Division of Economics
A.J. Palumbo School of Business Administration
Duquesne University
Pittsburgh, Pennsylvania

# DO FOOD STAMPS BENEFITS CROWD OUT CONTRIBUTIONS TO FOOD-RELATED CHARITIES?

John Ricco

Submitted to the Economics Faculty
in partial fulfillment of the requirements for the degree of
Bachelor of Science in Business Administration

December 2013

Faculty Advisor Signature Page

Matt E. Ryan, Ph.D. Date
Assistant Professor of Economics

*Previous studies indicate that welfare benefits partially crowd out charity. This research, however, does not present a thorough analysis of non-religious charities and does not disaggregate welfare benefits into specific programs. To address these two shortcomings, I exploit a provision of the 1996 welfare reform law to identify the causal impact of Food Stamps benefits on contributions to food-related charities. The results suggest that the crowd-out effect was between 7 and 16 cents on the dollar in counties with active food-related charities. This finding is robust to a variety of specifications.*

JEL classifications: H40, H53, I38

Keywords: Crowd-out, Food Stamps, SNAP, charity

## Table of Contents

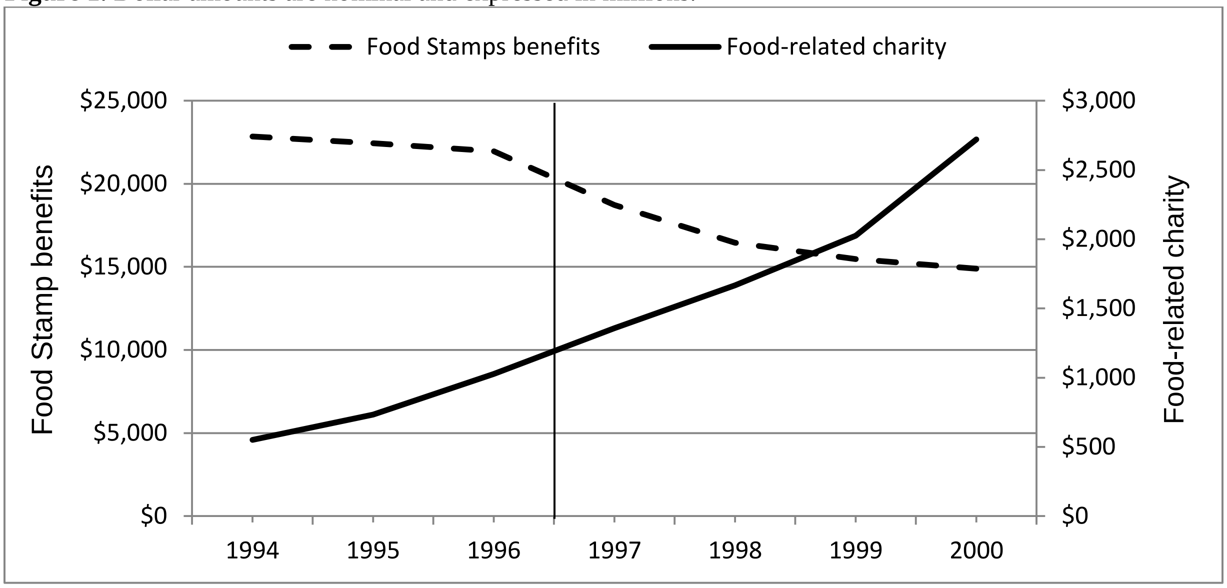
## I. Background

Both governments and charities provide services aimed at helping the poor. Governments finance such services through taxation, whereas charities mainly rely on private donations to fund their endeavors. If donors view their contributions to charity and taxpayer-funded welfare spending as substitutes, they might respond to increases in welfare spending by reducing their contributions to charity—that is, welfare programs may crowd out private giving. Because the net provision of charitable activities in an economy ultimately depends on the magnitude of crowd-out, it is useful to measure this effect (Gruber, 2007, p. 195).

One major welfare program in the United States is the Supplemental Nutrition Assistance Program (SNAP), formerly known and henceforth referred to as Food Stamps. This program aims to alleviate hunger among America's poor by subsidizing food purchases for eligible individuals and families. At the same time, there is a large network of food-related charities that offer services which are comparable to those provided by the Food Stamps program. Among these charities are food banks and pantries, soup kitchens, Meals on Wheels programs, and congregate meals, all of which offer low- or no-cost food to the disadvantaged.

While many researchers have examined government crowd-out of private giving, I am the first to explore the relationship between Food Stamps and food-related charities. Using county-level panel data, I empirically address the following question: To what extent does government spending on Food Stamps crowd out contributions to food-related charities? To answer this, I follow Hungerman (2005) and exploit a natural experiment that unfolded in the mid-1990s: The curtailing of welfare spending under the Personal Responsibility and Work Opportunity Reconciliation Act of 1996. Figure 1 shows that from 1994 to 2000 (the years covered in this analysis), Food Stamps benefits decreased while contributions to food-related charities more than quadrupled.

**Figure 1.** Dollar amounts are nominal and expressed in millions.




Of course, other factors may have contributed to these trends. Because unobservable phenomena (such as economic conditions and shocks) may simultaneously drive contributions to charity and welfare spending, ordinary least squares (OLS) estimates of the crowd-out effect may suffer from endogeneity bias. Following the crowd-out literature, I address this problem by employing an instrumental variables method. Specifically, I follow Hungerman (2005) and utilize a provision of the 1996 welfare reform law—immigrants' sudden ineligibility for welfare benefits—to instrument for Food Stamps spending. The results provide evidence for partial crowd-out: In counties with active networks of food-related charity, an additional dollar of cuts to Food Stamps benefits in the mid-1990s was met with a 7 to 16 cent increase in contributions to these charities. This finding is robust to a number of specifications.

This paper proceeds as follows: Section II provides an overview of the crowd-out literature, Section III considers the data and the empirical strategy, Section IV presents regression results, and the analysis concludes with Section V.

## II. Literature Review

Although the crowd-out literature is extensive, researchers have yet to reach a consensus regarding the relationship between governments and charities.  Theoretical and empirical estimates of the crowd-out effect range from complete crowd-out to crowd-in. In this section, I first review the theoretical literature; I then survey past empirical work, breaking down the literature by type of study (government grant crowd-out vs. welfare crowd-out).

### *II.A. Theoretical Research*

Early theoretical models of crowd-out predict that government contributions to a public good totally displace private contributions (Warr, 1982; Roberts, 1984). That is, in the context of charity, an additional dollar of either government grants to charities or welfare spending leads to a one dollar decrease in private contributions to charity. As argued by Andreoni (1988), the extreme result of complete, one-for-one crowd-out is driven by the untenable assumption of perfectly altruistic agents.

Andreoni (1989, 1990) models a different motive for giving. He assumes that agents derive utility from the act of giving itself, an effect he dubs warm glow. Under this assumption, the crowd-out effect is partial, meaning that an increase in government contributions to a public good reduces private contributions by an amount less than the increase. Hungerman (2009) extends the warm glow model to include the effect of diversity and finds ambiguous results: Depending on how diversity influences warm glow, crowd-out may be large or small.

Lastly, other theoretical work focuses on the confounding role of fundraising. Andreoni and Payne (2003) find that charities respond to government grants by reducing fundraising efforts which in turn reduces private contributions. This is distinct from the classic theory of crowd-out in which donors give less because they have already contributed through taxes. Dokko

(2009) extends this model to include warm glow giving and finds that crowd-out may be either large or small depending on donors' search costs.

*II.B Empirical Research: Government Grant Crowd-Out*

One category of empirical crowd-out research is concerned with the effect of government grants to charities on private contributions. Some researchers narrow their focus to specific types of charities (Kingma, 1989; Payne, 1998; Dokko, 2009); others employ datasets that include various types of organizations (Andreoni and Payne, 2011; Heutel, forthcoming). The results vary widely, ranging from Andreoni and Payne's estimate of 72 percent crowd-out to Heutel's finding of modest crowd-in. It is worth noting that Andreoni and Payne (2003, 2011) and Dokko (2009) quantify the aforementioned role of fundraising, finding evidence that charities do in fact respond to government grants by reducing fundraising efforts, and that this explains a substantial portion of the crowd-out effect.

*II.C. Empirical Research: Welfare Crowd-Out*

The other side of the empirical literature is concerned with the effect of welfare spending on private giving.  Using broad measures of government transfers and private contributions to charity, Abrams and Schmitz (1979, 1984) provide early estimates of about 30 percent crowd-out. Lindsey and Steinberg (1990) look at the relationship between federal grants to states, state spending, and charity, and find evidence for crowd-in.

Recent research emphasizes finding causal relationships in the face of endogeneity; these papers make use of instrumental variables techniques for identification. Schoeni (2002) examines the effect of unemployment insurance benefits on private familial transfers to the unemployed and finds a crowd-out effect of 28 to 40 percent. Other research uses major changes in welfare laws to test the substitutability of charitable activity undertaken by religious organizations and welfare benefits (Hungerman, 2005 & 2009; Gruber and Hungerman, 2007). Such papers find evidence for partial crowd-out ranging from 3 to 38 percent. However, it is unclear whether these results can be extrapolated to non-religious charitable organizations. Also, with the exception of Hungerman (2009), these studies do not disaggregate welfare benefits into specific programs. I address these shortcomings of the literature in this paper.

## III. Methodology

### *III.A Data*

In this analysis, I employ a county-level panel dataset covering the years 1994-2000. The charity data come from the National Center for Charitable Statistics (NCCS), a nonprofit information repository. All 501(c)(3) organizations are required to publicly disclose financial information by means of filing a Form 990 tax return; the NCCS digitizes and houses the data contained in these forms.[1] I use data from the NCCS's Core Files database which includes all 501(c)(3) organizations with gross receipts of at least $50,000 and select organizations that do not meet that threshold.

There are three primary limitations regarding the nature of the charity data. First, the NCCS's sampling methodology for the organizations with gross receipts less than $50,000 dollars is unclear. If smaller charities are systematically underrepresented in my dataset, and if such charities experience crowd-out of a different magnitude than larger organizations, then regression estimates may be biased; however, the direction of any bias cannot be determined *a priori.* Second, charities report financial data by fiscal year whereas government data on welfare, demographics, and economic conditions is reported by calendar year. Fortunately, a large

[1]IRS definition of a 501(c)(3) organization: "The exempt purposes set forth in section 501(c)(3) are charitable, religious, educational, scientific, literary, testing for public safety, fostering national or international amateur sports competition, and preventing cruelty to children or animals."

majority of charities begin their fiscal year in January (the median fiscal year beginning month in the dataset is January; the mean is March), so matching fiscal years to calendar years should not be problematic (for instance, if a charity's fiscal year begins in March of 1994, it is matched with explanatory data from the calendar year 1994). Lastly, while I am more concerned with the impact of Food Stamps benefits on *private* contributions to food-related charities, the NCCS's Core Files database does not disaggregate contributions into public support (private contributions) and government support (government grants). Therefore, I am technically only able to estimate the impact of Food Stamps benefits on *all* contributions, and I potentially introduce omitted variable bias if grants are a determinant of private contributions. However, this is not particularly worrying for two reasons. First, there is an economic argument to be made for including grants in the dependent variable: It may be that welfare benefits crowd out the need for governments to directly support charity. Second, an analysis of more complete data from 1998-2003 suggests that on average, government grants are only one-tenth the size of private contributions.

In order to define food-related charity, I use definitions from the National Taxonomy of Exempt Entities (NTEE), a classification system used by the IRS to categorize nonprofits. The dataset includes organizations with NTEE codes K30, K31, K34, K35, and K36. Descriptions of these codes can be found in Table 1.

**Table 1.** Descriptions of NTEE codes. Descriptions from NTEE's website.

| NTEE Code | Description |
|---|---|
| K30 | *General/undefined food-related charities*: "Organizations (not specified by the codes below) that provide access to low- or no- cost food products to children, seniors, or indigents by distributing groceries, providing meals, providing facilities for storing food or making available land on which people can grow their own produce." |
| K31 | *Food banks/pantries*: "Organizations that gather, store and distribute food to indigents at no charge or at low cost." |
| K34 | *Congregate meals*: "Organizations (also known as nutrition sites or senior nutrition programs) that provide hot meals on a regular basis, usually for elderly individuals but also for disabled adults or other target populations." |
| K35 | *Soup Kitchens*: "Organizations that provide meals in a central location for indigent people." |
| K36 | *Meals on wheels:* "Organizations that prepare and deliver regular hot meals to elderly individuals, people with disabilities or people with AIDS or other targeted conditions who are unable to shop and/or prepare food for themselves or to travel to a site where a meal is being served. Also known as home delivered meals." |

Food Stamps data come from the USDA and are available for approximately 95 percent of all counties. I also include a number of relevant covariates: demographic controls (percent over the age of 65, percent black, and percent Hispanic), educational attainment controls (percent without a high school degree and percent with a four year college degree), economic controls (per-capita income and unemployment rate), and other welfare spending that might influence food-related charity (Temporary Assistance to Needy Families [TANF] benefits).[2] Data for these covariates come from the Census Bureau, the Bureau of Economic Analysis, and the Bureau of Labor Statistics. In addition to the counties for which Food Stamps data is unavailable, I drop three counties with incomplete census data (0.014% of all observations), resulting in a sample of 20,727 county-year observations. Lastly, TANF benefits are left-censored at $50,000—there are 18 such county-year observations (0.45%) contained in the sample used in the main regressions. I consider these values to be zero.

*III.B Empirical Strategy*

I estimate various specifications of the following model:

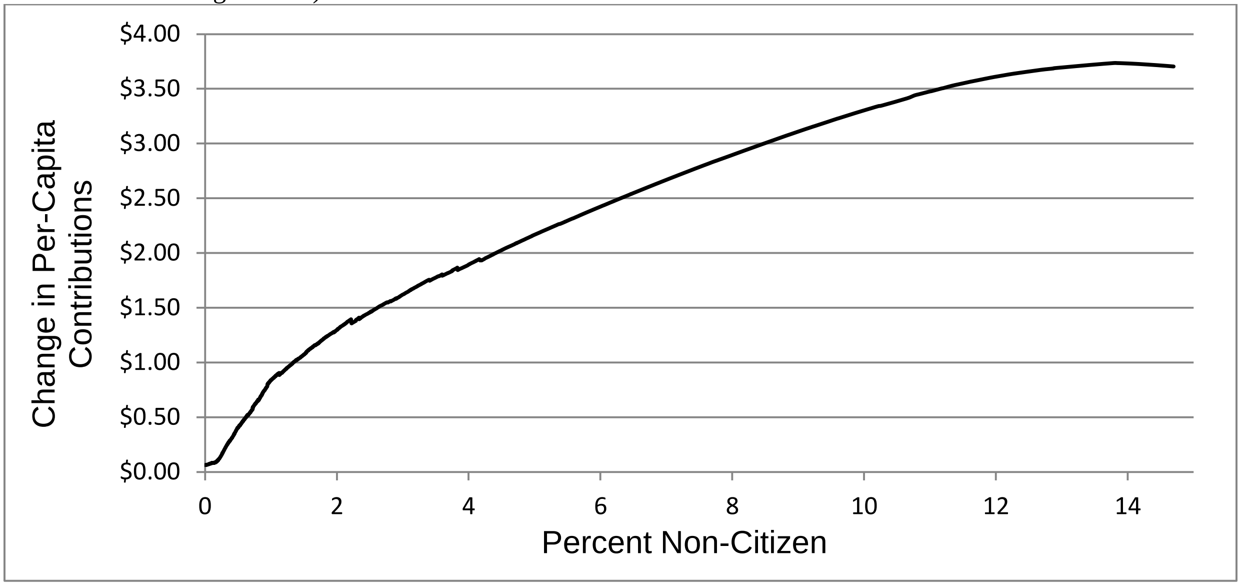
[2] Before the welfare reform, TANF was called Aid to Families with Dependent Children (AFDC).

$$CONT_{it} = \alpha + \beta_1 FS_{it} + \beta_2 X_{it} + e_{it}$$

where $CONT_{it}$ is per-capita contributions to food-related charities located in county *i* in year *t*, $FS_{it}$ is per-capita Food Stamps benefits received by individuals and families who live in county *i* in year *t*, and $X_{it}$ is a set of control variables for county *i* in year *t*. The coefficient of primary interest is $\beta_1$; a negative value indicates crowd-out.

One of the foremost problems in the crowd-out literature is endogeneity—it is likely that that unobserved factors impact both welfare benefits and charity. For instance, if a county experiences a natural disaster, it would ostensibly see an increase in both welfare benefits and contributions to charities located in that area. Because it is difficult to account for such phenomena, estimates obtained using OLS might be biased and inconsistent. If this is the case, a two stage least squares (2SLS) regression is preferable. To instrument for Food Stamps benefits, I follow Hungerman (2005) and make use of a provision of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA). A provision of this reform restricted immigrant eligibility for a number of major welfare programs, Food Stamps included. After suddenly losing eligibility, non-citizens might have turned to food-related charities for help. Figure 2 suggests that, at the very least, this was a possibility: Counties with larger shares of non-citizens experienced greater increases in charity relative to counties with smaller shares of non-citizens.

**Figure 2.** The relationship (LOWESS-smoothed curve) between non-citizen population and change (average after reform minus average before) in contributions to food-related charities.[3]




As such, I use the percent of the population that is non-citizen interacted with a dummy variable indicating whether the law was in effect as an instrument for Food Stamps benefits. The first stage of the two-stage process is:

$$FS_{it} = \alpha + \beta_1(NC_{it})(D_1) + \beta_2 X_{it} + e_{it}$$

where $NC_{it}$ is the percent of the population that is non-citizen in county *i* in year *t* and $D_1$ is the aforementioned dummy variable for which a value of one is assigned to years 1997-2000.

In order for this strategy to be valid, non-citizens must have been disproportionately affected by the welfare reform. A provision of PRWORA made it such that most non-citizens lost eligibility for Food Stamps and TANF. The restrictions for Food Stamps, as shown in Table 2, were severe.

[3] Although there are counties with percent non-citizen values greater than 15, such observations are not included in Figure 2 as they are extreme and represent far less than 1% of the sample.

**Table 2.** Food Stamps eligibility restrictions. Information from Zimmerman and Tumlin (1999).

| Type of Non-Citizen | Eligibility before PRWORA | Eligibility after PRWORA |
|---|---|---|
| Refugees/Asylees | Eligible | Eligible |
| Legal Permanent Residents | Eligible | If arrived after law, ineligible. If arrived before law, ineligible except if under 18, over 64, or disabled. |
| Undocumented immigrants | Ineligible | Ineligible |

Participation in the Food Stamps program among non-citizens declined in response to these new rules. Due to the generally restrictive nature of PRWORA, the number of all poor households receiving Food Stamps benefits declined by 15 percent from 1994 to 1997. Yet for poor households headed by a non-citizen, this figure was 27 percent (Fix and Passel, 1999).[4] This suggests that PRWORA's restrictions on immigrant eligibility led to considerably less use of Food Stamps benefits among non-citizens, a result that is confirmed in other research (Capps, 2001; Haider et al, 2004). For a lengthier discussion regarding the theoretical justification of this specific instrumental variables method, see Hungerman (2005).

A final consideration regarding the empirical strategy is how to address the abundance of counties that do not have food-related charities during the years covered in this analysis. Of the total 2,961 counties, only 27 percent report at least one year of a nonzero value for contributions (such observations are henceforth referred to as the mid-sized sample); 19 percent report nonzero values for all seven years (small sample). Theoretically, the zeros might be an indication of complete crowd-out—there may be a level of Food Stamps benefits at which food-related charities are fully crowded out and do not provide any services. Because the distribution of the dependent variable is highly skewed due to the excess of zeros, traditional estimation techniques are not possible with the full dataset. A conservative approach is to use the small sample, qualify

[4] Poor is defined as income being less than 200 percent of the poverty level.

the interpretation of results (making clear that this estimate of crowd-out only applies to counties where complete crowd-out did not occur), and perform robustness checks using more expansive datasets.

## IV. Results

### *IV.A Summary Statistics*

Summary statistics of the variables in both the small sample and the full dataset can be found in Table 3. Monetary values are converted to year 2000 dollars and are expressed in per-capita terms.

**Table 3.** Means with standard errors shown in parentheses.

| Variable | Small Sample | Mid-Sized Sample | Full Dataset |
|---|---|---|---|
| Contributions to food-related charities | 7.14 (0.21) | 5.69 (0.16) | 1.54 (0.04) |
| Food Stamps benefits | 70.66 (0.74) | 73.23 (0.66) | 80.71 (0.40) |
| Fundraising expenses | 0.13 (0.01) | 0.10 (0.01) | 0.02 (0.00) |
| Percent over the age of 65 | 13.21 (0.06) | 13.34 (0.05) | 14.67 (0.02) |
| Percent non-citizen | 3.52 (0.06) | 3.08 (0.05) | 1.85 (0.02) |
| Percent Black | 9.17 (0.18) | 9.12 (0.16) | 8.91 (0.10) |
| Percent Hispanic | 7.58 (0.18) | 6.99 (0.15) | 5.71 (0.08) |
| Percent without a high school diploma | 19.9 (0.11) | 21.08 (0.10) | 25.17 (0.06) |
| Percent with at least a 4 year degree | 21.97 (0.13) | 20.58 (0.11) | 15.45 (0.05) |
| Income (in thousands of dollars) | 19.78 (0.07) | 19.12 (0.06) | 16.73 (0.02) |
| Unemployment Rate | 4.84 (0.03) | 5.00 (0.03) | 5.54 (0.02) |
| TANF benefits | 61.19 (0.94) | 57.76 (0.75) | 47.57 (0.35) |

The small sample contains 4,011 county-year observations, mid-sized contains 5,621, and the full dataset contains 20,712.

### *IV.B Main Results*

Table 4 presents information regarding the main regression results:

**Table 4.** Main results. Driscoll-Kraay standard errors are used. County and year dummies are included. P-values are reported in parentheses.

| **Variable** | **(1)<br>OLS** | **(2)<br>First stage** | **(3)<br>Second stage** |
|---|---|---|---|
| Food Stamps benefits | -0.069 *(0.000)* | -- | -0.164 *(0.058)* |
| Percent non-citizen * post-96 dummy | -- | -1.164 *(0.010)* | -- |
| Fundraising expenses | 0.225 *(0.044)* | -0.309 *(0.003)* | 0.196 *(0.038)* |
| Percent over the age of 65 | -0.898 *(0.000)* | 2.107 *(0.002)* | -0.628 *(0.034)* |
| Percent Black | 1.391 *(0.001)* | -4.96 *(0.000)* | 0.984 *(0.037)* |
| Percent Hispanic | -1.234 *(0.001)* | 0.460 *(0.260)* | -1.282 *(0.001)* |
| Percent non-citizen | 1.528 *(0.003)* | -1.693 *(0.015)* | 1.218 *(0.034)* |
| Percent without a HS diploma | 1.298 *(0.000)* | 3.586 *(0.001)* | 1.519 *(0.000)* |
| Percent with at least a 4 year degree | 2.095 *(0.000)* | 6.475 *(0.001)* | 2.624 *(0.000)* |
| Income (in thousands of dollars) | -2.236 *(0.000)* | -0.297 *(0.897)* | -2.168 *(0.001)* |
| Unemployment Rate | 0.483 *(0.036)* | 2.263 *(0.003)* | 0.742 *(0.053)* |
| TANF benefits | 0.001 *(0.910)* | 0.095 *(0.011)* | 0.012 *(0.291)* |
| F statistic | 2,631 | 2,788 | 909 |
| R^2 | 0.13 | 0.76 | 0.12 |
| N | 4011 | 4011 | 4011 |

The dependent variable is per-capita contributions to food-related charities. The results are robust to heteroskedasticity, serial correlation, and cross sectional dependence (tests for these anomalies can be found in Appendix A). Regression (1) shows the results for an OLS model with fixed effects. The Food Stamps benefits coefficient is significant and negative, suggesting that this program partially crowds out contributions to food-related charities (a more complete interpretation of this result is considered later in this subsection). The coefficients for the covariates follow intuition. Counties with more fundraising expenses, racial and ethnic minorities, unemployment, and a population with unequal educational attainment see higher levels of contributions to food-related charities; additional income and older populations are associated with less giving. TANF benefits have a practically negligible impact.

As discussed in Section III.B, even after using county and year dummies to account for unobserved heterogeneity, the OLS regression might provide incorrect estimates if Food Stamps is endogenous. To test for endogeneity empirically, I use a form of the Durbin-Wu-Hausman test for panel data as described by Davidson and MacKinnon (1993). The test (the null hypothesis is that OLS provides consistent estimates) returns a p-value of 0.069; a case can be made for either rejecting or failing to reject the null hypothesis depending on which significance level is chosen. Because endogeneity is a major theoretical concern, and because past research always does so, I report 2SLS results.

Regression (2) contains the first stage results where Food Stamps benefits is the dependent variable. The instrument is significant and negative, indicating that counties with larger shares of non-citizens saw relative declines in Food Stamps benefits after PRWORA was passed. Additionally, this instrumental variables approach appears to satisfy validity and relevance criteria. The Hansen-J-statistic of 0 demonstrates exact identification, and the F-statistic in the first stage (2,788) suggests it is not weak. Regression (3) reports the second stage results of the 2SLS model. As was the case in the OLS regression, the estimate for Food Stamps benefits is negative; however, it is marginally significant at the 5 percent level in this model. Signs of the coefficients for covariates are unchanged. TANF is insignificant—this suggests that donors who give to food-related charities respond to changes in Food Stamps benefits but do not respond to changes in other welfare programs, providing evidence that crowd-out occurs because donors view these as substitutes.

How should the crowd-out effect be interpreted here? The results suggest that all else equal, in counties with active food-related charities, an additional dollar of cuts to Food Stamps benefits in the mid-1990s was met with a 7 to 16 cent increase in contributions to these charities.

This estimate of partial crowd-out is well within the range of previous researchers' findings. Context is crucial, however. Because this analysis uses only a portion of all counties, the crowd-out effect for the counties without food-related charities should not be assumed to be the same; I address this in further detail in Section IV.C. Moreover, while I examine crowd-out in the context of an exogenous decrease in welfare spending, most studies examine the impact of *increases* in welfare benefits; donors might respond differently to these scenarios. Nonetheless, these results indicate that donors view welfare and charity as substitutes.

*IV.C Robustness Checks*

In this subsection, I consider a number of alternative models in order to evaluate the robustness of the main results. First, one of the principle implications of the main specification is that food-related charity is influenced by Food Stamps only, not TANF. However, it may be the case that TANF is endogenous as well, and that failing to instrument for this variable in the 2SLS model is driving this result. While the fixed effects OLS model suggests this is not the case (Food Stamps is negative and significant; TANF has a marginally significant coefficient very close to zero), this is a possibility worth exploring.

There are a number of ways to address this. It is important to note that including two endogenous variables in a single equation requires more instruments. Before attempting to use more than one instrumental variable, I employ two strategies that circumvent the practical difficulties associated with multiple endogenous variables. First, I consider models in which the single endogenous variable is combined welfare benefits (the sum of Food Stamps and TANF benefits). The idea behind this approach is that if TANF does not influence contributions to food-related charities, then the coefficient will be biased towards zero. Second, I run a regression in which the only endogenous variable is TANF benefits; such a model might reveal that the main results are driven by selectively choosing to instrument for Food Stamps and not TANF. Table 5 contains information regarding the results of these regressions.

**Table 5.** Aggregated welfare and TANF-only results. Driscoll-Kraay standard errors are used. County and year dummies are included. P-values are reported in parentheses.

| **Variable** | **(1) Welfare: OLS** | **(2) Welfare: 2SLS** | **(3) TANF endogenous** |
|---|---|---|---|
| Combined welfare benefits | -0.026 *(0.029)* | -0.071 *(0.061)* | -- |
| TANF benefits | -- | -- | -0.089 *(0.106)* |
| Food Stamps benefits | -- | -- | -0.050 *(0.001)* |
| Fundraising expenses | 0.235 *(0.043)* | 0.214 *(0.038)* | 0.210 *(0.041)* |
| Percent over the age of 65 | -0.907 *(0.000)* | -0.531 *(0.098)* | -0.510 *(0.095)* |
| Percent Black | 1.637 *(0.001)* | 1.586 *(0.001)* | 1.710 *(0.001)* |
| Percent Hispanic | -1.217 *(0.001)* | -1.252 *(0.001)* | -1.240 *(0.001)* |
| Percent non-citizen | 1.800 *(0.002)* | 1.952 *(0.001)* | 2.110 *(0.001)* |
| Percent without a HS diploma | 1.104 *(0.000)* | 0.996 *(0.000)* | 0.880 *(0.024)* |
| Percent with at least a 4 year degree | 1.785 *(0.000)* | 1.869 *(0.000)* | 1.700 *(0.002)* |
| Income (in thousands of dollars) | -2.02 *(0.001)* | -1.434 *(0.059)* | -1.270 *(0.113)* |
| Unemployment Rate | 0.425 *(0.043)* | 0.676 *(0.052)* | 0.660 *(0.048)* |
| F statistic | 2,303 | 1,764 | 5,170 |
| R^2 | 0.12 | 0.52 | 0.13 |
| N | 4011 | 4011 | 4011 |

The coefficients for Food Stamps benefits in regressions (1) and (2) are less than half of what they are in the respective main models. This suggests that including TANF benefits biases the estimate towards zero, providing evidence that Food Stamps is the program driving the crowd-out. In regression (3), TANF is insignificant. Moreover, Food Stamps is negative and significant which was not the case for TANF in the main results. These results suggest that food-related charity is crowded out by Food Stamps but not other forms of welfare.

A final means of testing whether food-related charity responds only to Food Stamps is to model both programs as endogenous. Again, this approach requires at least one more instrumental variable. Although many of PRWORA's provisions were at the federal level, the law made it such that states were given certain liberties with administering welfare dollars. One such example is that states could exercise considerable freedom in developing TANF sanctions policies; that is, states controlled the extent to which recipients were penalized for failing to adhere to compliance requirements. Pavetti and Bloom (2001) examine state sanctions policies and classify each state into one of three categories: stringent, moderate, and lenient. As such, I use dummy variables indicating the sanctions policy of the state in which the county is located—conditional upon the law being in effect—as additional instruments. This strategy has merit in theory: Sanctions policies should influence welfare benefits (Rector and Youssef (1999) find evidence that this is the case) but not contributions to food-related charities. Table 6 contains results for a regression in which both Food Stamps and TANF benefits are treated as endogenous.

**Table 6.** Both Food Stamps and TANF are endogenous. Driscoll-Kraay standard errors are used. County and year dummies are included. P-values are reported in parentheses.

| **Variable** | **(1)**<br>**Food Stamps & TANF endogenous** |
|---|---|
| Food Stamps benefits | -0.098 *(0.066)* |
| TANF benefits | -0.036 *(0.136)* |
| Fundraising expenses | 0.210 *(0.040)* |
| Percent over the age of 65 | -0.611 *(0.049)* |
| Percent Black | 1.379 *(0.002)* |
| Percent Hispanic | -1.258 *(0.001)* |
| Percent non-citizen | 1.673 *(0.002)* |
| Percent without a HS diploma | 1.194 *(0.000)* |
| Percent with at least a 4 year degree | 2.126 *(0.000)* |
| Income (in thousands of dollars) | -1.766 *(0.011)* |
| Unemployment Rate | 0.668 *(0.054)* |
| F statistic | 1,355 |
| R^2 | 0.12 |
| N | 4011 |

First, are these instruments relevant and valid? In each first stage regression, the F statistics are large (1,166 and 1,445) and every instrument is individually significant and the 1% level. A Hansen J test, however, produces a marginally significant test statistic (p-value of 0.0645), suggesting that these instruments may not provide an exogenous source of variation. For reasons stated above this seems theoretically unlikely, but at any rate these results should be interpreted with caution. Regression (1) provides further evidence that Food Stamps benefits crowd out contributions to food-related charities and that TANF benefits do not. On the whole, these robustness checks suggest that food-related charity responds more strongly to changes in Food Stamps benefits than to TANF benefits.

A second concern surrounding the main findings is whether the results can be extrapolated to counties beyond those that had nonzero charity values across all seven years. As previously mentioned, the nature of the charity data makes it difficult to obtain estimates for all counties. While it may be impossible to use traditional techniques to estimate the magnitude of crowd-out in counties that do not have food-related charities (i.e. counties where complete crowd-out may have occurred), it is possible to broaden my sample and still use OLS and 2SLS. As such, I perform robustness checks using the mid-sized sample (counties that have at least one year of nonzero contributions). Table 7 contains information regarding these regressions.

**Table 7.** Results using mid-sized sample. Driscoll-Kraay standard errors are used. County and year dummies are included. P-values are reported in parentheses.

| Variable | (1)<br>OLS | (2)<br>2SLS |
|---|---|---|
| Food Stamps benefits | -0.058 (0.001) | -0.242 (0.044) |
| Fundraising expenses | 0.283 (0.049) | 0.225 (0.056) |
| Percent over the age of 65 | -0.669 (0.000) | -0.173 (0.587) |
| Percent Black | 1.158 (0.003) | 0.634 (0.104) |
| Percent Hispanic | -0.877 (0.001) | -0.965 (0.002) |
| Percent Non-citizen | 0.911 (0.012) | 0.405 (0.368) |
| Percent without a HS diploma | 0.988 (0.000) | 1.460 (0.001) |
| Percent with at least a 4 year degree | 1.860 (0.000) | 2.835 (0.001) |
| Income (in thousands of dollars) | -1.548 (0.000) | -1.467 (0.001) |
| Unemployment Rate | 0.265 (0.124) | 0.677 (0.070) |
| TANF benefits | 0.002 (0.757) | 0.026 (0.075) |
| F statistic | 451 | 1,387 |
| R^2 | 0.09 | 0.09 |
| N | 5621 | 5621 |

These results are broadly consistent with those of the main specification (in which the small sample is used). If we are to believe that Food Stamps is endogenous and that fixed effects cannot address the full extent of unobserved heterogeneity, the crowd-out effect in the mid-sized sample appears to be about 24 cents on the dollar, somewhat larger than the result of the main specification. Moreover, this specification provides further evidence that donors respond to changes in Food Stamps benefits but not TANF benefits. Thus, it is safe to say that the findings of the main specification can be extrapolated to a broader sample of counties.

Finally, I consider the possibility that there is a lag in donors' responses to changes in Food Stamps benefits. It is reasonable to think that it might take time for donors to learn about funding for Food Stamps or the extent of food insecurity in a community. The results of regressions that use lagged explanatory variables can be found in Table 8.

**Table 8.** Lagged variables regressions. Driscoll-Kraay standard errors are used. County and year dummies are included. P-values are reported in parentheses.

| Regression Number | OLS or 2SLS? | Small or mid-sized sample? | Number of lagged periods | Food Stamps coefficient |
|---|---|---|---|---|
| (1) | OLS | Small | 1 | -0.062 *(0.002)* |
| (2) | OLS | Small | 2 | -0.053 *(0.002)* |
| (3) | OLS | Mid-sized | 1 | -0.057 *(0.001)* |
| (4) | OLS | Mid-sized | 2 | -0.055 *(0.000)* |
| (5) | 2SLS | Small | 1 | -0.096 *(0.271)* |
| (6) | 2SLS | Small | 2 | -0.108 *(0.125)* |
| (7) | 2SLS | Mid-sized | 1 | -0.155 *(0.143)* |
| (8) | 2SLS | Mid-sized | 2 | -0.149 *(0.069)* |

The fourth column provides the crowd-out estimates for each model. The results are mixed: While the OLS specifications suggest that there is a lag in donors' responses to changes in Food Stamps benefits, the 2SLS results are insignificant. However, it appears as if OLS is the correct model to use in this case. Durbin-Wu-Hausman tests of exogeneity indicate that the OLS parameters are consistent, perhaps because lagging Food Stamps circumvents any endogeneity issues. At any rate, these results suggest that it may take time for donors to respond to changes in Food Stamps benefits.

## V. Conclusion

The purpose of this analysis was to determine whether Food Stamps benefits crowd out contributions to food-related charities. Because an OLS model would likely suffer from endogeneity bias, I employ a 2SLS method and use a provision of the 1996 welfare reform law as a means of disentangling causation. Specifically, I use the percent of non-citizens to instrument for Food Stamps benefits. The main results and subsequent robustness checks indicate that contributions to food-related charities increased in response to cuts to Food Stamps benefits, and that magnitude of the crowd-out effect in counties with active charities was between 7 and 16 cents on the dollar.

Do these results have implications for the current policy landscape? On November 1st 2013, a provision of the 2009 stimulus bill that increased funding for Food Stamps expired, leading to material cuts in benefits for the program's recipients. According to the Center on Budget Policy and Priorities, households of four enrolled in Food Stamps saw $36 reductions in monthly benefits on average. Given the findings of this analysis, if we consider Food Stamps benefits and services provided by food-related charities to be similar, the net reduction for a family of four who lives in a county with an active food-related charity might be closer to $30.

Future research should focus on addressing the empirical limitations of this study. Specifically, more expansive charity data that differentiates between private donations and government grants might help researchers gain a better understanding of the relationship between welfare and charity. Additionally, a more complex analysis of the entire dataset would provide a fuller understanding of crowd-out. Perhaps a Heckman sample selection model is a possible avenue for further exploration.

Future research should also concern itself with quantifying the importance of context. For example, one unaddressed possibility is that donors and charities respond differently to increases and decreases in welfare spending. Researchers may be able to shed light on this by identifying an exogenous increase in Food Stamps benefits and examining its influence on contributions to food-related charities.

## VI. References


Abrams, B. and M. Schmitz. 1978. "The Crowding-Out Effect of Government Transfers on Private Charitable Contributions." Public Choice, 33(1): 29-39.

Abrams, B. and M. Schmitz. 1984. "The Crowding-Out Effect of Government Transfers on Private Charitable Contributions: Cross-Sectional Evidence." National Tax Journal, 37: 563-568.

Andreoni, J. 1988. "Privately Provided Public Goods in a Large Economy: The Limits of Altruism." Journal of Public Economics, 35: 57-73.

Andreoni, J. 1989. "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence." The Economic Journal, 100: 1447-58.

Andreoni, J. 1990. "Impure Altruism and Donations to Public Goods: A Theory of Warm Glow Giving." Journal of Political Economy, 97: 464-477.

Andreoni, J. and A. Payne. 2003. "Do Government Grants to Private Charities Crowd Out Giving or Fundraising?" American Economic Review, 93(3): 792-812.

Andreoni, J. and A. Payne. 2011. "Is Crowding Out Due Entirely to Fundraising? Evidence from a Panel of Charities." Journal of Public Economics, 95: 334-343.

Capps, R. 2001. "Hardship among Children of Immigrants: Findings from the 1999 National Survey of America's Families." New Federalism: National Survey of America's Families Working Paper, Series B(29): 1-7.

Davidson, R. and J. MacKinnon. 1993. Estimation and Inference in Econometrics. New York: Oxford University Press.

Dean, S. and D. Rosenbaum. 2013. "SNAP Benefits Will Be Cut for All Participants In November 2013." Center on Budget and Policy Priorities report.

Dokko, J. 2009. "Does the NEA Crowd Out Private Contributions to the Arts?" National Tax Journal, 62: 57-75.

Kingma, B. 1989. "An Accurate Measurement of the Crowd-Out Effect, Income Effect, And Price Effect for Charitable Contributions." Journal of Political Economy, 97: 1197-1207.

Fix, M and J. Passel. 1999. "Trends in Noncitizens' and Citizens' Use of Public Benefits Following Welfare Reform: 1994-1997." Urban Institute Research report.

Gruber, J. 2007. Public Finance and Public Policy. New York: Worth.

Gruber, J. and D. Hungerman. 2007. "Faith-Based Charity and Crowd Out During the Great Depression." Journal of Public Economics, 91: 1043-1069.

Haider, S., R. Schoeni, Y. Bao, and C. Danielson. 2004. "Immigrants, Welfare Reform, and the Economy." Journal of Policy Analysis and Management, 23: 745–764.

Heutel, G. Forthcoming. "Crowding Out and Crowding In of Private Donations and Government Grants." Public Finance Review.

Hungerman, D. 2005. "Are Church and State Substitutes? Evidence from the 1996 Welfare Reform." Journal of Public Economics, 89: 2245-2267.

Hungerman, D. 2009. "Crowd Out and Diversity: A Theory of Cold Glow Giving." Journal of Public Economics, 93: 729-740.

Lindsey, L. and Richard Steinberg. 1990. "Joint Crowdout: An Empirical Study of the Impact of Federal Grants on State Government Expenditures and Charitable Donations." NBER Working Paper, 3226.

"National Taxonomy of Exempt Entities." NCCS.Urban.org. National Center for Charitable Statistics, n.d. Web.

Roberts, R. 1984. "A Positive Model of Private Charity and Public Transfers." Journal of Political Economy, 91: 136-148.

Pavetti, L. and D. Bloom. 2001."State Sanctions and Time Limits." <u>The New World of Welfare</u>. Washington, D.C.: Brookings Institution Press.

Payne, A. 1998. "Does the Government Crowd-Out Private Donations? New Evidence from a Sample of Non-Profit Firms." Journal of Public Economics, 69: 323-345.

Rector, R. and S. Youssef. 1999. "The Determinants of Welfare Caseload Decline." Heritage Working Paper, 99(4).

Schoeni, R. 2002. "Does Unemployment Insurance Displace Familial Assistance?" Public Choice, 110(1-2): 99-119.

Warr, P. 1982. "Pareto Optimal Redistribution and Private Charity" Journal of Public Economics, 19: 131-183.

Zimmerman, W. and K. Tumlin. 1999. "Patchwork Policies: State Assistance for Immigrants under Welfare Reform." The Urban Institute Working Paper, 24.

## VII. Appendices

### *Appendix A: Tests for Statistical Anomalies*

**Table A1.** Variance Inflation Factor test for multicollinearity.

| Variable | VIF | 1/VIF |
|---|---|---|
| Food Stamps benefits | 4.10 | 0.244 |
| Fundraising expenses | 1.01 | 0.991 |
| Percent over the age of 65 | 1.23 | 0.809 |
| Percent Black | 1.52 | 0.659 |
| Percent Hispanic | 1.28 | 0.782 |
| Percent without a HS diploma | 3.82 | 0.261 |
| Percent with at least a 4 year degree | 3.77 | 0.265 |
| Income (in thousands of dollars) | 3.26 | 0.306 |
| Unemployment Rate | 1.80 | 0.554 |
| TANF benefits | 1.78 | 0.561 |
| Mean VIF | 2.36 | -- |

**Table A2.** Levin-Lin-Chu unit root tests (null hypothesis: variable is non-stationary).

| Variable | Time trend? | P-value: small sample | P-value: mid-sized sample |
|---|---|---|---|
| Contributions to food-related charities | No | 0.000 | 0.000 |
| Contributions to food-related charities | Yes | 0.000 | 0.000 |
| Food Stamps benefits | No | 0.000 | 0.000 |
| Food Stamps benefits | Yes | 0.000 | 0.000 |

**Table A3.** Durbin-Wu-Hausman tests for endogeneity.

| Model | Variable | P-value |
|---|---|---|
| Table 4, regression (3) | Food Stamps benefits | 0.0690 |
| Table 5, regression (2) | Combined welfare benefits | 0.0768 |
| Table 5, regression (3) | TANF benefits | 0.0238 |
| Table 6, regression (1) | Food Stamps benefits | 0.1692 |
| Table 6, regression (1) | TANF benefits | 0.1909 |
| Table 7, regression (2) | Food Stamps benefits | 0.0071 |
| Table 8, regression (5) | Food Stamps benefits | 0.2618 |
| Table 8, regression (6) | Food Stamps benefits | 0.6505 |
| Table 8, regression (7) | Food Stamps benefits | 0.0868 |
| Table 8, regression (8) | Food Stamps benefits | 0.6469 |

**Table A4.** Other tests for statistical anomalies.

| Test | Null hypothesis | P-value: small sample | P-value: mid-sized sample |
|---|---|---|---|
| Woolridge test for autocorrelation | No first-order autocorrelation | 0.0578 | 0.0477 |
| Modified Wald test for group-wise heteroskedasticity | Constant variance | 0.000 | 0.000 |
| Pesaran's test for cross sectional dependence | No cross sectional dependence | 0.000 | 0.000 |
| Hausman test of fixed vs random effects | Differences in coefficients not systematic | 0.000 | 0.000 |