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# Do grant funding and pro-environmental spillovers influence household hazardous waste collection?

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ABSTRACT

Agency and state grant funding should be disseminated in ways so it will result in better management of *household hazardous waste* (HHW) and environmental sustainability. Since location seems to matter in HHW collection activities, it is important to consider *pro-environmental spatial spillovers* that occur, based on agency actions and waste collection behavior taking place in other locations. These may influence HHW-related practices in close-by regions. Using a county-level spatio-temporal dataset that consists of economic, demographic, and HHW data in California from 2004 to 2015, we evaluate the impact of HHW grants on HHW collection activities while considering pro-environmental spillovers. We employ a research design that controls for confounding factors across the North, Central and South Regions, and over time. The research models assess causal relationships using a *random effects panel data model with instrumental variables* to estimate the grants' influences, while considering spatial effects and unobservable bias. Several findings were obtained: (1) HHW grants had positive effects on waste collection in a consistent way across multiple models that we tested; (2) positive spatial spillover effects occurred for HHW collection activities due to the pro-environmental activities of nearby counties. This research contributes to the growing body of research on geospatial policy analytics, ways to establish the basis for causal inference, and the use of robustness checks to develop a deeper understanding of how to make waste management grant programs more effective in the regions where they are implemented.

## 1. Introduction

*Household hazardous waste* (HHW) arises from household products that have not been consumed or used in the household, and are potentially harmful to the people who live in a residence, and to their neighbors if they are not disposed of properly. According to the U.S. Environmental Protection Agency (EPA), HHW typically contains corrosive, toxic, ignitable, or reactive ingredient, including pesticides and weed killers, cleansers and detergents, motor oils and automotive components such as antifreeze, batteries and light bulbs, and paint and varnish (U.S. EPA, 2014). Such waste is difficult and costly for a household to disposed of safely. As a result, this kind of waste often gets handled very irresponsibly: it is poured down household drains, onto the ground beside the road or in parks, into nearby storm sewers, or set out for collection with regular trash.

Improper disposal of such toxic waste causes hazardous substances to contaminate the environment, leading to polluted ground water, which is still a main source of drinking water in the United States (U.S. EPA, 2015). This has the potential to create adverse health effects for people living in the vicinity of the contamination too. Thus, it is crucial for municipal and regional governments, in collaboration with producers and waste management service providers, to effectively manage HHW collection and disposal.

Government grants for HHW management via programs in California (CalRecycle, 2016) and New York (New York State Department of Environmental Conservation, 2017) have been crucial to communities. They have provided the necessary funding for projects to establish or expand HHW collection and recycling drop-off facilities, curb-side and take-back programs, and collection events. Assessing causal effects of grants on HHW collection activities can help policy-makers evaluate if the dissemination of HHW grants made a positive impact on environmental quality where people live.

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Previous studies have shown that the patterns of waste collection vary with location. Examples include: the recycling of electronic waste in the rural areas of China (Tong & Wang, 2004); the collection of municipal solid waste in an island city of China (Zhang et al., 2014); and waste recycling in the U.K. (Abbott, Nandeibam, & O'Shea, 2011). Pollution and other environmental problems caused by improper disposal of HHW may spread over geographic areas. So applying geolocational data analytics approaches is appropriate to provide a spatial perspective on key environmental issues. This kind of thing has been done in studies conducted on pro-environmental tourist travel (Barr & Prillwitz, 2012), pollution-generating plant relocation (Liu, 2013), and geographic inequality in pollution mitigation (Bakhtsiyarava & Nawrotzki, 2017). Similarly, in analyzing the effects of grants on HHW collection output, the spatial dimension should be considered. This is because environmental sustainability activities in a locality may encourage similar kinds of beneficial activities nearby.

This research also investigates the *spatial effects of pro-environmental spillovers.* This term is defined as the influence of pro-environmental activities, such as HHW collection, government announcements of new recycling programs, and news of advancing performance of recycling from close-by counties or regions. Such effects are likely to arise under two conditions. First, the participation of households is related to the extent to which they exhibit pro-environmental behavior, which is strongly influenced by what is happening around them (Agovino, Crociata, & Sacco, 2016). Second, strategic interactions among local governments may encourage pro-environmental activities to a greater extent when they cooperate in achieving higher environmental quality (Brueckner, 2003).

Impact evaluations that identify the causal effects of policies in spatial terms are in short supply due to data availability issues, the absence of randomization in empirical designs, and other practical barriers (Gibbons, Nathan, & Overman, 2014). Establishing causal relationships is critical in assessing environmental policy to obtain unbiased evidence with better internal validity (Ferraro, 2009). When carrying out a randomized controlled experiment is not an option, the available identification strategies include research designs that can address selection for unobservable factors that are present in the setting (Gibbons et al., 2014). The selection of strategies depends on the sources of variation in the variables associated with the treatment and in the data overall (Baum-Snow & Ferreira, 2015, chap. 1).

Given the nature of the observational data in this research, we employ a spatial panel data model that considers unobservable, time-invariant effects from neighboring counties that may influence HHW collection activities in a county that is nearby. HHW grants were not randomly awarded to waste agencies in the counties, as one may expect with a government agency that seeks to maximize the value of grant money disseminated to improve environmental outcomes. As a result, we applied an instrumental variable (IV) method to isolate the unobserved factors that may have determined the amount of grants awarded to specific counties. To our knowledge, this research is the first empirical study that attempts to model the effects of HHW grants on HHW collection outcomes, by measuring spatial spillover effects from pro-environmental activities in nearby geographic areas. Besides using econometric methods, we perform data tests and robustness checks to support causal inference.

This empirical research uses HHW collection and demographic data in California due to the state's diverse geography and demographics. HHW has been banned from trash in California since 2006, when California's Department of Recycling (CalRecycle) mandated that waste management agencies in the state should report annually on HHW collection and disposition activities. Different waste agencies manage HHW programs in the counties they cover. We observed some collaboration among the counties also. For example, Calaveras County developed a “medical sharps” collection strategy with the Central Sierra Sharps Coalition that has involved four counties: Alpine, Calaveras, El Dorado, and Tuolumne (CalRecycle, 2016). Such programs need to be considered when estimating the impact of HHW-related policies and strategies on HHW collection activities.

We model the spatial effects of HHW grants on HHW collection. The effects are then quantified to create a basis for meaningful policy analysis. Our goal is to provide impact assessments of waste collection beyond associational results and findings. We asked three research questions: (1) What mechanisms involving spatial dependencies operate across counties and regions? (2) Are there pro-environmental locational effects of HHW collection activity among neighboring counties? (3) What are the impacts of HHW grants on the amount of HHW collected considering spatial dependencies?

Our objectives in answering these research questions focus on how impact evaluations can offer insights into what drives the amount of HHW collected so that policy-relevant questions can be answered. Our first objective is basic: to identify the extent to which the amount of HHW grants awarded to counties in a region influenced their population-normalized HHW collection performance. A second objective is to estimate the differential effects of such awards across different geographic and demographic environments. A third objective is to explore whether pro-environmental activities in close-by areas may affect HHW recycling outcomes.

## 2. Theory and hypotheses

In economic theory, individual households make choices to maximize their well-being under the constraints they face. This study broadens the theoretical framework to analyze the HHW collection activities to include theoretical insights from other areas in the Social Sciences. We do this to explain environmental behavior, including the social dilemmas, and pro-environmental behavior and its geographical contagion effects. These insights led us to establish a model that represents the causal relationships between HHW collection outputs and HHW-related policies, such as HHW grants, with consideration of the spatial effects from close-by areas.

The success of HHW collection programs depends on household participation in separating and collecting HHW. With the participation of only a few households, the local government is unlikely to be able to divert hazardous materials from contaminating the environment. When the environment is contaminated by HHW from nearby counties, even the households that participated in the HHW collection program are not likely to be free from environmental contamination. HHW pollution can spread through land and ground water across county boundaries. Everyone in the vicinity will suffer if most households do not separate and deliver their HHW to be recycled or processed properly. This situation is a social dilemma in maintaining good environmental quality (Hage, Söderholm, & Berglund, 2009).

To resolve this dilemma, cooperation among households and local governments in neighboring counties is required. Cooperation leads to geospatial spillovers of HHW collection activities among nearby households and local governments. Cooperation should happen if there is evidence that they have exhibited pro-environmental attitudes and behavior, in which they weigh the long-term societal and environmental consequences of their decisions (Vugt, Meertens, & Lange, 1995). Similarly, households that exhibit pro-environmental behavior should be willing to separate their HHW and dispose of it properly because they are aware of the danger of hazardous material contamination to the environment and to people's health. The spatial spillovers can cross administrative boundaries so similar spillovers also should be observable for nearby counties.

Pro-environmental behavior is subject to geographic contagion due to *socio-spatial transmission effects* (Truelove, Carrico, Weber, Raimi, & Vandenbergh, 2014). In a province-level study in Italy, Agovino et al. (2016) found that pro-environmental behavior (proxied by the rate of waste separation prior to collection) in a province was influenced by the behavior of nearby provinces. Thus, proximity to regions with pro-environmental behavior may positively influence neighboring regions with less-than-best pro-environmental records. Similar to Italy, socio-spatial effects in HHW collection and recycling activities can be viewed at the province or county level. Thus, HHW collection activities from households in nearby counties should have *positive spatial effects* on collection in other counties when households cooperate.

Spatial effects may occur at the local government level as well. In Public Economics, the decision of a jurisdiction may be affected by decisions undertaken in neighboring jurisdictions due to the interaction among the local governments (Brueckner, 2003). The related interactions may facilitate resource transfers or collaboration in facility improvement projects. These interactions are motivated to achieve higher environmental quality so that neighboring counties will also manage their HHW properly. As an example, local governments in 22 rural counties in California formed the Environmental Services Joint Powers Authority (2018) in 1993. It provides regulatory advocacy and technical support related to recycling and hazardous waste management.

Besides pro-environmental behavior, according to the *theory of planned behavior* (Ajzen, 1991), households may not cooperate in diverting HHW if the tasks are perceived to be difficult. This is especially true if HHW collection and recycling facilities are too far away or inconvenient to access. So, a local government's role in providing the necessary HHW facilities and programs is crucial. The establishment of HHW programs is supported by state governments through HHW grant funding in some regions. As more new facilities become available and existing facilities are improved due to the projects funded by such grants, households should be more likely to participate in waste collection programs due to their increased awareness of them and the accessibility of collection facilities. Thus, more HHW can be collected, recycled, and most importantly, diverted from polluting the environment. This should result in grant funding having positive effects on HHW collected.

## 3. Context and data

California was selected for this study due to its diverse geography and demographics, and active pro-environmental approach, that has the potential to create pro-environmental spillover effects.

### 3.1. The regions and counties of California

Based on cultural and political differences, California has three main regions (See Fig. 1.).

The North Region is comprised of 39 counties, the Central Region has just 9 counties, and the South Region has 10 counties. The North Region is demographically and geographically similar to the Central Region. In the North Region, the Sacramento Valley is surrounded by the Coastal Mountains, the Klamath Mountains, and the Cascade Mountains. The Coastal Mountains are fronted by the beaches of the coastline that face the Pacific Ocean. In the North and Central Regions, the San Joaquin Valley is positioned between the Coastal Mountains and the Sierra Nevada Mountains. The Central Region includes Fresno, Kings, Madera, Merced, Monterey, San Benito, Stanislaus, Tulare and Tuolumne Counties. In the South Region, in contrast, the Mojave and Colorado Deserts cover most of the surface area (World Atlas, 2017).

As the most populous state in the U.S. since 1962, in 2015 California had a total population of 38.95 million people. It had a 54.3% owner-occupied housing unit rate in 2011–2015, and had a high proportion of well-educated people with 81.8% high school graduates in 2011–2015. Its median household income was $61,818 in this same period (U.S. Census Bureau, 2015).

### 3.2. Primary data sources for the study

**Geospatial data for counties.** Our data for California were obtained from the Database of Global Administrative Areas (GADM, Version 2.8) (2015). California has 58 counties overall, and the geospatial data contain information about their borders with one another. For our map projection, we used the North American Datum of 1983 (NAD 83) that has been officially adopted by California (Public Resources Code, 2005). Implemented in 1986, NAD 83 provides "horizontal" control data based on the locations of "monuments" (as well as "vertical" control data for altitudes) for the U.S., Canada, Mexico, and Central America. The system is based on geocentric origins for 250,000 points of geolocation, including 600 Doppler satellite stations (National Geodetic Survey, 2009).

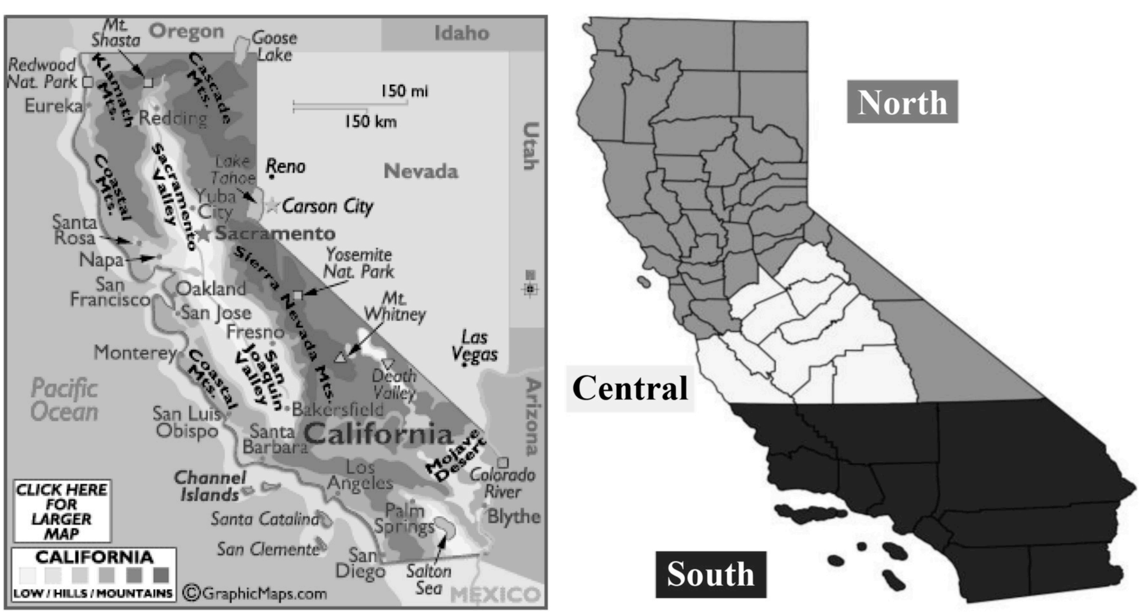


**Fig. 1.** California geography and regions.
Source: Used by permission of WorldAtlas.com (2017).

Table 1
California counties included in the study dataset, by region, 2004–2015

| # | North (in dataset) | # | North (not in dataset) | # | Central (in dataset) | # | Central (not in dataset) |
|---|---|---|---|---|---|---|---|
| 1 | Alameda | 23 | Alpine | 1 | Fresno | 8 | Mariposa |
| 2 | Butte | 24 | Amador | 2 | Kings | 9 | San Benito |
| 3 | Contra Costa | 25 | Calaveras | 3 | Madera | | |
| 4 | El Dorado | 26 | Colusa | 4 | Merced | | |
| 5 | Humboldt | 27 | Del Norte | 5 | Monterey | | |
| 6 | Lake | 28 | Glenn | 6 | Stanislaus | | |
| 7 | Marin | 29 | Inyo | 7 | Tulare | | |
| 8 | Mendocino | 30 | Lassen | | | | |
| 9 | Napa | 31 | Modoc | # | South (in dataset) | | |
| 10 | Nevada | 32 | Mono | 1 | Imperial | | |
| 11 | Placer | 33 | Plumas | 2 | Kern | | |
| 12 | Sacramento | 34 | Siskiyou | 3 | Los Angeles | | |
| 13 | San Francisco | 35 | Sierra | 4 | Orange | | |
| 14 | San Joaquin | 36 | Sutter | 5 | Riverside | | |
| 15 | San Mateo | 37 | Tehama | 6 | San Bernardino | | |
| 16 | Santa Clara | 38 | Trinity | 7 | San Diego | | |
| 17 | Santa Cruz | 39 | Tuolumne | 8 | San Luis Obispo | | |
| 18 | Shasta | | | 9 | Santa Barbara | | |
| 19 | Solano | | | 10 | Ventura | | |
| 20 | Sonoma | | | | | | |
| 21 | Yolo | | | | | | |
| 22 | Yuba | | | | | | |

**HHW data from CalRecycle.** CalRecycle has overseen waste management in California since 2010. Previously, it was known as the California Integrated Waste Management Board (CIWMB), which was established in 1989 and performed services that are similar to what CalRecycle does now. We collected HHW-related data from CalRecycle Form 303. It has historical HHW data from 2004 and is submitted annually by public agencies responsible for HHW management by October 1 each year, for the reporting period from July 1 to June 30 of the past year (CalRecycle, 2014). Although the waste data are at the agency level and contain details by waste material types, we aggregated the total amount of county-level HHW data, and normalized it based on county population data.

**Demographic data from the U.S. Census Bureau.** The demographic data for this study include population density, mean household income, and percentage of high school graduates. They were collected from the American Community Survey (U.S. Census Bureau, 2015) for the years 2004–2015.[1] The data cover only 39 of 58 counties in California, so this aspect of our data collection limited the size our panel data (See Table 1 for the counties included or excluded, and the regions they are associated with.). We also use taxable sales as a proxy for year-to-year economic activity. For this, data were collected from the California State Board of Equalization (2015) for 2004 to 2015.

### 3.3. HHW grant data collection and its accompanying issues

In California, HHW grants are awarded annually to local governments, cities, counties, and waste management agencies to establish or expand their HHW collection or recycling facilities for enhancing the local environment's sustainability since the 1990s (CalRecycle, 2016). Grants have been awarded every July, which is the state's fiscal year start and the beginning of the HHW reporting period each year. Fig. 2 shows the grant amounts awarded from 2004 to 2015 to the 39 counties.

The amount was $3.5-$4.5 million before 2009 and $1.0-$1.5 million in and after 2009. This funding reduction coincides with the January 2010 transfer of waste management responsibilities to CalRecycle from CIWMB, and the diminished funds available from the State's budget that accompanied this change. Other than in 2004 and 2015, more grant funding typically was awarded to the North Region counties despite a higher population in the South Region counties. For example, Yuba County (North) received about $12/person, but Los Angeles County (South) received only $0.30/person during the study period. The latter had a larger tax base to build infrastructure.

Since the term of the grants was for three years, we use the *cumulative grant award over 3 years* as the grant variable (*3YCumGrant$*) in our analysis. We compared this variable with the HHW collection density for each Californian region and its county type using boxplots.[2] (Besides this footnote, see Appendix Figure A1 for a fuller explanation, and what we learned from the comparisons of the visual non-parametric boxplots). The 2013 Rural-Urban Continuum Code (RUCC) published by the U.S. Department of Agriculture's Economic Research Service (2013) is used to classify the county by population size, degree of urbanization, and adjacency to a metro area.

We aggregated all datasets by county and year. The definitions and the descriptive statistics for the variables used in our study are presented in Tables 2 and 3, respectively.

## 4. Estimation approach

The estimation that we conducted to establish causal relationships was challenging for two main reasons. First, spatial dependencies exist in HHW collection activities. This is due to the effects of pro-environmental behavior among households and also the interactions among local governments. Ignoring such spatial dependencies would result in biased estimates, as their effects spill over into the observation of HHW collections by geolocation and by year.

Second, although the HHW grant awards were established before

[1] Demographic data for 2004 were backward extrapolated by using the annual growth rate calculated from historical data from 2005 to 2012.

[2] The term of CalRecycle's HHW grants for counties in California was three years. This led us to select the *cumulative grant award over three years* (*3YCumGrant$*) to be our primary indicator for the HHW grant variable in our models. Appendix Figure A1's purpose is to assess how *3YCumGrant$* visually compares with HHW collection density (*CollDens*) as a potential driver of how much effort is being put toward mitigating hazardous waste-driven pollution through pro-environmental grants versus actual success with higher levels of HHW collection density. This led us to compare variables for each California Region and County Type, with Rural-Urban Continuum Codes (RUCCs).

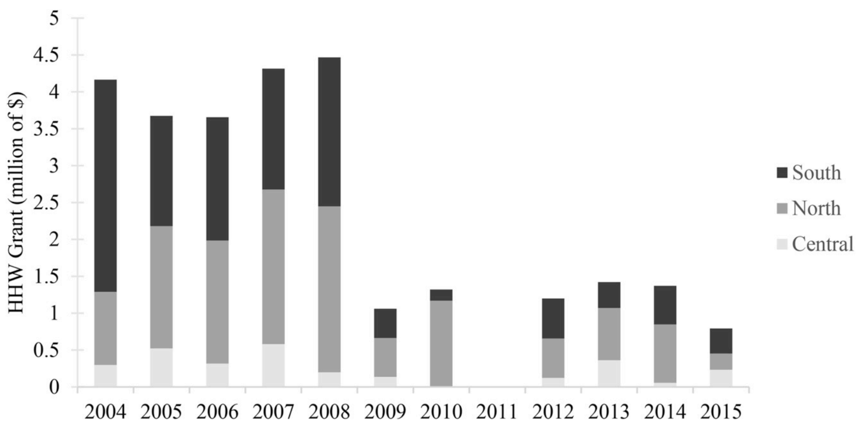


**Fig. 2.** HHW Grants Awarded to 39 Counties in Study, by Region, in 2004–2015 ($ million)
**Notes.** No regular HHW grants were awarded in 2011 by CalRecycle. The funding was allocated to a one-time grant to support a safe, convenient and cost-effective infrastructure for collecting and disposing of home-generated medical sharp waste instead (CalRecycle, 2016). The actual amounts awarded amount were not provided by the CalRecycle website.

**Table 2**
Variable definitions for county-level and HHW-Related variables.

| Variables | Definitions |
|---|---|
| *EduHS%* | % population over age 25 with high school diploma |
| *PopDens* | County population density (people per sq mi) |
| *HHInc* | Mean household income in county ($) |
| *TaxSales$* | County taxable sales ($ per person) |
| *3YCumGrant$* | 3-year cumulative HHW grants awarded ($ million per person) |
| *CollDens* | Quantity HHW collected (lbs per person) |

**Table 3**
Descriptive statistics of the county-level variables.

| | Mean | Std. Dev. | Median |
|---|---|---|---|
| *EduHS%* | 82% | 8% | 85% |
| *PopDens* | 977 people/sq mi | 2760 people/sq mi | 182 people/sq mi |
| *HHInc* | $76,400 | $20,700 | $73,400 |
| *TaxSales$* | $13.98/person | $3.37/person | $13.93/person |
| *3YCumGrant$* | $0.44/person | $0.90/person | $0.10/person |
| *CollDens* | 3.79 lbs/person | 3.53 lbs/person | 2.63 lbs/person |

Notes. Obs.: 468, 39 counties, 2004–2015. *EduHS%, PopDens, HHInc* were collected from the American Community Survey (U.S. Census Bureau, 2015); *TaxSales$* data were from the California State Board of Equalization (2015); and *3YCumGrant$* and *CollDens* were obtained from CalRecycle (2014, 2016).

the beginning of the HHW collection survey, the grants were not awarded randomly to local governments and waste agencies. In California, the eligible local governments and waste agencies submitted project proposals and then were selected on a competitive basis. The grant applications were reviewed based on criteria such as the need for the funding, the proposed work plan, and the planned budget. Discretionary criteria points were given to projects in rural areas, small cities, and underserved populations. Additional points were also given to agencies that had not received any grants in the last two years (CalRecycle, 2016). Thus, the HHW grants variable is endogenous due to unobserved factors that would likely affect the amount and decision to award grants to particular counties.

Additionally, there likely was autocorrelation between the HHW collection levels in the previous years that were also unobservable, resulting in serial correlation of the error terms. Although serial correlation affects the efficiency of the estimators, it does not affect their unbiasedness and consistency, if the model is correctly specified (Wooldridge, 2013).

Our research approach takes into consideration these challenges (See Appendix Figure B1 for an overview of the methods sequence that we used to deal with these problems in a highly-readable flowchart form.). Briefly, we first developed a baseline spatial panel data model to explain the relationship between HHW collection and grants. A set of Lagrange multipliers tests were employed to test the model for serial correlation, spatial autocorrelation, and random effects (Baltagi, Song, Jung, & Koh, 2007). In the random effects specification, the unobservable time-invariant county effects were assumed to have homoscedastic variance and orthogonal to each of the explanatory variables. To test the validity of this assumption in our panel data, we used the spatial Hausman test to compare the random and fixed effects estimators (Mutl & Pfaffermayr, 2011).

After confirming the presence of county-level random effects, serial correlation, spatial dependence in the error terms, and the specification assumptions, we ran the model using random effects estimators and the ***instrumental variable*** (IV) ***method*** to handle endogeneity with the *3YCumGrant$* variable, spatial-lag dependence, and the error term structure.

Different spatial weights used in the model are known to result in different estimates (Corrado & Fingleton, 2012). So, we performed sensitivity analysis with various spatial weight matrices. To further check the robustness of the estimates, we investigated whether there were plausible alternative explanations for the changes in the HHW collection outputs.

### 4.1. Model specification

The panel data model has spatial-lag dependence and county effects, in which HHW collection in a specific year is a function of related grant funding:

$$CollDens_{it} = \alpha + \lambda \sum_{j=1}^{J} w_{ij} CollDens_{jt} + \gamma 3YCumGrant\$_{it} + \boldsymbol{X_{it}}\beta + \mu_i + e_{it}$$

Here, $i$ indexes the $I$ counties; and $j$ is the index of another interacting county among the $J$ counties in the sample; $t$ is an index for year. $CollDens_{it}$ is HHW collection density normalized by the county population (lbs/person); and $3YCumGrant\$_{it}$ is the amount of HHW grants normalized by county population (in \$/person) over three years. Further, $\boldsymbol{X_{it}}$ is a vector of control variables; $w_{ij}$ is a pre-specified spatial weights matrix for HHW collection for the spatial autocorrelation analysis; and $\lambda$ is the associated scalar parameter of the spatial lag of *CollDens*. Finally, $\mu_i$ is a vector of time-invariant county-specific effects; $\alpha$ is the intercept; and $e_{it}$ represents white-noise errors.

For the control variables, we used county demographic variables, which include mean household income (*HHInc*), population density (*PopDens*), and education level (*EduHS%*). These variables have been used in previous empirical research and recycling and HHW management (Abbott et al., 2011; Lim-Wavde, Kauffman, & Dawson, 2017; Sidique, Joshi, & Lupi, 2010). Better-educated households are more aware of the risks of HHW, so they should be motivated to separate and recycle household waste. Households with higher incomes have more time and

**Table 4**
Joint and conditional Lagrange multiplier test results.

| Test | LM | Null Hypothesis |
|---|---|---|
| Joint | 749.35** | No spatial or serial error correlation; no random region effects |
| C.1 Conditional | 9.18** | No spatial error correlation; allows error correlation, random region effects |
| C.2 Conditional | 57.27** | No serial correlation; allows error correlation and random region effects |

Notes. Test stats.: Lagrange multipliers (LM). Signif.: $^{**}p < 01$.

access for participating in HHW collection programs or taking waste to HHW facilities. In contrast, though prior empirical research on recycling showed that population density was positively linked with recycling (Sidique et al., 2010), it was negatively associated with HHW collected (Kinnaman & Fullerton, 2000). This may be due to lack of space, discouraging households from separating and delivering waste to the appropriate facilities.

The spatial weight matrix, $w_{ij}$, defines the relationships between variables.[3] California is ~560 miles east to west, and ~1040 miles north to south. It has diverse geography and land areas. The North Region consists of counties with smaller land areas, and farms, forests, mountains, and valleys; the Central Region is similar. The South Region, has counties with larger land areas, including desert expanses, coastal cities and suburbs. If contiguity-based weighting were used, some counties would have many neighboring counties, while others relatively few. Moreover, HHW collection programs in one county may affect several others nearby, not only those that share the same boundaries.

The research design of this work applies an *adaptive distance-based weight matrix*. This was calculated using a *bi-square distance function* with an *adaptive distance limit*, but a fixed number of neighboring counties (Anselin, 2016; Anselin, Florax, & Rey, 2004). This ensured the same number of neighboring counties when spatial weights for pairs of counties were calculated. The weight matrix was row-standardized with 0-values on the diagonal, and rows of the neighbors matrix summed to unity.

The bi-square distance function is discontinuous, and excludes observations beyond some distance ($b$). In addition, the weights decrease as the distance between the assigned reference points ($d_{ij}$) increases. The *distances between counties* were calculated via *population centroid coordinates*, for which the coordinates of the county seats were used.[4,5] Compared with the possible use of *geographic county centers*, the application of *population centroids* is important for capturing spatial autocorrelation and the uneven distributions of the population in counties where waste collection occurred (Patuella and Arbia, 2016). The latter is appropriate to support research at the county level for household patterns of HHW collection and recycling, and captures more of the knowledge from our field study of HHW collection and recycling in California.

Before estimating the model, we tested the data for spatial autocorrelation, serial correlation, and random effects using *joint and conditional Lagrange multiplier* (LM) *tests* (Baltagi et al., 2007). The results are reported in Table 4. The joint conditional test was rejected; this indicated the existence of spatial or serial correlation or random county effects. The C.1 and C.2 conditional tests were also rejected, so there may be spatial error and serial correlation (Croissant & Millo, 2019).

### 4.2. Generalized moments estimation

We employed the *generalized spatial two-stage least squares* (GS2SLS) estimation procedure proposed by Kelejian and Piras (2017). The procedure involves several steps. *Generalized moments* (GM) estimators are first defined based on the related moment conditions[6] to estimate the variance components for the general spatial panel model (Kapoor, Kelejian, & Prucha, 2007). In this step, we selected the GM estimators that take into account all of the moment conditions, and applied an optimal weighting scheme. Given the estimates of the variance components, we found that the model can be transformed to account for spatial error lags and the variance-covariance matrix of the error terms. Since the spatial lag of the dependent variable (*CollDens*) was endogenous, we implemented an IV procedure as in Baltagi and Liu (2011), using instruments proposed by Kelejian and Prucha (1998). Coefficients were then obtained from *feasible generalized least squares* (FGLS) estimation (Wooldridge, 2002).

To resolve the endogeneity issue with the HHW grants variable, we included another IV that is correlated with HHW grants, but not directly correlated with the amount of HHW collected. For this purpose, we used a binary variable (*CalRecyle*) set to 1 from 2009 onwards. This variable indicates the drastic reduction in the amount of HHW grants (illustrated in Fig. 2) when CalRecycle took over waste management responsibilities in California in January 2010. Changes in waste management practices influence the amount of grants awarded, but they seemed to not influence HHW collection output directly (at least in our dataset). The county-level taxable sales amount per capita (*TaxSales$*), which represents economic activity in a county, also was used as an IV. This is because counties with higher economic activity may need fewer grants than those with lower activity. They have the funds available, and can use them on sustainability and pollution mitigation-related expenditures. This seems as though it did not influence HHW collection output right away also.

## 5. Spatial panel data estimation results

Table 5 summarizes our findings from the GMM estimation for the effects of HHW grants and spatial spillover effects on HHW collection outputs. The "Random Effects" column reports coefficient estimates of

[3] There are three types of weights (Brundson and Singleton, 2015). *Contiguity-based weights* consider the other counties that share the same boundary as their neighbors. *Distance-based weights* are specified using a distance function separating the counties; the neighbors can be determined using the $k$-nearest neighbor criterion or distance bands. *Kernel weights* combine the distance-based thresholds together with continuously-valued weight functions, such as bi-square, tri-cube, exponential, or Gaussian functions (Lloyd, 2010). We performed sensitivity analysis by calculating the weight matrices using these functions, and the bi-square function supported better detection of more counties in spatial clusters compared to other functions.

[4] The function is: $w_{ij} = \left\{\left(1-\left(\frac{d_{ij}}{b}\right)^2\right)^2 \ if \ |d_{ij}| < b\right.$, and 0 otherwise (Gollini, Lu, Charlton, Brundson, & Harris, 2015). For a fixed number of neighbors, we needed a large enough sample size to calculate the spatial autocorrelation.

[5] A *county seat* is the city that is the administrative capital of a county.

[6] *Moment conditions*, according to Hansen (2001) and other authors, are functions of a model's estimated parameters. They yield an expected value of 0 when the parameters of the model reach their true values in the estimation process. The generalized method of moments (GMM) has been characterized as minimizing sample averages of the moment conditions for the data against a selected mathematical norm or vector distance.

**Table 5**
GMM estimation results for HHW grants and spatial spillovers.

| Variables | (1) Random Effects Only | | (2) Spatial Random Effects | |
|---|---|---|---|---|
| | Coef. | SE | Coef. | SE |
| *3YCumGrant\$* $\gamma$ | 1.44** | 0.54 | 1.12** | 0.54 |
| *Spatial Lag, HHW Output*, $\lambda$ | – | – | 0.68** | 0.26 |
| *Intercept a* | −43.34** | 14.11 | −34.85** | 13.61 |
| *EduHS%* $\beta_1$ | 9.00** | 4.56 | 9.26** | 3.92 |
| ln *(HHInc)* $\beta_2$ | 3.88** | 1.37 | 2.88** | 1.32 |
| ln *(PopDens)* $\beta_3$ | −0.79 | 0.44 | −0.77** | 0.33 |
| Pseudo-$R^2$ | 93.5% | | 92.7% | |
| Correlation$^2$ | – | | 29.7% | |
| SSE | 380.7 | | 430.5 | |

Notes. Baseline model: random-effects; dep. var.: *CollDens*; 468 obs. (39 counties x 12 years). IV for *3YCumGrant\$: CalRecycle*, *TaxSales\$*. Spatial weights were based on the adaptive bi-square distance function with 30 nearest neighbors. Spatial Hausman test: $\chi 2 = 5.15, p = 0.27$); could not reject the null hypothesis that the random effects estimator is consistent. Pseudo-$R^2$ = 1 – (variance of model residuals/variance of HHW collection density) (*CollDens*); correlation$^2$ = square of correlation between *CollDens* predicted by the model and the empirical value of *CollDens*. The difference between Pseudo-$R^2$ and Correlation$^2$ indicates how much variation is explained by fixed or random effects specifications (Elhorst, 2014). Spatial errors were not considered. Signif.: $^{**}p < 0.01$, $^{*}p < 0.05$.

**Table 6**
Statistical results for differences between means.

| Awarded Grant | (1) Mean ln *(HInc)* | (2) Mean *EduHS%* | (3) Mean ln *(PopDens)* | (4) Mean *TaxSales\$* |
|---|---|---|---|---|
| No | 11.21 | 0.82 | 5.47* | 13.73* |
| Yes | 11.21 | 0.82 | 5.77* | 14.42* |
| *p*-value (for *t*-test) | 0.90 | 0.67 | 0.02 | 0.03 |

Note. 486 obs. (39 counties × 12 years). Method: paired *t*-tests of means for counties that did or did not receive an HHW grant for HHW collection output/population, *CollDens/PopDens* for household income, educational level, population density and taxable sales as a proxy for county economy. Signif: $^{*}p < 0.05$.

the random effects model ignoring the spatial dependence. The "Spatial Random Effects" column reports coefficient estimates of parameters in the spatial random effects model.

The coefficient $\gamma$ of HHW grants (*3YCumGrant\$* $\gamma$) was positive and significant in both the random effects ($\gamma = 1.44, p < 0.01$) and spatial random effects estimates ($\gamma = 1.12, p < 0.05$). These findings indicate that, all else equal, the HHW grants had positive effects on HHW collection density (*CollDens*), rather than negative or no effects. The effect estimate was lower after spatial dependence was included in the model though ($\gamma = 1.44 > 1.12$). This means that if the spatial effects were excluded, the effects of HHW grant funding on the HHW collection output would have been over-estimated – a central finding of this work that is supportive of our overall perspective on the nuanced nature of how spatial effects may influence how well HHW grants work when they are offered to different counties. After isolating the influence from neighboring counties, we found that \$1 more in grants awarded to a county led to about 1.1 pounds more HHW collected per person in the county ($p < 0.05$). This is interesting, because even with the special attention that we gave to spatial influences and a sound model to represent the complexity of HHW collection in counties, the same kinds of results as have been reported in prior research (Agovino et al., 2016; Truelove et al., 2014) continue to be present when we estimate more complex and realistically-specified models.

The coefficient of the spatial lag for HHW collection output, $\lambda$, was also positive ($p < 0.01$). This confirms the presence of positive spillover effects of HHW collection activities from the nearby counties $j$ to county $i$ within a region. In other words, the pro-environmental activities in a county appear to have been positively influenced by other nearby counties – a second major demonstration in our empirical results of what we conjectured was true, based on theory, at the start of this work.

Further, and as we expected, the coefficient of county demographic variables had the same signs in both the random effects and spatial random effects estimations. The education level ($\beta_1 = 9.00, p < 0.05$; 9.26, $p < 0.05$) and household income ($\beta_2 = 3.88, p < 0.01$; 2.88, $p < 0.05$) were positive and significant for the two models. In contrast, the coefficient of population density (*PopDens*) was not significant ($\beta_3 = -0.79,\ p \cong .10$) for the random effects model, while it was negative and significant ($\beta_3 = -0.77, p < 0.05$) for the spatial random effects model.[7] So higher education level and household income lead to a greater amount of HHW collected in a county, while the effects of higher population density appear to diminish the beneficial effects that are created for HHW collection. Based on the magnitude of the coefficients, the most important control variable appears to be a county's education level. However, the evidence suggests but does not confirm that higher population density interferes with households' effectiveness in disposing of HHW to reduce toxic chemical pollution. This finding is consistent with a prior study conducted by the authors (Lim-Wavde, Kauffman, & Dawson, 2017).

## 6. Robustness checks

We next make an attempt to push our results a little farther. We wish to see whether it is possible to establish causal relationships among HHW grants, HHW collection output, and the spatial effects that are in play across California's counties. For this, we used a spatial panel data model with random effects estimators to address spatial correlation issues and unobserved county effects. We also employed an IV procedure to address the endogeneity of the treatment variable, HHW grants. However, there were threats to the *internal validity* of the extent to which causal inference for HHW grants can be asserted. The key question was: Are the causal effects valid for the population also?

First, the HHW grants during our study period were discretionary grants: CalRecycle selected awardees based on their merit and eligibility. The selection scheme could have biased the results though. Some counties might have had a higher chance of getting a grant than others, though the criteria for winning were highly publicized and the scores obtained were readily discoverable via Freedom of Information Act (FOIA) requests. We earlier discussed why this may be the case.

The methodology we applied, IV estimation, was aimed at addressing bias from unobservable confounding factors. In spite of this though, our approach may still not have addressed selection bias completely. To check if this were the case, we performed *t*-tests to compare the means of the two focal variables for counties that: received or did not receive a grant in a given year; or had higher or lower population density. The results indicated that counties which received grants had higher population density, as well as economic activities on average. (See Table 6.) This is something an analyst would readily expect, in spite of CalRecycle's effort to make the grant award process transparent and fair. During our study period, for example, the Los Angeles, Riverside, and Sacramento city-counties were awarded grants more often than others. In our data, only Nevada County was not awarded any grants during this time. Thus, the estimated effects of

[7] We calculated the *variance inflation factors* (VIFs) of the variables and found no multicollinearity issues.

HHW grants may be biased downward in our estimations. This is because counties with higher population density and economic activities had lower HHW collection outputs normalized by population.[8]

Second, HHW grants have been awarded in California since 1990, well before the start of our study period in 2004. The counties did not receive grant funds the same year they were announced; there was a time lag.[9] Because of variation in the frequency and timing of grant disbursement, an extended analysis based on the sequence of the grants awarded to counties is useful to identify their potentially heterogeneous effects over the years. However, we do not have complete demographic and economic activity data during that period. So in our extended analysis, we included an additional control variable: the *sum of the grants received from 1990 to 2003*, *normalized by the county population in 2004*. The extended analysis results showed mixed positive effects of HHW grants in a revised spatial random effects model covering the years 1990–2015. The coefficient of the main effect variable (*Grant* $\gamma = 0.92$, $p < 0.10$) was positive and the *Spatial Lag* for *CollDens* was also positive ($\lambda = 0.55$, $p < 0.05$), while the HHW grants received from prior years was positive and significant in the production of HHW collection output (*GrantPrev* $\beta_4 = 0.77$, $p < 0.01$). (See Appendix Table C1 for the results.)

Third, the HHW collection density variable (*CollDens*) aggregates the HHW for various material categories. Some counties seem to have had more uneven distributions in different material categories. *Analysis of variance* (ANOVA) tests of the distribution of electronic waste showed that the average amount of this waste was higher in the North Region, compared to the South and Central Regions. When we broke the analysis down by material categories, the estimated effects of HHW grants (not reported due to space limitations) differed in more nuanced ways across the categories.

Fourth, our spatial panel model addresses spatial autocorrelation issues, which reflect the real-world nature of our data in the study, however, our model estimations used a pre-determined weight matrix based on the nature of the spatial influences or the geography of the spatial units. Existing theories of spatial dependence typically do not permit the derivation of a specific functional form for calculating the spatial weights (Plümper & Neumayer, 2010). Similarly, in pro-environmental contagion research (e.g., Truelove et al., 2014), no theory guides the calculation of the weight matrix. So, to check the robustness of the results, we did sensitivity analysis using alternative weight matrices with fewer or more fixed neighboring counties.

Sensitivity analysis of the random spatial estimations results was conducted, for spatial weights with the 25 and 35 nearest neighbors around the 30 neighbors that were defined in Table 5 earlier, is provided in Appendix Table C2.[10] The results suggest, that when the number of neighbors was fewer than 35 – and also fewer than 30, HHW grants seemed to have monotonically smaller effects on normalized HHW collection outputs through *3YCumGrant$* $\gamma = 1.06$ ($p < 0.05$) for the 25 nearest neighbors versus $\gamma = 1.12$ ($p < 0.05$) for the 30 nearest neighbors, and finally compared to $\gamma = 1.16$ ($p < 0.05$) for the 35 nearest neighbors.

Further, based on the sensitivity analysis we conducted, HHW collection activities from closer-by counties seem to have had greater effects on HHW collection output in a given county. We can see this from the *Spatial Lag* for *CollDens* estimate, reflecting the influence from other nearby counties. The variable's coefficient is $\lambda = 0.73$ ($p < 0.01$), and thus represents a larger pro-environmental influence of the 25 nearest neighbors versus $\lambda = 0.68$, ($p < 0.01$) for the 30 nearest neighbors, and $\lambda = 0.67$ ($p < 0.05$) for the 35 nearest neighbors. We suspect that these results are picking up the dilution of the effects in the presence of more counties and a mix of pro-environmental spillover levels, though we have not included a causal test for this effect using our current modeling approach. Moreover, we only were able to study a total of 39 counties in California.

Finally, did HHW grants awarded to other nearby counties affected the likelihood of a grant being awarded in other nearby counties? To measure spatial correlation of HHW grants, we calculated the value *global Moran's I* (Moran, 1950) for each year.[11] There was no evidence for significant spatial patterns though. Thus, county-to-nearby-county grant award patterns seem unfounded – at least in our data. In addition, the published grant evaluation criteria that CalRecycle uses do not consider this in awarding a grant: they do not recognize the potential benefits of pro-environmental spatial spillovers – though they indeed may be present. So follow-on research is required to sort out the details of the mechanism at work, in spite of our effort to theorize about it.

## 7. Conclusion

This article highlights the importance of considering location and demographics in assessing the direct impact and indirect spillover effects of environmental policy-related grant funding to support improved HHW collection to control how much toxic substances are released into the environment.

### 7.1. Empirical findings and contrasts with prior research

Its primary empirical findings are as follows:

- **Finding 1 (Direct Causal Effects of HHW Grants).** *We identified beneficial causal effects from HHW grants, tested in cumulative 3-year total value terms, on population-normalized HHW collected at the county level in California.*

There are numerous other past studies and programs in different states in the U.S. (e.g., Alaska, Arizona, Hawaii, Minnesota, Oregon, Pennsylvania, Wisconsin, and others), as well as in foreign countries

[8] To overcome this issue, many studies employ *propensity score matching* (PSM) to reduce possible bias (López-Valpuesta & Sánchez-Braza, 2016; O'Keefe, 2004). We checked whether PSM would be useful to match data observations for the treated counties with the untreated ones, based on known characteristics of the counties. But the standard PSM approach was not useful for our content because of the time-varying grants and other confounding factors. So we further assessed the appropriateness of using a *covariate-balanced generalized propensity score* (CBGPS) approach (Imai & Ratkovic, 2013). It minimizes the association between a continuous treatment variable and other related covariates to obtain optimal weights to adjust the covariate balance in a model (Fong, Hazlett, & Imai, 2016). However, we found that use of the weights did not change the estimated results, and thus we concluded that they are reasonably robust without using these more complex approaches.

[9] The counties that received the grants the earliest were mostly the metro counties, such as Los Angeles, San Francisco, Alameda, Orange, and Fresno Counties. From 1990 to 2003, some counties were also awarded funding more often than the others, such as Los Angeles, San Bernardino, San Diego, Santa Clara, and Ventura Counties.

[10] *Neighbors* means the nearest neighboring counties within some predefined distance; they are not necessarily adjacent to the a given county. The number of neighbors is used to calculate adaptive distance-based weights.

[11] According to the Environmental Systems Research Institute's (2019) ArcGis Pro's online documentation, *global Moran's* $I = n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j / \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \sum_{i=1}^{n} z_i^2$. In this relation, $z_i$ is the deviation of an attribute for feature $i$ from its mean ($x_i - X$), $w_{i,j}$ is the spatial weight between features $i$ and $j$, and the double summation term on the left of the denominator is the aggregation of all the spatial weights. This math expression computes "an inferential statistic, which means that the results of the analysis are always interpreted within the context of its null hypothesis. … [It] states that the attribute being analyzed is randomly distributed among the features in your study area; said another way, the spatial processes promoting the observed pattern of values is random chance. Imagine that you could pick up the values for the attribute you are analyzing and throw them down onto your features, letting each value fall where it may. This process (picking up and throwing down the values) is an example of a random chance spatial process. When the *p*-value returned … is statistically significant, you can reject the null hypothesis."

(e.g., Environment Canada's program, total waste control in Singapore, and HHW management approaches in Japan, Sweden – which imports garbage! – and Finland). They have all reported similar kinds of direct results for funding HHW collection through grants. For example, the Texas Association of Regional Councils (2015), which does annual reporting on waste management grant programs, reported on 226 projects' impacts reflecting grants of $5.3 million. The solid waste grantees diverted 135 million pounds of recyclables overall, with 100 million pounds of trash and recyclable materials from community collections in the 2014–2015 fiscal year. Over its 20 years since 1995, 4,376 grants were made, resulting in 4.2 million pounds of recyclables, and 14,000 tons of HHW materials. In addition, the availability of HHW grants from government agencies is a proxy for their general effectiveness, since there is considerable accumulated knowledge about their impacts.

Another example is New Mexico's Eight Northern Indian Pueblos Council (2016), which obtained a 4-year, $200,000 EPA General Assistance Program (GAP) grant, and resulted in the removal of 10,500 pounds of HHW where there had never been any earlier organized form of HHW collection. The measurement approach was basic: the grant initiated a new form of waste pick-up.

The difference between our study's contribution of new knowledge and results, in contrast to other funding assessments like those for Texas and New Mexico (and many other states) is that we were able to identify the marginal impacts of HHW grants in different county and regional contexts. To do this, we used a spatial random effects model with an IV to explore the causal implications of HHW grants at the county level. This modeling approach also can be used to project future HHW and other kinds of waste collection output driven by waste management grants, so it is quite general, rather than specific to HHW products.

- **Finding 2 (Indirect Causal Effects of Locations and Demographics).** *We uncovered evidence of beneficial indirect causal effects due to HHW grants that arose from the contrasting geographic and demographic environments of counties and regions in California, where the grant money was spent.*

Our approach is useful for policy-makers to estimate the amount of HHW collected and diverted from polluting the environment, through the effective allocation of additional grant funding for the most households to participate, and what geographic and demographic factors influence it. Along these lines, in other research (Lim-Wavde, Kauffman, & Dawson, 2017), we quantified the marginal cost of enhancing household informedness, so people could do their own "household utility calculus" for recycling. This can help the households to decide whether to participate in HHW collection programs, which require costly, inconvenient planned behavior (Ajzen, 1991) and a sense of the value of environmental action. Different county geography – urban or rural, crowded or comfortable, farmland or mountains, and so on – is likely to have an impact on how socio-spatial transmission effects operate, influencing the strength of the indirect effects on HHW collection that we discovered are present.

There also are drawbacks to the kind of empirical results that Findings 1 and 2 represent. They only came at the cost of methodological sophistication and research design considerations that government agency staff members may not have the time or the training to utilize. Also, other research has not used the cross-spatial and causal inference approach that we have applied. So potential users have not yet seen their application demonstrated for how to make causal inferences on policy design and management decisions. Such methods improve our understanding of the underlying social dilemma of separating our own trash (Hage et al., 2009) and opting for public transport or ride-sharing (Vugt et al., 1995) – over the true health costs that we have to endure in the long run from not managing HHW properly.

- **Finding 3 (Spatial Proximity, Geographic Contagion, and Pro-Environmental Spillovers Seem to Matter).** *Pro-environmental activities exhibit geographic contagion due to socio-spatial transmission and spatial proximity effects, that also are likely to be influenced indirectly by geographical and demographic factors that characterize different counties and regions in California.*

We used the word "seem" in the name of Finding 3 because our results are not as strong as those associated with Findings 1 and 2. Thus, if we err, we prefer to do so on the cautious side of not over-claiming theory-driven results that may not stand the test of repeated investigation. The primary elements that are missed out include more in-depth empirical probing of the mechanism(s) at work that create(s) the indirect network effects, a theoretical basis for the specification of the spatial weight matrix (strengthening the basis for causal inference), and being able to more fully understand what is happening when HHW output is "unbundled" and its component waste types are separately analyzed.

Prior research that we reviewed has noted that pro-environmental behavior resulting in more HHW recycling and collection has the potential to be influenced by socio-spatial transmission effects (Truelove et al., 2014), geographic contagion (Agovino et al., 2016), and spatial spillovers from close-by counties (Lim-Wavde, Kauffman, Kam, & Dawson, 2017). An important contribution of our research results and the causal inference methods behind them is that pro-environmental spillovers are likely to be affected such that there is a tendency to overestimate the effects of HHW grants and other policies.

### 7.2. Policy implications and limitations

A direct policy implication of spillover effects is that they should be taken into account when a regional waste management agency plans HHW-related policies. Their primary purpose should be to maximize household participation in HHW collection and recycling programs. So policy-makers need to avoid the potentially harmful impacts that they need to be recognize from policy analytics research.

Another policy implication is related to the model in this research. It was developed to help policy-makers assess the effectiveness of their HHW funding programs and policies on the basis of publicly-available data. We also sought to address confounding factors and plausible rival interpretations subject to considerable underlying complexity. This makes it so that policy-makers will be more capable of uncovering hidden biases in their policy and program evaluations, and making better decisions about grant allocations for establishing and expanding HHW collection and recycling facilities in different geographic and demographic environments.

In spite of these research and practical contributions, it is important for us to briefly point out some limitations of our work. This research used aggregated HHW collection data, so we were not able to analyze variations in the HHW categories with the same precision to obtain evidence for causal inferences. In addition, the kinds of spatial spillovers that we assumed were present (similar to Agovino et al., 2016, and others) only happen when the people in the regions that were studied cooperated to improve the quality of the environment around them, by demonstrating collaborative pro-environmental behavior.

In addition, spillover effects from close-by counties may not arise without adequate environmental and social awareness in the community – which are essentially a matter of *citizen informedness* (Lim-Wavde & Kauffman, 2018). So the model used in this research is applicable to other regions when the people or the local government are keen to cooperate in maintaining good environmental quality for the whole region, such as in California, but it may not be applicable to other regions or countries without such traits. Other kinds of spatial spillovers have been studied in the literature as a source of beneficial network effects, including *knowledge, industry, and growth spillovers* (Capello, 2007). These spatially-bounded spillovers create value for households and local governments across a region without any expenses, and complement pro-environmental activities, in contrast to the kinds of pro-environmental activities that we studied.

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## APPENDIX A. TWO-VARIABLE COMPARISONS: BY REGIONS AND COUNTY TYPES

The Region and Rural-Urban Continuum Codes (RUCCs) selected for the California county analysis are:

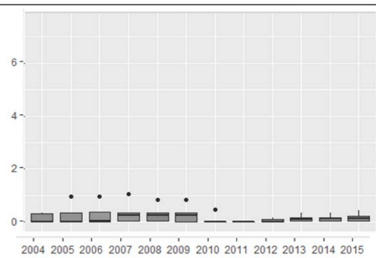
- 1 – counties in metro areas of 1 million or more population
- 2 – counties in metro areas of 250,000 to 1 million population
- 3 – counties in metro areas of fewer than 250,000 population
- 4 – urban population of 20,000 + and adjacent to a metro area

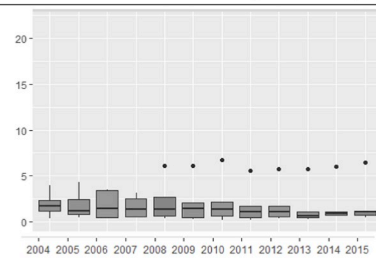
The left boxplots are 3-year cumulative HHW grants (*3YCumGrant$*) and the right boxplots are HHW collection density (*CollDens*). The boxplots can be interpreted as follows, according to Galarynx (2018). A *boxplot* is “a standard way of displaying the distribution of data based on a five-number summary (the ‘minimum,’ 1st quartile (Q1), 2nd quartile (median), 3rd quartile (Q3), and the ‘maximum’).” It can tell you about your outliers and what their values are. It can also tell you if your data [are] symmetrical, how tightly your data [are] grouped, and if and how your data [are] skewed.” The boxplots shown in this figure are typical box-and-whisker plots, with the vertical lines above and below the box indicating maximum and minimum values. The black circles above a boxplot are used to indicate outliers. In addition, a black horizontal line in the middle of a box indicates the value of the median (2nd quartile) in the empirical data. Boxplots are purposely non-parametric and non-statistical. When the different parts of a box are asymmetrical, this indicates how dispersed the data are. We include a number of comments on the different comparisons of the variables between a Region and its individual County Types, one by one. Our hope is to share intuition on the nature of our data. For additional information, see Tukey (1977).

The boxplots and their accompanying interpretation now follow.

**Comparison 1: Cumulative HHW Grants and Collection Density – Central Reg., RUCC 2**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density (Lbs / Person) |
|---|---|

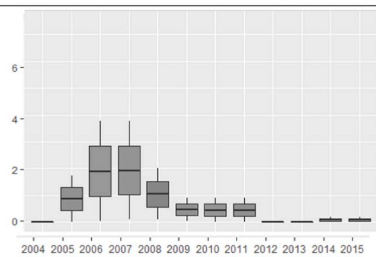


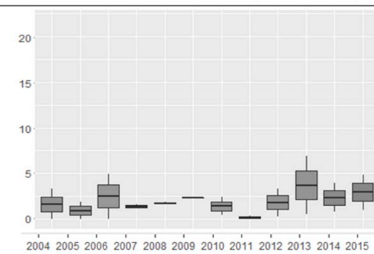




**Interpretation**. RUCC 2 is for counties in metro areas of 250,000 to 1 million inhabitants in Central California. We note the visual association between larger HHW grants during 2004-2009, and the accompanying larger normalized HHW collection densities from 2005-2010 (to 2012), suggesting there were impacts with the HHW grant program. From 2010, the grant program was reduced, and fewer gains were made with HHW collection. We emphasize these are visual associations, and not causal results.

**Comparison 2: Cumulative HHW Grants and Collection Density – Central Reg., RUCC 3**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density (Lbs / Person) |
|---|---|

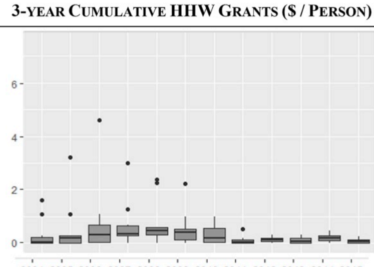


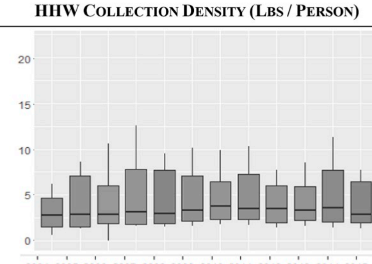




**Interpretation.** RUCC 3 is for counties in metro areas of fewer than 250,000 population in Central California. The RUCCs received more HHW grants, especially in 2006 to 2010, which appears to be associated with gains in HHW collecton that continued to grow up to 2010. Therafter, HHW collection continued to grow through 2015, only with less grant resources that were likely to have driven it. The visual associations between these are harder to describe

**Comparison 3: Cumulative HHW Grants and Collection Density – North Reg., RUCC 1**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density (Lbs / Person) |
|---|---|

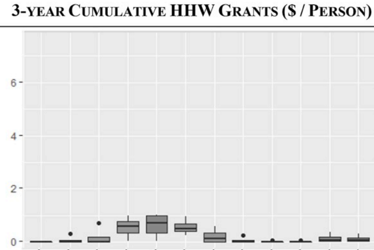


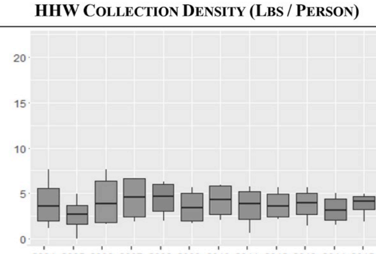




**Interpretation.** RUCC 1 **represents** counties in metro areas of 1 million or more population, the largest population centers in the region. The HHW grants that were given were modest, but the HHW collection gains in the state were substantial, suggesting other large funding sources in the more populous cities.

**Comparison 4: Cumulative HHW Grants and Collection Density – North Reg., RUCC 2**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density (Lbs / Person) |
|---|---|

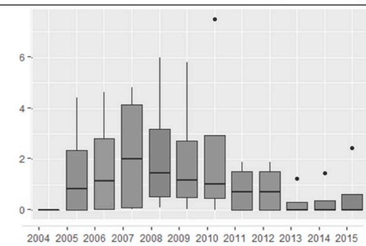
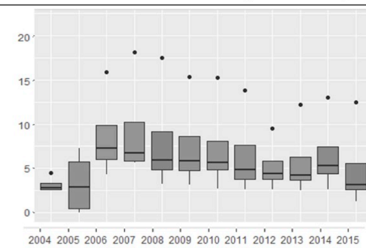



**Interpretation.** RUCC 2 is for counties in metro areas of 250,000 to 1 million inhabitants in North California. The HHW grant funding was modest, so there must have been other sources of support for improving the extent to which normalized HHW collection occurred, as shown in the right-side figure.

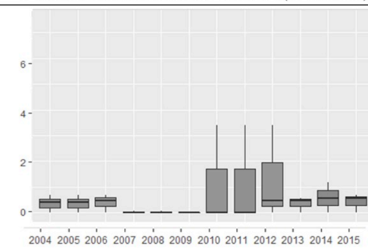
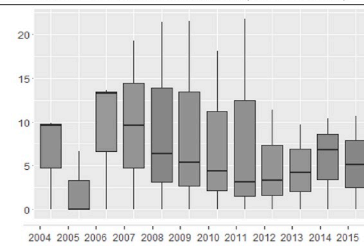
**Fig. A1.** HHW Grants vs. HHW Collection Density

**Comparison 5: Cumulative HHW Grants and Collection Density – North Reg., RUCC 3**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density(Lbs / Person) |
|---|---|
|  |  |

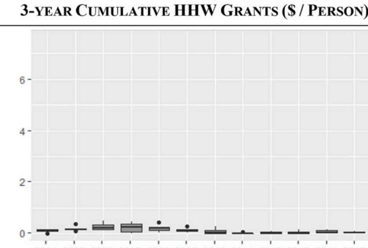
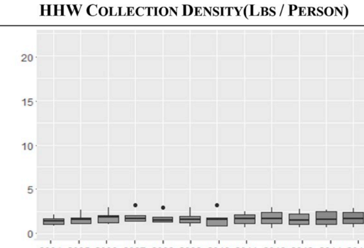
**Interpretation.** RUCC 3 is for counties in metro areas of fewer than 250,000 population in the North. We can see the substantial funds granted to these counties during the study period, and the likely impacts

**Comparison 6: Cumulative HHW Grants and Collection Density – North Reg., RUCC 4**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density(Lbs / Person) |
|---|---|
|  |  |

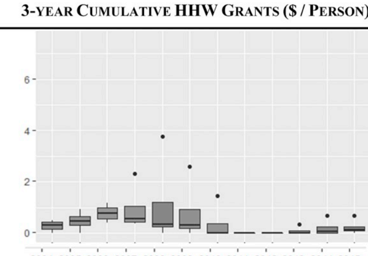
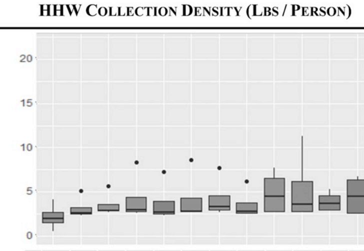
**Interpretation.** RUCC 4 is an urban population of 20,000+ that is adjacent to metros in North California. More HHW grant funds were granted after CalRecycle began in 2009. During much of the study's timeline though, considerable HHW collection was achieved, with skewed distributions, and quite large maximum amounts in specific jurisdictions.

**Comparison 7: Cumulative HHW Grants and Collection Density – South Reg., RUCC 1**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density(Lbs / Person) |
|---|---|
|  |  |

**Interpretation**. An emerging pattern is that fewer HHW grant funds were given to the largest urban population centers in the state, the highly populated urban areas in California. There were more funds available from corporate sources and community taxes, which enabled modest growth over the years in normalized HHW collection in these areas.

**Comparison 8: Cumulative HHW Grants and Collection Density – South Reg., RUCC 2**

| 3-year Cumulative HHW Grants ($ / Person) | HHW Collection Density (Lbs / Person) |
|---|---|
|  |  |

**Interpretation.** RUCC 2 in South California comprises counties in metro areas of 250,000 to 1 million population, reflecting suburban areas. The visual boxplots are based on relatively more complete data (maximum, minimum, and median, with outliers).The modest dollar amounts of HHW grants in 2004 to 2009 appear to be associated with increasing and then a steadier level of normalized HHW collected over the years. Even when HHW grant funding decreased after CalRecycle was established, HHW collection appeared to hold steady. It is likely that corporate and other financial support for HHW collection supplemented the grant funding that was available in 2011 to 2015.

## APPENDIX B. MODELING AND ESTIMATION

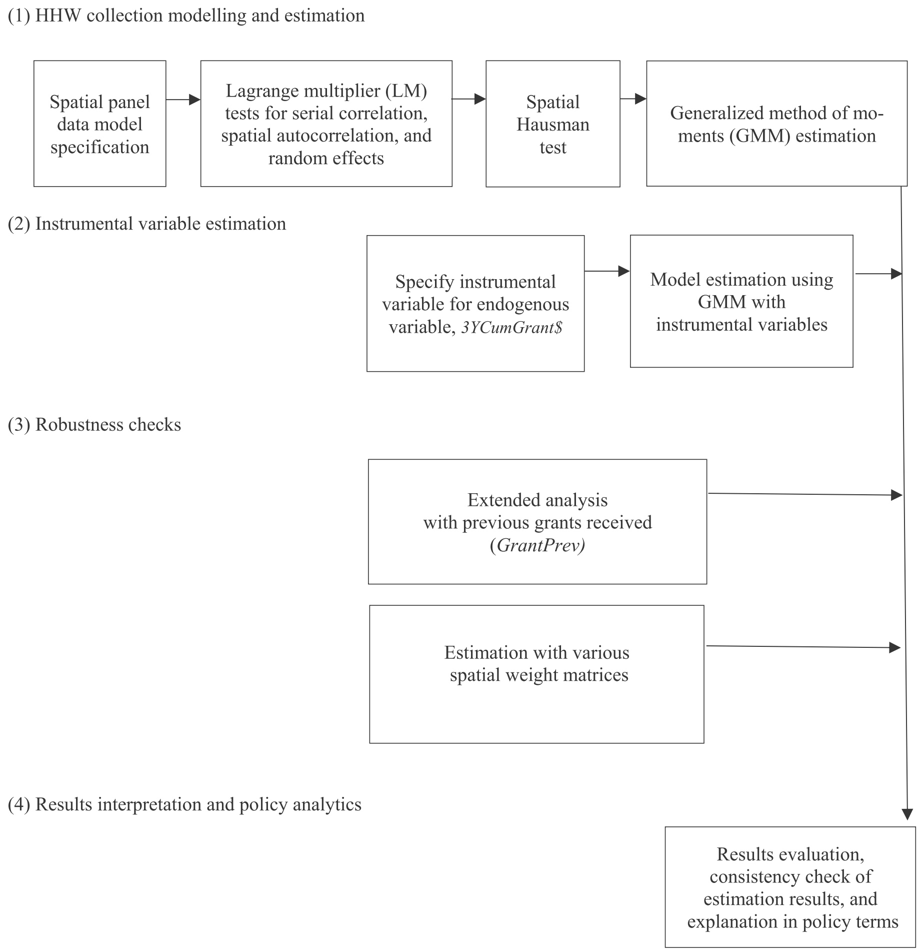



**Fig. B1.** Research Methods Roadmap

## APPENDIX C. ROBUSTNESS CHECK

**Table C1**
GMM Estimation Results for HHW Grants and Spatial Spillovers with Consideration of Previous Grants Received, 1990–2003

| Variables | Spatial Random Effects | |
|---|---|---|
| | Coef. | SE |
| *3YCumGrant\$* $\gamma$ | 0.92 | 0.51 |
| *Spatial Lag, HHW Output,* $\lambda$ | 0.55* | 0.23 |
| *Intercept* $\alpha$ | −48.51** | 12.84 |
| *EduHS%* $\beta_1$ | 6.52** | 3.73 |
| ln *(HHInc)* $\beta_2$ | 4.19** | 1.33 |
| ln *(PopDens)* $\beta_3$ | −0.37*** | 0.31 |
| *GrantPrev* $\beta_4$ | 0.77** | 0.26 |
| Pseudo-$R^2$ | 93.0% | |
| Correlation$^2$ | 38.9% | |
| SSE | 410.1 | |

**Notes**. Baseline model: spatial random effects; dep.var.:*CollDens*; 468 obs. (39 counties x 12 years). IV for *3YCumGrant\$: CalRecycle* and *TaxSales\$*. *GrantPrev* is the sum of grants received from 1990 to 2003. Spatial weights based on adaptive bi-square distance function with 30 nearest neighbors. Pseudo-$R^2$ = 1 − (variance of model residuals/variance of HHW collection density); Correlation$^2$ = square of correlation between HHW collection density predicted by model and empirical HHW collection density. The difference between Pseudo-$R^2$ and Correlation$^2$ indicates how much variation is explained by fixed or random effects (Elhorst, 2014). Spatial errors not considered. Signif.: $^{**}p < 0.01$, $^{*}p < 0.05$.

**Table C2**
Spatial Panel Data Model Estimation Results with Different Spatial Weights

| | Spatial Random Effects | | | | | |
|---|---|---|---|---|---|---|
| Variables | (1) 25 neighbors | | (2) 30 Neighbors | | (3) 35 Neighbors | |
| | Coef. | SE | Coef. | SE | Coef. | SE |
| *3YCumGrant$* $\gamma$ | 1.06** | 0.53 | 1.12** | 0.54 | 1.16** | 0.54 |
| *Spatial Lag (CollDens)*, $\lambda$ | 0.73** | 0.25 | 0.68** | 0.26 | 0.67** | 0.28 |
| *Intercept* $\alpha$ | −33.25** | 13.48 | −34.85** | 13.61 | −33.75** | 14.05 |
| *EduHS%* $\beta_1$ | 7.80** | 4.03 | 9.26** | 3.92 | 9.98** | 3.96 |
| ln (*HHInc*) $\beta_2$ | 2.80** | 1.30 | 2.88** | 1.32 | 2.72** | 1.38 |
| ln (*PopDens*) $\beta_3$ | −0.71** | 0.34 | −0.77** | 0.33 | −0.75** | 0.35 |
| Pseudo-$R^2$ | 92.0% | | 92.7% | | 92.5% | |
| Correlation$^2$ | 28.5% | | 29.7% | | 29.8% | |
| SSE | 466.4 | | 430.5 | | 436.7 | |

**Notes.** Baseline model: spatial random-effects; dep. var.: *CollDens*; 468 obs. (39 counties x 12 years). IVs for *Cum3YGrant$*: *CalRecycle* and *TaxSales$*. Spatial weights calculated using an adaptive bi-square distance function for the 25, 30 and 35 nearest neighbors. Spatial errors were not considered. Signif.: $^{**}p < 0.01$, $^{*}p < 0.05$.

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