THE UNIVERSITY OF OREGON

ECONOMICS OF RECYCLING AND HEALTH POLICY

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE DIVISION OF THE GRADUATE STUDIES OF THE
UNIVERSITY OF OREGON
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

DEPARTMENT OF ECONOMICS

BY
SHAN ZHANG

EUGENE, OREGON
APR 2022

Dedication Text

Epigraph Text

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

ABSTRACT

This dissertation estimates the Willingness To Pay (WTP) for preventative public health policies during the COVID-19 pandemic and the effect of a trade policy on the international recycling market, coastal cleanups, waste pollution flow, and local pollution relocation in the U.S. In Chapter 1, I provide a comprehensive overview of each dissertation chapter.

In Chapter 2 (with Trudy Ann Cameron), we take advantage of a 2003 general-population choice-experiment survey of U.S. residents. This survey was designed to determine the willingness of people to bear the costs of public policies to reduce illnesses and avoid premature deaths in their communities. We re-estimate that the aggregate WTP across the U.S. adult population from March 2020 to May 2021 is about 3 trillion dollars in the context of the 2020-21 COVID-19 pandemic.

Chapter 3 demonstrates that China's Green Sword policy (GS policy or the Waste Import Ban) decreased the net weight of U.S. plastic scrap exports to China by 90 percent. At the same time, it increased the U.S. net weight of plastic waste exports to South/Southeast Asia and Central/South America by 150 percent and 41 percent, respectively. Using the machine learning counterfactual method, I find that many individual countries in Southeast Asia have seen significant increases in recyclable wastes imported from the U.S after China's GS policy.

In Chapter 4, I examine the effect of China's GS policy on U.S. emissions and local pollution relocation. Using the synthetic control method, I find that many states, such as California, New York, and Texas, have seen statistically significant increases in methane emissions after the GS policy took effect. To gain a more detailed understanding of the effects of the GS policy on local pollution relocation, I use facility-level disposal transportation data in California and I show Environmental Justice implications. The preliminary

results show that after the GS policy, although minority communities continue to be exposed to more pollution relocation, lower-income and more remote white communities have experienced a greater increase in waste pollution inflows. A potential mechanism could be that the lower-income White communities have relatively lower political costs as destination communities. The more polarized the vote is between counties and the state average, the more likely it is for counties with a lower political cost to receive waste pollution from outside.

Chapter 5 (with Rebecca Taylor) examines the effect of China's GS policy on beach clean-up. The preliminary results show that the more a country imported scraps overseas, the more items were collected per person on their beaches. This reveals that many recyclable scraps imported to the country were not recycled or disposed of properly.

CHAPTER 1

INTRODUCTION

My dissertation seeks to provide insight on critical policy questions related to public health during the Covid-19 pandemic, recycling, and waste pollution relocation internationally and locally. I examine heterogeneity in response to (and as a result of) a set of public health and environmentally related policies. To answer these questions, I use various methods such as machine learning, spatial analysis and reduced-form causal inference. Chapter two is a joint work with Trudy Ann Cameron. Chapters three and four are my own work. Chapter five is a joint work with Rebecca Taylor.

Chapter 2 demonstrates that during COVID from 2020 March until 2021 May, the estimated national-cumulative Willingness To Pay (WTP) to prevent cases and deaths at the community level is roughly about 3 trillion dollars. To estimate this WTP, we take advantage of a 2003 general-population choice-experiment survey of U.S. residents designed to determine people's willingness to bear the costs of public policies to reduce illnesses and avoid premature deaths in their communities. We re-estimate earlier models, omitting all respondent-specific individual characteristics and adding new county-level data on various contextual variables circa 2003. Then we transfer our re-estimated model to the context of the 2020-21 COVID-19 pandemic. Our estimated aggregate WTP across the U.S. adult population from March 2020 to May 2021 is about 3 trillion dollars. If preferences over public health programs, conditional on context, remained relatively stable over time, our findings may be relevant for predicting contemporary willingness to bear the costs of public health measures, either retrospectively for the current pandemic, or prospectively for future pandemics.

Chapter 3 shows the effect of China's waste import ban (Green Sword Policy) on the

U.S. recycling market and international wastes flow. I propose two-way fixed effects and event study models to analyze the impact of the changes in international recycling policies on the U.S. recycling market. In the past, the U.S. recycling industry has relied heavily on the strong demand for recyclable materials overseas, mainly to China. However, starting in 2013, China enacted a series of policies that restricted waste imports from overseas, including from the U.S. After China's policy change, many other South and Southeast Asian countries followed similar approaches to restrict waste pollution. Using the event study model, I show the dynamic impact of policy changes on total U.S. exports of recyclables before and after the points in time when these policy changes were announced and took effect.

After China launched its Green Sword (GS) policy to stop the inflow of recyclable wastes due to high environmental costs in 2017, as a major exporter of recyclable wastes, the U.S. has had to find local solutions for its recyclables. In Chapter 4, I investigate how the GS policy has affected the recycling industry, Greenhouse gas emissions, and local pollution relocation in the U.S., as well as what implications this policy has for existing environmental injustice. I use empirical methods and provide causal evidence that state-level methane emissions from the U.S. waste industry increased after the GS policy. Heterogeneous changes in domestic methane emissions across states relate to the historical trade volume of recyclable wastes and stringency of environmental regulations. I use spatial analysis and find that waste pollution tended to relocate to areas with minority communities prior to China's GS policy. However, after China's GS policy, pollution inflows increased for lower-income and remote White communities as a result of the exogenous trade policy shock. I then explores the relationship between political costs and local pollution relocation. One potential mechanism to explain my result could be that as marginal transportation costs decrease, the marginal effects of political costs on the local pollution relocation increase. Thus, the more polarized white communities become the communities being affected the most by the GS policy.

Chapter 5 examines the effect of international scrap trade on beach cleanups. We utilize the International and National Beach Cleanup data, which keeps records of beach cleanup programs by locations (countries or U.S. states), type of materials, total items collected, and the total number of people who participated in the programs. The preliminary results show that the total items collected per person are positively correlated with the total scraps (mainly plastic and paper scraps) imported among the developing countries that were importing scrap materials. In the U.S. (which was exporting scraps), the total items collected per person is negatively correlated with the total scraps exported in a state. These results show that the scraps exported from developed countries to developing countries were not all properly disposed of or recycled in the past two decades. Many of these exported environmental externalities ended up in the ocean or on the coast of the importing countries.

CHAPTER 2

WILLINGNESS TO BEAR THE COSTS OF PREVENTATIVE PUBLIC HEALTH MEASURES

2.1 Introduction

Many policies and regulations are intended to protect human life and health. In the context of the current global pandemic, given the externalities associated with infectious disease, public health policies are essential. To analyze the benefits and costs of public health measures, policymakers must take into account the level of (and heterogeneity in) people's willingness to bear the costs of appropriate public health measures.

It is challenging to monetize the social benefit from costly policies to protect human life and health. Economists typically use a measure called the Value of a Statistical Life (VSL) to quantify society's willingness to bear the costs of small reduction in mortality risks for a large number of people. VSL can be interpreted as a marginal rate of substitution between individual private mortality risk and money. Mathematically, VSL is the marginal utility of a small reduction in mortality risk divided by the marginal utility of a small change in income. In 2006, for example, the U.S. Environmental Protection Agency (EPA) estimated that people in the U.S. are willing to pay about $7,000,000 for one "statistical" life. This number means, for example, people are willing to pay about $70, on average, to reduce the probability of death by 1/100,000 for 100,000 people.[1]

For the COVID-19 pandemic, Echazu and Nocetti (2020) calculate society's overall willingness to pay for morbidity and mortality risk reductions. They estimate that the aggregate social WTP for a sizeable reduction in infection risk during a pandemic may be on the order of $3T to $7T. This dramatic estimate for WTP (for all statistical lives "lost") for risk reduc-

1. EPA's estimates of the value of a mortality risk reduction were reviewed in a white paper called "Valuing Mortality Risk Reduction in Environmental Policy" included 33 studies between 1988 to 2009. See line 694 in this white paper.

tion during an *infectious* pandemic likely reflects the fact that people are willing to pay not just for a reduction in their own risk of illness and death, but also to permit reductions in the stringency of pandemic restrictions. Cameron (2010) points out that VSL, as a "one-size-fits-all" measure, can hinder our ability to understand distributional effects of risk-reducing policies or interventions. A single VSL—where the majority of estimates of the VSL are derived from labor-market studies where the risk in question is sudden death in an industrial workplace accident—may also fail to reflect the particular features of COVID-19 as a specific health threat. Likewise, the populations for which wage-risk VSLs are typically estimated (prime-aged white male workers in hazardous occupations) may be a poor approximation to the characteristics of the populations most seriously affected by COVID-19.

The research described in this paper constitutes an exercise in "benefits function transfer" (Smith et al., 2002), where the "study sample" is an existing survey-based choice experiment fielded to more that 1400 respondents in a representative probability sample of households in counties across the U.S. in 2003 (Bosworth et al., 2009). The goal in that original study was to determine the social benefits from public health policies to reduce illness and deaths from different types of health threats in the respondent's community. For the current benefits transfer task, the "policy samples" consist of the populations of all counties across the U.S. during the 2020-21 COVID-19 pandemic.

Benefits transfer has been widely use to in environmental economics to supply information for benefit-cost analyses to support policy decisions when a new study is not affordable or when no time is available to conduct a thorough new study (Richardson et al., 2015). Benefits *function* transfer exercises can involve study and policy samples at different point in time where conditions may be different. For example, Price et al. (2017) evaluate the temporal stability of willingness-to-pay values from two identical stated preference surveys undertaken in 2004 and 2012. The surveys were designed to capture the trade-offs between (a) risk reductions for two health endpoints related to tap water, and (b) monetary costs.

Across these two time periods, their study found no significant differences in real-valued WTP, or in the structure of heterogeneous preferences.[2]

In the broader environmental benefits literature, it is also a common practice to estimate a benefits function for one country, and to attempt to transfer this benefits function to another country. These efforts can be challenging, however, because there are often cultural differences between countries (especially between developed and developing countries) that can call into question whether the preferences estimated in one country should be *expected* to hold in another country (Ready and Navrud, 2006; Brander et al., 2007; Lindhjelm and Navrud, 2008). In this paper, fortunately, we seek to transfer a benefits function only between two different time periods in the U.S. This requires only that we assume that U.S. preferences over public health policies and net incomes be relatively stable across time, after controlling for changes over time in the variables that systematically affect these preferences. It also requires the assumption that *cross-sectional* differences among U.S. counties in 2003 have similar effects on public health policy preferences as do changes over time in the characteristics of these U.S. counties.

Instead of using a single one-size-fits-all VSL, our research estimates people's WTP for public health policies that reduce both illnesses and deaths, in light of both the relevant cost and the expected duration of such policies. Furthermore, rather than focusing on *private* WTP to reduce an individual's personal mortality risk, we emphasize a specifically *public* program, where people are asked their WTP for reduction in the risk of illness and deaths in their broader community. In our current analysis, we interpret *counties* as communities. Although counties are not the smallest geographic regions we might use, they are the most appropriate administrative units in the context of the original survey. During a public health crisis like the COVID-19 pandemic, data on cases and deaths are also commonly reported at the county level.

2. Benefit function transfers maybe be derived from just one study, or they may combine the results for several related studies to "triangulate" the conditions for which a new benefits estimate is needed.

Assessing people's willingness to pay for community-level public health policies is essential for public health policymakers for four reasons. First, people from the same community often have more in common than do people from different communities, in terms of sociodemographics, ethnicities, economic status, and health characteristics. To the extent this is true, community characteristics may systematically affect individuals' preferences for public health policies. Second, during an infectious pandemic like COVID-19, people's behaviors and actions are intimately related to the health and well-being of *others* who live in the same community. Third, pandemic policies have often been tailored to conditions in specific counties as authorities attempt to allocate public health resources more efficiently. Fourth, many communities struggle with specific types of health risks systematically. For example, Lincoln et al. (2014) find that Black communities tend to suffer more from obesity and depression than do White communities. Yancy (2020) finds that during COVID-19, infection rates within Black-dominated communities have sometimes been three times higher than that in a White-dominated communities. Even more strikingly, the COVID-19 death rate for Black communities has been as much as six times higher than in White communities. With more-refined knowledge about their population's willingness to bear the costs of community-level health policies, county-level decision makers can implement public health measures with greater confidence that their strategies will deliver positive net social benefits for their constituents.

In this research, we re-analyze some high-quality stated-preference choice-experiment survey data from an original 2003 study reported in Bosworth et al. (2009) that reveals people's preferences for randomized public policies that benefit community-level health.[3] To permit out-of-sample forecasting, our re-analysis substitutes county-level explanatory variables for the individual-specific variables that were largely relied-upon to explain respondents' choices

3. The 2003 survey was one of four surveys funded by research grants from the U.S. EPA and the National Science Foundation, and was fielded using Knowledge Networks, the leading research-quality representative consumer panel available in the U.S. at the time.

in the original study. We collect new data on county-level policy contexts with the requirement that measures for all these county-level variables be available for both (a) the 2003 context and (b) the contemporary context of the 2020-21 pandemic. We need to control for differences, both across counties and between 2003 and 2020-21, in each county's mix of socio-demographic characteristics, incomes, political affiliations, health status, and access to medical care. If people's preferences for policies to reduce risks to public health have remained sufficiently stable between 2003 and 2020-2021, after controlling for shifts in all of these explanatory variables, lessons from our 2003 survey can illuminate people's likely policy preferences today. While we cannot identify a premium for infectious diseases, it will be helpful at least to understand what people would be willing to give up simply to avert illnesses and premature deaths at the scale of the current pandemic.

We first estimate a latent class model and discern three classes of preferences. Within each class, people's preferences are driven by different combinations of policy attributes and community characteristics. There is evidence of considerable heterogeneity. Next, we use LASSO methods to help select the most important observable determinants of heterogeneity in support for public health policies using our 2003 data. Then, based on the updated community-level characteristics in counties across the U.S. in 2020-21, we use the fitted model to predict overall WTP for policies to reduce monthly generic cases and deaths on a scale commensurate with county-level casualties from the COVID-19 pandemic. For example, we find that people from Black-dominated counties have a higher WTP for public health policies in these pandemic times than those from White-dominated counties. Residents of counties that have populations which are younger or more highly educated have lower WTP for public health interventions to reduce illnesses and deaths on a scale such as COVID-19 risks, compared to those who live in counties with older and less-educated populations.

Stated preference methods, such as those employed for this paper, are used frequently to quantify preferences in health economics, health technology assessment, risk-benefit analysis, and health services research (Mühlbacher and Johnson, 2016). A few contemporary survey-based discrete choice experiments have sought to understand public perceptions of COVID-19 pandemic interventions and to identify preference classes across individuals. (Rees-Jones et al., 2020) conduct a survey of 2,516 Americans concerning their preferences for both short- and long-term expansion to governmental-provided healthcare and unemployment insurance programs. That study finds that preferences for such programs are positively affected by the county's COVID-19 deaths, unemployment caused by COVID-19, and how respondents perceive the consequences of COVID-19. Chorus et al. (2020) use survey-based choice experiments to infer people's preferences from the trade-offs they are willing to make among policy effects, including health-related effects, impacts on the economy, education, and personal income. They find that "the average citizen, to avoid one fatality directly or indirectly related to COVID-19, is willing to accept a lasting lag in the educational performance of 18 children, or a lasting (3 years) and substantial (15%) reduction in net income of 77 households."

In an earlier, pre-COVID context, Cook et al. (2018) use a survey in Singapore regarding the trade-offs between risks of infectious diseases and the inconvenience of government interventions to prevent outbreaks of infectious disease. They find that respondents preferred more-intense interventions and preferred scenarios with fewer deaths and lower taxes. Li et al. (2020) use a survey-based choice experiment in three U.S. states and empirically quantify "willingness to stay home." They find broad support for statewide mask mandates. Their estimate of WTP to reduce new positive cases is large, and demographic and socioeconomic factors are the main drivers of the heterogeneity in individuals' willingness to stay home. Reed et al. (2020) also use a survey-based choice experiment in the U.S. to quantify Americans' acceptance of COVID-19 infection risks from lifting public health restrictions earlier and to reduce economic impact of the pandemic.[4]

4. They find four classes of people among all respondents: "risk-minimizers", "waiters", "recovery-supporters", and "openers". Political affiliation, race, household income, and employment status were all

Other recent papers focus on factors that affect people's responses to COVID-19. Cattapan et al. (2020) find that the need for community engagement is pressing in a pandemic crisis. Engagement is essential to ensure that policy-making is built on equity, access, and inclusion. Adeel et al. (2020) find that the sub-national policies of U.S. states and Canadian provinces are more important than the national-level policies in each country.

Some studies focus on the benefit-cost analysis of restrictive public health policies during COVID-19. For example, Viscusi (2020) applies a standard Value of a Statistical Life (VSL) to monetize COVID-19 deaths for the first half of 2020 and produces a U.S. mortality cost estimate of $1.4 trillion. Miles et al. (2020) conduct a benefit-cost analysis of U.K. public health policies during COVID and find that the costs of continuing severe restrictions are large compared to benefits. Dorantes et al. (2020) use county-level data on COVID-19 mortality and infections, as well as the county-level information on the adoption of non-pharmaceutical interventions (NPI) and find that NPIs slowed infection rates in counties where the healthcare system might otherwise have been overwhelmed by the pandemic. They also suggest that political ideology might have limited the effectiveness of those measures in Republican-dominated counties.

2.2 Data

2.2.1 The original 2003 survey

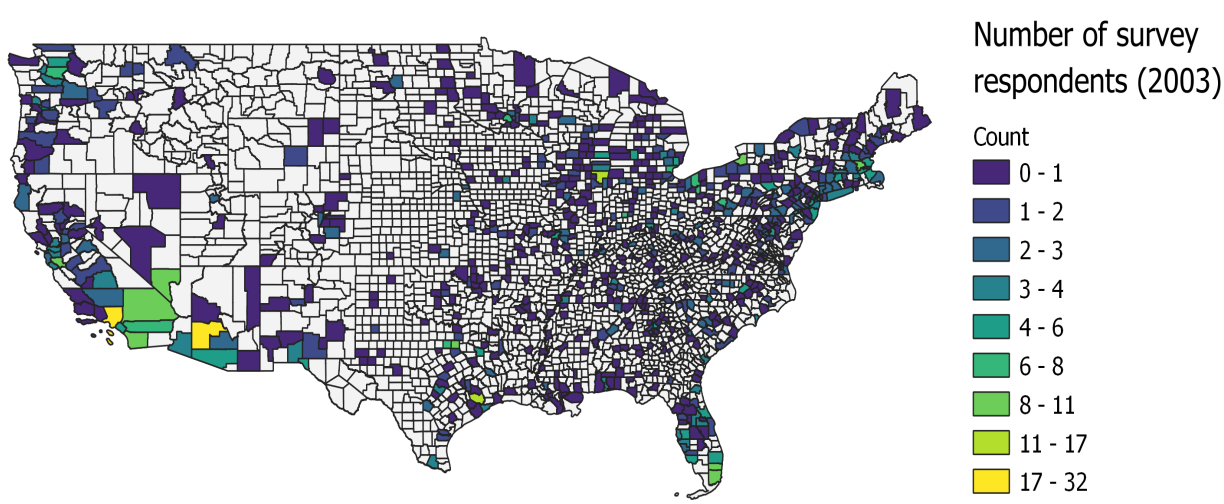
Our survey from 2003 was originally employed in an analysis that takes advantage of the characteristics of individual survey respondents to explain their policy preferences in that 2003 context. The original analysis described is in Bosworth et al. (2009). The 2003 survey produced 1,466 completed responses, and was designed specifically to elicit individuals' will-

associated with class membership.

ingness to pay for *publicly* provided health policies.[5] Each respondent faces a choice between either of two different health policies and the status quo. For example, Policy A might be described as reducing air pollutants that cause heart disease; and Policy B might reduce pesticides in foods that cause adult leukemia. The status quo "Neither Policy" option would involve no change in community health risks, but also no cost to the respondents' household. Each policy is also described in terms of a set of attributes that includes cases and premature deaths prevented in this community, duration of the policy, and the cost of the policy. The randomized illness labels include respiratory disease, cancer, leukemia, colon/bladder cancer, asthma, lung cancer, heart disease, heart attack, and stroke. See Appendix Figure A1 for one instance of the randomized choice sets used in the survey.

The original survey was fielded in June of 2003 and was distributed to members of a premium nationally representative consumer panel (Knowledge Networks) that produced a representative sample of respondents from counties throughout the conterminous U.S. The essentially national scope of the survey captured extensive geographic variation in sociodemographics, voting patterns, health status, and access to medical care. Figure 2.1 maps the geographic distribution of our 1,466 respondents.

Figure 2.1: Survey: Counties with 1 to 32 on-line respondents



5. See Johnston et al. (2017) for an inventory of current best practices in SP research.

The main policy attributes described in each policy choice task include monthly cost, policy duration, the size of the affected population, illnesses avoided and premature deaths averted. Our basic model allows for "status quo" effects, i.e., a discrete mass of utility, positive or negative, associated with the "Neither Policy" option, regardless of the specified attributes of either of the the two public health policies under consideration. Importantly, each policy choice was followed by a "self-interest" question about the degree to which the respondent or their family would personally benefit from that particular public health policy. Briefly, the relevant policy attributes for the present study were:

- **Affected population in thousands:** Across respondents, but not within a respondent's version of the survey, the original survey varies the size of the population affected by the policy. While it would have been ideal to describe this population as that of the respondent's own county, the anonymity of the survey prevented the tailoring of policy options specifically to match each respondents' county of residence. We asserted, about each pair of policies, that these two policies will be implemented for the "X thousand people living around you." We randomized X (among 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20 (2-3% in each case), 30 (4%), and 50, 100, 500, and 1,000 (8-15% each).

- **Policy duration:** Each prospective policy to reduce public health risks was described as a commitment to pay the cost of the policy for a specified time period.

- **Total illnesses avoided and deaths averted:** Over the specified time horizon, each policy is described as being expected to result in a specific number of cases avoided and a specific number of premature deaths averted. Preliminary models revealed that WTP for these public health policies is not simply linear in these policy attributes. Instead, people appear to derive diminishing marginal utility from additional avoided illnesses or averted premature deaths. Likewise, preferences are nonlinear in the policy's duration and in the size of the affected population.[6]

- **Status quo (or conversely, "Any policy") effects:** Respondents are allowed to choose "Neither policy" in every choice set, if they do not like either of the offered policies. Best practices in choice modeling include making an allowance for a status-quo effect. Equivalently, we use an indicator that equals one for "any policy (regardless of its effectiveness or duration)" and zero for the "Neither policy" alternative.

- **Monthly cost to your household:** Each prospective policy was associated with a specified private household cost, expressed both per month and annually, with a reminder of the duration of the commitment.

6. For the models in this paper, we employ logarithmic or shifted logarithmic transformations for these variables, since these functions seem best to explain people's choices.

Given that we need a model that can be transferred to the 2020-21 COVID-19 context, we must forgo the use of any of the available individual-specific variables that were collected by the 2003 survey for those respondents. In place of these individual-specific variables, we recruit new county-level variables that are both available and consistently measured both close to the time of the original 2003 survey and likewise close to the time of the current pandemic.

Most of our 1,466 respondents made five policy choices each. For our estimating sample, then, the 14,466 non-status-quo policies described in our choice experiments have randomized levels of each attribute, with the attribute levels in each case designed to span a wide range of possible policy choice scenarios, fortunately the original design spans the potentially relevant ranges of attributes for the 2020-21 pandemic. The arbitrary randomized distribution of the program design attributes used in the 2003 survey is summarized in Table 2.1.

Table 2.1: Descriptive statistics, public health policy design variables, choice experiments posed within the 2003 estimating sample

	mean	sd
Pop. affected/county pop.	2.706	8.341
Duration of policy (months)	167.9	116.6
Baseline illnesses	1004.7	2334.5
Number of illnesses avoided	606.9	13854.
Baseline deaths	96.16	472.0
Number of deaths avoided	102.1	467.9
Policies	14466	

2.2.2 *County-level sociodemographic and contextual heterogeneity*

Respondents to the original survey considered an aggregate of 7,233 choice sets. The randomized design of the choice experiments permits the estimation of a set of homogeneous preferences without any risk of the omitted variables bias. In this paper, however, we seek to identify important dimensions of preference heterogeneity. We permit policy preferences to vary systematically with the characteristics of the community-of-residence (county) for each respondent. Models with adequate preference heterogeneity allow us to predict changes in demand for public health policies, over time, in response to changes in sociodemographics, political ideologies, and healthcare access.[7] The cross-sectional variation in the original

7. See data source in Table B6 in Appendix.

sample can be exploited to accomodate differences in the composition of county populations across the 17-year interval between the 2003 study period and the 2020-21 policy period.

2.3 Estimating specification

We specify indirect utility as linear in net income. This is a common practice and is expedient because this functional form allows the individual's own household income level to drop out of the utility difference that drives the model. This leaves only the policy cost as a dollar-denominated measure that can be used to calculate the marginal rates of substitution that can be interpreted as marginal willingnesses to pay for avoided illnesses and avoided premature deaths.[8]

Preliminary exploration of the data has revealed that people tend to experience diminishing marginal utility from illnesses prevented and premature deaths averted. Given that microeconomic theory does not guide the functional form of utility beyond an expectation of diminishing marginal utility, we generalize our additively separable shifted-logarithmic form to a more flexible translog-type specification that is quadratic in these shifted log transformations, by including the square of each logged variable and the interaction between these logged terms, as well as a translog-type specification for the changes in the numbers of

8. This description of the model assumes a basic familiarity with utility-theoretic conditional logit choice models.

illnesses and deaths associated with policy A.[9]

$$
\begin{aligned}
V_i^A &= \alpha\left(Y_i - c_i^A\right) \\
&+ \beta_1 log\left(\Delta illnesses^A + 1\right) + \beta_2 log\left(\Delta illnesses^A + 1\right)^2 \\
&+ \beta_3 log\left(\Delta deaths^A + 1\right) + \beta_4 log\left(\Delta deaths^A + 1\right)^2 \\
&+ \beta_5\left[log\left(\Delta illnesses^A + 1\right) log\left(\Delta deaths^A + 1\right)\right] + \beta_6(0) + \epsilon^A
\end{aligned}
\tag{2.1}
$$

where β_6 is the lump of utility associated with the status quo alternative, which involves no policy. For Policy A in equation (2.1), of course, there is no status-quo utility increment/decrement.[10] Under the status quo alternative, in the absence of the policy, there will be no cost, but also no changes in the baseline numbers of illnesses or deaths, so that indirect utility will be determined simply by the individual's income and any utility associated with the status quo:

$$V_i^N = \alpha\left(Y_i\right) + \beta_6(1) + \epsilon^N \tag{2.2}$$

Thus, in a pairwise choice between just Policy A and No Policy (N), the utility-*difference* will depend on the cost of the policy, the expected cases of illness avoided, and the expected

9. A shifted logarithmic transformation adds one to the argument of the log function, ensuring that the function takes a value of zero when the argument is zero. An alternative to our specification in equation (2.1 where utility is expressed in terms of *reductions* in illnesses and deaths (which should be "goods") would be to use *absolute* illnesses and deaths, with and without each policy (which would imply that each attribute was a "bad", likely to confer a negative marginal utility).

10. If the interaction term in equation (2.1 does not have a statistically significant coefficient, the level curves of the indirect utility function would to be circular, rather than elliptical.

number of premature deaths averted under the chosen policy:

$$\begin{aligned}
V_i^A - V_i^N = {} & \alpha \left(-c_i^A\right) \\
& + \beta_1 log \left(\Delta illnesses^A + 1\right) + \beta_2 \left[log \left(\Delta illnesses^A + 1\right)\right]^2 \\
& + \beta_3 log \left(\Delta deaths^A + 1\right) + \beta_4 \left[log \left(\Delta deaths^A + 1\right)\right]^2 \\
& + \beta_5 \left[log \left(\Delta illnesses^A + 1\right) \times log \left(\Delta deaths^A + 1\right)\right] \\
& + \beta_6(-1) + (\epsilon^A - \epsilon^N)
\end{aligned} \tag{2.3}$$

Note that if baseline levels of illness or death are to affect utility within this particular framework, they need to be interacted with the changes in the numbers of illnesses and deaths under each policy. To limit the complexity of the specification, we will allow baseline illnesses to shift only the marginal utility of reductions in the number of illnesses, and allow baseline deaths to shift only the marginal utility of reductions in the number of deaths. We also allow the baseline marginal utility parameters in the equation (3) to vary with selected sociodemographic variables for each respondent's county. The coefficients on these interactions capture the extent to which these county-level variables affect the underlying preference parameters $\beta_1, ..., \beta_6$. As is typical, we assume that the marginal utility of net income is approximately constant.[11]

11. This description of the basic model assumes pairwise choices between a single policy and the status quo. In the data, however, respondents are asked to choose between a pair of policies and the status quo alternative. The model in equation (2.3) can readily be generalized to accommodate three-way policy choices.

2.4 Results

2.4.1 Identifying important dimensions of heterogeneity: LASSO Estimation

Table 2.2 provides parameter estimates for a set of three increasingly complex specification. After employing our shifted log transformations, Model 1 in Table 2.2 is even simpler than equation (2.3), being linear and additively separable. Model 2 is a homogeneous-preferences model that is consistent with equation (2.3), involving some key interactions between the basic attributes. Model 3 permits preferences to vary systematically with the characteristics of each respondent's county (circa the 2003 time period). To identify the subset of more-important sources of systematic heterogeneity in policy preferences across counties, we force the basic attributes into the model. We then interact each of the basic with all of the available county-level data and subject just these interaction terms to LASSO variable selection.
characteristics and select the most important interactions using LASSO model estimation.[12] We use a LASSO model with 10-fold cross-validation to yield the variables and interactions in the model specification in section 3. We then use the LASSO-selected variables in a conditional logit model with individual fixed effects to produce both the parameter means and their asymptotic variance-covariance matrix for use in deriving WTP estimates for our 2020 WTP simulation.[13] Table 2.2 provides the preliminary results based on LASSO-selected variables and binary choice model estimation.

12. Package LASSO algorithms for logit models appear to be limited to binary choice specifications. We assume that the same set of preferences underlie our three-way choices as would drive the two pairwise choices that would be consistent with these three-way choice would remain the preferred alternatives if it was to be paired with either of the two non-chosen alternatives in pairwise choices.

13. Double Lasso: Use machine learning Lasso algorithm to select the variables. Then take the selected variables back into the condition logit regression with individual fix effect, in this case.

Table 2.2: WTP Model Estimation

	parsim.	homogen.	lasso
Preferred alternative in choice scenario			
Monthly cost	-0.00293***	-0.00277***	-0.00477**
... $\times$ (Affected pop/1000)$^{-1}$		-0.00210	-0.00395
... $\times$ Δ unempl (v last month)			0.00333*
Log(Δ ill/mo/cap + 1)	0.00461***	0.00535***	-0.0000169
... $\times$ County prop. aged 65+			-0.0466**
... $\times$ County prop. Asian			-0.0300*
... $\times$ PM 2.5 concentration			0.000631***
... $\times$ (Affected pop/1000)$^{-1}$		-0.00163	-0.000891
... $\times$ Rep/(Dem+Rep), Pres. Election			0.00971**
... $\times$ Log(Δ ill/mo/cap + 1)	-0.0000135***	-0.0000121***	-0.0000116***
... $\times$ Log(base ill/mo/cap + 1)		-0.0000672	-0.000000267
... $\times$ Log(Δ dth/mo/cap + 1)	-0.0000281*	-0.0000274	-0.0000395***
Log(base ill/mo/cap + 1)	-0.000936	0.000739	
... $\times$ County prop. Black			0.00192
... $\times$ County prop. Asian			0.0608
... $\times$ County prop. Hispanic			0.0310**
... $\times$ County prop. uninsured			-0.0395
... $\times$ Δ unempl (v last month)			-0.00236
Log(Δ dth/mo/cap + 1)	0.0110***	0.0110***	0.0224***
... $\times$ County prop. Asian			-0.0583
... $\times$ County prop. Hispanic			-0.00997
... $\times$ (Affected pop/1000)$^{-1}$		-0.000299	-0.00134
... $\times$ County fractional. (0-1)			-0.0150*
... $\times$ Log(base dth/mo/cap + 1)	-0.00468***	-0.00289**	-0.00235
Log(base dth/mo/cap + 1)	-0.000605	-0.0967*	
... $\times$ County prop. Black			-0.146
... $\times$ County prop. Asian			0.0778
... $\times$ (Affected pop/1000)$^{-1}$		0.379**	0.320
... $\times$ Log(base dth/mo/cap + 1)		-0.00129*	-0.00201**
... $\times$ Log(duration)		0.0230***	0.0111*
Log(duration)	-0.139***	-0.153***	
... $\times$ County prop. aged 18-24			-0.0572
... $\times$ County prop. aged 25-44			-0.199
... $\times$ County prop. aged 65+			-0.0630
... $\times$ County prop. Asian			-0.289
... $\times$ County prop. Hispanic			-0.128
... $\times$ (Log(med.inc/100K))^2			0.0104
... $\times$ Δ unempl (v last month)			-0.0673**
1=Any policy	0.961***	1.015***	0.655**
... $\times$ County prop. Black			-0.374
... $\times$ County fractional. (0-1)			0.973
... $\times$ 1=Saw baseline info	0.00235*	0.00248**	0.00239**
... $\times$ 1=Saw baseline info	0.147***	0.114***	0.0948**

continued...

continued...

2.5 Benefit transfer: 2020-21 WTP to avoid COVID-19 illnesses and deaths in each month

In contrast to the wide variety of choice scenarios presented to respondents in our 2003 study sample, we wish to use our estimated model to simulate WTP in 2020-21 by a representative individual in each U.S. county to prevent the numbers of COVID-19 cases and deaths recorded in each month for which data are available. We wish to simulate a measure of the household costs that people would have been willing bear, if a public health policy in 2020-21 could reduce new illnesses and baseline deaths to zero. COVID-19 is infectious, so until all of the cases are eliminated, people cannot return to a normal life. Table 2.3 shows the hundreds of new COVID cases each month across the entire U.S., along with the thousands of the reported deaths. The policy we wish to simulate for 2020-21 is the reduction of these baseline cases and deaths to zero.

Table 2.3: Descriptive statistics, 2020-21 COVID-19 new Cases and Deaths (in hundreds), county-level.

Month	**03/2020**	**04/2020**	**05/2020**	**06/2020**	**07/2020**
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
COVID-19 cases	0.58	2.74	2.24	2.62	5.97
	4.91	17.28	11.72	14.05	31.05
COVID-19 deaths	0.014	0.18	0.13	0.07	0.08
	0.16	1.61	0.79	0.39	0.44
Month	**08/2020**	**9/2020**	**10/2020**	**11/2020**	**12/2020**
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
COVID-19 cases	4.54	3.74	5.84	13.50	19.77
	28.01	12.01	16.50	40.97	83.00
COVID-19 deaths	0.09	0.07	0.07	0.11	0.23
	0.46	0.29	0.19	0.30	0.71
Month	**1/2021**	**2/2021**	**3/2021**	**4/2021**	**5/2021**
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
COVID-19 cases	19.11	7.33	5.51	6.05	2.82
	85.75	25.84	19.96	20.46	8.79
COVID-19 deaths	0.29	0.22	0.12	0.08	0.05
	1.42	1.06	0.57	0.36	0.21
Observations	3142	3142	3142	3142	3142
3142					

2.5.1 *Preferences for a representative individual in each county, for each county-month of the 2020-21 pandemic*

In lieu of each individual respondent's characteristics, our estimating specification explains the choices of individuals using only the characteristics of the county in which the individual resides. The distribution of characteristics of the U.S. counties used in simulating our WTP amount for 2020 are shown in Table 2.4.

Table 2.4: Descriptive statistics, 2003 estimating sample vs 2020 simulation sample, county-level heterogeneity

	2003 Study Sample[a]		2020 Policy Sample[b]	
	mean	(sd)	mean	(sd)
County prop. aged 0-17	0.254	(0.0289)	0.22	(0.033)
County prop. aged 18-24	0.096	(0.029)	0.086	(0.033)
County prop. aged 65+	0.129	(0.038)	0.193	(0.046)
County prop. White	0.773	(0.168)	0.835	(0.161)
County prop. Black	0.114	(0.129)	0.091	(0.146)
County prop. Asian	0.029	(0.044)	0.013	(0.026)
County prop. Hispanic	0.105	(0.137)	0.093	(0.138)
County prop. Native American	0.008	(0.026)	0.015	(0.058)
County prop. uninsured	0.160	(0.057)	0.114	(0.050)
County fractionalization (0-1)	0.383	(0.219)	0.280	(0.196)
Rep/(Dem+Rep), Pres. Election	0.511	(0.121)	0.667	(0.161)
County Med. Income	34766.67	(9392.89)	37219	(10592.8)
Hospitals per 10000 population	0.221	(0.338)	0.56	(0.876)
County prop. college degree	0.509	(0.104)	0.524	(0.107)
County overall Poverty	0.124	(0.0433)	0.144	(5.65)
County pm25	11.066	(2.623)	6.59	(1.47)
County prop. Fair or Poor Health	0.158	(0.043)	0.179	(0.047)
Avg. Num. Physically Unhealthy Days	3.566	(0.72)	3.99	(0.6.95)
Avg. Num. Mentally Unhealthy Days	3.475	(0.682)	4.183	(0.594)
County prop. Smoker	0.203	(0.046)	0.175	(0.035)
County prop. Obesity	0.272	(0.0404)	0.33	(0.054)
County prop. Excessive Drink	0.165	(0.04)	0.175	(0.0317)
Primary Care Physicians Rate	0.906	(0.442)	0.543	(0.034)
Preventable Hospitalization Rate	70.7	(19.4)	48.67	(18.28)
Δ unempl (Jun. '03 vs previous month)	0.678	(0.408)		
Δ unempl (Mar. '20 vs previous month)			0.467	(0.934)
Δ unempl (Apr. '20 vs previous month)			7.663	(4.928)
Δ unempl (May '20 vs previous month)			-2.119	(2.451)
Δ unempl (Jun. '20 vs previous month)			-1.887	(2.227)
Δ unempl (Jul. '20 vs previous month)			-0.594	(1.523)
Δ unempl (Aug. '20 vs previous month)			-1.179	(1.354)
Δ unempl (Sep. '20 vs previous month)			-0.682	(1.258)
Δ unempl (Oct. '20 vs previous month)			-0.649	(1.092)
Δ unempl (Nov. '20 vs previous month)			0.0454	(1.052)
Δ unempl (Dec. '20 vs previous month)			0.2093	(1.024)
Δ unempl (Jan. '21 vs previous month)			0.4107	(1.058)
Δ unempl (Feb. '21 vs previous month)			-0.182	(0.593)
Δ unempl (Mar. '21 vs previous month)			-0.375	(0.570)
Δ unempl (Apr. '21 vs previous month)			-0.5905	(0.573)
Δ unempl (May. '21 vs previous month)				
Observations	1466 respondents			3142 counties

[a] Descriptive statistics, across respondents, for the counties in which they reside;

[b] Descriptive statistics across 3142 counties or other county FIPS geographic areas.

2.5.2 *Parametric bootstrap estimates of predicted WTP in each county-month*

We estimate our models in utility space, so the calculations of WTP involve dividing other coefficients by the estimated marginal utility of net income, where all the maximum likelihood parameters in the model are distributed asymptotically joint normal. We used a large number of draws from the joint distribution of the parameters to calculate the predicted distribution of WTP to reduce to zero all COVID cases and deaths in each county-month, with the distribution being determined by the noise in the parameters' estimates. Given that there were no opportunities for respondents to record a negative willingness to pay, we interpret negative calculated point values of WTP values as zero, using a Tobit-like interpretation. We calculate monthly average WTP to reduce to zero all cases and deaths from COVID-19 from March 2020 to February 2021 across all counties in the U.S.

Table 2.5 shows for a representative county resident across all U.S. counties' average WTP to reduce the risk of COVID-19 from March 2020 to February 2021. These monthly estimates vary by the changes of monthly new cases, deaths, and unemployment rate at the county level. May, July, August, September, and October 2020 had relatively high WTP to reduce new COVID cases and deaths compared to other months. These monthly WTP amounts were larger during the first wave of the pandemic spring and summer. The average monthly WTP decreased from November 2020 to Feb 2021. Figure 3 shows the progression in the distribution of U.S. counties' WTP to reduce the risk of COVID-19 from March 2020 to February 2021. These distributions (each month from Mar 2020 to Feb 2021) are all right-skewed.[14] The dashed vertical lines are the average WTP to reduce the risk of COVID-19 each month across representative residents of all counties. August 2020 had the highest average WTP of all counties (90 percentile).

14. Plots include only the lowest 90 percent of cases, to prevent the distributions from being bunched near zero.

Table 2.5: County Representative Individual's
(monthly) WTP to Reduce COVID-19 cases and death through 2020-21

Month	**03/2020**	**04/2020**	**05/2020**	**06/2020**	**07/2020**
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
WTP(dollars)	111.19	954.69	230.93	255.78	1084.63
	(483.69)	(5902.04)	(989.29)	(1014.05)	(8863.67)
Month	**08/2020**	**09/2020**	**10/2020**	**11/2020**	**12/2020**
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
WTP(dollars)	377.38	453.63	532.97	636.93	693.35
	(1228.37)	(2068.25)	(1834.24)	(2278.77)	(2445.96)
Month	**01/2021**	**02/2021**	**03/2021**	**04/2021**	**05/2021**
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
WTP(dollars)	679.62	500.20	432.96	433.46	366.32
	(2830.37)	(2038.80)	(1676.48)	(1691.01)	(1202.98)
Observations	3142	3142	3142	3142	3142

[c] The monthly median WTP to reduce COVID-19 cases and deaths are: Mar20 (0), Apr20 (321.12), May20 (0), Jun20 (6.82), Jul20 (384.86), Aug20 (113.33), Sep20 (164.62), Oct20 (204.56), Nov20 (309.94), Dec20 (342.14), Jan21 (327.46), Feb21 (232.55), Mar21(189.10), Apr21 (180.07), May21(163.82);

Figure 2.2: Benefit Transfer 2020 - 2021

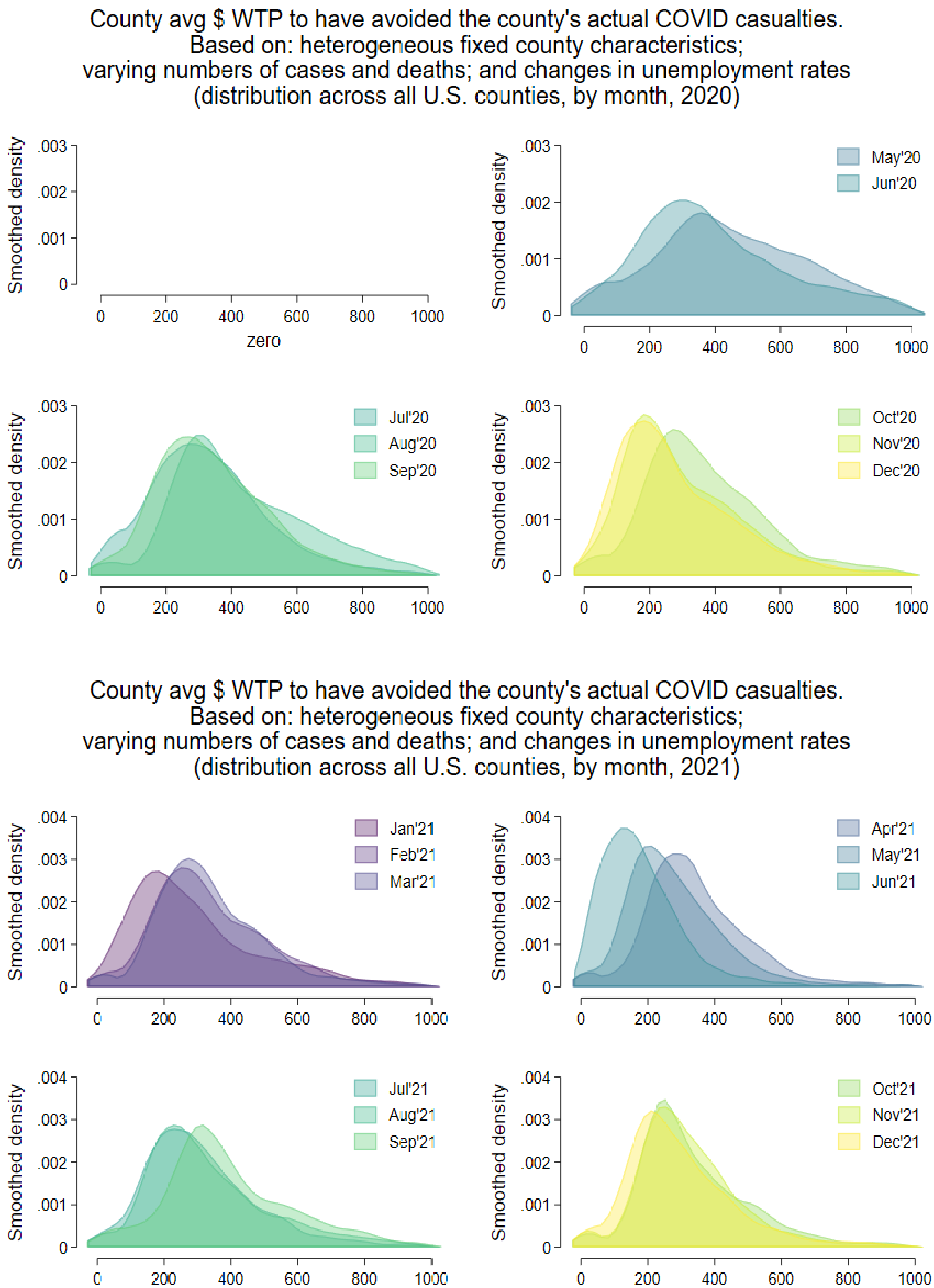


Figure 2.3: Example: WTP to avoid cases and deaths December 2021

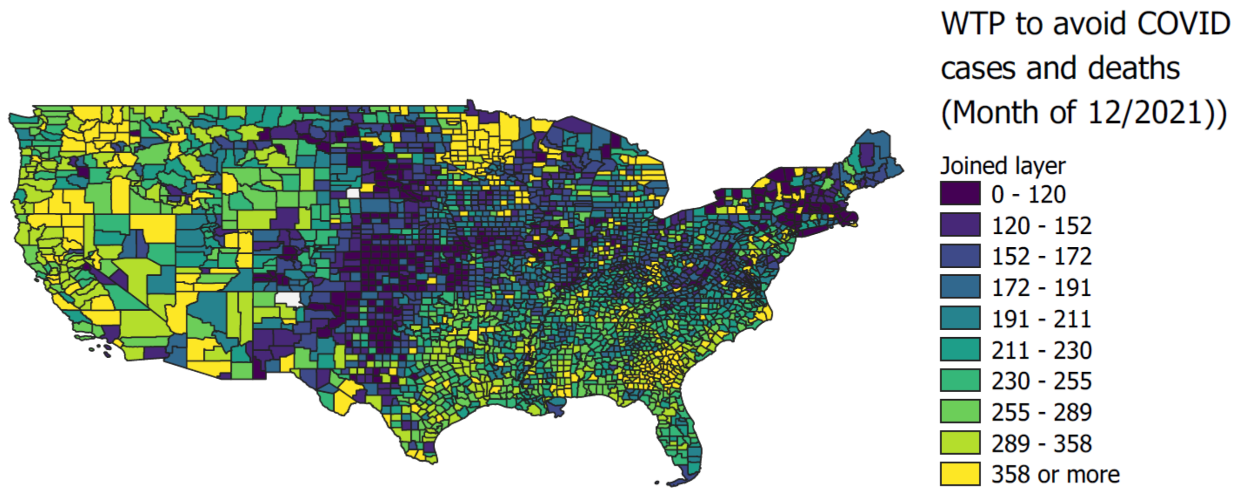
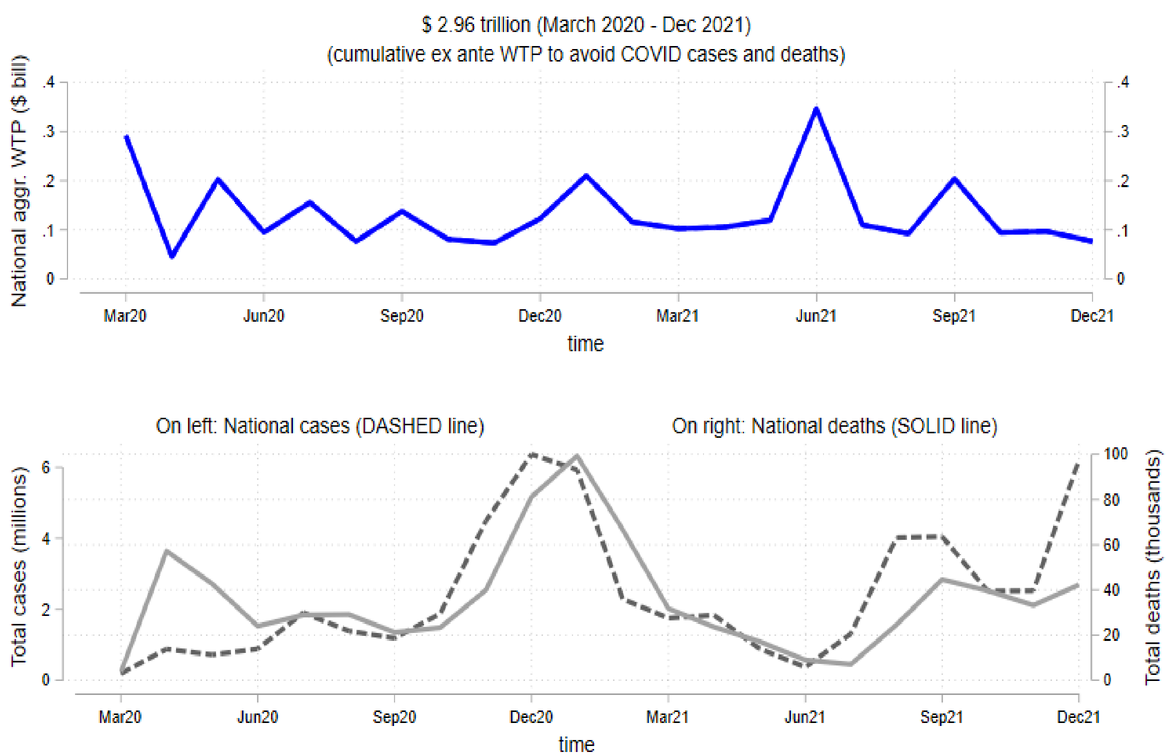


Figure 2.4: Monthly national aggregate WTP. Cumulative $3T



2.5.3 Scaling to monthly total WTP amounts to avoid COVID-19 cases and deaths

Our benefits transfer exercise predicts monthly WTP amounts for a representative adult in each U.S. county over the course of the pandemic from March 2020 through February 2021. It is possible to scale these WTP amounts to a national average for all U.S. adults by weighting these county averages by the population of adults aged 18 and over in each county. We use county populations aged 18 and over, according to the 2019 5-year ACS estimates, to build a set of weights that sum to the overall number of counties. To get a rough estimate of the national average WTP in each month, we multiply the WTP point estimate for each county in that month by the corresponding weight, sum, and divide by the number of counties to yield average WTP that can be applied for all 251 million adults in the U.S.

Then the aggregate WTP across the whole population of U.S. adults is just this national average times 251 million. These totals, by month, are, for 2020: March (123 billion), April (606 billion), May (118 billion), June (125 billion), July (402 billion), August (104 billion), September (130 billion), October (160 billion), November (221 billion), December (253 billion); and for 2021: January (262 billion), February (192 billion), March (174 billion), Apr (179 billion), and May (154 billion). The cumulative U.S. national WTP of all adults over 18 through March 2020 to May 2021 is about 3 trillion dollars.

It may be tempting to compare this aggregate WTP amount to the sizes of the various "stimulus packages" provided during the pandemic. However, the context for the trade-offs between policy cost and reductions in cases and deaths, in our study sample, did not include an economic shutdown or excessive job losses or business failures. The various stimulus packages during the pandemic were intended to compensate for the collateral economic damages caused by the pandemic, rather than simply to reduce cases and deaths. Our 3 trillion dollar estimate of WTP for March 2020 through Apr 2021 should probably be interpreted as people's *net* WTP to reduce cases and deaths, after the compensation for other pandemic costs represented by the various stimulus programs.

2.5.4 Systematic heterogeneity in predicted WTP to Reduce COVID-19 cases and deaths

We first employ the latent class model uses policy attributes in the utility-difference function, but introduce county-level covariates for each respondent to explain each person's probability of preference-class membership in 2003. In our latent class model, we find three distinct classes of people driven by different features of the preventative public health policies. We label these three preference classes as "cost-conscious," "comprehensive," and "indifferent-or-altruistic."[15] Then, we explore the systematic heterogeneity in predicted WTP to Reduce COVID-19 cases and deaths in our 2020-21 simulation. We find that the counties with a population where the proportion of people aged below 45 is lower than the national median have a higher WTP to reduce the risk of COVID-19, especially when entering the winter season (Nov 2020 to Feb 2021). For different ethnic and political groups, we find that for our policy sample in2020-21, counties with a higher proportion of Black residents greater than the median have a higher WTP to reduce the risk of COVID-19 than White counties. For political affiliation, we find that Democrat-dominated counties have a higher WTP through March 2020 to April 2021. For the health access level, the higher health-access counties with the primary care physicians rates and preventable hospitalization rates above the median rates among all counties have a higher WTP to reduce the risk of COVID-19 through public health policies and interventions. And lastly, for income level, the WTP of higher-income counties is higher than the lower-income counties.[16]

15. See Latent class analysis detail in Appendix C2.

16. See heterogeneity analysis details in Appendix C3.

2.6 Conclusions

This paper models people's willingness to bear the costs of public health policies to reduce health risks to their communities. We re-purpose an existing 2003 survey of public health policy preferences, omitting the available individual-level characteristics for the 2003 sample, and expanding the variety of county-level characteristics employed. Almost 18 years have passed since the original nationwide survey. However, the U.S. EPA is still making use of a suite of empirical estimates of people's willingness to trade off money for mortality risk reductions—the so-called "value of a statistical life"—from the 1970s, 1980s, and 1990s, after scaling these numbers up to current dollars. This suggests an implicit assumption that people's preferences with respect to mortality risks are highly stable over time.

We have noted several examples of stated-preference choice experiments concerning COVID-19, conducted very early during the current pandemic. However, none of these contemporaneous studies has elicited such detailed data from its survey respondents.

In our re-analysis of the 2003 survey data, we use both a latent class model and a conditional logit model with heterogeneous preferences (where variable selection is based on double LASSO estimation). In our latent class model, we identify three distinct preference classes in our sample: "cost-conscious," "comprehensive," and "indifferent-or-altruistic." In our conditional logit model with heterogeneity in preferences, we allow for heterogeneity only with county-level demographic characteristics and other contextual variables, rather than any individual-specific characteristics. We first use a machine learning algorithm—double LASSO—to winnow down all of the possible interaction terms between the policy attributes and the county-level characteristics that are available for both the 2003 context and the 2020 context.

Finally, we simulate WTP amounts during the COVID-19 pandemic by transferring our fitted model from our "study" sample in 2003 to our "policy" sample consisting of all U.S. counties in 2020. We replace the "cases prevented" and "premature deaths prevented" attributes for the randomized public health policies described in the original stated-preference choice experiments with the actual county-level monthly COVID-19 cases and deaths during March 2020 through February 2021. We also update all the county-level characteristics from the 2003 era to the 2020 era. We interpret predicted WTP amounts in 2020-21 as WTP for a representative adult in every U.S. county. To illustrate the heterogeneity implied by our model, we split the set of all U.S. counties into different subgroups to explore how their predicted WTP to have avoided COVID-19 cases and deaths has varied differently across the months of the pandemic. The heterogeneity in WTP amounts within a given month stems from all the different county characteristics that interact with the policy attributes. The main drivers of the month-to-month variation are the actual cases and deaths in each county and the change in unemployment in that county since the previous period, since these are the only county characteristics for which the values change over time.

We find that people in counties with younger populations have higher WTP to reduce the risk of COVID-19 than people in counties with older populations. There are also differences across different ethnic mixes across U.S. counties, driven partly by different preferences across these groups, but also by different case and death rates, and the different patterns of unemployment across thes counties over time. Republican-dominated counties have lower WTP than Democratic counties. Counties with higher levels of health-access have higher WTP to reduce the risk of COVID-19 compared to counties with lower levels of health-access. The counties that have lower income (or suffer a higher poverty rate) are less willing to pay the cost to reduce the risk of COVID-19 compared to the counties with a higher income (lower poverty rate).

Our estimated aggregate WTP across the U.S. population from March 2020 to April 2021 is about 3 trillion dollars. In April 2020, the U.S. had the highest total WTP to reduce cases and deaths of COVID-19 because of the drastic increase in new COVID-19 cases, deaths, and unemployment during the month. The large aggregate WTP persisted for the rest of

2020 and started decreasing in February 2021 as the pandemic is more under control because of the vaccination and the stabilized unemployment numbers.

Information about the public's willingness to bear the costs of pandemic control will be important in the event of future pandemics, or even in the event that the current pandemic continues longer than expected. An understanding of systematic differences in this willingness to pay across counties with different sociodemographics can potentially help county-level governments decide upon locally appropriate and acceptable public health interventions.

CHAPTER 3

THE EFFECT OF INTERNATIONAL RECYCLING POLICIES ON THE U.S. RECYCLING INDUSTRY

3.1 Introduction

Recycling is the process of collecting and processing materials that would otherwise be thrown away as trash. The processed materials can then be converted into new products. Recycling can protect the environment by decreasing various types of pollution such as hazardous emissions from incineration, the dumping of plastic into the ocean, and contributions to landfills that generate methane and contribute to global climate change.

Although recycling behavior is often viewed as a form of environmental social responsibility, it can also be influenced by economic factors. The prices of recyclable materials depend on the supply and demand in the market. The recycling industry in the U.S. has relied on international markets more than the domestic markets in past decades. Many states and cities have extensive municipal programs for the collection and sorting of recyclable materials but a limited domestic market. A lack of manufacturing companies that can make use of the reprocessed materials explains the weakness of domestic demand. In 2015, the U.S. exported 4.5 billion pounds of scrap plastic for recycling, over half of which was sold to China.[1] China developed a vast industry to recover some valuable types of plastic and use them to make new products that could be sold back to the U.S. The rest of the recyclable materials, because they were too contaminated to be useful, ended up in landfills in China or were dumped in the ocean.

1. **McCormick, Erin** 2019."Where does your plastic go? Global investigation reveals America's dirty secret." The Guardian, June 17. https://www.theguardian.com/us-news/2019/jun/17/recycled-plastic-america-global-crisis

The international market for recyclables has changed drastically over the past three years. China, historically the largest recyclable scrap importer in the world, began in 2013 to restrict the importation of solid waste that contains recyclable materials through a series of policies. In July 2017, China announced the National Sword policy that bans the importation of certain types of solid waste, including plastic, paper, and metal scrap. The policy began officially on January 1, 2018. Policy changes in China caused a significant diversion of U.S. scrap exports to other South and Southeast Asian countries. Recyclers operating in Indonesia, Thailand, Vietnam, and Malaysia bought, but were quickly overwhelmed by, the sheer volume of materials that China no longer accepted.[2] From 2018 to 2020, many other countries began to require more-stringent inspection of scrap imports, to limit scrap-importing licenses, and to ban certain types of scrap imports entirely. In addition to increasingly restrictive policies from individual countries, the global recycling market has also been affected by an agreement signed in compliance with the Basel Convention.[3] The approval of the Basel Convention amendments concerning plastic waste can be expected to have long-term effects on the flow of recyclable plastics to these countries as of the January 1, 2021 effective date of these amendments.

As a consequence of this series of changes in international policies, recycling costs have increased for many cities in the U.S. With fewer buyers, recycling companies are attempting to recoup their losses by charging cities more—in some cases four times as much as they used to charge. With weak market demand, the prices of scrap materials that serve as inputs to the recycling industry have dropped dramatically. According to Fastmarket RISI, the price of Old Corrugated Containers (OCC), previously one of the most popular recyclables, dropped

2. **Parker, Laura** 2018."China's ban on trash imports shifts waste crisis to Southeast Asia." National geographic, Nov 16. https://www.nationalgeographic.com/environment/2018/11/china-ban-plastic-trash-imports-shifts-waste-crisis-southeast-asia-malaysia/

3. **Basel Convention** An international treaty that was designed to prevent the transfer of hazardous waste from developed countries to less developed countries.

from around \$140/ton in 2017 to around \$40/ton in 2019. The price of unsorted mixed paper scrap dropped from \$95/ton to \$2.5/ton. The value of mixed plastic scrap, which most of the importing countries have recently decided to ban, dropped from \$20/ton to -\$10/ton. As recycling profits hit bottom and their costs skyrocket, municipalities are facing decisions about whether to raise taxes, cut other municipal services or abandon recycling efforts they have been making since the recycling movement began in about 1970.[4]

This proposed research will focus mainly on the recycling industry in California. As the most populous U.S. state and the largest sub-national economy in the world, California has been the largest recyclable waste exporter in the U.S. in past decades. Since 2018, many recycling centers and material recovery facilities in California have closed as their profits have dwindled. According to the California Legislative Analyst's Office (LAO), the state government has drastically increased the budget for recycling support to reimburse the industry for their losses. Lawmakers in California, collaborating with another eight states in the U.S., are pushing Extended Producer Responsibility (EPR) to require producers to reduce plastic packaging or use recyclable materials. Although the recycling industry has stalled, residents and businesses continue to consume and generate more waste than ever before. Haque et al. (2021) find that waste volumes surged during the COVID-19 pandemic because of increased demand for single-use plastics and personal protective equipment, and increased volumes of disposable components of medical equipment.

With this background in mind, my goal for the proposed project is twofold; in the short run, I will evaluate the effects of a series of changes in international recycling policies on total exports of recyclables, their prices, and eventually the price elasticity of supply of recyclables in California. Over a longer time horizon, I plan to use my model to predict

4. **Corkery, Michael** 2019."As Costs Skyrocket, More U.S. Cities Stop Recycling." The New York Times, Mar 16. https://www.nytimes.com/2019/03/16/business/local-recycling-costs/

price elasticities of supply for recyclables that can be extended to all states in the U.S. based on a machine learning algorithm employed with my California data. The price elasticity of supply of recyclables is a central parameter to estimate for evaluating various policies—e.g., tax credits to incentivize domestic market demand for recycling materials, bans on the use of certain types of hazardous recyclable materials, and an enforcement of a new EPR requirement designed to shift the costs associated with the recycling products so that they are borne less by consumers and more by producers, since producers actually have control over product design. I will use a quantitative model to evaluate and compare these policies meant to address the current recycling market inefficiency.

In main innovations in my research will include (1) the first use of multiple event study approach to analyze the effects of new restrictions on international trade in recyclables; (2) an assessment of how the California recycling industry reacts and adapts to the series of international policies by measuring the implied price elasticity of the supply of recyclables; and (3) the calibration of a structural model to permit consideration of a number of policy counterfactuals.

3.1.1 Relevance to the Existing Literature

Only a few existing papers have researched recycling costs and optimal recycling rates. Bohm et al. (2010a) finds that the economies of scale for recycling eventually disappear at a high level of recycling. Kinnaman (2014) study the socially optimal recycling rate in Japan and find that average social costs are minimized when recycling rates are well below observed and mandated levels. This result indicates that Japan and perhaps other developed countries might be setting inefficiently high recycling goals. Higashida and Managi (2014) find that recyclable waste imports by a developing country from developed countries increase with expanding industrial activities and economic growth. Lee et al. (2018) study the recycling policies in China between 2006 and 2018 and find that countries such as China, with a trade surplus, systematically import more scrap goods. This trade surplus also translates into more health hazards associated with these imported wastes. The 2018 ban on importation of scrap into China will slightly decrease China's trade surplus from 4% to 3.96%. The pollution associated with China's recycling industry is expected to decrease by about 7%-10%. Overall, China's ban on scrap imports has the potential to improve social welfare in China by about 0.38%, despite its consequence of raising production costs. Many news articles have talked about the likely effects of the new recycling import policies of various countries on the U.S. recycling market. As yet, however, there appears to have been no rigorous empirical analysis of the consequences of these policies from the perspective of the U.S. recycling industry.

3.1.2 Data

I identified three primary data sources for this research. First, I used data provided by UN Comtrade Database (2021), which include the total value of the U.S. monthly plastic scrap export data by partner countries from 2010 to 2020. I will also use the total value and weight from the UN Comtrade Database (2021) to calculate the unit price of the plastic scrap by month. Second, I used Center for Research and Expertise on the World Economy (2021a) for gravity model control variables including distance between country pairs, GDP, trade balance, and etc.

Third, in addition to the CEPII gravity datasets, I selected an additional set of predictor variables to add to the model which, based upon our research and reflections upon the international plastic scrap trade, I understood to be potentially influential in determining the ultimate trade value of total plastic scrap exports from the United States. These variables are Export/Import price index (End Use / All Commodities) from U.S. Bureau of Labor

Statistics, Bilateral tariffs (UN Trade Analysis Information System (TRAINS)) from Trade Analysis Information System (TRAINS) World Bank (2021), Commodity Price Index (for energy, including crude oil, fuel, etc.) from International Monetary Fund (IMF)Commodity Price Index (2021), International Exchange Rate (all currencies against U.S. dollars) from International Monetary Fund (IMF) (2021), Commodity Terms of Trade (import export) from International Monetary Fund (2021), FOB and CIF plastic scrap unit price, Source from Center for Research and Expertise on the World Economy (2021b), Manufacturing, value added (percentage of the total GDP) from World Bank (WB) World Development Indicator (2021). U.S. monthly unemployment rate from Federal Reserve St. Louis (2021b), and International Crude Oil price from Federal Reserve St. Louis (2021a).

3.2 Two-way Fixed Effect Approach

I will use a two-way fixed effects model to estimate the effect of China's Green Sword policy on the U.S. recyclables export. My analysis requires a strategy to control for unobserved time-varying covariates that coincide with the date(s) of policy implementation, and could bias estimates of the policy's effect. The basic strategy is to use a method analogous to that employed by Davis (2008), Auffhammer and Kellogg (2011), and Burger et al. (2014), where time serves as the treatment assignment variable. I will add a flexible global n^{th}-order polynomial time trend g(t) to my baseline specification:

$$y_{it} = \alpha + \beta D_{it} + \gamma X_{it} + g(t) + \theta Z_i + \nu T_t + \epsilon_{it} \tag{3.1}$$

In this specification, y_{it} is the outcome variables $log(Export_{it}^{Recy})$. I start by studying only one major policy change—China's National Sword policy. The term D_{it} in equation (1) is an indicator variable for whether the policy is being enacted or not for jurisdiction i at time t. X_{it} is a vector of socioeconomic covariates for jurisdiction i at time t. Z_i and T_t are the jurisdiction and time fixed effects. Intuitively, the function g(t) will control for unobserved factors that evolved smoothly over time and are unrelated to the timing of recycling import policies. As long as g(t) is continuous at the policy date, β will correspond to the magnitude of the treatment effects at the policy date.

Next, departing from the baseline specification, I will adopt the approach of Sandler (2014) and extend my specification to a two-way fixed effects events study model. The model specification is

$$y_{it} = \alpha + \sum_{d=-D, d\neq -1}^{D} 1(t - e^i = d)\beta_d + \gamma X_{it} + \theta Z_i + \nu T_t + \epsilon_{it} \tag{3.2}$$

y_{it} ¡/span¿ is trade value of plastic scrap between the U.S. and region i at time t. $1(t-e^i = d)$ is an indicator variable for whether the GS policy is d periods away from being enacted. X_{it} is a vector of socioeconomic covariates for region i at time t. Z_i and T_t are the region and time fixed effects.

3.3 Preliminary Results

Before any rigorous analysis of the policy effect on the U.S. plastic scrap export, I started with some time trends of the U.S. plastic scrap export value to the world and sub-regions from 2010 to 2020. The three dashed lines are three significant policy change dates from China:

- The effective date of the Green Fence policy[5]
- The announcement of the National Sword policy[6]
- The effective date of the National Sword policy[7]

3.3.1 Total Export Trade Value and Netweight

Figure 1 shows that the U.S. recyclable plastic scrap export value decreased, especially after 2018. Figure 2 shows that the Green Fence policy decreased the U.S. total plastic export to China and increased export to other regions, including Other Asian countries, Other North American countries, and Central/South American countries. After the National Sword policy was announced and took effect, most of the decrease in plastic scrap exports to China diverted to other South/Southeast Asian countries. A few of them shifted to African and Central/South American countries. Figure 2 shows the total net weight (kg) of the U.S. recyclable plastic scrap export around the time when the policy was announced and took effect. The time trends of total net weight (kg) across regions are consistent with the time trends of total export value.

5. China's Green Fence policy was started in 2013 aiming to increase the standard of recyclables import inspection.

6. China's National Sword policy was announced in 2017 aiming to ban certain types of scrap materials (including plastic scrap) completely.

7. China's National Sword policy took effect in 2018.

Figure 3.1: U.S. Plastic Scrap Export by Regions

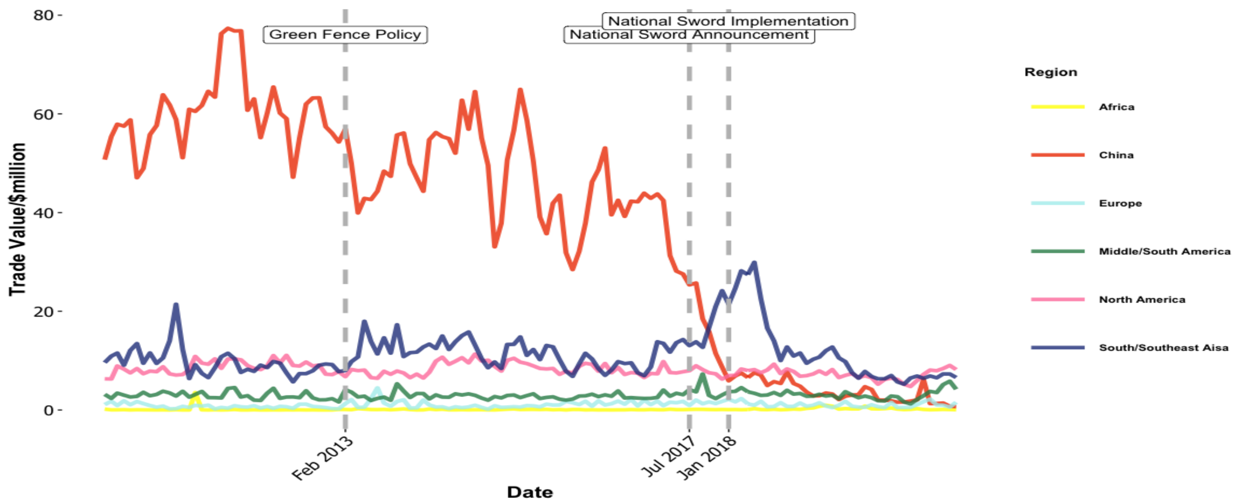


Figure 3.2: The U.S. Total Plastic Scrap Export Value (Dollars) by Geographical Regions.

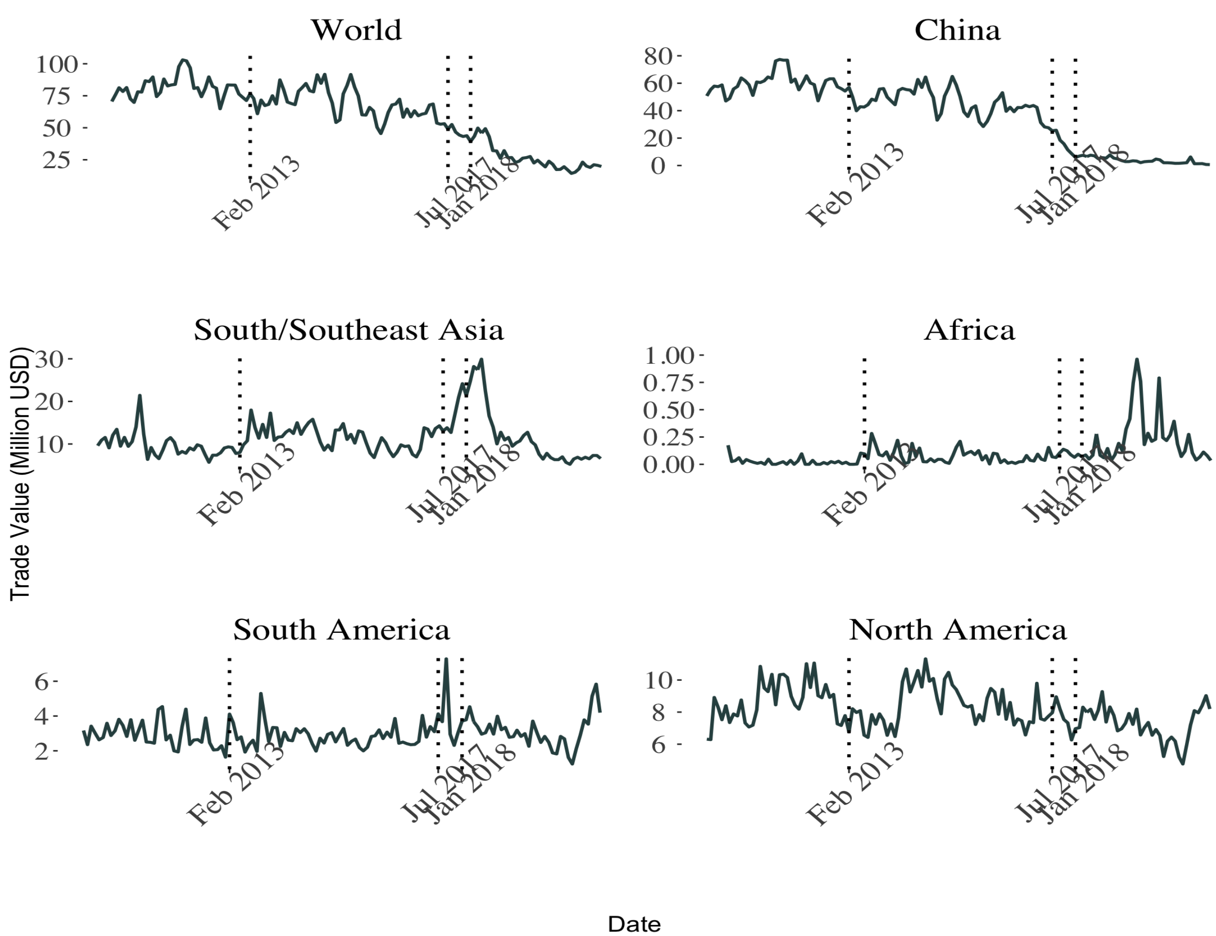


Figure 3.3: The U.S. Total Plastic Scrap Export Weight (kg) by Geographical Regions.

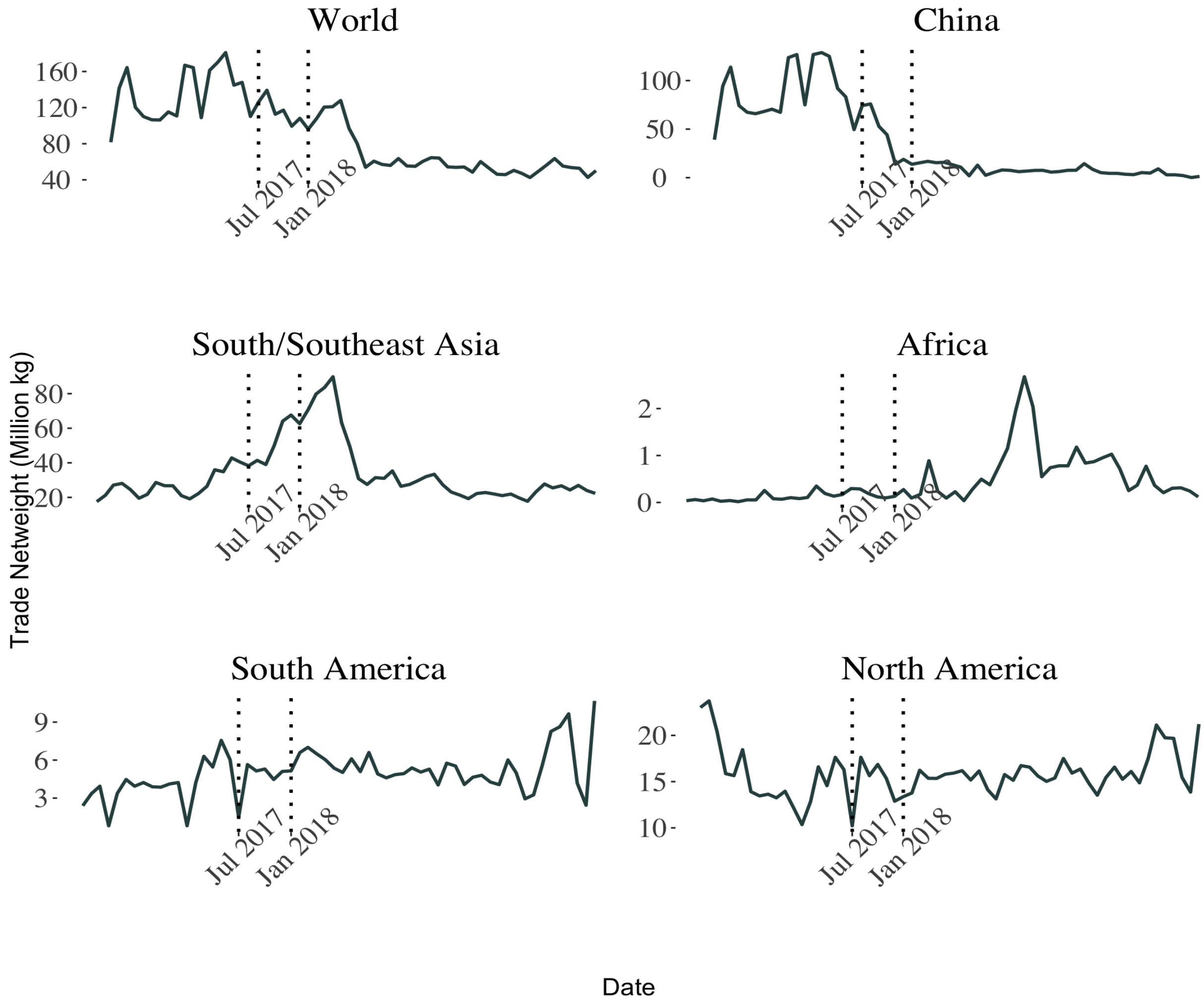


Figure 3.4: The U.S. Total Plastic Scrap Export Value by Geographical Countries/Regions.

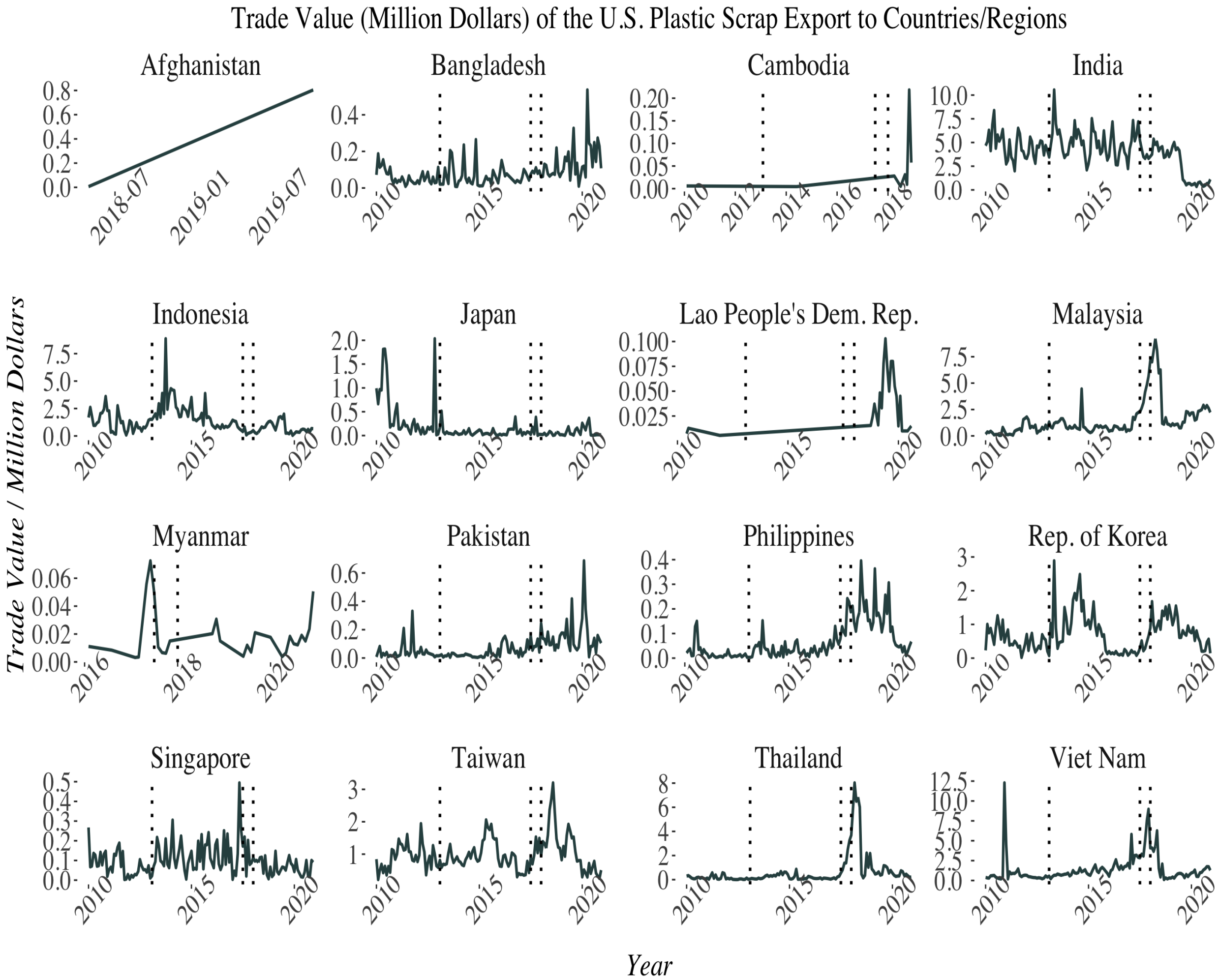


Figure 3.5: The U.S. Total Plastic Scrap Export Value by Geographical Countries/Regions.

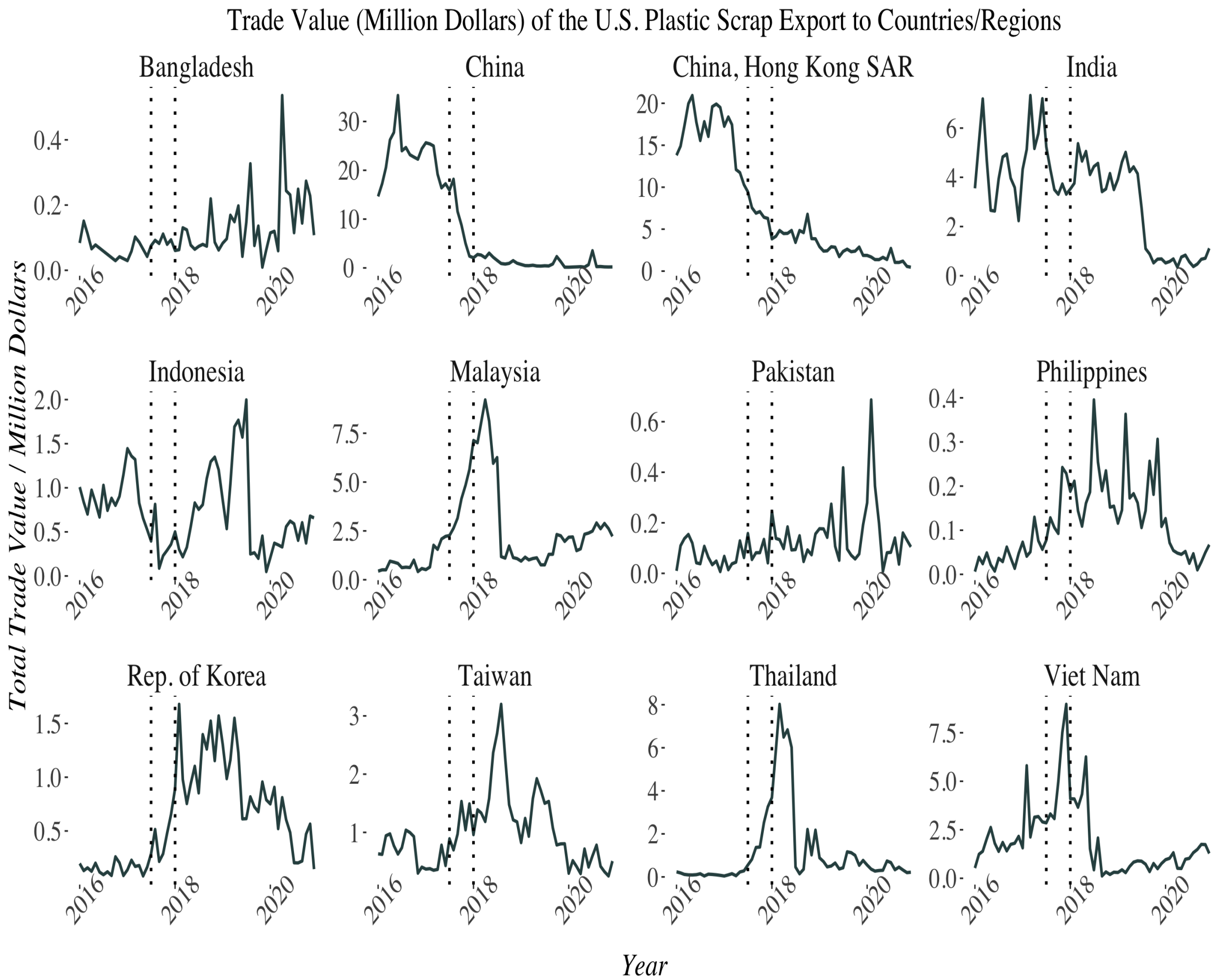


Figure 3.6: The U.S. Total Plastic Scrap Export Netweight by Geographical Countries/Regions.

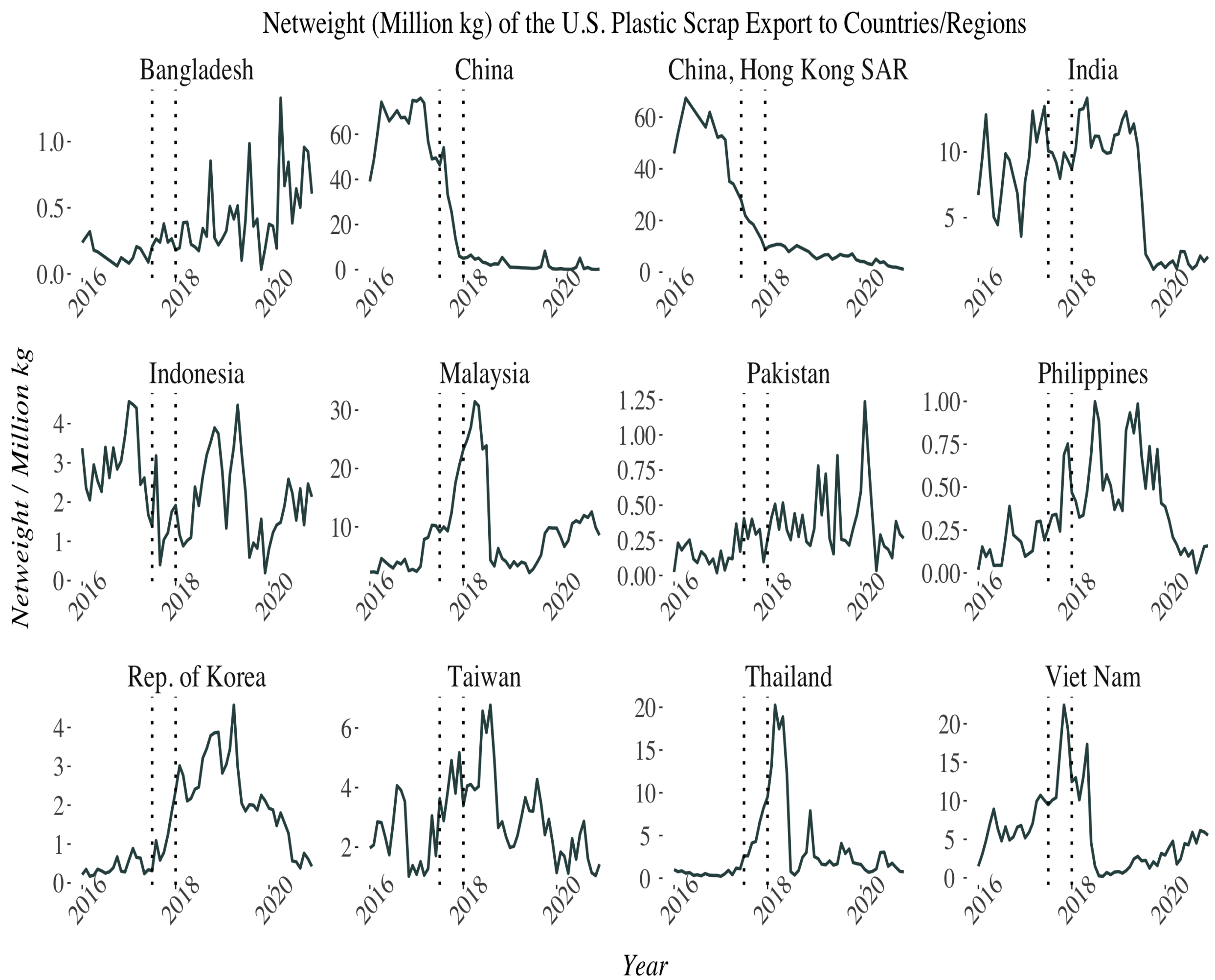
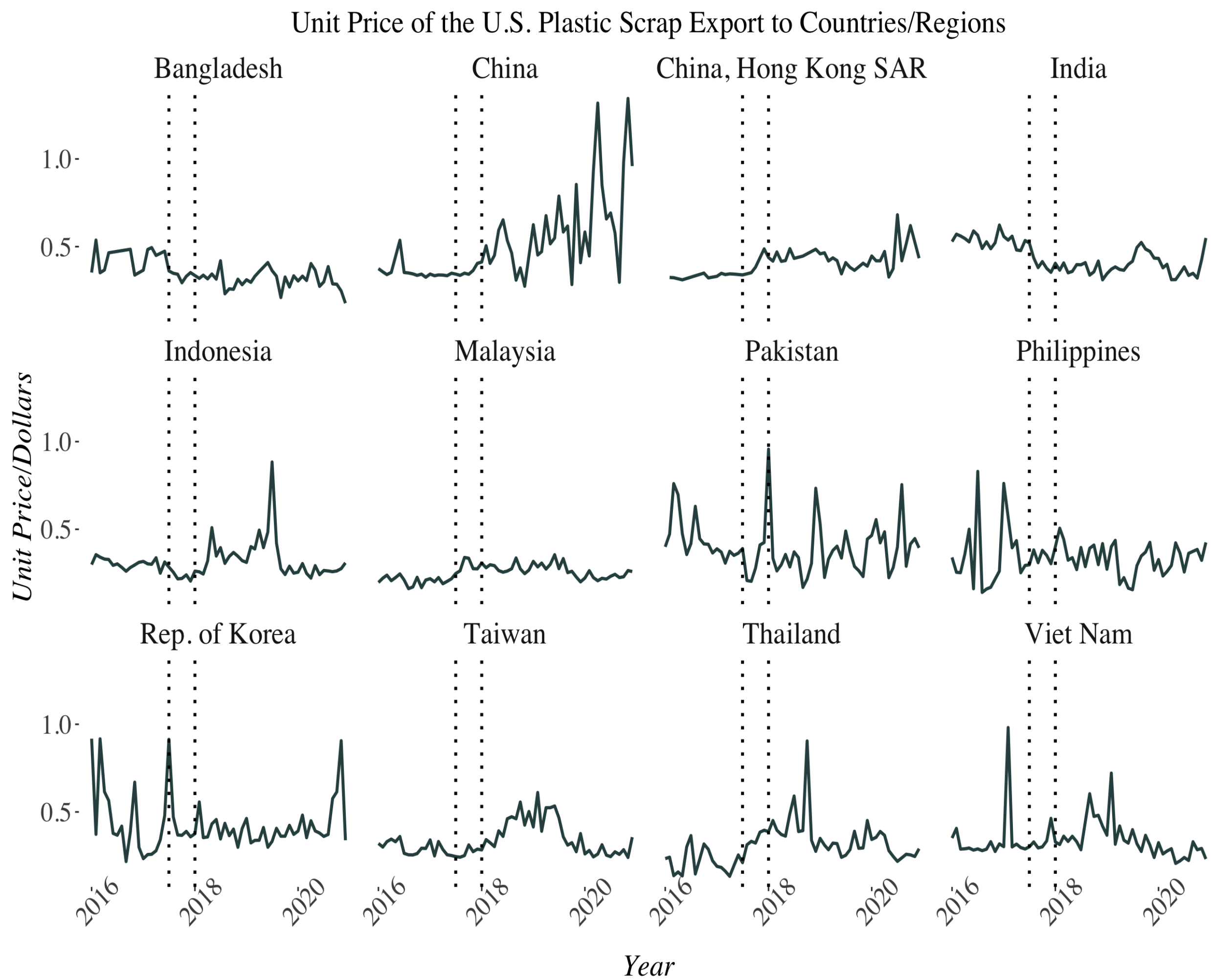


Figure 3.7: The U.S. Total Plastic Scrap Export Unit Price by Geographical Countries/Regions.



For the empirical analysis of the policies, I first examined the average treatment effects of international recycling policies on the U.S. plastic scrap export (logged total value), controlling for the gravity model variables such as distance among two trading countries, GDP per capita of the trading countries; and some macroeconomic indicators such as manufacturing add-in value, exchange rate, and global oil price. I also added a polynomial time-trend to control the unobservable factors that could have affected the outcome over time. The international recycling policies I chose are China's Green Fence policy, which started in 2013 aiming to increase the standard of recyclables import inspection; and China's National Sword policy, which took effect in 2018 aiming to ban certain types of scrap materials (including plastic scrap) completely. The three treatment dummy variables are China's Green Fence Policy on Feb 2013, the announcement of China's National Sword Policy in Jul 2017, and its effective date in Jan 2018. Table 3.1 shows the preliminary results of policy treatment effects. I started with a quasipoisson-generalized linear model (glm) with regular control variables. Column 1 shows that the Green Fence policy decreased the total value of U.S. plastic scrap export to China by 58 percent. After the National Sword policy announcement, the magnitude of the negative effect became more prominent–decreased the total value of U.S. plastic scrap export to China by 121 percent. After the National Sword Policy took effect, the total value of U.S. plastic scrap export to China decreased by 208 percent, which is much lower than the total plastic scrap trade value between the U.S. and China in the pre-policy era. Then I used the gravity model (ppml) and controlled for both gravity-macroeconomic variables and a polynomial time-trend in order to control for unobserved time-varying covariates. Column 2 shows that the coefficients on the treatment effects are consistent with the previous model, which demonstrates that the results are robust. Finally, I used the fepois model that includes the country and year fix effects in addition to all the other controls. Column 3 shows that the estimates of treatment effects are slightly different in magnitude, however, the signs and the significance are consistent with the previous two models.

Table 3.1: Policy Effect on Total U.S. Plastic Export Value (Log.U.S. Dollars)

Model	glm	ppml	fepois
$Green\_Fence\_Policy_{jt}$	-0.58^{***}	-0.50^{***}	-0.76^{***}
	(0.08)	(0.06)	(0.22)
$National\_Sword\_Policy(announced)_{jt}$	-1.21^{***}	-1.12^{***}	-1.01^{***}
	(0.21)	(0.17)	(0.13)
$National\_Sword\_Policy(effected)_{jt}$	-2.08^{***}	-1.89^{***}	-2.25^{***}
	(0.40)	(0.31)	(0.15)
Control Variables	Yes	Yes	Yes
Polynomial Time Trend	No	Yes	Yes
Country Fix Effect	No	No	Yes
Year Fix effect	No	No	Yes
Observations	4524	4524	4524

[a] $Policy_{jt}$ dummy is whether the policy change happens at country j at time t;

Table 3.2 shows the policy effects on the total net weight of the U.S. plastic scrap export to China. The announcement of the policy decreased the total amount of the U.S. plastic scrap export to China by around 50 percent, and the effect of the policy decreased the net weight of the U.S. plastic scrap export to China by around 200 percent.

Table 3.2: Policy Effect on Total U.S. Plastic Export (Log.Net Weight/kg)

Model	glm	ppml	fepois
$National\_Sword\_Policy(announced)_{jt}$	-0.53^{***}	-0.70^{***}	-0.52^{***}
	(0.25)	(0.10)	(0.13)
$National\_Sword\_Policy(effected)_{jt}$	-2.08^{***}	-1.99^{***}	-2.45^{***}
	(0.43)	(0.42)	(0.15)
Control Variables	Yes	Yes	Yes
Polynomial Time Trend	No	Yes	Yes
Country Fix Effect	No	No	Yes
Year Fix effect	No	No	Yes
Observations	3876	3876	3876

[a] $Policy_{jt}$ dummy is whether the policy change happens at country j at time t;

In Table 3.3, I examined how the policy change in China (used to be the biggest importer of plastic scrap) affects the recyclable plastic trades in the world and other geographical subregions. I used China's policy dates as treatment dummies. Table 3 shows that China's plastic import ban did not decrease the total value of U.S. plastic scrap export worldwide. Instead, it leads to a 74 percent increase in U.S. plastic export across all countries on average.red(wired) The decrease in total U.S. plastic export that China once accepted has diverted to other regions of the world. Column 2 shows that the policy change in China increased the U.S. plastic scrap export to other South/Southeast Asian countries. After China's National Sword policy took effect, the total value of the U.S. plastic scrap export to South/Southeast Asian countries increased by 155 percent. Figure 3 shows the U.S. plastic scrap export to some selected Asian countries. From the time trends of these countries, I find consistent increasing patterns in plastic scrap trade when China's policies were announced and took effect. The total value of plastic scrap export from the U.S. to North America—Canada and Mexico—decreased slightly by 23 percent, as most of recyclable plastics that Canada imported from the U.S. usually end up being sold to China.[8] When the National Sword policy was first announced, there was a temporary increase (71 percent) in the U.S. plastic scrap export to Central/South America. However, between the time that the National Sword policy was announced and when it took effect, the U.S. exporters found new buyers from South/Southeast Asian countries, and the U.S. plastic scrap export to Central/South America decreased by 75 percent and went back to the origin.

Table 3.3: Policy Effect on Total U.S. Plastic Export Value (Log.U.S. Dollars) across Regions

Region	World	Asia	North America	Central/South America
$Green\_Fence\_Policy_t$	0.08	0.48	-0.32^{***}	-0.02
	(0.11)	(0.45)	(0.07)	(0.25)
$National\_Sword\_Policy(announce)_t$	-0.35^{***}	1.07^{***}	-0.11	0.58^{*}
	(0.08)	(0.20)	(0.12)	(0.23)
$National\_Sword\_Policy(effective)_t$	-0.65^{***}	1.58^{***}	-0.23^{*}	-0.75^{**}
	(0.12)	(0.39)	(0.11)	(0.25)
Control Variables	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
Country Fix Effect	Yes	Yes	Yes	Yes
Year Fix effect	Yes	Yes	Yes	Yes
Observations	8144	1056	264	1188

[a] $Policy_t$ dummy is whether the policy change happens at time t.

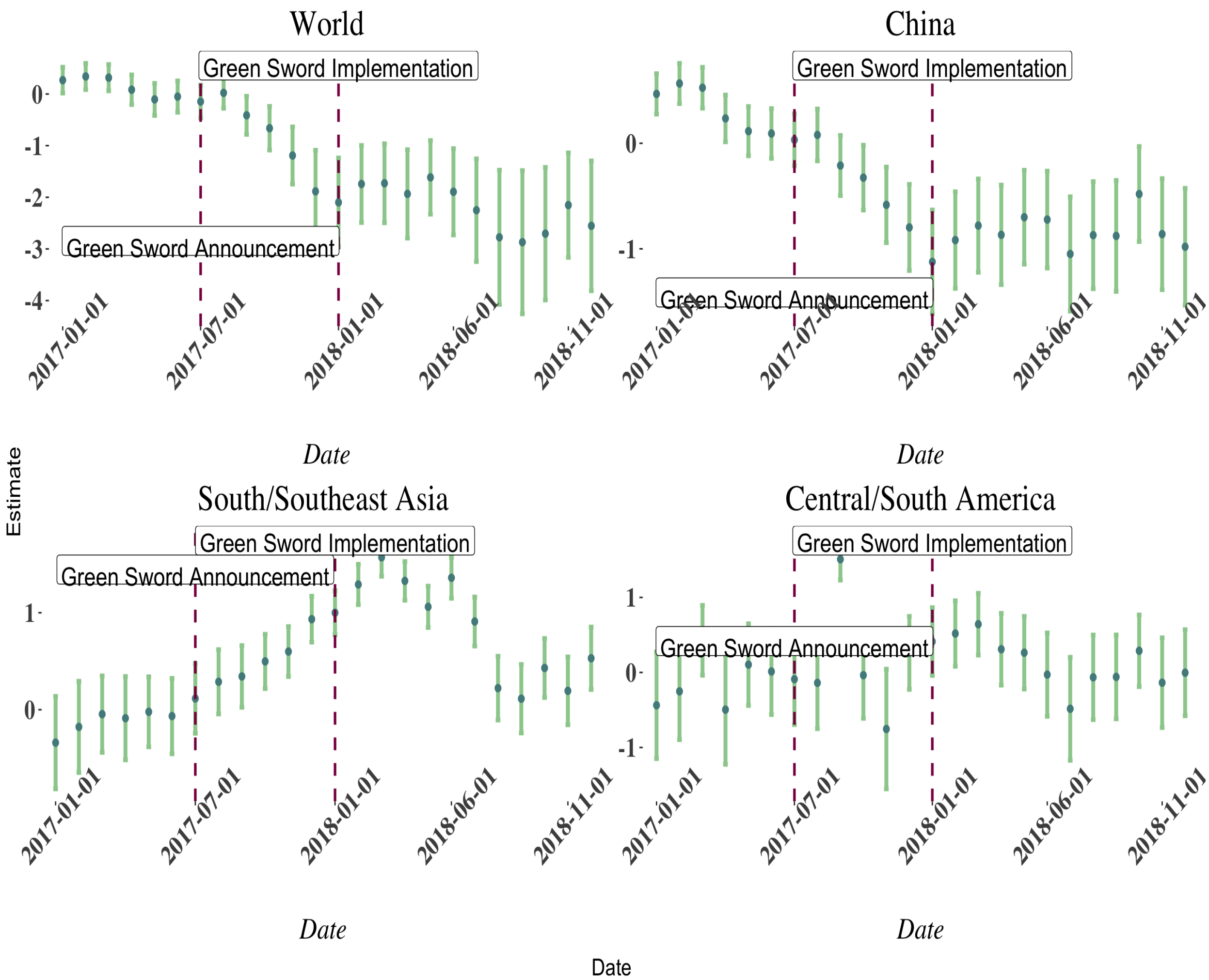
After studying the models for the average treatment effect of policy changes, I did the

8. **The Energy Mix** "Canadian Recycling Industry Scrambles after China Begins Refusing Plastic Waste." https://theenergymix.com/2019/05/16/canadian-recycling-industry-scrambles-after-china-begins-refusing-plastic-waste/

event study for the National Sword policy in order to discover the dynamic effect of the policy on the U.S. total plastic scrap export. I started with the dynamic impact of the policy change directly on the U.S. plastic scrap export to China. I chose a time ranging between twelve months before and after the policy took effect (Jan 2018). Table 4 shows that two months before the National Sword Policy was announced (Jul 2017), the negative impact (around 70 percent reduction) on the U.S. plastic scrap export to China started to show. There was a sharp decrease—about 300-400 percent reduction—of plastic trade value between China and the U.S. the first twelve months after the policy took effect. The abrupt change of the plastic scrap trade value between the U.S. and China reveals the power of the National Sword policy enforcement. Figure 4 shows the dynamic effects (coefficients) of the National Sword policy twelve months before and after the policy took effect.

In the extension of the event study only on the U.S. plastic scrap export to China, I studied the policy effect on different geographical sub-regions and examined how the world and regions react to the abrupt change of the recyclables trade market. Table 5 shows the event study by four geographic regions. The significant policy change from China did not change the U.S. worldwide total plastic scrap export during the first twelve months after the National Sword Policy took effect. However, if I divide the world into sub-regions, I found that exporting to South/Southeast Asian countries started to increase four months after China's policy was announced. The positive effect becomes more prominent and more significant right before and after China's policy took effect. The total value of the U.S. recyclable export increased temporarily, both in North America and Central/South America, right after China's National Sword Policy was announced and took effect. The increases in Central/South America were more significant than in North America. Within the first three months after the National Sword policy was announced, the total value of the U.S. plastic scrap export to North America and Central/South America increased by 90 percent and 219 percent on average. However, the temporary increases right after the policy announcement in both North American and Central/South America dissipated over time as South/Southeast Asian countries became the primary buyers for the U.S. recyclable plastics that were once accepted by China. The temporary increases in the U.S. plastic scrap export to North America and Central/South America also reveal that these countries did not have an actual and consistent manufacturing demand for those materials. Figure 5 shows the dynamic effects (coefficients) of the National Sword policy twelve months before and after the policy took effect on the total value of U.S. recyclable plastic export to the world, South/Southeast Asia, North America and Central/South America.

Figure 3.8: Event Study by Countries



I selected six specific policies to study in this research, including recycling policy changes by China, Thailand, Malaysia, Vietnam, India, and Indonesia between 2018 and 2020. I have the exact dates (month-year) of the announcement and enactment of these policies. By employing six event-period dummy variables, I examined the dynamics of the combined treatment effects of multiple policies on the total value of the U.S. recycling industry. Table 6 shows the result of multiple event studies. The treatment dummies have interacted with the "size" of the policy. For China's policy, I used the percentage of U.S. plastic scrap export to China among all trade partner countries from the year 2010 to 2018. For the "size" of policies of all other South/Southeast Asian countries, I used the percentage of U.S. plastic export to each country in 2018. Two months after China's National Sword Policy was announced, the multiple event study shows that there was a negative effect on the U.S. total plastic export until China's policy took effect. However, after China's policy took effect, the impact of the policy becomes positive until more policies were changed in other South/Southeast Asian countries. Figure 6 shows the dynamic effects (coefficients) of the cumulative policies (including China's policy and other South/Southeast Asian countries' policies) on the total value of the U.S. plastic scrap export from 2017 to 2019.

Table 3.4: Multiple Event Study—Policies Effect on U.S. Plastic Scrap Export

Pre-Policy		Post-Policy		Post-Policy	
2017-01		**2018-01**	0.42^{***}	2019-01	
			0.08		
2017-02		2018-02	0.58^{***}	2019-02	
			0.07		
2017-03		2018-03	0.71^{***}	2019-03	
			0.07		
2017-04		2018-04	0.59^{***}	2019-04	
			0.07		
2017-05		**2018-05**	0.58^{***}	**2019-05**	
			0.07		
2017-06	-0.035	**2018-06**	0.45^{***}	2019-06	
	0.072		0.05		
2017-07	-0.14	**2018-07**	0.13^{*}	2019-07	
	0.073		0.05		
2017-08	-0.07	2018-08	-0.25^{***}	**2019-08**	
	0.07		0.05		
2017-09	-0.26^{***}	2018-09	-0.33^{***}	2019-09	
	0.07		0.05		
2017-10	-0.65^{***}	**2018-10**	-0.022	2019-10	
	0.08		0.04		
2017-11	-0.82^{***}	2018-11	-0.07^{***}	2019-11	
	0.07		0.02		
2017-12	-0.82^{***}	2018-12		2019-12	
	0.06				
Time Trend	Yes		Yes		Yes
Control Variables	Yes		Yes		Yes
Country Fix Effect	Yes		Yes		Yes
Year Fix effect	Yes		Yes		Yes
Observations	4524				

[c] 2017-07 National Sword Policy announced date; 2018-01 National Sword Policy effective date.

[d] 2018-05 Indonesia now requires 100 percent inspection of scrap plastic imports.

3.3.2 Placebo Test

Figure 3.9: Event Study Placebo Test

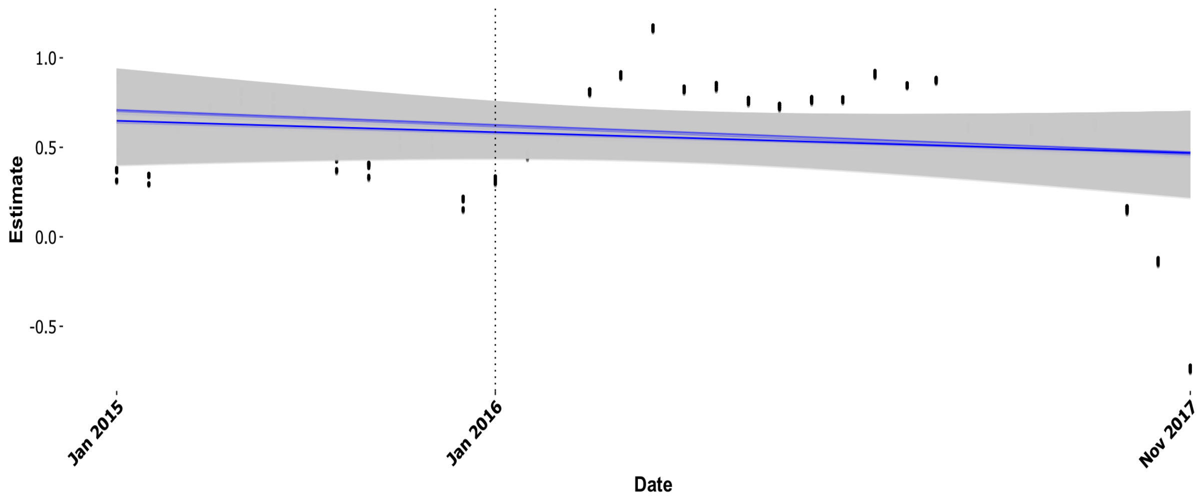
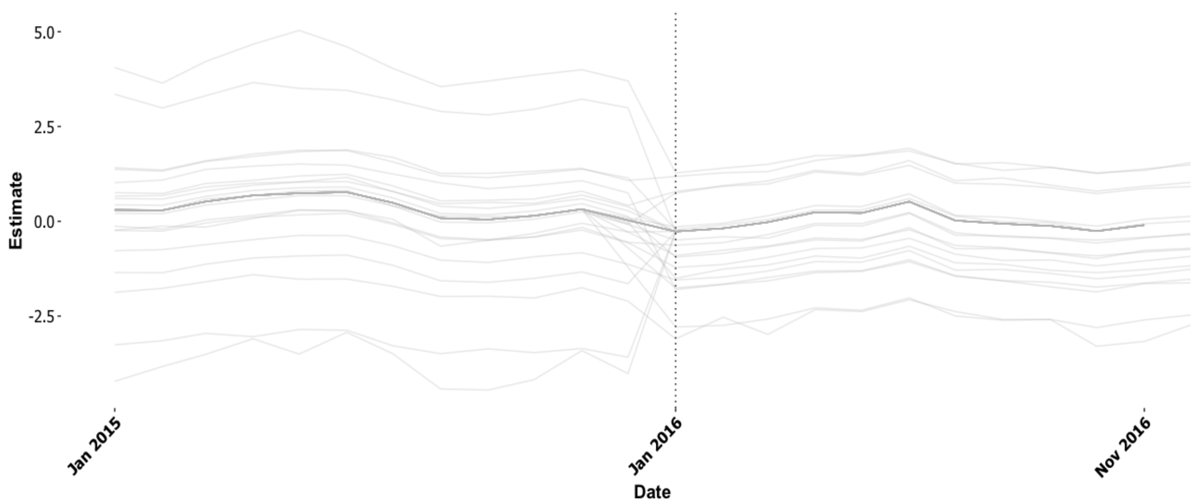


Figure 3.10: Panel Fixed Effect Model Placebo Test



3.3.3 Policy Efficacy

Multiple countries enacted similar policies to control the plastic scrap import from overseas. However, there has been a difference in the efficacy of those policies. Table 7 shows the policy efficacy of controlling plastic scrap import for four countries—China, India, Malaysia, and Thailand. I found that China and India's policy had a stronger effect than Malaysia and Thailand's since China and India were able to decrease the plastic scrap import by 200-300 percent because of the policy. However, plastic scrap export to Malaysia and Thailand increased by 300-400 percent, even with their policies they enacted. The efficacy of the policy could depend on the stringency of the policy content or the its implementation. For an example of policy content, Malaysia halted the plastic scrap import permits, while the other three countries banned plastic scrap import. This potentially resulted in an increase in plastic scrap import in Malaysia because the content of the policy was not as stringent as that of the other three. For an example of policy implementation, Thailand used a similar plastic scrap ban as China and India; however, the effectiveness of Thailand's policy was much weaker than that of China and India.

Figure 3.11: Policy Efficacy by Countries in South/Southeast Asian Countries

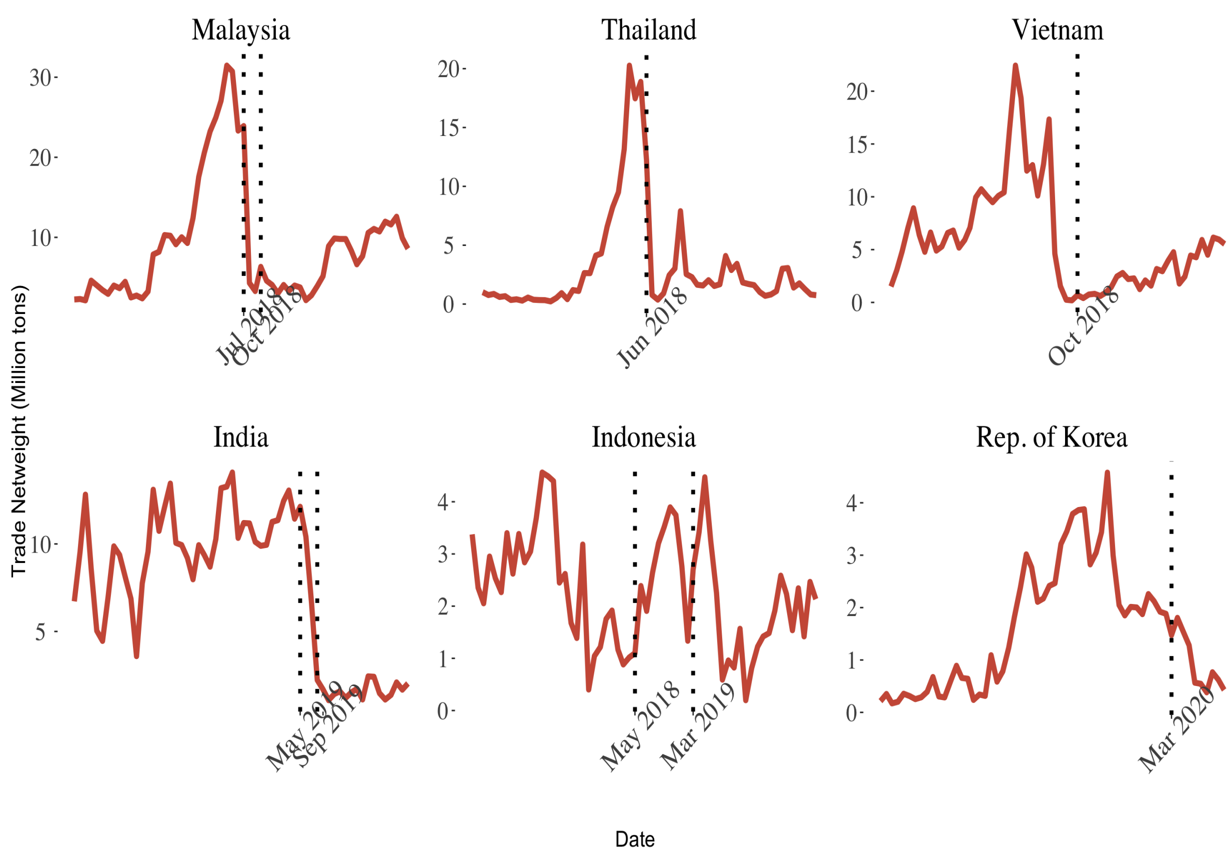


Table 3.5: Policy Efficacy across Countries

Country	China	India	Malaysia	Thailand
[0.4cm] $Policy_{jt}$	0.92^{***}	0.16	-0.58	-0.09
	(0.16)	(0.23)	(0.33)	(0.28)
$Policy_{jt} * Country_j$	-3.37^{***}	-2.11^{*}	4.38^{***}	3.73^{**}
	(0.29)	(0.93)	(0.31)	(0.35)
Control Variables	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
Country Fix Effect	No	No	No	No
Year Fix effect	No	No	No	No
Observations	14088			

[a] $Policy_t$ dummy is whether the policy change happens at time t.

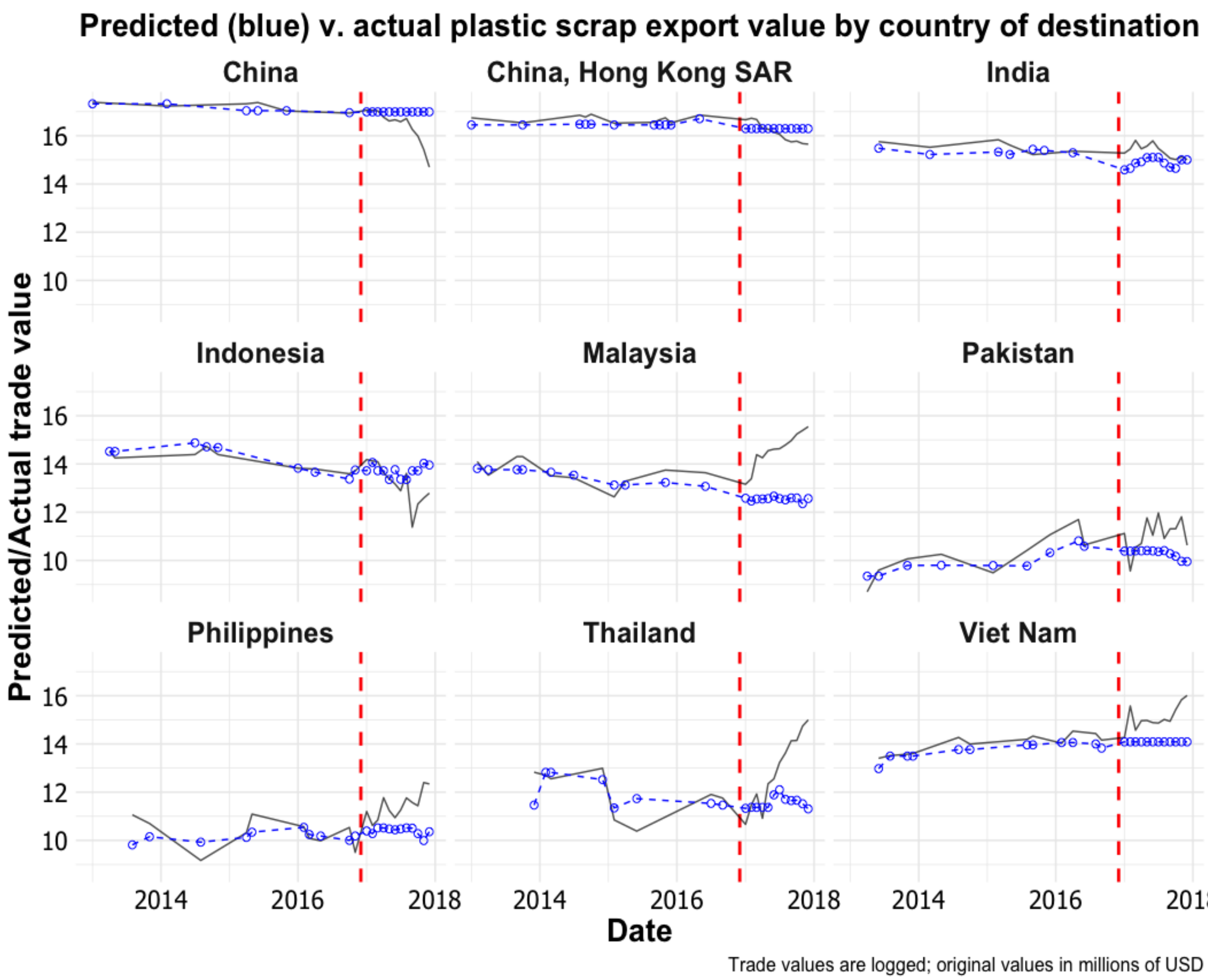
[b] $Policy_t * country_j$ interaction term of policy dummy and country dummy.

3.3.4 Robustness Check

Placebo test

3.4 Machine Learning Approach

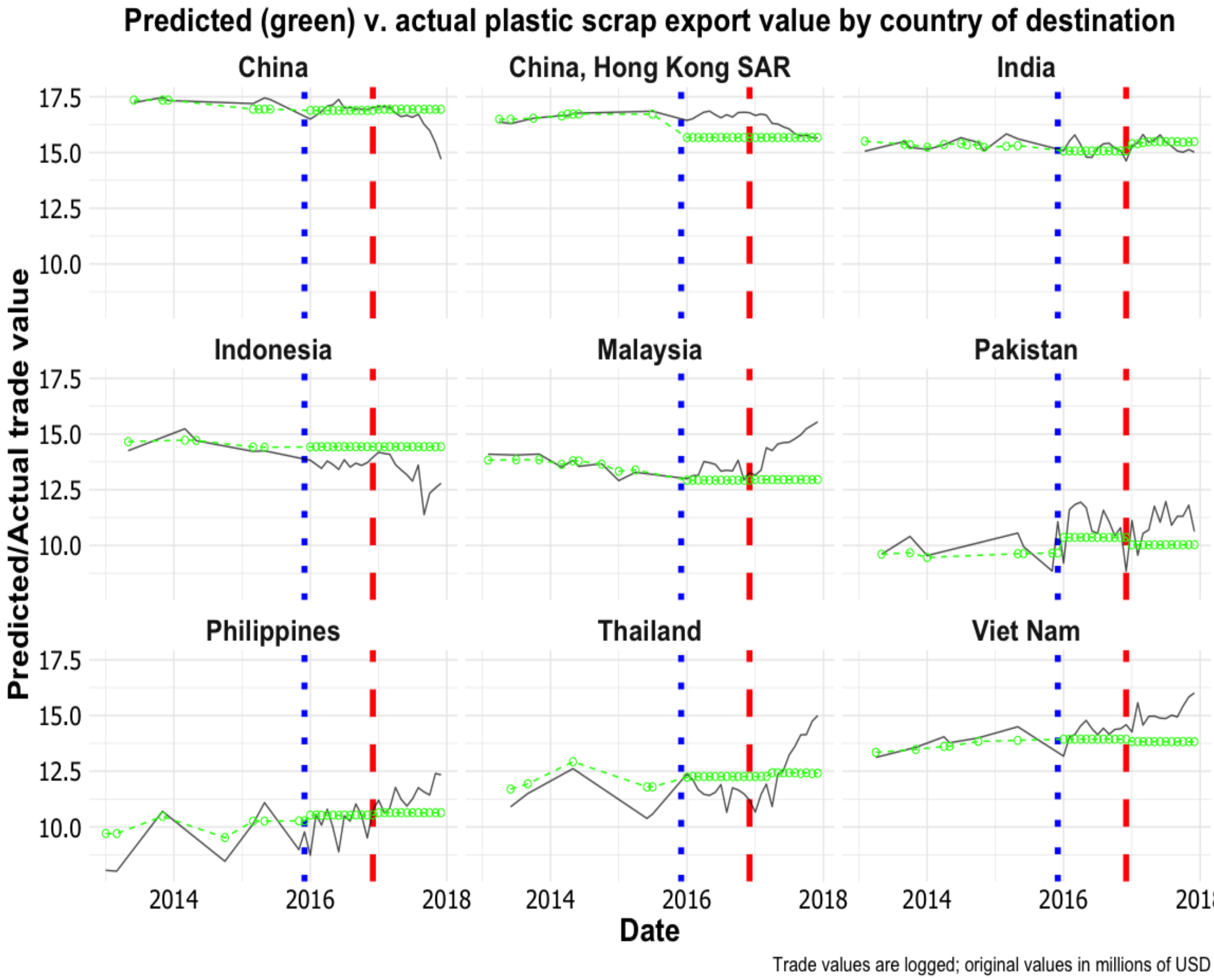
Figure 3.12: The Effect of GS Policy on U.S. Plastic Scrap Export to Countries using Boosting



3.4.1 Robustness

Placebo test

Figure 3.13: Machine Learning Counterfactual Method Robustness Check



3.5 Future Work

After identifying to the extent possible the causal treatment effects of these policies. I expect to be able to write a quantitative model similar to that used by Lee et al. (2018) of a small open economy in the U.S. with (1) a representative consumer, (2) an intermediate-good producer who reprocesses recyclable materials, (3) a final-good producer who uses the recyclable materials to produce new products, and (4) the government. I could then solve the equilibrium and calibrate the model using my predicted price elasticity and other parameters from the existing literature. Eventually, I plan to conduct a counterfactual analysis of selected policy options, such as offering tax credits for purchasing products made with recycled materials, imposing a ban on the use of particular hazardous recyclables, and extending producers' responsibility for minimizing waste by increasing their use of recycled materials.

3.6 Conclusion

In chapter 3, I focus on the international effects of China's GS policy on the recyclable wastes market. Many papers have investigated the patterns of international waste pollution flow. I evaluate how China's GS policy shock resulted in a disruption of existing patterns of international waste flow. More specifically, I ask these two questions: (1) How does China's GS policy affect U.S. trade in recyclables and its recycling industry? (2) How have the recycling markets of other countries reacted to this policy shock? To answer these two questions, I use panel fixed-effects models and machine learning counterfactual methods. I estimate the impact of China's GS policy on total exports of recyclable materials from the U.S. to different regions of the world.

The preliminary results suggest that China's GS policy decreased the net weight of U.S. plastic scrap exports to China by 90 percent. At the same time, it increased the U.S. net weight of plastic waste exports to South/Southeast Asia and Central/South America by 150 percent and 41 percent, respectively. Next, I investigate the causal effect of China's GS policy on the U.S. recyclable wastes exports to a specific country. I produce a control group using machine learning algorithms[9] to predict the counterfactual U.S. plastic waste exports to each country if China's GS policy had not been implemented. The difference between predicted counterfactual trade value (control) and the actual trade value (treatment) is to the causal effect of the GS policy on the plastic waste export from the U.S. to each coun-

9. Random Forest and Boosting ensemble methods

try. The preliminary results show that individual countries in Southeast Asia have seen significant increases in recyclable wastes imported from the U.S. [10] within a year of the GS policy's implementation. This analysis shows that the GS policy shifted the international waste pollution relocation from China to other developing countries.

10. specifically Malaysia, the Philippines, Pakistan, Thailand, and Vietnam have seen significant increases by 21.1%, 16%, 15%, 15.5%, and 13.5% respectively

CHAPTER 4

THE EFFECTS OF CHINA'S WASTE IMPORT BAN ON POLLUTION RELOCATION IN THE U.S.

4.1 Introduction

Recycling has contributed to U.S. prosperity and protection of the environment in the past decades. U.S. recycling rates increased from less than 7 percent in 1960 to the current rate of about 32 percent. As China joined the WTO in 2001 and started trade with the U.S., the U.S. was able to export a significant share of its recyclable materials for manufacturing use in empty shipping containers going back to China. However, beginning in 2017, China implemented its Green Sword (GS) Policy to stop importing these recyclable wastes from the U.S. due to their high domestic environmental costs. As a result, the U.S. recycling industry is facing pressure either to send recyclable materials to domestic landfills or to process these recyclables on its own. Sending recyclable materials to domestic landfills would cause methane pollution, water pollution, and etc. While processing these recyclables on its own could increase local air pollution.

In this paper, I evaluate empirical evidence necessary to answer the following questions: (1) What is the effect of the GS policy on U.S. state-level methane emissions from landfill facilities? (2) What factors correlate with the GS policy's heterogeneous causal effects on methane emissions across U.S. states? (3) What are the distributional effects of the GS policy on environmental outcomes for local communities (at county and census tract level) in the state of California? Does international trade and environmental policy affect local Environmental Justice (EJ)?

My analysis consists of two main parts. In the first part of analysis at the state-level, I use methane emission as the main environmental outcome for the following reasons: first, the U.S. EPA has begun reevaluating its regulations on methane pollution within the oil and gas industry under the Clean Air Act (CAA).[1] Landfills are the largest non-industrial sector that generates methane pollution (105.5 million metric tons of CO2 eq. of methane were emitted in 2020).[2] Consequently, the EPA will likely reevaluate its regulations on landfills in light of their methane emissions. Second, methane emissions that are calculated by EPA directly reflect the quantities of disposal (including the recyclables) that each facility accepts, and indicate the amount of pollution that is deposited into the environment.[3] Thus, methane emissions can be used as an indicator of other types of pollution that are contributed by wastes (including the recyclables). I use synthetic control method to construct a synthetic methane emissions trend for each state from the waste industry. Then I compare it with the actually methane emission level of each state to provide the evidence of causal effect. I also correlated the causal effects of the GS policy on each state with state-level recyclables export, economic, and environmental regulations' stringency in order to understand the mechanism of the effects. In the second half of analysis at local-level in the state of California, I used the quantity (tons) of disposal transported across different regions as my main outcome. Since the tons of disposal are directly related to the amount of methane emissions and air pollution depending on the type of destination facilities. I applied the gravity model, which is normally used in international trade literature, into a local-level disposal flow. To do so, I combine data for economic, demographic, industrial indicators of both the origin and destination community as well as the distance between the two locations and estimate the relationship between these characteristics of the communities and the amount of pollution

1. https://www.epa.gov/newsreleases/us-sharply-cut-methane-pollution-threatens-climate-and-public-health

2. Greenhouse Gas Reporting Program (GHGRP): Figure 1: Direct GHG Emissions Reported by Sector (2020)

3. GHGRP Methane Emission Computation Methodology: https://www.epa.gov/ghgreporting/ghgrp-methodology-and-verification

they sent or received.

I find that states like California, Florida, New York and Georgia have increased in methane emissions from the landfill facilities after the GS policy took effect.

The main contribution of this paper is that this is the first paper which uses granular data from the United States – such as facility level pollution emissions and inter-regional waste transfers – to study the policy's impact on both the level and distributional impacts on environmental outcomes in the U.S. Work in progress involves the following tasks: (1) explain how methane emissions from the waste industry might increase in certain states but decrease in other states as a consequence of China's GS policy; (2) investigate more factors that correlate with the heterogeneous effects of the GS policy on methane emissions across U.S. states, e.g. the tipping fees (disposal fees), ownership of land, government budget for municipal recycling, employment, income and compensation of the local waste industry, etc.; and (3) use the more granular data from CalRecycle to examine the distributional effects of China's GS policy on environmental outcomes for local communities in California.

4.2 Literature Review

This paper contributes to the literature on policies to increase recycling rates. Various papers study the efficiency of curbside recycling programs in the U.S. and other developed countries. For example, Aadland and Caplan (2006) find that the social net benefit of curbside recycling is almost zero. Bohm et al. (2010b) indicate that both marginal cost and average costs of recycling systems exceed those of waste collection and disposal systems. Kinnaman (2014) uses data from Japan with external costs and benefits from the U.S. and Europe and estimates an optimal recycling rate of 36%. Kinnaman et al. (2014) find that the average social costs are minimized with recycling rates well below observed and mandated levels in Japan, indicating many developed countries may be setting inefficiently high recycling goals. In my paper, I study the trade policy from China and show that in the absence of an overseas market for recyclables, the U.S. recycling market is inefficient despite a ”efficient” recycling rate.

Another genre of literature related to recycling focuses on the behavioral economics of curbside recycling and local recycling policies. Halvorsen (2010) finds that the opportunity cost of time has a significant negative effect on household recycling. Kurz et al. (2000) find that socioeconomic status of area was the strongest predictor of recycling participation, with recycling attitudes and sense of community also having some effect, and general environmental concern being found to have no effect. Best and Kneip (2019) finds that reducing behavioral costs of participation in household waste recycling through curbside collection have no effect on paper recycling, but increase recycling participation for plastic and packaging. For specific local recycling policies, much research has studied the bottle law of California. Ashenmiller (2009) finds that between 36% and 51% of the material generated by the redemption centers would not have been captured by existing curbside recycling programs. Ashenmiller (2011) finds that deposit refund for recycled bottles increases the income of very low wage quite meaningfully. Berck et al. (2020) identifies three key attributes that explain the the disposal decisions of consumers for their beverage containers: the refund amount, the volume of recyclable material generated by the household, and the effort associated with bringing recyclable materials to recycling centers. By using counterfactual policy analysis, they show that increasing the refund has the largest changes in consumer surplus accruing to white and higher-income consumers. Berck et al. (2021) also find that increasing the recyclables redemption value would not lead to major recycling increases. In my paper, instead of studying the endogenous mechanism of recycling, I take the angle of the international trade policy and use it as an instrument to explore the relationship between the recycling programs and local environmental outcomes in the U.S.

In recent year, more papers start focusing on the relationship between international trade policies and environmental outcomes. Shapiro (2016) studies how international trade affects CO2 emissions and analyzes the welfare consequences of regulating the CO2 emissions from shipping. The study finds that the benefits of international trade exceed trade's environmental costs due to CO2 emissions. While proposed regional carbon taxes on the CO2 emissions from shipping would increase global welfare and increase the implementing region's GDP, however, they would also harm poor countries. Shapiro (2018) finds that most of the emissions reductions in the U.S. were caused by changes in environmental regulation, rather than changes in productivity and trade, between 1990 and 2008. Shapiro (2021) finds that in most countries, import tariffs and non-tariff barriers are substantially lower on dirty than on clean industries, which creates a global implicit subsidy to CO2. Adding to these literature on how does trade policies on regular products implicitly affect the global carbon emissions and local air pollution, my paper study the policy that directly restrict the trade of negative externalities and its causal effects on the local environmental outcomes in the U.S.

Last, my paper also contributes to the literature on environmental gentrification and Justices implications. Banzhaf and Walsh (1994), as the first empirical study addressing environmental equity, find no consistent or statistically significant relationship between racial ethnic composition of tracts and commercial facilities for hazarous waste. Baden and Coursey (2002) find that Hispanics, not African Americans, are disproportionately exposed to the most dangerous hazards. Many papers are related to neighborhood gentrification. Cameron and McConnaha (2006) consider spatial patterns in selected census variables over three decades in the vicinity of four Superfund sites. They find many examples of moving and staying behavior, inferred from changes in the relative concentrations of a wide range of sociodemographic groups in census tracts near the site. Depro et al. (2011) suggest that the remediation of contaminated sites may not help the households that were originally exposed to the environmental bads; instead it may benefit the richer households that migrate into the area. Banzhaf and Walsh (2008) use a Tiebout model and provide strong empirical support for the notion that households "vote with their feet" in response to changes in environmental quality. Banzhaf and Walsh (2013) find that investments of public good in low-public good communities can actually increase segregation. Depro et al. (2015) identify nuisance-driven residential mobility by estimating willingness to pay for cleaner air across race groups. They find that Hispanics may dislike cancer risk but are less willing to trade other forms of consumption to avoid it. Ho (2020) studies the hauling costs and the perspective of environmental justice of Not-In-My-Backyard (NIMBY) policies. The study finds that NIMBY regulations would reduce intercounty waste transport at substantial efficiency costs, and these regulations also tend to lead to substitution of waste away from facilities that are near white residents and toward facilities that are near Hispanic residents. In the most recent works of environmental justice and market-based pollution control policies, Hernandez-Cortes and Meng (2020) estimate how "environmental justice" (EJ) gap changed following the 2013 introduction of California's carbon market. They find that EJ gaps across California for criteria air pollutants have fallen as a consequence of the carbon market. Shapiro and Walker (2021) studies if US air pollution offset markets disproportionately relocate pollution to or from low-income or minority communities. They find these pollution offset markets do not substantially increase or decrease the equity of environmental outcomes. Lastly, Banzhaf et al. (2019) summarise four potential mechanisms of EJ: disproportionate siting, coming to nuisance, Coasean bargaining, and political economy and government. My contribution to EJ literature is that this is the first paper to look at how an exogenous international trade policy affects the existing EJ problems in the U.S. In addition to investigate EJ issues after the policy shock, I explore more factors that could potentially affect pollution relocation, such as local environmental regulation stringency, economies of scale, and vertical integration of the industry.

4.3 Data

My analysis consists of three main data sources. First, I use methane emissions from landfill facilities reported by the U.S. EPA Greenhouse Gas Reporting Program (GHGRP) from 2010 to 2020 as one main environmental outcome. I choose methane emissions as my main environmental outcome for two reasons: (1) methane emission is the most "localized" greenhouse gas. Reduction in methane emissions has a much quicker effect on the local temperature than reduction in CO2. (2) methane emission can serve as a proxy for other pollution, such as land, air, water pollution, caused by recyclable wastes. The GHGRP requires reporting of greenhouse gas (GHG) data from large GHG emission sources, fuel and industrial gas suppliers, and CO2 injection sites in the United States. Approximately 8,000 facilities are required to report their emissions annually. The industries in the GHGRP data system include power plants, petroleum and natural gas systems, minerals, chemicals, pulp and paper, refineries, waste, etc.

Second, I use more granular facility-level data from California Department of Resources Recycling and Recovery (CalRecycle). Utilizing Recycling and Disposal Reporting System (RDRS) and Disposal Report System (DRS) from CalRecycle, I extract the quarterly disposal flow data that capture the amount of disposal transported by origin of jurisdiction and destination of facility within the state of California. The disposal flow data contains 464 origin jurisdictions and 276 disposal facilities in total from 2002 to 2021 in California.

Third, I use a group of other data sources for control variables in my analysis, such as data on exports from the U.S. Trade Census, U.S. EPA Enforcement and Compliance Historical data, quarterly employment and wages at county-level from Bureau and Labor and Statistics (BLS), and racial composition and median income at census-block level from the U.S. Census.

4.4 Empirical Method and Identification

4.4.1 State-level Methane Emissions

Summary Statistics

The U.S. EPA requires facilities from all industry sectors (exclude smaller emitters) to self-report their methane emissions annually since 2010. All of the facility-level data are documented in the Greenhouse Gas Reporting Program (GHGRP).[4] The methane emissions, especially from the landfills are hard to monitor, the EPA typically has two or three ways to calculate the methane emission through different models, and the GHGRP system normally takes the higher value of the calculations from different models. Table 4.1 shows the summary statistics of the GHG emissions from the waste sector in the U.S. from 2010 to 2020 annually.

4. According to *Next Generation Compliance* by Cynthia Giles, the compliance rate of the GHGRP program is relatively high compared to many other programs inside of the Federal U.S. EPA.

Table 4.1: EPA: Waste Sector - Greenhouse Gas Emissions Reported to the GHGRP Summary Statistics

Year	2010	2011	2012	2013	2014	2015
Number of facilities	1303	1328	1342	1331	1328	1255
Total emissions (MMT.CO_2e)	110.9	104.6	105.3	102.1	101.7	101
Facility emissions mean (TMT.)	85.1	78.8	78.5	76.7	76.6	80.5
Facility emissions sd (TMT.)	90.7	83.8	86.3	85.5	85.7	85.6
Emissions by greenhouse gas (CO_2e)						
Carbon dioxide (CO_2)	9.9	10.7	10.8	11.1	11.1	11.4
Methane (CH_4)	101.1	94.1	94.7	91.2	90.8	89.9
Nitrous oxide (N_2O)	0.352	0.352	0.356	0.353	0.352	0.351
Year	2016	2017	2018	2019	2020	2021
Number of facilities	1227	1221	1218	1204	1201	TBD
Total emissions (MMT.CO_2e)	98.2	96.8	99.6	101.4	96.9	TBD
Facility emissions mean (TMT.)	80	79.3	81.8	84.2	80.7	*TBD*
Facility emissions sd (TMT.)	89	90.5	97.6	102.5	92.3	*TBD*
Emissions by greenhouse gas (CO_2e)						
Carbon dioxide (CO_2)	11.7	10.6	11	10.7	10.3	*TBD*
Methane (CH_4)	86.7	86.4	88.8	90.9	86.2	*TBD*
Nitrous oxide (N_2O)	0.358	0.344	0.352	0.345	0.335	*TBD*
Sample size: 12,757						

[a]

4.4.2 Empirical Strategy

To study the effect of China's Green Sword policy on the methane emission in the U.S. I need control group that does not affected by the GS policy. As a "one policy affect all", it is hard to define treatment and control group geographically. Instead, I use industries in the GHGRP that also emit greenhouse gas, especially methane, but not directly affected by the GS policy as my control group. The control industries include power plants, petroleum and natural gas, minerals, chemicals, metals, paper and pulps. The treatment group is waste industry, mostly landfills. Although I have many industries in my control group, there isn't one industry that has the same pre-policy trend as the waste industry. I then utilize the synthetic control method, using other industries from all other states in my control pool and come up with a synthetic pre-policy trend that is the same as the actual pre-policy trend of landfill emissions. And the difference between the synthetic post-policy landfill emissions trend and the actual landfill emissions trend is the causal effect of the GS policy on the U.S. state-level methane emissions from the landfills. I use the same processor for the waste industry for all 50 states excluding Washington DC.

4.4.3 Local Pollution Relocation

Summary Statistics

I utilize the CalRecycle data for the local-level pollution relocation analysis in the U.S. Fig.1 shows the locations of all landfill facilities in CalRecycle RDRS and DRS systems. The data contains the origin of jurisdictions and destination facilities of the disposal flow in the state of California. Table 2 shows the summary statistics of the disposal flow from 2002 to 2021 (Q1 and Q2).

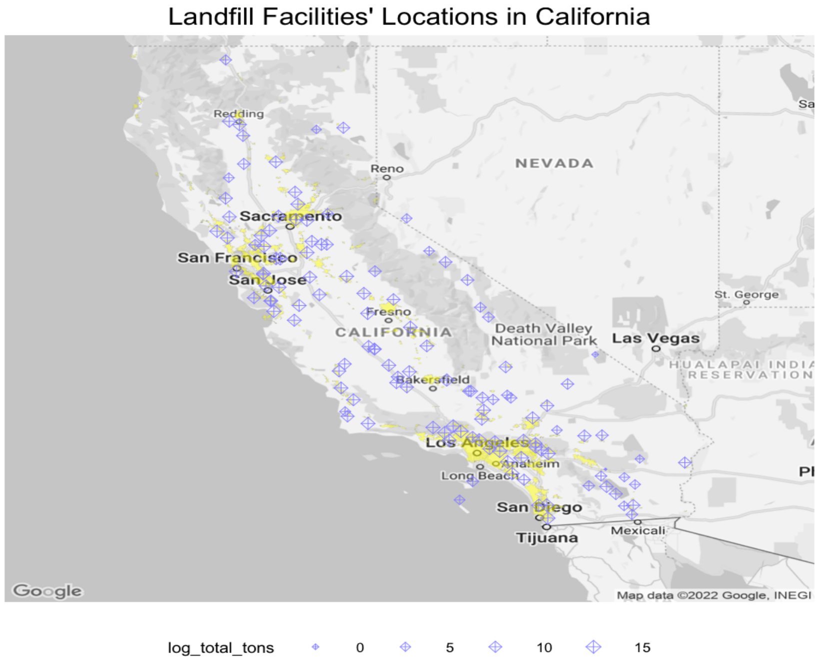


Figure 4.1: CalRecycle: Recycling and Disposal Reporting System (RDRS) Facility locations in California

Table 4.2: CalRecycle: Recycling and Disposal Reporting System (RDRS) Disposal Flow Summary Statistics (Thousand Tons)

	Origin Jurisdiction			Destination Facility			Distance	
Year	No.Jurisdictions	mean	s.d.	No.Facilities	mean	s.d.	mean	s.d.
2002	434	86.6	214.6	162	232.0	476.8	93268.81	121558.11
2003	421	94.4	271.5	158	251.6	501.4	93999.98	121038.61
2004	424	96.2	269.5	152	268.3	522.9	96119.29	122285.50
2005	419	100.3	283.9	149	281.9	534.5	94582.46	119467.32
2006	412	99.5	271.9	148	276.9	517.2	89818.86	109109.33
2007	414	93.6	261.8	142	272.9	507.3	92219.36	110654.31
2008	417	84.2	235.0	133	264.0	465.9	89426.58	103020.75
2009	412	74.7	211.2	134	229.7	431.2	98708.38	120417.03
2010	417	72.0	201.1	131	229.4	414.6	101730.55	123606.08
2011	416	71.5	204.2	134	221.9	408.5	76377.90	90855.24
2012	414	70.3	203.9	131	222.1	405.2	71611.71	71466.73
2013	412	72.7	214.1	133	225.2	405.6	85801.69	101646.75
2014	411	75.1	235.4	130	237.5	427.2	87060.02	99073.64
2015	410	80.3	250.8	128	257.2	456.1	89210.46	104974.34
2016	420	82.9	257.4	126	276.3	473.1	90100.95	102781.80
2017	420	89.2	275.3	127	294.9	501.5	90308.26	103444.24
2018	417	94.7	284.8	128	308.5	519.3	90324.10	98780.01
2019	418	96.5	288.9	127	317.6	532.9	87028.51	90222.94
2020	419	96.2	285.3	128	314.8	528.8	87824.51	83693.56
2021(Q1Q2)	419	46.5	137.0	128	152.2	271.3	77786.49	76857.25
Sample Size	281339							

Table 4.3: CalRecycle: Recycling and Disposal Reporting System (RDRS) Disposal Flow Summary Statistics

	Origin County			Destination County		
Year	No.county_o	mean	s.d.	No.county_d	mean	s.d.
2002	56	671.3	1615.4	51	737.1	1542.3
2003	56	709.9	1686.7	50	795.1	1610.1
2004	57	715.5	1691.5	50	815.7	1629.9
2005	56	750.2	1755.4	49	857.4	1705.8
2006	56	731.9	1694.9	46	891.1	1721.6
2007	58	668.1	1586.1	45	861.2	1616.9
2008	58	605.4	1436.8	44	798.1	1454.5
2009	58	530.7	1260.1	44	699.5	1268.7
2010	58	518.0	1206.2	45	667.7	1199.5
2011	58	512.8	1199.6	46	646.6	1174.6
2012	57	510.5	1191.8	45	646.6	1167.5
2013	57	525.4	1216.3	45	665.5	1188.0
2014	58	532.3	1245.6	45	686.1	1138.1
2015	57	577.6	1330.2	45	731.6	1185.5
2016	58	600.3	1391.8	45	773.7	1248.7
2017	58	645.7	1471.8	45	832.2	1298.3
2018	58	680.8	1512.6	46	858.4	1319.7
2019	58	695.3	1593.4	45	896.2	1364.5
2020	57	706.9	1618.7	48	839.5	1414.1
2021(Q1Q2)	58	335.9	781.5	48	405.8	686.7
Sample Size	281339					

The state analysis is the first step towards understanding the causal effect of China's GS policy on aggregate emission levels. In order to gain a more detailed understanding of the local environmental effects of the GS policy, I then use facility-level data on disposal flows from 2002 to 2021 provided by CalRecycle to explore the pollution flow mechanisms and Environmental Justice (EJ) implications. I investigate the distributional effects of the GS policy on waste flows for local communities (at both county and census block levels) in the state of California. I apply a gravity-type model that includes the distances between the origins and destinations of inter-regional waste flows and tipping fees as well as racial composition, socioeconomic characteristics, environmental regulations, and waste industries' economies of scale of both origin and destination communities. The model specification is as follows:

$$log(Y_{ijt}) = \alpha + \beta_1 log(Dist_{ij}) + \beta_2 log(X_{it}) + \beta_3 log(X_{jt}) + \epsilon_i + \theta_j + \mu_{ij} + \eta_t + \gamma_f + \lambda_{ijt}$$

The dependent variable Y_{ijt} is the tons of the disposal transported from county i to county j in quarter t. $Dist_{ij}$ is the distance between origin county i and destination county j. X_{it} and X_{jt} are racial composition, socioeconomic factors, regulation of environmental stringency, and economies of scale of waste industry of origin and destination county i and j. I present the results that adjusted for different fixed effects including the origin county fixed effects (ϵ_i), destination county fixed effects (θ_j), year fixed effects, quarter fixed effects, year-quarter fixed effects (η_t), and origin-county-year-quarter fixed effects (λ_{ijt}).

4.5 Preliminary Result

4.5.1 State-level Methane Emissions Synthetic Control

Taking advantage of the fact that other industries which also emit GHG were not affected by China's GS policy, I use synthetic control methods and provide causal evidence of state-level changes in methane emissions from the waste industry due to China's GS policy. After the GS policy took effect, states like California, Washington, New York, Virginia and Texas have seen significant increases in methane emissions in their waste industry by 0.5%, 0.51%, 0.6%, 0.55%, and 0.31% respectively.Other states like Florida, Georgia, Alabama, Kentucky, Louisiana, Ohio and Oregon have also seen significant increases in methane emissions, by 0.22%, 0.19%, 0.5%, 0.3%, 0.15%, 0.2% and 0.21% respectively. Second, I examine the key features of states that drive heterogeneous changes in domestic methane emissions. This analysis utilizes U.S. EPA Enforcement and Compliance Historical data and data on exports from the U.S. Trade Census. I find that the more recyclable wastes a state sent before the GS policy, the higher the increase in methane emissions the state experiences after the GS policy. I also find that the higher the rate of significant violations a state has with regard to environmental regulations in general, the greater the increase in methane emissions in that state after the GS policy. Fig.2 shows the synthetic control result for the state of California.

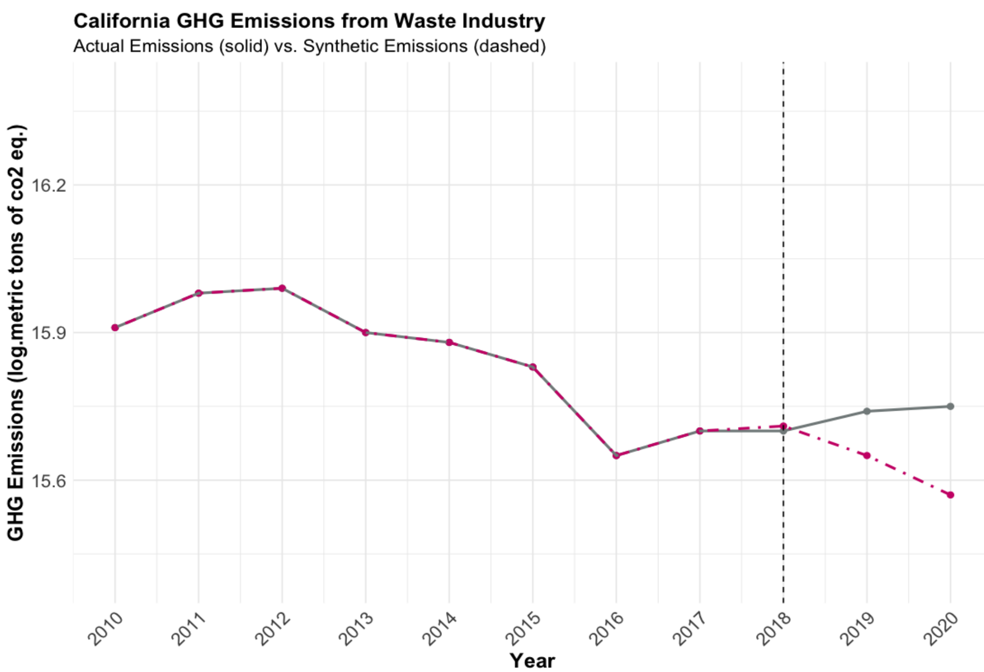


Figure 4.2: Synthetic control: GS policy effect on California Methane Emission

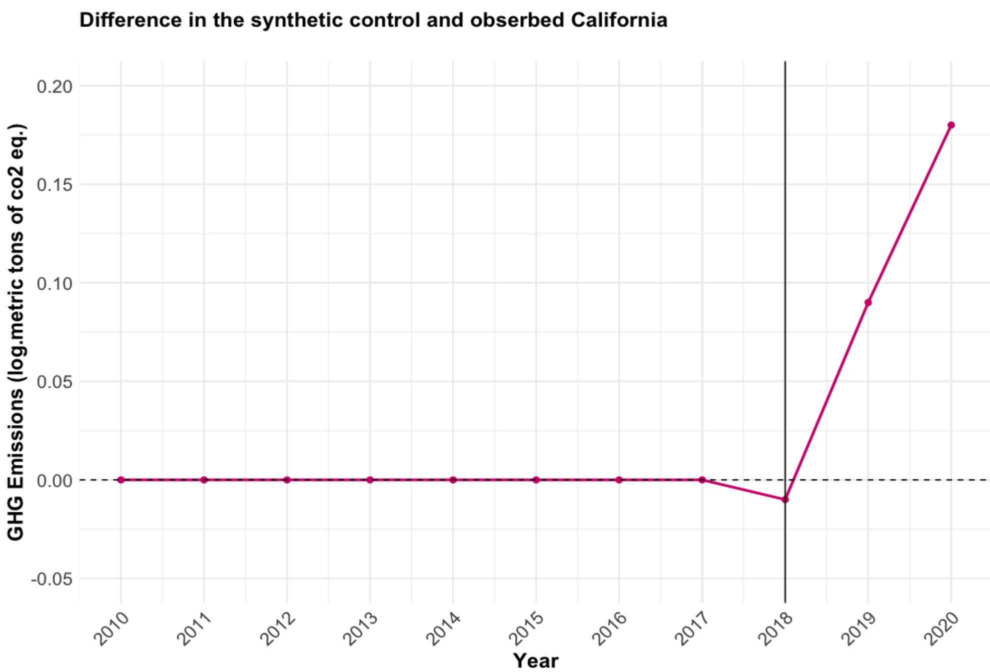


Figure 4.3: Difference in synthetic control and observed California Methane Emission

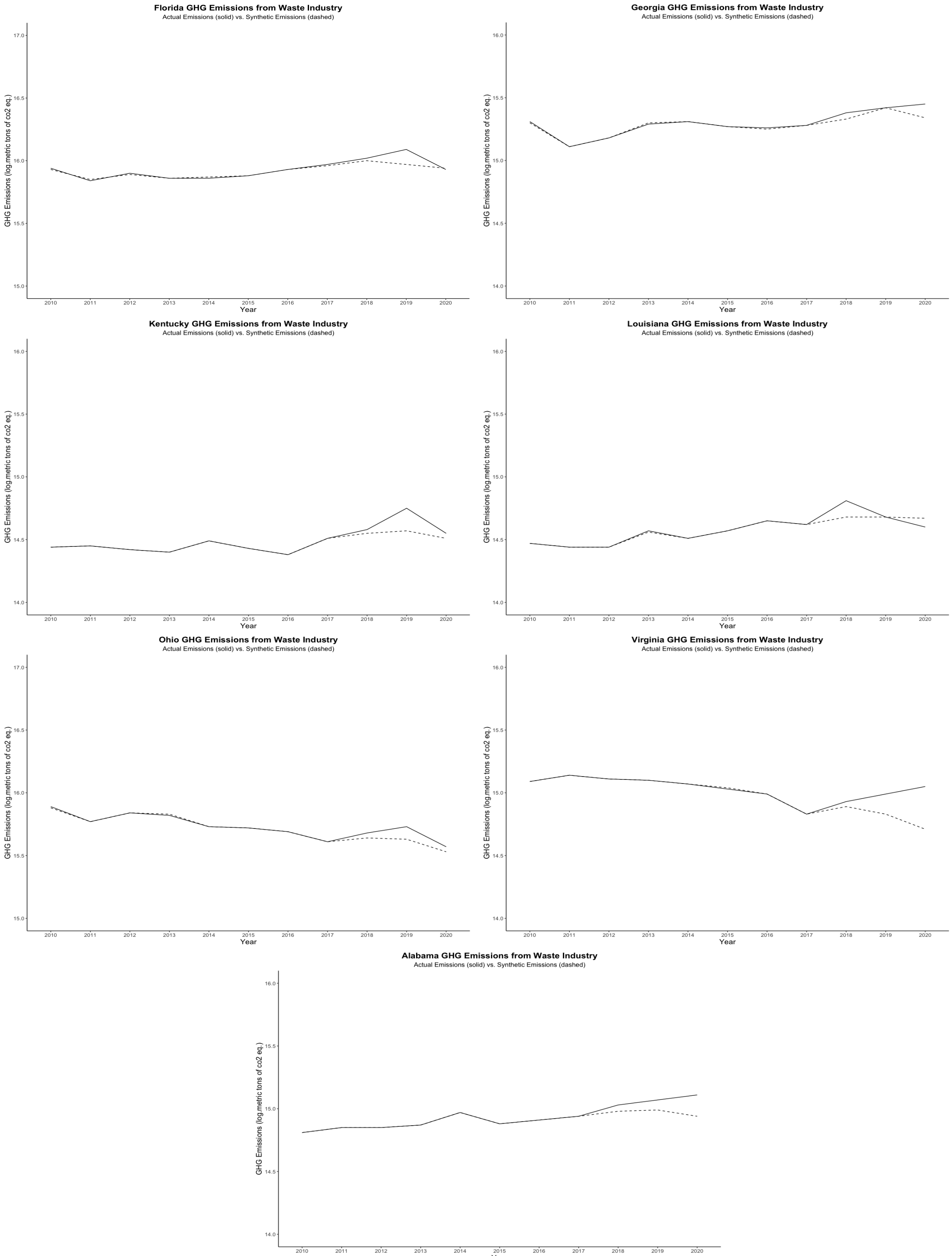


Figure 4.4: Synthetic Control: State-level Policy Effect Estimation

To further validate the results from the synthetic control method, I use three different placebo tests. First, I use each of the control industries as my "fake" treatment industry, and use other industries in the control group (exclude the "fake" treatment) to calculate pre-policy trend of emissions. In Fig. 3 (a), the grey lines are the placebo causal effect of China's GS policy on the California's emissions. The black line is the actual causal effect of the GS policy on California's emissions. After calculating the p-value of my actual estimate, I find the increase in emissions in California is 10 percent statistically significant. In Fig. 3 (b), I change the actual treatment year (2018) to the placebo treatment years (2013, 2014, 2015, 2016 and 2017). I find that all of the placebo treatment years have the same upward trend (increase in emissions) in 2018. These placebo tests show that the estimate from the synthetic control is valid in the state of California.

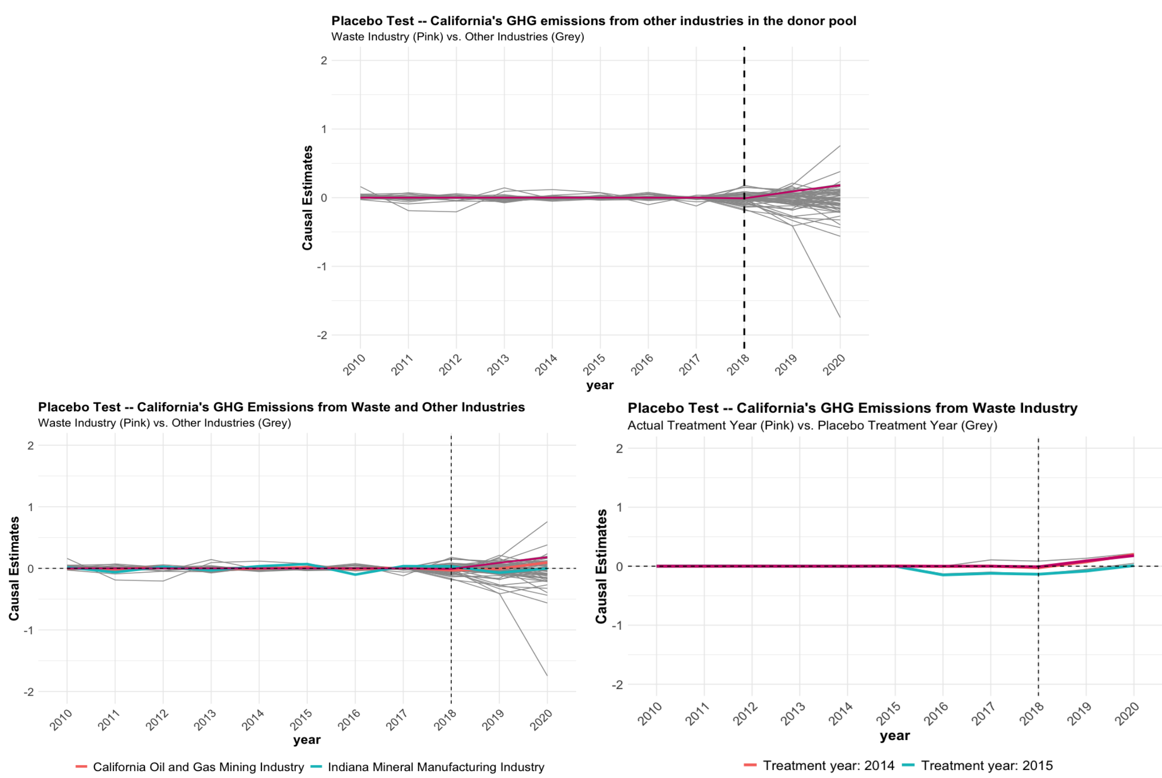


Figure 4.5: Placebo tests for GS policy's effect on California methane emission

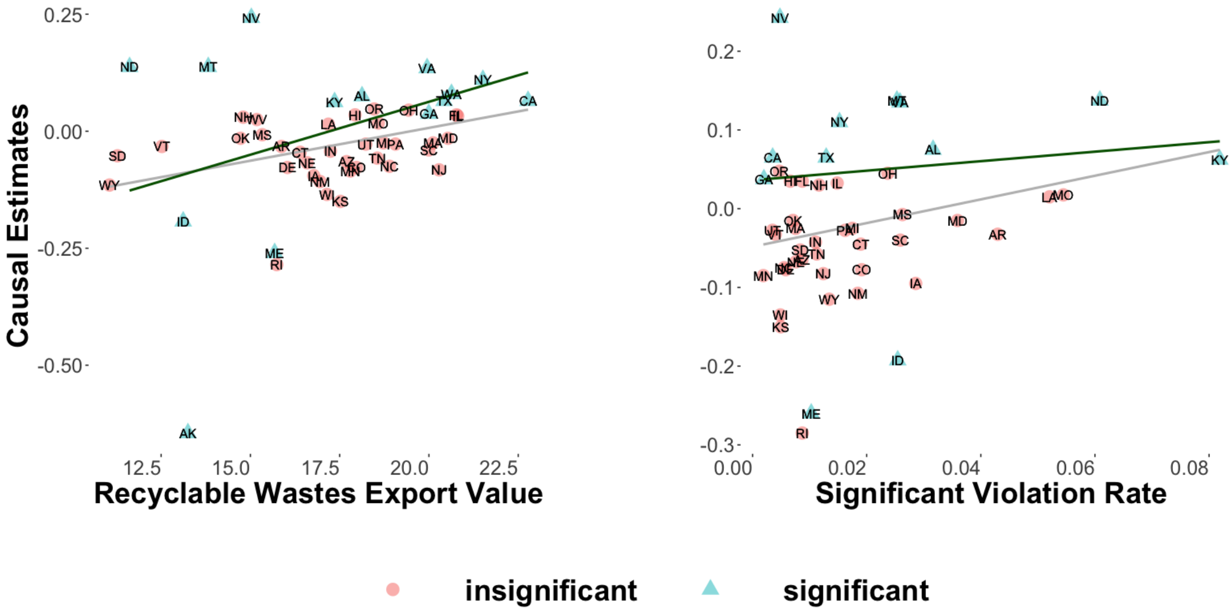


Figure 4.6: Difference in synthetic control and observed California Methane Emission

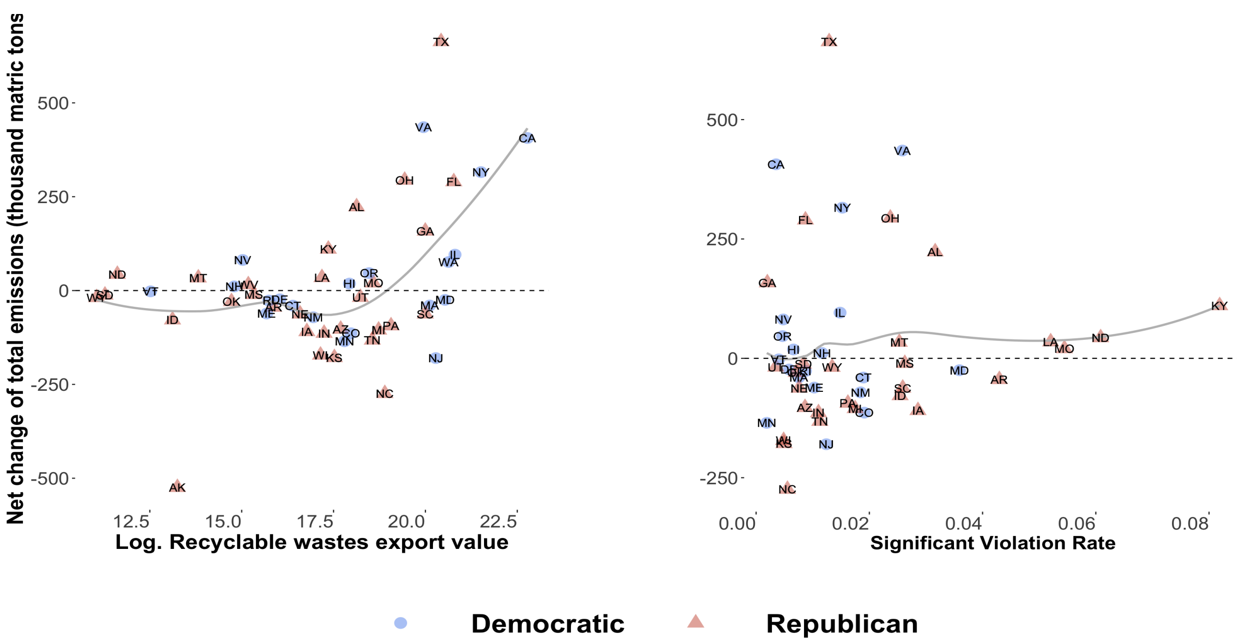


Figure 4.7: Difference in synthetic control and observed California Methane Emission

4.5.2 California Disposal Flow: Gravity Model

4.5.3 Summary Statistics

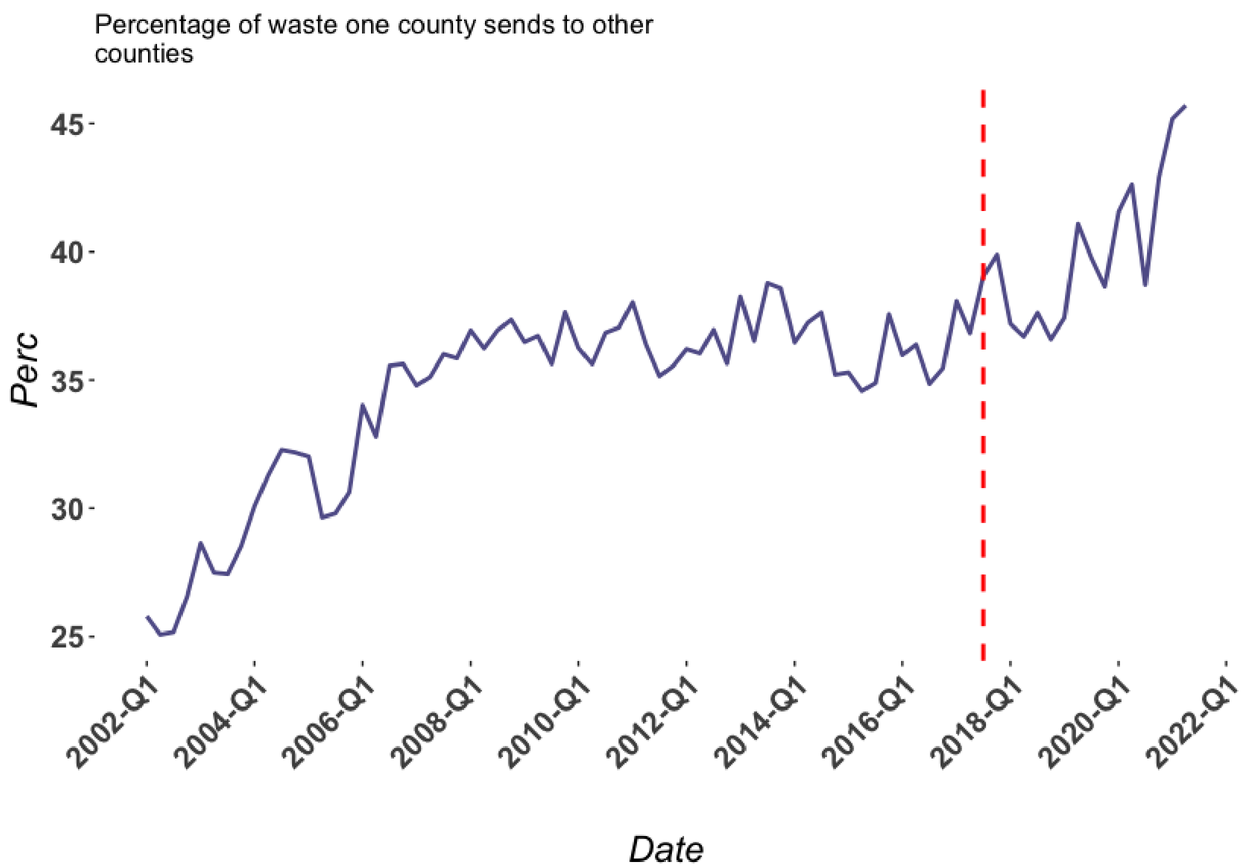


Figure 4.8: Percentage of Disposal One County Sends to Other Counties

Table 4.4: Summary Statistics of County Data of California

	Origin County		Destination County	
	Mean	S.D.	Mean	S.D.
White Population	1,309,981	2,259,458	1,264,266	2,215,611
Black Population	149,139	291,359	143,098	285,398
Hispanic Population	821,575	1,533,960	796,107	1,500,608
Asian Population	292,026	493,663	276,997	485,365
Quarterly Establishments	133,304	167,399	125,023	163,933
Quarterly Employment (m1)	1,407,737	1,559,714	1,327,692	1,533,174
Quarterly Employment (m2)	1,413,590	1,566,082	1,333,178	1,539,004
Quarterly Employment (m3)	1,420,042	1,573,397	1,339,159	1,546,411
Toatl Quarterly Wage (billion $)	20.1	22.5	18.7	22.1
Average Weekly Wage ($)	1,068	419.8	1,019	366.8
Total Population	3,387,818	3,702,578	3,221,639	3,702,578
Quarterly Tipping Fee ($)	33.462	9,047,622	31.554	7,864,242
White Population Percentage	0.729	1,048,084	0.730	1,021,568
Black Population Percentage	0.063	0.037	0.069	0.038
Hispanic Population Percentage	0.437	0.09.0	0.461	0.086
Asian Population Percentage	0.135	0.15	0.129	0.14
Distance	89,533.4	105,541	89,533.4	105,541
Observations				

Table 4.5: Summary Statistics of Community Characteristics by Facilities

	3km Buffer	5km Buffer	10km Buffer
[0.4cm] height			
White Perc	57.12	53.67	52.37
	(27.07)	(25.91)	(24.01)
Black Perc	2.78	3.24	4.07
	(4.98)	(4.83)	(4.93)
Hispanic Perc	32.79	35.19	35.50
	(25.65)	(24.91)	(22.48)
Asian Perc	5.86	6.57	6.77
	(10.03)	(10.22)	(9.26)
Native American Perc	1.45	1.32	1.29
	(4.71)	(3.69)	(3.11)
Median Income	63.156	61.137	59.921
($Thousand)	(24.616)	(21.974)	(20.503)
Observations	264		

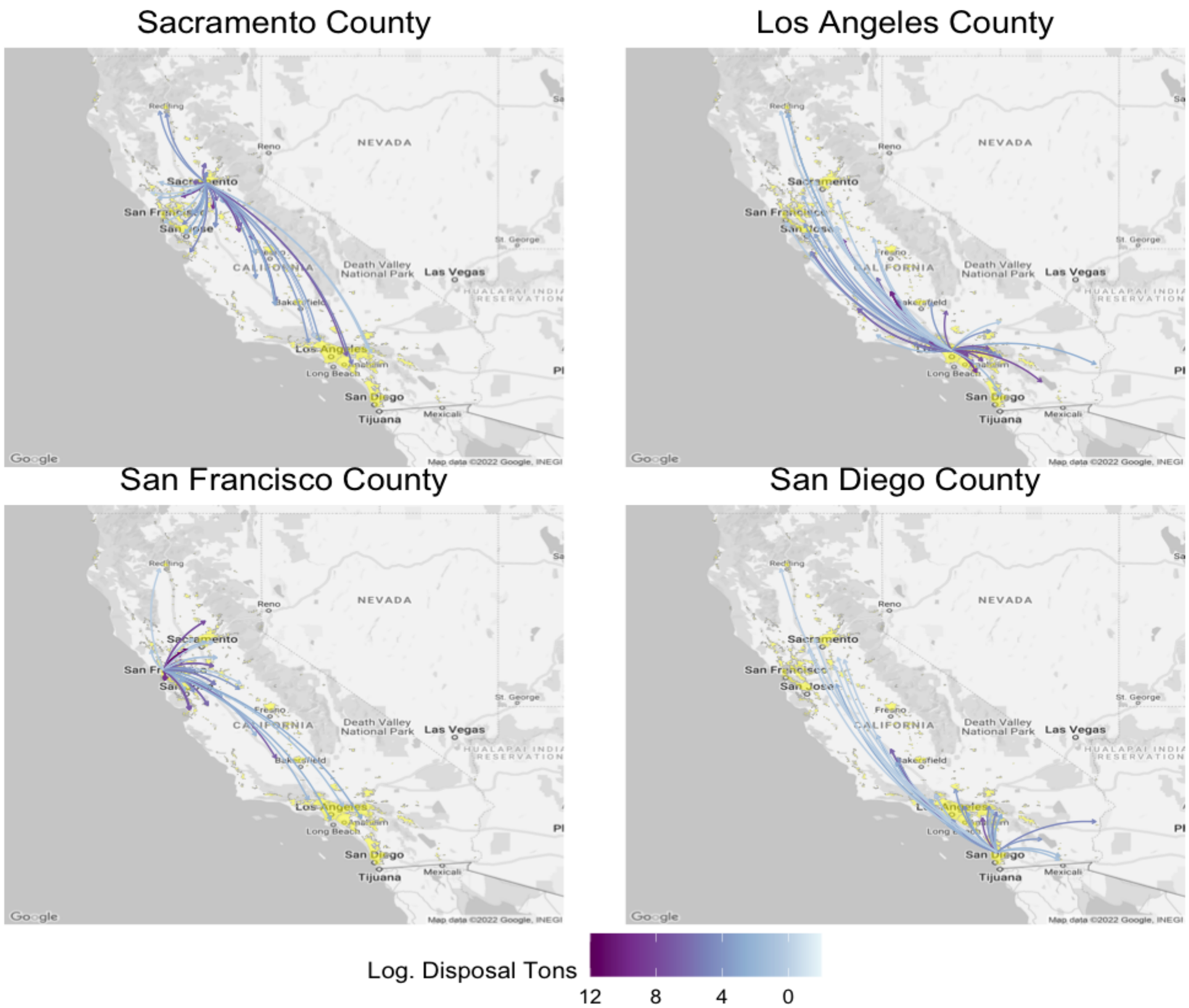


Figure 4.9: Average Net Increase of Disposal Flow after China's GS Policy

4.5.4 Environmental Justice Implication

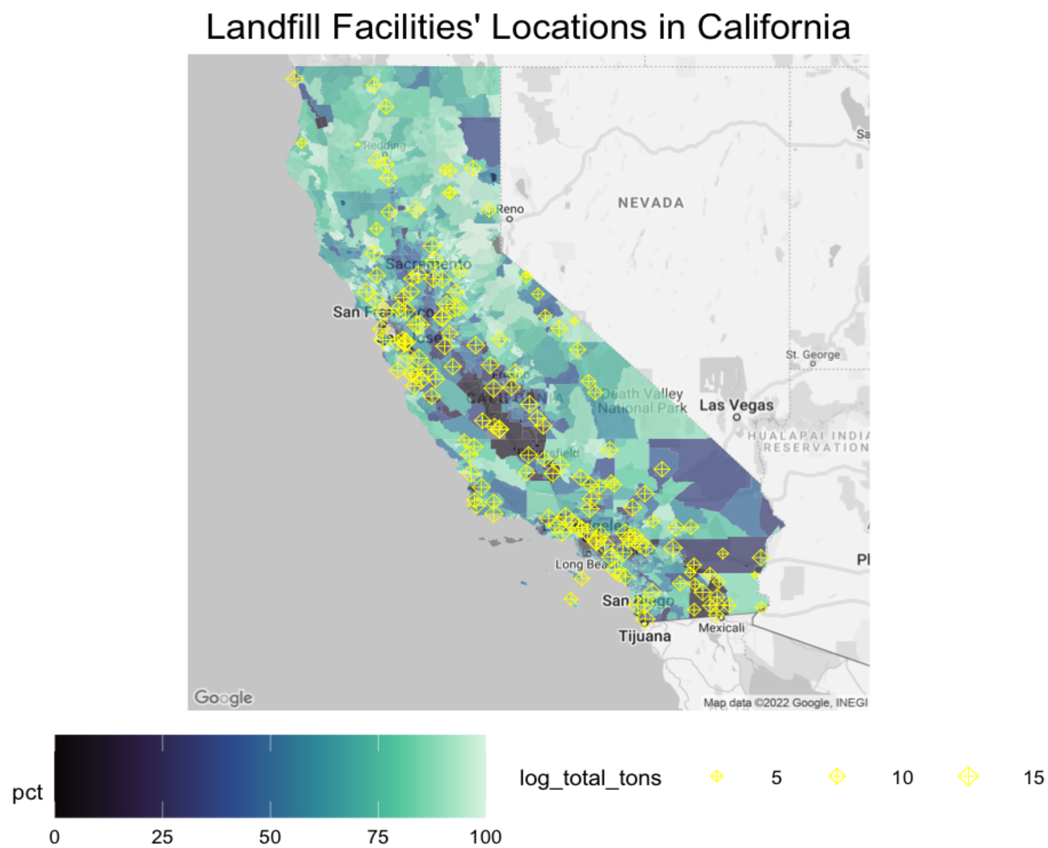


Figure 4.10: Landfill locations by Racial Compositions in California

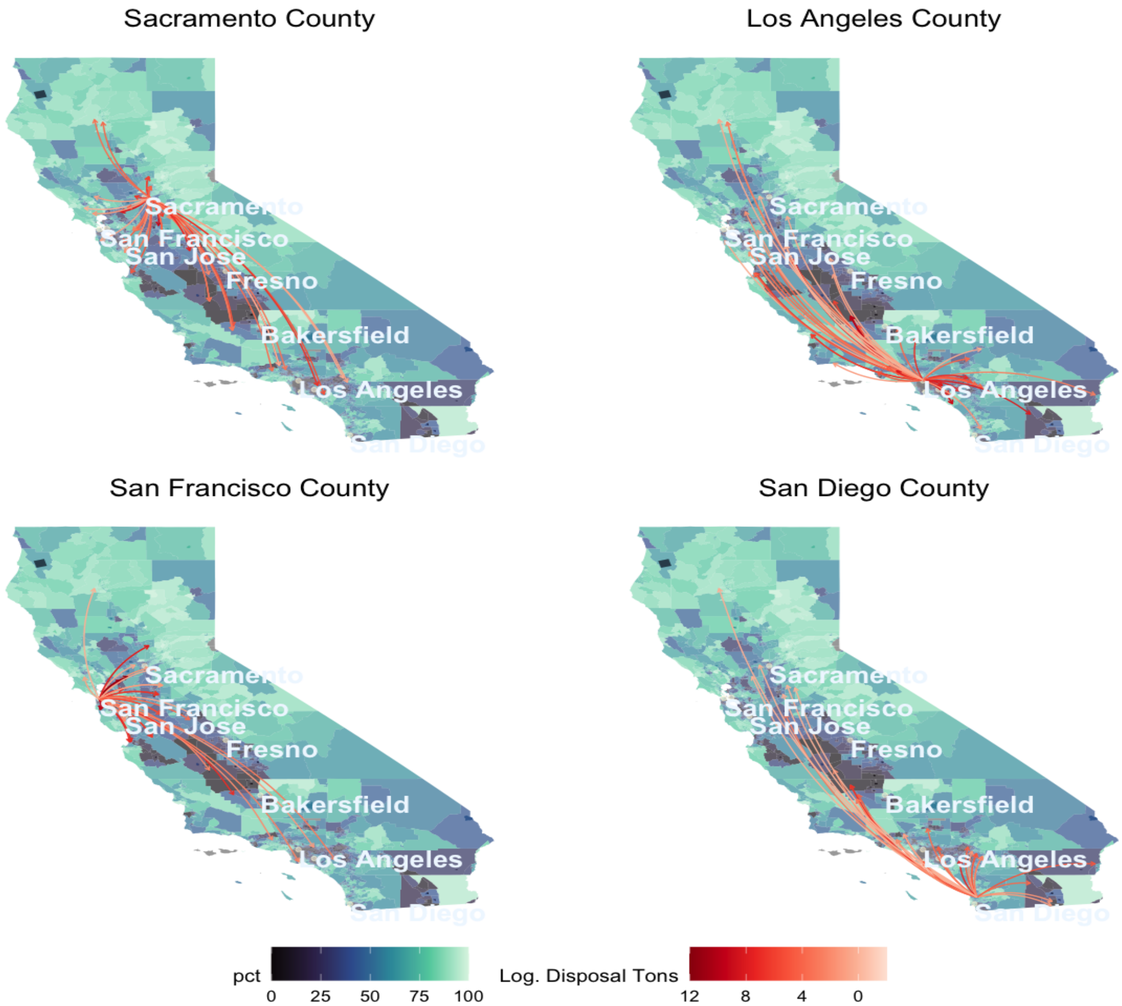


Figure 4.11: Average Net Increase of Disposal Flow after China's GS Policy by Perc of White of the Community

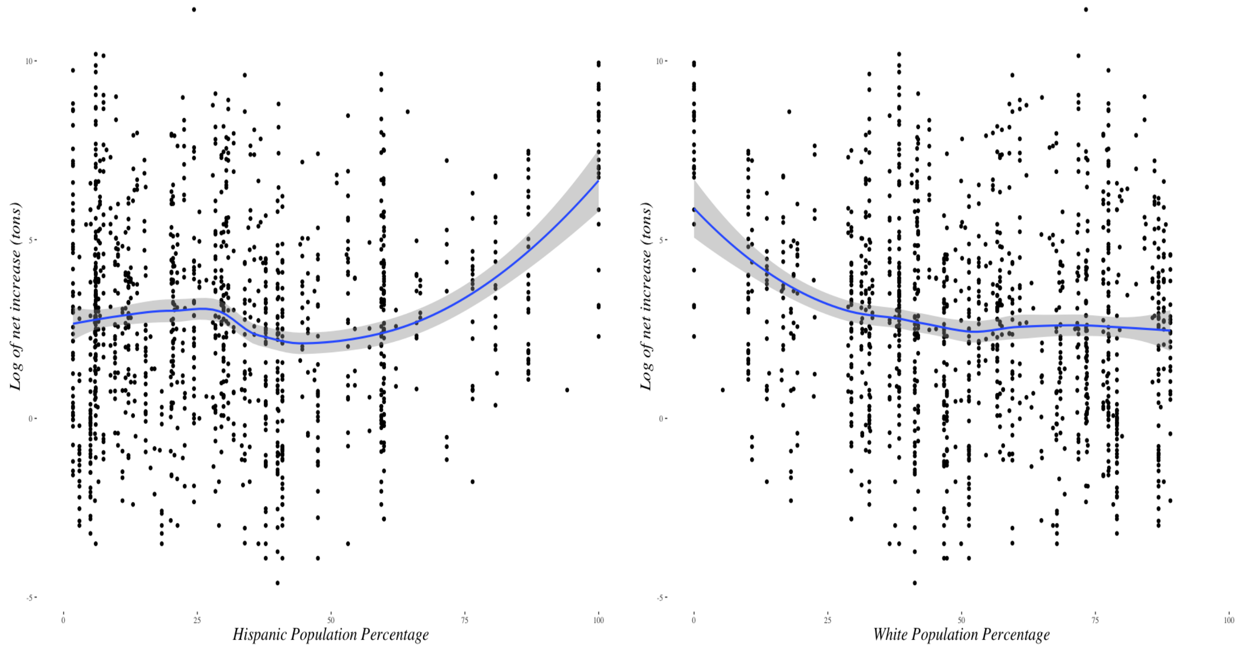


Figure 4.12: Average Net Increase of Disposal Flow and Racial Percentage by Perc of White of the Community

4.5.5 Model Specification

The state analysis is the first step towards understanding the causal effect of China's GS policy on aggregate emission levels. In order to gain a more detailed understanding of the local environmental effects of the GS policy, I then use facility-level data on disposal flows from 2002 to 2021 provided by CalRecycle to explore the pollution flow mechanisms and Environmental Justice (EJ) implications. I investigate the distributional effects of the GS policy on waste flows for local communities (at both county and census block levels) in the state of California. I apply a gravity-type model that includes the distances between the origins and destinations of inter-regional waste flows and tipping fees as well as racial composition, socioeconomic characteristics, environmental regulations, and waste industries' economies of scale of both origin and destination communities. The model specification is as follows:

$$log(Y_{ijt}) = \alpha + \beta_1 log(Dist_{ij}) + \beta_2 R_i + \beta_3 R_j + \beta_4 log(X_{it}) + \beta_5 log(X_{jt}) +$$

$$\epsilon_o + \theta_d + \mu_{od} + \eta_t + \lambda_{odt}$$

The dependent variable Y_{ijt} is the tons of the disposal transported from county i to county j in quarter t. $Dist_{ij}$ is the distance between origin county i and destination county j. X_{it} and X_{jt} are racial composition, socioeconomic factors, regulation of environmental stringency, and economies of scale of waste industry of origin and destination county i and j. I present the results that adjusted for different fixed effects including the origin county fixed effects (ϵ_i), destination county fixed effects (θ_j), year fixed effects, quarter fixed effects, year-quarter fixed effects (η_t), and origin-county-year-quarter fixed effects (λ_{ijt}).

This analysis reveals the factors that affect inter-regional pollution flows. The preliminary results show that before China's GS policy, counties with increasing shares of minorities (Black, Hispanic and Asian) among their populations tend to receive more pollution from other counties. To further investigate whether the GS policy amplifies environmental injustice due to increased transportation of wastes across local regions in California, I interact all of the county-level characteristics in my specifications with the GS policy indicator variable. The preliminary results suggest that the environmental injustices imposed on minority communities remain. However, pollution inflows increased for low-income White communities as a result of an increase in waste flows across regions after the exogenous GS policy shock. One potential mechanism of the pattern change of pollution relocation could be that recyclables suddenly have no market demand because of the quick change of the policy. The local recyclers needed to process the materials elsewhere in a short time because of the high storage costs and incoming recyclables from curbside recycling programs. As the costs of landfills in the White communities are relatively low compared to storage costs, extra disposal caused by the GS policy flows to these communities as a result.

4.6 Preliminary Results

Table 4.6: GF Policy Effect on California Cross-county Disposal Transport

Depended Vars	model1	model2	model3	model4	model5	model6	model7	model8	model9	model10	model11
[0.4cm] height											
White d	−0.352***	−0.625***	−0.555***	−0.623***	−0.623***	−0.633***	−0.628***	−0.628***	−0.623***	−0.203***	−0.621**
	(0.049)	(0.041)	(0.038)	(0.039)	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)	(0.044)	(0.206)
Black d	−0.074**	0.085**	0.149***	0.141***	0.140***	0.125***	0.127***	0.127***	0.142***	−0.055***	0.144
	(0.024)	(0.027)	(0.021)	(0.021)	(0.021)	(0.021)	(0.026)	(0.026)	(0.021)	(0.007)	(0.095)
Hispanic d	−0.104*	-0.020	0.030	0.052	0.050	0.050	0.051	0.052	0.046	0.141***	0.046
	(0.046)	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)	(0.036)	(0.035)	(0.202)
Asian d	0.349***	0.201***	0.129***	0.137***	0.138***	0.169***	0.167***	0.167***	0.136***	0.170***	0.134
	(0.019)	(0.021)	(0.017)	(0.017)	(0.017)	(0.017)	(0.021)	(0.021)	(0.016)	(0.014)	(0.094)
Median Income d		1.790***	2.018***	1.975***	1.968***	1.878***	1.880***	1.883***	1.967***	0.763***	1.957***
		(0.050)	(0.037)	(0.048)	(0.037)	(0.049)	(0.048)	(0.048)	(0.037)	(0.045)	(0.366)
Economies of scale d			0.043***	0.014***	0.014***	0.014***	0.014***	0.013***	0.013*	−0.066***	0.013
			(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.020)
Distance				−0.268***	−0.268***	−0.315***	−0.315***	−0.315***	−0.272***	−0.988***	-0.273
				(0.023)	(0.023)	(0.014)	(0.014)	(0.014)	(0.023)	(0.020)	(0.153)
Covariates											
Population d	0.104	0.184*	0.029	0.081	0.083	0.084	0.079	0.079	0.091	-0.128	0.090
	(0.109)	(0.078)	(0.075)	(0.076)	(0.075)	(0.072)	(0.073)	(0.073)	(0.075)	(0.086)	(0.456)
Tipping fee (qrt) o					-0.172	-0.159	-0.101	-0.138	-0.151	−0.442***	-0.177
					(0.130)	(0.126)	(0.117)	(0.118)	(0.119)	(0.086)	(0.182)
Tipping fee (qrt) d					-0.216	−0.242*	−0.252*	−0.250*	−0.243399*	0.763***	-0.177
					(0.116)	(0.102)	(0.107)	(0.115)	(0.115)	(0.107)	(0.222)
Establishments (qrt) o						0.048	0.351	0.397	0.484	0.388***	0.773
						(0.206)	(0.367)	(0.352)	(0.367)	(0.092)	(0.673)
Establishments (qrt) d						−0.618**	−1.231**	−1.321**	−1.401**	0.191	-1.266
						(0.234)	(0.471)	(0.454)	(0.461)	(0.111)	(0.672)
Employment (qrt-m1) o							-1.233	-1.607	11.610	10.424	8.668
							(0.909)	(0.930)	(10.868)	(9.386)	(7.911)
Employment (qrt-m2) o							4.613	4.730	17.892	10.876	14.796
							(2.674)	(2.680)	(13.780)	(11.478)	(9.216)
Employment (qrt-m3) o							-3.745	−4.209*	8.679	7.033	6.497
							(2.022)	(2.089)	(9.605)	(8.804)	(7.034)
Employment (qrt-m1) d							1.642*	2.110**	-12.093	−20.800*	-13.124
							(0.775)	(0.791)	(9.199)	(8.518)	(7.075)
Employment (qrt-m2) d							-3.825	-3.882	-17.993	-15.086	−19.490*
							(2.034)	(2.048)	(11.089)	(9.873)	(7.983)
Employment (qrt-m3) d)							3.523*	4.116*	-9.735	−16.383*	-10.139
							(1.556)	(1.608)	(8.335)	(8.029)	(6.407)
Total Wage (qrt) o								0.620**	-38.660	-28.554	-30.552
								(0.222)	(34.171)	(29.456)	(24.009)
Total Wage (qrt) d								−0.881***	41.256	52.222*	44.847*
								(0.148)	(28.492)	(26.139)	(21.333)
Average Wage (wk) o									39.287	28.850	31.361
									(34.215)	(29.451)	(24.008)
Average Wage (wk) d									-42.138	−54.157*	−45.560*
									(28.510)	(26.118)	(21.313)
Control Variables	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No

Table 4.7: GF Policy Effect on California Cross-county Disposal Transport

Depended Vars	model1	model2	model3	model4	model5	model6	model7	model8	model9	model10	model11
[0.4cm] height											
White d	-0.352^{***}	-0.625^{***}	-0.555^{***}	-0.623^{***}	-0.623^{***}	-0.633^{***}	-0.628^{***}	-0.628^{***}	-0.623^{***}	-0.203^{***}	-0.621^{**}
	(0.049)	(0.041)	(0.038)	(0.039)	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)	(0.044)	(0.206)
Black d	-0.074^{**}	0.085^{**}	0.149^{***}	0.141^{***}	0.140^{***}	0.125^{***}	0.127^{***}	0.127^{***}	0.142^{***}	-0.055^{***}	0.144
	(0.024)	(0.027)	(0.021)	(0.021)	(0.021)	(0.021)	(0.026)	(0.026)	(0.021)	(0.007)	(0.095)
Hispanic d	-0.104^{*}	-0.020	0.030	0.052	0.050	0.050	0.051	0.052	0.046	0.141^{***}	0.046
	(0.046)	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)	(0.036)	(0.035)	(0.202)
Asian d	0.349^{***}	0.201^{***}	0.129^{***}	0.137^{***}	0.138^{***}	0.169^{***}	0.167^{***}	0.167^{***}	0.136^{***}	0.170^{***}	0.134
	(0.019)	(0.021)	(0.017)	(0.017)	(0.017)	(0.017)	(0.021)	(0.021)	(0.016)	(0.014)	(0.094)
Median Income d		1.790^{***}	2.018^{***}	1.975^{***}	1.968^{***}	1.878^{***}	1.880^{***}	1.883^{***}	1.967^{***}	0.763^{***}	1.957^{***}
		(0.050)	(0.037)	(0.048)	(0.037)	(0.049)	(0.048)	(0.048)	(0.037)	(0.045)	(0.366)
Economies of scale d			0.043^{***}	0.014^{***}	0.014^{***}	0.014^{***}	0.014^{***}	0.013^{***}	0.013^{*}	-0.066^{***}	0.013
			(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.020)
Distance				-0.268^{***}	-0.268^{***}	-0.315^{***}	-0.315^{***}	-0.315^{***}	-0.272^{***}	-0.988^{***}	-0.273
				(0.023)	(0.023)	(0.014)	(0.014)	(0.014)	(0.023)	(0.020)	(0.153)
Covariates											
Population d	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Tipping fee (qrt) o					✓	✓	✓	✓	✓	✓	✓
Tipping fee (qrt) d					✓	✓	✓	✓	✓	✓	✓
Establishments (qrt) o						✓	✓	✓	✓	✓	✓
Establishments (qrt) d						✓	✓	✓	✓	✓	✓
Employment (qrt-m1) o							✓	✓	✓	✓	✓
Employment (qrt-m2) o							✓	✓	✓	✓	✓
Employment (qrt-m3) o							✓	✓	✓	✓	✓
Employment (qrt-m1) d							✓	✓	✓	✓	✓
Employment (qrt-m2) d							✓	✓	✓	✓	✓
Employment (qrt-m3) d)							✓	✓	✓	✓	✓
Total Wage (qrt) o								✓	✓	✓	✓
Total Wage (qrt) d								✓	✓	✓	✓
Average Wage (wk) o									✓	✓	✓
Average Wage (wk) d									✓	✓	✓
Control Variables	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×
Location Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
Observations	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739

Table 4.8: GS Policy Effect on California Cross-county Disposal Transport

Depended Vars	model1	model2	model3	model4	model5	model6	model7	model8	model9	model10	model11
[0.4cm] height											
White d	0.021***	0.006*	0.006*	0.004	0.004*	0.005*	0.005*	0.005*	0.005*	0.007***	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.020)
Black d	0.033***	0.032***	0.037***	0.035***	0.036***	0.036***	0.037***	0.037***	0.037***	0.004	0.036
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.022)
Hispanic d	0.025***	0.017***	0.017***	0.016***	0.016***	0.017***	0.017***	0.017***	0.017***	0.014***	0.017
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.019)
Asian d	0.048***	0.030***	0.028***	0.025***	0.026***	0.027***	0.027***	0.027***	0.027***	0.022***	0.027
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.024)
Median Income d		1.516***	1.523***	1.554***	1.547***	1.544***	1.545***	1.548***	1.548***	0.708***	1.538***
		(0.043)	(0.044)	(0.036)	(0.035)	(0.035)	(0.034)	(0.034)	(0.034)	(0.031)	(0.282)
Distance			−0.240***	−0.258***	−0.258***	−0.258***	−0.263***	−0.265***	−0.265***	−0.961***	-0.264
			(0.015)	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.022)	(0.171)
Economies of scale d				−0.001	−0.001	−0.001	−0.002	−0.002	−0.002	−0.074***	-0.002
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.024)
Covariates											
Tipping fee (qrt) o					✓	✓	✓	✓	✓	✓	✓
Tipping fee (qrt) d					✓	✓	✓	✓	✓	✓	✓
Establishments (qrt) o						✓	✓	✓	✓	✓	✓
Establishments (qrt) d						✓	✓	✓	✓	✓	✓
Employment (qrt-m1) o							✓	✓	✓	✓	✓
Employment (qrt-m2) o							✓	✓	✓	✓	✓
Employment (qrt-m3) o							✓	✓	✓	✓	✓
Employment (qrt-m1) d							✓	✓	✓	✓	✓
Employment (qrt-m2) d							✓	✓	✓	✓	✓
Employment (qrt-m3) d)							✓	✓	✓	✓	✓
Total Wage (qrt) o								✓	✓	✓	✓
Total Wage (qrt) d								✓	✓	✓	✓
Average Wage (wk) o									✓	✓	✓
Average Wage (wk) d									✓	✓	✓
Control Variables	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×
Location Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
Observations	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739	273,739

[a]

4.6.1 County-level Estimates

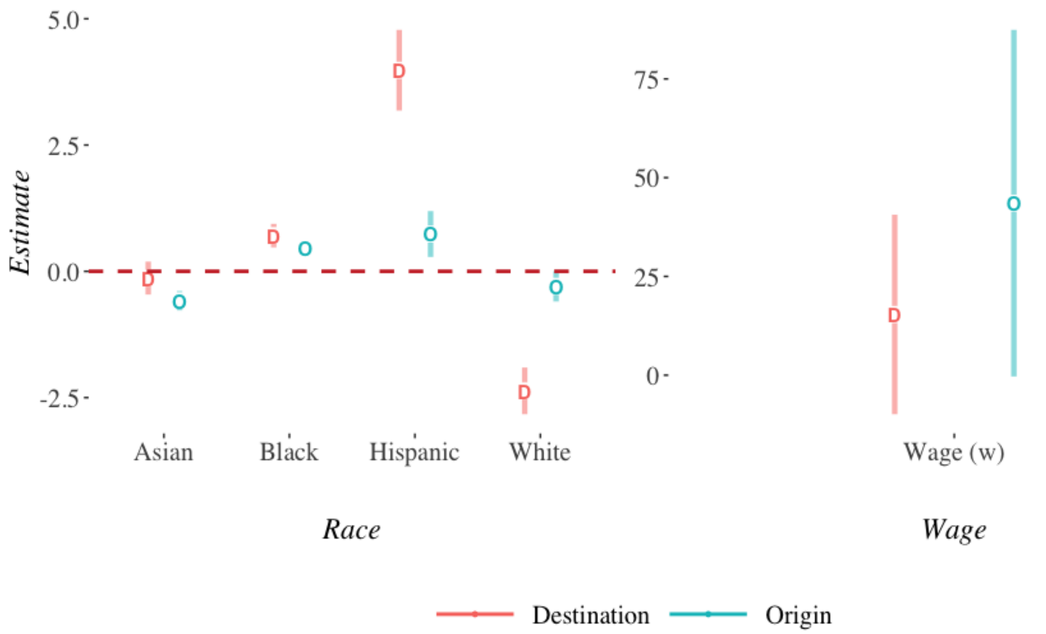


Figure 4.13: Gravity Model: Estimate of Racial Composition and Weekly Average Wage

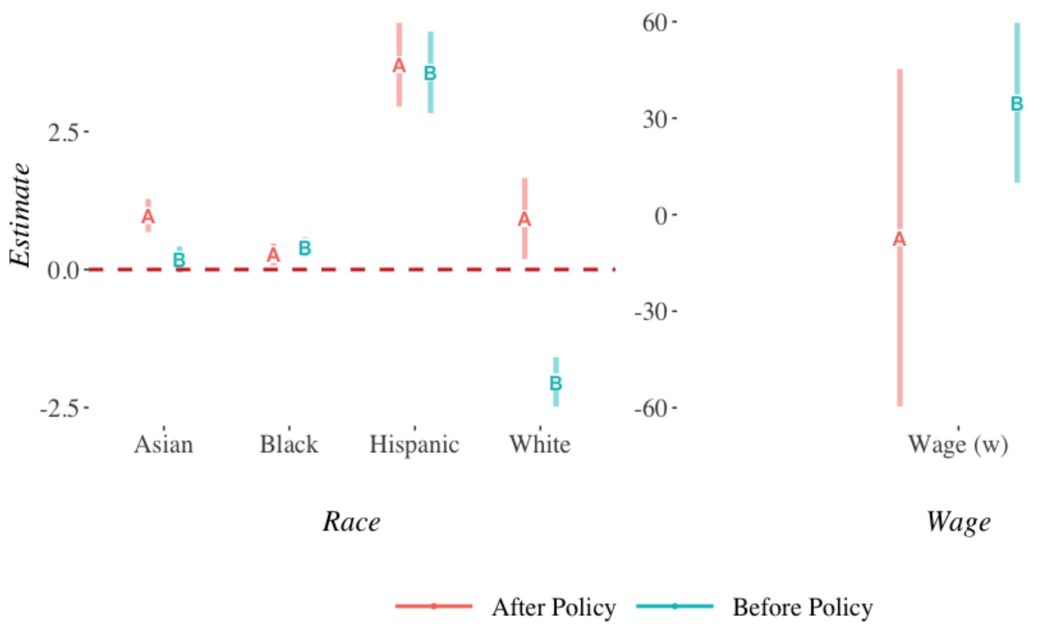


Figure 4.14: Gravity Model: Estimate of Racial Composition and Weekly Average Wage before and after GS Policy

4.6.2 Community-level Estimates

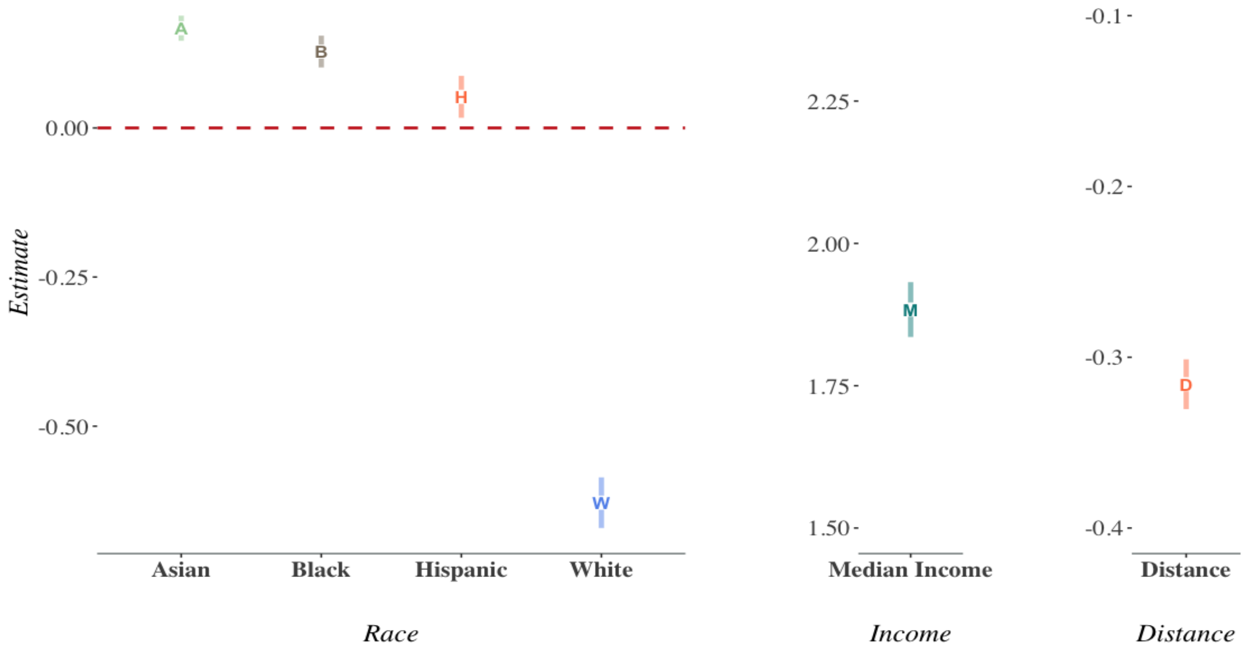


Figure 4.15: Gravity Model: Estimate of Racial Composition and Median Income

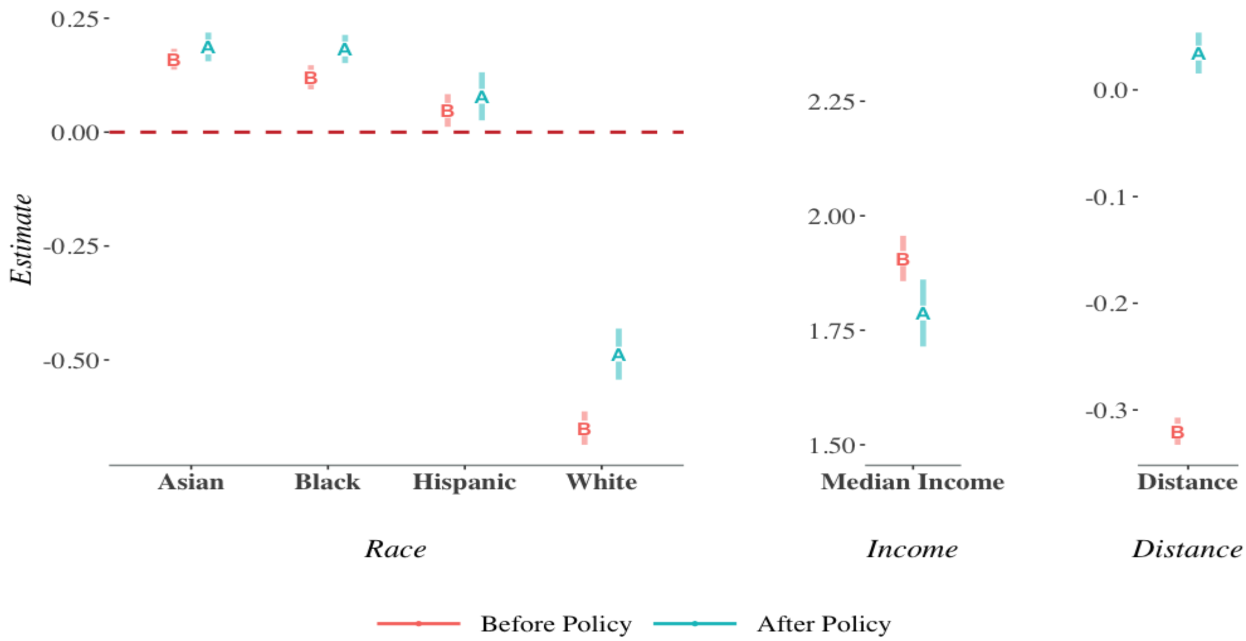


Figure 4.16: Gravity Model: Estimate of Racial Composition and Median Income before and after GS Policy

This analysis reveals the factors that affect inter-regional pollution flows. The preliminary results show that before China's GS policy, counties with increasing shares of minorities (Black, Hispanic and Asian) among their populations tend to receive more pollution from other counties. To further investigate whether the GS policy amplifies environmental injustice due to increased transportation of wastes across local regions in California, I interact all of the county-level characteristics in my specifications with the GS policy indicator variable. The preliminary results suggest that the environmental injustices imposed on minority communities remain. However, pollution inflows increased for low-income White communities as a result of an increase in waste flows across regions after the exogenous GS policy shock. One potential mechanism of the pattern change of pollution relocation could be that recyclables suddenly have no market demand because of the quick change of the policy. The local recyclers needed to process the materials elsewhere in a short time because of the high storage costs and incoming recyclables from curbside recycling programs. As the costs of landfills in the White communities are relatively low compared to storage costs, extra disposal caused by the GS policy flows to these communities as a result.

4.7 Economies of Scale or Vertical Intergration

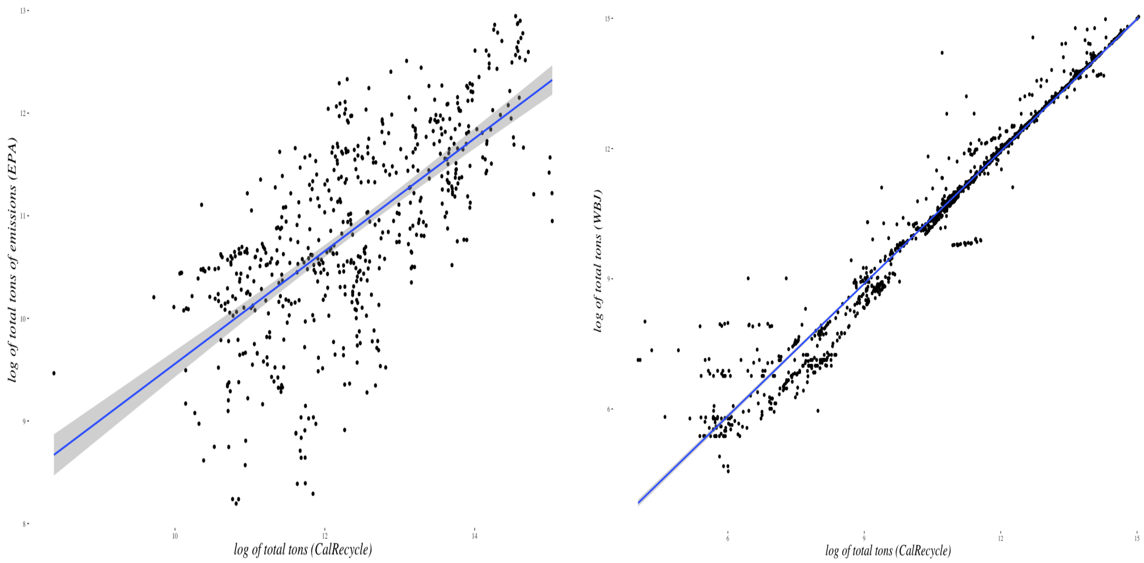


Figure 4.17: CalRecycle Data Comparison with EPA (left) and WBJ Data (right).

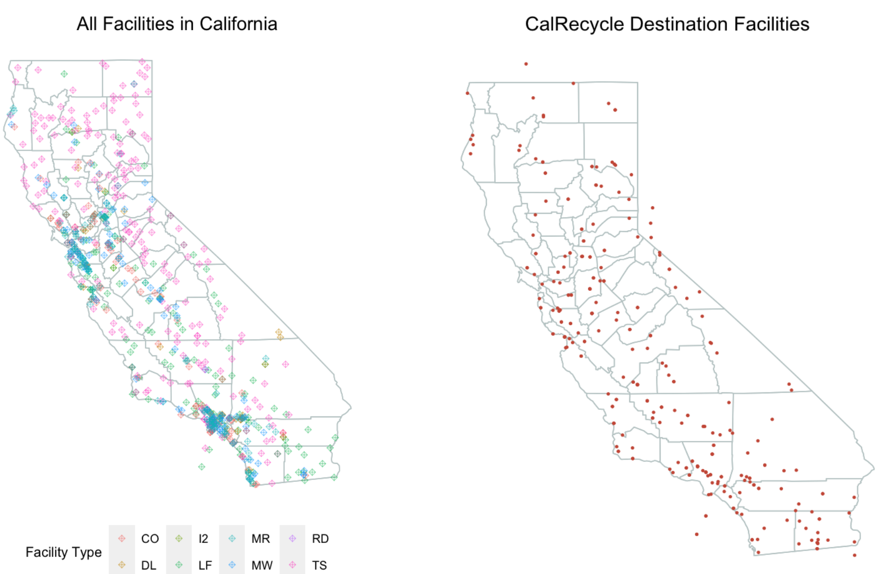


Figure 4.18: Facility Locations in WBJ (left) and CalRecycle (right).

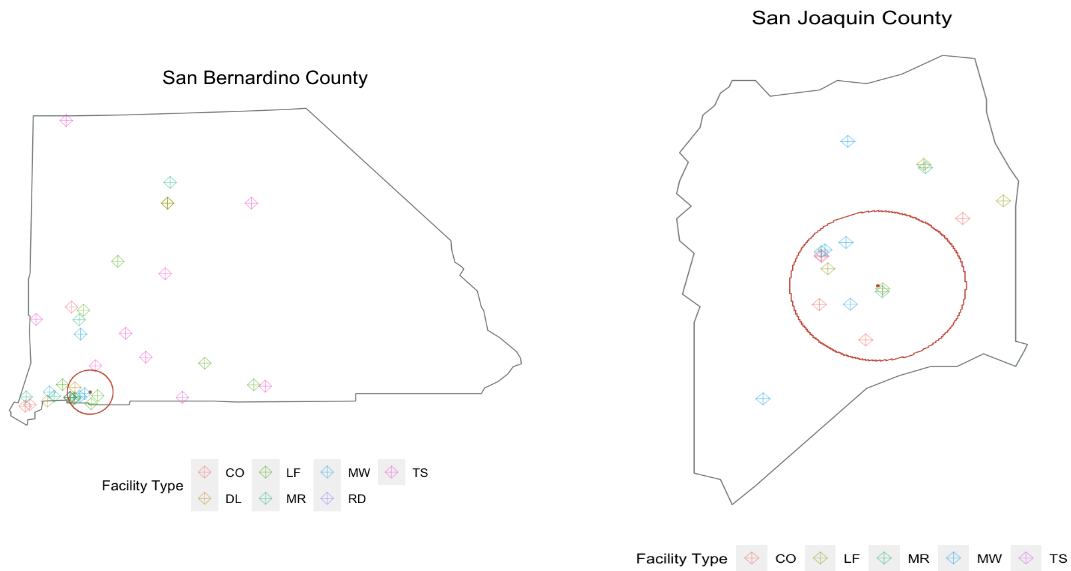


Figure 4.19: Economies of Scale (15km buffer) of Waste Industry in San Bernardino (left) and San Joaquin (right) county.

4.8 Political Cost v.s. Transportation Cost

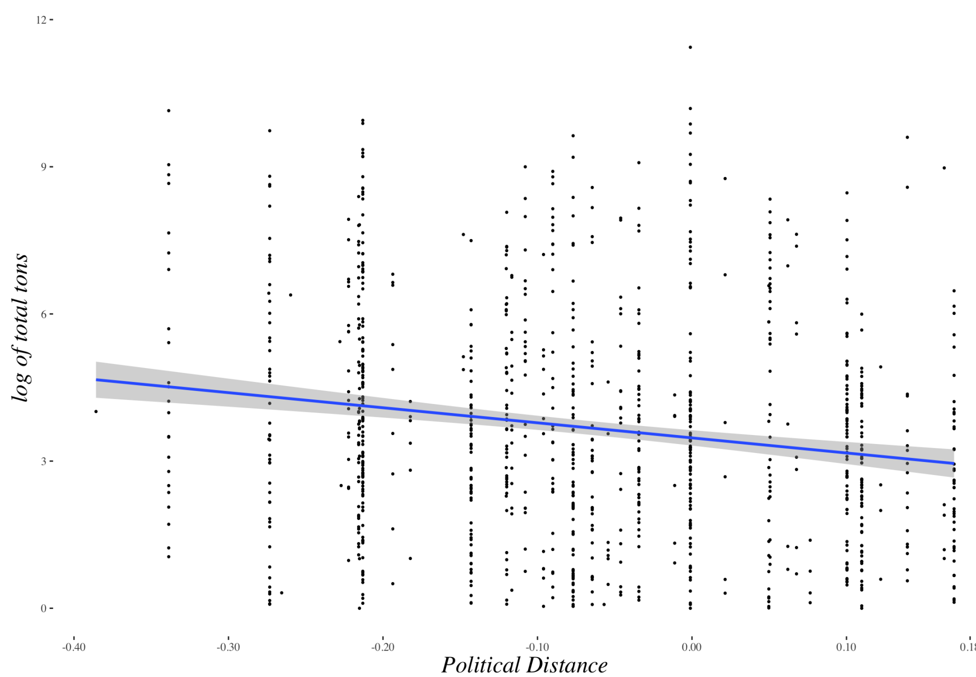


Figure 4.20: Difference in synthetic control and observed California Methane Emission

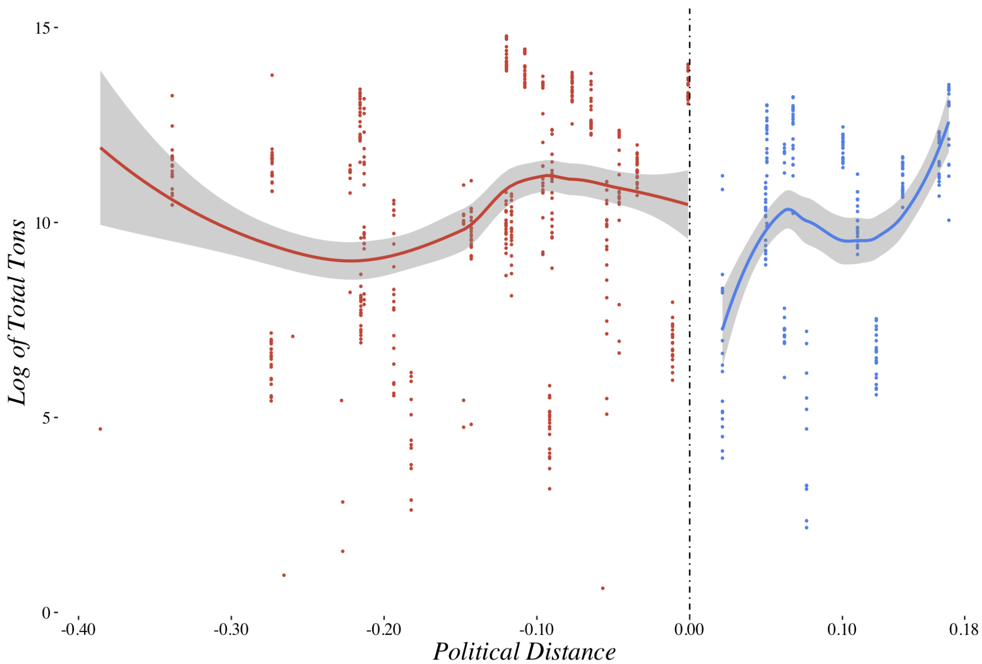


Figure 4.21: Regression Discontinuity of Political Costs and Log Total Tons of Waste Relocation over time

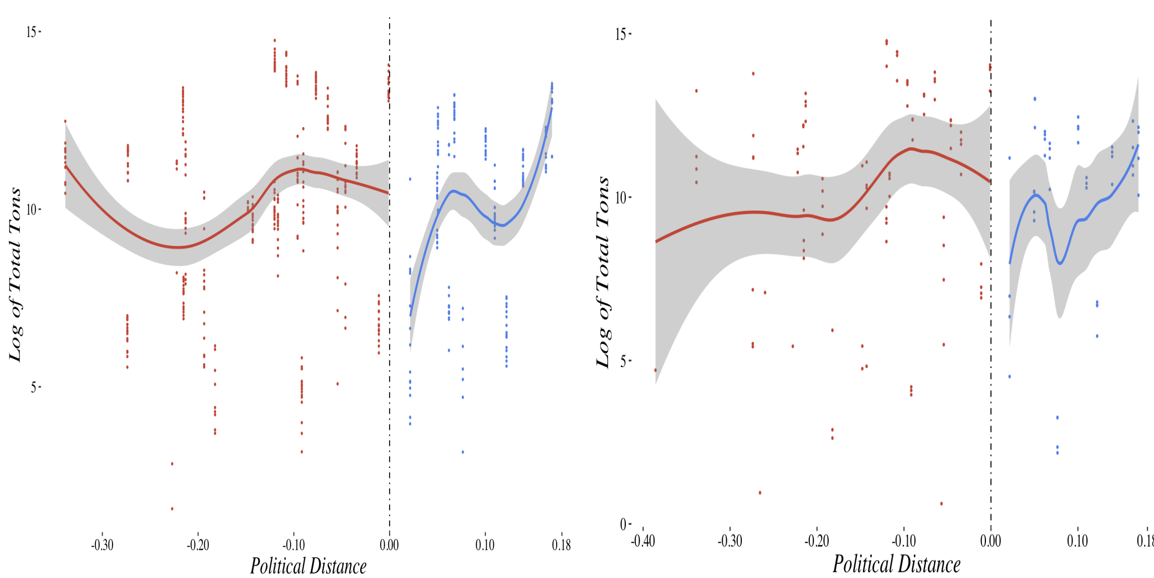


Figure 4.22: Regression Discontinuity of Political Costs and Log Total Tons of Waste Relocation before (left) and after (right) GS Policy.

CHAPTER 5

THE EFFECTS OF CHINA'S WASTE IMPORT BAN ON BEACH CLEANUP

5.1 Introduction

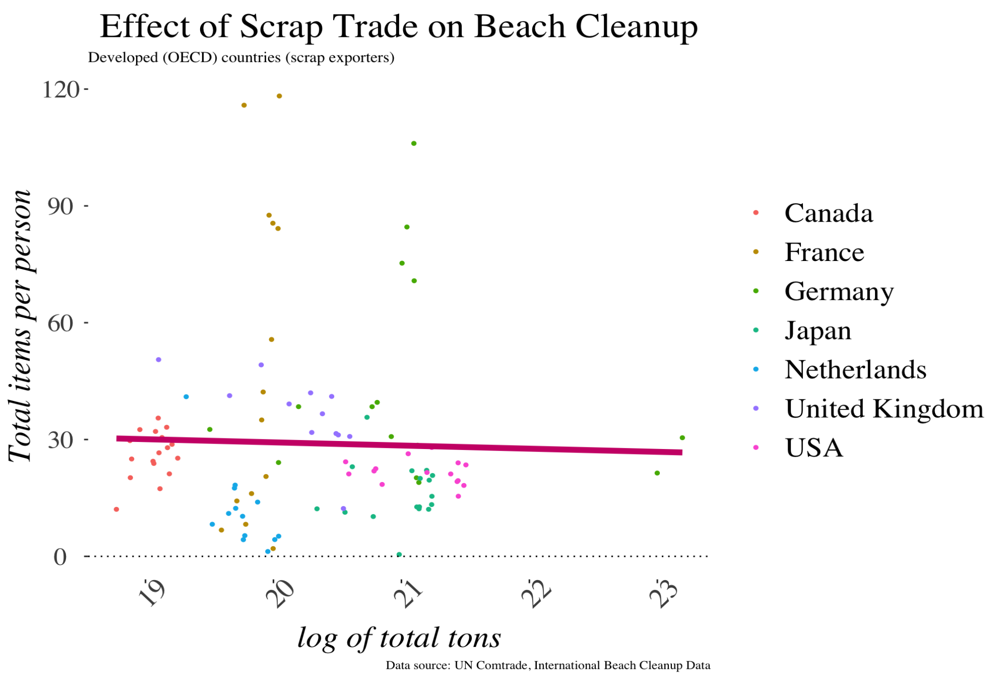


Figure 5.1: Correlation between Scrap Trade and Beach Cleanups in Developed Countries

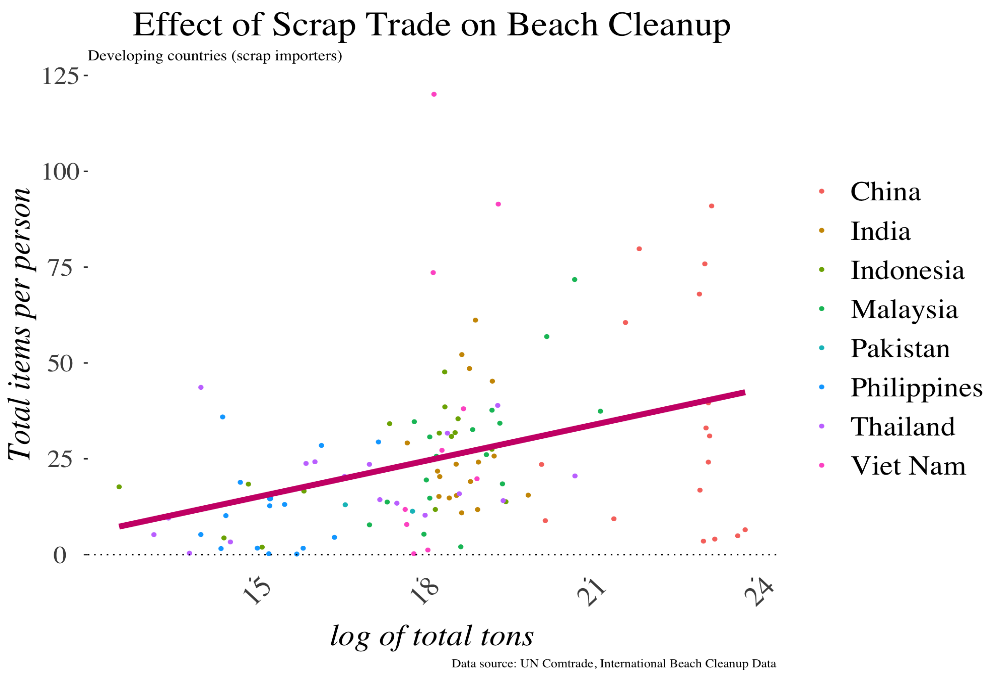


Figure 5.2: Correlation between Scrap Trade and Beach Cleanups in Developing Countries (include China)

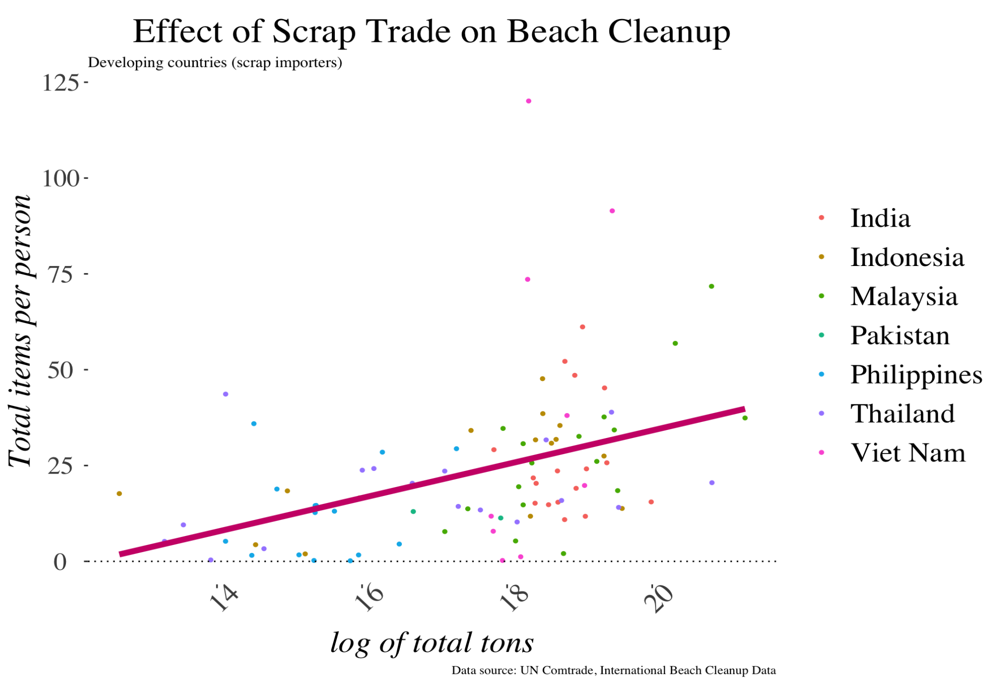


Figure 5.3: Correlation between Scrap Trade and Beach Cleanups in Developing Countries

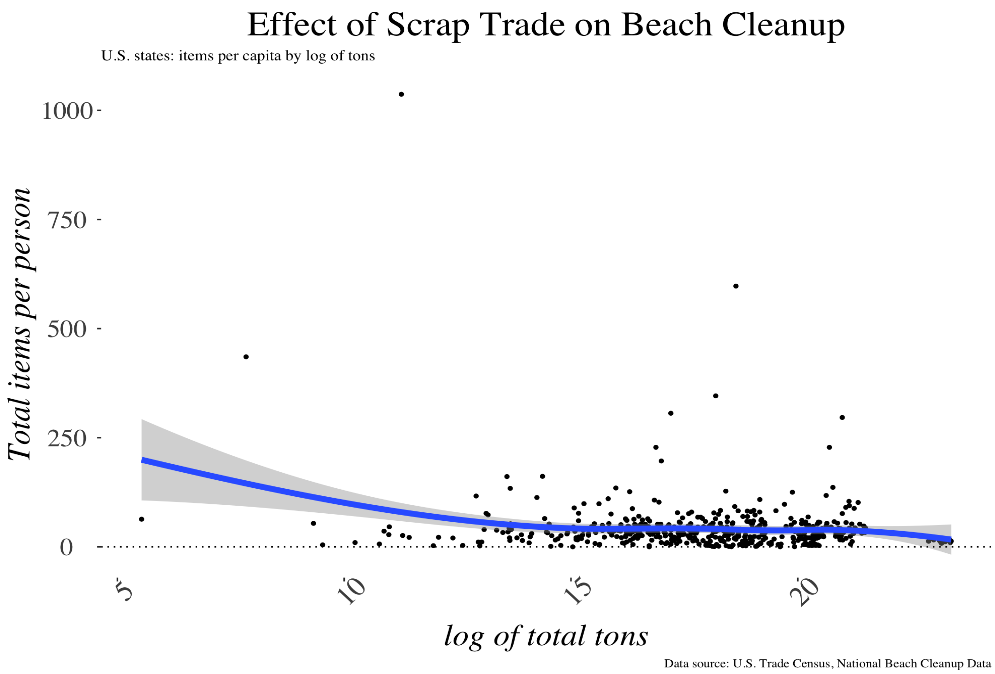


Figure 5.4: Correlation between Scrap Trade and Beach Cleanups across states in the U.S.

REFERENCES

Aadland, D. and Caplan, A. J. (2006). "Curbside Recycling: Waste Resource or Waste of Resources?". *Journal of Policy Analysis and Management*, 25(4):855–74.

Adeel, B. A., Catalano, M., Catalano, O., Gibson, G., Muftuoglu, E., Riggs, T., Sezgin, H. M., Shvetsova, O., Tahir, N., VanDusky, J., Zhao, T., and Zhirnov, A. (2020). COVID-19 Policy Response and the Rise of the Sub-National Governments. *Canadian Public Policy*, 46:565–584.

Ashenmiller, B. (2009). "Cash Recycling, Waste Disposal Costs, and the Incomes of the Working Poor: Evidence from California" . *Land Economics*, 85(3):539–551.

Ashenmiller, B. (2011). "The Effect of Bottle Laws on Income: New Empirical Results". *American Economic Review*, 101(3):60–64.

Auffhammer, M. and Kellogg, R. (2011). Clearing the Air? The Effects of Gasoline Content Regulation on Air Quality. *American Economic Review*, 101(6):1–52.

Baden, B. M. and Coursey, D. L. (2002). "The locality of waste sites within the city of chicago: a demographic, social, and economic analysis" . *Resource and Energy Economics*, 24(1-2):53–93.

Banzhaf, S., Ma, L., and Timmins, C. (2019). "Environmental justice: The economics of race, place, and pollution" . *Journal of Economic Perspectives*, 33(1):185–208.

Banzhaf, S. H. and Walsh, R. P. (1994). "Environmental equity: the demographics of dumping" . *Demography*, 31(2):229–248.

Banzhaf, S. H. and Walsh, R. P. (2008). "Do People Vote with Their Feet? An Empirical Test of Tiebout's Mechanism" . *American Economic Review*, 93(3):843–63.

Banzhaf, S. H. and Walsh, R. P. (2013). “Segregation and Tiebout sorting: The link between place- based investments and neighborhood tipping” . *Journal of Urban Economics*, 74:83–98.

Berck, P., Blundell, M., Englander, G., Gold, S., He, S., Horsager, J., Kaplan, S., Sears, M., Stevens, A., Trachtman, C., Taylor, R., and Villas-Boas, S. B. (2021). “Recycling Policies, Behavior and Convenience: Survey Evidence from the CalRecycle Program” . *Applied Economic Perspectives and Policy*, 43(2):641–658.

Berck, P., Sears, M., Taylor, R. L., Trachtman, C. C., and Villas-Boas, S. B. (2020). “Reduce, Reuse, Redeem: Deposit-Refund Recycling Programs in the Presence of Alternatives” . *CUDARE Working Paper, California University Department of Agricultural and Resource Economics.*

Best, H. and Kneip, T. (2019). “Assessing the Causal Effect of Curbside Collection on Recycling Behavior in a Non-randomized Experiment with Self-reported Outcome” . *Environmental and Resource Economics*, 72:1203–1223.

Bohm, R., Folz, D., Kinnaman, T., and Podolsky, M. (2010a). The Costs of Municipal Curbside Recycling and Waste Collection. *Resources, Conservation, and Recycling*, (September):864–871.

Bohm, R., Folz, D. H., Kinnaman, T. C., and Podolsky, M. J. (2010b). ”The Costs of Municipal Waste and Recycling Programs”. *Resources, Conservation and Recycling*, 54(8):64–71.

Bosworth, R., Cameron, T. A., and DeShazo, J. R. (2009). Demand for environmental policies to improve health: Evaluating community-level policy scenarios. *Journal of Environmental Economics and Management*, 57(3):293–308.

Brander, L., Beukering, P. V., and Cesar, H. S. (2007). The recreational value of coral reefs: A meta-analysis. *Land Economics*, 63:209–218.

Burger, N., Kaffine, D., and Yu, B. (2014). Did California's hand-held cell phone ban reduce accidents? *Transportation Research Part A: Policy and Practice*, 66(1):162–172.

Cameron, T. A. (2010). Euthanizing the value of a statistical life. *Review of Environmental Economics and Policy*, 4(2):161–178.

Cameron, T. A. and McConnaha, I. T. (2006). "Evidence of Environmental Migration" . *Land Economics*, 82(2):273–90.

Cattapan, A., Ackerverney, J. M., Dobrowolsky, A., Findlay, T., and Mandrona, A. (2020). Community Engagement in a Time of Confinement. *Canadian Public Policy*, 14:288–298.

Center for Research and Expertise on the World Economy (2021a). CEPII Gravity Database. Accessed: 2021-03-02 `http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=8`.

Center for Research and Expertise on the World Economy (2021b). CEPII Trade Unit Values (TUV) data. Accessed: 2021-03-09 `http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=2`.

Chorus, C., Sandorf, E. D., and Mouter, N. (2020). Diabolical dilemmas of COVID-19: An empirical study into Dutch society's trade-offs between health impacts and other effects of the lockdown. *PLoS ONE*, 15:1–19.

Cook, A. R., Zhao, X., Chen, M. I., and Finkelstein, E. A. (2018). Public preferences for interventions to prevent emerging infectious disease threats: A discrete choice experiment. *BMJ Open*, 8:1–12.

Davis, L. (2008). The Effect of Driving Restrictions on Air Quality in Mexico City. *Journal of Political Economy*, 116(1):31–57.

Depro, B., Timmins, C., and O'Neil, M. (2011). "Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data" . *American Economic Review*, 101(3):620–24.

Depro, B., Timmins, C., and O'Neil, M. (2015). "White flight and coming to the nuisance: Can residential mobility explain environmental injustice?" . *Journal of the Association of Environmental and Resource Economists*, 2(3):439–468.

Dorantes, C. A., Kaushal, N., and Muchow, A. N. (2020). Is the Cure Worse than the Disease? County-Level Evidence from the COVID-19 Pandemic in the United States. *NBER Working Paper No. 27759*, pages 1–35.

Echazu, L. and Nocetti, D. C. (2020). Willingness to pay for morbidity and mortality risk reductions during an epidemic. Theory and preliminary evidence from COVID-19. *GENEVA Risk and Insurance Review*, 45(2):114–133.

Federal Reserve St. Louis (2021a). Global price of Brent Crude (POILBREUSDM). Accessed: 2021-04-09 `https://fred.stlouisfed.org/series/POILBREUSDM`.

Federal Reserve St. Louis (2021b). U.S. Monthly Unemployment Rate. Accessed: 2021-03-09 `https://fred.stlouisfed.org/series/UNRATE`.

Halvorsen, B. (2010). "Effects of Norms and Opportunity Cost of Time on Household Recycling". *Land Economics*, 84(3):501–16.

Haque, S., Uddin, S., Sayem, S., and Mushfique, K. (2021). Coronavirus disease 2019 (COVID-19) induced waste scenario: A short overview. *Journal of Environmental Chemical Engineering*, (Feb).

Hernandez-Cortes, D. and Meng, K. C. (2020). "Do Environmental Markets Cause Environmental Injustice? Evidence from California's Carbon Market" . *NBER Working Paper*, (27205).

Higashida, K. and Managi, S. (2014). Determinants of trade in recyclable wastes: Evidence from commodity-based trade of waste and scrap. *Environment and Development Economics*, 19(2):250–270.

Ho, P. (2020). “Not in My Backyard” Make Matters Worse? Environmental Justice Concerns in Solid Waste Disposal” . *Working Paper*.

International Monetary Fund (2021). Macroeconomic and Financial Data. Accessed: 2021-03-05 `https://data.imf.org/?sk=2CDDCCB8-0B59-43E9-B6A0-59210D5605D2&sId=1390030341854`.

International Monetary Fund (IMF) (2021). International Exchange Rate (all currencies against U.S. dollars). Accessed: 2021-03-06 `https://www.imf.org/external/np/fin/data/param_rms_mth.aspx`.

International Monetary Fund (IMF)Commodity Price Index (2021). Commodity Price Index. Accessed: 2021-03-05 `https://www.imf.org/en/Research/commodity-prices`.

Johnston, R. J., Boyle, K. J., Vic Adamowicz, W., Bennett, J., Brouwer, R., Ann Cameron, T., Michael Hanemann, W., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., and Vossler, C. A. (2017). Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists*, 4(2):319–405.

Kinnaman, T. C. (2014). ”Effects of Norms and Opportunity Cost of Time on Household Recycling”. *Resources, Conservation and Recycling*, 85:5–10.

Kinnaman, T. C., Shinkuma, T., and Yamamoto, M. (2014). ”The Socially Optimal Recycling Rate: Evidence from Japan”. *Journal of Environmental Economics and Management*, 68:54–70.

Kurz, T., Linden, M., and Sheehy, N. (2000). “Attitudinal and Community Influences on

Participation in New Curbside Recycling Initiatives in Northern Ireland" . *Environment and Behavior*, 39(3):367–91.

Lee, J., Wei, S., and Xu, J. (2018). An Unhealthy Trade Surplus? *University of Toronto Mississauga*.

Li, L., Long, D., and Rad, M. R. (2020). Stay-at-Home Orders and the Willingness to Stay Home During the COVID-19 Pandemic: A Stated-Preference Discrete Choice Experiment. *SSRN*.

Lincoln, K. D., Abdou, C. M., and Lloyd, D. (2014). Race and socioeconomic differences in obesity and depression among black and non-hispanic White Americans. *Journal of Health Care for the Poor and Underserved*, 25(1):257–275.

Lindhjelm, H. and Navrud, S. (2008). How Reliable Are Meta-Analyses for International Benefit Transfer? *Ecological Economics*, 66:425–435.

Miles, D., Stedman, M., and Heald, A. (2020). LIVING with COVID-19: BALANCING COSTS against BENEFITS in the FACE of the VIRUS. *National Institute Economic Review*, 253:60–76.

Mühlbacher, A. and Johnson, R. F. (2016). Choice Experiments to Quantify Preferences for Health and Healthcare: State of the Practice. *Applied Health Economics and Health Policy*, 14:253–266.

Price, J., Dupont, D., and Adamowicz, W. (2017). Willingness to accept tradeoffs among Covid-19 cases, social-distancing restrictions, and economic impact: A nationwide US study. *Environmental and Resource Economics*, 68:643–662.

Ready, R. and Navrud, S. (2006). International benefit transfer: Methods and validity tests. *Ecological Economics*, 60:429–434.

Reed, S., Gonzalez, J. M., and Johnson, F. R. (2020). Willingness to accept tradeoffs among Covid-19 cases, social-distancing restrictions, and economic impact: A nationwide US study. *medRxiv*, 11:1438–1443.

Rees-Jones, A., Attoma, J., Piolatto, A., and Salvadori, L. (2020). COVID-19 Changed Tastes for Safety-Net Programs. *NBER Working Paper No. 27865*, pages 1–20.

Richardson, L., Loomis, J., Kroeger, T., and Casey, F. (2015). The role of benefit transfer in ecosystem service valuation. *Ecological Economics*, 115:51–58.

Sandler, D. (2014). Multiple event studies in public finance and labor economics: A simulation study with applications. *Journal of Economic and Social Measurement*, 39(1-2):31–57.

Shapiro, J. S. (2016). "Trade Costs, CO2, and the Environment" . *American Economic Journal: Economic Policy*, 8(4):220–54.

Shapiro, J. S. (2021). "The Environmental Bias of Trade Policy" . *Quarterly Journal of Economics*, 136(2):831–886.

Shapiro, J. S. and Walker, R. (2021). "Where is Pollution Moving? Environmental Markets and Environmental Justice" . *AEA Papers and Proceedings*, 111:410–14.

Shapiro, Joseph S.and Walker, R. (2018). "Why is Pollution from U.S. Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade" . *American Economic Review*, 108(12):3814–54.

Smith, V. K., Van Houtven, G., and Pattanayak, S. K. (2002). Benefit transfer via preference calibration: "Prudential Algebra" for policy. *Land Economics*, 78:132–152.

Trade Analysis Information System (TRAINS) World Bank (2021). Bilateral tariffs. Accessed: 2021-03-04 `https://databank.worldbank.org/source/unctad-%5E-trade-analysis-information-system-(trains)`.

UN Comtrade Database (2021). United Nation. Accessed: 2021-03-02 https://comtrade.un.org/data/.

Viscusi, W. K. (2020). Pricing the global health risks of the COVID-19 pandemic. *Journal of Risk and Uncertainty*, 61:101–128.

World Bank (WB) World Development Indicator (2021). Manufacturing, value added. Accessed: 2021-03-09 https://data.worldbank.org/indicator/NV.IND.MANF.ZS.

Yancy, C. W. (2020). COVID-19 and African Americans. *JAMA - Journal of the American Medical Association*, 323(19):1891–1892.