5-2017

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DOI: https://doi.org/10.1016/j.resconrec.2016.10.007

Published in Resources, Conservation and Recycling, 2017 May, Volume 120, Pages 88-107
https://doi.org/10.1016/j.resconrec.2016.10.007

Household informedness and policy analytics for the collection and recycling of household hazardous waste in California

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Keywords:
Environmental information
Household hazardous waste
Household informedness
Informedness elasticity
Policy analytics
Recycling
Sustainability
Waste management

A B S T R A C T

Collection and recycling of *household hazardous waste* (HHW) can vary due to differences in household incomes, demographics, material recyclability, and HHW collection programs. We evaluate the role of *household informedness*, the degree to which households have the necessary information to make utility-maximizing decisions about the handling of their waste. Household informedness seems to be influenced by HHW public education and environmental quality information. We assess the effects of household informedness on HHW collection and recycling using panel data, community surveys, drinking water compliance reports, and census data in California from 2004 to 2012. The results enable the calculation of the responsiveness or *elasticity of the output quantities* of HHW collected and recycled for differences in household informedness at the county level. There are three main findings: (1) provision of HHW public education has a positive effect on the amount of HHW collected and recycled, but may have a negative effect on HHW collected in some circumstances; (2) environmental quality information about contaminant violations in drinking water has a negative association with the amount of HHW collected; and (3) when information is sent directly via mail to households, an increase in the number of *contaminant level* (MCL) *violations* is positively related to the amount of HHW collected. Understanding how these effects work in California can help waste management policy-makers and practitioners in other locations to plan appropriate information policies and programs to maximize household participation in HHW collection and recycling based on household informedness and demographic characteristics.

1. Introduction

Household hazardous waste (HHW) is defined as leftover household products that contain corrosive, toxic, ignitable, or reactive ingredients, such as paints, cleaners, oils, batteries, and pesticides (U.S. Environmental Protection Agency, 2014). Often this waste is disposed of improperly, for example, by pouring it down a household drain, onto the ground, into storm sewers, or simply disposing of them together with the regular trash. If this happens, the waste materials can contaminate the land and infiltrate the ground water, and consequently create adverse effects on the environment and people's health (U.S. EPA, 2015). Due to these damaging effects, improving HHW management is essential.

A 2015 review of HHW management performance reported that the amount of HHW collected was only about 0.12% to 1.88% of *municipal solid waste* (MSW) or general trash (Inglezakis and Moustakas, 2015).[1] This amount may not include HHW that is mixed in general trash or disposed of improperly. The diversion of HHW from general trash can be enhanced through various HHW collection programs. The success of these programs depends on household participation in identifying, segregating, storing and transferring HHW to the collection system.

Besides the convenience and effectiveness of HHW collection programs, household informedness is an essential aspect that can encourage household participation. In this study, we define *household informedness*, a construct we first proposed in an earlier conference presentation (Lim-Wavde et al., 2016), as the degree to which households have the necessary information to make utility-maximizing decisions about the handling of their waste. We focus on household informedness for waste management, though it also is applicable in other disciplines, such as Information Systems,

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[1] The authors derived this from average value data in previous studies on HHW in 20 European countries, several states in the U.S., Mexico, Canada, Greenland, Japan, India, Pakistan, Hong Kong, and Nepal from 1992 to 2013.

Marketing, Economics, Environmental Management, and Social Science. Research related to informedness has been conducted in other disciplines as well. For example, Shimshack et al. (2007) reported on consumers who received mercury advisories from the U.S. Food and Drug Administration, and then reduced their canned fish consumption. Li et al. (2014) also showed that informedness about prices and products determined the choices they made. And Byrne et al. (2016) performed an experiment to understand the impacts of different levels of informedness for electricity use related to decision-making for household-level utility maximization. The theories used in these studies are applicable for information policy and waste management for hazardous waste collection, recycling and environmental sustainability.

Household informedness can be influenced through the provision of environmental quality information and public education. Information in the form of notification or alerts about environmental quality can impact household perceptions about the quality of the environment they live in. In HHW public education, people receive information about what types of household materials are hazardous, what alternative non-hazardous products can replace them, and how to properly dispose of hazardous waste (Lund, 2001). This may reduce the generation of hazardous waste, and increase household participation in HHW programs that are provided.

Our study focuses on the effect of household informedness. These effects can be assessed by observing changes in the amount of HHW collected and recycled in the presence of different county and demographic characteristics. However, quantifying the causal effects of household informedness on HHW recycling and collection is not a simple task. The field of waste management has been largely *opaque* because of the complexity of the issues, the diversity of practices among people, firms and local institutions, and the difficulty to observe people's behavior toward their waste (Wijen, 2014). Properly managing waste involves managing heterogeneous stakeholders (households, firms, waste facilities, and local and federal government), as well as other factors (socioeconomic and environmental awareness). Waste reduction relies heavily on people's willingness to participate in reducing, reusing, and recycling their waste, but given the heterogeneity of the stakeholders and variety of factors, there is diversity in behavior and practices.

We selected California for this empirical research because it has diverse county characteristics and accessible annual reporting on HHW collection, disposition, programs, and grant awards. We use data published by California's Department of Resources Recycling and Recovery (CalRecycle), the Annual Compliance Report for Public Water Systems by the California Department of Public Health (CDPH), the American Community Survey, and U.S. census data from 2004 to 2012 for our analysis. Although causal evidence is ideally generated using randomized experiments, randomization is often not feasible in social science settings such as HHW waste management. So causal effect estimates may be hard to establish.[2]

Our study is based on utility maximization theory. It focuses on waste management decisions at the household level. Previous studies by Kinnaman and Fullerton (2000) and Callan and Thomas (2006) used a similar theory; they also considered disposal unit pricing levels as discussed by Hong (1999), however, these studies were based on cross-sectional data analysis at the community-level. Sidique et al. (2010) used county-level panel data analysis and also discussed the effects of recycling education on the general recycling rate. They also mentioned that the environmental quality which the household perceives may influence the household's utility function. However, this factor was specified as a function of the amount of waste disposed, the amount of waste recycled, and demographic characteristics. They did not consider that recycling would also be affected by the environmental quality information that a household receives from local governments and environmental agencies. Our study considers information about how violations with respect to the *maximum contaminant level* (MCL) in drinking water may affect HHW collection and recycling.

There are a few empirical studies about the generation of solid waste and recycling by households, particularly involving empirical analyses that have examined household waste behavior responses to trash price changes and regulation (van den Bergh, 2008). Jenkins et al. (2003) analyzed the effectiveness of two waste programs – *curbside pick-up* and *waste drop-off* – on the rate of recycling of five different waste materials: glass bottles, plastic bottles, aluminum, newspaper, and yard waste. In a mail survey of California households, Saphores (2006) found that gender, education, convenience, and environmental beliefs were the key factors which influenced the willingness of households to drop off electronic waste at recycling centers. There also are empirical studies on the factors which affect recycling rates that leverage county-level panel data. For example, Sidique et al. (2010) found that variable pricing of waste disposal increased the rate of recycling in counties in the state of Minnesota, and Abbott et al. (2011) found that the methods chosen for recycling collection are determinants of the observed recycling rates. In addition, a proper infrastructure of recycling facilities is critical (Bartelings and Sterner, 1999).

While previous empirical studies investigated the influence of socioecononomic factors, the effectiveness of waste collection programs, environmental attitudes and activism, and various waste management policies, our research evaluates the role of household informedness in the context of a special kind of waste, HHW. Household informedness is rarely discussed in the waste management literature perhaps because it is difficult to obtain data to measure the degree to which households have the necessary information to make the best decisions in managing their waste.

A few studies assessed the influence of information on recycling behavior and household recycling decisions. Martinez and Scicchitano (1998) showed that public media programs had positive effects on recycling and these effects were greater for households with higher levels of education. Nixon and Saphores (2009) found that sharing recycling information via family or friends, and at school or at work were the most effective in influencing household decisions to recycle. Largo-Wight et al. (2012) recommended educational campaigns to promote recycling behavior among college students should emphasize positive attitudes towards recycling, behavioral facilitation of recycling (e.g., convenience to recycle), the moral obligations involved, and social norms for prosocial recycling. However, these studies were mainly based on survey data and did not examine the influence of information on the amount of waste recycled. The household informedness construct in this study emphasizes how informedness influences the outcomes that are observed, especially the amount of HHW collected and recycled.

Our research represents the first empirical study to our knowledge to measure and quantify the effect of household informedness on HHW collection and recycling using county-level waste collection data. Our research contributes insights related to impact assessment of household informedness and the quantification of household informedness elasticity on HHW collection and recycling output.

An increase in HHW collection will lead to less hazardous waste being disposed of improperly so there is less polluted water and

[2] Public education about HHW also may suffer from a possible *policy-related endogeneity* issue. The decision of local government to provide HHW public education may be a purposeful action to meet certain waste collection targets. From our data, we observed that grant awards used for HHW public education programs seemed to be fewer in number when the amount of HHW collected increased. For this problem, we applied an instrumental variable to see if it were possible to address this bias.

land, fewer health problems and fewer expenses required for cleaning up a polluted environment. Recycled HHW also can bring extra revenue and substitute for scarce resources. By examining changes in the amount of HHW collected over time due to better household informedness, policy-makers will be able to estimate the economic and environmental benefits related to their information policies and strategies. They will be able to determine their cost-benefit relationships and the accrual timing of the impacts. In this way, they can manage information program cost planning better.

Our research questions are as follows: (1) How has household informedness influenced the amount of HHW collected? We investigate whether household informedness through public education and information on the quality of their local environment had an influence on the quantity of HHW collected. (2) Did household informedness have indirect effects on HHW that was recycled? There have not been any previous studies that measured the household's role in increasing the amount of HHW which was recycled. And yet, if greater environmental informedness results from educating households to separate their HHW properly, it may make it easier for a waste management firm to process the HHW, resulting in a higher amount of HHW recycled. And (3) how can the impact of household informedness on HHW collection and recycling output be quantified? Our approach to this question is to calculate *household informedness elasticity* of HHW collection and recycling.[3] This form of output elasticity represents the responsiveness of a change in the amount of HHW collected to a change in household informedness. This is useful for policy-makers to gauge the responsiveness of their policies and strategies that use educational campaigns and information programs to encourage a greater amount of HHW to be collected and recycled.

To answer the above research questions for recycling within California, we developed models of HHW collection with appropriate household informedness variables and socioeconomic factors. We used this model to estimate the relationships between household informedness factors and the amount of HHW collected. We then developed a more complex model that represents the relationships between the functions for the amount of HHW recycled and HHW collected (including HHW recycled and not recycled). By estimating a simultaneous equations model, we were able to gauge the direct effects of household informedness on the amount of HHW collected, and at the same time, the indirect effects of household informedness on the amount of HHW recycled. Finally, we used these estimates to calculate the household informedness elasticity to capture responsiveness of HHW collection and recycling output.

2. Theoretical framework

Our study analyzes *household informedness* for decisions on handling waste at the household level, particularly HHW, based on utility maximization theory in consumption. We recognize two types: *informedness via public education* and *informedness via environmental information*.

Public education about HHW has long been a part of waste management in developed countries. For example, within California, information about HHW is provided in public education programs on recycling and hazardous waste, and typically uses ads, posters, brochures, newsletters, website information or special events to inform the public (CalRecycle, 2015c). These kinds of information help households to identify the potential hazards of corrosive, toxic, reactive and ignitable materials found in common household leftovers. Such programs can indirectly decrease a household's cost of HHW collection and recycling because they can improve their informedness about the best practices for handling waste, know-how about HHW, and access to various HHW collection and recycling programs. As HHW collection costs for household time and effort decrease, households collect and recycle more HHW. So we state:

- **Hypothesis 1 (Overall Effect of Public Education on HHW Collected).** *HHW-related public education increases the overall amount of HHW collected*

HHW-related public education usually also can be used as a *source control measure* that aims to decrease the use of hazardous materials in households. It can do this through the provision of information about alternative non-hazardous materials that can replace more commonly-used, but also more hazardous products (Lund, 2001). For example, using baking soda with white vinegar is a safer substitute for chemical oven cleaner. This kind of public information can help to reduce the generation of HHW at the source for HHW materials that have non-hazardous substitutes. Thus, we offer:

- **Hypothesis 2 (Category-Specific Direct Effect of Public Education on HHW Collected).** *HHW-related public education directly decreases the amount collected of a few HHW materials that have non-hazardous substitutes*

HHW public education may also have an indirect effect on the amount of HHW recycled. As households become more informed about good practices in separating, storing and preparing their HHW for pick-up, it becomes easier and cheaper for a waste management organization to process the HHW for recycling. For example, leftover paints that are kept sealed in dry areas in their original containers and labels are desirable for recycling (PaintCare, 2016). They will be easier to sort and recycle than those that are not stored properly. Similarly, HHW public information often recommends that used oil should be kept in sealed, leak-proof containers and not be mixed with other liquids or debris. Following up on this advice as instructed will prevent the contamination of used oil. The contamination may make it too costly or impossible to recycle the used oil (Clean LA, 2016b). Thus, another hypothesis is appropriate:

- **Hypothesis 3 (Indirect Effect of Public Education on Overall HHW Recycled).** *HHW-related public education indirectly increases the overall amount of HHW recycled*

Environmental quality information in the form of notifications and alerts may influence a household's perception of environmental quality and change the household's behavior. Previous studies also have shown that public notifications, information disclosures and advisories related to environmental quality have significant effects in households' behavioral change. For example, Shimshack et al. (2007) found that the U.S. Food and Drug Administration's (FDA) mercury advisories reduced consumption of canned fish. With the economics of household utility maximization for handling waste in mind (Morris and Holthausen, 1994) and when the cost of suffering from water contamination is more than the cost of disposing HHW properly, households prefer to participate in HHW collection programs.

We use the *number of maximum contaminant level* (MCL) *violations in drinking water* to measure the environmental quality information that households obtained, and, as a result, became

[3] The language that we are using here is akin to *price elasticity of demand* in Economics. The idea is that a unit move in price results in a change in demand due to consumers' sensitivity to having to pay more. In our case, the idea is that additional information is likely to have either a positive or a neutral effect, in that the household is able to make improved utility-maximizing decisions or freely dispose of the information if they feel that it is not needed. This is similar to price elasticity in that not everyone is sensitive to an additional dollar of price due to their income levels.

Table 1
Material categories, collection programs, and disposal methods, CalRecycle form 303.

Material Category	HHW Collection Programs	HHW Disposal Method
Flammable and Poison	Permanent facilities	Destructive incineration
Inorganic and Organic Acid	Mobile facilities	Fuel incineration
Inorganic and Organic Base	Temporary or periodic facilities	Landfill
Oxidizers, Peroxides, Acid, Base	Door-to-door (residential) programs	Neutralization treatment
PCB-containing	Curbside programs	Recycled
Reclaimable	Load checks	Reused
Asbestos	Others (e.g., special events)	Stabilization
Universal		Steward
Electronic		

aware of the quality of their environment. The number of MCL violations that occur in a county in a period depends on environmental quality there; so the higher the count, the worse the environment quality is. This occurs due to the presence of more contaminants in the drinking water. This information is provided to the household via direct mail or via public notifications. According to the California Department of Public Health (2012), when MCL standards are violated, the water systems operator must notify the affected consumers, and these notifications are widely covered by local news media. Households whose water supplies come from large water suppliers (serving more than 10,000 people) receive annual reports about their drinking water quality by direct mail. Small water suppliers (serving fewer than 10,000 people) are only required to post such information publicly. When there are MCL violations in the drinking water, households perceive the environmental quality to be low or even unacceptable for people's health.

The households that receive this information perceive environmental quality to be low. Without this information, even though the environment quality is low, the household may not be aware of it. If households consider the perceived quality of the environment in their utility maximization when handling HHW, those that experience low environmental quality will be more motivated to dispose of their HHW properly, and participate in collecting and recycling HHW. On the other hand, households living where environmental quality is perceived to be high may be less motivated to do so. Thus, we have:

- **Hypothesis 4 (Effect of Environmental Quality Information on Overall HHW Collected)**. *Information on low environmental quality in a county increases the amount of HHW collected when households perceive there is a problem*

3. Research setting and data

3.1. Household hazardous waste in California

California, the third largest and most populous state in the U.S., has 58 counties; 37 are metropolitan and 21 are non-metropolitan. They have diverse demographic characteristics, income levels, and geography. Solid waste management in the state is managed by CalRecycle (2015a), which oversees all of California's waste handling and recycling programs. Its programs include: educating the public and assisting local governments and businesses on best practices for waste management; fostering market development for recyclable materials; regulating waste management facilities, beverage container recyclers, and solid waste landfill; monitoring the recycled content of newsprint and plastic containers; and cleaning up abandoned and illegal dump sites (U.S. EPA, 2013a,b).

CalRecycle (2014a,b) has mandated that each public agency that manages HHW in California must report the collection and disposal of the waste materials in a report called "CalRecycle Form 303." The survey data, which are published annually on CalRecycle's website, provide details on the quantity of HHW collection and disposal, based on material categories or types, collection program types, and disposal methods that are summarized in Table 1.

In California, the collected HHW materials are identified in nine categories: Flammable and Poison, Acids, Bases, Oxidizers, PCB-containing, Reclaimable, Asbestos, Universal, and Electronic Waste. All these are now banned from the trash (CalRecycle, 2014a).[4] (See Fig. 1.)

Separate laws have been passed in California and other places regarding HHW. Electronic device waste, for example, is regulated under the Electronic Waste Recycling Act of 2003. This California law requires retailers to collect Electronic Waste recycling fees from consumers upon the purchase of new or refurbished electronic products (CalRecycle, 2015b). Leftover oil-based paint (in the Flammable and Poison category) and latex paint (in the Reclaimable category) are managed by the Paint Stewardship Program (involving paint retailers) and are regulated under the California Paint Stewardship Statute of 2010 (AB 1343, Chapter 420). The California Oil Recycling Enhancement Act of 1991 requires oil manufacturers to pay fees ($0.26 per gallon before and $0.24 after January 1, 2014) to CalRecycle for lubricating oil sold in California. Due to these specific material regulations for Electronic, Reclaimable, and Flammable and Poison Waste, it is not surprising they are the highest HHW by volume collected (Fig. 1 again).

Waste collection programs for HHW in California include permanent, mobile, temporary and periodic facilities, door-to-door residential and curbside programs, load checks, and special events, including Electronic Waste and clean-up events. More than half of total HHW has been collected by permanent facilities. Temporary facilities contributed around 20% of HHW collected since 2004, but the quantity decreased to around 10% by 2014. Recycling-only facilities have contributed only 6% of HHW. Other program types that include special HHW collection events have increased recently to about 10%.

CalRecycle (2014a) reported that more than half of total HHW have been recycled,[5] and 1–3% of HHW were landfilled in California from 2004 to 2014. In 2013, California recycled 63% of its

[4] *Flammable and Poison Waste* consists of flammable solids or liquids, bulk flammable liquids, oil-based paints, poisons, and reactive and explosive materials. *PCB-containing Waste* includes PCB-based paints, transformer oil, and PCB-containing ballasts. *Reclaimable Waste* indicates automotive antifreeze and batteries, latex paint, motor oil and oil products, recyclable oil filters, and other reclaimable materials. *Universal Waste* includes things such as: mercury-switches, thermometer and novelties, mercury containing thermostats, mercury-containing waste, lamps, and rechargeable batteries. The final category is *Electronic Waste*, which includes covered, non-covered, and other electronic devices. In addition, CalRecycle (2014c) reported that conditionally-exempt small-quantity generators were allowed to dispose of some Universal Waste, such as fluorescent lamps, non-lead and non-acid batteries, mercury thermostats, and electronic devices until early 2006, but the regulations have changed.

[5] HHW materials, such as used oil, precious metals, and scrap metals can be recycled and reused safely (U.S. EPA, 2000). For example, mercury can be recovered from broken thermometers. Precious metal components such as silver can be recovered from photographic fixer waste. And used oil can be refined and returned to its original purpose or processed into different oil products. Other non-recyclable

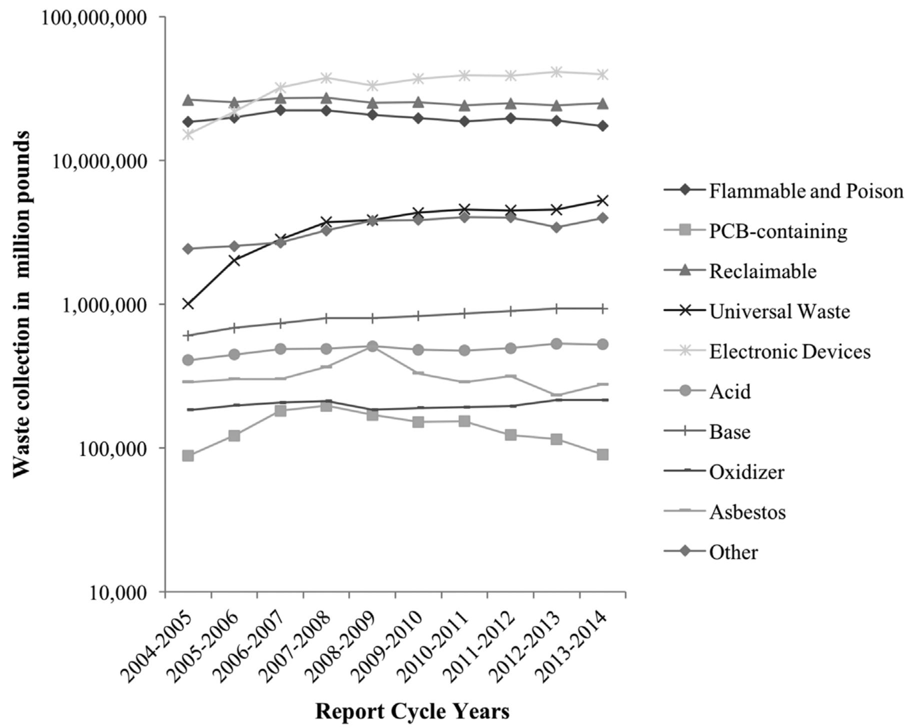


Fig. 1. HHW quantity collected in California, by waste type, 2004–2014.
Note: Reclaimable Waste was the most collected HHW until Electronic Waste overtook it in 2006. In 2013, Electronic Waste accounted for 45% of total HHW (~93 million pounds), followed by the Reclaimable Waste (25%) and then the Flammable and Poison Waste categories (19%). Aerosol Container Waste collection was separately reported in the CalRecycle Form 303 until the 2005–2006 report cycle. Since 2006, non-empty aerosol containers are included in Universal Waste, and Flammable and Poison Waste, and other HHW, based on the contents of the containers (CalRecycle, 2014a).

HHW. Destructive incineration (12%) and waste stewardship (12%) are the second and third most popular disposal methods by quantity. Before 2012, the quantity of HHW disposed by fuel incineration was more than HHW disposed of by destructive incineration, but their quantity decreased gradually to 7% in 2013.

3.2. *Data and variable description and construction*

For this discussion, the reader should refer to Table 2 with the definitions of the study variables.

3.2.1. *Agency data at the county level*

We use California HHW data collected annually via CalRecycle Form 303 for the period of July 1 to June 30 each year from 2004 to 2012. The data focus on collection and disposal. In the collection data, we have information on the county, reporting agency, report cycle (year of report), material category and type, program type (e.g., permanent facility, temporary facility, recycling-only, door-to-door, etc.), and weight of waste (in pounds) in California counties. The *reporting agency* refers to a public agency or waste management authority that owns or operates waste management facilities and plans waste management programs. A county can have one or multiple waste management agencies. In the disposal data, we have information on the reporting agency, report cycle, and weight of waste that goes to different disposal streams, including destructive or fuel incineration, landfill, neutralization treatment, recycled, reused, stabilization, and steward. HHW collection and disposal data are aggregated into county-level datasets.

3.2.2. *Census data at the county level*

County-level census data are used to represent characteristics of the counties and demographic characteristics of households living in California. We collected data from public sources, such as the American Community Survey (U.S. Census Bureau, 2012). The data from 2005 to 2012 include county mean household income, population, density per capita, and education level (via the percentage of high school graduates).[6] Reporting agency-level census data were not available; so we assumed that each agency had similar characteristics as others in the same county, thereby allowing us to match the reporting agencies with the respective county characteristics.

3.2.3. *Proxies for household informedness*

To investigate the effect of household informedness, we use data that proxy for public education and environment quality information. For the HHW public education variable, we extracted the data from the CalRecycle HHW grant database (www.calrecycle.ca.gov/homehazwaste/Grants). This database contains the amount of grants awarded to waste facilities or agencies for HHW-related projects. We searched project descriptions for the words "public education" or "public information," and marked projects that include HHW public education. Then, we counted the projects for each county in each year. These were used to create a variable for the three-year cumulative number of projects with HHW public education to proxy for HHW-related public education. We use the three-year cumulative number of projects, based on the idea that HHW public education may have a cumulative effect in the following years; this is similar to Sidique et al.'s (2010) approach.

materials can be processed via destructive incineration, fuel incineration, landfill, and neutralization treatment.

[6] County data for 2004 were *backwards extrapolated* by using the annual growth rate in historical data from 2005 to 2012.

Table 2
Variable definitions.

Variable Names	Definitions
HHW collection	
HHWCollQ	Quantity of HHW collection (in pounds)
ReclCollQ	..........................–Reclaimable Waste (in pounds)
FPCollQ	..........................–Flammable and Poison Waste (in pounds)
EWCollQ	..........................–Electronic Waste (in pounds)
AcidCollQ	..........................–Acid Waste (in pounds)
AsbCollQ	..........................–Asbestos Waste (in pounds)
BaseCollQ	..........................–Base Waste (in pounds)
OxCollQ	..........................–Oxidizer Waste (in pounds)
PCBCollQ	..........................–PCB-containing Waste (in pounds)
UWCollQ	..........................–Universal Waste (in pounds)
County characteristics	
Pop	County population from 2004 to 2012 (in millions of people)
MeanHHInc	County mean household income from 2004 to 2012 ($000s)
LandArea	County land area (in 000 s of square feet)
Density	County density (in 000 s of square feet per capita)
EduHS%	Percent population over 25 years old who earned a high school diploma
Household informedness	
3YCum#PubEdu	3-year cumulative number of projects with public education program that received HHW grant(s)
#MCLViolLg	Number of MCL violations for large suppliers of drinking water
#MCLViol	Total number of MCL violations
Other factors	
RUCC	Rural-urban continuum code, 1 to 5, with 1 as the base case
DHHWGrant	Binary variable to indicate whether HHW grant(s) awarded
HHWRecQ	Quantity of recycled HHW in pounds
EWasteFee	Electronic Waste recycling fee based on the Electronic Waste Recycling Act of 2003
UsedOilFee	Used oil fee required to be paid by oil manufacturers based on Senate Bill 546; this represents the fee change in California Oil Recycling Enhancement Act
#CCNews	Number of news articles from county-level news sources on climate change
#CCNewsCA	Number of news articles from California state-level news sources
#CCNewsIdw	Number of news articles from county-level news sources with inverse weighted distances for counties (that had no news articles themselves) from others that had them for county seat geo-coordinates

To represent environmental quality information, we acquired the number of maximum contaminant level (MCL) and water quality monitoring violations records from the annual compliance report by California Department of Public Health, submitted to the U.S. Environmental Protection Agency from 2004 to 2012. The data include type of violation, violation counts, and number of population affected.

3.2.4. County type stratifiers

We used a *county classification* approach on the (2013) *Rural-Urban Continuum Codes* (*RUCC*) published by the U.S. Department of Agriculture, Economic Research Service (2013). It distinguishes among metropolitan counties by their population size and non-metropolitan counties by their *degree of urbanization* and *adjacency to a metro area*. (See Appendix A, Tables A1–A2 for details.)

3.2.5. Regulation-related proxies

During our study period, there were two regulations that may have affected the collection of HHW. First, California's Electronic Waste Recycling Act of 2003 regulated recycling fees for covered Electronic Waste based on the size of the video display devices. These categories were: (1) more than 4 but less than 15 inches; (2) at least 15 but less than 35 inches; and (3) 35 or more inches (CalRecycle, 2016). Since we used aggregate HHW data for our data analysis, we employed the average value of the fee of all categories: $8 in 2005 to 2008; $16 in 2009 to 2010; and $8 again in 2011 to 2012. We capture this change in the variable *EWasteFee* in our models to control for the influence of the Electronic Waste Recycling Act. Second, Senate Bill 546 (Lowenthal, 2009), signed in 2009, made changes to the earlier California Oil Recycling Enhancement Act. The changes took effect in 2010. They were: the restructuring of lubricating oil recycling fees; a used oil recycling incentive payment system; streamlining of the used oil grant program; and better handling and management of used oil. According to this bill, the fee was $0.16/gallon in 2004–2009 and $0.26/gallon in 2010–2013. This change is represented in the variable *UsedOilFee* to control for the influence of California Oil Recycling Enhancement Act on the amount of HHW collected.

3.2.6. County and state-level news about climate change

We captured *state-level* and *county-level news articles* related to climate change from Factiva (1999). Climate change is a well-known topic that may affect local environmental policies. News of climate change may have encouraged more environmental sustainability projects like HHW public education, but it does not have any direct effects on HHW collection. Thus, it can be used as an instrumental variable for HHW public education to address endogeneity. The state-level news articles on climate change came from California sources, such as the *Inside Cal/EPA* newsletter, *The Recorder* (California edition), and *California Builder and Engineer* magazine. The county-level news data only covered 15 counties in California, so we estimated the news effects in counties that had no local news sources for climate change based on their proximity to those that had such sources. We assume that news spilled over from one county to neighboring counties; the nearer ones would have a higher effect than more distant ones. So we applied an *inverse distance weighting function* to impute the effects of news in neighboring counties.[7]

[7] The calculation is: $\#CCNewsIdw_c = \frac{\Sigma_{c'} w_{c'} \#CCNews_{c'}}{\Sigma_{c'} w_{c'}}, \mathit{if} dist(c, c') \neq 0,$ and $\#CCNewsIdw_c = \#CCNews_c, \mathit{if} dist(c, c') = 0,$ where $w_{c'} = \frac{1}{dist(c,c')^2}$. *#CCNewsIdw* is the imputed number of climate change-related news articles; *#CCNews* is the number of climate change related news articles; c is the index for a county, c' is the index for a county other than county c. $d(c,c')$ is a distance function calculated between a coordinate in county c and in county c' using the *Haversine method*, which assumes a spherical earth. We use the longitude and latitude of the *county seat* as the point coordinate in the county because the county seat usually is the most populous city in the county. So we use it as the *population center* of a county.

3.2.7. Creation of the panel dataset with the study variables

The descriptive statistics for the main study variables are provided in Table 3. To produce this panel dataset, we combined the aggregate HHW collection, disposition, county characteristics, household informedness and other variables, based on the county and report cycle year.

The American Community Survey did not provide demographic characteristics data for a few counties in some years. We also could not obtain HHW data from a few counties in some years, for example, Lake County only reported the HHW collected amount in 2007–2008; and Madera County did not report the HHW collected amount 2004–2005 or 2006–2007. So we had to omit rows with missing values. We also ran a Bonferroni outlier test (Fox and Weisberg, 2011) to detect any extreme or unusual data points, which led to the removal of one county-level data point from our panel data. As a result, the panel data contain 333 data points for 39 counties.

4. Empirical models

We next present our empirical research strategy and methods to analyze the influence of household informedness based on the county-level data that we gathered.

4.1. Empirical research strategy and methods

We estimate a model of HHW collection that is a function of appropriate household informedness variables and socioeconomic factors. We begin with a linear and separable fixed-effects model to estimate the association between household informedness and HHW collection. Then we use a *two-stage least squares* (2SLS) model to acquire causal estimates of informedness-driven HHW collection.

Estimating the indirect effects of household informedness on the amount of HHW recycled requires an understanding of the relationship between the linear functions for the total HHW collected and recycled. This is because these outcome variables are likely to be jointly determined, and HHW recycling may influence the amount of HHW that is not recycled. For this kind of situation, the use of a simultaneous equations model is suitable (Greene, 2012; Wooldridge, 2002).

We develop a system of equations to represent the demand functions and estimate the effects of informedness on the amount of HHW that is collected and HHW that is recycled. The resulting system of equations model is estimated using *seemingly unrelated regression* (SUR), which recognizes the cross-correlation of the equations' error terms (Zellner, 1962). This allows us to estimate these together instead of separately. Thereafter, we shift to estimate a two-stage least squares (2SLS) model with instrumental variables. Finally, we use a *three-stage least squares* (3SLS) model that combines SUR and instrumental variables estimation together with 2SLS. Household informedness elasticity of HHW collection and recycling output is calculated using the 3SLS estimation results.

In the extended analysis, we stratify the fixed-effects model by material category and estimate the coefficients of the model by using 2SLS for each material category. Some counties did not report waste collection for some HHW material categories in certain years, however. The decision to collect certain HHW materials by local governments may have depended on factors such as household income, education level, and grant awards provided. So we suspect there was some selection bias in the material-specific models. To correct this bias, we re-estimate the models using Heckman's two-step method.

The modeling and estimation process is summarized in Appendix B. We next discuss the baseline model for HHW collection. We distinguish between HHW that is collected and then recycled.

4.2. Model 1: HHW collection

We start with a baseline model in which HHW collection is a function of household informedness via public education, and environmental quality information. This model allows us to estimate the impact of informedness on HHW collection outputs. If we stratify this model by HHW material category, we can also observe different influences of informedness on certain HHW materials. The model is:

$$\begin{aligned}\ln(\mathit{HHWCollQ}_{ct}) &= \gamma_0 + \gamma_1 \mathit{3YCum\#PubEdu}_{ct} + \gamma_2 \mathit{\#MCLViolLg}_{ct} \\ &+ \gamma_3 \mathit{\#MCLViol}_{ct} + \gamma_4 \mathrm{DHHWGrant}_{ct} + \gamma_5 \ln(\mathrm{Density}_{ct}) \\ &+ \gamma_6 \mathrm{EduHS\%}_{ct} + \gamma_7 \ln(\mathrm{MeanHHincome}_{ct}) + \gamma_8 \ln(\mathrm{Pop}_{ct}) \\ &+ \gamma_9 \mathrm{EWasteFee}_{ct} + \gamma_{10} \mathrm{UsedOilFee}_{ct} + \sum_{r=2}^{5} \theta_r \mathrm{RUCC}_r + \varepsilon_{ct}, \qquad (1)\end{aligned}$$

with subscripts for county c and report cycle year t.

Household informedness via public education is proxied by the three-year cumulative number of projects with a public education program (*3YCum#PubEdu*). Environmental quality information is proxied by two things. One is the total number of MCL violations (*#MCLViol*) in the county regardless of the size of the water suppliers. This variable is a proxy for the environmental quality that households perceived when they were informed about these MCL violations via direct mail, public notices, newspapers or other media. A large number of MCL violations represents lower environmental quality, and a lower number represents higher environmental quality. The other is the number of MCL violations from large water suppliers that are sent to households via direct mail (*#MCLViolLg*). This proxy variable represents information about the number of MCL violations delivered directly to households. We include it because MCL violation information may affect HHW collection when it is sent directly to households.

Based on previous studies, we expect that the variation in waste collection and recycling activities generally is influenced by socioeconomic factors: household income, population, density, and education level (Richardson and Havlicek, 1978). These factors cannot be controlled easily by waste management policy-makers, but are useful to predict and explain waste collection patterns, and the recycling behavior of people living in different counties. People's behavior with respect to HHW ought not to be the same as for general trash, so we use these factors as control variables to account for county variability in HHW collection.

Regarding the socioeconomic factors, we expect more educated people to be more aware of the risks of HHW and that they can easily obtain information related to HHW and environmental quality. Households with higher incomes have more time and opportunities to participate in HHW collection programs or deliver their waste to HHW facilities. Counties with more population generate more waste; and this is the same case as for general trash. On the other hand, population density may be negatively associated with the quantity of HHW collected because high population density in the county may discourage people from participating in HHW collection programs due to socioeconomic reasons that are unobservable.

We use a binary variable to indicate whether a county received grants for HHW projects (*DHHWGrant*) as a control. In California, HHW grants are awarded to help local waste management agen-

Previous studies, such as McConnell (1965), used the coordinates of county seats as the population centers, instead of the *mathematical centroid*.

Table 3
Descriptive statistics for the variables.

Variables	Mean	StdDev	Median	Min	Max	Skew	Kurtosis
Pop	969,056	1,665,021	415,825	63,986	9,946,947	4.14	18.80
Density	961	2653	185	25	17,546	5.39	29.64
EduHS%	0.82	0.08	0.84	0.62	0.96	−0.59	−0.56
MeanHHInc	75,247.00	18.567	73,343	47,002	137,575	0.78	0.15
DHHWGrant	0.37	0.48	0	0	1	0.53	−1.73
3YCum#PubEdu	0.49	0.79	0	0	4	1.60	2.01
#MCLViol	11	35	0	0	254	4.54	22.42
#MCLViolLg	0.72	2.46	0	0	4	1.60	2.01
HHWCollQ	2,262,873	3,056,300	1,417,106	49,305	23,867,787	3.97	18.79
ReclCollQ	660,211	711,997	397,820	0	3,998,194	2.15	5.54
FPCollQ	530,349	806,967	290,539	0	5,822,124	3.57	14.93
EWCollQ	837,943	1,494,284	480,143	0	15,267,130	5.34	38.04
AcidCollQ	12,745	18,415	6736	0	113,578	3.15	11.24
AsbCollQ	7783	18,084	200	0	183,440	4.47	30.39
BaseCollQ	21,118	38,217	8283	0	244,957	3.68	14.82
OxCollQ	5182	6983	2412	0	41,824	2.62	7.98
PCBCollQ	3693	5694	1866	0	41,107	3.80	17.47
UWCollQ	90,997	108,818	61,215	0	625,152	2.38	6.37
ln(HHWCollQ)	14.11	1.04	14.16	10.81	16.99	−0.19	0.49
ln(HHWRecQ)	13.62	1.28	13.77	2.30	16.76	−2.33	17.46
#CCNewsCA	156	110	167	0	325	−0.10	−1.16
#CCNewsIdw	9	19	3	0	137	4.00	18.26
EWasteFee	8.94	4.57	8	0	16	0.01	−0.08
UsedOilFee	0.19	0.05	0.16	0.16	0.26	0.68	−1.55

cies to establish or expand HHW collection programs by conducting various projects such as to upgrade the existing HHW collection facilities, to hold free HHW collection events, to purchase new processing machines, to educate the public regarding improper disposal of HHW, and so on. These projects provide more opportunities for households to participate in HHW collection programs so the counties that receive the grants may produce a higher amount of HHW collected than the ones that do not receive them. Higher priority was given to new HHW programs in rural areas, under-served areas, and multi-jurisdictional HHW programs. Greater emphasis was also given to applicants (cities, counties, qualifying Indian tribes, and local agencies) that had not received HHW grants in the two previous cycle years.

The *RUCC*s distinguish the counties based on their *degree of urbanization* and *adjacency to a metro area*. (See Fig. 2.) We observe that this classification seems to matter. The average of the HHW collection amount is the highest for the base case for $RUCC_1$, followed by $RUCC_2$, $RUCC_4$, $RUCC_3$, and $RUCC_5$. Thus, we also include this categorical variable as one of the controls in our model.

4.3. Model 2: HHW collected versus HHW collected and recycled

We next specify a model that recognizes the simultaneity of HHW that is collected versus HHW that is collected and recycled. The simultaneity captures a more realistic representation of the underlying process in HHW collection and recycling. Not all HHW collected is recycled; some is recycled and some is not recycled. Using this model, we want to know if there are indirect effects of household informedness on the amount of HHW recycled. The system, for county *c* and report cycle year *t*, is:

$$\begin{aligned}\ln(HHWCollQ_{ct}) &= \alpha_0 + \alpha_1 \ln(HHWRecQ_{ct}) + \alpha_2 3YCum\#PubEdu_{ct} \\ &+\alpha_3\#MCLViolLg_{ct} + \alpha_4\#\mathrm{MCLViol}_{ct} + \alpha_5\mathrm{DHHWGrant}_{ct} \\ &+\alpha_6\ln(\mathrm{Density}_{ct}) + \alpha_7\mathrm{EduHS\%}_{ct} + \alpha_8\ln(\mathrm{MeanHHIncome}_{ct}) \\ &+\alpha_9\ln(\mathrm{Pop}_{ct}) + \varepsilon_{ct} \qquad (2)\end{aligned}$$

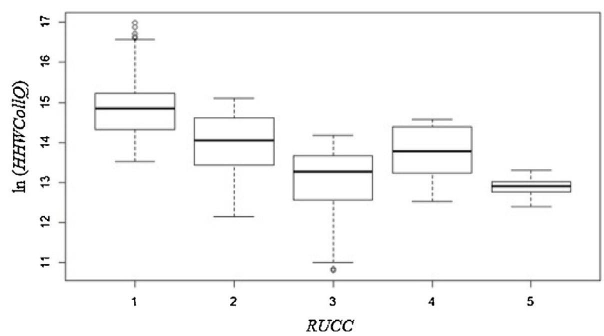
$$\begin{aligned}\ln(HHWRecQ_{ct}) &= \beta_0 + \beta_1 3YCum\#PubEdu_{ct} + \beta_2\#MCLViolLg_{ct} \\ &+\beta_3\#MCLViol_{ct} + \beta_4 DHHWGrant_{ct} + \beta_5\ln(Density_{ct}) \\ &+\beta_6 EduHS\%_{ct} + \beta_7\ln(\mathrm{MeanHHIncome}_{ct}) + \beta_8\ln(\mathrm{Pop}_{ct}) \\ &+\beta_9\mathrm{EWasteFee}_{ct} + \beta_{10}\mathrm{UsedOilFee}_{ct} + \sum_{r=2}^{5}\theta_r\mathrm{RUCC}_r + \varepsilon_{ct} \qquad (3)\end{aligned}$$

If HHW public education can successfully inform households about how to store and sort their HHW properly, the amount of HHW collected and recycled (*HHWRecQ*) should increase. Thus, we expect to find a positive effect of HHW public education (*3YCum#PubEdu*) on HHW recycled. On the other hand, HHW public education may have positive effects on the amount of HHW collected, however, a change in the amount of HHW collection associated with HHW public education may also arise from source reduction. To capture the unobserved source reduction, we include *HHWRecQ* on the right-hand side of *HHWCollQ* equation as a control variable. Doing so allows us to measure the effects of HHW public education (*3YCum#PubEdu*) on the amount of HHW collected (*HHWCollQ)* while holding the amount of HHW recycled constant (*HHWRecQ*). This also enables us to observe the association between the amount of HHW collected (*HHWCollQ*) and the amount of HHW collected and recycled (*HHWRecQ*). The specification of the relationship between the functions is similar to that of Callan and Thomas (2006).

Similarly, we believe that information on low environmental quality likely encourages HHW recycling, particularly when it is provided directly to households. So we expect to find positive effects of *#MCLViolLg* and *#MCLViol* in the *HHWReqQ* equation. We also included these variables in the *HHWCollQ* equation because a change in the HHW collected due to environmental quality information may arise from source reduction as well.

We also use binary variables for the availability of HHW grant awards and socioeconomic factors (household income, population, density, and education level) as control variables in both equations. These are the same controls as in the HHW Collection Model (Model 1).

Similar to the study by Callan and Thomas (2006), the inclusion of *HHWRecQ* in *HHWCollQ* Eq. (2) allows us to decompose the effects



$RUCC_1$:	Counties in metro areas of 1 million population or more.
$RUCC_2$:	Counties in metro areas of 250,000 to 1 million population.
$RUCC_3$:	Counties in metro areas of fewer than 250,000 population.
$RUCC_4$:	Urban population of 20,000+ and adjacent to metro area.
$RUCC_5$:	Urban population of 20,000+ and not adjacent to metro area.
ln(HHWCollQ):	Natural log of HHW collection amount in pounds.

Fig. 2. Boxplot of HHW collection amount by Rural-Urban Continuum Codes (for fixed effects).

of the household informedness variables into direct and indirect effects through *HHWRecQ*. Based on the model specification, we can calculate the household informedness elasticity of HHW collection output, *Elasticity*, for public education as follows:

$$\begin{aligned} Elasticity &= \left(\frac{d\ln(HHWCollQ)}{d3YCum\#PubEdu}\right)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\ &= \left(\frac{\partial\ln(HHWCollQ)}{\partial 3YCum\#PubEdu}\right)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\ &+ \left[\left(\frac{\partial\ln(HHWCollQ)}{\partial\ln(HHWRecQ)}\right)\left(\frac{\partial\ln(HHWRecQ)}{\partial 3YCum\#PubEdu}\right)\right]\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\ &= \alpha_2\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) + \alpha_1\beta_1\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\ &= (\alpha_2+\alpha_1\beta_1)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \end{aligned} \tag{4}$$

The first term in Eq. (4), $\alpha_2\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right)$, is the effect of HHW public education, as it is made available, on HHW collection, with the amount of recycled HHW held constant. It captures source reduction activity due to public information on non-hazardous household products that can replace hazardous household products. The second term is derived from the reduced form of the system of Eqs. (2) and (3). It estimates the indirect effects of HHW public education on HHW recycled. This includes the change in the amount of HHW collected from changes in the amount of recycled due to the influence of public education. We also calculated the household informedness elasticity of HHW collection via environmental quality information, as in Eq. (4).

5. Estimation results

We next present our modeling process and estimation results for the HHW Collection Model (Model 1) with fixed-effects and 2SLS. Then we offer a discussion of the estimation results for the HHW Collected versus HHW Collected and Recycled Model (Model 2) with 3SLS.

5.1. Model 1: baseline and 2SLS estimation results

Table 4 presents the results using a baseline fixed-effects model and a 2SLS fixed-effects model. The coefficient estimate of HHW public education was not significant in the fixed-effects baseline model. (See Table 4, Fixed-Effects Baseline Model.) This estimation did not address the endogeneity of the HHW public education variable. For MCL violation information though, we found that when information was sent directly via mail, an increase of one MCL violation was associated with a small but still significant increase in the amount of HHW collected of 4% (=$e^{0.04}$−1, calculated from the coefficient 0.04, $p<0.05$). But, in general, an increase of one MCL violation was associated with a decrease by 0.5% (=$e^{-0.005}$−1, from the estimated coefficient −0.005, $p<0.01$) of the HHW amount collected.

Table 4
Fixed-effects model estimation results.

Variables	Fixed-Effects Baseline Model Coef. (SE)		Fixed-Effects Estimated with 2SLS Coef. (SE)	
Intercept	-8.23^{***}	(2.82)	-8.28^{***}	(2.84)
3YCum#PubEdu	0.07	(0.05)	−0.04	(0.15)
#MCLViolLg	0.04^{***}	(0.02)	0.04^{***}	(0.02)
#MCLViol	-0.005^{***}	(0.001)	-0.005^{***}	(0.001)
DHHWGrant	0.10	(0.08)	0.15	(0.10)
ln(*Density*)	-0.09^{**}	(0.04)	-0.09^{**}	(0.04)
EduHS%	3.33^{***}	(0.61)	3.22^{***}	(0.64)
ln(*MeanHHIncome*)	1.06^{***}	(0.25)	1.04^{***}	(0.25)
ln(*Pop*)	0.62^{***}	(0.06)	0.64^{***}	(0.07)
EWasteFee	0.01	(0.01)	0.02	(0.01)
UsedOilFee	0.49	(0.84)	0.28	(0.90)
$RUCC_2$	−0.02	(0.11)	−0.03	(0.11)
$RUCC_3$	−0.11	(0.16)	−0.07	(0.17)
$RUCC_4$	0.42^{**}	(0.21)	0.44^{**}	(0.21)
$RUCC_5$	-0.60^{**}	(0.26)	-0.53^{*}	(0.28)
Adj. R^2	66.6%		66.2%	

Note. Baseline model: fixed-effects; dep. var.: ln (*HHWCollQ*); 333 obs. Base case $RUCC_1$ is omitted. For 2SLS, instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*, weak instruments stat. = 37.27^{***}; Wu-Hausman = 0.53. Signif.: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

We next performed a 2SLS estimation with the number of news articles related to climate change from California state-level news sources (*#CCNewsCA*) as an instrumental variable in place of the endogenous public education variable. The *weak instruments statistic* results showed that our instrumental variable was not weak, while the Wu-Hausman test statistic implied that the fixed effect estimates and the estimates with 2SLS were both consistent so the endogeneity might not matter.[8] We did not use *#CCNewsIdw* as an instrumental variable because the weak instrument statistic was not significant; thus it would be a weak instrument in the model, and so not useful. The 2SLS coefficient estimate of household informedness via public education was −0.04 ($p=0.81$, not significant). We suspect that HHW public education's effect on HHW generation were not captured very well in this model. For MCL violation information, the estimates were the same as those of the baseline model estimates.

In both estimations, the county characteristics had the same signs as expected. The estimates of *EduHS%*, *MeanHHIncome*, and *Pop* were positive and significant. So the higher the percentage of high school graduates, mean household income, and county population, the larger was the quantity of HHW collected. The coefficient of higher population *Density* in a county was negative; this shows

[8] This statistic is from an *F*-test of the first-stage regression for weak instruments (Kleiber and Zeileis, 2015).

that the higher the population density, the lower was the amount of HHW collected.

The counties in $RUCC_4$ had an average about 55% ($= e^{-0.44} - 1$, from the estimated fixed effect 2SLS coefficient of 0.44, $p < 0.05$) more than the amount of HHW collected in the counties in $RUCC_1$ while holding the other variables constant. This is surprising because $RUCC_4$ counties are non-metropolitan with an urban population of 20,000 or more and are adjacent to a metropolitan area. These include Lake, Mendocino, and Nevada Counties in our panel data. Although the average amount of HHW collection in these counties was only about 1.1 million pounds per year, the amount of HHW collected per person ranged from 3.1 to 21.8 pounds/person in a year. This suggests that some counties in this area may have been actively collecting HHW, or these counties may have been collecting HHW from the residents of the neighboring counties as well. Further geospatial analysis needs to be performed to investigate this peculiarity.

5.2. Model 2: system of equations estimation results

To adjust our analysis to achieve a more realistic representation of the underlying process, we developed a system of equations that included dependent variables for HHW collected and HHW recycled. Our estimation strategy was to start with *seemingly unrelated regression* (SUR) for the multi-equation system, recognizing the commonality in the information in the error terms.[9] But this left out any consideration of the endogeneity of variables and true simultaneity in the processes. So we switched to a more realistic representation of the system involving simultaneous equations – 3SLS estimation that enables us to address endogeneity with HHW collection and environmental quality information variables using an instrumental variable, *#CCNewsCA*, to correct for the possible endogeneity bias.

The SUR and 2SLS estimation results are shown in Appendix C, Tables C1 and C2. The Hausman test for 3SLS consistency was 36.76 and greater than 0.05 ($p = 0.06$). So we concluded that the 3SLS estimates were consistent and more efficient than the 2SLS estimates. (See Table 5 for the 3SLS results.)

The coefficient estimates for the county characteristics variable had the same signs in the *HHWCollQ* and *HHWRecQ* equations. These were also the same as the corresponding estimates in the fixed-effects model (Model 1). The coefficient estimate for the HHW recycled variable was significant and positive at 0.50. This means that a 1% increase in the amount of HHW collected was associated with a small 0.5% increase in the amount of HHW recycled. Our interpretation is that the amount of HHW recycled increased proportionately more than the amount of HHW collected (recycled and not recycled).

The estimate for the *3YCum#PubEdu* variable in Table 5 for *HHWRecQ* is 0.48 ($p < 0.10$) and it had somewhat less of its variation explained – only 39.5%. The results still suggest that the provision of one project with HHW public education in a county was associated with an indirect increase in the amount of HHW recycled by about 61.5% ($= e^{0.48} - 1$). On the other hand, the coefficient estimate for this variable in the *HHWCollQ* equation is −0.14 and it is significant too ($p < 0.10$). Plugging these coefficients into Eq. (4), the informedness elasticity of HHW collection output for public education $(\alpha_2 + \alpha_1\beta_1)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right)$, evaluated at the point of means was 0.003 ($= (-0.14 + 0.50 \times 0.48) \times 0.49/14.11$).

We also found that when information about an increase in the MCL violations was released at the county level, it was associated with a decrease in the amount of HHW recycled of about 0.4%. This suggested that the county could have been doing more in advance of the MCL violation information dissemination to improve HHW recycling, if only on the margin. From this, we estimate the household informedness elasticity of HHW collection output for MCL violations was −0.004 ($= (-0.003 + 0.50 \times -0.004) \times 11/14.11$), again quite small. A more interesting finding is that when such MCL violation information was sent directly to households via postal mail, this was associated with an increase of around 2% for HHW collection. We also estimate that informedness elasticity of HHW collection for environmental information related to MCL violations information via direct mail was about 0.001 ($= (0.02 + 0.50 \times 0) \times 0.72/14.11$). Note that this variable is not significant for *HHWRecQ* so this information may or may not increase the amount of HHW recycled. Table 6 summarizes the household informedness elasticities of HHW collection and recycling.

[9] SUR estimation only allows us to model the cross-equation error term correlations.

Table 5
3SLS estimation results for HHW collected versus HHW collected and recycled.

Variables	HHW Collected Coef. (SE)		HHW Collected and Recycled Coef. (SE)	
Intercept	−3.70**	(1.70)	−10.59**	(4.72)
ln(*HHWRecQ*)	0.50***	(0.03)	–	
3YCum#PubEdu	−0.14*	(0.08)	0.48*	(0.25)
#MCLViolLg	0.02*	(0.01)	0.04	(0.03)
#MCLViolL	−0.003***	(0.001)	−0.004*	(0.002)
DHHWGrant	0.16**	(0.06)	−0.18	(0.17)
ln(*Density*)	−0.05	(0.03)	−0.11	(0.07)
EduHS%	1.54***	(0.39)	4.13***	(1.06)
ln(*MeanHHIncome*)	0.50***	(0.17)	1.22***	(0.42)
ln(*Pop*)	0.34***	(0.04)	0.57***	(0.11)
EWasteFee	–		0.00	(0.02)
UsedOilFee	–		1.51	(1.48)
$RUCC_2$	–		0.06	(0.18)
$RUCC_3$	–		−0.04	(0.28)
$RUCC_4$	–		0.59*	(0.36)
$RUCC_5$	–		−1.20**	(0.47)
Adj. R^2	81.7%		39.5%	

Note. Model: simultaneous eqns.; estimation: 3SLS; 333 obs. Dep. vars.: HHW collected is ln (*HHWCollQ*); HHW recycled is ln (*HHWRecQ*). Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*. Estimated with SystemFit package in R (Henningsen and Hamann, 2007). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6
Household informedness elasticities of HHW collection and recycling outputs.

Household Informedness Elasticity of:	Estimated Elasticity Value	
HHW Collection Output		
HHW public education	0.003	($p < 0.10$)
MCL violations information	−0.004	($p < 0.10$)
MCL violations information via direct mail	0.001	($p < 0.10$)
HHW Recycling Output		
HHW public education	0.017	($p < 0.10$)
MCL violations information	−0.003	($p < 0.10$)
MCL violations information via direct mail	0.000	($p > 0.10$)

Note. The estimated values of household informedness elasticity of HHW collection and recycling outputs suggest their responsiveness to changes in informedness. These values are significant at the 10% level, except for MCL violation information via direct mail for HHW recycling output, which is not different from zero ($p > 0.10$). The estimated informedness elasticity for HHW collection outputs was calculated as in Eq. 4, evaluated at the point of means. This includes the direct effect of household informedness on HHW collection outputs, and the indirect effect of household informedness on HHW recycling output. The estimated elasticity value for HHW recycling output was derived from the coefficient estimates of the household informedness variables in Eq. 3, also evaluated at the point of means. The significance level of informedness elasticity is the smallest level of significance of the coefficient estimates used to calculate it. The idea is that the aggregate significance level of the estimated predication is no greater than that of the least significant component that has an effect on the aggregate value.

The magnitudes of these estimated values were less than 1, so we conclude that HHW collection and recycling in California were relatively *informedness-inelastic*. (See Table 6.)

The estimation that we made for household informedness elasticity of HHW collection output for HHW public education deserves further discussion. The coefficient estimates of *3YCum#PubEdu* in the *HHWCollQ* and *HHWReqQ* equations were significant ($p < 0.10$), but with different signs. The negative estimate of *3YCum#PubEdu* in the *HHWCollQ* equation gives evidence of a possible negative effect of HHW public education on the amount of HHW collected. Additionally, the coefficient estimate of 0.04 for *#MCLViolLg* in the *HHWRecQ* equation had a standard error of 0.03 ($p = 0.12$, not significant). This result shows that MCL violation information sent via mail mattered in terms of HHW collection, but it may not have had any effect on HHW recycling. Beyond this, the other coefficient estimates in the elasticity computation were significant, suggesting public education and MCL violation information mattered for collection and recycling. We include significance estimates for the informedness elasticities below.

6. Extended model for the categories of household hazardous waste

In this section, we discuss some extended models to estimate the amount of HHW collected by HHW material category. The estimation results of these models show that the provision of HHW public education had negative effects on HHW collection outputs in some circumstances. They are related to a couple HHW material categories that represent household products which have alternatives that household consumers can buy that use non-hazardous materials. We present the estimation results for the HHW collection output stratified by material category.

HHW-related campaigns and outreach may have motivated and encouraged households to recycle their HHW and participate in HHW collection programs. However, they may also have caused waste source reduction. Model 1 did not capture the changes in the provision of HHW-related public education that led to waste source reduction. Since waste source reduction was most likely to happen for HHW materials that had non-hazardous and more efficient substitutes, we extended the analysis using Model 1 by stratifying the prior estimation model via the material categories. When the effect of HHW-related public education that led to source reduction was stronger than motivating households to recycle, we expected to see a negative coefficient for the HHW-related public education variable in the model.

We also estimated the HHW collection models for each of the HHW material categories. The dependent variable in the model is the natural log of the HHW collected amount for each material category: Reclaimable Waste (*ReclCollQ*), Flammable and Poison Waste (*FPCollQ*), Electronic Waste (*EWCollQ*), Acid Waste (*AcidCollQ*), Asbestos Waste (*AsbCollQ*), Base Waste (*BaseCollQ*), Oxidizer Waste (*OxCollQ*), PCB-containing Waste (*PCBCollQ*), and Universal Waste (*UWCollQ*). The purpose was to analyze the informedness effects and other factors influence on HHW collection outputs that may have varied among different material categories. The material categories' 2SLS estimation results are provided in Appendix D, Table D1, with PCB-containing and Universal Waste omitted due to poor model fit.

We observe that some counties did not collect waste in certain HHW material categories in certain years. Some selective HHW collection programs were not available in small counties. For example, Madera County did not report any HHW collection before 2005. Also, Lake County only collected Electronic and Universal Waste in 2007–2008. And San Luis Obispo, Kern, Madera and Imperial Counties did not collect Asbestos Waste during our study period. In some other counties, there were zero values for a few HHW materials in some years. For example, Humboldt County reported that it collected Electronic Waste only in Report Cycle 2006–2007 to 2008–2009, while Mendocino County collected Electronic Waste in Report Cycle 2004–2005 to 2006–2007. These led us to consider the possibility of selection bias in HHW material-specific collection output amounts.

So we estimated the coefficients of the baseline model stratified by material category using *Heckman's two-step estimation method*. This let us resolve possible sample selection bias, as in Suwa and Usui (2007). In the first step, we employed a probit estimation model and identified the factors that may affect a local government's decision on whether to collect waste in a specific HHW material category. These factors include the percentage of high school graduates, mean household income, and the number of HHW grants in a county. The probit analysis results are provided in Appendix D, Table D3. The probit analysis showed a positive and significant coefficient for mean household income related to Acid, Base, Oxidizer, and Asbestos Waste. This means that household income influenced the decisions of local waste managers as to whether they collected the HHW material; counties with higher household income had a higher probability to collect these HHW materials. The HHW grant variable (*DHHWGrant*) estimate was positive and significant only for Base and Asbestos Waste.

Based on this estimation, we derived the *inverse Mills ratio* and added it to Model 1 to take selection bias into account. We also used the instrumental variable *#CCNewsCA* inplace of the endogenous HHW public education variable. The results for the fixed-effects model with Heckman's method are provided in Appendix D, Table D2. There was evidence of selection bias only for Oxidizer Waste, for which the inverse Mills ratio was significant ($p = 0.01$).

The coefficient estimate of *3YCum#PubEdu* for Reclaimable Waste was negative and significant in the fixed-effects model with 2SLS. This negative coefficient once again may have resulted from waste source reduction. Reclaimable Waste consists of left-over motor oil, used oil filters, latex paint, auto batteries, and antifreeze. Public education and outreach programs related to Reclaimable Waste in California have included mass media campaigns to motivate people to recycle. However, there are other kinds of campaigns that can reduce the generation of Reclaimable Waste. For example, CalRecycle promoted using synthetic motor oil, such as polyalphaolefin oil (PAO), instead of conventional oil (CalRecycle, 2005). This synthetic oil extends oil-change intervals up to 25,000 miles. CalRecycle also created advertising messages that debunked the "3000-mile myth" that car owners need to change their motor oil frequently, which was usually unnecessary according to car manufacturers (California Integrated Waste Management Board, 2007). These campaigns are likely to result in decreased household consumption of motor oil.

In the Heckman method results, the estimates of *3YCum#PubEdu* for Acid, Base, Oxidizer, and Asbestos Waste were also negative and significant.[10] This suggests that provision of HHW-related education had a negative association with the collection of these waste materials too. This is likely to be the result of source reduction campaigns related to specific HHW materials. A more recent example is Los Angeles County, which is now advising the public on how to reduce the generation of HHW, and offering a substitution list of non-toxic cleaning products on the county website (Clean LA, 2016a). Public information regarding Asbestos Waste in California has been disseminated since the years this study cov-

[10] The estimate of *3YCum#PubEdu* for Flammable and Poisons Waste was also negative and significant. However, the χ^2 test of the probit model for this waste was not significant so we chose not to include the results from the Heckman method for this kind of HHW in our analysis.

ers, through information about types of asbestos and the risks of asbestos exposure to health. Friable asbestos may contain more than 1% asbestos. Example includes acoustical ceiling (popcorn texture), pipe insulation, and blown-on insulation coating. These may cause lung diseases, such as asbestosis, mesothelioma, and lung cancer (Department of Toxic Substances, 2003). This kind of information may encourage households to recycle asbestos material with the help of professional asbestos removal contractors.

For drinking water quality information in the form of MCL violation counts (*#MCLViol*), the coefficients in the extended model with fixed effects were negative and significant for Reclaimable Waste, Flammables and Poisons, Oxidizers, and Asbestos. The coefficient of *#MCLViolLg* was more rarely significant though – in fact, just for Oxidizers at 0.07 (with 2SLS, $p < 0.01$) and at 0.03 (with Heckman's method, $p < 0.05$). Only about 10% of Oxidizer Waste collected was reused and recycled according to the CalRecycle HHW disposition data in 2004–2012. This again suggested that MCL violation information via mail may have increased the amount of HHW collected, but not necessarily increased the amount of HHW recycled if the HHW was not mostly recycled. More data would have strengthened our estimation capabilities for the various categories because they lacked sufficient observations in some cases to establish significant coefficient estimates for the variables.[11]

The coefficients for high school graduate percentage, mean household income, and population in the fixed-effects model and the model with 2SLS were positive and significant for most of the material categories. This suggested that these demographic factors generally had positive associations with the amount of HHW collected, regardless of the material category. The coefficients of population density were mostly not significant, except for Electronic Waste, with -1.56 ($p < 0.001$) in the 2SLS estimation of the fixed-effects model. This suggested that higher population density was associated with less Electronic Waste collected.

7. Discussion

We next discuss the main findings related to the influence of household informedness on HHW collection and recycling outputs. Table 7 summarizes our hypotheses and the test results.

Our Overall Effect of Public Education on HHW Collected Hypothesis (H1) in California was only partially supported. The HHW public education variable was not significant in Model 1. This was probably because this model did not adequately capture the variability in the waste material types, the negative effects from waste source reduction efforts, and the bias from local governments' purposeful actions.[12] Nonetheless, the estimated household informedness elasticity value of HHW collection outputs for HHW public education derived from Model 2 was positive and significant at the 10% level. Although this value was calculated based on a system of equations that held the amount of HHW recycled constant, still it partially supported Hypothesis 1.[13]

HHW-related campaigns and outreach also provide information about alternative non-hazardous household products and better practices that can reduce the generation of HHW. We obtained support for the Category-Specific Direct Effect of Public Education on HHW Collected Hypothesis (H2), suggesting that HHW-related public education can decrease the amount of HHW from household products with non-hazardous substitutes. Our extended analysis by material category showed that HHW-related public education was negatively associated with the amount of Reclaimable, Acid, Base, Oxidizer, and Asbestos Waste collection. The negative association suggested that media campaigns and information related to synthetic oil use as an alternative to conventional motor oil and alternative household products without these hazardous materials had a stronger influence on households to reduce waste generation than to participate in collection programs. We also wonder if the public did not necessarily see these as true substitutes, regardless of the body of knowledge that shows that they are, and yet we see evidence of this in the motor oil example. Initially, the general recommendation was to change a car's motor oil every 3500 miles, but now it is more widely believed that a car doesn't need its oil changed for 7000 miles. This may account for the drop in waste generation over time as less motor oil would have been necessary. Due to the difference between synthetic and conventional motor oil, consumers may have been slower to switch to more costly synthetic motor oil. Thus, synthetic motor oil may be a technical substitute for conventional motor oil, but it has characteristics that make it less-than-best. This may explain our results.

These results showed that the impact of HHW-related public education was multifaceted; it seems to have had a positive effect on the amount of HHW collected, but it also may have had a negative effect in some circumstances due to source reduction measures. These countervailing effects may have been working simultaneously. Whether the positive or negative effect was stronger depended on the HHW material type. Some household products can be substituted easily with other products with less hazardous material; some cannot. It also depended on the maturity of the collection program. The positive effect may have been most pronounced in the early stage of the collection program and the source reduction effect may have come afterward. It may have taken less time for local governments to encourage households to deliver their waste to facilities or events than to persuade them to change the selection of their household products or to change their consumption behavior.[14]

Our data analysis supported the Indirect Effect of Public Education on Overall HHW Recycled Hypothesis (H3) that HHW-related public education had some influence on the overall amount of HHW recycled. We used a system of equations to model HHW collection and recycling simultaneously to estimate the indirect effect of HHW-related public education on the amount of HHW recycled despite the unobserved source reduction practices. This result indicated the importance of HHW-related public education in maximizing the proportion of recycled HHW from the total amount of waste collected in HHW collection programs.

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[11] As we noted for the other models. we were not able to estimate all the HHW categories; our models did not fit the data for PCB-containing and Universal Waste very well, so we dropped them from consideration.

[12] An anonymous reviewer suggested that we should model the relationship between the *probability of recycling HHW* and household informedness. We modeled this using a *generalized linear model* (GLM) with a logit link and a quasi-binomial distribution. We used the proportion of the amount of HHW recycled relative to the HHW collected in pounds as the dependent variable. *3YCum#PubEdu* was not significant so this model also may not have been able to capture the variation in the effects of the material categories. It also did not capture the negative effects from waste source reduction measures.

[13] Additionally, when we performed the analysis for the different material categories, we found a positive association between HHW-related public education and the amount of PCB-containing and Universal Waste collected. But these relationships occurred in models for which our confidence in their overall fit was quite low (to the point that we have not reported the details of the results.) So it is not appropriate, in our view, to suggest that HHW-related public education increased the participation of households in HHW collection programs for household waste in these material categories. A majority of households have Universal Waste, and a lot of public environmental education probably focused on it.

[14] We further note that the *theory of planned behavior* (Ajzen, 1991) has been used in studies related to public communication campaigns (Wood, 2006; Largo-Wight et al., 2012) to explain the gap between one's intent to behave some way and then doing it. According to the theory, the success of HHW public education to influence households' behavior in disposing of HHW properly should be determined by *perceived behavioral controls*, such as disposal convenience of HHW, or perceived ease of HHW delivery to recycling facilities. Our model did not touch on this, since we did not conduct a field survey in this work.

Table 7
Summary of hypotheses test results.

No.	Hypothesis Description	Results	Comments
H1	**Overall Effect of Public Education on HHW Collected Hypothesis:** *HHW-related public education increases the overall amount of HHW collected.*	Partially supported	Positive household informedness elasticity of HHW collection
H2	**Category-Specific Direct Effect of Public Education on HHW Collected Hypothesis:** *HHW-related public education directly decreases the amount collected for a few HHW materials that have non-hazardous substitutes.*	Supported	Negative and significant coefficient in Model 1, extended by material category for Reclaimable, Acid, Base, Oxidizer, and Asbestos Waste
H3	**Indirect Effect of Public Education on Overall HHW Recycled Hypothesis:** *HHW-related public education indirectly increases the overall amount of HHW recycled.*	Supported	Positive and significant coefficient in Model 2's *HHWRecQ* equation
H4	**Effect of Environmental Quality Information on Overall HHW Collected Hypothesis:** *Information on low environmental quality in a county increases the amount of HHW collected, when households perceive there is a problem.*	Supported under certain conditions	Positive and significant *#MCLViolLg* (MCL violation count information sent by direct mail) in Model 1

There was some support for the Effect of Environmental Quality Information on Overall HHW Collected Hypothesis (H4) but only under limited conditions. This hypothesis is about the effect of information on low environmental quality in a county. We found that the MCL violation information had a positive association with the amount of HHW collected, but only when it was delivered to households via direct mail. Surprisingly, we found that when people perceived the drinking water quality to be low, the lower was the amount of HHW collected in the county. This suggested that the direct channel for environmental quality information may have had more impact on household environmental awareness than the indirect channels, such as public notices and newspapers.

Simply relying on public media to convey the information may not be as effective as delivering the information through a more direct and interpersonal channel in influencing public behavior though (Nixon and Saphores, 2009). And there is also the possibility that there are lag effects from the time of awareness to actions to recycle and improve environmental quality. Our research design did not consider this. Also, the effect of the MCL violation information depended on the number of violations; we found that there was more of an impact on HHW collection and recycling outputs when the violation count changed greatly.

The findings related to the impact of household informedness on HHW collection may have varied not only due to the waste material category but also due to other unobservable factors, such as the diversity of California's population. The state has long been viewed as ungovernable due to its size and diversity. Over 200 initiatives to sub-divide California into smaller states have been launched, and these initiatives began soon after the state entered the union. A new initiative was launched in 2016 to subdivide California into nine different states. The spillover effect of informedness from one county to its neighbors is another factor that is difficult to observe. We will investigate these issues in future research by creating a geospatial and geotemporal research design.

In addition to the findings related to household informedness, we learned that the socioeconomic characteristics of the counties in California were an important determinant of the HHW collection and recycling outputs. Our model estimates showed that education level, household income level, and population were positively associated with HHW collection and recycling outputs, as we expected. On the other hand, our model estimates showed a negative association between population density, and HHW collection and recycling outputs, respectively. This is also not surprising though because households in high population density areas may have more opportunities to dispose of HHW illegally. So they may have been less motivated to participate in HHW collection programs.

We also calculated the household informedness elasticity of HHW collection and recycling output. Analogous to price elasticity of demand, informedness elasticity is useful to gauge the responsiveness of households in terms of HHW collection and recycling outputs as more educational and environmental information becomes available to them. This can help local governments and waste managers to assess how much more effort or costs need to be invested in improving household informedness related to HHW and the environment to achieve the most household participation and desirable output in collection programs.

The household informedness elasticity of HHW collection outputs from HHW-related public education consists of two components: the direct effects of HHW-related public education on HHW collection outputs (holding the amount of HHW recycled constant) and the indirect effects on HHW recycling output. By holding the amount of HHW recycled constant, we attempted to isolate the effects from source reduction. Although there was uncertainty in the elasticity estimates, we found a higher estimate for the positive effect of HHW-related public education on HHW recycling compared with HHW collection. This confirmed our conjecture about the negative effect from waste source reduction activities related to HHW collection. This also implied that measuring the effect of HHW public education based on the amount of HHW collected only – without considering the source reduction effect – may underestimate the impact.

For California during the 2004 to 2012 period, we found that the HHW collected and recycled amounts were *informedness-inelastic*. The responsiveness of HHW collection outputs to the differences in household informedness via HHW-related public education and environmental information seem to have been be relatively low. Informedness via HHW-related public education and environmental information was inelastic probably because many households in California already were well-informed about HHW before 2004 so that more campaigns about HHW did not result in more HHW collection.[15]

[15] The varied effects of HHW-related public education across different material categories may reflect the disparate levels of informedness related to different HHW material categories. Households would have benefited from more information about Reclaimable and Asbestos Waste, which has been collected in California since 1992. Universal Waste was completely banned from trash in 2006. So investing more effort and cost in promoting such recycling would have improved HHW collection and recycling in this category relatively more too.

8. Conclusion

We assessed the role of household informedness in the collection and recycling of HHW outputs using econometric analysis. We also evaluated the effectiveness of HHW-related public education and environmental quality information in influencing households to participate in collection programs, and to improve their pro-environmental behavior by decreasing their generation of HHW. After estimating the effects of household informedness, we introduced a new impact estimator – *household informedness elasticity of HHW collection and recycling outputs* – that is useful to gauge the responsiveness of HHW collected and recycled as more educational and environmental information is available.

We demonstrated the transformation of data collected from various public sources into policy analytics findings that give insight into the mechanism for the impact of household informedness in waste management, particularly HHW. By understanding this mechanism, local governments and waste managers can devise effective strategies and policies related to public information that promote pro-environmental behavior and encourage households to manage their waste better. Implementing these strategies will enhance participation in delivering their existing HHW and mitigating the generation of new HHW.

The empirical models we used in this research were useful to capture the relationships between household informedness and the quantity of HHW collected. We note the limitations with the linearity assumption of the estimation models and the measurement approach that we adopted for the estimation of the impacts of informedness. We may be able to improve the estimation models by adding non-linear relationships in future research, but all signs suggest that we will need more data to make this worthwhile.

We measured the extent to which the informedness level was influenced by HHW public education with the number of 3-year cumulative projects with an educational campaign on HHW. It is likely that the quality of any individual educational program might differ from another, but we expect that, on average, there will still be a similar influence. With better data, we can estimate their effects more accurately.

Although we included estimates of household informedness impacts on HHW collection by material category, we did not perform a detailed analysis for each of the specific HHW materials. Each HHW material category may have different educational campaigns, hazardous risks, and regulations. So our estimates of the impacts of household informedness may be more applicable to HHW in general, but may not be as effective for a specific material category model-wise, such as PCB-containing and Universal Waste.

Further, our models can be refined and expanded to develop more targeted policy analytics for waste management that involves households, local governments, and other stakeholders. But, unmistakably, this research highlights the challenges facing policy-makers in creating programs that improve waste management and recycling. This research contributed a novel approach to quantifying the impact of household informedness in a way that may be useful for policy-makers in assessing the costs and benefit of their educational campaigns and information programs related to HHW at the county level. This kind of assessment will help state-level waste managers and governments in planning the appropriate information policies and strategies to increase household informedness for collecting more HHW generated by households and reduce this waste as much as possible at its source. This will prevent HHW from contaminating our land and water, so that we all can enjoy living in a healthy and sustainable environment that is free from hazardous waste.

Acknowledgments

This research was partly supported by the Fujitsu-SMU Urban Computing and Engineering (UNiCEN) Corp. Lab, a public-private partnership between the Agency for Science, Technology and Research (A*STAR), Fujitsu Limited and Singapore Management University (SMU). Kustini Lim-Wavde also thanks the Living Analytics Research Centre (LARC)'s SMU-CMU Doctoral Programme Exchange, as well as the Post-Graduate Research Programme Office at SMU for generous funding for this research in the 2014, 2015 and 2016 academic years. All of the findings and opinions expressed are the sole responsibility of the authors. We benefited by presenting some aspects of this work at the 2016 International Conference on Energy Informatics, Environment, Energy and Applications, held in Hong Kong on March 23-24, 2016, and at SMU. We also benefited from discussions on this topic with Haibo Zhai and Chris Hendrickson from Engineering and Public Policy at Carnegie Mellon University, and Zhuolun Li, Youngsoo Kim, Truc Viet Le, Jun Liu, Dan Geng, and Ai Phuong Hoang at SMU.

Appendix A. Metro and non-metro counties in California

Table A1
County definitions in the state.

Code	Description
Metro Counties	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Non-Metro Counties	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2500 to 19,999, adjacent to a metro area
7	Urban population of 2500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2500 urban population, adjacent to a metro area
9	Completely rural or less than 2500 urban population, not adjacent to a metro area

Source: U.S. Office of Management and Budget (2010).

Table A2
CA counties, metro/non-metro, and rural-urban continuum codes (RUCC).

RUCC	County
1	Alameda, Contra Costa, El Dorado, Los Angeles, Marin, Orange, Placer, Riverside, Sacramento, San Benito, San Bernardino, San Diego, San Francisco, San Mateo, Santa Clara, Yolo
2	Fresno, Kern, Merced, Monterey, San Joaquin, San Luis Obispo, Santa Barbara, Santa Cruz, Solano, Sonoma, Stanislaus, Tulare, Ventura
3	Butte, Imperial, Kings, Madera, Napa, Shasta, Sutter, Yuba
4	Lake, Mendocino, Nevada, Tehama, Tuolumne
5	Humboldt
6	Amador, Calaveras, Colusa, Glenn, Modoc, Siskiyou
7	Del Norte, Inyo, Lassen, Mono, Plumas
8	Alpine, Mariposa, Sierra, Trinity

Source: U.S. Office of Management and Budget (2010).

Appendix B. Modeling and estimation

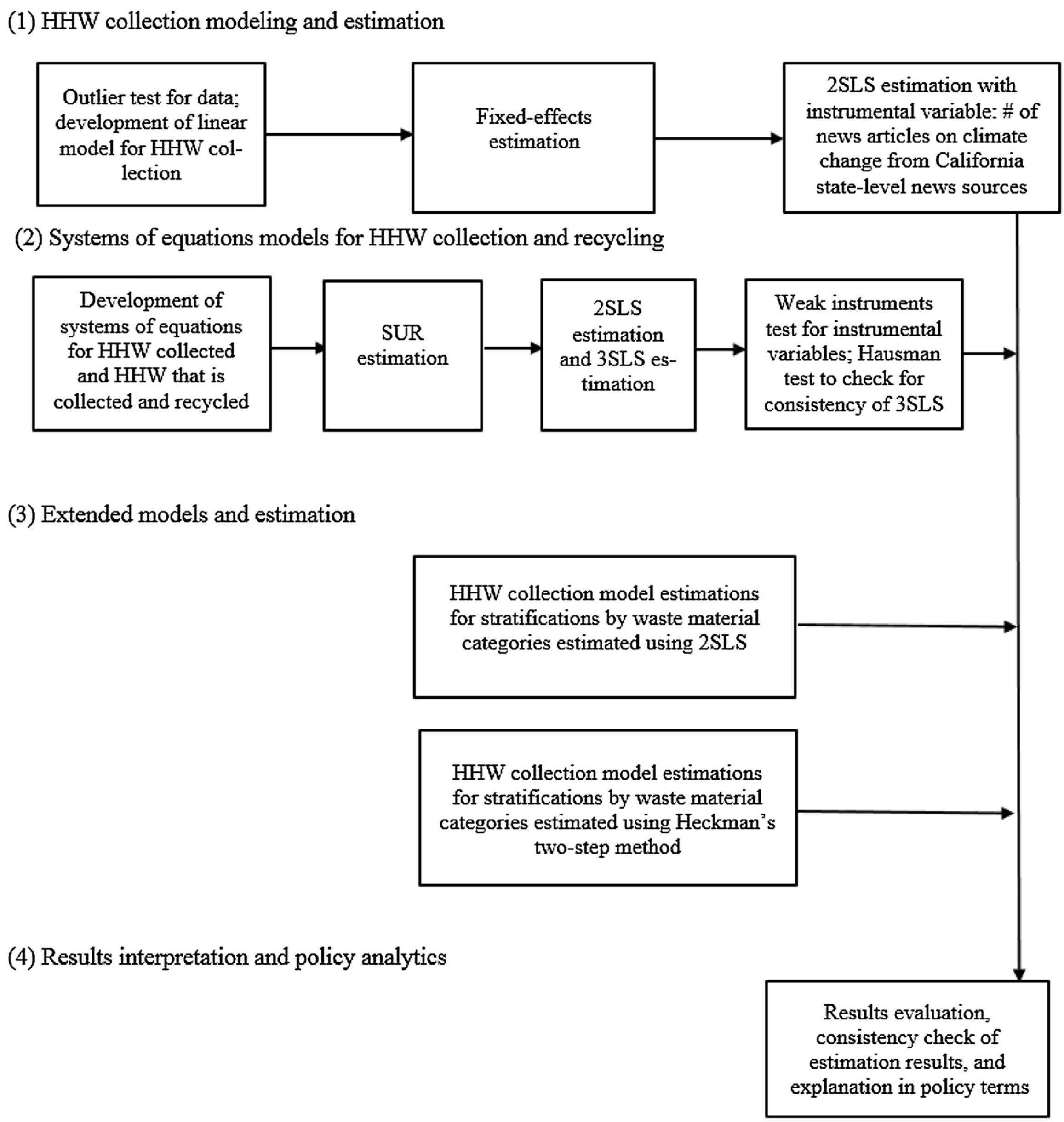

Fig. B1. Empirical research process used in this study.

Appendix C. Estimation results: additional details

Table C1
SUR estimation results for HHW collected versus collected and recycled.

Variables	HHW Collected Coef. (SE)		HHW Collected and Recycled Coef. (SE)	
Intercept	-4.67^{***}	(1.63)	-10.88^{**}	(4.54)
ln(*HHWRecQ*)	0.46^{***}	(0.02)	–	
3YCum#PubEdu	0.02	(0.03)	0.11	(0.08)
#MCLViolLg	0.02^{*}	(0.01)	0.04^{*}	(0.02)
#MCLViol	-0.003^{***}	(0.001)	-0.004^{**}	(0.002)
DHHWGrant	0.08	(0.05)	0.00	(0.12)
ln(*Density*)	-0.05^{*}	(0.03)	−0.11	(0.07)
EduHS%	1.80^{***}	(0.37)	3.80^{***}	(0.99)
ln(*MeanHHIncome*)	0.61^{***}	(0.16)	1.17^{***}	(0.40)
ln(*Pop*)	0.35^{***}	(0.03)	0.65^{***}	(0.09)
EWasteFee	–		0.01	(0.01)
UsedOilFee	–		0.84	(1.37)
$RUCC_2$	–		0.03	(0.17)
$RUCC_3$	–		0.12	(0.26)
$RUCC_4$	–		0.66^{*}	(0.34)
$RUCC_5$	–		-0.93^{**}	(0.42)
Adj. R^2	83.0%		43.4%	

Notes. Model: Simultaneous equations; estimation: SUR; 333 obs. Dep. vars.: HHW collected is ln (*HHWCollQ*); HHW recycled is ln (*HHWRecQ*). Estimated with the SystemFit package in R (Henningsen and Hamann, 2007). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C2
2SLS estimation results for HHW collected versus collected and recycled.

Variables	HHW Collected Coef. (SE)		HHW Collected and Recycled Coef. (SE)	
Intercept	-4.20^{**}	(1.66)	-10.77^{**}	(4.73)
ln(*HHWRecQ*)	0.46^{***}	(0.03)	–	
3YCum#PubEdu	-0.13^{*}	(0.08)	0.51^{**}	(0.25)
#MCLViolLg	0.02^{**}	(0.01)	0.04	(0.03)
#MCLViol	-0.003^{***}	(0.001)	-0.004^{*}	(0.002)
DHHWGrant	0.15^{**}	(0.06)	−0.20	(0.17)
ln(*Density*)	-0.05^{*}	(0.03)	−0.12	(0.07)
EduHS%	1.69^{***}	(0.39)	4.23^{***}	(1.06)
ln(*MeanHHIncome*)	0.55^{***}	(0.17)	1.23^{***}	(0.42)
ln(*Pop*)	0.37^{***}	(0.04)	0.56^{***}	(0.11)
EWasteFee	–		0.00	(0.02)
UsedOilFee	–		1.63	(1.49)
$RUCC_2$	–		0.08	(0.18)
$RUCC_3$	–		−0.02	(0.29)
$RUCC_4$	–		0.55	(0.36)
$RUCC_5$	–		-1.20^{**}	(0.47)
Adj. R^2	82.0%		38.7%	

Notes. Model: simultaneous equations; estimation: 2SLS; 333 obs. Dep. vars.: HHW collected is ln (*HHWCollQ*); HHW recycled is ln (*HHWRecQ*). Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*. Estimated with SystemFit package in R (Henningsen and Hamann, 2007). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix D. Material categories analysis

Table D1
Fixed-effects model with 2SLS estimation results stratified by material category.

MATERIALS	RECLAIM-ABLES	FLAMM. & POISON	ELECT. WASTE	ACIDS	BASES	OXIDIZER	ASBESTOS
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Intercept	***-12.60**** (4.59)	***-24.64**** (4.19)	-30.53 (22.52)	***-30.65**** (4.36)	***-40.69**** (7.70)	***-33.93**** (6.27)	***-75.60**** (16.65)
3YCum #PubEdu	**-0.39*** (0.20)	-0.19 (0.20)	2.05 (1.33)	-0.01 (0.21)	-0.16 (0.37)	0.20 (0.30)	-0.99 (0.79)
#MCLViolLg	0.00 (0.02)	0.03 (0.02)	0.16 (0.12)	-0.01 (0.02)	-0.02 (0.04)	0.07* (0.03)	0.05 (0.09)
#MCLViol	-0.004* (0.002)	***-0.004**** (0.002)	-0.010 (0.009)	0.000 (0.002)	0.004 (0.003)	-0.004* (0.002)	***-0.018**** (0.007)
DHHW Grant	***0.37**** (0.15)	**0.23*** (0.14)	-0.65 (0.90)	0.16 (0.14)	0.23 (0.25)	0.11 (0.21)	0.80 (0.55)
ln(*Density*)	-0.07 (0.07)	-0.05 (0.06)	***-1.56**** (0.34)	-0.10 (0.07)	0.04 (0.12)	0.00 (0.10)	-0.22 (0.25)
EduHS%	***2.18**** (1.03)	***3.50**** (0.95)	***14.46**** (5.12)	***4.08**** (0.98)	2.05 (1.74)	2.68* (1.42)	3.25 (3.76)
ln(*MeanHH Income*)	***1.35**** (0.40)	***2.08**** (0.36)	1.38 (1.99)	***2.18**** (0.38)	***3.10**** (0.67)	***2.55**** (0.55)	***5.61**** (1.45)
ln(*Pop*)	***0.72**** (0.10)	***0.85**** (0.09)	***1.77**** (0.53)	***0.92**** (0.10)	***0.97**** (0.17)	***0.81**** (0.14)	***1.28**** (0.37)
UsedOilFee	-1.45 (1.33)	—	—	—	—	—	—
EWasteFee	—	—	-0.02 (0.08)	—	—	—	—
$RUCC_2$	-0.26 (0.17)	0.14 (0.16)	-0.53 (0.85)	0.22 (0.16)	0.04 (0.29)	-0.20 (0.24)	-0.82 (0.63)
$RUCC_3$	-0.34 (0.27)	0.31 (0.25)	-0.90 (1.36)	0.24 (0.26)	-0.34 (0.46)	-0.33 (0.37)	0.73 (1.00)
$RUCC_4$	-0.22 (0.35)	0.44 (0.32)	-1.93 (1.70)	0.16 (0.33)	0.56 (0.58)	0.58 (0.47)	-2.19* (1.26)
$RUCC_5$	-0.38 (0.44)	***1.09**** (0.41)	***-9.91**** (2.24)	0.46 (0.43)	***2.17**** (0.75)	***1.24**** (0.61)	-1.18 (1.63)
Adj. R^2	50.0%	60.3%	12.0%	62.3%	47.3%	50.7%	27.6%
Wu-Hausman	***7.67****	1.32	2.05	0.05	0.75	0.43	1.54

Notes. Model: fixed effects; dep. var.: natural log of HHW collected amount +1 (to retain data points with native values of 0) for each waste material category: Reclaimable (*ReclCollQ*), Flammable and Poison (*FPCollQ*), Electronic (*EWCollQ*), Acid (*AcidCollQ*), Asbestos (*AsbCollQ*), Base (*BaseCollQ*), Oxidizer (*OxCollQ*) Waste, 333 obs. PCB, Universal Waste omitted due to poor model fit. Base case $RUCC_1$ is omitted. Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*; weak instrument stat. = 46.24***. Coef. with $p < 0.10$ highlighted in gray; coef. with $p < 0.05$ are in bold and italics also. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D2
Fixed-effects model with Heckman estimation results stratified by material category.

Materials / Variables	Reclaimables Coef. (SE)	Flamm. & Poison Coef. (SE)	Elect. Waste Coef. (SE)	Acids Coef. (SE)	Bases Coef. (SE)	Oxidizer Coef. (SE)	Asbestos Coef. (SE)
Intercept	-8.70** (3.58)	-20.87*** (3.27)	14.06 (41.26)	-29.11*** (3.83)	-34.34*** (6.89)	-23.39*** (4.87)	-47.15 (39.55)
3YCum #PubEdu	-0.33*** (0.06)	-0.17*** (0.05)	0.08 (0.12)	-0.16*** (0.05)	-0.26*** (0.08)	-0.29*** (0.06)	-0.42** (0.79)
#MCLViolLg	0.00 (0.02)	0.04** (0.02)	0.04 (0.03)	-0.01 (0.02)	-0.02 (0.02)	0.03* (0.02)	0.12 (0.12)
#MCLViol	-0.003** (0.001)	-0.004*** (0.001)	-0.003 (0.002)	0.001 (0.001)	0.002* (0.001)	-0.004*** (0.001)	-0.005 (0.012)
DHHW Grant	0.30** (0.09)	0.18** (0.08)	-0.03 (1.08)	0.15* (0.08)	-0.14 (0.19)	0.10 (0.12)	0.13 (0.54)
ln(*Density*)	-0.04 (0.05)	-0.02 (0.05)	-0.31*** (0.11)	-0.07* (0.04)	-0.04 (0.08)	-0.03 (0.06)	-0.10 (0.17)
EduHS%	2.56*** (0.82)	3.78*** (0.73)	4.09 (2.91)	3.30*** (0.70)	-0.41 (1.19)	-0.25 (0.84)	-11.76** (4.78)
ln(*MeanHH Income*)	1.04*** (0.33)	1.76*** (0.30)	-0.83 (3.47)	2.09*** (0.35)	2.83*** (0.57)	1.82*** (0.41)	5.08 (3.11)
ln(*Pop*)	0.67*** (0.07)	0.80*** (0.06)	0.55*** (0.12)	0.92*** (0.06)	0.94*** (0.10)	0.87*** (0.08)	0.62*** (0.23)
UsedOilFee	-2.15** (0.93)	—	—	—	—	—	—
EwasteFee	—	—	0.07** (0.03)	—	—	—	—
$RUCC_2$	-0.30** (0.13)	0.10 (0.11)	0.12 (0.22)	0.13 (0.11)	-0.13 (0.19)	-0.17 (0.15)	-0.74 (0.46)
$RUCC_3$	-0.44** (0.19)	0.21 (0.17)	-0.44 (0.34)	0.28 (0.17)	0.19 (0.28)	-0.30 (0.21)	0.97 (0.68)
$RUCC_4$	0.39* (0.23)	1.02*** (0.20)	0.64 (0.40)	1.06*** (0.22)	1.20*** (0.36)	1.20*** (0.27)	0.83 (1.67)
$RUCC_5$	-0.39** (0.19)	1.11*** (0.04)	-2.13*** (0.62)	0.46 (0.30)	2.09*** (0.39)	1.40** (0.24)	0.48 (1.70)
Inverse Mills Ratio	-2.02 (2.32)	-2.07 (1.61)	-3.29 (12.91)	-0.11 (1.32)	-2.11 (1.65)	-1.74** (0.71)	-0.34 (2.90)
Adj. R^2	64.7%	73.6%	20.5%	76.0%	60.4%	65.6%	19.8%

Notes. Model: fixed effects, Heckman's two-step estimation; dep. var.: ln HHW collected amount by wastecategory: Reclaimable (*ReclCollQ*), Flammable and Poison (*FPCollQ*), Electronic (*EWCollQ*), Acid (*AcidCollQ*), Asbestos (*AsbCollQ*), Base (*BaseCollQ*), Oxidizer (*OxCollQ*), 333 obs. Base case $RUCC_1$ omitted; estimates for PCB, Universal Waste omitted due to poor model fit. Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*. Coef. with $p < 0.10$ are highlighted in gray; coef. with $p < 0.05$ bold and italics. Estimated with sampleSelection in R (Toomet and Henningsen, 2008). Signif.: *** $p < 0.01$, $|^{**}$ $p < 0.05$, * $p < 0.10$.

Table D3
Fixed-effects model with Heckman estimation results stratified by material category: probit analysis.

Materials	Reclaim-ables	Flamm. & Poison	Acids	Bases	Oxidizer	Asbestos
Variables	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Intercept	-39.07 (353.78)	-31.10 (37.45)	-30.22 (18.94)	***-24.58***** (10.23)	***-50.25****** (16.75)	***-25.60****** (3.94)
DHHW Grant	—	—	—	0.82* (0.44)	0.60 (0.41)	***0.32***** (0.16)
EduHS%	-7.71 (9.10)	-7.81 (9.60)	-2.33 (2.63)	0.95 (1.72)	0.94 (1.70)	1.53 (1.05)
ln(*MeanHH Income*)	3.81 (3.53)	3.67 (3.40)	3.12* (1.76)	***2.30***** (0.96)	***4.64****** (1.55)	***2.19****** (0.38)
χ^2	5.40	4.41	***7.87*****	***15.90******	***25.60******	***64.35******
McFadden R^2	39.7%	22.0%	23.0%	16.5%	26.5%	14.5%
# censored	1	1	3	11	11	128
# observed	332	332	330	322	322	205

Notes. Model: probit; dep. var.: binary variable to indicate HHW material collected for each waste material category: Reclaimable (*DReclCollQ*), Flammable/Poison (*DFPCollQ*), Acid (*DAcidCollQ*), Asbestos (*DAsbCollQ*), Base (*DBaseCollQ*), and Oxidizer (*DOxCollQ*); 333 obs. Estimates for Electronic, PCB-containing, and Universal Waste omitted due to poor model fit. Coef. with $p < 0.10$ highlighted in gray; coef. with $p < 0.05$ in bold and italics. Estimated with sampleSelection in R (Toomet and Henningsen, 2008). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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