The effects of eligibility and voluntary participation on the distribution of benefits in environmental programs: an application to green stormwater infrastructure*

Daniel A. Brent

Joseph H. Cook

Allison Lassiter

Abstract

Many cities provide incentives for private landowners to install green stormwater infrastructure (GSI) to reduce stormwater runoff and deliver co-benefits of urban greening. We analyze how participation in a GSI subsidy program affects the spatial distribution of urban greening. The distributional effects manifest in two stages: program eligibility and participation decisions. Eligibility, determined by hydrological factors, is positively correlated with wealthier and whiter areas. Within eligible areas, the wealthiest households and least white neighborhoods have lower participation rates. The findings highlight the importance of considering eligibility and participation in balancing the joint goals of environmental quality and environmental justice.

Key Words: green stormwater infrastructure, distributional effects, policy analysis, environmental justice

JEL Codes: Q25, Q52, Q53, L95

*Corresponding author: dab320@psu.edu. The authors thank Shanti Colwell and Bob Spencer at Seattle Public Utility for help accessing the data and information about green stormwater infrastructure policy. We are also grateful to participants at Penn State's Water Insight Seminar for helpful comments. This work is/was supported by the USDA National Institute of Food and Agriculture and Hatch/Multi-State Appropriations under Project #PEN04631 and Accession #1014400.

1 Introduction

Voluntary environmental policies, such as subsidies or rebates for environmentally friendly products, often generate both public and private benefits. For example, installing an energy efficient appliance will contribute to public goods of reduced greenhouse gases and local air pollution while simultaneously saving the owner money on their utility bills. The type of households or firms that participate in voluntary environmental programs, along with their funding sources, will determine the distributional consequences of those programs. These policies may enhance or hinder environmental justice objectives by diverting resources to specific groups. We investigate the distributional consequences of voluntary environmental policies in subsidies for green stormwater infrastructure (GSI) by examining how participation varies across wealth, income, and race. Eligibility decisions by program managers and participation decisions by eligible household shape the spatial distribution of local co-benefits of GSI policies primarily designed to reduce stormwater runoff.

Cities around the world have made significant public investments in urban greening. Urban greening is associated with increased walkability, reduced stress, better air quality, and improved cardiometabolic health (Cavanagh et al., 2009; Currie and Bass, 2008; Pughet al., 2012; Kardan et al., 2015; South et al., 2018; Sugiyama et al., 2008; South et al., 2015). Greening reduces urban heat island effects (Bowler et al., 2010; Ziter et al., 2019), which is especially salient as many cities face increasingly hot summers (Jiang et al., 2019). Greening also helps manage urban stormwater runoff volumes and quality. Consumers value the local public benefits of urban greening as several studies show that trees and green space capitalize into private home values (Sander et al., 2010; Netusil et al., 2010; Kadish andNetusil, 2012).

The benefits of urban greening are not delivered equitably in many cities, even though the costs of urban greening are borne by all taxpayers or utility ratepayers. In the United States, for example, neighborhoods that were historically "redlined" and subject to racial discrimination have fewer trees and are hotter than areas that were not redlined (Hoffmanet al., 2020; Locke et al., 2020; Wilson, 2020)[1]. Analysis of Atlanta, Georgia, U.S. indicates that Black communities currently have the least access to urban green spaces (Dai, 2011). Similarly, even without a history of redlining researchers in Australia find low-income neighborhoods are less green (Astell-Burt et al., 2014).

Many water and stormwater utilities run programs that promote broad-scale urban greening by implementing GSI. The impetus of most GSI programs is to reduce runoff during storms that deliver enough stormwater to exceed the capacity of the conveyance system or wastewater treatment plant, resulting in untreated wastewater being discharged into local water bodies. In the U.S., these discharges, known as combined sewer overflows (CSOs), constitute violations of the Clean Water Act. Many water agencies are required to reduce their CSOs and operate under consent decrees with the U.S. Environmental Protection Agency. Proposed CSO solutions include implementing multi-billion dollar stormwater management programs (U.S. EPA 2017), many of which rely heavily on GSI (BenDor et al., 2018).[2] In addition to reducing stormwater runoff, GSI facilities like bioswales, raingardens, and green roofs contribute to the larger suite of co-benefits associated with urban greening.

Cities use three primary forms of GSI policies. First, GSI is often required for new construction or additions as part of zoning regulations. Second, local governments and utilities install and maintain GSI in public spaces. Examples include large bioswales, retention ponds, green streets, and raingardens in public spaces like parks and rights-of-way. Research suggests, however, that in some cities there is not enough public land available to achieve the density of GSI needed to meet stormwater reduction targets required for water quality goals (Montalto et al., 2007). Therefore, the third type of policy focuses on subsidizing installation of GSI on private land, such as single family residential properties. Cities justify subsidies because GSI is a quasi-public good that provides a combination of private and public benefits. This quasi-public good nature also means that private benefits flow to homeowners and immediate neighbors who install subsidized GSI, including capitalizing into home values, while all ratepayers or taxpayers bear the cost. Research indicates that consumers are willing to pay for GSI on their properties (Zhang et al., 2015; Iftekhar et al., 2021). Because GSI subsidies transfer resources from ratepayers to participating homeowners and neighbors, there are equity and environmental justice consequences of these policies.

We study the distributional impacts of voluntary GSI policies using data from the Rain- Wise program in Seattle and surrounding King County that subsidizes raingardens and cisterns. Our primary research question is how private benefits of the RainWise program are distributed across ratepayers funding the program. In RainWise, as in many other voluntary environmental programs, there are two channels that drive distributional impacts: 1) the screening of whether a homeowner is eligible for participation and 2) the choice to participate. GSI program managers will rationally target GSI investments to places that are likely to lead to the largest water quality benefits, which may inadvertently correlate spatially with income or even mimic historic patterns of housing discrimination. For example, if installations to prevent CSOs have the largest impact when installed near a water body that receives stormwater flows, the eligibility stage could be regressive, as water-adjacent or waterfront homes often sell at a premium. Furthermore, almost all programs have homeownership as the primary eligibility screen, which is strongly correlated with income in the United States (Bhutta et al., 2020). We also analyze the distributional impacts of private decisions to participate in voluntary GSI programs, conditional on eligibility. These features may vary depending on the location, eligibility constraints, and the design of the program.

We make three contributions to the literature. First, we estimate the distributional impacts of a voluntary environmental program using household-level observational data. Prior research on GSI adoption has used neighborhood-level participation rates and did not focus on environmental justice concerns (Ando and Freitas, 2011; Lim, 2018). We examine the distributional effects across three key variables: wealth, income, and race. Using household-level data is important when participation effects are non-linear, since average Census block group characteristics can mask heterogeneous effects. Second, we consider how both the household participation decision and the utility's eligibility criteria affect the overall distributional effects of the policy. This is critical because we find that eligibility and voluntary participation channels have opposing effects on the progressivity of the program. Third, we utilize a novel method for measuring the type of households that select into voluntary programs by using housing sales prior to a household signing up for a program. This isolates the selection effect from any potential capitalization effect from GSI. Housing sales data are often available at the household level, which makes prior sales an attractive metric for studying distributional effects of programs where the location of the participating homes is known.

We find that RainWise administrators (inadvertently) chose eligible areas that were, on average, wealthier than a typical Seattle neighborhood, which is in turn wealthier than a typical King

County neighborhood. Our results show that, conditional on eligibility, upper middle-class households are most likely to participate. Within eligible areas, the wealthiest households and neighborhoods with the highest concentration of minorities have lower participation rates. The challenge of recruiting the most disadvantaged households persists even though resources were deployed to specifically target low-income and minority households. The aggregate distributional effects depend on both eligibility and participation. Among all ratepayers, the average home price is similar for program participants and nonparticipants, but conditional on eligibility, participants live in less expensive homes than non-participants. Examining the effects across the housing value distribution shows that the least and most expensive homes in King County are less likely to participate relative to homes in the upper-middle portion of the housing value distribution. Applying quantile regression to our hedonic selection model we find highly nonlinear selection effects across the house price distribution. We also examine variation in the cost of individual GSI installations. GSI in the wealthiest homes are substantially less cost-effective in terms of the gallons of stormwater mitigated per dollar. This suggests wealthier homes may prioritize aesthetic features of GSI, and that selection effects do have economic consequences.

Our research engages with growing discussions of how to evaluate benefits from environmental policy. Much of the environmental justice movement, including the EPA[3] and the academic literature, has focused on exposure to environmental hazards such as pollution, toxic waste, and water contamination (Mohai et al., 2009; Banzhaf et al., 2019). Recent examples in economics show that the Clean Air Act has reduced absolute differences in racial disparities in air pollution exposure while relative differences persist (Colmer et al., 2020). We contribute to this literature by examining the distributional implications of the co-benefits from GSI policy, as opposed to the direct effects of reducing pollution. We also contribute to the growing economics literature on GSI. Most of the current literature uses stated preference (Londoño Cadavid and Ando, 2013; Newburn and Alberini, 2016; Brent et al., 2017; Ando et al., 2020) and revealed preference (Zhang et al., 2015) methods to estimate the willingness to pay (WTP) for the benefits of GSI. We focus on who receives those benefits when cities employ policies incentivizing voluntary installation on private property.

2 Background & Setting

Seattle discharged 1.1 billion gallons of raw sewage annually by CSOs from 2006-2010 (Times, 2013). The city's consent decree with the U.S. EPA requires reducing CSOs by 95% by 2025 (EPA), 2013). As part of the EPA consent decrees, King County and Seattle developed an integrated stormwater management plan with a prominent role for GSI. Seattle and King County plan to collectively reduce 700 million gallons of their stormwater mitigation requirements through GSI.[4] The costs of stormwater mitigation were estimatedat $700 million for King County and $600 million for the City of Seattle, managed by King County Land and Water Division and Seattle Public Utilities (SPU), respectively.[5] The City and County work collectively towards their stormwater mitigation requirements. They construct, own, and operate public GSI, and require any new construction (or renovations that increase impervious surface) to include mandatory on-site private GSI.[6]

RainWise is a voluntary GSI program subsidizing cisterns and/or raingardens on private residential properties and is jointly operated by King County and SPU. Each utility is responsible for funding RainWise in specific eligible CSO basins, though all eligible basins are within Seattle city limits.[7] A CSO basin is an area that drainsto a specific CSO location (see Figure A.1 in the Appendix) based on the sewer network. Eligibility is restricted to basins deemed most critical to meet water quality goals.[8]

All residential properties in an eligible basin can receive RainWise subsidies for cisterns, and raingarden eligibility is further restricted by land stability, drainage, and distance to contaminated sites.[9] RainWise cisterns and raingardens must be installed by an approved contractor. The homeowner signs a contract that the system must be maintained fora minimum of five years.

Uptake of RainWise is relatively low: the program began in 2008 and as of July 2018there were 1,525 participating households among roughly 60,000 eligible households. From 2015-2018, the last three years of our data, an average of 266 households per year have signed up. The average RainWise rebate covers 90% of the GSI installation costs. The average project costs slightly more than $5,100. However, the upfront costs are borne by the homeowner and the subsidies count as taxable income. The City and County were aware that these constraints, and the remaining out of pocket costs, might limit participation among low-income households. In response, a RainWise Access grant program was created to provide an additional $1,000 for low-income homeowners.

RainWise provides a mix of public and private benefits. The primary public benefit in- tended to be delivered by the program is improved water quality through reduced peak stormwater runoff and subsequent reduction of CSOs. The private benefits are reduced nuisance flooding (e.g., basement flooding) and, if installing a cistern, access to free irrigation water for gardens. Figures A.2 and A.3 in the Appendix provide examples of raingardens and cisterns funded through RainWise as well as quotes from homeowners describing their motivations. It is likely that participants sign up for RainWise due to a mix of private and public benefits. Some participants mentioned the private benefits of subsidized land- scape renovation, while other participants described the importance of public water quality benefits.

RainWise staff market the program in four ways. First, they send direct postcard mailings to eligible households. Second, they use social media ad campaigns as well as the continuous presence of agency-run social media and the 700 million gallon website. Third, they run workshops to promote the program. Finally, they staff booths at third-party events such as festivals. Upon reviewing outreach material obtained through a public records request, they appear to be targeted spatially (eligible basins) and opportunistically (festivals) rather than by demographics. In addition to formal outreach efforts some RainWise participants place RainWise signs in their front yards and there is anecdotal evidence that peer effects are an important determinant in participation.

One exception to the targeted marketing is the active efforts to promote equitable access to RainWise though the City's Racial Equity Toolkit (RET). The RET seeks to address, "challenges experienced by RainWise (RW) customers and contractors who are low-income, recent immigrants, and/or from communities of color."[10] Clearly RainWise managers are aware of a perception of unequal access and have active goals of making RainWise participation more equitable.

The distributional effects of RainWise depend on the distribution of both the benefits and the costs of the program, which is funded by wastewater charges. Even though all the areas eligible for the RainWise program are all within Seattle city limits, the program is jointly funded by Seattle Public Utilities and King County Wastewater Treatment Division (KCWTD). Because both generate their revenue from ratepayers, the costs of the programs for households in the respective service areas depend on the wastewater rates. KCWTD applies a fixed charge of $47.37 for each single family residence and charges multifamily, commercial, and industrial users $47.37 for each 7.5 hundred cubic feet (HCF) of water. SPU's sewer rates are $15.55 per HCF. Wastewater is estimated as the total metered water use net of any outdoor water use. It is equal to metered water use during winter months (November-April) because SPU assumes there is no outdoor water use. During summer months it is equal to the average of the prior winter's water use. According to SPU, the typical monthly bill for stormwater only in 2021 is $71.68. Households with in- comes at 70% of the state median income or below are eligible for Utility Discount Program, which gives them a 50% credit on their bill. The City separately charges property owners a fee (levied on the annual property assessment) for stormwater management services based on each property's estimated impact on the City's drainage system, though this revenue stream is separate from the one funding RainWise. In all, it is difficult to argue that the rate structure used by either jurisdiction to raise money for RainWise is progressive. KCWTD charges a fixed, non-volumetric charge which is regressive. For SPU's volume-based charge to be progressive, the city's Utility Discount Program would need to have high uptake, or the income elasticity of water use would need to be highly elastic. A recent meta-analysis found the central estimate to quite inelastic (0.15 or lower) (Havranek et al., 2018), and we have no information on the percentage of eligible low-income households who use the Utility Discount Program.

From the perspective of a water agency with mandated stormwater reduction targets, implementing GSI in the areas with the highest degree of impact in reducing CSOs is essential. In some cases, however, hydrologically important intervention areas may not spatially coincide with areas that would gain most from the co-benefits of urban greening. Prioritizing based on hydrology may also inadvertently target areas with higher-income households. There are other ways to develop rationales for siting GSI components (Hopkins et al., 2018; McPhillips and Matsler, 2018). Heckert and Rosan (2016) suggest a Green Infrastructure Equity Index to prioritize investment locations. The dual challenges of equitably distributing urban greening and meeting stormwater goals raises the question of whether water agencies should be tasked with delivering urban greening to all. Jennings et al. (2017) discuss green space planning projects in cities that are directly targeted to support equity, without being linked to stormwater.

Recent demographic and economic changes in Seattle, located in King County (WA), are important when considering the distributional impacts of GSI policy. King County, the twelfth most populous U.S. County, has seen explosive growth in recent years, with the population expanding by over 50% since 1990 compared to 32% for the U.S. overall. Our study area is wealthy, with a median income over $95,000 in 2018. Since 2000 only New York City has experienced a larger increase in median income.[11]

3 Data

We merge four data sources to generate our final datasets. Our GSI data include geo- referenced records on all public and private GSI installations in Seattle obtained by a Public Disclosure Request to the City of Seattle. Our focus is on the RainWise program, and we use the proximity to public and private mandatory GSI installations as explanatory variables in our model for RainWise participation. Parcel characteristics come from the King County Assessor's Office for all residential parcels in King County. They were merged with arms-length residential housing sales from the King County Assessor's Office. We collect demographic data at the Census block group level from the U.S. Census American Community Service using a weighted average of the five-year samples depending on the year of observation. The City of Seattle also maintains a geospatial data on tree canopy that we merge with all parcels in Seattle.We calculate the percentage of each Census block group covered by tree canopy. Since this dataset is developed by the City of Seattle it is not available outside of Seattle city limits.Most of the GSI records have a parcel identification number (PIN) that we use to mergewith the Assessor data; the remainder were merged spatially.[12]

We generate several variables for the analysis. First, we use sales data from the Assessor's Office to predict housing prices for all homes as a proxy of household wealth. This includes properties not sold during our study period. We think this is a more transparent proxy for housing values than assessed values, another common proxy for house values.[13]The prediction model regresses real housing sale prices on property characteristics, year- by-month fixed effects and fixed effects at the subarea level, the finest available spatial geometry. The prediction model results are presented in Table A.1 in the Appendix. We generate three spatial proximity variables that vary over time: the cumulative number of RainWise participants, private GSI installations, and public GSI installations within a onemile radius for each year of the sample. These spatial variables are calculated based on the cumulative counts at the start of the year to avoid contemporaneous factors that affect both household adoption and peer adoption. We also calculate two static proximity variables:the number of parks within a mile of a property and the percentage of each Census block group covered by trees.

We use two datasets for our empirical analysis. The first consists of a yearly panel of all residential properties within the eligible areas. We use this data to model voluntary participation in the RainWise program. The second dataset uses all residential arms-lengths housing transactions both inside and outside RainWise eligible areas. We use this transaction dataset to estimate a hedonic selection model, focusing on transactions *before* RainWise GSI was installed to isolate the distributional effect from any capitalization of GSI into the value of the property.

We begin by describing summary statistics on the first of two channels through which the private GSI program can have distributional impacts: the administrative choice of which areas are eligible. The panels of Figure 1 overlay the areas of Seattle that were determined to be eligible for the program by RainWise staff (shown with dark outlines) with Census block group level data on four key variables. The top panels show that eligible areas, particularly those in eastern Seattle near Lake Washington, are among the neighborhoods in Seattle with the highest home values and highest median incomes. There are, however, eligible areas that have lower incomes and home values, notably in south Seattle, where the percentage of non-white residents is higher (bottom-right panel). There is no discernible pattern between tree cover and RainWise eligibility (bottom left panel).

The summary statistics for both datasets are in Table 1. The first three columns present sample means for properties in King County excluding Seattle, in the City of Seattle excluding the eligible area, and the eligible area. The last two columns present p-values from t-tests for equality of means for the RainWise-eligible areas compared to Seattle and King County (excluding Seattle), respectively.[14] The t-tests were performed using the sample of households for the parcel characteristics from the King County Assessor, and we collapse the data to block groups to perform the t-tests for the ACS variables. Panel (a) of Table 1 shows the sample statistics for all the residential parcels and panel (b) only includes parcels that were sold during the sample period.[15]

Both samples show that homes are more expensive in Seattle compared to homes out-side of the Seattle city limits in King County. However, even within Seattle, homes are significantly more expensive in the RainWise eligible areas, though characteristics such as lot size, square footage and the age of the home also differ by area. This is likely because the eligible areas were determined based on hydrologic priority and are therefore close to major water bodies that households view as valuable recreational and visual amenities. The median income is higher in the eligible area compared to ineligible areas of Seattle. How-ever, the median income of King County outside of Seattle is slightly higher than the eligible area. There are no differences in tree cover between

Seattle and the eligible area. Census block groups in eligible areas have a lower percentage of non-white residents and a higher percentage of residents with four-year college degrees than Seattle overall or King County (excluding Seattle). These summary data do not capture who in the eligible areas chooses to sign up for RainWise, but rather highlight the challenge in balancing environmental and equity goals when setting eligibility for voluntary environmental programs like RainWise.

Next, we non-parametrically examine both eligibility and participation by wealth using deciles of housing values. Panel (a) of Figure 2 shows the share of households in each decile of home values that were eligible for the program. The housing value deciles were created using data from both King County and Seattle, since ratepayers in both jurisdictions fund the program. Across all ratepayers, 12.5% of households were eligible for RainWise.The first three housing value deciles have a much lower share of eligible households at roughly 5%, whereas deciles 5-10 all have a higher share of eligible households. Panel (b) of Figure 2 shows the participation rates conditional on eligibility in green (average=2.3% of eligible households participated). Among eligible households, the participation rate is roughly flat for the first seven housing value deciles, and then sharply declines forthe most expensive properties. The figure also shows the overall participation rates within each housing value decile in tan (average=0.3% of all households in King County and Seattle participated). Since inexpensive homes are less likely to be eligible, the overall participation rate is highest for the middle income deciles.

4 Methodology

We examine the distributional effects of private, voluntary GSI policies. Drawing from the Mohai et al. (2009) review of the environmental justice literature with respect to both in- come and racial composition, we evaluate how participation in the RainWise program varies across three key variables: housing values, median income, and the percentage of non-white residents. Housing values are a proxy for wealth and a key advantage of housing valuesis the availability of property-level data. We use median income measured from the U.S. Census at the block group level. The percentage of non-white residents determines whether underrepresented minorities also benefit from increased green infrastructure through Rain- Wise.[16] We explored using the percentage of Black residents as a measure of racial representation and found no statistically-significant patterns. Only 5% of residents in King County are Black, however, whereas almost 30% of the population is non-white. Asian is the largest minority ethnic group at 15% and there are substantial numbers of non-native English speakers. RainWise has specifically targeted language as a barrier and developed marketing and outreach material in Spanish, Chinese, and Vietnamese. Lastly, we also con- sider neighbor variables to incorporate the role of peer effects in RainWise participation.We do not attempt to causally identify peer effects, but rather discuss how peer effects can amplify existing patterns of participation.

We use two primary models to estimate the distributional effects of RainWise. Our first approach estimates the probability that a household will sign up for RainWise in a given year, using program data from 2010-2018. Our second model is a hedonic selection model that uses observed housing sales as the dependent variable and a variable indicatinga property will sign up for RainWise in the future as the primary independent variable. The interpretation of the RainWise variable in the hedonic model is whether homes that eventually sign up for RainWise aremore or less expensive than houses that do participate. Using sales prior to RainWise adoption ensures that we estimate a selection effect as opposed to a capitalization effect of RainWise. Each of the models, including the statistical techniques to estimate the models, are presented in the following subsections.

4.1 Participation Model

The participation model is formalized in equation 1.

$$RW_{it} = \alpha + \theta_1 \ln(HomeValue_{it}) + \theta_2 \ln(MedInc_{it}) + \theta_3 NonWhite_{it} + \boldsymbol{\beta X_{it}} + \epsilon_{it} \quad (1)$$

In this model the dependent variable, RW_{it}, is a dummy {0,1} if household *i* signs up for RainWise in year *t*. Our parameters of interest are $\theta_1 - \theta_3$, which are the coefficients on predicted home values, median income, and % non-white residents. We use the natural log of predicted home values and median income to fix the scale in percentage terms. We include additional explanatory variables in $\boldsymbol{X_{it}}$ such as housing characteristics, demographics at the block group level, neighbor GSI variables, and year fixed effects.[17] The general interpretation of the model coefficients is the impact of a variable on the probability of a parcel signing up for RainWise in a given year. Because the dependent variable in our selection model, RW_{it}, is binary and therefore not normally distributed, we use a logit model. We cluster our standard errors at the block group level.

4.2 Hedonic Selection Model

A limitation of the participation model is the lack of property-level data on income or home price. As described above we estimate home values in a predictive model, which is not as accurate a proxy for household wealth as the actual sale price of the home. Therefore, wealso estimate a model where we focus on homes sold during our study period. The tradeoffis a smaller sample that may not be representative: not all homes were sold during thistime. Examining the two datasets in Table 1 reveals some differences although the general magnitudes and differences between King County, Seattle, and the RainWise eligible areasare similar in the two samples.

$$\ln(P_{it}) = \alpha + \delta_1 RW_{pre,it} + \delta_2 Sea_i + \delta_3 Eligible_i + \epsilon_{it} \quad (2)$$

The dependent variable is the natural log of the real sales price (in January 2018 dollars), so the coefficients are interpreted as the marginal effect on home values in percentage terms.The primary variable of interest, $RW_{pre,it}$, is a dummy equal to one if a house was sold priorto RainWise participation. This variable captures the types of homes that will eventually participate in RainWise. The Sea_i and $Eligible_i$ variables are dummies indicating that thehome was in the Seattle city limits and the eligible area, respectively. The hedonic modeluses data from all of King County to evaluate how housing prices depend on both eligibility and adoption. In the hedonic model we do not include any controls or spatialfixed effects because we explicitly want the RainWise coefficient to capture selection effects. Excluding controls ensures that we capture whether homes that eventually sign up are inmore desirable neighborhoods or have more bedrooms, bathrooms, or square footage.

To clarify our hedonic selection model, consider a standard hedonic model that attempts to estimate the capitalization effect of RainWise. The standard hedonic model would replace $\delta_1 RW_{pre,it}$ in equation 2 with $\tilde{\delta}_1 RW_{post,it}$, where $RW_{post,it}$ is an indicator for a home that sold *after* RainWise GSI was installed. Typically $\tilde{\delta}_1$ will capture two effects: the capitalization effect of GSI on home values and a selection effect if participation in RainWise is correlatedwith unobservables affecting housing values. By contrast, our parameter δ_1 eliminates thecapitalization effect because $RW_{pre,it}$ captures sales occurring *before* RainWise GSI is installed while retaining the selection effect. Therefore, the regression isolates how selection into RainWise affects property values.

5 Results

5.1 Participation Model Results

We begin with the results from the participation model. Again, all the participation models are run exclusively on properties located within eligible areas. We present the results of the average marginal effects from the logit regressions in graphical form in Figures 3 and 4. The full table of results for the logit regressions, along with the alternative models used for robustness, is available in the Appendix.

We estimate two variations of the logistic regression. The first model presents the average marginal effect of the three key variables on participation, presented in panel (a) of Figure 3. Higher valued homes in eligible areas are less likely to participate, on average.The interpretation of the home value results is that a 100% increase in home value would decrease the annual participation rate by 0.1 percentage points. This is relative to an average annual participation rate of 0.25%. The median income of the Census block group in which the house is located does nothave a meaningful impact on participation.[18] Census block groups with a higher percentageof non-white residents have a lower probability of participating in RainWise. Changing a neighborhood from all white to all non-white would decrease the annual participation rateby almost 0.4 percentage points.

We estimate a second logistic regression to examine the full distribution of the variables rather than focusing on their average effects. This is important for environmental justice considerations where the outcomes of the poorest or neighborhoods with high concentrations of minorities are critical. We replace the three key variables (home value, income,percent non-white) with indicators for deciles of each variables, with the fifth decile omitted. The decile *cutoffs* are based on data for all ratepayers though these estimation models
only use data for properties located in RainWise-eligible areas.

The results are presented in panel (b) of Figure 3. One can interpret these decile coefficients as the marginal effect on participation of being in that decile relative to the fifth decile. For example, panel (b) shows that homes within the highest two housing value deciles (blue) are significantly less likely to participate relative to the fifth decile. A house- hold in the highest home-value decile is 0.1 percentage points less likely to sign up in agiven year than a home in the fifth decile. The pattern is noisier for median income; per-haps due to only having variation at the block group level. All the coefficients for the percentage of non-white residents are negative, indicating that participation is highest in the omitted fifth decile. There is a monotonic decreasing pattern and Census block groups with the largest minority populations are least likely to participate. We note that since the fifth decile is omitted and all the coefficients are negative, that the fifth decile of non-white had the highest participation rate. The general pattern is the same if we omit the first decile instead of the fifth except for a positive and insignificant coefficient for the fifth decile.

Other studies have found evidence that peer effects guide individual decisions for GSI adoption (Lim, 2018) as well as other environmental outcomes for residential homeowners (Bollinger and Gillingham, 2012; Bollinger et al., 2020). We present the results for the neighbor variables in Figure 4. We focus on the counts within 1 mile of the property of four variables: RainWise installations, mandatory private GSI, public GSI installations, and parks. The variables are all standardized, so the interpretation is the effect of a one standard deviation change in the variable. The three GSI variables vary over time and are the cumulative counts in a given year. RainWise installations show strong positive peer effects: households who live in neighborhoods where more of their neighbors have adopted Rain- Wise are more likely to participate themselves. This may be due to a positive amenity value of RainWise installations, or a simple advertising effect: participants often put a yard sign provided by the utility next to their raingarden.

We find negative peer effects, however, for mandatory private GSI installations. One reason may be that mandatory private GSI may consist of features that are not as attractive or functional as RainWise. Alternatively, since mandatory GSI is required for new construction or additions the regions of the city experiencing a building boom may be negatively correlated with RainWise adoption. We find no effect of proximity to public GSI or parks on RainWise participation. We do not interpret the peer effects as causal due to the reflection problem documented by Manski (1993). Therefore, we cannot distinguish if a RainWise installation truly causes an increase in their neighbors' adoption probabilities, or if there are spatial unobserveables driving clusters of adoptions. Either way it is clear that neighborhood-level penetration is an important factor in RainWise participation.

5.2 Robustness for participation model

The panel nature of the dataset and time-varying neighborhood characteristics present a complication. Namely, we must make an assumption about how to treat the time periods after a household adopts RainWise. In a panel logit model, coding the dependent variable as one after adoption incorrectly allows factors that occur after adoption to affect predicted adoption. For example, suppose household A signed up in 2015 and their neighbor, household B, signed up in 2016. Clearly, household B's adoption decision did not affect household A, since household A had already signed up. If we code our RainWise variable for household A as one after adoption (i.e., in 2015, 2016, and 2017) the model incorrectly allows household B's adoption to affect household A's probability of adoption. We drop the post-adoption observations from the sample – another option is coding them as zero - but neither approach is entirely correct. Instead, we supplement a panel logistic model with a time-varying survival model which accounts for the fact that households "drop out" of the sample after they participate in RainWise. Survival models are common in epidemiology to estimate the duration until death or the probability of survival. In our setting 'death' is represented by a household signing up for RainWise. We choose Aalen's additive regression model (Aalen, 1989) that accommodates time-varying hazard rates since some of our variables change over time such as the number of neighbors that sign up for Rain- Wise. As further robustness checks we estimate a linear probability model (LPM) and a Cox proportional hazard model.

We examine the impact of housing values and neighbors' RainWise adoption from the results of the survival model by plotting the cumulative regression coefficients from Aalen's model in Figure A.5.[19] These curves plot the cumulative impact of a unit change of the variable (from its mean) on the RainWise adoption rate over time. Both the average effects and the decile effects are in the Aalen's model are similar to the panel logit estimator. Additionally, the LPM and Cox models also produce similar estimates as shown in Table A.3.

Our last robustness check relates to the inclusion of variables capturing peer effects. Even though we are not estimating causal effects in our model if the endogenous neighbor variables are correlated with the core distributional variables it may change their estimated parameters. As a robustness check we replicate the results presented in Figure 3 in a model that excludes the neighbor variables. The results, shown in Figure A.6 in the Appendix, are essentially the same.

5.3 Hedonic Selection Model Results

The results for the hedonic selection model are presented in Table 2. Recall that the Rain- Wise variable identifies a home sold before the homeowner signs up for RainWise. The RainWise variable's interpretation is the difference in housing prices for homes that signup for RainWise relative to homes that do not sign up. The first three columns of Table2 use all sales in King County. Column (1) does not include dummy variables for Seattleand the eligible area (Eligible). Therefore, the interpretation is the unconditional effect on selection that encompasses *both* eligibility and voluntary participation relative to all King County residents. Homes that in the future will sign up for RainWise are 3% less expensivethan other homes in King County and the effect is not statistically significant. The model in column (1) does not account for the fact that only certain homes are eligible, and that alleligible homes are in Seattle. Column (2) controls for whether the home is in the Seattle city limits, and the selection effect decreases to -15%. This is because homes in Seattle aremore expensive than the average King County home. The joint effect of being in Seattle andparticipating in RainWise is a positive 2%. Next, when controlling for the eligible area and Seattle the selection effect decreases to -21%. Again, as shown in the non-parametric analysis, homes in RainWise-eligible areas are more expensive than the average Seattle home.The joint effect of the being in Seattle, in an eligible area, and participation is 3.7%. The joint effects are calculated through linear combinations of the parameters, and neither linear combination is statistically different than zero. Finally, focusing only on the voluntary participation channel (model 4), we find the selection effect is -18%: among homes locatedin eligible neighborhoods, houses that will eventually adopt RainWise sell for 18% less.

To investigate effects across the housing value distribution, we estimate quantile regressions for quantiles ranging from 0.05 to 0.95 in increments of 0.05 based on Firpo (2007). The quantile regressions only include the RainWise indicator and therefore have the interpretation of the difference in each house price quantile among the houses that will eventuallysign up for RainWise compared to homes that never sign up. For example, the coefficienton the median represents the difference in the median home price for eventual RainWise participants and non-participants. We estimate the quantile regression on three different samples: King County, Seattle, and the eligible area (Eligible). The results are presentedgraphically in Figure 5 where the solid line is the point estimate, and the shaded area is the 95% confidence interval.

In King County, lower quantiles (0.05-0.4) have positive coefficients, indicating that among lower-valued homes RainWise participants reside in more expensive houses. The King County results incorporate the strong eligibility effect: the lowest priced eligible homes are more expensive than many homes in King County. For example, the 10th percentile home is about 10% more expensive for RainWise participants compared to non- participants. This indicates that within King County the least expensive homes are less likely to participate in RainWise. This effect turns negative around the median and is strongly negative for more expensive homes. The 90th percentile is about 20% lower for participants than non-participants. The general downward trend across the housing price distributions indicates that the selection effects become stronger and more negative among more expensive housing value quantiles. The pattern is essentially replicated but shifted down for Seattle and the eligible area. RainWise homes are less expensive across the housing value distribution in Seattle and the eligible area, with the largest effect among the most expensive homes. The difference in the 90th percentile across RainWise participation statusis 30% in Seattle and almost 40% in the eligible area.

We find that homes that will eventually sign up for RainWise sell for significantly lessthan other eligible homes. One explanation is that property owners sign up for RainWiseas part of larger renovation projects, and therefore we are simply capturing homes thatare in poor condition. To investigate whether future RainWise homes are "fixer-uppers" or lower valued homes in good condition, we merged building permit data from King County Assessor to the sales data. We defined a RainWise renovation home as a transaction where a home was sold prior to RainWise installation, and the home had a building permit afterthe RainWise installation. Across King County 8% of transacted properties have a building permit associated with their parcel, compared to 5% of RainWise homes that were sold. This argues against the notion that our RainWise variable is picking up homes in poor condition that sign up for RainWise as part of a larger construction project.

5.4 Project costs

We also examine whether the size of the project scales with the environmental justice variables. We regress the total cost of the project, and share of the project that was subsidized,on our home values, median income, tree canopy, and non-white. This model focuses on RainWise participants, and the sample consists of households that signed up for RainWise.

The results are in Table A.2 in the Appendix. A one standard deviation increase in home value increases the total cost of a RainWise project by approximately $200, or roughly 4%. Block groups with more non-white residents have more expensive projects. There is no discernible effect of any of these variables on the percentage of the project funded by Rain-Wise, although this might be due the fact that RainWise funded such a high percentage of most projects.

Each RainWise project provides an estimate for the gallons of mitigated stormwater. We examine the relative cost effectiveness of RainWise dollars by dividing the gallons of mitigated by the cost of the project. More expensive homes on average have lower cost effectiveness; and most of the effects are concentrated in the most expensivehomes. This provides suggestive evidence that landscaping in expensive RainWise homesmay prioritize aesthetics over stormwater mitigation. Homes in block groups with more non-white residents also have projects with lower cost effectiveness.

6 Conclusion

Policymakers and the public are increasingly concerned about the distributional effects of environmental policy. While private benefits flow to homeowners who install subsidized GSI on private property, all ratepayers bear the cost of subsidies in order to achieve the public good of lowered CSOs and improved water quality. As a result, GSI subsidies are transfers from ratepayers to participating homeowners. Are these transfers a net subsidy to participants? Or are they being compensated for their willingness to accept a landscape feature that provides public stormwater benefits but zero or negative private benefits? Although it is possible that participating homeowners find Rain- Wise installations ugly or onerous to maintain, anecdotal evidence from the city suggests homeowners gain private benefits. Stated preference research from other settings has found that households perceive raingardens as a net positive and have a positive willingness-to-pay for them (Newburn and Alberini, 2016; Londoño Cadavid and Ando, 2013; Brent et al., 2017; Iftekhar et al., 2021). Furthermore, given that the SPU and King County subsidize approximately 90% of the installation costs, the private benefits need not be large before the payment is net utility-improving subsidy to participants. Who gains private benefits by receiving direct subsidies?

We decompose the distributional effects of the policy into impacts at the eligibility stage and the participation stage. We find that RainWise administrators selected eligible areas with more expensive homes than other Seattle homes, which are in turn more expensivethan King County properties. We find that subsidies for GSI on private land primarily benefit upper middle-class households when using home values as a proxy for wealth. The richest and poorest deciles are least likely to benefit directly by having a RainWise installation in their yard. Neighborhoods with a higher non-white population are also less likely to participate in RainWise. The lack of participation of the poorest households and non-white neighborhoods exists despite efforts by program managers to specifically target these groups through top-up subsidies and a Racial Equity Toolkit.

As of late 2018, the total spending on RainWise projects was $7.6 million dollars. The program is believed to have reduced stormwater by an estimated 22 million gallons. While the investment is impressive, there is still significant additional stormwater retention necessary to achieve the goal of 700 million gallons. To date RainWise has accounted for roughly 10% of total gallons of stormwater reduced through GSI. If RainWise's relative share of total GSI remains constant there will need to be more than a threefold increase in the current RainWise installations. As RainWise continues or expands, there are likely opportunities to incorporate consideration of the distributional costs and benefits.

Our results prompt raise two important questions about how to incorporate environ-mental justice priorities into GSI policy. The first question regards the tradeoff between water quality improvements and equitable placement of GSI. While estimating the spatial heterogeneity of water quality benefits from distributed public and private GSI is beyond our research scope, Lim and Welty (2017) suggest only very extreme differences in GSI placements will meaningfully affect water quality. This opens the possibility of relaxing eligibility requirements to achieve more equitable access to urban greening. Another question reflects the external validity of our results. Our finding that, conditional on eligibility, high income households are less likely to participate depends on the initial set of eligible homes. If RainWise expands to less affluent areas, would we find the same pattern that *relatively* wealthy homes do not participate? Generalizing outside of Seattle is also difficult since the demographics of prioritized areas from a water quality perspective may differ in other locations. Just because eligibility was concentrated among wealthy white areas in Seattle does not mean that the most impactful GSI placement in other cities would exclude marginalized communities.

Finally, we find strong suggestive evidence of peer effects in the participation decision, consistent with other research for private incentives to adopt environmentally friendly land- scaping (Lim, 2018;

Brelsford and De Bacco, 2018; Bollinger et al., 2020). Peer effects create both challenges and opportunities for increasing participation in low-income neighbor- hoods. Low- and moderate-income residents are interested in participating in GSI programs (Mason et al., 2019), and targeted campaigns to reach these residents may have positive effects on uptake. If RainWise chooses to strategically expand eligible areas while implementing targeted campaigns, it may be possible to reduce or even eliminate distributional impacts. High-quality causal estimates of the magnitude of peer effect could help identify the critical mass of initial low-income participants necessary to achieve equity goals.

References

Aalen, Odd O, "A linear regression model for the analysis of life times," *Statistics in medicine*, 1989, *8* (8), 907–925.

Ando, Amy W. and Luiz P C Freitas, "Consumer demand for green stormwater management technology in an urban setting: The case of Chicago rain barrels," *Water Resources Research*, 2011, *47* (12), 1–11.

Ando, Amy W, Catalina Londoño Cadavid, Noelwah R Netusil, and Bryan Parthum, "Willingness-to-volunteer and stability of preferences between cities: Estimating the ben- efits of stormwater management," *Journal of Environmental Economics and Management*, 2020, *99*, 102274.

Astell-Burt, Thomas, Xiaoqi Feng, Suzanne Mavoa, Hannah M Badland, and Billie Giles-Corti, "Do low-income neighbourhoods have the least green space? A cross-sectional study of Australia's most populous cities," *BMC Public Health*, 2014, *14* (1), 292.

Banzhaf, Spencer, Lala Ma, and Christopher Timmins, "Environmental justice: The eco- nomics of race, place, and pollution," *Journal of Economic Perspectives*, 2019, *33* (1), 185–208.

BenDor, Todd K., Vivek Shandas, Brian Miles, Kenneth Belt, and Lydia Olander, "Ecosystem services and U.S. stormwater planning: An approach for improving urban stormwater decisions," *Environmental Science and Policy*, 2018, *88* (July), 92–103.

Bhutta, Neil, Jesse Bricker, Andrew C Chang, Lisa J Dettling, Sarena Goodman, Joanne WHsu, Kevin B Moore, Sarah Reber, Alice Henriques Volz, and Richard Windle, "Changes in US family finances from 2016 to 2019: Evidence from the Survey of Con-sumer Finances," *Federal Reserve Bulletin*, 2020, *106* (5).

Bollinger, Bryan and Kenneth Gillingham, "Peer effects in the diffusion of solar photo- voltaic panels," *Marketing Science*, 2012, *31* (6), 900–912.

_ **, Jesse Burkhardt, and Kenneth T Gillingham**, "Peer Effects in Residential Water Conservation: Evidence from Migration," *American Economic Journal: Economic Policy*, 2020, *12* (3), 107–33.

Bowler, Diana E, Lisette Buyung-Ali, Teri M Knight, and Andrew S Pullin, "Urban greening to cool towns and cities: A systematic review of the empirical evidence," *Landscapeand urban planning*, 2010, *97* (3), 147–155.

Brelsford, Christa and Caterina De Bacco, "Are 'Water Smart Landscapes' Contagious? An epidemic approach on networks to study peer effects," *Networks and Spatial Economics*, 2018, *18* (3), 577–613.

Brent, Daniel A, Lata Gangadharan, Allison Lassiter, Anke Leroux, and Paul A Raschky, "Valuing environmental services provided by local stormwater management," *Water Re- sources Research*, 2017, *53* (6), 4907–4921.

Cavanagh, Jo-Anne E, Peyman Zawar-Reza, and J Gaines Wilson, "Spatial attenuation of ambient particulate matter air pollution within an urbanised native forest patch," *Urban Forestry & Urban Greening*, 2009, *8* (1), 21–30.

Colmer, Jonathan, Ian Hardman, Jay Shimshack, and John Voorheis, "Disparities in PM2. 5 air pollution in the United States," *Science*, 2020, *369* (6503), 575–578.

Currie, Beth Anne and Brad Bass, "Estimates of air pollution mitigation with green plants and green roofs using the UFORE model," *Urban ecosystems*, 2008, *11* (4), 409–422.

Dai, Dajun, "Racial/ethnic and socioeconomic disparities in urban green space accessibility: Where to intervene?," *Landscape and Urban Planning*, 2011, *102* (4), 234–244.

EPA), U.S. Environmental Protection Agency (US, "Seattle, Washington and King County, Washington Settlement," Technical Report 2013.

Firpo, Sergio, "Efficient semiparametric estimation of quantile treatment effects," *Econometrica*, 2007, *75* (1), 259–276.

Havranek, Tomas, Zuzana Irsova, and Tomas Vlach, "Measuring the income elasticity of water demand: the importance of publication and endogeneity biases," *Land Economics*, 2018, *94* (2), 259–283.

Heckert, Megan and Christina D Rosan, "Developing a green infrastructure equity index to promote equity planning," *Urban Forestry & Urban Greening*, 2016, *19*, 263–270.

Hoffman, Jeremy S, Vivek Shandas, and Nicholas Pendleton, "The effects of historical housing policies on resident exposure to intra-urban heat: A study of 108 US urban areas," *Climate*, 2020, *8* (1), 12.

Hopkins, Kristina G, Nancy B Grimm, and Abigail M York, "Influence of governance structure on green stormwater infrastructure investment," *Environmental Science & Policy*, 2018, *84*, 124–133.

Iftekhar, Md Sayed, Fan Zhang, Maksym Polyakov, James Fogarty, and Michael Burton, "Non-market values of water sensitive urban designs: A case study on rain gardens," *Water Resources and Economics*, 2021, *34*, 100178.

Jennings, Viniece, April Karen Baptiste, Osborne Jelks, Renée Skeete et al., "Urban greenspace and the pursuit of health equity in parts of the United States," *International Journal of Environmental Research and Public Health*, 2017, *14* (11), 1432.

Jiang, Shaojing, Xuhui Lee, Jiankai Wang, and Kaicun Wang, "Amplified urban heat islands during heat wave periods," *Journal of Geophysical Research: Atmospheres*, 2019, *124* (14), 7797–7812.

Kadish, Jonathan and Noelwah R. Netusil, "Valuing vegetation in an urban watershed," *Landscape and Urban Planning*, 2012, *104* (1), 59–65.

Kardan, Omid, Peter Gozdyra, Bratislav Misic, Faisal Moola, Lyle J Palmer, Tomáš Paus, and Marc G Berman, "Neighborhood greenspace and health in a large urban center," *Scientific reports*, 2015, *5*, 11610.

Lim, Theodore C. and Claire Welty, "Effects of spatial configuration of imperviousness and green infrastructure networks on hydrologic response in a residential sewershed,"*Water Resources Research*, 2017, *53* (9), 8084–8104.

Lim, Theodore Chao, "An empirical study of spatial-temporal growth patterns of a voluntary residential green infrastructure program," *Journal of Environmental Planning and Management*, 2018, *61* (8), 1363–1382.

Locke, Dexter, Billy Hall, J Morgan Grove, Steward TA Pickett, Laura A Ogden, Carissa Aoki, Christopher G Boone, and Jarlath PM O'Neil-Dunne, "Residential housing segregation and urban tree canopy in 37 US Cities," 2020.

Londoño Cadavid, Catalina and Amy W. Ando, "Valuing preferences over stormwater management outcomes including improved hydrologic function," *Water Resources Re- search*, 2013, *49* (7), 4114–4125.

Manski, Charles F, "Identification of endogenous social effects: The reflection problem," *The review of economic studies*, 1993, *60* (3), 531–542.

Mason, Lisa Reyes, Kelsey N Ellis, and Jon M Hathaway, "Urban flooding, social equity, and "backyard" green infrastructure: an area for multidisciplinary practice," *Journal of Community Practice*, 2019, *27* (3-4), 334–350.

McPhillips, Lauren E and A Marissa Matsler, "Temporal evolution of green stormwater infrastructure strategies in three US cities," *Frontiers in Built Environment*, 2018, *4*, 26.

Mohai, Paul, David Pellow, and J Timmons Roberts, "Environmental justice," *Annual review of environment and resources*, 2009, *34*, 405–430.

Montalto, Franco, Christopher Behr, Katherine Alfredo, Max Wolf, Matvey Arye, and Mary Walsh, "Rapid assessment of the cost-effectiveness of low impact development for CSO control," *Landscape and Urban Planning*, 2007, *82* (3), 117–131.

Netusil, N. R., S. Chattopadhyay, and K. F. Kovacs, "Estimating the Demand for Tree Canopy: A Second-Stage Hedonic Price Analysis in Portland, Oregon," *Land Economics*, 2010, *86* (2), 281–293.

Newburn, David A and Anna Alberini, "Household response to environmental incentives for rain garden adoption," *Water Resources Research*, 2016, *52* (2), 1345–1357.

Pugh, Thomas AM, A Robert MacKenzie, J Duncan Whyatt, and C Nicholas Hewitt, "Effectiveness of green infrastructure for improvement of air quality in urban street canyons," *Environmental science & technology*, 2012, *46* (14), 7692–7699.

Sander, Heather, Stephen Polasky, and Robert G Haight, "The value of urban tree cover:A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA," *Ecological Economics*, 2010, *69* (8), 1646–1656.

South, Eugenia C, Bernadette C Hohl, Michelle C Kondo, John M MacDonald, and Charles C Branas, "Effect of greening vacant land on mental health of community- dwelling adults: a cluster randomized trial," *JAMA network open*, 2018, *1* (3), e180298– e180298.

_ **, Michelle C Kondo, Rose A Cheney, and Charles C Branas**, "Neighborhood blight, stress, and health: a walking trial of urban greening and ambulatory heart rate," *American Journal of Public Health*, 2015, *105* (5), 909–913.

Sugiyama, Takemi, Eva Leslie, Billie Giles-Corti, and Neville Owen, "Associations of neighbourhood greenness with physical and mental health: do walking, social coherence and local social interaction explain the relationships?," *Journal of Epidemiology & Community Health*, 2008, *62* (5), e9–e9.

Times, Seattle, "Seattle, King County Settle with EPA Over Water Pollution," *Seattle Times*, 2013.

Wilson, Bev, "Urban Heat Management and the Legacy of Redlining," *Journal of the Ameri-can Planning Association*, 2020, pp. 1–15.

Zhang, Fan, Maksym Polyakov, James Fogarty, and David J. Pannell, "The capitalized value of rainwater tanks in the property market of Perth, Australia," *Journal of Hydrology*, 2015, *522* (June 2013), 317–325.

Ziter, Carly D, Eric J Pedersen, Christopher J Kucharik, and Monica G Turner, "Scale-dependent interactions between tree canopy cover and impervious surfaces reduce day- time urban heat during summer," *Proceedings of the National Academy of Sciences*, 2019, *116* (15), 7575–7580.

Tables

Table 1: Summary statistics and difference in means

(a) Summary statistics and difference in means for all properties

Variable	Mean KC	Mean Seattle	Mean RW Eligible	T-KC	T-SEA
House Value	624321	637740	704639	0	0
Med. Income	89454	78985	88810	0.793	0.001
Non-White	0.314	0.319	0.287	0.122	0.054
Tree Canopy		0.254	0.253		0.656
Lot	28090	6180	5190	0	0
Sq.ft.	2198	1833	1859	0	0
Year Built	1977	1953	1944	0	0
Degree	0.427	0.6	0.661	0	0
Observations	508684	156236	63806		

(b) Summary statistics and difference in means for properties sold (2010-2018)

Variable	Mean KC	Mean Seattle	Mean RW Eligible	T-KC	T-SEA
House Price	624693	663593	758955	0	0
Med. Income	102177	89342	100541	0.461	0
Non-White	0.353	0.362	0.31	0	0
Tree Canopy		0.262	0.256		0.382
Lot	18762	5190	4470	0	0
Sq.ft.	2361	1856	1910	0	0
Year Built	1984	1964	1955	0	0
Degree	0.485	0.662	0.752	0	0
Observations	184189	56206	22414		

Note: The sample in panel (a) includes all residential properties in King County. Housing values in panel (a)are based on 2018 dollars and reflect the predicted values based on a regression model. The sample in panel (b) shows data for all arms-length residential property sales in King County from 2010-2018. Housing sales inpanel (b) are the sale price in 2018 dollars. Year Built, Lot and Sq.ft. are based on the King County Assessorand are measured at the property level. Black, Med. Income, and Degree are from the ACS and measured at the block group level. Degree is the percentage of the Census block group with a college degree or higher. Tree Canopy is measured at the neighborhood level and is only available within the City of Seattle; King County data are intentionally blank. T-KC and T-SEA show the p-values for t-tests of difference in means for the RainWise eligible sample and the rest of King County and Seattle, respectively. The t-tests account for the unit of observation (block group or property).

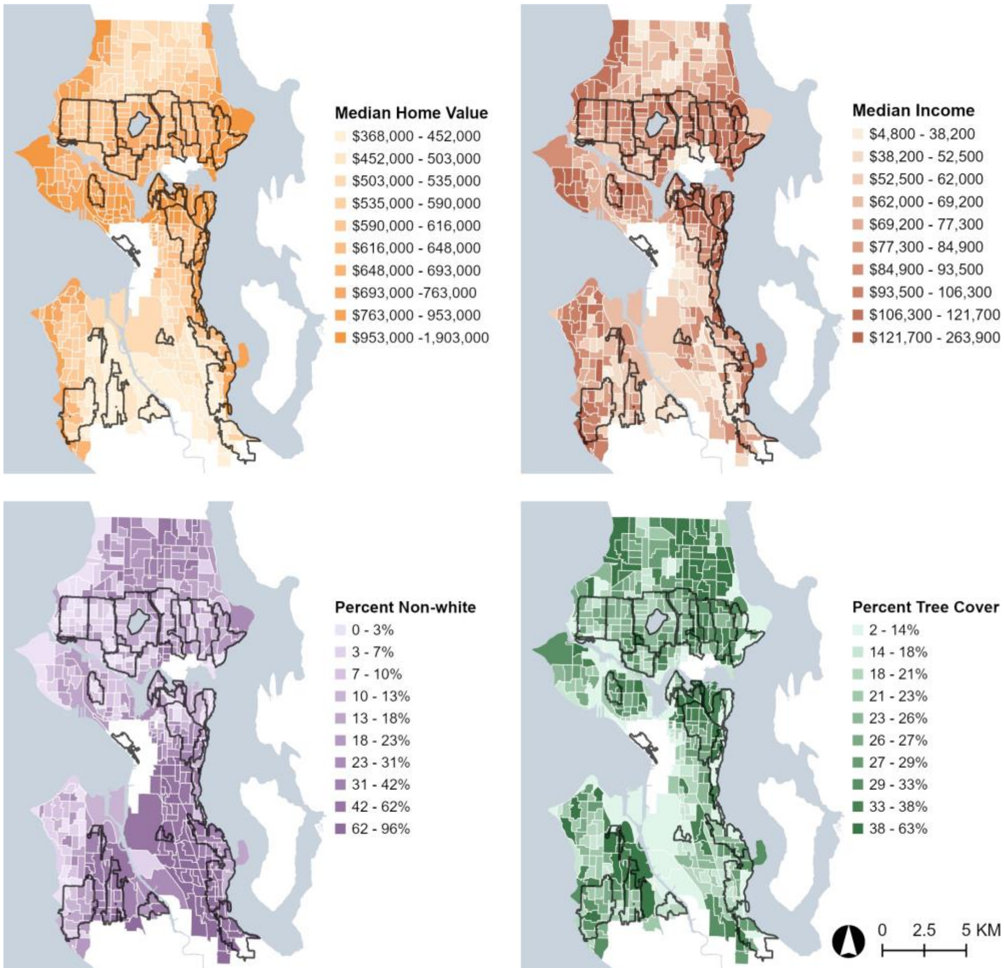
Table 2: Pre-adoption hedonic selection model

	King County (1)	King County (2)	King County (3)	Eligible (4)
RainWise	−0.032	−0.151***	−0.213***	−0.181***
	(0.062)	(0.047)	(0.050)	(0.057)
Seattle		0.173**	0.124*	
		(0.068)	(0.067)	
Eligible			0.126**	
			(0.054)	
Observations	180,334	180,334	180,334	21,890
R^2	0.072	0.097	0.102	0.132
Adjusted R^2	0.071	0.097	0.101	0.127

Notes: The dependent variable is log of home price in 2018 dollars. Robust standard errors are clustered at the household level. *p<0.1; **p<0.05; ***p<0.01

Figures

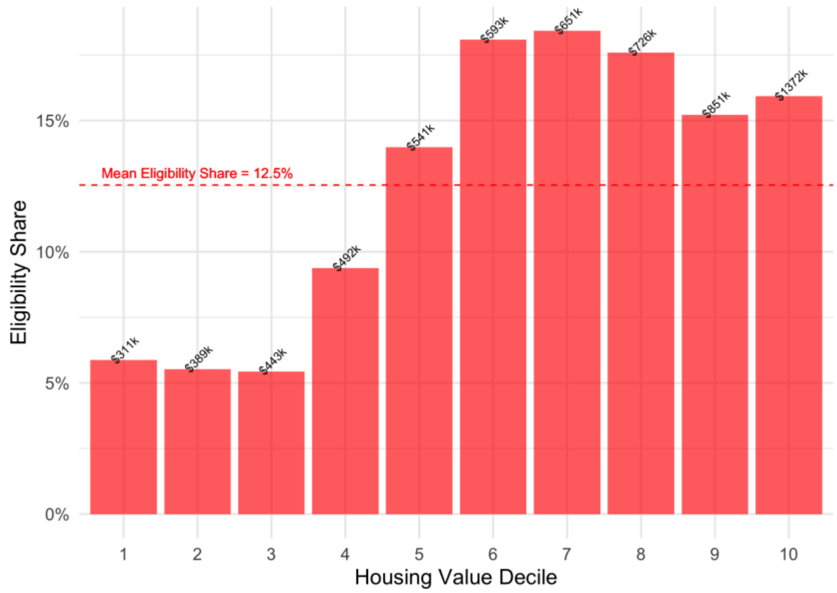
Figure 1: Map of RainWise eligibility and combined sewer overflow locations



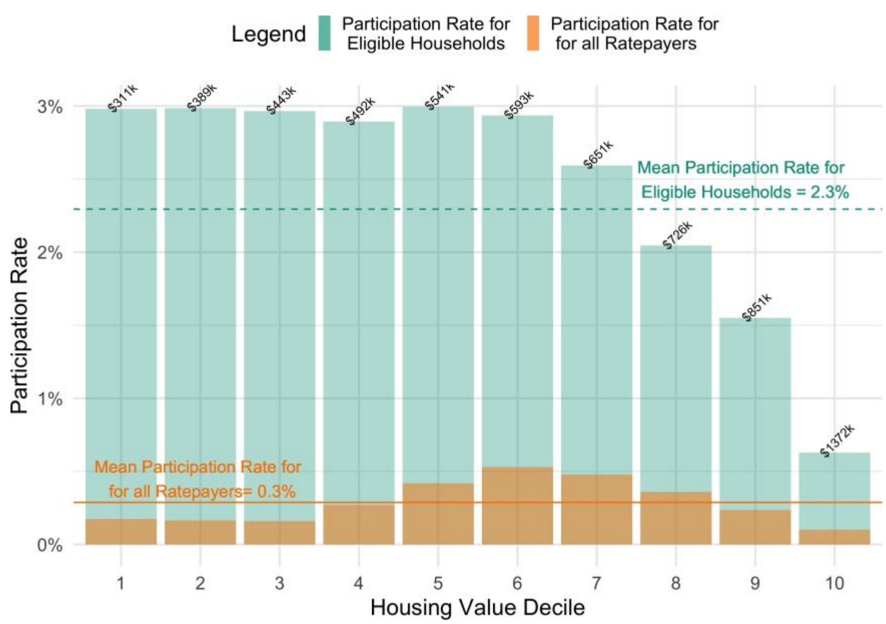
Note: The map shows average for four key variables by Census block group: median home value, median income, percent Black and percent tree cover. The boundaries of the RainWise eligible areas funded by King County are shown in Black and those funded by SPU are shown in gray.

Figure 2: Eligibility and participation by housing value deciles

(a) Eligibility shares



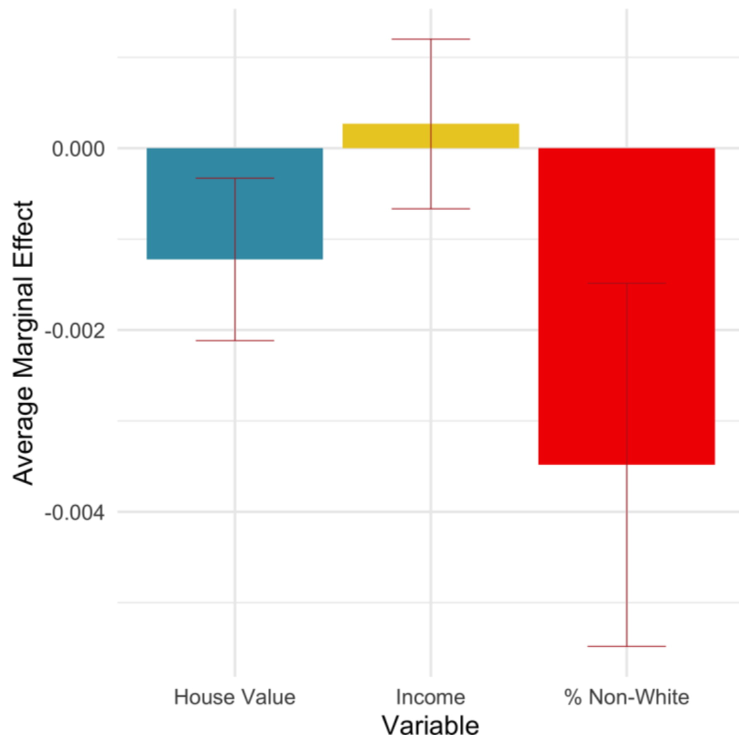
(b) Participation rates



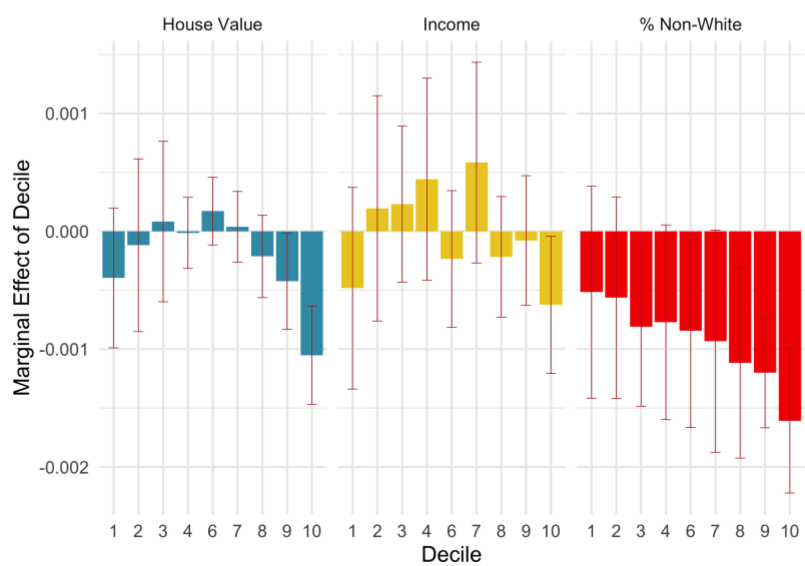
Note: The vertical axis in panel (a) measures the share of eligible homes within each housing value decile. The deciles are created using predicted housing values for all ratepayers in King County. If eligibility were evenly distributed across the county each decile would contain 12.5% eligible homes. Panel (b) shows the participation rates for both eligible households and the overall participation rate by housing value decile. The participation rate for all ratepayers within each decile is calculated by multiplying the participation rate for eligible house- holds by the eligibility share. The labels on top of each bar show the mean home pricewithin each decile in thousands of dollars.

Figure 3: Marginal effects of environmental justice variables on RainWise participation

(a) Average effects

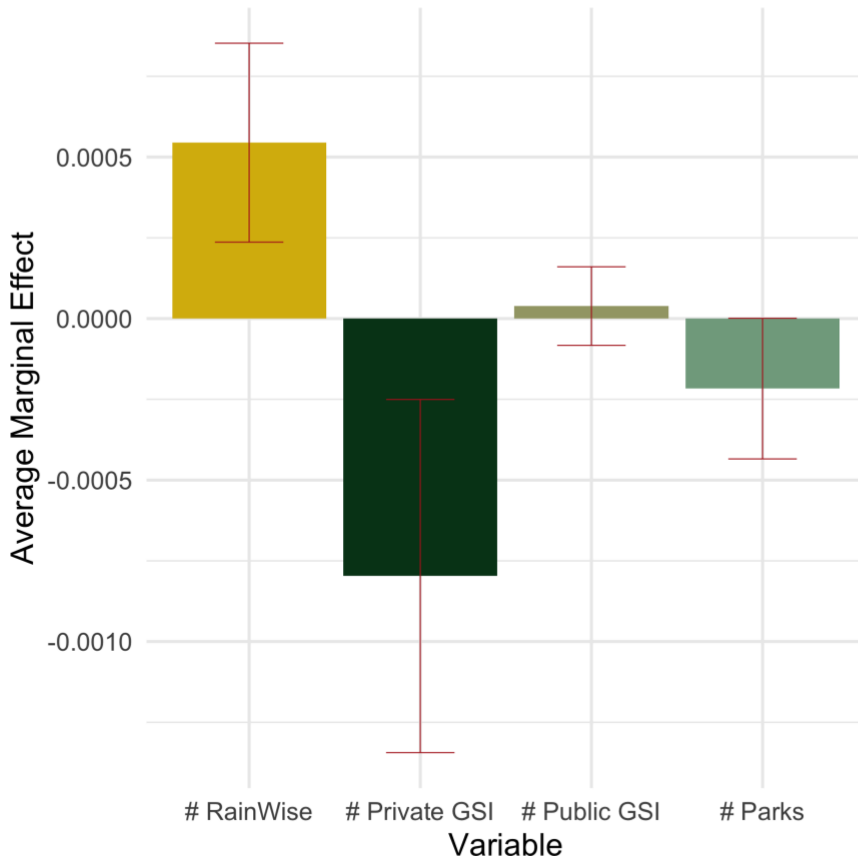


(b) Effects by decile



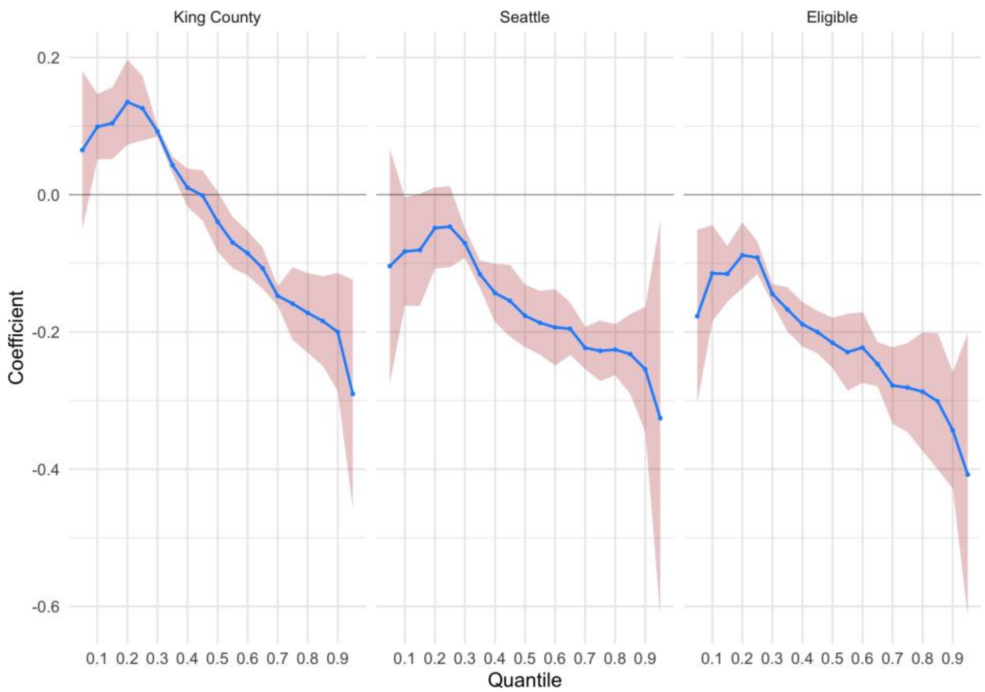
Notes: These plots show the marginal effects on key variables on RainWise participation from a logit regression. The solid bars are the coefficient estimates and the error bars represent 95% confidence intervals from standard errors clustered at the block group level. The vertical axis represents the change in the probability of participating in RainWise fora unit change in the variable. The full table of results for the logit regressions is availablein Table A.3.

Figure 4: Neighbor and neighborhood impacts on RainWise participation



Notes: These plots show the marginal effects on key variables on RainWise participation from a logit regression. The solid bars are the coefficient estimates and the error bars rep- resent 95% confidence intervals from standard errors clustered at the block group level.The vertical axis represents the change in the probability of participating in RainWise fora unit change in the variable. The horizontal axis shows key neighbor and neighbor- hood variables: the number of neighbors within 1 mile that signed up for RainWise (#RainWise), the number of neighbors within 1 mile that installed private GSI due to new construction or additions ($ Private GSI), the number of public GSI installations within 1mile (Public GSI), and the number of parks within 1 mile. The full table of results for the logit regressions is available in Table A.3.

Figure 5: Quantile regressions selection effects



Notes: The figure graphs the coefficients and 95% confidence intervals from quantile regressions of the log of real house prices on future RainWise participation for different samples. The interpretation of the coefficient is the difference in logged house price quantile among future participants and non-participants. The coefficient for the 0.5th quantileis difference in the median house price among future RainWise participants and houses that will not participate in percentage terms (approximately). The regressions control for year fixed effects but no other covariates. The quantiles range from 0.05 to 0.95 in increments of 0.05.

Notes

[1]Beginning in the 1930s and continuing through the 1970s, the Home Owners' Loan Corporation categorized the desirability of neighborhoods for loans and investment using race. Their least desirable category was outlined on maps in red and often had higher concentrations of Black residents.

[2]GSI was formalized as a method of managing CSOs in 2019 with the Water Infrastructure Improvement Act, which requires the Environmental Protection Agency (EPA) to promote the use of GSI (H.R.7279).

[3]See the EPA's work and definition of environmental justice at https://www.epa.gov/environmentaljustice.

[4]More information on the program is available at https://www.700milliongallons.org/.

[5]The summary of the consent decree is available at https://www.epa.gov/enforcement/seattle-washington-and-king-county

[6]This program is formalized in the Stormwater Code and run by the Seattle Department Construction and Inspections. The details of the regulations are available at http://www.seattle.gov/sdci/codes/codes-we-enforce-(a-z)/stormwater-code. More details on the King County requirements are available at https://kingcounty.gov/~/media/depts/permitting-environmental-review/dper/documents/forms/Residential-Drainage-Review-Requirements. ashx

[7]Seattle is within King County so even though all eligible RainWise basins are in Seattle, King County and SPU share the responsibility of funding and operating RainWise since runoff reductions will count towardseach utility's consent decree.

[8]As part of a public records request we asked for any formal decision criteria for how eligible basins were selected, and none were provided.

[9]See the raingarden eligibility requirements at https://700milliongallons.org/wp-content/uploads/2020/08/What-determines-rain-garden-eligibility.pdf.

[10]The documentation for the RET was made available through a public records requests and is available from the authors.

[11]Data are available at https://www.kingcounty.gov/independent/forecasting/King%20County%20Economic%20Indicators/Household%20Income.aspx.

[12]In general RainWise data have PINs, but public GSI and mandatory private GSI have spatial coordinates but no PIN. We dropped 15 RainWise observations that we were unable to merge either spatially or with administrative records.

[13]Assessed values can be affected by petitions, are updated at different times, and do not disclose the methodology.

[14]Tree canopy data is not available in King County outside of Seattle.

[15]Although we only use eligible properties in the participation model we show the summary statistics for all three samples to better understand distributional implications of eligibility. All eligible properties are in Seattle, but the program is partly funded by property owners in King County outside of the Seattle city limits.

[16]The correlation of these variables is shown in Figure A.4 in the Appendix.

[17]The neighbor GSI variables are the number of RainWise installations, mandatory private GSI, public GSI,and parks within 1 mile from parcel i at year t.

[18]We use the natural log transformation for both home values and median income in the participation models.

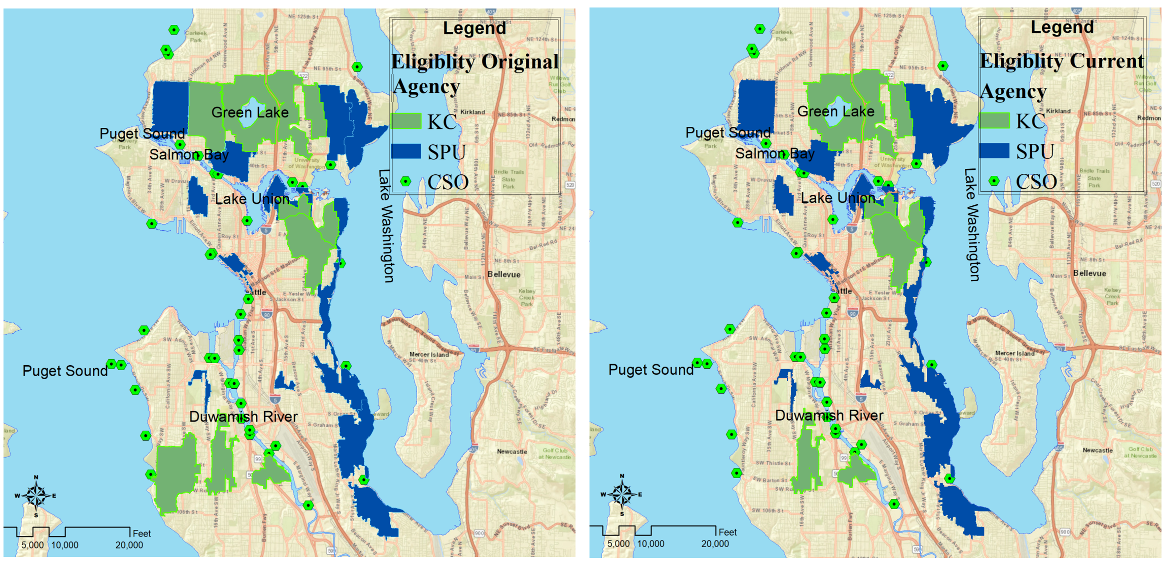
[19]To conserve space only the primary distributional variables are presented in Figure A.5, but we include all variables presented in Table A.3 in the Aalen's regression model.

The effects of eligibility and voluntary participation on the distribution of benefits in environmental programs: an application to green stormwater infrastructure

Online Appendix

Figure A.1: RainWise eligibility and CSO locations

(a) Ever Eligible **(b) Elgible in 2018**

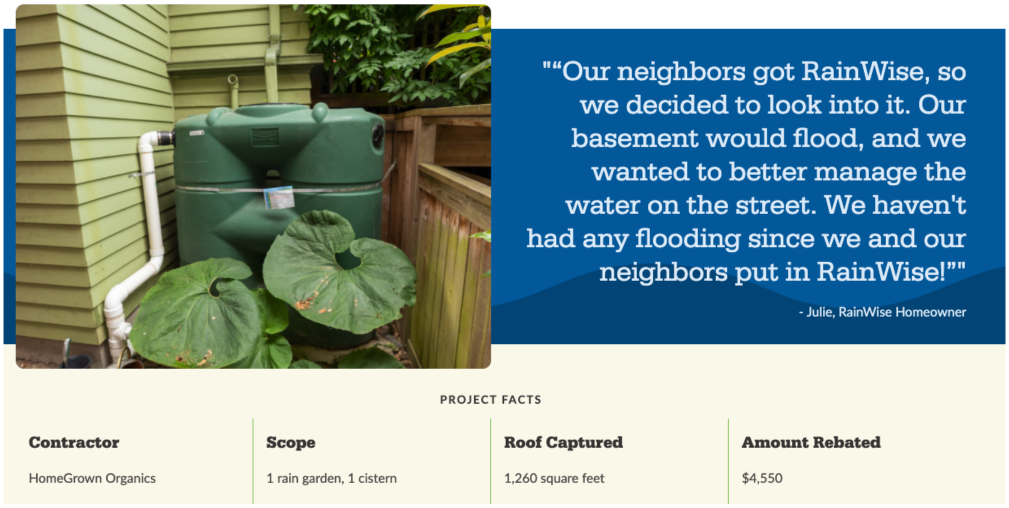


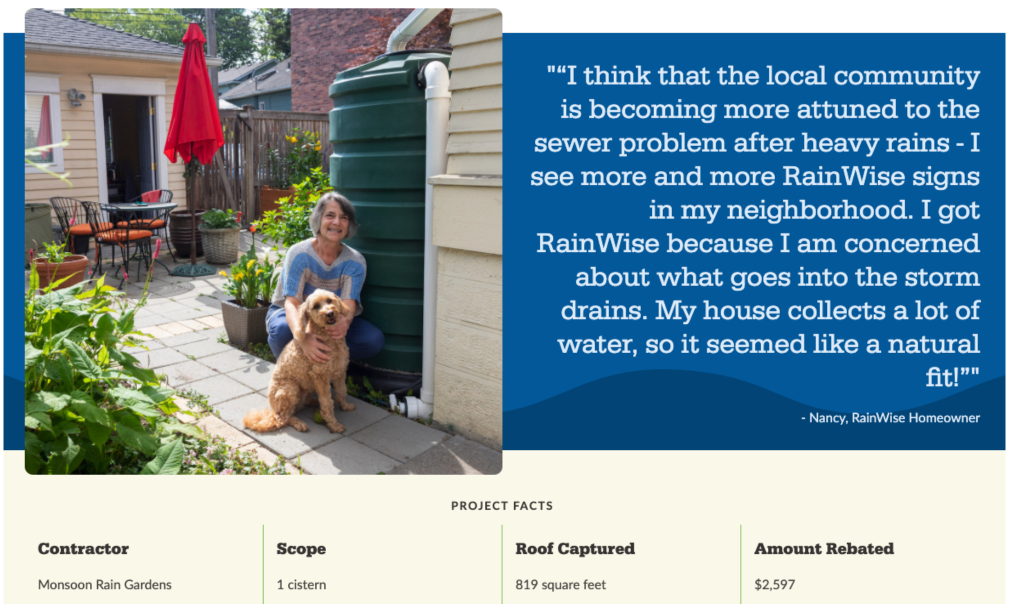
Notes: The map shows eligible areas and CSO outfall locations by funding agency. Panel (a) shows all basins that were ever eligible for RainWise including two basins funded by King County that were eventually closed. Panel (b) shows the eligible areas as of 2018. The basins' colors designate which utility funds and operates RainWise. The CSO outfall locations are shown with green circles.

Figure A.2: RainWise raingarden examples

Notes: The examples are screenshots from 700milliongallons.org case studies and reproduced with permission. The specific links are below and were accessed on May 6, 2021. More examples are available at https://700milliongallons.org/projects/.
https://700milliongallons.org/case_study/maria-rainwise-homeowner/
https://700milliongallons.org/case_study/karen-rainwise-homeowner/
https://700milliongallons.org/case_study/paul-rainwise-homeowner/

Figure A.3: RainWise cistern examples





Notes: The examples are screenshots from 700milliongallons.org case studies and reproduced with permission. The specific links are below and were accessed on May 6, 2021. More examples are available at https://700milliongallons.org/projects/.
https://700milliongallons.org/case_study/julie-rainwise-homeowner/
https://700milliongallons.org/case_study/nancy-rainwise-homeowner/

Figure A.4: Correlation between distributional variables

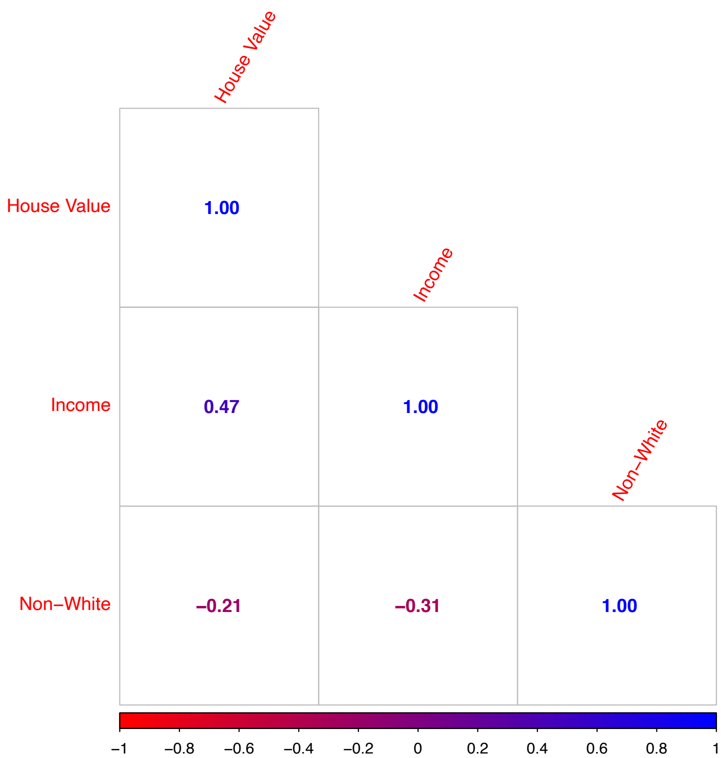
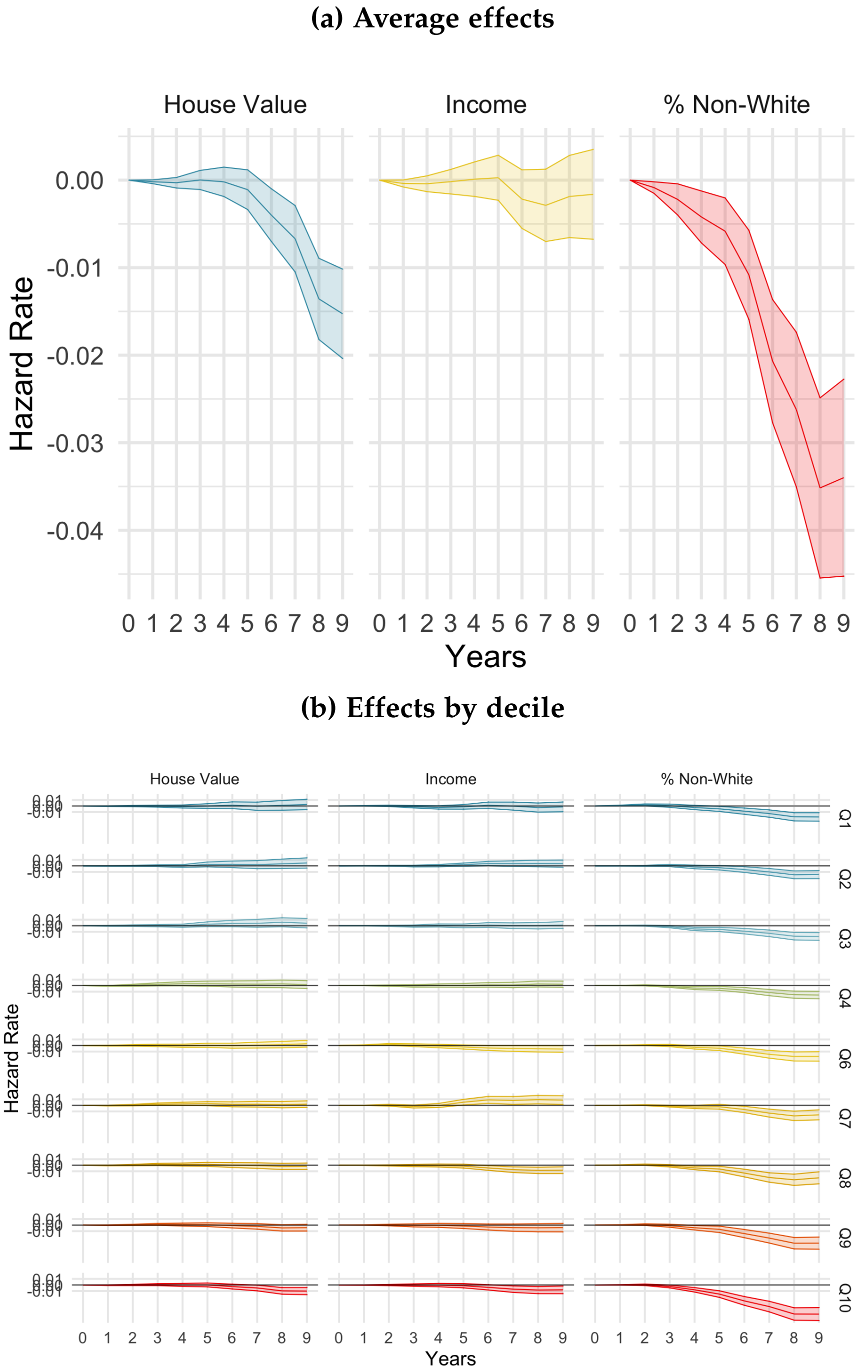


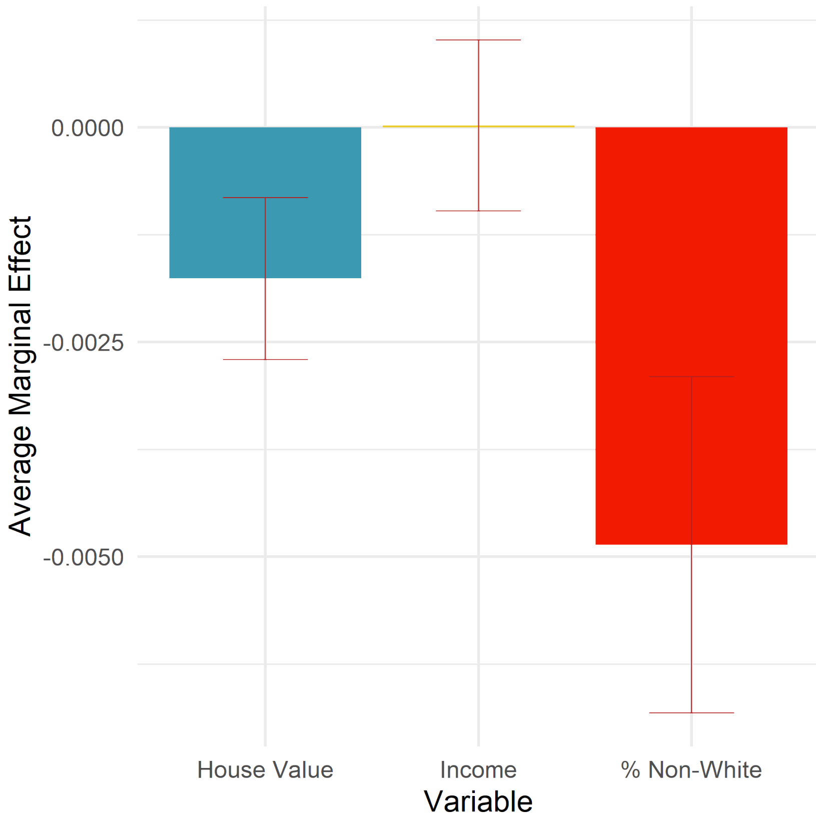
Figure A.5: Hazard rates for RainWise



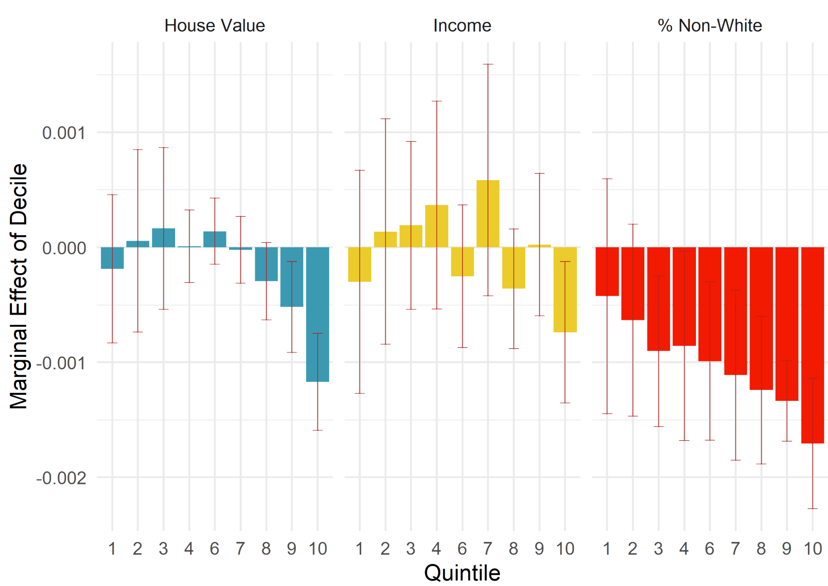
Notes: The figure presents the cumulative regression coefficients for Aalen's additive regression model over time. The vertical axis represents the hazard rates, which in our case is the probability of adopting RainWise. The solid lines are the cumulative regression coefficient, which shows the effect of a unit change in the variable on the hazard rate at any point in time. The shaded area is the 95% confidence interval. Panel (a) shows the marginal effects of the variable of three key environmental justice variables: the log of predicted home values (Home Value), the log of median income (Income), and the percentage of a block group's residents that are non-white (% Non-White). Panel (b) presents shows the deciles of these same variables where the rows represent different deciles. Each cell in panel (b) represents one time-varying parameter estimate. The years are relative to the start of the program so year zero represents 2010.

Figure A.6: Marginal effects of environmental justice variables on RainWise participation without neighbor variables

(a) Average effects



(b) Effects by decile



Notes: These plots show the marginal effects on key variables on RainWise participation from a logit regression without the neighbor variables. The solid bars are the coefficient estimates and the error bars represent 95% confidence intervals from standard errors clustered at the block group level. The vertical axis represents the change in the probability of participating in RainWise for a unit change in the variable.

Table A.1: Housing value prediction model results

	King County	King County	King County
	(1)	(2)	(3)
Sq. Ft.	207.655***	214.061***	159.572***
	(1.440)	(1.359)	(1.417)
Lot	−0.019***	−0.024***	0.002
	(0.005)	(0.005)	(0.005)
Beds	−43,887.140***	−48,307.850***	−20,715.050***
	(1,117.165)	(1,054.220)	(1,031.203)
Baths	38,616.930***	43,868.760***	8,931.012***
	(1,804.357)	(1,702.585)	(1,647.080)
Year Built	−150,477.900***	−61,001.780***	16.346
	(3,722.378)	(3,576.261)	(4,032.156)
Age of Home Sq.	38.089***	15.125***	−0.003
	(0.950)	(0.913)	(1.027)
Year Renovate	−2,134.287***	−1,302.063***	−183.305
	(253.115)	(238.882)	(227.340)
Year Renovate Sq.,	1.075***	0.653***	0.089
	(0.127)	(0.120)	(0.114)
Improvements	9.792***	8.744***	8.654***
	(0.236)	(0.222)	(0.249)
Condition	Yes	Yes	Yes
Traffic	Yes	Yes	Yes
Rainier	Yes	Yes	Yes
Olympics	Yes	Yes	Yes
Cascades	Yes	Yes	Yes
Lake Washington	Yes	Yes	Yes
Skyline	Yes	Yes	Yes
Waterfront	Yes	Yes	Yes
Observations	538,814	538,814	538,814
R^2	0.177	0.269	0.345
Adjusted R^2	0.177	0.268	0.344

Notes: The results are from a linear regression where the dependent variable is the real sale price in 2018 dollars. The Column (1) has no spatial or time fixed effects, column (2) adds year-month fixed effects, and column (3) adds year-month and sub area fixed effects. Sub areas is the finest spatial geography for neighborhoods maintained by the King County Assessor. All regressions include dummies for condition of the structure, proximity to traffic, waterfront access, and different mountain, skyline, or water views. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.2: Cost and rebate model results

	Average Effects			Quantiles		
	Total	Percent	Gallon/Dollar	Total	Percent	Gallon/Dollar
$\ln(\hat{Price})$	926.93^{**}	0.00	-1.19^{***}			
	(353.90)	(0.02)	(0.15)			
ln(Med. Inc.)	-337.51	0.01	0.31^{**}			
	(274.40)	(0.01)	(0.12)			
% Non-White	506.28^{***}	0.00	-0.23^{***}			
	(94.24)	(0.00)	(0.04)			
Project Cost		-0.09^{***}	0.11^{**}		-0.09^{***}	0.11^{**}
		(0.00)	(0.04)		(0.00)	(0.04)
Price Q1				-223.34	0.03	0.24
				(328.98)	(0.01)	(0.14)
Price Q2				-67.35	0.03^{*}	0.26^{*}
				(271.85)	(0.01)	(0.12)
Price Q4				198.80	0.01	-0.21^{*}
				(211.43)	(0.01)	(0.09)
Price Q5				622.40^{*}	0.02	-0.56^{***}
				(295.66)	(0.01)	(0.13)
Income Q1				144.08	0.03^{*}	0.26
				(336.05)	(0.01)	(0.14)
Income Q2				43.48	0.02	-0.01
				(227.15)	(0.01)	(0.10)
Income Q4				-248.50	0.02	0.00
				(244.14)	(0.01)	(0.10)
Income Q5				-397.57	0.02	-0.12
				(342.29)	(0.02)	(0.15)
% Non-White Q1				-182.52	0.00	0.18
				(261.36)	(0.01)	(0.11)
% Non-White Q2				-29.36	-0.01	-0.01
				(272.99)	(0.01)	(0.12)
% Non-White Q4				709.64^{*}	-0.04^{**}	-0.67^{***}
				(321.62)	(0.01)	(0.14)
% Non-White Q5				1208.61^{***}	-0.01	-0.68^{***}
				(355.39)	(0.02)	(0.15)
Num. obs.	1472	1468	1468	1472	1468	1468

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: The table shows results from a linear regression where the dependent variable is a either the total project cost (Total) or the percentage of the cost that was subsidized(Percent). A fully subsided project will have the dependent variable in the percentage regression equal to one. The average effects variables are all standardized. The sample only includes homes that signed up for RainWise and had valid cost data. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Participation model results

	Average Effects			Deciles		
	LPM	Logit	Cox	LPM	Logit	Cox
ln($\hat{Price}$)	-0.00200^{**}	-0.00122^{**}	-0.77951^{***}			
	(0.00068)	(0.00046)	(0.17000)			
ln(Med. Inc.)	0.00010	0.00027	0.17375			
	(0.00066)	(0.00048)	(0.12781)			
% Non-White	-0.00598^{***}	-0.00348^{***}	-2.25448^{***}			
	(0.00176)	(0.00102)	(0.22091)			
# RainWise	0.00170^{***}	0.00054^{***}	0.36662^{***}	0.00175^{***}	0.00048^{**}	0.36245^{***}
	(0.00035)	(0.00016)	(0.03595)	(0.00036)	(0.00015)	(0.03796)
# Private GSI	-0.00199^{***}	-0.00080^{**}	-0.51638^{***}	-0.00222^{***}	-0.00091^{***}	-0.65327^{***}
	(0.00052)	(0.00028)	(0.06240)	(0.00055)	(0.00028)	(0.06593)
# Public GSI	0.00007	0.00004	0.02457	−0.00003	−0.00002	−0.01662
	(0.00010)	(0.00006)	(0.03010)	(0.00013)	(0.00008)	(0.03255)
# Parks	0.00007	−0.00022	-0.13865^{***}	0.00016	−0.00007	−0.05061
	(0.00012)	(0.00011)	(0.04201)	(0.00015)	(0.00010)	(0.04441)
Price Q1				−0.00056	−0.00040	-0.32377^{*}
				(0.00070)	(0.00030)	(0.16066)
Price Q2				−0.00003	−0.00012	−0.08842
				(0.00077)	(0.00037)	(0.15309)
Price Q3				0.00029	0.00008	0.06407
				(0.00068)	(0.00035)	(0.14244)
Price Q4				0.00004	−0.00001	−0.00681
				(0.00036)	(0.00015)	(0.11131)
Price Q6				0.00034	0.00017	0.12082
				(0.00032)	(0.00015)	(0.09306)
Price Q7				0.00006	0.00004	0.03225
				(0.00032)	(0.00015)	(0.09997)
Price Q8				−0.00051	−0.00021	−0.15847
				(0.00037)	(0.00018)	(0.11485)
Price Q9				-0.00093^{*}	-0.00042^{*}	-0.33915^{*}
				(0.00044)	(0.00021)	(0.13972)
Price Q10				-0.00184^{***}	-0.00105^{***}	-1.05986^{***}
				(0.00053)	(0.00021)	(0.20615)
Income Q1				−0.00077	−0.00048	-0.41215^{*}
				(0.00114)	(0.00044)	(0.16980)
Income Q2				0.00016	0.00019	0.13380
				(0.00070)	(0.00049)	(0.15875)
Income Q3				0.00008	0.00023	0.15694
				(0.00059)	(0.00034)	(0.12911)
Income Q4				0.00032	0.00044	0.28818^{**}
				(0.00068)	(0.00044)	(0.10535)
Income Q6				−0.00067	−0.00024	−0.18623
				(0.00074)	(0.00030)	(0.11191)
Income Q7				0.00076	0.00058	0.35861^{**}
				(0.00086)	(0.00043)	(0.11127)
Income Q8				−0.00078	−0.00022	−0.16818
				(0.00059)	(0.00026)	(0.12479)
Income Q9				−0.00024	−0.00008	−0.06047
				(0.00070)	(0.00028)	(0.14189)
Income Q10				−0.00072	-0.00062^{*}	-0.55633^{*}
				(0.00073)	(0.00030)	(0.23931)
% Non-White Q1				−0.00129	−0.00052	-0.44349^{***}
				(0.00149)	(0.00046)	(0.11512)
% Non-White Q2				−0.00145	−0.00056	-0.48336^{***}
				(0.00144)	(0.00044)	(0.11283)
% Non-White Q3				−0.00205	-0.00081^{*}	-0.74890^{***}
				(0.00135)	(0.00034)	(0.11980)
% Non-White Q4				−0.00170	−0.00077	-0.67818^{***}
				(0.00140)	(0.00042)	(0.11172)
% Non-White Q6				−0.00203	-0.00084^{*}	-0.85517^{***}
				(0.00168)	(0.00042)	(0.15255)
% Non-White Q7				−0.00171	−0.00093	-0.99250^{***}
				(0.00189)	(0.00048)	(0.16481)
% Non-White Q8				−0.00273	-0.00112^{**}	-1.36103^{***}
				(0.00226)	(0.00041)	(0.18071)
% Non-White Q9				−0.00382	-0.00120^{***}	-1.68482^{***}
				(0.00212)	(0.00024)	(0.22282)
% Non-White Q10				-0.00590^{*}	-0.00161^{***}	-2.34048^{***}
				(0.00257)	(0.00031)	(0.18834)
Num. obs.	568024	568024	563835	568087	568087	563898

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: The results are from a linear probability model regression where the dependent variable is a dummy equal to one if a household participated in RainWise in a given year. Robust standard errors are clustered at the block group level. *p<0.1; **p<0.05; ***p<0.01