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Patterns in Trash: Factors that Drive Municipal Solid Waste Recycling

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PATTERNS IN TRASH:

FACTORS THAT DRIVE MUNICIPAL SOLID WASTE RECYCLING

A Thesis Presented

by

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DEDICATION

To all those who have come before and to all those yet to come who fight for social and environmental justice.

ACKNOWLEDGMENTS

I would like to thank my advisors, Craig Nicolson, Charlie Schweik, and Anita Milman for their thoughtful guidance. I would also like to thank my fellow graduate students for their support and my dear Stéphanie for all her help and support along the way. Finally, I would like to acknowledge the work of previous researchers in this field, whose findings informed and inspired my study.

ABSTRACT

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FEBRUARY 2014

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Municipal recycling is driven by a variety of factors. Yet how these factors change over time is not well understood. I analyze a suite of contextual and program variable in multiple time periods, spanning 16 years, in the Commonwealth of Massachusetts. Based on the models run, I reach the surprising conclusion that most program variables have an insignificant effect on recycling rates. These findings can inform municipal officials and waste managers as they seek new ways to increase municipal recycling participation.

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CHAPTER 1

THE BIG PICTURE

The road from ancient to modern civilization is littered with the remains of societies that failed because they were unable to adapt to changing environmental realities (Diamond 2011). Today society faces an enormous set of environmental challenges including climate change, deforestation, loss of biological diversity, overfishing, and overhunting. Because the problems society faces are of mankind's making they are within the power of humankind to solve.

The driving force behind many of the environmental, social, and economic, challenges of our time can be traced to mankind's consumption. Many resources are being consumed faster than the natural world can replace them and they are not being equitably shared among people (World Wildlife Fund et al. 2013). Additionally, consumption-driven pollution is overwhelming natures' pollution absorption capacity. Left unaddressed, this situation threatens to cause the resource shortages, environmental degradation, economic instability, and social strife that have historically driven social decline and collapse (Diamond 2011). To avoid this undesirable future it is critical to bring human demands on the planet more in line with what the earth can sustainably provide. While meeting this challenge will likely require many hard choices, innovation, and profound changes, one easy and noncontroversial place to start is with trash.

Trash, or municipal solid waste (MSW), is composed of things that people use and then throw away, such as food scraps, packaging, newspapers, yard trimmings, and old appliances. Society defines these things as waste because they have served their purpose and are no longer useful in their current form. However, the word waste also has a second meaning, it can be used to describe a missed opportunity. So, while trash may be waste, the way society currently manages trash is *a* waste.

Based on a United Nations sample of 78 countries, about 75 percent of the world's trash is being thrown in landfills or burned (United Nations 2011). In the sample, this represented about 690 million tons annually. This is a huge lost opportunity. Disposing of trash in these ways creates environmental problems such as ground water contamination from landfills, greenhouses gases from decomposing organic matter[1], and toxic air pollution from incinerator smokestacks (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2010a). At the same time it wastes a source of valuable raw materials, which means each year 690 million tons (and growing) of new raw materials must be harvested from virgin sources and processed using large amounts of energy.

Landfills have been used since about 500 B.C. in ancient Greece (Louis 2004) and garbage incinerators have been used in the United States for over 125 years (Walsh 2002). These disposal methods were developed to address public hygiene and space constraints and were adequate solutions to the problems of their times. Today's trash, however, is a complex mix of materials (Figure 1) including glass, rubber, metal, plastics, e-waste, and hazardous materials that are better managed through other means. With rising population and per capita consumption, global trash output is expected to double to about 2.6 billion tons by 2025 (World Watch Institute 2012). It therefore makes sense to put efficient waste

[1] In the United States, landfills are the third largest generator of methane, a gas that has an impact on climate change 20 times greater than carbon dioxide (United States Environmental Protection Agency 2013).

management systems in place now that seek to maximize the environmental, social, and economic benefits of trash processing.

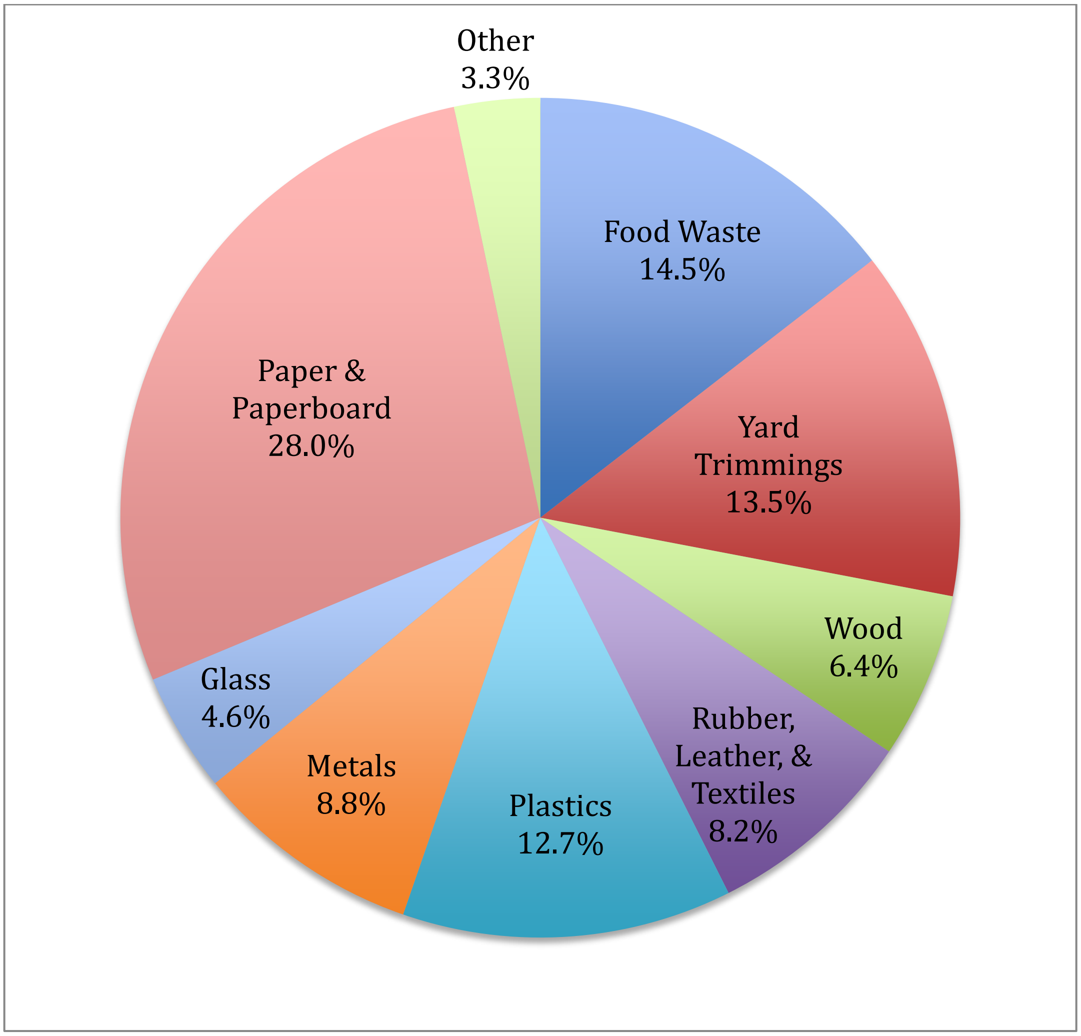

Figure 1: United States Waste Composition 2011 (250 Million Tons) Adapted from: (United States Environmental Protection Agency 2011).

An alternative to landfills and incinerators is recycling. Recycling is the collection and processing of manmade goods into the raw materials necessary to make new goods and the breaking down of organic waste into compost.[2]

Waste in the United States

Though it accounts for just 4.4 percent of the world's population, the United States (US) is the world's single largest consumer of goods (Themelis and Kaufman 2004) and generates 17.4 percent of the world's trash (World Watch Institute 2012; United States Census Bureau 2013). Therefore nowhere on the planet is it more important to correctly manage waste than in the US.

Between 1960 and 2005 the total tonnage of MSW produced in the US steadily increased from about 88 million tons to 253 million tons. Since that time, it has basically remained level, with a slight decrease to 250 million tons. From 1960 to 2000, per capita waste generation also jumped from 2.68 pounds per person per day to 4.74 pounds per person per day. Since then it has declined slightly to 4.4 pounds per person per day (Figure 2) (United States Environmental Protection Agency 2011).

[2] In addition to composting, anaerobic digesters can also process organic material into compost and biogas, but these are not widely used in the United States for municipal solid waste, so they will not be covered here.

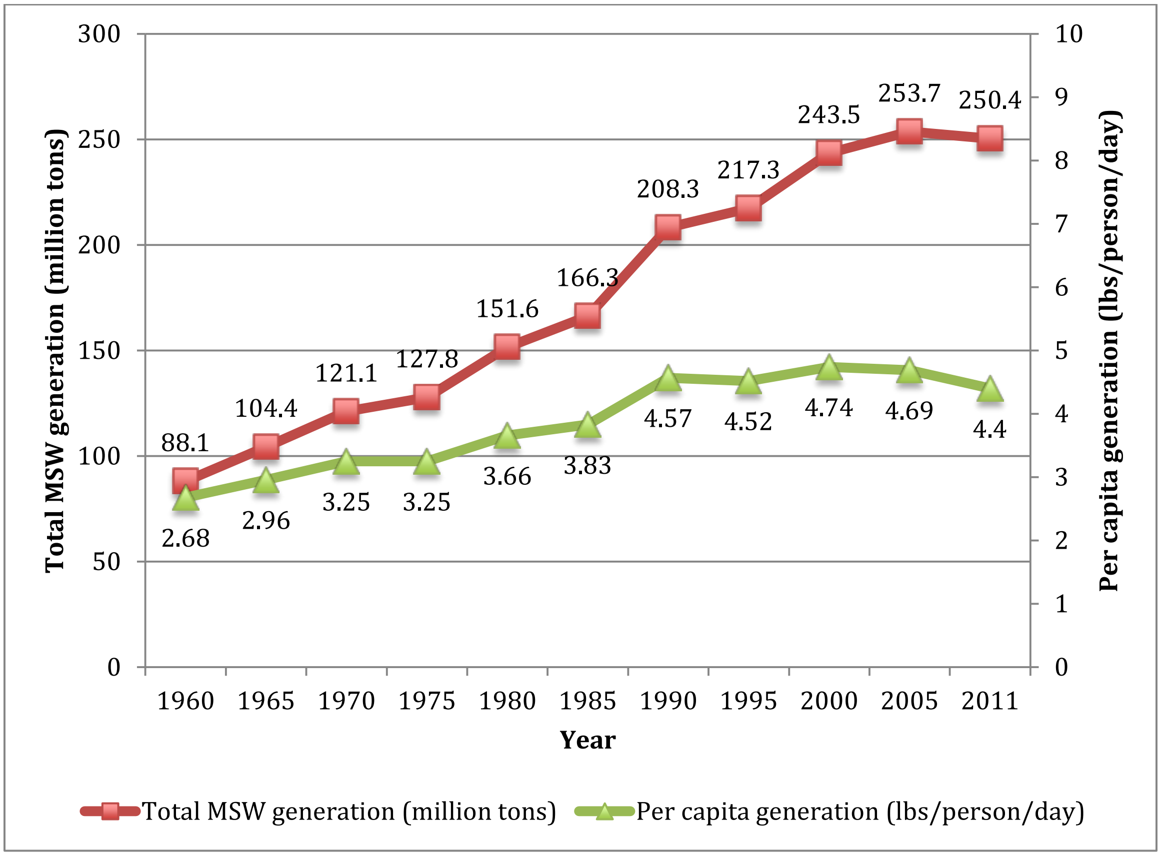

Figure 2: MSW Generation Rates from 1960 to 2011. Adapted from: United States Environmental Protection Agency 2011

Recycling in the United States

Over the last thirty years, municipal recycling in the US has transformed from an oddity to a critical component of modern waste management (Kinnaman 2006). In 1960 the national recycling rate was 6%. This remained fairly constant until about 1985. Between 1985 and 1995, the recycling rate grew aggressively from 10% to 25%. Since that time it has been continuing to rise, but at a much reduced pace (Figure 3) (United States Environmental Protection Agency 2011).

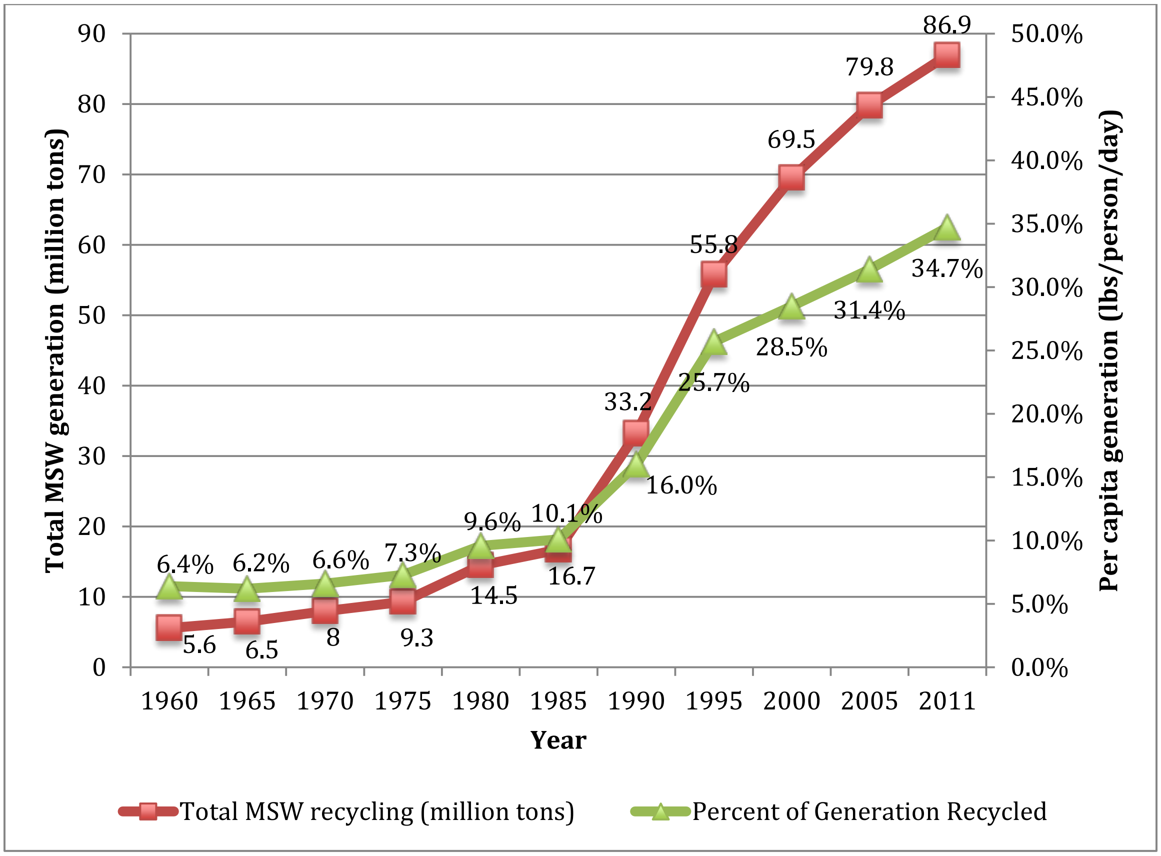

Figure 3: MSW Recycling Rates from 1960 to 2011. Adapted from: United States Environmental Protection Agency 2011

Today, at least 83% of the United States' population has access to basic recycling services (United States Environmental Protection Agency 2009). The evolution of recycling over the last three decades has been shaped in no small part by the Resource Conservation and Recovery Act (RCRA) of 1976 (Kinnaman 2006). The RCRA came about as a reaction to land-based pollution. In the years before the RCRA was passed, the Clean Air and Clean Water Acts were enacted. In response, some industry simply shifted their hazardous waste disposal to open land dumping (United States Environmental Protection Agency 1976). In addition to industry, poorly built municipal landfills were leaching toxic waste and causing serious environmental and public health concerns.

The RCRA addressed these issues by federally regulating land-based waste disposal. As a consequence, all landfills across the United States had to meet certain minimum design and operational criteria (United States Environmental Protection Agency 2012). Consequently, many landfills were forced to close as they fell out of compliance with this new statute (Kinnaman 2006). This resulted in a drop in landfill capacity and an increase in tipping fees (the price paid per ton to dump in a landfill) (Bohm et al. 2010; Jenkins et al. 2003). By the 1980s, this, in combination with a growing population, created a perceived landfill crisis, which spurred communities to find alternative ways to deal with their trash (Kinnaman 2006).

For many, recycling became an attractive solution to this problem because in addition to easing capacity fears, it addressed the social marginal costs of traditional waste disposal methods. It also reduced the need for citing new politically unpopular landfills or incinerators, and provided individual citizens with a way to participate in the environmental movement. Many households embraced the idea of recycling because they derived an altruistic benefit from it (Kinnaman 2005). As Kinnaman points out, parents and children gain utility from the very act of recycling and their decision making on what type of program they prefer is represented by a preference for curbside services for which they have a willingness to pay $7.17 per month (Kinnaman 2005; Kinnaman 2006). As a result of all these factors, over a 20-year period from the mid-1970s to the mid-1990s, recycling experienced tremendous growth. Curbside recycling collection programs[3] grew from only 177 in 1977 to 7,375 in 1995, serving 46% of the US population (Chowdhury 2009; Glenn 1987; United States Environmental Protection Agency 1993; United States Environmental Protection Agency 1996). In this same time, national recycling rates went from 7% to 26%, fueled by 10 boom years starting in 1985, where the rate grew an average of about 15%/year (United States Environmental Protection Agency 2009).

Starting around 1996 however, recycling rate growth fell dramatically to an average of only 2%/year through 2010. As a result, the national recycling rate in 2010 was only about 34% according to the EPA (Figure 4) (United States Environmental Protection Agency 2010). Columbia University and *BioCycle's* the "State of Garbage in America" puts this figure even lower, showing a slight decline to about 24% (Haaren, Themelis, and Goldstein 2010). This trend of sluggish growth or actual decline is somewhat disturbing as it occurred at a time when convenient curbside collection services expanded to reach 70% of the US population, recycling information became easier to obtain via the internet, and the environmental and social justifications for recycling became only more pressing (United States Environmental Protection Agency 2009). Additionally, the example of Austria, Germany and others shows that with the right mix of policies and programs it is possible to achieve national recycling rates almost double what the United States has so far achieved (European Environmental Agency 2013).[4]

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[3] Curbside recycling is when recyclable materials are placed in a bin on the street curb where a hauler picks them up.

[4] In 2013, Austria had a 63% recycling rate and Germany had a 62% recycling rate (European Environmental Agency 2013).

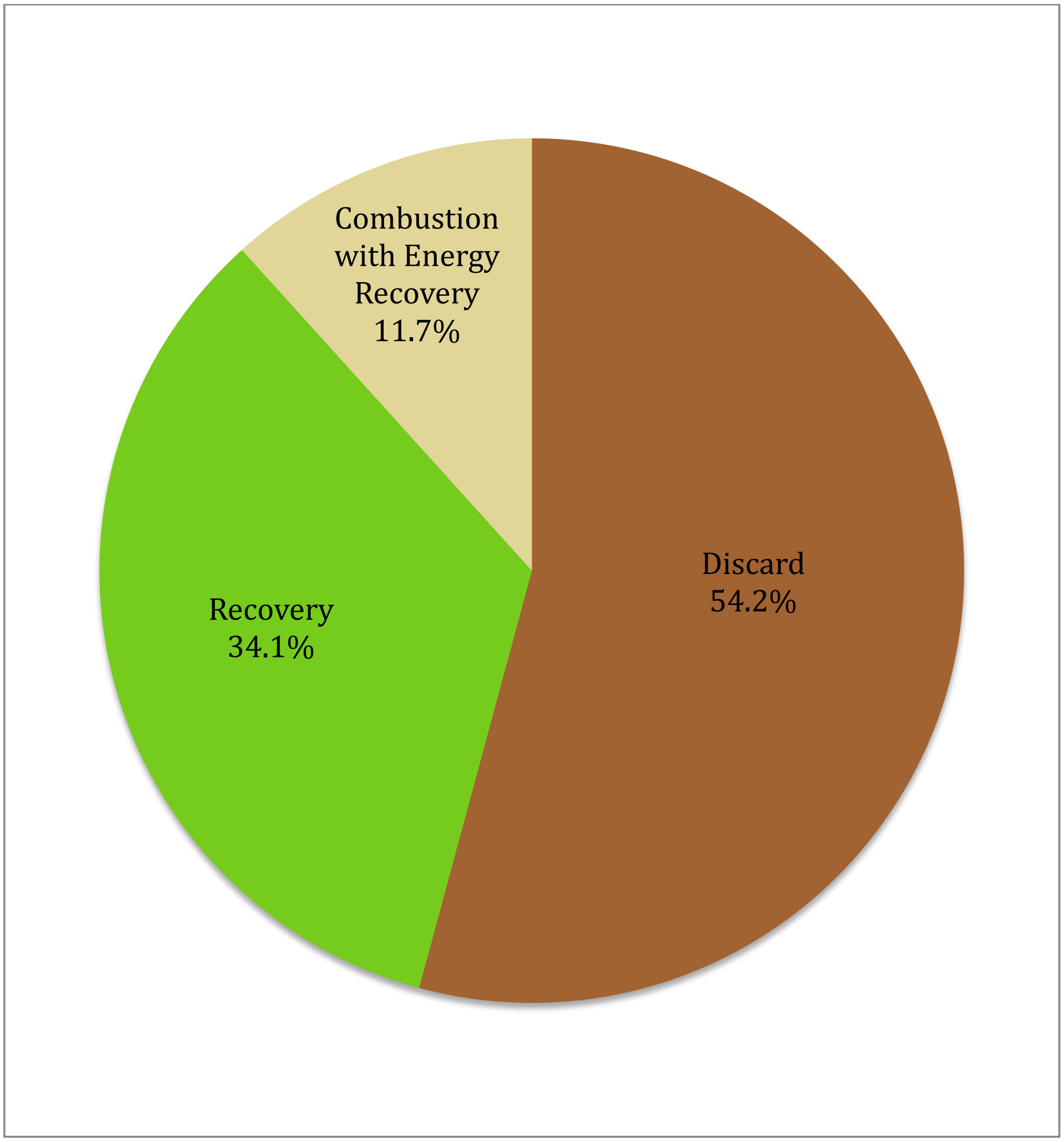

Figure 4: MSW Management in the United States 2010. Adapted from: United States Environmental Protection Agency 2010

So what happened in the United States? The incredible recycling growth of 1985-1995 was largely fueled by an expansion of recycling infrastructure (United States Environmental Protection Agency 2001). As more collection programs came online the nation's recycling rate rose. Expansion of these programs was based around collecting products that were easy to separate from the trash stream and had ready markets for resale. The targeting of these "low hanging fruits" such as aluminum, ferrous metal, glass, and paper helped drive initial recycling growth (Folz 1999). But recovery rates vary significantly across materials (Figure 5).

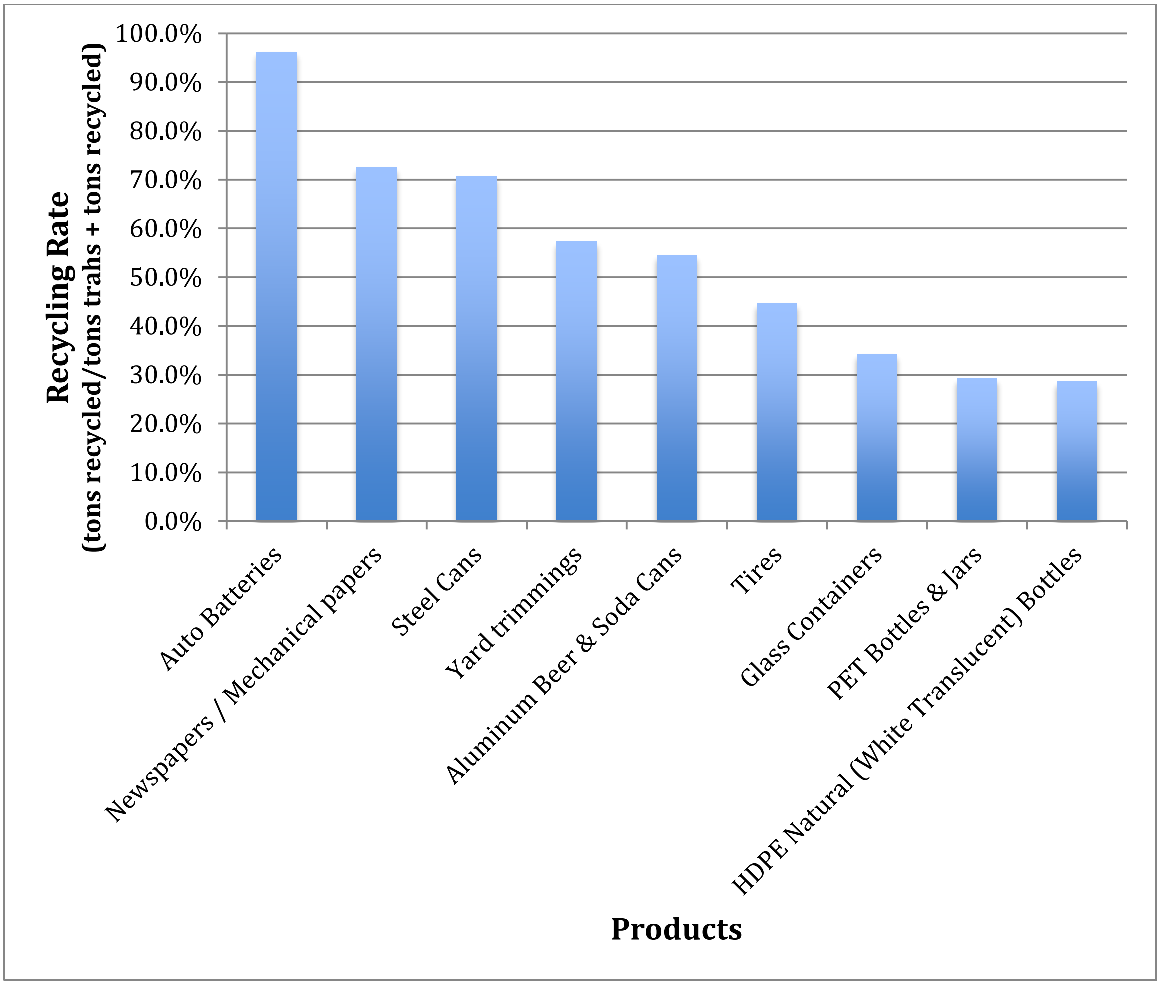

Figure 5: Recycling Rates of Selected Products 2011. Adapted from: United States Environmental Protection Agency 2011

As the "low hanging fruits" were harvested however, the remaining mix of materials had less certain economic offsets and fewer investments were made in new programs. By

1996, the boom in expanding services had slowed, with the notable exception of curbside recycling programs, which experienced huge growth between 1994 and 2000, adding 6108 programs (United States Environmental Protection Agency 2001; Bohm et al. 2010). The reason this expansion did not lead to a dramatic increase in recycling rates is somewhat unclear. It may be that towns served by these new programs already had successful drop-off centers so the addition of curbside did not lead to increased participation. The literature is not well developed in this regard.[5]

Another possible reason why the recycling rate has stagnated since the mid 1990s is because of reductions in packaging. To better understand this effect it is important to remember that while the recycling rate is a useful and flexible metric it does have drawbacks. Recycling rate is calculated by taking the total tonnage of waste diverted from landfills or incinerators (including recyclable materials, compost, and hazardous waste) and dividing it by the total tons of waste collected *and* diverted. This yields the percent of materials not thrown in landfills or burned

One problem with using recycling rate is that it does not capture overall reductions in municipal solid waste tonnage. Say for example in 2005 a town produced 8,000 tons of recyclables and 2,000 tons of trash. Their recycling rate is calculated to be 80%.[6] Lets assume that in 2010 the town is made up of exactly the same people buying exactly the

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[5] The results and analysis presented in this thesis shed more light on why expanding curbside programs didn't boost recycling rates higher.

[6] 8,000 / (8,000 + 2,000) = 8,000 / 10,000 = 80%

same product. One would again expect them to have an 80% recycling rate. However say that over the 5-year period, the packaging for those products has changed. Manufacturers have been trying to reduce their impact on the environment and save money on shipping costs so they've found ways to make their packaging weight only *half* of what it did in 2005. In this example, these packages are still made of the same materials and the amount that can't be recycled remains the same. So now the town produces 4,000 tons of recyclables (half of what it did in 2005) and still 2,000 tons of trash. The recycling rate is calculated to be only 66.7%![7] Using just the recycling rate one would say the town is not doing as well managing its MSW. But in reality the environmental situation is much improved: there is less overall waste, less need for raw materials, and energy savings from reduced transport and processing.

It is easy to imagine a circumstance in which people are recycling slightly more materials, but because packaging reductions are also occurring, the overall effect on recycling rate is balancing out near zero. When one looks at Massachusetts there is evidence this trend is playing out (Table 1). Looking only at recycling rate, 2009 has a lower rate than 2005. Using just the rate it appears that Massachusetts is not handling its MSW as well as it did in 2005. However, looking at the total MSW generated, one sees that Massachusetts actually produced 1,700,000 *less* tons than in 2005! This may be part of what has been

[7] 4,000 / (4,000 + 2,000) = 4,000 / 6,000 = 66.7%

happening over the last decade and an example of why recycling rate is not a perfect measure of successful MSW policy.[8]

Table 1: Tons of MSW Generated and Diverted in Massachusetts

	YEAR			
	2003	**2005**	**2007**	**2009**
Total MSW	8,460,000	9,310,000	8,370,000	7,610,000
MSW Diverted	2,870,000	3,300,000	2,740,000	2,620,000
recycling rate	33.9%	35.4%	32.7%	34.4%

Yet, while packaging reductions may help explain some of the slowdown in recycling rate growth, the real question is: with recycling rates leveling off, is it possible to recycle more than the mid-30% range? Since there are numerous examples of municipalities within Massachusetts, and cities and countries around the globe that are achieve recycling rates above 60% it is clear that more materials can be recycled (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2009; European Environmental Agency 2013). Therefore the question then becomes: *how* are higher recycling rates achieved? What factors allow some communities to achieve high recycling

[8] However, recycling rate is still quite useful and assuming people are purchasing roughly the same products across the state, the highest rates in an area can be thought of as the theoretical maximum rates if good recycling programs are in place. This allows one to analyze what variables lead to those high rates.

rates, while others languish? What policy tools are available to recycling manager to boost rates? To help answer these questions it is critical to know what factors lead to successful recycling programs and to understand how these factors may change as programs mature over time. Yet with regards to change over time, little work has been done in this area.

Recycling in Massachusetts

To provide insight into this area, my study focuses on municipalities of the Commonwealth of Massachusetts (Figure B1) over a 16-year period (1997-2012).[9] I analyze a suite of program and contextual variables to see which ones significantly influence recycling across that time. Program variables are policies and trash/recycling program characteristics that state or municipal officials and waste managers have control over. Contextual factors capture characteristics of people or the municipality that are outside the control of municipal waste managers; this includes spatial factors such as density and socioeconomic factors. The metric I use to measure recycling is the recycling rate. Recycling rate is a useful and flexible metric that allows for comparison between large and small communities and across different scales (e.g. town to state, state to country).

While new metrics that take source reduction into account are staring to become more popular and are now being used in addition to recycling rate by the Commonwealth of Massachusetts, I use recycling rate because it was the metric used by the Commonwealth of Massachusetts between 1997-2008. During that period, Massachusetts collected municipal-level recycling rate data with a consistent methodology for all 351 communities within the state. Between 2009 and 2012 it collected even more detailed recycling data, with a slightly

[9] See Table A1 for the spread of municipal recycling rates by year.

modified methodology, for all 352 municipalities (Figure 6).[10] These 16 years of data allow for a precise community-level analysis of factors contributing to recycling success over time.

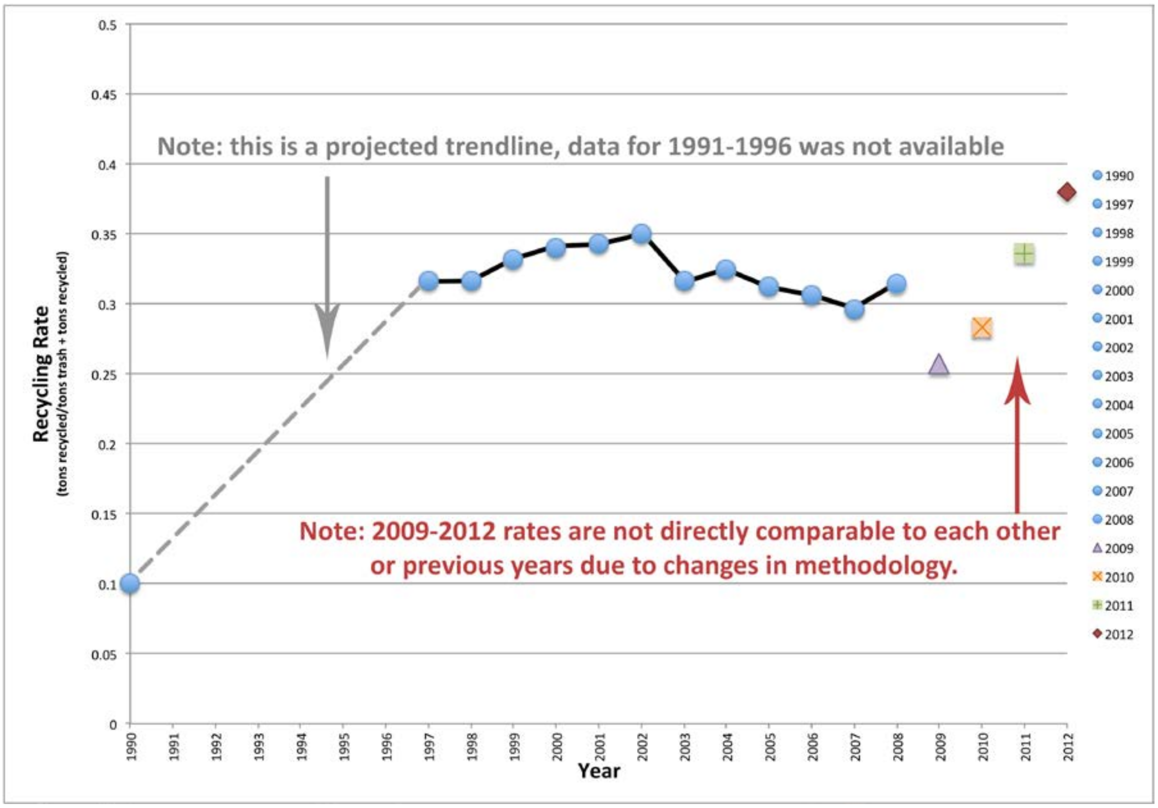

Figure 6: Average Massachusetts recycling rates (1990-2012). [11]

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[10] In 2008 the number of municipalities increased from 351 to 352 when the village of Devens became officially recognized.

[11] *Note:* The 1990 rate is the statewide recycling rate reported by Massachusetts. The 1997-2012 average Massachusetts rate was calculated by averaging all available municipal recycling rates. This is different than the statewide recycling rate, which is calculated by dividing total tons recycled by total tons recycled plus trashed. Due to a change in measurement methodology and available data, 2009-2012 rates are not directly comparable to previous years or each other. They are presented here for crude comparative purposes, but they should not be considered to be showing a trend. The

Besides the attractive dataset, the Commonwealth is a useful study site because, over the last 20 years, trends in the Commonwealth's recycling rates have been similar to national patterns. This suggests factors at work in Massachusetts are likely also at work nationally. Therefore, lessons learned from successful municipalities in Massachusetts, may be transferable to other parts of the country. Additionally, since 1990, Massachusetts has operated under a series of ambitious decennial MSW Master Plans[12], the most recent of which set a goal of zero waste by 2050 (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2010a; The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2000). If this plan is effective it could serve as a guide to other states and the federal government. Therefore, understanding what forces drive success in Massachusetts has consequences far beyond the borders of this one state.

Viewed through the lens of systems analysis, municipal solid waste is a highly dynamic system: new recycling technologies and innovations interact with population fluctuations, purchasing habit changes, and new types of materials such as iPods, cell phones, flat screen televisions, and other difficult-to-recycle products enter the waste stream. The goal of this study, looking across a time period spanning 1997-2012 is to

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1990 data was acquired from the 2000 Solid Waste Master Plan (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2000).

[12] The first Municipal Solid Waste Master Plan was introduced in 1990, with one following in 2000, and another in 2010.

analyze a set of policy and contextual factors that have been shown in other studies to influence recycling rates in order to answer three research questions:

Question 1)

At a given point in time, how significant is the influence of recycling policies relative to contextual factors, which are largely outside of policymaker's control?

Question 2)

At a given point in time, which recycling initiatives and policies provide the greatest boost to recycling rates?

Question 3)

Are the effects of these policies consistent over time or do the policies effectiveness in boosting recycling rates decline over time?

Past Studies

Literature Review

Soon after recycling programs were launched, researchers began systematically analyzing and quantifying which factors were important to making a program successful. A few studies that are particularly relevant to my work will be highlighted here. Then the variables I use in my study will be discussed in relation to their appearance in previous literature.

Key Studies

In 1991, Folz conducts one of the first studies in this field, surveying 264 recycling coordinators nationwide. He uses multiple linear regression to analyze a suite of independent program variables and measure their impact on recycling participation. He finds that legally mandating recycling is significant and that it can boost participation by a factor of 2 relative to non-mandated programs. However, the voluntary programs he studies may achieve high participation rates if they have curbside pickup, distribute free recycling bins, use private contractors, offer community composting, and do a public education and marketing campaign. He also finds setting a recycling rate target is beneficial and including the community throughout the program design and implementation is important. He finds having the recycling picked up the same day as trash is not important. Interestingly, he also finds that commingling of recyclables (putting all the materials such as metal, plastic, glass, and paper in the same bin)[13] is not important (Folz 1991).

In a separate analysis from 1991, Folz and Hazlett use this same dataset and multiple linear regression method to study the effect of socio-economic factors on recycling participation and the waste diversion rate[14]. Looking at both curbside and drop off recycling programs, they conclude there is no significant link between socio-economic factors or political leanings and recycling participation or diversion success. They do find however, some differences within drop-off and curbside programs, such as drop-off recyclers are more likely to be women, older, and more educated. Overall however, they emphasize program factors to be far more important. For

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[13] *Commingling* is more commonly known as *single stream* recycling.

[14] D*iversion rate* is equivalent to *recycling rate*.

example they find issuing non-compliance fees in mandatory programs to be a very successful mechanism to boost rates. Like Folz's earlier study, they also find recycling success strongly linked with targeted educational and publicity campaigns aimed at residents (Folz and Hazlett 1991). These two early studies are important comparison points for my study, because they employ some of the same variables and methods that I use, specifically using multiple linear regression to analyze program and contextual factors.

Another study quite relevant to my work is from Callan and Thomas (1997). Like Folz and Hazlett (1991) they use multiple linear regression to look at the effect of program variables and socio-economic factors on recycling rate. Important to my work, they also use the same observational units as I do: the 351 municipalities of the Commonwealth of Massachusetts. Looking at recycling rates from 1994 and 1995, they model the following program variables: unit pricing (also known as Pay-As-You-Throw (PAYT))[15], curbside recycling, access to the Materials Recycling Facility (MRF) in Springfield, grants for recycling education, grants for equipment, and curbside trash service. They also use the following contextual factors: education (number of residents over 25 who have attended a 4 year college), housing value (median value of single family home), housing age (proportion of single family homes built before 1960), housing density (single family homes per square mile), population (in thousands), suburban or rural setting, and type of town (resort, retirement, rural, other) (Callan and Thomas 1997).

They find unit pricing, especially in combination with curbside recycling to be strongly influencing recycling rate. They mention the downside to unit pricing is it may encourage illegal

[15] Pay-As-You-Throw (PAYT) is a unit based pricing scheme. With PAYT, individuals pay per unit of garbage they dispose of. PAYT is usually enforced by garbage haulers only collecting rubbish if it is in a special bag or has a sticker that homeowners are required to purchase. PAYT is in contrast to flat fee pricing where waste disposal charges are worked into property taxes and individuals can throw away as much as they want without paying more.

disposal or burning; therefore offering free curbside recycling services is a way to offset the illegal disposal of recyclables. They find unit based pricing increases recycling 6.6 percentage points and when used in combination with curbside recycling service it increases recycling 12.1 percentage points. They theorize curbside recycling boosts participation, by lowering opportunity cost for participants. Similarly, unit pricing (PAYT) for disposal provides an incentive to recycle more and throw away less to avoid paying the trash disposal fee (Callan and Thomas 1997).

Access to the state run MRF in Springfield is found significant at the 0.01 level and is causing as 9.5 percentage point increase in recycling rate. They suggest this may be the result of economies of density, small communities are able to save money by pooling together and using this one centralized facility, and these cost savings in turn encourage more recycling by communities (Callan and Thomas 1997).

They find equipment grants not to be significant, and educational grants to be only mildly significant, leading to a 2.55 percentage point increase in recycling. But they note, the grants they study had just been awarded, and therefore may not have had time to have a real effect yet. They find income, education, and urbanization to be significant, with education having a larger impact than income. Overall they find that socio-economic factors play a larger role, than they originally theorized (Callan and Thomas 1997). Callan and Thomas conduct two further studies (2001 and 2006) using Massachusetts, but these focus more on the economics of recycling and on estimating the interaction between trash and recycling demand.

While these and other studies provide valuable insights and heavily informed my current work, they were constrained by their times. Recycling programs were new and these studies, for the most part, look only at a snapshot in time. They use one or perhaps a couple of years of data and describe the factors important in that time period (Everett and

Peirce 1993; Noehammer and Byer 1997). In doing so, they do not illuminate how the factors that make recycling successful change as programs evolve over time. Are certain variables very important when a program starts but others are more important to sustain high rates? The existing literature provides scant answers to these questions.

One exception is a 1999 study conducted by Folz, which is to my knowledge the first and only study looking at how different program and contextual factors influenced rates over time. Folz uses a nationwide sample of 158 cities and analyzes changes occurring between 1989 and 1996. Similar to his earlier work, Folz uses participation and trash diversion rates as dependent variables[16]. He finds voluntary programs are able to achieve success equal to mandatory programs when they have time to develop. He finds composting, full time recycling coordinators, and same day pickup of materials to be significant variables that increase recycling rates across time. He also finds curbside recycling to be the greatest factor determining success in voluntary programs (Folz 1999).

Yet since Folz (1999), I am aware of no further work looking at how factors important to recycling change over time. This seems like a critical area to understand if recycling rates in mature programs are to improve. Because recycling programs have now been up and running for a few decades in the Commonwealth of Massachusetts and because the state has been diligently tracking recycling rates over the last 16 years there is a unique opportunity to fill this gap in the literature. My findings will provide unique insights at both the community and state level that can inform future MSW policy.

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[16] Folz also adds the inflation-adjusted cost of the recycling program as a dependent variable.

In addition to the key studies mentioned above, my work is also informed by a number of studies from others who have looked at contextual and program variables related to recycling success. The variables I use will now be defined and related to their appearance in previous literature. I am also including some variables that I think may be influencing rates that have not been previously studied. Their inclusion is based on their presence in Massachusetts' recycling surveys and I am testing whether these variables are actually important to recycling success. I examine the dependent variable and two main classes of independent variables: 1) contextual variables such as socio-economic and geographic factors and 2) program variables.

Dependent Variable

Recycling Rate

Recycling rate is the dependent variable. It is a function of independent contextual and program variables. It is the ratio of tons MSW diverted from trash (recycled, composted, sent to a swap shop, hazardous goods collected) to *total* tons of MSW collected (including both trash and diverted materials). This is a useful and important metric that is employed in the studies mentioned above (Callan and Thomas 1997; Folz 1991; Folz and Hazlett 1991).

Contextual Variables

Density

To measure density I use number of people per square mile. I expect that as population density increase so to will recycling rate because denser areas will have more recyclables per square mile and thus will be more attractive markets for recycling companies. However, denser more urbanized areas may make storing recyclables more costly. Previous studies in Massachusetts (Callan and Thomas 1997; Callan and Thomas 2006) use housing density as an independent variable impacting recycling success. Callan and Thomas (1997) measure population and housing density (number of homes per square mile) and find number of single family homes to be significant only at the 0.10 level. They find a negative relationship that as housing density increases recycling decreases. In their 2006 study they suggest housing density may be quadratic and have a negative impact at low or high densities. They cite Jenkins (1993) and Podolsky and Speigel (1998) as the theoretical basis behind housing density leading to a negative demand for trash disposal services which boosts recycling demand. But they do not find this to be statistically significant. I do not use housing density because accurate housing data is not available for all time periods. In 1997, they also use population (which is linked to population density) and find it to be significant at the 0.05 level. As population increases recycling decreases. I don't analyze population because population density is a more useful measure as it captures the spatial component and is reflective of recycling haulers benefiting from the concentration of goods in a given area. The counter point to this idea is that dense areas have limited space for storing and placing goods on the curb, so unless convenient programs are in place, at high densities, trash may be the default and recycling is not utilized. But overall, I expect density to have a positive effect on recycling.

Persons per Household

This is the average number of persons per household. Theoretically, there may be an economizing effect from purchasing in greater bulk so less packaging waste is generated. The effect this has on recycling rate is somewhat uncertain because it could have a slightly positive effect on recycling rate if the packaging is not recyclable or a slightly negative effect on rate if the packaging is recyclable. This may seem counterintuitive, but because of the way recycling rate is calculated, by reducing packaging that is recyclable the recycling rate is lowered because less recyclable materials are being collected. While not specifically using recycling rate as their metric, other studies (Callan and Thomas 2006; Sidique, Lupi, and Joshi 2010) use it as a measure of recycling success so I wanted to test its effect on rates. Callan and Thomas (2006) use Massachusetts' municipalities as their study area and measure trash and recycling disposal demand. They find persons per household to be statistically significant and that as persons per household increases recycling demand decreases. However, their dependent metric is pounds per capita, not recycling rate. Sidique et al. (2010) conduct a survey of drop off recycling participants at eight drop off centers in the Lansing area of Michigan. They find that for these programs, more individuals in a household increases recycling drop off. This may suggest larger homes recycle more, especially if a PAYT program is in place. In both studies recycling rate is not the dependent variable, so the effect that persons per household will have on recycling rate is less clear, but is worth investigating.

Age

I use median age. The theory behind age is that it can capture availability of free time and generational attitudes. One of the obstacles to recycling is the time it takes to clean and sort materials. Older retired individuals with no children at home should have more free time to recycle. Older individuals were also part of the environmental awakening of the 60s and 70s and understand that environmental protection requires personal commitment and action. On the other hand, younger individuals have grown up with recycling as part of their lives, so are perhaps more predisposed to participate in recycling activities. Several studies have looked into the effect of this variable (Callan and Thomas 2006; Sidique, Lupi, and Joshi 2010; Folz and Hazlett 1991). Callan and Thomas (2006) find older individuals have greater demand for recycling services. While it is a different metric than the recycling rate metric I use, the results suggest age has a positive effect on recycling rate. Sidique et al. (2010) find that for drop programs, participation is higher among older individuals, which suggests older people may recycle more. Likewise, Folz and Hazlett (1991) find older people are more likely to participate in drop off programs. If this participation is driven by free time, the significance of age may be negated in curbside programs because they have a lower opportunity cost. My study does not run a separate analysis on curbside and drop off programs, so the effect on age in one program type versus another is not analyzed. Based on these studies I expect age will have a positive effect on recycling rates.

Education

The percent of population with a Bachelor's degree is the metric I use. The expectation is that higher education is linked to higher recycling rates because higher education is linked with higher environmental values and greater appreciation for valuing future time periods. Callan and Thomas (2006) provide a thorough list of studies that show this relationship between education and understanding of MSW's potential to harm the environment (Van Liere and Dunlap 1980; Granzin and Olsen 1991; Lansans 1992; Smith 1995). Several recycling studies also provide empirical evidence that show education to be an important factor in influencing recycling (Callan and Thomas 2006; Callan and Thomas 1997; Folz and Hazlett 1991). Callan and Thomas (2006) find substantial collinearity among demographic variables, but find education to be a significant driver of recycling demand. They find it is quadratic ($EDUCATION^2$), and the boost from education begins to reduce when more than 21% of the town has bachelor's degrees. Using recycling rate as their metric in 1997, Callan and Thomas also find education to have a positive effect on recycling and the relationship to be quadratic. Folz and Hazlett (1991) further add support, with their finding that more educated people tend to participate more in drop-off programs.

Income

Per capita income is used. Theoretically, income allows for greater consumption, but also greater purchasing of recyclable content. It is also a proxy for a municipality's ability to invest in quality recycling programs. I expect higher income will have a positive effect on recycling rate. Callan and Thomas (1997) find income to be significant at the 0.1 level and having a positive effect on recycling rates (Callan and Thomas 1997). Likewise, Sidique et al. (2010) find that for drop programs, participation is higher among individuals with higher income (their metric is household income), which suggests people with higher income may recycle more (Sidique, Lupi, and Joshi 2010). Contrary to these two studies, in their bivariate analysis Folz and Hazlett (1991) find that in mandatory programs higher income is correlated with *decreased* trash diversion. But for voluntary programs they find higher per capita income is correlated with higher citizen participation at a significant 0.05 level. In their multivariate analysis however, income is not significant (Folz and Hazlett 1991). In their 2006 study, Callan and Thomas do not find income to be a significant driver of recycling demand. They theorize higher income earners may consume more, but also donate more, so the effect this has on recycling rate ends up being neutral (Callan and Thomas 2006).

Unemployment

The unemployment rate is a proxy for economic conditions. High unemployment means it is less likely a municipality will have the funds it needs to invest in quality recycling programs. If a PAYT program is present, unemployment may lead to a boost in rates as people try to save money, but if PAYT is not present it could lead to a decline in rates because people will be more concerned with finding work and less concerned with recycling. To my knowledge, this has not been used before in the literature as a factor influencing recycling rates, but with the 2001 economic downturn and the 2009 Great Recession, I am curious to see if this metric captures the effect of economic stress on recycling participation. I expect unemployment will have a negative effect on recycling rates.

Political Affiliation

This is a proxy variable representing environmental attitudes and I use the ratio of registered Democrats to Republicans. The expectation is that Democrats are more willing to fund government programs such as recycling and are also more sympathetic to participate in environmental causes like recycling. Therefore, a higher ratio of Democrats to Republicans should be linked with increased recycling rate. Three studies inform this theory (Konisky, Milyo, and Richarson Jr. 2008; Folz and Hazlett 1991; Sidique, Lupi, and Joshi 2010). Konisky et al. (2008) analyze responses to the 2007 Cooperative Congressional Election Study, which is comprised of a nationally representative sample of 1,000 individuals. They find Republicans less likely to support further environmental actions. Folz and Hazlett don't use democrat to republican but moralistic versus individualistic and find those with individualistic leanings participate more in recycling programs. While not directly translatable to Democrats or Republicans it provides support for the idea of investigating political attitudes. Sidique et al. (2010) do not find environmental beliefs are a significant indicator of recycling participation in drop off programs. They found conforming to social norms was more important.

Community Preservation

This is a proxy variable representing environmental attitudes and legislative commitment to the environment. Having a Community Preservation Act implies a value being placed on the environment and it therefore seems reasonable that these attitudes may be applicable to recycling. This is informed by the work of Meyer and Konisky (2007) who look at local environmental institutions (LEIs). They look specifically at communities implementing the Massachusetts Wetland Protection Act and find that LEIs do generate positive environmental outcomes (Meyer and Konisky 2007). The connection to recycling is admittedly a bit thin, but their finding suggests that having a Community Preservation Act indicates a legislative commitment to the environment, which may spill over into recycling and it is worth testing here.

Community Preservation Years

Like Community Preservation, which is informed by Meyer and Konisky (2007), this is a proxy for recycling attitudes. Having a Community Preservation Act for many years implies a willingness to make a sustained environmental investment. It therefore seems reasonable that this might suggest increased willingness to invest in recycling. As the number of years increases that a Community Preservation Act has been in place I expect an increase in recycling rate may be observed.

Community Preservation Cost

Like Community Preservation, which is informed by Meyer and Konisky (2007), this is a proxy for recycling attitudes. It is the surcharge percent levied by a town for Community Preservation. A willingness to spend more on community preservation implies a willingness to make substantial environmental investments. It therefore seems reasonable that this might suggest increased willingness to invest in recycling. As the cost of a Community Preservation Act increases we expect an increase in recycling rate may be observed.

Region Central

The three Region variables describe a municipality's location in Massachusetts. A 1 means it is located in Central Massachusetts. A 0 value in all three regions means it is located in Western Massachusetts. Callan and Thomas (1997) specifically look at access to the Springfield MRF and find this is having a significant effect of increasing the recycling rate 9.5 percentage points (Callan and Thomas 1997). This location variable can be thought of somewhat as a proxy for Callan and Thomas' MRF access variable, because Western MA is used as the unit of comparison, so if the community is located outside Western MA, it does not have access to the MRF and thus would be expected to have a lower rate. It is also being used to capture other underlying factors such as proximity to major cities and recycling markets.

Region Northeast

This is one of the three Region variables, for the theory and justification for its inclusion see *Region Central*.

Region Southeast

This is one of the three Region variables, for the theory and justification for its inclusion see *Region Central*.

Program Variables

PAYT

PAYT is a dummy variable representing the use of a Pay-As-You-Throw (PAYT) program in the municipality. A 0 indicates no PAYT and a 1 indicates there is a PAYT program. Pay-As-You-Throw creates a market-based incentive to reduce trash disposal. Homeowners are charged per unit of trash (usually measured as a bag or bin) they throw away, which should encourage recycling (which is free) to avoid paying the fee. Thus the presence of PAYT should increase the recycling rate. The Commonwealth of Massachusetts 2010 Municipal Solid Waste Master Plan suggests PAYT is a proven way to boost rates (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs

2010a). This is also supported by Callan and Thomas (1997) who find unit-based pricing[17] to be a significant factor that boosts the recycling rate 6.6 percentage points, or 12.1 percentage points when in combination with curbside service (Callan and Thomas 1997). Jenkins et al. (2003) look at 20 metropolitan statistical areas and they are not able to conclude that PAYT is significant. They find convenience (from curbside recycling) a bigger factor in boosting recycling rates (Jenkins et al. 2003). Likewise, Kinneman (2006) looks at fourteen studies that analyze PAYT price elasticity in regards to disposal demand. He concludes that unit-based pricing is inelastic and suggests this may be because the price is set too low to cause a change in behavior. Yet, for five of the six studies he cites, for a PAYT bag or tag program[18] a $1 fee causes a reduction of between 7.93 and 22.89 pounds per week. As Kinnaman notes, the average household disposes of 30 pounds of garbage per week, so a $1 fee reduces garbage disposal by between 26 and 75 percent and when one averages all the studies it is about a 40 percent reduction (Kinnaman 2006). So it is seems odd that he concludes this is not having a big impact on recycling.

PAYT Years

This is the number of years a community has had a PAYT program. While PAYT is extensively analyzed in the literature, to my knowledge, PAYT Years has not been specifically used before. But longevity of the program seems like an important aspect to

[17] *Unit-based pricing* is also known as *PAYT*.

[18] In a PAYT bag program, households purchase special bags and only these bags will be collected by the municipal trash service. In a tag program households purchase tags that they affix to their own bags.

analyze. Do recycling rates increase in older PAYT programs because people become more familiar and comfortable with them and using PAYT becomes a social norm[19]? Or will there be an initial spike in participation as people react to the price signal, but then as they adjust to paying the fee the incentive to avoid the cost will diminish, because they have adapted to the new price. Based on my understanding of PAYT and following social norms, I expect that as longevity of a PAYT program increase so to will recycling rate.

PAYT Cost

This measures the cost of a PAYT program in cents per gallon paid to dispose of trash. This is a market-based approach to boosting recycling rates. Higher cost to use PAYT should encourage increased use of recycling and higher recycling rates. In addition to the studies previously mentioned that deal with PAYT (Callan and Thomas 1997; Jenkins et al. 2003; Kinnaman 2006), Callan and Thomas (2006) specifically use PAYT price per gallon and find it significant at the 0.1 level. Their metric is recycling demand, but they find increased PAYT cost is associated with increased recycling demand (Callan and Thomas 2006). This suggests it should also increase the recycling rate.

Tipping Fee

Tipping Fee is the cost in dollars per ton the municipality pays for trash disposal. Avoiding tipping fees is a market-based incentive to increase recycling, so the expectation is that as the costs of tipping fees increase so to will the recycling rate. Noehammer and Byer (1997) conduct an extensive literature review and analyze the results of four surveys. They find that as Tipping Fee increases recycling participation also increases (Noehammer and

[19] Sidique et al. (2010) find social norms to be a strong driver of recycling behavior.

Byer 1997). Bohm et al. (2010) use the same database as Folz (1999), which comes from a national survey of recycling program coordinators. For this study their final sample is comprised of 428 communities. They find Tipping Fee to be a significant contributor to municipal trash costs (Bohm et al. 2010). Folz (1999) also finds avoided trash disposal costs is one of the key reasons why recycling can be more cost effective than trash (Folz 1999).

Single Stream

This is a dummy variable with a value of 1 if the municipality has single stream recycling, a value of 0 if it does not. Single stream services allow residents to put all of their recyclable content into 1 bin. This added convenience should reduce the opportunity cost residents would otherwise incur from sorting recyclables and make recycling just as convenient as trash. Thus I expect it will boost rates. The Massachusetts's 2010 Municipal Solid Waste Master Plan supports this expectation and suggests single stream is a proven way to boost rates (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2010a). Folz (1991) however, find comingling of different materials (single stream) does not have an effect of rates (Folz 1991).

Mandatory

This is a dummy variable with a value of 1 if the municipality has enforced mandatory recycling, a value of 0 if it does not. Mandating recycling makes it illegal to throw away recyclable materials. This should reduce recyclables being placed in the trash, especially if the program is enforced through fines or refusal to haul trash if it contains recyclables. Therefore, if recycling is mandated it should increase the recycling rate. Massachusetts's 2010 Municipal Solid Waste Master Plan supports this expectation and suggests making recycling mandatory is a proven way to boost rates (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2010a). Several studies in the literature also support this idea (Folz 1991; Everett and Peirce 1993; Noehammer and Byer 1997; Folz 1999). Folz (1991) finds mandatory recycling programs have recycling rates twice as high as voluntary programs. Everett and Pierce (1993) conduct a national survey of recycling programs and have a complete sample of 357 municipalities. They find mandatory programs have a higher material recovery rate[20] than voluntary programs. Based on their literature review and analysis of four surveys, Noehammer and Byer (1997) find mandatory programs tend to achieve higher participation than voluntary programs. They find enforced mandatory generally outperform unenforced mandatory, which both tend to outperform voluntary programs. But they emphasize that if voluntary programs are well designed, they can achieve participation equal to mandatory programs. This finding agrees with Folz (1999) who finds that while mandatory programs generally have higher participation and diversion rates well designed voluntary programs that use curbside service can achieve high rates as well. Jenkins et al. (2003) analyze 20 metropolitan areas and do not find mandatory recycling to be having a significant effect on recycling rates for the five materials they study (Jenkins et al. 2003).

Mandatory Years

This variable captures the number of years a municipality has had enforced mandatory recycling. The expectation is that the longer a mandatory program is in place, the more likely it is that people have internalized the act of recycling and make it a regular part of their routine. Making recycling legally mandatory, sends the message that recycling

[20] *Material recovery rate* is equivalent to *recycling rate.*

is a social norm, which can be a strong driver of behavior (Sidique, Lupi, and Joshi 2010). As this behavior over time becomes routine, it is likely that rates will increase. The literature cited for Mandatory is relevant here as well.

Trash Service

This variable represents the percent of households served by municipal trash program. This is not used in existing literature, but Massachusetts collects data on number of households in the program and I thought it could possible be a useful metric to capture if a trash program that serves a large percent of the population will drive recycling rates down. The theory behind this is that trash services makes it convenient to throw away unwanted goods. If a high percentage of the town has access to municipal trash services this may act to reduce the recycling rate. If this variable and the Recycling Service variable have about the same value (meaning that both trash and recycling services are available to about the same percent of the population), then they may be counteracting each other and not having much of an effect.

Recycling Service

This variable represents the percent of households served by municipal recycling program. This is not used in existing literature, but Massachusetts collects data on number of households in the program and I thought it could be a useful metric to capture if a program that serves a large percent of the population increases recycling rates. The theoretical basis is that recycling services make it convenient to recycle unwanted goods. If a high percentage of the town has access to municipal recycling services this should increase the recycling rate. If this variable and the Trash Service variable are about the same, then they may be counteracting each other and not having much of an effect.

Curbside Trash and Recycle

Curbside Trash and Recycle is a dummy variable with a value of 1 if the municipality offers curbside trash and recycling service, a 0 if it does not (meaning they just have drop off centers). In some sample years, the municipalities that offered curbside trash and curbside recycling services are perfectly correlated so they are combined into this one variable, in other years they are not perfectly correlated, so they are entered into the models as separate variables. Curbside recycling services make it convenient to recycle, while curbside trash services make it convenient to throw goods away, so when they are perfectly correlated, they may be counteracting each other and having no effect on recycling rate. However, if PAYT is present or there are high Tipping Fees this may encourage people to utilize the recycling option and this would boost rates. Folz (1991) finds curbside recycling is the single most important variable to increase recycling rates in voluntary programs (Folz 1991). Jenkins et al. (2003) find curbside recycling to be more effective than drop off. They find curbside leads to higher recycling rates for the five materials they studied (Jenkins et al. 2003).

Curbside Trash

When Curbside Trash and Curbside Recycling are not perfectly correlated they are broken into two separate variables. Curbside Trash is a dummy variable with a value of 1 if the municipality offers curbside trash service, a 0 if they do not (meaning they just have drop off centers). Curbside Trash service makes it convenient to throw goods away, which may lead to decreased recycling rates if curbside recycling is not offered. While Curbside Recycling has been used in many studies, to my knowledge, Curbside Trash has not been studied before in the literature.

Curbside Recycling

When Curbside Trash and Curbside Recycling are not perfectly correlated they are broken into two separate variables. Curbside Recycling is a dummy variable with a value of 1 if the municipality offers curbside recycling service, a 0 if they do not (meaning they just have drop off centers). Curbside recycling services make it convenient to recycle, which should increase rates. If PAYT is present this may boost recycling even more. This variable has been found to increase recycling rates in the Folz (1991) and Jenkins et al. (2003) studies that are described above for the Curbside Trash and Recycling variable. Additionally, Callan and Thomas (1997) find Curbside Recycling to be significant and positively influencing recycling rates in Massachusetts.

Subscription Trash

This is a dummy variable with a value of 1 if the municipal trash program is subscription based, a 0 if it is not. Subscription trash puts the onus on citizens to individually purchase trash-hauling services. Since some items cannot be recycled it seems logical that individuals would need to purchase trash services and would only purchase recycling for philosophical reasons or if it led to an overall economic benefit. This benefit would only occur if recycling were cheaper than trash, if not, it would be similar to making recycling PAYT. While I don't have data on cost of subscription trash versus subscription recycling, having subscription trash suggests a less sophisticated waste management program and since recycling centers are capital intensive, I think it reasonable that subscription based programs are less likely to offer good recycling services. While it is not used in existing literature, Massachusetts collects data on this variable and it is an interesting metric for the reasons stated above.

Subscription Recycling

This is a dummy variable with a value of 1 if the municipal trash program is subscription based, a 0 if it is not. Subscription recycling puts the onus on individual citizens to purchase recycling services. Unless these services are the same or cheaper than trash disposal, this would seem to discourage recycling, unless it is done for philosophical reasons. I do not have good data on costs of subscription trash versus subscription recycling, but at the least, subscription based programs show a lack of investment in recycling on the part of municipalities, which I expect would lead to less robust programs and lower recycling rates. While it is not used in existing literature, Massachusetts collects data on this variable and it is an interesting metric for the reasons stated above.

Solid Waste Fee

Solid Waste Fee is a dummy variable with a value of 1 if the municipality has a solid waste flat fee, a 0 if it does not. A solid waste flat fee is usually levied through property taxes. It charges individuals the same amount for trash services regardless of the amount of waste they thrown away. This obscures the true costs of waste disposal and offers no incentive for individuals to reduce waste disposal in order to reduce costs. This is not used in existing literature, but Massachusetts collects data on this variable and it intuitively seems like it should have an effect on recycling rates.

Carts Trash

This is a dummy variable with a value of 1 if the municipal trash program provides trash carts to residents, 0 if it does not. Trash carts make it easy to store trash and may lead to decreased recycling rates. If trash cart sizes are small however and recycling cart sizes are large this may increase recycling rates because it encourages filling the recycling cart. There is insufficient data on cart sizes to conduct an analysis but this variable was included because the Commonwealth of Massachusetts reports it in their recycling survey and I wanted to test its effect. To my knowledge, this has not been used in existing literature.

Carts Recycle

This is a dummy variable with a value of 1 if the municipal recycling program provides carts to residents, 0 if it does not. Providing recycling carts communicates the message to citizens that recycling is important. Recycling carts also make it easy to recycle, which should boost rates. If recycling cart sizes are small however and trash cart sizes are large this may decrease recycling rates because it discourages recycling. Unfortunately, I don't have data on cart sizes. Analyzing the presence of free recycling carts is a variable used in the literature (Folz 1991; Everett and Peirce 1993; Noehammer and Byer 1997). Folz (1991) finds providing free bins boosts recycling rates. Everett and Pierce (1993) find providing recycling carts boosts material recovery rates if the program is voluntary. Strangely, if it is mandatory they find providing bins has a negative effect. Noehammer and Byer (1997) find free bins boost participation for voluntary recycling programs. They don't find free bins boost participation rates in mandatory programs, but they also don't cause a decrease. This study uses participation rates and not material recovery rates like Everett and Pierce, but the findings here suggest one might not see the negative effect on material recovery rates that Everett and Pierce (1993) observe when free bins are provided in a mandatory program.

Bins Compost

Bins Compost is a dummy variable with a value of 1 if the municipality distributes compost bins, a 0 if they do not. Composting reduces the amount of material that ends up in the waste stream. If the composition of trash and recyclables remains constant this reduction in trash would boost the recycling rate. If this backyard compost were to be quantified it would boost the recycling rate even more because not only would it be deducted from the trash amount, but it would also be added to the diverted amount. While Folz (1991) finds composting boosts recycling rates, he does not study bin distribution and to my knowledge this variable has not been previously investigated.

Yard Waste

Yard Waste is a dummy variable with a value of 1 if the municipality offers yard waste curbside or drop off service, a 0 if it does not. Yard waste service diverts this organic matter from either becoming trash or ending up un-quantified in a backyard or forest. Capturing this material as compost in the municipal program should boost recycling rates. This theory agrees with Folz (1991) who finds that composting boosts rates.

Food Waste

Food Waste is a dummy variable with a value of 1 if the municipality offers food waste curbside or drop off service, a 0 if it does not. Like Yard Waste, capturing food waste as municipal compost instead of trash or backyard compost will reduce the overall amount of trash and increase the amount of diverted materials, thus boosting the recycling rate. This theory agrees with Folz (1991) who finds that composting boosts rates.

Municipal

This is a dummy variable with a value of 1 if the municipal trash/recycling program includes municipal buildings, a 0 if it does not. To my knowledge, this is not used in the existing literature but municipal buildings generate a lot of recyclable materials. Recycling haulers have a financial incentive to maximize the amounts they reclaim from these concentrated sources. Offering recycling services also lets employees know that the town government supports recycling. This may encourages employees to recycle at work and perhaps encourages them to recycle more at home as well. Lastly, as Sidique et al. (2010) find, recycling is driven partly by conforming to social norms, so seeing recycling in the workplace may help install recycling behavior as a social norm. Thus I expect that offering municipal recycling services to municipal buildings may have a slightly positive effect on recycling rates.

School

School is a dummy variable with a value of 1 if the municipal trash/recycling program includes school buildings, a 0 if it does not. To my knowledge, this is not used in the existing literature but schools are large buildings that generate a lot of recyclable materials. Recycling haulers have a financial incentive to maximize the amounts they reclaim from these concentrated sources. Offering recycling services also lets employees know that the town government supports recycling. This may encourages employees to recycle at work and perhaps encourages them to recycle more at home as well. It may also train children to recycle, who then bring that behavior home, which encourages the family to recycle more. Lastly, as Sidique et al. (2010) find, recycling is driven partly by conforming to social norms, so seeing recycling in school may help install recycling behavior as a social norm for both students and faculty. Thus I expect that offering municipal recycling services to schools may have a slightly positive effect on recycling rates.

Business

Business is a dummy variable with a value of 1 if the municipal trash/recycling program includes businesses, a 0 if it does not. To my knowledge, this is not used in the existing literature, but offering recycling services to businesses increases the available materials to recycling haulers and works to create a larger recycling economy, which may attract higher quality haulers. Getting employees in the habit or recycling at work may also encourage them to recycle more at home. Lastly, as Sidique et al. (2010) find, recycling is driven partly by conforming to social norms, so seeing recycling in the workplace may help install recycling behavior as a social norm. Thus I expect that offering municipal recycling services to schools may have a slightly positive effect on recycling rates.

Swap Shop

Swap Shop is a dummy variable with a value of 1 if the municipality operates a swap shop or reuse area at their transfer station, 0 if it does not. Swap shops give a second life to materials that would otherwise be trash, while simultaneously reducing consumption of new products. Thus I expect the presence of swap shops to divert waste from landfills and therefore boost the recycling rate. Eventually of course, products that are taken form the swap shop will end up as trash or recycling, but it slows down the rate of trash generation and thus should boost the recycling rate. To my knowledge this has not previously been used in the literature, but seems intuitively like an important variable to understand.

Hazardous Categories

This is the number of categories of hazardous waste that the municipality collects year round. I am using this to assess convenience of hazardous waste collection and also as a proxy variable to assess the robustness of a municipality's waste reduction efforts. Although not used as a variable in the existing literature, I expect that making hazardous waste collection easy will increase the use of collection programs because for individuals with limited space there is a cost associated with storing unusable hazardous goods. Additionally, when a municipality offers more categories of hazardous waste collection year round it suggests it has a more robust recycling program overall.

Hazardous Events

This is the number of hazardous waste collection events offered by the municipality that year. I expect this will increase rates because for individuals with limited space there is a cost associated with storing unusable hazardous goods. Having many hazardous waste collection events should encourage the use of such programs and reduce disposal of such items in the garbage.

Hazardous Regional

This is a dummy variable with a value of 1 if the hazardous waste collection events are open to other municipalities in the region, 0 if they are not. Regional events allow citizens from many other towns to access hazardous waste collection services. This should increase recycling overall, although if neighboring towns heavily use a program, but do not offer one, this variable may not capture the positive effect some programs are having because it only captures the effect on the recycling rates of the town that offers the program. This variable is not used directly in the literature, but making hazardous waste collection event regional might have a benefit as this helps establish recycling these materials as a social norm in the region. Sidique *et al* (2010) get at recycling benefiting from conforming to social norms.

Hazardous Reciprocal

This is a dummy variable with a value of 1 if the hazardous waste collection events were reciprocal, 0 if they were not. To my knowledge this is not used in existing literature, but reciprocal agreements allow residents of certain communities to use the hazardous waste collection events of their partner and vice versa. This increases the number of events residents have access to and should increase the participation and recycling rate.

Highlighting Key Contextual and Program Variables

Above I describe many variables that have been shown in previous studies to be effective and I introduce some new variables that I suspect may be influencing recycling rates. To draw attention to the most important of these variables I will briefly highlight the key contextual and program variables. Based on the literature review, the key contextual variables are Age, Education, and Region[21]. To a lesser extent, Density also seems like it may be important. The key policy variables are PAYT, Single Stream, Mandatory, Curbside Recycling, and to a lesser extent offering some kind of organic waste Composting service.

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[21] This is largely being used to capture access to the Springfield MRF, so it can also be classified as a program variable.

CHAPTER 2

DATA, METHODS AND MODELS

To understand what factors have been influencing rates between 1997 and 2012 I executed six steps: 1) constructing a database, 2) exploratory data analysis, 3) testing collinearity, 4) multiple linear regression modeling, 5) testing model stability, 6) synthesizing across time.

Step 1: Database

Building the Database

A series of six databases covering the periods of 1997-1999, 2006-2008, 2009, 2010, 2011, and 2012 were created. The years 1997, 1998, and 1999 were merged into one database and averaged because recycling rates are quite variable year to year. The same was done for 2006, 2007, and 2008. By averaging over a three-year period some of the natural year-to-year variation in recycling rate is reduced and a clearer picture of the recycling trend emerges. This averaging was not done for the 2009, 2010, 2011, or 2012 because the categories of recycling tonnage data needed to calculate recycling rates changes between the years, so direct comparison across years was not possible.

Each of the six databases contains the dependent variable, *recycling rate*, and a host of independent contextual and program variables for all 351 Massachusetts municipalities. These databases were drawn together from disparate sources. Data for all variables were not available for all time periods, so there is some variation between the contextual and program variables included in different time periods. Recycling rate data for 1997-2008 comes from a report on residential recycling rates compiled by the Massachusetts

Department of Environmental Protection (DEP) (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2009). Recycling Rates for 2009-2012 are calculated from surveys of municipal recycling coordinators compiled by the Commonwealth of Massachusetts DEP. Program variables for the 2009-2012 time period are also sourced largely from those surveys. PAYT, Mandatory, and Region data are sourced from DEP reports. Socio-economic data comes from the United States Census Bureau and the Massachusetts Department of Revenue[22].

Bringing together and synthesizing these disparate sources into one database is one of the contributions of my study. These sources had not previously been assembled together for these time periods, so past studies were not able to analyze the system in a way that takes into account both program and contextual factors over such a long time period.

Refining the database

Missing Values

After the database was assembled, it was then screened for missing values. In each time period, there were municipalities for which no recycling rate was reported or that did not report the tonnage information necessary to calculate the rate. Municipalities that did not have data for the dependent variable (*recycling rate*) were dropped from further analysis. Missing values for independent variables were assigned NA. If an individual contextual or program variable had more than 70 percent NA the model was run with and

[22] **For a full list of data sources see Table 2 and Table A2 through**

Table A6.

without that variable. In some time periods this affected two variables related to number of yard waste curbside pickup and drop off days. In both cases, the variable in question was not found to be significant, so was dropped from further analysis so as not to unduly reduce the sample size. In some cases, a variable had many NA, but did not reach the 70% threshold. In this case the model was again run with and without the variable. This applied to Single Stream and Mandatory, which I decided to keep in the analysis for most time periods, but dropped for 2010 because they were not found significant in the *All Variables* model so I didn't want to unduly reduce the sample size.

Suspected Data Errors

Next, the databases were screened for suspected data errors. Data points were deemed suspicious if the values did not correspond to expectations based on data values from previous or subsequent years. The only contextual or program variable this applied to was Persons Per Household. In calculating this variable, housing data from the Massachusetts recycling surveys was used. Data was deemed to be a suspected data error if the number of houses increased significantly and then decreased significantly the following year, or there were far more houses than residents and the municipality is not in a vacation area. An illustrative example of this is the town of Attleboro, that has a an estimated 2007-2011 population of 43,459 yet reported 42,068 houses in 2009, 17,164 houses in 2010, 42,000 houses in 2011, and 16,457 in 2012. It seems very unlikely that Attleboro has almost as many houses as people and that between 2009 and 2011 they demolished and then rebuilt about 25,000 homes. It seems more likely that in 2009 and 2011 the person filling out the survey accidentally listed their population instead of number of houses. Or perhaps the DEP surveyor entered the data incorrectly into the database. There were only seven municipalities in 2009, eight in 2010, eight in 2011, and six in 2012 that had NA inputted because of suspected housing data error.

Data points were also deemed suspected data errors if the values were beyond the realm of possibility based on an understanding of the norms for that variable. The only example of this was for the town of Shrewsbury, which reported a $496,000 per ton tipping fee (while the next most expensive town charged $230 and the average for the rest of the state was $71). Here NA was imputed.

For the 2009 to 2012 databases, some municipalities were also eliminated because of suspected data errors with their reported recycling rate. First municipalities that had a 100% recycling rate were eliminated because this falsely perfect rate was found to be coming from insufficient tonnage reporting. Next suspicious year-to-year changes were examined. Because of difference in how rates are calculated for those periods, rates are not directly comparable across years. However, there is still some expectation that rates will be reasonably similar. Because recycling rates above 60% and below 5% are not common, if rates were calculated to be above or below these thresholds they were examined for consistency across years. If the recycling rate was off by a factor of 3 compared to the previous or subsequent year then the rate was deemed to be suspicious and NA was imputed. There were only a few instances of municipalities being eliminated for this reason. Only two towns were eliminated in both 2009 and 2010. In 2011, six towns were eliminated and in 2012 seven were eliminated for this reason.

Outliers

Linear regression is sensitive to outliers, therefore I needed to identify if particular points were unduly affecting the results. Outliers were examined to see what effect they had on the model. If data points were beyond 1.5 x the Interquartile Range they were investigated. The models were run with and without the inclusion of outliers. In only a small handful of cases were the outliers actually eliminated. Three particularly high unemployment data points were dropped for 1997-1999 because they were slightly skewing the results. One Democrat to Republican ratio observation was dropped for 2006-2008 because it was high enough to be slightly skewing the results. I tried dropping five other suspected outliers for Density and Income, but these did not factor into the final model because they had NA values for other variables.

Step 2: Exploratory Data Analysis

With the database in a suitable state for analysis, summary statistics were generated for the different independent variables. These were then examined to get a sense of the system. Next, simple univariate linear regression was used to explore the relationships between recycling rate and the independent contextual and program variables. This provided insight on whether some of my theoretical expectations were met in terms of these variables having a univariate effect on recycling rate. Plots were generated with trend lines, lowess fit lines, and 95 percent confidence intervals. For those variables where a relationship was evident, this visual inspection graphically showed the strength of the univariate relationship.

Step 3: Testing Collinearity

Next, collinearity was tested by creating a series of plots that showed the correlation and univariate relationship between pairs of the independent variables. This step provides insight into the relationships between independent variables. This becomes important, when interpreting the results, because if two variables are nearly completely correlated and one of them is doing a good job explaining some of the variance in the model, it is difficult to definitively say which one is actually contributing to the adjusted r^2.

Step 4: Multiple Linear Regression

In keeping with the literature (Folz 1991; Folz and Hazlett 1991; Callan and Thomas 1997), I used multiple linear regression models to analyze the dependent variable (*recycling rate*) as a function of many independent contextual and program variables. Looking at the variables in this multivariate way allows me to identify key variables and best-fit models.

The model building and refinement process consisted of four sub steps:

1) All Variables
2) Stepwise Linear Regression Algorithm
3) Sensitivity Analysis (via Manual Backward Multiple Linear Regression)
4) Occam's Reduced Form

Sub step 1: All Variables

In step, 1 the model is constructed in the statistical software package R, (R Core Team 2013). All the variables that I think are influencing recycling rates are included and the model is then run. In keeping with the literature, an ordinary least squares method is used for parameter estimation (Callan and Thomas 1997).

Sub step 2: Stepwise Linear Regression Algorithm

In step 2, the model is refined using the *step()* function in R with a forward and backward stepwise linear regression algorithm utilizing Akaike Information Criteria (AIC). AIC uses a penalized goodness of fit to measure potential models. It balances between how well the model fits the data and how complex the model is. Using AIC helps to guard against over-fitting a model. Forward stepwise is a procedure that starts with no variables in the model. Then variables are added one at a time based on its improvement to the model. At each step the AIC value is minimized until adding addition variables no longer improves the fit of the model. The backward stepwise procedure begins by including all variables in the model and then removes them one by one until the AIC value is minimized. Using both forward and backward stepwise tests at each stage whether variables should be included or excluded from the model. This is done until the AIC value is minimized.

Sub step 3: Sensitivity Analysis (via Manual Backward Multiple Linear Regression)

While stepwise regression can be a helpful procedure to identify which variables are having an effect, it is important not to rely solely on the judgment of a computer based algorithm to select the best model. Step 3 is a manual stepwise procedure where variables that are not highly significant or are having only a minimal effect on the explanatory power of the model (adjusted r^2) are dropped out. I did this by manually dropping the least significant variables and observing the effect on adjusted r^2. I refined the model until all remaining variables were significant at the 0.05 level. I also looked at the effect on adjusted r^2 and often found that at this point any further reduction would cause the adjusted r^2 to drop more than 0.015.

Sub step 4: Occam's Reduced Form

Step 4 pays homage in its name to Occam's razor, named for William of Ockham, who advocated for the idea that when competing theories make the same prediction the one with the least assumptions is preferable. In this spirit, my models for each time period are further refined to their most basic critical components. What I am calling the *Occam's*

Reduced Form model is that combination of independent variables for which removing any of the variables results in a significant drop in adjusted r^2. I define a significant drop as a drop of more than 3 percentage points in the adjusted r^2 value. I also generate a series of figures with the number of variables on the x-axis and adjusted r^2 on the y-axis to visually identify the "cliff" at which a rapid drop in adjusted r^2 takes place when one of the variables is removed.

Step 5: Testing Model Stability

To test the stability of the *Sensitivity Analysis* and *Occam's Reduced Form* model in each time period I ran a 1,000-permutation bootstrap. For each time period, bootstrapping creates a new database by randomly drawing municipalities from the existing database one at a time until it creates a full sample equal to the number of municipalities in the original database. Each time it draws a municipality into the new dataset it replaces it in the original, so that when it draws from the database again there is a chance that the municipality will be picked again. In this way, bootstrapping creates a new database from an existing database. By doing sampling with replacement, this new dataset has a different mix of municipalities. The *Sensitivity Analysis* and *Occam's Reduced Form* models were then run on this new dataset and the adjusted r^2 was calculated. In this way, 1,000 new datasets were created and 1,000 adjusted r^2 values were calculated for both models. The distribution of these adjusted r^2 values can then be plotted in a density plot to show the adjusted r^2 in the real dataset compares to the spread of adjusted r^2 calculated from the bootstrapped datasets. If the model is fairly stable then this spread should be normally distributed and fairly centered around the observed r^2 from the original dataset.

Step 6: Synthesis

In the final step, the variables that were most frequently significant over the different time periods were chosen and a model was created using these variables in each of the time periods. To provide a consistent picture of how key variables change over time, all variables that appear in the *Manual Sensitivity* models from each time period were selected and ranked by the number of times they appear as significant. The *Occam's Reduced From* model results were also analyzed to see which variables were consistently the strongest contributors to adjusted r^2. Based on this analysis the three key variables were selected. These three variables were then used as the model in each time period and the coefficient estimates were then compared across time periods. This last step provides a consistent view of which variables are most important and how their coefficient estimates have changed over the 16 years of data.

Using Methods to Answer Research Questions

I used these six steps to generate the data necessary to answer the three research questions. For Question 1 (At a given point in time, how significant is the influence of recycling policies relative to contextual factors, which are largely outside of policymaker's control?), I looked at which variables were significant according to the *Occam's Reduced Form* models for each time period and I conducted a relative importance test on these results using the *calc.relimp* function in the R statistical software package. For Question 2 (At a given point in time, which recycling initiatives and policies provide the greatest boost to recycling rates?) I used the *Sensitivity Analysis* and *Occam's Reduced Form* model results to see the significance and coefficient estimates for the program variables. For Question 3 (Are the effects of these policies consistent over time or do the policies effectiveness in boosting recycling rates decline over time?), I used the coefficient estimates from the *Synthesis* models.

CHAPTER 3

RESULTS AND DISCUSSION

In the 1997-1999 period I will present the results for *Step 2: Exploratory Data Analysis* and *Step 3: Testing Collinearity* to help the reader better understand my methods. However to save the reader from excessive detail these results will not be shared in the text for future time periods. For *Step 4: Multiple Linear Regression*, the full results for 4 time periods (1997-1999, 2006-2008, 2010, and 2012) will be presented and discussed. For the first time period in which variables appear, they *will be presented* in detail with discussion on how the Results correspond with existing literature. For subsequent time periods, unless the algebraic signs or significance changes, I *will not discuss* in as great detail how the Results relate to existing literature. To spare the reader from excessive detail and keep the focus on key findings, the various model coefficient estimates results for 2009 and 2011 will not be discussed. They can however be viewed in Table A7 through Table A11.

1997-1999

Results: Exploratory Data Analysis

Summary statistics show the mean and standard deviation for the different variables (Table 2)[23]. I also graphically analyzed univariate relationships between the variables and recycling rate. Overall, individual variables have low r^2. One of the stronger univariate relationships is between recycling rate and education (Figure 7). Figure 8 additionally showcases the relationship between five socio-economic variables and recycling rate. For Figures of select additional variables see

Figure **B2** - Figure B4.[24]

Table 2: Variables with summary statistics 1997-1999 (n = 324)

Variable Name	Mean	Standard Deviation	Data Year	Source
RECYCLING RATE	0.316	0.123	1997-1999	1
DENSITY	1293.176	2276.412	1997 & 2010	2 & 3
AGE	38.933	3.677	2000	4
EDUCATION	0.350	0.159	2000	5

[23] **In subsequent years these will not be presented in the text. For additional years see Table A2 through**

Table A6.

[24] To spare the reader from detail that is unnecessary to the larger study, these univaraite plots will not be presented for subsequent years.

INCOME	27629.485	8854.752	1999	3
UNEMPLOYMENT	0.034	0.012	1997-2008	6
POLITICAL AFFILIATION	2.280	1.518	1998	7
REGION CENTRAL	0.213	0.410	2008	8
REGION NORTHEAST	0.256	0.437	2008	8
REGION SOUTHEAST	0.244	0.430	2008	8
PAYT	0.207	0.406	2012	9
PAYT YEARS	1.340	3.182	2012	9

Sources

1	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2009)
2	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2000a)
3	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2010a)
4	(United States Census Bureau 2000a)
5	(United States Census Bureau 2000b)
6	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2000b)
7	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2008)
8	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2008)
9	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012a)

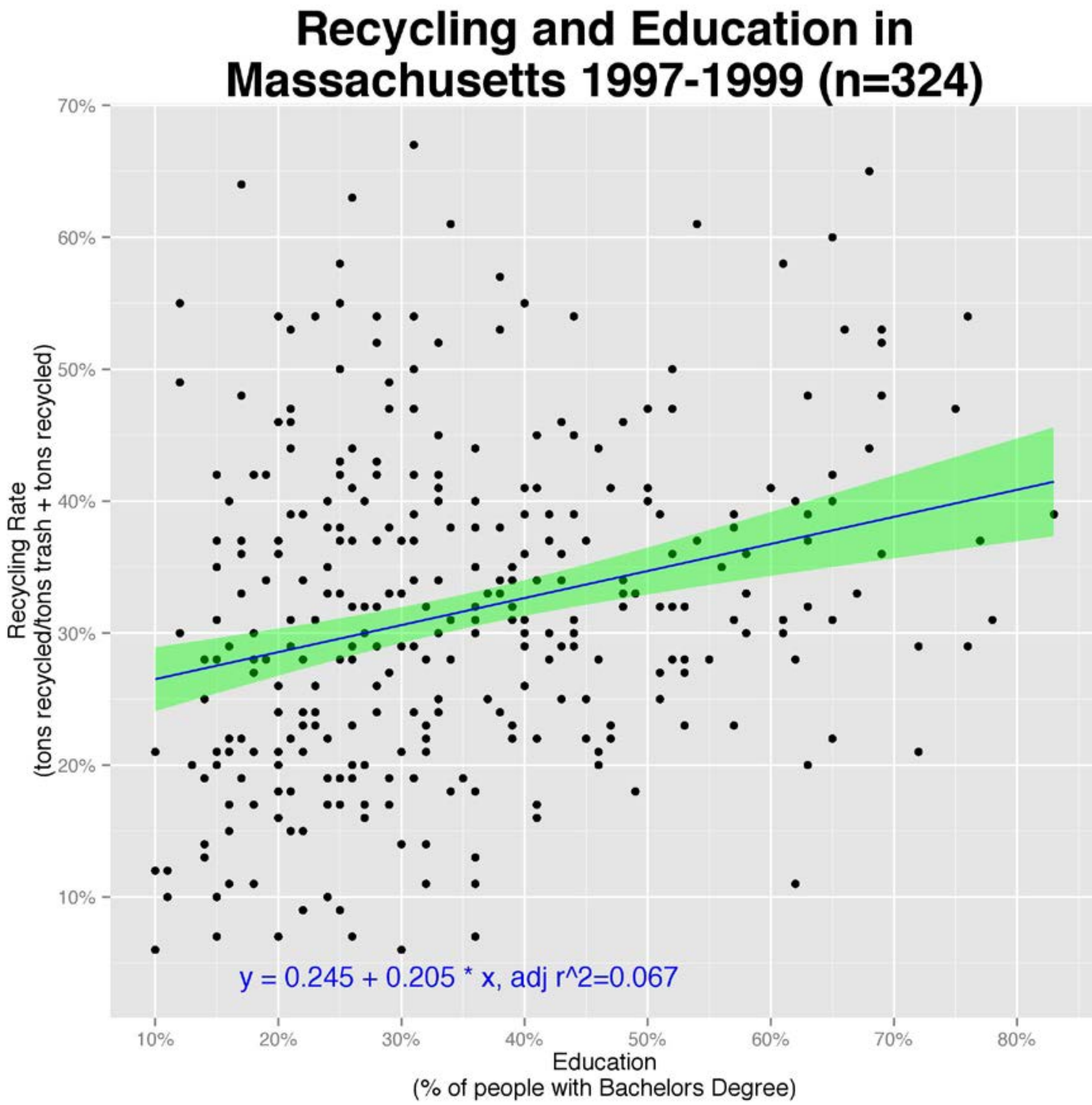

Figure 7: Bivariate relationship between education and recycling rate

Results: Testing for Collinearity

To give the reader a sense of how collinearity was established, Figure 8 is presented. This shows the relationships between five socio-economic variables and the dependent variable recycling rate. The lower left section plots the relationship between the variables with a Lowess fit line and the upper right section shows Spearman correlation values. It is clear from a bivariate analysis that Income and Education are strongly correlated and highly collinear. As we would expect, Unemployment is strongly linked to Income and Education.

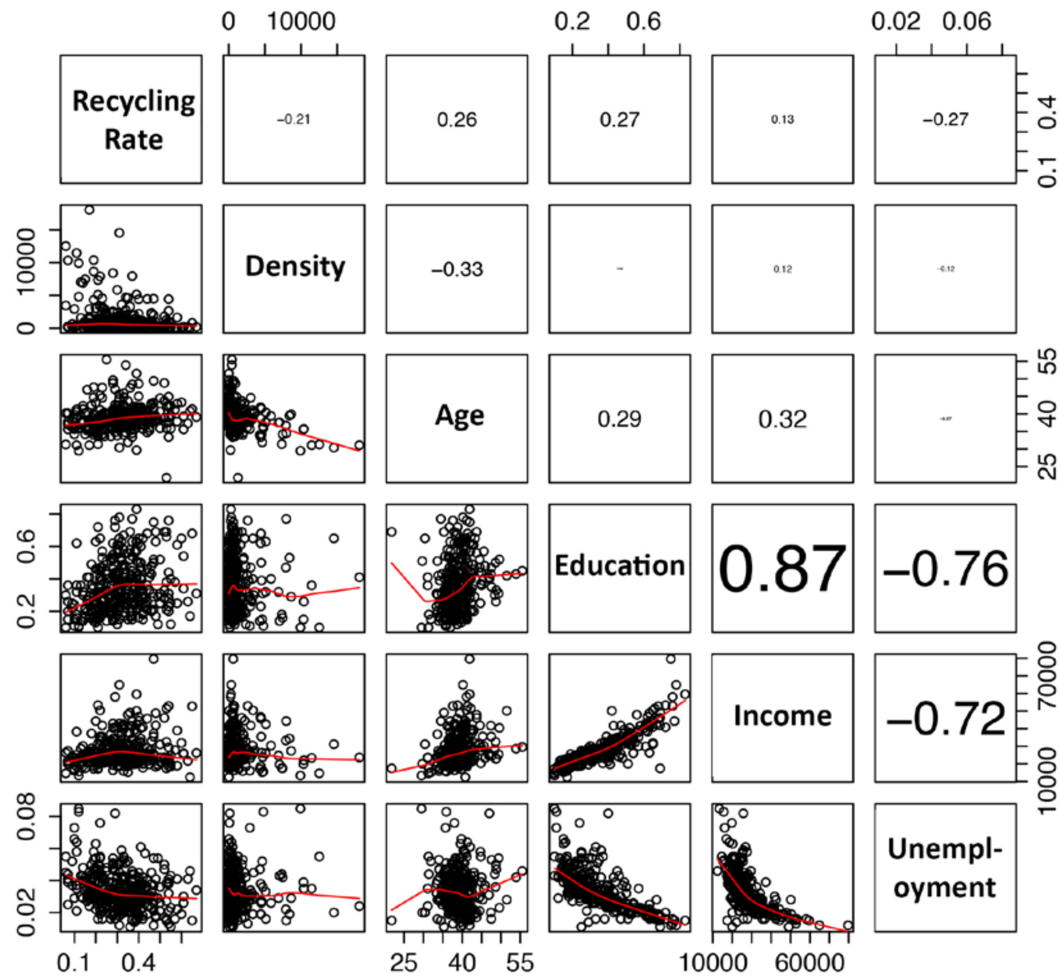

Figure 8: Collinearity among five socio-economic variables in 1997-1999 with correlations.

Results: Multiple Linear Regression

Sub Step 1: All Variables

The full model has 11 variables and the model specification is:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{LOG DENSITY} + \beta_2\text{AGE} + \beta_3\text{EDUCATION} + \beta_4\text{INCOME} + \beta_5\text{ UNEMPLOYMENT} + \beta_6\text{POLITICAL AFFILIATION} + \beta_7\text{REGION CENTRAL} + \beta_8\text{REGION NORTHEAST} + \beta_9\text{REGION SOUTHEAST} + \beta_{10}\text{PAYT} + \beta_{11}\text{PAYT YEARS} + \varepsilon$$

ε represents the disturbance term

After eliminating observations with missing values, the original sample of 351 is reduced to 324. Overall, the model performs as expected and generally supports existing literature. The amount of variance explained by the model (adjusted r^2) is somewhat low at only 0.278. However, this is in line with expectations. Due to a lack of data, the only policy variables in this model are PAYT and PAYT YEARS (which are really only capturing 1 policy)[25], yet past studies suggest policy variables are a stronger driver of recycling rates than contextual factors. Thus a low adjusted r^2 value is expected when there are only 2 policy variables in the model.

The full results and estimations are in **Table 3**.

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[25] The *REGION* variables are also capturing some program factors. They are being used partly to capture the effect of the Springfield MRF, which is a program factor, but it also captures contextual factors like differing regional attitudes. For categorical parsimony it is classify as contextual.

Table 3: 1997-1999 All Variables Model

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.230	0.090	2.543	0.011	*
β_1	LOG DENSITY	0.002	0.006	0.273	0.785	
β_2	AGE	0.005	0.002	2.296	0.022	*
β_3	EDUCATION	0.175	0.078	2.236	0.026	*
β_4	INCOME	-2.05E-06	1.50E-06	-1.363	0.174	
β_5	UNEMPLOYMENT	-2.394	0.716	-3.343	0.001	***
β_6	POLITICAL AFFILIATION	-0.006	0.005	-1.051	0.294	
β_7	REGION CENTRAL	-0.026	0.020	-1.285	0.200	
β_8	REGION NORTHEAST	-0.060	0.025	-2.390	0.017	*
β_9	REGION SOUTHEAST	-0.050	0.020	-2.460	0.014	*
β_{10}	PAYT	0.048	0.026	1.869	0.063	.
β_{11}	PAYT YEARS	0.007	0.003	2.131	0.034	*

Residual std. error	0.1044 on 312 DF	*** significant at the 0.001 level
R2	0.303	** significant at the 0.01 level
R2 (adjusted)	0.278	* significant at the 0.05 level
F-statistic	12.31 on 11 and 312 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	324	

The analysis begins by discussing the variables that are not significant in the model. The finding that *LOG DENSITY* is not significant is in agreement with Callan and Thomas

(1997). The algebraic sign agrees with my expectations, but disagrees with Callan and Thomas. *INCOME* is not found to be significant, which also agrees with Callan and Thomas (2006), who measure recycling demand and theorize this insignificance may be the result of higher income earners consuming more, but also donating more. This finding also agrees with Folz and Hazlett (1991), who find income to be insignificant in their multivariate analysis.[26] Sidique et al. (2010) measure participation and find income to be significant, but they do not use education as a metric. My analysis shows strong collinearity between education and income[27], but education is a better predictor of recycling rates. I suspect if Sidique et al. used education in their analysis, income may have become insignificant.

POLITICAL AFFILIATION is not found to be significant. This is supported by Sidique et al. (2010), who do not find a link between environmental beliefs (which I associate more with Democrats) and participation in drop off programs. Folz and Hazlet use moralistic versus individualistic political leanings, and find individualists more likely to participate in drop off programs, but this offers little guidance. While not significant, the algebraic sign suggests that an increase in the ratio of Democrats to Republicans causes a *decrease* in the recycling rate. This is counter to expectations based on Konisky et al. (2008). While not directly studying recycling, Konisky et al. (2008), find Republicans less likely to support further environmental action, which I feel suggests they would have less support for recycling programs. However, their findings were based on a nationwide random sample of

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[26] In their bivariate analysis they find that for mandatory programs lower income is correlated with increased trash diversion, but in voluntary programs it is higher income that is correlated with increased trash diversion.

[27] In the sample, *INCOME* and *EDUCATION* have a correlation of 0.87.

1,000 individuals. Massachusetts is perhaps the "bluest" state in the nation with only 11% of towns in the sample having more Republicans than Democrats and thus the political demographics of Massachusetts would not be well represented by a national study on political beliefs. Therefore, perhaps this negative relationship is capturing some underlying contextual factors that are collinear with political beliefs.[28] Or perhaps, extremely high ratios of Democrats to Republicans do have some impact on recycling rates. But with this not being a significant variable in this time period I will leave it at that for now.

REGION CENTRAL has the anticipated negative algebraic sign, but is not found to be significant, meaning being located in Central Massachusetts does not correspond with a significantly different recycling rate from what is expected in Western Massachusetts.[29] This variable is not used in the literature, but it seeks to capture spatial factors contributing to recycling success, one of which is the presence of a material recovery facility (MRF) in Springfield, which is used by Callan and Thomas (1997). Since Central MA is closest to Western MA, perhaps some communities in the Central region were able to access the MRF and this is contributing to the lack of significance for this variable.

In the *All Variables* model, *PAYT* is only significant at the 0.1 level, but it has the anticipated positive algebraic sign, suggesting the presence of *PAYT* is associated with a 4.8 percentage point increase in recycling rate. The lack of significance of *PAYT* at the 0.05-

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[28] More urban areas tend to have higher concentrations of Democrats and perhaps it is the factor of limited urban spaces for storing recyclables that are creating a negative relationship with recycling rate.

[29] Western Massachusetts is the default *REGION* value against which the other regions are being compared.

level is in line with Jenkins et al. (2003), who study 20 metropolitan statistical areas and are not able to conclude *PAYT* is significant. It differs from expectations however, and does not agree with Callan and Thomas (1997), who find *PAYT* significant, leading to a 6.6 percentage point increase in recycling rate. It also differs from the expectations expressed by The Commonwealth of Massachusetts in their Solid Waste Master Plan (2010). I suspect *PAYT* is a significant factor, but the significance is being obscured by the collinearity of *PAYT YEARS*.

PAYT YEARS is significant at the 0.05 level and is associated with a 0.7 percentage point increase in recycling rate for every additional year that *PAYT* has been in place. So a municipality with a 10-year old *PAYT* program could expect a 7-percentage point boost to their recycling rate from this variable. The finding that *PAYT YEARS* is indeed significant, is in line with expectations informed by Jenkins et al. (2003) who find that length of recycling program boosts rates, which suggests length of PAYT would also work to boost rates. This is likely occurring because people become more familiar with programs over time and participation becomes a part of their regular routine.

AGE was also found to be significant, which agrees with expectations based on previous literature. While they use demand for recycling services as their metric, Callan and Thomas (2006) find older individuals have greater recycling services demand, which suggests they recycle more. Sidique et al. (2010) and Folz and Hazlett (1991) use participation as their metric and find that older individuals participate more in drop off programs. This suggests older individuals are more likely to recycle, which my findings confirm. For this time period, each additional year of median age is associated with a 0.5 percentage point increase in recycling rate. In Massachusetts at this time, the low end for median age is around 37 and the high is around 53, so holding all other variables constant, the recycling rate difference across this range would be 8 percentage points[30].

In keeping with how *AGE* is sometimes handled in the literature, I tried making it a quadratic term, which intuitively makes sense that at some point if the population is too old they may be less able to recycle. However, when the quadratic term was tried, both *AGE* and AGE^2 came out as not significant. Therefore the simpler term was used.

EDUCATION is significant, with a 1 percentage point increase in number of people with bachelors degree associated with a 0.175 percentage point increase in recycling rate. In Massachusetts' municipalities, for this time period, the low end for percent with bachelor's degree is around 10% and the high end is around 75%. Holding all other variables constant, the high end towns would be expected to have a recycling rate 11.375 percentage points higher than the low end towns.[31] The positive association between education and recycling rate meets expectations and the findings of previous studies. Folz and Hazlett (1991) find more educated people participate more in drop off recycling programs and Callan and Thomas (2006) find education to be a significant driver of recycling demand.

The results suggest *UNEMPLOYMENT*, which to my knowledge has not been used previously in the literature, is highly significant at the 0.01 level. A 1 percentage point increase in the unemployment rate is associated with a 2.394 percentage point *decrease* in

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[30] 53 – 37 = 16 and 16 x 0.5 = 8

[31] 75 – 10 = 65 and 65 x 0.175 = 11.375

recycling rate. In Massachusetts, the 1997-1999 low end for unemployment is around 1.5% and the high end around 7.5%. Holding all other variables constant there is a 14.364 percentage point decrease in recycling rate across that spread. *UNEMPLOYMENT*, is a particularly interesting metric to test because the data spans the 2001 economic downturn and the 2009 Great Recession, so I will see if this variable is perhaps a more useful indicator of recycling participation than other economic data, such as per capita income. I theorize that the immediate stress of looking for work makes people less interested in long-term environmental problems and also less motivated to invest time in sorting recyclables.

REGION NORTHEAST and *REGION SOUTHEAST* are negatively associated with recycling rate, which agrees with expectations. Callan and Thomas (1997) find a positive association between recycling rates and access to the Springfield MRF. Communities in Northeastern and Southeastern Massachusetts would not have access to that facility and thus would have lower recycling rates. The results show that a town being located in Northeastern Massachusetts is associated with a recycling rate 6.0 percentage points lower than if it were located in Western Massachusetts. A town being located in Southeastern Massachusetts is associated with a recycling rate 5.0 percentage points lower than if it were located in Western Massachusetts.

Summary: All Variables

Overall the results for the *All Variables* model confirm my hypotheses. One exception was *INCOME*, which I expected to be significant. But some of the theory that higher income would lead to higher recycling is being captured by the strong correlation between *INCOME* and *EDUCATION*. It is also being captured by the strong negative correlation between *INCOME* and *UNEMPLOYMENT*. I also expected *PAYT* to be significant at the 0.05 level, but it is only 0.06. Although the algebraic sign indicates it is having the positive influence on recycling rate that was anticipated. Also, the fact that *PAYT YEARS* is significant means that by default, having a *PAYT* program is indeed significant.

<u>Sub Steps 2 and 3:</u>

Running the stepwise linear regression algorithm and conducting a manual sensitivity analysis drops 4 variables from the model: *LOG DENSITY*, *EDUCATION*, *INCOME*, and *REGION CENTRAL*. The model is reduced to seven variables:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{AGE} + \beta_2\text{UNEMPLOYMENT} + \beta_3\text{POLITICAL AFFILIATION} + \beta_4\text{REGION NORTHEAST} + \beta_5\text{REGION SOUTHEAST} + \beta_6\text{PAYT} + \beta_7\text{PAYT YEARS} + \varepsilon$$

ε represents the disturbance term

The reduced model performs on par with the *All Variables*, yielding an adjusted r^2 of 0.272.[32] The low adjusted r^2 value is again expected because there is only data for the *PAYT* policy variables. The significance of all variables is improved and the coefficient estimates are very close to their values in the *All Variables* model.

The full results and estimations are in **Table 4**.

[32] This is essentially equivalent to the 0.278 for the *All Variables* model

Table 4: 1997-1999 Sensitivity Analysis (Six Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.193	0.066	2.913	0.004	**
β_1	AGE	0.006	0.002	3.697	2.57E-04	***
β_2	UNEMPLOYMENT	-3.149	0.506	-6.226	1.51E-09	***
β_3	REGION NORTHEAST	-0.049	0.015	-3.321	0.001	**
β_4	REGION SOUTHEAST	-0.038	0.015	-2.596	0.010	**
β_5	PAYT	0.053	0.026	2.071	0.039	*
β_6	PAYT YEARS	0.007	0.003	2.195	0.029	*

Residual std. error	0.105 on 317 DF	*** significant at the 0.001 level
R2	0.285	** significant at the 0.01 level
R2 (adjusted)	0.272	* significant at the 0.05 level
F-statistic	21.07 on 6 and 317 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	324	

AGE shows a slightly stronger effect than it did in the *All Variables* model, with a 0.6 percentage point increase in recycling rate for every 1 year increase in median age. Holding all other variables constant, going from a low end median age town in Massachusetts, with a value of 37 to a high median age town with a value around 53, is associated with a 9.6 percentage point increase in recycling rate.

UNEMPLOYMENT has more impact in this reduced model and going from a town with low end unemployment around 1.5% to a higher end town with unemployment near 7.5% is associated with an 18.9 percentage point decrease in recycling rate, which is quite substantial, considering the mean recycling rate in the sample is 31.6% for this time period.

REGION NORTHEAST and *REGION SOUTHEAST* are roughly the same value as they were in the *All Variables* model, but both have a slightly reduced negative effect on recycling rates. *PAYT* is significant in this model, which meets expectations, and it has a slightly more positive effect on recycling rates with a 5.3 percentage point boost. In the sample, this is equivalent to 16.8 percent of the mean recycling rate.[33] Finally, *PAYT YEARS* is once again significant as expected, and having the exact same effect of a 0.7 percentage point increase to rates for every additional year of PAYT.

Summary: Sensitivity Analysis

Dropping five variables out of the model had an extremely minimal reduction on adjusted r^2. It increased the significance of remaining variables and had only a minimal impact on the coefficient estimates. There is a lot of variance around the predicted versus observed values (**Figure 9**). This is reflective of the low r^2 value.

[33] 5.3 / 31.6 = 0.168 = 16.8%

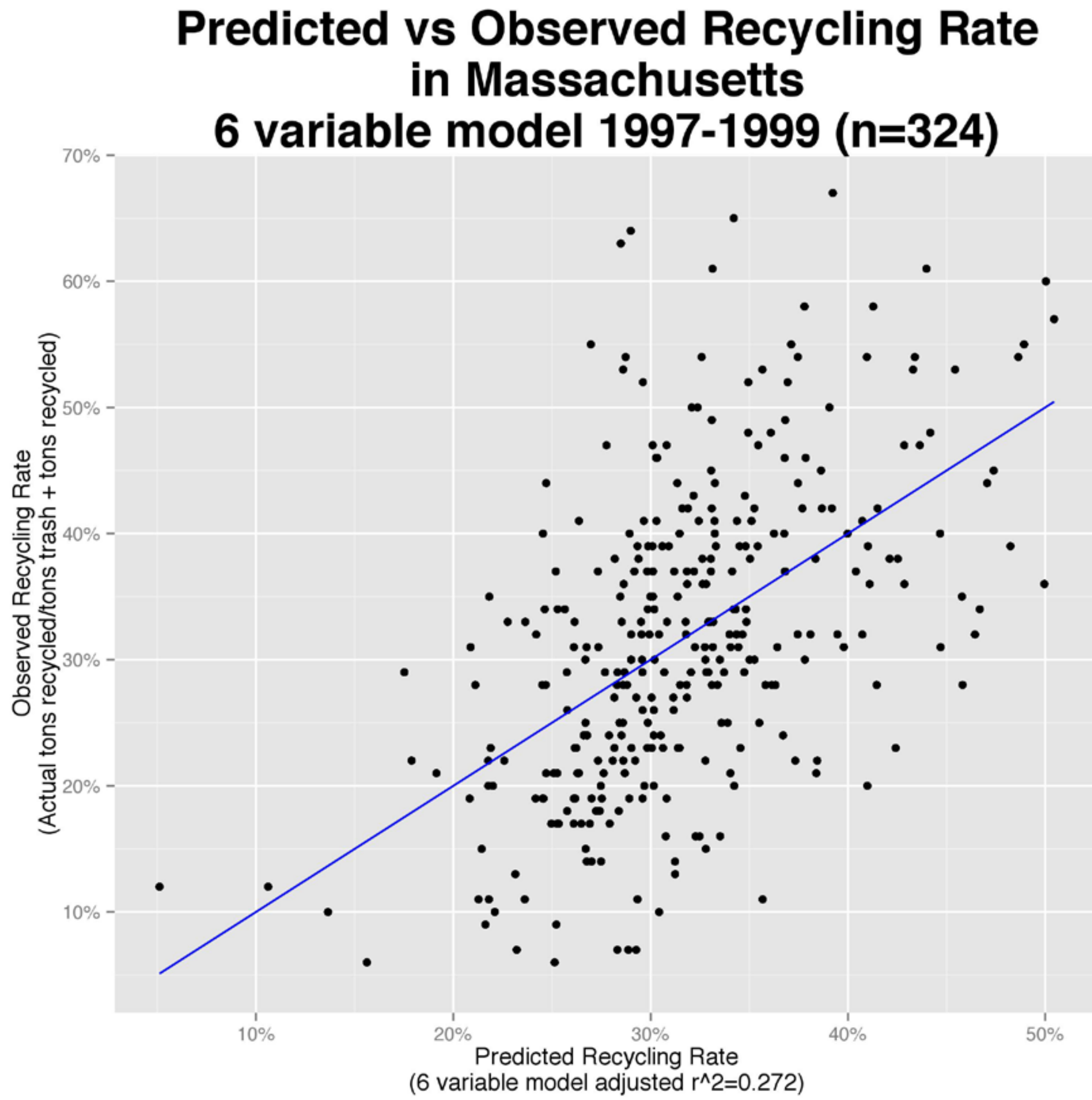

Figure 9: Predicted versus observed recycling rate for the 6 variable model.

Sub Step 4: Occam's Reduced Form

The reduced model is further refined until removing any additional variables causes a significant drop in adjusted r^2. This can be seen through visual inspection (**Figure 10**). Three variables remain and the model specification is:

RECYCLING RATE = $\beta_0 + \beta_1$AGE + β_2UNEMPLOYMENT + β_3PAYT YEARS + ε

ε represents the disturbance term

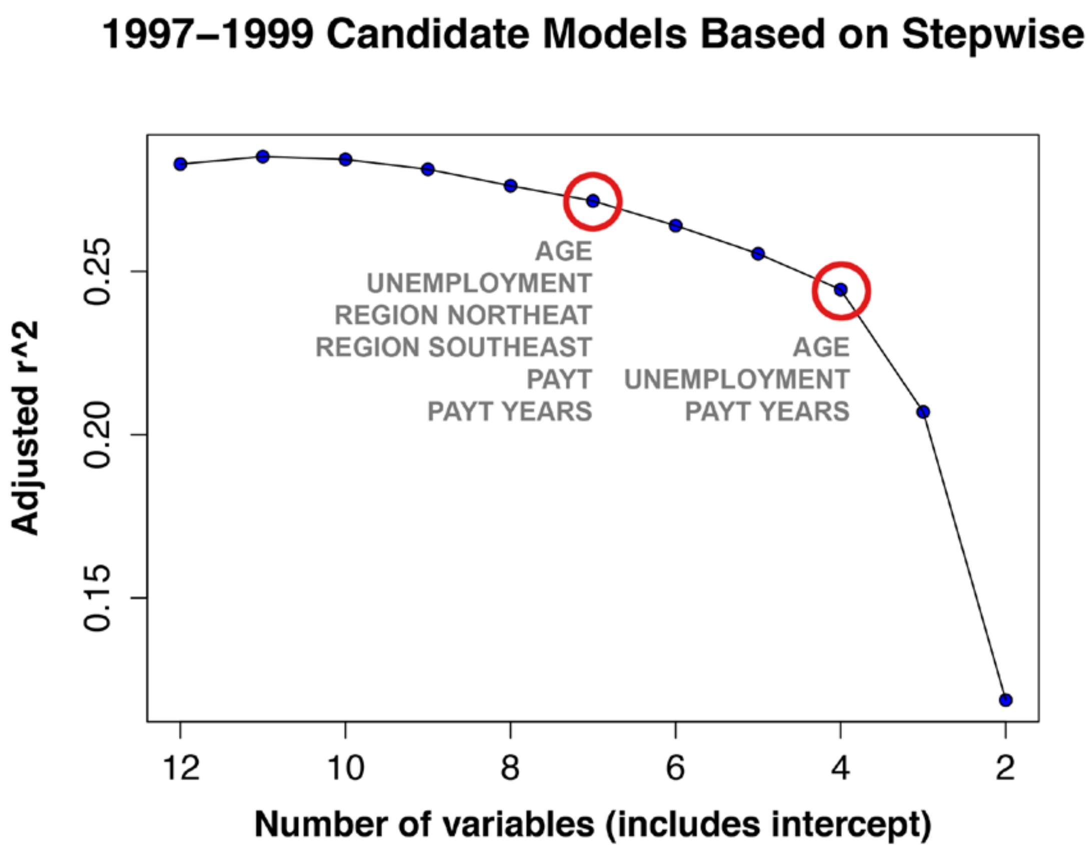

Figure 10: Graphical representation of potential models and their adjusted r^2.

The extremely reduced model keeps just the three most important variables. Moving from the *Sensitivity Analysis* to *Occam's Reduced Form,* the adjusted r^2 drops about 4 percentage points (approximately 1.3 points for each reduction in variables) to 0.243. This reduction is expected. Reducing the model beyond these three critical variables causes a significant drop in explained variance (**Figure 10**). The significance and coefficient estimate for *AGE* and *UNEMPLOYMENT* remain virtually unchanged. The coefficient for *PAYT YEARS* has almost doubled, which is the result of it capturing some of the variance that was previously explained by *PAYT*.

The full results and estimations are in **Table 5**.

Table 5: 1997-1999 Occam's Reduced Form (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.172	0.065	2.634	0.009	**
β_1	AGE	0.006	0.002	3.597	3.73E-04	***
β_2	UNEMPLOYMENT	-3.028	0.486	-6.237	1.41E-09	***
β_3	PAYT YEARS	0.014	0.002	7.199	4.35E-12	***

Residual std. error	0.1074 on 320 DF	*** significant at the 0.001 level
R2	0.243	** significant at the 0.01 level
R2 (adjusted)	0.235	* significant at the 0.05 level
F-statistic	34.15 on 3 and 320 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	324	

Summary: Occam's Reduced Form

It is interesting that *REGION* only accounts for about 14% of the adjusted r^2 value[34] in the six-predictor model. This suggests that while the MRF in Springfield is important in explaining recycling rates it is not one of the most critical components for this time period. Running a relative importance test in R (*calc.relimp*), reveals that the program variable, *PAYT YEARS*, accounts for 50% of the explanatory power of the model, while *UNEMPLOYMENT* accounts for about 36% and *AGE* about 14%.

Results: Testing Model Stability

To test stability of the *Sensitivity Analysis* and *Occam's Reduced Form* models, 1,000 bootstrap permutations were run and the model is found to be fairly robust (**Figure 11** and **Table 6**)[35].

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[34] This was calculated by subtracting the adjusted r^2 from the 3 variable model (0.235) from the adjusted r^2 of the 6 variable model (0.272), which equals 0.037 and dividing it by 0.272. This equals 0.136 or ≈ 14%.

[35] The results of the 3 variable *Occam's Reduced Form* are similar, so they will not be displayed.

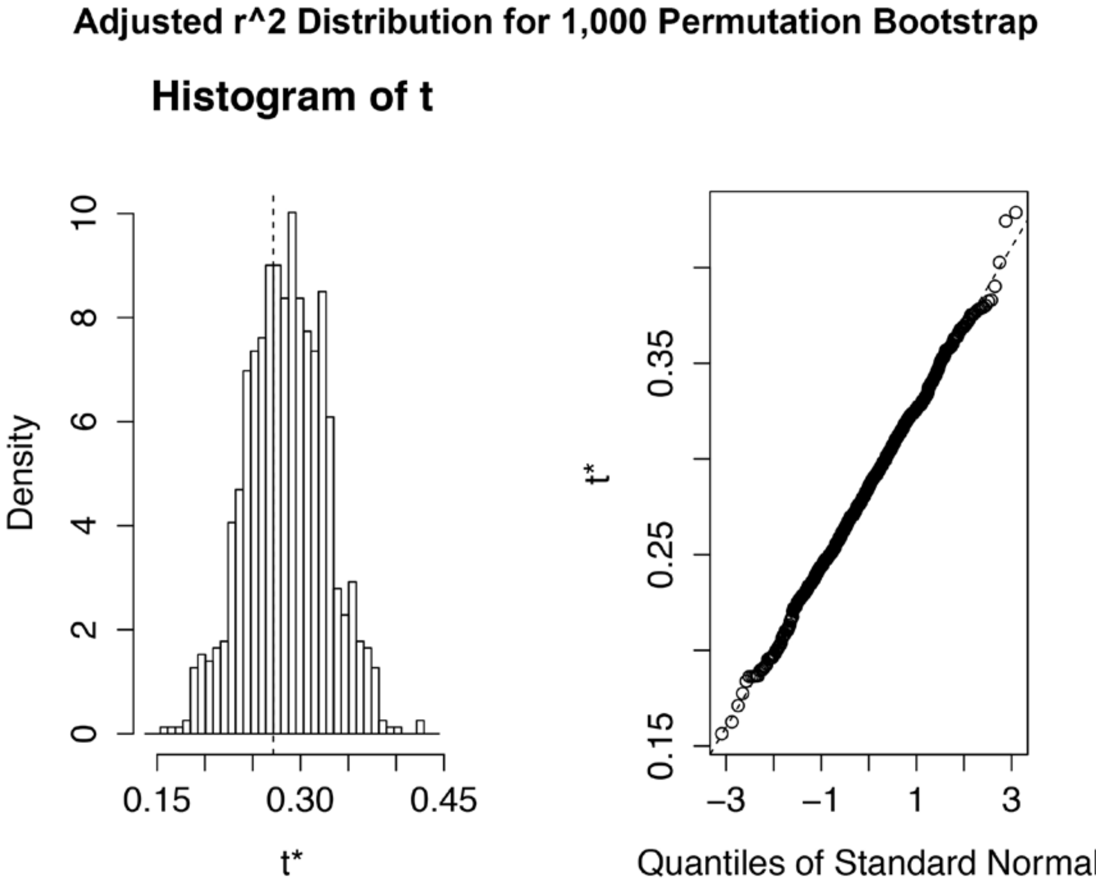

Figure 11: Adjusted r^2 distribution from a 1,000 permutation bootstrap of the six variable *Sensitivity Analysis*.

Table 6: 1997-1999 adjusted r^2 95% confidence intervals for 6-variable model based on 1,000 bootstrap permutations

Adjusted r^2	0.272
Lower (2.5%)	0.183
Upper (97.5%)	0.340

Summary: 1997-1999 All Models

The models were generally in line with expectations and with previous literature. Perhaps the most interesting finding is that just three variables: *AGE*, *UNEMPLOYMENT*, and *PAYT YEARS* are responsible for most of the explained variance. The low adjusted r^2 was expected, but disappointingly low. With the addition of more program variables in subsequent time periods, this value is expected to improve.

2006-2008

Results: Multiple Linear Regression

Sub Step 1: All Variables

The full model has 22 variables and the model specification is:

$$\begin{aligned} \text{RECYCLING RATE} = {} & \beta_0 + \beta_1\text{LOG DENSITY} + \beta_2\text{PERSONS PER HOUSEHOLD} + \beta_3\text{AGE} + \\ & \beta_4\text{EDUCATION} + \beta_5\text{INCOME} + \beta_6\text{ UNEMPLOYMENT} + \beta_7\text{POLITICAL} \\ & \text{AFFILIATION} + \beta_8\text{COMMUNITY PRESERVATION} + \beta_9\text{COMMUNITY} \\ & \text{PRESERVATION YEARS} + \beta_{10}\text{ COMMUNITY PRESERVATION COST} + \\ & \beta_{11}\text{REGION CENTRAL} + \beta_{12}\text{REGION NORTHEAST} + \beta_{13}\text{REGION} \\ & \text{SOUTHEAST} + \beta_{14}\text{PAYT} + \beta_{15}\text{PAYT YEARS} + \beta_{16}\text{SINGLE STREAM} + \\ & \beta_{17}\text{MANDATORY} + \beta_{18}\text{MANDATORY YEARS} + \beta_{19}\text{CURBSIDE} + \\ & \beta_{20}\text{RECYCLING SUBSCRIPTION} + \beta_{21}\text{TRASH SUBSCRIPTION} + \\ & \beta_{22}\text{SOLID WASTE FEE} + \varepsilon \end{aligned}$$

ε represents the disturbance term

After eliminating observations with missing values, the original sample of 351 is reduced by half to 173. By reducing the sample I am able to study the effect of more variables, which is good because it is important for policymakers to understand which variables may be contributing to recycling success. However, losing about half of the potential sample means the results risk being biased. Arriving at an n=173, was a compromise between including more variables and keeping the sample large enough so that it would be representative of the state as a whole. If *SINGLE STREAM* is dropped there are 301 municipalities that remained and the *All Variables* model has an adjusted r^2 of 0.42. But I decided, despite its abundance of NAs, *SINGLE STREAM* is an important variable to keep, because of its reputation as an important contributor to recycling success (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2010a). After trying different iterations of the model with and without variables with many NAs, I feel the appropriate balance was struck.

The model has an adjusted r^2 of 0.522. The great improvement in adjusted r^2 is perhaps partly due to the reduced sample size. One might think the inclusion of more program variables is also boosting the adjusted r^2, but a quick inspection reveals that only one of these new variables is significant, which is quite surprising. The coefficient estimates and significance are only partly in line with expectations and existing literature, although this time period had not previously been studied in Massachusetts. Three big exceptions to expectations are the coefficients and significance of: *SINGLE STREAM*, *MANDATORY*, and *CURBSIDE*, which will be discussed in some detail.

The full results and estimations are in Table 7.

Table 7: 2006-2008 All Variables Model

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.084	0.146	-0.577	0.565	
β_1	LOG DENSITY	0.019	0.009	2.056	0.041	*
β_2	PERSONS PER HOUSEHOLD	0.009	0.017	0.514	0.608	
β_3	AGE	0.007	0.002	3.245	0.001	**
β_4	EDUCATION	0.290	0.073	3.951	1.19E-04	***
β_5	INCOME	-4.74E-07	0.000	-1.086	0.279	
β_6	UNEMPLOYMENT	-0.640	0.618	-1.036	0.302	
β_7	POLITICAL AFFILIATION	-0.012	0.004	-2.697	0.008	**
β_8	COMMUNITY PRESERVATION	-0.054	0.038	-1.424	0.156	
β_9	COMMUNITY PRESERVATION YEARS	0.004	0.005	0.687	0.493	
β_{10}	COMMUNITY PRESERVATION COST	0.012	0.014	0.885	0.378	
β_{11}	REGION CENTRAL	-0.131	0.027	-4.934	2.12E-06	***
B_{12}	REGION NORTHEAST	-0.136	0.030	-4.580	9.70E-06	***
β_{13}	REGION SOUTHEAST	-0.101	0.028	-3.589	4.49E-04	***
B_{14}	PAYT	0.075	0.020	3.728	2.73E-04	***
B_{15}	PAYT YEARS	0.003	0.002	1.699	0.091	.
B_{16}	SINGLE STREAM	-0.005	0.017	-0.269	0.788	
B_{17}	MANDATORY	-0.030	0.034	-0.882	0.379	
B_{18}	MANDATORY YEARS	0.001	0.003	0.481	0.631	

B_{19}	CURBSIDE	0.015	0.023	0.646	0.519	
B_{20}	RECYCLING SUBSCRIPTION	-0.087	0.066	-1.308	0.193	
B_{21}	TRASH SUBSCRIPTION	-0.103	0.042	-2.433	0.016	*
B_{22}	SOLID WASTE FEE	-0.018	0.016	-1.162	0.247	

Residual std. error	0.08467 on 150 DF	*** significant at the 0.001 level
R2	0.6095	** significant at the 0.01 level
R2 (adjusted)	0.552	* significant at the 0.05 level
F-statistic	10.64 on 22 and 150 DF	. significant at the 0.1 level
p-value	< 2.20E-16	
n	173	

Contextual Factors

The contextual factors that were not significant in the model will be discussed first.[36] *PERSONS PER HOUSEHOLD* is a metric used by Callan and Thomas (2006) and Sidique et al. (2010). Callan and Thomas measure recycling demand and find persons per household to be statistically significant and that as persons per household increases recycling demand decreases. However, this finding is not completely relevant to my study, because they are measuring pounds per capita, not recycling *rate*, so it makes perfect sense that total pounds of recyclables reduces with larger packaging (because larger packages

[36] Variables that yield results similar to the 1997-1999 time period will not be discussed in great detail. For a more detailed discussion of how those variables relate to the literature, please see the earlier time period.

contain more volume per square inch of packaging material), but the effect this has on recycling rate is less clear.

While nowhere near significant, the algebraic sign agrees with expectations from Sidique et al. (2010), who find that for drop off programs, more individuals in a household increases participation in recycling drop off programs. However, recycling rate is the metric used in my study, not participation, so the findings of Sidique et al. may not be terribly relevant. Larger homes may participate more in drop off programs simply because they generate more recyclables and have less space to store them, so they must make frequent trips to the drop off center. In this case, they may be generating just as much trash, so there is no change in rates. Or, more individuals in a house may lead to social pressures to conform to norms, which may boost recycling (Sidique, Lupi, and Joshi 2010). Or the increased housing density may indicate there are children, which perhaps makes individuals more willing to participate in recycling because they see it as part of the bigger picture of ensuring a sustainable planet for their children, which could boost recycling rates. In any event, the model does not find this variable to be significant.

INCOME is again found insignificant, which agrees with the 1997-1999 findings. It is also once again highly correlated with education at 0.69. Interestingly, *UNEMPLOYMENT*, which was one of the three most important variables in the1997-1999 time period, is not significant for the 2006-2008 period. The algebraic sign agrees with the earlier findings, but the effect of *UNEMPLOYMENT* on recycling rate is vastly reduced and statistically insignificant. This may be reflective of changing economic conditions. Perhaps communities that had high unemployment and low rates in the late 1990s were able to make investments in recycling infrastructure in the early 2000s or communities with low rates in this time period already had recycling infrastructure in place, so when the unemployment rate increased recycling was already ingrained in citizens. A final potential explanation could be that PAYT programs had nearly doubled from about 68 in 1997-1999 to 125 by 2006-2008 (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012a). In tight financial times, these programs may be particularly effective at encouraging those with limited resources to recycle more as a way to reduce their trash disposal costs. Thus, with the proliferation of PAYT perhaps the cost benefit equation of recycling changed for those dealing with unemployment.

None of the three *COMMUNITY PRESERVATION* variables were a good indicator of recycling success. To my knowledge these metrics have never been used before as a proxy for assessing environmental attitudes and legislative commitment in regards to recycling rate. Their lack of significance in the model suggests their lack of use is for good reason; they may not be appropriate proxies.

Before discussing the program factors, the contextual factors that *are* significant will be discussed. *LOG DENSITY* was not found significant in the earlier period, but in the 2006-2008 period it is significant at the 0.5 level. A 1% increase in *LOG DENSITY* is associated with a 0.019 percentage point increase in recycling rate. Holding all other variables constant, going from a municipality on the low end of density, in Massachusetts, to the high end is associated with an 11.4 percentage point increase in recycling rate.[37]

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[37] In log units, the low end of density is about 3 and the high end is about 9.

9 – 3 = 6 and 6 x 0.019 = 0.114 (to converted to percent for recycling rate multiply by 100 = 11.4%).

AGE is again significant at the 0.01 level, which supported expectations, existing literature, and the findings of the 1997-1999 models. *AGE* has a slightly more positive effect on recycling rate in this period, going from 0.005 in period 1, to 0.007 in period 2. For this period a 1 year increase in median age is associated with a 0.7 percentage point increase in recycling rate. In the 2006-2008 sample, the low end for median age is around 32 and the high is around 52, so holding all other variables constant, the recycling rate difference across this range would be 14 percentage points.[38]

EDUCATION is highly significant, again agreeing with expectations, earlier findings, and the literature. It has a stronger effect in this time period with a 1 percentage point increase in percent of population with bachelors degree associated with a 0.290 percentage point increase in recycling rate. In the 2006-2008 sample municipalities, the low end for percent with bachelor's degree is around 10% and the high end is around 75%. Holding all other variables constant, the high end towns are expected to have a recycling rate 18.85 percentage points higher than the low end towns.[39]

POLITICAL AFFILIATION was not significant in the earlier model, but is here. *POLITICAL AFFILIATION* is a kind of proxy for environmental attitudes, so this change in significance runs somewhat counter to Sidique et al. (2010) who find environmental beliefs are not linked with recycling participation. The negative algebraic sign agrees with the

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[38] 52 - 32 = 18 and 18 x 0.007 = 0.14 (in % form = 14%)

[39] 75 -10 = 65 and 65 x 0.290 = 18.85% (note: education is already in % form, so move decimal place to make in % form for this variable)

1997-1999 results. The coefficient estimate means that for each 1 unit increase in the ratio of Democrats to Republicans the recycling rate decreases by 0.012 percentage points. In the sample this range goes from about 1:1 to 10:1, which means going from a low ratio to high ratio municipality one can expect a 10.8 percentage point decrease in recycling rate.[40] As was touched on in the 1997-1999 period however, Massachusetts is a special case when it comes to political affiliation. For the larger sample of 331 towns, for which there is political data, only 10 municipalities, or about 3%, have more Republicans than Democrats. So the *POLITICAL AFFILIATION* variable used here is not so much capturing differences between Democrats and Republicans as it is capturing differences between Democrats. Therefore, this variable may not be capturing the environmental beliefs between Democrats and Republicans that it is intended to. It may instead be capturing differences between mildly Democratic and heavily Democratic areas, or some unmeasured collinear variable. It would be interesting to study this variable in greater detail to see if *POLITICAL AFFILIATION* is indeed *driving* the reduction in recycling rate.

The three *REGION* variables are all significant in this model, including *REGION CENTRAL*, which was not significant in 1997-1999. Interestingly, the effect on recycling rate for *REGION NORTHEAST* and *REGION SOUTHEAST* has doubled from period 1 to an expected reduction of 13.6 percentage points for municipalities in the Northeast and 10.1 for municipalities in the Southeast. The Central region coefficient estimate has quintupled to a 13.1 percentage point reduction. The addition of *REGION CENTRAL* may be the result of communities in Central Massachusetts, that once had access to the Springfield MRF, no longer having access to the facility, but there is not data on this. It could also be that the

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[40] 10 – 1 = 9 and 9 x 0.012 = 0.108 = 10.8%

MRF expanded its services to more communities in Western Massachusetts between the time periods and this boosted the rate in that part of the state. **Table 8** shows the mean recycling rate from the larger sample (331 municipalities) for this time period. It is clear that Western MA is significantly different from the rest of the state and I suspect the Springfield MRF is playing a large part in this difference.

Table 8: 2006-2008 Mean Recycling Rate by Region (n=331)

REGION	Mean Recycling Rate (in %)
WESTERN	34.2
SOUTHEAST	29.8
NORTHEAST	29.5
CENTRAL	26.1

Program factors

The most interesting result from this time period is the clear lack of significance for so many program variables. The only ones that are highly significant are *PAYT* and *TRASH SUBSCRIPTION*. It could be that the program variables are interacting in ways that are important to the recycling rate, but when put into the model as individual terms, there is collinearity and their significance is lost. But with so many variables being nowhere near significant, this seems unlikely.[41] The negative algebraic sign, on variables that were expected to increase rates, is also surprising.

I begin by discussing the variables that are not significant. Surprisingly, *SINGLE STREAM* is nowhere near significant and in fact has a negative algebraic sign. This is a startling finding. Single stream allows individuals to throw all recyclable materials into 1 bin, which greatly reduces the burden on individuals to sort through their recyclable goods. Single stream recycling only requires individuals to think briefly whether or not the material in their hand is recyclable before they throw it into either their trash or recycle bin, which makes recycling virtually as simple as throwing trash away. Yet this added convenience seems to have no effect on recycling rate. This finding agrees with Folz (1991) who finds comingling (single stream) does not boost recycling rates. However this contrasts sharply with the Commonwealth of Massachusetts' 2010 Solid Waste Master Plan that speaks of the success of single stream and encourages its further adoption.

The finding that *MANDATORY* recycling is an insignificant variable is perhaps even more startling, because this contradicts much of the peer reviewed literature. The negative sign is also surprising because it suggests *MANDATORY* recycling is linked with a decrease in recycling rate, but again the finding is not statistically significant, so no conclusions can be drawn. Although they don't all use the same metric for recycling success, studies by Folz (1999), Noehammer and Byer (1997), and Everett and Peirce (1993) all suggest *MANDATORY* recycling is a significant program variable. The only study I am aware of that

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[41] Refer to the p-values in

Table 7.

contradicts these findings and agrees with mine is Jenkins et al. (2003), who analyze a 1992 dataset for 20 metropolitan statistical areas and find *MANDATORY does not have* a significant effect on recycling rates for the five materials they studied.

MANDATORY YEARS is also not found to be significant. After analyzing the dates of the previous studies there could be a clue as to why the *MANDATORY* and *MANDATORY YEARS* findings differ from expectations and previous work. My study uses 2006-2008 data, while all the other studies use data from before 1999. It could be that making a program mandatory was very important when recycling programs were first starting, because it forced people to change the way they thought about trash. But over the years, attitudes, social norms, and behaviors have shifted and recycling is mainstream. People no longer recycle because they are told to; they recycle because it is the normal thing to do. This theory is supported by Sidique et al. (2010) who find social norms are a strong driver of participation in drop off recycling programs. It is also in line with Folz (1999), who conducts the only other study to look at recycling over time and finds that while making a program mandatory was very important in 1989, by 1996 voluntary programs were just as successful.

CURBSIDE captures both curbside trash and curbside recycling services, which are perfectly correlated in the sample. The finding that it is insignificant disagree with Jenkins et al. (2003), who finds it boosted rates for all five materials they study and Folz (1991), who finds it to be the single most important variable in voluntary programs. It also disagrees with Callan and Thomas (1997) who find curbside service significant at the 0.05 level, providing a 4.15 percentage point boost to recycling rate. The lack of significance also goes against my intuition that something that makes recycling easier should increase rates.

But as **Table 9** shows, the larger sample of 331 municipalities shows virtually no difference between communities with and without curbside recycling. In fact, looking at it in this univariate way shows communities with curbside recycling actually have a slightly *lower* average recycling rate. This lack of significance may be the result of the extremely high correlation between offering curbside trash and curbside recycling services. In the smaller sample of 173, on which the model is based, this correlation is exactly 1. This means that communities have *either* drop off trash and recyclables *or* curbside trash and recyclable service. In both cases, trash and recycling are equally convenient, so the advantage of curbside disappears. If communities had curbside recycling paired with drop off trash, this might change the convenience factor and boost recycling. PAYT in combination with curbside (Callan and Thomas 1997) may also boost recycling, but this was not specifically tested here.

Table 9: 2006-2008 Curbside Programs (n=331)

Status (with n)	Mean Recycling Rate (in %)
Curbside (159)	30.1
No Curbside (172)	30.5

I expected *RECYCLING SUBSCRIPTION* to have a slightly negative effect on rates, because it puts the onus on individuals to purchase recycling services. To my knowledge, this variable has not previously been used in the literature. While it has the anticipated algebraic sign, the variable is insignificant.

To my knowledge, *SOLID WASTE FEE* is not used in existing literature but it is an interesting variable because it hides the cost of trash disposal in property taxes. The upside of this is that it discourages illegal trash disposal since every homeowner has access to trash services. The downside is that individuals perceive trash services as "free" and since they are not charged per unit of trash they dispose of, there is no incentive to throw away less. As expected, the algebraic sign for this variable is negative, but it is not found to be significant.

TRASH SUBSCRIPTION is the only new variable that is significant. The negative relationship between a subscription trash program and recycling rate met expectations. The coefficient estimate means that if a community has *TRASH SUBSCRIPTION* it can expect a 10.3 percentage point decrease in its recycling rate.

PAYT YEARS is found significant at the 0.1 level, which is less significant than in the 1997-1999 *All Variables* model. Its impact on recycling rate is also reduced by 0.4 percentage points to a 0.3 percentage point increase in recycling rate for every additional year a community has *PAYT*. *PAYT* itself is found to be highly significant, and is having a larger effect on recycling rate than in 1997-1999. Here, a community with *PAYT* program can expect a 7.5 percentage point increase in recycling rate, holding all other variables constant. This is equivalent to 24% of the sample's mean recycling rate.

Summary: All Variables

The full *All Variables* model explains a high percent of variance and generally is in line with the 1997-1999 results. However, the lack of significance of so many program variables was a big surprise. The fact that *SINGLE STREAM*, *MANDATORY*, and *CURBSIDE* had no effect of recycling rate is an interesting finding. In fact, looking at a larger sample of

331 municipalities, the mean recycling rate is actually *slightly higher* for those without *SINGLE STREAM* and *CURBSIDE* (**Table 10**).

Table 10: Mean recycling rate for communities with and without select program variables (2006-2008) (n=331)

Means (in %)		
Variable	YES	NO
SINGLE STREAM	29.4	31.7
MANDATORY	30.9	30.1
CURBSIDE	30.1	30.5

Sub Steps 2 and 3:

After running a stepwise linear regression algorithm and conducting a sensitivity analysis, the model is reduced to seven variables. The reduced model specification is:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{AGE} + \beta_2\text{EDUCATION} + \beta_3\text{REGION CENTRAL} + \beta_4\text{REGION NORTHEAST} + \beta_5\text{REGION SOUTHEAST} + \beta_6\text{PAYT} + \beta_7\text{TRASH SUBSCRIPTION} + \varepsilon$$

ε represents the disturbance term

The reduced model performs on par with the *All Variables* model, yielding an adjusted r^2 of 0.528.[42] The significance of all variables is improved and the coefficient estimates are very close to their values in the full *All Variables* model.

The full results and estimations are in **Table 11**.

Table 11: 2006-2008 Sensitivity Analysis (Seven Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.005	0.068	-0.080	0.936	
β_1	AGE	0.006	0.001	3.982	1.02E-04	***
β_2	EDUCATION	0.259	0.045	5.776	3.70E-08	***
β_3	REGION CENTRAL	-0.099	0.022	-4.555	1.01E-05	***
β_4	REGION NORTHEAST	-0.085	0.022	-3.835	1.78E-04	***
β_5	REGION SOUTHEAST	-0.073	0.021	-3.520	0.001	***
β_6	PAYT	0.095	0.015	6.294	2.69E-09	***
B_7	TRASH SUBSCRIPTION	-0.144	0.034	-4.308	2.83E-05	***

Residual std. error	0.087 on 165 DF	*** significant at the 0.001 level
R2	0.547	** significant at the 0.01 level
R2 (adjusted)	0.528	* significant at the 0.05 level
F-statistic	28.5 on 7 and 165 DF	. significant at the 0.1 level
p-value	< 2.20E-16	
n	173	

[42] This is essentially equivalent to the 0.552 for the *All Variables* model. In fact, only 0.024 is lost from the adjusted r^2 after dropping 15 variables.

Summary: Sensitivity Analysis

AGE, REGION CENTRAL, *REGION NORTHEAST*, and *REGION SOUTHEAST* all experience slight reductions in their coefficient estimates. *EDUCATION*, *PAYT*, and *TRASH SUBSCRIPTION* all see slight increases in their effect on recycling rate. Dropping fifteen variables out of the model had an extremely minimal reduction on adjusted r^2. While there is some variation between expected versus observed rates, **Figure 12** shows an improvement over **Figure 9** from the 1997-1999 time period.

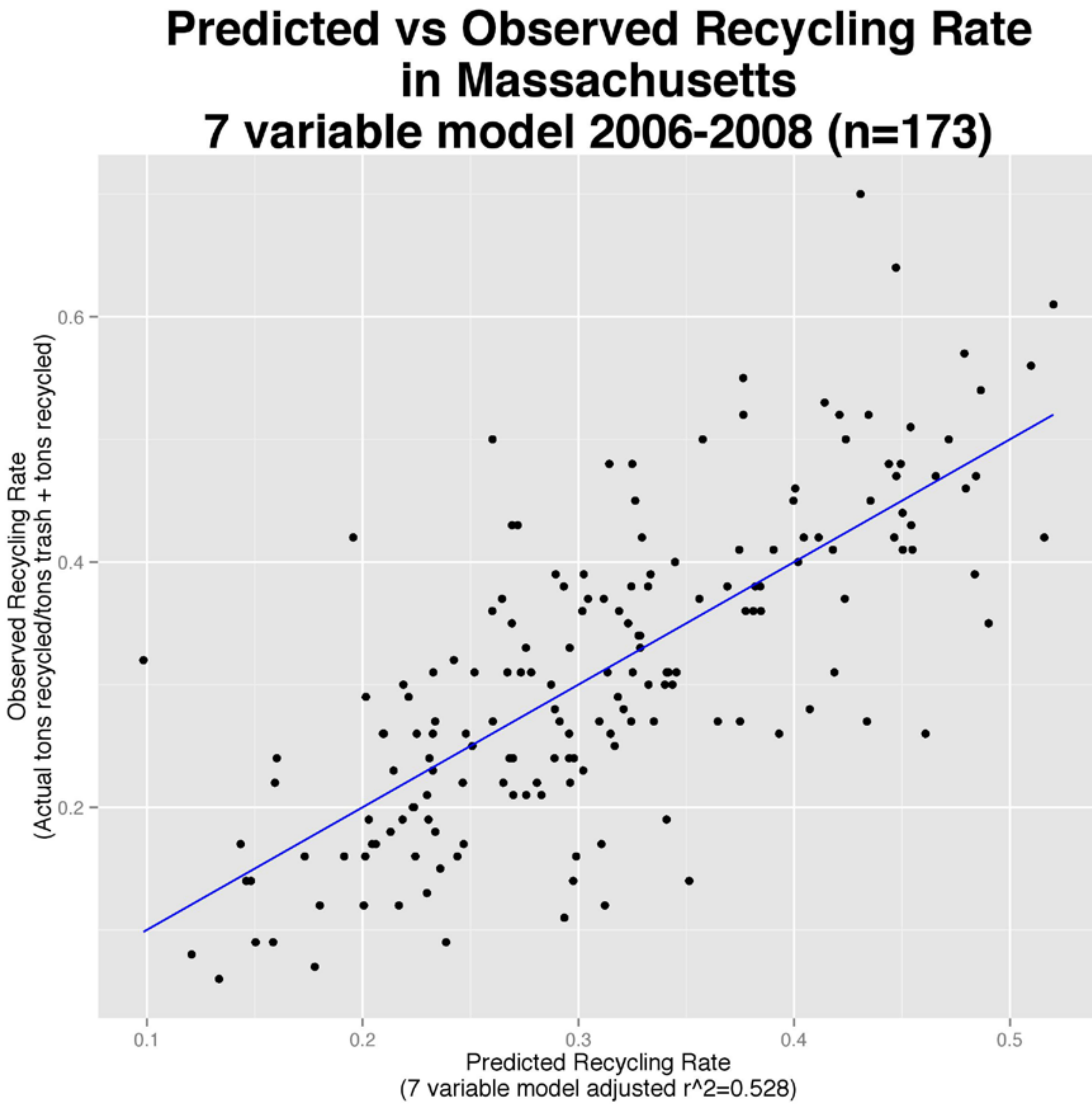

Figure 12: Predicted versus observed recycling rate for the 7 variable model.

Sub Step 4: Occam's Reduced Form

The reduced model is further refined until removing any additional variables causes a significant drop in adjusted r^2. The screening can also be done through visual inspection **Figure 13**. Three variables remain and the model specification is:

RECYCLING RATE = $\beta_0 + \beta_1$AGE + β_2EDUCATION + β_6PAYT + ε

ε represents the disturbance term

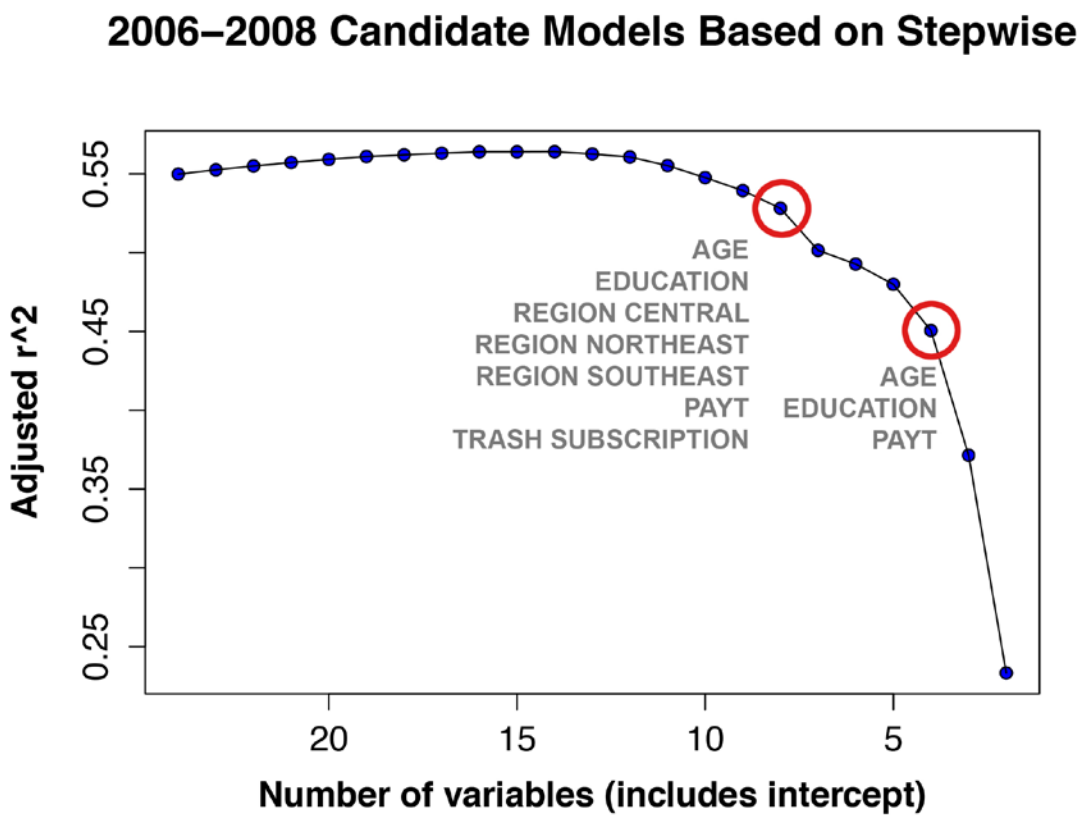

Figure 13: Graphical representation of potential models and their adjusted r^2.

Dropping the three *REGION* variables and *TRASH SUBSCRIPTION* reduces the adjusted r^2 to 0.447, which averages a 2 percentage points reduction for every dropped variable.[43] Reducing the model beyond these three critical variables causes a significant drop in explained variance (**Figure 13**). Compared to the *Sensitivity Analysis* model, the coefficients for *AGE* and *PAYT* have a slightly stronger effect on recycling rate. *EDUCATION* has a slightly reduced effect.

The full results and estimations are in **Table 12**.

Table 12: 2006-2008 Occam's Reduced Form (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.197	0.061	-3.230	0.001	**
β_1	AGE	0.009	0.001	6.514	8.04E-10	***
β_2	EDUCATION	0.214	0.044	4.907	2.17E-06	***
β_3	PAYT	0.122	0.015	8.187	6.26E-14	***
Residual std. error	0.094 on 169 DF		*** significant at the 0.001 level			
R2	0.456		** significant at the 0.01 level			
R2 (adjusted)	0.447		* significant at the 0.05 level			
F-statistic	47.26 on 3 and 169 DF		. significant at the 0.1 level			
p-value	< 2.20E-16					
n	173					

[43] 0.528 – 0.447 = 0.081 and 0.081 / 4 (the number of dropped variables) ≈ 0.020 or about 2 percentage points.

Summary: Occam's Reduced Form

The three *REGION* variables and *TRASH SUBSCRIPTION* have a significant effect on recycling rate, but their relatively small percentage of explained variance (adjusted r^2) means that the three remaining variables are a bit more reliable predictors of recycling success. Running a relative importance test in R, reveals that the program variable, *PAYT*, accounts for 50% of the explanatory power of the model, while *AGE* accounts for about 33% and *EDUCATION* about 17%.

Results: Testing Model Stability

To test stability of the *Sensitivity Analysis* and *Occam's Reduced Form* models, 1,000 bootstrap permutations were run and the model is found to be fairly robust (Figure 14 and **Table 13**)[44].

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[44] The results of the 3 variable *Occam's Reduced Form* are similar, so to spare the reader they will not be displayed.

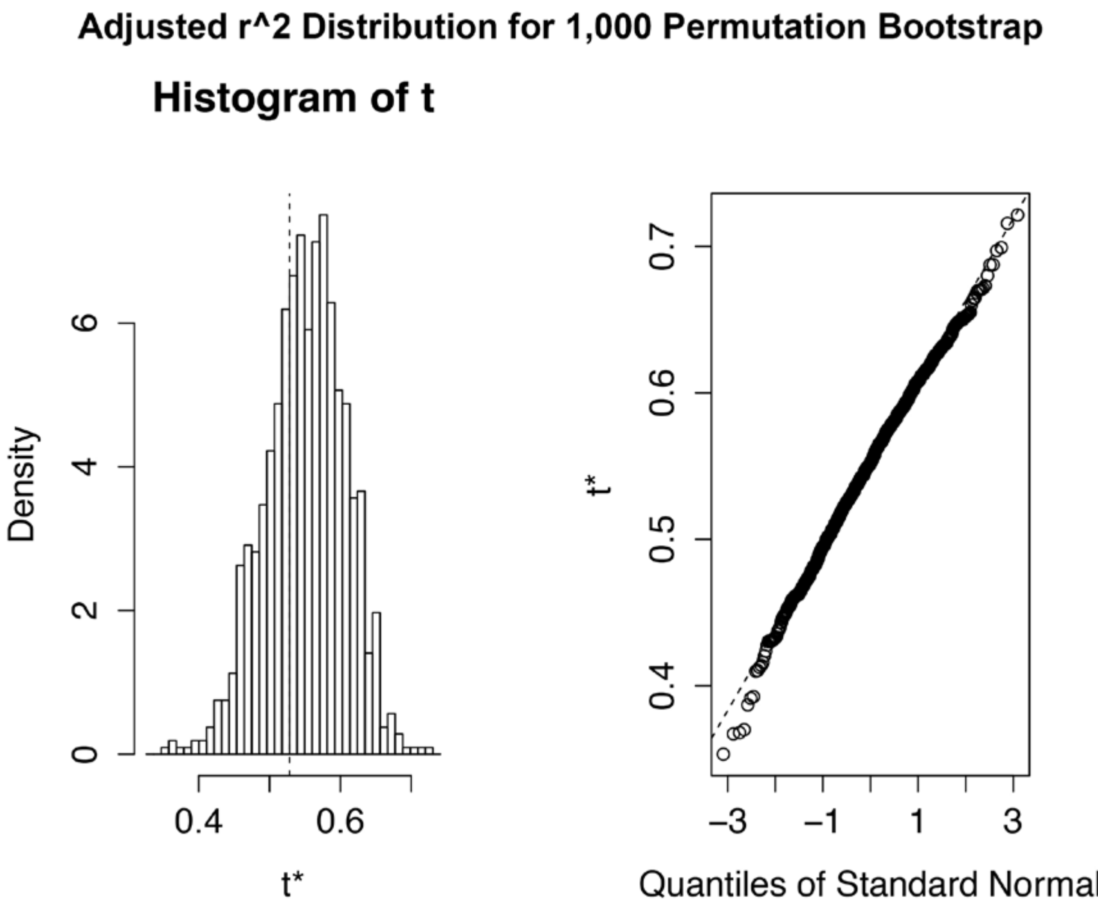

Figure 14: Adjusted r^2 distribution from a 1,000 permutation bootstrap.

Table 13: 2006-2008 adjusted r^2 95% confidence intervals for 7-variable model based on 1,000 bootstrap permutations

Adjusted r^2	0.528
Lower (2.5%)	0.364
Upper (97.5%)	0.610

Summary: 2006-2008 All Models

The most interesting findings from the 2006-2008 time period are:

1) Based on the models run, *SINGLE STREAM*, *MANDATORY*, and *CURBSIDE* are not significantly influencing recycling rate
2) The *REGION* variables are once again important, with *REGION CENTRAL* joining the other 2 regions as significant
3) *AGE* and one of the *PAYT* variables are key in both the 1997-1999 *Occam's Reduced Form* model and the 2006-2008 *Occam's Reduced Form* model. *UNEMPLOYMENT* was dropped out in favor of *EDUCATION*.
4) The percent of adjusted r^2 explained by program variables versus contextual variables is split exactly 50/50 in the *Occam's Reduced Form* model. But this is from one program variable and 2 contextual variables.

<u>2009</u>

To save the reader from data overload, the model specification for 2009 will not be given here. For a list of variables used in the model and summary statistics see

Table A3*. For a graphical representation of the model selection process see* Figure B5*. For model results, please see* Table A7 *and* Table A8*.*

2010

Results: Multiple Linear Regression

Sub Step 1: All Variables

The full model has 24 variables and the model specification is:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{LOG DENSITY} + \beta_2\text{PERSONS PER HOUSEHOLD} + \beta_3\text{AGE} + \beta_4\text{EDUCATION} + \beta_5\text{INCOME} + \beta_6\text{POLITICAL AFFILIATION} + \beta_7\text{REGION CENTRAL} + \beta_8\text{REGION NORTHEAST} + \beta_9\text{REGION SOUTHEAST} + \beta_{10}\text{PAYT} + \beta_{11}\text{PAYT YEARS} + \beta_{12}\text{TRASH SERVICE} + \beta_{13}\text{RECYCLING SERVICE} + \beta_{14}\text{TRASH CURBSIDE} + \beta_{15}\text{TRASH BOTH} + \beta_{16}\text{RECYCLING CURBSIDE} + \beta_{17}\text{RECYCLING BOTH} + \beta_{18}\text{YARD WASTE} + \beta_{19}\text{YARD WASTE CURBSIDE} + \beta_{20}\text{YARD WASTE FROP OFF} + \beta_{21}\text{FOOD WASTE} + \beta_{22}\text{MUNICIPAL AND SCHOOL} + \beta_{23}\text{BUSINESS} + \beta_{24}\text{HAZARDOUS CATEGORIES} + \varepsilon$$

ε represents the disturbance term

After eliminating observations with missing values, the original sample of 352 is reduced to 245. The model performs reasonably well with an adjusted r^2 of 0.408. The reduction in adjusted r^2 is perhaps partly due to natural variation from the larger sample size. It might also be the result of the recycling rate being based solely on 2010 data. Recycling rates for municipalities in Massachusetts can vary significantly year-to-year. This is perhaps due to measurement error when the tonnages are being calculated or perhaps it is some of the real variation that is expected in such a dynamic system. The earlier time periods use a 3-year average to calculate recycling rates, which helps to smooth out these year-to-year rate swings. Starting in 2009 however, the Commonwealth of Massachusetts changed its data collection methods. Consequently the available data to calculate rates from 2009-2012 varies slightly year to year. I therefore decided that for the 2009-2012 period the rate would be calculated solely on the tonnage data from that year. This introduces some variability, which may be reflected in reduced adjusted r^2.

There was insufficient data on *MANDATORY*, *TRASH SUBSCRIPTION*, or *SINGLE STREAM* for this time period, but *CURBSIDE RECYCLING* is in the model and for this time period is found significant. Some interesting new program variables are also found to be significant. The coefficient estimates and significance are generally in line with expectations and existing literature.

The full results and estimations are in **Table 14**.

Table 14: 2010 All Variables Model

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.020	0.108	0.189	0.850	
β_1	LOG DENSITY	-0.008	0.008	-0.933	0.352	
β_2	PERSONS PER HOUSEHOLD	0.013	0.010	1.252	0.212	
β_3	AGE	0.005	0.002	2.654	0.009	**
β_4	EDUCATION	0.198	0.054	3.679	2.94E-04	***
β_5	INCOME	4.21E-07	0.000	1.222	0.223	
β_6	POLITICAL AFFILIATION	0.002	0.004	0.471	0.638	
β_7	REGION CENTRAL	-0.044	0.022	-1.988	0.048	*
β_8	REGION NORTHEAST	-0.067	0.026	-2.576	0.011	*
β_9	REGION SOUTHEAST	-0.061	0.021	-2.908	0.004	**
β_{10}	PAYT	0.087	0.020	4.427	1.50E-05	***
β_{11}	PAYT YEAR	0.001	0.001	0.891	0.374	
B_{12}	TRASH SERVICE	-0.084	0.090	-0.936	0.350	
β_{13}	RECYCLING SERVICE	0.018	0.089	0.197	0.844	
B_{14}	TRASH CURBSIDE	-0.111	0.068	-1.615	0.108	
B_{15}	TRASH BOTH	-0.103	0.070	-1.463	0.145	
B_{16}	RECYCLING CURBSIDE	0.144	0.067	2.170	0.031	*
B_{17}	RECYCLING BOTH	0.131	0.067	1.965	0.051	.
B_{18}	YARD WASTE	0.019	0.022	0.867	0.387	
B_{19}	YARD WASTE CURBSIDE	5.42E-05	0.001	0.085	0.932	
B_{20}	YARD WASTE DROP OFF	-8.60E-05	7.25E-05	-1.186	0.237	
B_{21}	FOOD WASTE	0.039	0.016	2.349	0.020	*

B_{22}	MUNICIPAL AND SCHOOL	-0.012	0.014	-0.839	0.403	
B_{23}	BUSINESS	0.019	0.013	1.401	0.162	
B_{24}	HAZARDOUS CATEGORIES	0.002	0.001	1.422	0.156	

Residual std. error	0.08943 on 220 DF	*** significant at the 0.001 level
R2	0.4664	** significant at the 0.01 level
R2 (adjusted)	0.4082	* significant at the 0.05 level
F-statistic	8.011 on 24 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	245	

Contextual Factors

The contextual factors that were not significant in the model will be discussed first.[45] *LOG DENSITY* is not significant in the 1997-1999 period, is significant in the 2006-2008 period, but is again not significant in 2010. The negative algebraic sign agrees with the 2006-2008 finding but disagrees with my original expectations. *PERSONS PER HOUSEHOLD* is not significant, in line with the period 2 models. For the third time, *INCOME* is again having an insignificant effect on recycling rate. *POLITICAL AFFILIATION* is likewise not significant. While this finding agrees with period 1 it is a change from period 2. The

[45] As was mentioned earlier, variables that yield results similar to earlier time periods will not be discussed in great detail. For a more detailed discussion of how those variables relate to the literature, please see the earlier time period.

algebraic sign has also flipped to positive, meaning that as the ratio of Democrats to Republicans increases the recycling rate increase. However, the coefficient estimate is quite small at 0.002 and again, the finding is nowhere near significant, so no conclusions can be drawn.

All five of the contextual variables that are significant in the 2010 model are also significant in the 2006-2008 model, although their coefficient estimates are generally a lot closer to the 1997-1999 values than the 2006-2008 values. Holding all other variables constant, a one-year increase in median *AGE* is associated with a 0.5 percentage point increase in recycling rate. This is the exact same value as 1997-1999 and is close to the 0.7 percentage point increase seen in 2006-2008. *EDUCATION* is slightly lower than in 2006-2008, with a 1 percentage point increase in *EDUCATION* associated with a 0.198 percentage point increase in recycling rate. *REGION NORTHEAST* and *REGION SOUTHEAST* coefficients are reduced by about half and *REGION CENTRAL* is reduced by about two-thirds from period 2. The 2010 coefficient values for *REGION* are again closer to the period 1 values. These changes in coefficients may be capturing some real change in the system, or it could be just part of the natural variability that is expected in such a complex system. Without more years for comparison it is hard to be sure.

Program Factors

The results from this time period better meet expectations for the significance of program variables. The program variables that are not significant will be addressed first. *TRASH SERVICE* and *RECYCLING SERVICE* measure the percent of households served by the municipal trash and recycling program. To my knowledge, these have not been used in existing literature. While the algebraic signs for these variables agree with expectations, they are not significant. *TRASH CURBSIDE* is closer with a p-value of 0.108. The negative algebraic signs are in line with expectations.

YARD WASTE, *YARD WASTE CURBSIDE,* and *YARD WASTE DROP OFF* all measure if the community offers yard waste collection and how often. In accordance with Folz (1991) who finds composting boosts rates, I expect collection and composting of yard waste boosts recycling rates. The positive algebraic sign of *YARD WASTE* supports this idea. As does the positive sign for the number of weeks yard waste is picked up, captured by the *YARD WASTE CURBSIDE* variable. *YARD WASTE DROP OFF*, which represents the number of days the drop off compost site is open, has a negative sign, which goes against expectations. However, none of the three variables is anywhere near significant, so no conclusions can be derived.

MUNICIPAL AND SCHOOL and *BUSINESS* represent whether those institutions have access to municipal recycling services. In this year, programs that served municipal buildings and programs that serve schools are perfectly correlated, so they are combined into one variable: *MUNICIPAL AND SCHOOL*. To my knowledge, these have not been used previously in the literature and they are insignificant variables in this time period.

HAZARDOUS CATEGORIES captures the robustness of the recycling program, by calculating how many categories of hazardous goods are collected year round. The higher the number of categories, the easier it should be for individuals to drop off these goods, thus keeping them out of the municipal waste stream and boosting the recycling rate. The algebraic sign is positive, but the variable is insignificant.

The final insignificant program variable is PAYT YEARS, which was significant in period 1, but only significant at the 0.1 level in period 2. This could be reflective of the number of years not being as important once programs have been in place for a certain amount of time. After people internalize the behavior of recycling, how long the program has been there may not matter.

PAYT is however once again an important variable. A community with *PAYT* can expect a recycling rate 8.7 percentage points higher than a community without *PAYT*. In the sample, this is equivalent to 30.5 percent of the mean recycling rate. This is slightly more than it was in 2006-2008.

RECYCLING CURBSIDE and *RECYCLING BOTH* describe if a municipality has curbside trash service or both curbside and drop off trash service. Jenkins et al. (2003) and Folz (1991) find curbside service to be significant factors in influencing recycling rate. The results show that communities that offer both curbside and drop off recycling can expect a 13.1 percentage point increase in recycling rate over communities who offer neither, this finding is significant at the 0.1 level. Communities that offer just curbside service can expect a 14.1 percentage point increase in recycling rate over those who don't, this is significant at the 0.05 level. This finding that curbside service is indeed significant is more in line with my expectations than the 2006-2008 finding of no significance. However, after closer inspection I do not have great confidence in these results.

To model curbside services I originally broke the data into four categories: communities that offer 1) curbside trash, 2) both curbside and drop off trash, 3) curbside recycling, 4) curbside and drop off recycling. When the mean recycling rates for a slightly larger sample of 254 communities (**Table 15**) are examined, it is clear that recycling rates are not very different between programs that offer just curbside and those that offer drop off and curbside service. The means are quite different though between communities that offer curbside and those that *just have* drop off. This suggests that communities that offer curbside *and* drop off are more similar to communities that offer *just curbside* than they are to communities that offer *just drop off*. This suggests that when communities offer both curbside and drop off services, the curbside services are used more frequently.

Table 15: Mean recycling rate for various trash and recycling programs types (2010)

Trash Program Type (with n)	**Mean Recycling Rate (in %)**
Trash curbside (109)	25.0
Trash curbside and drop off (32)	25.9
Trash just drop off (113)	32.0
Recycling Program Type (with n)	**Mean Recycling Rate (in %)**
Recycling curbside (69)	26.1
Recycling curbside & drop off (70)	24.8
Recycling just drop off (115)	31.7

Informed by an understanding of the means, I combined *RECYCLING CURBSIDE* and *RECYCLING BOTH* into a new category that just captures whether curbside services are offered, regardless of whether drop off is also offered. The same was then done for trash. This yielded 2 categories, communities that have *CURBSIDE TRASH* and communities that have *CURBSIDE RECYCLING*. The model was run again with these two variables and again

CURBSIDE RECYCLING was significant at the 0.05-level and positive with a coefficient of 0.138.[46] However, when the correlation between *CURBSIDE TRASH* and *CURBSIDE RECYCLING* is tested, it was found to be 0.984. In fact there are only two towns, Clinton and Pembroke, out of the 141 towns with curbside services that have curbside trash but *not* curbside recycling. Their 13% and 11% recycling rates respectively were skewing the results. When these two towns are dropped from the sample, *CURBSIDE TRASH* and *CURBSIDE RECYCLING* are perfectly correlated and when these are combined into one variable, *CURBSIDE*, it is insignificant.

The lesson that can be derived from this analysis is that if communities offer curbside trash and recycling services, *CURBSIDE* is not a significant variable. However, if communities offer curbside trash, but *not* curbside recycling, they may expect to see lower recycling rates. However, this finding is only based on two communities, so it does not carry much weight. It would be interesting to see the effect if communities offered curbside recycling, but only drop off trash. I expect this might boost recycling rates.

A final point on curbside versus drop off, looking at the means in **Table 15** it is somewhat surprisingly that *CURBSIDE* is not a significant variable because communities with just drop off actually have a higher recycling rate. However, when this is analyzed in a multivariate way, other variables do a better job of explaining the variation, so curbside versus drop off is not statistically significant.

FOOD WASTE is a dummy variable with a value of 1 if the municipality offers curbside or drop off food waste collection, a 0 if they do not. Holding all other variables

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[46] 0.138 is essentially equivalent to the 0.144 observed in the *All Variables* model.

constant, a community with *FOOD WASTE* service can expect a recycling rate 3.9 percentage points higher than a community that does not have such service. This finding is significant at the 0.05 level. This supports expectations and Folz (1991) finding that composting increases recycling rate.

Summary: All Variables

The full *All Variables* model explains a fairly high percent of variance and generally is in line with the 1997-1999 and 2006-2008 results. One notable change between 2006-2008 and 2010 is the significance of *RECYCLING CURBSIDE* in this latter time period, but as was explained this result does not hold up to close scrutiny. It is encouraging to see more program variables such as *FOOD WASTE* being significant in this time period, because these are the variables over which town officials and MSW managers have more control.

<u>Sub Steps 2 and 3:</u>

After running a stepwise linear regression algorithm and conducting a sensitivity analysis, the model is reduced to seven variables. The reduced model specification is:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{AGE} + \beta_2\text{EDUCATION} + \beta_3\text{REGION CENTRAL} + \beta_4\text{REGION NORTHEAST} + \beta_5\text{REGION SOUTHEAST} + \beta_6\text{PAYT} + \beta_7\text{FOOD WASTE} + \varepsilon$$

ε represents the disturbance term

The reduced model actually does a slightly better job than the *All Variables* at explaining the variance, yielding an adjusted r^2 of 0.41.[47] This very slight gain comes despite eliminating 17 variables. Fifteen of these were insignificant in the *All Variables* model. Eliminating the two significant variables, *RECYCLING CURBSIDE* and *RECYCLING BOTH* also has no real effect on the model. This is perhaps unsurprising because the *CURBSIDE* variable was not significant in the 2006-2008 period and, as was described above, this significance was coming from only 2 towns. By reducing the model, the significance of the remaining seven variables is improved and the coefficient estimates are very close to their values in the full *All Variables* model.

The full results and estimations are in **Table 16**.

Table 16: 2010 Sensitivity Analysis (Seven Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.019	0.056	0.339	0.735	
β_1	AGE	0.004	0.001	3.234	0.001	**
β_2	EDUCATION	0.217	0.039	5.515	9.08E-08	***
β_3	REGION CENTRAL	-0.044	0.019	-2.398	0.017	*
β_4	REGION NORTHEAST	-0.059	0.019	-3.166	0.002	**
β_5	REGION SOUTHEAST	-0.058	0.016	-3.640	3.35E-04	***
β_6	PAYT	0.112	0.012	9.034	5.98E-17	***
B_7	FOOD WASTE	0.036	0.016	2.277	0.024	*

[47] The *sensitivity* model has an adjusted r^2 of 0.41, compared to 0.408 for the *All Variables* model.

Residual std. error	0.089 on 237 DF	*** significant at the 0.001 level
R2	0.427	** significant at the 0.01 level
R2 (adjusted)	0.41	* significant at the 0.05 level
F-statistic	25.22 on 7 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	245	

The reduced model is remarkably similar to the 2006-2008 *Sensitivity Analysis* model. The only variable that is different is *FOOD WASTE*, for which there was not previously any data. For 2010, there was no data on *TRASH SUBSCRIPTION*, which was in the 2006-2008 *Sensitivity Analysis* model. The other six variables are the same between the 2010 and 2006-2008 *Sensitivity Analysis* models. Compared to the earlier period, the estimates for *AGE*, *EDUCATION*, and the three *REGION* variables are slightly lower while *PAYT* is slightly higher.

Summary: Sensitivity Analysis

Dropping seventeen variables out of the model actually improved the adjusted r^2. While this model does not explain quite as much variance as the 2006-2008 *Sensitivity Analysis* model, it does a reasonable job of predicting recycling rate (**Figure 15**).

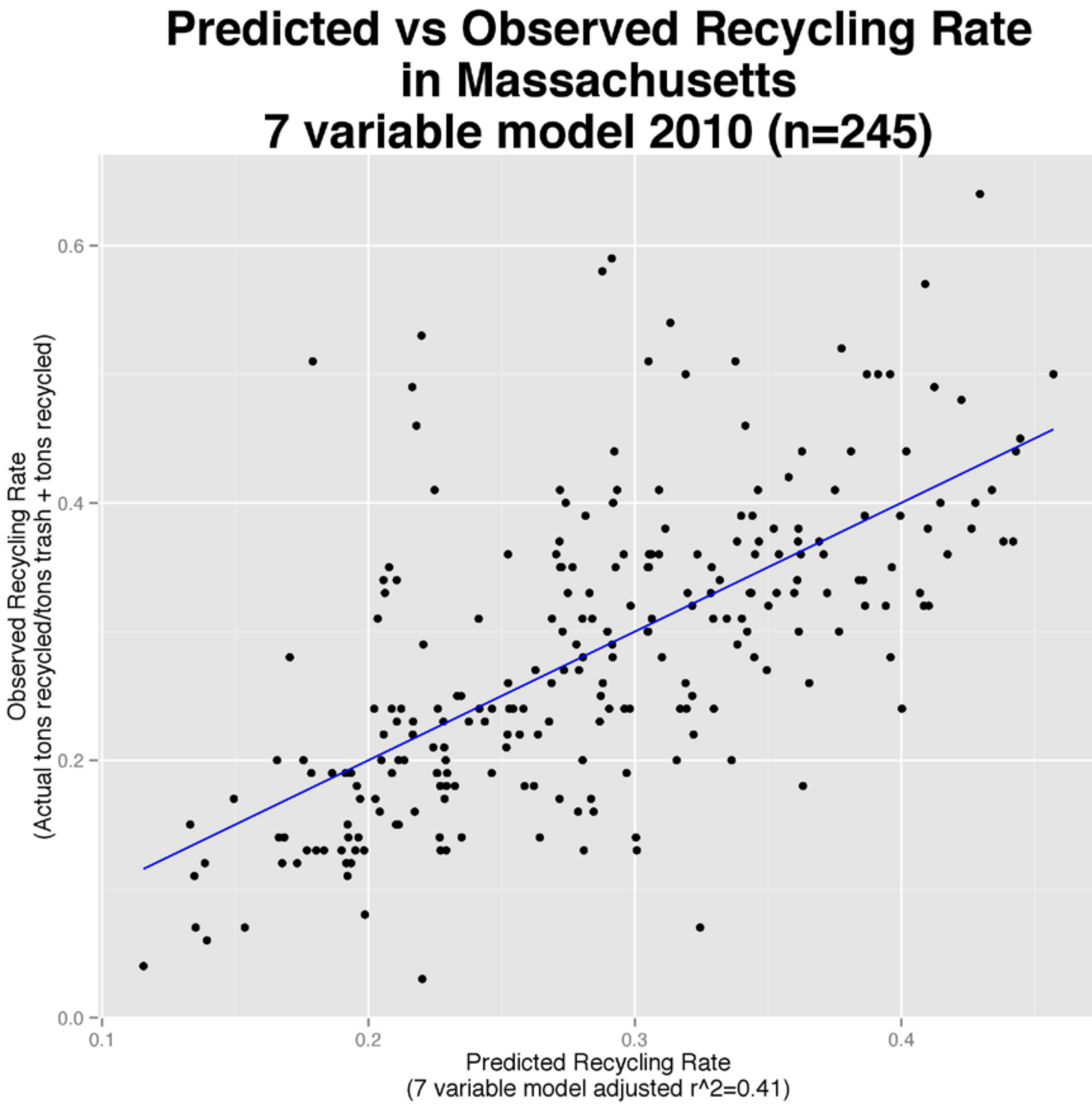

Figure 15: Predicted versus observed recycling rate for the 6 variable model.

Sub Step 4: Occam's Reduced Form

The reduced model is further refined until removing any additional variables causes a significant drop in adjusted r^2. This analysis is aided through visual analysis (**Figure 16**). Three variables remain and the model specification is:

RECYCLING RATE = $\beta_0 + \beta_1$AGE + β_2EDUCATION + β_6PAYT + ε

ε represents the disturbance term

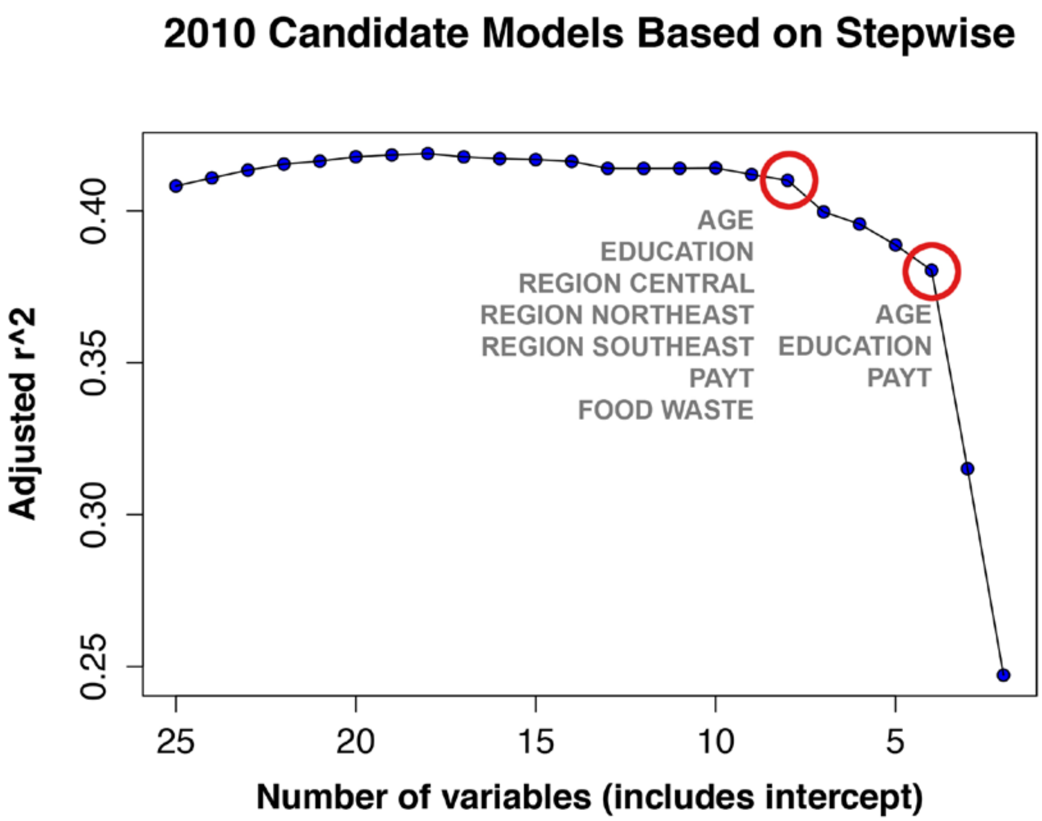

Figure 16: Graphical representation of potential models and their adjusted r^2.

Dropping the three *REGION* variables and *FOOD WASTE* reduces the adjusted r^2 to 0.371, which averages a 1 percentage point reduction for every dropped variable.[48] Reducing the model beyond these three critical variables causes a significant drop in explained variance (**Figure 16**). Compared to the *Sensitivity Analysis* model, the coefficients for *AGE* and *PAYT* have a slightly stronger effect on recycling rate. *EDUCATION* has a slightly reduced effect.

The full results and estimations are in Table 17.

Table 17: 2010 Occam's Reduced Form (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.062	0.050	-1.251	0.212	
β_1	AGE	0.005	0.001	4.725	3.92E-06	***
β_2	EDUCATION	0.180	0.037	4.929	1.54E-06	***
β_3	PAYT	0.123	0.012	10.189	1.66E-20	***

Residual std. error	0.092 on 241 DF	*** significant at the 0.001 level
R2	0.378	** significant at the 0.01 level
R2 (adjusted)	0.371	* significant at the 0.05 level
F-statistic	48.88 on 3 and 241 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	245	

48 0.41 – 0.371 = 0.039 and 0.039 / 4 (the number of dropped variables) ≈ 0.01 or about 1 percentage points.

The 2010 results are fairly similar to the 2006-2008 *Occam's Reduced Form* results. The three critical variables are exactly the same and the *PAYT* coefficient estimate is only 0.001 greater than in 2006-2008. The *AGE* estimate is about 44 percent less than it was in the earlier period and the *EDUCATION* estimate is about 15 percent less.

Summary: Occam's Reduced Form

The three *REGION* variables and *FOOD WASTE* have a significant effect on recycling rate, but their relatively small percentage of explained variance (adjusted r^2) means that the three remaining variables are a bit more reliable predictors of recycling success. Running a relative importance test in R, shows that the program variable, *PAYT*, accounts for 69% of the explanatory power of the model, while *AGE* accounts for about 15% and *EDUCATION* about 16%. The amount of variance explained by the program variable is higher in this time period than it is in period 1 and period 2.

Results: Testing Model Stability

To test stability of the *Sensitivity Analysis* and *Occam's Reduced Form* models, 1,000 bootstrap permutations were run and the model is found to be fairly robust (**Figure 17** and Table 18)[49].

[49] The results of the 3 variable *Occam's Reduced Form* are similar, so to spare the reader they will not be displayed.

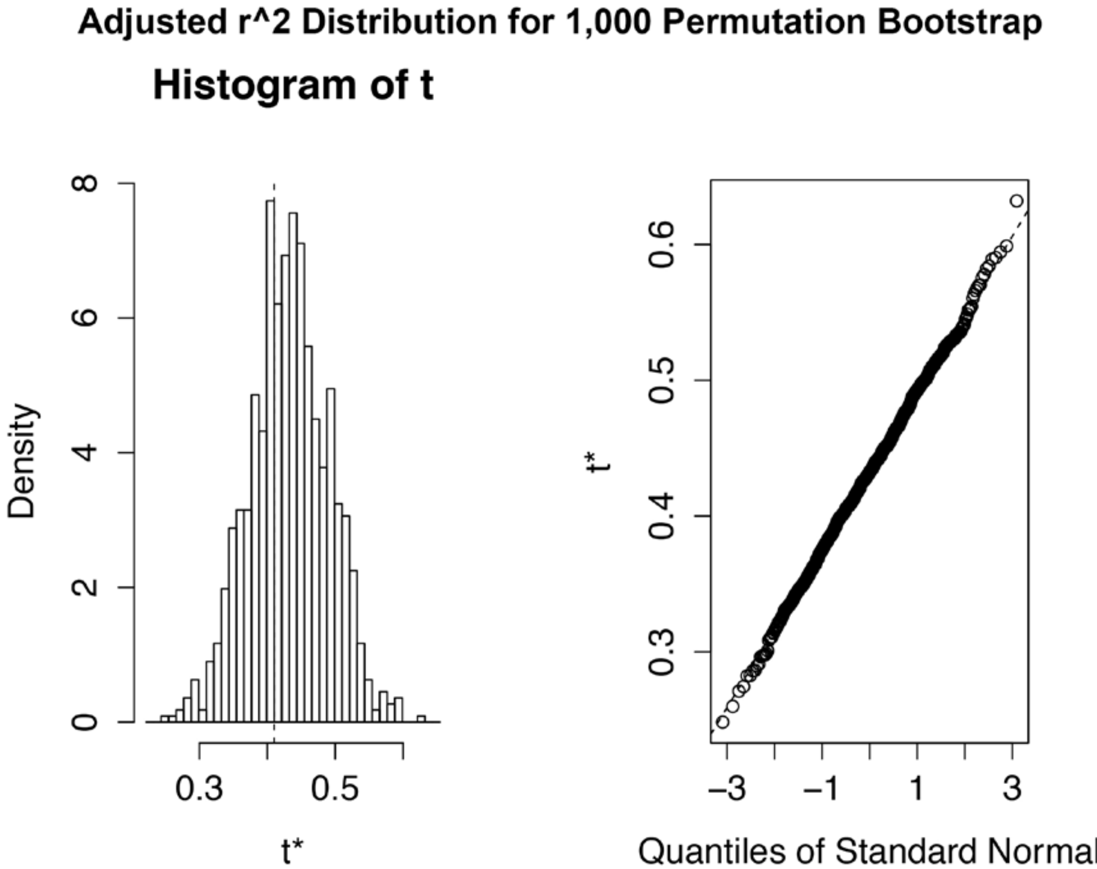

Figure 17: Adjusted r² distribution from a 1,000 permutation bootstrap.

Table 18: 2010 adjusted r² 95% confidence intervals for 7-variable model based on 1,000 bootstrap permutations

Adjusted r^2	0.41
Lower (2.5%)	0.261
Upper (97.5%)	0.500

Summary: 2010 All Models

The most interesting findings from the 2010 time period are:

1) The key variables in this time period are *AGE*, *EDUCATION*, and a *PAYT*. These results are unchanged from 2006-2008.
2) The three *REGION VARIABLES* are once again significant, but their coefficient estimates are smaller than in period 2
3) *RECYCLING CURBSIDE* and *RECYCLING BOTH* are significant in the *All Variables* model, but upon closer investigation this finding was only based on 2 towns skewing the results. It is critical to test this variable in more time periods.
4) The percent of adjusted r^2 explained by program variables versus contextual variables is 69 percent to 31 percent in the *Occam's Reduced Form* model. This gives more weight to the program variable than in previous time periods.

2011

To save the reader from data overload, the model specification for 2011 will not be given here. For a list of variables used in the model and summary statistics see Table A5*. For a graphical representation of the model selection process see* Figure B6*. For results please see* Table A9*,* Table A10*, and* Table A11*.*

2012

Results: Multiple Linear Regression

Sub Step 1: All Variables

The full model has 36 variables and the model specification is:

RECYCLING RATE = $\beta_0 + \beta_1$LOG DENSITY + β_2PERSONS PER HOUSEHOLD + β_3AGE + β_4EDUCATION + β_5INCOME + β_6UNEMPLOYMENT + β_7POLITICAL AFFILIATION + β_8COMMUNITY PRESERVATION + β_9COMMUNITY PRESERVATION YEARS + β_{10}COMMUNITY PRESERVATION COST + β_{11}REGION CENTRAL + β_{12}REGION NORTHEAST + β_{13}REGION SOUTHEAST + β_{14}PAYT + β_{15}PAYT YEARS + β_{16}PAYT COST + β_{17}TIPPING FEE + β_{18}SINGLE STREAM + β_{19}MANDATORY + β_{20}TRASH SERVICE + β_{21}RECYCLING SERVICE + β_{22}TRASH LIMIT + β_{23}CURBSIDE TRASH AND RECYCLE + β_{24}CARTS TRASH + β_{25}CARTS RECYCLE + β_{26}BINS COMPOST + β_{27}YARD WASTE + β_{28}FOOD WASTE + β_{29}MUNICIPAL + β_{30}SCHOOL + β_{31}BUSINESS + β_{32}SWAP SHOP + β_{33}HAZARDOUS CATEGORIES + β_{34}HAZARDOUS EVENTS + β_{35}HAZARDOUS REGIONAL + β_{36}HAZARDOUS RECIPROCAL + ε

ε represents the disturbance term

After eliminating observations with missing values, the original sample of 352 is reduced by more than half to 143. Similar to the 2006-2008 dataset, I strove for the right balance between including variables that were theorized to be important to the model and keeping the sample size large enough to be representative of the larger population. Despite some program variables having many NAs, they were kept in the model because these variables have been suggested as important to recycling success.

The model performs reasonably well with an adjusted r^2 of 0.477. The adjusted r^2 is larger than 2010, which is perhaps partly due to the smaller sample size. It may also be the result of the recycling rate being based solely on 2012 data, which as was discussed in the 2010 section, can create some natural year-to-year recycling rate variability.

Somewhat surprisingly, only 1 program variables is significant at the 0.05 level. If these results hold true in the more refined models, it runs counter to expectations that program variables should be able to explain a high percent of recycling rate variance.

The full results and estimations are in Table 19.

Table 19: 2012 All Variables Model

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.275	0.238	-1.155	0.251	
β_1	LOG DENSITY	-0.020	0.014	-1.469	0.145	
β_2	PERSONS PER HOUSEHOLD	0.037	0.024	1.558	0.122	
β_3	AGE	0.008	0.003	2.237	0.027	*
β_4	EDUCATION	0.385	0.090	4.298	3.84E-05	***
β_5	INCOME	-6.17E-07	4.52E-07	-1.366	0.175	
β_6	UNEMPLOYMENT	0.719	0.596	1.205	0.231	
β_7	POLITICAL AFFILIATION	0.009	0.006	1.369	0.174	
β_8	COMMUNITY PRESERVATION	-0.056	0.054	-1.035	0.303	
β_9	COMMUNITY	-2.38E-04	0.006	-0.043	0.966	

	PRESERVATION YEARS					
β_{10}	COMMUNITY PRESERVATION COST	0.037	0.018	2.091	0.039	*
β_{11}	REGION CENTRAL	-0.007	0.039	-0.181	0.857	
B_{12}	REGION NORTHEAST	0.013	0.041	0.312	0.756	
β_{13}	REGION SOUTHEAST	-0.038	0.038	-0.997	0.321	
B_{14}	PAYT	0.024	0.038	0.626	0.533	
B_{15}	PAYT YEARS	-0.002	0.002	-1.076	0.284	
B_{16}	PAYT COST	0.015	0.006	2.401	0.018	*
B_{17}	TIPPING FEE	0.001	0.001	1.708	0.091	.
B_{18}	SINGLE STREAM	-0.022	0.023	-0.973	0.333	

Continued on next page

Table 19, continued

B_{19}	MANDATORY	-0.002	0.021	-0.078	0.938	
B_{20}	TRASH SERVICE	-0.232	0.151	-1.537	0.127	
B_{21}	RECYCLING SERVICE	0.156	0.150	1.041	0.300	
B_{22}	TRASH LIMIT	-0.024	0.027	-0.896	0.372	
B_{23}	CURBSIDE TRASH AND RECYCLE	0.023	0.035	0.657	0.512	
B_{24}	CARTS TRASH	-0.017	0.030	-0.565	0.573	
B_{25}	CARTS RECYCLE	0.020	0.030	0.677	0.500	
B_{26}	BINS COMPOST	0.015	0.021	0.717	0.475	
B_{27}	YARD WASTE	0.008	0.039	0.204	0.839	
B_{28}	FOOD WASTE	0.018	0.036	0.484	0.630	

B_{29}	MUNICIPAL	0.032	0.044	0.727	0.469	
B_{30}	SCHOOL	0.014	0.027	0.501	0.617	
B_{31}	BUSINESS	0.020	0.021	0.934	0.352	
B_{32}	SWAP SHOP	-0.023	0.026	-0.874	0.384	
B_{33}	HAZARDOUS CATEGORIES	0.004	0.002	1.914	0.058	.
B_{34}	HAZARDOUS EVENTS	-0.001	0.004	-0.222	0.825	
B_{35}	HAZARDOUS REGIONAL	-0.021	0.022	-0.939	0.350	
B_{36}	HAZARDOUS RECIPROCAL	0.045	0.023	1.971	0.051	.
Residual std. error	0.093 on 106 DF	*** significant at the 0.001 level				
R2	0.610	** significant at the 0.01 level				
R2 (adjusted)	0.477	* significant at the 0.05 level				
F-statistic	4.6 on 36 and 106 DF	. significant at the 0.1 level				
p-value	4.80E-10					
n	143					

Contextual Factors

The contextual factors that were not significant in the model will be discussed first.[50] *LOG DENSITY* is once again not significant and the negative algebraic sign runs counter to expectations that denser areas would have higher rates. The relationship may be

[50] As was mentioned earlier, variables that yield results similar to earlier time periods will not be discussed in great detail. For a more detailed discussion of how those variables relate to the literature, please see the earlier time period.

nonlinear, where density benefits recycling rates to a point, but as density increase too high the recycling rate begins to decline. This could result from overly dense areas having a lack of space to store recyclables. Squared terms for this variable were tried in some time periods, but it did not seem to greatly improve the results, so the simpler specification was used.

PERSONS PER HOUSEHOLD, *INCOMES*, *UNEMPLOYMENT*, *POLITICAL AFFILIATION*, *COMMUNITY PRESERVATION*, and *COMMUNITY PRESEVATION YEARS* all come out as insignificant. *UNEMPLOYMENT* and *POLITICAL AFFILIATION* were each only found significant in 1 time period, 1997-1999 and 2006-2008 respectively. In the 2012 model, the algebraic signs for both suggest a positive relationship, which seems very counterintuitive for *UNEMPLOYMENT*. The p-values are far from significant however, so no conclusions can be drawn.

COMMUNITY PRESERVATION COST is significant, which may affirm the belief that this can be used as a proxy to express environmental commitment. Holding all other variables constant, each additional percentage point that a community charges homeowners, for Community Preservation, is associated with a 3.7 percentage point rise in recycling rate. While certainly not causal, it may be reflective of a community's willingness to turn environmental beliefs into concrete action, which suggests they would be more likely to support robust recycling programs and would have higher participation in these programs.

Interestingly, the *REGION* variables, which are almost always significant in the other time periods, are not even close to being significant in 2012. This may be the result of MRFs being built in other parts of the state, or it is capturing some other underlying shift in the system such as expansion of *PAYT*, which negates the effect of *REGION*. It could also be that the reduced sample size is somehow biased in a way that the *REGION* variables is sensitive to.

Once again *AGE* and *EDUCATION* are significant. *AGE* has a slightly larger coefficient estimate with a 1 year increase in median *AGE* associated with a 0.8 percentage point rise in recycling rate. *EDUCATION* has a much larger coefficient than in any previous period. In 2012, a 1-percentage point rise in percent of population with a bachelor's degree is associated with a 0.385 percentage point increase in recycling rate. The *EDUCATION* range in the sample for this period goes from municipalities with about 15% of residents having Bachelor's degrees to about 75%. This is a projected recycling rate difference of 23.1 percentage points between low to high towns.[51]

Program Factors

Meeting expectations, a few new program variables are significant at the 0.1 level. But some of the program variables that are not significant are again surprising. *SINGLE STREAM* and *MANDATORY* are again nowhere near significant and in fact have negative algebraic signs, suggesting they reduce recycling. This is a particularly interesting finding because the Commonwealth of Massachusetts' Municipal Solid Waste Master Plan touts these as important programs that should be expanded.

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[51] 75 – 15 = 60 and 60 x 0.385 = 23.1

TRASH SERVICE and *RECYCLING SERVICE* are again insignificant. A new variable, *TRASH LIMIT*, represents whether a trash limit is enforced at the curb, which depending on the limit, one would intuitively think should encourage recycling. But this is insignificant. *CURBSIDE TRASH AND RECYCLE* is a combination of curbside trash and curbside recycling service. These variables are combined, because they are perfectly correlated in the sample. *CURBSIDE TRASH AND RECYCLE* is not significant which means curbside recycling is not significant for this time period.

CARTS TRASH, *CARTS RECYCLE*, *BINS COMPOST* are new variables for this period and deal with whether communities distribute free bins. To my knowledge, *CARTS TRASH* had not previously been used in the literature and it is found to be insignificant. *CARTS RECYCLE* is used more widely in the literature and found significant by Noehammer and Byer (1997), Everett and Peirce (1993), and Folz (1991). The algebraic sign for this variable is positive, but the p-value is statistically insignificant. *BINS COMPOST* has not been used in the literature, but as Folz (1991) and others show, composting has a positive impact on rates. However, while the algebraic sign once again agrees with expectations, the p-value is insignificant. These bins may be having a positive effect on reducing municipal waste, but since the metric is recycling rate and the compost from these bins ends up in backyards instead of at the curb, the tons composted is never measured and so it is not included when the recycling rate is calculated.

YARD WASTE is once again not significant, which agrees with the 2010 findings. *FOOD WASTE* was significant in 2010, but is not significant in 2012. This could be because *FOOD WASTE* programs were cut back or because people stopped using them as much. It could also be that food programs started in towns that were very enthusiastic to have these programs and in the 2 years since 2010, the programs spread to less enthusiastic towns, so they did not have the same boost to recycling rate. Or it could be the result of reduced sample size.

MUNICIPAL and *SCHOOL*, were perfectly correlated and combined into 1 variable in 2010, but are separate here. These two variables and *BUSINESS* are once again insignificant.

HAZARDOUS EVENTS and *HAZARDOUS REGIONAL* are not found to be significant, but *HAZARDOUS CATEGORIES* and *HAZARDOUS RECIPROCAL* are significant at the 0.1 level. These four variables are all capturing the robustness of hazardous waste disposal. Holding all other variables constant, a one category increase in the number of *HAZARDOUS CATEGORIES* that a community collects year round is associated with a 0.4 percentage point increase in recycling rate. Moving from the low end of 1 category to the high end of 17 categories collected is therefore associated with a 6.4 percentage point increase in recycling rate.[52] Likewise offering reciprocal hazardous waste events, where members of other selected communities are invited to drop hazardous waste, is associated with a 4.5 percentage point increase in recycling rate.

Noehammer and Byer (1997) find that as *TIPPING FEE* increase the recycling rate increases. *TIPPING FEE* is also found by Bohm et al. (2010) to be a significant contributor to the municipal trash costs and Folz (1999) finds avoided trash disposal costs is one of the key reasons why recycling can be more cost effective than trash. My findings concur with these studies that tipping fee is significant at the 0.1-level and that as tipping fee increase so

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[52] 17 - 1 = 16 and 16 x 0.004 = 0.064 (6.4%)

to does recycling rate. The results show that every $1 increase in tipping fee is associated with a 0.1 percentage point increase in recycling rate. In Massachusetts the low end for *TIPPING FEE* is about $18 and the high end is about $115. Holding all other variables constant, moving from a low *TIPPING FEE* town to a high *TIPPING FEE* town is associated with a 9.7 percentage point increase in recycling rate.[53]

Finally, the Pay-As-You-Throw variable *PAYT COST* is significant, but *PAYT* and *PAYT YEARS* are not. These are all dealing with the same program however, so there is definitely a lot of collinearity between the variables and it seems that *PAYT COST* is just a bit better at explaining the variance. This is the first year for which *PAYT COST* data was available. The coefficient for *PAYT COST* means that every 1 cent per gallon increase in *PAYT COST* is associated with a 1.5 percentage point rise in recycling rate. The low end of PAYT cents per gallon in the sample is about 3 cents and the high is about 12. Holding all other variables constant, going from the low to high end in the sample is associated with a 13.5 percentage point increase in recycling rate.[54] The finding of significance agrees with Jenkins et al. (2003) and Callan and Thomas (2006).

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[53] $115 - $18 = $97 and 97 x 0.1 = 9.7

[54] 12 – 3 = 9 and 9 x 1.5 = 13.5

Summary: All Variables

The full *All Variables* model explains a fairly high percent of variance and generally is in line with the 1997-1999, 2006-2008, and 2010 results. Perhaps disappointingly for recycling managers, *SINGLE STREAM*, *MANDATORY*, and *RECYCLING CURBSIDE* are all insignificant in 2012. It is somewhat encouraging to see other program variables being significant in this time period, because these are the variables over which town officials and MSW managers have more control.

Sub Steps 2 and 3:

After running a stepwise linear regression algorithm and conducting a sensitivity analysis, the model is reduced to seven variables. The reduced model specification is:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{LOG DENSITY} + \beta_2\text{AGE} + \beta_3\text{EDUCATION} + \beta_4\text{POLITICAL AFFILIATION} + \beta_5\text{PAYT COST} + \beta_6\text{HAZARDOUS CATEGORIES} + \beta_7\text{HAZARDOUS RECIPROCAL} + \varepsilon$$

ε represents the disturbance term

The reduced model actually does a much better job than the *All Variables* model at explaining the variance, yielding an adjusted r^2 of 0.51.[55] Eliminating 29 variables improves the model substantially. Interestingly, two variables that were not significant in the full

[55] The *sensitivity* model has an adjusted r^2 of 0.51, compared to 0.41 for the *All Variables* model.

model are significant in the reduced model. Perhaps because so many variables are eliminated, the coefficients for the seven variables that remain in the model are more changed from the *All Variables* model than they were in previous time periods. Also, only three variables in this time period also appear in the *Sensitivity Analysis* models from 2006-2008 and 2010.

The full results and estimations are in Table 20.

Table 20: 2012 Sensitivity Analysis (Seven Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.052	0.128	0.403	0.688	
β_1	LOG DENSITY	-0.016	0.007	-2.250	0.026	*
β_2	AGE	0.005	0.002	2.055	0.042	*
β_3	EDUCATION	0.295	0.048	6.115	9.77E-09	***
β_4	POLITICAL AFFILIATION	0.008	0.004	1.998	0.048	*
β_5	PAYT COST	0.020	0.003	6.990	1.15E-10	***
β_6	HAZARDOUS CATEGORIES	0.004	0.002	2.510	0.013	*
B_7	HAZARDOUS RECIPROCAL	0.037	0.018	1.994	0.048	*

Residual std. error	0.091 on 135 DF	*** significant at the 0.001 level
R2	0.534	** significant at the 0.01 level
R2 (adjusted)	0.51	* significant at the 0.05 level
F-statistic	22.07 on 7 and 135 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	143	

LOG DENSITY, which was not significant in the full *All Variables* model is significant here. A 1% change in density is associated with a 0.016 percentage point decrease in recycling rate. Holding all other variables constant, going from a municipality on the low end of density, in the Massachusetts sample, to the high end is associated with a 9.6 percentage point decrease in recycling rate.[56] This decrease is not in line with original expectations or the 2006-2008 result, which shows density is associated with an increase in recycling. The change in significance across time and the switch of algebraic signs may by the result of a bias from the small sample size that density is sensitive to. Or it could be that some real world change to the system is being reflected. Perhaps the 2009 Great Recession led to cuts in recycling program budget in densely populated cash-strapped cities. This perhaps led to service reductions, which reduced participation and this is what is being reflected in these new coefficient estimates. Or, this could be the result of density being nonlinear. At low and high densities there may be reductions in the recycling rate. To address this, squared terms were tried for *LOG DENSITY* but it was not significant at the 0.05 level and it reduced the overall strength of the model.

The coefficient estimate for *AGE* and *EDUCATION* are reduced by more than 25 percent from the *All Variables* model. Moving from the low end of median *AGE* of around 33 years to the high end of around 57 years yields a 12-percentage point increase in recycling rate.[57] Likewise for *EDUCATION*, moving from the low end of 15% to the high end of 80% with bachelor's degrees yields a 19.2-percentage point increase in recycling rate.[58]

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[56] In log units, the low end of density is 2012 is about 3 and the high end is about 9. 9 – 3 = 6 and 6 x 0.016 = 0.096 (to converted to percent for recycling rate multiply by 100 = 9.6%).

[57] 57 – 33 = 24 and 24 x 0.005 = 0.12 (in percent form 12%)

The coefficient for *POLITICAL AFFILIATION* is just slightly reduced from the all-variable model, but the important change here is that it is a significant variable. The positive algebraic sign is consistent with 2010, but disagrees with the 2 earlier periods. It could be a bias from the small sample size or it could be that the initial expectations are correct that more Democratic areas are more willing to invest in government programs such as recycling that are perceived to help the environment. Holding other variables constant, a 1 unit rise in the Democrat to Republican ratio is associated with a 0.8 percentage point increase in recycling rate. Moving from the low end ratio of about 1 to the high end ratio around 11, there is an 8 percentage point increase in recycling rate.[59]

TIPPING FEE was significant at the 0.1-level in the *All Variables* model but is not included in the reduced *Sensitivity Analysis* model. *TIPPING FEE* describes the effect that increased price for trash disposal has on recycling rate. Perhaps this price signal is better represented by *PAYT COST*, because the *TIPPING FEE* is usually hidden in property taxes, whereas *PAYT COST* is borne by individuals every time they put their trash on the curb. This constant interaction with the cost of waste disposal through *PAYT COST* seems to have a stronger effect on behavior than *TIPPING FEE*.

The *PAYT COST* coefficient is 33 percent higher in the *Sensitivity Analysis* model than in the *All Variables* model, which is likely capturing some of the variation that was previous

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[58] 80 – 15 = 65 and 65 x 0.295 = 19.175

[59] 11 – 1 = 10 and 10 x 0.008 = 0.08 (in percent form 8%)

explained by *TIPPING FEE*. The coefficient estimate for *HAZARDOUS CATEGORIES* is the same and for *HAZARDOUS RECIPROCAL* is slightly less.

Summary: Sensitivity Analysis

Dropping twenty-nine variables out of the model improved the adjusted r^2 and yields a model that predicts rates close to the observed rates (**Figure 18**).

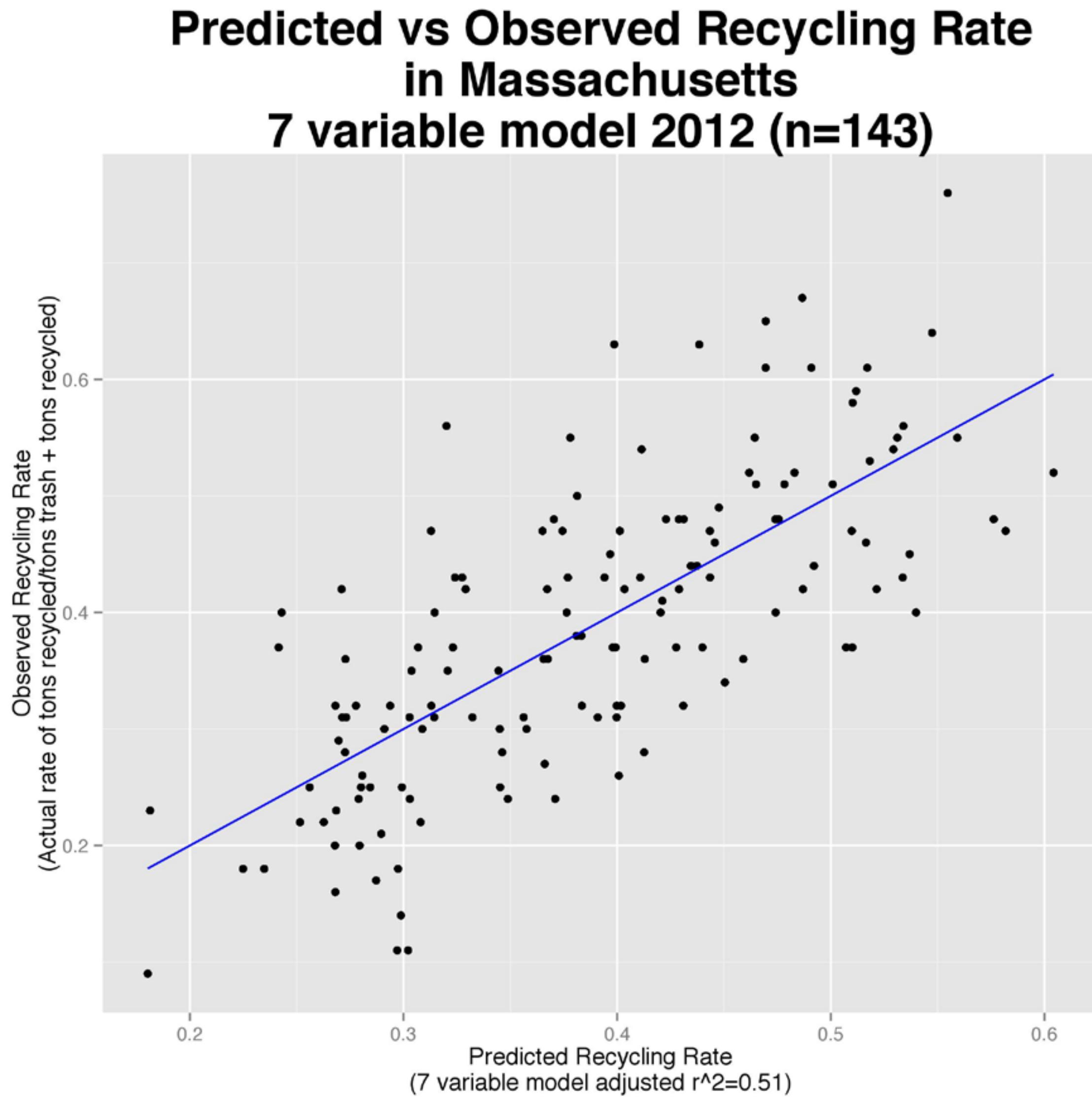

Figure 18: Predicted versus observed recycling rate for the 7 variable model.

Sub Step 4: Occam's Reduced Form

The reduced model is further refined until removing any additional variables causes a significant drop in adjusted r^2. This can be seen through visual inspection (Figure 19). Three variables remain and the model specification is:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{AGE} + \beta_2\text{EDUCATION} + \beta_3\text{PAYT COST} + \varepsilon$$

ε represents the disturbance term

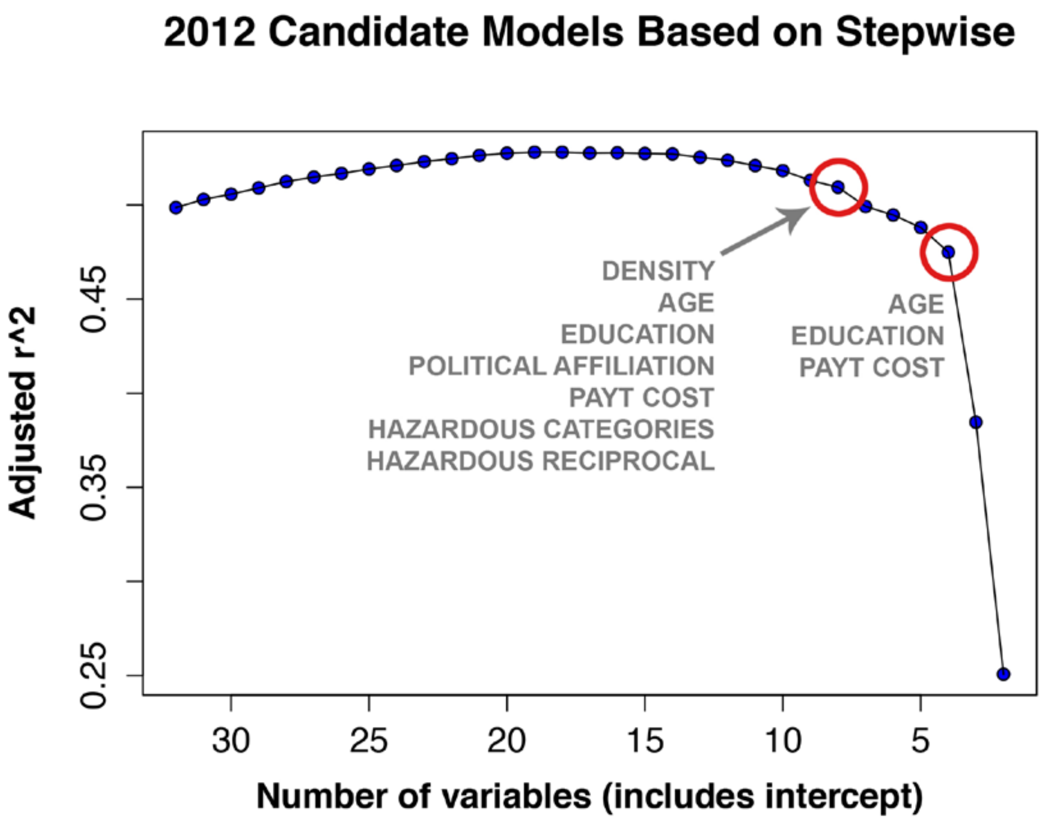

Figure 19: Graphical representation of potential models and their adjusted r^2.

Dropping *LOG DENSITY*, *POLITICAL AFFILIATION*, and the two *HAZARDOUS* categories reduces the adjusted r^2 to 0.475, which averages less than a 1 percentage point reduction for every dropped variable.[60] Reducing the model beyond these three critical variables causes a significant drop in explained variance (Figure 19). Compared to the *Sensitivity Analysis* model, the coefficient for *AGE* has nearly doubled, while *EDUCATION* is slightly reduced and *PAYT COST* is roughly the same.

The full results and estimations are in Table 21.

Table 21: 2012 Occam's Reduced Form (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.131	0.073	-1.802	0.074	.
β_1	AGE	0.009	0.002	5.008	1.64E-06	***
β_2	EDUCATION	0.253	0.048	5.302	4.40E-07	***
β_3	PAYT COST	0.021	0.003	7.841	1.06E-12	***
Residual std. error	0.094 on 139 DF		*** significant at the 0.001 level			
R2	0.486		** significant at the 0.01 level			
R2 (adjusted)	0.475		* significant at the 0.05 level			
F-statistic	43.82 on 3 and 139 DF		. significant at the 0.1 level			
p-value	< 2.2e-16					
n	143					

[60] 0.51 – 0.475 = 0.035 and 0.035 / 4 (the number of dropped variables) ≈ 0.01 or about 1 percentage points.

Summary: Occam's Reduced Form

The four dropped variables have a significant effect on recycling rate, but their relatively small percentage of explained variance (adjusted r^2) means that the three remaining variables are more important predictors of recycling success. Running a relative importance test in R, reveals that the program variable, *PAYT COST*, accounts for 50% of the explanatory power of the model, while *AGE* accounts for about 28% and *EDUCATION* about 22%. The amount of variance explained by the program variable is the same as period 1 and 2 and a bit less than period 3.

Results: Testing Model Stability

To test stability of the *Sensitivity Analysis* and *Occam's Reduced Form* models, 1,000 bootstrap permutations were run and the model is found to be fairly robust (**Figure 20** and Table 22).[61].

[61] The results of the 3 variable *Occam's Reduced Form* are similar, so to spare the reader they will not be displayed.

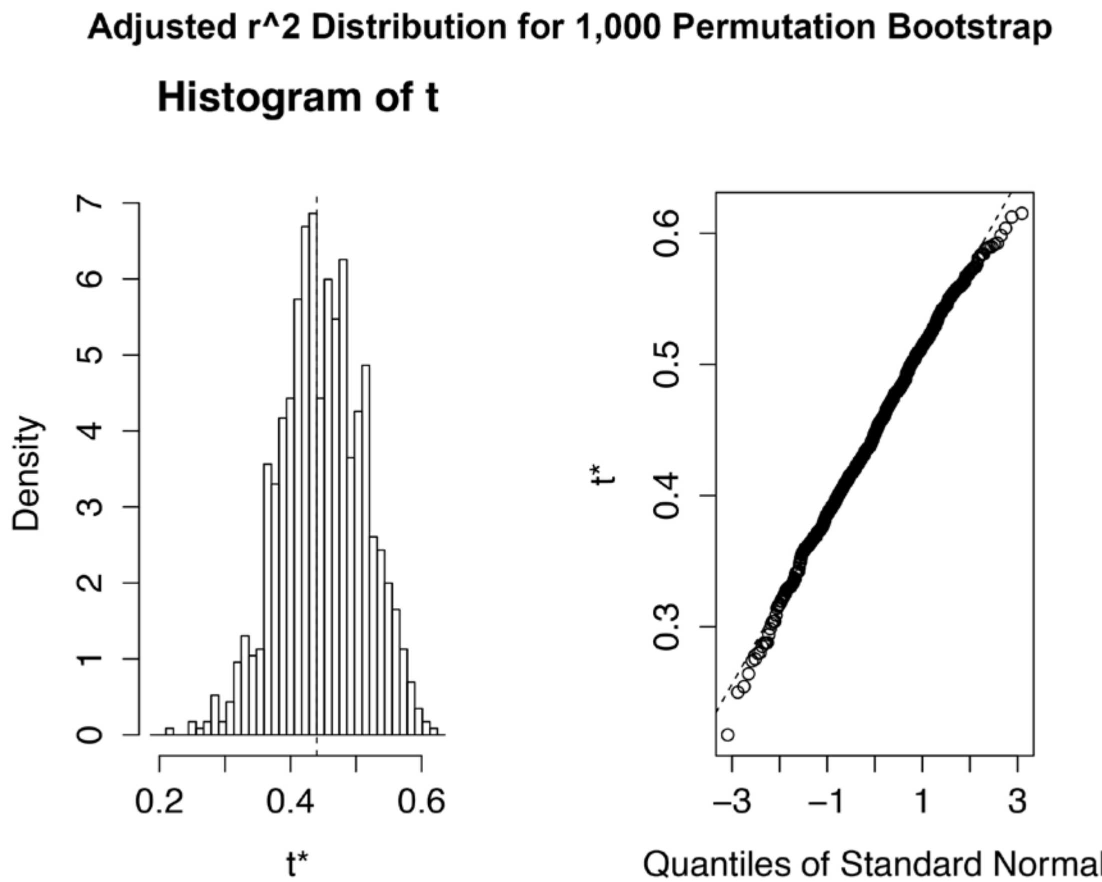

Figure 20: Adjusted r^2 distribution from a 1,000 permutation bootstrap.

Table 22: 2012 adjusted r^2 95% confidence intervals for 7-variable model based on 1,000 bootstrap permutations

Adjusted r^2	0.509
Lower (2.5%)	0.393
Upper (97.5%)	0.599

Summary: 2012 All Models

The most interesting findings from the 2012 period are:

1) The key variables are once again *AGE*, *EDUCATION*, and a version of *PAYT* (here it is *PAYT COST*). These results are extremely consistent across time periods.
2) The three *REGION* variables are not significant in any model in 2012. In almost all previous time periods they were all significant in both the *All Variables* and *Sensitivity Analysis* models.[62]
3) Based on the models run, *SINGLE* STREAM, *MANDATORY*, and *CURBSIDE TRASH AND RECYCLE* are once again not significant variables.
4) The percent of adjusted r^2 explained by program variables versus contextual variables is 50/50 in the *Occam's Reduced Form* model. This gives the exact same weight to program variable as the first two time periods.

Results: Synthesis Across Time

Background

To provide a consistent picture of how key variables change over time, all variables that appear in the *Sensitivity Analysis* models from each time period (Table 23) are selected and ranked by the number of times they appear as significant (**Table 24**). The *Occam's*

[62] The only exception is *REGION CENTRAL*, which was not significant in 1997-1999.

Reduced Form model results were also analyzed to see which variables were consistently the strongest contributors to adjusted r^2.

Table 23: Coefficients and Standard Errors for variables as they appear in the four time periods

	1997-1999		2006-2008		2010		2012	
Variable	**coef**	**std err**	**coef**	**std err**	**coef**	**std err**	**coef**	**std err**
DENSITY							-0.016	0.007
AGE	0.006	0.002	0.006	0.001	0.004	0.001	0.005	0.002
UNEMPLOYMENT	-3.149	0.506	-	-	-	-		
EDUCATION			0.259	0.045	0.217	0.039	0.295	0.048
POLITICAL AFFILIATION							0.008	0.004
REGION CENTRAL			-0.099	0.022	-0.044	0.019		
REGION NORTHEAST	-0.049	0.015	-0.085	0.022	-0.059	0.019		
REGION SOUTHEAST	-0.038	0.015	-0.073	0.021	-0.058	0.016		
PAYT	0.053	0.026	0.095	0.015	0.112	0.012		
PAYT COST							0.020	0.003
PAYT YEARS	0.007	0.003						
SUBSCRIPTION TRASH			-0.144	0.034				
FOOD WASTE					0.036	0.016		
HAZARDOUS EVENTS							0.004	0.002
HAZARDOUS RECIPROCAL							0.037	0.018
coef = coefficient								
std err = standard error								

Table 24: Frequency of variables being significant in the four time periods

Variable	# of periods
AGE	4
EDUCATION	3
PAYT	3
REGION NORTHEAST	3
REGION SOUTHEAST	3
REGION CENTRAL	2
LOG DENSITY	1
UNEMPLOYMENT	1
POLITICAL AFFILIATION	1
PAYT COST	1
PAYT YEARS	1
SUBSCRITION TRASH	1
FOOD WASTE	1
HAZARDOUS EVENTS	1
HAZARDOUS RECIPROCAL	1

Although *REGION* was significant in 3-time periods it was not significant in 2009 or 2011. Additionally, it did not appear in any of the *Occam's Reduced Form models.* Taking only the three most frequently critical variables from different time periods yields the following three-variable model, which was tested in all time periods:

$$\text{RECYCLING RATE} = \beta_0 + \beta_1\text{AGE} + \beta_2\text{EDUCATION} + \beta_3\text{PAYT} + \varepsilon$$

ε represents the disturbance term

Results

In the 2006-2008 and 2010 periods *AGE*, *EDUCATION*, and *PAYT* are already the variables in the three-variable model (**Table 12** and Table 17 respectively). The full results for the 1997-1999 and 2012 periods are provided in Table A12 and

Table A13. For ease in discerning patterns, the coefficients and relative important results of all time periods are compiled (Table 25).

Table 25: Coefficients for the 3 variable Occam's Consistent model in the 4 time periods

Variable	**1997-1999**		**2006-2008**		**2010**		**2012**	
	coef	rel imp	coef	rel imp	coef	rel imp	coef	rel imp
AGE	0.005	12%	0.009	33%	0.005	15%	0.008	30%
EDUCATION	0.185	30%	0.214	17%	0.180	16%	0.270	26%
PAYT	0.106	58%	0.122	50%	0.123	69%	0.116	45%
adj r^2	0.202		0.522		0.371		0.44	
sample n =	324		173		245		143	
coef = coefficient								
rel imp = relative importance is the % of adj r^2 (variance) explained by the variable								

It is clear that across all time periods *PAYT* is consistently the most important variable, accounting for between 45% and 69% of explained variance. *AGE* and *EDUCATION* swap importance between periods with each being the second most important variable in two periods. The coefficient values for all variables fluctuate. The highest value for *AGE* is 80% larger than the lowest *AGE* value. The high mark for *EDUCATION* is 50% larger than the low mark. *PAYT* is more stable, only changing about 15% from its lowest to highest point. The coefficient estimate fluctuations in *AGE* and *EDUCATION* are likely reflecting some of the natural variability in the system.

Another possibility is that it is resulting from biases in the sample size. The 2006-2008 period and the 2012 period have smaller sample sizes than the other periods. These are also the periods in which *AGE* and *EDUCATION* have their highest coefficients. As the sample size reduces, it may be that a sampling bias is being captured. Perhaps older more educated towns have more money to hire a seasoned recycling program director. This director manages the program well and increases rates. They also meticulously fill in the Massachusetts Recycling Survey, which is the source of my data. Recycling managers in other towns may also be the trash manager, which means they are busier and perhaps sometimes leave categories blank. These blank categories lead to these towns being dropped because of missing values. Thus the sample has a bias towards older more educated towns that have a full time recycling coordinator. This is all of course hypothetical, but serves to showcase one way this coefficients fluctuation could be explained.

The consistent important of *AGE*, *EDUCATION*, and *PAYT* across so many time periods, over 16 years of data, gives a high degree of confidence that these truly are important contributors to recycling rate success. The significance of *AGE* is perhaps capturing the fact that recycling can require more time than trash disposal because of the cleaning and sorting of materials. Older retired individuals with no children in the house may have more free time and thus are better able to participate in recycling activities. *AGE* may also be capturing some environmental values present in the older generation. Perhaps the relationship between age and recycling rate is because older individuals went through the environmental awakening of the 1960s and 1970s so they feel a deeper commitment to environmental causes, while younger people may take a clean environment for granted and not be aware that preserving a healthy environment requires personal action and commitment on their part.

EDUCATION is capturing the relationship between increased environmental awareness and time spent in school (Van Liere and Dunlap 1980; Granzin and Olsen 1991; Folz and Hazlett 1991; Lansans 1992; Smith 1995; Callan and Thomas 2006). This idea is well supported in the literature and my results add support to those findings. *PAYT* is capturing the economic effect of making people internalize what was traditionally an externality. Because waste disposal costs are often charged through property tax, the cost of trash disposal is somewhat hidden. *PAYT* utilizes market forces by creating an economic incentive to reduce trash to avoid paying a direct fee. This causes people to recycle more and throw away less, not perhaps because they are "green" but because it is in their own best interest to do so. *PAYT* may also be effective because it is increasing people's awareness of the environmental costs of trash disposal by sending a price signal that forces people to internalize the costs of what was previously an externality. This increased environmental awareness may also be helping to increase recycling rates.

Case Study: Examining PAYT

To highlight the effect these variables have on recycling rate throughout the time periods, a detailed look at one of them will now be presented. Here I examine what the empirical results of my study show to be the most important variable: *PAYT*.

The first step is to look at summary statistics for the recycling rate in communities that have *PAYT* and communities that do *not* have *PAYT* (Table 26).[63]

[63] For 2009 and 2011 data, please see

Table 26: Recycling Rate Summary Statistics for PAYT vs NO PAYT municipalities

	YEARS							
	1997-1999		2006-2008		2010		2012	
	NO	**PAYT**	**NO**	**PAYT**	**NO**	**PAYT**	**NO**	**PAYT**
n =	259	68	206	125	155	99	100	94
Minimum	0.06	0.15	0.06	0.09	0.03	0.07	0.03	0.14
Maximum	0.65	0.67	0.90	0.70	0.59	0.64	0.64	0.76
Range	0.59	0.52	0.84	0.61	0.56	0.57	0.61	0.62
Mean	0.294	0.399	0.266	0.364	0.235	0.357	0.332	0.432
Std. Dev.	0.115	0.113	0.113	0.127	0.103	0.096	0.129	0.12
Mode	0.28	0.32	0.26	0.30	0.24	0.33	0.31	0.47
Median	0.29	0.40	0.296	0.36	0.22	0.35	0.31	0.43
25% (Q1)	0.21	0.32	0.19	0.273	0.16	0.31	0.24	0.36
75% (Q2)	0.37	0.48	206	125	0.3	0.403	0.42	0.515

In all time periods, it is clear from the central tendency summary statistics that communities that have *PAYT* experience a substantially higher average recycling rate than communities that do not have *PAYT*.

The results of t-tests confirm there is a statistically significant difference between communities with and without *PAYT*. To save the reader from data overload, only results from period 1 will be presented in the text (Table 27).[64]

Table A14.

[64] For 2006-2008, 2009, 2010, 2011 and 2012 data please see Table A15.

Table 27: t-test comparing recycling rate means for PAYT vs NO PAYT municipalities

1997-1999			
Descriptive Statistics			
VARIBALE	*Sample size*	*Mean*	*Variance*
NO PAYT	259	0.294	0.013
PAYT	68	0.399	0.013
Summary			
Degrees Of Freedom	325	*Hypothesized Mean Difference*	0.E+0
Test Statistics	6.687	*Pooled Variance*	0.013
Two-tailed distribution			
p-level	9.95E-11	*t Critical Value (0.05%)*	3.516
One-tailed distribution			
p-level	4.97E-11	*t Critical Value (0.05%)*	3.321

Figure 21 highlights this difference graphically through a density plot for the 1997-1999 period. For density plots for other years, please see Figure B7 - Figure B11.

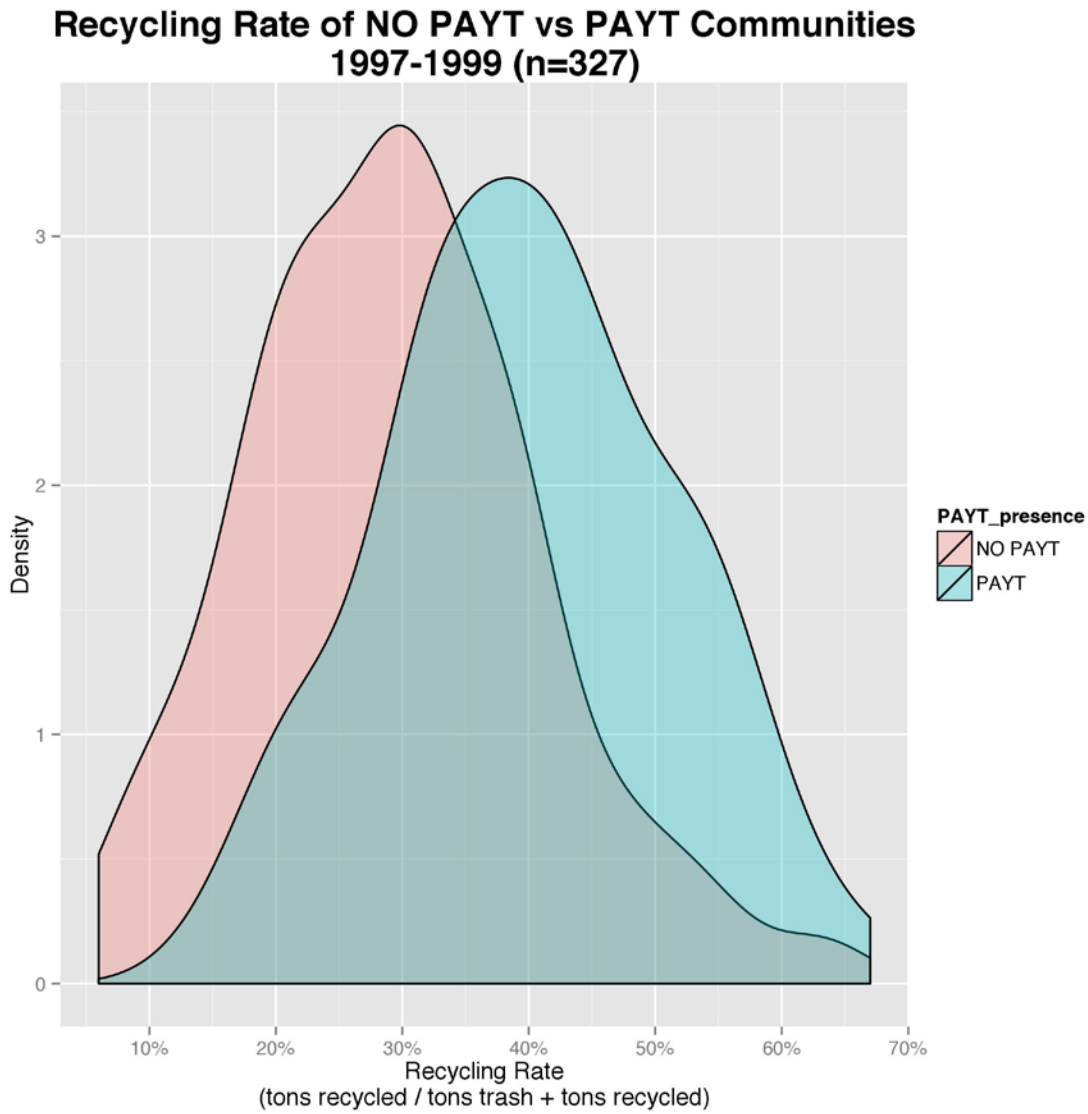

Figure 21: Recycling rate density plot distribution for towns with and without PAYT

It is clear from the analysis that *PAYT* communities enjoy a recycling rate statistically significantly higher than communities without such programs. With at least 100 communities in Massachusetts not having *PAYT* there is a significant opportunity to boost the state's average recycling rate by instituting PAYT in all communities.

CHAPTER 4

PUTTING IT ALL TOGETHER

Key Findings

Based on the multiple linear regression models that were run for all time periods (with the understanding that not all variables were available in all time periods and that sampling bias and collinearity could be influencing the results), the key findings from this study are:

1) PAYT is the single most important variable influencing recycling rate
2) *AGE* and *EDUCATION* are the most significant contextual variables
3) On average, the policy variables explain a little more of the variance than the contextual variables
4) *REGION* has traditionally been important to recycling rate, but this may be changing with time. Future studies will need to examine whether *REGION* still matters today.
5) *SINGLE STREAM*, *MANDATORY*, and *CURBSIDE* recycling are not significant variables based on the models that were run. More study needs to be done to see if sampling bias or collinearity issues were obscuring the results.

Answering Research Questions

The original research questions guiding this study were: Question 1) At a given point in time, how significant is the influence of recycling policies relative to contextual factors, which are largely outside of policymaker's control? Question 2) At a given point in time, which recycling initiatives and policies provide the greatest boost to recycling rates? Question 3) Are the effects of these policies consistent over time or do the policies effectiveness in boosting recycling rates decline over time?

Looking across the different models it is clear that the relative influence of program variables is slightly higher than contextual variables. Using the consistent *Synthesis Across Time* model, *PAYT* explains between 45% and 69% of variance while *AGE* and *EDUCATION* explain the rest. In regards to question 2, the surprising result is that the only policy that is consistently effective is *PAYT* (although not all policies had data available for all time periods). For the time periods in which they appear and based on the multiple linear regression models that I ran, *MANDATORY*, *SINGLE STREAM*, and *CURBSIDE* are not found to increase rates at the municipal level. It is particularly interesting that *MANDATORY* and *CURBSIDE*, which are found by earlier studies to be significant are not significant here. It may be that these variables are important when a program starts, but over time their influence on recycling rates diminishes. There may also be some collinearity among the program variables that is obscuring their significance. More statistical analysis is needed to test for potential collinearity.

The importance of *REGION* in many of the *Sensitivity Analysis* models suggests MRFs may be important, as this variable is partly capturing a municipality's location in regard to MRF access. Finally, some form of composting service may be important. But the only strongly empirically supported variable is *PAYT*. In regards to question 3, the *Synthesis Across Time* model provides a consistent view across the 16 years of data. The only policy variable included is *PAYT* and the coefficient estimates remain relatively stable across time periods, suggesting this program's effectiveness is not changing over time. Unfortunately, I was not able to acquire data for earlier time periods, so the data I have access to is mostly after the mid 1990s plateau in recycling rates. It would be interesting to see how the impact of *PAYT* when first introduced compares with the impact it was having in later time periods.

Caveats

While I believe this study offers valuable insights, its important to highlight some of the possible shortcomings of this work. Multiple linear regression models are used to analyze the variables. In the models there is an assumption of normal distributions and linear relationships between the dependent and independent variables. For some variables, such as *AGE*, I realize that the relationship may theoretically be better described using a polynomial. The idea being that perhaps being older helps boost recycling to a point, but after a certain age people are less able to recycle so the rate would come down in a town with too high of a median *AGE*. Squared terms for this variable were used in a few time periods, but the results were not improved and sometimes resulted in the variable not being significant. For the sake of simplicity, squared versions of variables were not tried in all time periods. So it is not possible to concretely say that in some cases a nonlinear term wouldn't be more effective at describing the relationship. In terms of assuming a normal distribution, some variables in the models, including the response variable, are bounded at 0 and 1. So a normal distribution is perhaps not entirely appropriate in theory. But in practice, predicted values were not less than 0 or greater than 1, so it didn't seem to be an issue.

Beyond modeling decisions, one challenge that has the potential to skew the results is the changing sample sizes. From 1997-2008 the state of Massachusetts collected recycling rate data on every town. Data on contextual and program variables was then acquired from a variety of sources. However, not all sources had good data for all time periods. Also, starting in 2009 and continuing through 2012 Massachusetts began collecting detailed recycling rate and program data using surveys that were completed by each town's recycling coordinator or trash official. This created a comprehensive database with a suite of program variables. However, these surveys ask for lots of information and as the surveys became more complex the participation rate and thoroughness of responses declined. The threat to my results is that there is a bias in those who did respond. Perhaps the factors that drive recycling rate in the communities who diligently filled out the entire survey are fundamentally different from the factors driving rates in other towns. It is certainly conceivable that towns that don't fill out the survey at all or don't fill them out completely have a less professional recycling staff and possibly a less developed program. One reason surveys weren't completed might be because the official didn't know the answers, which speaks to the quality of that program and suggest that having a professional recycling coordinator may be an important variable to consider. Or perhaps town officials didn't reply to the survey because they knew they had a low recycling rate. They could intentionally not respond to shield the town from public criticism. This is of course hypothetical, but it is important to keep in mind when considering the results.

Beyond the issue of possibly biased sampling, another issue is lack of data for variables. Because data were not available for all variables in all time periods it is not possible to make completely equal comparisons across time. The 1997-1999 period is particularly lacking in program variables. 2009 is missing *MANDATORY* and 2010 is missing *MANDATORY* and *SINGLE STREAM*. I am keenly interested in those variables in particular because the 2010 Massachusetts Municipal Solid Waste Master Plan has been advocating for their continued adoption. *FOOD WASTE* is also only in the 2010, 2011, and 2012 models. This is an important variable to understand because Massachusetts is currently trying to develop food waste collection and is piloting some programs, yet there is only 3 years on which to base any conclusions. *TIPPING FEE* and *PAYT COST* are two variables that would have been helpful to have had more data on, but unfortunately I was only able to use *TIPPING FEE* in 2012 and *PAYT COST* in 2011 and 2012. *SWAP SHOP* is another variable for which there was only 2011 and 2012 data. When looking at the overall study results it's important to note these shortcomings.

Another potential shortcoming comes from using *RECYCLING RATE* as the dependent variable. As was previously discussed, there are some drawbacks to using this as a metric for MSW success, because it does not capture overall MSW tonnage reductions. In this vein, the effect that the variable *BINS COMPOST* has on the overall picture of recycling success is likely far under represented by the recycling rate metric. If people are using backyard compost bins this reduces the overall amount of waste that ends up being handled by the municipality. But because that waste is not collected, it doesn't get factored into municipal tonnage figures and thus would not appear in the recycling rate. If the municipality picked up the compost from the curbside however, then it would be counted towards the rate. This is a case of measurement error where the metric is limiting the ability to capture some of the subtleties of the MSW system.

Issues of missing data for variables are important as is the potential skewing of results from biased sampling. But, assuming the sample used for analysis is not biased, and by looking at the years for which there is data and conducting a sensitivity analysis, the analysis suggests some variables are not *critical* to shaping recycling rate. For example, while *FOOD WASTE* is significant in the 2010 *All Variables* model, it drops out of the refined model and it is not significant in 2011 or 2012. So it seems reasonable to say that having *FOOD WASTE* collection is possibly a good thing, but it is not a principal driver of recycling rates. Likewise, while data for *MANDATORY*, *SINGLE STREAM,* and *CURBSIDE* are missing from some years, their lack of significance in the years for which there is data suggests they may not necessarily be the most important factors influencing rates. More work however needs to be done on these to assess if issues of collinearity are obscuring the importance of these variables. In 2011, *SWAP SHOP* is in fact significant in both the *All Variables* and *Sensitivity Analysis* models, contributing a 5-percentage point boost to recycling in both models. However it drops out of the 2011 *Occam's Reduced Form* model and is not significant in any 2012 model. I hesitate to make a firm conclusion on this variable because I only had data for two time periods. It may not be significant in 2012, because the smaller sample size. Perhaps towns with swap shops do divert more waste, but they have less formalized trash services and the municipal officials in these towns just didn't feel like filling out the 2012 recycling survey from which my database is derived. These towns were then dropped from the study. It is certainly a variable worth watching in the future.

Policy Recommendations

Based on the models I ran, two of the three most important drivers of recycling success are contextual variables that municipal officials and recycling program coordinators have little control over. There is no straightforward way to quickly make your town older or more educated. This leaves officials with only PAYT.

Having PAYT is associated with, on average across the municipalities that have implemented it, about a 10-percentage point boost in recycling rate. Of the programs I evaluated, it is the only program variable that proved to be consistently significant over the full 16 year study period. Therefore, I suggest that all communities that do not current have PAYT should adopt it. Looking at a sample of 194 municipalities for 2012, there are 100 communities without PAYT and 94 with it. If these 100 communities adopted PAYT, it is projected that Massachusetts' statewide average recycling rate would go from 38% to 43.2%.[65]

The finding on *AGE* may not be of much use to policy makers. If *AGE* is important because older people have more free time, then my recommendation would be to do everything possible to make recycling as quick and easy to do as throwing away trash. Intuitively, this would suggest perhaps instituting single stream of curbside programs. However, the lack of significance of *SINGLE STREAM* and *CURBSIDE* suggests this would not be effective. Perhaps then *AGE* is not reflective of an increased ability to recycle because of more free time, but is reflecting an environmental outlook that is ingrained in the older generation. If this is the case, perhaps the philosophy that drives older individuals to recycle can be ingrained in the younger generation and this would boost rates. It is clear more study is needed to find out why *AGE* is important and I recommend a survey of older recyclers to find out what drives them.

While policymakers can't easily control *EDUCATION* levels in their town, they may be able to boost recycling rates with targeted educational campaigns. The literature cited earlier states that *EDUCATION* is important because it instills a greater understanding of the ways in which MSW can create environmental damage (Van Liere and Dunlap 1980; Granzin and Olsen 1991; Lansans 1992; Smith 1995). If this is true, perhaps educational marketing campaigns could be launched to try and instill these values in less educated

[65] This assumes that towns with PAYT see a 10-percentage point recycling rate increase. This 0.10 number is based on results from the *Occam's consistent* model. I added 0.10 to the recycling rate of the 100 towns without PAYT. I then added the rates for towns with PAYT and took the total average.

areas. If bottled water companies can convince people to pay top dollar for a product they can get virtually for free from their tap, perhaps there is hope that marketing can shift recycling behavior. I recommend further investigation into this area.

Most of the *REGION* variables are significant in about half of the time periods studied, with the regional effect generally becoming less in the later periods of the study.[66] I suspect this is capturing the impact of private MRFs in other regions of the state. The first MRF in Massachusetts was built with government support in Springfield. Since then, privately run MRFs have been built in other parts of the state. I suspect this may be what is causing *REGION* to be less important over time. This is an area that needs more study so I recommend the state further investigates this and conduct an analysis to see if existing MRFs have enough capacity to handle the current demand. If they do not, incentives to building more MRFs should be investigated.

According to the multiple linear regression models I ran, *SINGLE STREAM*, *MANDATORY* and *CURBSIDE* programs do not have an effect on recycling rates. This requires more study because data for these variables were not available for all time periods and further investigation is needed into possible sampling bias and collinearity among the program variables for the periods in which I did have data. The effectiveness of *SINGLE STREAM* and *MANDATORY* are key points made in Massachusetts' 2010 Municipal Solid Waste Master Plan and the recommendation made in that text is to expand these programs. Intuitively it seems like those variables should boost rates, but my study (with the possible sampling bias and collinearity limitations described above) finds no empirical support for

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[66] 2 *REGION* variables are significant in 1997-1999, 3 are significant in 2006-2008 and 2010, and 1 is significant in 2011. None are significant in 2009 or 2012.

that conclusion. I advise the Massachusetts Department of Environmental Protection (DEP) to investigate further and review their information to make sure their recommendations are derived from thorough analysis. Based on the *CURBSIDE* findings (which again require further analysis of sampling bias and collinearity) I don't see any benefit in adding curbside recycling and trash service to areas that don't have it. However, if only drop off is offered for trash and recycling, offering curbside recycling but keeping trash drop off may boost rates.

Future Research

My findings could be useful in several potential avenues of future study. One such area is to repeat this type of analysis in a different state or region. This would show if the same variables that are found to be important here in Massachusetts are also important elsewhere. In doing so, the scope of inference from this study could be expanded to new areas. Another avenue of future investigation would be to build off these findings and do case studies on those municipalities that have maintained high rates throughout the 16 years or who have gone from low to high rates. This would involve conducting qualitative interviews with MSW managers, government officials, and residents of these towns to find out why their programs work so well. One could also look at the suite of contextual and program variables I've assembled and do further analysis to see if these variables explain why these incredibly high performing towns are different from the rest of the state.

Conclusion

To increase recycling in the United States it is critical to understand what factors are important contributors to recycling success. By looking over a 16-year period in Massachusetts and testing a series of multiple linear regression models I have shown which variables are the most critical. Importantly, this study has also illuminated which factors do not appear to be important. In these tight fiscal times, communities and the Commonwealth can save money by shifting resources towards programs that work and cutting resources from programs that don't. The simple act of directly charging people for their trash seems to be the most effective tool in this regard.[67]

Coming into this study, my expectation was that program variables would have much greater power than contextual variables in explaining the variance in the system. Yet surprisingly, in many models and time periods, contextual variables explain about the same amount of variance as programs variables.

The lack of significance for certain program variables is also surprising (but further study is necessary to make sure my findings are not being influenced by sampling bias or collinearity issues). *SINGLE STREAM* intuitively would seem to boost rates and is advocated for by the Commonwealth of Massachusetts, but I do not find empirical support for this conclusion (The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2010a). *MANDATORY* and *CURBSIDE* have been empirically shown to boost recycling rates in the past, yet were not found to do so in my study. It may be that *MANDATORY* was important when recycling programs were starting but it becomes less

[67] This is a lesson of potential interest in the carbon tax debate

effective over time. The only other study that looks at changes to recycling over time finds *MANDATORY* to be significant, but that voluntary programs are able to become equally effective over time if the right mix of programs were in place (Folz 1999). That study was conducted in the late 1990s and my study adds weight to those finding.

The most important determinant of recycling success is *PAYT*, which is encouraging because it is a policy tool that municipal officials can implement. If PAYT was in place in every municipality in Massachusetts the models suggest there could be a significant increase in the statewide recycling rate.

My findings may be disheartening to recycling and municipal officials because so many program variables are not found to be effective and the only consistently significant program variable is PAYT. Unfortunately, based on the models I ran, the program variables that are an easy political sell do not seem to be effective. Variables that make recycling easier and more convenient for homeowners are seemingly having no impact on recycling rates. PAYT may not be politically attractive because it asks citizens to pay for something, which they have traditionally received for "free".[68] The positive political spin for this is that in a time of strained municipal budgets, expensive programs that make recycling convenient may be able to be cut without hurting recycling rates. And PAYT is not capital intensive. It pays for itself and there are no heavy startup costs. This may provide some comfort to municipal officials as they worry about the political implications of following some of my recommendations.

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[68] Because trash disposal costs are often hidden in property taxes, asking citizens to directly pay for their trash may be perceived as a tax.

The United States has the dubious honor of being the planet's number one garbage producer (Themelis and Kaufman 2004). While others around the world, particularly the European Union, have brought their waste management practices into the 21st century the United States has been technologically and legislatively lagging behind (European Environmental Agency 2013). Perhaps fuelled by American optimism and the pioneer spirit that greener pastures always lay over the next horizon, we as a nation seem to be struggling to come to terms with the fact that we live in a world of finite resources. The combination of population growth and increased expectations for standards of living are putting unprecedented strain on the natural world and creating a natural capital deficit. By continuing on this path, humanity is building its prosperity on a tinderbox foundation.

Recycling is not a panacea for the difficult situation society faces, but it is one small way in which those societies who consume the most can begin to bring their consumption more in line with what the earth can actually sustain. By reusing materials, standards of living can remain constant while pollution and energy consumption are reduced.

The way we think about and deal with trash in the United Sates must change and the last few decades has shown that this can change. Compared to 30 years ago, amazing strides have been made in waste management. Convenient recycling services are now available to the vast majority of United States' citizens. The task now is to build on this growth and become even more efficient recyclers. By highlighting program and contextual factors that increase recycling success, I hope my findings will help inform decision makers in Massachusetts and around the country as we collectively strive to make recycling programs more successful and build a sustainable and equitable future.

APPENDIX A

ADDITIONAL TABLES

Table A1: Recycling rate and the number of municipalities with that rate 1997-2012.

	Year															
Rec. Rate	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009**	2010**	2011**	2012**
Rate > 90%	0	0	0	0	0	0	0	0	0	0	1	1	*1	0	*3	*3
81% - 90%	0	0	0	*2	0	0	0	0	0	1	0	1	0	0	*2	*2
71% - 80%	2	1	0	0	3	1	4	1	0	0	0	0	0	0	*3	1
61% - 70%	6	9	8	8	8	14	6	8	7	4	5	7	*1	1	9	13
51% - 60%	27	19	31	29	25	35	18	22	21	15	20	24	6	16	21	23
41% - 50%	44	57	57	55	65	51	50	50	54	52	42	55	16	25	36	54
31% - 40%	101	94	87	71	81	80	85	76	76	90	79	76	59	78	81	53
21% - 30%	86	90	76	68	73	60	80	81	85	84	96	85	54	67	59	37

11% - 20%	54	48	34	40	34	41	46	39	54	50	58	52	62	61	30	11
1% - 10%	12	10	11	5	8	5	10	7	12	12	15	14	14	7	4	4
0% or DNR	19	23	47	73	54	64	52	67	42	43	35	37	139	97	104	151
Total	351											352				
Rec. Rate = Recycling rate, which is the amount of waste recycled, composted, or otherwise diverted, divided by the total amount of trash and diverted materials collected																
DNR = Did Not Report																
The number of municipalities rises to 352 in 2008 because the town of Devens was formed																
* rates are suspicious when compared to municipality’s previous and following year rates																
** new metric used to for 2009-2012 rates. Rates not directly comparable to previous years.																

Table A2: Summary statistics and data sources 2006-2008 (n=173).

Variable Name	Mean	Standard Deviation	Data Year	Source
RECYCLING RATE	0.313	0.127	2006-2008	1
DENSITY	1831.266	3111.711	2008 & 2010	2 & 3
PERSONS PER HOUSEHOLD	2.657	0.464	2008	2 & 4
AGE	42.079	5.176	2007-2011	5
EDUCATION	0.390	0.165	2007-2011	6
INCOME	33740.879	23374.396	2008	7
UNEMPLOYMENT	0.052	0.016	2006-2008	8
POLITICAL AFFILIATION	3.080	2.117	2008	9
COMMUNITY PRESERVATION	0.318	0.467	2012	10
COMMUNITY PRESERVATION YEARS	1.376	2.375	2012	10
COMMUNITY PRESERVATION COST	0.740	1.134	2012	10
REGION CENTRAL	0.179	0.385	2008	4
REGION NORTHEAST	0.301	0.460	2008	4
REGION SOUTHEAST	0.191	0.394	2008	4
PAYT	0.370	0.484	2012	11
PAYT YEARS	3.035	5.881	2012	11
CURBSIDE	0.613	0.489	2008	4
RECYCLING SUBSCRIPTION	0.017	0.131	2008	4
TRASH SUBSCRIPTION	0.046	0.211	2008	4

SOLID WASTE FLAT FEE	0.364	0.483	2008	4
MANDATORY	0.150	0.358	2012	12
MANDATORY YEARS	1.480	4.291	2012	12

Sources

1	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2009)
2	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2011)
3	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2010a)
4	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2008)
5	(United States Census Bureau 2012)
6	(United States Census Bureau 2011)
7	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2012a)
8	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2010b)
9	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2008)
10	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012b)
11	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012a)
12	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012c)

Table A3: Summary statistics and data sources 2009 (n=177).

Variable Name	Mean	Standard Deviation	Data Year	Source
RECYCLING RATE	0.261	0.120	2009	1
DENSITY	1884.836	3073.200	2007-2011 & 2010	2 & 3
PERSONS PER HOUSEHOLD	2.585	0.487	2007-2011 & 2009	1 & 2
AGE	41.938	5.340	2007-2011	2
EDUCATION	0.389	0.165	2006-2010	4
INCOME	34226.915	24664.259	2008 & 2010	5 & 6
POLITICAL AFFILIATION	3.054	2.107	2008	7
REGION CENTRAL	0.192	0.395	2008	8
REGION NORTHEAST	0.311	0.464	2008	8
REGION SOUTHEAST	0.175	0.381	2008	8
PAYT	0.345	0.477	2012	9
PAYT YEARS	3.266	6.189	2012	9
CURBSIDE	0.644	0.480	2010	1
HOUSEHOLDS SERVED	0.811	0.288	2010	1
SINGLE STREAM	0.237	0.427	2010	1

Sources

1	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2010b)
2	(United States Census Bureau 2012)
3	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2010a)
4	(United States Census Bureau 2011)

5	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2012a)
6	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2012b)
7	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2008)
8	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2008)
9	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012a)

Table A4: Summary statistics and data sources 2010 (n=245).

Variable Name	Mean	Standard Deviation	Data Year	Source
RECYCLING RATE	0.285	0.116	2010	1
DENSITY	1471.653	2475.143	2007-2011 & 2010	2 & 3
PERSONS PER HOUSEHOLD	2.604	0.723	2007-2011 & 2010	2 & 1
AGE	42.980	5.331	2007-2011	2
EDUCATION	0.406	0.162	2006-2010	4
INCOME	37140.359	26537.958	2010	5
POLITICAL AFFILIATION	2.782	2.049	2008	6
REGION CENTRAL	0.180	0.385	2008	7
REGION NORTHEAST	0.269	0.445	2008	7
REGION SOUTHEAST	0.269	0.445	2008	7
PAYT	0.392	0.489	2012	8
PAYT YEARS	4.261	7.118	2012	8
TRASH SERVICE	0.803	0.215	2010	1
RECYCLING SERVICE	0.812	0.217	2010	1
TRASH CURBSIDE	0.429	0.496	2010	1
TRASH BOTH	0.122	0.328	2010	1
RECYCLING CURBSIDE	0.265	0.442	2010	1
RECYCLING BOTH	0.278	0.449	2010	1
YARD WASTE	0.759	0.428	2010	1
YARD WASTE CURBSIDE	5.204	11.073	2010	1
YARD WASTE DROP OFF	121.522	116.619	2010	1

FOOD WASTE	0.163	0.370	2010	1
MUNICIPAL AND SCHOOL	0.576	0.495	2010	1
BUSINESS	0.343	0.476	2010	1
HAZARDOUS CATEGORIES	7.257	4.699	2010	1
Sources				
1	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2011)			
2	(United States Census Bureau 2012)			
3	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2010a)			
4	(United States Census Bureau 2011)			
5	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2012b)			
6	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2008)			
7	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2008)			
8	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012a)			

Table A5: Summary statistics and data sources 2011 (n=218).

Variable Name	**Mean**	**Standard Deviation**	**Data Year**	**Source**
RECYCLING RATE	0.340	0.134	2011	1
DENSITY	1349.569	2329.337	2007-2011 & 2010	2 & 3
PERSONS PER HOUSEHOLD	2.569	0.616	2007-2011 & 2011	2 & 1
AGE	42.744	5.234	2007-2011	2
EDUCATION	0.399	0.168	2006-2010	4
INCOME	37008.734	27564.312	2010	5
POLITICAL AFFILIATION	2.820	2.050	2008	6
REGION CENTRAL	0.188	0.392	2008	7
REGION NORTHEAST	0.261	0.440	2008	7
REGION SOUTHEAST	0.261	0.440	2008	7
PAYT	0.445	0.498	2012	78
PAYT YEARS	4.959	7.704	2012	8
PAYT COST	2.528	3.278	2012	8
SINGLE STREAM	0.303	0.461	2012	1
MANDATORY	0.280	0.450	2012	1
TRASH SERVICE	0.804	0.222	2012	1
RECYCLING SERVICE	0.821	0.221	2012	1
TRASH LIMIT	0.174	0.380	2012	1
CURBSIDE TRASH AND RECYCLE	0.573	0.496	2012	1
CARTS TRASH	0.092	0.289	2012	1
CARTS RECYCLE	0.165	0.372	2012	1

BINS COMPOST	0.550	0.499	2012	1
YARD WASTE	0.761	0.427	2012	1
FOOD WASTE	0.092	0.289	2012	1
MUNICIPAL	0.931	0.254	2012	1
SCHOOL	0.688	0.464	2012	1
BUSINESS	0.394	0.490	2012	1
SWAP SHOP	0.349	0.478	2012	1
HAZARDOUS CATEGORIES	8.202	4.480	2012	1
HAZARDOUS EVENTS	2.119	3.442	2012	1
HAZARDOUS REGIONAL	0.445	0.498	2012	1
HAZARDOUS RECIPROCAL	0.252	0.435	2012	1

Sources	
1	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012d)
2	(United States Census Bureau 2012)
3	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2010a)
4	(United States Census Bureau 2011)
5	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2012b)
6	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2008)
7	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2008)
8	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012a)

Table A6: Summary statistics and data sources 2012 (n=143).

Variable Name	Mean	Std. Dev.	Data Year	Source
RECYCLING RATE	0.386	0.129	2012	1
DENSITY	1394.657	2233.887	2007-2011 & 2010	2 & 3
PERSONS PER HOUSEHOLD	2.595	0.567	2007-2011 & 2012	2 & 1
AGE	42.967	4.720	2007-2011	2
EDUCATION	0.408	0.167	2006-2010	4
INCOME	38633.084	30738.390	2010	5
UNEMPLOYMENT	0.067	0.023	June 2012	6
POLITICAL AFFILIATION	2.796	1.993	2008	7
COMMUNITY PRES.	0.413	0.494	2012	8
COMMUN. PRES. YEARS	3.154	4.112	2012	8
COMMUN. PRES. COST	0.816	1.131	2012	8
REGION CENTRAL	0.168	0.375	2008	9
REGION NORTHEAST	0.336	0.474	2008	9
REGION SOUTHEAST	0.210	0.409	2008	9
PAYT	0.455	0.500	2012	10
PAYT YEARS	4.385	7.334	2012	10
PAYT COST	2.305	2.980	2012	10
TIPPING FEE	70.126	15.946	2012	1
SINGLE STREAM	0.350	0.479	2012	1
MANDATORY	0.343	0.476	2012	1
TRASH SERVICE	0.825	0.189	2012	1
RECYCLING SERVICE	0.840	0.184	2012	1

TRASH LIMIT	0.224	0.418	2012	1
CURB TRASH & RECYCLE	0.587	0.494	2012	1
CARTS TRASH	0.147	0.355	2012	1
CARTS RECYCLE	0.182	0.387	2012	1
BINS COMPOST	0.538	0.500	2012	1
YARD WASTE	0.769	0.423	2012	1
FOOD WASTE	0.077	0.267	2012	1
MUNICIPAL	0.944	0.231	2012	1
SCHOOL	0.748	0.436	2012	1
BUSINESS	0.371	0.485	2012	1
SWAP SHOP	0.350	0.479	2012	1
HAZARDOUS CATEG.	8.741	4.584	2012	1
HAZARDOUS EVENTS	1.413	2.670	2012	1
HAZARDOUS REGIONAL	0.308	0.463	2012	1
HAZARDOUS RECIP.	0.245	0.431	2012	1

Continued on next page

Table A6, continued

	Sources
1	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2013)
2	(United States Census Bureau 2012)
3	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2010a)
4	(United States Census Bureau 2011)
5	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2012b)
6	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2013)
7	(The Commonwealth of Massachusetts, Department of Revenue (DOR), Division of Local Services 2008)
8	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012b)
9	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2008)
10	(The Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs 2012a)

Table A7: 2009 All Variables Model

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.177	0.157	1.126	0.262	
β_1	LOG DENSITY	-0.024	0.010	-2.515	0.013	*
β_2	PERSONS PER HOUSEHOLD	0.013	0.019	0.698	0.486	
β_3	AGE	0.003	0.002	1.248	0.214	
β_4	EDUCATION	0.229	0.063	3.655	0.000	***
β_5	INCOME	-7.29E-08	4.43E-07	-0.165	0.869	
β_6	POLITICAL AFFILIATION	0.000	0.005	0.076	0.940	
β_7	REGION CENTRAL	-0.022	0.025	-0.883	0.379	
β_8	REGION NORTHEAST	-0.013	0.028	-0.448	0.654	
β_9	REGION SOUTHEAST	-0.022	0.026	-0.843	0.400	
β_{10}	PAYT	0.091	0.023	3.925	1.28E-04	***
β_{11}	PAYT YEARS	0.000	0.002	-0.158	0.874	
B_{12}	SINGLE STREAM	0.000	0.018	0.026	0.979	
β_{13}	CURBSIDE RECYCLE	0.022	0.023	0.938	0.350	
B_{14}	HOUSEHOLDS SERVED	-0.047	0.028	-1.652	0.101	

Residual std. error	0.09393 on 162 DF	*** significant at the 0.001 level
R2	0.436	** significant at the 0.01 level
R2 (adjusted)	0.387	* significant at the 0.05 level
F-statistic	8.933 on 14 and 162 DF	. significant at the 0.1 level
p-value	2.85E-14	
n	177	

Table A8: 2009 Sensitivity Analysis (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.323	0.033	9.780	2.94E-18	***
β_1	LOG DENSITY	-0.028	0.004	-6.321	2.13E-09	****
β_2	EDUCATION	0.223	0.043	5.244	4.55E-07	***
β_3	PAYT	0.086	0.015	5.584	8.97E-08	***

Residual std. error	0.092 on 173 DF	*** significant at the 0.001 level
R2	0.419	** significant at the 0.01 level
R2 (adjusted)	0.409	* significant at the 0.05 level
F-statistic	41.54 on 3 and 173 DF	. significant at the 0.1 level
p-value	< 2.20E-16	
n	177	

Note: The *Sensitivity Analysis* model yields a three variable model, so there is not an *Occam's Reduced Form* model for this time period.

Table A9: 2011 All Variables Model

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.229	0.148	-1.551	0.123	
β_1	LOG DENSITY	0.025	0.011	2.205	0.029	*
β_2	PERSONS PER HOUSEHOLD	0.002	0.017	0.141	0.888	
β_3	AGE	0.004	0.002	1.916	0.057	.
β_4	EDUCATION	0.345	0.073	4.716	4.71E-06	***
β_5	INCOME	-3.15E-07	4.46E-07	-0.707	0.480	
β_6	POLITICAL AFFILIATION	2.10E-04	0.005	0.045	0.964	
β_7	REGION CENTRAL	-0.048	0.031	-1.555	0.122	
β_8	REGION NORTHEAST	-0.054	0.036	-1.519	0.131	
β_9	REGION SOUTHEAST	-0.073	0.028	-2.613	0.010	**
β_{10}	PAYT	0.055	0.030	1.790	0.075	.
β_{11}	PAYT YEARS	0.001	0.002	0.456	0.649	
B_{12}	PAYT COST	0.008	0.005	1.754	0.081	.
β_{13}	SINGLE STREAM	-0.006	0.020	-0.313	0.754	
B_{14}	MANDATORY	0.015	0.019	0.813	0.417	
B_{15}	TRASH SERVICE	-0.097	0.118	-0.820	0.413	
B_{16}	RECYCLING SERVICE	0.055	0.115	0.481	0.631	
B_{17}	TRASH LIMIT	0.001	0.024	0.054	0.957	
B_{18}	CURBSIDE	0.003	0.029	0.097	0.923	
B_{19}	CARTS TRASH	0.008	0.030	0.285	0.776	
B_{20}	CARTS RECYCLE	0.025	0.025	1.000	0.319	
B_{21}	BINS COMPOST	-0.032	0.017	-1.927	0.056	.

B_{22}	YARD WASTE	0.030	0.026	1.142	0.255	
B_{23}	FOOD WASTE	-0.018	0.028	-0.651	0.516	
B_{24}	MUNICIPAL	0.035	0.033	1.054	0.293	
B_{25}	SCHOOL	0.006	0.021	0.275	0.784	
B_{26}	BUSINESS	0.017	0.018	0.921	0.358	
B_{27}	SWAP SHOP	0.050	0.019	2.563	0.011	*
B_{28}	HAZARDOUS CATEG.	0.004	0.002	2.157	0.032	*
B_{29}	HAZARDOUS EVENTS	0.002	0.002	0.857	0.393	
B_{30}	HAZARDOUS REGIONAL	0.015	0.018	0.795	0.428	
B_{31}	HAZARDOUS RECIPROC	0.001	0.018	0.035	0.972	

Residual std. error	0.1075 on 186 DF	*** significant at the 0.001 level
R2	0.4456	** significant at the 0.01 level
R2 (adjusted)	0.3532	* significant at the 0.05 level
F-statistic	4.823 on 31 and 186 DF	. significant at the 0.1 level
p-value	4.92E-12	
n	218	

Table A10: 2011 Sensitivity Analysis (Seven Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.187	0.109	-1.710	0.089	.
β_1	LOG DENSITY	0.021	0.007	3.260	0.001	**
β_2	AGE	0.004	0.002	2.244	0.026	*
β_3	EDUCATION	0.281	0.045	6.218	2.68E-09	***
β_4	PAYT	0.057	0.027	2.151	0.033	*
β_5	PAYT COST	0.008	0.004	1.973	0.050	*
β_6	SWAP SHOP	0.050	0.017	2.883	0.004	**
B_7	HAZARDOUS CATEGORIES	0.005	0.002	2.838	0.005	**

Residual std. error	0.107 on 210 DF	*** significant at the 0.001 level
R2	0.382	** significant at the 0.01 level
R2 (adjusted)	0.362	* significant at the 0.05 level
F-statistic	18.55 on 7 and 210 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	218	

Table A11: 2011 Occam's Reduced Form (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.107	0.025	4.272	2.91E-05	***
β_1	EDUCATION	0.336	0.045	7.489	1.80E-12	***
β_2	PAYT	0.087	0.015	5.716	3.63E-08	***
β_3	HAZARDOUS CATEGORIES	0.007	0.002	4.340	2.19E-05	***

Residual std. error	0.11 on 214 DF	*** significant at the 0.001 level
R2	0.322	** significant at the 0.01 level
R2 (adjusted)	0.312	* significant at the 0.05 level
F-statistic	33.81 on 3 214 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
N	218	

Table A12: 1997-1999 Occam's Consistent (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	0.054	0.065	0.833	0.406	
β_1	AGE	0.005	0.002	2.663	0.008	**
β_2	EDUCATION	0.185	0.039	4.702	3.84E-06	***
β_3	PAYT	0.106	0.015	7.013	1.39E-11	***

Residual std. error	0.11 on 320 DF	*** significant at the 0.001 level
R2	0.21	** significant at the 0.01 level
R2 (adjusted)	0.202	* significant at the 0.05 level
F-statistic	28.3 on 3 and 320 DF	. significant at the 0.1 level
p-value	2.94E-16	
n	324	

Note: These are the results from a model that uses these three variables consistently across the 4 time periods. To discern patterns over time, these results can be compared with **Table 12**, **Table 17** and **Table A13**.

Table A13: 2012 Occam's Consistent (Three Variable Model)

Parameter	Variable	Estimate	STD Error	t value	p-value	sig.
β_0	(Intercept)	-0.136	0.075	-1.818	0.071	.
β_1	AGE	0.008	0.002	4.757	4.87E-06	***
β_2	EDUCATION	0.270	0.050	5.433	2.42E-07	***
β_3	PAYT	0.116	0.017	6.999	1.00E-10	***

Residual std. error	0.097	*** significant at the 0.001 level
R2	0.452	** significant at the 0.01 level
R2 (adjusted)	0.44	* significant at the 0.05 level
F-statistic	38.2 on 3 and 139 DF	. significant at the 0.1 level
p-value	< 2.2e-16	
n	143	

Note: These are the results from a model that uses these three variables consistently across the 4 time periods. To discern patterns over time, these results can be compared with **Table 12**, Table 17 and Table A12.

Table A14: Recycling Rate Summary Statistics for PAYT vs NO PAYT municipalities (2009 and 2011)

	YEARS			
	2009		2011	
	NO	**PAYT**	**NO**	**PAYT**
Count	136	74	134	107
Minimum	0.03	0.05	0.07	0.10
Maximum	0.61	0.58	0.63	0.81
Range	0.58	0.53	0.56	0.71
Mean	0.215	0.334	0.301	0.38
Std. Dev.	0.111	0.09	0.127	0.129
Mode	0.16	0.35	0.24	0.33
Median	0.19	0.34	0.29	0.35
25% (Q1)	0.15	0.28	0.21	0.31
75% (Q2)	0.26	0.38	0.38	0.443

Note: For the 1997-1999, 2006-2008, 2010, and 2012 data, see Table 26.

Table A15: t-test of mean recycling rate for PAYT vs NO PAYT municipalities

2006-2008			
VARIBALE	*Sample size*	*Mean*	*Variance*
NO PAYT	206	0.266	0.013
PAYT	125	0.364	0.016
Degrees Of Freedom	329	*Hypothesized Mean Difference*	0.E+0
Test Statistics	7.276	*Pooled Variance*	0.014
Two-tailed distribution			
p-level	2.53E-12	*t Critical Value (0.05%)*	3.516
One-tailed distribution			
p-level	1.27E-12	*t Critical Value (0.05%)*	3.32
2009			
VARIBALE	*Sample size*	*Mean*	*Variance*
NO PAYT	136	0.215	0.012
PAYT	74	0.334	0.008
Degrees Of Freedom	208	*Hypothesized Mean Difference*	0.E+0
Test Statistics	7.878	*Pooled Variance*	0.011
Two-tailed distribution			
p-level	1.83E-13	*t Critical Value (0.05%)*	3.536
One-tailed distribution			
p-level	9.14E-14	*t Critical Value (0.05%)*	3.338
2010			
VARIBALE	*Sample size*	*Mean*	*Variance*
NO PAYT	155	0.235	0.011

PAYT	99	0.357	0.009
Degrees Of Freedom	252	*Hypothesized Mean Difference*	0.E+0
Test Statistics	9.412	*Pooled Variance*	0.01
Two-tailed distribution			
p-level	< 2.2e-16	*t Critical Value (0.05%)*	3.527
One-tailed distribution			
p-level	< 2.2e-16	*t Critical Value (0.05%)*	3.33
2011			
VARIBALE	*Sample size*	*Mean*	*Variance*
NO PAYT	134	0.301	0.016
PAYT	107	0.38	0.017
Degrees Of Freedom	239	*Hypothesized Mean Difference*	0.E+0
Test Statistics	4.752	*Pooled Variance*	0.016
Two-tailed distribution			
p-level	3.49E-06	*t Critical Value (0.05%)*	3.529
One-tailed distribution			
p-level	1.74E-06	*t Critical Value (0.05%)*	3.332
2012			
VARIBALE	*Sample size*	*Mean*	*Variance*
NO PAYT	100	0.332	0.017
PAYT	94	0.432	0.015
Degrees Of Freedom	192	*Hypothesized Mean Difference*	0.E+0
Test Statistics	5.605	*Pooled Variance*	0.016
Two-tailed distribution			
p-level	7.14E-08	*t Critical Value (0.05%)*	3.541

One-tailed distribution			
p-level	3.57E-08	*t Critical Value (0.05%)*	3.342

APPENDIX B

ADDITIONAL FIGURES

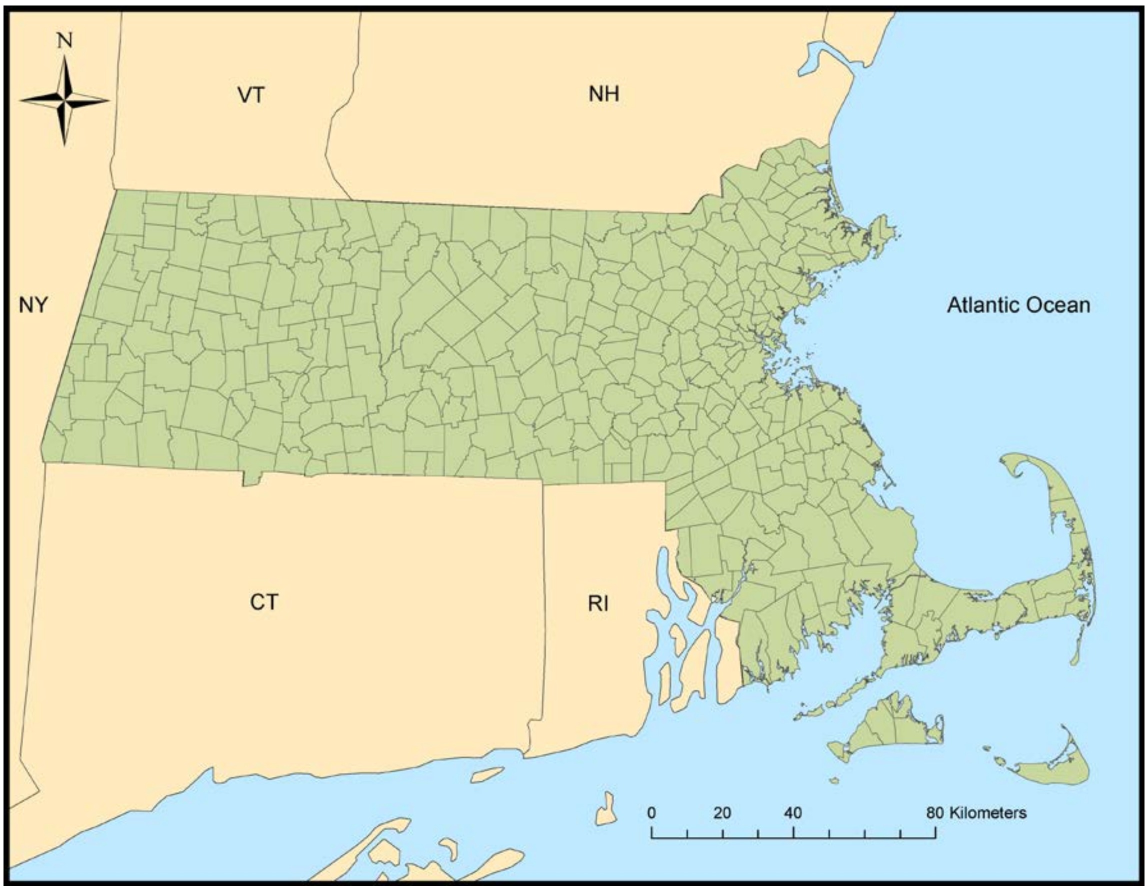

Figure B1: The Commonwealth of Massachusetts with municipal political boundaries.

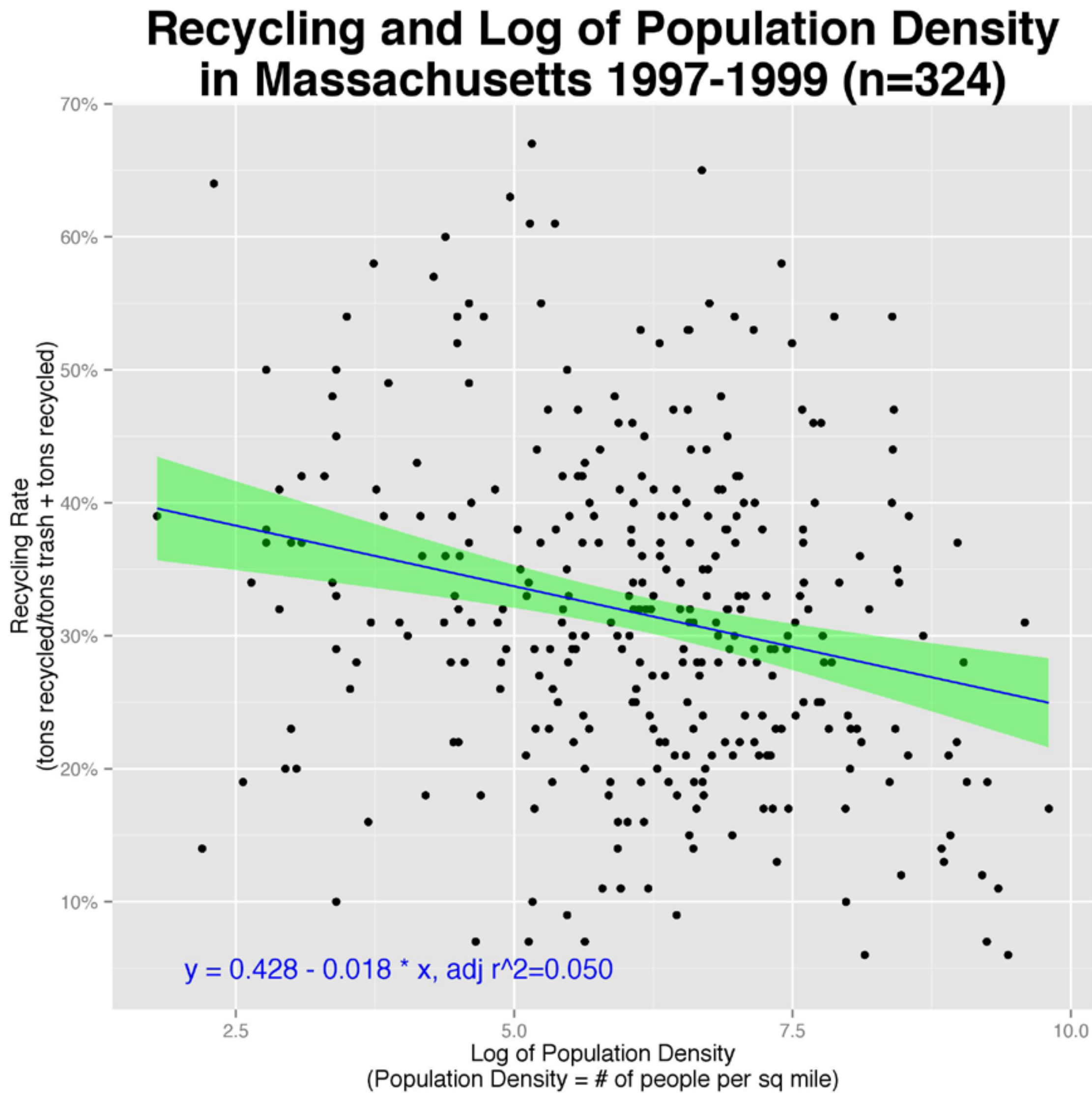

Figure B2: Bivariate relationship between log population density and recycling rate.

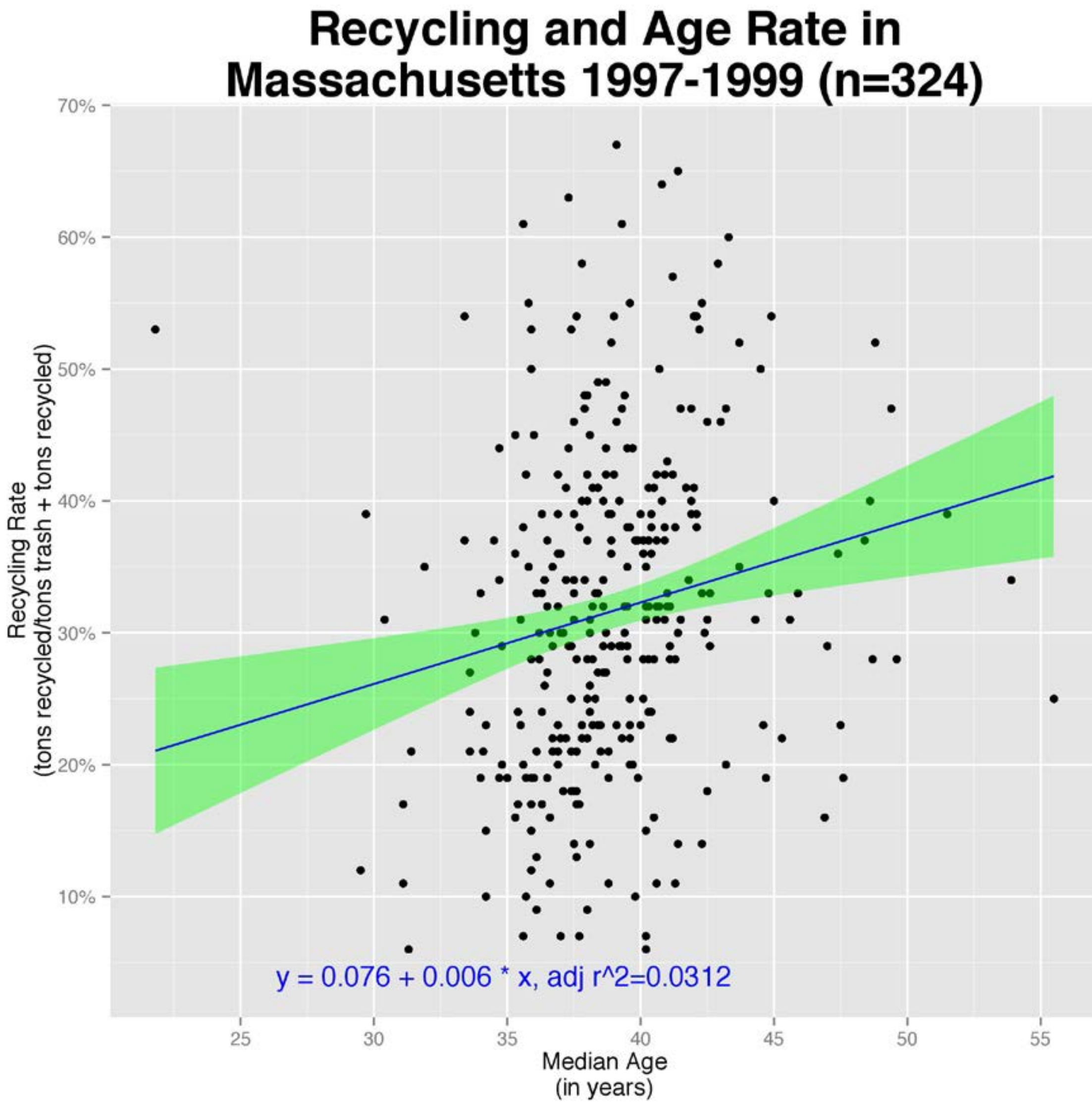

Figure B3: Bivariate relationship between age and recycling rate.

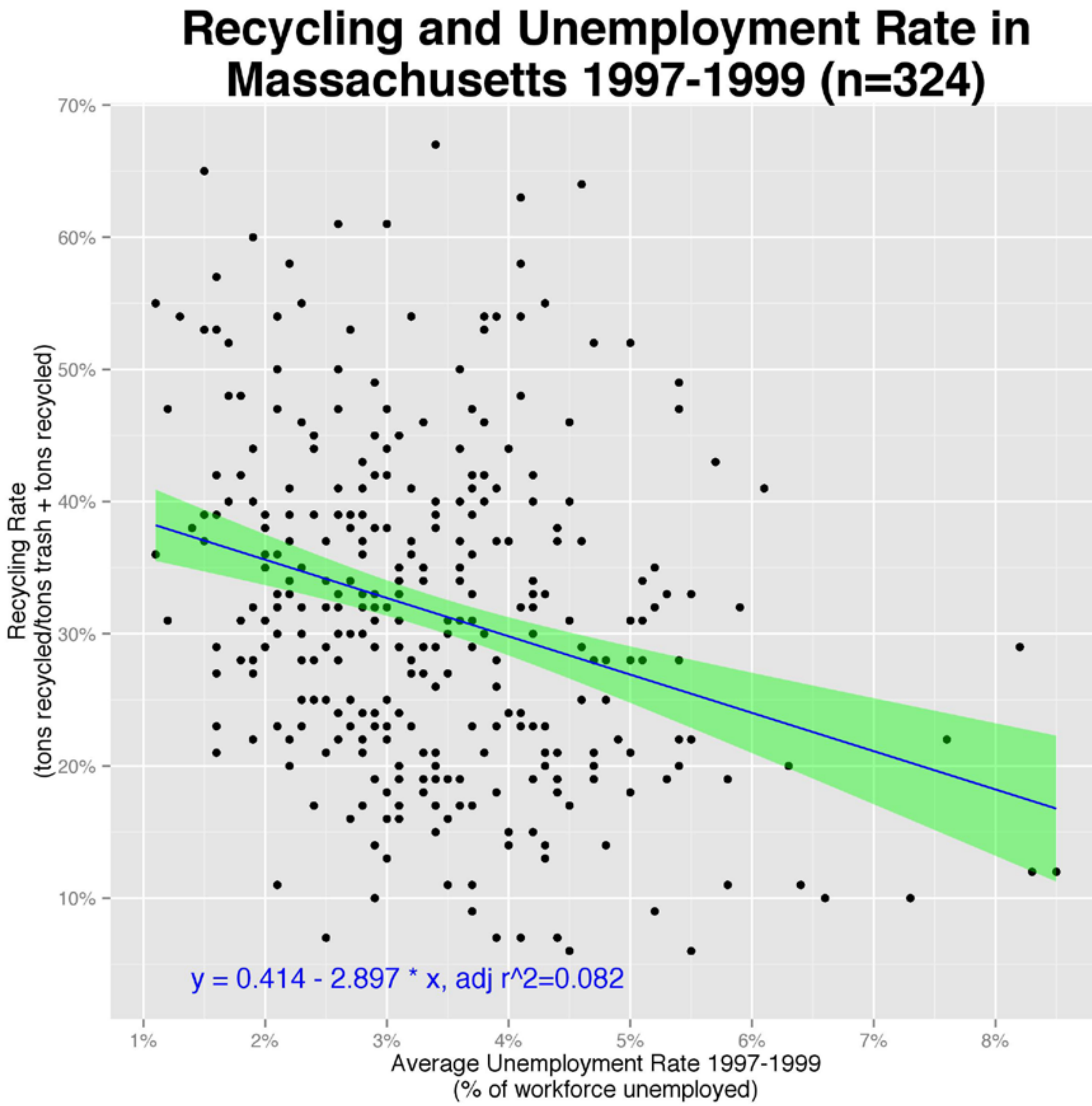

Figure B4: Bivariate relationship between unemployment and recycling rate.

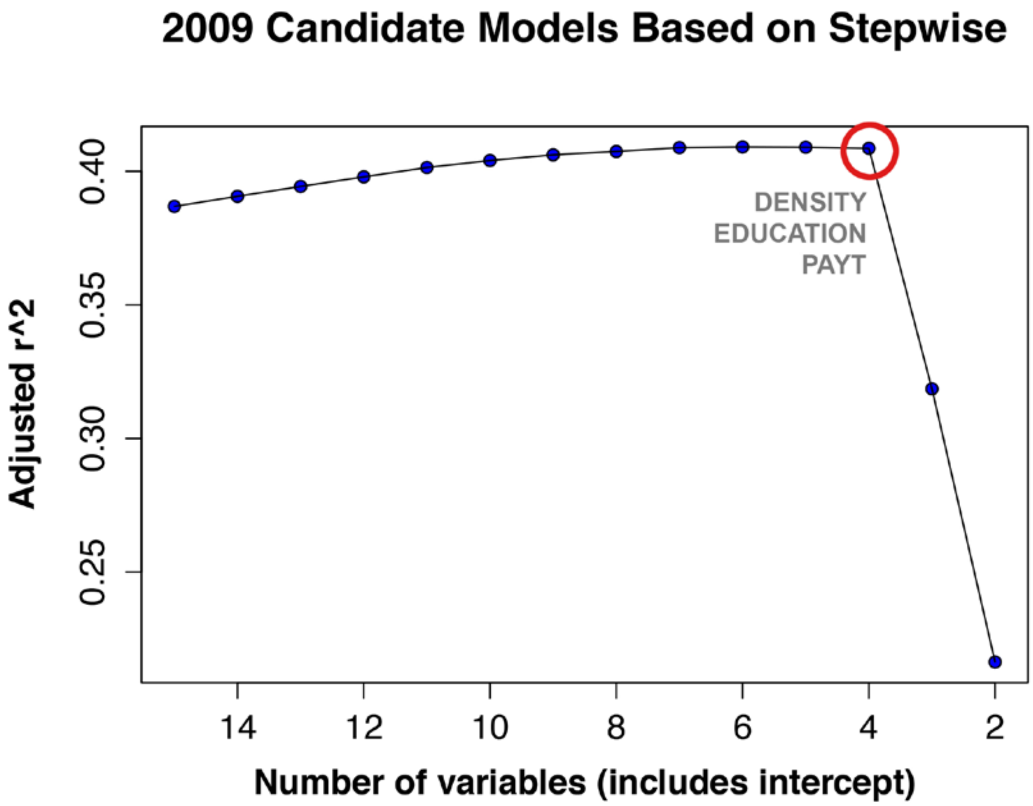

Figure B5: Graphical representation of the model selection process 2009

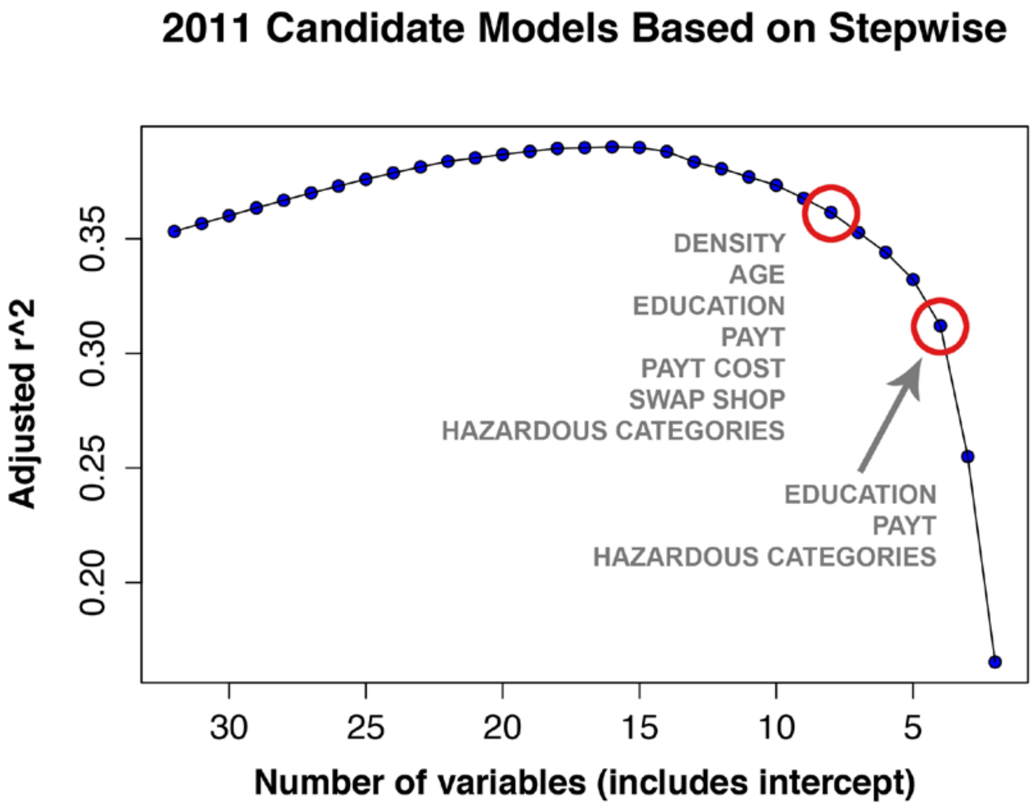

Figure B6: Graphical representation of the model selection process 2011

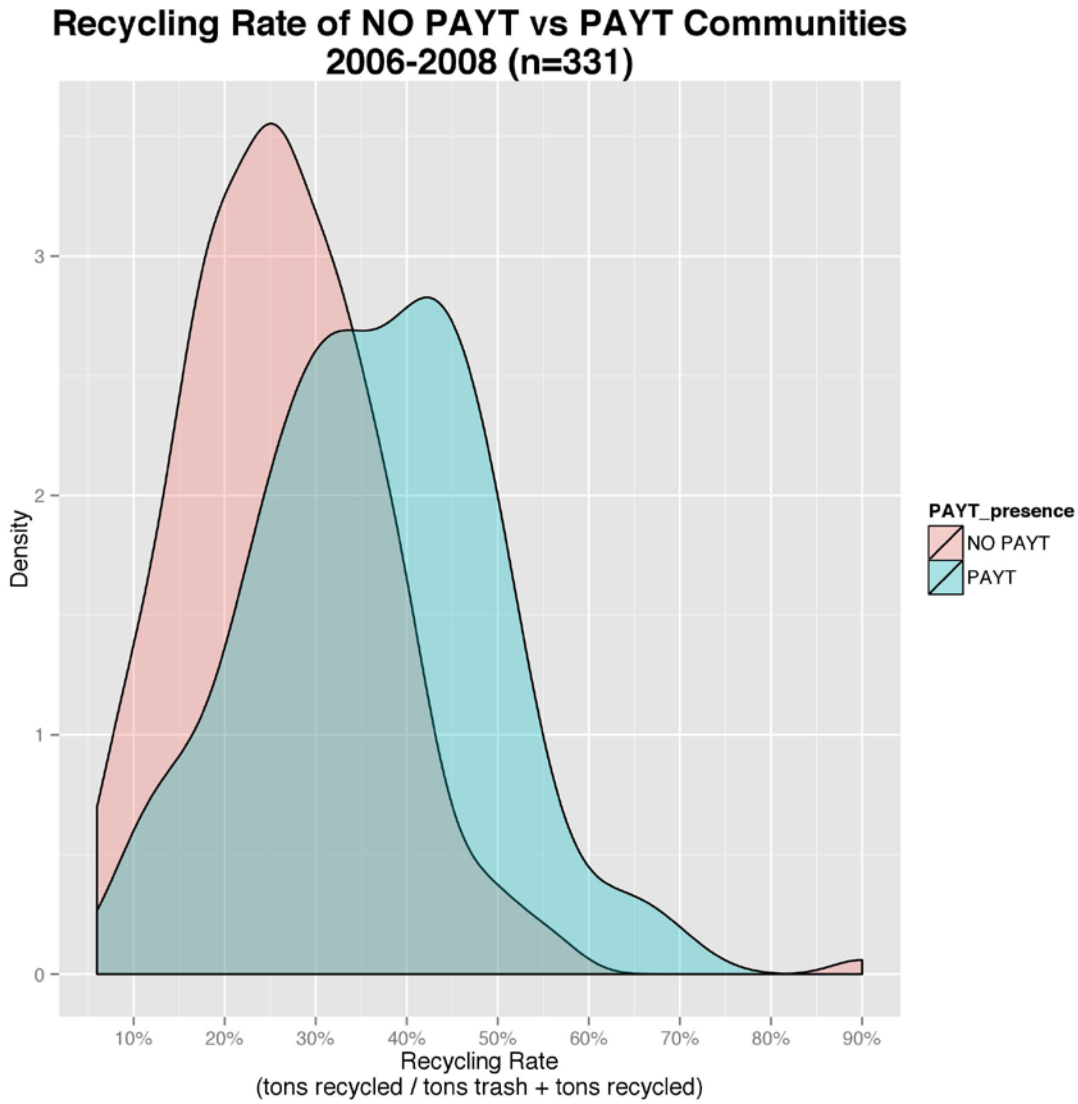

Figure B7: Recycling rate density plot distribution of NO PAYT versus PAYT communities 2006-2008 (n=331)

Note: This is a density plot highlighting the difference in recycling rate between municipalities with PAYT and without PAYT. The 1997-1999 plot can be seen in **Figure 21**, other years are in Figure B8 - Figure B11.

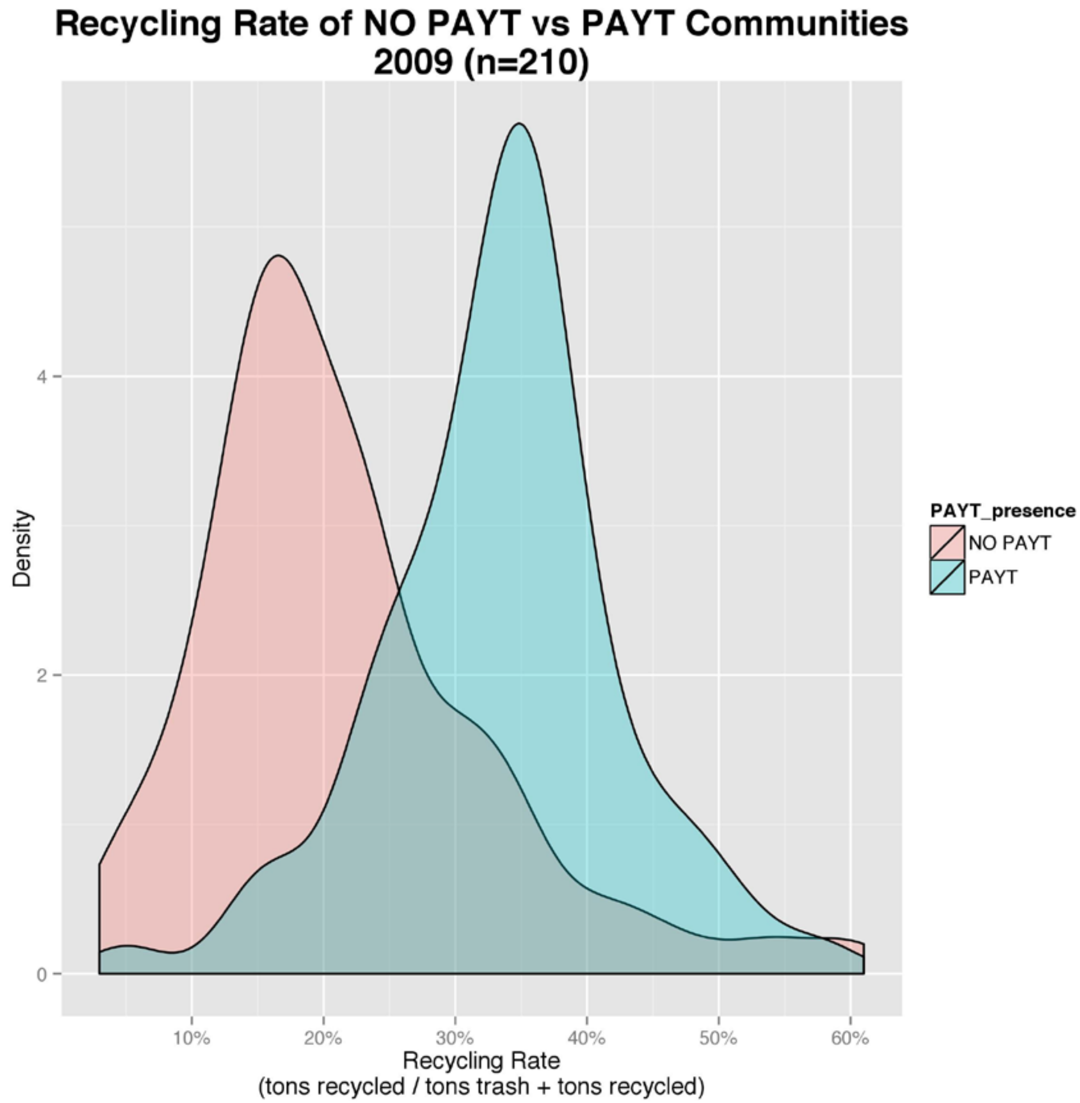

Figure B8: Recycling rate density plot distribution of NO PAYT versus PAYT communities 2009 (n=210)

Note: This is a density plot highlighting the difference in recycling rate between municipalities with PAYT and without PAYT. The 1997-1999 plot can be seen in **Figure 21**, other years are in Figure B7, Figure B9, Figure B10, and Figure B11.

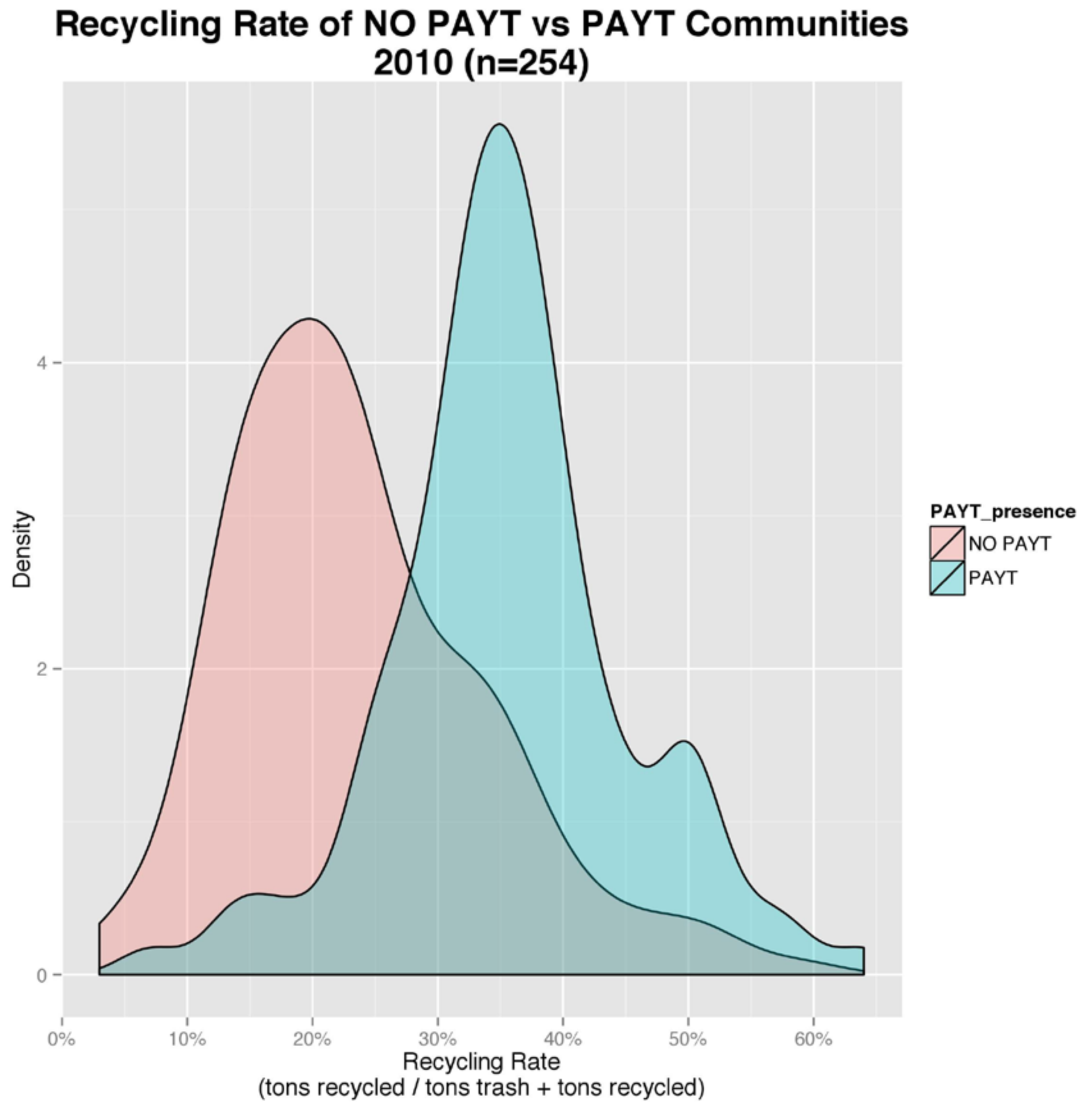

Figure B9: Recycling rate density plot distribution of NO PAYT versus PAYT communities 2010 (n=254)

Note: This is a density plot highlighting the difference in recycling rate between municipalities with PAYT and without PAYT. The 1997-1999 plot can be seen in **Figure 21**, other years are in Figure B7, Figure B8, Figure B10, and Figure B11.

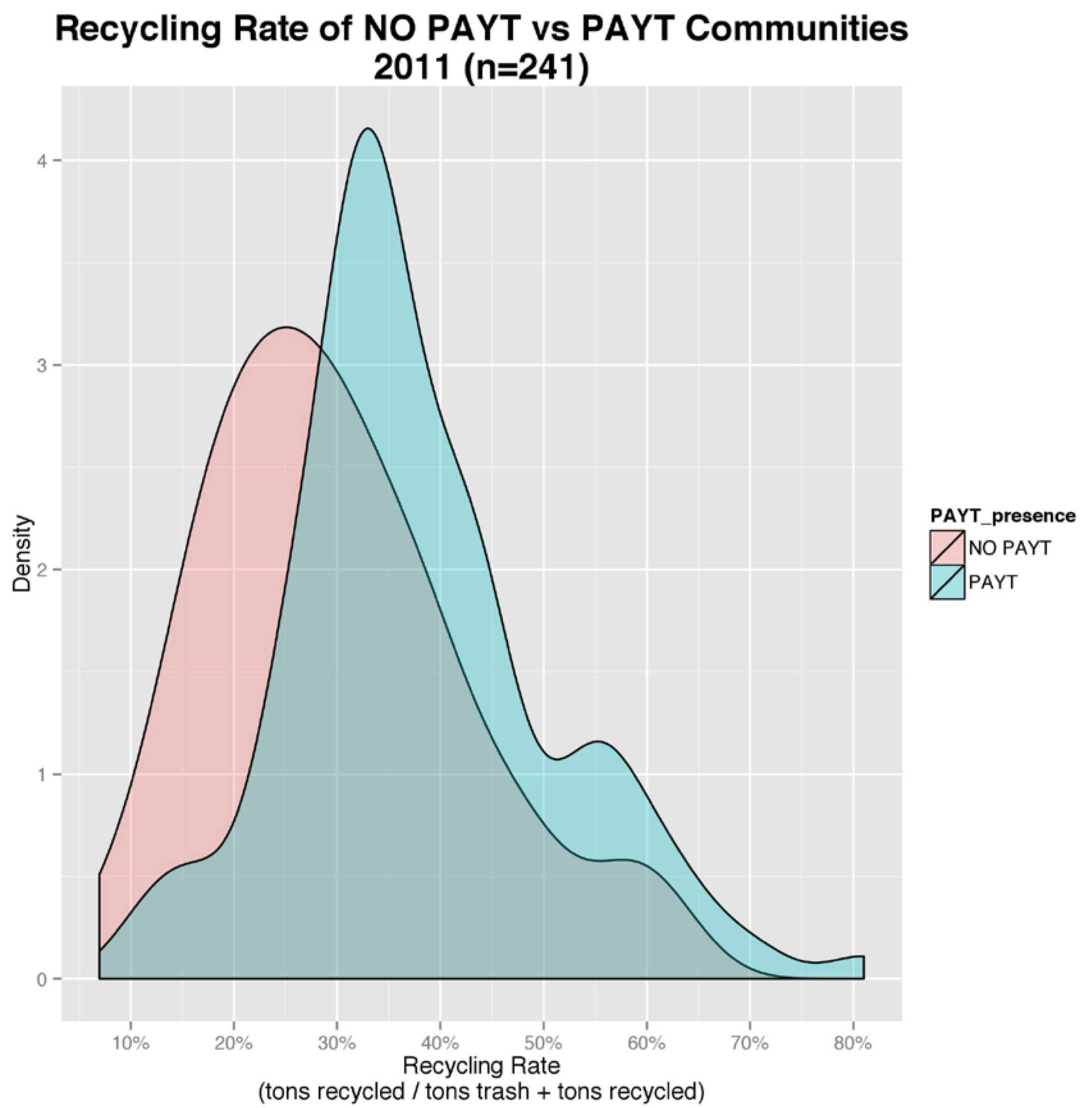

Figure B10: Recycling rate density plot distribution of NO PAYT versus PAYT communities 2011 (n=241)

Note: This is a density plot highlighting the difference in recycling rate between municipalities with PAYT and without PAYT. The 1997-1999 plot can be seen in **Figure 21**, other years are in Figure B7, Figure B8, Figure B9, and Figure B11.

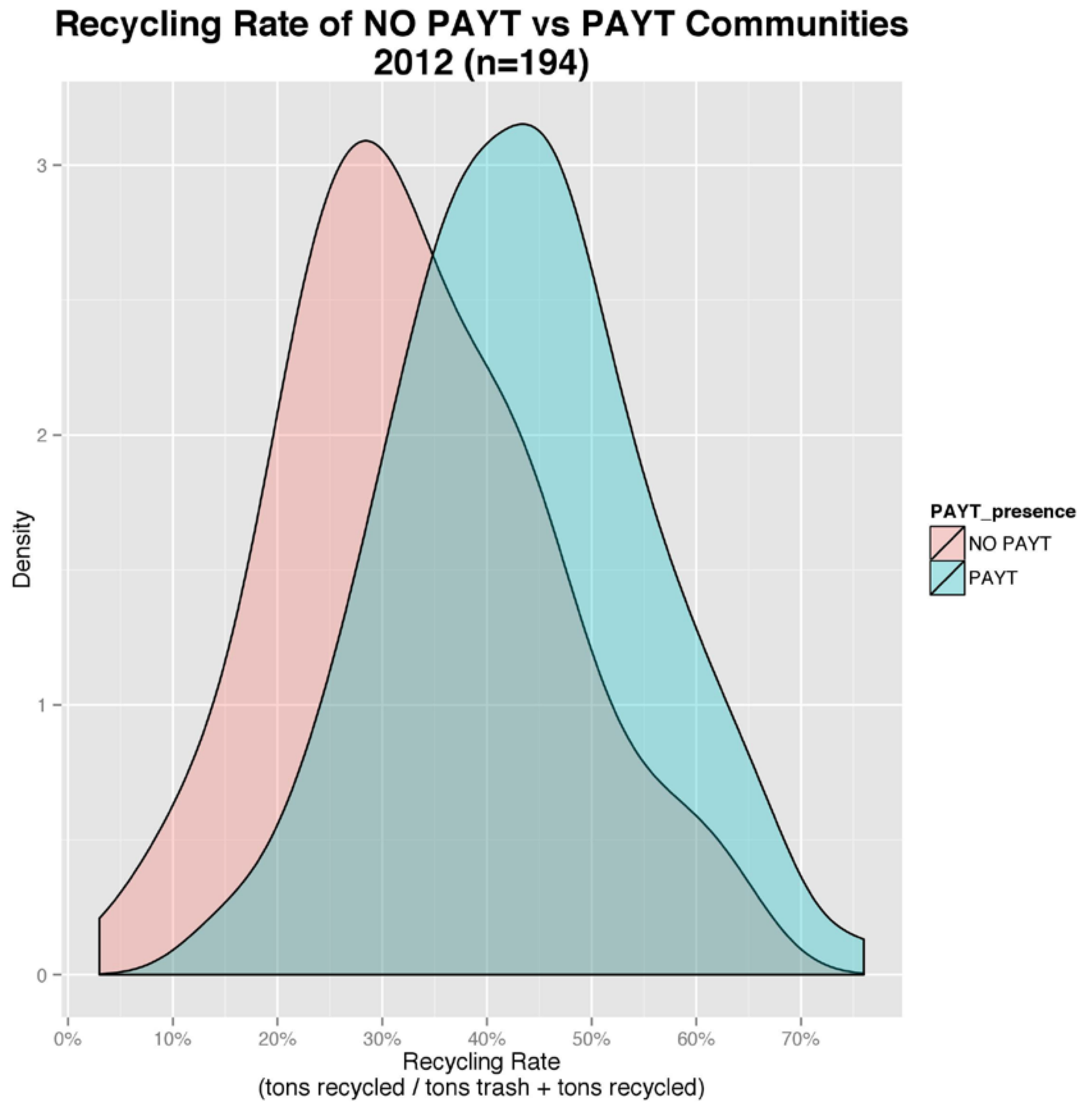

Figure B11: Recycling rate density plot distribution of NO PAYT versus PAYT communities 2012 (n=194)

Note: This is a density plot highlighting the difference in recycling rate between municipalities with PAYT and without PAYT. The 1997-1999 plot can be seen in **Figure 21**, other years are in Figure B7 - Figure B10.

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