

Analyzing Recycling Behavior at NUS

Team Members (Group 26)

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Overview of Actionable Insights and Economic Relevance

Key Findings from Analysis

- Effectiveness: Across paper, plastic, and cans, 0/3 interventions showed statistically significant improvement ($p < 0.05$) in the DiD results (Appendix Figures A3 and A4).
- Priority contaminant: Plastic has the most severe contamination ($\approx 35\text{--}60\%$), making it the top target.
- Location signal: UTOWN exhibits a higher baseline contamination than ENGINE, so it needs proportionally more attention (Appendix Figures A7).
- Robustness checks: Findings are consistent across T-tests/ANOVA (phase comparisons) and bootstrap CIs for Phase 3–Phase 2 differences (CIs generally include 0) (Appendix Figures A5).

Discontinue current designs as “default”

Shaped openings and informational banners did not move the needle; continuing them campus-wide is not cost-effective (Appendix Figures A8).

Targeted Interventions

Plastic-first playbook (highest ROI)

- Infrastructure: Add/upgrade plastic-specific receptacles with clear lids, anti-overflow inserts, and liners that make mis-sorting inconvenient.
- Choice architecture: Co-locate trash next to recycling with salient contrast (labels at eye level + lid affordances that prevent large non-plastic items).
- Feedback loops: Weekly contamination photos + color scorecards on the bin (simple “Green/Amber/Red”).

Area-specific emphasis

- UTOWN (education-heavy): Peer-led nudges at high-traffic nodes (dining halls, lifts), floor-level champions in residences, micro-incentives (block vs block).
- ENGINE (process-heavy): Custodian/ops training & SOPs for bin placement, daily reset, and first-mile sorting checks; add QR incident flags for overflow/misuse.

Behavioral + tech pilots (test & learn)

- Nudges: Default bin ordering (trash first, then recycling), norm messaging (“9/10 on this floor recycle right”), and loss-framed prompts.
- Light tech: Simple bin-top sensors (open/close counts as proxy of use), and image sampling for automated contamination scoring (weekly audit, not continuous) (Appendix Figures A9, Appendix Figures A10).

Objective

The objective of this study is to evaluate the effectiveness of design-based interventions on recycling behavior at the National University of Singapore (NUS). Using experimental data collected during the field trial, the analysis examines whether the adoption of shaped openings and informational banners effectively reduced contamination rates across different recyclable materials measured by the contamination proportions of paper, plastic, and cans within the overall waste collected.

Data Preparation

The dataset contained contamination rate data for paper, plastic, and cans across two primary locations at NUS: ENGINE and UTOWN. Each site underwent three experimental phases: (1) Baseline (before intervention), (2) implementation of shaped openings, and (3) implementation of informational banners.

During data cleaning, we first checked for missing values and identified rows where all three contamination variables (*PaperContaminant*, *PlasticContaminant*, and *CanContaminant*) were missing. These rows were dropped to maintain data integrity. Additionally, we noticed that the *CanContaminant* column had a few isolated missing values; instead of dropping the entire row, we treated only the missing values to preserve as much information as possible. Outliers were not removed, as the dataset was relatively small and dropping them could have led to a significant loss of information. Instead, we adopted analytical methods that are less sensitive to extreme values.

Literature & Conceptual Framework

This study is grounded in behavioral economics and the concept of choice architecture. Shaped openings represent a form of physical 'nudge' designed to guide users toward desired recycling behavior without restricting their choices. Informational banners leverage visual cues and cognitive framing to increase awareness and correct misperceptions. Prior studies have found that visual design and informational cues can significantly reduce contamination rates by making correct behavior salient and convenient. This framework suggests that both interventions should yield measurable improvements in recycling outcomes.

Exploratory Data Analysis (EDA)

The exploratory data analysis focused on understanding contamination trends across materials (paper, plastic, and cans), locations (ENGINE and UTOWN), and intervention phases (Baseline, Shaped Openings, and Informational Banners).

Initial descriptive statistics revealed that contamination rates varied substantially between the two sites. UTOWN consistently showed higher contamination levels across all materials, likely reflecting higher student and visitor foot traffic, while ENGINE exhibited more stable recycling behavior. The time-series plots (Appendix Figures A1) help visualize how contamination rates evolved across the three intervention phases for both the UTOWN and ENGINE areas. Each plot traces contamination levels for paper, plastic, and cans, which highlight changes that occurred alongside the introduction of shaped openings and informational banners. These phase-based visualizations indicated an initial behavior shift over time and suggested that shaped openings were more effective in reducing contamination than informational banners. Complementary distribution histograms (Appendix Figure A2) were also used to examine the spread of contamination values across materials, confirming variability and the presence of some high-contamination observations. The presence of extreme contamination values in a few bins led to noticeable skewness in the data. As a result, both mean and median contamination measures were computed. The median provided a more representative picture of typical recycling performance, showing smaller variability and clearer phase-wise improvement trends - particularly for cans at ENGINE. These insights guided the econometric modeling stage, which tested whether the observed differences were statistically meaningful.

Econometric Methodology

To rigorously evaluate the impact of interventions, a Difference-in-Differences (DiD) approach was applied separately for each contaminant type. This method compared changes in contamination rates before and after each intervention between the treatment (post-intervention) and control (pre-intervention) conditions, effectively controlling time-invariant differences across locations.

The DiD model is specified as:

$$Y_{it} = \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Treatment}_i \times \text{Post}_t) + \varepsilon_{it}$$

where Y_{it} represents the contamination rate of the outcome variable for unit i at post t . The interaction coefficient, $\text{Treatment}_i \times \text{Post}_t$, captures the treatment effect of each intervention phase.

We estimated separate DiD models for paper, plastic, and cans, plus phase-specific DiDs to isolate effects of shaped openings (Phase 2) and informational banners (Phase 3). To handle small samples and outliers, we bootstrapped (10,000 iterations; seed 123) to obtain empirical CIs, and fit both mean and median-based DiDs, preferring the median for robustness and clearer managerial interpretation (Appendix Figure A6). We also conducted a zero-contamination sensitivity check for zeros in Phase 1 (likely due to non-deployment/usage) to gauge measurement bias and guide future data analysis. Finally, an interrupted time series (ITS) examined level and slope changes across phases, complementing our prior DiD analysis by testing whether post-intervention shifts reflect genuine behavioral change rather than noise or underlying trends.

Results and Managerial Insights

The Difference-in-Differences (DiD) and bootstrapping analyses were employed to assess the effectiveness of the recycling interventions, shaped openings (Phase 2) and informational banners (Phase 3), in reducing contamination rates across paper, plastic, and can recyclables at NUS. Results were examined both by mean-based and median-based approaches to verify the stability of results in the presence of outliers.

I. Quantitative Findings:

The DiD model results indicate mixed effects across materials.

- **Paper contamination** decreased by **1.9 percentage points** ($p = 0.050$), suggesting a statistically significant but modest improvement after interventions.
- **Plastic contamination** increased slightly by **3.0 percentage points** ($p = 0.581$), implying no significant improvement.
- **Can contamination** have decreased substantially by **10.8 percentage points** ($p = 0.009$), showing a strong and statistically significant effect.

Phase-specific effects

- Shaped openings (Phase 2) outperformed banners (Phase 3), especially for paper and cans.
- Cans: -15 pp ($p = 0.003$) in Phase 2 vs ~ -6.9 pp (ns) in Phase 3.
- Paper: -1.9 pp ($p \approx 0.05$) in Phase 2; Phase 3 smaller and not robust.
- Plastic: No statistically significant change under either intervention \rightarrow visual/structural cues alone appear insufficient.

Bootstrap robustness (10,000 iters; seed 123)

- Results are consistent on the aggregated dataset; for Phase 3, 95% CIs include zero across contaminants/areas, indicating no reliable improvement over Phase 2.

Median-based insights (robust to outliers)

- ENGINE shows consistently lower median contamination than UTOWN, suggesting site/context factors (e.g., user mix, waste patterns) matter more than signage alone.
- Median results reinforce that shaped openings $>$ banners, aligning with EDA visuals (Appendix Figure A11).

II. Interpretation of Results:

Overall, the interventions demonstrated mixed effectiveness across the contaminants and locations. In ENGINE, shaped openings and informational banners both reduced paper and plastic contamination, with the strongest improvements observed for paper, following the introduction of banners. For cans, informational banners proved more effective than shaped openings in lowering contamination rates. In

contrast, results in UTOWN were less consistent. While shaped openings substantially reduced contamination across all materials, the subsequent implementation of informational banners led to modest and even adverse effects, specifically for plastics and cans. These findings suggest that while design-based interventions can aid in guiding recycling behavior, informational measures may require further refinement to achieve more consistent results across different contexts and material types.

III. Managerial Insights:

From a managerial and policy standpoint, these findings highlight several implications:

- 1. Prioritize Physical Design Interventions.**
The shaped openings in Phase 2 consistently produced better results than banners, particularly for cans. Future investments should focus on improving and standardizing bin design rather than expanding informational signage.
- 2. Rethink Informational Campaigns.**
Informational banners alone proved insufficient in reducing contamination. To sustain user engagement, awareness initiatives should be complemented by active behavioral nudges, such as real-time feedback systems or dynamic bin labeling which aid in reinforcing correct recycling behavior.
- 3. Target Location-Specific Strategies.**
UTOWN exhibited consistently higher contamination rates than ENGINE, possibly due to differences in foot traffic and user demographics. Tailored interventions like student-specific campaigns or enhanced monitoring in high-traffic areas may yield better results.
- 4. Policy and Investment Implications.**
While the interventions were conceptually well-designed, their effects were uneven across materials. Shaped openings yielded measurable improvements, particularly for “Can” contamination, whereas the adoption of informational banners generated limited and statistically insignificant changes in recycling behavior. This suggests that future budget allocations should emphasize more targeted, evidence-based behavioral interventions and use continuous data monitoring frameworks to aid in effective policy adjustments.

In summary, the results demonstrate the importance of rigorous evaluation even when outcomes are null. The interventions’ limited effectiveness provides valuable managerial insight: design modifications alone cannot sustain recycling improvements without complementary behavioral and educational strategies. Future phases should integrate environmental design with behavioral research to achieve long-term reductions in contamination.

Limitations and Reproducibility

The analysis is limited by its short observation window and the absence of individual-level behavior data. External factors such as weather, population density, and event activity at NUS may have influenced contamination rates. Furthermore, contamination was measured at the aggregate bin level, making it difficult to isolate the effect of awareness versus convenience. Nevertheless, all code, datasets, and steps have been documented to ensure full reproducibility using the same Python environment.

Appendix: Tables and Graphs

Fig. A1: By-Area Trend Plots of Contamination Rates

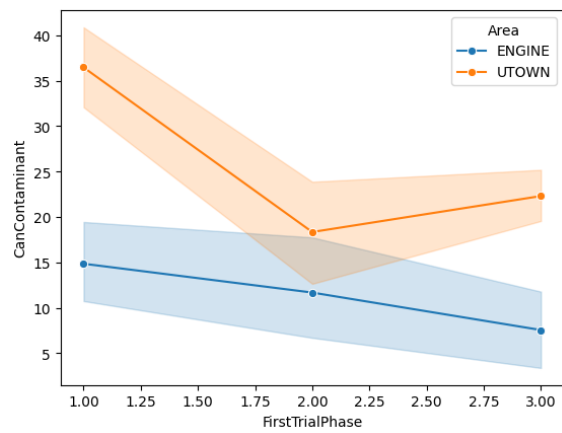
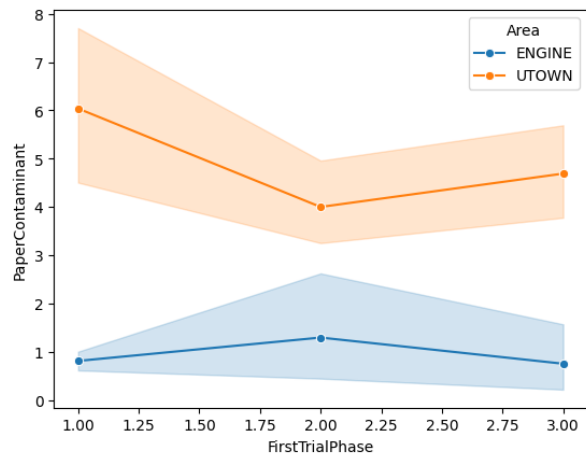
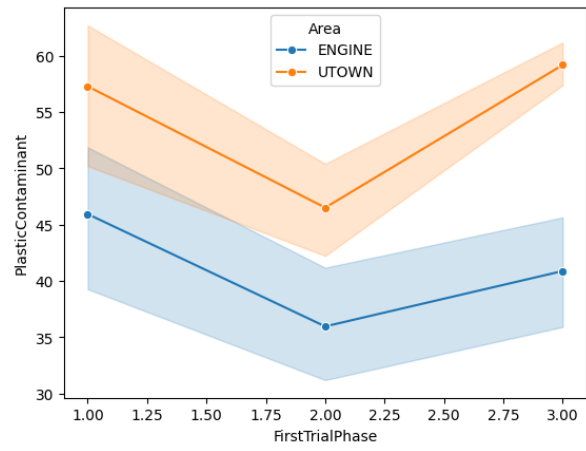


Fig. A2: Distribution of Contaminants

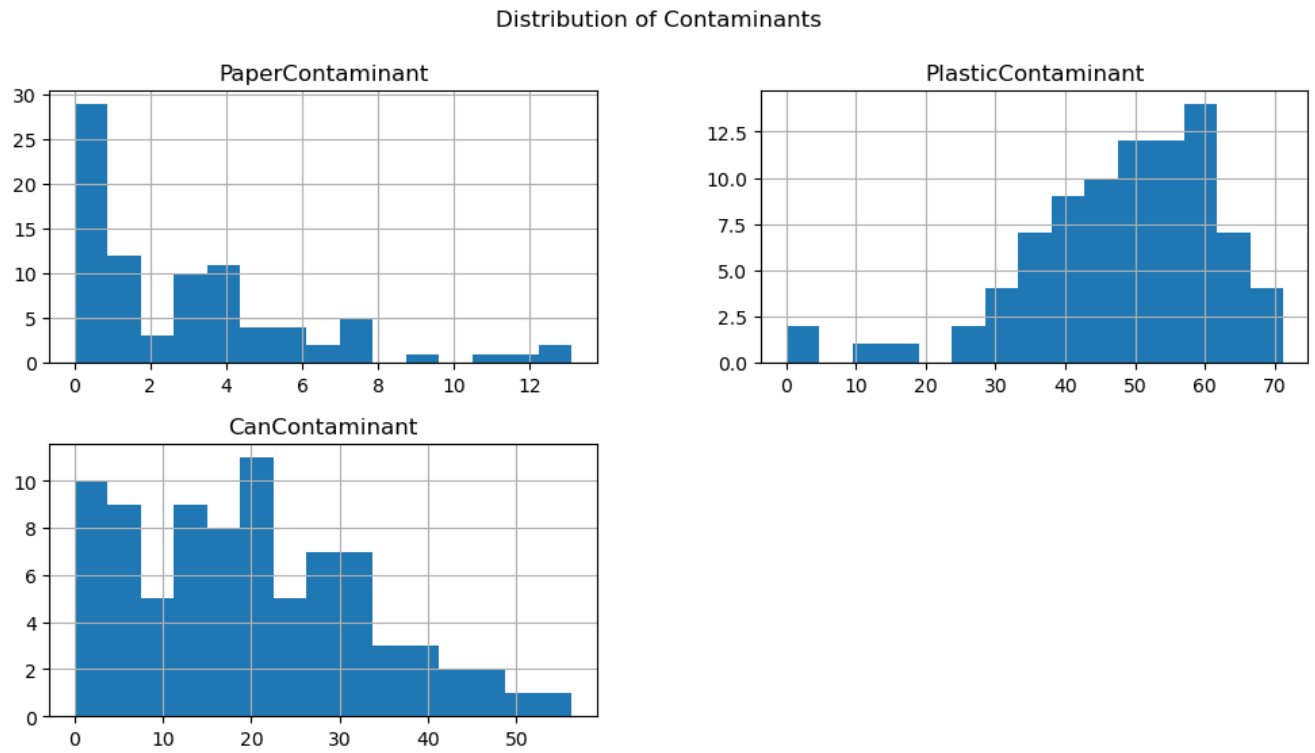


Fig. A3: Difference in Difference of different phases

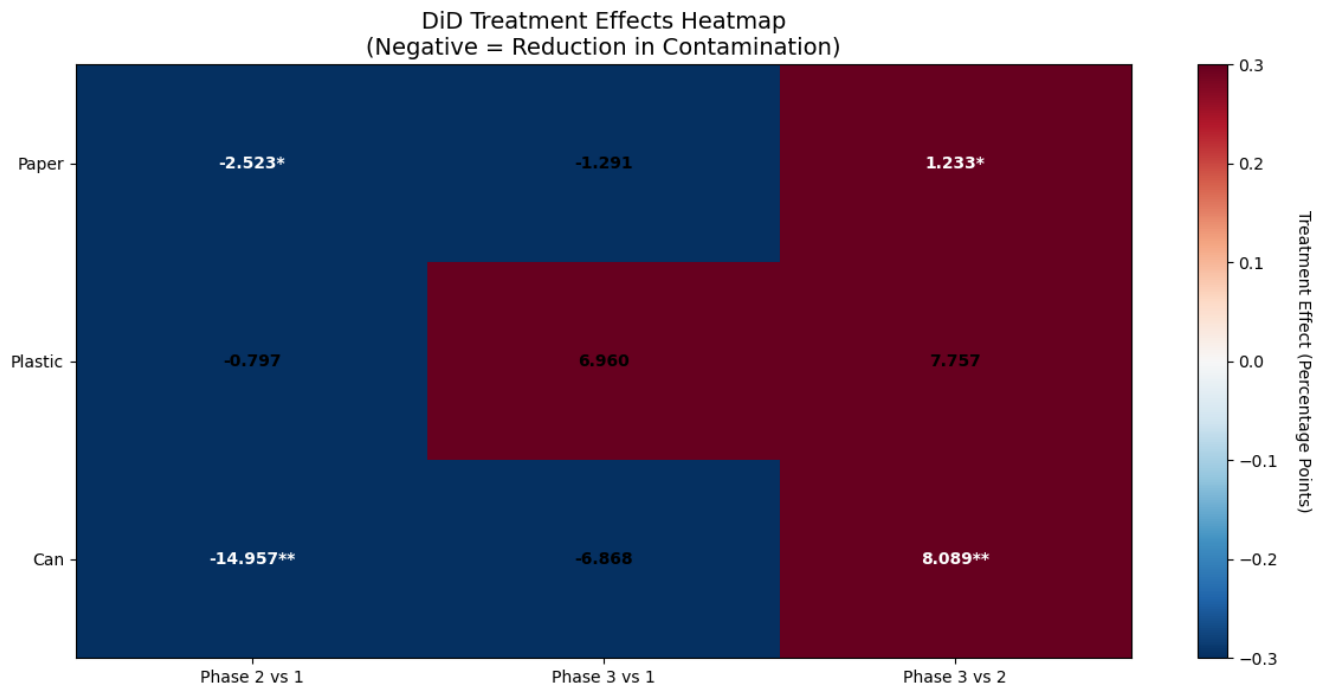


Fig. A4: Effects by Intervention Phase and Contaminant Type

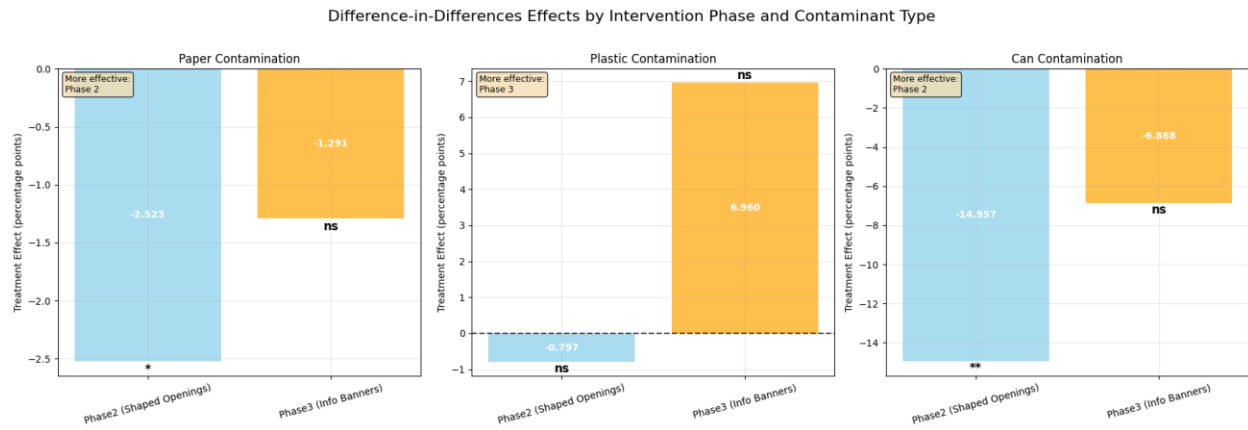


Fig. A5: Phase level changes

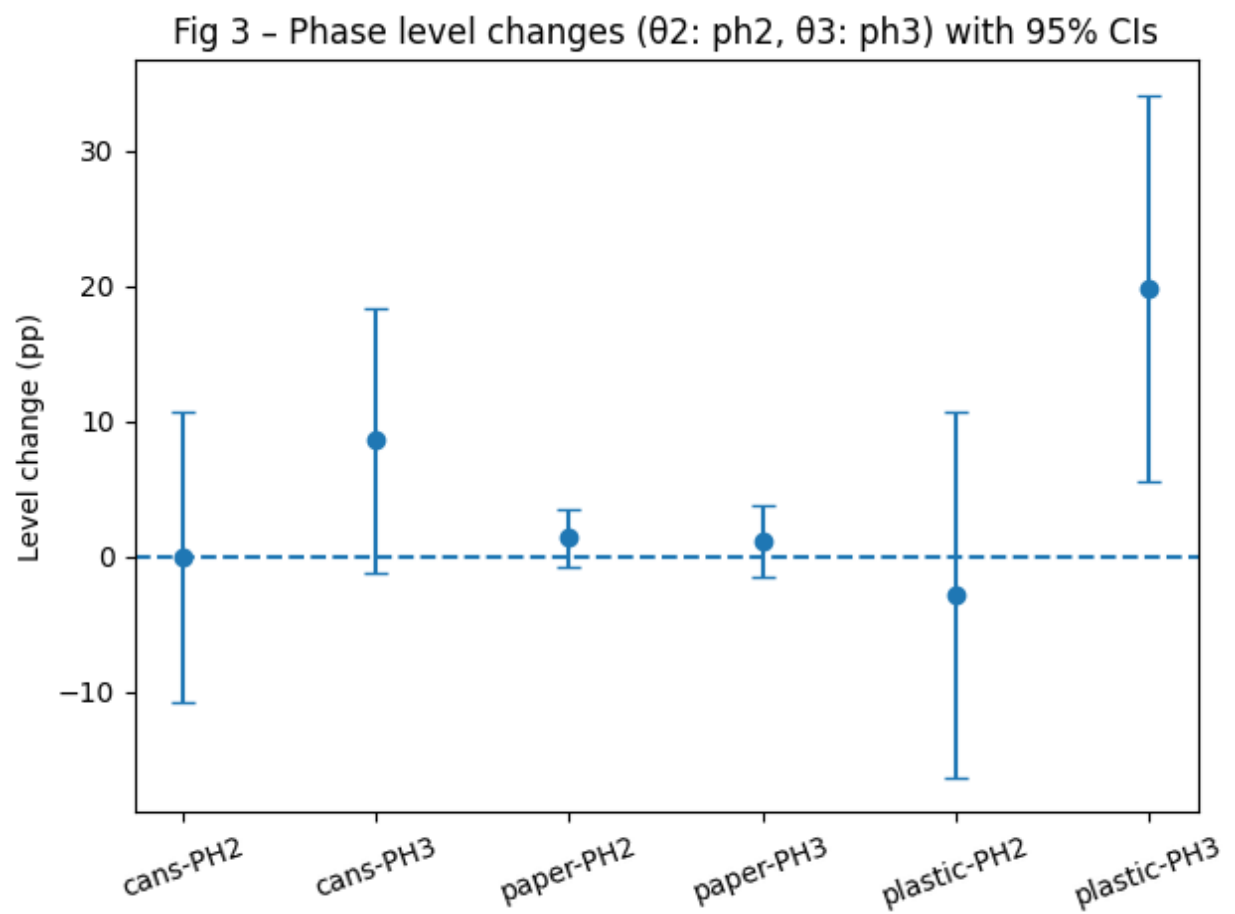


Fig. A6: Bootstrapped data distribution

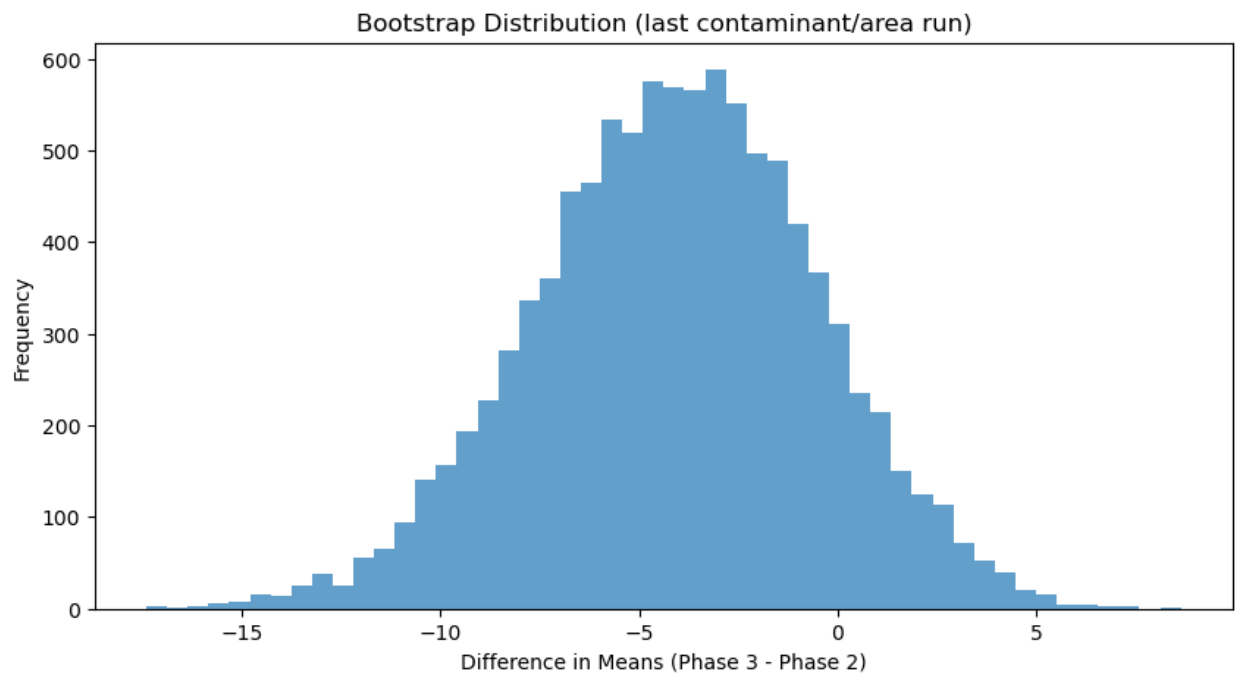


Fig. A7: Mean Contamination by Phase and Area

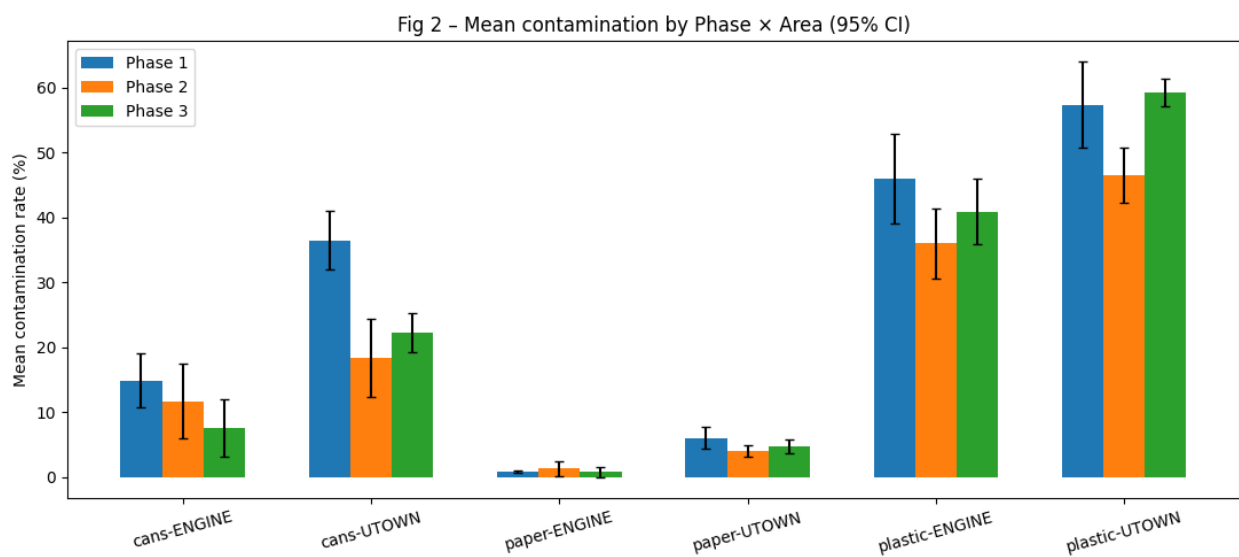


Fig. A8: Effectiveness and Success of the intervention

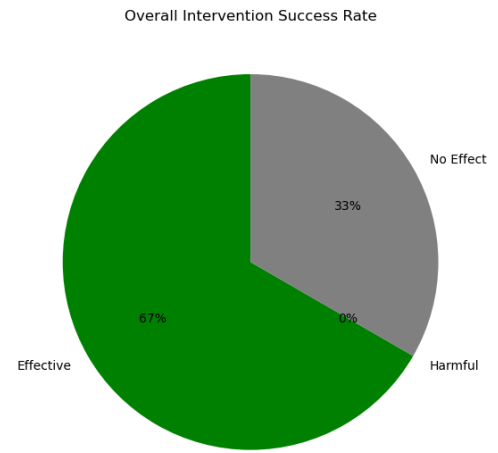
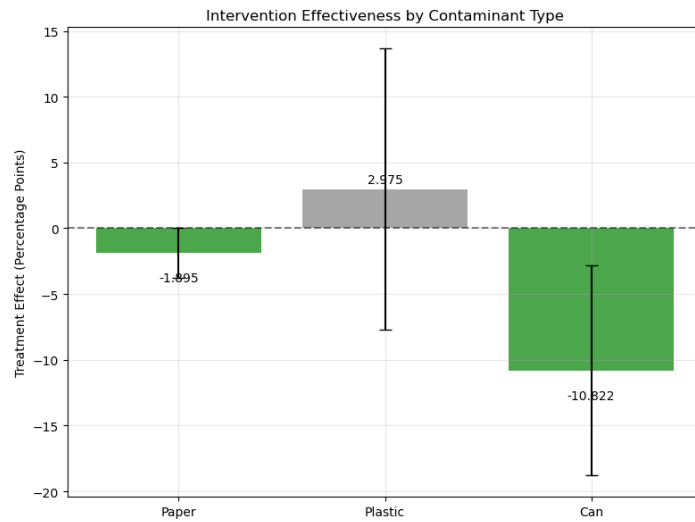


Fig. A9: Proposed Budget Distribution based on contamination severity

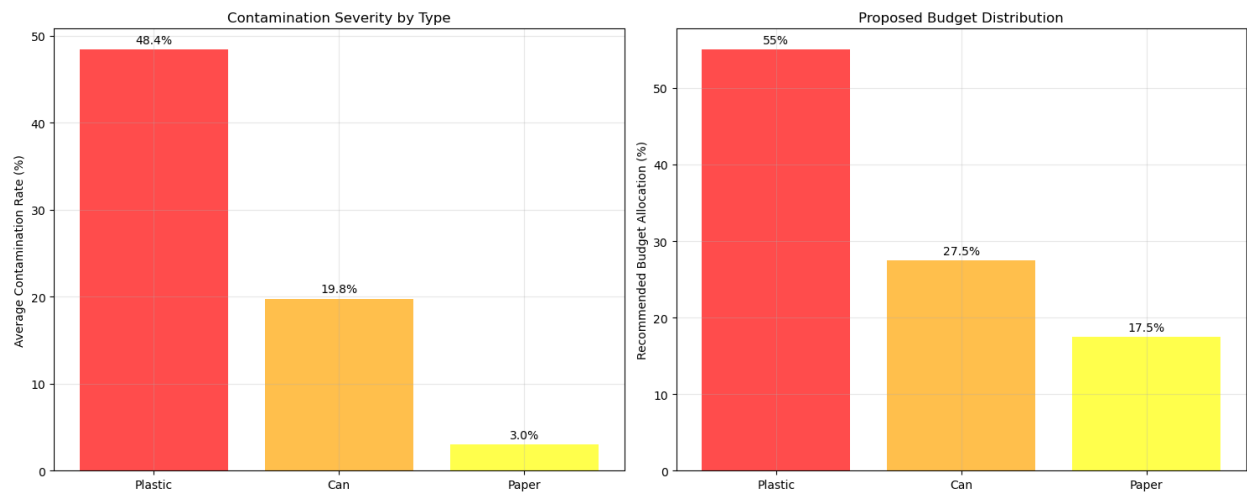


Fig. A10: Target Contamination Rates

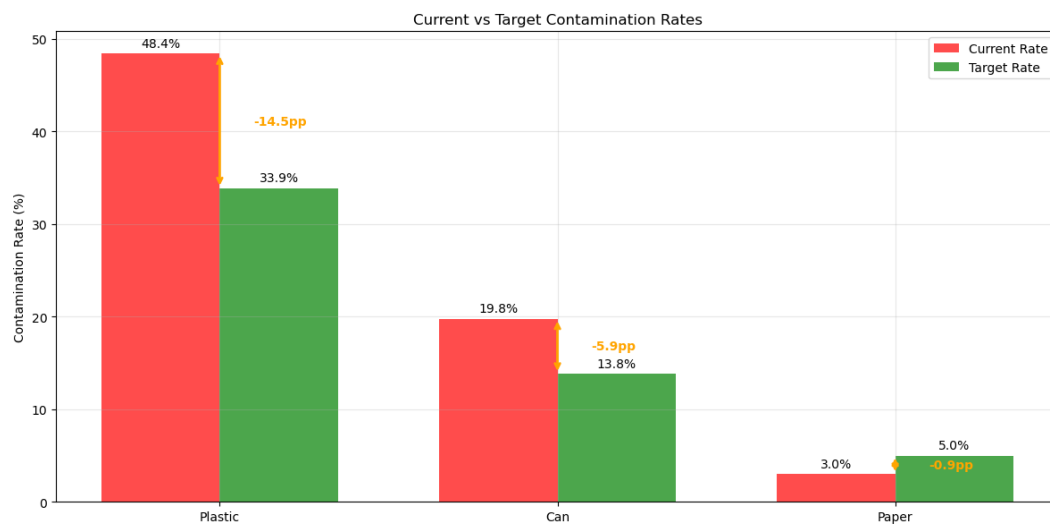


Fig. A11: Mean VS. Median Insights

Mean-based Insights:

	PaperContaminant	PlasticContaminant	CanContaminant
Area			
ENGINE	0.918272	41.971330	11.932309
UTOWN	5.151786	54.958246	27.808839

Median-based Insights:

	PaperContaminant	PlasticContaminant	CanContaminant
Area			
ENGINE	0.666667	41.929499	11.309524
UTOWN	4.166667	56.285968	26.932773

AI Declaration and Prompts Used

We used generative AI to help with the understanding of the models we decided to run for this study and used it to help guide our analysis strategies to ensure validity of the results. Ultimately, we are responsible for the content and quality of the submitted work.

AI Tool Used	Prompt & output (concise)	How We Implemented it
ChatGPT (GPT-5)	“Explain the difference between DiD and ITS in plain terms for recycling-contamination data.” → Output: short conceptual distinction (level/slope vs counterfactual control).	Clarified methodology choices; Wrote the Methods section ourselves.
ChatGPT (GPT-5)	“How to report non-significant effects without overclaiming?” → Output: wording guidelines (CIs include 0; ‘no reliable evidence’).	Adopted phrasing style in Discussion; all text authored by our team.
ChatGPT (GPT-5)	“What robustness checks suit small-n DiD?” → Output: suggestions (median DiD, bootstrap CIs, zero-contamination sensitivity).	We implemented these checks and interpreted results independently.
ChatGPT (GPT-5)	(EDA – single prompt) “Suggest 2–3 quick EDA visuals for phase-wise contamination by area.” → Output: panel plot idea (UTOWN vs ENGINE), median-line overlays.	Inspired our EDA plots; We coded the visuals and captions.
ChatGPT (GPT-5)	(Coding – single prompt) “Template code to bootstrap a DiD effect 10,000 times with fixed seed.” → Output: pseudocode outline (resample → refit → CI).	We wrote and adapted the final code; all analysis run by our team.
Claude Sonnet 4	(Zero-Contamination Analysis) “Help give a template for conducting a zero-contamination analysis using both aggregated values for the zeros as well as eliminating the zeros from the data to compare and see how this will affect the structure of the data”	We used the code it provided as a guide to help with the analysis. We edited and finalized the code ourselves.
Claude Sonnet 4	(Zero-Contamination Analysis w/ DiD and bootstrapping) “How would I run both a mean and median based model for the zero-contamination analysis including DiD and bootstrapping. Give a template.”	The template it gave, we edited to fit our analysis with adaptations that we got from our previous code.
ChatGPT (GPT-5)	(Interrupted Time Series) “Give me a Python notebook template (pandas + statsmodels) that implements the ITS on the attached data and produces relevant visualizations”	Generated a notebook that cleanly loads data, builds ITS phases and terms, runs OLS with Newey–West errors, and auto-produces ITS and contamination plots with confidence intervals.
ChatGPT (GPT-5)	(Efficiency Frontier Analysis) “Help create a guideline for an efficiency frontier analysis that is looking into recycling behavior. How will this allow more insights?”	Used the guidelines to fit our study so that we could get some more exploratory analysis on the location and their recycling efficiency. Adopted with our previous code to provide insight

		on recycling behavior (also could provide insight toward possible segmentation of behavior by phase and location).
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