Garbage Policy or *Garbage* Policy? Assessing American Composting Programs as a Tool for Landfill Greenhouse Gas Reduction

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Abstract

Despite widescale adoption of recycling programs, only 7% of the one thousand largest American cities have a curbside composting program. Nonetheless, composting programs have the potential to greatly reduce greenhouse gas emissions, since the anaerobic decomposition of organic material in landfills accounts for more than 15% of American methane emissions each year. Despite the growing popularity of composting, no research has examined how the roll-out of curbside composting programs in American counties has impacted municipal solid waste (MSW) landfill methane emissions. This paper uses landfill-level emissions data from the Environmental Protection Agency Inventory of U.S. Greenhouse Gas Emissions and Sinks, to employ a staggered-adoption difference-in-differences and event-study design that estimates the causal effect of curbside composting on annual county-level, per-household landfill emissions. Since curbside composting programs are implemented by municipalities, but multiple municipalities in a county may share a landfill, this paper uses continuous treatment difference-in-differences, where treatment is the share of households in a county that are covered by a municipal curbside composting program. This paper finds weak evidence that curbside compost collection reduces MSW landfill methane emissions, but the effects are not statistically significant at a 5% level due to a combination of measurement error, low sample-size, and a demanding empirical strategy. Nonetheless, this paper contributes to research and policy by cleaning and publicizing inaccessible data, providing a framework for future research to evaluate the success of composting policies, and adding to the growing but preliminary literature of applied-works using a continuous treatment difference-in-differences design.

Contents

1 Introduction[1]

Municipalities often market composting programs as an environmentally friendly alternative to disposing of organic waste in conventional landfills, with the added benefit that organic materials can be used to improve soil quality for both commercial and residential purposes. Perhaps the largest benefit of composting comes from its potential to reduce municipal solid waste (MSW) landfill methane (CH_4) emissions. In 2019, MSW landfill CH_4 emissions accounted for more than 15% of total American CH_4 emissions, the third largest single-source of emissions behind enteric fermentation and natural gas systems (USEPA, 2021). Beyond the United States, the IPCC found that in 2006, the waste sector was responsible for more than 5% of global greenhouse gas (GHG) emissions (Eggelston *et al.*, 2006). CH_4 emissions have a greenhouse effect over 25 times that of carbon dioxide (CO_2); therefore, policymakers interested in GHG reduction should take interest in MSW landfills, as modestly-priced policies that abate CH_4 have the potential to be extremely cost-effective (USEPA, 2022a).

In MSW landfills, CH_4 emissions are produced from the anaerobic decomposition of organic materials (Lou and Nair, 2009). When carbon-based organic material breaks down in absence of gaseous oxygen (O_2), it emits CH_4. However, in the presence of O_2 gas, decomposing organic waste emits CO_2 and water (H_2O), rather than CH_4. Industrial composting facilities use a plethora of techniques to turn, mix, and aerate organic mass to avoid anaerobic decomposition (Briassoulis *et al.*, 2021). Through this simple mechanism, diverting household waste from landfills to composting facilities has the potential to greatly reduce the global-warming impact of household waste.

Despite the emission-reducing potential of composting, the adoption of curbside compost collection programs in the United States has been lacklustre. In 1998, San Francisco became the first major city in the United States to introduce a curbside composting program. Initially a pilot program for food scrap collection, the program was highly successful and participation was made mandatory for all residents. In the decades following, residential food waste collection programs spread across cities and counties from coast to coast. By 2017, 202 communities in 24 states had implemented some form of a curbside composting program (BioCycle, 2017). Despite the spread of curbside composting programs, they remain a rarity in American municipalities. As of October

[1] This section draws heavily from Weaver (2022), submitted for ECON 573.

2020, only 7% of the one thousand largest American cities have a program, representing less than 3% of the American population (GreenBlue Organization, 2020).

Despite the gradual adoption, no research has examined how the rollout of curbside composting programs in the U.S. has impacted landfill CH_4 emissions in a real-world setting. **This paper asks what effect the rollout of curbside composting in American counties has on county-level per-household MSW landfill CH_4 emissions.** Many curbside composting programs are opt-in or mandatory but lack a credible probability of penalties for not participating. Accordingly, the existence of a curbside composting program does not guarantee that adequate organic waste is being diverted from landfills, nor does it guarantee that household organic waste is a large-enough component of MSW landfills that household composting collection will significantly reduce emissions. Some literature exists to show that curbside organics collection has effectively diverted waste from landfills, but they examine a more local scale and do not provide a causal estimate of the impact that programs have on landfill emissions (Alacevich *et al.*, 2021; Taylor and De Silva, 2021). **Whereas previous technical research analyzes the effect of removing organic matter from landfills, this paper makes a unique contribution by analyzing the real-world effectiveness of curbside composting policies.**

Composting programs are implemented at the municipal level, but multiple municipalities may share a landfill. As such, I aggregate emissions and households with curbside collection to the county-level. I employ a difference-in-differences (DID) methodology to estimate the effect of curbside compost collection on county-level per-household MSW landfill CH_4 emissions. The first empirical specification defines a binary treatment indicator as the first year some residents of a county get curbside collection. This specification uses two-way fixed-effects (TWFE) to account for the staggered timing of curbside composting rollout. Under the right assumptions, the estimate measures the average treatment effect of curbside collection in treated counties on county-level per-household MSW landfill CH_4 emissions. The treatment effects will not be time-invariant, since MSW landfill CH_4 emissions tend to form 0.5 to 3 years after organic matter has been disposed, and peak a few years later (Haeming *et al.*, 2011). As such, this paper uses an event-study design to capture treatment effects by year, and to test for pre-treatment parallel trends. One empirical problem is that the number of households receiving curbside collection services in a county may differ, and therefore the “dose” of treatment is not uniform. I draw from the new and growing literature on continuous treatment DID (Chaisemartin and D'Haultfoeuille, 2020; Callaway *et al.*, 2021; Chaisemartin *et al.*, 2022) to dose-adjust the binary treatment indicator by the fraction of households in a county with curbside collection. I use both simple TWFE with continuous treatment and a heterogeneity-robust estimator from Chaisemartin and D'Haultfoeuille (2022).

Unfortunately, measurement error and a low sample size of treated counties results in imprecise estimates that are not statistically significant at a 5% level. Similarly, the point-estimates imply implausible amounts of household waste being diverted from landfills after the introduction of a county-wide curbside collection program, perhaps due to a violation of identifying assumptions. Nonetheless, the estimates are consistently negative across multiple specifications, indicating that in spite of the estimation noise, there is some weak evidence to suggest curbside collection programs are reducing county-level MSW landfill emissions. As data improves, sample timeframe increases, and more curbside collection programs are adopted, this paper provides a framework for future research to evaluate the success of those policies.

This paper is divided into seven sections. Section 2 provides background on American landfills, landfill CH_4 measurement, and a literature review. Section 3 describes the datasets used for the empirical analysis. Section 4 describes the empirical strategy, identifying assumptions, and interpretation of the causal estimate for each model specification. Section 5 discusses results and their interpretations. Section 6 provides a discussion of the contributions and limitations of this paper. Finally, Section 7 offers concluding remarks and potential directions for future research.

2 Background

2.1 U.S. MSW Landfills and CH_4 Emission Measurement

While composting facilities have grown in prominence over the past two decades, landfills still accept over half of all municipal solid waste in the United States.[2] MSW landfills produce CH_4 emissions through the anaerobic decomposition of organic waste, and in the presence of leachate. Landfill gas collection systems are constructed with vertical wells that introduce piping into the landfill. Through vacuum induction, the gas is transported to a collections facility, where it is

[2] Figure 3 in the Appendix describes total MSW by composition from 1960 to 2018. More tonnes of food waste are disposed of at MSW landfills than plastics and metals combined.

measured, processed, and either flared or used as natural gas (USEPA, 2022a). If the CH_4 emissions are not sufficiently collected, landfill gas emits directly into the atmosphere. MSW landfills are required to report their emissions to the EPA if their annual Carbon dioxide equivalent (CO_2e) emissions exceed 25,000 metric tonnes (USEPA, 2015). This is equivalent to 1,000 metric tonnes of CH_4 per year in terms of GWP. MSW landfill emissions are calculated through two methods. First, if a landfill is equipped with a collection system, CH_4 emissions are calculated by directly measuring the amount of CH_4 recovered in the collection system, then calculating the amount not-recovered by estimating the collection efficiency and adjusting for "destruction efficiency" and soil oxidation (USEPA, 2015). The difference between this amount and the recovered amount are the reported emissions. Destruction efficiency refers to the percent of captured methane that is not emitted into the atmosphere at the landfill (USEPA, 2015). This refers to the percent of emissions that are successfully flared or transported off-site for use in natural gas markets.[3] The second method for estimating emissions is used by MSW landfills without a gas collection system. Instead, methane generation is modelled as a function of landfill-specific data (USEPA, 2015):

$$\begin{aligned} G_{CH_4} &= \left[\sum_{x=S}^{T-1}\left\{W_x \times MCF \times DOC \times DOC_F \times F \times \frac{16}{12}\left(e^{-k(T-x-1)} - e^{-k(T-x)}\right)\right\}\right] \\ M_{CH_4} &= G_{CH_4} \times (1 - OX) \end{aligned} \tag{1}$$

Equation 1 is a first-order decay model, where G_{CH_4} is the total annual CH_4 generated in year T, and M_{CH_4} is net CH_4 emissions. The model uses the mass of degradable organic carbon (DOC), the fraction of DOC dissimilated (DOC_F)[4], the fraction of CH_4 in landfill gas, a methane correction factor (MCF)[5], and a rate constant for decomposition k[6] The model is dynamic, beginning in landfill opening year S and incorporating each subsequent year x. The implication of the decay model is that CH_4 emissions from deposited organic waste peak 3 to 5 years after their disposal, so the emissions are not instantaneous and instead follow an exponential growth and decay path $(\frac{16}{12}) \times (e^{-k(T-x-1)} - e^{-k(T-x)})$. Figure 4 in the Appendix depicts the time-path of landfill CH_4 emissions, peaking a few years after disposal. In absence of CH_4 collection, the net CH_4 emissions

[3]Flaring is the more common option, which burns highly flammable CH_4 into CO_2 and water.
[4]Usually modelled as $DOC_F = 0.5$.
[5]Landfill MCF = 1 unless waste is aerated. Dry tomb landfills have $MCF < 1$.
[6]k is a function of precipation, recirculated leachate, and waste composition.

(M_{CH_4}) are the gross annual CH_4 generation G_{CH_4} scaled by the soil oxidation factor $(1 - OX)$. If an MSW landfill has a collection system, CH_4 reductions from composting should explicitly materialize in CH_4 measurement with a reduction in the amount of gas collected. Using the EPA CH_4 generation model, emissions reductions will materialize, albeit less precisely, from a change in parameters that are functions of waste quantity and composition (DOC, DOC_F, and k).

2.2 Literature Review — Policy Evaluations[7]

Most research on composting and landfill emissions has been scientific, technical work (Lou and Nair, 2009; Cossu *et al.*, 2003; Cogger, 2005; Favoino and Hogg, 2008). Despite controlled scientific evidence, few studies have examined the real-world effectiveness of composting programs at the community level. Existing studies are mostly concerned with the effect of curbside composting programs on overall waste reduction. The earliest work from Bartelings and Sterner (1999) proposes a model of characteristic demand for waste services using survey data, but stops short of evaluating any real-world policy changes. Alacevich *et al.* (2021), examine the rollout of a Swedish household composting program to show that households that participated not only reduced the amount of landfill-bound waste per household, but also total household waste. The most recent and relevant literature by Taylor and De Silva evaluates the impact of curbside composting programs on household landfill waste in local councils of New South Wales (NSW), Australia. Taylor and De Silva ask how much household waste is diverted from landfills to composting facilities when local governments implement curbside collection services, and whether these services have any spillover effects on total household waste and recycling waste. Specifically, they use a TWFE event-study model to show that curbside composting diverted an average of 4.2kg per household per week ($\frac{1}{4}$ of pre-treatment household waste) from landfills to composting facilities. Despite finding strong evidence of household compliance, GHG emissions are only considered in a back-of-the-envelope calculation using estimates from technical literature. Theoretically, they argue a statewide curbside composting program in NSW could divert approximately 671,007 tonnes of organic waste from landfills each year, and reduce landfill emissions by anywhere from 6% to 26%.

Despite significant policy contributions and a well-specified empirical strategy, this paper has two major shortcomings. First, the scope is limited to a single province in Australia, and the

[7] This section draws heavily from Weaver (2022), submitted for ECON 573.

sample size is limited. Only 24 local councils implemented a curbside composting program, so there remain questions over external validity. Second, and far more significantly, the paper focuses on the behavioural response of households in terms of waste diversion, but does not explicitly estimate a causal effect. There are three reasons why a back-of-the-envelope calculation is insufficient for a reliable estimate of GHG reduction. First, implicit in this calculation is the assumption that households are perfectly sorting their waste. Assuming away imperfect sorting would overestimate the mass of purely organic waste being taken out of landfills, and positively bias the hypothetical calculation. Second, the estimates of GHG emissions per ton of organic waste come from a 2011 report from the NSW Department of Environment, Climate Change, and Water. Geographical variation, temperature, landfill structure, and waste composition may change the GHG emissions per ton of organic waste in different settings. Third, the suggested interval of reduced GHG emissions (6% to 26%) based on the 2011 report is wide and imprecise. The high (26%) and low (6%) scenarios are based on different landfill and waste characteristics, so explicitly estimating a causal effect may offer a more precise point-estimate and confidence interval.

I seek to address the two major gaps in the current literature by using new data, a new econometric method, a broader scope, and a new dependent variable to get an explicit causal estimate of the effect of curbside compost collection on MSW landfill CH_4 emissions. Specifically, I use U.S. EPA inventory of GHG Emissions and Sinks data and a nationwide community composting survey to expand the scope to over 1,000 MSW landfills in the United States. I also use continuous treatment TWFE DID estimation to get a dose-adjusted causal estimate.

3 Data

This paper uses emissions data from the EPA Inventory of Greenhouse Gas Emissions and Sinks, and compost collection data from the BioCycle Nationwide Survey (2017). The data are supplemented by the 2010 Census of Population, the 5-Year American Community Survey (ACS), and the Massachusetts Institute of Technology (MIT) Election Data and Science Lab. Section 3.1 discusses the EPA Inventory of GHG Emissions and Sinks, Section 3.2 summarizes the Biocycle Nationwide Survey, and Section 3.3 highlights other datasets used in this paper. Finally, Section 3.4 discusses the process of creating a nationwide, county-level 8-year unbalanced panel dataset, as well as five robust variations to the panel.

3.1 EPA Inventory of U.S. Greenhouse Gas Emissions and Sinks (2010-2019) [8].

The EPA Inventory of U.S. Greenhouse Gas Emissions and Sinks publicly reports detailed GHG emissions from 2010 to 2019 by polluting facility, facility location, and emission type. For this paper, only the subset of facilities in the municipal waste management sector are relevant (subpart code HH). Each emitting facility is identified by name, latitude, longitude, and U.S. industrial classification. GHG emissions are reported in aggregate, and more importantly, by specific GHG type. By EPA standards, only CH_4 emissions are recorded for MSW landfills. Even more comprehensive data links emissions to specific processes through which GHG gasses are emitted.[9] The dataset includes all MSW landfills that exceed 25,000 metric tonnes of carbon dioxide equivalent (CO_2e) emissions, as per EPA regulations (USEPA, 2015). Section 2.1 comprehensively outlines the MSW landfill emission measurement process and EPA regulatory standards. Table 4 in the Appendix gives an overview of municipal waste facilities available in the the U.S. GHG Emissions and Sinks dataset. The dataset covers the period of 2010 to 2019, with 1235 unique MSW landfills in 2010 and 1124 in 2019. This could be for two reasons. First, landfills can shut down or reduce their emissions below the 25,000 CO_2e threshold, and are therefore no longer required to report CH_4 emissions. Second, there could be simple recording errors. Since I am unable to verify why there are less recorded facilities in 2019 than 2010, I reorganize the data into an unbalanced panel containing all possible observations, and a balanced panel that keeps *only* facilities that report in all years (2010 to 2019). The balanced panel contains 1037 observations annually, for a total of 10,370 observations over ten years. These results are plotted in Appendix Figure 5. Omitting the unbalanced observations does not introduce any systematic distortion between emissions trends in the balanced and unbalanced panel; rather, the annual emissions appear to be shifted downwards by a constant amount in the balanced panel. This implies that the general downward trend in MSW landfill CH_4 emissions is not due to reduced reporting, and the unbalanced facilities are not systematically different from the balanced facilities in terms of CH_4 emission trends.

[8] This section draws heavily from Weaver (2022), submitted for ECON 573.

[9] For instance, the data distinguishes between emissions from stationary combustion of materials versus anaerobic decomposition in landfills.

3.2 BioCycle Nationwide Survey

The BioCycle Connect Non-Profit organization runs a nationwide survey to collect information on communities with access to household organics and food scraps collection from 1995 to 2017. In the 2017 survey, each community with curbside and drop-off composting was identified along with the year each program was implemented, the number of households affected, and the compost processing facility that the household organic waste is redirected to. In total, there are 202 communities with drop-off or curbside composting collection in the 2017 survey, representing roughly 5 million households with curbside collection and 6.5 million with drop-off composting.[10] This paper uses curbside collection as the treatment of interest, since drop-off composting is less convenient for households, and requires them to take their household organic waste to a drop-off facility on their own initiative. The 2017 BioCycle Nationwide Survey is only reported in PDF format, so I manually convert the data into CSV format. Summary statistics on the 2017 BioCycle Nationwide Survey can be found in Appendix table 5.

3.3 Other Datasets

To retrieve county-level demographic data, this paper uses the 5-Year American Community Survey (ACS). The 5-Year ACS is an ongoing survey by the U.S. Census Bureau that provides annual estimates of population and demographic data for all American geographies in the Census of Population. This includes county-level data on population, number of households, average household size, median income, and the percent of households renting their home. I also access county-level voting records from the MIT Election and Science Lab to use as a control, since voting records provide insight into the environmental consciousness of a county's electorate.

3.4 Panel Dataset Construction and Assumptions

Curbside composting programs are implemented by communities, but multiple communities in a county may share a county landfill. If one community gets composting services but others sharing a landfill do not, then the fraction of households served by the landfill with composting can only be calculated if the denominator (all households using that landfill) is identified. Without

[10] A more recent survey was conducted in 2021, but it does not include the year each program is implemented, and therefore the data can not be converted to a panel dataset.

granular data matching households to their primary MSW landfill, households cannot be reliably matched to MSW landfills in any county with more than one facility without knowing the exact jurisdictional boundaries each facility.[11] On average, communities with composting service have 2.3 facilities in their county; therefore, matching communities to specific facilities is not reliable nor feasible. To address this problem, I create a county-level panel dataset of composting exposure and landfill methane emissions by aggregating facility-level MSW landfill emissions and community-level households with curbside collection. The assumption motivating this panel is that community-composting and landfill-emissions data can be compared at the county level, since it is very likely that municipalities in a county possessing one or more municipal landfills will send their waste to the landfills in their county. This assumption and county-level aggregation are much preferred alternatives to mapping all MSW landfill jurisdictions at the household level.

The U.S. GHG Emissions and Sinks dataset does not have reliable information on the county of each facility; however, the longitude and latitude of each facility are available. I exploit this information to geolocate the exact county FIPS[12] of each facility with a U.S. Government API Area tool[13]. With each observation matched to a FIPS code, I calculate annual aggregate MSW landfill CH_4 emissions by county. There are 808 unique counties in 2010, but only 658 in 2019. In Appendix Figure 6, I geographically map the intensity of annual MSW landfill CH_4 emissions by county. While most urban counties have data on landfill CH_4 emissions, the data is sparse in the midwest. It is possible there are no MSW landfills in these counties, or that these facilities have emissions below the EPA reporting threshold. The data shows that urban population centres tend to have much higher average annual CH_4 emissions than more rural areas. The counties near Houston, Orlando, and Cincinnati shine brightest in the map, indicating that they are the worst emitters. In total, the 73.3% of the 2010 U.S. population is covered by counties reporting MSW landfill emissions data.

The BioCycle Nationwide survey identifies programs based on their community or policy-jurisdiction, rather than at the county-level. As such, I use a city-to-county matching developed by the U.S. Economic Development Administration and Indiana University to match communities

[11]To the best of my knowledge, no dataset reports these jurisdictions across the U.S., so obtaining this data would require independently finding and cleaning spatial data for each of the 1000+ facilities.

[12]FIPS codes are unique codes that identify American counties.

[13]`https://geo.fcc.gov/api/census/#!/block/get_block_find`

with their respective counties.[14]. In 16 of 202 communities, some fraction of the treated community's population is split between two or more counties. In absence of the exact geographic location of households affected by these 16 composting programs, I use a population-weighted average to distribute the number of households affected by a composting program to each county. Only 9 of these communities have more than 5% of their population in another county. After assigning treated households to counties, I clean the data to remove problematic observations. I define a problematic observation as a community that satisfies one or more of the following conditions: (1) I am unable to match a county to the treatment region, (2) there is no reported start date for curbside and/or drop-off collection, and (3) the community receives treatment multiple times, with no indication of how many households were affected in each year of treatment (this problem is unique to Boulder, Colorado). After removing these observations, there are 159 communities remaining. Finally, I create a cumulative panel dataset of each county from 2010 to 2017 reporting the aggregate number of households with access to curbside and drop-off compost collection in each county-year. The resulting county-level composting panel is mapped in Appendix Figure 7.

3.5 Panel Datasets: Summary Statistics

The final dataset is a county-level panel from 2010 to 2017 that merges MSW landfill emissions with the number of households receiving curbside and drop-off comosting services, as well as ACS demographic data and MIT Election Lab voting records. I create six robust variations of the final panel dataset, each based on different assumptions in the aggregation to a county-level data panel. The six datasets are summarized in table 1:

Table 1: County-Level MSW Landfill Emission and Household Composting Access Datasets

Dataset (Abbreviation)	Included Counties	MSW Landfill Facilities	Keep only "Safe Counties"*
UU	Unbalanced	Unbalanced	No
BU	Balanced	Unbalanced	No
BB	Balanced	Balanced	No
SUU	Unbalanced	Unbalanced	Yes
SBU	Balanced	Unbalanced	Yes
SBB	Balanced	Balanced	Yes

* Safe counties are counties that do not contain any communities that are removed for lacking a treatment start-date and/or receive treatment multiple times with no breakdown by year and dosage.

[14] https://www.statsamerica.org/CityCountyFinder/

Beginning with the least conservative, highest-observation dataset (UU), I include all non-zero reporting facilities, and all composting communities that do not classify as "problematic". I do not drop counties with both landfill and compost data even if a "problematic" community was removed that county in the aggregation process. The UU dataset includes 6,962 observations, 923 unique counties, 1312 unique facilities, and 113 underlying communities with composting programs. Of those counties, 48 receive treatment. The most conservative, lowest-observation dataset (SBB) includes only balanced facilities (and by implication, balanced counties), and drops a whole county in all periods if a "problematic" community exists in that county, no matter how small the "problematic" community is. The SBB dataset includes 6,206 observations, 776 unique counties, 865 unique facilities, and 76 underlying communities with composting programs. Of those counties, 38 receive treatment. Complete summary statistics for the UU, BU, BB, SUU, SBU, and SBB datasets can be found in Appendix tables 6, 7, 8, 9, 10, and 11. Across all datasets, there is a proportional downward trend in annual aggregate MSW landfill CH_4 emissions.[15] In all six datasets, there are many county-year observations with a small share of households receiving curbside collection (less than 10% of households have curbside collection), but there is a large right-hand tail of a few counties with nearly 100% coverage.[16] Finally, among all 6 datasets, the number of households receiving treatment (curbside collection) has not been uniform across years. Far more households received treatment in 2013 and 2017 than in 2010 and 2014-2015 respectively. This is of particular importance for assessing TWFE weights in the continuous treatment empirical strategy, since higher doses of treatment occur in different years.[17]

4 Empirical Strategy

4.1 Classic Binary Treatment TWFE Estimation

The simplest specification for estimating the average effect of curbside composting programs on county-level MSW landfill CH_4 emissions per household is with TWFE and a binary treatment variable, estimated with Ordinary Least Squares (OLS). The estimating equation takes the following

[15] Appendix Figure 8 plots this trend for each dataset.
[16] Appendix Figure 9 plots a histogram of treated county-years by their share of compost coverage.
[17] Appendix Figure 10 plots the number of new households receiving curbside collection by year, 2010-2017.

form:

$$CH_{4ct}^{hh} = \beta^{twfe} \cdot C_{ct} + \lambda_c + \lambda_t + X_c \cdot \delta + \epsilon_{ct} \tag{2}$$

Equation 2 describes county-level per-household methane emissions in year t (CH_{4ct}^{hh}) as a function of whether a county c has a curbside composting program in year t ($C_{ct} = 1$). Equation 2 also includes county and year fixed effects λ_c & λ_t since the rollout of composting programs is staggered, and counties experience treatment in different periods. I include X_c as a vector of county c characteristics. Among these characteristics are some combination of population, average household size, fraction of households renting their homes, median income, the number of MSW landfills in the county, the share of households with drop-off composting, and the share of votes cast for the Democratic presidential candidate in the most recent election. Standard errors are clustered at the county-level.

The coefficient β^{twfe} estimates the average treatment effect on treated counties (ATT). ATT is the average effect of having curbside collection on MSW landfill emissions in counties that received a program. This interpretation only holds under three strict assumptions. First, the treatment effect must be homogenous across all counties and years of implementation (homogenous treatment effects). Second, there must be parallel trends between counties that are treated, never-treated, and not-yet-treated. This implies that, in absence of a curbside collection program, MSW landfill CH_4 emissions in treated counties would have evolved the same as counties that are never-treated or not-yet-treated. With covariates (X_c), the parallel trends assumption states that per-household CH_4 emissions would have trended parallel, conditional on county-level characteristics. Finally, the usual SUTVA conditions apply. For instance, the existence of a composting program in one county should not impact the MSW landfill emissions of a neighbouring county (no spillovers).

To check for conditional parallel-trends, as well as dynamic effects, I extend the TWFE binary treatment specification to an event-study. It is well established that organic waste begins producing CH_4 6 months to 3 years after it is deposited in a landfill, and therefore the treatment effects of curbside compost collection will be dynamic, theoretically reaching their largest magnitude 5 to 10 years after implementation of a composting program USEPA (2015).[18] The TWFE event-study

[18] See Figure 4

with binary treatment can be specified using the following equation:

$$CH_{4ct}^{hh} = \sum_{k=K_0}^{-2} \gamma_k \cdot C_{ck} + \sum_{k=0}^{K_1} \beta_k^{twfe} \cdot C_{ck} + \lambda_c + \lambda_t + X_c \cdot \delta + \epsilon_{ct} \tag{3}$$

All variables are as specified in Equation 2. Equation 3 includes a year-specific treatment effect β_k^{twfe} for each year k where k denotes the number of years before or after the reference year (chosen as one-year prior to treatment in this specification (-1)). C_{ck} is the binary treatment variable, which equals 1 if the observation year t is k years from treatment. K_0 and K_1 are the minimum and maximum lag and lead from treatment. In the 2010-2017 timeframe, $K_0 = -6$ and $K_1 = 6$.

4.2 Classic Continuous Treatment TWFE Estimation

The major limitation of binary treatment is that it does not capture differences in treatment intensity. Curbside composting programs implemented at the municipal level rarely cover the entire county; therefore, treatment "dosage" can vary significantly across counties. This violates the homogenous-dose assumption of SUTVA. In all 6 datasets, the share of households receiving treatment (curbside collection) varies considerably across county-years; therefore the coefficient in the binary treatment Equation 2 (β^{twfe}) will be biased towards zero if it is interpreted as the ATT of providing a whole county with curbside collection.[19]

A growing number of papers have used continuous treatment DID (for instance, Lindo *et al.* (2017); Normington *et al.* (2019)). To account for varying treatment dosage, I estimate a variation on Equation 2 where the binary treatment variable C_{ct} is weighed by the fraction of county households that are covered by a curbside collection program in period t:

$$\omega_{ct} = \frac{\text{Households with Curbside Collection}_{ct}}{\text{Total Households}_{ct}}$$

Thus, the binary TWFE model can be re-estimated with continuous treatment as follows:

$$CH_{4ct}^{hh} = \beta^{twfe} \cdot C_{ct} \cdot \omega_{ct} + \lambda_c + \lambda_t + X_c \cdot \delta + \epsilon_{ct} \tag{4}$$

Callaway *et al.* (2021) build on early work by Angrist and Imbens (1995) to provide the first

[19] Appendix Figure 9 plots a histogram of treatment doses across county-years for each dataset.

comprehensive work on the assumptions required to get a causal interpretation of the continuous DID coefficient estimate in both a traditional 2x2 DID and TWFE model. Estimating Equation 4 with least squares yields a different estimate than in the binary specification, and requires additional assumptions. Unlike binary treatment, continuous treatment has both a level effect and a causal response effect. The level effect of dose d is the "difference between a unit's potential outcome under treatment d and its untreated potential outcome" (Callaway *et al.*, 2021). The causal response of an incremental increase in a unit's treatment dosage is the difference in potential outcomes for the unit under higher and lower dosage scenarios. The causal effect identified by the β^{twfe} estimator depends on the assumptions made with regards to parallel trends. This paper uses the strong parallel trends assumption with multiple periods and variation in treatment timing, which states that in absence of treatment dose d in period t, the potential outcomes of all treated groups g would have evolved the same as groups of all other doses, including those which are untreated. Formally:

$$
\begin{aligned}
&\forall g \in G,\ t = 2, ..., T \ \&\ d \in D, \\
&\mathbb{E}[Y_t(g,d)) - Y_{t-1}(0)|G = g, D = d] = \mathbb{E}[Y_t(g,d)) - Y_{t-1}(0)|G = g] \\
&\ \&\ \mathbb{E}[\Delta Y_t(0)|G = g, D = d] = \mathbb{E}[\Delta Y_t(0)|D = 0]
\end{aligned} \tag{5}
$$

In this paper, the groups g refer to treatment-cohort counties, and per-household CH_4 emissions in year t for group g with dose d are denoted as $Y_t(g,d)$. The third line in these assumptions states that parallel trends with the never-treated counties must hold unconditionally to dosage and group. As of present, Callaway *et al.* (2021) conclude that for β^{twfe} to interpret as an average causal affect across doses and groups, there must be homogenous causal responses and time-invariant treatment effects. This is problematic, given the aforementioned rationale to expect dynamic and heterogeneous treatment effects from curbside compost collection. Furthermore, it implies that the regression-based event study has no direct equivalent for continuous treatment. As such, I turn to an additional estimator for robustness in Section 4.3.

4.3 Chaisemartin and D'Haultfoeuille (2022) TWFE Estimation

It is highly unlikely that treatment effects are homogenous across counties. The treatment dosage varies significantly by county, and even effects from constant doses likely differ by county, since the CH_4 emitted from a kilogram of organic waste varies based on landfill-specific parameters in Equation 1. This is a problem, since the TWFE estimator is not robust to heterogenous treatment effects in staggered designs, as estimated treatment effects are not uniformly weighted across treatment-time (Goodman-Bacon, 2018). Even TWFE event-studies are not robust to heterogenous treatment effects (Sun and Abraham, 2018). Alternative estimators that are consistent and robust to heterogenous treatment effects have been proposed by Goodman-Bacon (2018), Borusyak *et al.* (2021), Callaway and Sant'Anna (2021), and Sun and Abraham (2018). All these estimators reweigh the treatment effects to yield a causal estimate of the ATT, but these estimators only apply to the binary treatment case.

Only a handful of papers have proposed alternative TWFE estimators that are robust to heterogenous treatment effects and continuous treatment (Chaisemartin and D'Haultfoeuille, 2020, 2022; Callaway *et al.*, 2021; Chaisemartin *et al.*, 2022). Of these four, only Chaisemartin and D'Haultfoeuille (2020) and Chaisemartin and D'Haultfoeuille (2022) have programmed and published their estimators for computational use.[20] By process of elimination, I opt to use the Chaisemartin and D'Haultfoeuille (2022) estimator (DID_M), since the estimator in Chaisemartin and D'Haultfoeuille (2020) is only capable of estimating instantaneous treatment effects.

The binary treatment DID_M estimator begins by estimating $DID_{g,l}$ for all treatment-year groups g and years after first treatment l (where $l = 0$ at first treatment). This estimator compares the evolution of outcomes between "switchers" (i.e. the counties that receive treatment for the first time in the same year T_g) with the counties that are never-treated or not-yet-treated up to l years after first treatment. This comparison looks from the first period before cohort g is treated ($T_g - 1$) to l periods after first treatment ($T_g + l$). The time-varying, dynamic estimates are then used to construct the DID_M estimator with a weighted average where the weighting corresponds to the number of "switchers" that are used in each time-varying effect (Chareyron *et al.*, 2020). The continuous treatment extension allows for treatment groups to be additionally categorized by treatment-dosages. The DID_M estimator linearly introduces county-characteristics as covariates X_c, and through Frisch-Waugh-Lovell theorem, compares conditional outcomes. There are several major assumptions for DID_M to estimate the treatment effect. First, there must be

[20]In May, Callaway *et al.* announced their code would be ready by mid-summer. To my dismay, they have yet to start. I will be sending a strongly worded letter. The Chaisemartin and D'Haultfoeuille (2020) estimator is only supported in the Stata package did_multiplegt.

no anticipation of treatment, such that a county's current outcomes are not determined by future expectations of treatment. Second, there must be independent groups, such that the potential outcomes of all county-groups in each period are mutually independent. Third, "shocks affecting a group's potential outcomes are mean independent of the group's treatment sequence" (Chaisemartin and D'Haultfoeuille, 2022). Similarly, shocks that affect a group's baseline never-treated potential outcome must not be correlated to whether the group will or has received treatment. Together, these assumptions imply that curbside composting programs are not systematically implemented earlier or later in a county because of their underlying landfill emissions trajectory. Finally, conditional parallel trends must hold such that in absence of treatment, the potential outcomes of county cohorts g that receive a treatment dose d must have evolved the same as among groups "with the same treatment as g at period one" who have yet to experience treatment in the timeframe.

Unlike a traditional event-study design which is not robust to staggered designs with heterogenous treament effects and continuous treatment, Chaisemartin and D'Haultfoeuille (2022) propose an alternate approach. Whereas the lags DID_l can be easily plotted and estimated, the problem arises in the leads: accordingly, Chaisemartin and D'Haultfoeuille (2022) propose instead to use placebos that compare "the outcome trends of switchers and non-switchers j years before the switchers switch." Finally, I bootstrap and cluster standard errors at the county-level. The DID_M estimator is not efficient, particularly when there is continuous treatment, since there are very few counties with similar treatment doses to compare. The share of households with curbside collection takes on a large range of continuous values between 0 and 1, so there are often few suitable controls for a county to compare against. As such, I follow Chaisemartin and D'Haultfoeuille (2020) and set a threshold to consider households that receive less than a 5 percentage point change in curbside collection coverage from their initial period as stable, and therefore suitable controls.

5 Results

The results are reported in three stages. First, I report the table of estimated average treatment effects on the treated (ATT) for the binary treatment specification, then the average causal response for continuous treatment. Finally, I present the event-studies for robust Chaisemartin and D'Haultfoeuille (2022) binary and continuous treatment. Before estimating each effect, I justify the inclusion of controls with a balance table and intuition. Regression tables for binary and continuous specifications (tables 2 and 3) and heterogeneity-robust event studies for the UU dataset (Figures 1 and 2) are located at the end of the section. More event-study results for different datasets and specifications can be found in Figures 11 through 28 of the Appendix.

I construct a balance-table of observables between counties that experience some dose of treatment in 2010 to 2017 and those that are never-treated. The difference in means between these variables motivates their inclusion, since it is clear that curbside collection is not randomly assigned. Counties with curbside collection have an average population over 4 times that of never-treated counties, have more MSW landfills in their borders, and have higher a median income, rental fraction, and average household size. It is clear that large, liberal, urban centres are receiving curbside composting, and so estimates of the ATT should be interpreted as the effect on these treated counties. In light of these differences, conditioning on covariates and invoking covariate-conditional parallel trends is a more reasonable assumption than assuming classic parallel trends between large, liberal urban centres and midsize, less dense republican counties. Appendix Table 13 describes these differences-in-means.

5.1 Binary Treatment Results

With binary treatment, table 2 presents the ATT estimates from both the standard TWFE coefficient β^{twfe} and the heterogeneity-robust estimator DID_M. The rows are the β^{twfe} and DID_M estimates for each dataset. The estimates are reported as controls are gradually introduced, beginning with simple demographic controls and ending with the share of households covered by a drop-off program. Standard errors are bootstrapped and clustered at the county-level. I begin with the UU dataset, and gradually move to the most conservative dataset (SBB). Similarly, I begin with no controls, followed by simple demographic controls (population, mean household size, renter fraction, and median income). These controls are likely important and unproblematic, since none are likely an outcome of curbside collection, and all are potentially important factors that influence the MSW characteristics of counties and households. I then introduce the number of facilities in a county, the share of votes for a democratic candidate, and the share of households covered by a drop-off program. These controls are more likely to be impacted by the rollout of curbside composting, and are therefore riskier covariates that also potentially overfit the estimate.

Few estimates are statistically significant at a 10% level, and those that are significant are not robust to the inclusion of covariates. Across both the DID_M and β^{twfe} estimators, the estimates mostly negative, statistically insignificant, and close to zero. This is not unexpected. As aforementioned, the binary treatment specification should bias the estimate towards zero because small, low-coverage curbside collection programs are considered to have the same unambiguous dose and importance as larger-scale programs. If conditional parallel trends hold, β^{twfe} should measure the average effect of curbside collection programs on per-household tonnes of MSW landfill CH_4 in treated counties. Rather than an instantaneous measure, DID_M averages the dynamic effects into a single estimate, weighted by the number of switchers in each year. The DID_M estimate tends to be a marginally stronger negative effect than β^{twfe}, but has larger standard errors.

5.2 Continuous Treatment Results

Table 3 reports the equivalent estimates for the continuous treatment specification. The β^{twfe} estimate gives the estimated average causal response of fully covering a previously-untreated county with curbside compost collection, among counties that receive some dosage of treatment. DID_M gives the equivalent heterogeneity-robust estimates as per Chaisemartin and D'Haultfoeuille (2022). Using only TWFE, the heterogenous-robust estimates for DID_M are weakly positive and insignificant; however, after conditioning on demographics, the effect becomes negative, and is mostly stable to additional covariates. This effect is more strongly negative than the binary treatment equivalents. Again, the estimates are not statistically significant at the 10% level, and the heterogeneity-robust estimates have particularly large standard errors.

5.3 Event-Study Results

In both the binary and continuous treatment designs, the causal effect of composting on landfill CH_4 emissions should theoretically be largest in magnitude 5 to 10 years after treatment. Figures 1 and 2 plot the UU dataset event-studies for the Chaisemartin and D'Haultfoeuille estimator using both binary treatment (Figure 1) and continuous treatment (Figure 2). Both figures include all covariates. Under the identifying assumptions discussed in Rection 4, the binary treatment event-study should give an estimate of the ATT in each period after treatment ($t = 0$). The continuous treatment event-study gives estimates of the average causal response to a county receiving full composting coverage in each year after treatment ($t = 0$). The magnitude of the negative effects are similar between the binary and continuous treatment specifications (roughly -0.1 to -0.2), corresponding to a reduction of 0.1 to 0.2 metric tonnes (100kg to 200kg) of CH_4 per household, per year. In both the binary and continuous treatment specification, the treatment effects are modest in magnitude for the first few years of treatment, gradually getting more negative until $t = 5$, when it is highest in magnitude (DID_{M_t} = -0.18 in both the continuous and binary specification). The 95% confidence intervals are unsurprisingly much larger with continuous treatment. Nonetheless, in both specifications, the estimates are not statistically significant at a 5% level. Finally, the placebo leads are all close to zero and statistically insignificant at the 95% level, with the exception of a small positive and significant spike in lead -2 in the continuous treatment specification. While overall the placebos are encouraging for conditional parallel trends, they are not sufficient to set aside concerns about the validity of the assumption.

I use a back-of-the-envelope calculation to compare the annual estimates to those of Taylor and De Silva (2021), who find that curbside compost collection diverts 25% of household waste from landfills per week. Taylor and De Silva (2021) use the benchmark that 1 tonne of organic matter emits 1.16 tonnes (250kg) of CO_2e (0.0464 tonnes of CH_4), and that 1 tonne of CH_4 is equivalent to 25 tonnes of CO_2e in terms of its GWP. The dynamic effects in Figures 1 and 2 show an annual reduction of 100kg to 200kg of CH_4 per household per year in a completely treated county. These estimates translate to a reduction of 41 to 82 kg of organic waste, per household, per week from entering landfills. In 2018, American MSW was produced at 87kg per household, per week, which is much higher in magnitude than in Australia (USEPA, 2020).[21]. Given this disparity, the MSW reduction from curbside composting in the U.S. should be higher than in Australia; however, the estimates of 41kg to 82kg of waste per household, per week (roughly 50% to 95% of weekly household waste) are implausibly high in light of Taylor and De Silva (2021). Given the wide confidence intervals and sobering implications from this rough calculation, the point-estimates in this paper are likely unreliable and overestimated.

More event-study figures are available in the Appendix for classical TWFE with binary treatment, and Chaisemartin and D'Haultfoeuille (2022) event-studies for all other datasets.

[21]Generation of MSW is 4.9 pounds per person, per day. The average household was 2.53 in 2018.

Table 2: Curbside Compost Collection on County-Level MSW Landfill CH_4 per Household

— Binary Treatment —

	Dependent Variable: County-Level Metric Tonnes of CH_4 per Household				
	(1) Two-Way Fixed Effects	(2) + Demographic Controls	(3) + Number of Facilities	(4) + Percent Voting Democrat	(5) + Share of Households with Drop-Off Compost
— UU Dataset —					
DID_M	0.06**	−0.05	0.05	−0.08	−0.08
	(0.02)	(0.09)	(0.07)	(0.10)	(0.10)
β^{twfe}	0.055	−0.006	−0.008	−0.050	−0.047
	(0.044)	(0.045)	(0.045)	(0.054)	(0.052)
— BU Dataset —					
DID_M	0.07*	−0.06	−0.06	−0.10	−0.09
	(0.04)	(0.13)	(0.11)	(0.06)	(0.10)
β^{twfe}	0.065	−0.003	−0.004	−0.051	−0.047
	(0.046)	(0.049)	(0.049)	(0.059)	(0.056)
— BB Dataset —					
DID_M	0.08**	−0.05	−0.05	−0.08	−0.08
	(0.04)	(0.08)	(0.12)	(0.11)	(0.06)
β^{twfe}	0.065	0.005	0.005	−0.043	−0.038
	(0.046)	(0.049)	(0.049)	(0.059)	(0.056)
— SUU Dataset —					
DID_M	0.06*	−0.05	−0.05	−0.08	−0.08**
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
β^{twfe}	0.055	−0.016	−0.019	−0.067	−0.062
	(0.044)	(0.046)	(0.046)	(0.056)	(0.054)
— SBU Dataset —					
DID_M	0.07	−0.05	−0.06	−0.09	−0.09
	(0.05)	(0.07)	(0.06)	(0.06)	(0.20)
β^{twfe}	0.065	−0.013	−0.015	−0.069	−0.063
	(0.046)	(0.050)	(0.049)	(0.060)	(0.058)
— SBB Dataset —					
DID_M	0.08*	−0.05	−0.05	−0.08	−0.08
	(0.04)	(0.08)	(0.12)	(0.11)	(0.06)
β^{twfe}	0.065	−0.005	−0.005	−0.059	−0.052
	(0.046)	(0.050)	(0.050)	(0.060)	(0.058)
Includes:					
Year and County FE	✓	✓	✓	✓	✓
Population		✓	✓	✓	✓
Mean Household Size		✓	✓	✓	✓
Renter Fraction		✓	✓	✓	✓
Median Income		✓	✓	✓	✓
Facility Number			✓	✓	✓
Democrat Share				✓	✓
Drop-Off Compost					✓

Notes: Standard errors bootstrapped and clustered at the county-level. β^{twfe} is the treatment coefficient estimate from TWFE regression. DID_M is the heterogeneous-treatment robust estimator from Chaisemartin and D'Haultfoeuille (2022). *p<0.1; **p<0.05; ***p<0.01

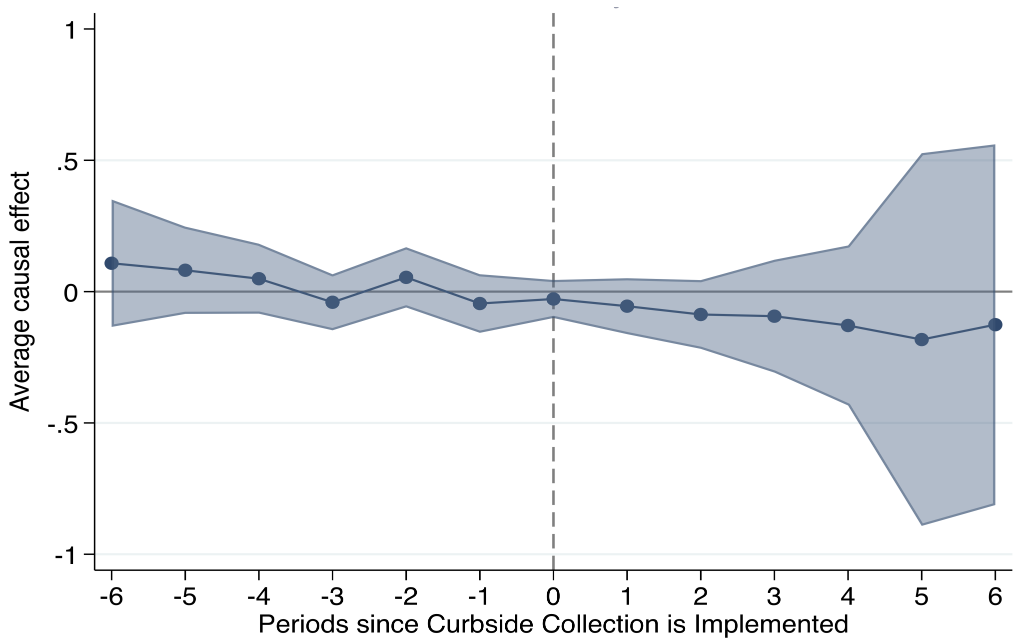
Table 3: Curbside Compost Collection on County-Level MSW Landfill CH_4 per Household

— Continuous Treatment —

	Dependent Variable: County-Level Metric Tonnes of CH_4 per Household				
	(1) Two-Way Fixed Effects	(2) + Demographic Controls	(3) + Number of Facilities	(4) + Percent Voting Democrat	(5) + Share of Households with Drop-Off Compost
— UU Dataset —					
DID_M	0.141	−0.220	−0.207	−0.202	−0.200
	(0.105)	(0.248)	(0.236)	(0.397)	(0.370)
β^{twfe}	0.057	−0.040	−0.040	−0.188	−0.175
	(0.129)	(0.150)	(0.150)	(0.169)	(0.163)
— BU Dataset —					
DID_M	0.164	−0.236	−0.232	−0.225	−0.222
	(0.112)	(0.392)	(0.429)	(0.328)	(0.419)
β^{twfe}	0.074	−0.034	−0.033	−0.191	−0.176
	(0.136)	(0.162)	(0.162)	(0.181)	(0.174)
— BB Dataset —					
DID_M	0.209	−0.188	−0.184	−0.184	−0.182
	(0.136)	(0.298)	(0.372)	(0.177)	(0.378)
β^{twfe}	0.074	−0.013	−0.013	−0.176	−0.160
	(0.136)	(0.165)	(0.165)	(0.182)	(0.174)
— SUU Dataset —					
DID_M	0.137	−0.233	−0.207	−0.200	−0.196
	(0.154)	(0.384)	(0.468)	(0.343)	(0.167)
β^{twfe}	0.057	−0.042	−0.044	−0.198	−0.185
	(0.129)	(0.148)	(0.148)	(0.166)	(0.161)
— SBU Dataset —					
DID_M	0.159	−0.250	−0.231	−0.222	−0.216
	(0.138)	(0.344)	(0.273)	(0.492)	(0.336)
β^{twfe}	0.074	−0.035	−0.036	−0.201	−0.185
	(0.136)	(0.160)	(0.159)	(0.177)	(0.171)
— SBB Dataset —					
DID_M	0.205	−0.202	−0.182	−0.182	−0.177
	(0.173)	(0.384)	(0.242)	(0.684)	(0.470)
β^{twfe}	0.074	−0.014	−0.014	−0.181	−0.164
	(0.136)	(0.163)	(0.163)	(0.178)	(0.173)
Includes:					
Year and County FE	✓	✓	✓	✓	✓
Population		✓	✓	✓	✓
Mean Household Size		✓	✓	✓	✓
Renter Fraction		✓	✓	✓	✓
Median Income		✓	✓	✓	✓
Facility Number			✓	✓	✓
Democrat Share				✓	✓
Drop-Off Compost					✓

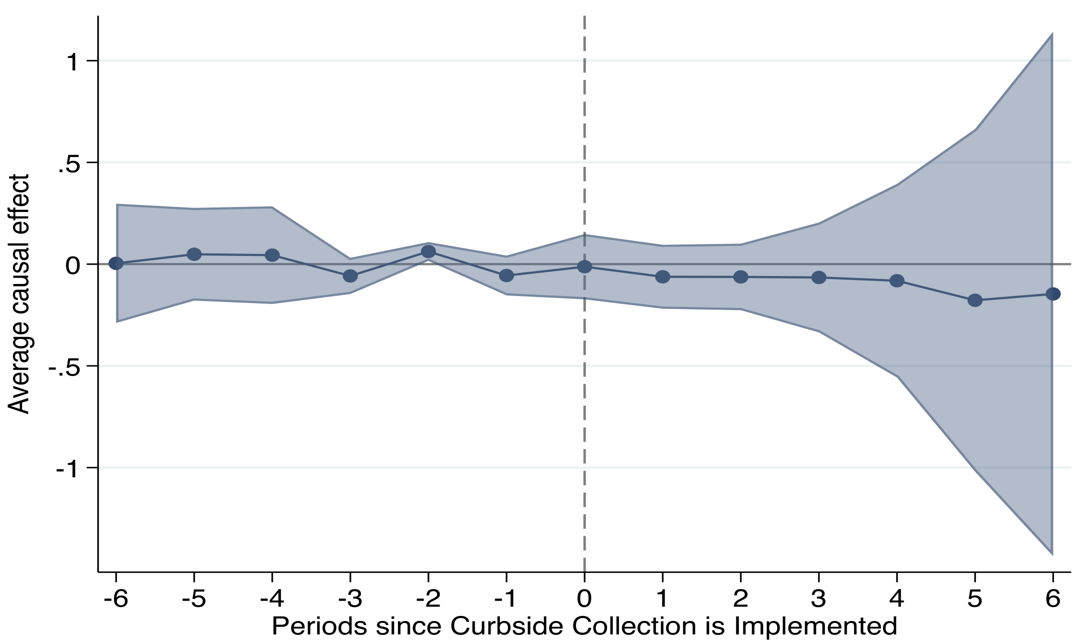
Notes: Standard errors bootstrapped and clustered at the county-level. β^{twfe} is the treatment coefficient estimate from TWFE regression. DID_M is the heterogeneous-treatment robust estimator from Chaisemartin and D'Haultfoeuille (2022).

Figure 1: de Chaisemartin (2022) DID_M Estimator, Binary Treatment, UU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



Conditioned on all covariates. Standard errors bootstrapped and clustered at the county-level. An average causal effect of -1 is a 1 metric tonne reduction in CH_4 per treated household, per year

Figure 2: de Chaisemartin (2022) Estimates, Continuous Treatment, UU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



6 Discussion

6.1 Limitations

The limitations of this paper stem from data quality and an inefficient, demanding empirical strategy. While some problems may be ameliorated in the future, many of them are unavoidable.

There is likely substantial measurement error in both the EPA Inventory of GHG emissions and BioCycle Nationwide Survey dataset. For landfills, imprecise estimates of soil oxidation, waste composition, decay rate, and recovery rate can all compound to produce substantial error in the final measurement of CH_4. So long as this measurement error is random, the DID estimators should remain consistent, albeit less efficient; however, there may be an incentive for high-emissions landfills to underreport their CH_4 emissions so as to avoid stringent regulations. There exists compelling evidence of underreporting (Maher and Kelly, 2021). In this case, the DID estimates will contain measurement bias. As a nationwide survey, BioCycle estimates of households with composting may be incorrectly measured, either through missing programs entirely and/or imprecisely rounding their estimates. [22] Unless communities usually receive composting services in increments of 100 households, I suspect there may have been some rounding. This measurement error is most likely classical, but nonetheless, measurement error in the independent variable causes bias and noise.

The second major issue comes from a lack of statistical power in the estimation, which may contribute to the noisy estimates. This paper uses a strategy that accommodates for staggered-adoption, continuous treatment dosage, and heterogenous, time-varying effects. Despite these demands, there are only 48 counties that are treated (out of 923) in the UU dataset, and even fewer in the others. This accounts for less than 400 observations of not-yet treated or treated county-years. Appendix table 12 provides these figures for each dataset. For dynamic effects, the number of counties treated each year is less than ten, and often with widely varying doses. The number of counties treated in 2011 or 2012 is very sparse, and as such, the confidence intervals are widest in the 5th and 6th year after treatment, when the effect should be most pronounced. This has further implications on identifying assumptions, since it is unlikely the conditional strong parallel trends assumption holds between a small number of uniquely-dosed "switchers" each treatment-period.

[22] The BlueGreen Organization has a similar dataset I intended to use as an IV for measurement error. My request to access to this data was met deafening silence.

Finally, the estimator of Chaisemartin and D'Haultfoeuille (2022) is known to be inefficient, yielding large standard errors (especially with continuous treatment).

The final limitations are in the design of the empirical strategy, rather than the data and estimation precision. First, counties that adopt composting may also enact other changes to waste policy at the same time. These changes could target residents, such as changes in garbage fees in pay-by-bag cities, or implementing state-level commerical regulations. Alternatively, these changes could be at the landfill-level. New technologies and methods of storing waste, such as transitioning to a "dry tomb" landfill, or introducing improved CH_4 recovery can reduce emissions.[23] It is reasonable to assume that municipalities with curbside composting programs are more likely to implement these other policies if they are motivated by an environmentally conscious electorate. If these simultaneous policies are not controlled for, the estimated causal effects would be biased by attributing the effect of these other programs to curbside composting. This is one explanation for why the point-estimates of the treatment effects are so implausibly large. The second issue is that landfills may not strictly serve residents of the county that they belong to. This would violate the stable unit treatment value assumption (SUTVA). If a treatment county has some of its waste stored in a neighbouring control county's landfill, then a curbside composting program could reduce the emissions of a neighbouring county.

While the issues with empirical design may be unavoidable, the limitations with data may hopefully ameliorate over time. As more communities adopt curbside compost collection, estimates may improve in precision and better satisfy the identifying assumptions. Improved composting data over a longer period of time (2010-2022) would also offer a better look into the dynamic effects of curbside compost collection. Finally, as the continuous treatment DID literature expands, more efficient estimators may become readily available.

6.2 Contributions

While there are obvious limitations, this paper still makes contributions for both policy and research in four regards. First, there is some weak evidence to suggest that curbside compost collection is reducing landfill CH_4 emissions per household, even though the point-estimates are

[23] It is worth noting that there is EPA data on estimates of landfill leachate levels, acreage, type of CH_4 collection system, and architecture. However, this data offers no simple way to aggregate to county-level, and requires significant cleaning. For these reasons, the data were not used in this paper.

not statistically significant at a 5% level. Second, I cleaned, geo-located, and aggregated data from the BioCycle Nationwide survey into a novel county-level panel dataset that merged with MSW landfill emissions data. This involved a considerable amount of data cleaning, and I intend to make the finished product publicly available for future use. Third, this paper brings attention to the inadequacies of data availability and standards (or lack-thereof) for composting data and emissions measurement. Composting program data are not meaningfully and regularly maintained outside of a few dedicated but under-equipped organizations and researchers. As a result, the data are imprecise, lacking in scale, and irregularly updated. Given the potential for GHG reductions through composting, access to reliable, precise data is important to assessing the cost-benefit of these programs. Similarly, this paper brings attention to some major concerns with the state of MSW landfill GHG emissions reporting, and potential for manipulation. Finally, this paper contributes to the emerging but largely preliminary literature of applied-works using continuous treatment difference-in-differences with staggered-adoption and heterogeneous, time-varying effects.

7 Conclusion

Curbside composting programs have the potential to greatly reduce GHG emissions from MSW landfills, since they divert organic waste from landfills where waste decomposes anaerobically. Anaerobic decomposition of organic waste emits a high concentration of CH_4, causing MSW landfills to be the third largest industrial emitter of CH_4 in the United States. Despite the growing popularity of curbside composting, there is a significant gap in the literature on the effectiveness of composting programs. No real-world academic studies have estimated the effect of curbside composting programs on county-level MSW landfill emissions. Using a continuous treatment TWFE and event-study design, as well as landfill emissions data from the EPA Inventory of U.S. GHG Emissions and Sinks, this paper estimates the causal effect of the staggered rollout of composting programs on county-level MSW landfill CH_4 emissions. Noise in the estimation from measurement error and a low sample size of treated counties result in imprecise estimates that are not statistically significant at a 5% level. Similarly, the point-estimates provide implausible implications in terms of the magnitude of household waste diverted from landfills after the introduction of a county-wide curbside collection program. Nonetheless, the estimates are consistently negative across multiple specifications, indicating that in spite of the estimation noise, there is some weak evidence to suggest curbside collection programs are reducing county-level MSW landfill emissions. As data improves, the sample timeframe increases, and more curbside collection programs are adopted future research will be able to evaluate the success of those policies, using the framework provided by this paper. Until then, composting and MSW landfill emissions will continue to evade the attention of economists, policymakers, and the American public.

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A Appendix Tables and Figures

Table 4: EPA GHG Inventory - MSW Landfill Summary (2010-19)

Year	Unique Facilities	Unique Counties	metric tonnenes of CH_4 (Unbalanced)	metric tonnenes of CH_4 (Balanced)
2010	1,235	808	100,996,886.99	96,168,103.73
2011	1,240	811	92,795,010.21	88,452,088.60
2012	1,252	814	93,404,052.32	88,669,610.98
2013	1,240	683	90,055,495.40	85,331,440.90
2014	1,237	682	89,666,196.50	84,794,507.50
2015	1,168	665	88,331,070.75	84,027,811.00
2016	1,144	661	85,355,210.75	81,041,658.75
2017	1,138	659	84,915,050.00	80,792,816.00
2018	1,136	659	87,138,148.25	82,919,754.25
2019	1,124	658	88,848,611.25	84,574,670.75

Balanced panel includes only the 1037 facilities present in all years.
Unbalanced panel covers 70.4% of the US Population.

Table 5: Nationwide BioCycle Survey (2017) — Summary Statistics

Affected Curbside Households	4,981,434
Affected Dropoff Households	6,584,781
Unique Communities:	202
Counties with Composting	98
Counties with Curbside	75
Counties with Dropoff	41

Includes communities missing treatment information.

Table 6: UU GHG and Compost Dataset — Summary Statistics

Year	Observations	Counties	Cumulative Households (Curbside)	Cumulative Households (Drop-Off)	CH4	Facilities
2010	862	862	1,482,765	2,177,436	100,996,887	1,220
2011	867	867	1,717,419	2,178,577	92,795,010	1,232
2012	881	881	1,881,915	2,233,577	93,404,052	1,249
2013	889	888	2,478,208	2,521,883	90,101,725	1,240
2014	889	889	2,502,722	2,521,883	89,666,196	1,237
2015	861	861	2,681,396	3,158,494	88,331,071	1,168
2016	857	857	2,853,342	3,548,979	85,355,211	1,144
2017	856	856	3,378,459	3,583,852	84,915,050	1,138
Total:	6,962	923	3,378,459	3,583,852	725,565,202	1,312

Observations reporting zero CH_4 emissions dropped after subsetting.
113 Unique communities with composting programs.

Table 7: BU GHG and Compost Dataset — Summary Statistics

Year	Observations	Counties	Cumulative Households (Curbside)	Cumulative Households (Drop-Off)	CH4	Facilities
2010	792	792	1,348,203	1,027,467	98,955,504	939
2011	792	792	1,582,857	1,028,608	90,846,343	945
2012	793	793	1,747,353	1,083,608	90,947,336	948
2013	794	793	2,098,606	1,083,608	87,309,075	937
2014	793	793	2,123,120	1,083,608	86,720,342	933
2015	793	793	2,301,794	1,710,433	85,672,093	913
2016	793	793	2,473,740	2,100,918	82,762,682	897
2017	793	793	2,998,857	2,135,791	82,152,682	893
Total:	6,343	793	2,998,857	2,135,791	705,366,056	962

Observations reporting zero CH_4 emissions dropped after subsetting.
105 Unique communities with composting programs.

Table 8: BB GHG and Compost Dataset — Summary Statistics

Year	Observations	Counties	Cumulative Households (Curbside)	Cumulative Households (Drop-Off)	CH4	Facilities
2010	788	788	1,348,203	1,027,467	96,986,438	873
2011	788	788	1,582,857	1,028,608	88,610,209	873
2012	789	789	1,747,353	1,083,608	88,475,415	873
2013	790	789	2,098,606	1,083,608	84,779,271	873
2014	789	789	2,123,120	1,083,608	84,285,211	873
2015	789	789	2,301,794	1,710,433	83,434,864	873
2016	789	789	2,473,740	2,100,918	80,637,133	873
2017	789	789	2,998,857	2,135,791	80,270,941	873
Total:	6,311	789	2,998,857	2,135,791	687,479,482	873

Observations reporting zero CH_4 emissions dropped after subsetting.
105 Unique communities with composting programs.

Table 9: SUU GHG and Compost Dataset — Summary Statistics

Year	Observations	Counties	Cumulative Households (Curbside)	Cumulative Households (Drop-Off)	CH4	Facilities
2010	847	847	996,653	1,980,208	99,511,501	998
2011	852	852	1,231,307	1,981,349	91,334,930	1,006
2012	866	866	1,393,294	2,036,349	91,992,618	1,022
2013	873	873	1,974,089	2,324,655	88,739,352	1,014
2014	875	875	1,994,086	2,324,655	88,490,470	1,008
2015	847	847	2,017,270	2,776,655	87,182,502	960
2016	844	844	2,169,955	3,040,655	84,387,375	942
2017	843	843	2,679,788	3,046,155	83,856,401	936
Total:	6,847	908	2,679,788	3,046,155	715,495,151	1,070

Observations reporting zero CH_4 emissions dropped after subsetting.
82 Unique communities with composting programs.

Table 10: SBU GHG and Compost Dataset — Summary Statistics

Year	Observations	Counties	Cumulative Households (Curbside)	Cumulative Households (Drop-Off)	CH4	Facilities
2010	779	779	996,653	1,027,467	97,509,768	928
2011	779	779	1,231,307	1,028,608	89,419,441	934
2012	780	780	1,393,294	1,083,608	89,569,650	937
2013	780	780	1,729,049	1,083,608	85,970,699	927
2014	780	780	1,749,046	1,083,608	85,560,742	923
2015	780	780	1,772,230	1,535,608	84,534,287	904
2016	780	780	1,924,915	1,799,608	81,794,846	889
2017	780	780	2,434,748	1,805,108	81,094,033	885
Total:	6,238	780	2,434,748	1,805,108	695,453,467	951

Observations reporting zero CH_4 emissions dropped after subsetting.
76 Unique communities with composting programs.

Table 11: SBB GHG and Compost Dataset — Summary Statistics

Year	Observations	Counties	Cumulative Households (Curbside)	Cumulative Households (Drop-Off)	CH4	Facilities
2010	775	775	996,653	1,027,467	95,572,203	865
2011	775	775	1,231,307	1,028,608	87,232,878	865
2012	776	776	1,393,294	1,083,608	87,150,244	865
2013	776	776	1,729,049	1,083,608	83,485,857	865
2014	776	776	1,749,046	1,083,608	83,153,492	865
2015	776	776	1,772,230	1,535,608	82,309,185	865
2016	776	776	1,924,915	1,799,608	79,669,297	865
2017	776	776	2,434,748	1,805,108	79,212,292	865
Total:	6,206	776	2,434,748	1,805,108	677,785,448	865

Observations reporting zero CH_4 emissions dropped after subsetting.
76 Unique communities with composting programs.

Table 12: Number of Treated and Not-Yet Treated Observations by Dataset

	Dataset	Observations	Counties
1	UU	376	48
2	BU	361	45
3	BB	361	45
4	SUU	315	40
5	SBU	304	38
6	SBB	304	38

Table 13: Covariate Balance Table - UU Dataset

Variable	Treated	Never-Treated
Facilities	2.26	1.35
AvgHHSize	3.24	3.11
MedianIncome	67,403	49,167
Population	1,021,205	225,276
RenterFraction	0.37	0.30
DemShare	0.59	0.42

Figure 3: Municipal Solid Waste by Composition Type (Figure from USEPA (2022b))

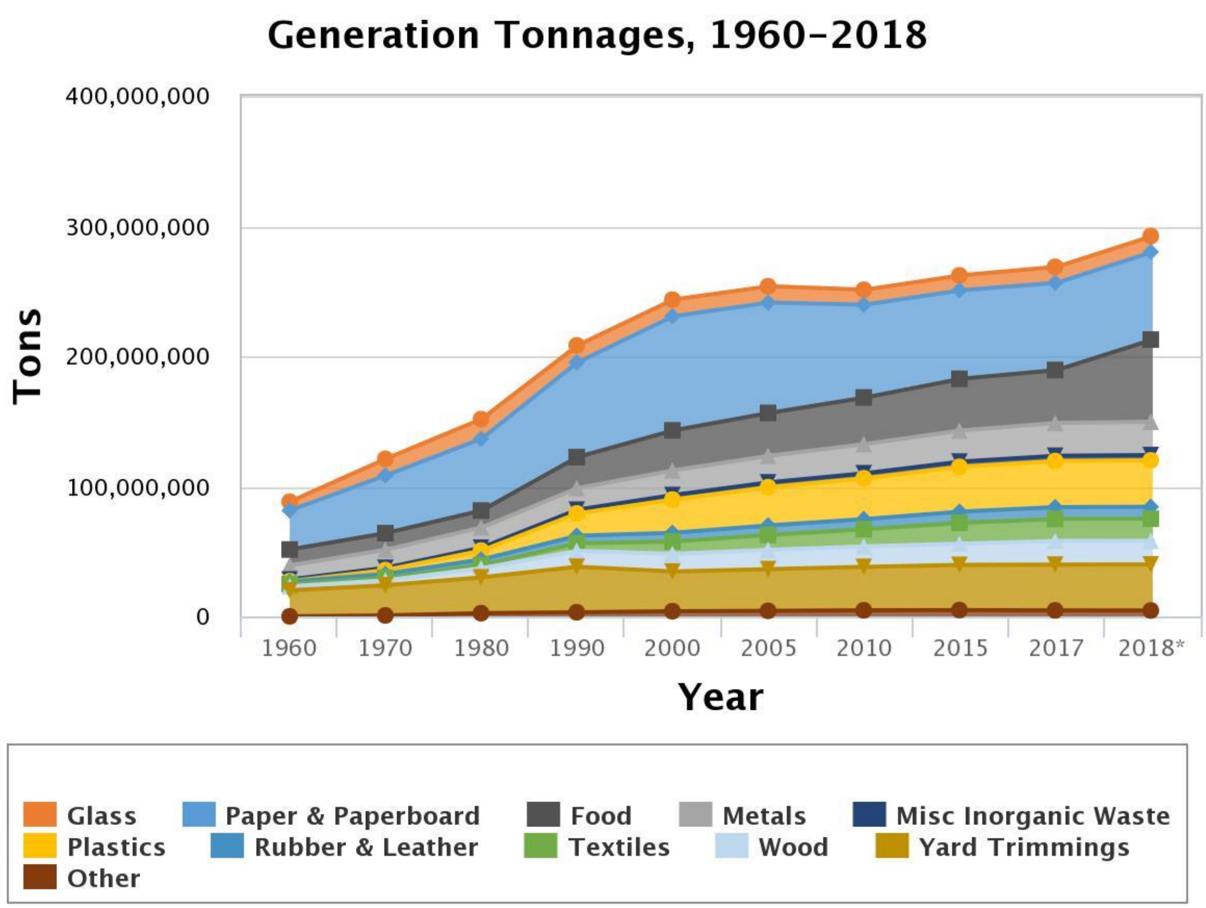


Figure 4: MSW Landfill Methane Generation Curve for 5 Years of Waste (EPA, 2015)

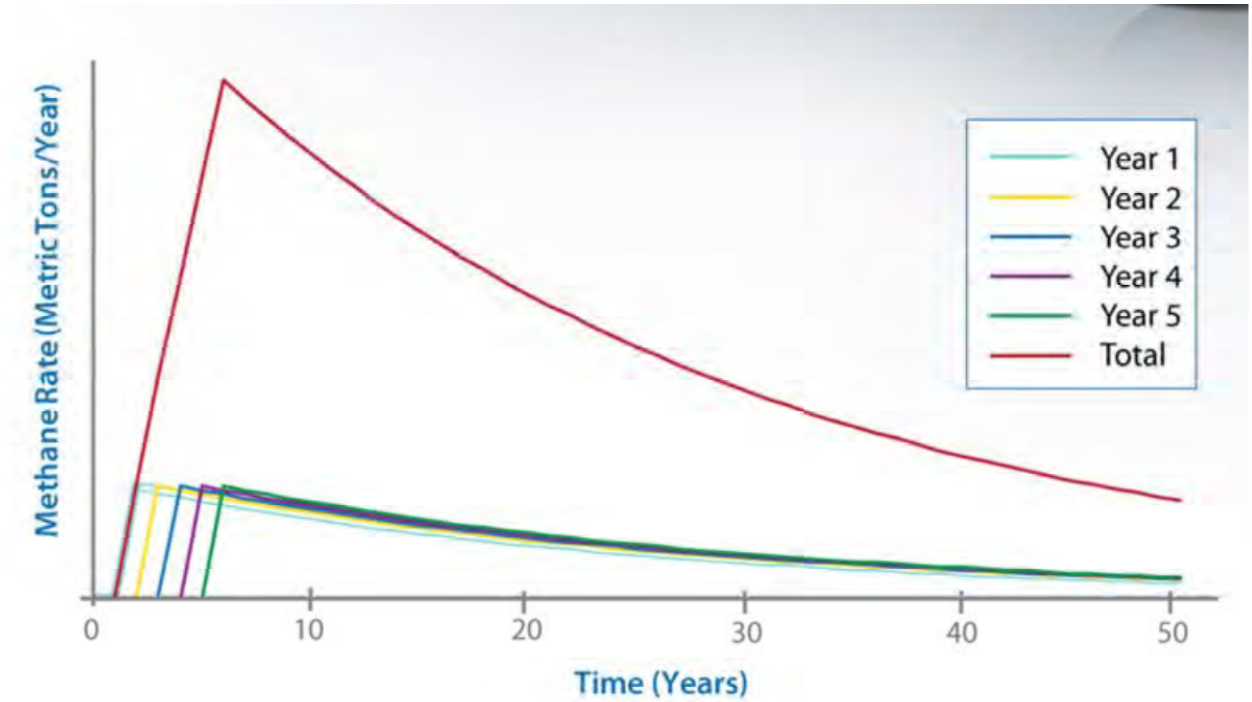
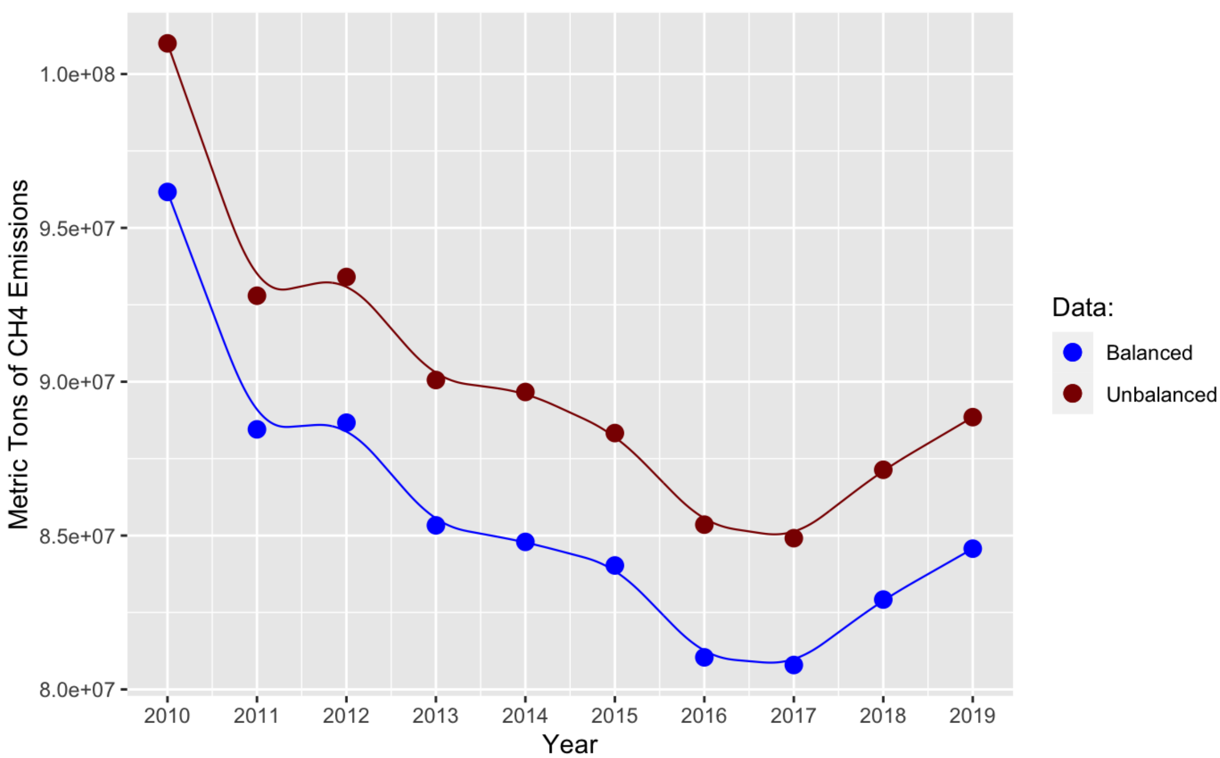
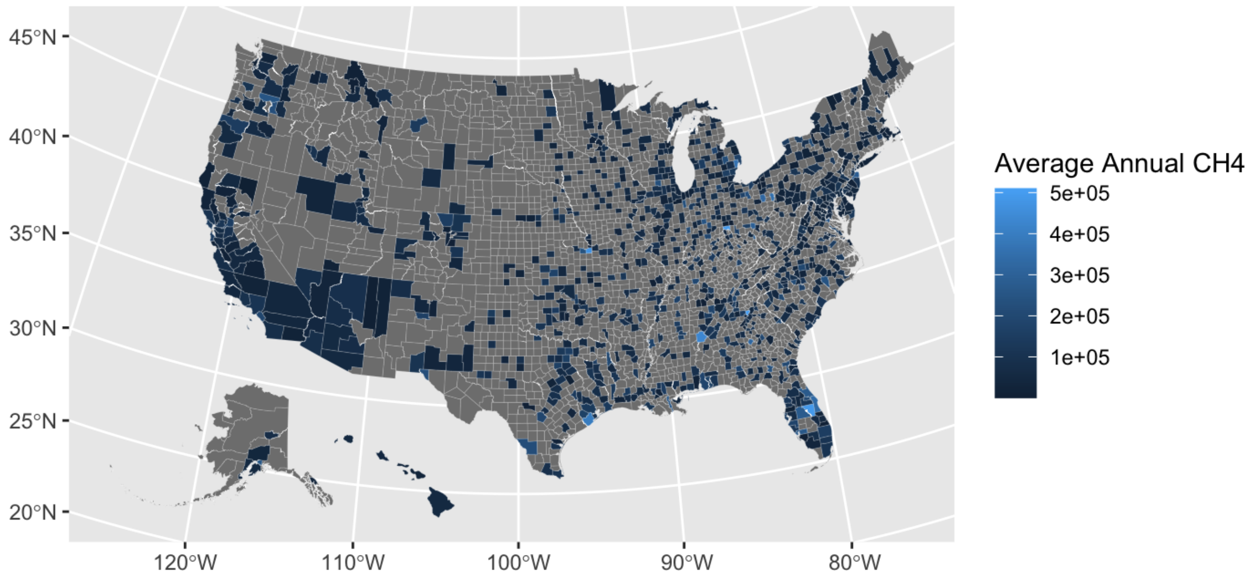


Figure 5: U.S. Municipal Waste Sector Methane Emissions by Year



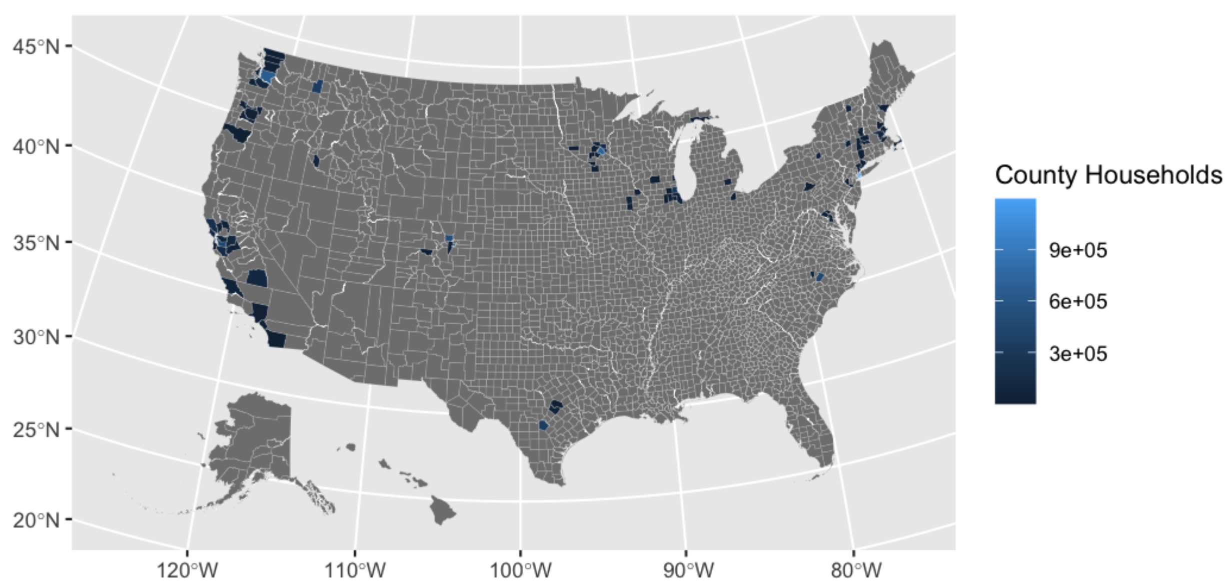
Source: U.S. Inventory of GHG Emissions and Sinks

Figure 6: Municipal Waste Sector — Average CH_4 Emissions by County



Source: U.S. Inventory of GHG Emissions and Sinks

Figure 7: Treated Households in Counties with Curbside Collection (2017)



Source: BioCycle Nationwide Survey, (2017)

Figure 8: Annual MSW Landfill CH_4 Emissions by Dataset

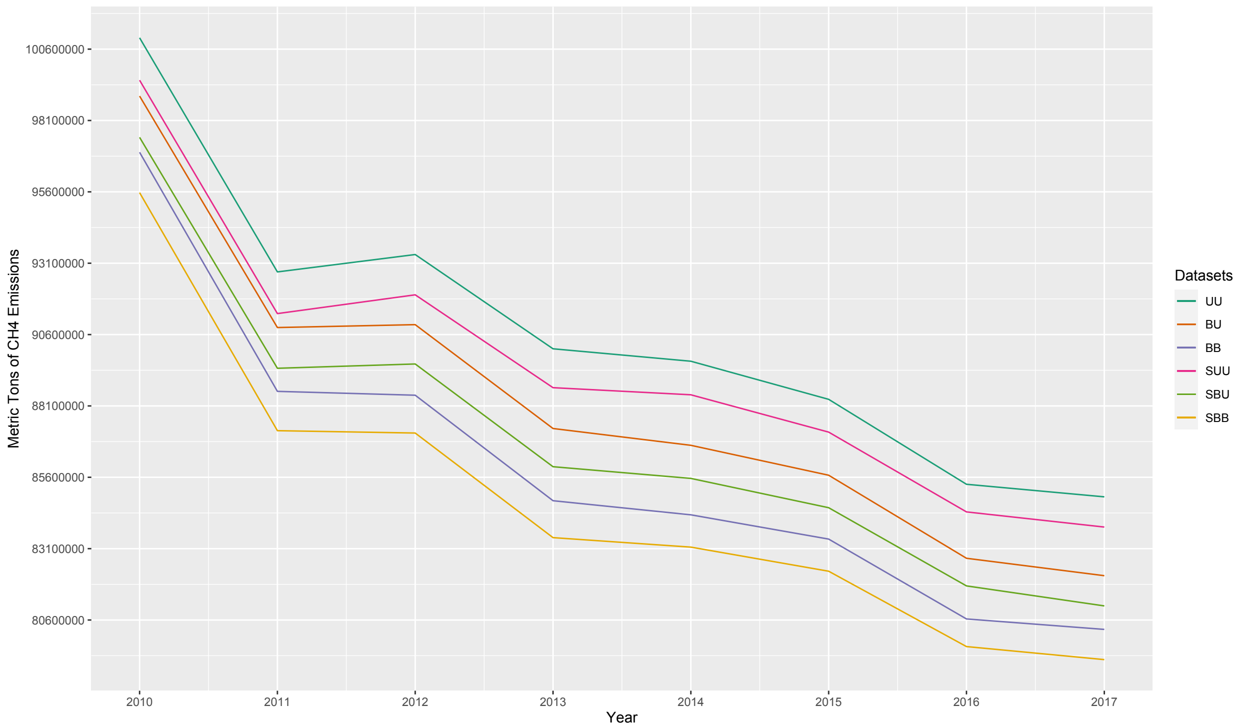


Figure 9: Share of Households with Curbside Collection by Dataset

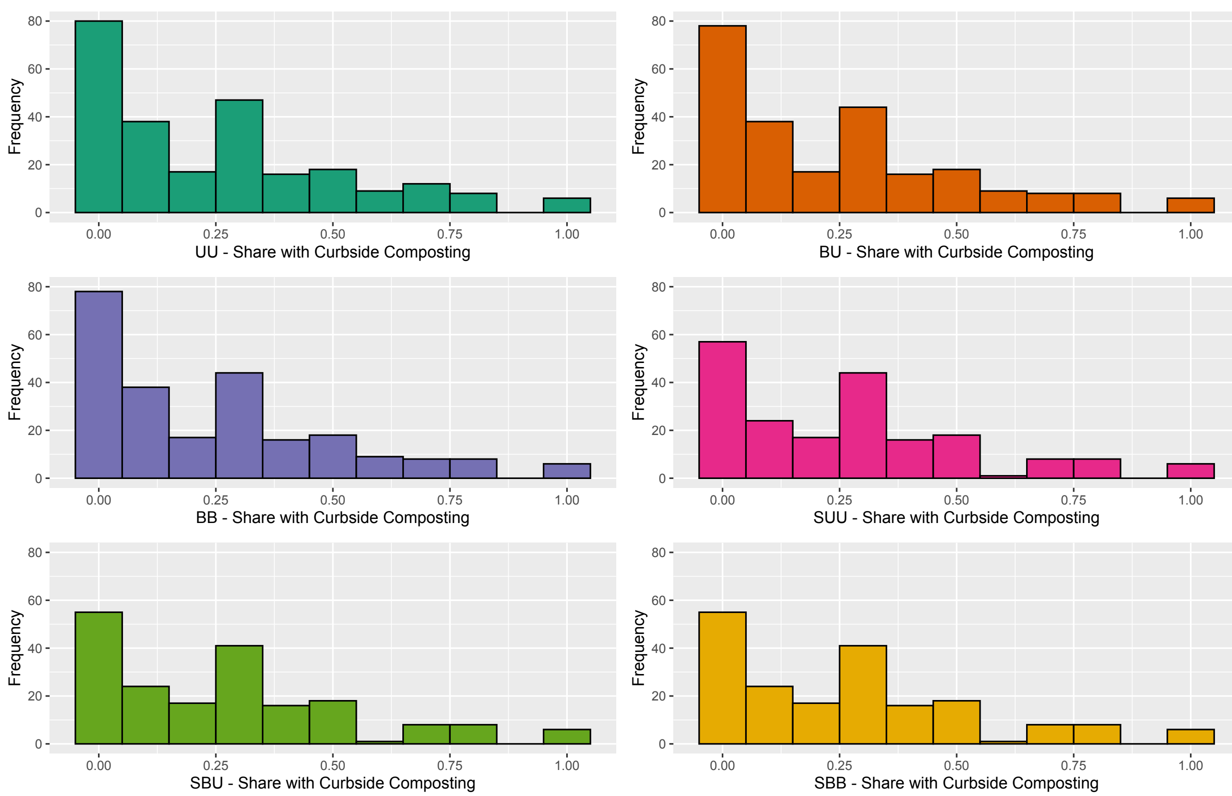


Figure 10: Number of Households Receiving Curbside Collection by Year

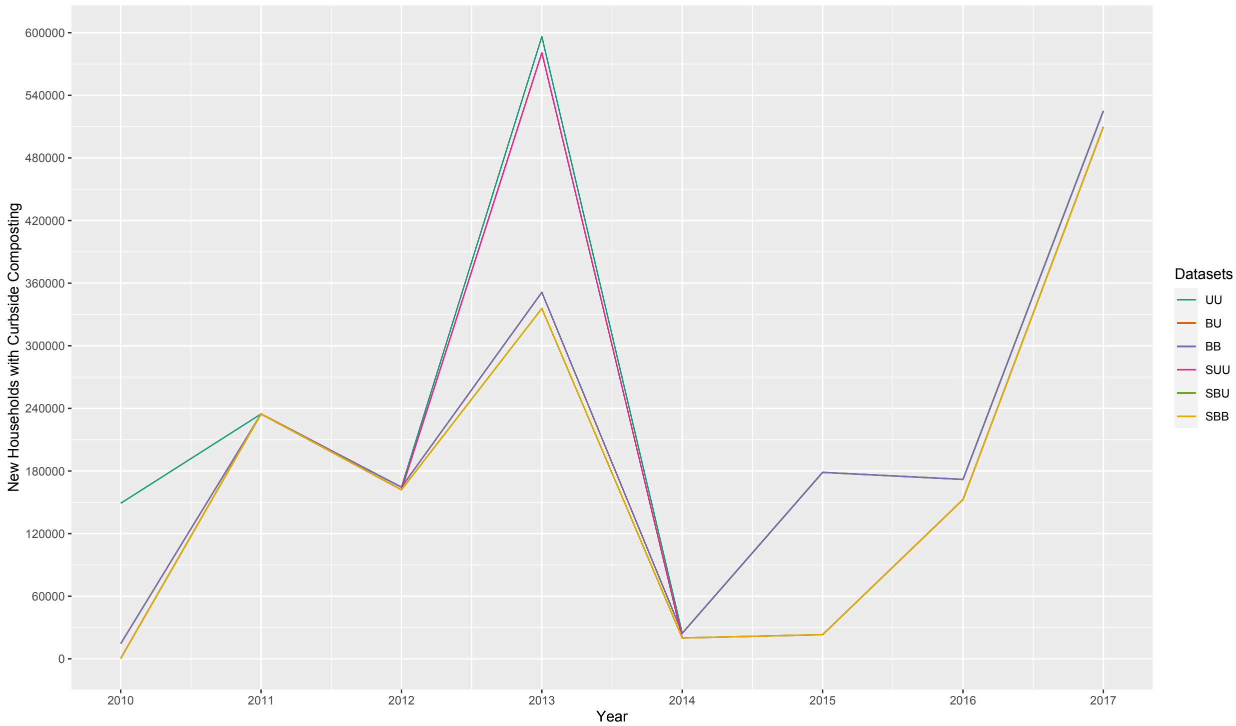
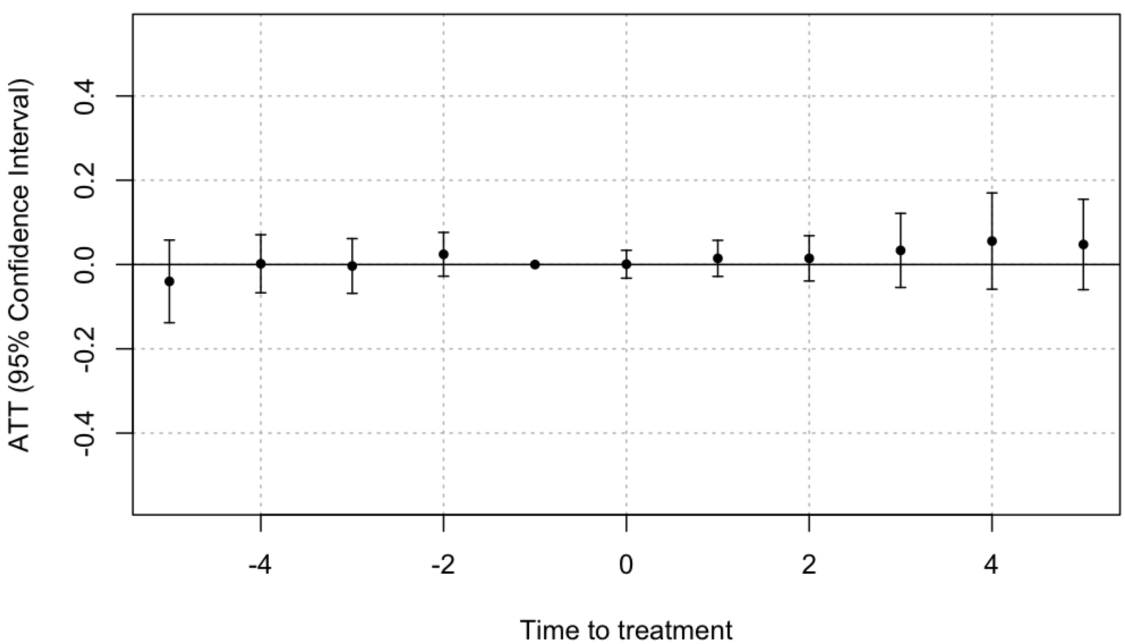
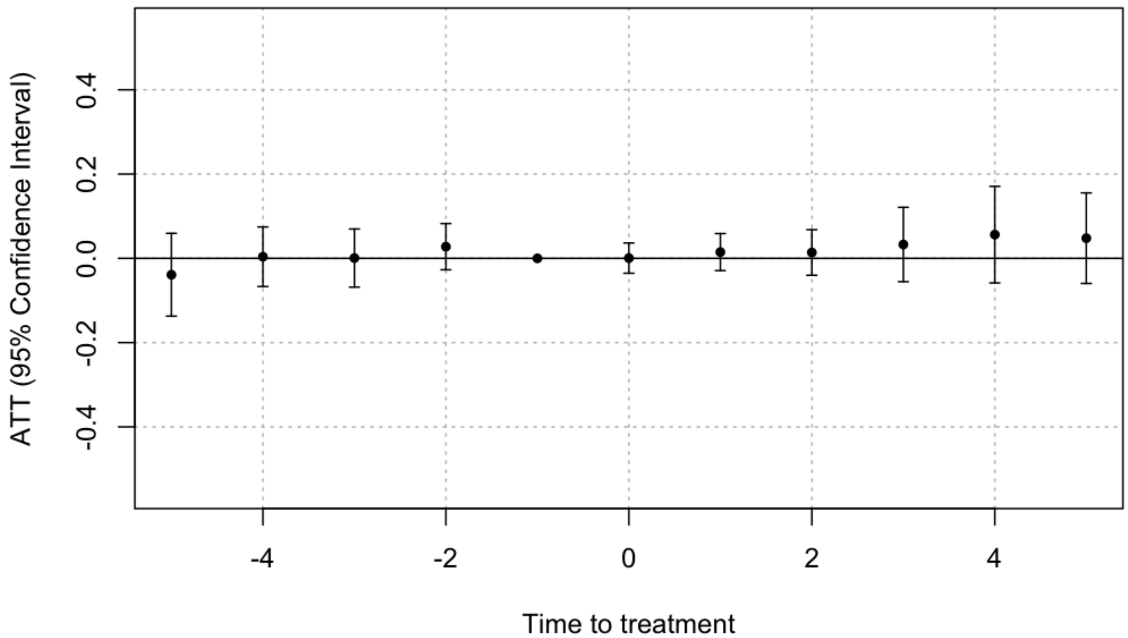


Figure 11: Classic TWFE Regression, Binary Treatment, UU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



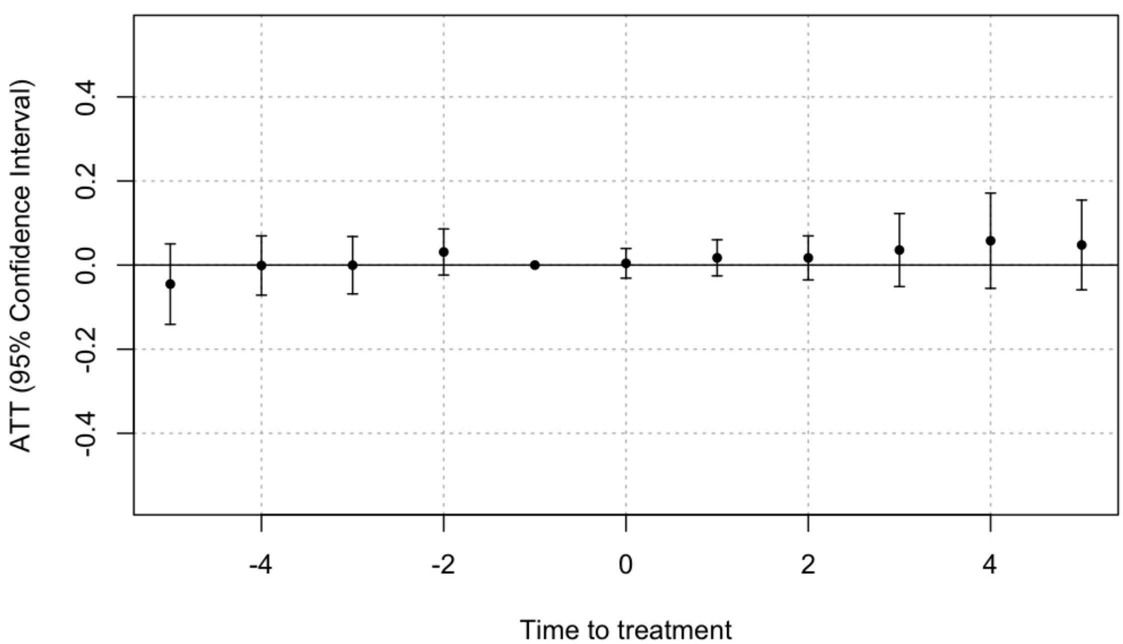
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 12: Classic TWFE Regression, Binary Treatment, BUDataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



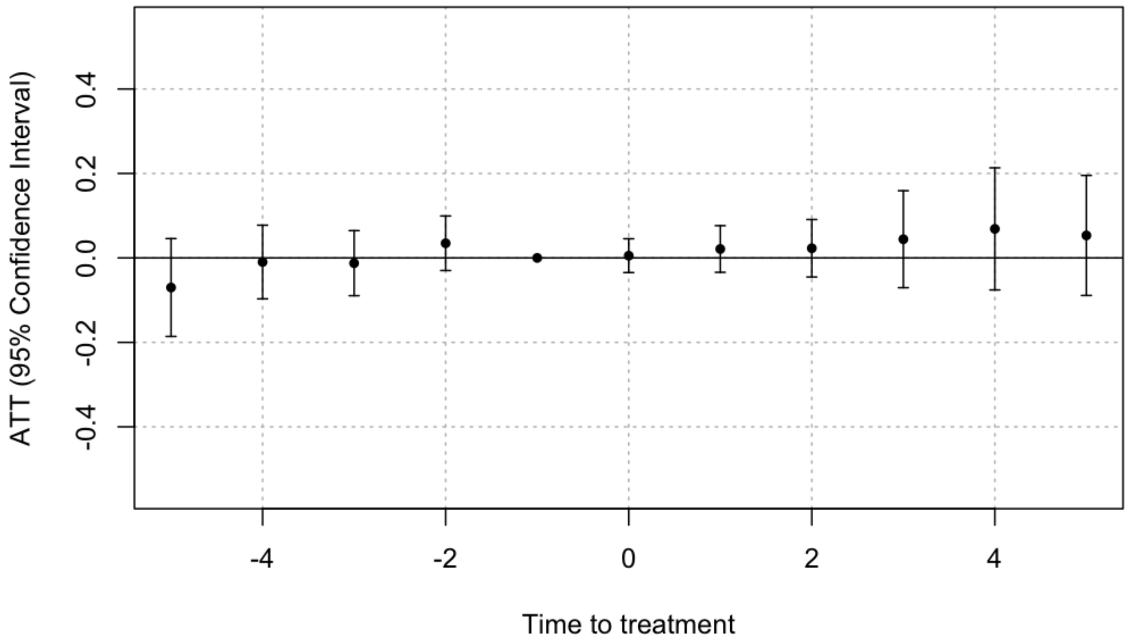
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 13: Classic TWFE Regression, Binary Treatment, BB Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



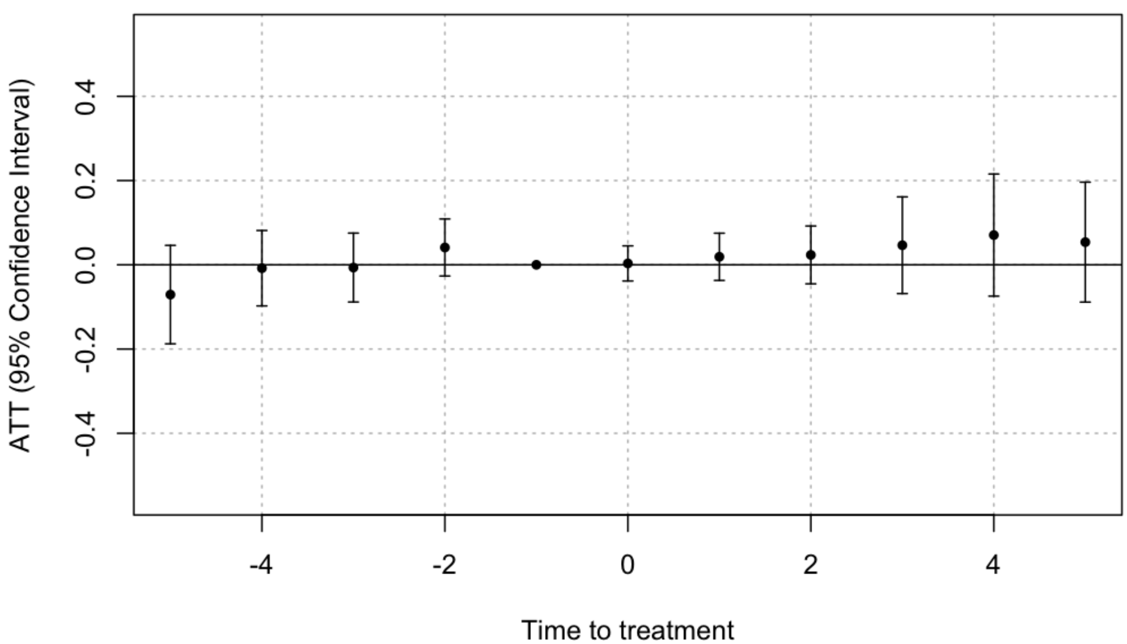
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 14: Classic TWFE Regression, Binary Treatment, SUU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



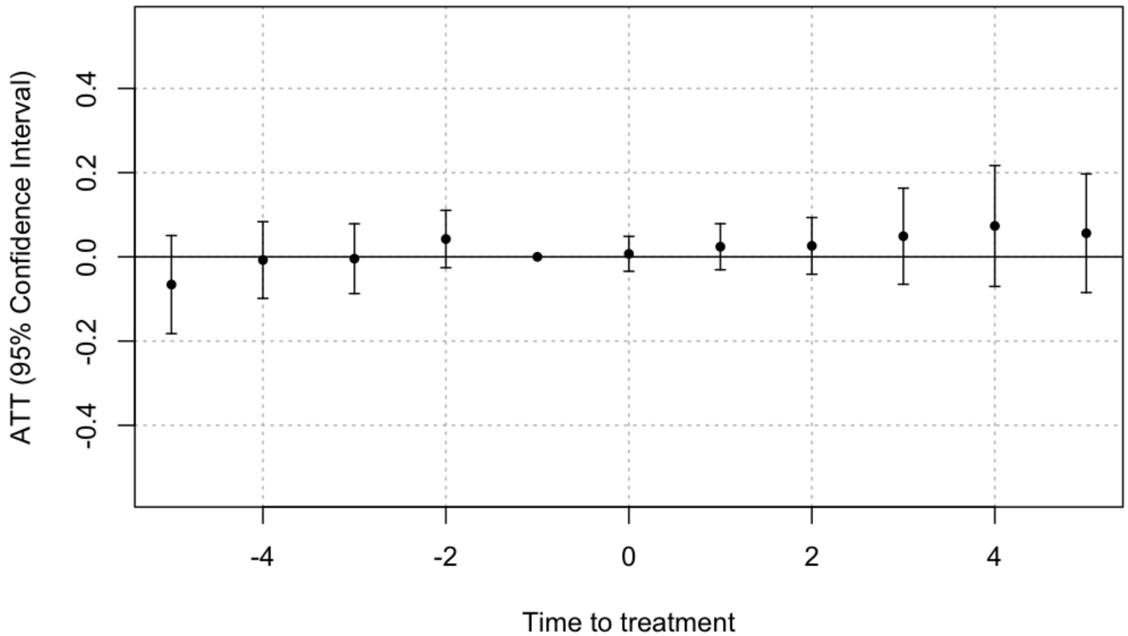
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 15: Classic TWFE Regression, Binary Treatment, SBU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



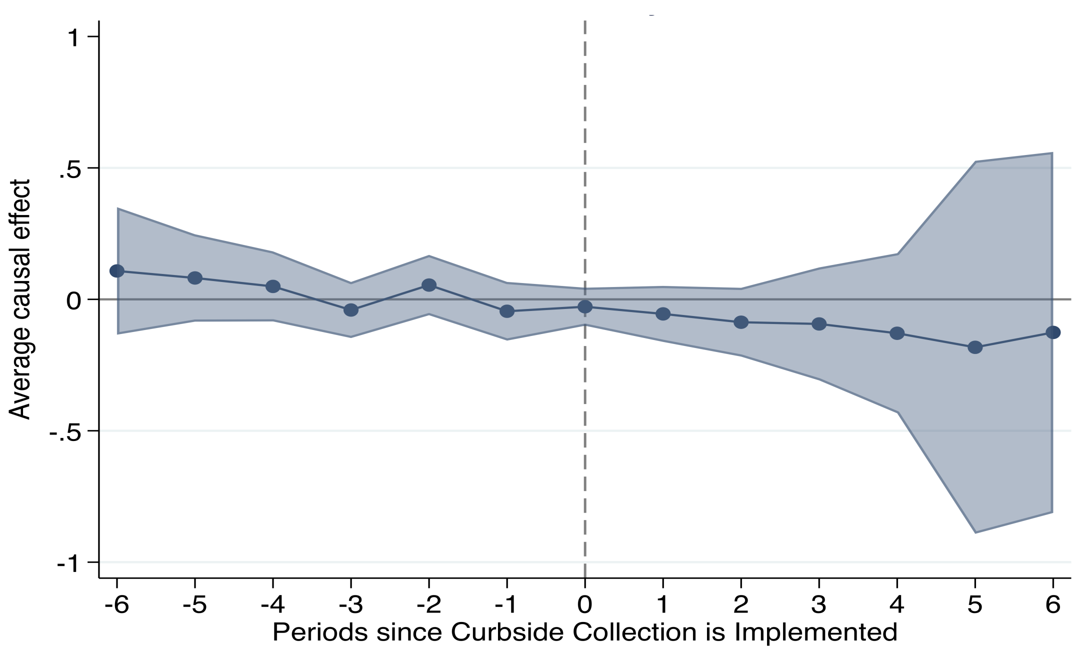
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 16: Classic TWFE Regression, Binary Treatment, SBB Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



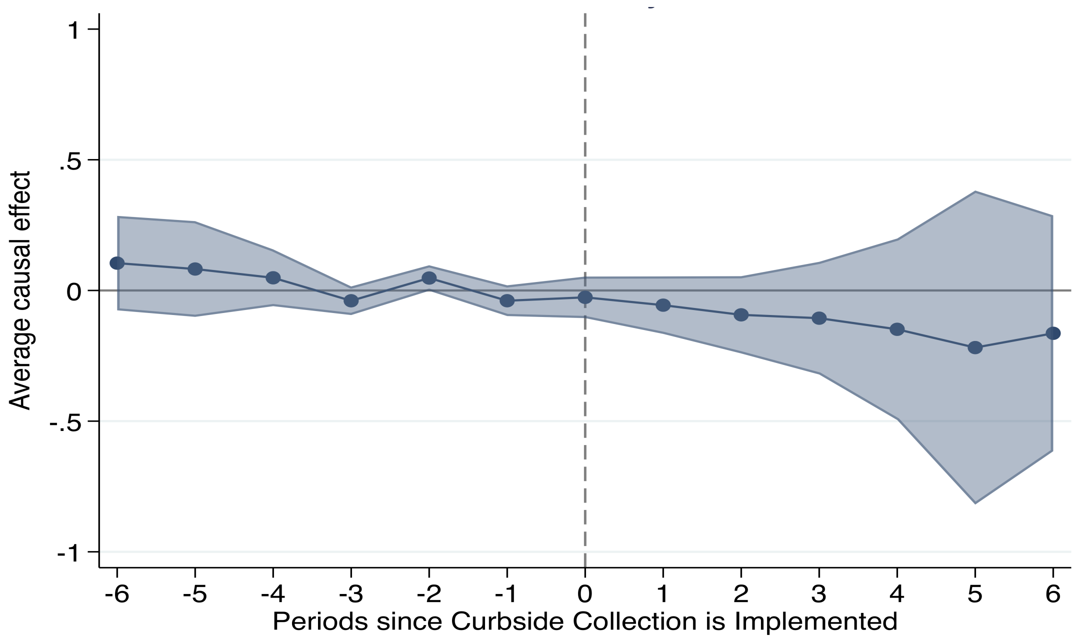
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 17: de Chaisemartin (2022) Estimates, Binary Treatment, UU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



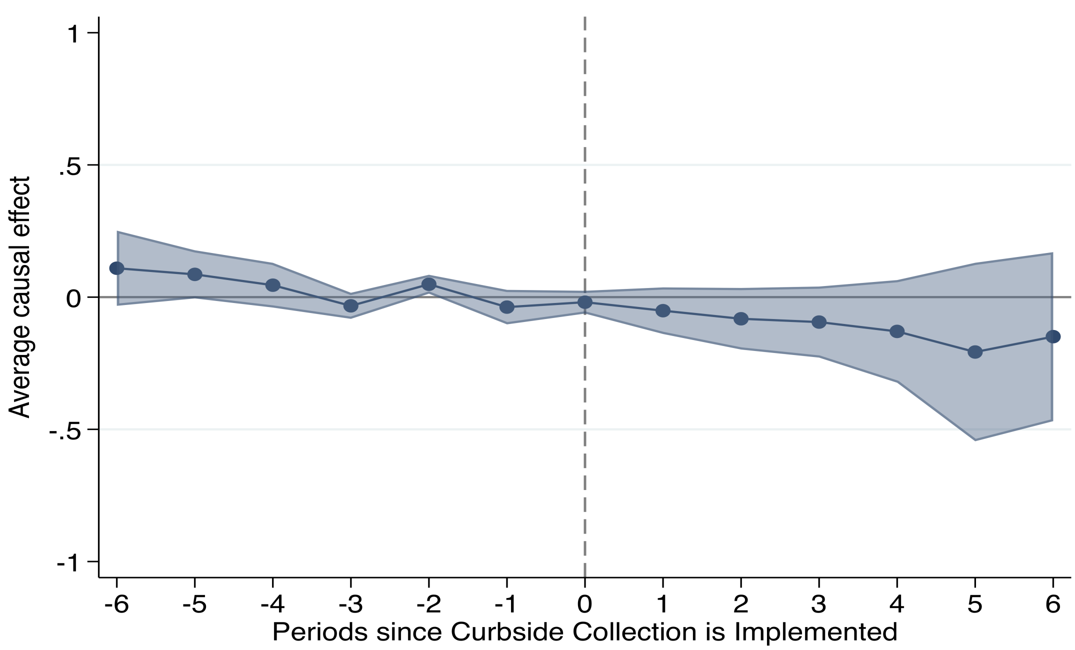
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 18: de Chaisemartin (2022) Estimates, Binary Treatment, BUDataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



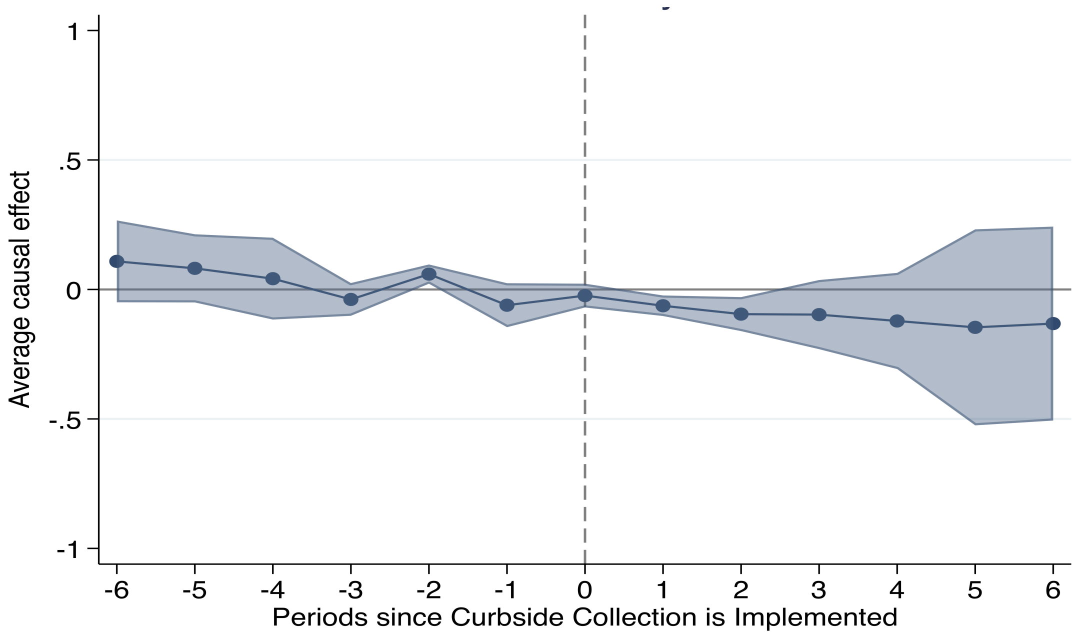
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 19: de Chaisemartin (2022) Estimates, Binary Treatment, BB Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



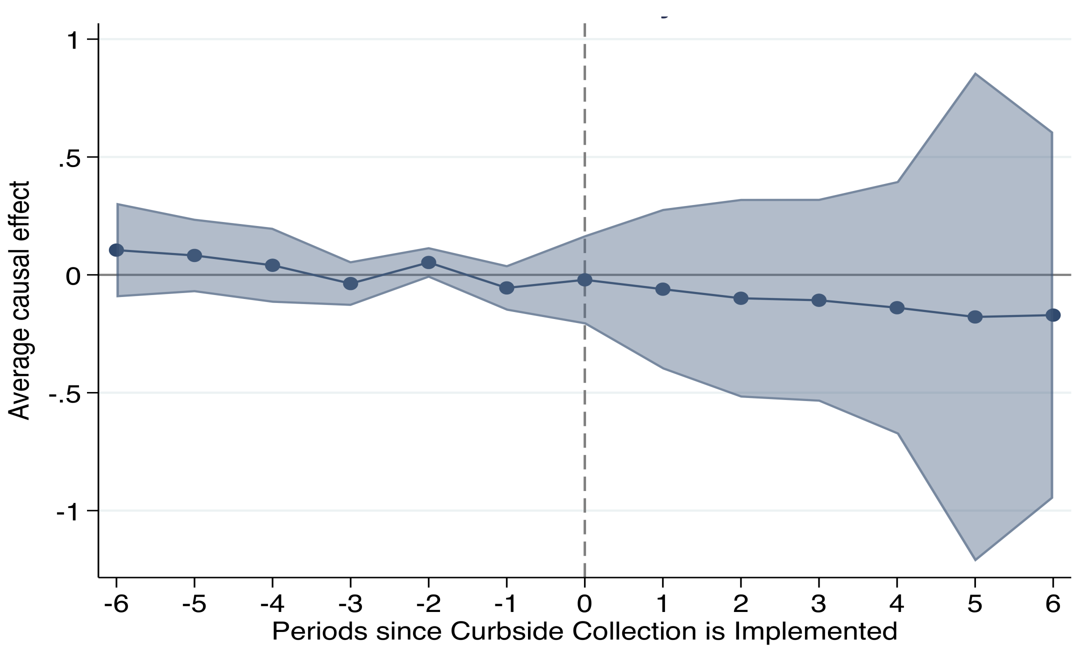
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 20: de Chaisemartin (2022) Estimates, Binary Treatment, SUU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



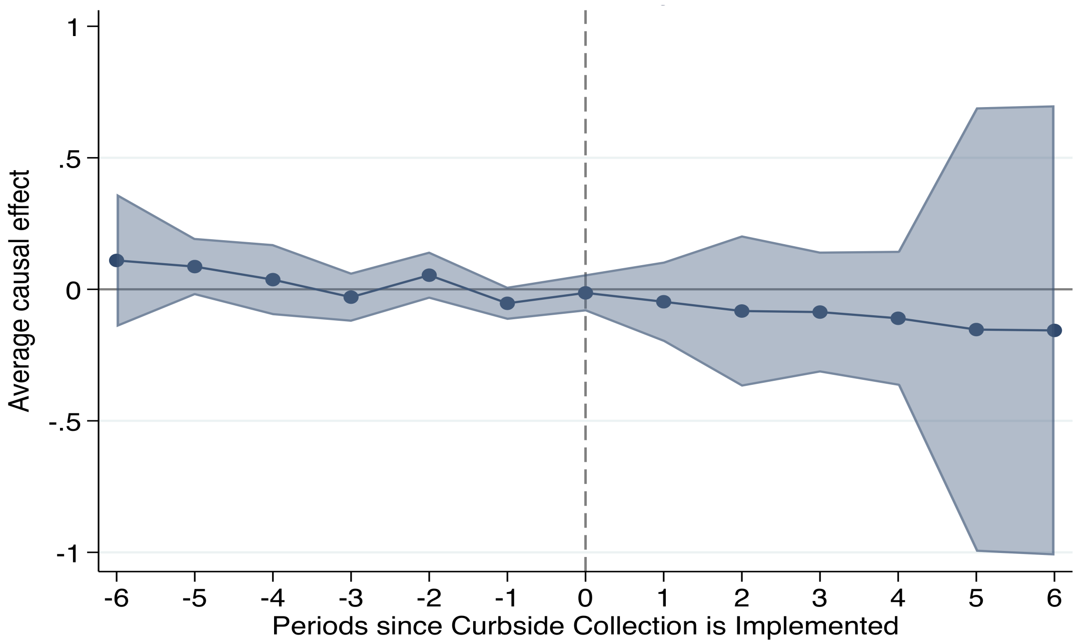
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 21: de Chaisemartin (2022) Estimates, Binary Treatment, SBU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



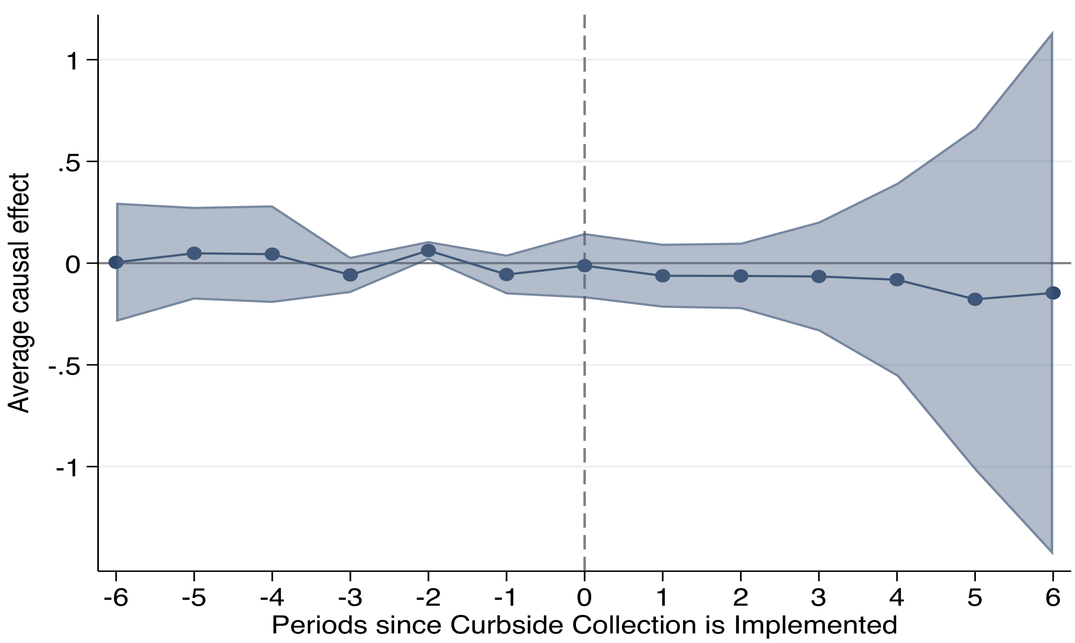
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 22: de Chaisemartin (2022) Estimates, Binary Treatment, SBB Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



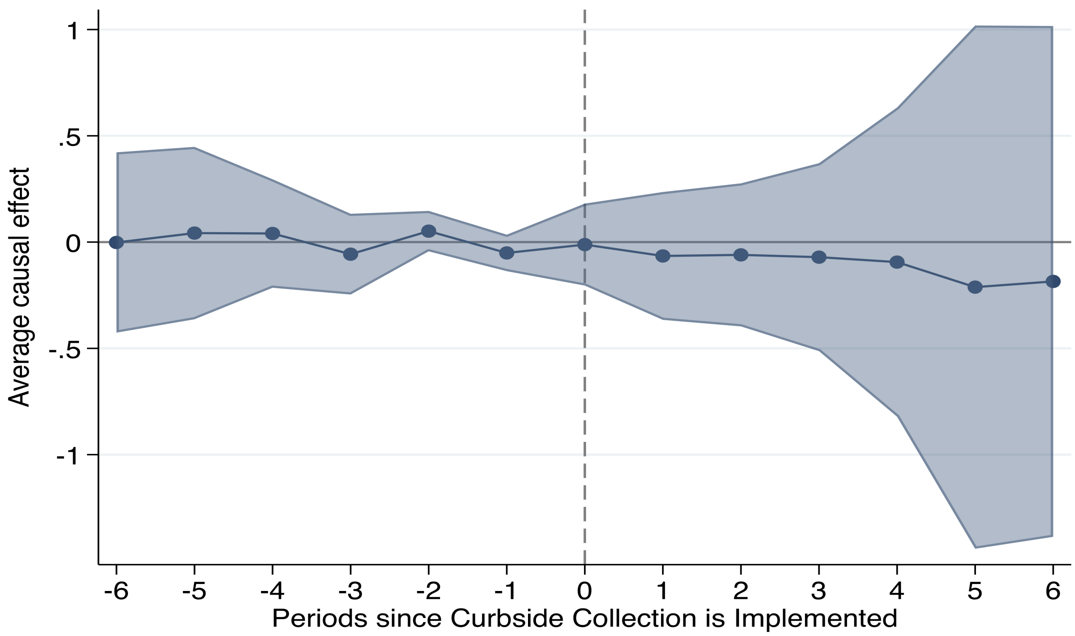
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 23: de Chaisemartin (2022) Estimates, Continuous Treatment, UU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



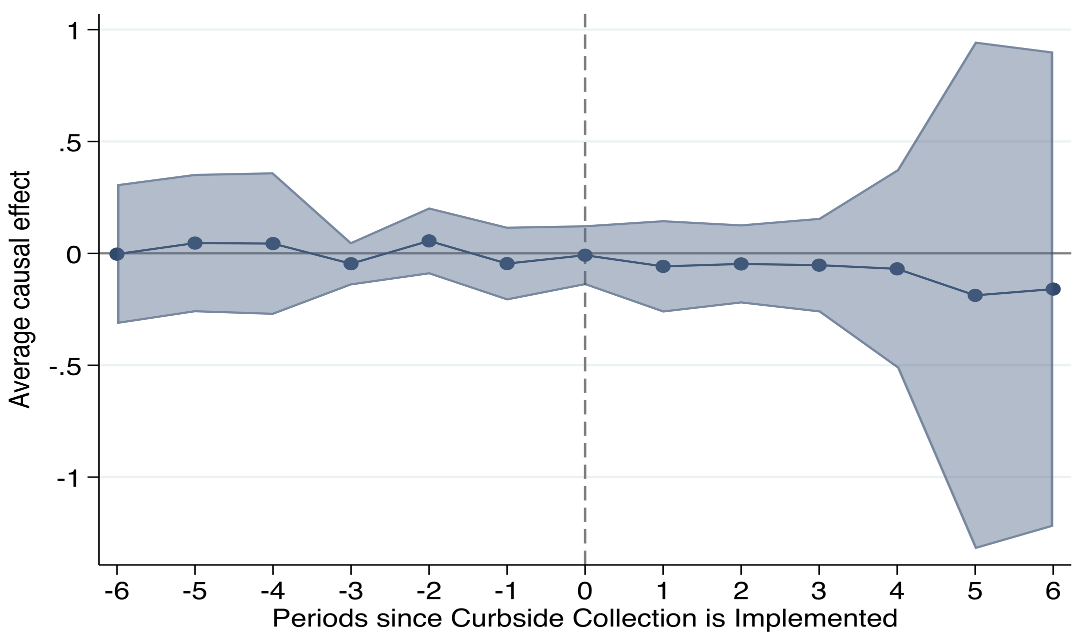
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 24: de Chaisemartin (2022) Estimates, Continuous Treatment, BUDataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



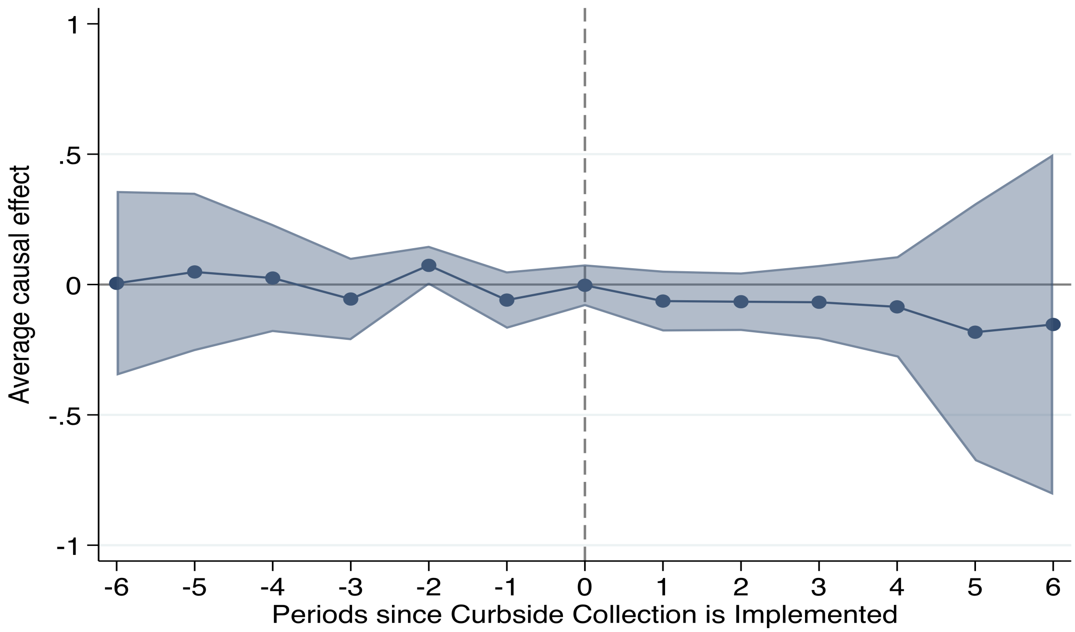
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 25: de Chaisemartin (2022) Estimates, Continuous Treatment, BB Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



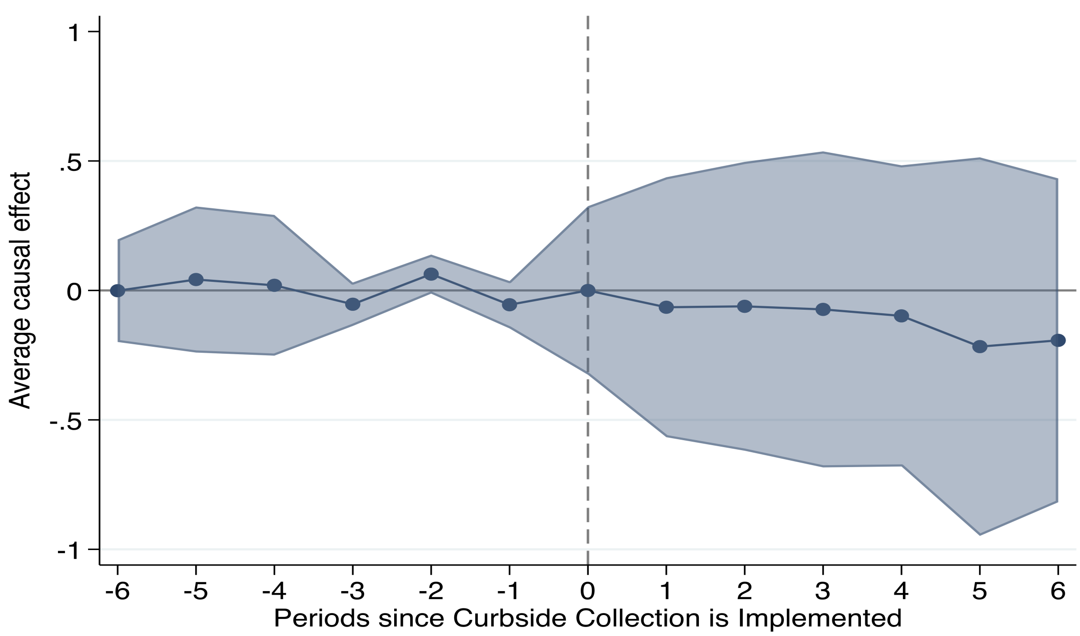
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 26: de Chaisemartin (2022) Estimates, Continuous Treatment, SUU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



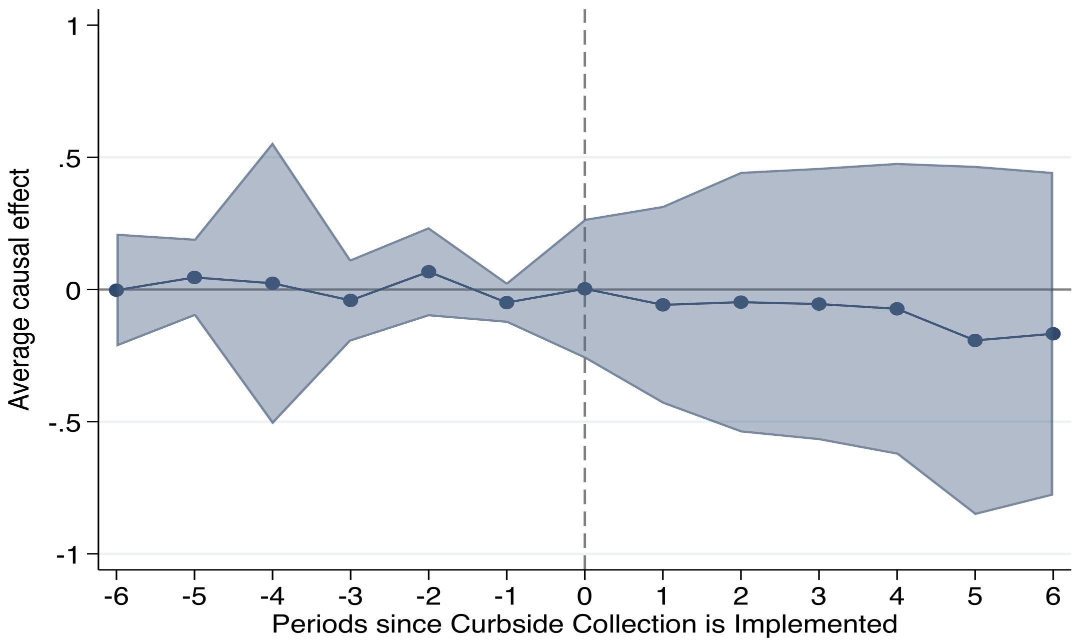
Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 27: de Chaisemartin (2022) Estimates, Continuous Treatment, SBU Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



Conditioned on all covariates. Standard errors clustered at the county-level.

Figure 28: de Chaisemartin (2022) Estimates, Continuous Treatment, SBB Dataset
— Dynamic Effects of Curbside Collection on Landfill CH_4 per Household —



Conditioned on all covariates. Standard errors clustered at the county-level.