to the construction process as well. Verifiers will visit the project along the way to document this.

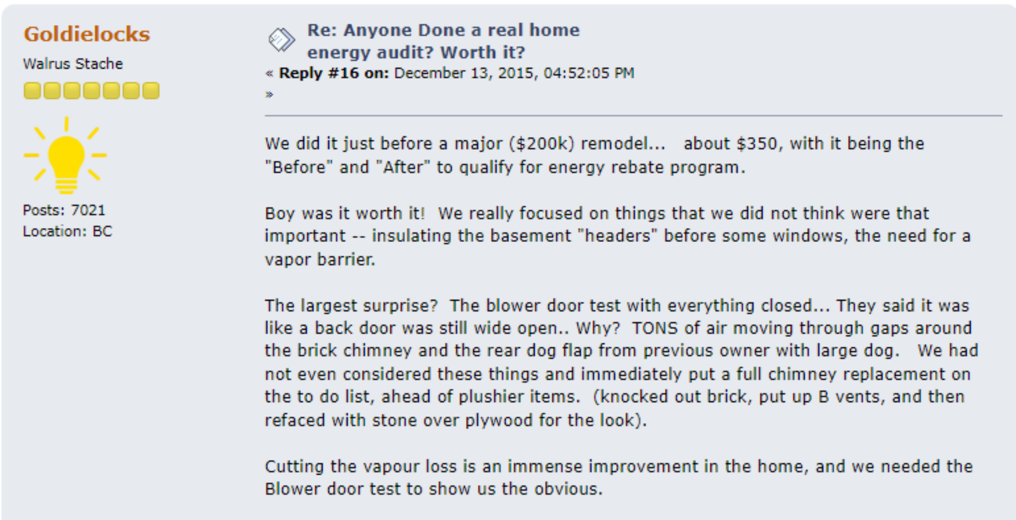
7 SIGN CHECKLIST
Your signature indicates that the project, to the best of your knowledge, includes everything claimed on the checklist.

8 VERIFIER SUBMITS CERTIFICATION PACKET
Your verifier will compile all of the necessary materials for Built Green's review.

9 BUILT GREEN REVIEWS DOCUMENTATION
Built Green then affirms everything in the packet is in order and that claimed action items have documentation proving they were taken. Expect about two weeks for project review.

10 CERTIFICATE AWARDED
Share this certificate with real estate agents and/or residents! It proves the project is indeed green.

Panel B: An Example of a Homeowner's Experience of Green Certification Process



Goldielocks
Walrus Stache
Posts: 7021
Location: BC

Re: Anyone Done a real home energy audit? Worth it?
« Reply #16 on: December 13, 2015, 04:52:05 PM »

We did it just before a major ($200k) remodel... about $350, with it being the "Before" and "After" to qualify for energy rebate program.

Boy was it worth it! We really focused on things that we did not think were that important -- insulating the basement "headers" before some windows, the need for a vapor barrier.

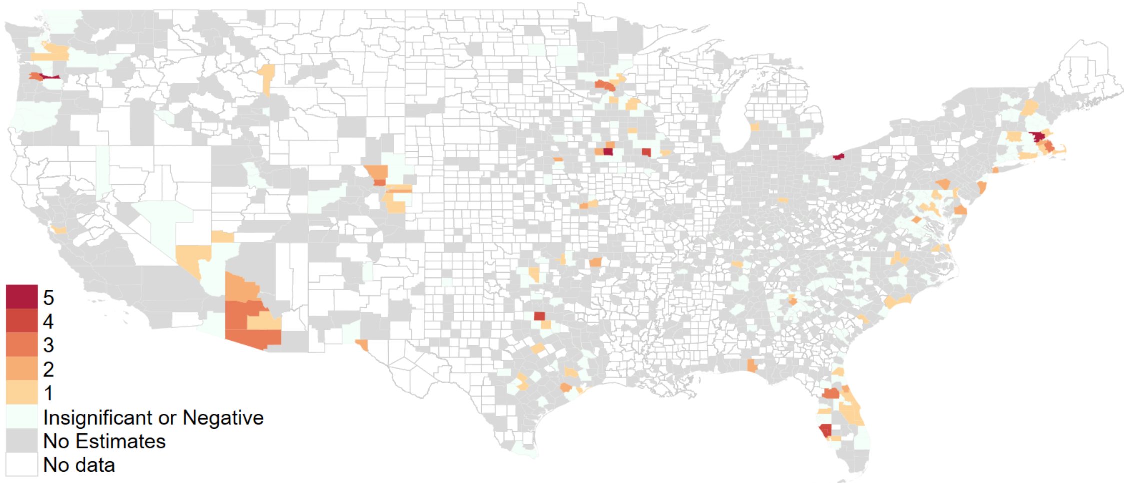
The largest surprise? The blower door test with everything closed... They said it was like a back door was still wide open.. Why? TONS of air moving through gaps around the brick chimney and the rear dog flap from previous owner with large dog. We had not even considered these things and immediately put a full chimney replacement on the to do list, ahead of plushier items. (knocked out brick, put up B vents, and then refaced with stone over plywood for the look).

Cutting the vapour loss is an immense improvement in the home, and we needed the Blower door test to show us the obvious.

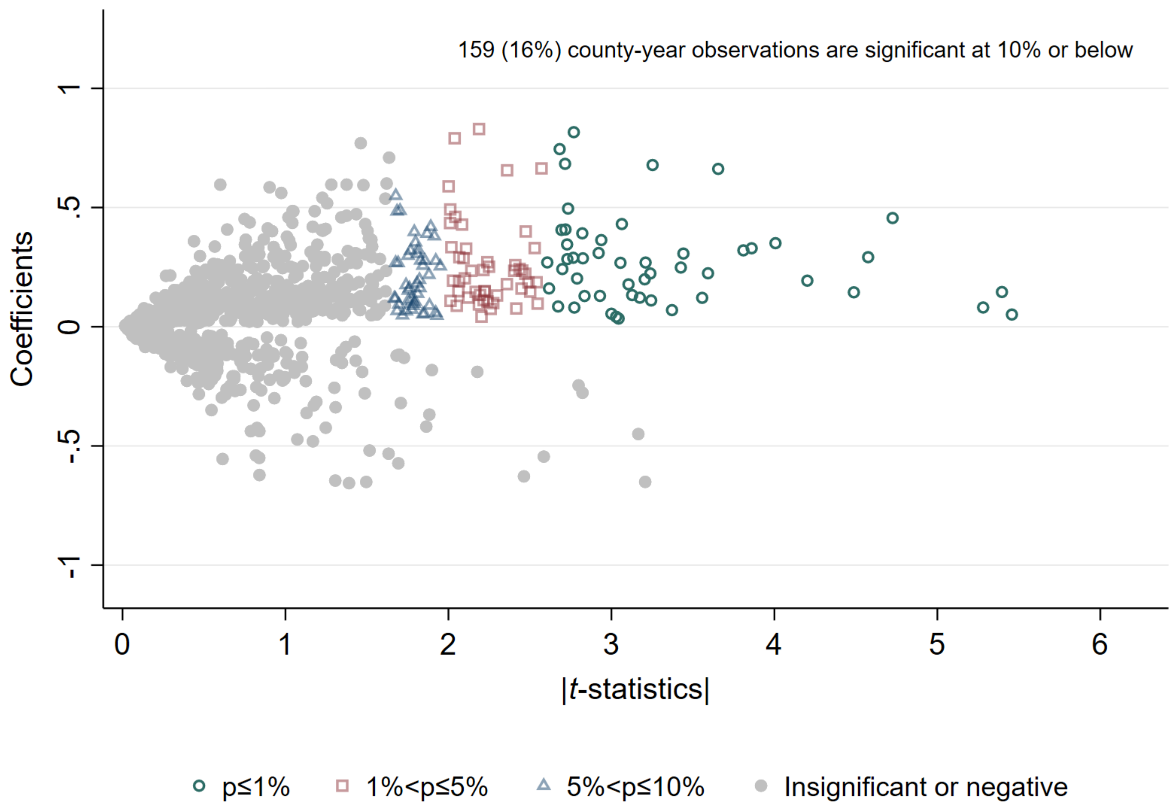
Figure A.5: County-Year-Level Green Certification Premium in House Prices

Panel A shows the spatial distribution of the premiums for green-certified homes estimated for each county and year using hedonic regressions of log transaction prices of single-family homes on property and mortgage characteristics and zipcode fixed effects. The regression equation is $y_{it} = \alpha + \beta\, Green_{it} + \gamma\, Control_{it} + \theta_z + \epsilon_{it}$. The control variables include property age, living area, # bedrooms, exterior materials, heat type, roof materials, a 0/1 indicator of mortgage-financed purchase, mortgage term, mortgage interest rate. The color intensity in Panel A represents the number of years (from 2018 to 2022) for which the β is positive and statistically significant at the 10% level or below. Panel B plots the βs and associated t-statistics estimated in Panel A.

Panel A: Spatial Distribution of Green Certification Premium



Panel B: Distribution of Estimated Green Certification Premium and t-Statistics



B Online Appendix: Supplementary Tables

Table B.1: Residential Energy Tax Credits Incentives and Green Homes

This table reports the results of regressing the residential energy tax credits (RETC) claimed by households to the Internal Revenue Service (IRS) on residential green certifications in a zipcode. The outcome variables in column (1) through (4) are respectively zipcode-level log residential energy tax credit amount ($Ln(A_{RETC})$), residential energy tax credit amount per household (A_{RETC}/# *Household*), log number of tax returns with residential energy tax credits ($Ln(N_{RETC})$), and the percentage of households filing for residential energy tax credits (*RETC Households* (%)). % *New Green Home* is the percentage of residential properties that were newly green-certified in a zipcode in a year. Control variables include zipcode-level house price index, the number of new single-family homes, population, per capita income, median age, and the percentage of people aged 25 and above with at least a college degree. All the models include zipcode and year fixed effects. Standard errors are clustered by zipcode and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	$\text{Ln}(\text{A}_{\text{RETC}})$	$\frac{\text{A}_{\text{RETC}}}{\text{\# Households}}$	$\text{Ln}(\text{N}_{\text{RETC}})$	RETC Households (%)
% New Green Home	0.070***	1.263***	0.031***	0.039***
	(0.01)	(0.26)	(0.01)	(0.01)
Housing mkt. & demog. controls	Y	Y	Y	Y
Fixed effects	Zipcode, Year	Zipcode, Year	Zipcode, Year	Zipcode, Year
R^2 (Adj.)	0.8567	0.6484	0.9082	0.7771
Observations	148,800	189,868	187,719	189,868

Table B.2: Building Permits and Green Homes

This table reports the results of regressing building permits obtained before certification on green status of the properties. The sample consists of green properties (G) and randomly selected non-green properties (NG). The outcome variables are: (i) an indicator that takes the value of one if household i obtained at least one building permit for their property within the four quarters prior to year-quarter q (in columns (1) and (2)); (ii) the number of building permits obtained within the same four-quarter period (in columns (3) and (4)); and (iii) the job value of the building permits obtained within the same four-quarter period (in columns (5) and (6)). *Green* is an indicator taking the value of one for green certified properties. The control variables include property age, living area, # bedrooms. The sample is constructed as follows. The green group G consists of all properties j that received green certification in year-quarter q between 2018 and 2022. The non-green group NG consists of the sample of properties selected by a random draw (with-replacement) of 50 non-green properties for every given property j that became green in year-quarter q (thus, non-green properties inherit the same value of q as the specific green property for which they were randomly drawn). Standard errors are clustered by zipcode and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	$\mathbb{1}$(Obtained Bldg. Permit)		# Bldg. Permit		Ln(Job Value)	
	(1)	(2)	(3)	(4)	(5)	(6)
Green	0.591***	0.582***	1.987***	1.820***	2.172***	1.770***
	(0.01)	(0.01)	(0.04)	(0.04)	(0.08)	(0.08)
Controls	N	Y	N	Y	N	Y
Zipcode FE	Y	Y	Y	Y	Y	Y
YQ FE	Y	Y	Y	Y	Y	Y
Model	OLS	OLS	PPML	PPML	OLS	OLS
R^2 (Adj.)	0.1001	0.0991	0.1498	0.1535	0.3728	0.4106
Observations	7,739,539	7,725,367	7,720,868	7,706,771	564,748	561,005

Table B.3: Price and Risk of Green versus Non-Green Homes

This table reports the results of regressing log house prices in columns (1) through (3) and county-year level standard deviation of residualized house prices in column (4) on green status. The residual is the observed price minus the predicted price ($r_{it} = p_{it} - \hat{p}_{it}$). The predicted price $\hat{p}_{it} = \hat{a}_i + \hat{\delta}_t$, where $\hat{a}_i$ and $\hat{\delta}_t$ represent respectively property and year-quarter fixed effects from the county-level standard repeat-sale regression of log price on the two fixed effects. *Green* is an indicator of the property's green status at the time of transaction. Green homes are restricted to those green-certified within two years prior to the transaction, while non-green homes are not certified at the time of transaction. The sample in columns (1) and (4) includes sales by individual buyers and sellers across the US during year 2018 and 2022, whereas in columns (2) and (3) includes those in Texas. The control variables in columns (1) to (3) include property age, living area, # bedrooms, exterior materials, heat type, roof materials, an indicator of mortgage-financed purchase, mortgage term, and mortgage interest rate. Column (3) includes the assessed improvement value and assessed land value as additional controls. Standard errors are clustered at the zipcode level in columns (1) through (3) and at the county level in column (4), and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Sample:	Home Sales (US)	Home Sales (TX)		Home Sales (US)
	(1)	(2)	(3)	(4)
Outcome:	Ln(Price)	Ln(Price)	Ln(Price)	SD(Residual)
Green	0.024***	0.072***	0.049***	-0.041***
	(0.00)	(0.01)	(0.01)	(0.01)
Ln(Assessed Improv. Value)			0.352***	
			(0.01)	
Ln(Assessed Land Value)			0.221***	
			(0.01)	
Controls	Y	Y	Y	N
Zipcode FE	Y	Y	Y	-
County FE	-	-	-	Y
Year FE	Y	Y	Y	Y
R^2 (Adj.)	0.73	0.65	0.70	0.54
Observations	6,096,075	204,818	204,818	13,414

Table B.4: Returns of Green versus Non-Green Home Improvements

This table reports the results of regressing investments returns on green status for a sample of properties which had home improvement loans. The outcome variable is the return on house transaction price (r_p) in column (1) and is return on assessed value of the property r_v in column (2). The return is calculated as $(p_2 - p_1)/p_1$. p_1 is the amount of the home improvement loan taken in year t. In column (1), p_2 is the transaction price adjusted for movements in median sale price in the zipcode from date of loan till the date of transaction. In column (2), p_2 is the assessed value in year $t+2$ adjusted for movements in median assessed value in the zipcode from year t to $t+2$. *Green* is an indicator taking the value of one for the home improvement loans that were followed by a green certification of the underlying property within a year. The sample in column (1) includes house sales across the US during year 2018 and 2022, and in column (2) includes homes in Texas only. Control variables in column (1) include property age, living area, # bedrooms, exterior materials, heat type, roof materials, mortgage term, mortgage interest rate, and indicators of mortgage-financed purchase, non-person buyer, and non-person seller. For column (2), controls exclude mortgage-related variables and non-person buyer and seller indicators. Standard errors are clustered by county and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	Investment Return	
	(1)	(2)
Return calculated using:	Transaction Price r_p	Assessed Value r_v
	(US)	(TX only)
Green	0.369*	0.320***
	(0.19)	(0.06)
Regression panel	Loan	Loan
Controls	Y	Y
Fixed effects	Zipcode, Year	Zipcode, Year
R^2 (Adj.)	0.08	0.27
Observations	31,719	4,089

Table B.5: Peer Effects in Subsamples of High and Low Housing Supply Constraints

Columns (1) and (3) of this table show the baseline estimates of Table III in the subsample of properties in above-median regulatory restrictiveness (potential seller's) markets, and columns (2) and (4) shows the same in the subsample of properties in below-median regulatory restrictiveness (potential buyer's) markets. The bottom row in the column header denotes the version of WRLURI. The outcome variable *Green* (=*10,000*) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. All the models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
Housing Supply Constraints:	High	Low	High	Low
[WRLURI Version:]	[2006]	[2006]	[2018]	[2018]
$N_G(\leq 0.1$ mi)	0.59***	0.57***	0.46***	0.42***
	(0.11)	(0.09)	(0.06)	(0.08)
$N_G(\leq 0.3$ mi)	0.23***	0.16***	0.33***	0.21***
	(0.02)	(0.02)	(0.04)	(0.02)
$N_G(\leq 0.5$ mi)	0.03***	0.06***	0.07***	0.05***
	(0.01)	(0.02)	(0.01)	(0.01)
Fixed effects	Zipcode, YQ	Zipcode, YQ	Zipcode, YQ	Zipcode, YQ
R^2 (Adj.)	0.0032	0.0017	0.0018	0.0028
Observations	223,231,911	208,599,408	483,002,288	321,170,238

Table B.6: Baseline Estimates for Subsample of Green Homes with Verified Ex-Ante Investments

This table shows the baseline estimates of Table III for the subsample of green homes with verified investments occurring within one year prior to the green certification date, where verified investments are proxied by building permits. The regression specification is from Equation (13). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
$N_G(\leq 0.1$ mi)	0.52***	0.32***	0.34***	0.34***
	(0.09)	(0.07)	(0.07)	(0.07)
$N_G(\leq 0.3$ mi)		0.13***	0.10***	0.09***
		(0.02)	(0.02)	(0.02)
$N_G(\leq 0.5$ mi)		0.02**	0.02**	0.02*
		(0.01)	(0.01)	(0.01)
Fixed effects	N	N	Zipcode, YQ	Zipcode × YQ
R^2 (Adj.)	0.0003	0.0004	0.0007	0.0015
Observations	81,757,257	81,757,257	81,757,254	81,751,343

Table B.7: Placebo Test: Peer Effects of Exposure to Inefficient Green Certifications

This table shows the baseline estimates of Table III in a sample of focal households whose green exposures arise exclusively from neighbors for whom the green certification processes revealed that their homes' efficiency were lower than that of an average home (inefficient green certificates). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a focal household obtains the first inefficient green certificate for his/her property. The green threshold for each program is defined in Table I. $N_G(\leq d\ mi)_{\boldsymbol{Placebo}}$ is the exposure measured as the number of neighbors who have obtained inefficient green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green $(=10{,}000)_{\text{Placebo}}$			
	(1)	(2)	(3)	(4)
$N_G(\leq 0.1\text{ mi})_{\text{Placebo}}$	2.52	1.43	1.47	1.17
	(2.56)	(2.66)	(2.75)	(2.81)
$N_G(\leq 0.3\text{ mi})_{\text{Placebo}}$		-1.60	-1.43	-1.66
		(1.63)	(1.71)	(1.78)
$N_G(\leq 0.5\text{ mi})_{\text{Placebo}}$		2.22*	1.20	1.05
		(1.25)	(1.28)	(1.24)
Fixed effects	N	N	Zipcode, YQ	Zipcode × YQ
R^2 (Adj.)	0.0000	0.0000	0.0023	0.0075
Observations	907,382,917	907,382,917	907,382,912	907,372,314

Table B.8: Baseline Estimates for Subsample of Green Homes with Prior Purchase Transaction

This table shows the baseline estimates of Table III for the subsample of green homes with a known purchase transaction that occurred at least two years prior to the date of green certification. The regression specification is from Equation (13). The outcome variable *Green* (*=10,000*) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d$ $mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
$N_G(\leq 0.1$ mi)	0.60***	0.32***	0.35***	0.36***
	(0.05)	(0.05)	(0.05)	(0.05)
$N_G(\leq 0.3$ mi)		0.20***	0.16***	0.15***
		(0.01)	(0.01)	(0.01)
$N_G(\leq 0.5$ mi)		0.07***	0.05***	0.05***
		(0.01)	(0.01)	(0.01)
Fixed effects	N	N	Zipcode, YQ	Zipcode × YQ
R^2 (Adj.)	0.0010	0.0013	0.0021	0.0031
Observations	1,037,628,885	1,037,628,885	1,037,628,881	1,037,618,310

Table B.9: Effect Heterogeneity by Conspicuous Green Investments

This table reports the heterogeneous green-peer effects by degree of conspicuousness of green investments. Conspicuousness $\mathbb{X}$ in column (1) is an indicator equal to one for properties in census tracts with at least one solar building permit ($\mathbb{1}$(*Solar Permit?*)); in column (2) is an indicator equal to one for census-tract-year level above-median percentage of properties with solar building permits ($\mathbb{1}$(*High Solar Permit* %)); and in column (3) is an indicator equal to one for census-tract-year level above-median percentage of green certifications from programs explicitly requiring photovoltaic (PV) solar generation over the last four quarters ($\mathbb{1}$(*High Grn Bldg. w/ Solar Program* %)). The programs that include PV are Build Green, Earth Advantage, Florida Green Building Coalition, Green Built Homes, GreenPoint Rated, Home Energy Score, LEED for Homes, National Green Building Standard, and Zero Energy Ready Home. Note that the HERS program is excluded from this ratio even though it considers PV solar generation in its certification, because it dominates the certifications (94%). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring $d = 0.1$, 0.3 and 0.5 miles. All the models control for outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{X} \times N_G(\leq d\ mi)$). All these variables are defined in Table II. All the models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)		
	(1)	(2)	(3)
Conspicuousness $\mathbb{X}$ =	$\mathbb{1}$(Solar Permit?)	$\mathbb{1}$(High Solar Permit %)	$\mathbb{1}$(High Grn Bldg. w/ Solar Program %)
$\mathbb{X} \times \text{N}_G(\leq 0.1\text{ mi})$	-0.105	-0.146	0.057
	(0.11)	(0.11)	(0.38)
$\text{N}_G(\leq 0.1\text{ mi})$	0.422***	0.383***	0.638***
	(0.09)	(0.08)	(0.20)
$\mathbb{X}$	0.012	0.155***	0.101
	(0.03)	(0.05)	(0.15)
Level: 0.3- & 0.5-mi N_G	Y	Y	Y
Interaction: $\mathbb{X} \times$ 0.3- & 0.5-mi N_G	Y	Y	Y
FE: zipcode and YQ	Y	Y	Y
R^2 (Adj.)	0.0024	0.0025	0.0030
Observations	334,626,734	201,078,467	88,681,649

C Online Appendix: Steps to Get the Text Similarity

Step 1: Text Extraction from Certification Reports

Starting with 45,602 certification reports downloaded from the GBR website, I first use the python package PdfReader to extract the text page by page.

Step 2: Text Pre-processing and Cleaning

To ensure consistency and remove noise, the extracted text from the certification reports undergoes a rigorous pre-processing and cleaning process:

- Expanding Contractions: Contractions are expanded using the python contractions library (e.g., "can't" is expanded to "cannot").
- Removing URLs: URLs are identified and removed using regular expressions.
- Normalizing Numerical Expressions: Dollar signs are standardized by replacing them with the word "dollar" while preserving the numerical value (e.g., "$2,500" to "2,500 dollar"). Similarly, percentage signs are replaced with the text "percent" while retaining the numerical component. Numeric ranges, such as "2–6%", are reformatted to a more readable form (e.g., "2 to 6 percent").
- Removing Punctuation and Special Characters: Punctuation and special characters are removed.
- Removing Program-Specific Phrases: Specific program names that do not contribute to the analysis are removed using regular expressions. For instance, phrases like "home energy score" are targeted and removed.
- Tokenization: The text is tokenized into individual words using NLTK's word_tokenize function.
- Removing Stopwords: Common English stopwords (e.g., "the", "and", "is") are removed using a predefined list from NLTK.
- Lemmatization: Words are lemmatized using WordNetLemmatizer (e.g., "running" becomes "run").

- Frequency-Based Filtering: Words that appear frequently across all documents but do not add significant meaning are identified and removed. Specifically, the top 10% of the most frequent words are filtered out.

- Reassembling Cleaned Text: After all cleaning steps, the processed words are reassembled into single strings for each document.

Step 3: Data Preparation for Similarity Calculation

After the text has been cleaned and standardized, the following steps are undertaken to prepare the data for similarity calculations:

- Combining Text from Multiple Pages: For each certification report, text from the first six pages is combined. This aggregation ensures that the most relevant content of each document is captured comprehensively.

- Matching Records: The cleaned text data is matched with both the focal and neighboring properties in the "focal property certificate × neighboring property certificate" panel, as constructed in Section 5.2.

Step 4: Text Similarity Calculation

With the cleaned text data prepared, text similarity calculations for the focal and neighboring property are performed using cosine similarity. A TF-IDF (Term Frequency-Inverse Document Frequency) Vectorizer is initialized to convert the text into numerical vectors, capturing the importance of terms in the context of each document. Cosine similarity measures the cosine of the angle between two vectors, providing a metric of similarity that ranges from 0 (completely dissimilar) to 1 (identical).