The Impact of Corrugated Cardboard & Plastics on Aggregate Waste in CRD

by

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Abstract

In 1989 the Capital Regional District (CRD) implemented a curbside recycling program referred to as the Blue Bin Program. Its purpose is to help extend the areas landfill life and help recycling plastics, metals, and paper. In 2000 additional materials were added to the list of items acceptable to be recycled through the Blue Bin Program; specifically, corrugated cardboard and rigid plastic. Data collected from the CRD's Annual Solid Waste Reports was used to assess the impact of allowance of additional recyclables materials in 2000 on total household waste generation. Fixed effects models estimated with Ordinary Least Squares (OLS) and Generalized Least Squares (GLS) show a clear indication that the percentage of recycling per-capita increased after the program expanded while the percent of garbage per-capita fell after 2000. The effect of expanding the Blue Bin program on total waste tonnage is unclear.

Special Thanks to my advisors Donna Feir and Chris Auld who were always patient with me

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1. Introduction

Interest in solid waste recovery and recyclability has been increasing in the Capital Regional District (CRD) due to limited capacity life of the Hartland Landfill. In 1989 the CRD implemented a new waste management program aimed at diverting waste from the landfill. The program initially included household waste items such as: glass bottles, tin, aluminum, and newspaper (Capital Regional District, 2014). Since then additional materials have been added to the list of acceptable items that can be placed in recycling. In this paper I estimate how recyclables, garbage, and aggregate waste tonnages respond to the allowance of additional materials to see if there is evidence that different disposal options influence how households discard waste. I focus on the program expansion in 2000 that added corrugated cardboard and rigid plastics to the list of recyclable materials using data I collected from the CRD. The results indicate that recycling tonnages increased and garbage tonnage decreased in response to the program. If households were simply just moving items that were acceptable to be recycled in to their Blue Bins that would have formally been garbage, but they were not changing their consumption behavior, then we should see aggregate waste stay constant. However, different models reveal conflicting results that estimate aggregate waste declining or increasing depending on which fixed effects model was used. If the recycling program was just having an effect on which bin people placed their waste in, and not their consumption habits, we should see aggregate waste remain unchanged.

It is important to note for this paper I will be using the term ‘Blue Bin’ to express materials that are able to be recycled while the term ‘garbage’ will be used to explain materials that are not eligible for recycling. When I refer to ‘aggregate waste’ this is representative of both Blue Bin materials and garbage.

2. Motivating Theory

A possible explanation for why aggregate waste may have risen stems from the concept of "guilt free disposal." This concept has been studied before in a field study, conducted by Gneezy and Rustichini, of a group day-care center. The researchers found that when parents were charged a fine for picking up their children late from school that, contrary to Gneezy and Rustichini's prediction, more parents arrived late. One conclusion drawn is that the fine removes the guilt of parents for picking up their children late; because they have paid the teacher for their time (Gneezy & Rustichini, 2000). This example reflects an incentive that lead to an unexpected outcome. The connection between the day care fine and recycling is that they are similar since both impose costs on participants. Like picking up a child late, people are incurring a cost of the time and energy to sort and correctly dispose of items when they recycle. Since they are incurring this cost they might feel less guilty about throwing away other items. Imagine a person standing in their garage that is stacked high with cardboard boxes. This person is faced with the option of recycling the boxes, throwing them away, or saving them for the next time he or she moves. I hypothesize that the allowance for the person to recycle will encourage them to recycle the boxes instead of saving them for future use. So when it comes time in the future to move again he needs to purchase more boxes. The story is simplistic and assumes individual's wellbeing is connected with their feelings of waste disposal, which is a strong assumption for most people. It is intended to paint the story of why the recycling program change in 2000 might alter people's behavior such that they recycle more but at the cost of consuming more and why we see the result of aggregate waste increasing.

A possible explanation for why aggregate waste might have fallen could be explained by Morris's and Holthausen's model of household of solid waste production and management. The model incorporated new waste management services to show how households responded to these additional waste options. This model illustrated that if households increased efforts to recycle then household aggregate waste decreased (Morris & Holthausen, 1994). This relationship also indicates that if recycling goes up and garbage falls the aggregate waste would remain constant.

3. Literature Review.

As far as I am aware, I am the first to try and evaluate a recycling program change to see if it affected other disposal streams. The literature that evaluated recycling programs and household waste, thus far has focused the determinants of waste and how household's efforts changed in response to alternative waste management programs.

3.1. Determinates of waste

A Swedish case study found that municipality household differences in recycling collection can be attributed to geographic, demographic, and socio-economic factors, and environmental preferences (Hage & Soderholm, 2008). Another case study in Dhaka, the capital of Bangladesh, found that factors such as household size and income influenced household waste. The study also found that the willingness to separate waste, measured through survey response, to be a determinant of household waste creation. The study used OLS to determine factors that influenced waste generation (Afroz, 2010). Using macroeconomic data, Johnstone and Labonne (2004) showed that household size, income, and urban density are highly correlated with waste generation. This research also showed the significance of the number of children per household in determining household waste generation. It is important to note this paper's model is based on household utilization maximization theory[1]. The model had municipal

[1] Which is different for how I proceed with my work so their results might not be in line with my own.

solid waste collection services dependent upon household size, number of children, number of working people, and the proportion of the population that lives in urban areas.

These 3 papers serve as a basis for why I use number of children and home value as controls in my regression models.

3.2. Effort Response to Waste Management Programs

There are numerous economic papers reviewing different policy implication of unit pricing (Jenkins, 2000), or bag limits (Ferrara & Missios, 2005) on recycling effort changes and frequency of adherence. Unit pricing has been found to change consumption behaviour to purchasing easier to recycle household materials (Jenkins, 2000). Other policy programs such as bag limits or ‘pay as you throw away’ also found that they reduced volume, not weight (Ferrara & Missios, 2005).

Previous research focuses on socio-economic factors that determine how much waste households produce (Hage & Soderholm, 2008; Afroz, 2010; Johnstone & Labonne, 2004) and what type of programs are more likely to change effort or frequency (Jenkins, 2000; Ferrara & Missios, 2005). However, these papers are missing the consequence of recycling programs on total household waste generation. This paper adds to the literature by being the first to evaluate the impact of recycling on garbage and aggregate household waste.

4.Description and Summary of Data

4.1. Data Collection

My data consist of cross-sectional time-series of household solid waste in the CRD municipalities. The data set contains 144 observations, which have been derived from various sources. Data for tonnage of garbage and Blue Bin materials by municipalities are from Annual

Solid Waste Reports from 1996-2011. Small portions of these reports were accessed through their online publications. For reports not accessible online, I collected data directly from the CRD office downtown and transcribed into digital form. Due to discrepancies in the ways the reports were made throughout the years only nine CRD municipalities of the thirteen are used[2]. The included municipalities are: Central Saanich, Colwood, Esquimalt, Langford, North Saanich, Oak Bay, Saanich, Sidney, and Victoria. While the excluded districts are: Metchosin, View Royal, Highlands and Sooke.

Population data exists for each municipality from years 2001-2011 but for years prior to 2001 I linearly extrapolated from 1996 to 2001 using Canadian Census (The Census of Canada, 1996). Data on number of children and average home value was taken from years 1996, 2001, 2006, 2011 Canadian Census and intermittent years were linearly estimated (The Census of Canada, 1996, 2001, 2006, 2011). Housing value was converted to reflect value in 2011 dollar terms. The data set is balanced across municipalities.

4.2. Information About Municipalities

i. When looking at average value of homes across districts, Oak Bay has the highest value of home. Types of dwellings change across municipalities. Meaning municipalities such as Sannich or Victoria tend to be more family based while Sidney or North Saanich tend to be single person or non-family homes (Statistics Canada, 2011). All municipalities within the CRD adhere to the same rules and regulations in regards to curbside pick-up of garbage and Blue Bin materials; any difference across municipalities is not a result of difference in program.

[2] Some years smaller municipalities would be included and the following year excluded. I confirmed with the CRD staff that these tonnages were then not being included in the reported tonnages of other nearby municipalities.

4.3. Limitation of Data

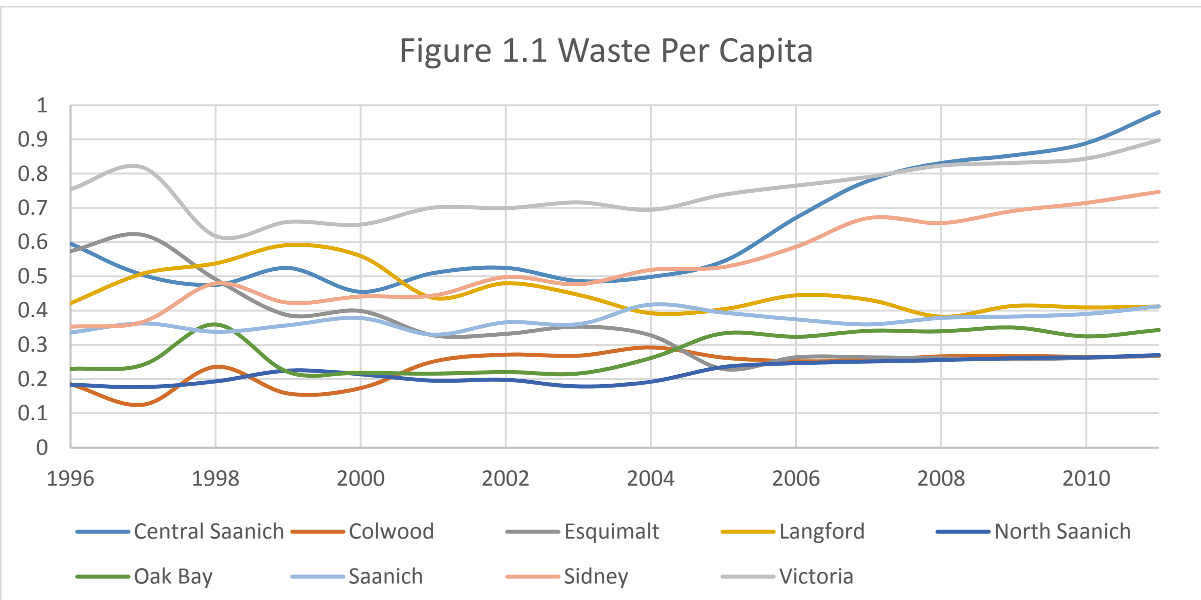
ii. As pervious literature has shown (Hage & Soderholm, 2008; Afroz, 2010; Johnstone & Labonne, 2004) there are many known factors proven to be determinants of household waste generation. Unfortunately my model lacks some of these explanatory variables due to my inability to ascertain such data for the specific municipalities in my data set. I ran into issues of inconsistent census reporting structure over varying years for the districts so I only had 1996 and 2001 for years with average and median household income data. Therefore, I used home value as a proxy for household income and house size which have been proven to be determinants of waste generation (Afroz, 2010; Johnstone & Labonne, 2004).

iii. Data does not account for changes in consumer good packaging, which would make up a large proportion of the composition of household waste. In a report looking at trends that are highly probable of having significant impact on Consumer Goods Industry, changes in packing were referenced as key factors. Due to the shift in green consumerism and regulatory changes there has become a demand for lighter and more efficient packaging (McKinsey & Company, 2010). A landfill digs found that there had been a significant change to lighter consumer packaging (Marsh & Bugusu, 2007). So a decrease in aggregate waste might be reflective of external changes and not changes that the model is measuring.

iv. It is important to note that data for the Victoria municipality is not be fully reflective of actual tonnage. Drivers weighing their trucks tend to overstate pick-ups from Victoria due to generalization of the Greater Victoria area. This was explained to me over the phone by Chris Robins the manager of Solid Waste Operations. I try to correct for this by evaluating data in percentages rather than levels and assume that the biased reporting has been occurring the same amount during the years my data set contains.

4.4. Summary Statistics

Figure 1.1 and Figure 1.2[3] depict the trends in aggregate waste and Blue Bin materials in kilograms per person for each district and across time. The data in these figures show that waste seems to be remaining fairly constant through time with the slight exception of Victoria, Central Saanich, and Sidney which all seem to be trending upwards. An interesting feature of Figure 1.2 is the jump in Blue Bin material per person at year 2000 except for Langford and Oak Bay.



[3] For both Figure 1.1 & 1.2 these trends are not controlled for average home value, number of children or a yearly trend.

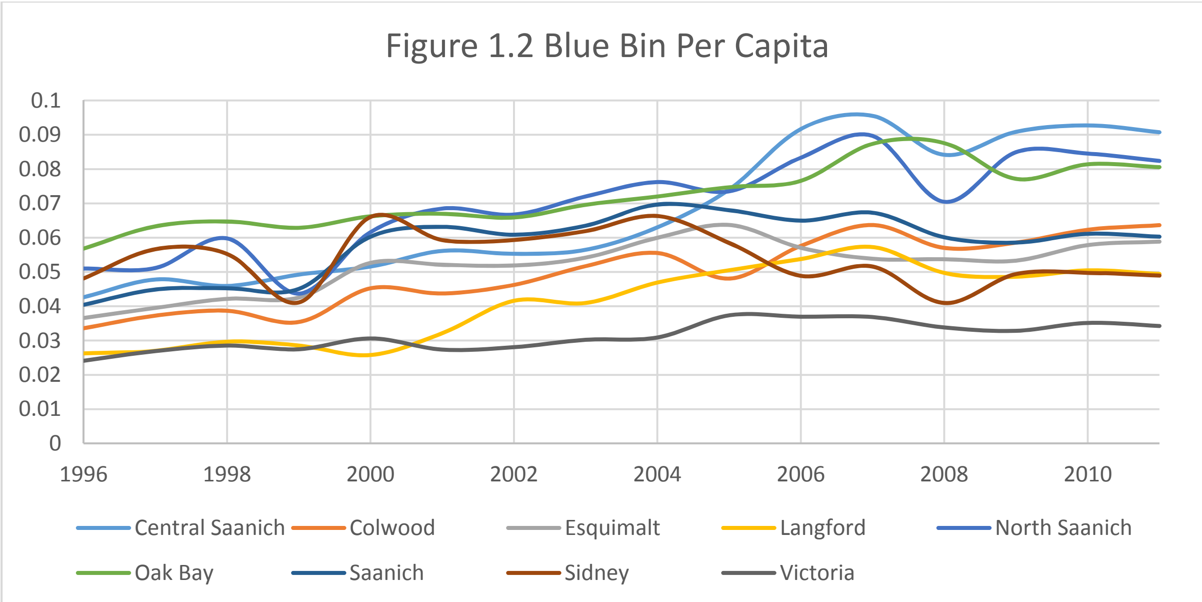


Table 1 shows that's there is large variation in the variables across districts. For example, the reported garbage materials per person are between 12.5 kg per person to 98 kg per person, which is a substantial difference. This differences might be attributed to socio-economic and demographic differences across municipalities (Statistics Canada, 2011). Blue Bin materials show less of a difference between reported recyclable materials per person. Population and home value are also quite variable across districts. Number of children also seems to be largely but this might be misleading since it's not reflective of the number of children relative to the population.

Table 1: Descriptive Statistics for Variables

Variable	Mean	Std. Dev.	Min	Max
Blue Bin Materials (kgs per capita)	5.51408	1.68703	2.41211	9.55155
Garbage Materials (kgs per capita)	42.57792	19.49309	12.48037	97.98402
Total Waste Materials (kgs per capita)	48.09201	19.13691	16.20734	107.059
Population	33072.55	33536.25	10411	112462

Child (children per district)	7976.25	8233.587	2240	30460
Home Value (averaged by districts. In 2011 $)	391420.8	159396	188466	776697

5. Empirical Strategy

In this section I explain why I logarithmically scale my dependent and independent variables for my model. I then go on to explain why I used several fixed effect modeling processes that included dummy variable estimation and first differences. These estimations are used to capture the short-term and long-term impacts after the year 2000 on recycling, garbage, and aggregate waste.

5.1. Model Specification

I start with assuming a linear relationship between the independent and dependent variables. The reason for adopting nonlinear right-hand variable is due to the skewed nature seen across the child variable representing the number of children from every district. There is also variation in the average home value variable.

Table 2: Summary stats for natural log of number of child and average home value compared with their linearized versions

Variable	Mean	Std. Dev.	Min	Max
child	7976.25	8233.59	2240	30460
logchild	8.55	0.77	7.53	10.32
avghome	391420.8	159396	188466	776697
logavghome	12.80	0.41	12.15	13.56

The adoption of nonlinear trend also makes sense because number of children and average home value do not have a linear relationship with the amount of garbage and recycling. Since a household would exhibit economies of scale for additional children it would make sense household waste not increase in a linear fashion with respect to number of children.

Looking at the normality of the residuals with a linear dependent variable then nonlinear using the natural log I found the residuals for the regression involving a non-linear dependent variable normally distributed rather then when modeled using a linear dependent variable. Further rational for writing the dependent variable in natural logs is the ease of interrupting coefficients. By using a log-log relationship I have assumed there is a constant elasticity relationship between waste per capita and number of children and average home value.

5.2. Fixed Effects Model

I have used several fixed effects models to estimate the impact of program policy change on household waste tonnage in the CRD. Due to my limited dataset, there is likely significant unobserved heterogeneity in districts that may be correlated with household garbage, waste and recycling. By using fixed effects for districts, I control for these unobservable characteristics of districts that are fixed over time..

It is important to note that equations listed below only show waste listed as the dependent variable but I estimated all equations with aggregate waste, garbage, and Blue Bin materials per capita as dependent variables.

Dummy Variable Estimation

I have estimated two equations using dummy variables. These equations explain the long run average difference before and after the program.

$$\text{LogWaste}_{it} = \beta + \beta_1 year_t + \varphi_2 Distdum_i + \beta_4 Policy_t + \beta_5 Logchild_{it} + \beta_6 Loghome_{it} + \epsilon_{it} \quad (1)$$

Equation (1) looks at measuring the percentage volume changes of waste in response to the policy change while controlling for different district effects and allowing for a linear time trend. I also adapted this equation to include a nonlinear time trend but estimates on parameters of interest have higher standard deviation and therefore lose statistical significance. This equation is referred to Base Line model in the results section.

$$\text{LogWaste}_{it} = \beta + \emptyset_1 yeardum_t + \varphi_2 Distdum_i + \beta_3 Logchild_{it} + \beta_4 Loghome_{it} + \varepsilon_{it} \quad (2)$$

Equation (2) allows for more of a flexible time trend through $\emptyset_1 yeardum_t$ which generates dummies for every year accept 2000 to avoid perfect multicollinearity. The year 2000 was omitted for ease of reading graphs found in result section.

For both equations the interpretations of estimates follows:

LogWaste_{it} is the total tonnage of waste in district i and at time t. LogWaste is a representation of 3 different dependent variables used when regression models. OLS predicts the average value for each. $\varphi_2 Distdum_{it}$ Represents the dummy variables for each district. The district dummy variables coefficients measure the average difference between being in that district and the reference district which is the district omitted in the regression. E.g. $\beta_3 D_{SANNICH\ t}$ β_3 would be the average difference between waste produced in Sannich and waste produced in the omitted district. $Policy_t$ is the variable of interest that takes on a value of 1 for the year 2000 and for the following years. This aims to look at the difference in waste tonnage before and after 2000, conditional on all other factors in the model. Interpreting $\beta_4 Policy_t$ coefficient would be the average difference between 1996-1999 and 2000-2011 in waste. The two groups are not symmetric and due to the heavier weighting of the more recent years this might result in magnitudes to not fully reflect immediate program change. I did not drop later years due having a small sample set to begin with. The variable $child_{it}$ is representing the number of children in each district over time. Interpreting the coefficient for $Logchild_{it}$ as a 1% percentage change in number of children in each district results in β_5 percentage change in waste.

The variable $home_{it}$ represents the average value of home for each district across time. Interpreting is similar to interpreting the coefficient for $Logchild_{it}$. I have controlled for ϵ_{it} to be normally distributed by estimating models with a robust command.

First Differences:

$$\Delta logWaste_{it} = logWaste_{it} - logWaste_{it-1} \qquad (3)$$

This model attempts address the problem of omitted variables in my regression, same as the previous model, but this model examines the instantaneous change in waste that might have been cause by the program change. This model's policy variable strictly takes on the value of 1 for year 2000. The short coming of this model is it might not reflect the true impact of the program change due to late onset of participation of households that might result of incorrect information of the program. Composition studies of the Hartland Landfill postulate changes in composition to be slow due to the gradual dissemination of information about the recycling program (Kvick, 2005).

5.3. *Estimation of Models*

To determine if the allowance of additional materials to the Blue Bin program affected aggregate waste and or garbage generation of household, I used Ordinary Least Squares (OLS) method to estimate the parameters of the 3 models. The relationship between the dependent and independent variables was examined through the value of the estimated coefficient, the standard error and corresponding p values. However these estimates might not be efficient if we assume that errors are no longer spherical.

Estimating the models using Generalized Least Squares (GLS) allows for serial correlation in the residuals unlike OLS. This autocorrelation arises from the number of children and house values being correlated across time, within regions. Upon further examination I was led to believe there was auto-correlation of the residuals when estimating with OLS. This might have been a symptom of omitted variables which would make my estimates biased. When undergoing the GLS estimation I assumed that districts follow their own autoregressive, AR(1), process. Meaning all the districts have errors that are following the same AR(1) process. Interpretation of GLS estimates will be same as OLS interpretation. Differences in estimated coefficient between the two methods is due to the small dataset.

6. Results

We can see from the first column in Table 3 that Blue bin materials per capita increased by approximately 19 percentage points in response to the policy change while garbage per capita fell by approximately 12 percentage points. We also can see if anything, aggregate waste fell by about 8 percentage points. However, when the model is estimated by GLS aggregate waste only seemed to decrease by 2 percent and garage decreased by 6 percent. Meanwhile the estimate for Blue Bin materials stayed relatively similar to the OLS estimate and kept statistical significance. Indicating a more robust estimate. Contradictorily, the OLS estimates from the first difference model suggest aggregate waste increased by 2 percent and garbage only fell less than 1 percent. GLS estimates using the first difference model also show the same signs for the aggregate waste and garbage estimates but with slightly different magnitudes. For both OLS and GLS the first difference model predicted an increase in Blue Bin Tonnage but with varying magnitudes.

Table 3: Results of estimating the models described above using equation (1) and equation (3)

Dependent Variable	**Base Line**		**First Differences**	
	OLS	**GLS**	**OLS**	**GLS**
	Coef. Policy Variable			
Log(Aggregate Waste)	-0.0828*	-0.0185	0.0194	0.0019
	0.048	0.029	0.044	0.031
Log(Garbage)	-0.1191**	-0.0609*	-0.0044	-0.02652
	0.054	0.034	0.051	0.036
Log(Blue Bin)	0.1857***	0.1765***	0.1579***	0.061***
	0.035	0.029	0.039	0.002

*significant at 10% level ** significant at 5% level *** significant at 1% level
Dependent variable reported in tonnage per capita terms
Independent variables include log(number of children) log(home value)
District dummies and a linear time trend pertain only to baseline model

I discovered that the immediate impact showed that aggregate waste did go up but results were not statistically significant; reflected in Table 3 for the first difference estimates. This was proven using the first differences model using OLS and GLS estimation. However, upon inspection of the changes in average of between the pre and post policy change years I found conflicting results. If I allowed for a linear time trend I found total waste declined slightly; seen in Table 3 base line estimates. When I allowed for a flexible time trend aggregate waste appears to increase one year after the program changed. This can be seen in Figures 2.1[4] and 2.2[4].

[4] Figures 2.1, 2.2 2.3, 2.4, 2.5, 2.6 found after bibliography

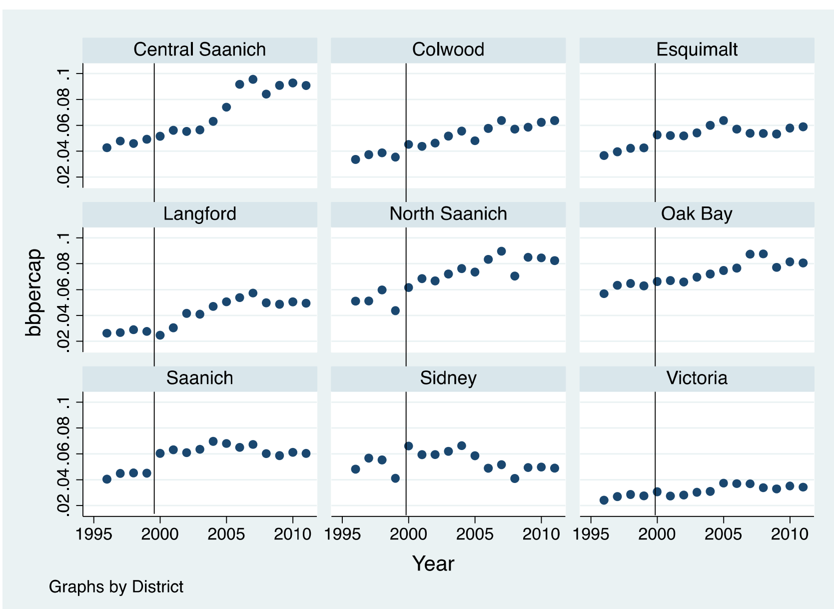
With such evidence I proceeded further by looking at the two components of total waste, garbage and recyclables, and estimated their changes using the various models. I found estimates for Blue Bin tonnage to be robust and each model showed that tonnage had increased after time of program changed with statistical significance. Visually it can also be seen in Figures 2.5[4] and 2.6[4] when estimated with equation (2).

When I used garbage as the dependent variable all models seem to show garbage was going down by some percentage; however, magnitude and statistical significance vary for various models indicating that the estimate might not be as robust as Blue Bin estimates. Which to me seemed interesting since if I can prove recycling has gone up with certainty and people were in fact just changing which bin they now placed plastics and corrugated cardboard, then it would make sense that estimates for garbage should decline with statistical significance. The fact that it does not may suggest need for further work into why it cannot be proven with statistical significance for all models. Furthermore, the fixed effected model that allowed for year dummies did show garbage increasing but one year after the program changed (figures 2.3[4] and 2.4[4]). I could not think of a possible explanation for such behavior therefore I conclude that garbage must have decrease by some amount in response to the programs.

The coefficients on average home value are the expected signs based on previous literature and are statistically significant. Number of children did not seem to have robust estimates and would sometimes show magnitudes that were seemingly implausible. The difference between my result and research done by Johnstone and Labonne might be due to the difference in modeling. Their model is based on household utilization maximization theory, so their results reflected the number of children per-household drove demand for waste services. By including these variables I was trying to ascertain whether the average effect of number of children and home value across time impacted the policy dummy variable. I estimated my fixed effects model including the two variables and excluding them. My estimates for the district dummies changed and the model with the additional variables had a higher adjusted R^2 reflecting that the repressors helped explain the changes in my dependent variables as well as changes across districts. However, the main findings from Table 3 are robust with their inclusion.

The standard error for the estimates for number of children is unexpectedly large which might suggest multicollinearity with the other regressors. I ran auxiliary regressions that treated each regressor as a dependent variable and the other regressors as independent variables and evaluated the R^2. There was not a strong relationship between the policy dummy and number of children or average home value. Since the goal of this paper is looking at the estimate for the policy dummy the fact that the other regressors are highly correlated is not of importance.

Graph 3: Blue Bin Tonnage Per Capita Across Districts



When estimating with OLS or GLS all models show that Blue Bin tonnage has increased on average since 2000 when additional materials were included in the program. It is interesting to note that changes in Blue Bin tonnage seem to be driven by specific municipalities. This can be seen in scatterplot graphs in Graph 3, indicating the trend in tonnage across time for each municipality. The vertical line in Graph 3 represents the year that the recycling program allowed the additional materials. For Colwood, Esquimalt, North Saanich, Saanich, and Sidney, there is a distinct jump in the plotted diagram. Results reflect what was seen in Graph 1.1 and 1.2 that there is significant differences in recyclables, garbage, and aggregate waste per person across the municipalities. These results might be the consequences of the difference in socio-economic factors across the municipalities. As stated in the literature review there is ample evidence to show waste generation is a function of demographic factors, socio-economic variables and environmental preferences. The results seem to suggest that there is differences across municipalities but not within them. Ergo households within these municipalities might share a lot of these waste-determining factors.

7. Discussion

In this paper I have established that within the CRD there has been an increase in Blue Bin materials per capita through the regions and that garbage per capita has decreased since 2000. However, since the program changed happened at once across all municipalities it is hard to distinguish if my results are a reflection of the program change or are reflecting other trends that are not captured by my models. One trend that could be leading to more aggregate waste is the change in food consumption patterns of households. Family life has been shifting, more women are working and people are staying later in the office, resulting in a shift towards ready to eat meals. A Canadian study found that from 1938 to 2011 there have been changes in sources of dietary energy amongst households. The study found the share of ready to consume dietary products rose from 28.7% to 61.7% (Moubarc et al, 2014). There is also evidence linking prepackaged meals and food to greater waste byproducts then their raw food counterparts (Marsh & Bugusu, 2007).

Another possible explanation is what Morris and Holthausen found that when households increase their efforts to recycle total household waste falls (Morris & Holthausen, 1994). This might be indicative that if a household is conscientious of their alternative waste disposal practices that they might make more of an effort to cut back on all waste.

8. Conclusion

It does seem from Table 3 that garbage went down when the program changed, reflecting that people were now placing corrugated cardboard and plastics in the Blue Bins instead of the garbage. However, results in Table 3 and Figure 2.1 show aggregate waste increased with estimates from the first difference model and dummy variable estimation with a flexible time trend, suggesting that garbage fell but not as much as recycling increased. The alternative to the previous explanations might be tied to my motivating idea. The presence of recycling offers a "guilt free" disposal method and that people that are conscientious of what they throw out might not feel as bad disposing of items when they have the option to recycle. Therefore the removal of guilt causes distortionary behavior and they end up throwing more goods away.

Nevertheless, estimates make it hard to distinguish which story[5] is more likely. What can be said with certainty is after the allowance of additional materials to the Blue Bin Program tonnages for recyclables per person increased on average. While garbage tonnage per person fell

[5] Referring to the previous explanation in the discussion section

after the program changed. It is unclear what happened to aggregate waste after the program changed. The research has also highlighted there is distinctly different disposal patterns across municipalities reaffirming the socio-economic differences reflect discrepancies in household waste generation.

It would be interesting to examine a larger data set and see if models estimate similar results. This information might also be relevant to the CRD since it shows recycling and garbage per per-person varies substantial differences across municipalities, which is most likely driven by socioeconomic and demographic differences within the CRD.

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10. Figures

Figure 2.1 Equation (2) estimates: OLS aggregate waste

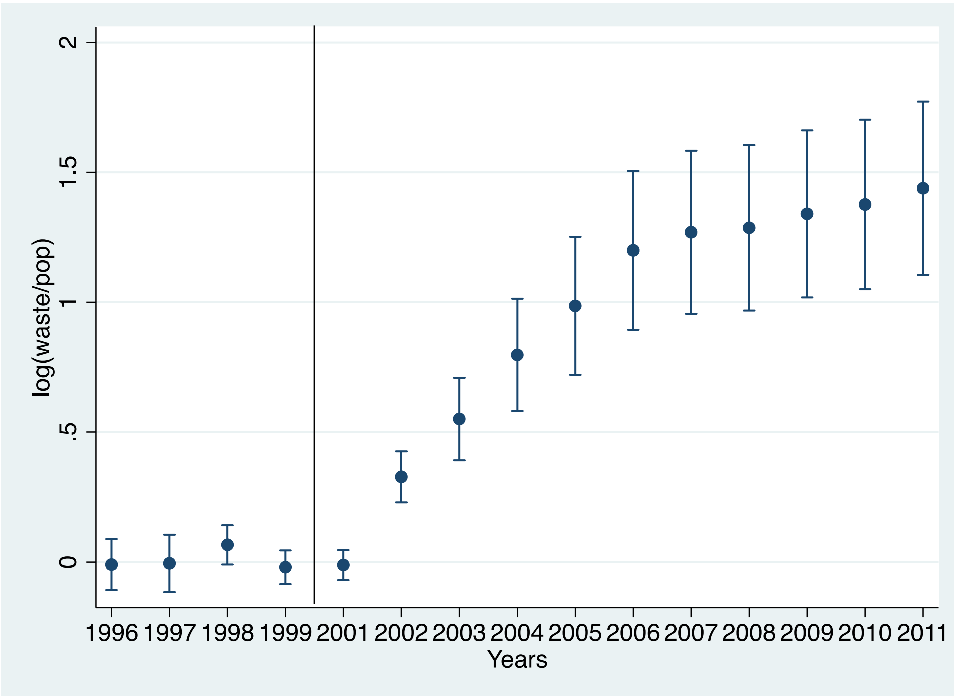

Figure 2.2 Equation (2) estimates: GLS aggregate waste

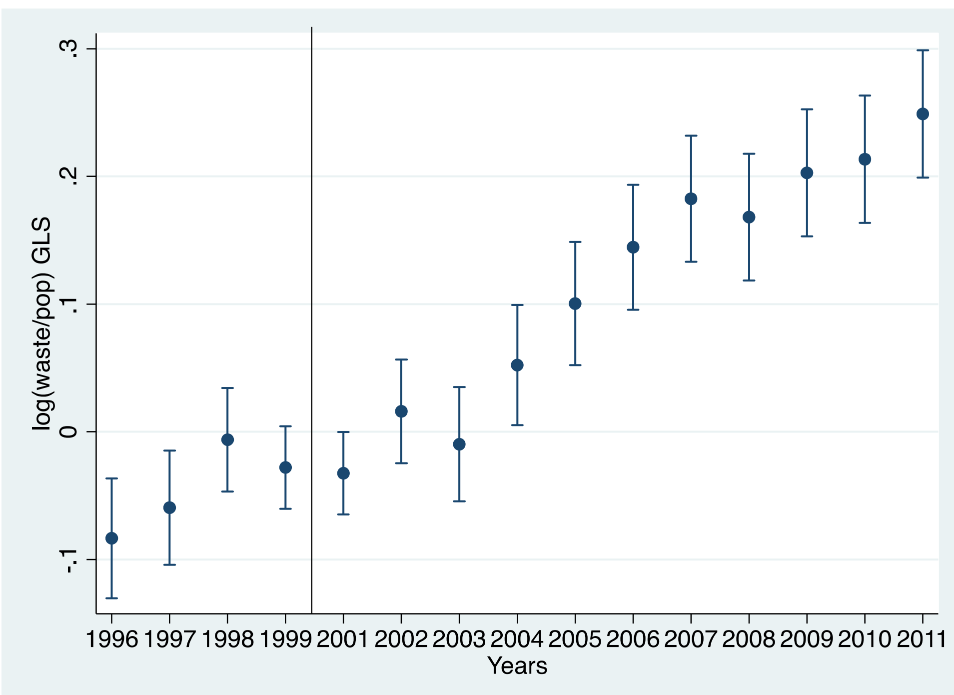

Figure 2.3 Equation (2) estimates: OLS Garbage

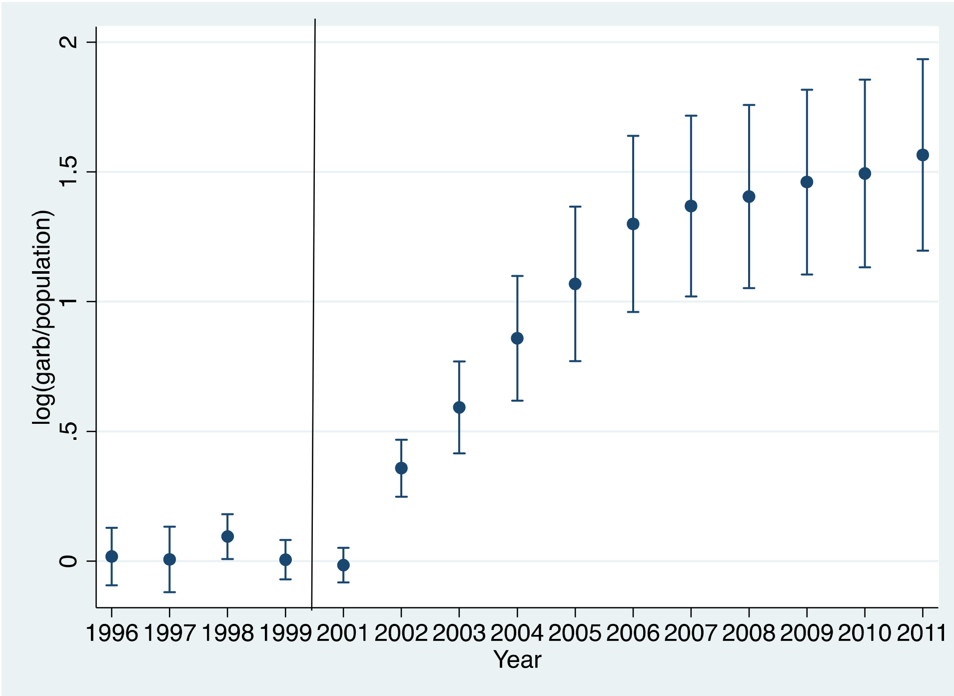

Figure 2.4 Equation (2) estimates: GLS Garbage

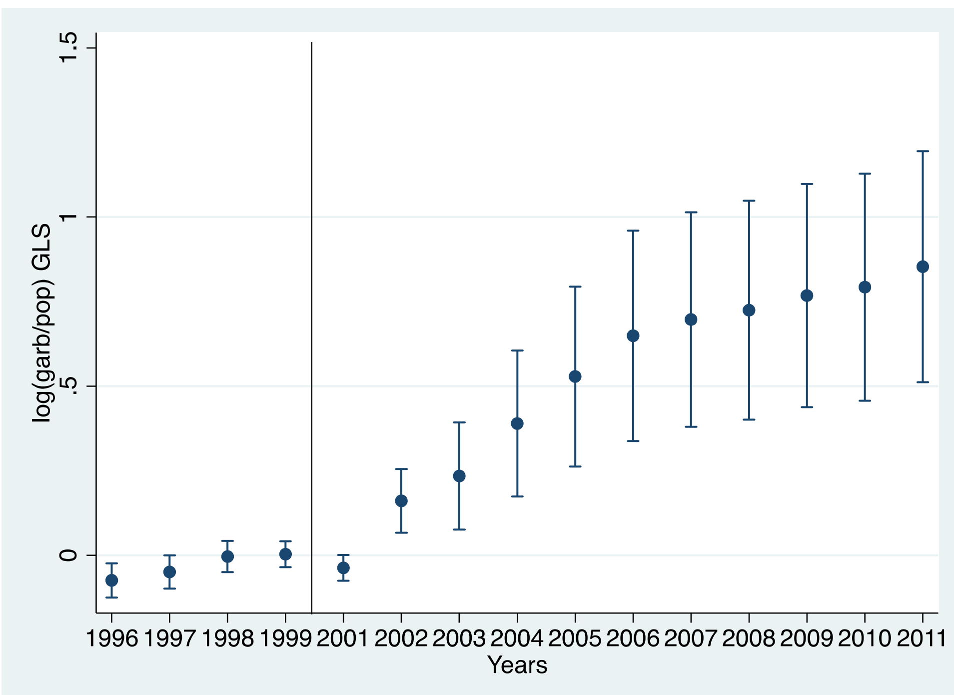

Figure 2.5 Equation (2) estimates: OLS Blue Bin

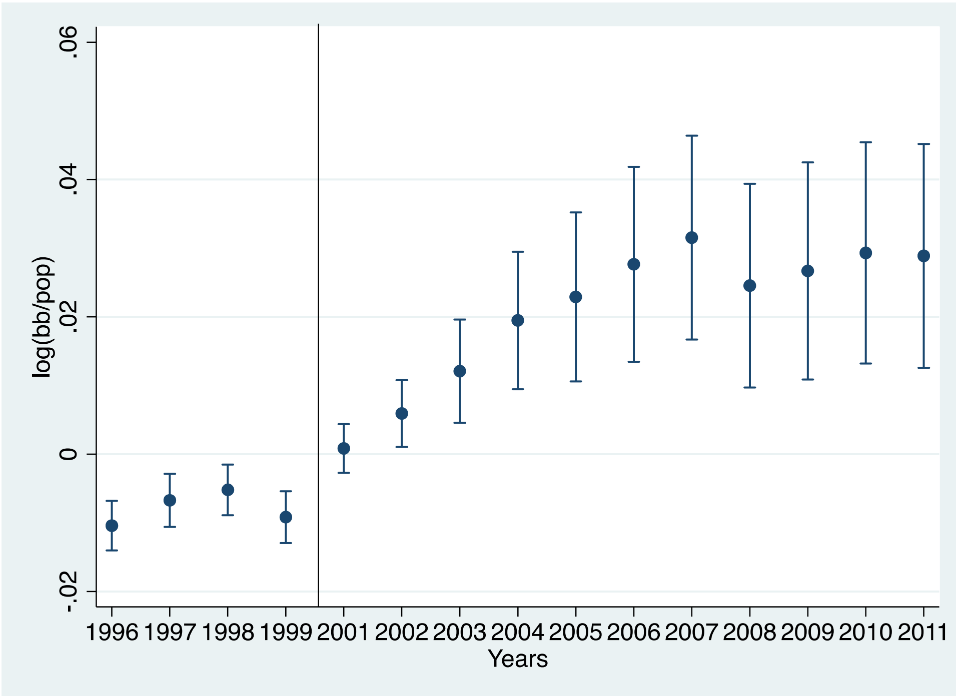

Figure 2.6 Equation (2) estimates: GLS Blue Bin