Green Neighbors, Greener Neighborhoods[*]

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Abstract

Are households' residential green certification decisions causally influenced by their green neighbors? A nearest-neighbor design based on within-0.1-miles neighbors shows that households with green neighbors are 1.8 times more likely to obtain a green certificate within one year than those without such neighbors. The green neighbors also increase the likelihood of multi-property owners certifying their secondary properties in faraway neighborhoods. The influence of neighbors is more pronounced where community interactions are stronger and where green homes fetch financial benefits. Furthermore, closer neighbors display higher certification and lender commonality. These findings align with beneficial information transmission, but not with peer mimicking.

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

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Peers can serve as a valuable source of information for important household decisions. They have been shown to influence for example investments in housing (Bailey, Cao, Kuchler, and Stroebel, 2018; Bayer et al., 2021), refinancing (Maturana and Nickerson, 2019; W. B. McCartney and Shah, 2022), foreclosures (Anenberg and Kung, 2014; Gupta, 2019), and consumption (Agarwal et al., 2021; Bailey et al., 2022). In this paper, I examine the role of immediate neighbor peers in the decisions of households to invest in the energy efficiency of their residential properties.

Investment in residential energy efficiency is relatively sparse. For example, almost 98 percent of the single-family homes in the US lack any energy efficiency certification. Such trends are often attributed to informational asymmetries about aspects such as technological compatibility of the house, potential energy efficiency gains and financing opportunities among various market participants including buyers and sellers, owners and renters, and borrowers and lenders (Matisoff et al., 2016; Howarth and Andersson, 1993; Ramos et al., 2015; Giraudet, 2020). Motivated from the literature showing that immediate neighbor peers can address such informational issues (Bayer et al., 2021; W. B. McCartney and Shah, 2022), I evaluate the causal effect of neighbors on decisions of households to obtain residential green certifications for their properties.

I report three main findings. First, the presence of one additional neighbor within 0.1 miles who obtained a green certificate increases the probability of a household also obtaining a green certificate by 1.8 times within the subsequent year. Moreover, for the case of multi-property owners (MPOs), this effect of green neighbors also percolates to their secondary properties in excess of the effect from the green neighbors of those secondary properties. This implies that the green-peer effect is driven by information transmission among neighbors. Second, households with green-certified properties are more likely to choose the same certificate and lender as used by their spatially proximate neighbors, corroborating the information transmission channel. Lastly, in areas where community interactions are stronger and in areas where green certifying residential properties is financially beneficial, this peer effect is more pronounced. These findings taken together suggest that the green-peer effect is informational and beneficial, and not solely a result of social utility.

Understanding the patterns in investments in residential energy efficiency is of boarder general interest. On the one hand, residential buildings contribute nearly five percent of total global energy-related emissions (UNEP, 2020). Understanding the factors that promote such investments can help inform policies aimed at sustainable housing, environmental conservation efforts, and attaining the global emission mitigation targets (IEA, 2019). Studying such investments is also relevant 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). Finally, such investments have important financial implications for households as they often finance the necessary capital through borrowing.

The key challenge in studying neighborhood peer effects is to establish causality. Neighbor assignments are rarely random, and households within the same neighborhood may be exposed to common, unobservable shocks, which in turn could confound the estimates of the effects (Manski, 1993). The nearest-neighbor research design aims to overcome these issues and has been used to document a series of causal peer effects (Bayer et al., 2021, 2022; W. B. McCartney and Shah, 2022; Towe and Lawley, 2013; W. McCartney et al., 2023).

I apply the nearest-neighbor research design of Bayer et al. (2021) to identify causal peer effects in residential green certifications. The idea is to estimate the impact of green certifications by hyper-local neighbors (of 0.1 miles) on a household's decision to green certify their home, while controlling for the same activity occurring within a slightly broader neighborhood (of 0.3 and 0.5 miles). This approach 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 an exact block (of 0.1 miles) within such a geography. The setting thus mimicks a quasi-random assignment of neighbors. Second, homeowner and property characteristics are broadly similar within small geographies (of 0.3 or 0.5 miles), such that unobservable differences are unlikely to drive the estimated difference in green certification decisions.

I begin the analysis by examining the peer effects of green neighbors on households' decisions to green certify their properties. I combine nationwide single-family housing data on property characteristics, ownership, transactions and mortgages with property-level green certificates. This allows me to identify a focal property's green certification status and the number of its green neighbors within 0.1, 0.3, and 0.5 miles. Panels A and B of Figure I respectively show a green and non-green focal property and their green neighbors. Regressing a focal property's green certification status on its green exposure—calculated as the number of its green neighbors within 0.1 miles who green certified their home for the first time in the past four quarters ($N_G(\leq 0.1$ $mi)$)—while controlling for the exposures within 0.3 and 0.5 miles provides the causal estimate of the effects.

The regression estimate suggests that one additional green neighbor within 0.1 miles raises the probability of a household also obtaining a green certificate by 1.8 times within the subsequent year. This magnitude is sizable relative to the peer effects documented in other similar settings. For example, the effect is 8% for investment property decisions (Bayer et al., 2021) and is 3.3% for refinancing decisions (W. B. McCartney and Shah, 2022). My estimate is robust to the inclusion of several spatial (zipcode) and temporal (year-quarter) and ownership tenure (i.e., owner × property) fixed effects and to a series of controls for property and neighborhood characteristics. These controls include property age, living area, # bedrooms, exterior materials, heat type, roof materials, 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.

To explain the green-peer effect, I propose an information transmission mechanism similar to the one in Maturana and Nickerson (2019). Here households receive information about the potential benefits of green certification from their neighbors and green certify their own homes. I show evidence in support of this mechanism in the certification of secondary properties owned by MPOs. I find that immediate green neighbors of the primary residence of MPOs (where they reside) have a statistically significant positive effect on MPOs' decisions to green certify their secondary properties (where they do not reside). Incidentally, this finding also rules out the alternative explanation that the positive effect of immediate green neighbors is driven solely by neighborhood characteristics such as preferences of the property developers and local green marketing campaigns.

The information transmission channel is further corroborated in a series of results. First, focal green households are significantly more likely to choose the same green certificate and lender as their immediate neighbors (within 0.1 miles) compared to slightly farther away neighbors (0.1 to 0.5 miles). Second, the green-peer effect is stronger in areas with a higher strength of local community interactions, characterized by stronger social ties, fewer non-owner-occupied properties, and higher quality neighborly interactions.

An alternative explanation for neighborhood peer effects is social utility, wherein households derive utility just by mimicking their neighbors' decision, regardless of whether the decision is financially beneficial (Bursztyn et al., 2014). If the green-peer effect I report in this paper were driven solely by social utility, its magnitude would not vary in sync with the potential financial benefits of residential green certifications. However, I find that the green-peer effect is more pronounced in counties estimated to exhibit statistically significant financial benefits for green-certified homes arising from housing markets (in terms of transaction prices and mortgage rate spread) as well as regulatory incentives. The green-peer effect thus appears to be driven by beneficial motives, rather than just by social utility. This is further reaffirmed by the finding that the green-exposed households who green certified their properties outperform the similarly exposed households who did not.

Finally, I find that the green-peer effect does not vary across areas with differing levels of belief about climate change or across areas with different tendencies to purchase an electric vehicle, a common pro-environmental behavior. In conclusion, the green-peer effect appears to be consistent with financial benefit-maximizing behavior.

This paper is novel as it is the first study documenting the causal peer effects in residential green certification decisions by households. Moreover, this paper is the first to utilize the nearest-neighbor design on a national scale—a computationally challenging task—whereas previous studies focus on much 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).

My paper contributes to three strands of the literature. The first is the well-developed literature on peer effects in financial decisions by households. Peer effects have been shown to exist in stock investment (Huang et al., 2021), house purchase (Bailey, Cao, Kuchler, and Stroebel, 2018), foreclosure (Gupta, 2019), and consumption (Agarwal et al., 2021). On the one hand, peer effects lead to beneficial outcomes in stock market participation (Hong et al., 2004; Brown et al., 2008) and refinancing (Maturana and Nickerson, 2019; W. B. McCartney and Shah, 2022). On the other hand, they may also lead to loss-making decisions in stock investment (Cookson et al., 2023; Hvide and Östberg, 2015), bitcoin investment (Han et al., 2023), and housing investment (Bayer et al., 2021) due to herding and contagious belief propagation. I add to this literature by studying green certification decisions of households, and find that the green-peer effect is financially beneficial.

My paper also contributes to the literature on peer effects in green activities in the housing market. These effects have been shown for solar photovoltaic panels (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Müller, 2021; Bigler and Janzen, 2023) and water conservation (Bollinger et al., 2020), but my paper differs in terms of underlying incentives, the mechanism, empirical design and the scope, and contributes complementary findings to previous studies.[1] My paper also complements

[1] First, my paper is primarily about housing markets and the focus is not only on whether there is a peer effect in obtaining green certifications, but more importantly on understanding how the financial incentives drive this effect. Whereas the key finding in my paper is that the peer effect is financially beneficial, the analysis in these other papers is centered on examining whether spillovers in green practices exist. They do not examine whether and how such decisions are influenced by housing market conditions, financial benefits, or households' evolving preferences. Second, the empirical methodology

Qiu et al. (2016) who investigate the spillovers in green certifications in the commercial real estate sector. However, an important dimension along which my paper differs is that I study spillovers in the decisions of households, which are more likely to suffer from informational asymmetries and constraints than the participants in commercial real estate markets.

My paper also speaks to the extensive literature on financial investments in green assets. Lanteri and Rampini (2023) show, using a theoretical model, that financial constraints influence decisions of firms (or households) to invest in clean technologies. Moreover, many studies have empirically examined the green investments by institutional investors (Krueger, Sautner, and Starks, 2020; Hartzmark and Sussman, 2019; Riedl and Smeets, 2017). My paper contributes new insights to this literature by studying green investments of households in residential properties.

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

1 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 or-

in my paper (nearest-neighbor design) is tailored to uncover causal estimates in hyper-local settings. On the other hand, the empirical method in Bollinger and Gillingham (2012); Bigler and Janzen (2023); Bollinger et al. (2020) relies on OLS and an IV for causal interpretation. Third, the outcome variable in my paper is the decision of households to obtain green certificates for their properties, which by definition is an extensive margin outcome of real investments in the property. The outcome variables in Bigler and Janzen (2023) are electricity consumption and adoption of electric vehicles (EVs) and solar panels (PVs). They do not distinguish whether the reduction in electricity consumption comes from households' investment in energy efficient practices or from a reduction in wasteful electricity usage (which only require behavioral changes but not real investments). Similarly, for EV and PV adoption, they do not distinguish whether it is driven by the demand-side factors—such as financial motives and green preferences of households—or the supply-side factors—such as incentives from governments (tax benefits) and lenders (cheaper financing).

ganizations. Such certifications commonly assess elements such as site, water, energy, indoor air quality, materials, operation, and maintenance.

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 II. 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. Figure III provides the distribution of the residential green certification programs. The Home Energy Rating System (HERS) is the most popular certification program in the US, comprising approximately 94% of all certified homes. Table I summarizes the programs by geographical coverage, attributes evaluated, and builder involvement. Among the 15 certification programs considered, six operate across the US and the remainder operate regionally. Programs also vary widely across the attributes they 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).

Green certifications can be initiated either by builders or by homeowners. Builders typically engage with certifying organizations throughout property construction or renovation. After construction is completed, qualified raters assess the compliance of the property. Homeowners often initiate the certification process through energy audits and consultation for green renovations.

2 Data, Sample Construction, and Summary Statistics

2.1 Data

The main empirical analysis utilizes two datasets: property, deed and mortgage data compiled by the Warren Group from county records offices and green certificate data from the Green Building Registry (GBR). 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 regulatory incentives for green certifications, 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. I utilize community interaction measures from Bailey, Cao, Kuchler, Stroebel, and Wong (2018), Chetty et al. (2022), and Rupasingha et al. (2006, with updates) and a range of socioeconomic and demographic data from the U.S. Census, IRS SOI, and HUD.

2.2 Sample Construction

Several steps are needed to process the raw data and create the panel on which nearest-neighbor regression specifications are estimated. To process the green certification data, I begin by examining each of the 15 certification programs and their scores (or rating categories) and create an indicator—Green—to uniformly represent the green certification status across these programs.[2] Table I provides 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.

Next, the property data are processed using the following steps. To identify whether a property is owned by individuals (households) or non-persons, I follow the procedure of Bayer et al. (2021) and categorize the ownership into individuals, trusts, banks, business, government and nonprofit organizations. I then exclude the following observations: (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, put together, allow me to identify single-family properties, respective tenures, and the ownership category. 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 the more than 73.8 million single-family properties in the sample.

Armed with the data on focal-neighbor property pairs and the green certification status of all properties, I count quarterly, for every individual-owned focal property, the number of neighboring properties (regardless of ownership type) within 0.1, 0.3 and 0.5 miles that became green in the previous four quarters (inclusive of the current quarter). 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. My final sample consists of 30,451,754 single-family properties located in 1632 counties across the US, resulting in a panel of 411,515,023

[2] This indicator identifies whether the score (or rating category) assigned to a given property under a given program exceeds that of an average US home. For example, the Home Energy Score Program (HES) indicates, "If your home scores a 5, it is expected to perform comparably to an average home in the U.S. in terms of energy use. If your home scores a 10, it ranks among the ten percent of U.S. homes expected to use the least amount of energy after accounting for climate. A home scoring a 1 is estimated to consume more energy each year than 85 percent of U.S. homes, again after accounting for local climate." I therefore assign properties rated under the HES program to be green certified (Green= 1) if their scores are higher than 5.

observations over the time period 2018–2022 on focal properties and their exposures to green certifications in their neighborhood calculated quarterly.

2.3 Summary Statistics

Table II reports the summary statistics for the main variables analyzed in this paper. The average probability of a household green certifying their house in a given quarter is 0.0032 percent. The average household has 0.05, 0.30 and 0.53 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 0.0429 percent of the households become green at a quarterly hazard rate of 0.0032 percent. A typical single-family property in the sample was built in the year 1975, has a living area of 1864.92 square feet, and has 2.51 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 2.07 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 $34,030.

3 Research Design

The main objective of this paper is to causally evaluate the effect of residential green certifications in the immediate neighborhood on the likelihood of a household also green certifying their house. 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 certification) 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:

$$\text{Proportional Diff}_{cid} = \frac{c_i - Avg(c_j)_{j\in[d-0.1:d]}}{c_i}, \; d \in \{0.1, 0.2, \ldots 0.5\}. \tag{1}$$

For a given characteristic c, Figure IV plots $\textit{Proportional Diff}_{cd}$, which is the average of $\textit{Proportional Diff}_{cid}$ 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 green certify their properties), 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 Figure V the proportional difference in green exposure of green-certified focal properties (G) and randomly selected non-green focal properties (NG) with distance.[3] We see that the proportional difference in green exposure remains stable as the distance from neighbors decreases from 0.5 miles to 0.3 miles, but it rises sharply as the distance decreases further to 0.1 miles. This suggests that households that green certified their houses experienced many more green certifications in their close neighborhoods than those who did not certify.

[3] 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 green property j from group G 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.

3.1 Regression Specification

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

$$Green_{it} = \alpha + \beta_1 \times N_G(\leq 0.1 \text{ mi}) + \beta_2 \times N_G(\leq 0.3 \text{ mi}) + \beta_3 \times N_G(\leq 0.5 \text{ mi}) + \theta_t + \theta_j + \epsilon_{it}, \quad (2)$$

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 neighbors' green certifications within 0.1 miles, denoted as $\text{N}_G(\leq 0.1 \text{ mi})$. 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—$\text{N}_G(\leq d \text{ mi})$, 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 4. Additionally, to account for local characteristics, I modify Equation (2) by adding *Property controls*$_{it}$ and *Neighborhood controls*$_{it}$ as follows:

$$\begin{aligned} Green_{it} = \alpha + \beta_1 \times N_G(\leq 0.1 \text{ mi}) + \beta_2 \times N_G(\leq 0.3 \text{ mi}) + \beta_3 \times N_G(\leq 0.5 \text{ mi}) \\ + \delta_1 \text{Property controls}_{it} + \delta_2 \text{Neighborhood controls}_{it} + \theta_t + \theta_j + \epsilon_{it}, \end{aligned} \quad (3)$$

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. Definitions of these variables are provided in Table II.

4 Main Results

I begin the analysis by visually analyzing the effect of green neighbors on green certification decisions of households. I plot in Figure VI the average probability that households green certify their properties against the number of their neighbors located at different distances who green certified their properties in the last four quarters.[4] We see in the figure, moving from left to right, that the probability of green certification 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 certification 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 (2) and report the results in Panel A of Table III. The coefficient on $N_G(\leq 0.1 \text{ mi})$ in column (1) is 0.66 and statistically significant, suggesting that the exposure to green neighbors within a 0.1-mile radius increases the likelihood of a household green certifying 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, $0.66/0.26 = 2.49$. It represents the change in the quarterly likelihood that households will obtain green certificates 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 certification increases by 2.49 times. The hazard ratio is reported separately at the bottom of the table under *Marginal Effect to Hazard Ratio*.

[4] Green neighbors located within d miles are defined as those who have green certified their homes 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 are green certified 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.

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 (2). The coefficient on $N_G(\leq 0.1 \text{ mi})$ is statistically significant, and the associated hazard ratio is 1.83 (= 0.35/0.19). This ratio indicates that one additional green neighbor within 0.1 miles increases the likelihood that a focal household obtains a green certificate in a given quarter by 1.83 times compared to a household with no green neighbors within 0.5 miles.[5] 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 fixed effects; column (4), zipcode fixed effects; and column (5), both. Column (6) includes zipcode × year-quarter fixed effects; and column (7), tenure and 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.

I repeat these regressions following Equation (3) 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 green certify their properties within the next year.

The analyses in the rest of the paper are based on the specification in column (5) 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

[5] 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 obtains a green certificate 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 0.16 times ($\beta_3/\alpha = 0.03/0.19$), or equivalently, by 16%; one located at 0.2 miles increases it by 1.42 times ($(\beta_2 + \beta_3)/\alpha = (0.24 + 0.03)/0.19 = 1.42$); and one located at 0.08 miles increases it by 3.21 times ($(\beta_1 + \beta_2 + \beta_3)/\alpha = (0.35 + 0.24 + 0.03)/0.19 = 3.21$).

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 Mechanism

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 (Maturana and Nickerson, 2019; Bayer et al., 2021; Bursztyn et al., 2014; Hong et al., 2004; Brown et al., 2008; Banerjee et al., 2013) commonly points to two mechanisms. The first is based on information transmission, wherein neighbors serve as an additional source of information and potentially reduce the informational barriers in decision making. The second is based on social utility, wherein households derive utility simply by following the same decision as their peers. I design tests in this section to understand if these mechanisms are at play.

5.1 The Role of Information Transmission in the Green-Peer Effect

5.1.A Peer Effects and Multi-Property Owners

In the information transmission mechanism, I hypothesize that focal households acquire knowledge from their neighbors about various aspects of green certifications. The households could learn about associated upfront costs of installation and green renovation, potential benefits from utility savings from efficiency gains 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 green certifications, and facilitates certification of their own homes.

Note that the increased probability of green certification 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 certification of the secondary properties of MPOs. If the information transmission mechanism is at work, MPOs would likely acquire information from the immediate neighbors of both their primary residence (where they reside) and their secondary properties (where they do not reside). The prediction thus from this mechanism would be that MPOs' decisions to green certify their secondary properties will be influenced by both sets of neighbors. However, if the certification decision of MPOs is driven solely by within-neighborhood-level characteristics, the prediction would be that immediate neighbors of primary residence of MPOs will have no influence on their certification decisions for their secondary properties.

I next examine which of the two predictions discussed above holds by estimating Equation (2) 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 residence and their secondary properties. I denote these exposures by *Primary's* $N_G(\leq d\ mi)$ and *Secondary's* $N_G(\leq d\ mi)$, where $d \in \{0.1, 0.3, 0.5\}$. Table IV reports the results. The sample in column (1) consists of the secondary properties of MPOs whose primary residence is $\leq$ 10 miles away. In columns (2) through (6), the primary residence is located respectively more than 10, 20, 30, 40, and 50 miles away. We see that the effect of immediate green neighbors of primary residence (*Primary's* $N_G(\leq 0.1\ mi)$) is statistically significant at about 0.007 bps in all columns except (1).[6] This finding supports the in-

[6] Note that the coefficients on *Primary's* $N_G(\leq 0.1\ mi)$ is many times smaller than those on *Secondary's* $N_G(\leq 0.1\ mi)$. This pattern is consistent with the idea that MPOs learn from the immediate neighbors of their primary residence about general information on residential green certification—akin to a necessary condition for the certification decision. In addition, they also learn from the immediate neighbors of their secondary properties about specific information on their properties—akin to a sufficient condition. To elaborate, general information could include awareness about potential benefits of residential green certification and existence of regulatory incentives, whereas specific information could pertain to the suitability of their secondary property for green upgrades, its solar potential, and the availability of local suppliers and services. In term s of stock market terminologies, the general information can be viewed as systematic information such as broader market trends and economic indicators, and the specific information as idiosyncratic information about individual stocks.

formation transmission mechanism and rules out the explanation that the green-peer effect is solely a result of within-neighborhood-level interactions and characteristics.

5.1.B Peer Commonalities in Green Certificates and Lenders

The information transmission mechanism can additionally be tested by examining the commonalities in the choices 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 such as the green-certifying organizations and lenders. 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 and lenders as their immediate neighbors.

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 1 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 1 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 0.6 and 1.2 percentage points for immediate neighbor peers in columns (1) and (2) respectively.

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. The idea is that if they receive information about green certification from their neighbor peers, they may also receive information on neighbors' lenders, who could be more amenable to financing the investments necessary for green certification as they have a prior lending relationship with owners of 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 certification. 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 certifications is pertinent and timely. Using these household pairs, I create a "focal household's mortgage × neighbor's mortgage" panel and define the indicator $\mathbb{1}$(Same Lender) to take the value of 1 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 (3) shows the result for all lenders, while column (4) 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 green certifying 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 certificates and lenders among close-neighbor peers corroborate the information transmission mechanism.

5.1.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 (2) 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 1 for above-median levels of the measure $\mathbb{X}$ of community interactions. The coefficient of interest is β_1 in the following equation:

$$\begin{aligned} Green_{it} = \alpha &+ \beta_1 \mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.1 \text{ mi}) \\ &+ \beta_2 \mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.3 \text{ mi}) + \beta_3 \mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.5 \text{ mi}) \\ &+ \beta_4 N_G(\leq 0.1 \text{ mi}) + \beta_5 N_G(\leq 0.3 \text{ mi}) + \beta_6 N_G(\leq 0.5 \text{ mi}) + \delta \mathbb{1}(\text{High } \mathbb{X}) + \theta_t + \theta_j + \epsilon_{it}. \end{aligned} \tag{4}$$

The first set of community interaction measures is based on social ties: the zipcode-level social connectedness index and social clustering, and county-level social capital (ASSN 2014).[7] 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.

I utilize a second set of proxies for community interactions based on the idea that the green-peer effect would be weaker in areas where information is less likely to flow with ease, either due to the absence of owners—who hold the decision-making authority to implement changes in the property (W. B. McCartney and Shah, 2022)—or due to a lack of neighbor interactions caused by high population density (Hawley, 2012). To proxy for the absence of owners, I use the percentage of investment properties and house flippers in a zipcode; to proxy for the population density, I use housing density, which equals the number of residential properties per acre in a census tract. The coefficient β_1

[7] The social connectedness index (within a zipcode) measures the strength of connectedness between two geographic areas using Facebook friendship ties (Bailey, Cao, Kuchler, Stroebel, and Wong, 2018), while social clustering measures the rate at which two friends of a given person are in turn friends with each other within a zipcode (Chetty et al., 2022). The idea behind this measure is that if a person's friends are friends with each other, they can act together to pressure or sanction that person, which enforces norms and induces pro-social behaviour and investment. Social capital (ASSN 2014) is the total number of ten types of social organizations in a county in 2014 (Rupasingha et al., 2006, with updates). These include nonprofit organizations; social organizations such as sports clubs, public golf courses, bowling and fitness centers; and associations with a professional, business, political, religious, or other orientation.

in columns (4) through (6) confirms the prediction that the green-peer effect is weaker in areas where the ease of information transmission is low.

In summary, all six heterogeneity tests utilizing the strength of local community interactions suggest that information transmission plays a role in the green-peer effect.

5.2 The Role of Social Utility in the Green-Peer Effect

In the previous section, I examined the green-peer effect through the lens of information transmission. An alternative mechanism for peer effects commonly 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). While such social utility is difficult to measure, the patterns observed in the peer effects can uncover insights into its role. In my case, if social utility drives the green-peer effect, then this effect would likely induce neighbors to green certify their homes even when doing so is not financially beneficial. With this implication in mind, I examine in this section: (i) how the green-peer effect varies across areas that differ in the potential benefits of residential green certification; and (ii) whether the green-exposed households realize higher financial returns from green certifying their homes relative to similarly exposed households who do not.

5.2.A Heterogeneous Peer Effects: The Role of Potential Green Benefits

As discussed above, green certification decisions that are induced by social utility (or peer mimicking)—without value-relevant information transmission—may result in certifications that are not financially beneficial. Hence to understand the role of social utility in the green-peer effect, I conduct a series of peer effect heterogeneity tests exploiting the variations in potential benefits of green-certified homes.

I begin by estimating the first set of potential benefits of green-certified properties relative to observationally equivalent non-green-certified properties in terms of higher house prices and lower rate spreads using hedonic regressions.[8] I use the regression of the following form on transaction-level data and estimate it separately for each county and year:

$$y_{it} = \alpha + \beta \, Green_{it} + \gamma \, Control_{it} + \theta_z + \epsilon_{it}. \tag{5}$$

The coefficient of interest is β, which estimates the difference in the outcome variable for a green-certified home relative to a non-green home. The first outcome variable is $ln(Price)$ for home-purchase transactions. Control variables 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. The second outcome variable is rate spread for home-purchase mortgages. It is the difference between the covered loan's annual percentage rate (APR) and the average prime offer rate (APOR) for a comparable transaction on the date the interest rate is set. The associated control variables exclude the 0/1 indicator of mortgage-financed purchase from the house-price regression and add the following: the number of lenders in a census tract, income, and debt-to-income ratio. All regressions include zipcode fixed effects.

Figure VII shows the counties where green-certified homes fetch potential financial benefits for the sample period. The color intensity in Panels A and B 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. I identify the county-year combinations where these potential benefits exist using the indicator $\mathbb{1}(\mathbb{B} \text{ exists})$, which equals 1 when the coefficient β is statistically positive at the 10% level or below.

I also estimate potential benefits of residential green certifications in terms of regulatory incentives. This is equal to the sum of unique county- and state-level green incen-

[8] Note that here I do not attempt to estimate the benefits of the residential green certifications in the absolute sense, as calculating the net present value of such investments is not feasible because the data on relevant costs and benefits of such certifications are not available. As a compromise, I employ hedonic regressions to infer the potential benefits of green-certified properties relative to non-green-certified properties as implied from the transactions in the housing markets. This approach is commonly used in the literature to estimate the contribution of a property or neighborhood characteristic to house prices (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).

tives 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 $\mathbb{1}(\mathbb{B}\text{ exists})$ which equals 1 for above-median levels of county-level incentives. The color intensity in Panel C represents the number of years (from 2018 to 2022) for which a county has an above-median number of regulatory incentives.

Having identified the county-time combinations where green-certified homes fetch the potential benefits, I next conduct a series of peer effect heterogeneity tests exploiting the variations in these benefits. I follow Equation (4) by replacing the indicator $\mathbb{1}(\text{High }\mathbb{X})$ with the indicator for the three potential benefits, $\mathbb{1}(\mathbb{B}\text{ exists})$. The coefficients on $\mathbb{1}(\mathbb{B}\text{ exists}) \times N_G(\leq d\ mi)$ in column (1) through (3) of Table VII suggest that the green-peer effect is stronger in the areas where the potential benefits are stronger.

To summarize, the green-peer effect is not uniform across areas that differ in the potential benefits of residential green certifications; it is stronger where benefits are higher, implying that this peer effect is not solely driven by social utility (or peer mimicking) but by value-relevant information transmission.

5.2.B Housing Transaction Returns from Peer-induced Green Certifications

If the green-peer effect exists due to social utility (peer mimicking), it is unclear *a priori* whether those households who green certify their houses—presumably due to green exposures from their immediate neighbors—would perform better or worse than those households who are similarly exposed but do not do so. However, if the peer effect exists due to value-relevant information transmission, the influenced households who follow their peers would be better off. I therefore evaluate in this section the housing transaction returns for the two sets of households to understand the dominating mechanism.

I create a sample of green-exposed households who green certified their homes and similarly-green-exposed households who did not certify their homes.[9] I then define an indicator $\mathbb{1}(Green)_i$ to take the value of 1 for the certifying households and 0 for the non-certifying households and estimate the following regression:

$$y_i = \alpha + \beta\, \mathbb{1}(Green)_i + \theta_{\text{buy year}} + \theta_{\text{sell year}} + \theta_{\text{green year}} + \epsilon_i. \tag{6}$$

The outcome variable y_i is the housing transaction returns measured in three ways: the annualized rate of return, sell residual, and buy 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 reaped by households who green certified their property 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. 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 12.5%. Similarly, the positive coefficient in column (2) indicates they sell their green-certified houses at a 7.7% higher price, and the negative coefficient in column (3) suggests that they buy at a 7.8% cheaper price (and subsequently green certify their houses). The superior performance of the certifying households in the housing market does not support the social utility mechanism but is consistent with the value-relevant information transmission mechanism.

In conclusion, the findings about the decisions of the MPOs, peer commonalities in certificates and lenders, effect heterogeneity by local community interactions and

[9] 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.

potential financial benefits of the certifications, and superior performance of certifying households consistently point to the value-relevant information transmission mechanism.

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.

I. Does the green-peer effect varies with green preference?

The beliefs of households about climate change and their green preferences are commonly used to explain a range of decisions such as stock investments (Choi et al., 2020; Fisman et al., 2023), mortgages, and EV purchase (Kahn, 2007). The question then arises: does the green-peer effect varies with green preference? I shed some light on the answer by first investigating the association between the percentage of residential green-certified homes in an area and two proxies for green preference, and then examining 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:

$$\%\ \text{Green Home}_{ct} = \alpha + \beta\, \text{Green Pref}_{ct} + \gamma\, \text{Controls}_{ct} + \theta_c + \theta_t + \epsilon_{ct}. \tag{7}$$

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.

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 (4), where $\mathbb{1}(\text{High } \mathbb{X})$ now represents an indicator that equals 1 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. It also suggests that the effects are not solely driven by evolving green preferences.

II. Do green certificates capture real green 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 ratio of the number of residential properties that are 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 ratio of the number of residential properties that are green-certified in a year as follows:

$$y_{zt} = \alpha + \beta \times \% \text{ Green Home}_{zt} + \gamma \text{ Controls}_{zt} + \theta_z + \theta_t + \epsilon_{zt}. \tag{8}$$

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 X, we see that a percentage point increase in the ratio of residential green-certified homes is associated with a 5.9% increase in the amount of RETCs, and column (2) suggests a \$0.66 increase in the amount of RETCs per household. Column (3) shows that a percentage point increase in the percentage of residential green-certified homes leads to a 3.4% increase in the number of tax returns with RETCs, and column (4) indicates a 0.009 percentage point increase in the percentage of households filing for RETCs. Overall, these findings illustrate that green certifications are indeed associated with real investments.

7 Conclusion

This paper studies the role of green neighbors in the decision of households to obtain residential green certifications. I construct a highly granular nationwide dataset of single-family property data combined with green certification data. 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 1.8 times more likely to obtain a green certificate for 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. Moreover, households are more likely to adopt the same certificate and lender as their closely located green peers. I also find that peer effects are more pronounced in areas where community interactions are stronger and where green certifying residential properties is financially beneficial. Furthermore, green-exposed households who green certify their homes perform better than similarly exposed counterparts who do not do so. I conclude from these findings that households learn information about green certification from their neighbors and obtain green certification for their own houses when it is financially beneficial.

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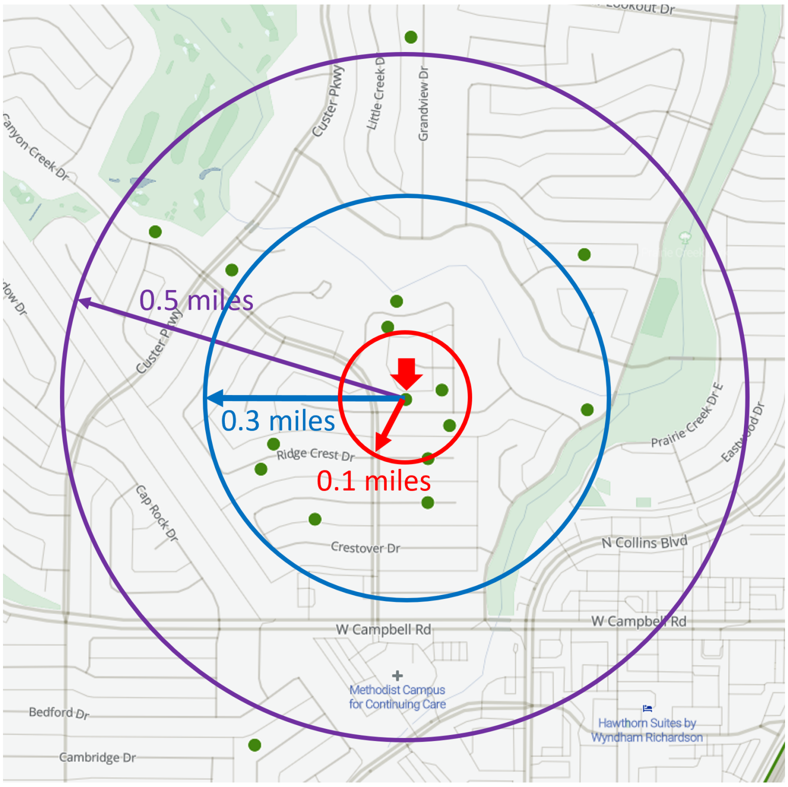
Figure I: Illustration of the Nearest-Neighbor Research Design

Panel A of this figure 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 of this figure 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

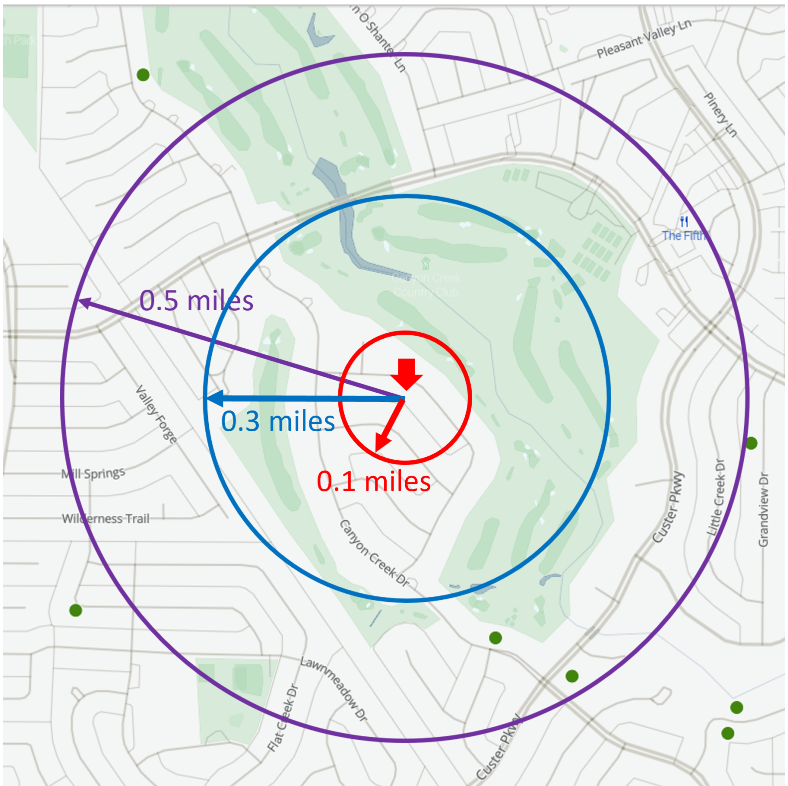
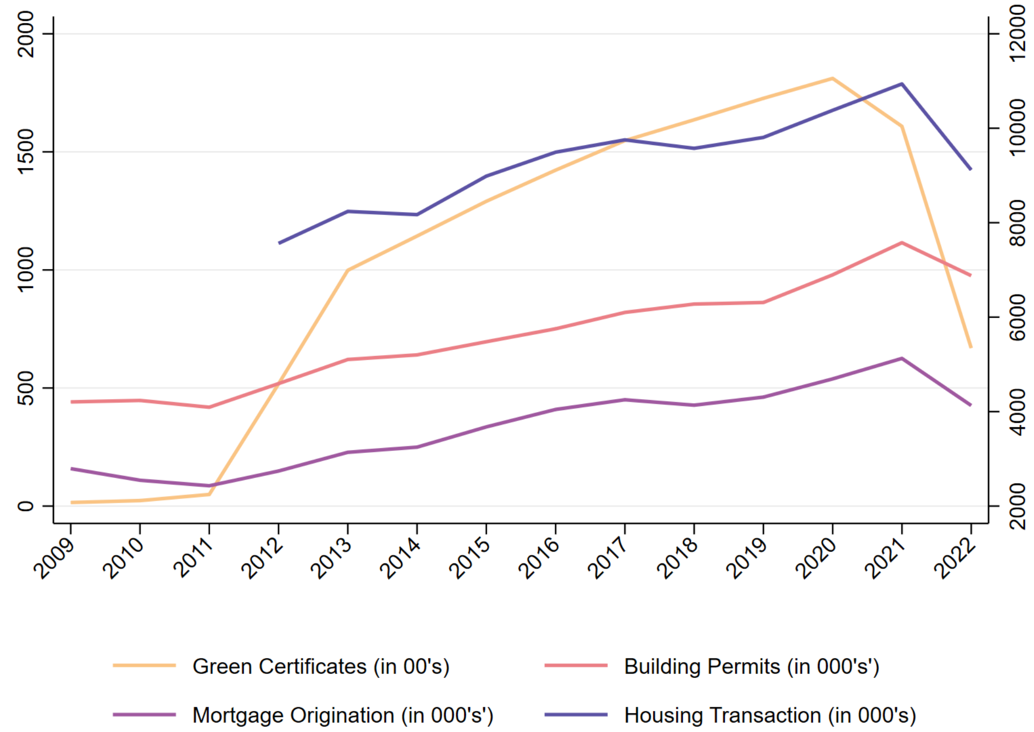


Figure II: Residential Green Certifications in the US

Panel A of this figure 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 originations 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 originations and housing transactions are plotted on the right axis. Panel B of this figure 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: Trends in Residential Green Certifications and Housing Market



Panel B: Green-certified Single-family Homes

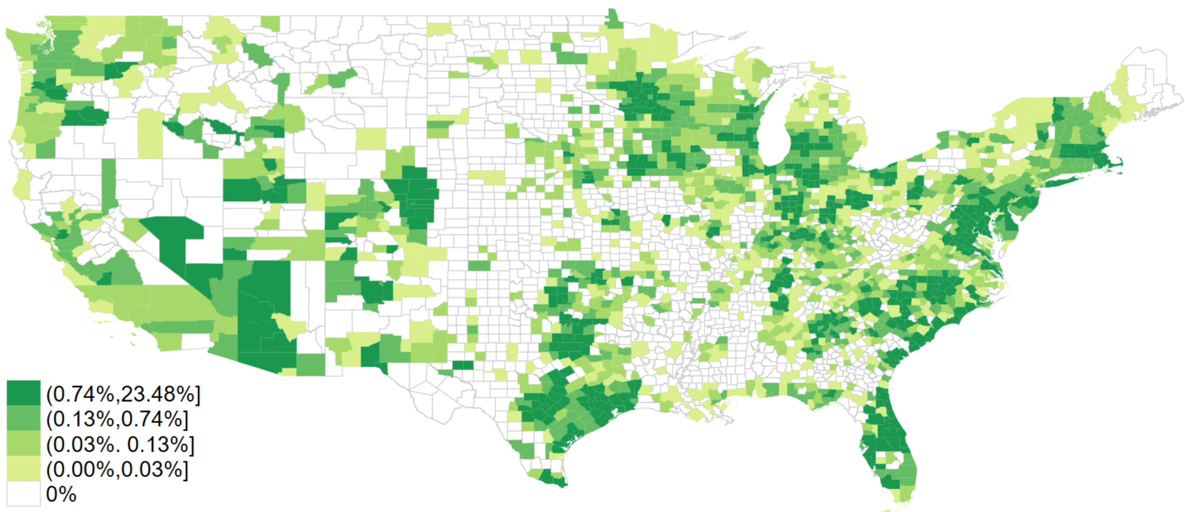


Figure III: Distribution of Residential Green Certification Programs

This figure shows the number of single-family homes certified under major green certification programs as of 2022.

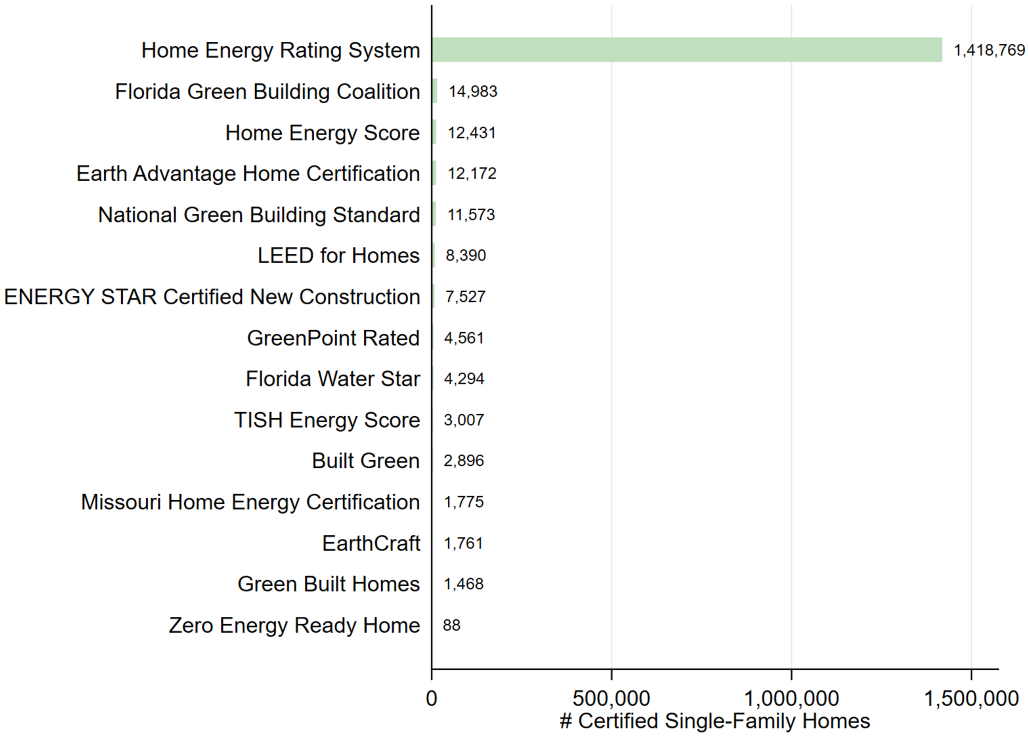


Figure IV: Characteristics of Focal and Neighboring Properties

This figure plots the characteristics of a focal property relative to the average across its neighboring properties within a given distance. I first calculate the proportional difference in characteristic c of focal property i and all its neighboring properties indexed by j located within a ring (donut) of d miles as follows:

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

I then calculate *Proportional Diff* $_{cd}$ as the average of *Proportional Diff* $_{cid}$ across all properties i for each characteristic c and plot it against d. 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).

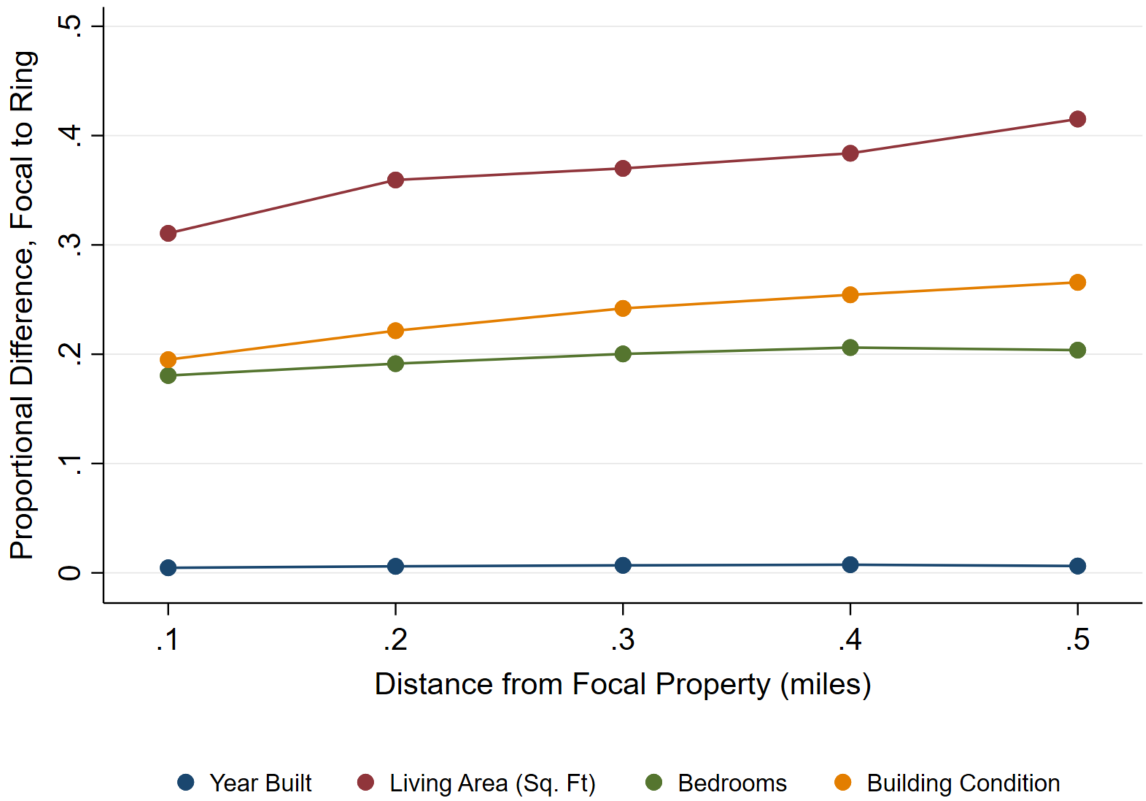


Figure V: Green Exposure of Green and Non-Green Properties

This figure 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 green property j from group G in year-quarter q. Then I re-index all properties in group G and NG by i and define green exposure $Exposure_{id}$ of a property i over a ring of d miles as the total number of neighboring properties within d-mile ring that became green during year-quarters $(q-3)$ and q. Here q is the year-quarter this 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.

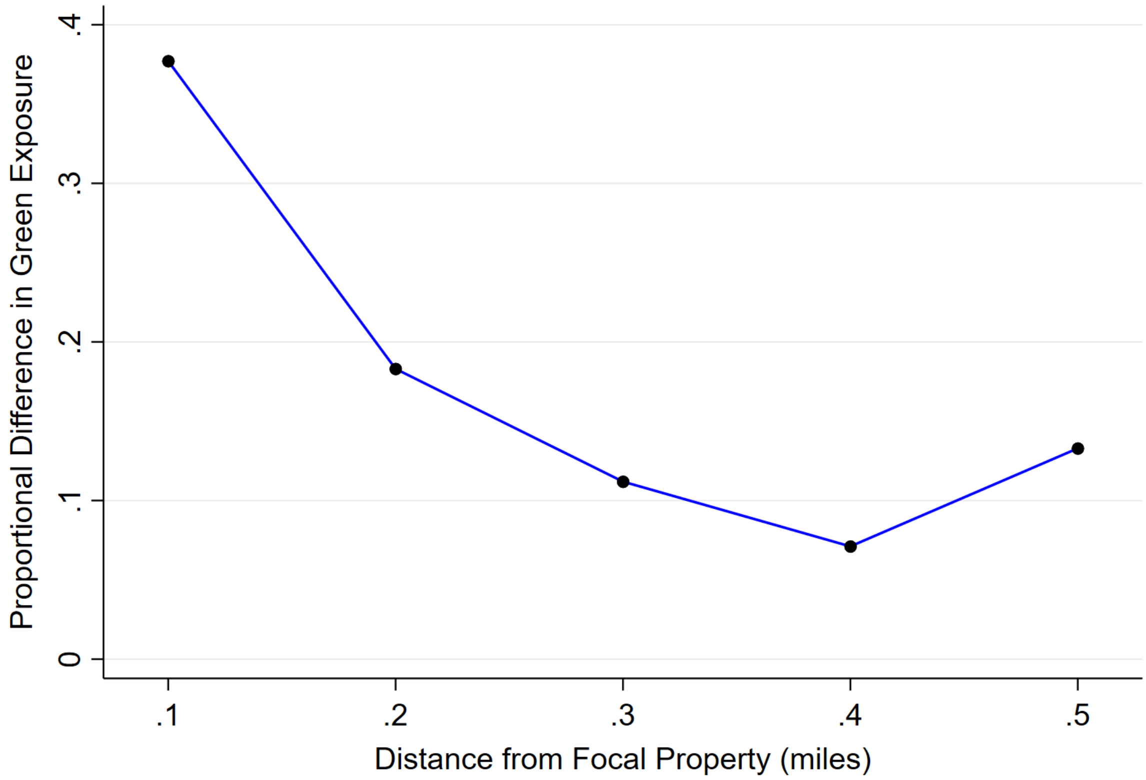


Figure VI: Probability of Green Certification and Green Exposure

This figure shows the average probability that a household green certifies their property against (on the x-axis) the number of neighbors located within d miles who have green certified their homes 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 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. The neighbors across different rings are counted independent of those located in other rings.

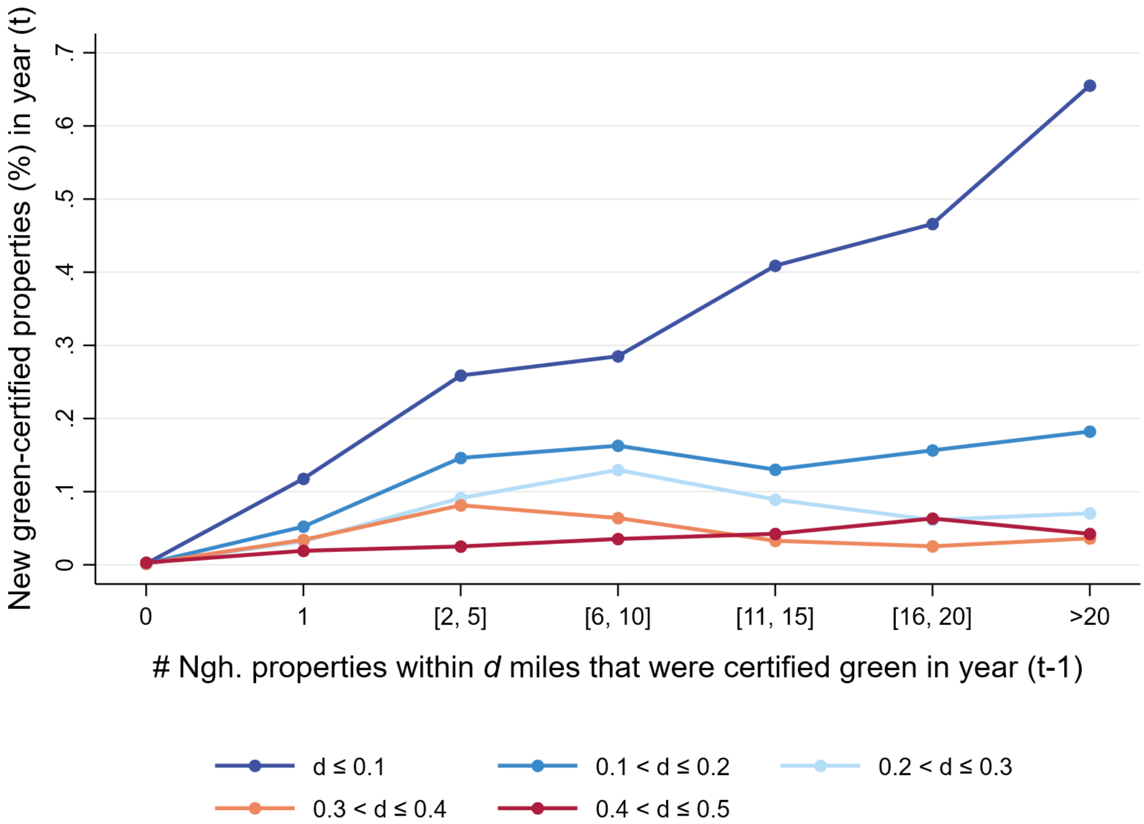
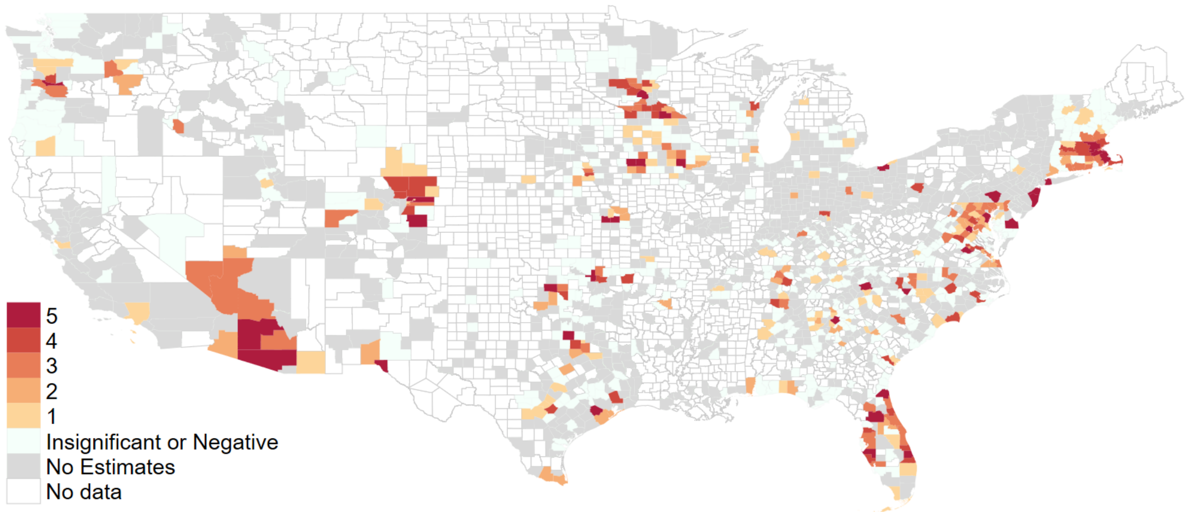


Figure VII: Benefits of Residential Green Certifications Measured at County Level

This figure illustrates the benefits of residential green certifications at the county level from 2018 to 2022. The certification benefit in Panel A is derived from separately estimating for each county and year a hedonic regression of transaction prices of single-family houses on a series of property and mortgage characteristics and zipcode fixed effects using the equation $y_{it} = \alpha + \beta\, Green_{it} + \gamma\, Control_{it} + \theta_z + \epsilon_{it}$. 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 coefficient on $Green_{it}$ is statistically positive at the 10% level or below. The certification benefit in Panel B is derived similarly as in Panel A, but (i) the outcome variable is rate spread for home-purchase mortgages, which is the difference between the covered loan's annual percentage rate (APR) and the average prime offer rate (APOR) for a comparable transaction on the date the interest rate is set; (ii) the controls exclude the 0/1 indicator of mortgage-financed purchase and include the number of lenders in a census tract, income, and debt-to-income ratio. The color intensity in Panel B represents the number of years (from 2018 to 2022) for which the coefficient on $Green_{it}$ is statistically positive at the 10% level or below. Panel C shows the regulatory incentive benefits. The color intensity represents the number of years (from 2018 to 2022) for which a county has an above-median number of regulatory incentives.

Panel A: Benefits in Terms of House Prices



Panel B: Benefits in Terms of Rate Spread

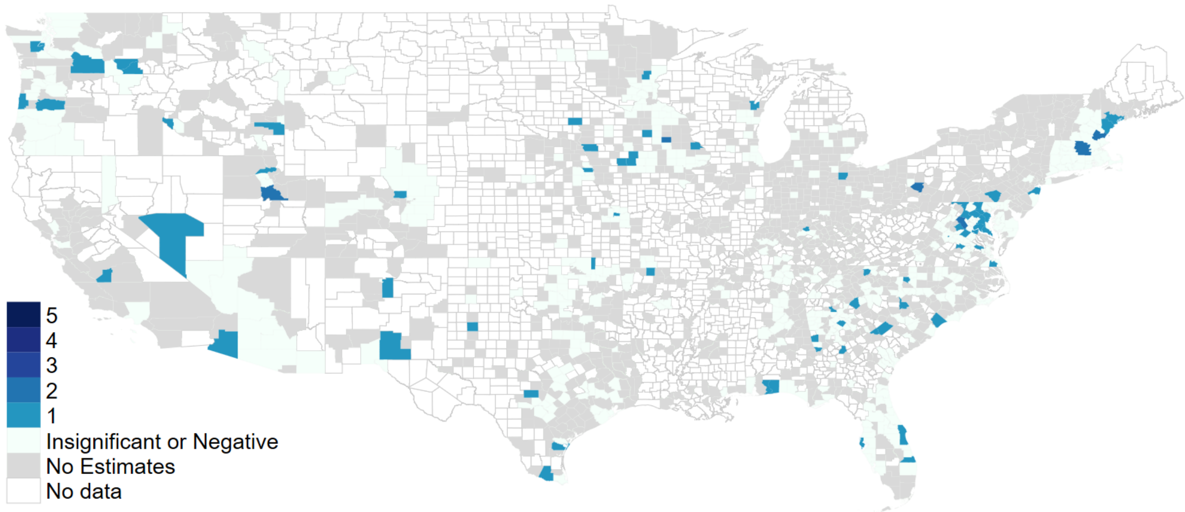


Figure VII: Benefits of Residential Green Certifications Measured at County Level (contd.)

Panel C: Benefits in Terms of Regulatory Incentives

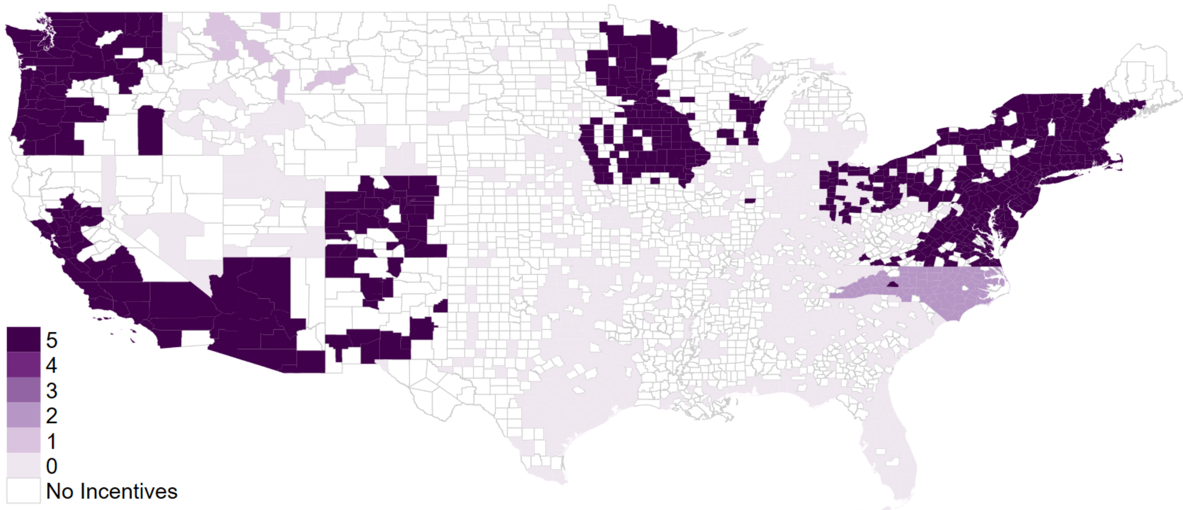


Table I: Green Certification Programs

This table reports the overview of 15 green certification programs. It includes their geographic coverage, attributes evaluated in their programs, whether builders are involved. 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	Builder Involved	Green Threshold
	(1)	(2)	(3)	(4)
Build 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	Yes	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)	411,515,023	0.32	0	56.33
$N_G(\leq 0.1$ mi)	411,515,023	0.05	0	1.71
$N_G(\leq 0.3$ mi)	411,515,023	0.30	0	3.50
$N_G(\leq 0.5$ mi)	411,515,023	0.53	0	4.97
Property Characteristics (Panel: Property level)				
Green (=10,000)	30,451,754	4.29	0	207.03
Year Built	30,451,754	1,975.81	1,979	28.11
Living Area (square feet)	30,451,754	1,864.92	1,689	776.39
# Bedrooms	30,363,686	2.51	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	736,388	2.07	1	3.41
Annual Price Growth (%)	1,669,840	4.52	4	8.82
AGI ($1,000) Per Capita	225,906	34.03	28	29.71

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

This table reports the effect of neighbors with green-certified homes on the decision of a focal household to also obtain a residential green certificate. The regression specification is from Equation (2). The outcome variable is an indicator taking the value of 10,000 if household i obtains the very first green certificate for his/her property in quarter t (*Green (=10,000)*). The variables of interest are the exposure of focal households to neighbors' green certification decisions. The exposure is measured as the number of neighbors who have obtained green certificates within quarters $t-3:t$ and are located within a ring of 0.1, 0.3 and 0.5 miles. These variables are denoted as $N_G(\le d\ mi)$, where $d \in \{0.1, 0.3, 0.5\}$. Column (1) estimates the green-peer effects of a green neighbor within 0.1 miles. Column (2) employs the nearest-neighbor design by controlling the green exposure within 0.3 and 0.5 miles. Column (3) incorporates year-quarter fixed effects in the nearest-neighbor design. Column (4) adds zipcode fixed effects. Column (5) includes both zipcode and year-quarter fixed effects. Column (6) includes zipcode × year-quarter fixed effects. Column (7) includes tenure and zipcode × year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and are reported in parentheses below the coefficients. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Baseline Results

	Outcome: Green (=10,000)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$N_G(\le 0.1$ mi)	0.66***	0.35***	0.35***	0.40***	0.40***	0.42***	0.43***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$N_G(\le 0.3$ mi)		0.24***	0.24***	0.18***	0.18***	0.17***	0.11***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$N_G(\le 0.5$ mi)		0.03***	0.03***	0.03***	0.03***	0.02***	0.01
		(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Constant	0.26***	0.19***	0.19***	0.21***	0.21***	0.21***	0.23***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Marginal Effect to Hazard Ratio							
$N_G(\le 0.1$ mi)	2.49	1.83	1.83	2.06	2.06	2.16	2.31
Fixed effects	N	N	YQ	Zipcode	Zipcode, YQ	Zipcode × YQ	Tenure, Zipcode × YQ
R^2 (Adj.)	0.0004	0.0006	0.0006	0.0029	0.0029	0.0047	0.1230
Observations	411,515,023	411,515,023	411,515,023	411,514,988	411,514,988	411,502,657	410,239,307

Table III: Peer Effects in Residential Green Certification (contd.)

This table reports the green-peer effects when adding property and neighborhood controls. The regression specification is from Equation (3). Column (1) replicates column (5) of Panel A, Table III in a sample of only those observations for which all control variables have non-missing values. Column (2) shows the results for the same sample after including the following property controls: property age, living area, # bedrooms, exterior materials, heat type and roof materials. Column (3) shows the results for the same sample after including the following neighborhood controls: 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 and % climate - worried at county level. Column (4) includes both the property controls and neighborhood controls. The definition of the property controls and neighborhood controls are provided in Table II. All models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and are reported in parentheses below the coefficients. *, ** 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)	0.81^{***}	0.81^{***}	0.59^{***}	0.60^{***}
	(0.14)	(0.13)	(0.12)	(0.12)
$N_G(\leq 0.3$ mi)	0.12^{***}	0.12^{***}	0.12^{***}	0.12^{***}
	(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.)	0.0047	0.0048	0.0049	0.0049
Observations	69,416,525	69,416,525	69,416,525	69,416,525

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

This table reports green-peer effects observed from primary residence to the secondary properties. The sample is formed using the secondary properties where MPOs do not reside. The regression specification follows Equation (2) and includes the green neighbor exposures from the residing property of the owners (*Primary's* $N_G(\leq 0.1\ mi)$). Column (1) reports the effects for primary–secondary pairs within a 10-mile distance. Column (2) to (6) present analogous results for the pair whose distance is greater than 10, 20, 30, 40, and 50 miles, respectively. All models control for the primary' and secondary' outing ring green neighbor exposure, as well as primary zipcode, secondary zipcode and year-quarter fixed effects. Standard errors are clustered by primary residence zipcode × year-quarter and secondary property zipcode × year-quarter and are reported in parentheses below the coefficients. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Secondary Property Green (=10,000)					
	(1)	(2)	(3)	(4)	(5)	(6)
Primary to Secondary Dist.:	≤ 10 mi	> 10 mi	>20 mi	>30 mi	>40 mi	>50 mi
Primary's $N_G(\leq 0.1$ mi)	0.358	0.007*	0.007*	0.007*	0.007*	0.007*
	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Secondary's $N_G(\leq 0.1$ mi)	0.586**	0.181***	0.175***	0.175***	0.176***	0.176***
	(0.29)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Primary's 0.3- & 0.5-mi ring controls	Y	Y	Y	Y	Y	Y
Secondary's 0.3- & 0.5-mi ring controls	Y	Y	Y	Y	Y	Y
Primary zipcode FE	Y	Y	Y	Y	Y	Y
Secondary zipcode FE	Y	Y	Y	Y	Y	Y
YQ FE	Y	Y	Y	Y	Y	Y
R^2 (Adj.)	0.4502	0.0049	0.0049	0.0049	0.0051	0.0051
Observations	841,425	15,953,863	15,764,664	15,679,964	15,625,381	15,582,378

Table V: Peer Commonalities in Green Certificates and Lenders

This table reports the probability of using the same green certificate and same lender as used by the spatially proximate neighbors. The variable of interest is an indicator ($\mathbb{1}$(Dist. $\leq$ 0.1 mi)) taking the value of 1 when the distance between focal household and neighbor is within 0.1 miles. In column (1) and (2), the regression panel is defined at the "focal property certificate × neighboring property certificate" level, where neighbors within 0.5 miles are included. The outcome variable is an indicator ($\mathbb{1}$(Same Cert.)) taking the value of 1 when the certificates are the same for the focal household and the neighbor. The sample in column (1) includes all certificates whereas in column (2) it excludes the most common certificate (HERS, Home Energy Rating System).

To analyze peer commonality in mortgage lenders in columns (3) and (4), I create the "focal household's mortgage × neighbor's mortgage" panel by selecting focal households who took mortgage within 90 days before green certifying their properties and their within-0.5-mile neighbors who took mortgage within one year after green certifying their respective properties. From these focal and neighboring households, I select those focal-neighbor pairs for which the mortgages of the focal households were taken within one year after the mortgage dates of their neighbors. The outcome variable is an indicator ($\mathbb{1}$(Same Lender)) taking the value of 1 when the mortgage lenders are the same for the focal household and the neighbor. The sample in column (3) includes all lenders whereas in column (4) it excludes the top three lenders in a county-year based on the aggregate loan amount in mortgage applications received by lenders. All regressions include focal property's tenure and zipcode × year-quarter fixed effects. Standard errors are clustered by focal zipcode × year-quarter and are reported in parentheses below the coefficients. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	$\mathbb{1}$(Same Cert.)		$\mathbb{1}$(Same Lender)	
	(1)	(2)	(3)	(4)
Sample:	All Cert.	Exc. Top Cert.	All Lenders	Exc. Top Lender
$\mathbb{1}$(Dist. $\leq$ 0.1 mi)	0.006***	0.012***	0.130***	0.141***
	(0.00)	(0.00)	(0.01)	(0.01)
Focal tenure FE	Y	Y	Y	Y
Focal zipcode × YQ FE	Y	Y	Y	Y
R^2 (Adj.)	0.4966	0.5759	0.3475	0.3495
Observations	7,354,334	787,800	230,802	200,329

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 (4). The outcome variable is an indicator taking the value of 10,000 if household i obtains the very first green certificate for his/her property in quarter t (*Green (=10,000)*). The strength of local community interactions is measured using the following six characteristics ($\mathbb{X}$): social connectedness, social clustering, social capital, % investment properties, % house flippers and housing density. The variable of interest in these regressions is the interaction term $\mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.1\ mi)$. In all models, $\mathbb{1}(\text{High } \mathbb{X})$ is a 0/1 indicator for observations with above-median values of the respective characteristic $\mathbb{X}$. The median for each characteristic $\mathbb{X}$ is calculated at zipcode level in column (1) and (2), at county level for column (3), at zipcode × quarter level for columns (4) and (5), and tract × year level for column (6). All the models control for both outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq d\ mi)$), where $d \in \{0.3, 0.5\}$. The definition of these variables is provided in Table II. All the models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and are reported in parentheses below the coefficients. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)					
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic $\mathbb{X}$:	Social Connectedness	Social Clustering	Social Capital	% Investment Properties	% House Flippers	Housing Density
[Median of $\mathbb{X}$ calculated at:]	[zipcode]	[zipcode]	[county]	[zipcode × yq]	[zipcode × yq]	[tract × year]
$\mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.1 \text{ mi})$	1.232***	1.683***	0.723***	-0.670***	-0.380***	-0.592***
	(0.42)	(0.44)	(0.17)	(0.26)	(0.11)	(0.15)
$N_G(\leq 0.1 \text{ mi})$	0.459***	0.469***	0.378***	1.037***	0.653***	0.840***
	(0.04)	(0.04)	(0.05)	(0.25)	(0.10)	(0.15)
$\mathbb{1}(\text{High } \mathbb{X})$			-0.141**	0.120***	0.054***	-0.039***
			(0.06)	(0.02)	(0.02)	(0.01)
0.3- & 0.5-mi ring controls	Y	Y	Y	Y	Y	Y
$\mathbb{1}(\text{High } \mathbb{X})$ × 0.3- & 0.5-mi ring controls	Y	Y	Y	Y	Y	Y
FE: zipcode and YQ	Y	Y	Y	Y	Y	Y
R^2 (Adj.)	0.0034	0.0031	0.0029	0.0029	0.0030	0.0033
Observations	373,501,484	404,113,704	411,514,988	411,514,988	411,514,988	254,884,535

Table VII: Effect Heterogeneity by Green Certification Benefits

This table reports the heterogeneous green-peer effects across counties with or without green benefits. The outcome variable is an indicator taking the value of 10,000 if household i obtains the very first green certificate for his/her property in quarter t (*Green (=10,000)*). The variable of interest in these regressions is the interaction term $\mathbb{1}(\mathbb{B}\text{ exists}) \times N_G(\leq 0.1\ mi)$. In column (1) and (2), the green benefit ($\mathbb{B}$) refers to higher house prices and lower rate spreads for green-certified properties vis-à-vis non-green properties; in column (3), it refers to the availability of regulatory incentives for residential green investments. The indicator $\mathbb{1}(\mathbb{B}\text{ exists})$ in column (1) and (2) is a county × year variable taking the value of 1 when the coefficient on $Green_{it}$ in Equation (5) $y_{it} = \alpha + \beta\ Green_{it} + \gamma\ Control_{it} + \theta_z + \epsilon_{it}$ is statistically positive at the 10% level or below. The indicator $\mathbb{1}(\mathbb{B}\text{ exists})$ in column (3) is a county × quarter variable taking the value of 1 for observations with above-median values of the number of regulatory incentives. All the models control for both outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{1}(\mathbb{B}\text{ exists}) \times N_G(\leq d\ mi)$), where $d \in \{0.3, 0.5\}$. The definition of these variables is provided in Table II. All the models include zipcode and year-quarter fixed effects. Standard errors are clustered by zipcode × year-quarter and are reported in parentheses below the coefficients. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)		
	Market-implied Benefits		Regulatory Benefits
	(1)	(2)	(3)
Benefit ($\mathbb{B}$) in terms of:	$\mathbb{B}$ =Ln(Price)	$\mathbb{B}$ =Rate Spread	$\mathbb{B}$ =Incentives
$\mathbb{1}(\mathbb{B}\text{ exists}) \times N_G(\leq 0.1\text{ mi})$	0.446***	0.343*	0.866***
	(0.11)	(0.20)	(0.10)
$N_G(\leq 0.1\text{ mi})$	0.307***	0.486***	0.327***
	(0.07)	(0.05)	(0.06)
$\mathbb{1}(\mathbb{B}\text{ exists})$	0.061**	0.275***	-0.182***
	(0.03)	(0.05)	(0.06)
0.3- & 0.5-mi ring controls	Y	Y	Y
$\mathbb{1}(\mathbb{B}\text{ exists})$ × 0.3- & 0.5-mi ring controls	Y	Y	Y
FE: zipcode and YQ	Y	Y	Y
R^2 (Adj.)	0.0034	0.0035	0.0032
Observations	205,431,202	183,621,267	389,238,251

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

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 V. 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 outcome variable in column (3) is the residual at time of purchase. 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 below the coefficients. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Outcome:	Return	Sell Residual	Buy Residual
$\mathbb{1}$(Green)	0.125***	0.077***	-0.078***
	(0.01)	(0.01)	(0.01)
Buy year FE	Y	Y	Y
Sell year FE	Y	Y	Y
Green year FE	Y	Y	Y
R^2 (Adj.)	0.0556	0.0141	0.0126
Observations	11,074	11,073	11,073

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

This table reports the following two relationships: (a) the correlation between green preference of households and residential green certifications in columns (1) and (2); and (b) the heterogeneous green-peer effects across areas with different degrees of green preference in columns (3) and (4).
In columns (1) and (2), the outcome variable is the ratio of the number of residential properties that are green-certified in a year in an area (% *Green Home*). The variable of interest in these regressions is green preference, which is proxied by % *Climate Worried* in column (1) and # *EV per HH* in column (2). % *Climate Worried* measures the percentage of adults in a county who are worried about climate change. # *EV per HH* represents the number of EV per household at zipcode level. *Housing mkt. & demog. controls* include 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.
In columns (3) and (4), the outcome variable is an indicator taking the value of 10,000 if household i obtains the very first green certificate for his/her property in quarter t (*Green (=10,000)*). The variable of interest in these regressions is the interaction term $\mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.1\ mi)$. Here $\mathbb{1}(\text{High } \mathbb{X})$ is a 0/1 indicator for observations with county-level above-annual-median values of the respective characteristic *X*—% *Climate Worried* and # *EV per HH*. Characteristic $\mathbb{X}$ is denoted in the header of column (3) and (4). These models control for both outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq d\ mi)$), where $d \in \{0.3, 0.5\}$. The definition of these variables is provided in Table II. The regressions in column (3) and (4) include zipcode and year-quarter fixed effects. Standard errors are reported in parentheses below the coefficients, 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)
Characteristic $\mathbb{X}$ =	-	-	% Climate Worried	# EV per HH
% Climate Worried	0.047***			
	(0.01)			
# EV per HH		0.854*		
		(0.51)		
$\mathbb{1}(\text{High } \mathbb{X}) \times \text{N}_G(\leq 0.1 \text{ mi})$			-0.096	0.072
			(0.16)	(0.20)
$\text{N}_G(\leq 0.1 \text{ mi})$			0.730***	1.113***
			(0.15)	(0.13)
$\mathbb{1}(\text{High } \mathbb{X})$			0.182*	-0.014
			(0.10)	(0.04)
Housing mkt. & demog. controls	Y	Y	-	-
0.3- & 0.5-mi ring controls	-	-	Y	Y
$\mathbb{1}(\text{High } \mathbb{X}) \times$ 0.3- & 0.5-mi ring 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	0.7844	0.0031	0.0036
Observations	11,233	65,670	328,482,351	129,004,214

Table X: Residential Energy Tax Credits Incentives and New Green Homes

This table presents the relationship between the residential energy tax credits (RETC) claimed by households to the Internal Revenue Service (IRS) and residential green certifications. 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* (%)). The variable of interest is the ratio of the number of residential properties that are green-certified in a year in a zipcode (% *Green Home*). 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 are reported in parentheses below the coefficients. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	$\mathrm{Ln}(\mathrm{A}_{\mathrm{RETC}})$	$\frac{\mathrm{A}_{\mathrm{RETC}}}{\text{\# Households}}$	$\mathrm{Ln}(\mathrm{N}_{\mathrm{RETC}})$	RETC Households (%)
% Green Home	0.059***	0.660***	0.034***	0.009**
	(0.00)	(0.10)	(0.00)	(0.00)
Housing mkt. & demog. controls	Y	Y	Y	Y
Fixed effects	Zipcode, Year	Zipcode, Year	Zipcode, Year	Zipcode, Year
R^2 (Adj.)	0.83	0.65	0.84	0.78
Observations	171,215	171,215	171,215	171,215