The Effect of China's Recyclable Waste Import Ban on Pollution Relocation in the U.S.

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Abstract

In 2017, China announced its Green Sword (GS) policy to ban all types of recyclable waste imports from overseas. As a result, U.S. recyclable waste exports to China decreased dramatically; many U.S. recyclable wastes are now processed domestically, contributing to pollution within the U.S. This paper examines the effects of China's GS policy on U.S. domestic methane emissions and on changes in the spatial patterns of local pollution. I find that after the GS policy, U.S. methane emissions from the waste industry increased by 10%. I also find that the resulting heterogeneous increases in state-level emissions are positively correlated with the amount of recyclable waste each state exported to China prior to the GS policy. Finally, I use local waste disposal transfer data for California and find that Black communities tended to receive more waste transfers prior to China's waste ban. However, after the waste ban, relatively more waste pollution relocated to lower-income White communities. I explore several potential mechanisms and find that land cost is likely the main explanation for this distributional effect.

Keywords: Recycling, GHG emissions, international trade policy, distributional effects, local pollution relocation, environmental justice.

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1 Introduction

International recyclable waste transfers are an important part of global pollution relocation. Over the past two decades, more than 1 billion metric tons of recyclable wastes were transferred from developed countries to developing countries through international trade.[1] As a large developing country, China imported a vast amount of recyclable waste to reuse in production (Kellenberg, 2012; Kellenberg, 2015; Higashida and Managi, 2014; Gregson and Crang, 2015; Lee et al., 2020). However, cleaning and reprocessing such materials caused severe air, water, and land pollution in China. In 2017, China announced its Green Sword (GS) policy to stop the importation of paper, plastic, and other types of scrap materials from overseas. Research shows that Chinese cities connected to waste importation and reprocessing have improved significantly in their air quality as a result of China's GS policy (Li and Takeuchi, 2021; Unfried and Wang, 2022).

The GS policy has greatly impacted the recycling industry and environmental outcomes in the U.S. China was formerly the largest importer of U.S. recyclable wastes.[2] Within a year after the GS policy was implemented, the U.S. recycling industry diverted its exports of recyclable wastes to other developing countries in South and Southeast Asia. However, after being overwhelmed with the sheer amount of waste, many of these developing countries followed China's example and likewise implemented policies to restrict/ban these waste inflows.[3] Given that recyclable waste export options have been reduced drastically for the U.S., most recyclable wastes now remain in the U.S. However, due to a diminishing manufacturing sector and stringent environmental regulations, these recyclable wastes cannot be reprocessed and reused domestically. Many of these recyclables are sent to landfills, contributing to methane emissions.

This paper quantitatively studies the consequences of China's waste ban on both the amount and distribution of U.S. emissions from the waste industry. I provide empirical evidence necessary to answer the following questions: (1) How has China's GS policy affected domestic emissions at the national level in the U.S.? (2) How do heterogeneous changes in emissions relate to recyclable waste exports at the state level in the U.S.? Focusing on California as a case study, (3) what are the distributional effects of China's policy on pollution relocation for local communities (at the census-block level)? And (4) what are the potential mechanisms to explain the distributional effects in those communities?

In the first part of my analysis, I study the causal effect of China's GS policy on U.S. domestic methane emissions. The biggest challenge is that this landmark GS policy affected all geographic regions in the U.S.; it is difficult to find a control group with regions that are not affected by the GS policy. To solve this problem, I use the EPA Greenhouse Gas Reporting Program, which includes emissions from all U.S. industries. The advantage of this program is that it contains

[1] Statistics according to the UN Comtrade data

[2] In 2016, China imported about 17 billion tons of recyclable wastes from the U.S., which accounted for 72.9 percent of the total recyclable wastes exported by the U.S.

[3] For example, in May 2018, Indonesia required 100 percent inspection of scrap paper and plastic imports. In March 2019, India announced a ban on scrap plastic imports.

emissions data from not only the waste industry but also other industries such as oil and natural gas, mineral, chemistry, power plants, etc. China's waste ban directly affected the emissions from the waste industry; however, it did not directly affect emissions from these other industries. I therefore use all other industries except for the waste industry as my control group. I then use the synthetic control method for the waste industry in each state of the U.S. and find that 11 states (particularly big states) have seen a statistically significant increase in methane emissions from their waste industry after the waste ban. For example, California has seen a 9% increase in methane emissions—a 2 million metric tons of CO_2 eq. net increase in emissions. After aggregating changes in methane emissions from all states, I find that the overall U.S. methane emissions from the waste industry increased by almost 10 million metric tons of CO_2 eq.[4] This increase was about 10% of total U.S. methane emissions from the waste industry in 2016. In the heterogeneity analysis, I find that the more waste a state exported before China's waste ban, the greater impact the waste ban had on the methane emissions of the state.

In the second part of my analysis, I further examine the relationship between U.S. emissions and recyclable waste exports. If states that historically exported higher amounts of waste experienced a greater increase in methane emissions after the GS policy, then recyclable waste exports should have been reducing the emissions of the state before the GS policy. I use the recyclable waste exports data by state and year from *U.S.A. Trade Online*, and emissions data from the waste industry by state and year from the *U.S. EPA GreenHouse Gas Inventory* for this analysis. To estimate the causal relationship between exports and emissions, I need to account for the fact that U.S. waste exports are endogeneous to U.S. economic activities and emissions. To solve this issue, I use a Bartik shift-share instrumental variable. This instrument takes the initial-year shares of recyclable waste exports by state and applies them to annual aggregated recyclable waste exports from the U.S. to China. The key assumption is that the initial-year shares of recyclable waste exports by state are unrelated to the future waste exports from the U.S. to China. Thus, the recyclable waste exports weighted by the initial-year shares are exogenous to future emissions and economic activities. Using this method, I find that before China's GS policy, for every additional metric ton of recyclable waste exported, U.S. domestic emissions were reduced by 0.83 metric tons of CO_2 eq. This result is consistent with the hypothesis that that U.S. recyclable waste exports have directly reduced domestic emissions from the waste industry. After China's GS policy, U.S. recyclable waste exports to China decreased by 12 million metric tons. This export reduction leads to about 11 million metric tons of CO_2 eq. increase in methane emissions from the waste industry in the U.S. This number is comparable to my result from the synthetic control method, which cross-validates my results from both methods.

In the third part of my analysis, I use California as a case study to examine the effects of China's GS policy on pollution relocation at the local community level.[5] Given that wastes tended to

[4]This number is calculated by aggregating the changes in emissions of all states whose synthetic control estimates can be judged to be statistically significant.

[5]California is chosen because (1) it is the largest state that exported recyclable wastes, and (2) it has unusually rich data at facility level, permitting a more rigorous analysis.

relocate to pollution haven countries like China before the GS policy, new local pollution havens have been sought as destinations for excess recyclable wastes after the GS policy. The *CalRecycle Recycling and Disposal Reporting System (RDRS)* allows me to study the distributional effects of the GS policy on local communities. This dataset contains detailed waste transfer records from origin jurisdictions to destination facilities from 2002 to 2020 within California. The system has over 400 origin jurisdictions and almost 150 destination facilities. According to the CalRecycle RDRS, nearly 800,000 tons of waste were transferred across local communities in California over the past 20 years. I take China's waste ban as a natural experiment to examine how waste pollution relocated after an exogenous policy shock. I collect the local characteristics of destination communities, such as racial composition, median income, economies of scale, and political vote shares. I compare how these characteristics affect waste transfers across communities before and after the GS policy. The results show that before the waste ban, communities with higher minority population shares, higher median income, a larger economy of scale, and higher Republican vote shares tended to receive more waste transfers from other jurisdictions. However, after the waste ban, communities with higher White population shares, lower median income, fewer economies of scale, and fewer Republican vote shares experienced a greater relative increase in waste inflows. This result suggests that the racial disparity concerning waste transfers seems to be narrowing after the exogenous GS policy shock.

In the final part of my analysis, I examine the mechanisms for why racial disparities related to waste transfers narrowed after China's policy shock using a simple theoretical model. I propose several potential cost metrics to explain the narrowing disparity. In my model, the amount of waste pollution received by the destination community is negatively correlated with land costs, transportation costs, and political costs of the destination community. I use population density and distance between origin and destination to proxy for the costs of land and transportation. For political costs, I use the absolute difference between the Republican vote share of the destination community and the Republican vote share of the county where the destination facility is located. The greater the political disparity between a community and its county, the lower the political cost is of sending waste to that community. Such communities are likely to have less political voice or resistance to waste pollution inflows. I use a simple OLS model with interactions to investigate which mechanisms have led to an increase in the relocation of waste to lower-income White communities. I find that before the GS policy, destination communities within a shorter distance and with lower political costs used to receive more waste pollution transfers. However, after the exogenous GS policy shock, communities with lower land costs seem to experience more significant waste inflows; and the political costs appear to have become less significant. Consequently, rural White communities with lower land costs are relatively more likely to experience greater waste transfers after China's GS policy.

My research makes several important contributions. My paper is the first to quantitatively examine the effects of China's landmark GS policy on the U.S. environment at the national, state, and local community levels. The recycling sector is a significant but under-investigated field in environmental economics. Despite China's GS policy being a large shock in this context, it has so far received relatively little research attention. In the past, many researchers studied the efficiency of recycling programs in the U.S. and other developed countries. These studies show that recycling programs in developed countries have mostly low efficiency and low social welfare (Aadland and Caplan, 2006; Bohm et al., 2010; Kinnaman, 2014; Kinnaman et al., 2014). My research shows that under China's exogenous policy shock, recycling in the U.S. not only has low efficiency but also affects the domestic environment negatively and unevenly.

Second, my paper is the first to study the causal relationship between trade volume and emissions. In recent years, more papers have begun to focus on the relationship between international trade policies and emissions (Shapiro, 2016; Shapiro, 2018). Copeland et al. (2021) show that nearly one-fourth to one-third of global pollution emissions stem from industrial processes related to international trade. With increasing exposure to trade, dirty industries in rich countries tend to relocate their production to developing countries with more-lenient environmental policies. Many international trade policies, such as tariffs, tended to impose more costs on "clean" industries than industries with pollution (Shapiro, 2021). Unlike the previous trade and environment literature, I focus on a high-pollution industry—the recycling industry—and a specific and relevant trade policy change. I find that before China's GS policy, recyclable waste exports directly reduced the domestic emissions in the U.S. This result supports the pollution haven hypothesis, which is that developed countries tend to relocate their pollution elsewhere through trade, typically to developing countries.

Third, this paper uses China's GS policy as a natural experiment and examines the effect of an exogenous policy shock on racial disparity with regard to waste transfers. Past research has shown that minority communities in the U.S. are often disproportionately exposed to hazardous waste and pollution, and residents of these communities are also less able to relocate to avoid such pollution (Banzhaf and Walsh, 1994; Baden and Coursey, 2002; Banzhaf and Walsh, 2008; Depro et al., 2015; Banzhaf et al., 2019). The remediation of contaminated sites may not help non-home-owning households that were exposed to pollution from these sites, but may instead benefit home-owners and richer households who subsequently migrate into the area and bring about gentrification (Cameron and McConnaha, 2006; Depro et al., 2011; Banzhaf and Walsh, 2013). My research focuses on how China's GS policy, as an exogenous shock, affects the racial disparity in waste transfers, based on the pre-existing racial disparity in the environment in the U.S. My research shows that minority communities in the U.S. are exposed to more waste transfers prior to the GS policy, which aligns with past research. However, this paper contributes to a new finding that, instead of minority communities, lower-income White communities received relatively more waste pollution after the GS policy. Racial disparities related to waste transfers seem to have narrowed after the exogenous GS policy shock. My analysis of the mechanisms indicates that after China's policy shock, lower land costs, rather than transportation or political costs, are more significant in determining the destinations of waste flows.

Fourth, this paper also discusses the "pollution displacement" problem. Many earlier papers document overall pollution displacement from the global North to South (Copeland et al., 1994; Cherniwchan, 2017). In particular, Tanaka et al. (2021) examine how a tightening of U.S. air-quality standards for lead in 2009 affected the relocation of battery recycling and changes in infant health in Mexico in the ensuing years. Pollution can also relocate from highly polluted regions to less polluted regions within a country (Henderson, 1996; Becker and Henderson, 2000; Greenstone, 2002; Shapiro and Walker, 2021). Such pollution relocation can be either unintentional or strategic. For example, Ho (2021) shows how NIMBY regulations, which restrict waste transfers between states, can unintentionally induce waste relocation across local communities within a state. Morehouse and Rubin (2021) show that to comply with the Clean Air Act that is regulated by the county, decision-makers strategically sited coal-fired power plants at the border of their counties so that emissions could be exported to neighboring counties through wind. Most of the pollution displacements being studied are caused by endogenous environmental regulations within the U.S. (Hernandez-Cortes and Meng, 2020; Shapiro and Walker, 2021). My study emphasizes the exogeneity of China's GS policy and its effects on local pollution relocation in the U.S. Compared to the importance of transportation costs and political costs before the GS policy, land costs appear to be the most important determinant of pollution relocation after the GS policy.

Finally, the results of my research can inform policies on domestic recycling. These policies will need prompt modification, given that international markets are rapidly changing. Recycling regulations are normally imposed and implemented by states or counties. Currently, several recycling bills are proposed by legislators from different states.[6] Due to the different needs and conditions of states, these bills sometimes propose opposing regulations on the current U.S. recycling industry. Some bills suggest establishing grant programs for education about recycling and improving recycling accessibility in communities; others propose extending the responsibility of producers for material use and shrinking existing residential recycling programs. My research shows that after an international policy change, all U.S. states, and even local communities, are affected to varying degrees. A national recycling strategy seems necessary. The international context for domestic recycling policies also can no longer be ignored.

The rest of the paper is organized as follows. Section 2 provides a brief background concerning international trade in recyclable waste and methane emissions in the United States and outlines my data sources. Section 3 identifies the impact of China's GS policy on domestic emissions in the U.S. Section 4 explores determinants of pollution relocation due to the GS policy in California and sheds some light on potential mechanisms. Section 5 concludes with a few caveats and suggestions for future research.

[6]Current bills on recycling include the RECYCLE Act of 2021, Recycling Infrastructure and Accessibility Act of 2022, and the Plastic Waste Reduction and Recycling Research Act. Most recently, the U.S. EPA finalized its first national recycling strategy as the Infrastructure Bill 2021 was passed to grant $350 million for solid waste and recycling.

2 Background and Data

2.1 Background

Methane Emissions from Recyclables. Methane emissions from landfills are the third largest source of human-related methane emissions in the U.S.[7] The main sources of methane emissions from landfills are the anaerobic decomposition of organic food, wood and paper scraps. The most-recycled products and materials in the U.S. that were affected by the GS policy are "mixed paper and paperboard" (accounting for approximately 85 percent of the total amount of recycled materials). After the GS policy, most of these U.S. recyclable paper products have been sent directly to landfills, contributing to methane emissions. Plastic scrap, which makes up 14 percent of the total recyclable waste exports from the U.S., is also greatly affected by the GS policy.[8] For many years, plastic waste was thought to be a pollutant that did not necessarily contribute to GHG emissions and climate change. Recently, however, Royer et al. (2018) have found that the degradation of plastic in landfills can also emit methane. Furthermore, the longer that plastic remains in a landfill, the more methane it emits.

In addition to the emissions and pollution from degradation of paper and plastic materials themselves, organic food residues on recyclables can also contribute to methane emissions from landfills. Before China's GS policy, recyclable materials were intentionally separated and cleaned for export. Thus they had less associated food waste. However, after China's GS policy, these recyclable materials are often merely thrown into the trash without being cleaned, contributing to an increase in landfill methane emissions. It is possible for methane emissions from landfills to be captured, converted, and used as energy resources (for electricity, renewable natural gas, and direct use). However, as of 2022, landfill gas (LFG) energy projects have been implemented for only about 20 percent of all landfill facilities in the U.S.[9]

I use methane emissions as my main environmental outcome for several reasons. First, as a greenhouse gas, methane is 85 times more potent for trapping heat than carbon dioxide. It also stays in the atmosphere for a shorter period of time than carbon dioxide. As such, curbing methane emissions will have a more immediate impact on reducing the rate of global warming in the near future. Second, the U.S. EPA has begun reevaluating its regulations on methane pollution within the oil and gas industry under the Clean Air Act (CAA).[10] Landfills also generate large amounts of methane pollution, so their regulations will eventually need to be reevaluated. Third, methane emissions are the only emissions that are tracked regularly in the waste industry. Emissions, especially from landfills, are hard to monitor. The EPA typically has two or three ways to calculate methane emissions using different models. For example, the Greenhouse Gas Reporting Program (GHGRP) administered by the U.S. EPA normally calculates methane emissions using the total amount of wastes received by the landfill, combined with other factors

[7] This claim is according to the U.S. EPA

[8] National Overview: Facts and Figures on Materials, Wastes, and Recycling

[9] LMOP National Map: Contains Data for Landfill Gas Energy Projects and Municipal Solid Waste (MSW) Landfills from the LMOP Database as of March 2022

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

such as precipitation and temperature. They then use several different models for estimating the methane emissions and pick the highest value out of the alternative estimates. As a result, landfill methane emissions directly reflect the total quantities of waste (including recyclables) that are deposited into the environment. Fourth, methane emissions can be used as a proxy for other types of pollution caused by recyclable wastes, such as soil and water pollution, as well as air pollution. These types of pollution are generally difficult to track, but they often co-occur with wastes that generate methane emissions. For example, plastic scrap in landfills eventually breaks down into microplastics in the soil which then seep into groundwater or other surrounding water sources, as well as the broader ecosystem.[11] In the case of air pollution, although methane and carbon dioxide make up 90 to 98% of total landfill gases, the remaining 2 to 10% of other gases from potentially recyclable wastes include volatile organic compounds (VOCs), nitrogen, oxygen, ammonia, hydrogen sulfides, and surface ozone for which even small amounts can affect the health of the people living nearby (Abernethy et al., 2021).[12]

China's Green Sword Policy. Within a decade after China joined the WTO in 2001, U.S. recyclable waste exports to China increased from 5 billion tons to 20 billion tons (constituting an increase from 27.2% to 59.8% of total recyclable waste exports from the U.S.). There are multiple reasons for this significant increase:

1. China served as an international pollution haven, and recycling processes that entailed pollution (in the form of physical waste by-products) were moving to countries like China that lacked stringent environmental regulations (Kellenberg, 2012, Kellenberg, 2015).

2. China has seen a large increase in economic development in the past two decades, especially in manufacturing industries (Bransetter and Lardy, 2006; Brandt et al., 2012). Recyclable wastes that are imported to a developing country from developed countries tend to increase with expanding industrial activity and economic growth in the developing country (Higashida and Managi, 2014). Thus, as China's manufacturing industry was expanding, many recyclables were processed in China because of China's lower wage and low disposal fees.

3. China often had a trade surplus with the U.S. so that ships returning from the U.S. to China were more likely to have excess capacity and could thus carry back recyclable wastes at relatively low marginal costs for transportation (Palma et al., 2011; Olivia, 2014).

Between 2010 and 2019, China's policies concerning environmental quality, regulation, and pollution saw a number of significant revisions (Greenstone et al., 2021). In 2013, China's government introduced the Green Fence (GF) policy, a program that involved intensive inspections of incoming shipments of imported scrap materials at ports of entry. However, the GF program had only a minimal effect on the total quantity of recyclable wastes being imported. In 2017, China launched a much more stringent version of the program, called the Green Sword (GS) policy, which imposed

[11] According to the UN Environmental Programme, most of this plastic disintegrates into particles smaller than five millimetres, known as microplastics, and these break down further into nanoparticles (less than 0.1 micrometre in size). These particles are now entering the food chain.

[12] Abernethy et al. (2021) shows that methane removal can reduce surface ozone and temperature.

much stricter contamination limits (0.5%) on recyclable materials, along with an outright ban on many types of recyclables. According to a notification from the China Environmental Protection Ministry to the WTO, by the end of 2017, China forbade the importation of 24 kinds of solid waste, including plastic waste, vanadium slag, unsorted paper, cotton, and textile materials.[13] Following the implementation of China's waste ban, U.S. exports of all affected recyclable materials dropped dramatically. For example, due to the GS policy, mixed paper and paperboard exports dropped from 15.1 billion tons in 2016 to just 5.4 billion tons in 2019 (a 64.24% decrease). Plastic scrap exports dropped from 2.89 billion tons in 2016 to 0.18 billion tons in 2019 (a 93.8% decrease). Other exports of recyclable wastes, such as cotton waste, man-made fibers, and textiles, decreased by 96.4%, 69.8%, and 99.5%, respectively.

China's GS policy caused a significant increase in scrap imports to South and Southeast Asian countries. Throughout 2018 and 2019, many countries, such as Indonesia, Thailand, Malaysia, Vietnam, and India enacted stringent policies similar to China policy to restrict waste inflows and control the growth of illegal processing facilities. Additionally, a modification to a major international treaty—the Basel Convention—was signed by 187 countries in 2019 to restrict the international flow of plastic scrap from developed to developing countries. Although the U.S. has not yet signed the Basel Convention, most of the importers of the U.S. recyclable wastes are in this agreement. Consequently, markets for wastes from the U.S. are much more limited than in the past.

2.2 Data

Trade Data. I use trade data on recyclable materials sourced from *U.S.A. Trade Online* for the years 2002 to 2020. This annual dataset contains the state of origin, destination countries, weight, and value of exports by HS4-level and HS6-level commodity codes.[14] Total export weight is aggregated over the vessel and air weights. I select those scrap commodities, at both the HS4 and HS6 levels, that have been affected directly by China's waste ban. I also use trade data for country-level recyclable waste exports from *U.N. Comtrade*. I also extract recyclable waste trade data between China and a set of 11 other countries (besides the U.S.) which have regularly traded in large quantities of recyclable waste materials.

Emissions Data. To estimate the general relationship between trade in recyclable wastes and pollution emissions, I use the *EPA Inventory of U.S. Greenhouse Gas Emissions and Sinks* as my source of data for state-level GHG emissions from the waste industry each year from 2002 to 2020. It is relevant to note that in this dataset, the state-level emissions before 2010 are estimated by national-level emissions weighted by state percentages of waste sent to landfills.[15] After 2010, the

[13] The WTO Committee on Technical Barriers to Trade Notification

[14] Among industry classification systems, Harmonized System (HS) Codes are commonly used throughout the export process for goods. HS6 commodity codes have 6 digits and are more disaggregated than HS4 commodity codes, which have 4 digits.

[15] The methodology used for 1990–2009 applies a state percentage of waste landfilled for this time frame as reported by landfills under subpart H.H. of the Greenhouse Gas Reporting Program (GHGRP) to the national

U.S. EPA calculates state-level methane emissions more accurately, by aggregating the annual emissions reported by individual facilities in the waste industry.[16]

To delve further into the increase in U.S. methane emissions at the state level, I use methane emissions from individual landfill facilities reported under the *U.S. EPA Greenhouse Gas Reporting Program (GHGRP)* from 2010 to 2020. The GHGRP requires reporting of Greenhouse Gas (GHG) data from all large GHG emission sources, fuel and industrial gas suppliers, and CO_2 injection sites in the United States. Approximately 8,000 facilities are thus 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, and, importantly for my analysis, the waste industry. The GHGRP also has a high compliance rate for two reasons. First, there is no quantity-based penalty for emissions for landfill owners, so landfill owners have no financial incentive to under-report their facilities' emissions. Second, landfill owners who fail to comply with the self-reporting requirement receive warning notices from the U.S. EPA. Thus, landfill owners also have incentives to report their facilities' emissions promptly to protect their reputations.[17] In my later discussion of statistical identification, a variety of other industries in the GHGRP dataset, excluding the waste industry, are used as control industries.

California Disposal Flow Data. I use facility-level data on disposal flows from 2002 to 2021 provided by the CalRecycle *Recycling and Disposal Reporting System (RDRS)* to explore some distributional effects of China's GS policy on pollution relocation in California. CalRecycle's RDRS quarterly data contains waste flows (in disposal tons) for each origin jurisdiction and destination facility from 2002 to 2021. The dataset contains over 450 origin jurisdictions and over 250 destination disposal facilities over time.

Other Data. I also use numerous other data sources to construct variables that capture destination community characteristics. For racial composition, I use *U.S. Census* data at the census-block level. For median income, I use *U.S. 5-year ACS* data at the census-block-group level. For economies of scale, I use data from the *Waste Business Journal* that contains geographic coordinates for all U.S. recycling-related facilities (including landfills, composters, recycling centers and transfer stations). Finally, for political ideologies, I use presidential election data at the precinct level from California's *Statewide Database (SWDB) for elections.*

Table 1 provides a succinct summary of all data sources used in this paper. The key datasets I construct for each of my three main analyses are as follows: (1) annual state-level panel data from 2010 to 2020 for U.S GHG emissions by industry; (2) annual state-level panel data from 2002 to 2020 for recyclable exports and GHG emissions from the waste industry; and (3) quarterly facility-level panel data from 2002 to 2020 for disposal flows, with census-block level community

estimates of methane (CH_4) emissions.

[16] time fixed effects are included in all estimating specifications to accommodate this change of measurement.

[17] Appendix Figure 3 shows the geographical distribution of landfill facilities in the U.S. according to the EPA GHGRP.

characteristics.[18]

2.3 Summary statistics

Table 2 presents summary statistics for recyclable waste exports by the U.S. and other major waste-exporting countries. In panel A, columns 1 and 2 show the U.S. total *value* of recyclable waste exports to China and the rest of the world from 2010 to 2020. Columns 3 and 4 show analogous total recyclable waste exports to China and the rest of the world for each of 11 other countries, including Australia, Austria, Canada, France, Germany, Portugal, New Zealand, the United Kingdom, Japan, Spain, and Finland.[19] Panel B shows the total *weight* of recyclable waste exports from the U.S. and these 11 other countries to China and to the rest of the world. Before 2017, the total value of U.S. recyclable waste exports to China accounted for more than half of the total value of U.S. recyclable waste exports to all non-US countries. Likewise, before 2017, U.S. recyclable waste exports to China, by weight, accounted for more than 70% of total U.S. recyclable waste exports. However, after China's 2017 waste ban, U.S. recyclable waste exports to China dropped dramatically, while exports to the rest of the world first increased, but then eventually decreased.

Appendix Tables 1 through 8 provide more information about my data. Appendix Table A.1 provides greater detail about the composition of recyclable wastes exported by value and weight. From 2002 to 2020, the U.S. exported 31,521 million USD and 15,464 million USD worth of mixed paper/paperboard and plastic scrap, which account for 66% and 32% of the total value of recyclable waste exports. After paper and plastic scrap, the most-exported recyclables, in order, are metal, fibers, cotton, iron/steel, and wool scrap.

Appendix Table A.2 provides details about the composition of GHG emissions by industry in the U.S. Industries such as waste, metal and refineries release most of their GHG emissions as methane (CH_4). Other industries, such as power plants, minerals, chemicals, and petroleum and natural gas produce more carbon dioxide (CO_2) than methane emissions. The pulp and paper industry emits about equal amounts of methane and carbon dioxide. Nitrogen dioxide (NO_2), as a percentage of total GHG emissions, is relatively low in all these industries, at least compared to methane and CO_2 emissions.

Appendix Table A.3 shows, the changes in overall levels of emissions for the waste industry over the years, and the changing numbers of facilities from 2010 to 2020.[20] Although total emissions from the waste industry increased after 2017, the total number of facilities decreased gradually. This implies that the average emissions from each facility increased over time. Appendix Ta-

[18]Both export data and emission data are at state level, as there is no smaller geographic unit for exports that can be matched easily to emissions. Although export data exist at the departure-port level, it is difficult to track whether the waste arriving at each port comes from within the state or from other states. Thus it is difficult to find a correlation between port-level exports and local emissions.

[19]These 11 other countries have all regularly traded with China in recyclable waste.

[20]Facilities in EPA GHGRP data are large emitters. The dataset exclude small facilities.

ble A.4 documents overall GHG emissions from different industries in the U.S. After China's GS policy, emissions from the waste industry increased both in total and on average. Other industries, such as power plants, metals, pulp and paper, and refineries have seen a decrease in their GHG emissions between 2010 and 2019.[21]

Appendix Table A.7 shows summary statistics for CalRecycle RDRS disposal flows from 2002 to 2020. The data contains about 464 origin jurisdictions and 263 disposal facilities, on average over time. Columns 2 and 4 of Appendix Table A.7 show that the average disposal quantities being shipped from the origin jurisdictions have increased since 2013, as have the disposal quantities received by the destination facilities. Columns 1 and 3 show that the numbers of origin jurisdictions and destination facilities have both decreased over time. Appendix Table A.8 then shows the summary statistics for community characteristics where the destination facilities in the CalRecycle RDRS data are located. These community characteristics are calculated for different buffers around each destination facility, for model robustness checks.

3 The impact of China's GS policy on Emissions in the U.S.

3.1 Raw Trends

Export Trends. Figure 1 shows the trends in recyclable waste exports from the U.S. to China and from the U.S. to the rest of the world. The value of recyclable waste exports to China increased after China joined the WTO in 2001 and then became relatively stable from 2013 to 2016. Starting in 2017, when China announced and implemented its GS policy, the value of recyclable waste exports dropped drastically. Meanwhile, the value of recyclable waste exports to the rest of the world was stable from 2002 to 2016. When China implemented the waste ban, its former recyclable waste inflows were diverted to other countries. Starting in 2017, the value of recyclable waste exports from the U.S. to the rest of the world increased temporarily, but decreased shortly afterwards due to similar policy changes in those other countries.[22] The trend in the net weight of recyclable waste exports shows an even larger and more direct impact of China's GS policy on U.S. exports to China and the rest of the world after 2017. These trends show that the waste ban has decreased recyclable waste exports from the U.S. to China and it also caused a temporary increase in recyclable waste exports from the U.S. to the rest of the world. However, this increase lasted for only a year. Thus, many recyclable wastes that used to be exported overseas are now being processed inside the U.S.

The composition of U.S. total recyclable waste exports is shown in Figure 2. The most-exported recyclable materials are paper/paperboard and plastic scraps. Paper/paperboard accounts for

[21]I selected the nine main industries out of 72 sectors in the GHGRP. Many sectors in the GHGRP are different combinations of main industries and are more narrowly defined.

[22]From 2017 to 2020, many other South Asian and Southeastern Asian countries—India, Malaysia, Indonesia, South Korea, Vietnam, and Thailand—have implemented policies similar to China's to restrict the recyclable waste imports from developed countries.

about 76% of total recyclable waste exports by value and about 90% of total exports by weight. Plastic scrap counts for about 22% of total exports by value and about 10% of total exports by weight. Figure 3 shows the trends over time in relative values of plastic scrap exports from the U.S. and another six OECD countries—Canada, France, Germany, Japan, Netherlands, and United Kingdom. Plastic scrap exports to China, from the U.S. as well as from the other six OECD countries, dropped by about 99 percent after China's waste ban, compared to their 2010 trade values. However, the GDP for U.S. plastic manufacturing has increased gradually over time. U.S. plastic scrap exports to the rest of the world were stable from 2010 to 2016. However, after China's GS policy, these flows increased temporarily but then decreased again. Similar patterns have appeared in the plastic scrap exports of the other six OECD countries to the rest of the world.

Emissions Trends. Figure 4 shows the trends in the total GHG emissions from the U.S. waste industry from 2010 to 2020 using EPA GHGRP data. The raw trend shows that from 2010 to 2016, total GHG emissions from the waste industry decreased over time. However, starting from 2017 when China's GS policy was implemented, total GHG emissions began to increase. In the waste industry, GHG emissions are mainly from methane, which accounts for more than 80% of the industry's total GHG emissions, followed by carbon dioxide and nitrous oxide. Although total emissions have increased since 2017, the number of facilities in the waste industry has decreased gradually in past decades. This shows that the average emissions by facility have also increased over time.

Figure 5 shows total GHG emissions from the waste industry, as well as from several other manufacturing industries in the U.S., from 2010 to 2020. The raw trends show that most of these industries, such as power plants, metals, pulp and paper, and refineries, have seen decreasing GHG emissions over the years. A few industries, however, such as chemicals, minerals, and petroleum and natural gas industries, have seen increasing GHG emissions. Comparing the emissions changes of all industries with the timing of China's waste ban, these raw trends show that the changes in GHG emissions of industries other than the waste industry appear to be exogenous to the waste ban.

3.2 State-level Emissions

Synthetic Control Method. To identify the effect of China's GS policy on state-level methane emissions in the U.S., I use the synthetic control method. This strategy relies on exogenous variation in methane emissions across all other industries in the EPA GHGRP (such as power plants, petroleum and natural gas systems, minerals, chemicals, refineries, etc.). Appendix Table A.2 shows the average emissions from industries across states by types of GHG. This identification strategy takes advantage of the fact that other industries in the GHGRP, which also emit GHGs, were negligibly affected by China's waste ban. To exclude the possibility that the exports of these other industries are correlated with the year of 2017 (when the U.S. started its "trade war" with China), and thus contaminate the control industries for emissions, I plot the exports (by weight/kg) of control industries in Appendix Figure A.5. The figure shows that the exports of the control industries, such as oil and gas, minerals, and chemicals, did not discernibly shift as of 2017.[23]

Given that waste industries from all states in the U.S. are affected to varying degrees by China's GS policy, data from the waste industry in other U.S. states (shown in Appendix Figure A.4b) cannot be assumed to represent an entirely uncontaminated control pool for the waste industry in any given U.S. state of interest. Appendix Figure A.4a plots the time trends for methane emissions from all industries (including the waste industry, in blue) using California as an example. As this figure suggests, simply using the other industries in the same state likewise may not provide a suitable control pool. Thus, I use all other industries from all states to greatly enlarge my control pool. For each U.S. state, separately, I use these other state-level industries as my control pool for the recyclable waste industry in the state in question. For my synthetic control approach, I fit a separate synthetic pre-policy trend that is as close as possible to the actual pre-policy trend for each state's landfill methane emissions (Abadie et al., 2012). The "model training" process seeks to minimize the prediction error over the period prior to China's GS policy:

$$\hat{Y^N_{11t}} = \sum_{j=2}^{J} \sum_{s=2}^{50} w_{js} Y_{jst} \tag{1}$$

Where $\hat{Y^N_{11t}}$ is the emissions from the waste industry for a given state (i.e. the industry "treated" by China's GS policy, indexed as industry $j = 1$) that would have been expected in the absence of China's GS policy, t is the year of these emissions, $j = 2, ..., J$ is a collection of untreated industries not affected by China's GS policy, and $s = 1, ..., 50$ are all states in the U.S.[24] Y_{jst} is observed emissions from the untreated control industries from all states. The synthetic control is defined as a weighted average across state-industry pairs in the "donor pool" of untreated controls. The weights on the emissions of industry j in state s are w_{js}.[25]

I use the trained model based on data for the pre-policy period to predict post-policy-date synthetic emissions in the absence of the GS policy for the waste industry in a given state. The difference between the synthetic post-policy landfill emissions trend and the actual landfill emissions trend, $\hat{\tau_{1t}}$, is the estimated causal effect of China's waste ban on U.S. state-level methane emissions from landfills:

$$\hat{\tau_{1t}} = Y_{11t} - \hat{Y^N_{11t}} \tag{2}$$

[23]Exports by industry can be obtained from the U.S.A Trade Online data by Standard International Trade Classification (SITC) code.

[24]Alaska is excluded from this analysis.

[25]For example, in the synthetic control of California, the donor pool includes state-industry pairs such as California oil and gas industry, Indiana mining manufacturing industry, etc.

I use the same process, separately, for the waste industry in each of the 50 U.S. states (excluding Washington DC) and calculate the estimated causal effects of China's GS policy on methane emissions for each state.

Figure 6 displays emissions from 2010 to 2020 from the waste industry for four selected states—California, Virginia, Texas, and New York—compared to their synthetic-control counterparts. The synthetic emissions for each state track very closely with the trajectory of actual emissions for the pre-GS policy period. This suggests that the synthetic trend for each state likely provides a reasonable approximation to the amount of methane that would have been emitted in each state from 2018 to 2020 in the absence of China's policy. Figure 7 suggests that China's waste ban has had a discernible effect on methane emissions from the waste industry in these four states, and these effects have increased over time.

Placebo Tests. To evaluate the robustness of my results and calculate effective p-values for my estimates, I run placebo tests by applying the synthetic control method to all state-industry pairs that were not affected by China's GS policy during the sample period of my study. If the placebo study shows that the marked change estimated for California's waste industry, for example, is unusually large relative to the emission changes for other state-industries that were not affected by China's waste ban, then my analysis can be assumed to provide statistically significant evidence that the waste ban causally increased domestic methane emissions from the waste industry in California.

Figure 8 shows my placebo test results for the four example states. The bright blue lines reveal causal estimates of the effects of China's waste ban on methane emissions in California, Virginia, Texas, and New York. The muted grey lines are the analogous causal estimates of the GS policy for other (non-waste) state-industry combinations that can be assumed not to be affected by the GS policy. The plots in Figure 8 show that the synthetic control estimates for the four states are above the 90th percentile of all placebo estimates, which proxies for a test of the statistical significance of the causal estimates for these four states. I then apply the same placebo-test strategy to all other states in the U.S. Appendix Table A.5 shows the causal estimates of China's GS policy on state-level methane emissions and the implied p-value calculated from the placebo tests for each state. Figure 9 shows the causal estimates of the GS policy on GHG emissions from the waste industry by state. States such as Nevada, Montana, Virginia, and New York show statistically significant percentage increases in GHG emissions after China's policy. Figure 9 also shows the net change in state-level emissions from landfills for each state in the U.S. after the GS policy. Larger states, such as California, New York, Texas, and Virginia have seen the largest absolute increases in methane emissions from landfills after the waste ban.

3.3 Emission Changes and Waste Export Exposure

To further explore potential factors that may correlate with the heterogeneous effects of China's GS policy on the U.S., I plot emission changes for each state against both total (historical) recyclable waste exports, and the percentage of paper as a share of waste exports. Autor et al. (2013) find that the regions (community zones) which have a higher trade exposure with China in manufacturing industries experienced larger decreases in manufacturing employment in the U.S. from 1995 to 2010. In the present paper, I explore whether a state with higher trade exposure with China, specifically in terms of recyclable wastes, has lower domestic emissions before the GS policy but increased emissions after the GS policy is implemented. Given that mixed paper/paperboard account for more than 80% of exported recyclable wastes and that these materials generate methane in landfills, I also explore whether states with a higher percentage of waste paper exports experience greater increases in methane emissions after the GS policy. Historical recyclable waste exports and the percentage of paper exports are calculated using annual trade data from *U.S.A. Trade Online*. Figure 10a shows that the increase in emissions due to the waste ban is positively correlated with historical recyclable waste exports. The more of its recyclable wastes a state exported overseas before the GS policy, the greater the increase in emissions it experienced after the GS policy. Since waste paper/paperboard is the largest contributor to methane emissions from landfills among all recyclable wastes, I also try to link the heterogeneous effects by states with the percentage of paper a state exported. However, I find a relatively weak correlation shown in Figure 10b. The GS policy had an effect on how much a state exported, and not how much of the export was paper.

The next step is to verify statistically the apparent finding that the greater a state's exposure to trade in recyclable wastes with China before the GS policy, the greater the increase in emissions the state experiences after the GS policy. I identify the general causal effect of recyclable waste exports on domestic emissions from the waste industry by starting with a simple OLS regression in levels as follows:

$$Methane_{it} = \alpha_0 + \beta_0 Export_{it} + \nu_i + \mu_t + e_{it} \tag{3}$$

$Methane_{it}$ is the level of emissions in state i in year t. $Export_{it}$ is the level of recyclable exports from state i to China in year t. I then take the first difference of emissions and exports:

$$\begin{aligned} \Delta Methane_{it} =& Methane_{i,t} - Methane_{i,t-1} \\ \Delta Export_{it} =& Export_{i,t} - Export_{i,t-1} \end{aligned} \tag{4}$$

After replacing equation (4) with equation (3), and taking the difference (subtracting the values in the previous year $t-1$ from the values in year t), I get the first difference model:

$$\underbrace{Methane_{i,t} - Methane_{i,t-1}}_{\Delta Methane_{it}} = \underbrace{\alpha_0 - \alpha_0}_{0} + \beta_0 \underbrace{(Export_{i,t} - Export_{i,t-1})}_{\Delta Export_{it}} + \underbrace{\nu_i - \nu_i}_{\text{0 for each i}} + \underbrace{\mu_t - \mu_{t-1}}_{\Delta \mu_t} + \underbrace{\epsilon_{i,t} - e_{i,t-1}}_{\Delta \epsilon_{it}} \tag{5}$$

$$\Delta Methane_{it} = a + \beta \Delta Export_{it} + v_i + u_t + e_{it} \tag{6}$$

where $\Delta Methane_{it}$ is the change in methane emissions in the waste industry for state i in year t, compared to the previous year. $\Delta Export_{it}$ is the change in recyclable waste exports to China from state i in year t, compared to the previous year. In differencing, any constant term in the model in levels drops out. a is therefore the linear time trend in the data. Year fixed effects u_t control every time pattern other than the linear time trend. State fixed effect ν_i drops out for each state i after taking the first difference. However, the first differences ($\Delta Methane_{it}$) can still vary across states. Thus, I add a state fixed effects term v_i back to the first difference model to control the variation in differences across states. I choose the first difference model in equation (6) over the fixed effect model in levels for the following reasons: (1) although the first difference model works just as a fixed effects model, it relies on no serial correlation in the differenced errors (a weaker assumption); and (2) the first difference model controls for variations in differences across states, which is a stronger control.[26] There are still several concerns regarding first difference OLS identification in this context:

1. On the one hand, GHG emissions from most industries are monitored by the U.S. EPA. For waste industry, it is difficult for landfills to get permits because they need to meet many environmental requirements. Given that the U.S. has relatively stringent environmental regulations on local pollution (such as the Clean Air and Clean Water Acts), it can be harder for recyclers to find facilities to process recyclable materials. As a result, emissions from the waste industry may be inversely related to the amount of recyclables being exported to China, reflecting the stringent domestic environmental regulation in the U.S.

2. Omitted variables (e.g. economic development) may increase both recyclable exports and domestic emissions. Thus there is a potential problem of endogeneity for the variable that measures the change of recyclable waste exports.

3. Instead of the observed demand policy shock from China (the waste ban), technological development—such as an increasing ability to reprocess recyclables cleanly and safely—could also decrease the supply of recyclable wastes to be exported.

To identify the causal effects of changes in U.S. recyclable waste exports on U.S. domestic methane emissions from the waste industry, I employ an instrumental variable that accounts for the potential endogeneity of U.S. recyclable exports. I use a Bartik shift-share instrument from the literature on international trade and labor economics, adapted to an environmental context (Bar-

[26] The fixed effects model builds on the assumption of no serial correlation prior to demeaning.

tik, 1991; Wong, 2021). The main IV is defined as follows:

$$IV_{it}^{Bartik} = \sum_{j} \left\{ \frac{E_{ijt_0}}{E_{jt_0}} \Delta Export_{ucjt} \right\} \tag{7}$$

where $\Delta Export_{ucjt}$ is the change in exports from the U.S. (u) to China (c) for recyclable waste of type j, in year t compared to the previous year. $\frac{E_{ijt_0}}{E_{jt_0}}$ is state i's share of exports from state i to China for recyclable waste j in the initial year t_0. The product of the initial share term and the current change in exports is then summed across all recyclable wastes j. In other words, the shift-share instrument is a data-regenerating process that shifts the initial export share of each state to the trajectory of the change in total recyclable waste exports from the U.S. to China over time. The initial year I use is 2004, the earliest year for which complete data is available for recyclable waste exports from the U.S. to China for recyclable materials affected by China's policy. Given that the construction of IV_{it}^{Bartik} excludes state i's current-period recyclable waste exports to China, the initial distribution of export shares of state i for waste j is exogenous (or at least predetermined), relative to the subsequent changes in methane emissions for state i.

One concern for my upcoming estimation is that changes in recyclable waste exports from the U.S. may be correlated with U.S. technological improvements and thus the supply of recyclable materials. In that way, U.S. recyclable exports may be endogenous to domestic emissions. Naive OLS estimates may overstate the true impact on domestic methane emissions of restrictions on recyclable waste exports from the U.S. to China. I thus employ a second alternative instrument that accounts for this potential endogeneity as follows:

$$IV_{it,others}^{Bartik} = \sum_{j} \left\{ \frac{E_{ijt_0}}{E_{jt_0}} \Delta Export_{ocjt} \right\} \tag{8}$$

Instead of using the change in exports from the U.S. to China, I construct the IV using the contemporaneous changes in export of recyclable wastes to China from 11 other developed countries, excluding the U.S. Specifically, I instrument for the measured change in U.S. exports of recyclable wastes with a non-U.S. analog $\Delta Export_{ocjt}$, where the o subscript, for "others" replaces the u subscript for "U.S." This variable is constructed using data for changes in recyclable exports (at the commodity level) from the 11 other high-income countries to China. These 11 countries are all OECD countries which have engaged in extensive trade in recyclable wastes with China during the past few decades.[27]

After constructing the main and alternative Bartik-type instruments, I fit models of the following form:

$$\text{First stage:} \Delta \widehat{Export}_{it} = \alpha + \beta \Delta IV_{it}^{Bartik} + \nu_i + \mu_t + v_{it} \tag{9}$$

[27] The 11 selected countries are: Australia, Austria, Canada, France, Germany, Portugal, New Zealand, United Kingdom, Japan, Spain, and Finland.

Where IV_{it}^{Bartik} is either the U.S. or the other-country version of the instrument. Then the fitted value for the first stage is employed in the second stage:

$$\text{Second stage:}\Delta Methane_{it} = \alpha + \beta \Delta \widehat{Export}_{it} + \nu_i + \mu_t + e_{it} \tag{10}$$

In the second-stage equation, $\Delta Methane_{it}$ is the annual change in methane emissions from the waste industry in state i.[28] The key coefficient of interest is β, the average annual change in methane emissions across U.S. states caused by a one-unit change in U.S. recyclable waste exports to China. I then use this average estimate to calculate the cumulative aggregate impact of China's GS policy on U.S. methane emissions from the waste industry for 2016 through 2019. The calculation is as follows:

$$\Delta \widehat{Methane}_{total} = \sum_{t=2016}^{2019} \beta \left[\sum_{state=i}^{I} \Delta Export_t^i \right] \tag{11}$$

I begin my regression by estimating the naive OLS specification in equation (1). The coefficient β is interpreted as the change in methane emissions from the waste industry for 1 metric ton change in recyclable waste exports. For the simple OLS specification, model 1 in Table 3 suggests that for every 1 metric ton reduction in recyclable waste exports, methane emissions from the waste industry in the U.S. increase by 0.49 metric tons per year. To address concerns about potential reverse causality and/or endogeneity, I then estimate 2SLS equations (4) and (5) using my basic Bartik shift-share instrument. Model 2 in Table 3 suggests that for every one metric ton reduction in recyclable waste exports, methane emissions increase by 0.722 metric tons of CO_2 equivalent per year. This large effect implies that the endogeneity of recyclable waste exports may have attenuated the estimated effect of changes in recyclable waste exports on domestic emissions. However, there is still a possibility that these may have been nontrivial supply shocks in the recyclable waste industry instead of just China's GS policy, which could also bias these estimates. Thus I estimate equations (3) and (4) again, but this time I use my alternative Bartik shift-share instrument constructed with the recyclable waste exports from a set of 11 non-U.S. countries to China. Model 3 in Table 3 suggests that for every one metric ton reduction in U.S. exports of recyclable wastes to China, methane emissions increased by 0.893 metric tons of CO_2 equivalents per year. This even-larger estimate reinforces my finding that the decrease in U.S. recyclable waste exports to China increased the U.S. domestic methane emissions in general. After estimating β—the average effect across all U.S. states annually, I then calculate the implied cumulative effect of the total reduction in recyclable waste exports due to China's waste ban on overall U.S. national increases in methane emissions from 2016 to 2019.[29] Over this time period, the total weight of recyclable waste exports decreased from nearly 18,000,000 metric tons to

[28] I use first-differenced estimator to address the problem of omitted variables that may bias the estimate.

[29] I exclude 2020 exports and emissions because of the COVID disruption in international trade and domestic emissions.

5,500,000 metric tons. Applying equation (6), the U.S. total methane emissions from the waste industry increased by approximately 8-11 million metric tons of CO_2 equivalents., which (for comparison) is about 9.68% of total methane emissions from the U.S. waste industry in 2016, or about 5.23% of total methane emissions from the U.S. petroleum and natural gas system in 2016.[30]

4 Determinants of Pollution Relocation: Evidence from California

A state-level analysis is the first step towards understanding the causal effect of China's waste ban on aggregate emission levels in the U.S. Among my state-level analyses, I find that California's methane emissions from the waste industry increased by 9.4 percent per year following China's GS policy.[31] To gain a more detailed understanding of the local environmental effects of the GS policy, I use facility-level data on disposal flows within California from 2002 to 2021 provided by the *CalRecycle* Recycling and Disposal Reporting System (RDRS) to explore some distributional effects of China's GS policy and propose some potential mechanisms to explain these effects.[32]

4.1 Raw Patterns

Waste Flows in California. To depict visually the distributional effects of China's policy on pollution relocation, I plot the spatial distribution of all destination facilities in the CalRecycle RDRS dataset on the map of California. Appendix Figure A.8 shows that most facilities in the CalRecycle data are located around urban areas (highlighted in yellow) in California, and fewer facilities are located in the more-remote areas/and agricultural regions. I then plot disposal flows on a California map using the coordinates of each origin jurisdiction and destination facility. To illustrate, I pick a city source (San Francisco) and a destination facility (Potrero Hill Landfill) and show general patterns of pollution relocation in the state of California for this origin and this destination. Figure 11 shows four things: (1) the different destinations for waste pollution shipped outside the source city; (2) the different origins for waste pollution shipped into the destination community; (3) the size of the increase in waste shipments from each origin jurisdiction after China's GS policy; and (4) how much of an increase in waste shipments each of the destination facilities received after China's GS policy. The maps in Figure 11 illustrate that most shipments of waste pollution are transported to destination facilities either in remote rural areas or in suburbs right outside of urban areas (yellow areas) of California. To further explore the characteristics of these destination communities where the receiving facilities are located, I then plot an analogous spatial map based on the racial composition and political affiliation for California.[33] Figure 12 shows that from Los Angeles, for example, most changes in pollution relocation have involved increased waste shipments to remote and light-shaded areas, with higher proportions of White residents, or to darker-shaded areas where larger shares of minority populations reside. Figure 13

[30] U.S. EPA: 1990-2020 National-level U.S. Greenhouse Gas Inventory Fast Facts

[31] Using U.S. EPA GHGRP data

[32] I compare the EPA GHGRP data with the CalRecycle RDRS data and find that the EPA data (in methane emissions) are highly correlated with CalRecycle disposal flow data (in tons). See Figure A.7 in Appendix.

[33] I use census-tract data for the racial composition map and precinct-level data for the political affiliation map.

shows that pollution relocation has also increased waste shipments to more-remote Republican-leaning districts. Appendix Figure A.9 and Appendix Figure A.10 shows the change of disposal flow based on median income and pollution vulnerabilities of the communities in Califorinia after China's waste ban.[34] To address the concern that disposal facilities are more likely to be sited in minority communities, I plot all landfill facilities in the CalRecycle dataset in relation to the racial composition and political affiliation of the communities. Appendix Figure A.11 shows that although many facilities are situated close to minority communities or Republican-leaning districts (darker green or red areas), some facilities are located in White communities or Democratic-leaning districts (lighter green or blue areas).

Altered Distributional Effects of Pollution Relocation. The maps that summarize disposal flows motivate my research question on the distributional effects of China's GS policy: How has China's GS policy, as a specific international trade policy shock, affected existing patterns of pollution relocation? Are there environmental justice concerns with regard to changes in waste pollution relocation?[35] Appendix Table A.8 shows the summary statistics for the characteristics of higher-resolution communities where facilities are located. I use data at the census block level and block group level to calculate the average racial composition and median income, for all census blocks that overlap, 3km, 5km, and 10km buffers around these destination facilities.

4.2 Distributional Effects

Correlation. To identify factors that potentially determine the disposal flows and the relocation of waste pollution, I start with some simple linear correlation plots. I select six characteristics of the destination community that may correlate with the waste pollution relocation that creates a net increase in disposal inflows. These characteristics include racial compositions (shares of White and Black populations), median income, economies of scale, and political affiliation. I define economies of scale for a community by counting the numbers of other related facilities/industries that are within a 15 km buffer around the destination facilities.[36] Figure 14 shows that the White share of the population of the destination community is negatively correlated with net increases in disposal inflows. However, the Black share of the population is positively correlated with the waste pollution inflows. This shows that the higher the share is of Whites in the population of the destination community, the lesser the increase in disposal inflows. The distances between the origins and destinations are negatively correlated with the net increase in waste inflows to destination communities. This shows that nearby communities tend to receive more waste. The median incomes of the destination community is also negatively correlated with the net increase in waste inflows, which shows that the lower the median income is of a community, the greater the

[34] Pollution vulnerability is reported by the Office of Environmental Health Hazard Assessment (OEHHA) CalEnviroScreen4.0. CalEnviroScreen is a screening methodology that can be used to help identify California communities that are disproportionately burdened by multiple sources of pollution.

[35] Pollution relocation refers to activities that transfer negative environmental externalities to places outside of the local community.

[36] The economies of scale is defined by the number of waste facilities that are within a 15 km buffer of the destination landfill facility of disposal shipment. Waste facilities can be composts (CO), landfills (LF), recycling centers (MR and MW), and transfer stations (TS). See more details in Appendix Figure A.12

increase in waste inflows it experiences after China's GS policy. Economies of scale for destination communities are negatively correlated with the waste inflows. The fewer similar facilities around the destination facility, the greater the increase in waste inflows to such communities. Finally, the Republican vote share of the destination community is positively correlated with waste inflows. This shows that the greater the Republican vote share is in the destination community, the greater the increase in waste inflows the destination community experienced after China's waste ban.

Gravity model. Knowing that California has seen a significant increase in methane emissions and waste pollution after China's GS policy, I investigate the distributional effects of China's policy on waste flows for local communities (at the census-block level) in the state of California. I apply a gravity-type model that includes the distances between the origins and destinations for inter-regional waste flows, and for each destination community, as well as the racial composition, median income, economies of scale in the waste industry, and the Republican vote share of residents.[37] The model specification is as follows:

$$\begin{aligned} Y_{ijt} =& \alpha + \beta_1 log(Dist_{ij}) + \beta_2 log(R_j) + \beta_3 log(X_{jt}) \\ &+ \beta_4 \Big[log(Dist_{ij}) \times 1(post) \Big] + \beta_5 \Big[log(R_j) \times 1(post) \Big] + \beta_6 \Big[log(X_{jt}) \times 1(post) \Big] \\ &+ \zeta o + \theta_d + \mu_{od} + \eta_t + \epsilon_{ijt} \end{aligned} \tag{12}$$

The dependent variable Y_{ijt} is the tons of the waste transported from jurisdiction i to destination community j in year-quarter t.[38] $Dist_{ij}$ is the distance between origin jurisdiction i and destination community j. R_j is the racial composition of destination community j. $1(post)$ is an indicator variable, which takes the value of 1 for the year of the waste ban and beyond. X_{jt} is a set of socioeconomic factors such as median income, economies of scale in the waste industry, and political affiliation for destination j.[39] To reveal any altered distributional effects caused by China's GS policy, I interact the characteristics of the destination communities with the policy indicator variable. In Appendix Table A.9, I present results that are adjusted for different types of fixed effects, including origin-county fixed effects (ζ_o), destination-county fixed effects (θ_d), year-quarter fixed effects (η_t), and an error term (ϵ_t).

Figure 15 shows my estimates of the altered distributional effects caused by China's GS policy. Before China's waste ban, the estimates and their 90% and 95% of CIs show that the sizes of waste flows are negatively correlated with distances between origin and destination communities. The greater the proportion of Black residents in the destination community, the more waste pollution the community receives from other places. The greater the proportion of White residents in the destination community, the less waste pollution the community receives. These coefficient estimates on the racial composition variable for the destination communities confirm that the

[37] The political affiliation data is from Statewide Database (SWDB) election data at the precinct level.

[38] I define the destination community as the areas that are within a 3km buffer of the destination facilities (Banzhaf et al. (2019)).

[39] Economies of scale of community j are measured by counting how many waste-related facilities are within a 5km buffer of the destination community.

well-documented racial disparities in pollution exposure also exist with regard to waste pollution relocation patterns. The median income and economies of scale of destination communities are both positively correlated with the amount of waste the destination communities receive.[40] The higher the percentage is of registered Republican voters in a destination community, the more waste pollution is transported to that community on average.

I then use the interaction terms in the model to compare pollution relocation patterns before and after China's GS policy. After China's waste ban, the positive coefficient on Black share of the population shows that Black communities continue to receive more waste pollution from elsewhere. However, White communities now are more affected—communities with a higher percentage of White populations have seen a greater increase in their incoming shipments of wastes. Communities that are more remote, have fewer economies of scale, and lower Republican vote shares receive more waste pollution from elsewhere after China's GS policy takes effect.

4.3 Mechanism

Theory model. In this section, I present a stylized model to illustrate the potential determinants of the observed altered waste shipments within California. The amount of waste being transported to other locations depends on the amount of waste generated by each origin jurisdiction and the cost of transporting this waste from that origin to each destination. The more waste the origin jurisdiction generates, the more waste can potentially be transported to other places. The lower the cost of transferring the waste, the more waste is likely to be transported to other locations. This relationship is captured by the following equation:

$$TranspWaste_{ijt} = f(\underset{+}{TotalWaste_{it}}, \underset{-}{Cost_{ijt}}) \tag{13}$$

$TranspWaste_{ijt}$ is the amount of waste transported from origin jurisdiction i to destination facility j at time t. $TotalWaste_{it}$ is the amount of waste generated in jurisdiction i at time t. $Cost_{ijt}$ is the monetary costs and non-monetary costs of transporting this waste along with its negative externalities from origin jurisdiction i to destination facility j at time t.

My empirical analysis, in the previous section, suggests several factors that affect inter-regional pollution flows. Before China's waste ban, waste pollution tended to be transferred to communities that have a higher percentage of Black residents. This is still the case after the GS policy. However, after China's GS policy, waste transfers shifted, to some extent, to lower-income White communities, and to less remote communities. The GS policy does not seem to have exacerbated the usual environmental disparity across communities with regard to waste pollution relocation. Instead, it has tended to narrow this relative disparity across communities. Although Black communities have continued to receive more waste shipments after the policy shock, White communities have experienced a greater increase in waste pollution, relative to the shipments they

[40] Comparing to all destination communities with a waste facility, communities with higher economies of scale may provide more job opportunities to the community and lead to higher median income.

received before the GS policy.

There are three potential mechanisms to explain this altered distributional effect. The reason some White communities are receiving more waste after China's GS policy may be due to some of their characteristics. These California communities tend to have (1) lower land costs; (2) lower transportation costs; (3) lower political costs. I assume the cost of waste relocation, in the case of recyclable waste transfers, depends on land values (LC_{jt}), transportation costs (TC_{ijt}), and political costs (PC_{ijt}) incurred in destination communities where the receiving facilities are located. I also assume that the amount of waste ($TotalWaste_i$) an origin jurisdiction generates is relatively constant over time.

$$Cost_{ijt} = f(\underset{+}{LC_j}, \underset{+}{TC_{ij}}, \underset{+}{PC_{ij}}) \tag{14}$$

Three metrics. First, land costs tend to be lower in places where population densities are lower. Waste pollution tends to be transferred to places with lower land costs, where tipping rates (i.e., disposal fees) are lower. I use population density (people/acre) as a proxy for land values.

$$LC_{jt} = f(\underset{+}{Population_{jt}}) \tag{15}$$

Second, waste pollution also tends to be transferred to closer locations to minimize transportation costs. I use distance (in kilometers) between the origin and destination as a proxy for the transportation costs.

$$TC_{jt} = f(\underset{+}{Distance_{ijt}}) \tag{16}$$

Third, waste shipments to some communities (in this case, voting precincts) might be motivated by political cost. I define political cost as the deviation of the destination community's vote share from that of its county.[41] If the community's vote share is very different to the vote share of its county, then this community has a lower political cost.[42] The vote share of the community is the percentage of those who vote Republican or Democrat among all registered voters in the population of the voting precinct.

$$P_{jt} = f(\underbrace{Votes_{jt} - Votes_{ct}}_{-}) \tag{17}$$

[41] Vote share is defined as the Democrats/Republican votes among all all registered voters.

[42] The voting data is from Statewide Data Base (SWDB). SWDB collects the Statement of Vote and the Statement of Registration along with various geography files from each of the 58 counties for every statewide election. The Statement of Vote is a precinct-level dataset and precincts in California change frequently between elections. The goal of the SWDB is to make election data available that can be compared over time, on the same unit of analysis—a precinct, a census block or a census tract.

$Votes_{jt}$ is the Republican/Democratic vote share of community where destination facility j is located at time t. $Votes_{ct}$ is the Republican/Democratic vote share of county c to which destination community j belongs at time t. The difference between the community and county vote shares reflects the political cost of transporting waste and its externalities to community j. The greater the difference is between the community and its county with political vote shares, the lower the political cost is for waste inflows to that community. For example, a very Republican community in an overall Democratic county can have a high vote discrepancy and, thus, a lower resistance to increased waste shipments for various reasons: (1) such a community may have less political influence within the county; (2) its residents may also have a very different philosophy from the county as a whole concerning environmental issues; or (3) it may be harder to change the minds of such voters in such communities about their political affiliations. Consequently, waste haulers may hear fewer complaints from such communities when increasing their shipments to such places. For all three of these reasons, these communities may put up the least resistance to increased waste relocation after China's GS policy shock. Figure 16 shows the spatial distribution of vote discrepancies across communities (precincts) in California. The lighter the color is, the more the destination community deviates from its county in political ideology, regardless of the dominant party in that county.

I estimate an ad hoc regression specification in order to examine which of these potential mechanisms best accounts for my finding that waste pollution has relocated relatively more to poorer, more remote, and White communities after China's GS policy shock. The regression is as follows:

$$Y_{ijt} = \alpha + \beta_1 C_{ij} + \beta_2 \left[C_{ij} \times 1(post) \right] + \mu_{od} + \eta_t + \epsilon_{odt} \tag{18}$$

C_{ij} are the three cost metrics: land cost, transportation cost, and political cost—approximated by population density, distance between origin and destination, and discrepancy (absolute difference) of political vote shares between community and county. Population density is from the 2010 census data at the census block-level. Vote data at the precinct-level is from the 2016 presidential election. I examine which of the three potential mechanisms appears to dominate as an explanation for the altered distributional patterns in waste pollution relocation.

Results. Table 4 shows that before China's waste ban, i.e., $1(post) = 0$, waste pollution tended to be relocated to remote places with low land values. Waste also tended to be transported to places with relatively low political costs. However, after the waste ban, more waste pollution has been relocated to farther destinations with lower land costs but higher political costs. Furthermore, the effect of land costs on the altered distributional patterns is more statistically significant (at 5% level) than the effect of political costs (at 10% level). Although land costs and political costs both seem to influence waste pollution relocation, these estimates suggest that land costs may be more important than political costs as a determinant of the decisions about where to transport excess amounts of waste pollution in the event of an exogenous policy shock.

5 Conclusion

This paper examines the effects of China's Green Sword Policy (waste import ban) on environmental outcomes in the U.S. The waste ban, designed to reduce China's waste imports from the U.S., has resulted in far-reaching consequences for the U.S. environment at national, state, and local levels. Following the implementation of the GS policy, policy-makers have been concerned about its effects on the U.S. recycling industry, but few researchers have studied these effects in a quantitatively rigorous fashion. My paper is the first empirical analysis of the impact of China's GS policy on the U.S. This paper uses methane emissions as a proxy for general pollution from wastes, and finds that the U.S. has seen a significant increase in landfill-related methane emissions after the GS policy, especially in larger states such as California, New York, Virginia, and Texas. Furthermore, the heterogeneous changes in state-level methane emissions have been positively correlated with the amount of waste previously exported to China by each state. This positive correlation suggests a potential causal relationship between waste exports and domestic emissions. In my analysis of U.S. waste export and emissions, I find that recyclable waste exports are inversely related to domestic methane emissions in the U.S. This result is consistent with the "pollution haven" hypothesis, namely that developed countries tend to relocate their wastes and associated negative externalities to developing countries in order to reduce domestic pollution levels.

Due to the dramatic decrease in global waste transfers ensuing from China's waste ban, many more U.S. recyclable wastes are now sent to local facilities for transfer to domestic landfills. My paper shows that under the exogenous GS policy shock, the racial disparity evident in patterns of waste transfer seems to have narrowed at the local level. In the U.S., minority communities have a history of being exposed more to waste pollution. However, after the waste ban, lower-income White communities experienced a relatively greater increase in waste inflows. This result can be explained by the land, transportation, and political costs of waste shipment to the destination communities. Before China's waste ban, closer and more politically marginalized communities were more likely to receive waste from elsewhere. However, after the waste ban, lower land costs took precedence over political costs for where wastes were sent. This result reveals how the exogenous GS policy shock affected mechanisms of waste pollution relocation within U.S. communities.

This study still has several limitations, however. First, the waste data used in the local pollution relocation analysis cannot accurately track the amount or composition of recyclable wastes that are transferred locally, since disposal data incorporates both regular and recyclable wastes. Second, this paper has examined the effects of China's waste ban on emissions and pollution relocation related to landfill facilities only; data specifically for recycling facilities are not yet publicly available due to privacy issues. Finally, the GS policy might not be the only factor that has caused the narrowing racial disparity for waste-transfer destinations; other unobserved factors such as local policies or ideological changes in environmental equity might have begun to have an effect on California's waste transfers around 2017.

Other questions for further study include what kind of spillover effects the GS policy might have had on international policies regarding pollution. Despite there being many new destination countries for U.S. recyclable wastes in Southeast Asia, Africa, and the Middle East, only some countries had a reaction to the GS policy and adjusted their domestic regulations to control the flow of waste imports, while others did not have a prompt change in policy to control the inflow of wastes. Another point of investigation would be waste transfers across states: my analysis finds that among 11 states that have experienced statistically significant increases, some are smaller states such as Nevada, North Dakota, Alabama, Kentucky, and New Hampshire. It is difficult to connect their significant increases in methane emissions with their own waste generation. It is worth noting that these relatively small states might have experienced significant methane emission increases because they are often neighbors of larger states. There is the possibility that larger states have transferred their excessive amounts of recyclable wastes to neighboring states for processing and disposal. Finally, my study has focused exclusively on California to see the effects of the GS policy at the local community level. However, as technology improves, more and more satellite data might become available to directly detect pollution caused by waste. Such data would be a valuable environmental measurement to employ in any future study of the long-term effects of China's GS policy on U.S. communities.

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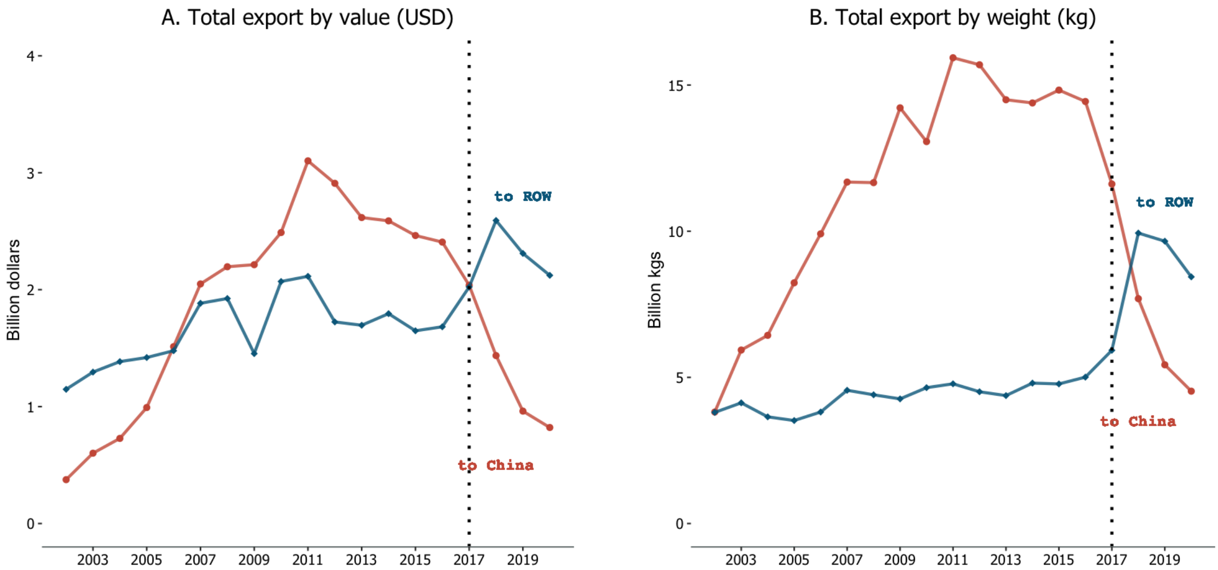
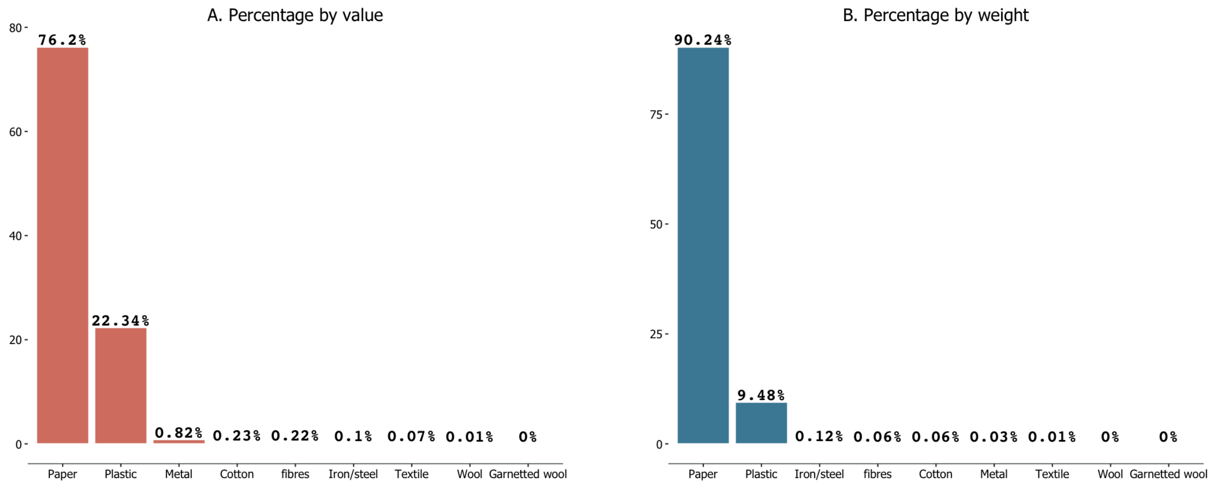
Figure 1: U.S. Recyclable Waste Export to China and the Rest Of the World (ROW)



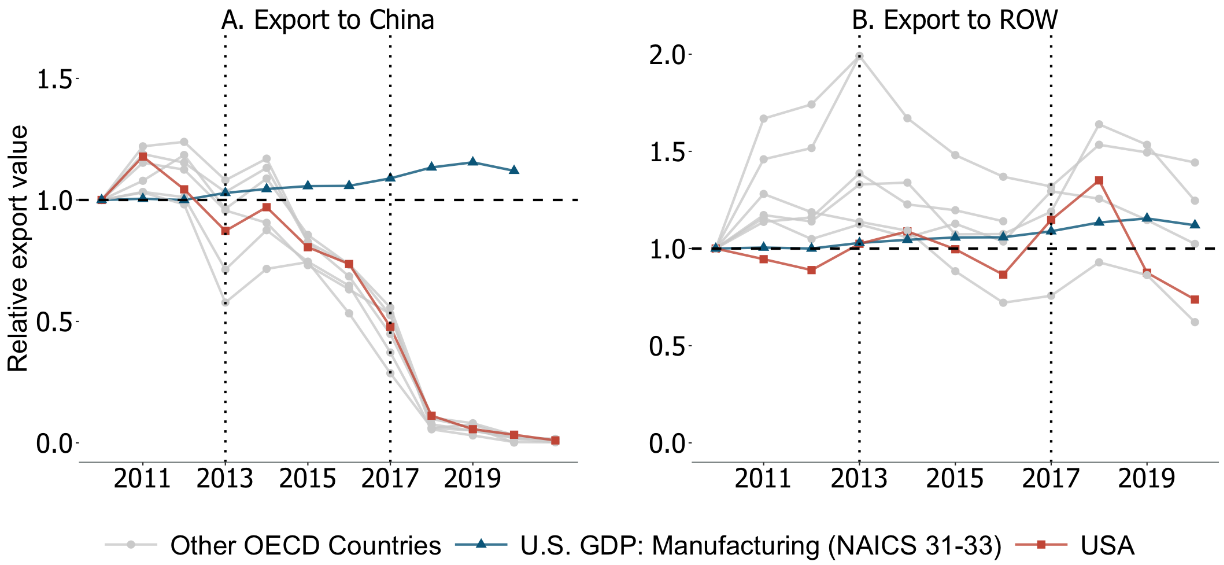
Notes: This figure shows that U.S. recyclable waste exports to China dropped dramatically after 2017 when China's Green Sword (GS) policy was announced and implemented. Meanwhile, U.S. exports in recyclable wastes to the rest of the world increased temporarily but decreased after 2018.

Figure 2: Composition of U.S. Recyclable Waste Exports to China



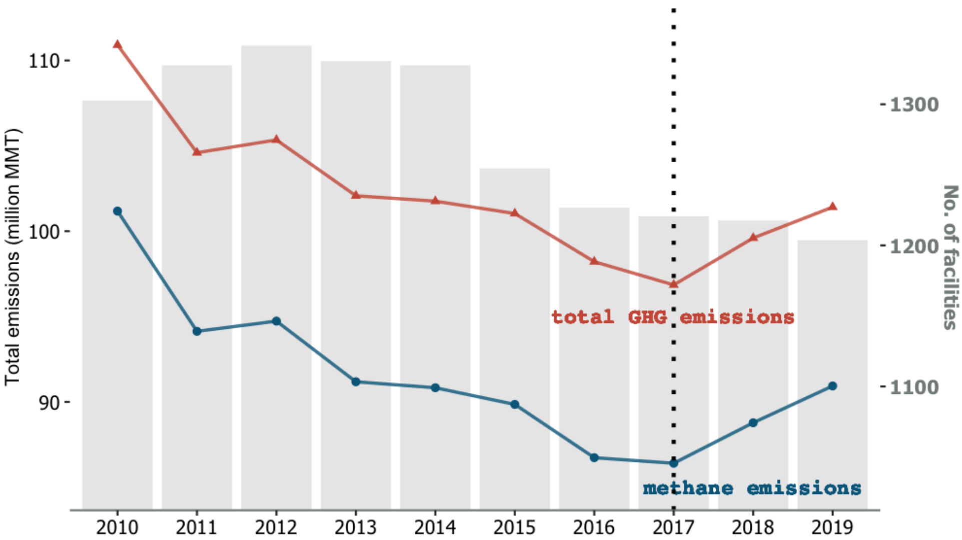
Notes: This figure shows the composition of recyclable wastes that were exported in the past two decades. The listed waste materials are all wastes that are directly affected by China's GS policy. Panel A shows the types and percentages of waste materials exported by value ($ USD). Panel B shows the types and percentages of waste materials exported by weight (kg). Paper and paperboard and plastic scraps are the most exported recyclable wastes by value and weight, followed by metal, iron/steel, fibre, cotton, etc.

Figure 3: U.S. Plastic Scrap Exports to China and to the Rest Of the World



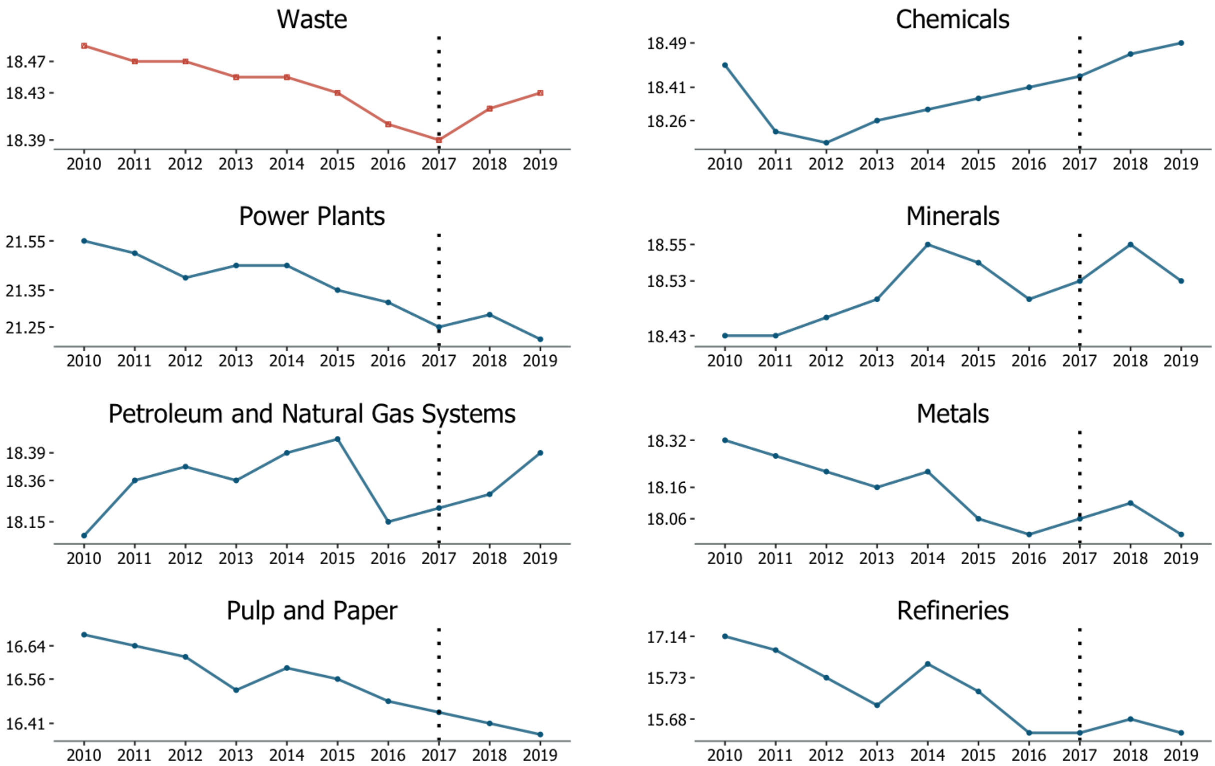
Notes: This figure shows the recyclable waste exports (taking plastic scrap as an example) of the U.S. (red line), as well as 6 other OECD countries (grey lines) to China and to the rest of the world from 2010 to 2020. The first dashed line in 2013 represents when China first implemented its Green Fence (GF) policy. The second dashed line in 2017 represents when China implemented its Green Sword (GS) policy. All of the export values are normalized by the 2010 export values for each country. The blue line represents the U.S. manufacturing GDP—NAICS 31-33 (the industry code) that includes the plastic industry. Although the plastic manufacturing GDP of the U.S. increased gradually over time, the U.S. plastic scrap exports to China dropped by almost 99 percent, especially after China's GS policy. Similar patterns are found in other OECD countries. After China's GS policy, the plastic scrap export of the U.S. and the other OECD countries increased temporarily to the rest of the world but then decreased.

Figure 4: U.S. Waste Industry GHG Emissions



Notes: Total emissions from the waste industry based on the aggregated reporting records from facilities for each year between 2010 and 2020. In the waste industry, total emissions are from methane (CH_4), carbon dioxide (CO_2), and Nitrous oxide (N_2O). However, the amount of CO_2 and N_2O are too small compared to CH_4. Thus, more than 80% of total emissions from the waste industry are CH_4. Although the number of facilities has decreased gradually over the years, the total emissions and methane emissions of facilities have increased since 2017.

Figure 5: U.S. Greenhouse Gas Emissions (log.MMT) by Industry



Notes: This figure shows the GHG emissions from the eight main industries in the EPA GHGRP data. Waste, Power plants, and petroleum and natural gas are the industries that have the highest emissions in the U.S. on average from 2010 to 2020. The waste industry (in red) has seen a decrease in methane emissions from 2010 to 2017 and an increase in methane emissions afterwards, both in total and on average. Changes in GHG emissions of other industries are exogenous to China's GS policy.

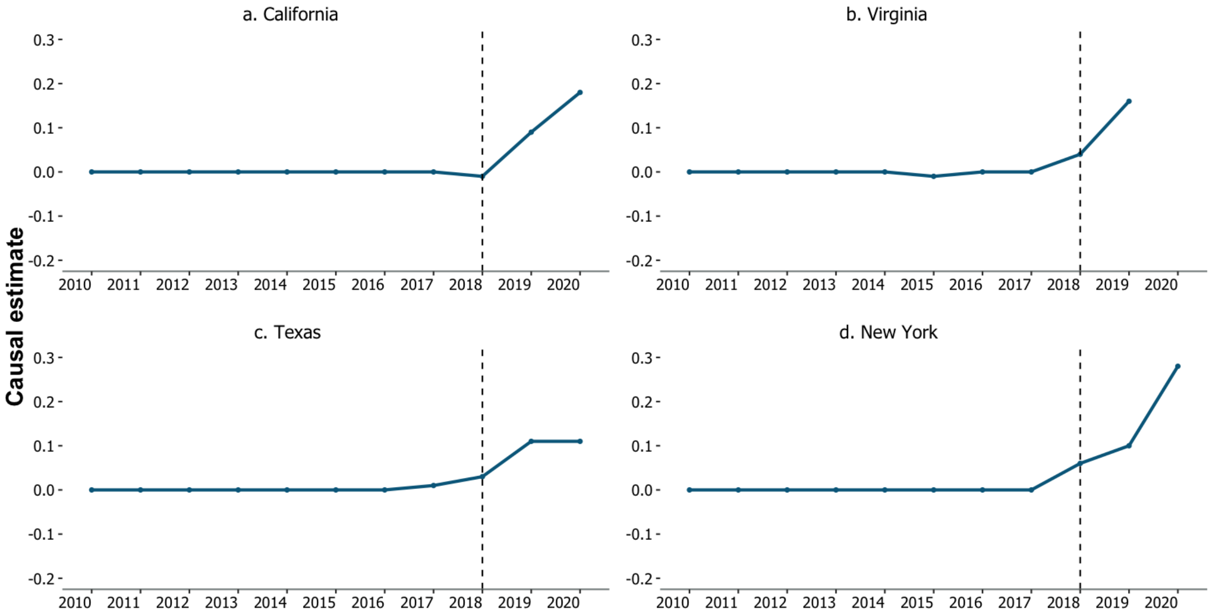
Figure 6: State-level Synthetic Control Results: Examples

Actual Methame Emissions (solid) vs. Synthetic Methane Emissions (dashed)

Note: This plot shows the synthetic control results from four selected states. The solid grey lines are the actual methane emissions from the waste industry in four states. The blue dashed lines are the synthetic methane emissions estimated by a function of other state-industries (controls) with different weights. The differences between the actual methane emissions and synthetic emissions are the causal effects of China's GS policy on the U.S. domestic methane emissions from the waste industry at state level. California, Virginia, Texas, and New York have all seen an increase in methane emissions after China's GS policy. Texas's methane emissions from the waste industry dropped in 2020. This may be caused by a variety of reasons due to the 2020 Covid-19 pandemic.

Figure 7: State-level Synthetic Control Results: Examples

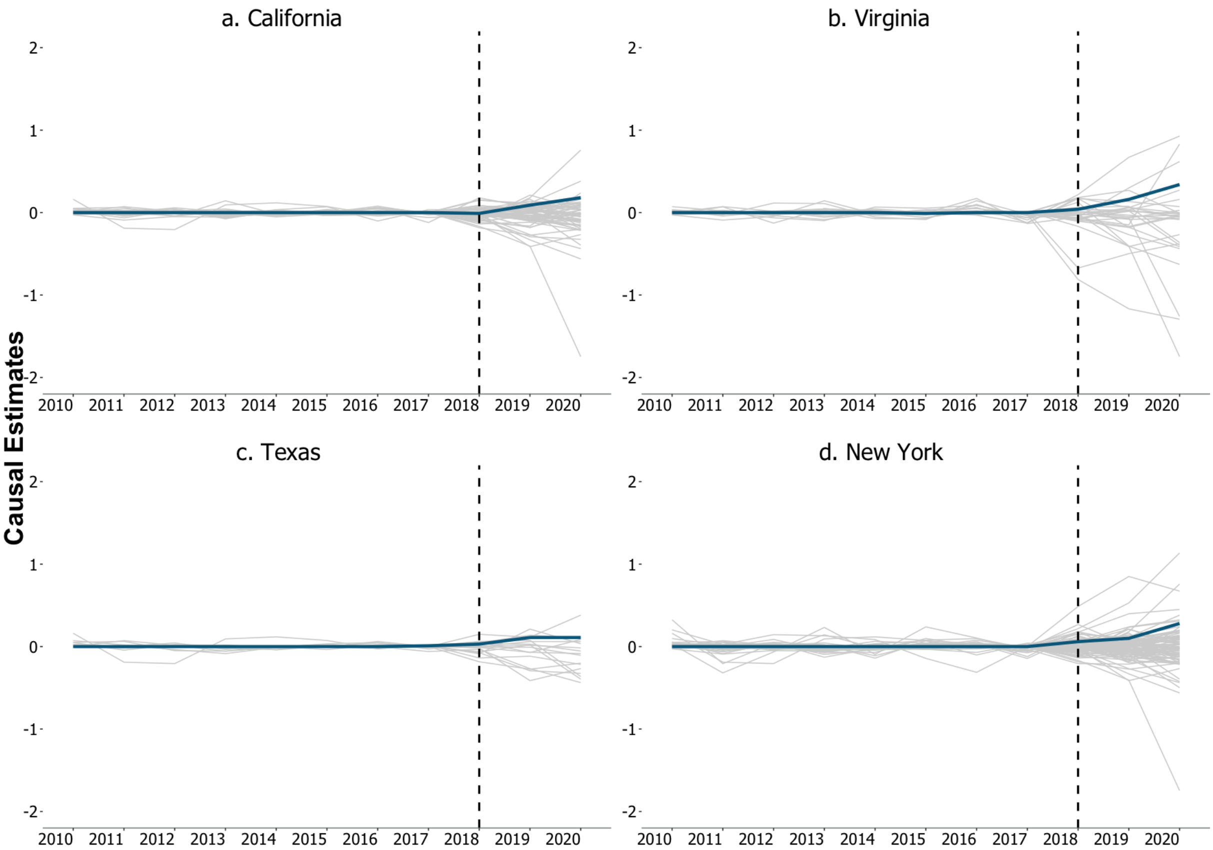
Causal Estimates (differences between actual and synthetic emissions)



Note: The causal estimates are calculated by subtracting the synthetic emissions from the actual emissions. Since the synthetic emissions are predicted in the absence of China's GS policy, the difference between actual and synthetic emissions is the causal effect of the GS policy on emissions from the waste industry for each state. All of the four example states have seen increasingly positive effects on methane emissions from the waste industry.

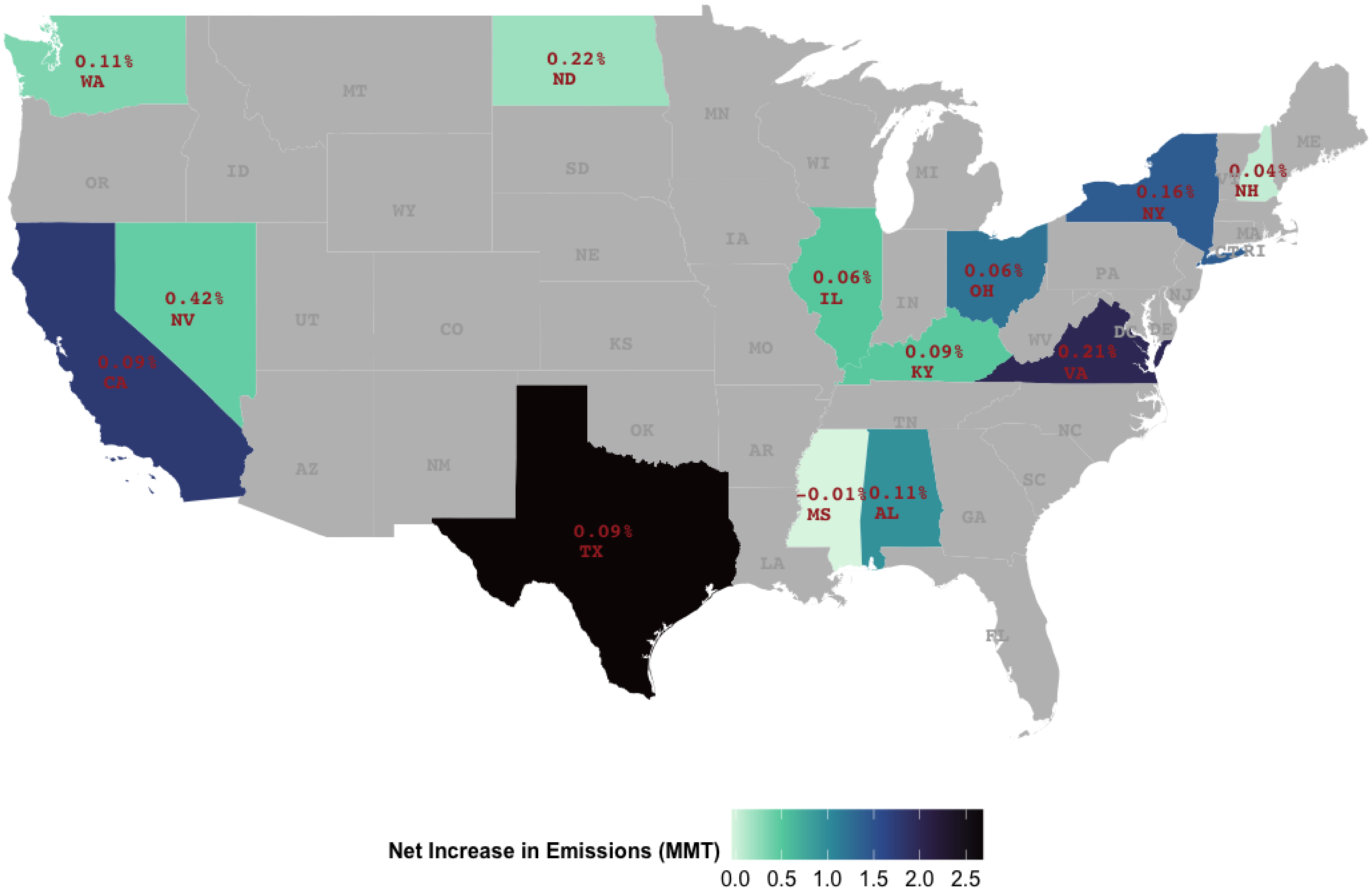
Figure 8: State-level Synthetic Control Results: Placebo Tests

Waste Industry (Blue) vs. Other Industries (Grey)



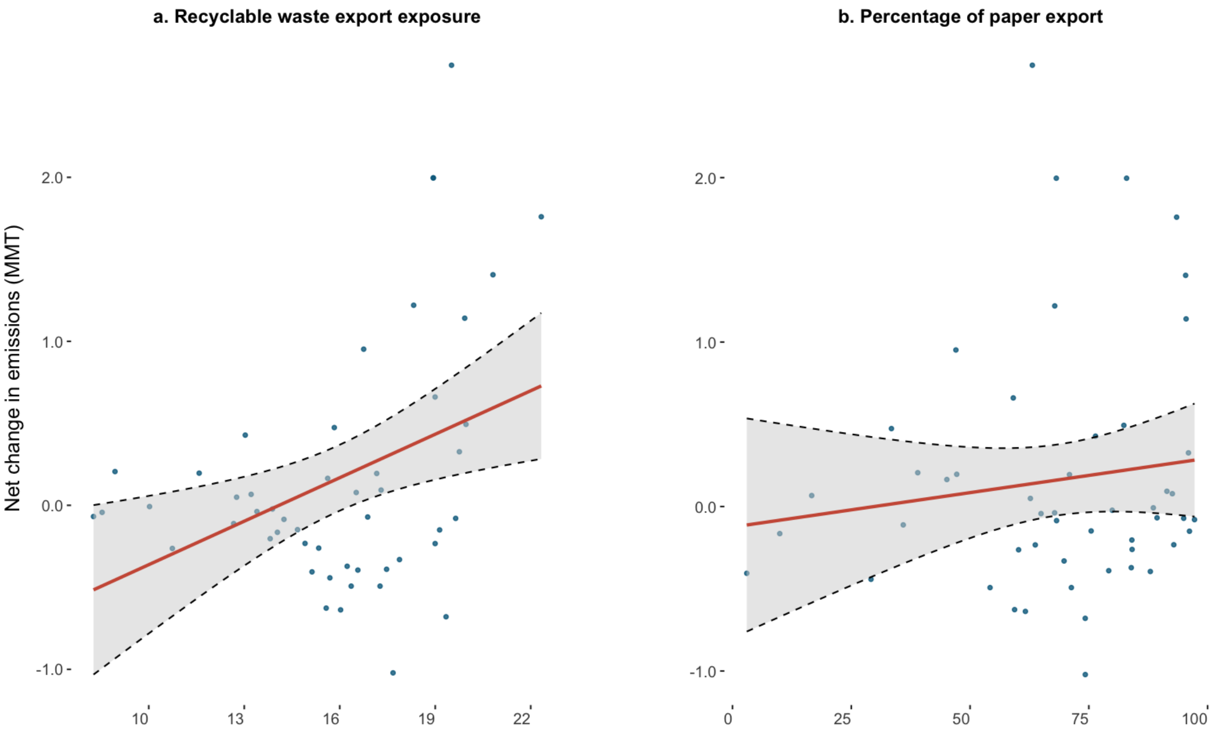
Note: This figure shows the placebo tests of the synthetic control methods for the four states. The blue lines are the causal effects of China's GS policy on the waste industry of each state. The grey lines are the causal effects of China's GS policy on other industries of different states. The p-value is calculated by the distribution of the post/pre-GS policy ratios of the MSPE for treatment industry of a state and all other control state-industry pairs.

Figure 9: State-level Synthetic Control Results—Estimates of the Percentage and Net Change in GHG Emissions from the Waste Industry



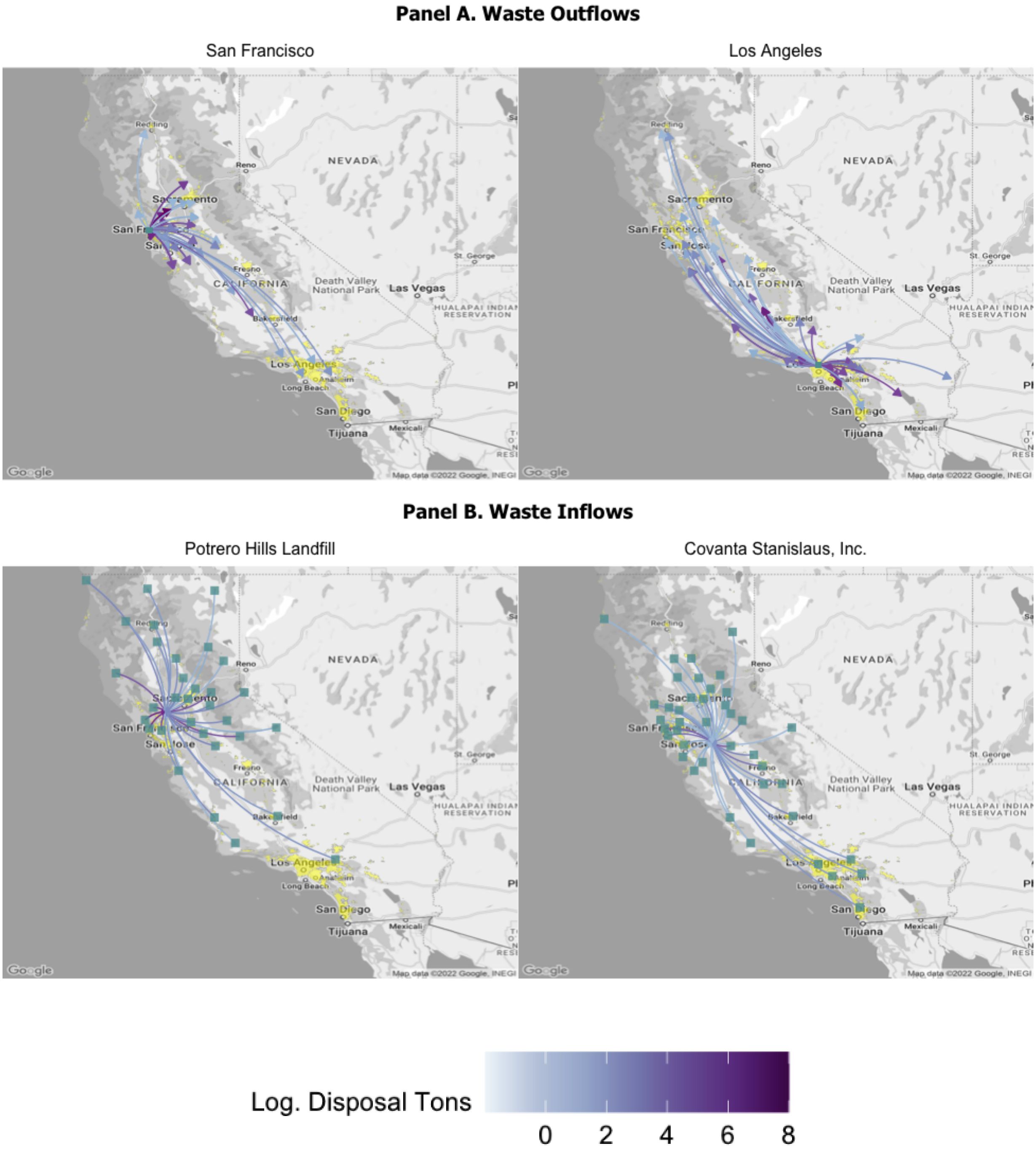
Notes: Colored states represent state-level estimates that can be considered statistically significant at the 10% level. Grey states represent state-level estimates that are statistically insignificant.

Figure 10: Pairwise correlations: heterogeneous effects of the GS policy on state-level emission changes



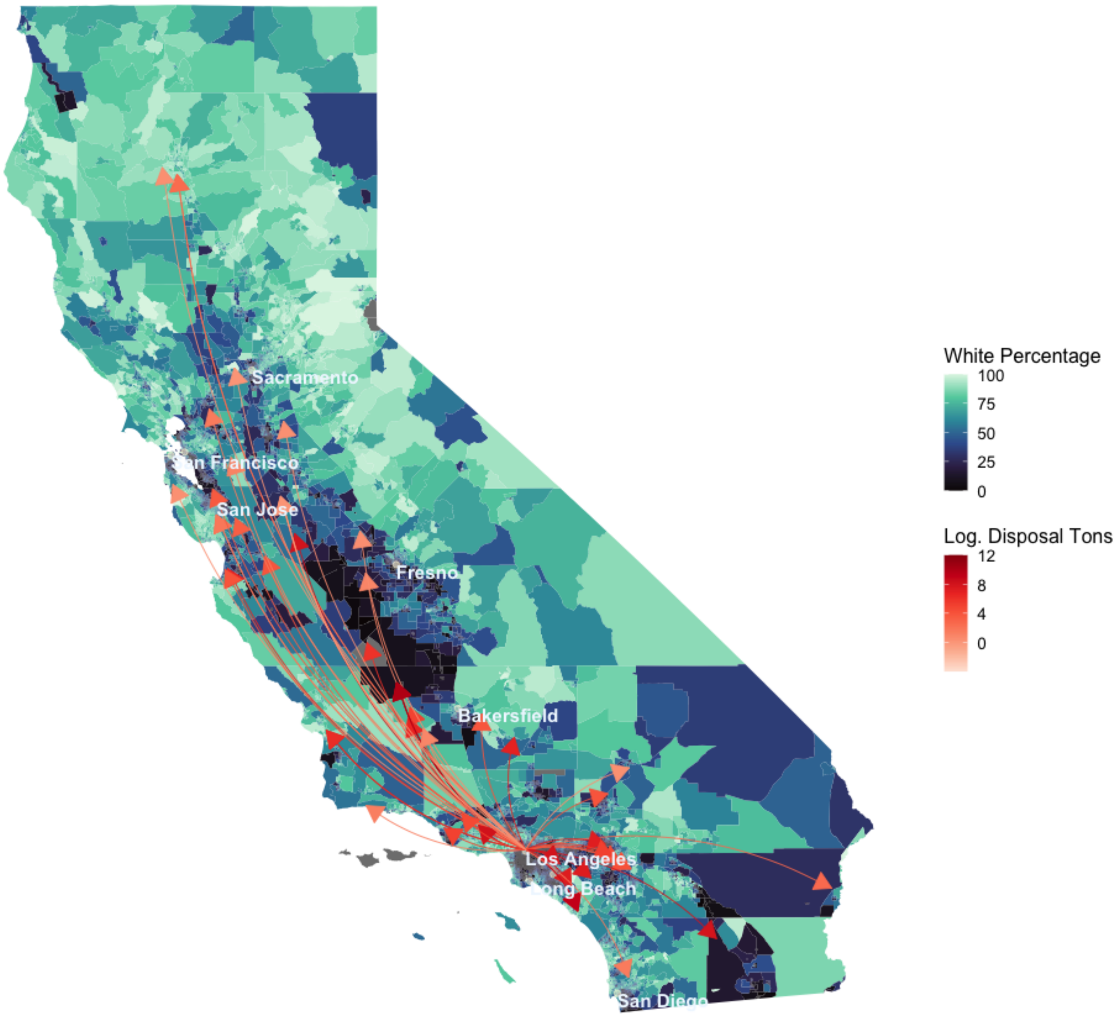
Notes: The methane emission increases for states are calculated by multiplying the methane emissions in 2016 with the percentage increases in emissions estimated by the synthetic control method. The blue dots (observations) are the net methane emission increases by states. The log of total recyclable waste exports (before China's GS policy) is used as a measurement of the export exposure of a state to China. The red lines are fitted lines for regression that regress the log of total recyclable exports and the percentage of paper exports on the net emission increases at the state level.

Figure 11: CalRecycle: Average Net Increase of Disposal Flow
after China's GS Policy



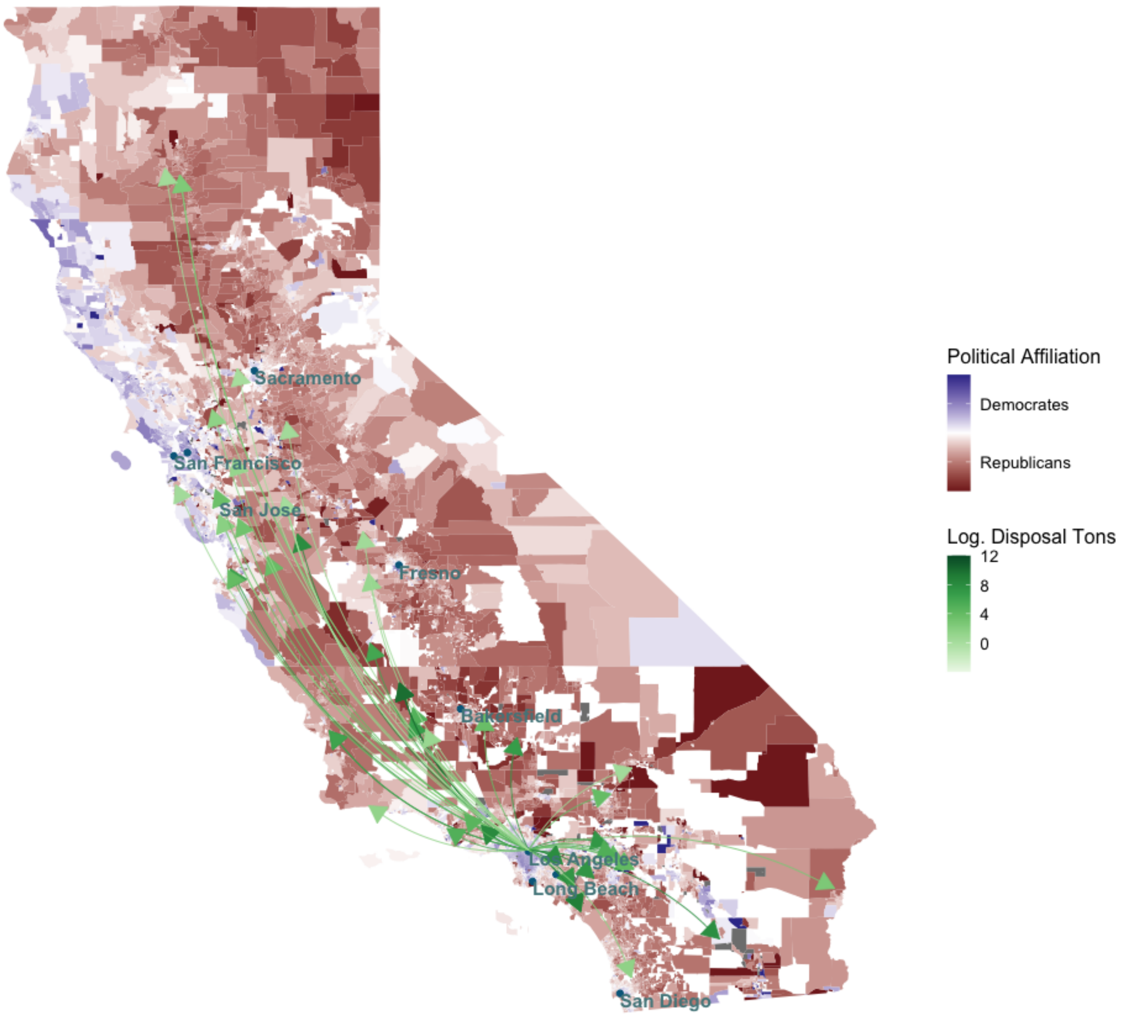
Note: These maps show the disposal flows from source cities (e.g.,San Francisco and Los Angleles) and disposal flows to destination facilities (e.g., Potrero Hills Landfill and Covanata Stanislaus, Inc.), as examples. They show (1) where the disposal goes from San Francisco and (2) where disposals originate for the Potrero Hills Landfill. The color of the arrows shows the increase in amount of disposal flows after China's GS policy. From the source city, most of the disposal has gone to rural or suburban areas outside the urban areas (yellow areas). Disposal that was transferred to closer rural areas increased more (represented by the darker color of curves with arrows) after China's GS policy.

Figure 12: CalRecycle: Average Net Increase of Disposal Flow by Racial Composition



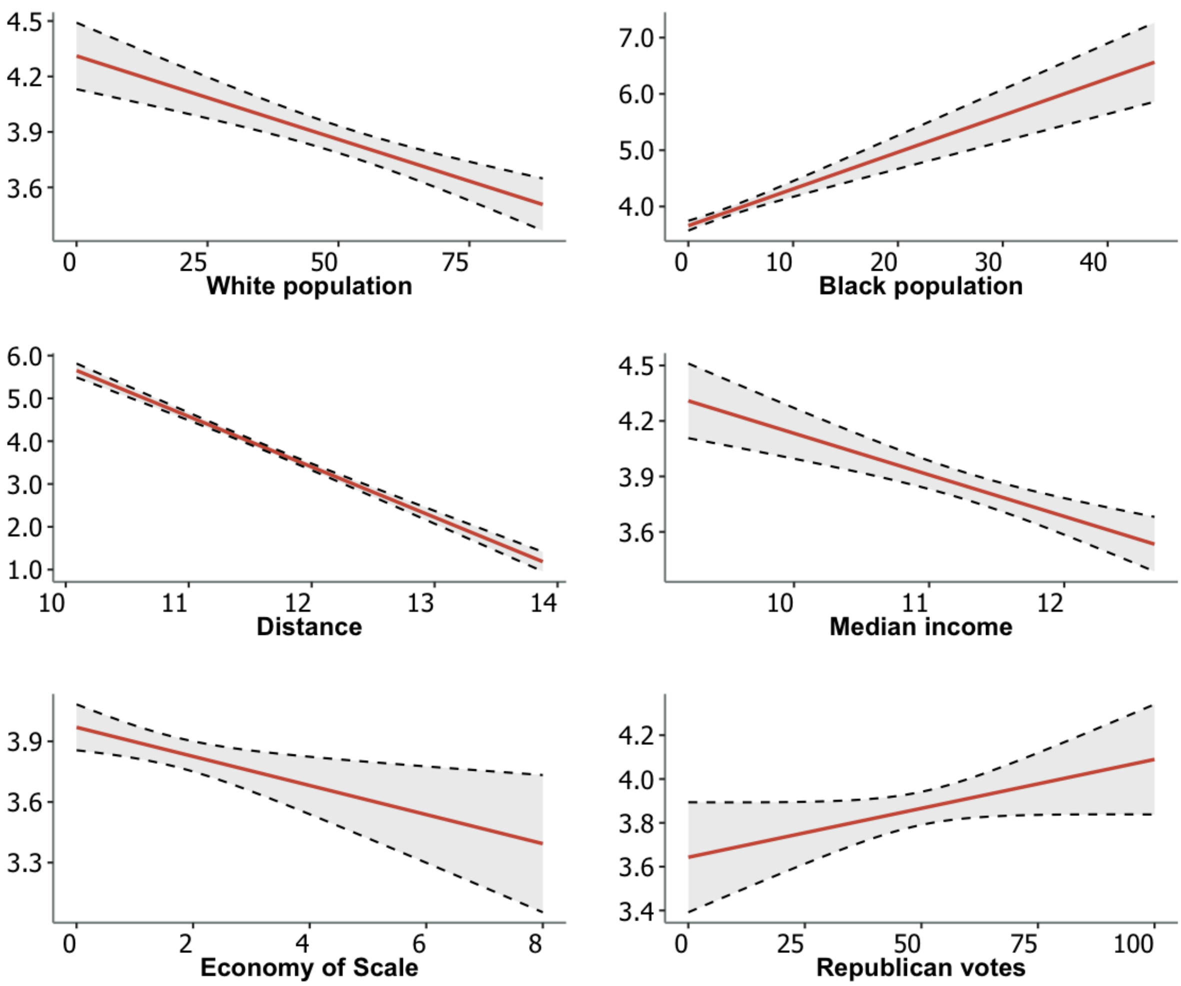
Note: This map shows the net increase in disposal flow after China's GS policy based on racial composition. The geographic unit for racial composition is the census tract. The color of the arrows shows the increase in amount of disposal flows after China's GS policy. The map shows that most of the destinations for disposal transfer are in "minority" areas (represented by darker blue/green). However, the "White" areas (represented by lighter green) have seen a greater increase (darker red arrows) in waste transfers after China's GS policy.

Figure 13: CalRecycle: Average Net Increase of Disposal Flow by Vote Shares



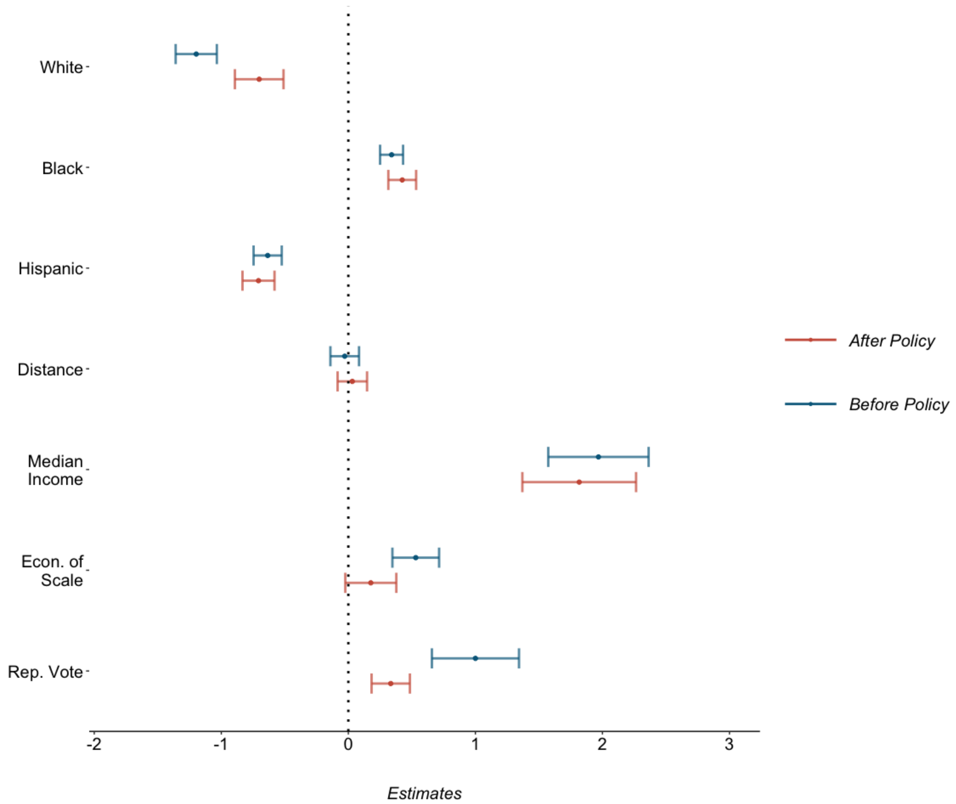
Note: This map shows the net increase in disposal flow after China's GS policy based on vote shares. The geographic unit for vote shares is the voting precinct. The map shows that more destinations of waste transfers are in Republican precincts (red) in California. The color of the arrows shows the increase in amount of disposal flows after China's GS policy.

Figure 14: Correlations of Disposal Flow and Destination Community Characteristics



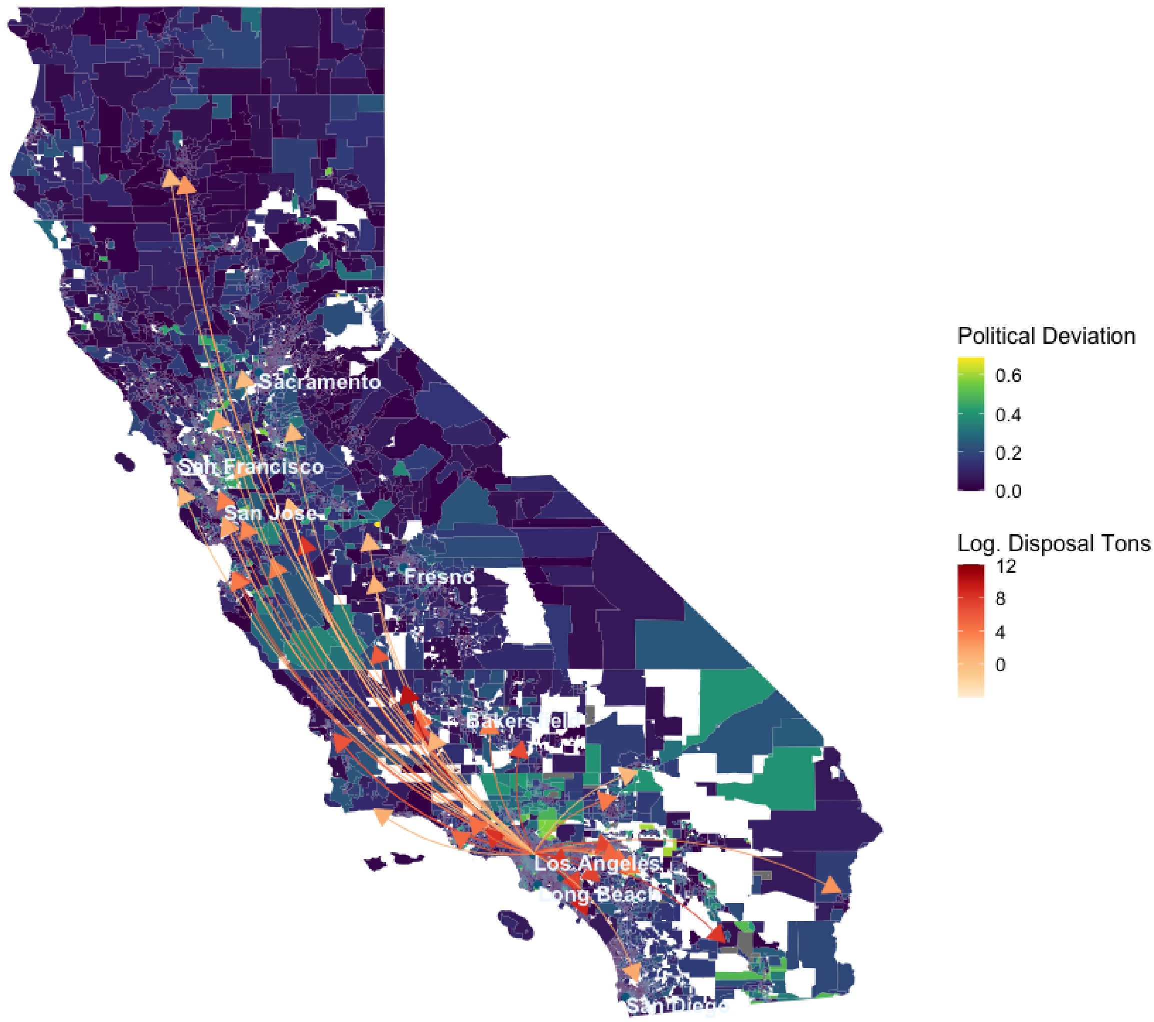
Note: These plots show potential factors determining the community-level waste pollution relocation in California after China's GS policy. The percentage of the White population, the distance between origin and destination, median income, and the economies of scale of destination communities are negatively correlated with the net increase in waste inflows. The percentage of the Black population and the percentage of Republican votes are positively correlated with the net increase in waste pollution inflows.

Figure 15: CalRecycle: Effect of destination community characteristics on waste flows before and after China's GS Policy



Note: This plot shows the results of the gravity model. The point estimates are reported in 90% (darker red/blue bars) and 95% (lighter red/blue bars) confidence intervals. Before the GS policy, the White share of the population in a community is *negatively* correlated with the amount of waste transported into the community. The Black share of the population is *positively* correlated with the amount of waste transported into the community. However, this pattern changed after the GS policy. The White communities have seen a greater increase in waste inflows than Black communities. The estimate (after the GS policy) that does not intersect with the CIs of estimates (before the GS policy) shows that the change is statistically significant.

Figure 16: Potential Mechanism: Disposal Flow Map by Political Deviation



Note: Political deviation is one of the three potential mechanisms to explain waste transfers across communities. Blue/green indicates the political deviation of a community from its county in terms of vote shares. Red indicates the net increase in the amount of waste being transferred after the GS policy. White spaces indicate where no data was available. Political deviation is calculated by the absolute difference between a community's Republican/Democratic vote share and its county's Republican/Democratic vote share. The higher political deviation a community has, the lower the political cost such a community has for waste pollution inflows.

Table 1: Data Sources Summary

	Spatial Unit	Years available	Frequency
UN Comtrade Data	country level	2002-2020	yearly
U.S.A Trade Online Data	state level	2002-2020	yearly
EPA GHG Inventory Data	state level	2002-2020	yearly
EPA GHG Reporting Program Data	facility level	2010-2020	yearly
CalRecycle Disposal Flow Data	jurisdiction by facility level	2002-2020	quarterly
U.S. Census Data	census block level	2000-2020	decennial
ACS 5-year Data	census block group level	2002-2017	5-year
Waste Business Journal	facility level	1992-2020	yearly
Statewide Database Election Data	precinct level	2000-2020	4-year

Notes: This table summarises all of the data sources that are used in this paper. Export and emission data are tracked by state and year. Disposal flow data is aggregated to origin jurisdiction, destination facility, and year. For the census data, since the geographic units are small and data frequency is low, I use 2010 census-block level data for racial composition, 2013 ACS 5-year data for median income, and 2016 precinct-level election data for vote share.

Table 2: Summary Statistics: Recyclable Waste Exports
by the U.S. and Other Countries

	I. U.S.		II. Other countries	
	Exports to China (1)	Exports to rest of world (2)	Exports to China (3)	Exports to rest of world (4)
Panel A. Total value ($ U.S. billion) over all U.S. states				
2010	3.54	2.85	3.30	4.05
2011	4.29	2.95	3.16	4.59
2012	3.96	2.41	3.76	4.89
2013	3.54	2.41	3.28	4.28
2014	3.57	2.51	3.13	4.52
2015	3.33	2.31	2.82	3.69
2016	3.16	2.29	2.62	3.55
2017	2.59	2.75	2.33	4.64
2018	1.53	3.49	1.36	5.14
2019	1.01	3.09	0.68	4.64
2020	0.86	2.78	0.33	4.33
Panel B. Total weight (billion kg) over all U.S. states				
2010	17.30	6.59	13.74	14.01
2011	20.03	6.58	14.11	15.58
2012	19.88	6.15	15.33	16.09
2013	18.39	6.05	14.03	12.85
2014	18.65	6.56	13.64	16.49
2015	19.04	6.50	14.24	9.39
2016	17.99	6.69	14.26	10.67
2017	14.31	8.08	11.19	6.29
2018	7.95	12.95	6.81	9.66
2019	5.59	12.21	4.23	11.85
2020	4.71	10.38	2.19	10.78

Notes: "Other countries" refers to 11 selected OECD countries—Australia, Austria, Canada, France, Germany, Portugal, New Zealand, United Kingdom, Japan, Spain, and Finland. They all have regular trade with China in recyclable wastes.

Table 3: Models to explain the changes in methane emissions
as a function of the changes in recyclable waste exports

Dependent Variable: Change in Methane Emissions			
	Naive OLS	2SLS Bartik shift-share IV	2SLS Bartik shift-share IV Other countries
	(1)	(2)	(3)
2003-2019 first differences			
Change in Exports	-0.492***	-0.722***	-0.893***
	(0.122)	(0.114)	(0.124)
2SLS first stage estimates:	Change in Exports regressed on IV		
IV^{Bartik}		1.11***	9.55***
		(0.038)	((0.465)
First stage F-statistics		50	34
State FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	897	897	897

Notes: Each column reports a separate regression. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. The first-differenced model is like the fixed effect model but with a less restrictive assumption. The intercept in this first-differenced model captures all unobserved factors that may affect the emissions but are constant over time. It also captures the linear time trend. The state-fixed effects control for the variations in differences in emissions. The year-fixed effects capture every time pattern other than the linear time trend.

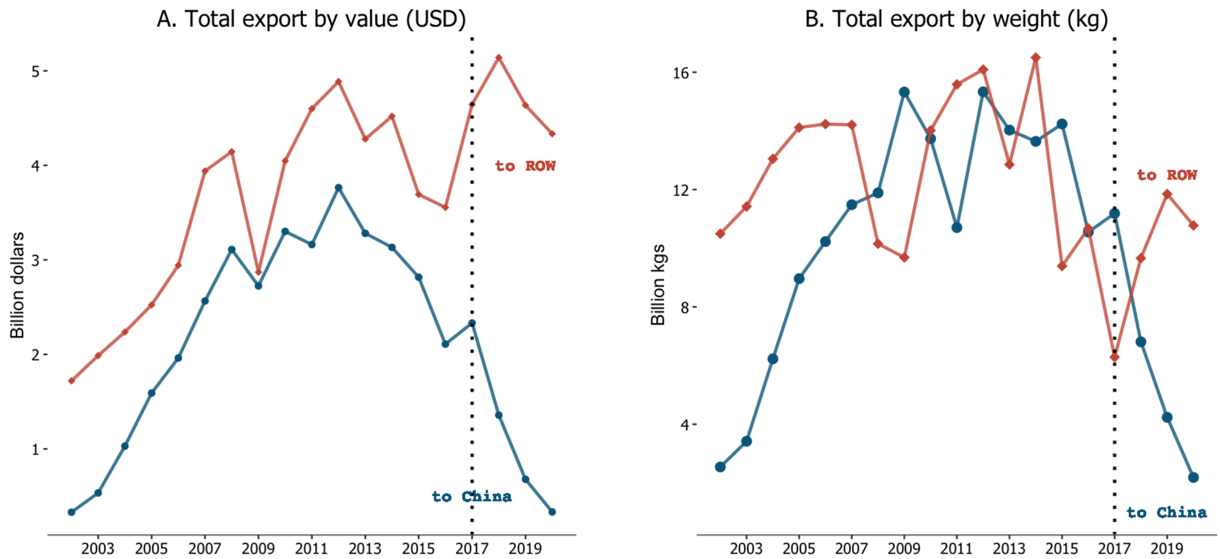
Table 4: Potential Mechanisms: Model Estimates

Dep.Variable: Disposal shipment (tons)	(1)	(2)	(3)	(4)
Transportation costs	-0.326***			-0.476***
	(0.113)			(0.112)
Transportation costs×1(*post*)	0.031			0.0196
	(0.049)			(0.063)
Land costs		0.019		-0.063
		(0.052)		(0.060)
Land costs×1(*post*)		-0.017		-0.057**
		(0.020)		(0.024)
Political costs			0.028	0.011
			(0.041)	(0.032)
Political costs×1(*post*)			-0.107*	-0.101*
			(0.062)	(0.057)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
R^2	0.642	0.638	0.654	0.664
Observations	293,238	291,016	210,767	209,647

Notes: Two-way clustered standard errors at the county-year level in all models. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Transportation costs are approximated by the distances between origin jurisdictions and destination facilities. Land costs are approximated by the population density of the communities where the destination facilities are located. Political costs are defined as the discrepancy (absolute difference) between the community Republican vote share (at the precinct level) and the county Republican vote share. For example, community A has 30 percent of Republican voters, and the county it resides in has 45 percent of Republican voters. The political cost of community A as a destination community for waste shipment is $|30\text{-}45| = |\text{-}5| = 5$, which is a "high" political cost. Because these communities, which have similar political ideologies as the county, are more likely to be resistant to the increased waste relocation due to the GS policy.

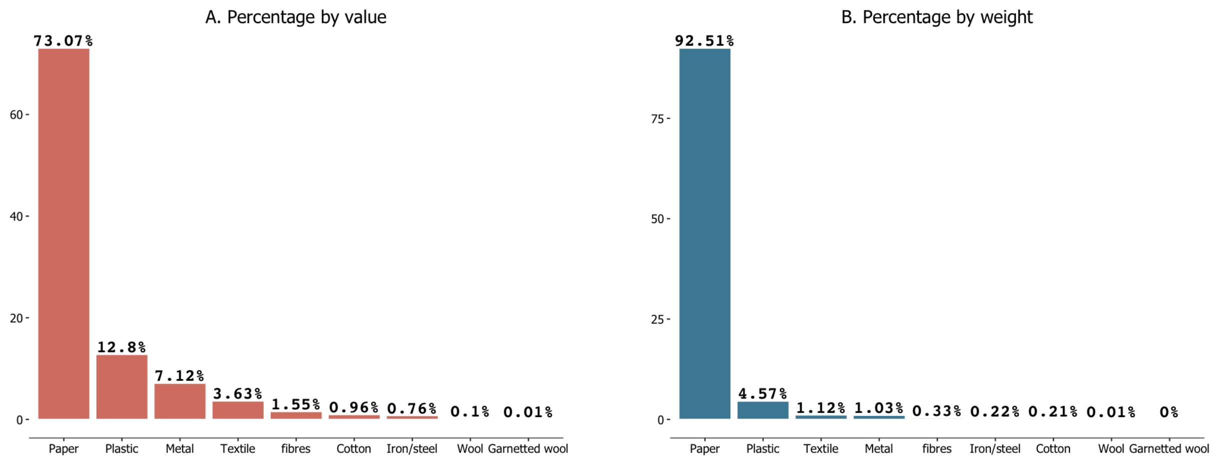
Appendix: Figures and Tables

Figure A.1: Other Countries' Recyclable Waste Export to China and the Rest Of the World (ROW)



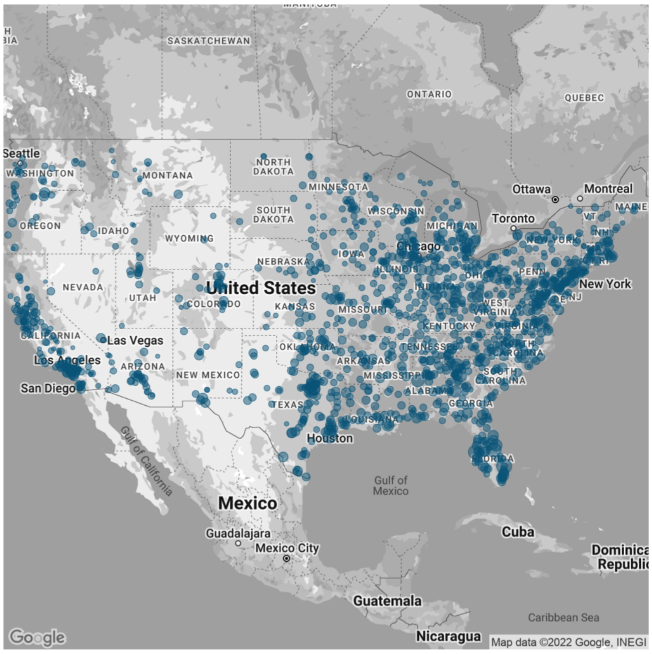
Notes: "Other countries" refers to 11 selected OECD countries—Australia, Austria, Canada, France, Germany, Portugal, New Zealand, the United Kingdom, Japan, Spain, and Finland. They all have regular trade with China in recyclable wastes. Recyclable waste exports from other countries to China decrease drastically by value and weight. Recyclable waste exports from other countries to the rest of the world increased temporarily and fell eventually after the GS policy. These plots show that most of the developed countries that used to export recyclable wastes are now dealing with these wastes on their own.

Figure A.2: Composition of U.S. Recyclable Waste Exports to the Rest of the World



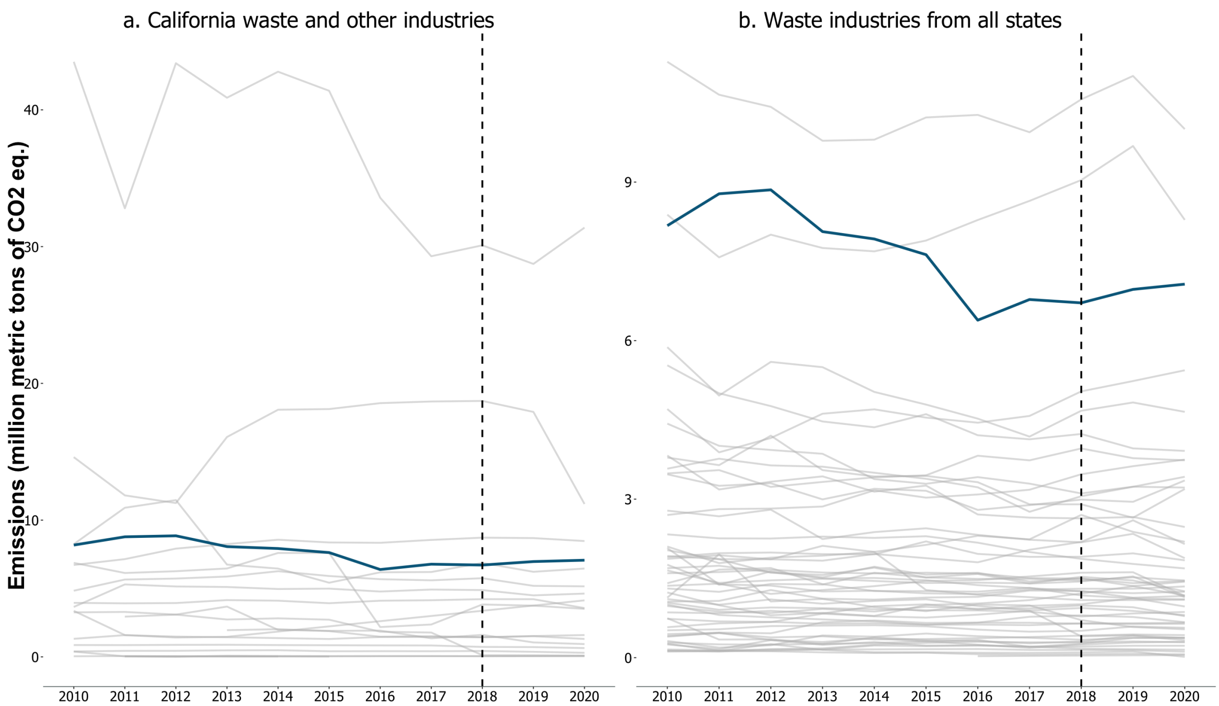
Notes: This plot shows the composition of recyclable waste materials exported from the U.S. to the rest of the world. Mix paper/paperboard is still the material that accounts for the most percentage of the total exports by value and weight. Plastic scrap is the second most exported recyclable waste. Compared to exports to China, the U.S. exported lower percentages of plastic scrap and higher percentages of metal, textile, fibers, and cotton scraps to the rest of the world.

Figure A.3: GHGRP: Waste Facilities Distribution



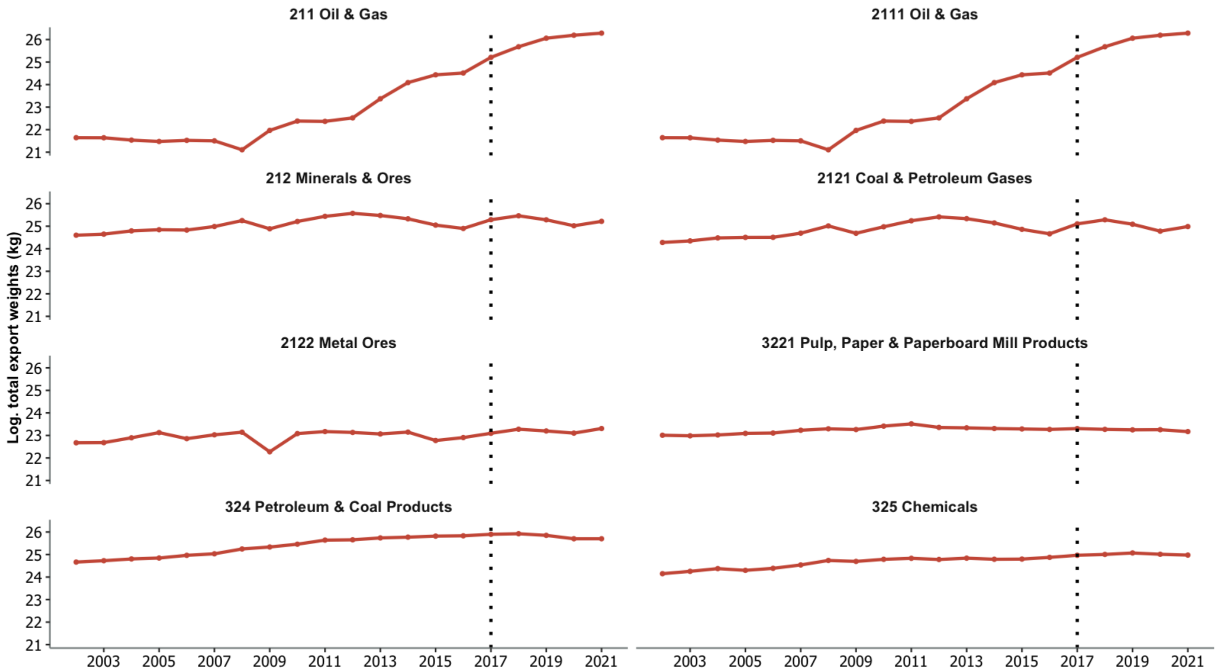
Notes: This map shows the locations of all landfill facilities in the U.S. according to the EPA Greenhouse Gas Reporting Program (GHGRP). There are more landfill facilities in states where populations are denser.

Figure A.4: Synthetic Control: Waste Industries and Other Industries



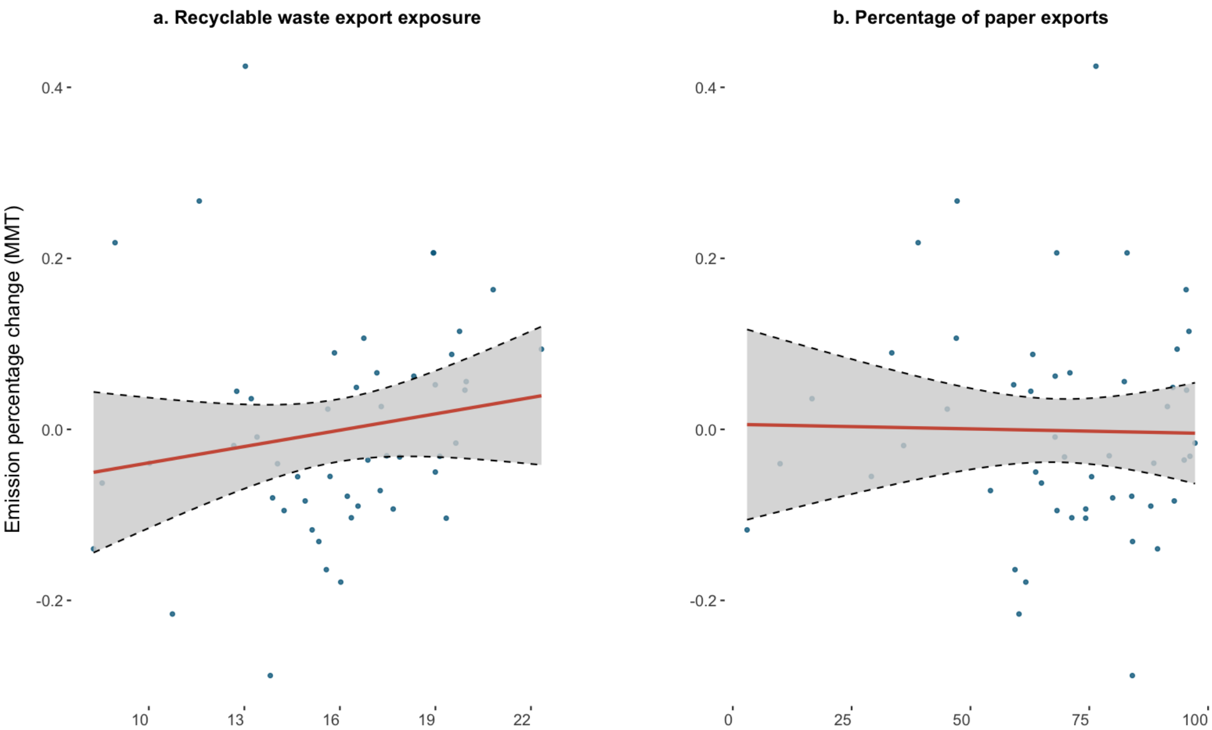
Note: In plot a, the blue line represents the methane emissions for California's waste industry; The grey lines represent emissions from non-waste industries in California. In plot b, the blue line represents methane emissions from California's waste industry, and the grey lines represent methane emissions from waste industries in other states. These plots show that "waste industries from other states" or "other industries within the same state" are both not the most suitable control group for the synthetic control.

Figure A.5: Synthetic Control: Exports of Other Control Industries



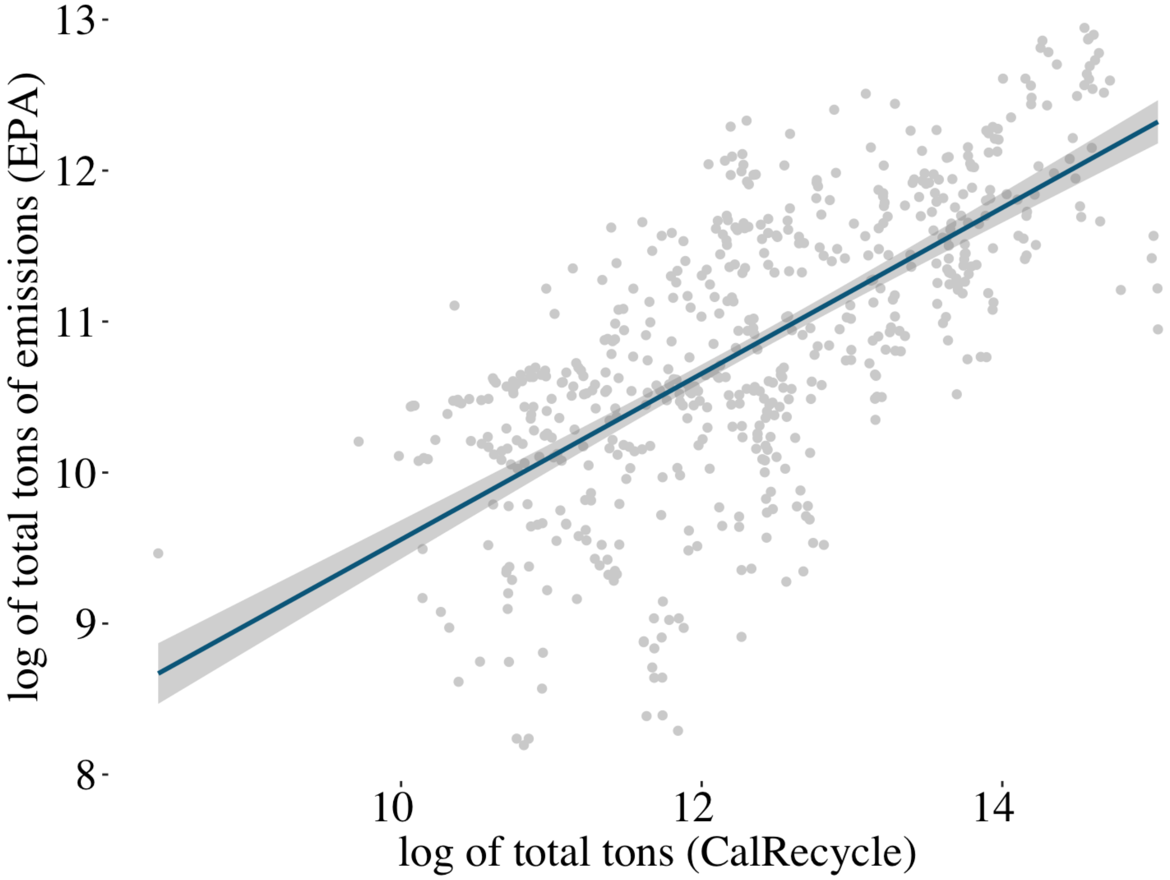
*Note:*These plots show the net export weight by manufacturing industries. The emissions of these manufacturing industries are used as control groups in the synthetic control method. The plots show no discernible changes in exports of the control manufacturing industries after 2017, which means that the emissions from the control industries are not contaminated by their exports.

Figure A.6: Pairwise correlations: heterogeneous effects of GS policy on state-level estimations



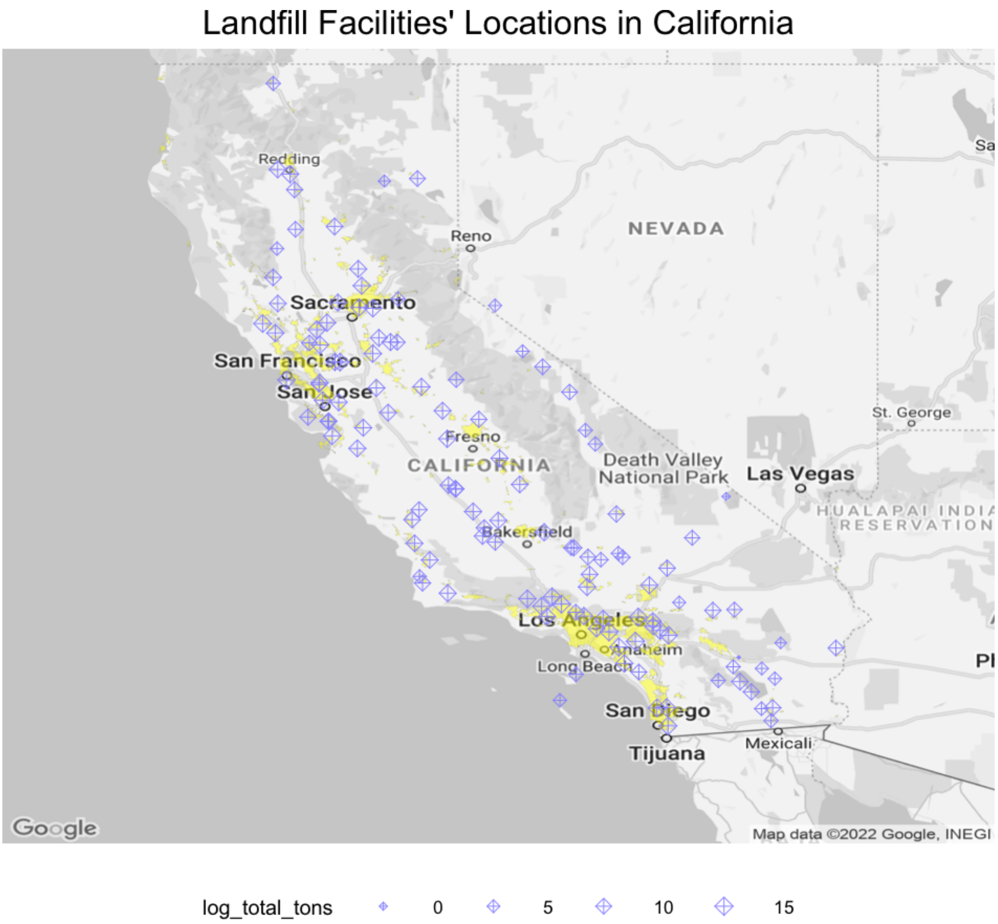
Notes: Figure a shows the correlation between the state-level causal estimates of the GS policy and the recyclable waste export exposure; Figure b shows the correlation between the causal estimates and the percentage of paper exports by each state. There is a positive correlation between the percentage change in methane emissions and recyclable waste export exposure by state. There is no apparent correlation between the percentage change in methane emissions and the percentage of paper scrap exports by state.

Figure A.7: Data Comparison: EPA GHGRP v.s. CalRecycle RDRS



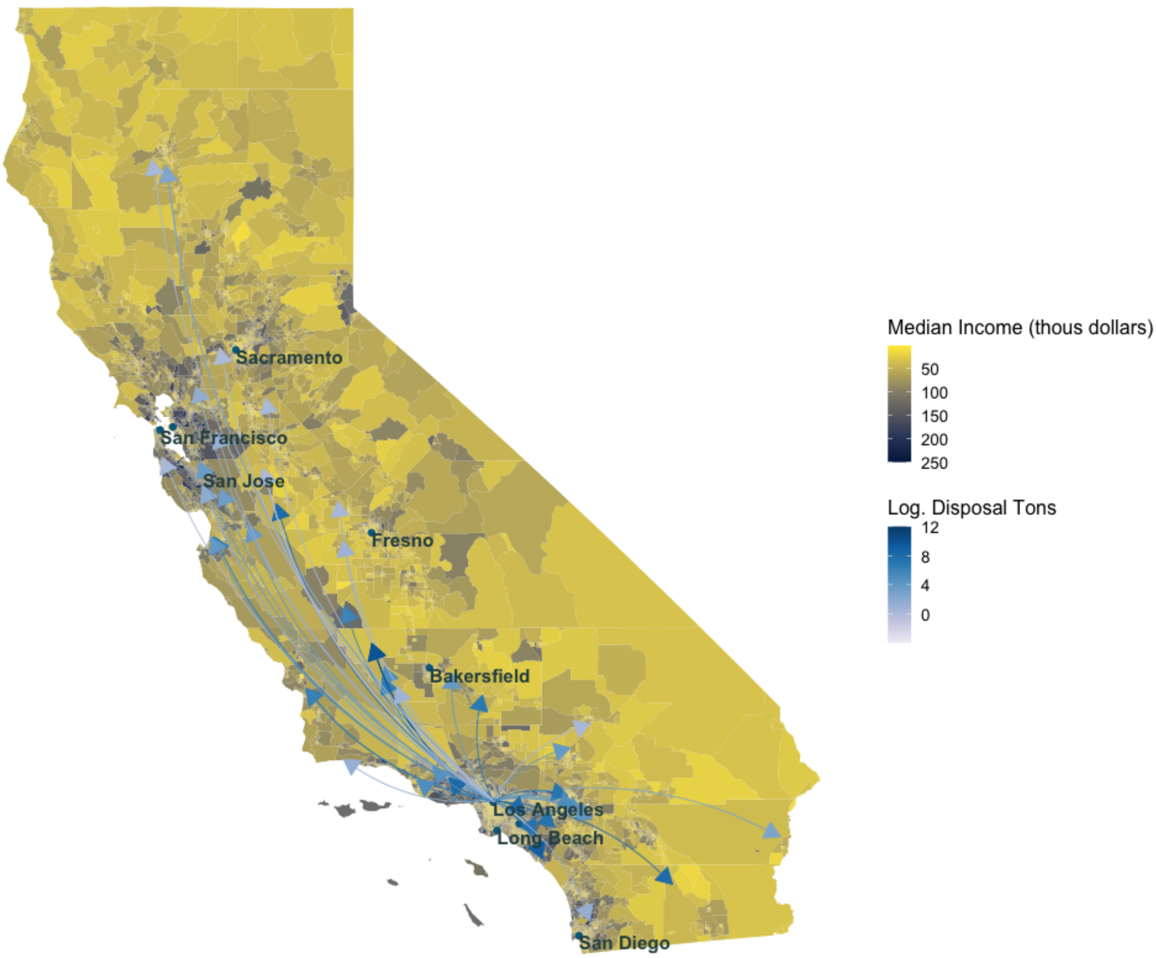
Note: To carry the result from the state-level estimate, I compare the two data sources for state and facility-level analysis. This plot shows that the emissions data in EPA GHGRP and tons of disposal data in CalRecycle are highly correlated. This correlation demonstrates that the result I find from the state-level analysis—California has seen an increase in methane emissions from the waste industry after China's GS policy—can be used in facility-level distributional effects analysis in California. Given that California has seen an overall increase in emissions and pollution from the waste industry due to China's GS policy, I will estimate how local communities have been affected differently by this policy change.

Figure A.8: CalRecycle: Recycling and Disposal Reporting System (RDRS) Facility locations in California



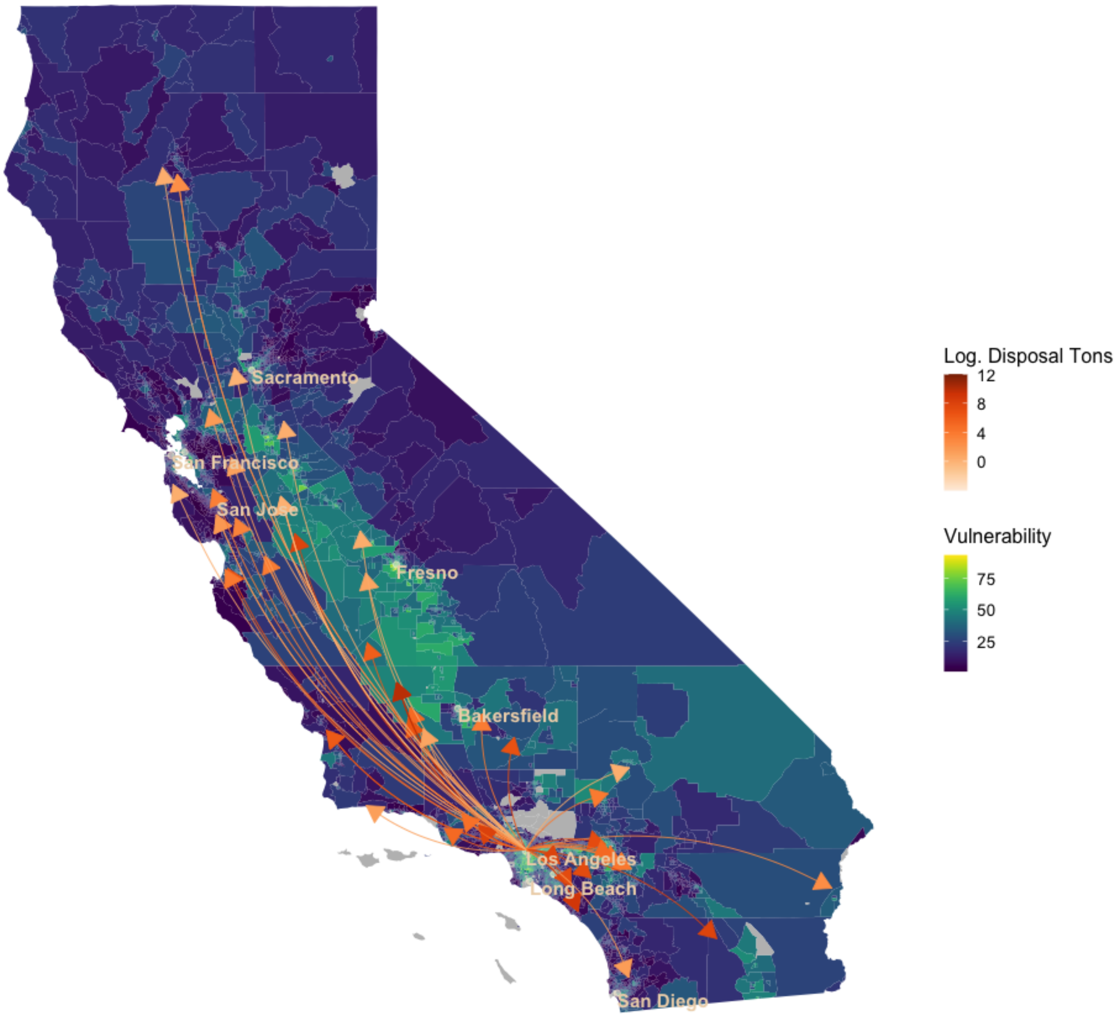
Note: This map shows the location of all landfill facilities in the CalRecycle RDRS data. The yellow areas are the urban areas in California. The map shows that most landfill facilities are located in rural regions or suburbs outside the urban areas. The size of the diamond marks represents the capacity of these landfill facilities.

Figure A.9: Disposal Flow Map by Median Income



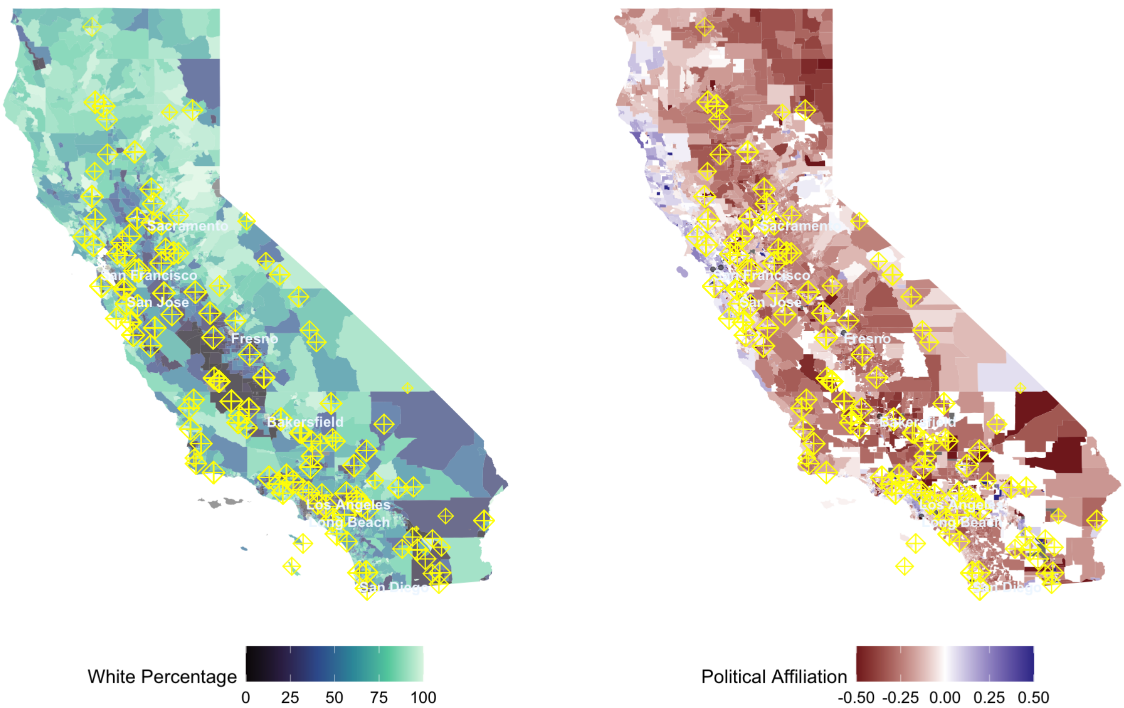
Note: The median income is mapped using 2013 ACS 5-year data at the census block group level. The color of the arrows shows the increase in amount of disposal flows after China's GS policy.

Figure A.10: Disposal Flow Map by Environmental Vulnerability



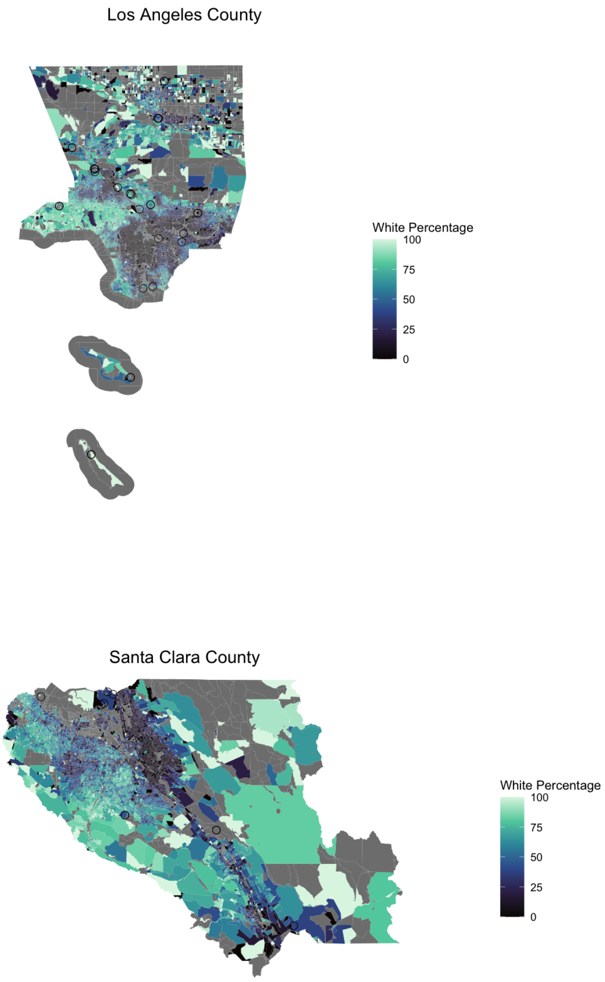
Note: Environmental vulnerability is calculated by the Office of Environmental Health Hazard Assessment (OEHHA). California Communities Environmental Health Screening Tool is a screening methodology that evaluates multiple pollution sources and stressors and measures a community's vulnerability to pollution. The higher the score is, the more vulnerable the community is to pollution. The color of the arrows shows the increase in amount of disposal flows after China's GS policy.

Figure A.11: CalRecycle: Recycling and Disposal Reporting System (RDRS)
Facility locations in California by racial and political affiliation



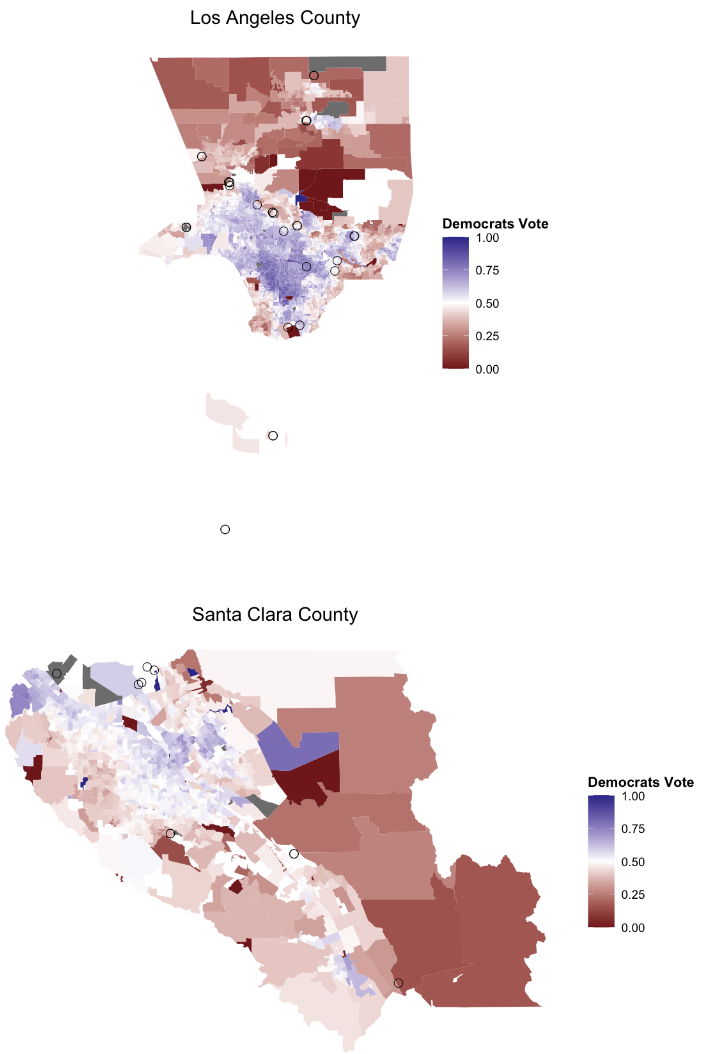
Note: This map shows the location of all landfill facilities in the CalRecycle RDRS data by racial composition and vote shares. Racial composition is plotted by census block group level, and the vote share is plotted by voting precinct. The left map shows that most destination facilities are located in the darker areas where more minority population resides. However, some facilities are still located in the lighter areas where the white population lives. The right plot shows that most destination facilities are located in Republican-leaning communities. Few of them are located in Democratic-leaning communities.

Figure A.12: Racial composition variation within county



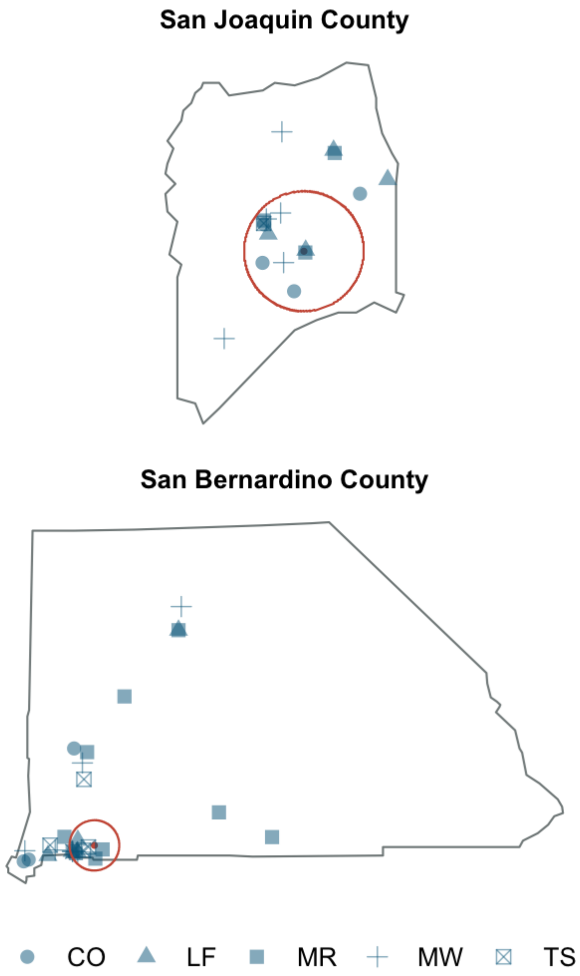
Note: This map shows the racial composition variations across different communities (within 3 km buffers of the destination facilities) in a county, for example, Los Angeles and Santa Clara. In the gravity-type model estimation, the racial composition variable is at the census block-level, and is time-invariant (as of 2010). Thus, when I add county fixed effects, the variation in racial composition is the different communities within a county. Some communities may include multiple census blocks.

Figure A.13: Voting variation within county



Note: Similar to the racial composition, vote shares of communities (with 3km buffers of the destination facilities) are also time-invariant (as of 2016) at the precinct level. Thus, when I add county fixed effects, the variation for vote share is the different communities within a county. Some communities may include multiple voting precincts.

Figure A.14: Economies of Scale of communities
where destination facilities are located



Note: This figure shows how economies of scale are defined. The map shows the number of facilities that are within a 15 km buffer of the destination facility of disposal shipment. The red dot is the destination facility from CalRecycle as a destination for disposal transfer. The diamond marks are other types of related facilities within a 15km buffer. They are composts (CO), landfills (LF), recycling centers (MR and MW), and transfer stations (TS). The more facilities around the destination landfill facility, the higher the economy of scale there is in the community where the destination landfill is located.

Table A.1: Summary Statistics: U.S. Recyclable Waste Exports (by Type of Materials)

	Total Value $ U.S. million (1)	Total Weight million kg (2)	Percentage of total value (3)	Percentage of total weight (4)
Slag, dross of manufacture of iron or steel	71.9	473	0.15	0.17
Slag, ash, and residues containing metals	292.9	70.2	0.61	0.003
Plastics	15464.1	38756.4	32.4	14.23
Paper and paperboard	31521.9	232466.6	66.11	85.38
Wool and animal hair	4.8	2.3	0.05	0.00008
Wool	0.15	0.02	0.0001	0.0000008
Cotton	116.1	199.5	0.24	0.007
Fibres	150.3	256.9	0.32	0.009
Textile	51.6	51.8	0.11	0.002

Notes: The listed waste materials are all wastes that are directly affected by China's GS policy. Columns (1) and (2) are the total value and weight of recyclable waste exports from the U.S. to China from 2003 to 2020. Columns (3) and (4) are the percentages of each waste material out of all waste materials exported.

Table A.2: Summary Statistics: U.S. GHG Emissions (MMT) by Industry

	Total Emissions (1)	Methane (2)	CO_2 (3)	NO_2 (4)
Power Plants	20485.96	35.94	20481.52	76.99
Minerals	1193.32	1.22	1198.38	2.39
Waste	**1118.70**	**1000.99**	**311.01**	**3.85**
Chemicals	1053.17	1.92	991.47	64.83
Petroleum and Natural Gas Systems	985.61	88.45	896.96	0.56
Metals	815.38	793.13	1.71	0.29
Pulp and Paper	190.61	560.45	487.80	3.89
Refineries	102.77	102.07	2.87	0.26

Notes: Emissions by industry is calculated by adding up the emissions from all facilities in each industry from 2010-2020. Power plants have the largest total emissions across all industries. The waste industry (in bold) has the highest methane emissions out of all industries.

Table A.3: 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						

Notes: Each observation in the sample is a reporting record from a facility from 2010 to 2020. The number of facilities has decreased gradually over the years. However, the total and average emissions of facilities have increased after 2017.

Table A.4: Summary Statistics: U.S. GHG Emissions by Industry

	Power Plants	Minerals	**Waste**	Chemicals	Petroleum and Natural Gas Systems	Metals	Pulp and Paper	Refineries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Sum over all states								
2010	2295.21	100.97	**110.91**	104.11	65.45	90.79	43.82	27.72
2011	2136.86	100.50	**104.59**	83.93	94.21	82.64	16.88	17.17
2012	1995.041	104.89	**105.35**	80.35	96.16	78.09	16.38	6.81
2013	2006.49	108.39	**102.07**	85.41	93.75	77.11	15.09	6.57
2014	1997.66	113.97	**101.76**	89.87	96.59	77.96	15.69	6.90
2015	1874.29	112.45	**101.03**	93.30	98.15	69.73	15.62	6.69
2016	1771.08	108.15	**98.21**	99.13	76.19	69.10	14.39	6.39
2017	1696.25	111.58	**96.85**	100.97	79.71	69.56	13.48	6.41
2018	1710.59	113.32	**99.59**	104.75	90.67	72.06	13.35	6.46
2019	1577.77	112.02	**101.41**	106.94	97.16	69.17	12.87	6.37
2020	1424.73	107.07	**96.91**	104.41	97.56	59.17	13.01	5.28
Panel B. Average cross all states								
2010	42.50	2.24	**2.17**	2.60	1.49	2.67	1.22	1.73
2011	39.57	2.28	**2.05**	2.09	2.00	2.36	4.97	1.07
2012	36.95	2.38	**2.07**	2.06	2.09	2.11	4.82	0.76
2013	37.16	2.46	**2.00**	2.19	2.08	2.14	4.31	0.82
2014	36.99	2.59	**1.99**	2.30	2.15	2.23	4.48	0.99
2015	34.71	2.56	**1.98**	2.39	2.18	1.99	4.34	0.96
2016	33.42	2.46	**1.89**	2.48	1.69	1.97	3.99	1.06
2017	32.00	2.54	**1.86**	2.46	1.81	2.05	3.74	1.07
2018	32.28	2.58	**1.92**	2.62	1.97	2.06	3.71	1.08
2019	29.77	2.55	**1.95**	2.74	2.16	1.98	3.58	1.27
2020	26.88	2.43	**1.86**	2.68	2.12	1.69	3.72	1.06
# of Facilities*	1446	364	**1268**	336	1225	280	143	15

Notes: # of facilities* are the average numbers of facilities in each industry during 2010 to 2020. Power plants, waste, and petroleum and natural gas are the industries that have the most facilities in the U.S. on average from 2010 to 2020. The waste industry (in bold) has seen a decrease in methane emissions from 2010 to 2017 and an increase in methane emissions afterwards, both in total and on average.

Table A.5: Synthetic Control Results: Estimates at state level

	Estimate (1)	Pr(>|z|) (2)	No. placebos (3)		Estimate (4)	Pr(>|z|) (5)	No. placebos (6)
Alabama	0.100**	0.040	24	Mississippi	-0.009**	0.020	50
California	0.087*	0.052	57	South Dakota	-0.063	0.500	8
Florida	0.043	0.260	49	Wyoming	-0.139	0.231	39
Georgia	0.050	0.211	37	Utah	-0.036	0.444	45
Hawaii	0.047	0.208	47	Maryland	-0.016	0.520	57
Illinois	0.043**	0.047	42	Delaware	-0.095	0.250	8
Kentucky	0.083**	0.024	40	Oklahoma	-0.019	0.439	82
Louisiana	0.020	0.313	31	Connecticut	-0.055	0.333	66
Missouri	0.023	0.571	6	Massachusetts	-0.031	0.489	47
Montana	0.230	0.333	5	Maine	-0.288	0.111	9
North Dakota	0.190*	0.100	5	Nebraska	-0.084	0.258	217
New Hampshire	0.043*	0.067	29	South Carolina	-0.049	0.352	105
Nevada	0.340*	0.100	9	Idaho	-0.216	0.500	2
New York	0.147**	0.011	87	Pennsylvania	-0.032	0.412	151
Ohio	0.060**	0.015	65	Arizona	-0.078	0.288	59
Oregon	0.063	0.211	37	Michigan	-0.031	0.493	73
Texas	0.083*	0.100	19	Colorado	-0.089	0.222	167
Virginia	0.180*	0.919	87	Iowa	-0.118	0.200	110
Washington	0.107*	0.067	15	Indiana	-0.055	0.353	34
West Virginia	0.033	0.214	14	Minnesota	-0.103	0.222	9
Tennessee	-0.072	0.333	33	Wisconsin	-0.164	0.127	110
Kansas	-0.179	0.428	7	New Jersey	-0.104	0.188	202
North Carolina	-0.093	0.463	41				

Notes: Each row (state) is a separate synthetic control and placebo test process. The number of placebos are the number of control state-industry pairs being used in the synthetic control process for each treatment state. P-value is calculated by post/pre-Proposition 99 ratios of the MSPE for treatment waste industry of a state and all its control state-industry pairs. Post- and pre-MSPE is calculated by taking the average of the differences between actual emissions and synthetic emissions over the years after and before China's GS policy. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.6: Synthetic Control Results: Emission increases across states
(million metric tons of CO_2 eq.)

	Avg. Emissions Before GS Policy 2010-2017 (1)	Tot. Emission Increase After GS Policy 2018-2020 (2)		Avg. Emissions Before GS Policy 2010-2017 (3)	Tot. Emission Increase After GS Policy 2018-2020 (4)
Alabama	2.957	0.988	Mississippi	4.634	-0.0380
California	7.823	1.797	South Dakota	0.186	-0.043
Florida	8.028	1.141	Wyoming	0.146	-0.068
Georgia	4.453	0.696	Utah	0.667	-0.071
Hawaii	0.561	0.078	Maryland	1.659	-0.079
Illinois	3.534	0.557	Delaware	0.213	-0.086
Kentucky	1.899	0.485	Oklahoma	1.982	-0.112
Louisiana	2.056	0.164	Connecticut	0.926	-0.148
Missouri	1.381	0.096	Massachusetts	1.599	-0.150
Montana	0.339	0.196	Maine	0.301	-0.204
North Dakota	0.294	0.206	Nebraska	0.913	-0.232
New Hampshire	0.390	0.049	South Carolina	1.579	-0.233
Nevada	0.281	0.428	Idaho	0.349	-0.263
New York	3.132	1.370	Pennsylvania	3.701	-0.331
Ohio	5.057	0.845	Arizona	1.430	-0.372
Oregon	1.035	0.194	Michigan	4.634	-0.390
Texas	10.297	2.702	Colorado	1.382	-0.395
Virginia	3.433	1.996	Iowa	1.148	-0.406
Washington	0.972	0.353	Indiana	0.349	-0.442
West Virginia	0.731	0.067	Minnesota	1.464	-0.493
Tennessee	2.485	-0.492	Wisconsin	1.406	-0.627
Kansas	1.666	-0.638	New Jersey	2.234	-0.679
North Carolina	3.501	-1.021			

Notes: Average emissions before the GS policy is calculated by taking the mean of total emissions of each state over the years 2010-2017. The total increase in emissions after the GS policy is calculated by summing up the emission increase in each year from 2018 to 2020. The larger states, such as California, Texas, and New York, have seen a greater increase in methane emissions from the waste industry after China's GS policy.

Table A.7: CalRecycle: Recycling and Disposal Reporting System (RDRS)
Disposal Flow within California, Summary Statistics (Thousands of Tons)

	Origin Jurisdiction		Destination Facility		Distance
	(1)	(2)	(3)	(4)	(5)
Year	no.jurisdictions	mean shipments sent (1000 tons)	no.facilities	mean shipments received (1000 tons)	mean (km)
2002	434	86.6	162	232.0	93.3
		(214.6)		(476.8)	(121.6)
2003	421	94.4	158	251.6	93.9
		(271.5)		(501.4)	(121.0)
2004	424	96.2	152	268.3	96.1.29
		(269.5)		(522.9)	(122.2)
2005	419	100.3	149	281.9	94.6
		(283.9)		(534.5)	(119.5)
2006	412	99.5	148	276.9	89.8
		(271.9)		(517.2)	(109.1)
2007	414	93.6	142	272.9	92.2
		(261.8)		(507.3)	(110.7)
2008	417	84.2	133	264.0	89.4
		(235.0)		(465.9)	(103.0)
2009	412	74.7	134	229.7	98.7
		(211.2)		(431.2)	(120.4)
2010	417	72.0	131	229.4	101.7
		(201.1)		(414.6)	(123.6)
2011	416	71.5	134	221.9	76.4
		(204.2)		(408.5)	(90.9)
2012	414	70.3	131	222.1	71.6
		(203.9)		(405.2)	(71.5)
2013	412	72.7	133	225.2	85.8
		(214.1)		(405.6)	(101.6)
2014	411	75.1	130	237.5	87.1
		(235.4)		(427.2)	(99.1)
2015	410	80.3	128	257.2	89.2
		(250.8)		(456.1)	(104.9)
2016	420	82.9	126	276.3	90.1
		(257.4)		(473.1)	(102.8)
2017	420	89.2	127	294.9	90.3
		(275.3)		(501.5)	(103.4)
2018	417	94.7	128	308.5	90.3
		(284.8)		(519.3)	(98.8)
2019	418	96.5	127	317.6	87.0
		(288.9)		(532.9)	(90.2)
2020	419	96.2	128	314.8	87.8
		(285.3)		(528.8)	(83.7)
Sample Size	281339				

Notes: Each observation in the sample is a waste shipment from origin jurisdiction to destination facility during 2002-2020. The average distance is calculated by taking the mean of origin-destination pairs in each year.

Table A.8: Summary statistics of community characteristics around each destination facility: mean (st. dev.)

	3 km Buffer	5 km Buffer	10 km Buffer
% White Population	57.12	53.67	52.37
	(27.07)	(25.91)	(24.01)
% Black Population	2.78	3.24	4.07
	(4.98)	(4.83)	(4.93)
% Hispanic Population	32.79	35.19	35.50
	(25.65)	(24.91)	(22.48)
Median Income	63.156	61.137	59.921
($Thousand)	(24.616)	(21.974)	(20.503)
	5 km Buffer		
Economies of Scale	1.96	4.04	6.42
(no. of facilities)	(1.79)	(3.95)	(6.39)
# of destination facilities	264		

Notes: # of facilities are all destination facilities from 2002 to 2020 in CalRecycle RDRS data. Racial composition is from U.S. Census decennial data 2010 at census block level. Median income is from the U.S. Census American Community Survey (ACS) 2013 at census block group level. Economies of scale is calculated using the Waste Business Journal (WBJ) data at facility level. See Appendix, Figure 4, for a detailed definition of economies of scale. I choose longer distance buffers for Economies of scale since there normally is no other facilities within a 3 km buffer of destination landfill facilities.

Table A.9: Altered distributional effects: Gravity-type model for waste flows from origin jurisdiction to receiving facilities and their local communities estimates, before/after China's GS Policy

Dep.Variable: Disposal shipment received (tons)	(1)	(2)	(3)	(4)
Distance (log km)	-0.300***	-0.233***	-0.216***	-0.029
	(0.078)	(0.078)	(0.084)	(0.113)
Distance (log)×1(*post*)	0.070*	0.068	0.061	0.059
	(0.041)	(0.048)	(0.045)	(0.048)
White share (log %)	-0.459***	-0.620***	-0.599***	-1.197***
	(0.184)	(0.027)	(0.183)	(0.163)
White share (log %)×1(*post*)	0.269*	0.267*	0.271*	0.496**
	(0.144)	(0.161)	(0.156)	(0.195)
Black share (log %)	0.152***	0.178***	0.200***	0.340***
	(0.047)	(0.063)	(0.078)	(0.091)
Black share (log %)×1(*post*)	0.069	0.092	0.083*	0.084**
	(0.045)	(0.057)	(0.049)	(0.039)
Hispanic share (log %)	-0.315	-0.203	-0.204	-0.635
	(0.214)	(0.211)	(0.199)	(0.111)
Hispanic share (log %)×1(*post*)	-0.061***	-0.065*	-0.044	-0.072
	(0.022)	(0.028)	(0.032)	(0.085)
Median income (log $)		1.702***	1.806***	1.969***
		(0.279)	(0.352)	(0.351)
Median income (log $)×1(*post*)		-0.097	-0.165**	-0.151***
		(0.062)	(0.069)	(0.048)
Economies of scale			0.121	0.531***
			(0.161)	(0.184)
Economies of scale×1(*post*)			-0.110	-0.354***
			(0.074)	(0.089)
Republican votes (log %)				1.000***
				(0.344)
Republican votes (log %)×1(*post*)				-0.667**
				(0.300)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
Observations	226,128	226,128	226,188	217,212

Notes: Two-way clustered standard errors at the county-year level in all models. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Economies of scale are the numbers of related facilities, such as transfer station, landfills, and recycling centers, that are within 5 km buffers of the destination facilities in CalRecycle RDRS data. Data for Republican votes is from California Statewide Database (SWDB) election data at the precinct level. It is defined as the percentage of the population that voted for the Republican party in the 2016 election year among all voting registrations.