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

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Abstract

In 2017, China announced its Green Sword (GS) policy to ban most recyclable waste imports from overseas. As a result, U.S. recyclable waste exports to China decreased dramatically. Many more U.S. recyclable wastes are now processed domestically, contributing to pollution within the U.S. This paper examines the policy's effects on U.S. domestic methane emissions and spatial patterns of local pollution. After the GS policy, total methane emissions from the waste industry increased by 12%. Heterogeneous increases in state-level emissions are positively related to the amount of pre-policy recyclable waste that each state exported to China. Furthermore, local waste disposal transfer data for California confirms that Black communities tended to receive more waste transfers prior to the GS policy. After China's waste ban, however, relatively more waste pollution relocated to lower-income White communities, narrowing the gap. Among several potential mechanisms for this distributional effect, land costs seem the likeliest explanation.

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

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1 Introduction

In 2017, China enacted its "Green Sword" (GS) policy, which prohibited the import of most plastics and other materials for recycling processors to use, effectively shutting down the world's largest market for recyclable waste. Before the policy, China accounted for 45% of the world's total waste imports since 1992, and 70% when including Hong Kong, which returned to Chinese sovereignty in 1997. Importation of wastes enabled China's factories to access inexpensive materials and support its emerging economy, but these imports resulted in increased land, water, air, and ocean pollution for China (Kellenberg, 2012; Kellenberg, 2015; Higashida and Managi, 2014; Gregson and Crang, 2015; Lee et al., 2020).

After the policy was enacted in early 2017, U.S. scrap exports of plastic to China decreased by 89%, while mixed paper exports fell by 96%.[1] Studies have shown that since the policy's implementation, Chinese cities connected to waste importation and reprocessing have significantly improved their air quality (Li and Takeuchi, 2021; Unfried and Wang, 2022).

China's GS policy has significantly affected the recycling industry in the United States, formerly the leading exporter of recyclable waste to China.[2] After China implemented the waste ban, the U.S. recycling industry attempted to redistribute the excess wastes that China no longer accepts, sending these materials instead to several lower-income countries across Southeast Asia and beyond.[3] However, lacking the necessary infrastructure for handling recyclables correctly, these countries were quickly overwhelmed by the volume of waste and have since enforced their own regulations on waste imports.[4] Thus far, no country has yet completely replaced China as the world's largest market for recyclable waste. Consequently, the United States has had to confront its own waste issues, exposing fundamental flaws in its recycling procedures. The escalating costs of processing recyclable materials have rendered the practice unprofitable, causing an increase in the quantities of plastics and paper waste that end up in landfills and incinerators, polluting the environment.

This paper describes a systematic assessment of the impact of China's waste import ban on the quantity and distribution of methane emissions from the waste industry, particularly landfill facilities, in the United States. 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 observed 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 consisting of regions that are not affected by the GS policy. To solve this problem, I use data from the EPA Greenhouse Gas Reporting Program, which includes emissions from all U.S. industries. The advantage of

[1] Data sourced from USA Trade Online.

[2] In 2016, China imported about 17 billion tons of recyclable waste from the U.S., which made up 72.9% of the total U.S. waste exported. Data sourced from USA Trade Online.

[3] Notable countries include Malaysia, Vietnam, Thailand, Indonesia, Turkey, and Kenya.

[4] "Global Policies on Recyclable Material Imports" on Calrecycle's website provides a list of policy changes related to recyclable waste exports. Available at: `https://calrecycle.ca.gov/markets/nationalsword/globalpolicies/`. 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.

this program is that it contains emissions data not only from the waste industry but also from other industries such as oil and natural gas, minerals, chemicals, power plants, etc. China's waste ban directly affected emissions from the waste industry; however, it did not affect emissions from these other manufacturing industries. I therefore use all other industries except for the waste industry as my control group. I then use the synthetic control method to estimate the effect of China's policy on each state 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 net increase of 2 million metric tons of CO_2 equivalent emissions. After aggregating changes in methane emissions from all states, I find that overall U.S. methane emissions from the waste industry increased by almost 10 million metric tons of CO_2 eq.[5] This increase was about 12% of total U.S. methane emissions from the waste industry using 2016 as a base year. In my heterogeneity analysis, I find that the more waste a state exported before China's waste ban, the greater the impact of the waste ban is 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 in general. If states that have historically exported greater amounts of waste experienced a greater increase in methane emissions after the GS policy, then logically, exporting recyclable waste should have been reducing the emissions of the state before the GS policy. I use 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 waste exports and emissions, I need to account for the fact that U.S. waste exports are endogenous. 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 counted as 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 lower by 0.83 metric tons of CO_2 eq. This result is consistent with the hypothesis that U.S. recyclable waste exports directly reduced domestic emissions from the waste industry before China's waste ban. After China's GS policy, U.S. recyclable waste exports to China decreased by 12 million metric tons. This export reduction coincides with an increase in methane emissions from the waste industry in the U.S. of about 11 million metric tons of CO_2 eq. This number is comparable to what I find using the synthetic control method, which cross-validates my results from the two approaches.

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.[6] Given that wastes tended to 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 commu-

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

[6]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.

nities in California over the past 20 years. I treat China's waste ban as a natural experiment to examine how waste pollution relocated after this exogenous policy shock. I collect the local characteristics of destination communities, such as distance from the origin jurisdictions, racial composition, median income, and economies of scale. 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 and greater economies of scale tended to receive more waste transfers from other jurisdictions. However, after the waste ban, more-distant communities with higher White population shares, lower median income, and fewer economies of scale 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 use a simple theoretical model to examine the mechanisms for why racial disparities related to waste transfers narrowed after China's policy shock. 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 to proxy land costs. I use distance between origin and destination multiplied by the national average oil price to proxy for the costs of 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 hypothesis is that the greater the political disparity is 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 then use a simple OLS model with interactions to investigate which mechanisms appear to have led to an increase in the relocation of waste to lower-income White communities. I find that before the GS policy, destination communities with lower transportation and political costs tended to receive more waste pollution transfers. However, after the exogenous GS policy shock, communities with lower land costs seem to have experienced more significant waste inflows; and the political costs appear to have become less significant. Consequently, rural White communities with lower land costs have been 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 examine quantitatively 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, several researchers have studied the efficiency of recycling programs within the U.S. and other developed countries. These studies have shown that recycling programs in developed countries tend to decrease urban waste generation but have low efficiency and low social welfare (Kinnaman, 2006; Aadland and Caplan, 2006; Bohm et al., 2010; Kinnaman, 2014; Kinnaman et al., 2014).[7] My research shows that as a consequence of China's policy shock, recycling in the U.S. affects domestic environmental quality negatively and unevenly.

My paper is also the first to study the causal relationship between trade in recyclable waste 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 pro-

[7] Low social welfare of recycling arises when the average social costs are not minimized. Social costs include all municipal expenditures and income, costs to recycling households to prepare materials, and the external costs associated with disposal and the external benefits gained from recycling.

cesses 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, tend to impose more costs on "clean" industries than industries with pollution (Shapiro, 2021). Unlike the previous literature on trade and the environment, 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, U.S. recyclable waste exports directly reduced the domestic emissions in the U.S. This result supports the pollution haven hypothesis, which is that developed countries reduce domestic pollution levels by relocating their pollution elsewhere through trade, typically with developing countries.

As a third contribution, this paper uses China's GS policy as a natural experiment and examines the effect of an exogenous policy shock on racial disparities arising from internal domestic 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).[8] My research focuses on how China's GS policy, as an exogenous shock, affects the racial disparity in waste transfers, relative to the pre-existing racial disparities in environment quality 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 a new finding that racial disparities related to waste transfers seem to have narrowed after the exogenous GS policy shock; instead of minority communities, lower-income White communities received relatively more waste pollution after the GS policy. My assessment of potential mechanisms indicates that after China's policy shock, land costs, rather than transportation costs or political costs, are more significant in determining the destinations for increased domestic waste flows.

As a fourth contribution, this paper also broadens discussion of 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 pollution 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 county-level Clean Air Act regulations, decision-makers appear to have strategically sited coal-fired power plants near downwind borders of their counties so that emissions could be exported to neighboring counties by prevailing winds. Most types of pollution displacements being studied, however, are caused by endogenous environmental regulations within the U.S. (Hernandez-Cortes and Meng, 2020; Shapiro and Walker, 2021). My study emphasizes the convenient exogeneity of China's GS policy and therefore its more-discernible caused effects on local pollution relocation in the U.S.

Finally, the results of my research can inform policies on domestic recycling. These policies will need timely modification when international markets are rapidly changing. Currently, sev-

[8] For example, Cameron and McConnaha (2006); Depro et al. (2011); Banzhaf and Walsh (2013) show that 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.

eral recycling bills are proposed by legislators from different states.[9] Due to the different needs and circumstances in different states, these bills sometimes propose competing 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 a significant international policy change, all U.S. states, and even local communities, are affected to varying degrees. Updated national and local recycling strategies in response to China's policy change seem 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.

2 Background and Data

2.1 Background

China's Green Sword Policy. China had become a destination for recycling processes that involved pollution due to its lack of stringent environmental regulations, making it an international pollution haven (Kellenberg, 2012, Kellenberg, 2015). With its accession to the WTO in 2001, China underwent rapid economic development and became one of the largest trading countries, particularly in manufacturing industries (Bransetter and Lardy, 2006; Brandt et al., 2012). Due to low-wage workers and lax environmental regulations, China was able to accept dirty and mixed recyclables, sort them by hand, and use them to produce new products (Kellenberg, 2012, Kellenberg, 2015).[10] The nature of its dominant trade flows also helped: container vessels would cross the Pacific eastbound loaded with Chinese products for North American markets and ferry scrap westbound for the return journey at rock-bottom prices. This made bulky scrap shipments to Chinese ports affordable (Kellenberg, 2012; Kellenberg, 2015; Bransetter and Lardy, 2006; Brandt et al., 2012; Higashida and Managi, 2014; Palma et al., 2011; Olivia, 2014). About half of all westbound trans-Pacific container traffic carried wastes for recycling.[11]

In the United States, the recycling industry has tended to use a "single stream" process, where all waste, including paper, plastics, cans, and bottles, is put into the same bin by households. Post-consumer sorting of recyclables by hand with low wages gave American contractors little incentive to weed out food scraps, plastic bags, and non-recyclable garbage, leading to increased contamination from food and waste and leaving unusable a significant amount of the exported materials. China imported 8.88 million tons of such plastic waste before the ban; Wen et al. (2021) find that 70.6% of this waste was either buried or mismanaged, with dumping in local

[9] 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.

[10] China's ascent as the top producer of synthetic goods and clothing led to an increase in its demand for plastic and paper waste as a raw material source.

[11] "A Chinese ban on rubbish imports is shaking up the global junk trade." The Economist, 2018.

canyons or incorporation of plastic into the soil of nearby fields.[12] Over the years, Chinese recyclers were overwhelmed by contaminated wastes. A lot of waste also came into the country illegally and added to the pollution of land and waterways.

As China's policies concerning environmental quality, regulation, and pollution evolved between 2010 and 2019 (Greenstone et al., 2021), 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 in 2013. 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 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. 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.[14]

China's waste ban was primarily driven by the nation's commitment to address environmental and health concerns, rather than as a response to their trade war with the U.S. While the U.S.-China trade war has included retaliatory tariffs and actions, the waste ban is a separate, long-term decision by the Chinese government to combat pollution, with the explicit goal of eliminating environmentally hazardous solid waste and avoiding public unrest. Given that major waste-exporting nations can no longer rely on exporting significant portions of their waste to China, these countries are being forced to reconsider their waste management practices.[15]

With China no longer accepting its recyclable waste, the U.S. initially turned to other countries to fill the void. Within the first six months of 2018, after China's waste ban, American recyclers exported plastic waste to Thailand, marking a staggering 1,985% increase from the 4,409 tons exported to Thailand during the same period in 2017. Similar trends were observed in other countries such as Malaysia (435% increase), Indonesia (56% increase), Vietnam (200% increase), and South Korea, which saw a significant surge in trash import by June of 2018.[16] However, these countries quickly found themselves overwhelmed and began implementing new policies to restrict waste imports. For instance, Malaysia sent back 60 containers in May 2019 of imported trash to the U.S. and other countries, with more containers scheduled for return as they increased inspections.[17] In 2019, more than 180 countries signed the new Basel Convention to impose strict limits on the exportation of plastic waste from wealthier nations to poorer ones. The United States is one of the few countries that have not ratified the global ban. As a result, the U.S. continues to export plastic scrap to developing countries such as Turkey and Kenya, where regulations on waste imports are still limited. However, the amounts of waste these countries accept is not comparable to the amount that China used to import.

[12] As plastic packaging becomes increasingly complex, with colors, additives, and multilayer mixed compositions, it is ever more difficult to recycle plastic scraps.

[13] The WTO Committee on Technical Barriers to Trade Notification. 2017

[14] Data sourced from USA Trade Online.

[15] "A Chinese ban on rubbish imports is shaking up the global junk trade." The Economist, 2018.

[16] "China's ban on trash imports shifts waste crisis to Southeast Asia." National Geographic, 2018.

[17] "Malaysia to send 3,000 tonnes of plastic waste back to countries of origin." Reuters, 2019.

While the United States has long relied upon its recycling system of "collect, sort, export", the removal of the export phase by China's waste ban has revealed fundamental flaws in the recycling processes in the U.S. Due to high labor costs in the U.S., hiring sufficient human sorters to manage the volume of waste is prohibitively expensive. Although improvements in automation could potentially sort some of the excess waste that is no longer sent to China, progress has been gradual. According to the National Recycling Coalition (NRC), the ban has also exposed issues caused by contaminated recyclables. The adoption of single-stream recycling in the U.S. has led to a reduction in the purity and value of recyclables, as it mixes paper, metal, glass, and plastics. Reprocessing firms in the U.S. require cleaner inputs than their Chinese counterparts, causing them to reject a significant amount of material that Material Recovery Facilities (MRFs) currently produce. With global scrap prices falling, waste-hauling firms have shifted the cost of sorting and baling recyclables onto municipalities. As a result, some cities and states have scaled back or halted curbside recycling programs since there is no market for the paper and plastic in their blue bins. Thus a large amount of recyclable wastes remains in the U.S. and is sent to landfills.

Landfills and methane emissions. According to the U.S. EPA, methane emissions from landfills are the third largest source of human methane pollution, following livestock and the oil and gas industry. The primary source of methane emissions from landfills is the anaerobic decomposition of organic food, wood, and paper scraps. The degradation of plastic in landfills can also emit methane, and the longer it remains, the more methane it emits (Royer et al., 2018). Importantly, China's GS policy affected the most-recycled products and materials in the U.S., particularly "mixed paper and paperboard" and "plastic scraps", which accounted for 85 percent and 14 percent of total recyclable waste exports from the U.S. by weight, respectively. Most of these recyclable paper and plastic products have ended up in landfills after the GS policy, contributing to methane emissions. Additionally, organic food residues on recyclables can also contribute to methane emissions from landfills. Before China's GS policy, recyclable materials were separated to some extent and cleaned by households, resulting in less associated food waste. However, after the GS policy, these potentially recyclable materials have often been merely thrown into the trash without being cleaned, contributing to an increase in landfill methane emissions.

I use methane emissions as my main environmental outcome for several reasons. First, as a greenhouse gas, methane is 85 times more potent than carbon dioxide in trapping heat. Reducing methane emissions could have an immediate effect on curbing climate change because methane stays in the atmosphere for a short time, unlike carbon dioxide. The U.N. assessment indicates that steep reductions in global methane emissions this decade would avoid nearly 0.3 degrees Celsius of additional warming by the 2040s and could help prevent the worst effects of climate change. In addition to the global effect, methane is highly flammable and can represent a local fire hazard. Although it is possible to capture methane emissions from landfills to convert and use them as energy resources (e.g., for electricity, renewable natural gas or direct use), as of 2022, only about 20 percent of all landfill facilities in the U.S. have implemented landfill gas (LFG) energy projects, according to the Landfill Methane Outreach Program (LMOP) National Map. Among those landfill facilities which can capture methane emissions, methane pollution can still leak into the atmosphere during the capture process. The capacity to collect methane at landfills often depends on the number of gas-capture wells used and the efficiency of the collection system.[18]

Secondly, the U.S. EPA regularly tracks methane emissions in the waste industry, and has been

[18] Landfill Gas (LFG) Energy Projects and Municipal Solid Waste (MSW) Landfills. `https://www.epa.gov/lmop/lmop-national-map`

collecting data from facility reports from 2010 up to 2022 through the U.S. EPA Greenhouse Gas Reporting Program (GHGRP). This dataset provides the most comprehensive information on emissions from landfill facilities in the U.S. Although satellite data can provide more precise measurements of methane emissions, the satellite data is available starting only in 2019 or 2020.

Thirdly, methane emissions can serve as an indicator for other types of pollution resulting from the disposal of recyclable waste. In addition to their impact on global climate change, other emissions associated with the disposal of waste can have local effects. While methane and carbon dioxide make up the bulk of landfill gas, the remaining 2% to 10% of gases can include local pollutants like nitrogen, oxygen, ammonia, sulfides, hydrogen, and other gases for which even small amounts can affect the health of the people living nearby. Exposure to elevated levels of ammonia and hydrogen sulfide can lead to health problems such as respiratory problems, eye and nose irritation, headaches, nausea, and breathing difficulties.[19] These pollutants are challenging to track, particularly around landfills, but often co-occur with methane emissions. Thus, I use methane emissions as a proxy for the amount of pollution released into the environment by recyclable wastes.

Methane emissions have increasingly come under regulatory scrutiny in the U.S., particularly within the oil, gas, and waste sectors. In 2021, the Biden administration reversed the Trump-era rollbacks, reinstating and bolstering the 2016 New Source Performance Standards (NSPS) aimed at the oil and gas industry's methane emissions. Furthermore, the administration has tightened regulations on methane emissions from landfills. Under the 2021 provisions of the Clean Air Act, landfills are mandated to implement a gas collection and control system within 30 months of hitting the EPA's pollution threshold. The goal of these regulations is to reduce methane emissions, which contribute significantly to climate change. In light of China's waste import ban, understanding the ban's effects on U.S. methane emissions from the waste sector becomes crucial for informed policy-making.

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.[20] The waste categories impacted by China's GS policy, classified by HS4 code, include: 2620 for metal wastes, 3915 for plastic wastes, 4707 for paper or paperboard wastes, 5202 for cotton wastes, 5505 for fiber wastes, 6310 for textile wastes, 2619 for iron or steel wastes, 5103 for wool wastes, and 5104 for garnetted stock of wool wastes.[21] 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 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

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

[20] 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 detailed than HS4 commodity codes, which have 4 digits.

[21] The waste commodities impacted by China's GS policy, identified more narrowly by HS6 code, include: 262099, 391510, 391520, 391530, 391590, 470790, 520210, 550510, 550520, 631010, 631090, 261900, 510310, 510330, 510320, and 510400.

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.[22] After 2010, the U.S. EPA calculates state-level methane emissions more accurately, by aggregating the annual emissions reported by individual facilities in the waste industry.[23]

To examine the effect of China's waste import ban on pollution emissions from U.S. landfill facilities, I utilize methane emissions data from 2010 to 2020 for individual landfill facilities reported under the *U.S. EPA Greenhouse Gas Reporting Program (GHGRP).* This program requires large greenhouse gas emission sources, fuel and industrial gas suppliers, and CO_2 injection sites in the United States to report their greenhouse gas data annually. The GHGRP includes various industries, such as power plants, petroleum and natural gas systems, minerals, chemicals, pulp and paper, refineries, and, crucially for my analysis, the waste industry (mostly landfills). Approximately 8,000 facilities are required to report their emissions each year. The GHGRP has a high compliance rate for two reasons. First, there is no quantity-based penalty for emissions for facility owners, so facility owners have no financial incentive to under-report their emissions. Second, facility owners who fail to comply with the self-reporting requirement receive warning notices from the U.S. EPA. Thus, facility owners also have incentives to report their emissions promptly to protect their reputations.[24] 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. To investigate the impact of China's GS policy on pollution relocation in California, I analyze data from CalRecycle's *Recycling and Disposal Reporting System (RDRS)* from 2002 to 2021. The RDRS provides facility-level information on disposal flows, including waste flows (in disposal tons), for each origin jurisdiction and destination facility. These data are collected quarterly and cover more than 450 origin jurisdictions and over 250 destination disposal facilities over the time period in question.

Other Data. To capture the characteristics of destination communities, I collect data from various sources. To measure racial composition, I utilize census-block level data from the *U.S. Census*. Median income data are obtained from the *U.S. 5-year ACS* at the census-block-group level. For economies of scale, I rely on data from the *Waste Business Journal*, which includes geographic coordinates for all recycling-related facilities across the United States, such as landfills, composters, recycling centers, and transfer stations. Lastly, I obtain voting data from California's *Statewide Database (SWDB) for elections*, specifically, presidential election data at the precinct level.

In this paper, Table 1 presents a concise overview of all the data sources used. The primary datasets constructed for the 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 GHG emissions from the waste industry and recyclable exports; and (3) quarterly facility-level panel data from 2002 to 2020 for disposal flows, along with community characteristics at the level of census blocks.[25]

[22] The methodology used for 1990–2009 applies (a.) 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 (b.) the national estimates of methane (CH_4) emissions.

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

[24] Appendix A.4 displays the distribution of landfill facilities in the U.S. according to the EPA GHGRP.

[25] Both export and emissions data are at the state level since there is no smaller geographic unit for exports that can be easily matched to emissions. Although export data exist at the departure-port level, it is challenging to

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

3.1 Raw Trends

Export Trends. The trends in exports of recyclable waste from the U.S. to China and the rest of the world are illustrated in Figure 1. Following China's entry into the WTO in 2001, the value of recyclable waste exports to China steadily increased and remained stable from 2013 to 2016. However, with the introduction of China's GS policy in 2017, the value of these exports dropped drastically. On the other hand, the value of exports to the rest of the world was steady from 2002 to 2016 but saw a temporary increase after China's waste ban redirected former recyclable waste inflows to other countries. However, this increase was short-lived due to policy changes in these other developing countries. The trend in the net weight of recyclable waste exports shows a more significant and direct impact of China's GS policy on U.S. exports to China and the rest of the world after 2017. These trends demonstrate that the waste ban has led to a decrease in recyclable waste exports from the U.S. to China and a temporary increase in exports to other countries. However, this increase lasted only a year. Consequently, the difference between the amounts of waste that were exported to China and those exported to other countries indicates that a significant amount of recyclable waste that was previously sent abroad is now being processed or disposed-of domestically in the United States.

The composition of total recyclable waste exports from the U.S. is depicted in Figure 2. Paper/paperboard and plastic scrap are the most-exported waste materials, constituting roughly 76% and 22% of total exports by value, respectively, and 90% and 10% of total exports by weight.[26] Appendix Figure A.3 shows the changes over time in the relative values of plastic scrap exports to China from the U.S. and from six other OECD countries, namely Canada, France, Germany, Japan, the Netherlands, and the United Kingdom. After China's waste ban, the U.S. and the other six OECD countries witnessed a decline of approximately 99% in their plastic scrap exports to China compared to their 2010 trade values. Nonetheless, the U.S. plastic manufacturing industry's GDP has steadily increased. Although U.S. exports of plastic scrap to the rest of the world were stable between 2010 and 2016, they increased temporarily after China's GS policy was implemented but subsequently declined. Similar patterns were observed in the plastic scrap exports of the other six OECD countries to the rest of the world.

Emissions Trends. The changes in total greenhouse gas (GHG) emissions from the U.S. waste industry can be observed in Figure 3, using data from the EPA GHGRP spanning from 2010 to 2020. The trend in total GHG emissions from the waste industry had been decreasing over time until 2017 when China's GS policy was implemented. Following this, the trend in total GHG emissions from the waste industry reversed and began to increase. Although total emissions have increased since 2017, the number of waste industry facilities has gradually decreased over the past few decades, indicating that the average emissions per facility have also increased over time. It should be noted that methane emissions make up more than 80% of the waste industry's total GHG emissions, followed by carbon dioxide and nitrous oxide.[27]

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track whether the waste arriving at each port originates from within the state or other states, making it difficult to establish a correlation between port-level exports and local emissions.

[26] Appendix Table A.1 provides the composition of recyclable waste exports from the U.S. to the rest of the world. From 2002 to 2020, mixed paper/paperboard and plastic scrap accounted for 73% and 13% of the total value of U.S. recyclable waste exports. The next most-exported recyclables, in order, were metal, textile, fibers, cotton, iron/steel, and wool scrap.

[27] Details regarding the composition of greenhouse gas (GHG) emissions by industry in the U.S. can be found in Appendix Table A.2. The waste, metal, and refinery industries primarily emit methane (CH_4) as their main

Data presented in Figure 4 depicts the total greenhouse gas (GHG) emissions from the waste industry as well as several other U.S. manufacturing industries from 2010 to 2020 in EPA GHGRP. The trends show that most industries, including power plants, metals, pulp and paper, and refineries, have experienced decreasing GHG emissions over the years. However, some industries, such as chemicals, minerals, and petroleum and natural gas, have seen an increase in GHG emissions. The trends suggest that there is no discernible change in GHG emissions for industries other than the waste industry during 2017 when China implemented the waste ban.

3.2 State-level Emissions

Synthetic Control Method. I employ the synthetic control method to assess the impact of China's GS policy on methane emissions at the state level in the United States. Given that the waste industries in all U.S. states were influenced to varying degrees by China's GS policy, it would not be appropriate to assume that data from waste industries in other states can serve as an uncontaminated control group for a specific state of interest. Instead, I rely on the exogenous variation in methane emissions from other industries within the US EPA GHGRP. These industries, which include power plants, minerals, chemicals, refineries, and petroleum and natural gas systems, were not directly affected by China's waste ban, making them a more-suitable control group.

However, when identifying the impact of China's waste ban on landfill emissions within each state, simply using other industries within the same state may not provide a suitable control group. This is because the waste industry typically ranks among the top 3 or 4 emitters of methane emissions (among 50 more emitters) in any given state, making it challenging to find a balanced control group for assigning weights (shown in Appendix Figure A.5). Obtaining a weighted average of (synthetic) emissions comparable to actual emissions from the waste industry would require a balanced inclusion of emissions from both higher-emitting and lower-emitting industries. To address this issue, I expand my control pool by including all other industries from all states. This allows me to use more industries from other states that have higher emissions than those from the waste industry in the state of interest.

To ensure that the emissions of these control industries were not correlated with the year 2017, potentially compromising the control group for emissions, I take several measures. Firstly, I plot the average greenhouse gas (GHG) emissions from the waste industry, as well as several other key U.S. manufacturing industries, across all states from 2010 to 2020 using data from the EPA GHGRP, as depicted in Figure 4. These plots clearly demonstrate that the emissions of the control industries did not exhibit any discernible shift around the year 2017. In addition to visual analysis, I also conduct rigorous statistical assessments by performing structural break tests for all industries across all states. These tests are designed to identify any control industries in states that might have experienced a significant change in methane emissions coinciding with China's waste ban. I retain in my control group all industries in any state that did not exhibit a structural break in emissions during 2017.

There is a potential concern that China may have increased its imports of raw materials from the U.S. when it ceased importing recyclable waste. For example, when China stopped importing paper scraps, there was a potential for China to import wood pulp directly from the U.S.

GHG, while the power plants, minerals, chemicals, and petroleum and natural gas industries emit more carbon dioxide (CO_2) than methane. The pulp and paper industry emits approximately equal amounts of methane and carbon dioxide, while nitrogen dioxide (NO_2) emissions are relatively low across all industries, at least in comparison to methane and CO_2 emissions.

paper and pulp industry, which could impact emissions from the U.S. paper and pulp industry and potentially contaminate the control group. Thus, I plot the exports (by weight/kg) for the control industries.[28] Appendix Figure A.6 indicates that there was no noticeable alteration in the exports of these control industries around 2017. I extend my investigation by conducting structural break tests to confirm that raw material exports by the industries within the control group remained unaffected by China's waste ban. This robust analysis provides reassurance that the control industries were indeed stable in this regard.

In my synthetic control approach, I first establish a separate synthetic pre-policy trend that closely resembles the actual pre-policy trend for each state's landfill methane emissions (Abadie et al., 2012). The "model training" process is designed to minimize the prediction error over the period leading up to China's GS policy implementation.

$$\hat{Y_{11t}^N} = \sum_{j=2}^{J} \sum_{s=2}^{48} w_{js} Y_{jst} \tag{1}$$

Where $\hat{Y_{11t}^N}$ 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 $s = 1, ..., 48$ are all of the lower-48 (conterminous) states in the U.S.[29] 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}.[30]

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:

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

I use the same process, separately, for the waste industry in each of the 48 U.S. states and calculate the estimated causal effects of China's GS policy on methane emissions for each state.

Figure 5 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 6 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.

[28] This analysis is based on data from the U.S.A. Trade Online by Standard International Trade Classification (SITC) code of control industries.

[29] Alaska and Hawaii are excluded from this analysis.

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

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 (i.e. industries in the control pool) 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 6 shows my placebo test results for the four example states. The 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 have been affected by the GS policy. The plots in Figure 6 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. Table 2 shows the causal estimates of China's GS policy on state-level methane emissions and the corresponding implied p-value calculated from the placebo tests for each state. Twelve states experienced an increase in methane emissions from their waste industry following China's waste ban. These states include Alabama (10%), California (8.7%), Illinois (4.3%), Kentucky (8.3%), North Dakota (19%), New Hampshire (4.3%), Nevada (34%), New York (14.7%), Ohio (6%), Texas (8.3%), Virginia (18%), and Washington (10.7%). In contrast, Mississippi was the only state to experience a significant decrease in methane emissions following China's waste ban, with emissions dropping by 0.9%. On average, these states collectively saw a methane emission increase of approximately 12.1%. Figure 7 shows the estimated increase in GHG emissions from the waste industry by state due to the GS policy. States such as Nevada, Montana, Virginia, and New York show statistically significant percentage increases in GHG emissions after China's policy. Figure 7 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

Autor et al. (2013) find that regions (community zones) in the U.S. with greater trade exposure to China related to manufacturing industries witnessed more substantial declines in manufacturing employment between 1995 and 2010. Building on these findings, I apply a similar framework to investigate whether the heterogeneous impacts of China's GS policy on state-level emissions are associated with the level of trade exposure to China concerning recyclable waste.

To explore this relationship, I create a plot that illustrates the changes in emissions for each state in relation to their total historical exports of recyclable waste. My objective is to assess whether states with higher trade exposure to China (particularly concerning recyclable wastes) experience a greater increase in emissions following enforcement of the GS policy. Figure 8a shows that the increase in emissions due to the waste ban is positively correlated with historical recyclable waste exports. The greater a state's export of recyclable wastes to China before the GS policy, the greater the increase in methane emissions it experienced after the GS policy.

In addition to trade exposure, I also attempt to link the heterogeneous effects across states to the percentage of its paper waste a state exported. Given that mixed paper/paperboard constitutes over 80% of exported recyclable wastes and these materials are the primary source of methane emissions among all recyclable waste materials in landfills, I explore whether states with a higher percentage of waste paper exports experienced greater methane emissions increases (the total emissions multiplied by the percentage increase) following the GS policy. However, as depicted in Figure 8b, the correlation in this regard appears relatively weak. The effects of the GS policy appear to correlate with the total volume of wastes a state exported rather than the composition of those exports.[31]

Since states with higher trade exposure to China before the GS policy tend to experience greater increases in emissions after the policy's implementation, my next step is to examine the direct causal relationship between waste exports and domestic landfill emissions. I start the analysis with a simple OLS regression in levels as follows:

$$Methane_{it} = \alpha_0 + \alpha t + \beta Export_{it} + \nu_i + \mu_t + e_{it} \tag{3}$$

$Methane_{it}$ 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 define the first differences of emissions and exports:

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

I take the difference between equation (3) and its lagged value, and substitute the differences defined in (4) to yield:

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

Where the differenced equation can be written compactly as:

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

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. The parameter 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. The state fixed effect ν_i drops out for each state i after taking the first difference. I choose the first difference model in equation (6) over the fixed effect model in levels for the following reasons: (1) the first difference model directly estimates the effect of changes in the independent variables on changes in the dependent variable. This can often be more straightforward to interpret, especially when discussing dynamic changes in waste exports and emissions; (2) by differencing the data, time-invariant state-specific effects are removed. This helps to reduce the bias from omitted variables that don't change over time; and (3) in models where the unobserved individual state effect is correlated with waste exports, but the first differences of waste exports are not correlated with the first differences of the errors, the first-difference model provides more consistent estimators. There are still several concerns regarding first difference OLS identification in this context:

[31] Appendix Figure A.7 shows a similar patterns for the correlation of percentage change (not net change) with (a.)*state-level waste exports* and (b.) the *percentage of paper exports*.

1. GHG emissions from most industries are monitored by the U.S. EPA. For the waste industry, however, 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 Act and the Clean Water Act), it can be harder for recyclers to find facilities to process recyclable materials due to emission caps and limited permits. Consequently, emissions from the waste industry may be inversely related to the amount of recyclables being exported to China to avoid the stringent domestic environmental regulations in the U.S.

2. The presence of omitted variables that vary across both locations and time, such as economic development, may simultaneously affect both recyclable exports and domestic emissions. Consequently, there exists a potential concern regarding endogeneity for the variable that quantifies the change in 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 address the first and second threats to identification, 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 (Bartik, 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 total U.S. exports to China of recyclable waste j in the initial year t_0. The product of the initial share term and the current change in total U.S. exports is then summed across all types of recyclable waste j. In other words, the shift-share instrument is a data-regenerating process that shifts the initial export share of each state according 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 are 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.

My third concern is that changes in recyclable waste exports from the U.S. to China may be correlated with U.S. technological improvements and thus the supply of recyclable materials. If such is the case, U.S. recyclable exports may be endogenous to domestic emissions. Naive OLS estimates may understate the true impact on U.S. 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 exports 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 to China (at the commodity level) from the 11 other high-income countries. These 11 countries are OECD countries which have engaged in extensive trade in recyclable wastes with China during the past few decades.[32] This instrument is valid because: (1) the instrument constructed using other OECD countries is highly correlated with U.S. waste exports (relevance); (2) this instrument is related to the U.S. methane emissions only through U.S. waste exports (exclusion restriction); and (3) this instrument does not have a direct effect on U.S. methane emissions (exogeneity).

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

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

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:

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

In the second-stage equation, $\Delta Methane_{it}$ is the annual change in methane emissions from the waste industry in state i. The key coefficient of interest is β, the average annual change in methane emissions across the lower-48 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 2017 through 2019. The calculation is as follows:

$$\Delta \widehat{Methane}_{total} = \sum_{t=2017}^{2019} \beta \left[\sum_{state=i}^{I} \Delta Export_t^i \right] \tag{11}$$

I begin my analysis 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 a one-metric ton change in recyclable waste exports. For this 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 of CO_2 equivalent per year.

To address the concerns about potential reverse causality and/or endogeneity described above, I 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 shows that the estimation bias from reverse causality tends to attenuate toward zero the point estimate of interest. The simple OLS point estimate shows that the greater the amount of waste was exported from the U.S., the less methane pollution was emitted domestically. However, the reverse causality is that the higher domestic emissions were, the greater the amount of waste was likely to be exported due to the stringent environmental regulations in the U.S., such as emission caps. Thus,

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

without accounting for this offsetting reverse causality, the simple OLS specification tends to underestimate the true negative effect of waste exports on domestic emissions. By taking the reverse causality into account, my estimate using the instrument has a greater magnitude compared to the OLS estimation.

However, there is still a possibility that there may have been other contemporaneous nontrivial supply shocks in the recyclable waste industry, aside from 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 using the recyclable waste exports to China from a set of 11 non-U.S. countries. 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. This could be due to U.S. supply-side shocks such as technology improvement; e.g., technology that processes wastes more efficiently could decrease both the exportation of wastes and methane emissions. Thus, without accounting for such supply-side shocks, the effect of waste exports to China on domestic emissions could also be underestimated. This may explain why my estimate using the alternative instrument is larger than the estimate using the basic instrument.

There are still possible additional threats to identification. The supply-side shocks like technology improvement may be correlated across high-income countries. In this event, my IV estimates may be contaminated by correlation between changes in U.S. waste exports and unobserved components of export supply. However, this will tend to bias downwards my estimate of the impact of waste export exposure on domestic methane emissions.

After estimating β—the average effect across all lower-48 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 2017 to 2019.[33] Over this time period, the total weight of U.S. recyclable waste exports to China decreased from nearly 18,000,000 metric tons to 5,500,000 metric tons. Using equation (6), total methane emissions from the U.S. waste industry increased by approximately 11-13 million metric tons of CO2 equivalents. To put this into perspective, this increase represents roughly 12.68% of the total annual methane emissions from the U.S. waste industry in the base year of 2016. Additionally, this change represents about 6.79% of total annual methane emissions from the U.S. petroleum and natural gas system in 2016, and about 1.7% of the annual methane emissions from all industries (including ruminant enteric fermentation, in 2016.)[34]

4 Determinants of Pollution Relocation: Evidence from California

My state-level analysis, above, is a first step towards understanding the causal effect of China's waste ban on aggregate methane-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

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

[34] The calculation relies on data from the U.S. EPA 1990-2020 National-level Greenhouse Gas Inventory Fast Facts. The estimated increase (12.68%) aligns closely with the average methane increase (12.11%) calculated in the previous section using the state-level synthetic control method. This consistency in results serves as cross-validation for my alternative methods.

following China's GS policy.[35] To gain a more-detailed understanding of the local distributional effects of China's 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). After identifying some distributional effects, I propose some potential mechanisms to explain these effects.[36]

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 a map of California. Appendix Figure A.9 shows that most facilities in the CalRecycle data are located around urban areas (highlighted in yellow) in California, and fewer facilities are located in 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 (e.g., Los Angleles) and a destination facility (e.g., Covanta Stanislaus, Inc.) and show general patterns of pollution relocation in the state of California for these locations. Figure 9 highlights four things: (1) the variety of destinations for waste pollution shipped outside the source city; (2) the variety of 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 9 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 waste- receiving facilities are located, I then plot an analogous spatial map based on the racial composition and general election vote shares for California.[37] Figure 10 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 closer and darker-shaded areas where larger shares of minority populations reside. Appendix Figure A.10 shows that pollution relocation has also increased waste shipments to more-remote Republican-leaning districts. Appendix Figure A.11 and Appendix Figure A.12 shows the changes in disposal flows based on median income and pollution vulnerabilities for destination communities in Califorinia after China's waste ban.[38] 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 election vote shares of the communities. Appendix Figure A.13 and Figure A.14 show 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

[35] Using U.S. EPA GHGRP data

[36] 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.8 in Appendix.

[37] I use census-tract data for the racial composition map and precinct-level data for the general election vote share map.

[38] Pollution vulnerability is reported by the Office of Environmental Health Hazard Assessment (OEHHA) CalEnvironScreen4.0. CalEnviroScreen is a screening methodology that can be used to help identify California communities that are disproportionately burdened by multiple sources of pollution.

in waste pollution relocation?[39] Appendix Table A.6 shows summary statistics for the characteristics of higher-resolution communities where facilities are located. I use higher-resolution data at the census-block 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 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 waste disposal inflows. These characteristics include distance between origin jurisdiction and destination facility, racial composition (shares of White, Black, and Hispanic populations), median income, and economies of scale. I define economies of scale for a community by counting the number of other related facilities/industries that lie within a 15 km buffer around each destination facility.[40] Figure 11 shows a negative correlation between waste flows and the distance from the origin jurisdiction to the destination facility. Essentially, the farther away a destination facility is located, the fewer waste materials flow into it. Additionally, disposal flow are negatively correlated with the percentage of White residents in the destination community. In contrast, the population percentage of Black residents in the destination community is positively correlated with waste pollution inflows.

Moreover, I notice a positive correlation between the median income of the destination community and the waste inflows. Communities with higher median incomes tend to receive more waste materials. This correlation might seem counter-intuitive, but it could be explained by the fact that the destination communities included in this analysis all have waste facilities. When comparing communities with waste facilities, a higher median income may indicate greater job opportunities and economic activities, including the operation of waste facilities.

Furthermore, my economies-of-scale measure for destination communities is negatively correlated with waste inflows. In other words, when there are fewer similar facilities around a destination facility, more waste materials flow into this facility. This correlation indicates that economies of scale do not necessarily result in higher waste receipts for a specific facility, but this does not preclude greater total waste inflows for a community hosting multiple waste facilities.

Fixed-effects model. To investigate the distributional effects of China's policy on waste inflows for local communities (at the census-block level), I apply a fixed-effects model that includes the characteristics of each destination community (distance, racial composition, median income, and economies of scale in the waste industry). 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 destina-

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

[40] My economies-of-scale measure is defined specifically by the number of waste facilities that are within a 15 km buffer of the destination landfill facility. Waste facilities can be composting facilities (CO), other landfills (LF), recycling centers (MR and MW), and/or transfer stations (TS). See more details in Appendix Figure A.18

tion community j in year-quarter t.[41] $Dist_{ij}$ is the distance between origin jurisdiction i and destination community j. The variable measure the R_j is the racial composition of destination community j. The indicator variable $1(post)$ takes a value of 1 for the year of the waste ban and beyond. The variables X_{jt} are a set of socioeconomic factors such as median income and economies of scale in the waste industry for destination j. 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, yielding the terms in square brackets in equation (12). In Appendix Table A.7, I present estimation results for equation (12) that are adjusted for different types of fixed effects, including origin-county fixed effects (ζ_o), destination-county fixed effects (θ_d), origin-destination-pair fixed effects (μ_{od}), year-quarter fixed effects (η_t), and an error term (ϵ_t).

Figure 12 shows my estimates of the distributional effect caused by China's GS policy. Before China's waste ban, the estimates show that the greater the proportion of Black residents in the destination community, the more waste pollution the community receives from other places. Conversely, 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 of the destination communities confirm that the well-documented racial disparities for pollution exposure in general also exist with regard to waste pollution relocation patterns. The median income and the economies-of-scale measure for destination communities are both positively correlated with the amount of waste the destination communities receive.[42]

I then use the interaction terms in the model to compare pollution relocation patterns before and after China's GS policy. Figure 13 shows my estimates of the altered distributional effects—β_4, β_5, and β_6 parameters in equation (12). The positive coefficient on the Black share of the population after China's waste ban shows Black communities do receive more waste pollution from elsewhere after the GS policy. However, the coefficient on the White share of the population increases relatively more after the GS policy. This shows that White communities are more negatively affected by the GS policy—i.e., communities with a higher population percentage of White residents have seen a greater average increase in their incoming shipments of wastes. Additionally, communities that have fewer economies of scale and lower median incomes have received relatively 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 an 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:

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

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

[42]Compared 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. Appendix Table A.6 presents 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 to ensure the model's robustness.

$TranspWaste_{ijt}$ 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. $Cost_{ijt}$ includes both the monetary costs and the 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 section 4.2 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 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 (1) lower land costs; (2) lower transportation costs; or (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 total amount of waste an origin jurisdiction generates ($TotalWaste_i$) increases at a relatively steady rate. The excess amount of wastes that needs to be transported to other local communities from the origin jurisdiction is a result of China's GS policy shock.

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

Three metrics. First, land costs tend to be lower in places where population densities are lower (Glaeser and Gyourko, 2003; Glaeser et al., 2005; Turner et al., 2014). 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.

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

Waste pollution tends to be directed to nearby locations to minimize transportation expenses. To approximate transportation costs, I employ the product of the distance (measured in kilometers) between the origin and destination and the national average oil price (in cost per kilometer). It is important to note that the distance per waste transfer varies depending on the origin, destination, while the national average oil price varies only by quarter.

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

Third, motivated by Figure 9 and Appendix Figure A.14, where waste facilities and thus waste shipments are more likely to be associated with Republican leaning communities in California, I propose that the waste shipments to some communities (in this case, voting precincts) might be affected by political cost. I define political cost as the deviation of the destination community's Republican vote share from that of its county. For example, if the community's vote share is very different from the vote share of its county, then waste shipment to this community have a lower political cost.[43] Vote share here denotes the ratio of Republican voters amongst all registered voters. The hypothesis is that a very Republican community in an overall Democratic county can have a high vote deviation 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 voting decisions. 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. The equation for measuring political costs is as follows:

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

$Votes_{jt}$ is the Republican vote share of a community j where destination facility is located at time t. At a more-aggregated level, $Votes_{ct}$ is the Republican vote share of county c to which destination community j belongs at time t. The absolute 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 between the community and its county in terms of these vote shares, the lower the political cost for waste inflows to that community. Appendix Figure A.15 shows the spatial distribution of political deviation across communities (i.e., voting precincts) in California. The lighter the color, the more the destination community deviates from its county in political ideology.

I estimate an ad hoc regression specification to examine which of these potential mechanisms seems best to account 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:

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

The C_{ij} variables are the three cost metrics: land cost, transportation cost, and political cost—approximated by population density, distance between origin and destination, and the discrepancy (absolute difference) in Republican vote shares between the community and its county. Population density is from the 2010 census 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 after China's GS policy.

Results. Table 4 shows that before China's waste ban, i.e., when $1(post) = 0$, 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-away destinations with lower land costs but higher political costs. Furthermore, the effect of land costs on these 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.

[43] The voting data are drawn from the Statewide Data Base (SWDB). The SWDB collects the Statement of Vote and the Statement of Registration along with various geography files from each of the 58 California counties for every statewide election. The Statement of Vote is a precinct-level dataset and precincts in California can change between elections.

5 Conclusion

This paper examines the effects of China's Green Sword Policy (a waste import ban) on environmental outcomes in the U.S. The waste ban, designed to reduce China's recyclable 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. This paper is the first empirical analysis of the impact of China's GS policy on the U.S. I use methane emissions as a proxy for general pollution from wastes, and find 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. China is no longer serving as a pollution haven for U.S. waste materials.

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 associated with waste shipments 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 appear to have dominated political costs in determining where wastes are sent. This result reveals how the exogenous GS policy shock affected mechanisms of waste pollution relocation across 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 specifically 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 a narrowing in the racial disparity for waste-transfer destinations; other unobserved factors such as local policies or ideological changes concerning environmental equity might simultaneously have begun to have an effect on California's waste transfers around 2017.

Other questions for further study include what types 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 of these countries reacted to the GS policy and adjusted their domestic regulations to control their inflows of waste imports, while others did not implement a prompt change in policy to control their inflow of wastes. Another point of investigation would be waste transfers across states: my analysis finds that among twelve states that have experienced statistically significant increases, some are states with smaller populations or economies such as Alabama, Kentucky, Nevada, New Hampshire, and North Dakota. 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 also the possibility of spillover effects from China's GS policy, i.e., larger states might have transferred their excessive amounts of recyclable wastes to neighboring states for processing and disposal. Finally, due to data limitations, my study has focused exclusively on California to examine the effects of China's GS policy at the local community level in the U.S. 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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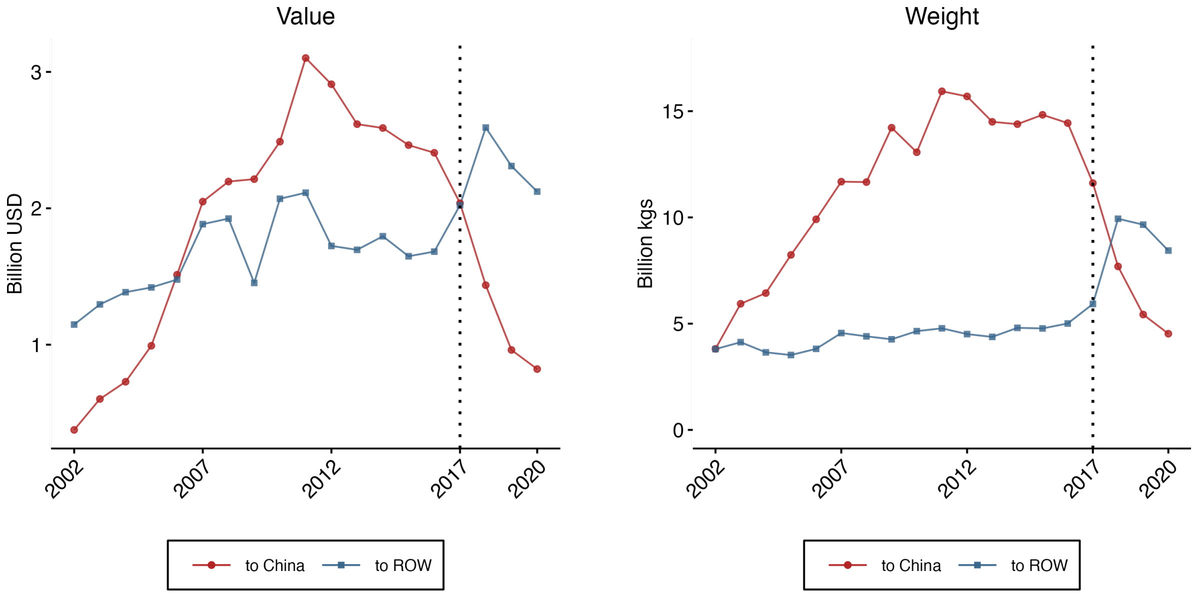
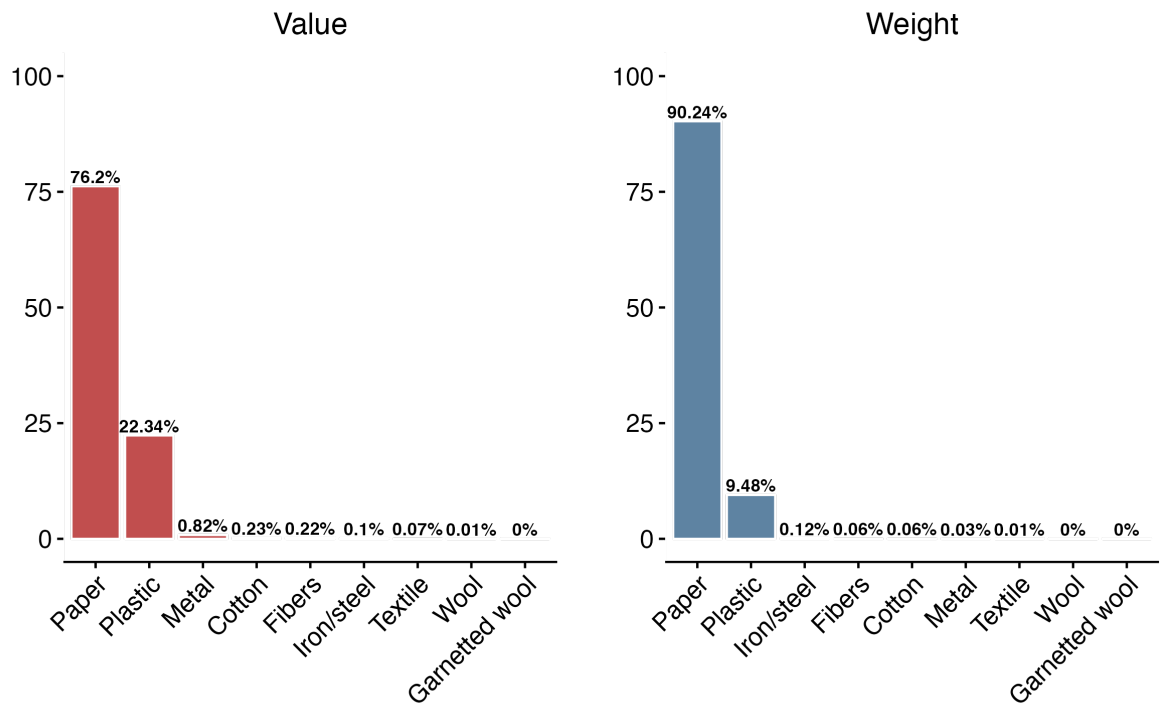
Figure 1: U.S. Recyclable Waste Exports to China and the Rest of the World (ROW)



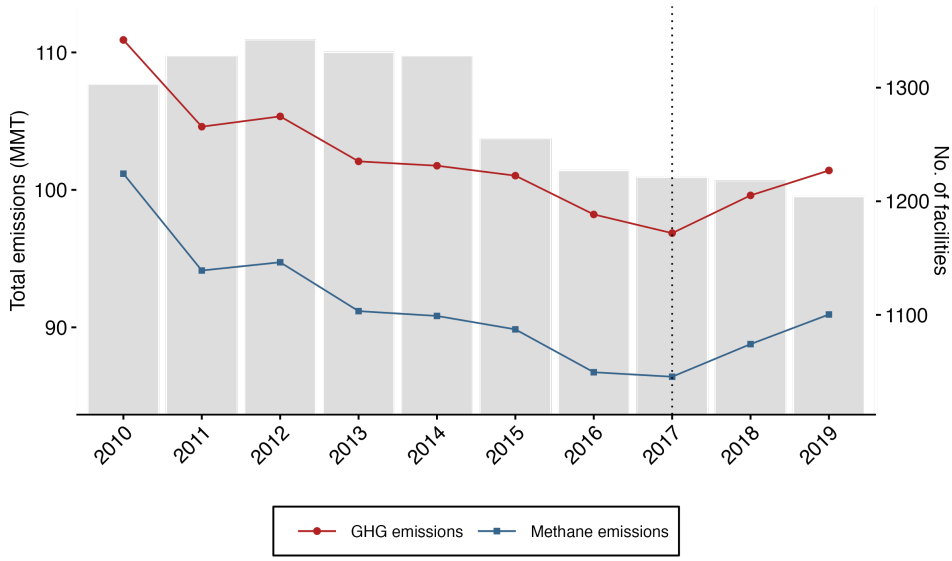
Notes: This figure shows that U.S. recyclable waste exports to China (by value and weight) dropped dramatically after 2017 when China's Green Sword (GS) policy was announced and implemented. Meanwhile, U.S. exports of recyclable wastes to the rest of the world increased temporarily but decreased after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

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



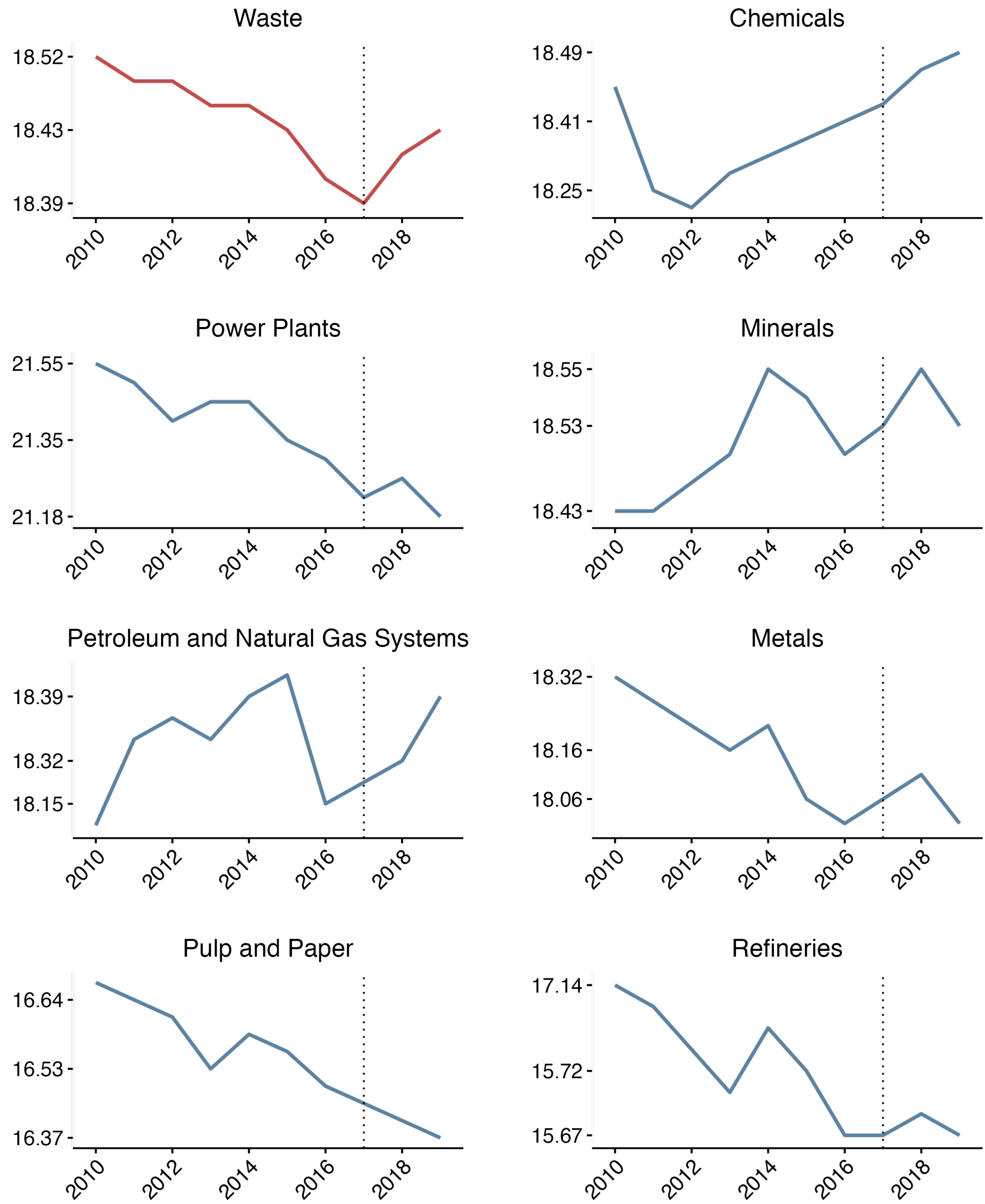
Notes: This figure shows the composition of recyclable wastes that were exported (by value and weight) in the past two decades. The listed waste materials are all wastes that are directly affected by China's GS policy. Paper/paperboard and plastic scraps are the most-exported recyclable wastes, followed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

Figure 3: 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 amounts of CO_2 and N_2O are too small compared to CH_4, meaning 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.

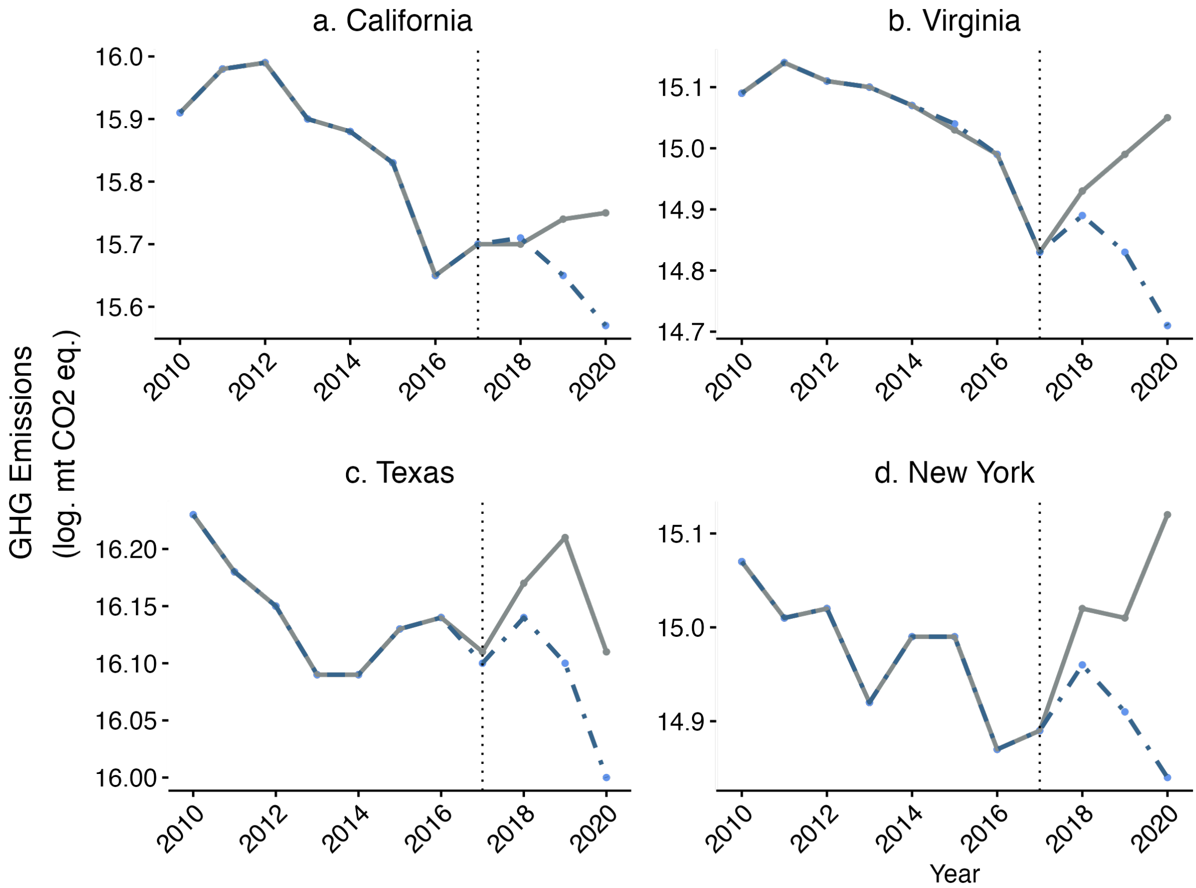
Figure 4: U.S. Greenhouse Gas Emissions (log.MMT) by Industry



Notes: This figure shows the average GHG emissions(log) from the eight main industries across all states in the EPA GHGRP data. Waste, power plants, and petroleum/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 on average. Changes in GHG emissions of other industries are exogenous to China's GS policy.

Figure 5: State-level Synthetic Control Results: Examples

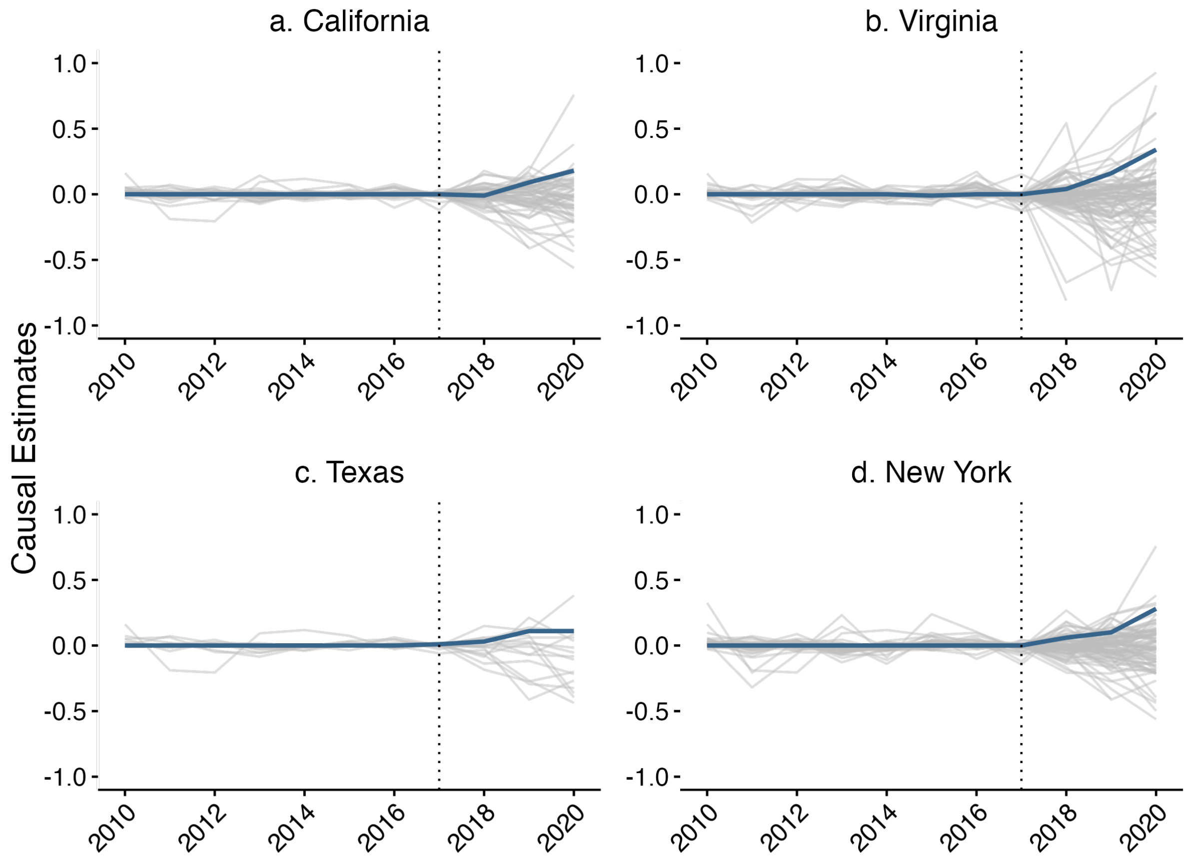
Actual Methame Emissions (solid) vs. Synthetic Methane Emissions (dashed)



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. 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 U.S. domestic methane emissions from the waste industry at the state level. California, Virginia, Texas, and New York have all seen an increase in methane emissions after China's GS policy. Texas' 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.

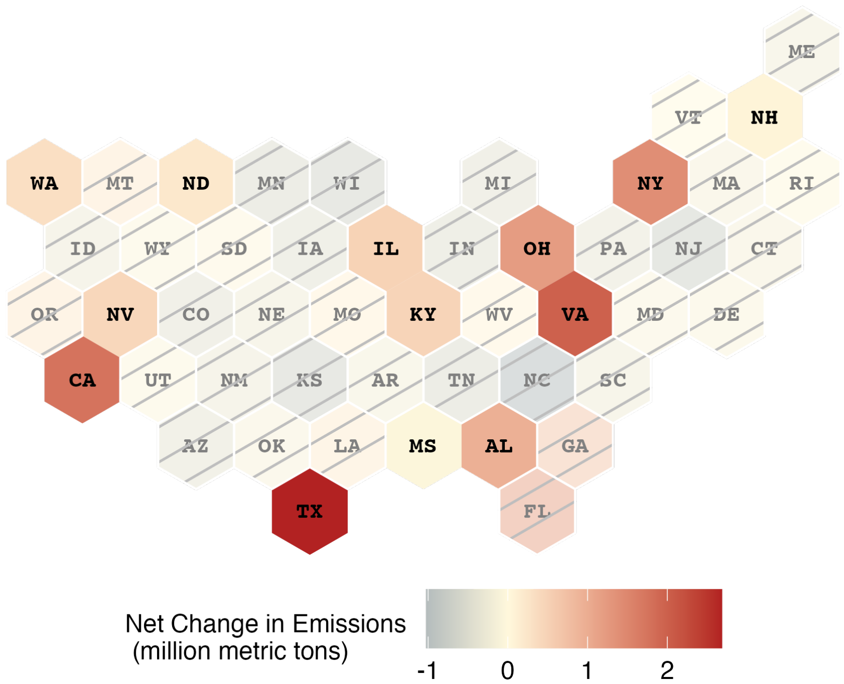
Figure 6: State-level Synthetic Control Results: Placebo Tests

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



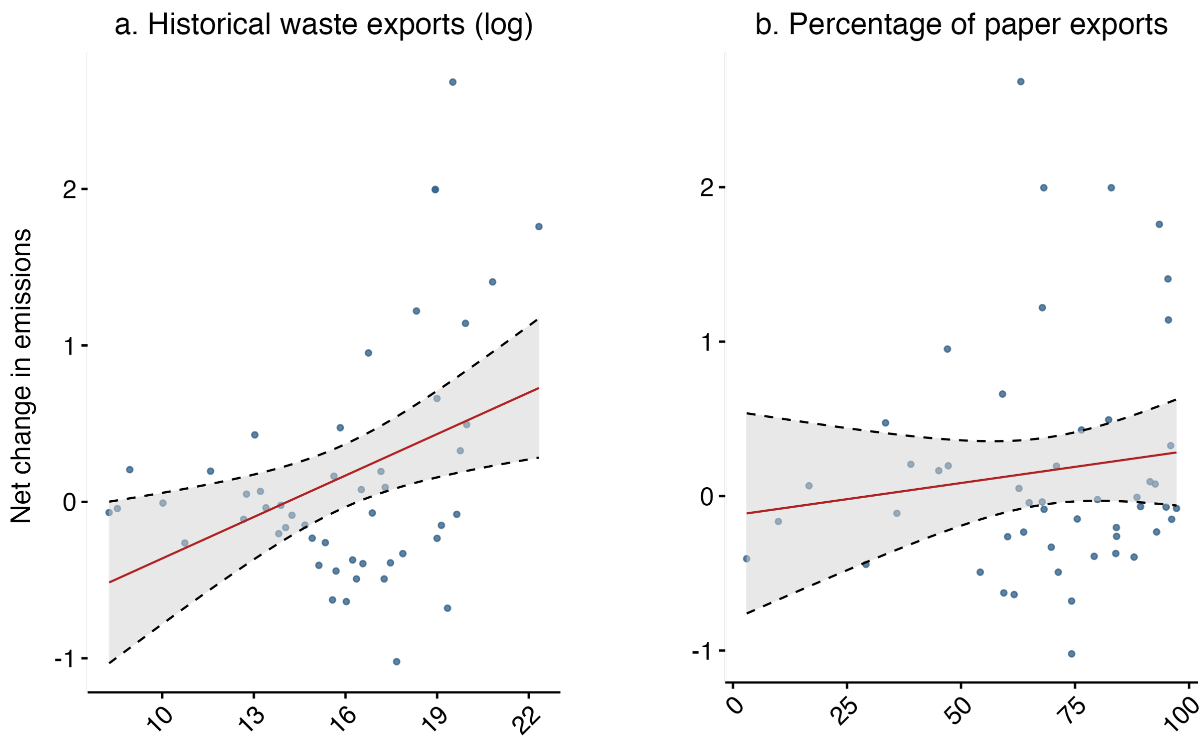
Note: This figure shows the placebo tests of the synthetic control methods for the four states. The blue lines are the causal effects of China's GS policy on the waste industry of each state. The grey lines are the causal effects of China's GS policy on other industries of different states. The p-value 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 7: State-level Synthetic Control Results—Estimates of the Percentage and Net Change in GHG Emissions from the Waste Industry



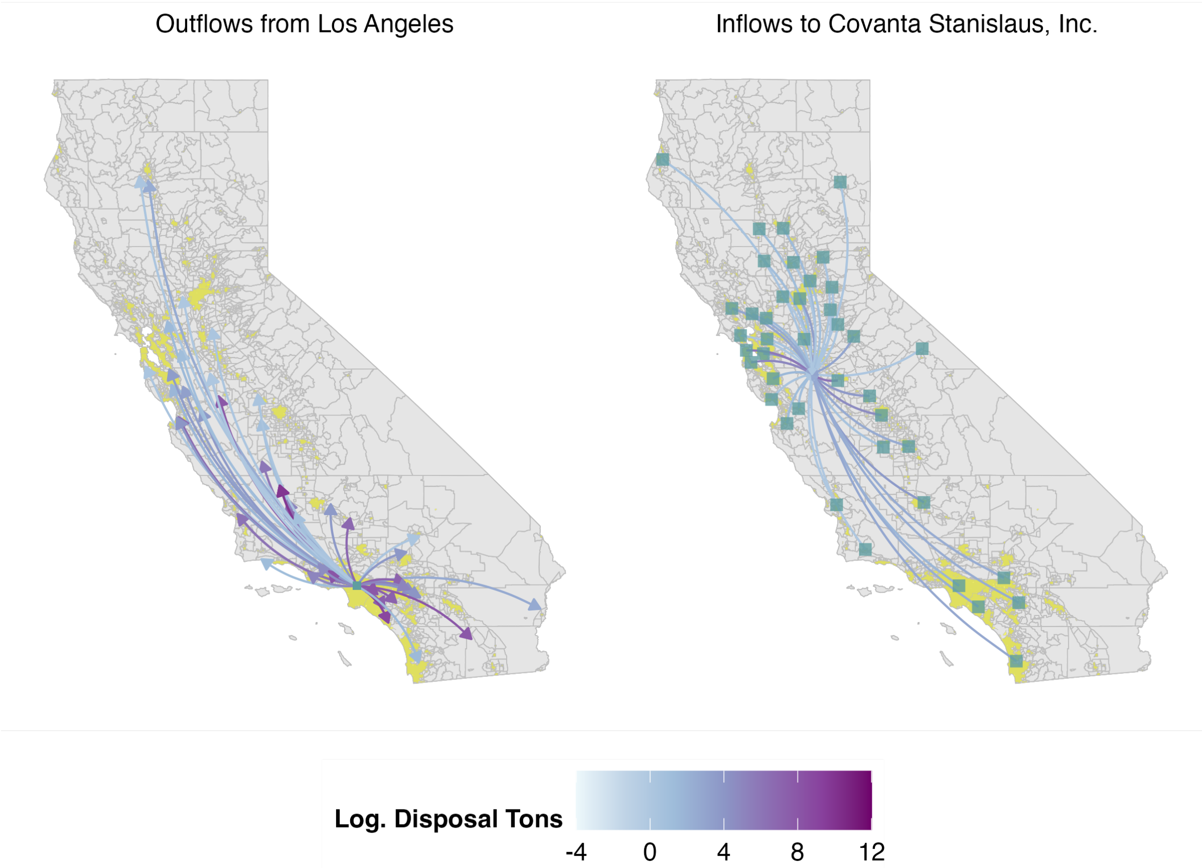
Notes: Colored states represent state-level estimates that can be considered statistically significant at the 10% level. Grey striped states represent state-level estimates that are statistically insignificant. Twelve states have seen a statistically significant increase in methane emissions from landfills following China's GS policy, while only one state, Mississippi, recorded a decrease in methane emissions, albeit of a smaller magnitude.

Figure 8: Pairwise relationships: heterogeneous effects of the GS policy
on state-level emission changes



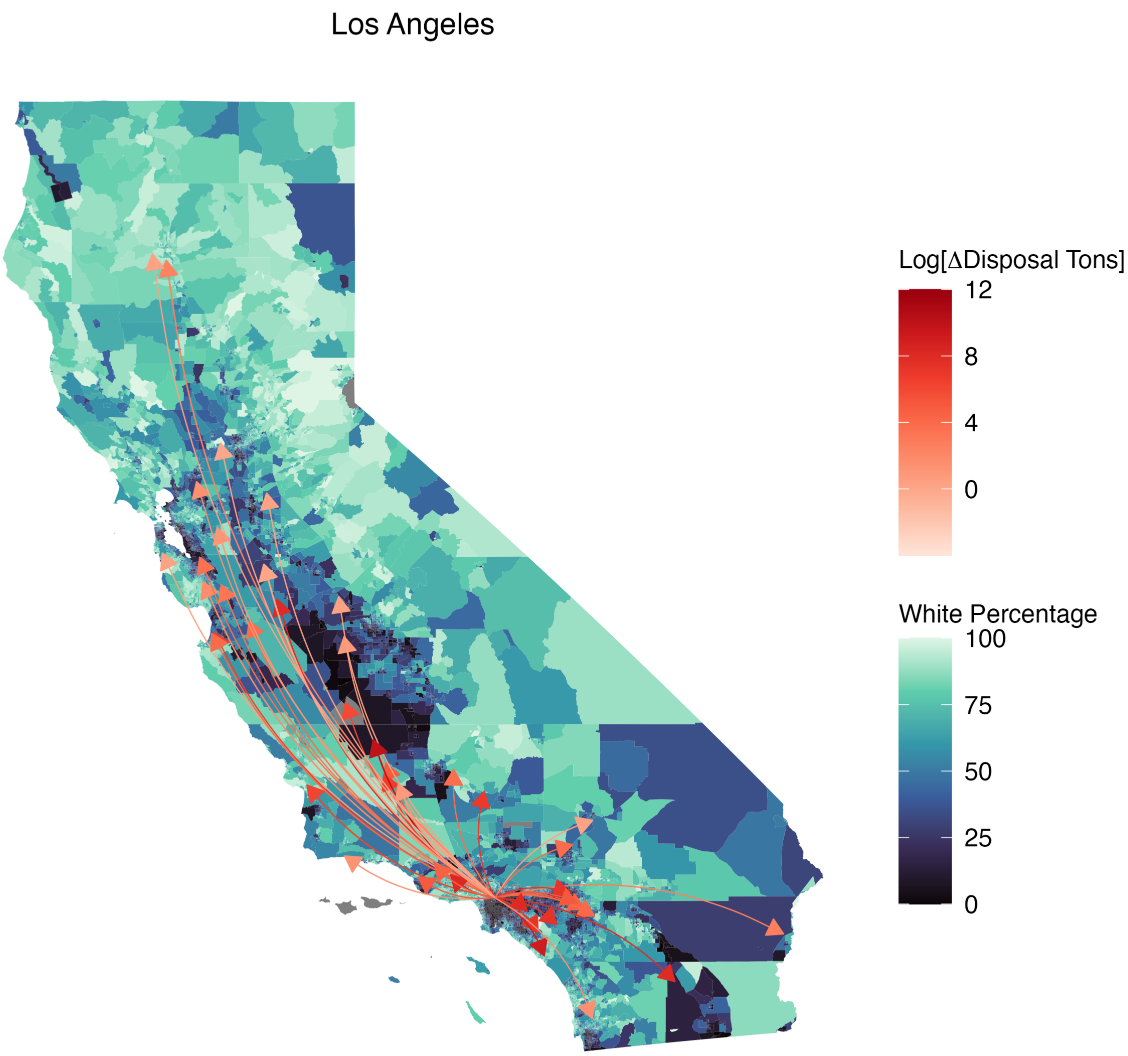
Notes: The methane emission increases for states are calculated by multiplying the methane emissions in 2016 by the percentage increases in emissions estimated by the synthetic control method. The blue dots (observations) are the net methane emission increases by state. The log of total recyclable waste 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 regressions that use (a.) the *log of total recyclable exports* and (b.) the *percentage of paper exports* to explain net emission changes at the state level.

Figure 9: CalRecycle: Example of Net Increase in Disposal Flows
after China's GS Policy



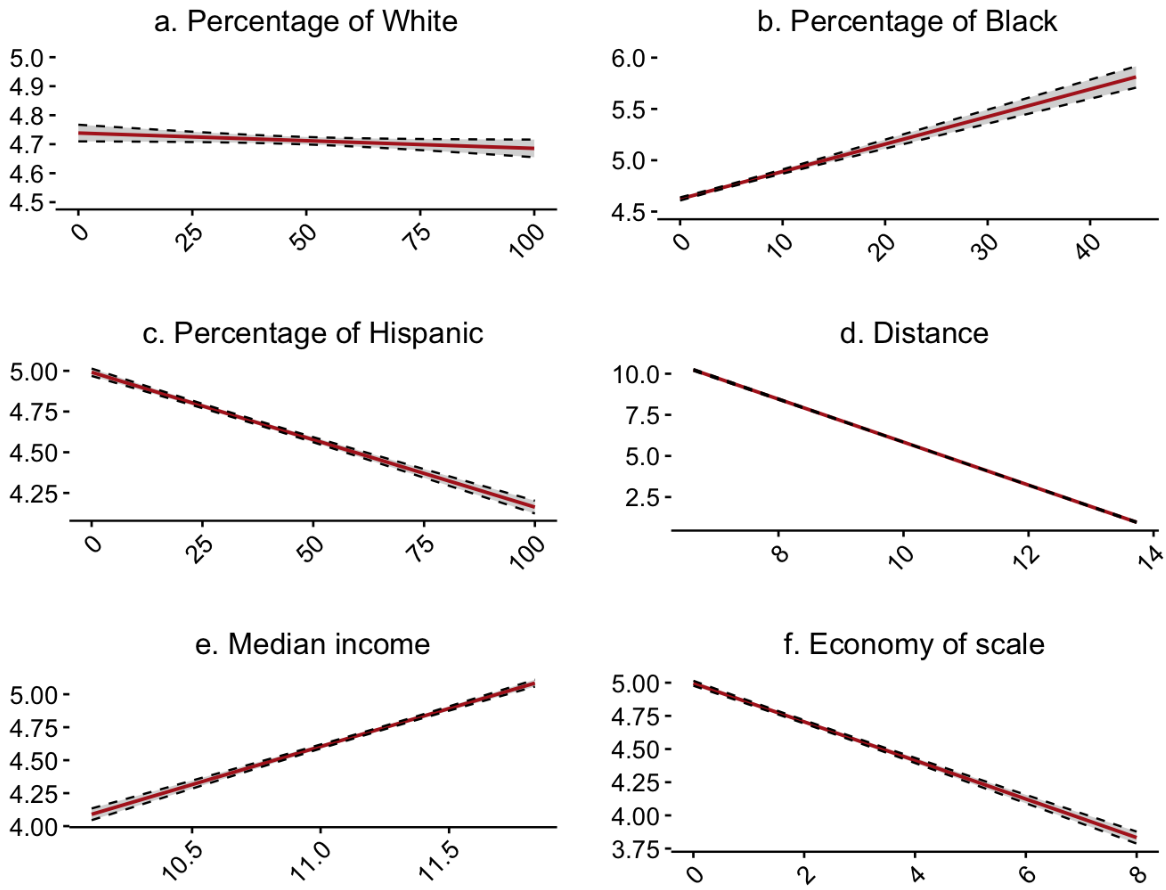
Note: These maps show change in disposal flows from source cities and change in disposal flows to destination facilities with Los Angeles and Covanata Stanislaus, Inc., as examples. They show (1) where the disposal goes from Los Angeles and (2) where disposals originate for Covanta Stanislaus, Inc. The colors of the arrows show 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 10: CalRecycle: Average Net Increase of Disposal Flow by Destination Racial Composition



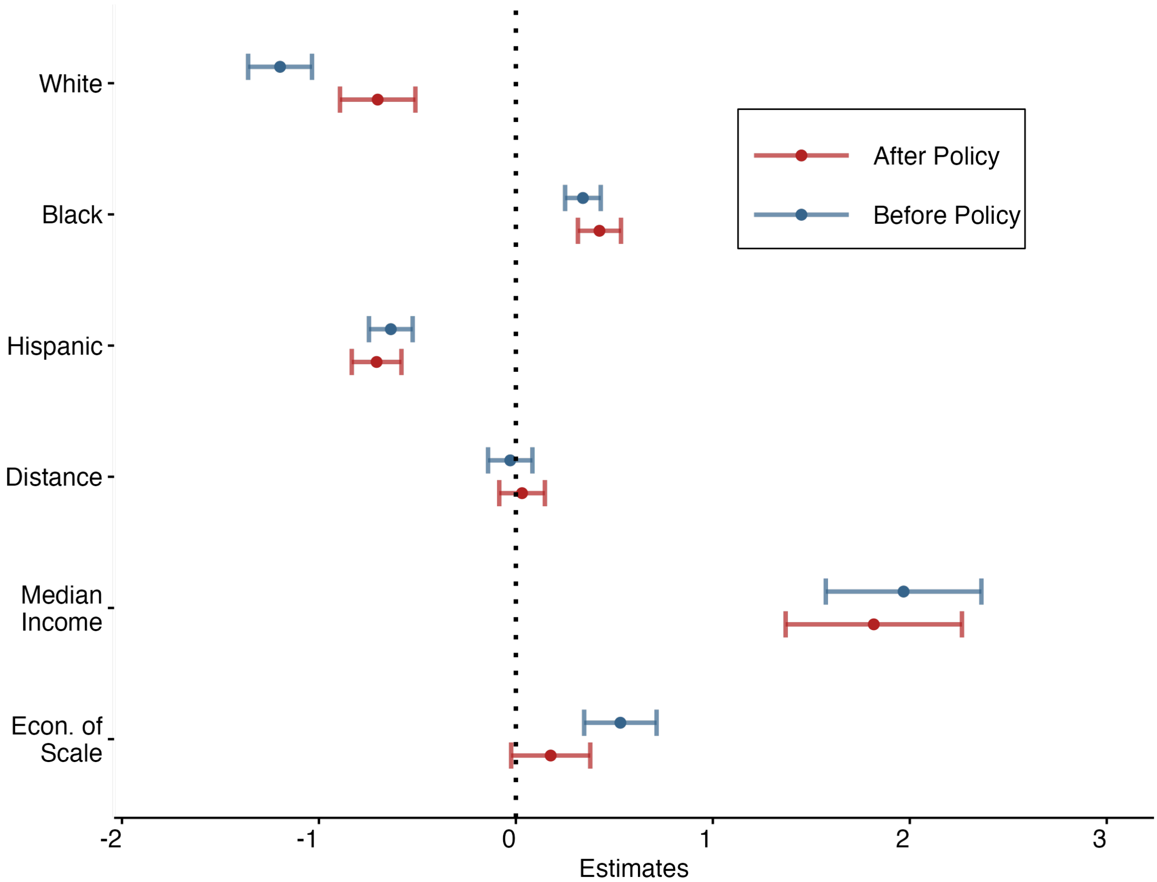
Note: This map shows the net increases in disposal flows after China's GS policy, based on racial composition. The geographic unit for racial composition is the census tract. The colors of the arrows show the increase in amount of disposal flows after China's GS policy.

Figure 11: Simple regressions of Net Disposal Inflows on Destination Community Characteristics



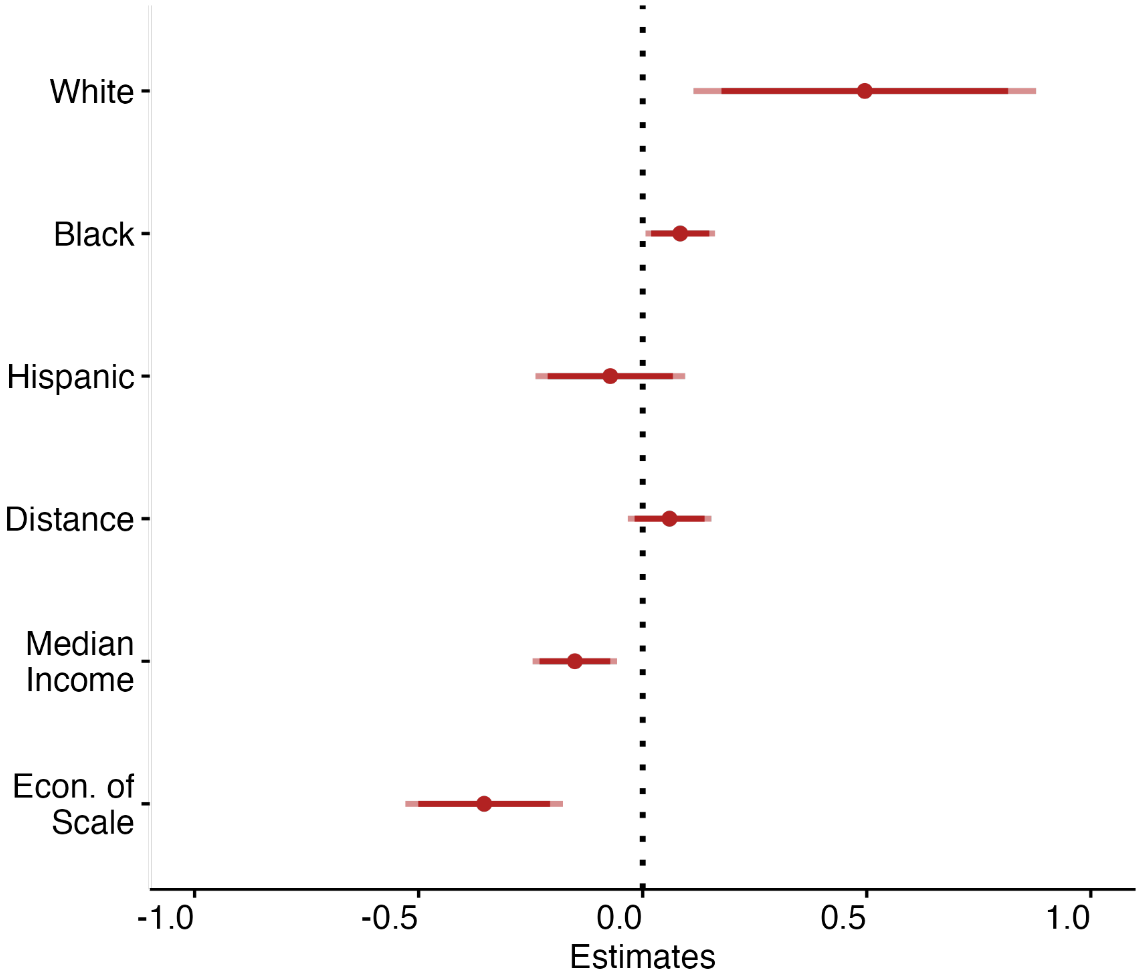
Note: These plots show potential factors determining the community-level waste pollution relocation in California before China's GS policy. The percentage of the White population and Hispanic population, the distance between origin and destination, median income, and the economies of scale of destination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

Figure 12: CalRecycle: Effect of Destination Community Characteristics on Waste Inflows before and after China's GS Policy



Note: This plot shows the results of the fixed-effects model with policy interactions. 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 statistically significant increase in waste inflows than Black communities.

Figure 13: CalRecycle: Estimates of Changes in Waste Inflows
by Destination Community Characteristics before and after China's GS Policy



Note: This plot shows the estimates for coefficients on the policy interaction terms in equation (12) within 90% and 95% CI. Compared to before China's GS policy, communities with a higher population proportion of White residents have seen a greater (significant) increase in waste inflows than communities with a higher population proportions of Black residents.

Table 1: Summary of Data Sources

	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	every 5 years
Waste Business Journal	facility level	1992-2020	yearly
Statewide Database Election Data	precinct level	2000-2020	every 4 years

Notes: This table summarizes all of the data sources 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: Synthetic Control Results: Estimates at the state level

	Estimate (1)	Pr(>|z|) (2)	No. placebos (3)		Estimate (4)	Pr(>|z|) (5)	No. placebos (6)
Alabama	0.100**	0.040	24	Arizona	-0.078	0.288	59
Arkansas	-0.043	0.173	75	California	0.087*	0.052	57
Colorado	-0.089	0.222	167	Connecticut	-0.055	0.333	66
Delaware	-0.095	0.250	8	Florida	0.043	0.260	49
Georgia	0.050	0.211	37	Hawaii	0.047	0.208	47
Idaho	-0.216	0.500	2	Illinois	0.043**	0.047	42
Indiana	-0.055	0.353	34	Iowa	-0.118	0.200	110
Kansas	-0.179	0.428	7	Kentucky	0.083**	0.024	40
Louisiana	0.020	0.313	31	Maine	-0.288	0.111	9
Maryland	-0.016	0.520	57	Massachusetts	-0.031	0.489	47
Michigan	-0.031	0.493	73	Minnesota	-0.103	0.222	9
Mississippi	-0.009**	0.020	50	Missouri	0.023	0.571	6
Montana	0.230	0.333	5	Nebraska	-0.084	0.258	217
Nevada	0.340*	0.100	9	New Hampshire	0.043*	0.067	29
New Jersey	-0.104	0.188	202	New York	0.147**	0.011	87
North Carolina	-0.093	0.463	41	North Dakota	0.190*	0.100	5
Ohio	0.060**	0.015	65	Oklahoma	-0.019	0.439	82
Oregon	0.063	0.211	37	Pennsylvania	-0.032	0.412	151
Rhode Island	-0.363	0.342	38	South Carolina	-0.049	0.352	105
South Dakota	-0.063	0.500	8	Tennessee	-0.072	0.333	33
Texas	0.083*	0.100	19	Utah	-0.036	0.444	45
Virginia	0.180*	0.092	87	Vermont	-0.043	0.333	6
Washington	0.107*	0.067	15	West Virginia	0.033	0.214	14
Wisconsin	-0.164	0.127	110	Wyoming	-0.139	0.231	39

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 selected by the algorithm in the synthetic control model for each treatment state. Each P-value is calculated by post/pre-proposition 99 ratios of the MSPE for the 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 3: Models to Explain Changes in Methane Emissions
as a Function of 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

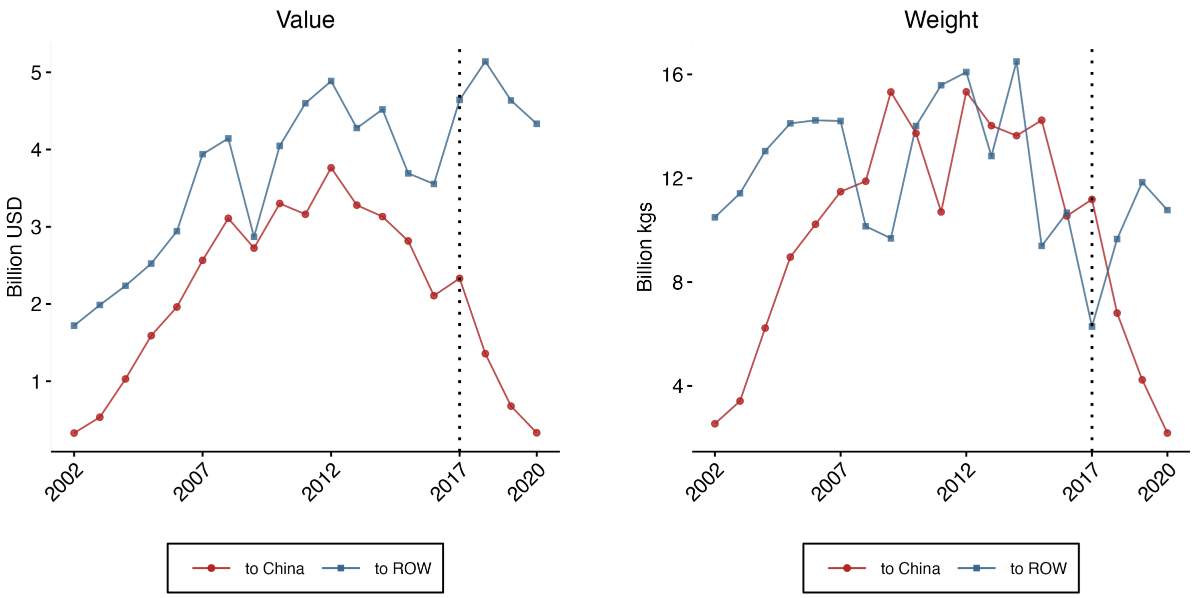
Table 4: Potential Mechanisms: Model Estimates

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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The results are the same when I restrict all models to the same 209,647 observations. Transportation costs are approximated by the distances multiplied by oil price. 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 Republican voters, and the county where it resides has 45 percent Republican voters. The political cost for community A as a destination community for waste shipment is |30-45| = |-5| = 5, which is a low deviation from its county and a "high" political cost. 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.

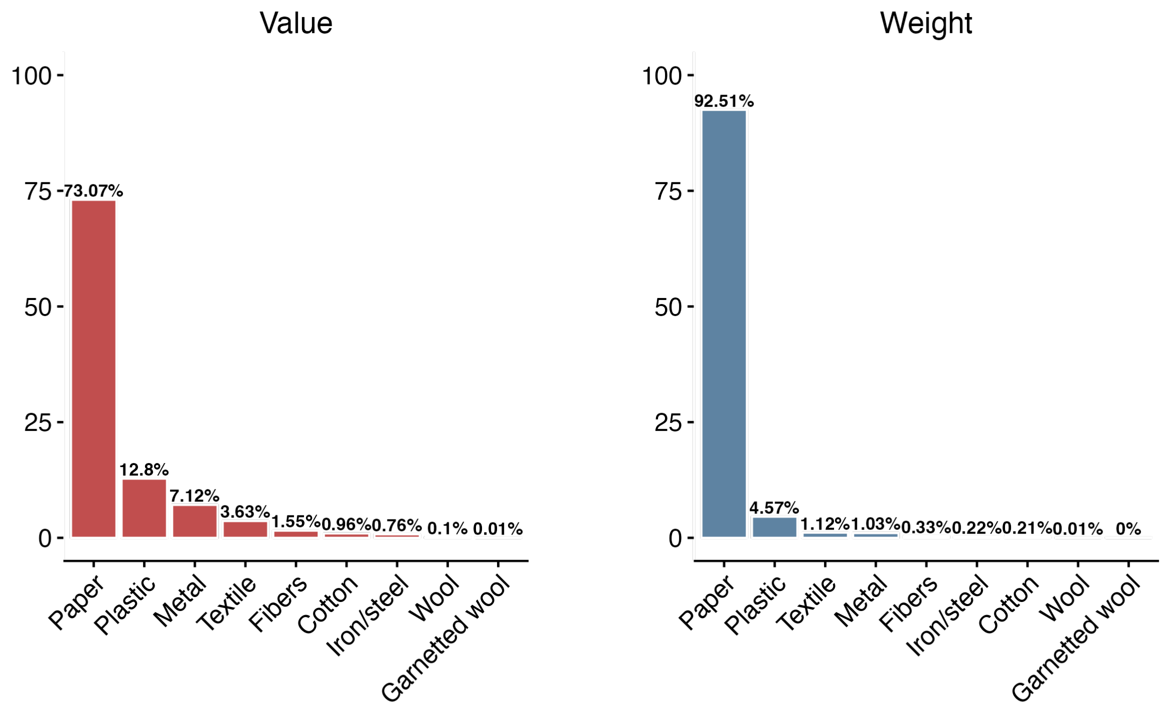
Online Appendix: Figures and Tables

Figure A.1: Recyclable Waste Exports by Other Countries to China and to the Rest of the World (ROW)



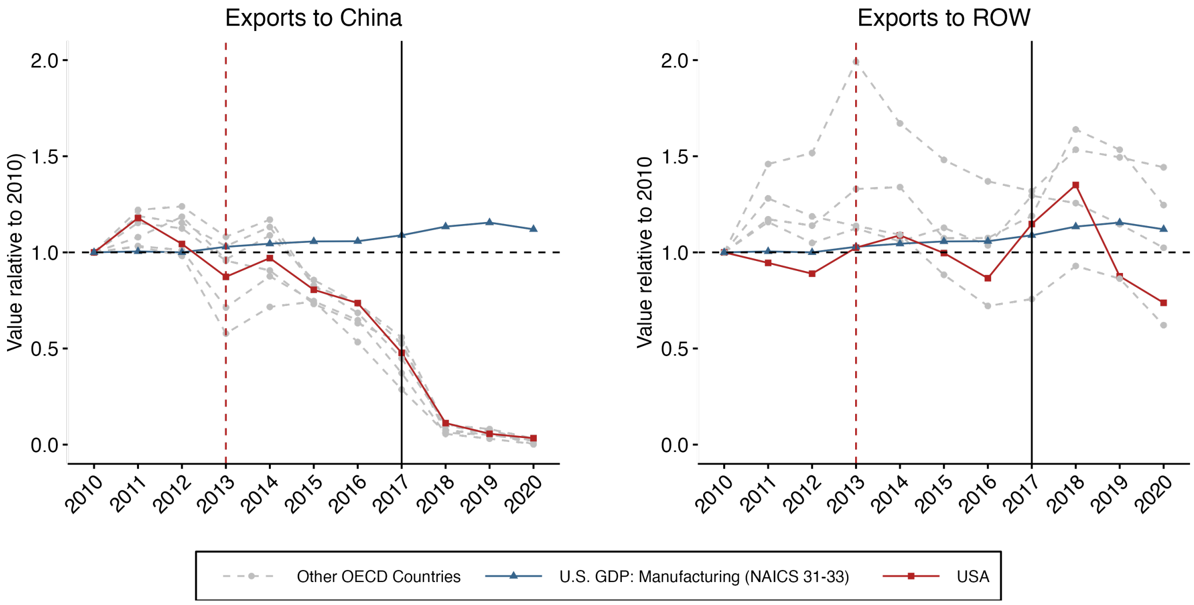
Notes: "Other countries" refers to 11 selected OECD countries—Australia, Austria, Canada, Finland, France, Germany, Japan, New Zealand, Portugal, Spain, and the United Kingdom. They all have regular trade with China in recyclable wastes. Recyclable waste exports from other countries to China decrease 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 these developed countries that used to export their recyclable wastes to China 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



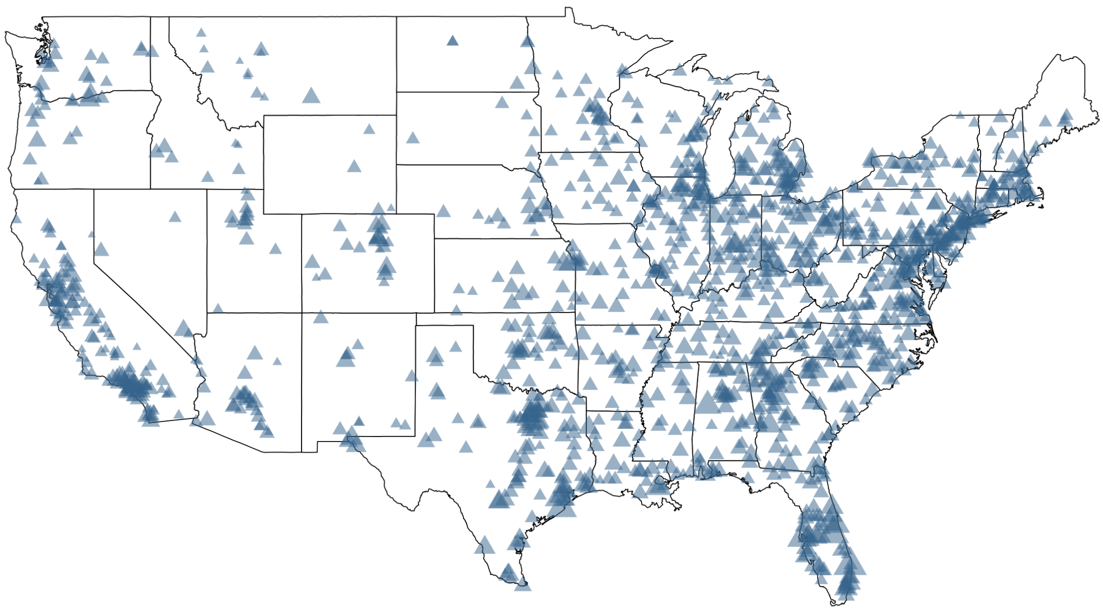
Notes: This plot shows the composition of recyclable waste materials exported from the U.S. to the rest of world. Mixed paper/paperboard is still the material that accounts for the greatest percentage of the total exports by value and weight. Plastic scrap is the second-most-exported recyclable waste.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

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



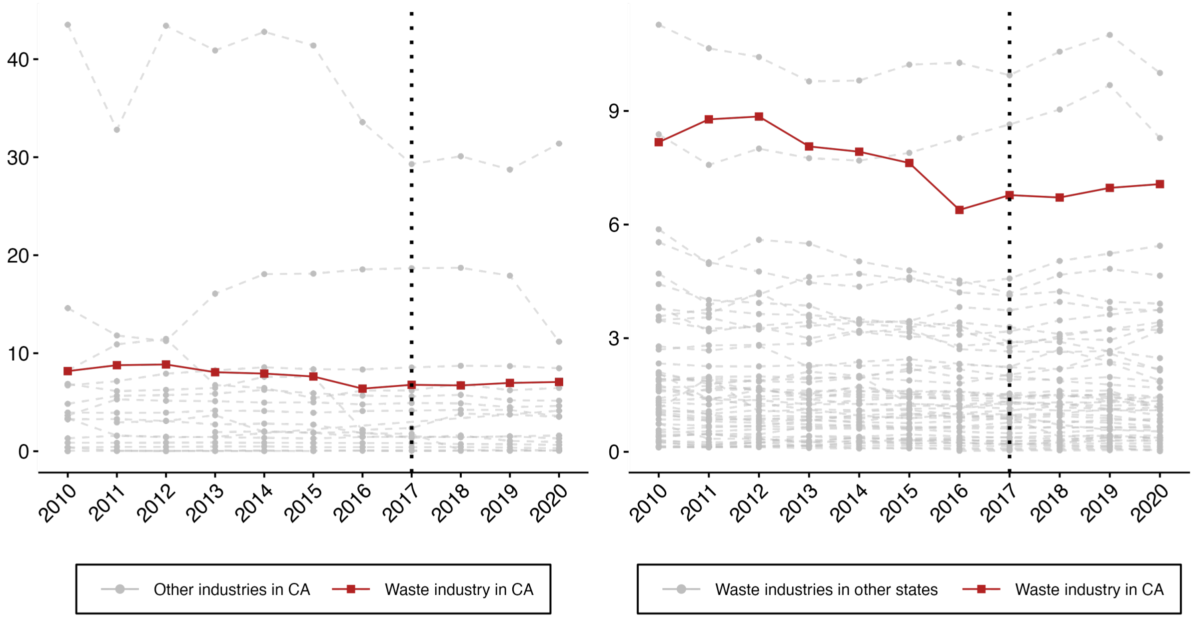
Notes: This figure shows the recyclable waste exports (taking plastic scrap as an example) of the U.S. (red line), as well as 6 other OECD countries (grey lines) to China and to the rest of the world from 2010 to 2020. The first dashed line in 2013 represents when China first implemented its Green Fence (GF) policy. The second solid 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), which 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 for other OECD countries. After China's GS policy, the plastic scrap exports of the U.S. and the other OECD countries increased temporarily to the rest of the world but then decreased.

Figure A.4: GHGRP: Distribution of Waste Facilities



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 greater.

Figure A.5: Synthetic Control: Waste Industries and Other Industries

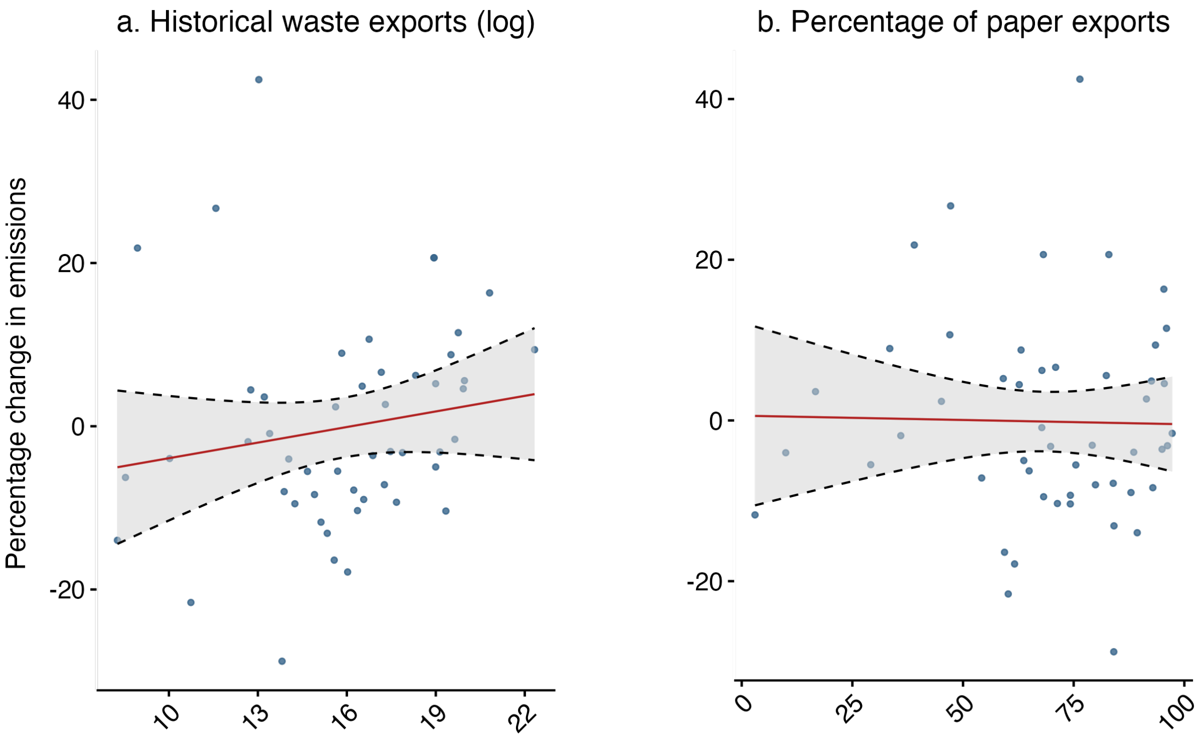


Note: In the left plot, the red line represents methane emissions for California's waste industry; The grey lines represent emissions from non-waste industries in California. In the right plot, the red line represents methane emissions from California's waste industry, and the grey lines represent methane emissions from waste industries in other states. These plots show that neither the "waste industries from other states" nor "other industries within the same state" are by themselves the most suitable control group for the synthetic control.

Figure A.6: Synthetic Control: Exports of Other Control Industries

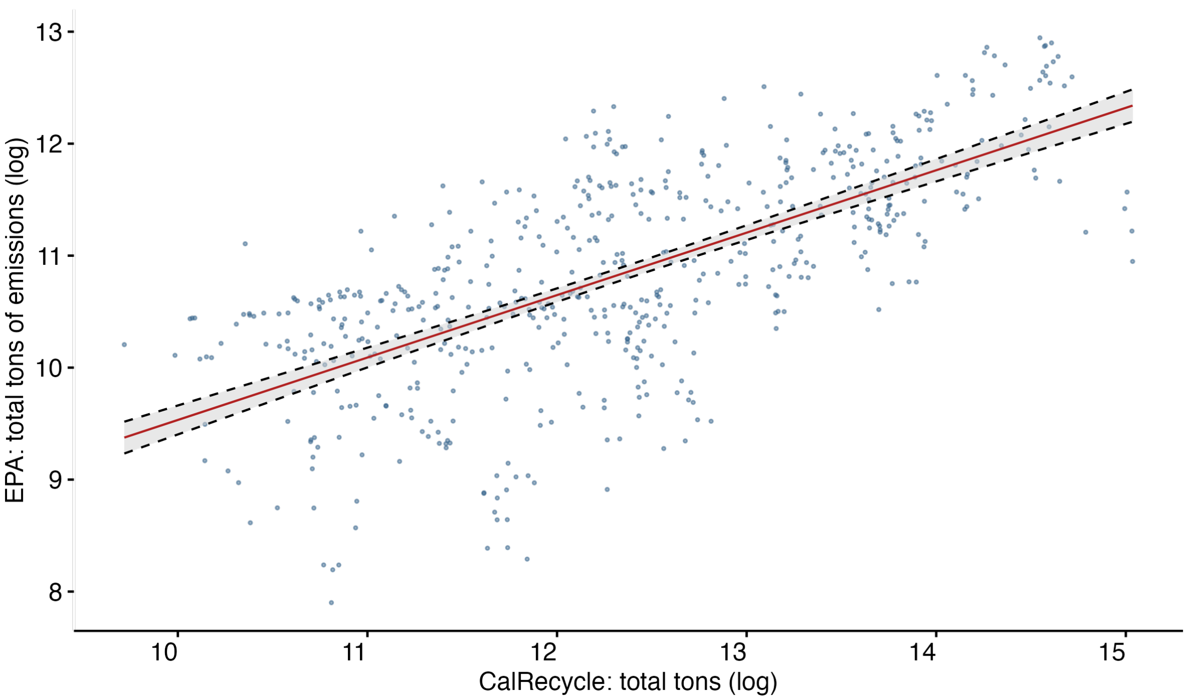
Note: These plots show the net export weight by manufacturing industry. The emissions of these manufacturing industries are used as control groups in the synthetic control method. The plots show no discernible changes in exports of the control manufacturing industries immediately as of 2017, which means the control industries are not directly affected by China's GS policy.

Figure A.7: Pairwise correlations: heterogeneous effects of the GS policy on state-level estimations



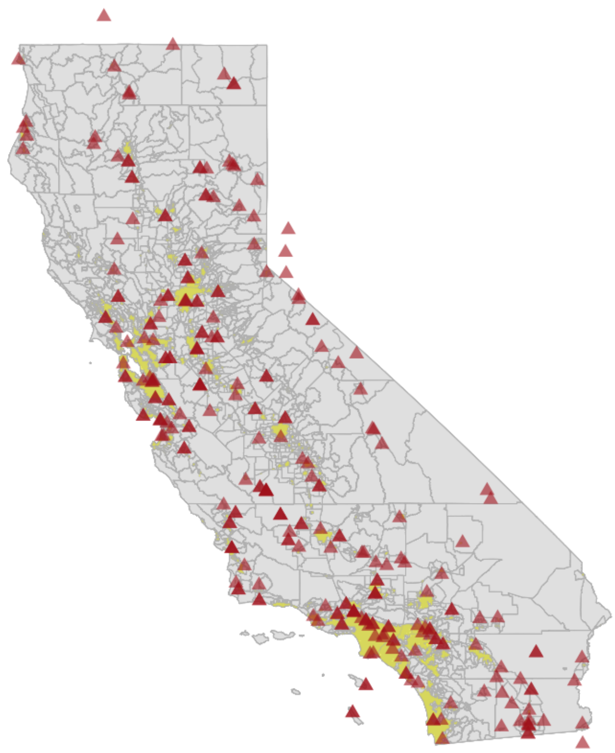
Notes: Figure a shows the correlation between the state-level causal estimates of the GS policy and each state's prior recyclable waste export exposure; Figure b shows the correlation between the causal estimates and the percentage of paper exports by each state. There is a positive correlation between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

Figure A.8: Data Comparison: EPA GHGRP v.s. CalRecycle RDRS



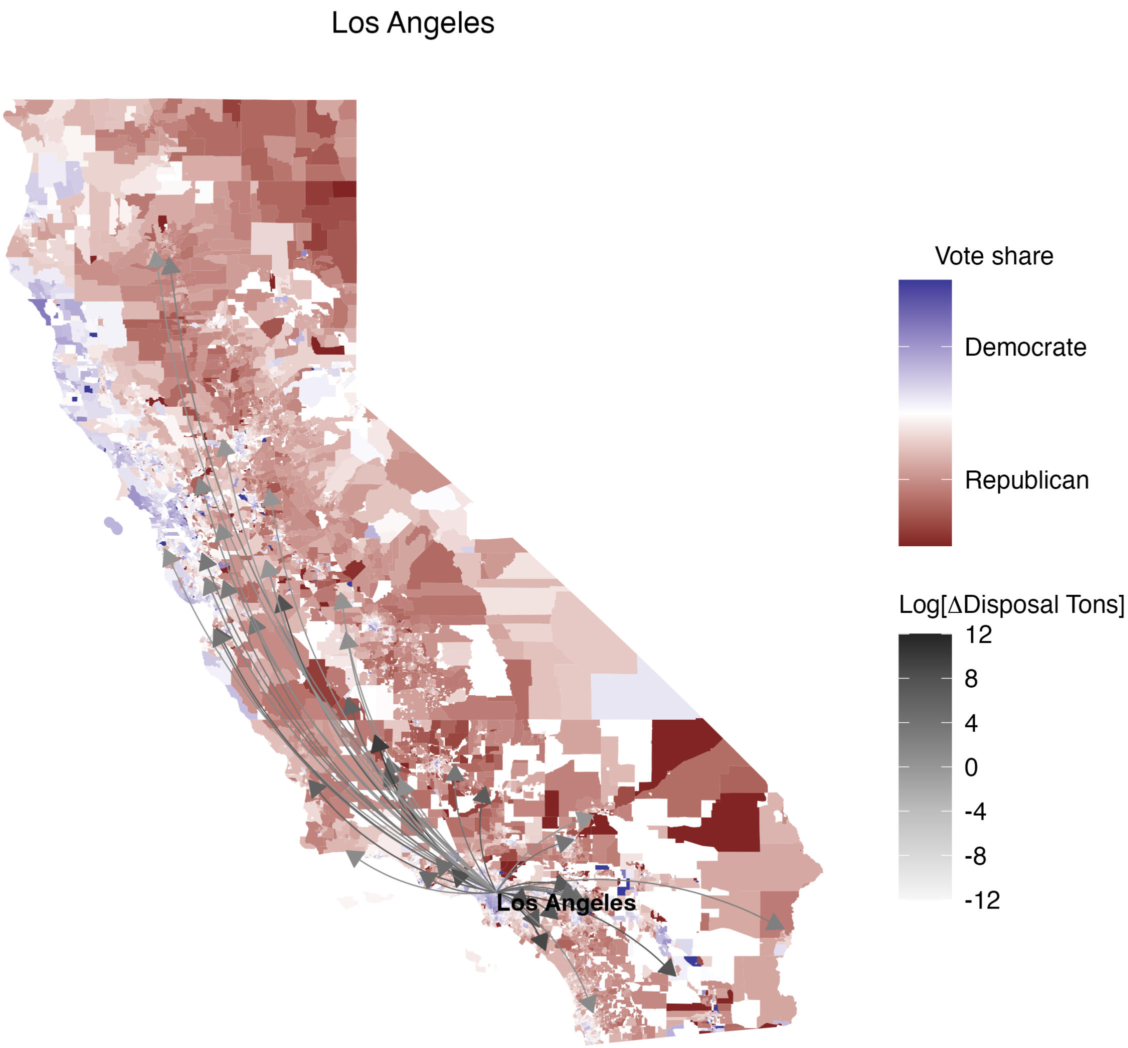
Note: To motivate the result from the state-level estimate, I compare the two data sources used for state and facility-level analysis. This plot shows that the facility-level emissions (log) for California in the EPA GHGRP data and facility-level tons of disposal (log) data in CalRecycle are highly correlated. The variables from the two datasets are different; therefore, the observed facilities do not align along a 45-degree line. However, this strong correlation demonstrates that the result I find from the state-level analysis—that California has seen a 9% increase in methane emissions from the waste industry after China's GS policy—can be used to motivate the analysis of facility-level distributional effects 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 estimate how local communities have been affected differently by this policy change.

Figure A.9: CalRecycle: Recycling and Disposal Reporting System (RDRS)
Facility locations in California



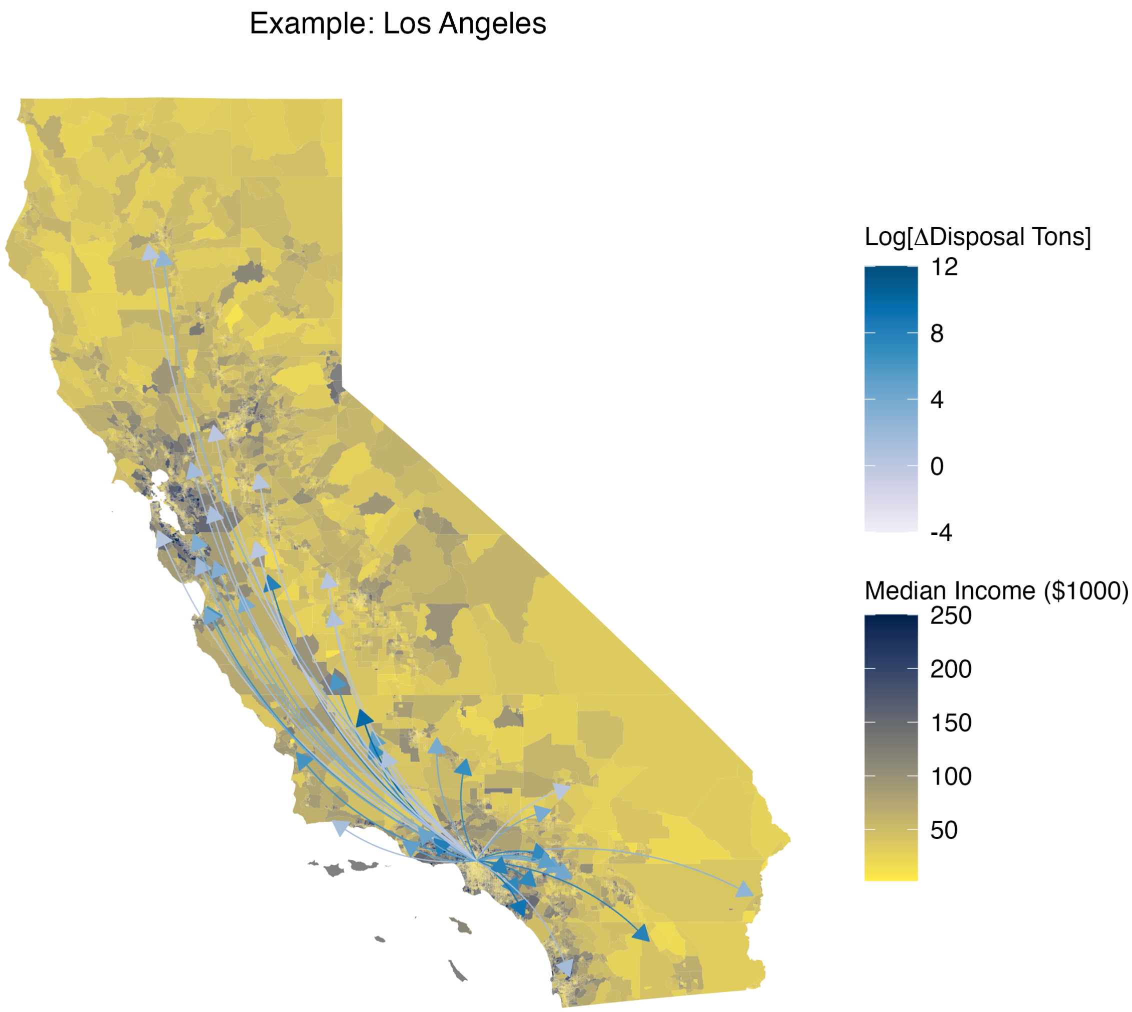
Note: This map shows the locations of all landfill facilities in the CalRecycle RDRS data. The yellow areas are the urban areas in California. The map shows that most landfill facilities are located in rural regions or suburbs outside the urban areas.

Figure A.10: CalRecycle: Average Net Increase in Disposal Flows by Republican Vote Shares



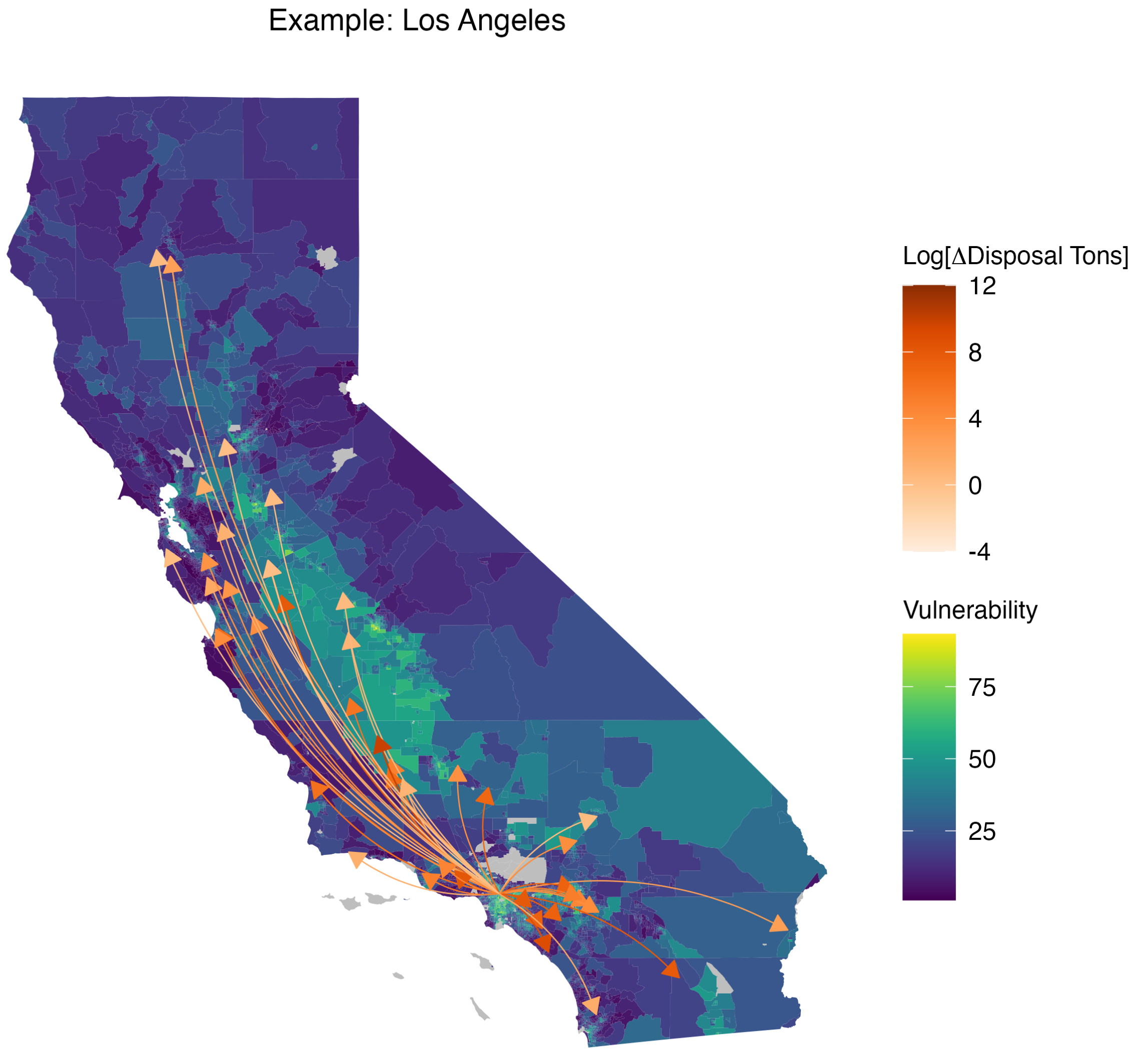
Note: This map shows net increases in disposal flows after China's GS policy, based on Republican vote shares. The geographic unit for vote shares is the voting precinct. The colors of the arrows show the net increase in total weight of disposal flows after China's GS policy.

Figure A.11: Changes in Disposal Flows by Median Income of Destination Community



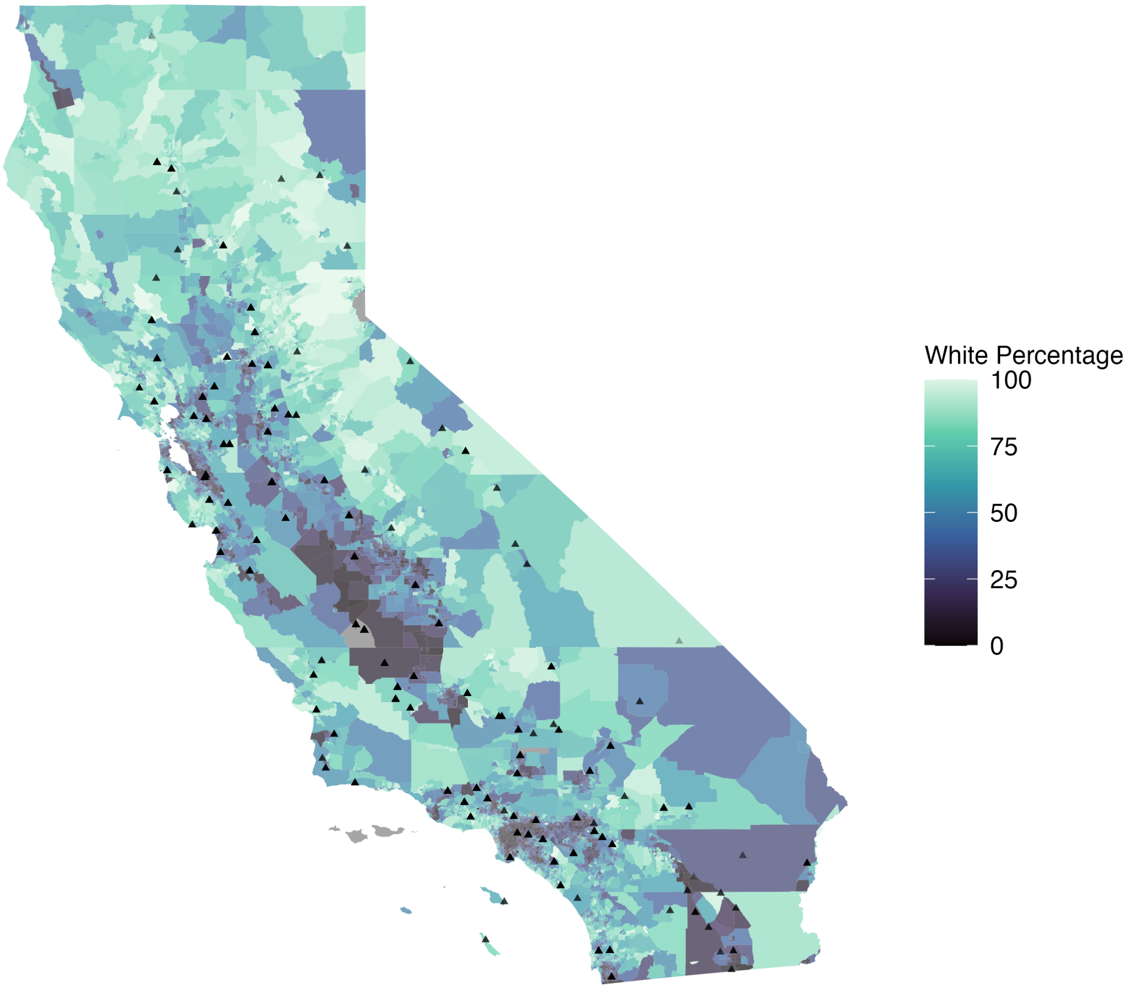
Note: The median income is mapped using 2013 ACS 5-year data at the census block group level. The color of the arrows shows the change in amount of disposal flows after China's GS policy.

Figure A.12: Disposal Flow Map by Environmental Vulnerability



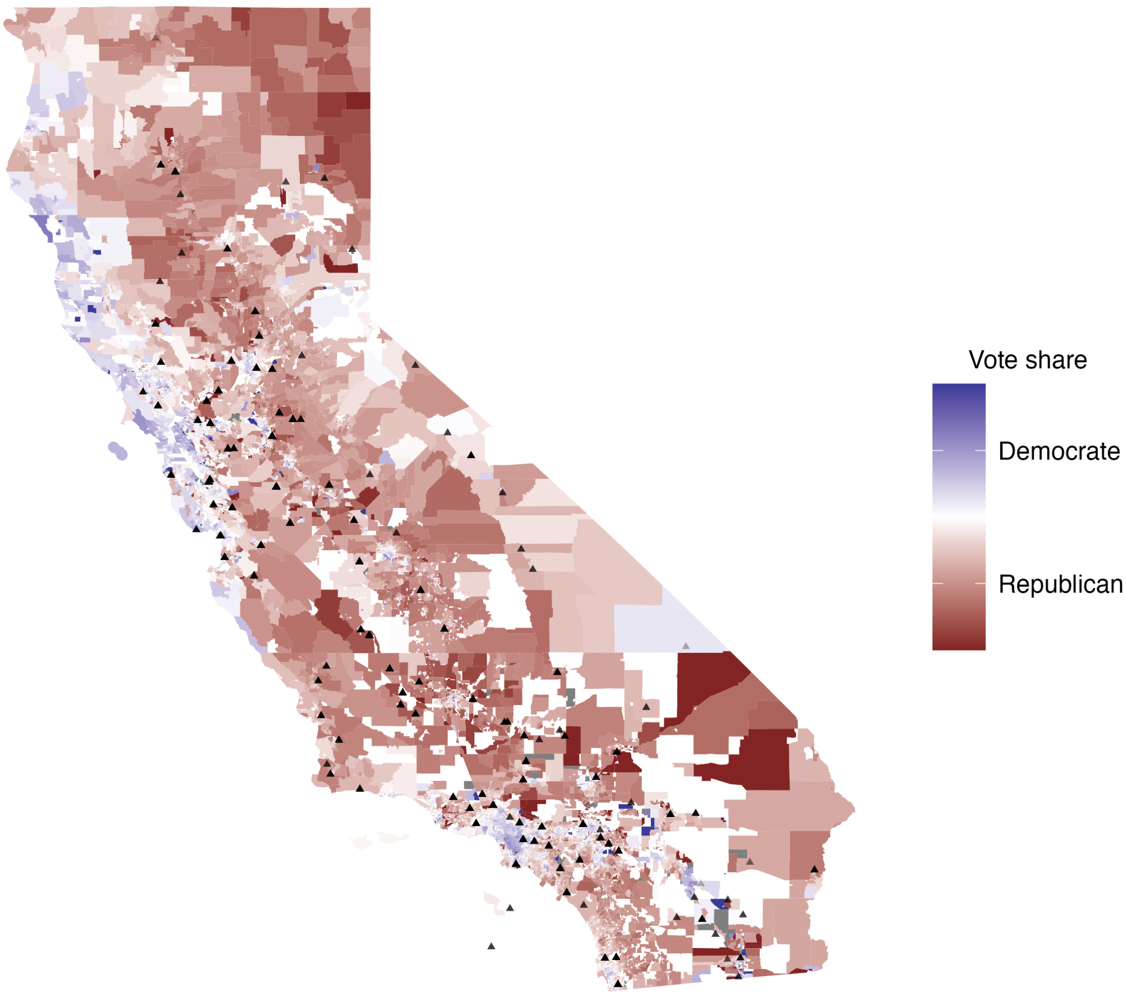
Note: "Environmental Vulnerability" is calculated by the Office of Environmental Health Hazard Assessment (OEHHA). California Communities Environmental Health Screening Tool is a screening methodology that evaluates multiple pollution sources and stressors and measures a community's vulnerability to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

Figure A.13: CalRecycle: Recycling and Disposal Reporting System (RDRS)
Facility locations in California by racial composition



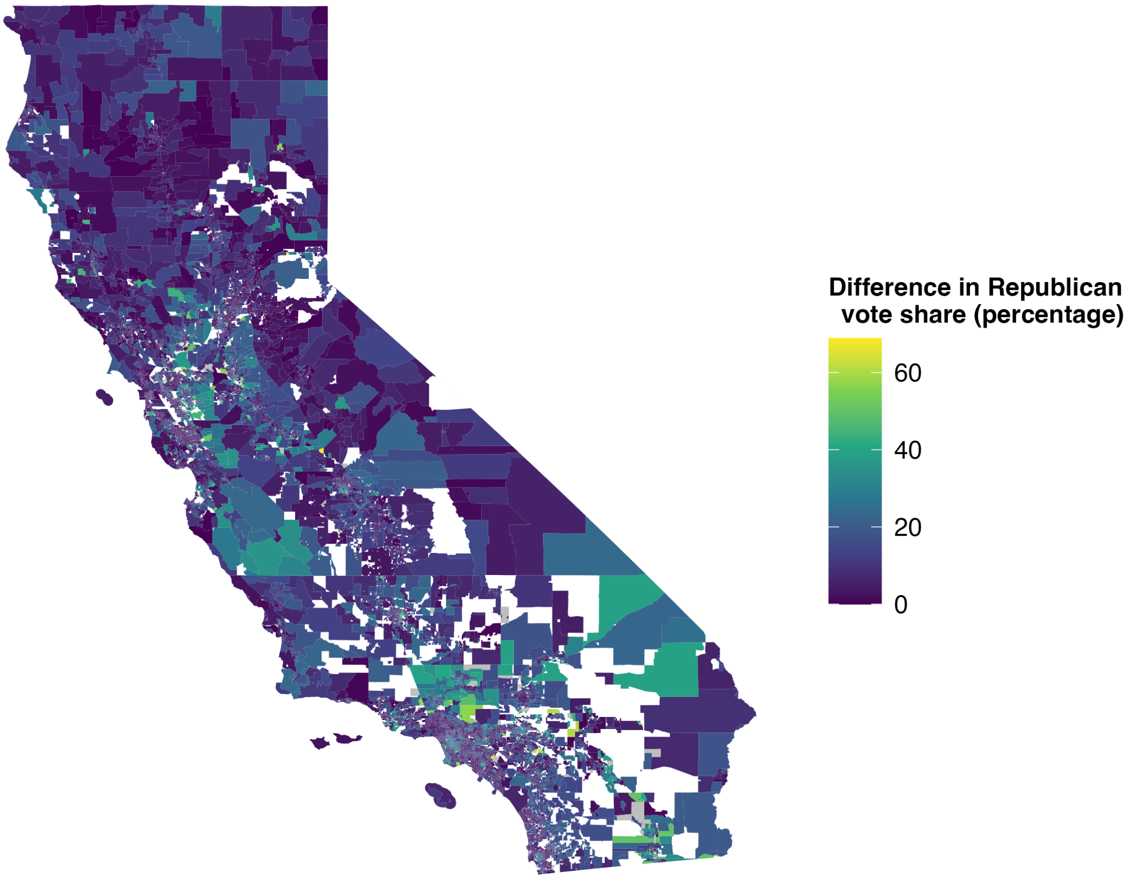
Note: This map shows the locations of all landfill facilities in the CalRecycle RDRS data by racial composition. Racial composition is plotted by census block group level. The map shows that destination facilities are more likely to be located in darker areas where higher minority populations reside. However, some facilities are still located in lighter areas where majority white populations live.

Figure A.14: CalRecycle: Recycling and Disposal Reporting System (RDRS)
Facility locations in California by Republican vote shares



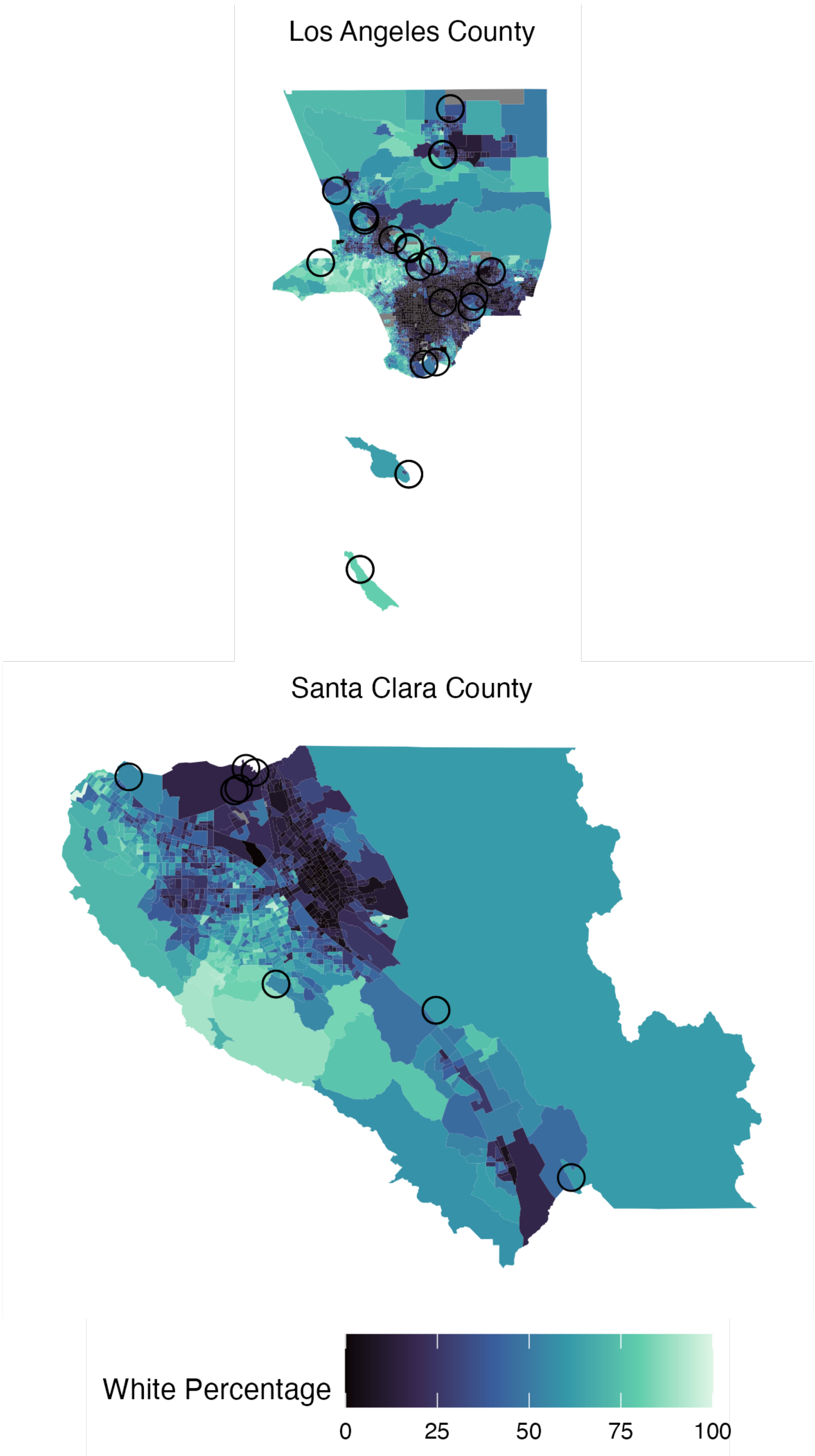
Note: This map shows the location of all landfill facilities in the CalRecycle RDRS data by vote shares. The vote share is plotted by voting precinct. The map shows that most destination facilities are located in communities with higher Republican vote shares. Fewer of them are located in Democratic-leaning communities.

Figure A.15: Potential Mechanism: Disposal Flow Map by Political Deviation



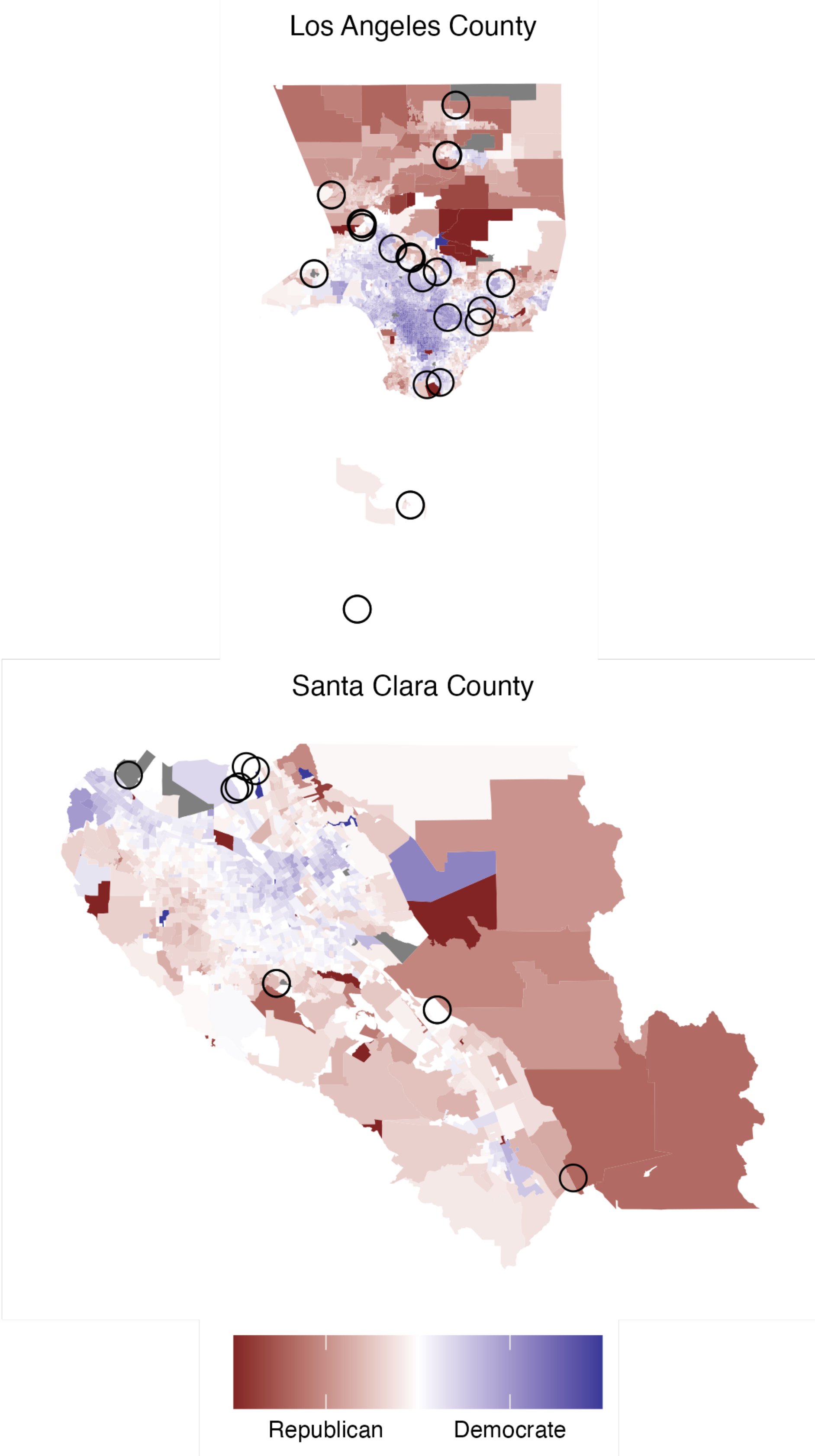
Note: Political deviation is calculated by the absolute difference between a community's Republican vote share and its county's Republican vote share. Political deviation is one of the three potential mechanisms to explain waste transfers across communities. Blue/green indicates the political deviation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

Figure A.16: Racial composition variation within sample counties and 3-km buffers around waste facilities



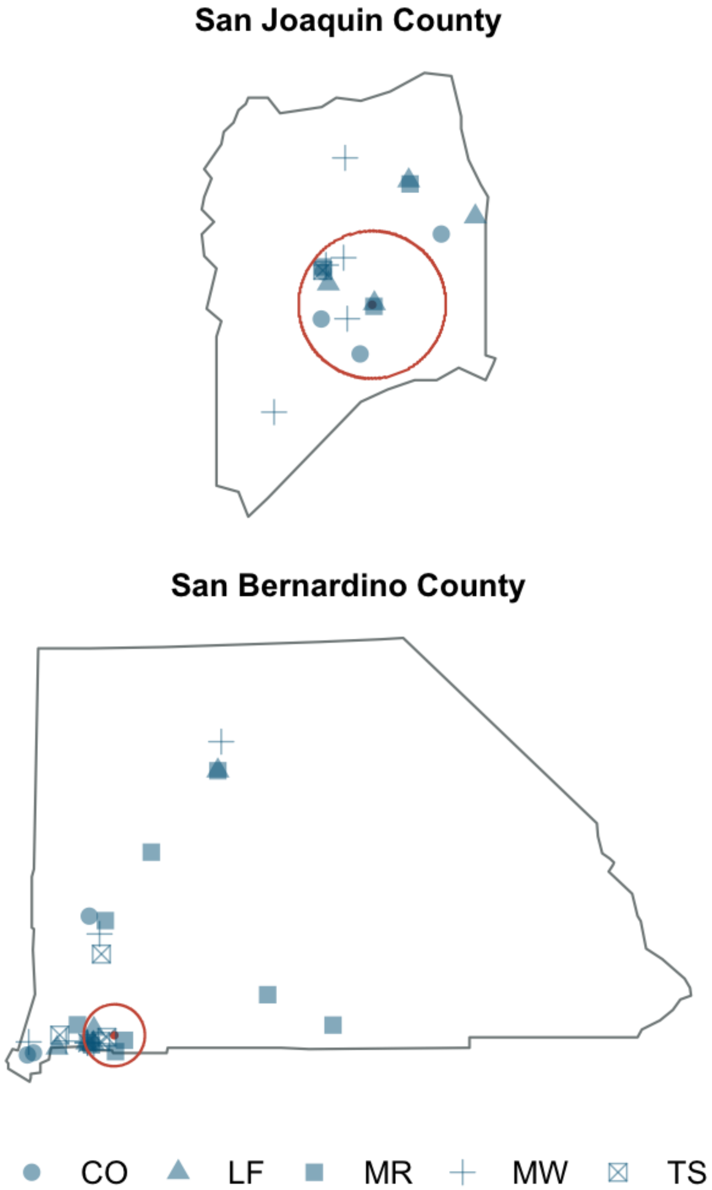
Note: This map shows the variation in racial composition variations across different communities (within 3 km buffers of the destination facilities) in specific counties, for example, Los Angeles and Santa Clara. In the fixed-effects model estimation, the racial composition variable is at the census-block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

Figure A.17: Variation in Republican vote shares within sample counties



Note: Similar to the racial composition, Republican 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 shares stems from different communities within a county. Some communities may include multiple voting precincts.

Figure A.18: Economies of Scale variable of communities
where destination facilities are located (Examples)



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 for disposal shipments. The red dot is the destination facility from CalRecycle as a destination for disposal transfer. The other marks are other types of related facilities within a 15km buffer. They are composting facilities (CO), landfills (LF), recycling centers (MR and MW), and transfer stations (TS). The more facilities around the destination landfill facility, the higher the economies of scale in the community where the destination landfill is located.

Table A.1: Summary Statistics: U.S. Recyclable Waste Exports, 2003-2020 (by Type of Material)

	Total Value $ U.S. million (1)	Total Weight million kg (2)	Percentage of total value (3)	Percentage of total weight (4)
Iron or steel	71.9	473	0.15	0.17
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: Total U.S. GHG Emissions (MMT) by Industry, 2010-2020

	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 - Summary Statistics of Greenhouse Gas Emissions Reported to the GHGRP

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)						
Total carbon dioxide (CO_2)	9.9	10.7	10.8	11.1	11.1	11.4
Total methane (CH_4)	101.1	94.1	94.7	91.2	90.8	89.9
Total nitrous oxide (N_2O)	0.352	0.352	0.356	0.353	0.352	0.351
Year	2016	2017	2018	2019	2020	
Number of facilities	1227	1221	1218	1204	1201	
Total emissions (MMT.CO_2e)	98.2	96.8	99.6	101.4	96.9	
Facility emissions, mean (TMT.)	80	79.3	81.8	84.2	80.7	
Facility emissions, sd (TMT.)	(89)	(90.5)	(97.6)	(102.5)	(92.3)	
Emissions by greenhouse gas (CO_2e)						
Total carbon dioxide (CO_2)	11.7	10.6	11	10.7	10.3	
Total methane (CH_4)	86.7	86.4	88.8	90.9	86.2	
Total nitrous oxide (N_2O)	0.358	0.344	0.352	0.345	0.335	
Sample size: 12,757						

Notes: MMT stands for million metric tons, while TMT denotes thousand metric tons. 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 since 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 from 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: Emission increases across states
(million metric tons of CO_2 eq.)

	Avg. Emissions Before GS Policy 2010-2017 (1)	Tot. Change in Emission After GS Policy 2018-2020 (2)		Avg. Emissions Before GS Policy 2010-2017 (3)	Tot. Change in Emission After GS Policy 2018-2020 (4)
Alabama	2.957	0.988	Arizona	1.430	-0.372
Arkansas	1.477	-0.178	California	7.823	1.797
Colorado	1.382	-0.395	Connecticut	0.926	-0.148
Delaware	0.213	-0.086	Florida	8.028	1.141
Georgia	4.453	0.696	Hawaii	0.561	0.078
Idaho	0.349	-0.263	Illinois	3.534	0.557
Indiana	0.349	-0.442	Iowa	1.148	-0.406
Kansas	1.666	-0.638	Kentucky	1.899	0.485
Louisiana	2.056	0.164	Maine	0.301	-0.204
Maryland	1.659	-0.079	Massachusetts	1.599	-0.150
Michigan	4.634	-0.390	Minnesota	1.464	-0.493
Mississippi	4.634	-0.0380	Missouri	1.381	0.096
Montana	0.339	0.196	Nebraska	0.913	-0.232
Nevada	0.281	0.428	New Hampshire	0.390	0.049
New Jersey	2.234	-0.679	New York	3.132	1.370
North Carolina	3.501	-1.021	North Dakota	0.294	0.206
Ohio	5.057	0.845	Oklahoma	1.982	-0.112
Oregon	1.035	0.194	Pennsylvania	3.701	-0.331
Rhode Island	0.148	0.148	South Carolina	1.579	-0.233
South Dakota	0.186	-0.043	Tennessee	2.485	-0.492
Texas	10.297	2.702	Utah	0.667	-0.071
Vermont	0.095	-0.011	Virginia	3.433	1.996
Washington	0.972	0.353	West Virginia	0.731	0.067
Wisconsin	1.406	-0.627	Wyoming	0.146	-0.068

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.6: 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	10 km Buffer	15 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. See Appendix Figure A.18 for a detailed definition of economies of scale. I choose longer distance buffers for economies of scale since landfills are normally large and there are rarely other facilities within a short-distance buffer of destination landfill facilities.

Table A.7: Altered distributional effects: Fixed-effects model for waste flows from origin jurisdiction to receiving facilities and their local community 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	226,128	217,212

Notes: Two-way clustered standard errors at the county-year level in all models. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.