An Analysis of Charitable Giving to the Eugene Water and Electric Board's Customer Care Program

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Abstract: We analyzed the funding of the Eugene Water and Electric Board's Customer Care program, examining the change from voluntary to mandatory contributions. This paper demonstrates the existence of a crowd-out effect as well as evidence in support of the warm glow theory. Ultimately, it allowed us to provide EWEB with information which could prove useful in determining future policy.

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Professor Bill Harbaugh Date

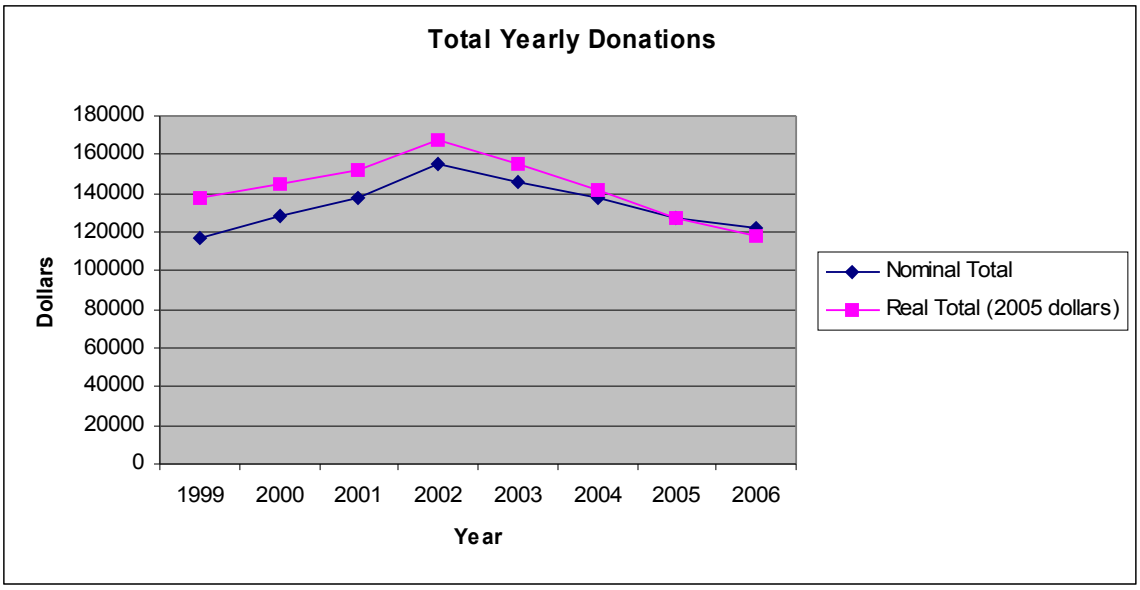
1. Introduction

The Eugene Water and Electric Board in Eugene, Oregon supports a Customer Care program that provides financial aid for qualifying customers. EWEB assigns more than $1.5 million per year to these low-income programs. However in the past 20 years, EWEB has only received $1 million total from voluntary donations. Obviously, the bulk of the funding comes from elsewhere.

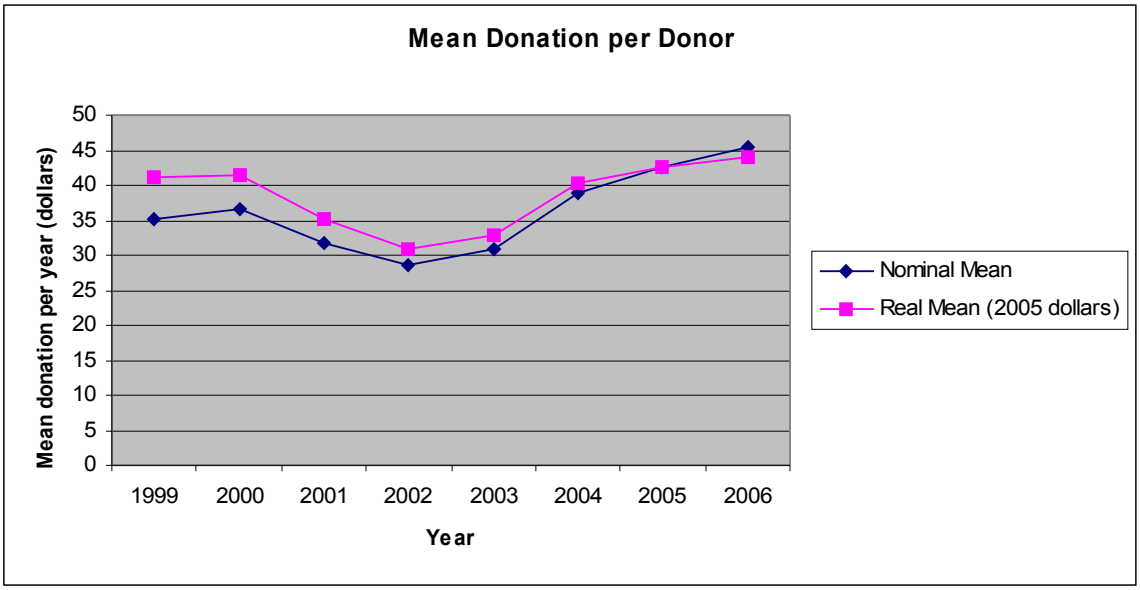
The program was started in 1986 and was funded solely through donations until 2001 when the price of utilities increased substantially. At this point, EWEB decided to switch the funding from donations to a mixed system using both voluntary contributions and a mandatory "tax" on the price of their services. This change was made in order to increase the total funding of the program and minimize the impact of a price increase on low-income customers. This paper analyzes the results of this natural experiment: the change in funding methods. It can potentially be an excellent way to test the theory of crowding-out, and can also show us a strong example of warm glow giving. When we discussed the idea with EWEB they were very interested and cooperative with our efforts.

Below are summary graphs and tables with statistics regarding donations received by EWEB.

Year	Nominal Total	Real Total (2005 dollars)
1999	117,028.95	137,196.89
2000	127,941.45	145,058.33
2001	137,762.21	151,887.77
2002	154,716.51	167,987.52
2003	146,370.33	155,382.52
2004	137,143.25	141,823.42
2005	127,417.8	127,417.80
2006	122,028.88	118,245.04



Year	Nominal Mean	Real Mean (2005 dollars)
1999	35.14	41.20
2000	36.52	41.41
2001	31.83	35.09
2002	28.44	30.88
2003	30.95	32.86
2004	38.82	40.14
2005	42.61	42.61
2006	45.38	43.97



We start with the relevant theory. First, we will discuss basic donation theory from public economics, including free-riding, and the use of taxation to stop it. Next is an explanation of the crowding-out theory and how it pertains to EWEB's Customer Care program. We will also discuss the theory of warm glow giving, and its implications on how donors receive utility. Kingma (1989) used empirical data to look for evidence of crowd-out in donations to public radio. His literature will be helpful in looking at possible crowding-out effects initiated by the mandatory surcharge. Bolton and Katok (1998) and Eckel, Grossman, and Johnston (2005) also found similar evidence of crowding-out in different empirical situations. Andreoni (1993) additionally found evidence of crowding-out through experimental means.

After our literature review, we will discuss in length our methods and our data. The data given to us has documented every individual donation received by EWEB since 1999, the address of the donor, and their customer code. Using their addresses, we can get an accurate depiction of many different characteristics of the donor by matching with Census data and the Regional Land Information Database (RLID) with additional data from the Lane Council of Governments (LCOG). Our final regression will show us which factors tend to cause a person to donate, and additionally, how much they ultimately do contribute. At this point, we hope to give useful recommendations to EWEB about popular support for the program, perhaps in order to increase donations to the program.

2. Literature Review

Public goods are non-rival in consumption, and therefore can be consumed by anybody, regardless of who pays for them. This makes each individual less likely to

voluntarily fund public goods, so typically a public good is under-provided. A contribution to a charitable organization is commonly viewed as a public good because of the altruistic feeling people get from knowing the needy are being helped by somebody, regardless of who it is. Simply put, if one person gives help to the needy, others may feel that they do not have to.

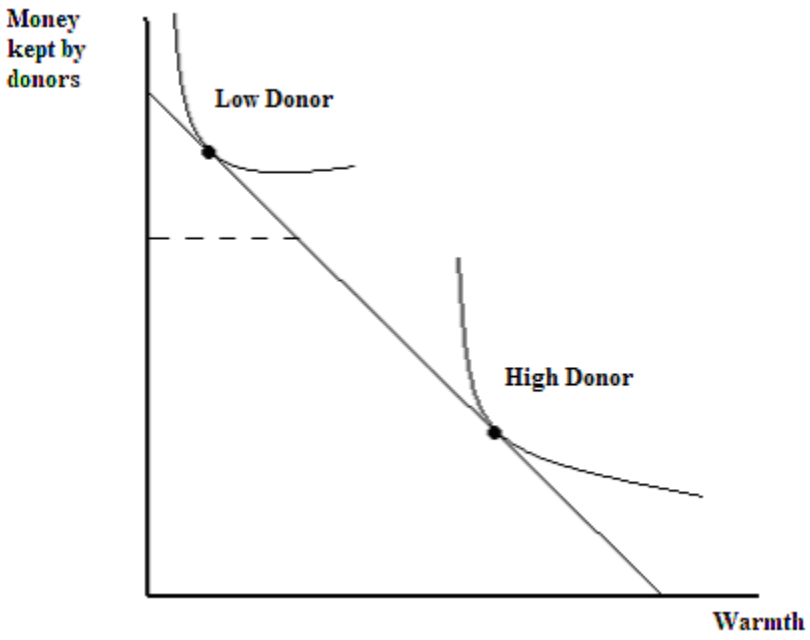
In a hypothetical economy with a public good and two possible donors, we can set up a prisoner's dilemma where each consumer has the option to contribute. If one person contributes, both receive the good.

		Consumer A	
		Contribute	Do not contribute
Consumer B	Contribute	Both benefit and pay	Both benefit, only B pays
	Do not contribute	Both benefit, only A pays	Neither benefit nor pay

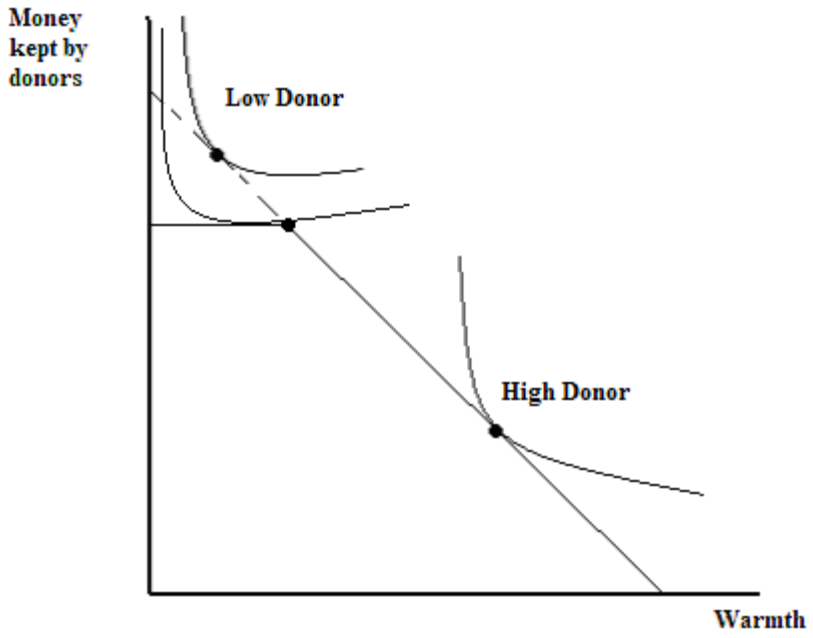
In this dilemma, the dominant strategy is to not contribute. Assume both consumers provided the public good until one realized he could benefit from the public good without contributing. He would stop paying and let the other contribute and fund the entirety of the public good. In the next period, the other consumer would retaliate and choose to not contribute, and there would be zero social benefit. This whole problem was brought about by one individual choosing to free ride, or attempting to receive the benefit of a public good without paying for it. Free riding creates a situation where people choose to pay for less of a public good than is socially optimal. Public goods must be provided in a different way, which is usually by a governing body and mandating contribution.

Taxation is one way to stop free riding from occurring. The government can set a level of the public good they think is socially optimal, and then force everybody in society to pay either an identical fraction of it or a weighted amount based on income or consumption. This solves two problems at the same time. First, it mandates that everybody is paying for the public good. Second, it sets the provision of the public good at a level that is socially optimal. However, a tax imposed by the government has been theorized and observed to reduce voluntary contributions to the public good the tax funds. This theory is called the crowd-out effect.

In our situation, crowding-out can be easily illustrated with a graph.



This is a consumption possibility frontier where a person can choose to contribute or keep their money. A person with high marginal utility of donating compared to their marginal utility of wealth contributes a significant amount of money, and the low donor does not donate much at all. Without any mandatory donations, this is each person's optimal point. This changes when donations become mandatory.



The dotted continuation of the frontier represents where the low donor used to be able to settle. The distance on the y-axis between the dotted intercept and the new solid line intercept represents the amount of the mandatory donation, or the tax. The new solid line represents their new possibilities, and because of the kink at the mandatory level, this minimum level becomes the settling point for the low donor. Their utility decreases because of the tax, but total warmth increases. In this case, the low donor is motivated by the total amount of contribution to the program, not necessarily how much he voluntarily contributes himself. He now voluntarily contributes nothing, but because the mandatory contribution is greater than his original voluntary contribution, total funding for the program increases.

It is referred to as the crowding-out theory, because the *mandatory* donation imposed by the tax crowds out the low donor's *voluntary* donation. It is important to understand what exactly this crowd-out effect means. If the theory of crowding-out is true, we should expect to see a drop in the average donation per donor at the time of the

rate change. In general, all policies regarding the provision of public goods can benefit from more knowledge concerning the crowd-out effect. More specifically, EWEB could use it in determining future policy changes regarding their Customer Care program. For example, if our results show that crowding-out did occur, then EWEB knows increasing the mandatory tax will decrease voluntary donations and by how much. There is also the possibility that the specific characteristics of the crowd-out effect can help EWEB determine what motivates a donor, which can be several different things ranging from pure altruism to warm glow. The theory of warm glow, in particular, proves to be interesting.

The crowd-out effect showed us one possible explanation for donations, the purely altruistic model, in which donors' utility is determined by the public benefit brought on by donations. Another alternate explanation for the incentive of donating to public goods is the warm glow theory. The warm glow theory postulates that donors receive utility not from knowing people are being helped by contributions, but simply by the act of donating themselves. The literal "warm glow" feeling a person receives from donating is the motive for giving in this case. An example of a donor motivated by warm glow would be a person who prefers the social prestige or image in the community to the money they donate. Warm glow giving is sometimes referred to as impure altruism because people donate for their own benefit rather than for the benefit of the people who the donations are directed towards.

Warm glow giving can heavily influence the crowd-out effect in our example. On our initial graph, the implementation of the mandatory contribution did not affect the high donor's total contribution. His voluntary donation was crowded-out dollar-for-dollar by

the tax, but his total contribution remained the same. Now say for instance the high donor was motivated entirely by warm glow giving. This donor's utility comes from how much they voluntarily donate, not from the amount of the total contribution. Therefore, to remain at the same level of utility, they must voluntarily contribute the same amount they did before the tax in addition to their mandatory payment. For this person, utility cannot be gained by involuntarily donating. Knowing they went above and beyond what was required makes them happy.

Kingma (1989) discusses at length the theory of the crowd-out effect and measures it through observing donations to public radio stations. He first presented four different models of utility in regards to charitable contributions, describing different ways a donor can receive utility. The pure public good model treats government spending as a perfect substitute for personal donations. If two things are perfect substitutes then the options cost the same, provide the same benefit, and are of the same quality, meaning a consumer would have no incentive to prefer one over the other. This implies that if one of the two goods were to become more expensive the consumer would naturally switch to the other, since they are equal in all regards but price. In Kingma's paper it means that a one-dollar increase in government spending towards a charity results in a one-dollar reduction in private contributions.

The impure altruism model treats government payments and the contribution of others as less than perfect substitutes, which results in a crowd-out effect, but less than dollar-for-dollar. A restricted version of the impure altruism model is also introduced, where a possible donor's contributions are independent of the total level of charity, meaning that the only motivation to donate for a person is the warm glow, or personal

satisfaction, they receive from donating, not the money going towards a public good. This model results in zero crowd-out effect because an increase in government payments to the charity has no effect on the donor's utility. Finally, a comprehensive model called the source-of-contributions model uses differing levels of utility gained from payments from different sources. A donor sees additional funds coming in from the government differently than they see additional donations from another agent. Therefore, they are crowded-out differently by government spending than they are from other agents' donations.

Kingma's sample size was 3,541 individuals, 1,783 of whom were donors to one or more of 63 different radio stations. Kingma's model claimed an individual's contribution to a public radio station depended on the before-tax income of the contributor, the total level of support given to the radio station by other listeners, the total level of support from non-member sources, the price of contributing (less than dollar-for-dollar due to tax deductions), the contributor's level of education, and the contributor's age.

Using his data, he found a small amount of crowd-out effect. His coefficient for the government spending variable was .015, meaning for a $10,000 increase in government spending on public radio, a person's donation fell by about $0.15 on average. Applied to the average 9000 donors per radio station, this resulted in a $1,350 crowd-out effect. It is certainly not dollar-for-dollar, but 13.5% is undoubtedly a significant amount.

Another important variable used by Kingma was income, which had a coefficient of .539. This signifies a $1000 increase in an agent's income should equate to a $0.54

increase in donations. This tells us a person's marginal propensity to donate which, as should be expected, is very small. Similarly, he found that a $1000 increase in donations from others should result in total funding increase of $865-$910, and at the same time a $.01-$.015 increase in consumption for each agent. Significance tests of these two variables (G and R) show that the two are not significantly different from each other, meaning that donors do not distinguish between donations from differing sources when considering their own donations.

Kingma concluded that agents receive utility from the amount they donate and also from the total level of contributions, regardless of where they come from. He also provided empirical evidence for a definite crowding-out effect.

Andreoni (1993) found crowding-out through experimental data. The experiment consisted of 108 subjects; six groups of 18 people further divided randomly into groups of three. The premise of the game was that each person was given seven tokens that represented their income. Each person could choose to donate any amount of his or her tokens to fund a public good. Their final payoff at the end of the experiment depended on the amount they donated plotted against how much the other two participants donated. The way he tested for crowding-out was that two of the participants from each group of three were automatically "taxed" two tokens, so they could only voluntarily donate a maximum of five. However, the payoff matrix for the taxed participants reflected an initial investment of two tokens, meaning that this tax went straight to the public good. Their payoff matrix looked different than that of people who were not taxed, showing a maximum contribution of five tokens and immediate payoffs. This means that they could

donate nothing and still come away with some payoff due to their involuntary contribution.

As in many free-riding simulations, such as the prisoners' dilemma used above, Nash equilibrium results in a final outcome that is not close to Pareto efficiency. In this experiment, the Pareto efficient donation is six tokens per person, while Nash equilibrium rests at three tokens per person. The average contributions were 2.78 tokens for the non-taxed group and 3.35 tokens for the taxed group, counting the two they were already taxed. Therefore, taxed participants donated 1.35 tokens on average to the public good, on top of their two-token tax.

In this game, crowding-out is determined by the difference between the taxed contribution and the non-taxed contribution. If the two average contributions are exactly the same, then complete crowding-out is present. If the taxed contribution is exactly two tokens higher than the non-taxed one, then no crowding-out is present. In this case, the taxed contribution was 0.57 tokens higher than the non-taxed one, meaning there exists a 71.5% average crowding-out. However, in the final rounds of each trial session, meaning this was to be the last game each group would play together, the average crowding-out was 84%. In two of the five end games, the private donation was completely crowded out by the taxations. This is perhaps due to the fact that there is a higher incentive to donate less than one may otherwise when it is known that the decision will not influence a partner's future decision-making process. In short, it makes sense to betray a teammate in the final round because he or she cannot betray a person back.

The results found by Andreoni (1993) are, in essence, similar to those found by Kingma (1989). They both find crowding-out to occur, albeit in differing severities. We

feel that the fundamental difference between the two levels of crowding-out found by Andreoni and Kingma can be explained by how aware of the tax donors are. The more aware they are that they are being taxed (i.e. already donating), more of their private donation will be crowded out. The less aware they are, the more they will donate voluntarily.

The method of taxation in the game is extremely similar to EWEB's model of mandatory surcharges on utility bills. Most crowding-out tests refer to government spending in general crowding-out private contributions, but in Andreoni's and EWEB's case, the mechanism for crowding-out is a tax going straight from a person's pocket towards the public good. As with the public radio example, government funding towards a public good is likely not treated the same way as a direct tax that goes entirely towards the public good. This experiment is as close to EWEB's situation as any we have seen, and its results are extremely relevant in our situation.

3. Data

As mentioned before, the data used in this paper comes from EWEB, the 2000 Census, and a combination of RLID and LCOG housing data. The census data was matched to the RLID/LCOG data on a block group level, a geographical division consisting of, in our case, anywhere from 215 to 990 households.

The first step we took was to merge our three data sets either by block group or street address. The data from EWEB was by far the smallest, with 30,562 observations. After merging that data with the RLID-LCOG-Census data by street address, we were able to allocate characteristics to about 11,000 of those 30,562 donors. There were also many donations coming from apartments, meaning we would be missing a lot of vital

data on these contributors, including our key income variable, house value. With no house values matched to these donations, we were forced to drop them from our regressions. In addition to entries not found in the RLID data, we were forced to drop several of the largest contributions because they came from P.O. Box addresses. However, some of these donations were over $30,000 each, meaning we probably would have dropped them anyway because it is likely they did not come from individuals, and also because including them might bias our results, making them less applicable to the smaller, more typical donations. It is unfortunate that we had to drop such a substantial portion of our donation data, but our initial sample was so large and comprehensive that we still have plenty of observations. The non-random nature of the deletions is a matter for concern, as there may be trends present in our dropped variable that would be worth examining if we had better data. Finally, we used the Consumer Price Index to inflate the contribution values from before 2005 to 2005 dollars, the year our house values were taken from. We also deflated 2006 contributions to the 2005 level. Putting dollar values in real terms is important because otherwise it would appear that contributions were growing more than they actually were, possibly shrinking our observed crowd-out effect.

We then created variables that would allow for easier interpretation, such as percent of households rented as opposed to total number of households rented. This would equalize statistics across block groups, making them legitimately comparable.

Furthermore, we created dummy variables for every year. This allows us to analyze trends by year, with 1999 being the base year. Knowing that the large rate increase occurred in 2001, a dummy variable allows us to determine the effect of the rate increase and subsequent surcharge on prices. It also creates a method to measure the

crowd-out effect that occurred, if any, from the 2001 switch in program funding. We also used the date of the most recent house sale, which came from our RLID data, to estimate the tenure of donors.

Finally, we created our variable that could best represent a donor's income. We figured this would be their house value from the RLID-LCOG data because it was recorded on an individual level. Matching it with our data from EWEB gave us plenty of observations to run regressions with. Then for regressions' sake, we created a variable for the log of the house values and also took house values divided by 100,000 and squared it so we could run quadratic regressions. Ultimately, our two most important variables were real donation values and house values. Their summary statistics, as well as the statistics for the most important Census variables are listed here.

Variable	Obs	Mean	Std. Dev.	Min	Max
Real Donations	30,204	38.01	48.3	0.01	1133.79
House Value	10,282	182,556	124828	54696	3,788,790
Median Age	241	37.9	7.4	19.6	71.3
Median Income	240	38,735.94	13342.3	7338	102,480
Percent Owned	224	65%	21%	2%	97%
Percent with Retirement Income	224	17%	8%	1%	50%

4. Methods

Before we began our regression analysis, we had many different beliefs on what we were going to see in our output tables. We considered the positive social benefit of charitable giving to be a normal good. A person with higher income would have a higher net marginal utility of providing for this public good, and therefore should donate more than a person with a low income. Assuming we were going to see a decrease in donations starting in 2001 due to the funding switch, we theorized about why this was going to happen. Obviously, there would be some sort of income effect. Donations were

bound to fall because each donor has less income than they did before the switch. However, we were interested in the cause behind any extra drop in donations, and subsequently the elasticity of this income effect. Before even looking at any regressions, we were predicting we would find less of the causality for falling donations in the income effect as we would in crowding-out, because the drop in income from a price increase of utilities would be extremely small relative to a person's yearly income.

When our data was finalized and we had made our hypotheses, we had to isolate the significant variables and run regressions with those. We figured our best regression would include the log of the total house value because it was our best approximation of income, and our dummy variables for years. The dummy variables require us to leave 1999 out of the regression, using it as a base year. The subsequent years' coefficients show us what happened to average donations relative to 1999, controlling for house value. The crowding-out hypothesis predicts we would see a large negative coefficient in 2001 with ambiguous effects from then on, showing the effect of the rate increase. Our dependent variable in most cases was going to be the log of real donations, plotted against our independent variables.

However, we also wanted to try a regression using linear, real donations plotted against linear house values and squared house values. This would give us a possible parabolic function relating income and donations.

5. Results

It is unfortunate that the characteristics attributed to donors may be an average of several hundred households, and ultimately the variables from the Census were much less significant than we had hoped. Median income, a variable which seems to be of obvious

significance, proved to be statistically significant but when viewed economically made little sense. Our results showed that for every $100,000 increase in median income for an entire block group, there would be a 2.45% increase in donations. However, when the highest median income for a block group is only $102,000 that result becomes economically insignificant. Other variables which we thought could be possible signifiers of a donor such as the median age and income of a block group, the percentage of the houses which are owned, and the percent of the block group who receives retirement income also proved to be of no significance. The following is our regression.

ldonreal	Coef.	Std. Err.	z	P>|z|
medianage	-.0027616	.0037614	-0.73	0.463
medianincome	5.67e-06	2.46e-06	2.31	0.021
pctowned	-.1124294	.1513933	-0.74	0.458
pctRetInc	-.1778058	.2849507	-0.62	0.533
_cons	3.160067	.0980067	32.24	0.000

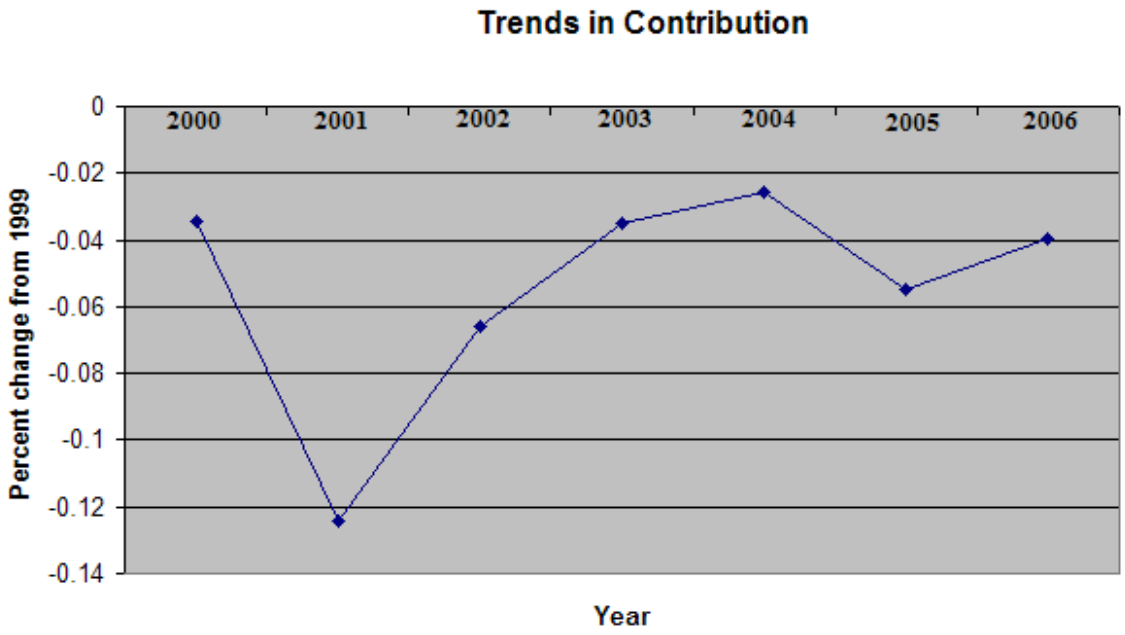
All of these variable were statistically insignificant except for median income, which is economically insignificant as the coefficient is too small to be realistically relevant. Along with median income, median age was surprising in providing no significance considering Kingma (1989) found age to be of significance. We feel that it is significant, despite our results, if only because of the positive relation between age and income. Our data did not turn out to be as helpful as we would have liked in attributing characteristics to donors due to the nature of block group data. Assigning average characteristics of several hundred households to the few observations actually found within that block group provided poor results in our analysis.

Kingma (1989) showed empirical evidence of crowding-out with his analysis of giving to public radio, and Andreoni (1993) demonstrated it experimentally. Our main regression plots the log of real donations against the log of house value and our seven

dummy variables for years in relation to 1999. Our findings agree with past findings and, again, we feel that our data is extremely strong. Our regression is as follows:

ldonreal	Coef.	Std. Err.	z	P>|z|
ltotval	.248057	.0382301	6.49	0.000
c00	-.0343694	.0154575	-2.22	0.026
c01	-.1241861	.0152957	-8.12	0.000
c02	-.0659682	.0151034	-4.37	0.000
c03	-.0352513	.015325	-2.30	0.021
c04	-.0257863	.0155667	-1.66	0.098
c05	-.0547614	.0158233	-3.46	0.001
c06	-.0394926	.0159924	-2.47	0.014
_cons	.2882426	.4605322	0.63	0.531

All of the variables from c00 to c06 are dummy variables where the numbers correspond to the year, i.e. c00 is a dummy for 2000 and c05 is a dummy for 2005. The base year for the dummy variables is 1999. This regression shows us one extremely important result; there was a noticeable crowd-out of donations in 2001, which was the year of the switch in program funding. Interpreting these results can be somewhat confusing, so it is important to keep them straight. Although the coefficient for each dummy variable is negative, we are not interested in their value alone, but their value relative to the years 1999 and 2001. It seems that donations were already falling in 2000, but dropped significantly in 2001 (12.4% to be specific). In general donations rose after that point, meaning that instead of being 12.4% below the 1999 donations, they were only 5.47% and 3.94% lower in 2005 and 2006, respectively.



The bottom line from this is that when the new funding method was introduced, donations were crowded out. The tax is, on average, equal to 1% of EWEB's total revenue each year and ends up raising over one million dollars annually. The crowding-out that occurred was not dollar-for-dollar, and is shown, by year (from 2000-2005), in this table.

Year	Tax Revenue	Total Donations	Mean Donations	Number of donors	Total Crowd-out	Percent Crowd-out
2000	0	146,000	41.82	3491	0	0%
2001	1370000	152,000	35.51	4275	27,000	1.97%
2002	1630000	168,000	31.34	5351	22,000	1.37%
2003	1600000	155,000	33.55	4623	- 10,000	- 0.64%
2004	1660000	142,000	40.72	3491	- 25,000	- 1.51%
2005	1690000	127,000	42.95	2968	- 7,000	- 0.39%

* Total crowd-out is in dollars, relative to the prior year.

As the table shows in the percent crowd-out column, the crowd-out effect was nowhere near dollar-for-dollar (if it were, percent crowd-out would be 100%). However, we must

also consider the fact that along with the change in the method of funding, there was also a 36% increase in the price of utilities. With no easy way to disentangle these two issues, we decided to look at the house value income elasticity to determine if the decrease in income caused by the rate increase would be significant enough to effect donations so drastically.

The house value elasticity was calculated to be .248, or for a 1% decrease in house value donations would fall by about .25%. This elasticity term is not quite as accurate as income elasticity would be because house value is just a proxy for income, but this is still sensible, and shows that the rather large decrease in donations in 2001 was not due to the rate increase. Although we cannot determine exactly what percentage change in a person's income the rate increase represents (because we do not know each donor's utility bill), its effect would not be large enough to create such a dramatic effect. For example, for the income effect to account for a 12% drop in donations, house value would have to depreciate by 48%, which is obviously unlikely. Additionally, in Lane County the median house value is around three times greater than the median income. So, in terms of our estimated income elasticity, a 1% decrease in a person's income should decrease his or her donation by about .75%.

Thus, our evidence for the crowd-out effect is sound, but much smaller than expected. We find that the switch in 2001 to mandatory contributions crowded out 1.97% of donations from the previous year.

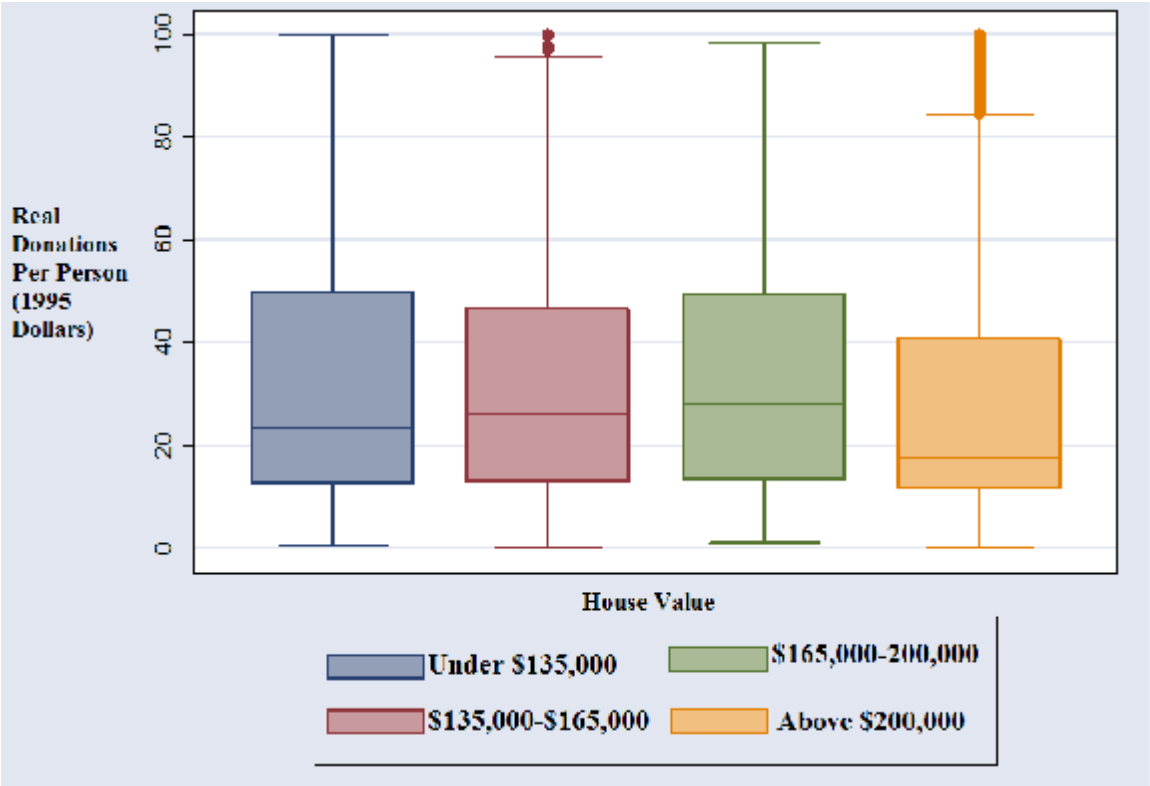
An additional regression we ran in a quadratic form allowed us to observe a curve in our house value to donation relationship which would not be possible with a linear regression. The regression plotted donations against house value plus squared

house value. The shape of our curve depended on the coefficient of our squared term. The results are as follows.

donreal	Coef.	Std. Err.	z	P>|z|
totval100k	6.215338	1.130398	5.50	0.000
sqdtotv~100k	-.1758636	.0453858	-3.87	0.000
cons	28.15813	2.108803	13.35	0.000

The negative coefficient on the squared term gives us a relatively flat, yet upside-down parabola, meaning that for our sample, an increasing house value increased donations to a certain point, after which donations fell as house value rose. This is an interesting shape, as a typically theorized shape for this relationship is a positive parabola, with middle incomes contributing the least. The curvature of the parabola in our regression is not extremely pronounced, but it is still interesting. Another way to look at our data in this way is through a box and whisker plot, which should show us a similar shape to the one our parabola estimates.

As predicted by our quadratic regression, donations slowly rose in mean as house value increased. Our plot divides the donors at the 25th, 50th, and 75th percentile, and surprisingly, the group with the lowest median donation was the group in the highest group of house values. This is illustrated in the following graph.



6. Conclusions

Our main regression showed us that there is a definite income effect in with these charitable donations. Additionally, donations in real dollars received dropped dramatically in 2001, but continued to rise each year after, although never reaching the 1999 level. This can be explained, as crowding-out would not just stop after the year the rates and funding were changed, but rather creates a lingering negative effect on donations as people slowly acclimate to the changes.

Ultimately, our crowd-out effect is smaller than it probably could have been, perhaps because of limited information. In Andreoni's (1993) experiment, it was extremely explicit that you were being taxed in order to provide a public good, so the crowding-out was severe. In Kingma's (1989) empirical analysis, it is unclear how aware the donors are of changes in government funding, but considering the relatively low level

of crowing-out compared to Andreoni, it seems they were not extremely conscious of the funding changes. Everybody could tell that rates were increasing in 2001, but not everybody knew about the mandatory surcharge placed on energy prices. Therefore, for some donors, the only effect we would see is an income effect that might be interpreted as crowd-out. If EWEB had made the funding switch better known, we predict we would have seen a larger crowd-out effect, so it was in the best interest of the community not to.

Without the presence of useful Census data, it is difficult to pinpoint any certain areas EWEB could target when looking for donations. Even income is not a fantastic measure of how much a person will donate, as shown by our parabolic function where people with extremely high incomes donated less than people with incomes slightly lower. Substantial generosity can come from the unlikeliest of places, so a possible donor can never be ruled out based solely on income or other statistics. EWEB is doing a very good job of raising funds for the Customer Care program, thanks to the tax. An article from the Eugene Register Guard, published on Sept. 3, 2003, it explains that EWEB raises an adequate of money for the program, but the difficulty lies in distributing it to those in need. The article reports that in 2002 EWEB wished to help around 8,000 households but only ended up reaching about 4,900 of them (Maben). Knowing this, it seems the real problem lies in finding the people for the money to go towards. We focused solely on the supply side of the donation question, but it seems that the demand side definitely deserves further consideration. Our paper provides a strong analysis of the crowd-out effect as well as support for warm glow theory, but in future research it may prove more useful to EWEB if an analysis were conducted concerning the best way to

reach out to those in need. Doing that seems to be an issue which could more greatly benefit the Customer Care program than increasing total funding.

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