Do Tax Credits Increase Charitable Giving? Evidence from Arizona and Iowa

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Abstract

In the United States, a majority of states have implemented tax credits that encourage charitable giving to specified groups of nonprofits. However, the impact of these policies on the nonprofits that they are designed to support is unknown. This paper estimates the causal effect of the two of the costliest programs. Arizona's Working Poor Tax Credit (WPTC) and the Endow Iowa Tax Credit provide stark contrast in their structures. The WPTC, which is the largest tax credit for charitable giving in terms of tax expenditure, provides a broadly targeted 100 percent credit with a cap of $200 per person. In contrast Endow Iowa, which is among the largest programs relative to the revenue of the targeted sector, provides a sharply targeted 25 percent credit with a cap of $300,000 per person. Using synthetic control methods, a data-driven approach to constructing realistic counterfactuals, I find no evidence to suggest that the Working Poor Tax Credit induced increased charitable contributions to the targeted Arizona nonprofits. In contrast, I estimate that the Endow Iowa program increased contributions to community foundations by 125 percent. Evidence suggests that the growth in contribution levels involved increases in both the number of community foundations and the level of contributions per foundation.

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1 Introduction

The nonprofit sector represents a private alternative to government provision of public goods. Institutions such as universities, hospitals, and museums are produced by both governments and nonprofits, while nonprofit charities supplement the work of government to decrease homelessness, cure diseases, and broaden economic opportunity. Where increases in government production must be paid for with tax revenues, nonprofit production draws voluntary contributions from donors. It is therefore not surprising that policy makers often look to the nonprofit sector to increase the well-being of their constituents without increasing their tax burden. In the U.S., a popular policy option at the state level has been the introduction of tax credits that encourage philanthropic giving directed toward a specific area of need.

Charitable tax credit (CTC) programs are meant to stimulate additional philanthropic giving and to direct it to an area in which policy makers perceive an increased need. De Vita and Twombley (2004) describe the policy goals as follows: "(1) to increase charitable giving, (2) to allow taxpayers to determine directly the utility or effectiveness of charitable services, and (3) to support antipoverty programs," (p. 1). Generally, CTC policies also require that donations are made to a nonprofit *within the state* in order to qualify for the credit. This additional goal is described, in a report on the Endow Iowa Credit, as reducing "the transfer of wealth to outside of the state," (Gullickson and Tilkes, 2013, p. 10).[1]

Research into the effectiveness of tax credits, in general, continues to generate interest. For example, a notable strand literature has examined tax credits for research and development (Bloom et al., 2002; Lokshin and Mohnen, 2012). Additional research into the efficacy of tax credits as policy instruments includes studies examining credits that encourage innovation clusters (Moretti and Wilson, 2014), retirement savings

[1] Gullickson and Tilkes (2013) provides a detailed description of the Endow Iowa program, presents findings on donor demographics, and estimates that making an Endow Iowa qualifiying donation is associated with an additional \$0.09 more in non-Endow Iowa contributions (Gullickson and Tilkes, 2013). Causal estimates were beyond the scope of their study.

production (Ramnath, 2013), or employment (Faulk, 2002). The effectiveness of tax credits designed to grow the nonprofit sector, however, has not been the subject of rigorous research.

The responsiveness of donors to changes in the after-tax price of giving has been well researched, but the effect on recipients (the charities themselves) has been largely ignored. In the existing research, the relationship between the changes in the after-tax price and the quantity of charitable giving is generally summarized by a price elasticity. A number of studies have estimated the elasticity relative to the U.S. federal deduction for charitable giving (Auten et al., 2002; Barret et al., 1997; Randolph, 1995). Since the tax deduction treats all giving equally, all donations have an after tax price of one minus the individual's marginal tax rate. Variation in marginal tax rates across time and across individuals can then be used to identify tax-price elasticity. By including variation in state income tax policy in their analysis, Bakija and Heim (2011) separately identify federal and state tax-price elasticities. In all of these studies, the price of charity varies by individual but does not vary by recipient. As such, these studies do no predict the effect of tax-credit polices that intentionally make giving to certain nonprofit organizations cheaper than giving to others.

Anecdotal evidence suggests that targeted charitable tax credits have large effects on the revenue streams of nonprofit organizations. In St. Louis, The Hunger Task Force of the Missouri Association for Social Welfare reported that a food pantry in St. Louis lost more than $30,000 in donations after a credit for giving to food pantries expired in 2011 (National Council of Nonprofits, 2015). In Detroit, the Coalition on Temporary Shelter (COTS) reported a 10 percent decline in charitable contributions following the repeal of Michigan's Homeless Shelter/Food Bank tax credit. A Grand Valley State study of charitable giving in Michigan found that donations of less than $400 fell from 2011 to 2012, the year in which the tax credits were removed (Johnson Center for Philanthopy, 2013). The results of these studies, however, were not causal and there were certainly other economic factors at play during this time.

This paper differs from the existing literature by performing a rigorous, empirical analysis of the effect of targeted (rather than across-the board) tax policies on the recipients of charitable donations (rather than on the donors). Specifically, I examine the Endow Iowa Tax Credit and Arizona's Working Poor Tax Credit (WPTC) to determine whether they increased the amount of contributions received by the targeted nonprofits. The greatest hurdle in answering this question is the development of appropriate counterfactuals. I estimate counterfactuals using the Synthetic Control Methods (SCM) described in Abadie and Gardeazabal (2003), Abadie, Diamond, and Hainmueller (2010), and Abadie, Diamond, and Hainmueller (2014). The methodology compares aggregate data for a treatment group to a synthetic, untreated version of itself.

I focus on the Endow Iowa Tax Credit and Arizona's Working Poor Tax Credit (WPTC) for two primary reasons. First, the programs provide stark contrast in their structures. While Endow Iowa provides a sharply targeted 25 percent credit with a cap of $300,000 per person, WPTC provides a broadly targeted 100 percent credit with a cap of $200 per person. Second, both programs are well suited to a rigorous analysis. The cost of each program is well documented; in each case the state department of revenue has tracked annual tax expenditure. The level of tax expenditures associated with both credits are large relative to similar programs in other states. Most importantly, both have clear regulations and public lists of qualifying organizations which make it possible to identify appropriate treatment and control groups.

My findings suggest that the Endow Iowa Tax Credit, at least in conjunction with the related County Endowment Fund Program led to higher contribution levels. I estimate large increases in donations—more than $45 million in additional annual contributions stemming from $2 to $6 million in credits and $6 to $11 million in grants. The primary result holds under a variety of alternative specifications for the synthetic control. Additional analysis is suggestive of both a growth in the number of community foundations and in increases in per-foundation contribution levels.

I find no evidence that Arizona's WPTC increased charitable contributions levels. I estimate the gross change in contributions by focusing on a non-random group of nonprofits that received high levels of qualifying donations. In my baseline specification, the aggregated group received lower levels of donations than their synthetic control.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of state tax credit policy, a theoretical framework for understanding the interaction between tax policy and contribution levels, and proposes testable hypotheses. This is followed by a description of the methodological framework used in the primary analysis including discussion of the underlying data, Synthetic Control Methods, and identification of the treatment and control groups. Section 4 presents the primary results for Iowa and Arizona. I include extensions in section 5 and a discussion of the findings in section 6.

2 Taxes, Credits, and Charitable Giving

2.1 Charitable Tax Credit Policies

This paper examines two very different tax credit programs. While the majority of states have some form of CTC program, those programs vary along multiple dimensions.[2] Three important variations are the nonprofits targeted by the credit, the size of the credit as a percentage of the donation, and the statutory credit cap (the maximum amount any one tax payer may receive). The Endow Iowa credit provides an example of a highly targeted 25 percent credit with a large cap on eligible donations. In contrast, Arizona's WPTC, provides an example of a broad-based, 100 percent credit with a low cap.

CTC programs vary greatly. Table 1 summarizes differences between CTC policies.[3] Credits range from 15 percent to 100 percent of the qualifying donation. The cap on the credits, meanwhile, ranges from a low of $100 for individuals (or $200 for couples) to a high of $300,000. The largest program in terms of expenditure is Arizona's Working Poor Tax Credit (WPTC), which cost the state $21.8 million in 2012.

[2] In 2013, I find 33 states offered at least one tax credit program to businesses and 20 offered charitable giving tax credits to individuals.

[3] The 14 credits included in table 1 are those for which I was able to obtain tax expenditure information.

The smallest programs are the Endow Kentucky Program and Nebraska's Qualified Endowment Credit. Part of this difference is in the type of giving the programs plan to stimulate. Programs such as Arizona's Working Poor Tax Credit (WPTC) and Michigan's Homeless Shelter and Food Bank Credit appear to be geared toward small donors making regular contributions to local nonprofits. Conversely, Endow Iowa, the Neighborhood Assistance Tax Credits in Connecticut and Delaware, and Missouri's Youth Opportunities Program, focus on larger, one-time gifts.

The Endow Iowa program provides a sharply targeted credit of up to $300,000 per tax payer. The credit program went into effect January 1, 2003. At the time, the credit was equal to 20 percent of donations made to any permanently endowed fund within a *qualified foundation*. Rather than directly providing public goods and services, foundations pool donations into a coordinated investment fund from which grants are given to other nonprofit charities. Foundations must apply to the Iowa Economic Development Authority to qualify for the program. Initially, taxpayers were allowed to take both the new credit and the preexisting deduction. Beginning in 2010, the credit was increased to 25 percent, but taxpayers were no longer allowed to include their donation as part of itemized deductions. The total amount of credits received by taxpayers is capped each year; beginning at $2 million for all of 2003 and 2004, but rising to $6 million as of 2012 (Gullickson and Tilkes, 2013).

Like many of of the tax credit programs described in table 1, Endow Iowa is not the only policy that the state has implemented to increase funding for the targeted nonprofit sector. A year after its implementation, the Endow Iowa Tax Credit was followed by the introduction of the County Endowment Fund Program. The County Endowment Fund distributes a small (0.5 percent in 2004 and 2005, 0.8 percent thereafter) percentage of state gaming tax revenue to community foundations associated with counties that do not have gaming licenses (Iowa Council of Foundations and Iowa Gaming Association, 2013). The program distributes the money annually, with the first distributions—funded with 2004 tax collections—distributed in 2005. In total, $92.7 million has distributed to community foundations (Iowa Department of Revenue, 2014).

The WPTC provides a broadly targeted tax incentive of no more than \$400 per individual. First implemented in 1998, the policy provides a non-refundable income tax credit for cash contributions to qualifying charitable organizations. Qualifying organizations are defined as those who spend at least 50 percent of their budget on Arizona residents who either receive Temporary Assistance for Needy Families (TANF) benefits, have household income less than 150 percent of the poverty level, or are chronically ill or disabled children. This definition allows contributions to a wide range of charities: 809 nonprofits qualified in the 2009 tax year (Gene, 2013). Initially, the credit only applied to donations in excess of a baseline amount donated in a base-year (generally the year before the individual first applies for the credit) and to individuals who itemized their deductions. The credit was equal to 100 percent of the first \$200 in excess contributions or \$400 for married couples filing jointly (Gene, 2013). Arizona altered the WPTC rules in 2009 and 2013. Beginning in 2009, the establishment of a baseline donation was removed and individuals were allowed to apply the credit to their first \$200 of contributions. Legislation in 2013 expanded the credit to non-itemizers, and increased the cap for donations to foster care organizations to \$400, or \$800 for married couples filing jointly (Gene, 2013).

Differences between the WPTC and Endow Iowa make the programs interesting points for comparison. The WPTC distributes a large number of credits (49,915 in 2009) in relatively small amounts, an average of \$272 per claim in 2009 (Gene, 2013). Conversely, Endow Iowa distributes fewer credits (3,074 in 2012), but awards an average credit of \$1,884 with more than 70 percent total tax-savings accruing to individuals who gave more than \$30,000. (Gullickson and Tilkes, 2013). Arizona's program qualifies a broad array of nonprofits, while Iowa focuses directly on community foundations. The specificity of Iowa's program may make estimating its impact easier. However, the breadth of Arizona's program means that it includes national organizations such as Big Brothers Big Sisters and Habitat for Humanity which can be compared to their counterparts in other states. The programs also differ in the percentage of donation credited (25 percent in Iowa and 100 percent in Arizona) and whether the credit is available to businesses (Endow Iowa is and WPTC is not). Finally, while the WPTC is a stand-alone program in Arizona, Endow Iowa is an example of a CTC program implemented in conjunction with related policies—in this case Iowa's County Endowment Fund program.

Despite their differences, both programs are relatively large and well suited to rigorous case studies. The WPTC is the largest credit program in terms of state expenditure. While the program is generally broad, I focus on a group of qualifying organizations for whom credits were equal to 2 percent of their charitable receipts. Endow Iowa distributed $5.8 million of credits in 2012 and, since its inception, credits were distributed in an amount equal to 3 percent of total charitable receipts by community foundations in the state. Both the WPTC and Endow Iowa were well documented and had clearly defined treatment groups with plausible controls. The annual tax expenditures associated with both Endow Iowa and Arizona's WPTC were closely tracked and reported by the state departments of revenue, along with detailed summaries of policy regulations and regulatory changes (Gullickson and Tilkes, 2013; Gene, 2013). The provisions of both the Endow Iowa Credit and the WPTC stipulate that only donations made to nonprofits that have pre-qualified with the state are eligible. The documentation of these pre-qualified nonprofits allowed for the identification of treated organizations and comparison groups in other states.

2.2 A Framework for Analysis

A primary goal of any charitable tax credit program is "to increase charitable giving" (De Vita and Twombley, 2004, p.1). This is accomplished by lowering the after tax price of a donation. The federal tax deduction for charitable gifts operates on the same premise, but does not specifically target a subset of the nonprofit sector. Targeted CTCs introduce additional factors by making some donations cheaper than others. First, targeted CTCs produce a substitution effect *between charities* that I model below. Through the model, I further compare the effects of Endow Iowa and Arizona's WPTC.

Additionally, CTCs alter the return to fundraising expenditures by targeted nonprofits; however, the impact of these changes is ambiguous. In Iowa, a third additional factor is at play. The County Endowment Fund Program provides direct government funding to community foundations. Fortunately, existing research provides a estimates with which to bound the impact of this program.

The model examines donations to two nonprofit charities, indexed 1 and 2, and assumes that there exists some $\bar{G}$ that defines a predetermined total amount that some individual wishes to contribute to charity. Setting a predetermined level of charitable giving for each consumer is a simplifying assumption imposed upon the model in order to focus on substitution between charities rather than between charitable giving and private consumption. Implications of relaxing this assumption are discussed following derivation of the model. Implicit in this assumption is a price elasticity for total charitable giving of -1 and the assumption that donors are motivated entirely by warm-glow.[4]

A price elasticity of -1 for total charitable giving implies that donors respond to changes in the price of donations by increasing their charitable gifts proportionally. As such, the increase in total charitable gifts is exactly equal to the value of the tax incentives awarded by the government. Moreover, the assumption that charitable donations are unit elastic implies that the cross-price elasticity on private consumption is 0, the income effect of tax incentives for charitable giving on private consumption is equally offset by substitution *into* charitable giving, and private consumption is fixed. This assumption corresponds to existing empirical estimates of the price elasticity of charitable giving which include both the income effect of a change in the after-tax price of donations and substitution *into* charitable giving and generally cluster around -1.[5]

The assumption that donors are entirely motivated by warm-glow excludes equilib-

[4]Warm-glow refers to the utility gains from the value of the gift and is often contrasted with altruism, or the utility gains from a public good produced by a government or a charity. Andreoni (1990) formalizes a model in which donors may be motivated by either warm-glow, altruism, or both.

[5]Auten, Sieg, and Clotfelter (2002) estimate elasticities between -0.79 and -1.26. A meta-analysis by Peloza and Steel (2005) reports that the weighted average of prior studies is -1.44 or -1.11 with outliers removed. More recently, Bakija and Heim (2011) separately estimate tax-price elasticity for changes in federal and state taxes, finding an elasticity of -1.16 at the state level.

rium effects from the model. I assume that donors care only about the value of their own gift and that neither the total level of contributions nor the output of the charity enter their utility functions. Therefore, no substitution between private consumption and charitable giving occurs in response to changes in the total level of revenue at either charity 1 or 2.[6]

To begin, let an individual's donation set be defined $G = (g_1, g_2)$ and define her budget constraint $\bar{G} = p_1 g_1 + p_2 g_2$ where p_1 and p_2 are the after-tax prices of giving to charity 1 and 2 respectively. In the absence of incentives, the price of giving is equal to one; the budget constraint is defined as $\bar{G} = g_1 + g_2$ and represented as a line with the slope -1. A diagram of this budget constraint appears in the top left panel of figure 1. Tax incentives alter the prices of donations g_1 and g_2 by offering a subsidy to donors. For a given subsidy rate s_j, the after-tax price is $p_j = 1 - s_j$. An uncapped, untargeted tax incentive sets some price $p_u = p_1 = p_2 \leq 1$. The new budget constraint, which appears in the top right panel of Figure 1, is defined as $\bar{G} = p_u(g_1 + g_2)$. The federal deduction for charitable giving is an untargeted incentive of this type with p_u equal to one minus the consumer's marginal tax rate. Targeted tax credit programs only change the price of the donation to the targeted nonprofit, g_1, leaving $p_2 = 1$. An uncapped, targeted program would therefore lead to the budget constraint

$$\bar{G} = p_1 g_1 + g_2 \tag{1}$$

with $p_1 \leq 1$ and a slope of $-p_1$.

A credit program with a cap creates a kink in the budget constraint, as shown in the bottom two panels of figure 1. Defining the credit cap as C, the kink occurs when

[6] The model also ignores the potential costs of learning about and filing for CTCs. In Iowa, community foundations generally help their donors register for the credits, for which they receive a certificate number from the Iowa Economic Development Authority. In Arizona, donors need only to complete form 321 and attach a receipt. Again, nonprofits are generally forthcoming with assistance, many provide information on-line and in fundraising documents, and some—e.g. Habitat for Humanity of Central Arizona and St. Vincent De Paul of Southern Arizona—even include a PDF of form 321 on their websites. I therefore assume that, at least among individuals who are considering donations to targeted nonprofits, the additional costs of applying for a credit are minimal.

the donor has contributed $g_1 \geq C/(1-p_1)$[7]. Therefore, the budget constraint for a targeted program with a cap can be written as

$$\bar{G} = \begin{cases} p_1 g_1 + g_2 & \text{if } g_1 \leq \frac{C}{1-p_1} \\ -C + g_1 + g_2 & \text{if } g_1 \geq \frac{C}{1-p_1} \end{cases} \tag{2}$$

Up to the cap, the slope of the budget constraint is, $-p_1$. Beyond the cap, the slope is -1 and the budget line is parallel to the initial budget constraint.

I model the budget constraint of a donor in Arizona and Iowa in the bottom panels of figure 1. An individual in Arizona may donate up to $200 to the targeted nonprofits and receive a 100 percent credit. With a 100 percent credit, $p_1 = 0$. A credit of this type shifts the budget constraint to the right, but does not alter the relative price of giving beyond the cap. For the first $200, the donor pays a price of zero and the budget constraint is represented as a horizontal line. Above the cap, the tax credit is no longer applied, so $p_1 = p_2$ and the budget constraint is represented by a line with slope -1. Endow Iowa alters the relative price of giving to the targeted nonprofits. A 25 percent credit leads to an after-tax price of 0.75. The cap on Endow Iowa is $300,000; the kink in the budget constraint does not occur until a donor has contributed $300,000/(1-.75)=$1.2 million to a community foundation. Figure 1 shows the effect of Endow Iowa on the budget constraint of a donor with $\bar{G}$ of $1.2 million dollars.

To complete the model, suppose there are five types of donors with G_0 representing the donation set in the absence of a tax incentive and G^* representing the donation set in the presence of some tax incentive. Assume that for each type, contributions to both charity 1 and charity 2 are normal goods. Additionally, assume that for each type, the total donation budget $\bar{G}$ is between $201 and $1.2 million so that they may spend beyond $C/(1-p_1)$ Arizona, but not in Iowa.[8] The first type donates exclusively

[7]The credit cap is the maximum amount the government is willing to distribute to an individual as a tax incentive. For some subsidy rate s_1, the donor can only receive subsidy until $s_1 g_1 = C$. Given $p_1 = 1 - s_1$, it follows that the cap is reached when $C = (1-p_1)g_1$ or $g_1 = C/(1-p_1)$.

[8]A contribution of $1.2 million far exceeds the size of a typical donation in Iowa. From 2005 to 2012 only thirteen donors qualified for the maximum credit award (Gullickson and Tilkes, 2013). As such, Iowa's cap can be treated as not binding and can be excluded from the model.

to the charity targeted by the credit program, charity 1. Her preferences could be described by the indifference curves in the top row of figure 2. The second donates to both nonprofits. For simplicity, I represent his preferences as Cobb-Douglas in the middle row of figure 2. The third donates exclusively to the untargeted charity, charity 2, but responds to tax incentives. I model the extreme case of this type in the bottom row of figure 2.[9] The fourth type donates exclusively to the charity for which there are no tax credits and does not respond to tax incentives. The fifth type does not donate. I exclude these last two types from Figure 2 because they would be unaffected by the policies in Iowa and Arizona. An untargeted tax deduction is represented in the left column of figure 2. In this scenario, donors who initially only donate to one charity are expected to continue to do so and donors who donate to multiple charities are likely to increase their giving proportionally.

The implications of and differences between the CTCs in Arizona and Iowa can be seen in figure 2 and explained by decomposing the donor's cross-price elasticity into a substitution effect and an income effect. The middle column of figure 2 shows the effect of a credit like Arizona's. Beyond the low credit cap, the relative price of the two charities is unaffected by the tax incentive. For donors of types 1 and 2 (preexisting donors contributing more than $C/(1-p_1)$ the substitution effect is zero and the donor reacts to the credit as if it were an untargeted, lump sum subsidy. Given the price of zero below the cap, donors of type 3 contribute exactly the amount that is subsidized to the targeted charity. Beyond the cap, the substitution effect is again zero and donors of this type make no change to their donations to the untargeted charity. This is displayed in the bottom, middle panel of figure 2.

The right column of figure 2 shows the effect of a credit like Iowa's in which consumers face a lower, nonzero, price for the targeted charity. Donors of type 1—shown in the top, right panel—increase their contributions from $\bar{G}$ to $\bar{G}/p_1$. Donors of type

[9] Figure 2 displays three of four types of extreme preferences. The top and bottom rows assume that charity goods are perfect substitutes. The middle row uses Cobb-Douglas preferences which imply that the charity goods are neither complements nor substitutes. Because it seems unlikely in reality, and the result is trivial, I do not model the case in which charities are perfect complements.

2 increase their contributions to the favored charity by an ambiguous amount. For donors who see the charities as gross substitutes, the substitution effect of lower prices is greater than the income effect of the subsidy. These donors reduce giving to the untargeted charity and increase giving to the targeted charity by more than the value of the credit. Other donors may see the see the charities as gross complements. In this case, the income effect of the subsidy is greater than the substitution effect. These donors increase giving to both the targeted and untargeted charities. Figure 2 shows the in-between case in which the substitution effect and income effect cancel out and only the donation to the targeted nonprofit is altered.[10] For Donors of type 3, the two charities are close substitutes. As such the substitution effect is very large, and any price reduction leads them to switch most of their donations from donations to untargeted charities to donations to the targeted charities. In the bottom, right panel of figure 2 the two charities are perfect substitutes, the substitution effect is infinite and the donors shift all of their contributions from the untargeted charity to the targeted charity.

What happens if the assumption that consumption is unaffected by incentives for charitable giving is relaxed? Begin by defining the budget constraint as a function of income M rather than $\bar{G}$. In the absence of a tax incentive, the budget constraint is defined as $M = g_1 + g_2 + x$ where x is the total expenditure on consumption. Targeted tax credit programs with a cap on credits induce the following budget constraint.

$$M = \begin{cases} p_1 g_1 + g_2 + x & \text{if } g_1 \leq \frac{C}{1-p_1} \\ -C + g_1 + g_2 + x & \text{if } g_1 \geq \frac{C}{1-p_1} \end{cases} \tag{3}$$

Below the cap we expect contributions to the targeted nonprofit to increase, but the amount is ambiguous. If the substitution effect between consumption and charity dominates, consumers decrease donations to charity 2 and consumption spending and increase contributions to the targeted nonprofit. This additional substitution from

[10] In the case of Cobb-Douglas preferences, such as those shown in the middle row of figure 2, a donor with utility defined $U = g_1^{\alpha} g_2^{1-\alpha}$ would respond to a tax incentive by increasing contributions to charity 1 from $\alpha\bar{G}$ to $\alpha\bar{G}/p_1$ and would maintain fixed levels of contributions to charity 2 of $(1-\alpha)\bar{G}$.

private consumption would lead to larger increases in contribution to the targeted nonprofit than in the baseline model. Moreover, if we assume that the marginal warm-glow utility from donating declines as the donor increases her contribution, substitution from private consumption into charitable giving could mitigate the decline in contributions to the untargeted charities that the model predicts. The more a donor substitutes from consumption to gifts to charity 1, the lower the marginal utility from additional gifts to charity 1 and thus the smaller the substitution effect from charity 2 to charity 1. If income effects dominate, consumers increase donations to both charities and consumption expenditure such that the increase in contributions to the targeted nonprofit is less than the value of the credits and therefore less than in the baseline model. Note that it would also be possible for contributions to charity 2 to rise while consumption expenditure fell, or vice versa.

As in the base model, consumers who contribute an amount greater than $\frac{C}{1-p_1}$ see no price change and the substitution effect is zero. As such, there should not be a decline in either donations to untargeted charities or consumption expenditures. Consumers receive the credit as a lump sum transfer and distribute it to maximize their utility. If donors increase private consumption, the predicted increase in contributions to both the targeted and untargeted nonprofits is smaller than in the base model (without adjustment).

This framework does not include endogenous changes in fundraising. If individual donations increase as expected, nonprofits get a better return for each dollar spent soliciting a new donor. Revenue maximizing charities, such as those modelled by Name-Correa and Yildirim (2013), would therefore increase their fundraising expenditures.[11] However, there is evidence that at least some nonprofits spend below the revenue maximizing level on fundraising (Khanna et al., 1995; Okten and Weisbrod, 2000). Without evidence to suggest that the nonprofits targeted by CTCs are revenue maximizers, the direction of endogenous fundraising change is ambiguous.

[11] Note, however, that the Name-Correa Yildirim model was not derived to examine the impact of a change in the tax-price of donations.

Analysis of Endow Iowa is further complicated by the presence of its sister County Endowment Program. Fortunately, the literature on the interplay between government grants and private giving provides information on the extent to which the grant program is likely to confound the estimated impact of Endow Iowa. Models of altruistic giving (donors motivated by public good production) such as Bergstrom, Blume, and Varian (1986) suggest that government spending on public goods should crowd out (reduce) private giving. Conversely, Payne (2001) explains that if donors posses imperfect information, government grants can serve as a signal of quality and thus crowd in (increase) donations. The model presented here, which assumes donors are motivated exclusively by warm-glow, suggests that donations are unaffected by government grants to charity.

Empirical estimates of crowd out help bound the likely impact of the County Endowment Program. Tinkleman (2010) summarizes 46 empirical studies on the impact of grants on private giving and finds that, while estimates vary, they center around zero and only eight include specifications in which crowd out is estimated to be greater than 50 percent. If the effect of the County Endowment Program is similar to the grant programs that have been studied in the past, the result of the program would be an increase in donations of between 50 and 150 percent of the value of the credits—$4.9 to $14.6 million dollars annually between 2004 and 2012. If the effect falls toward the middle this distribution, the County Endowment Program would increase revenue levels by exactly the value of the grants and, as in the model described above, private contributions would be unaffected by the program.

2.3 Hypotheses

The primary hypothesis of this study is as follows.

Hypothesis 1 *Charitable Tax Credit programs increase the level of contributions received by targeted nonprofit organizations.*

This hypothesis is born from from stated policy goals and the extensive empirical literature surrounding tax deductions for charitable giving. De Vita and Twombley (2004) note that CTC programs share the common goal of increasing charitable giving and Gullickson and Tilkes (2013) state that Endow Iowa began "in an effort to spur philanthropy across Iowa" (p. 10). Moreover, existing studies of donor response to tax incentives—e.g., Auten et al. (2002), Peloza and Steel (2005), and Bakija and Heim (2011)—have found strong evidence that tax incentives increase charitable giving.

The framework presented in 2.2 leads to three additional hypotheses.[12] First as illustrated in the middle frame of figure 2, WPTC is likely to lead to positive spillover, increasing donations to untargeted nonprofits. Second as illustrated in the bottom-right frame of figure 2, Endow Iowa likely leads to substitution between charities and negative spillover, reducing donations to untargeted nonprofits. Third, the total increase in contributions will be greater than the cost of the tax credits awarded. This occurs because the increase in contributions induced by Endow Iowa will be equal to the sum of the credits received by donors and substitution from charities that do not qualify for credits to those that do.

While these hypotheses suggest contrasts between Iowa and Arizona, I do not formalize any hypotheses about direct comparisons. The model described in the previous section allows for analysis of the alternative subsidy rates and credit caps proposed in Iowa and Arizona. However, it ignores the important difference in the type of nonprofit organization targeted by the credit. The model would allow for direct comparison between credit programs if the two charity types and donor preferences were held constant across states. Since the two programs target different sectors, however, this is not the case. Even where the existing hypotheses suggest comparison relative to the value of the credits awarded, as is the case with Hypothesis 4, I do not formalize a hypothesis because the the synthetic control methodology described in section 3 does no provide

[12] As in the base model, these hypotheses assume that donors have a fixed budget for charitable giving, a price elasticity for charitable gifts of -1, are motivated entirely by warm-glow, and see charitable gifts as normal goods and that there are no equilibrium effects induced by changes in fundraising behavior by charities.

an appropriate empirical test.

Under the model, donors who contribute enough to receive the full credit cap see no change in prices and respond to the subsidy as if it were a lump-sum increase in income. This leads the following hypothesis.

Hypothesis 2 *Arizona's WPTC led to positive spillover, increasing donations to untargeted nonprofits.*

The model shows that donors who see charities as perfect substitutes will increase their donations to the targeted nonprofit, g_1, by the amount of the credit and leave their donations to charity 2 unchanged. This holds true whether or not they would have donated to the targeted nonprofit in the absence of a credit (that is whether they have preferences represented in the top or bottom row of figure 2). For all other donors, we should expect to see an increase in donations to both targeted and untargeted nonprofits. The expected result is therefore an increase in total contributions by the amount spent on the credits, with some level of positive spillover for untargeted nonprofits from donors who do not see the charities as substitutable. Since the model assumes a fixed budget for charitable giving, the total increase in donations must be equal to the value of the tax credits. In Arizona, the model predicts that some of these additional resources are spent on untargeted charities. Therefore, the increase in contributions to targeted nonprofits in Arizona should be less than the value of the credits.

When CTC subsidies are greater than zero and less than 100 percent, and the donors budget does not allow them to reach the credit cap, there is the potential for large substitution effects. Unless a large number of people see the targeted and untargeted nonprofits as complements, the model predicts the following.

Hypothesis 3 *The Endow Iowa tax credit should produce a large substitution effect between charities and reduce donations to untargeted charities.*

While donors who see the two goods as gross complements would increase contributions to the untargeted nonprofits, this increase can be no greater than the value of the subsidy received by the donor. In contrast, donors who see the two charities as gross substitutes may decrease their donation to the untargeted charity by up to 100 percent In the extreme case in which charities are perceived as perfect substitutes, donors may switch from giving exclusively to untargeted nonprofits to giving exclusively to targeted nonprofits. The size of the reduction in contributions to untargeted charities in Iowa remains ambiguous. It is determined by the number of individuals who see the charities as substitutes, their budget constraints, and the size of the substitution effect. A large segment of the effect may be driven by the donors who only began giving to community foundations after the introduction of Endow Iowa.

Under the assumption that private consumption is unaffected by a change in the price of donations, the total increase in charitable giving to targeted nonprofits is equal to the value of the tax credits awarded plus (minus) the reduction (increase) in contributions to untargeted charities.[13] Therefore, if hypothesis 3 is valid, the following hypothesis should be as well.

Hypothesis 4 *Endow Iowa led to an increase in charitable giving to targeted nonprofits that is greater than the value of credits disbursed.*

If the price elasticity of charitable giving is -1, and existing research suggest that this is (at least approximately) the case, any additional money given to the taxpayer as a subsidy for donations will be passed on in the form of donations. Under the assumption that Endow Iowa induces substitution from untargeted charities to targeted charities, the increase in donations to the targeted sector must be larger than the value of the credits. Additionally, the increase in contributions caused by Endow Iowa would be greater (relative to the cost of the credits) than the increase in contributions caused by Arizona's WPTC. This follows because WPTC is not expected to cause the substitution effect that the model predicts for Endow Iowa.

[13] If that assumption is relaxed, the total increase in charitable giving is equal to to the value of the tax credits awarded plus (minus) the value of contributions shifted between untargeted and targeted charities plus (minus) any decrease (increase) in private consumption.

3 A Case-Study Approach Using Synthetic Control Methods

3.1 Data

In order to assess the effects of the Endow Iowa Tax credit and Arizona's WPTC, I analyze contribution data reported on IRS 990 forms and compiled by the National Center for Charitable Statistics (NCCS). The NCCS Core files for 501(c)3 public charities include data on total revenue, contributions (inclusive of both grants and donations), membership dues, and program service revenue as well as classifications from the National Taxonomy of Exempt Entities (NTEE).[14] NCCS Core files include tax returns filed since the 1989 tax year. Since there is variation between the fiscal years of the nonprofits and the federal tax year in which the filings were received, I use datasets that begin with the 1990 fiscal year in all baseline estimates.

The primary outcome variable in this study is total contributions per capita. Total contributions includes gifts, grants, and "membership dues".[15] This figure is taken directly from IRS form 990: from Part I, line 1d through 2005; from Part I, line 1e in 2006 and 2007; and from Part VIII line 1h from 2008 onward. The 2008, 2009, and 2010 NCCS files include some returns filed using the "old" Form 990 and account for this change. The first page of the 2011 Form 990 appears as figure 3. The inability to differentiate between types of contributions, and single out monetary donations, would be a problem if the goal of this research were to precisely estimate the tax-price elasticity relative to CTCs. However, the question of interest regards the overall economic impact of CTCs; as such, total contributions is the ideal outcome variable. By using

[14] The NTEE classifications consist of a letter followed by a two digit number. The letter classifications divide charities into broad categories such as "Education" (B) or "Mental Health and Crisis Intervention" (F). The two digit classifications further subdivides the charities into more specific categories such as "two-year colleges" (B41) or "substance abuse treatment" (F22).

[15] Membership dues are distinct from gifts in that the member receives services in return for their payment. As such, the payment is not tax deductible. A museum might provide free admission to members, who would only be able to claim payments made above and beyond the cost of membership as a charitable donations. Revenue from the museum gift shop, or single-day tickets would likely be counted as program service revenue.

this aggregate measure, I incorporate substitution effects that may lead to a reduction in in-kind donations or private grants. Additionally, the aggregated contribution measure incorporates secondary effects on grants and membership that occur in response to changes in the level of private donations.

Although there is not a consistent measure of fundraising expenditure throughout the time series, I am able to derive a metric for each nonprofit in each year. Prior to 2008, the NCCS data includes total fundraising expenses taken directly from Part I line 15 of Form 990. I use this variable without adjustment. The 2008 version of Form 990 led to a critical adjustment in the NCCS data series. Data pulled from returns filed using the forms from 2008 forward do not include data for total fundraising.[16] Where total fundraising is unavailable, I construct an alternative measure by summing expenditures on professional fundraising services (Part IX Line 11e) and direct expenses from fundraising and gaming events (Part VIII Lines 8b and 9b).

I supplement the NCCS data with population estimates from the National Cancer Institute (SEER), Inequality estimates from Frank (2009), and state level personal income data from the Bureau of Economic Analysis. Monetary data is inflated to 2012 dollars using the Bureau of Labor Statistics Consumer Price Index - All Urban Consumers (CPI-U). Unemployment rate statistics from BLS are used to examine the robustness of counterfactuals.

Annual tax expenditures associated with Endow Iowa were reported in Gulikson and Tilkes' Endow Iowa Evaluation Study (2013). Information on grants distributed as part of Iowa's County Endowment Fund Program were provided by the Iowa Department of Revenue and are available online at https://tax.iowa.gov/report/Distributions. Tax expenditures for WPTC are available from annual versions of *The Revenue Impact of Arizona's Tax Expenditures* produced by the Arizona Department of Revenue's Office of Economic Research and Analysis.

[16] In 2008, 2009, and 2010, NCCS files include total fundraising for tax returns completed using old 990 forms.

3.2 Synthetic Control Methods

Synthetic Control Methods were first described in Abadie and Gardeazabal (2003) and further developed in Abadie, Diamond, and Hainmueller (2010) and Abadie, Diamond, and Hainmueller (2014) — henceforth ADH (2010) and ADH (2014). While SCM remains a novel approach, recent studies have implemented the methodology to study economic liberalization (Billmeier and Nannicini, 2013), flat tax reforms (Adhikari and Alm, 2015), motion picture production tax incentives (Button, 2015), and the economic impacts of German reunification (Abadie et al., 2015), Norway's petroleum endowment (Mideksa, 2013), and two Italian earthquakes (Barone and Mocetti, 2014).

Following ADH (2010) and ADH (2014), I create a synthetic state time series as a weighted combination of J untreated states in a "donor pool". (I describe the specific donor pools for Iowa and Arizona in greater detail in section 3.3.) The weighting vector, $W = (w_2, ..., w_{J+1})$, is selected to minimize the distance between the treated state and its synthetic control during the pre-intervention period. Mechanically, W solves the constrained minimization problem

$$W^* = \underset{W}{\operatorname{argmin}} \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{4}$$

$$s.t.$$

$$W'i = 1, \;\; w_j \geq 0, \;\; \text{for} \;\; j = (2, ..., J+1)$$

where X_1 is a vector of predictor variables for the treated state, X_0 is a matrix made up of vectors of predictor variables for each state in the donor pool, and V is a diagonal matrix that weights the relative importance of the predictor variables.

The primary outcome variable in my analysis is the natural log of per capita contributions. I use the per capita measure so that population does not carry undue influence in determining the weights given to the states in the donor pool. As robustness checks, I mirror the analysis using per capita donations without the log transformation and the natural log of total (rather than per capita) contributions.

The predictor variables in X_0 and X_1 serve to identify the combination of states that most closely match treated state time series to a counter-factual in the pre-intervention period. As such, they should be correlated with the outcome variable and not with the policy change. Note that the predictor variables do not need to have a causal relationship with contribution levels. If a predictor is highly correlated with an unobservable trait that affects contribution levels, it leads to a "better" synthetic control, even if there is no direct causal relationship.

I propose ten potential sets of predictor variables, listed in table 2. The lists include four groups of potential predictors. The first is the variable of interest: contributions per capita or its natural log. Second, I include descriptors of the nonprofits of interest in the state: the per capita level of fundraising expenditures, and the per capita level of program revenue. These variables are associated with the underlying economic health of the nonprofits. The third group includes measures of the income distribution in each state: per capita income, the Gini coefficient, and the income share of the top 1 percent. We should expect giving to be higher in states with higher income levels. The relationship between inequality and charitable giving is not settled, but recent work by Payne and Smith (2015) suggests a positive relationship. Finally, the state population is included to account for differences in the nonprofit sector between large states and small states that may arise as a result of scale or agglomeration effects. With the exception of the inequality metrics, all predictor variables are log-transformed in the baseline estimate. Only the population variable is log-transformed in the robustness check based on per capita, rather than log per capita, contributions.

The period of time prior to policy implementation is used as a calibration period to select the best set of predictor variables. For each set, I generate synthetic controls for all states with complete data in the period from 1990 to 1994 and then estimate the average root mean square prediction error (RMSPE) in the following pre-intervention period: 1995 to 1998 in the case of Iowa and 1995 to 1997 in the case of Arizona.[17] RMSPE measures the degree to which the synthetic control fits the data series of the

[17] The WPTC was implemented in 1998.

treated state and is defined as:

$$RMSPE = \left(\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_t^{treated} - Y_t^{synth})^2\right)^{\frac{1}{2}} \tag{5}$$

where $Y_t^{treated}$ and Y_t^{synth} are the outcome variable and its synthetic counterfactual indexed by year t. The set of predictor variables that provides the best fit (lowest RMSPE) during the calibration period forms the vector X_1 and the matrix X_0 that are used to create the synthetic counterfactual.

After selecting the predictor variables, X_0, using the pre-intervention calibration period, I construct a synthetic control using the period directly before intervention and estimate the difference between the treated state and its synthetic control over the post intervention period. In the case of Iowa, the pre-treatment period runs from 1993 to 2002 and the post-treatment period runs from 2003 to 2012. For Arizona, the pre-treatment period runs from 1990 to 1997 and the post-treatment period runs from 1998 to 2012.

Once a synthetic control has been created, I estimate the difference-in-differences (DID) between the treated state and its counterfactual. The DID estimate represents the increase (or decrease) in the treated state relative to the increase (or decrease) in the synthetic control. In other words, the estimate for the causal effect of the policy is the change in the treated state minus the change that would have happened in absence of the policy. Specifically, given any CTC policy p, define DD_p as:

$$DD_p = (\bar{Y}_{post}^{treated} - \bar{Y}_{post}^{synth}) - (\bar{Y}_{pre}^{treated} - \bar{Y}_{pre}^{synth}) \tag{6}$$

where $\bar{Y}_{post}^{treated}$ and $\bar{Y}_{post}^{synth}$ are the average annual (log) per capita contributions in the post-intervention period for the treated state and its synthetic control and $\bar{Y}_{pre}^{treated}$ and $\bar{Y}_{pre}^{synth}$ are the average annual (log) per capita contributions in the pre-intervention period. If the CTC is effective at increasing donations, the estimate of DD_p will be positive.

Additionally, I create alternative counterfactuals that I refer to as "Expected Iowa" and "Expected Arizona". The Expected state time series adds the tax expenditures associated with the CTC program. In Iowa, I also add the revenues distributed through the County Endowment Program. The creation of these expected series provides two primary benefits. First, it allows me to estimate the benefits of the policies net of their costs. Second, it provides a test of hypothesis 4 which proposes that the growth in contributions in Iowa should be greater than the value of the credits. In Iowa, I also construct a third counterfactual that includes the value of the grants provided through the County Endowment Program but does not include the value of Endow Iowa Credits. This series provides an estimate of the gross effect of Endow Iowa alone, under the assumption that County Endowment Program grants neither crowded in nor crowded out private contributions.[18]

Following ADH (2010), Billmeier and Nannicini (2013), and ADH (2014), I estimate p-values for both sets of estimates by running series of placebo experiments over the untreated states. The intuition is that by counting the number of times an estimate is larger for a placebo than it is following a policy change, we can calculate the probability that the estimate is a false positive. As such, I generate a synthetic control for each state in the donor pool and calculate its corresponding DID estimator, DD_j. The p-value for DD_p is determined by its location within the distribution of estimators DD_j. If there are k placebo estimates larger than DD_p the p-value is calculated as $(k+1)/(J+1)$. Where DD_p is negative, I calculate the p-value as $((J-k)+1)/(J+1)$.

ADH (2014) propose a ratio estimator for use in statistical inference:

$$Ratio_p = \frac{RMSPE_{post}}{RMSPE_{pre}} \tag{7}$$

The ratio estimator has no economic significance, but is used as an alternative statistic from which to generate a p-value. Where the p-value associated with DD_p describes the likelihood that the average estimated difference between the treated group and

[18]This assumption is consistent with the model presented in section 2.2.

its synthetic control could occur at random, the p-value associated with the $Ratio_p$ estimator describes the likelihood that the relative fit (or lack of fit) of the synthetic control could occur at random.

3.3 Identification of Treatment Groups and Donors to the Controls

In Iowa, the treatment group consists of all community foundations in the state. The pre-qualified community foundations to whom donations are eligible for credits are a subset of a broader class of community foundations identified under the National Taxonomy of Exempt Entities (NTEE) code **T31**. By comparing T31 community foundations in Iowa to those in other states, I identify an "intent-to-treat" effect.

To construct the donor pool, I exclude all states that have, at any time since 1992, given special tax treatment to planned gifts or donations to community foundations. This excludes Kansas, Kentucky, Michigan, Montana, North Dakota, and Nebraska. Next, I remove Arizona, which instituted a broad-based tax credit program. I remove two states, Hawaii and Utah, for which there is missing data. Finally, Wyoming and Delaware are removed from the baseline analysis in which per capita contributions are log-transformed because they have years of zero contributions. Both states are included in the untransformed robustness check. The remaining donor pool consists of 38 states and the District of Columbia (i.e. $J = 39$).

Figure 4a displays per capita contributions to community foundations in Iowa compared to those in the other 49 states and those in the donor pool. The vertical line indicates the implementation of the Endow Iowa program and thus separates the pre-treatment period from the post treatment period. Iowa shows a large spike in per capita contribution in 2002.

Most of the increase in contributions in 2002 over 2001 can be attributed to Council Bluffs Community Betterment Foundation (CBCBF) who received $75 million in contributions that year. This was the largest level of annual contributions to any Iowa community foundation in the dataset. This total was six times higher than the level of contributions received any other year for which we have data. Contributions to

CBCBF did not qualify for the Endow Iowa Tax Credit. Since CBCBF appears to be an outlier and single year spikes in the level of the outcome variable make it difficult to find a strong synthetic control, I drop CBCBF from the baseline estimates. The resulting series of per capita contribution levels in Iowa, excluding the outlier, appears in figure 4a as well. Alternative estimates based on aggregates including CBCBF are presented along with other robustness checks.

The trends in figure 4a show that per capita giving to community foundations in Iowa was lower than the United States average in the pre-intervention period. Additionally, we can see the impact of the 2008 recession on giving and the appearance that Iowa's community foundations were hit harder by the recession than an average across all other states.

Table 3 displays the average, per capita level of contributions to community foundations in Iowa (excluding CBCBF), the donor pool from which I build the control, and the United States as a whole. Iowa has more community foundations, per person, than the United States average. However, those foundations spend less on fundraising than their counterparts in the rest of the country. Iowa is slightly poorer, and slightly less unequal than both the donor pool and the national average. SCM will empirically derive a control that is more similar to Iowa than either the entirety of the donor group or the full sample of other states.

Since the rules that govern Arizona's WPTC are so broad, it is not possible to identify a single class of eligible nonprofits. One option is to examine the impact of the WPTC on an aggregate of the entire nonprofit sector. However, the value of Arizona's WPTC credits are equal to only 0.2 percent of all charitable receipts and therefore we are unlikely to be able to discern an impact at this level.[19]

Rather than identifying an intent-to-treat group, as in Iowa, in Arizona I focus on a group of "highly treated" nonprofits. In order to receive the tax credit, Arizona taxpayers must report which qualifying organization received their donation. A 2013

[19] Using the methodology described in section 3.2 and a state-wide nonprofit aggregate I find that, compared to a synthetic control, Arizona nonprofits received eight percent fewer contributions *after* the introduction of the WPTC.

report by the Arizona Department of Revenue lists the twenty nonprofits who received the most donations that qualified for the tax credit in 2009 (Gene, 2013). Among these recipients, eight were part of national nonprofit networks with sister organizations in other states. Of these, six appeared annually in the NCCS data: Big Brothers Big Sisters, Boys and Girls Clubs, Goodwill Industries, Habitat for Humanity, St. Vincent De Paul Society, and the United Way. I estimated the impact of the WPTC on an aggregate made up of these six nonprofits. In 2009, credits received by donors to these nonprofits were equal to two percent of their charitable receipts. For comparison, the value of Endow Iowa is roughly three percent of total contributions to community foundations.

The "highly treated" group is not a random subset of the treatment group. Rather, these six nonprofits represent organizations that were treated by the policy but also were, endogenously, recipients of larger than average levels of credits. The resulting analysis therefore estimates a the local average treatment effect among well-organized nationally-networked nonprofits and an upper-bound estimate of the average treatment effect. Put another way, this framework tests the hypothesis that charitable contributions to *some nonprofits* increased as a result of the Working Poor Tax Credit.

I form a donor pool for the highly treated nonprofits from their counterparts in other states. Six states—Kansas, North Carolina, West Virginia, Michigan, and Missouri—are excluded due to CTC programs for which these nonprofits were eligible or due to important policy changes during the period under study.[20] I additionally form donor pools with which to create synthetic controls for each of the six national nonprofits

[20] I exclude Kansas due to its Community Service Tax Credit Program which provides credits for contributions to approved capital fundraising drives by nonprofits in community service, crime prevention, and healthcare access (Kansas Department of Commerce, 2014). Local affiliates of The United Way, Habitat for Humanity, Boys and Girls Clubs, and Big Brothers Big Sisters all qualified for credits under the program (Kansas Department of Commerce, 2014). North Carolina is removed because of a program that, until 2014, allowed non-itemizers to take a 7 percent credit on charitable donations in excess of 2 percent of their incomes (Revenue Research Division, 2013). Two states are removed due to programs with eligibility requirements that are similar to the WPTC. Virginia's Neighborhood Assistance Program and West Virginia's Neighborhood Investment Tax Credit provide credits for charitable gifts to nonprofits that meet certain criteria regarding their work with low income residents (in Virginia) or economically disadvantaged areas (in West Virginia) and are available to both individuals and businesses (Department of Social Services, 2014; West Virginia State Tax Department, 2012). Finally, I exclude Michigan and Missouri from the donor pool because each state had a variety of tax credits and a number of policy changes over the period of analysis.

independently. In this case, I aggregate affiliates of each nonprofit within each state. Because some nonprofits did not continually operate or did not continually file tax returns in every state, the donor pools for the six individual nonprofits are smaller than the donor pool for the aggregate.

Figure 4b displays per capita contributions to the highly treated nonprofits in Arizona compared with the contribution levels to their sister organizations in the other 49 states and DC and in the donor pool. The vertical line appears at the introduction of the Working Poor Tax Credit. Arizona saw an increase in contribution in the period leading up to the introduction of the WPTC. SCM provide a data-driven approach to finding a control that matches that trend.

Summary statistics for the highly treated nonprofits in Arizona and their sister organizations in the donor states, and the United States as whole are displayed in table 4. Incomes in Arizona are below the national average. Of special interest and concern, total fundraising spending in Arizona is, on a per capita basis, less than one seventh of the national average. The methodology described above addresses these differences in two ways. First, the difference-in-difference estimator controls for differences in levels, relying instead on an assumption of identical trends pretreatment. Second, the synthetic Arizona is created specifically to match Arizona's pretreatment trends.

4 Results

4.1 Iowa

The baseline estimates displayed in figure 5 point to a large increase in contributions to community foundations in Iowa. The estimate of the net change in contributions for the causal impact of Iowa's policy (a combination of the Endow Iowa Tax Credit and the County Endowment Fund Program) is a 63 percent increase in per capita contributions (a change of 0.49 in log levels). The estimate of the gross change in contributions suggests a 125 percent increase (a change of 0.81 in log levels). This represents more than $45 million in additional philanthropic spending annually at a cost of less than $6 million in lost tax revenue. Figure 5 displays the time series of log per capita contributions to community foundations in Iowa and its baseline synthetic control. Contributions to community foundations in Iowa rose sharply beginning in the second year after the introduction of the Endow Iowa Tax Credit. The level of giving predicted by the synthetic control, in contrast, shows little evidence of an increasing trend after 2000.

The synthetic Iowa in the baseline estimate is comprised of a weighted average of eight states that lead to the best fit along the set of predictor variables listed in line 9 of table 2. Predictor list 9, pre-intervention average levels of all of the potential predictor variables along with the level of contributions in the first and last years of the pre-treatment period, was selected using the calibration process described in section 3.2. The weighting matrix W used to create the synthetic control is displayed in table 5. Only eight of the states in the donor pool are used to create the synthetic Iowa. Table 5 shows that Vermont is given the greatest weight (26.7 percent) followed by West Virginia, Ohio, Indiana, Maryland, Louisiana, Wisconsin, and Arkansas.

We should be cautious not to infer a causal effect from what could be random variation in the data. Contribution levels to foundations are not consistent year to year and the trends displayed in figure 5 are fairly erratic. I use the placebo procedure described in section 3.2 to estimate the likelihood that the increase in contributions observed in Iowa could have occurred in the absence of a CTC policy. The results of these placebo tests are shown in the right panel of figure 5. ADH (2010) discuss the possibility of using a cut-off point to remove placebos that are poorly fit by their synthetic controls in the pre-intervention period. However, they note the lack of a systematic way to determine such a cut-off and propose that the ratio estimator—presented in equation 7—removes the influence of a poorly fit placebo.[21] I estimate p-values associated both directly from the DID estimate and using the ratio estimator.

The placebo experiments, displayed in the right panel of figure 5, indicate that

[21] ADH 2010 use the ratio between pre and post Mean Squared Prediction Errors. I follow ADH 2014 in using the ratio of RMSPE, but this does not affect the calculation of p-values.

estimates of increases in contributions of the magnitude found after introduction of the Endow Iowa tax credit are unlikely to have occurred in the absence of a CTC policy. The solid black line indicate the gap in log per capita contributions to community foundations between Iowa and its synthetic control. The dashed black line shows the same results net of the cost of Endow Iowa and the Community Endowment program. The gray lines display the difference between the placebo states and their respective synthetic controls. Positive (negative) values indicate years in which contributions to Iowa or a placebo were higher (lower) than to the synthetic control. Contributions to community foundations are driven by large, one-time donations and, as such, can be erratic. Despite the volatility in the data, Iowa generally appears toward the top of the distribution during the post-intervention period. I estimate that the p-values associated with the estimate of the gross change in contributions are 0.05, using the distribution of DID estimates, and 0.13 using the distribution of ratio estimators. The p-values associated with the estimate of the net change in contributions of additional giving beyond the cost of the program, are 0.18 and 0.28. While the total increase in contributions is unlikely to have occurred randomly, the results do not rule out a scenario in which the causal increase in donations is no more than the cost of the tax credit.

The most critical threat to a causal interpretation to these estimates is the possibility that the divergence between Iowa and its synthetic control was induced by a shock other than the introduction of Endow Iowa tax credits. Annual variation in contribution levels is too large to differentiate between Endow Iowa and the County Endowment program at the aggregate level. The SCM analysis presented here estimates the average treatment effect across the post-treatment period and is unable to differentiate between two closely related and closely timed policies. The firm-level estimates described in section 5.4, however find some evidence of different treatment effects. Additionally, any shock to the economy or market for charitable giving that occurred in Iowa or the synthetic control, but not the other, could cause contribution levels to diverge. It is not possible to fully rule out the possibility of all potential, unobservable shocks. However, we can rule out the possibility of any shocks that are highly correlated with observable trends.

Figure 6 compares Iowa and its synthetic control across six measures that would pick up evidence of such a shock: fundraising expenses, unemployment, per capita income, inequality, per capita state and municipal expenditures, and per capita state and municipal revenue, with all monetary metrics measured in log form.[22] The synthetic control generally follows the same trends as the real Iowa under most measures. I therefore rule out the possibility of a change in any unobservable shock that would be closely correlated with the state-wide economy or government spending. This analysis cannot do the same, however, for shocks correlated with both contribution levels and fundraising expenditures. The top left panel shows that the synthetic Iowa experienced erratic levels of fundraising spending by community foundations and poorly fits the true Iowa time series. In fact, a number of the donor states, especially Vermont, reported years in which no community foundation reported any fundraising expenditure.

To control for the possibility that the erratic fundraising levels in the synthetic Iowa are symptom of either unobserved shocks to the control or a vastly different environment that makes it a poor control, I create an alternative synthetic Iowa in which I treat fundraising expenditure as the primary variable of interest. The synthetic control for fundraising expenditure by community foundations in Iowa is displayed in figure 7. I then use the weights which optimized pre-treatment fit in fundraising to create an alternative time series for contribution levels. Using this new time series as a control for contributions in Iowa, leads to an estimate of a 106 percent increase (an estimate of the gross change in contributions of 0.72 and an estimate of the net change in contributions of 0.36 in log levels) in contributions after introduction of Endow Iowa. These results are only slightly smaller than those in the baseline. As such, shocks correlated with fundraising can be ruled out as threats to causality. Additional robustness checks are discussed in section 4.3.

[22]Synthetic control values displayed in figure 6 are weighted averages of logged values—rather than the log of weighted averages. This is consistent with the calculation of synthetic controls described in section 3.2.

4.2 Arizona

In the baseline specification, I estimate a small decline in contributions (9 percent) to a group of "highly treated" nonprofits in Arizona following introduction of the Working Poor Tax Credit. Figure 8 displays time series of per capita contributions to nonprofit charities in Arizona and its synthetic control. On a per capita basis, WPTC tax expenditures grew from 14 cents in its first year (1998) to $3.33 in 2012. In 2009, the only year for which data on credit awards was available at the organization level, donations to the six highly treated nonprofits accounted for 24 percent of all WPTC credits. The Expected Arizona time series assumes that this percentage—rather than the level of credits awarded—held constant from 1998 to 2012. Figure 8 shows that after the introduction of the tax credit, in more years than not, these six nonprofit received lower levels of contributions in Arizona than a synthetic counterfactual. The majority of that difference comes after 2004. Results of the placebo experiments are shown in the right panel of figure 8. An average decline of 9 percent occurred in the placebo experiments about one third of the time.

The synthetic Arizona in the baseline estimate is comprised of a weighted average of eight states that lead to the best fit along the of predictor variables listed in line 3 of table 2. Predictor list 3 includes the average and the values for the first and last year in the pre-intervention period for all the potential predictor variables. Somewhat surprisingly, more than 60 percent of the variable weight (matrix V) is given to the average population in the pre-intervention period. I perform robustness checks that exclude population as a potential predictor variable. The weighting matrix W used to create the synthetic control is displayed in table 6. Georgia dominates in terms of weight, making up more than 49 percent of the control. I perform robustness checks in which each state is (independently) excluded from the donor pool.

As I did with Iowa, I look for evidence that some abnormality in Arizona or a donor state—particularly Georgia—may have biased the estimates. Figure 9 compares Arizona and its synthetic control across fundraising expenses, unemployment, per capita income, inequality, per capita state and municipal expenditures, and per capita state and municipal revenue, with all monetary metrics measured in log form.[23] There is some deviation in fundraising expenditures after the WPTC went into effect, but this result could be endogenous. The synthetic control tracks the true Arizona across all other measures closely, including in the timing of economic downturns.

4.3 Robustness

The estimated effects of Endow Iowa and Arizona's WPTC are based upon the comparison to a synthetic counterfactual. Two concerns, however, remain. First, I want to ensure that none of the choices that I made have biased the results. Second, as with any DD based estimate, there is the potential that an unobservable change in the control group could bias the results. I therefore re-estimate the treatment effect of Iowa and Arizona's CTC policies under alternative methodological choices and using alternative control groups in order to test the robustness of my results.

Methodological choices described in sections 3.2 and 3.3 do not appear to have affected the estimates. Robustness checks for Endow Iowa appear in table 7. My decision to remove the apparent outlier, Council Bluffs Community Betterment Foundation improved estimated precision (lowering the p-value associated with the ratio metric) but did little to effect the estimated treatment effect. The choice to convert monetary values into natural log form before estimation follows the existing literature. Yet, since SCM does not make the same normality assumptions as traditional regression-based analysis, and because I estimate an average treatment effect rather than a pseudo-elasticity, this decision is arbitrary. SCM analysis without converting to natural log form suggests a $13.60 increase in contributions and placebo estimates suggest a lower statistical likelihood of a false positive. Similarly, I iterate the analysis without converting the level of contributions to a per capita measure, but still log-transforming the data, and estimate an increase in contributions that is almost identical to the baseline.

[23]As was the case with figure 6, Synthetic control values displayed in figure 9 are weighted averages of logged values—rather than the log of weighted averages.

The calibration procedure used to choose a combination of predictor variables proved not to be robust across choices of pre-treatment time period. I therefore examine the results using each of potential predictor variable lists. The range of estimates of the treatment effect appear similar no matter which group of predictor variables is used. List 9, used in the baseline for Iowa, produces the largest estimate. The smallest estimate still suggests a 55 percent increase (0.44 in log levels) in contributions and a 26 percent (0.24 in log levels) increase beyond the costs of Endow Iowa and the County Endowment Program..

I further examine whether the Iowa results are reliant on any one state being included as a donor state. The results appear both in table 7 and figure 10. In figure 10, the back line represents the gap between log per capita contributions in Iowa and its baseline synthetic control. Each gray line represents the gap re-estimated with a donor state excluded. Removing Vermont or West Virginia from the donor pool reduces the estimated impact of Endow Iowa, while removing the other donors has almost no effect. Even without Vermont or West Virginia, however, I would estimate a (gross) increase in contributions of more than 50 percent. Estimated effects using non-log transformed per capita contributions were also re-estimated with the removal of each donor state, as well without the two states—Wyoming and Delaware—that had years of zero contributions. Again, results were similar to those that appear in table 7.

One might question whether geographically dissimilar states such as Maryland or Vermont can contribute appropriately to a counterfactual Iowa. For this reason I perform a robustness check in which the donors are limited to neighboring states. The resulting synthetic control is comprised of Missouri (83 percent), Wisconsin (13 percent), and South Dakota (4 percent) provides the only negative point estimate. An alternative, albeit arbitrary, comparison Iowa to the average across each of its neighboring states suggests an increase in contributions of 36 percent.

Robustness checks for Arizona's WPTC appear in table 8. The first thing to note is that the baseline finding of a decline in contributions is not robust across specifications. Given the magnitude and the p-values associated with the estimate this is not surprising. Estimates range from a 36 percent increase to a 21 percent decrease in contributions, but rarely do I find a p-value below 0.2. Notably, much of the negative result may be driven by the presence of Georgia in the donor pool. Even without Georgia, however, estimates are smaller and the p-values are larger than those found in Iowa.

4.4 Secondary Hypotheses

I am unable to either reject Hypothesis 2 or its alternative. Hypothesis 2 predicts that Arizona's WPTC led to increased donations to untargeted nonprofits. Table 9 displays SCM-based difference-in-difference estimates of spillover effects. I find no evidence of an increase in contributions to nonprofits in Arizona that were unlikely to qualify under the WPTC. I classify nonprofits as untargeted if they were not classified under NTEE codes J, L, O, P, or T which would define them as focusing on areas targeted by the WPTC—Employment, Housing and Shelter, Youth, Human Services, or Philanthropy. I also examine the possibility of spillover to affiliates of the group of "highly treated" nonprofits in neighboring states. No clear pattern emerges that would support or refute hypothesis 2.

Tests of Hypothesis 3 also prove inconclusive. The theoretical model presented in section 2.2 predicts that Endow Iowa should have induced substitution away from untargeted charities toward Community Foundations in Iowa. If this is the case, we should see a decline in contributions to other nonprofits, relative to their counterfactuals.

I examine two types of nonprofits that may be perceived as substitutes to community foundations in Iowa. The first category are nonprofits in Iowa that would not have qualified for the credit. I examine all other nonprofits, other nonprofits classified in the broad Public and Societal Benefit Sector (NTEE codes R, S, T, U, V, and W) and other nonprofits classified as belonging to either the community improvement and capacity building sub-sector (NTEE code S) or the philanthropy, volunteerism, and grant making sub-sector (NTEE code T). I find mixed results. In the case of the smallest and most similar comparison group, I estimate a decline in contributions, but one that is replicated in 38 percent of placebo experiments. I find an increase in contributions to nonprofits in the broader Public and Societal Benefit sector and a decline in the category of all other nonprofits.

The second category of substitutes is community foundations in states that border Iowa. Here, too, results are mixed. A large increase in contributions to community foundations in South Dakota is statistically significant at the $\alpha = 0.1$ level, although the ratio test fails to meet that threshold. Note that three of the other five states that border South Dakota—Montana, Nebraska, and North Dakota—all enacted programs to promote planned giving and endowed charitable funds in the 1990s and 2000s. The increase in contribution levels in South Dakota could be the result of spillover effects from any or all of these programs. No clear pattern emerges from the results in Minnesota, Wisconsin, Illinois, and Missouri.

My analysis is generally supportive of Hypothesis 4 but fails to reject the alternative. Hypothesis 4 predicts that Endow Iowa produced an increase in contributions that is greater than the associated value of the tax credits. As discussed in section 4.1, the point estimates of the net change series displayed in table 7 are positive. While these results are robust across a range of specifications, placebo tests suggest that the estimates are not strong enough to reject the alternative hypothesis (that credits caused an increase in contributions no greater than the cost of lost revenue) at even the $\alpha = 0.1$ level of confidence.

5 Extensions and Inference on the Causal Mechanisms

5.1 Modest Growth in Per-Foundation Contribution Levels in Iowa

In order to understand the mechanism by which contributions increased in Iowa, it is necessary to estimate the effect of the policies on the number of foundations and the average effect of the policies at the organization level. This is analogous to studies of individual giving that differentiate between changes at the intensive and extensive margins. Here, rather than determining whether people are giving more or there are more givers, I examine whether foundations are receiving more or there are more foundations.

To estimate the impact of the policies on average contributions per foundation, I use more traditional, panel methods of DID estimation. As discussed in section 3.2, I use DID in order to estimate the increase in donations relative to the expected level in absence of the policy. While SCM are ideal for case studies in which the outcome of interest is a state-wide aggregate, at the organization level, I use fixed effects regressions of the form

$$Y_{ist} = \alpha_s + \lambda_t + \delta^* Iowa^* Post + [X_{ist}\beta] + \epsilon_{ist} \tag{8}$$

where i indexes the organization and t indexes the year. In alternate specifications, I allow s to index treatment, state, or organization ($s = i$). The coefficient of interest δ is the DID estimator. As such it analogous to DD_p from equation 6. I take the natural log of all monetary variables, and the control for state population, before running the regression. The regression is run with and without controls, X_{ist}. Initially, I estimate the equation using a ten year balanced panel from 1998 to 2007.

The results in columns 1 and 2 of table 10 suggest that contribution levels in Iowa increased by more than 25 percent following the passage of Endow Iowa. Columns 3 and 4 show that this finding is robust to the inclusion of state-level and firm-level controls. Columns 3 and 4 display estimates with and without fundraising, which almost certainly has an effect on contributions but is also likely to be endogenous to the treatment. The results are similar under both specifications.

Table 11 displays the sensitivity of the results to panel construction. I find a positive treatment effect when I iterate the analysis on both shorter and longer balanced panels. Moreover, the treatment effect remains statistically significant at at least the $p < 0.05$ level. However, the result does not hold when I run the same regression on the larger unbalanced panel. If the unbalanced panel is biased by attrition, then the estimates in table 11 from the balanced panels are better estimates of the causal effect. With the exception of the longest, narrowest panel (column 3), estimates of the per-foundation treatment effect are still far below the synthetic control-based estimates of aggregate change. An increase in the number of community foundations would explain this discrepancy.

5.2 Growth in the Number of Community Foundations

To estimate the impact of the Endow Iowa tax credit on the number of foundations I follow the synthetic control methodology described in section 3.2, replacing per capita contributions with the number of community foundations per million people. I present the results of this analysis in figure 11. Panel (a) shows that the number of community foundations is rising (on a per capita basis) in both Iowa and its synthetic control. The growth in Iowa outpaces its control, and the DID estimate is positive (0.25 in log levels or 28 percent). However, the period with the most rapid growth in the number of community foundations appears to be before implementation of Endow Iowa. Panel (b) of figure 11 displays the results of the placebo tests. The estimated DID p-value is 0.17.

SCM estimates and robustness checks for the change in number of community foundations are displayed in table 12. The baseline estimate suggests an 28 percent increase in the number of community foundations. As above, I run robustness checks using the natural log of the outcome variable, including CBCBF in the Iowa data, using alternate predictor variable lists, and dropping each donor from the baseline estimate. The alternative specifications yield similar results.

Among tax-filers, the number of Community Foundations in Iowa grew from 35 in 2001 to 55 in 2012, 57 percent growth. Nationally, the number of Community Foundations grew 48 percent, while growth in donor states Indiana and Wisconsin was only 33 percent and 29 percent. The fact that the dataset only includes organizations that filed IRS 990 forms may actually understate the growth in the sector. A report by the Iowa Council of Foundations and Iowa Economic Development Authority (2014) states the number of community foundations in the state has grown to at least 130. Two types of community foundations would not appear in the dataset (a) those that received less than $50,000 in gross receipts (contributions plus other revenue) and (b) affiliates of larger community foundations that filed 990 Forms jointly. Iowa's affiliate network is now extensive. Generally, these networks consists of newer, local (county) foundations and older, regional foundations (Iowa Council of Foundations and Iowa Gaming Association, 2013).

5.3 Endogenous Fundraising

It is possible that endogenous changes in fundraising could either increase or decrease the impact of a charitable tax credit. Figures 7 and 12 display the result of a synthetic control analysis for fundraising expenditure levels after Endow Iowa and Arizona's WPTC. There is no evidence of either a marked increase or decrease in fundraising levels relative to the synthetic control in either case. Arizona diverges from the synthetic control, but only during the period after the IRS Form 990s had changed.

Given that I find an increase in the number of community foundations in Iowa and no change in aggregate fundraising levels, a decline in per-foundation fundraising expenditures should be expected. Table 13 displays estimates of the effect of Iowa's policy on fundraising by individual community foundations. I find a decline in per-foundation fundraising levels that is robust across a variety of specifications.[24]

The growth in the number of foundations, at least partially, explains how aggregate fundraising spending could remain steady while per-foundation fundraising appeared to fall. The decline in fundraising expenditure at the foundation-level could be the result of collaboration between foundations. Since the passage of the Endow Iowa Tax Credits and County Endowment Fund Program, community foundations have, in a sense, subdivided themselves. Donor response may be related to the combination of the new tax incentives and the opportunity to contribute to more localized public goods.

[24] Individual year effects λ_t account for the change in metrics for Fundraising Expenditure described in section 3.1.

5.4 Disentangling Endow Iowa from the County Endowment Fund Grants

In order to disentangle the causal effects of Iowa's CTCs from the County Endowment Fund program, I re-estimate equation 8 with unique treatment dummies for each program. The results of these regressions, using a balanced panel from 1998 to 2007, appear in table 14. The first two columns show an increase in contributions tied to the introduction of the CTC and decline in contributions following the Endowment Fund program. After including a separate treatment variable for the Endowment Fund, the estimate of increased contributions coincident with the introduction of Endow Iowa remains robust across the various balanced panels but, again, is not robust to the expansion to an unbalanced panel. The estimated decline in contributions coincident with the introduction of Endowment Fund grants is not robust to alternative specifications of balanced panels.

The estimates of changes in per capita fundraising expenditure in columns 3 and 4 of table 14 further suggest that causal impacts are driven by Endow Iowa rather than the Community Endowment Fund. Moreover, even after the inclusion of separate treatment effects, the estimated decline in fundraising is robust across the balanced and unbalanced panels.

It is possible that forward looking residents anticipated the impacts of the County Endowment Fund program. I also cannot rule out the possibility that the impact of Endow Iowa changed, for some reason other than interaction with the County Endowment Program, concurrent with the initial disbursement of County Endowment grants. In either case, the differential effects of the policies cannot be uniquely identified.

5.5 Credit Programs in Other States

I focus on CTC programs in Iowa and Arizona because are were large, well documented, and well defined. As an extension, I explore three additional charitable tax credit programs—Missouri's credits for donations to food pantries, Missouri's Youth Opportunity Program, and Oklahoma's Donations to Biomedical Research Institutes

Credit—with substantial caveats. These programs are smaller, relative to the size of the nonprofit sectors that they target, than Endow Iowa and I was unable to find a group of "highly treated" nonprofits with affiliates in other states as I did in Arizona. In each case, however, the criteria that determines targeted nonprofits is well defined and the introduction of the policy falls within the sample period. Synthetic control results for all three appear in figure 13.

Missouri enacted a tax credit for donations to food pantries in 2007, with a provision to sunset in August of 2011. Donors could take a credit of fifty percent of qualifying donations up to \$2,500 and the total tax expenditure was capped at \$2 million annually, but less than \$1 million were claimed each year (Oversight Division, 2011). The \$793,000 in credits distributed in 2010 represented less than 0.6 percent of all contribution to food pantries. In 2013, the credit was reinstated. Since credits were available for part, but not all of 2011, I truncated the synthetic control analysis at 2010. The results in figure 13 show an increase in contributions, but one that is too small to differentiate from statistical noise.

Since 1996, Missouri's Youth Opportunities Program (YOP) has provided a 50 percent tax credit, up to \$200,000, for qualifying donations to support specific programs at approved nonprofits. Rather than targeting a specific nonprofit sector, YOP credits may be awarded to any nonprofit engaged in a program targeting at-risk youth (Missouri Department of Economic Development, 2013). Credits appear to have been awarded disproportionally to organizations categorized by NTEE as the Youth Development sector (such as Big Brothers Big Sisters), but nonprofits as diverse as Catholic Family Services and the Center Of Creative Arts also qualified based on specific programs. SCM estimates suggest a decline in contribution levels to the Youth Development sector, but the pre-treatment fit (shown to the left of the vertical line in figure 13 panel b is insufficient to draw inference.

Oklahoma's program, which began in 2005, provides donors a credit of 50 percent of the amount donated, not to exceed \$1,000. In 2012, Oklahoma distributed \$514,000 in credits. This represents less than 0.02 percent of the \$2.8 billion in total contributions to the nonprofit medical research sector in Oklahoma. Even if all of the credits went to donors who would not have otherwise donated, the effect may be imperceptible in contrast to the size of the sector. Therefore, a non-result is relatively uninformative. Figure 13 panel c shows the result of the SCM analysis; there is no evidence that the CTC program altered contribution levels.

Of additional interest is the repeal of CTCs programs. Michigan ended a 23 year CTC program that targeted community foundations in 2012 (Tax Analysis Devision, Office of Revenue and Tax Analysis, 2014). Figure 14 displays contributions to community foundations in Michigan in comparison with Iowa and the rest of the United States. Little can be said with only one year of contribution data since the policy change, yet it is fertile ground for future research.

6 Discussion

This paper provides the first rigorous, empirical analysis of the relationship between charitable tax credit policies and contributions to nonprofit organizations. Using synthetic control methods, I perform case studies of two contrasting CTC programs. In Iowa, I find as much as a 125 percent increase on per capita contributions to community foundations, the sector targeted by the Endow Iowa Tax Credit and the related County Endowment Fund program. Increased contributions occurred as the number of community foundations rose. Foundations that existed at the time that Endow Iowa was implemented saw increased contributions, although the effect on average levels is less clear. I find no evidence that nonprofits in Arizona received higher levels of contributions in response to the Working Poor Tax Credit. In the baseline estimate, point estimates suggest that the tax credit reduced contributions relative to a counterfactual.

It is important to differentiate the effects estimated in this paper from the tax-price elasticities estimated in the prior literature. Bakija and Heim (2011) and the extensive literature summarized by Peloza and Steel (2005) estimate the price elasticity of charitable giving using variation in the after-tax price of donations either across time, across donors, or both. In contrast, I estimate reduced form treatment effects in Iowa and Arizona. As such, the estimates in this paper include the effect of substitution *between* charities. Moreover, they include changes in contribution levels caused by behavioral responses to the policy changes such as changes in fundraising activities and the creation of new nonprofit entities.

These distinct results in Iowa and Arizona may be circumstantial, but there are four vital differences between the programs that could have caused Iowa's policy to outperform Arizona's. First, the structure of Arizona's credits—a 100 percent credit with a cap of $200 for individuals or $400 for couples—might have failed to provide appropriate incentives to donors. While more than $21 million in total credits were given to taxpayers in 2012 alone, the model presented in section 2.2 suggests that most individuals would treat these funds as small $200 lump sum transfers. In contrast, the same model suggests that Iowa's program had the potential to induce substitution between charities. Second, Iowa sharply targeted their credit program to incentivize contributions to a specific sector. The growth in contributions coincided with a growth in the number of foundations operating in the area the policy targeted. The Iowa legislature may have been pointing nonprofit entrepreneurs to an area of (perceived) need. It is possible that a broad policy such as Arizona's policy would fail to have similar effect. Third, both business and individuals are eligible for Endow Iowa credits while only individuals qualify for Arizona's WPTC. Fourth, Iowa followed their tax credit with the County Endow program.

While this paper does not fully differentiate between the effects of Endow Iowa and the County Endowment program, the literature on grants to nonprofit organizations suggest that it would be unusual for a grant program to induce the large effects found in Iowa. Tinkleman (2010) summarizes 46 empirical studies and finds only six that estimated levels of additional giving of greater than 50 percent. In contrast, I estimate additional giving of more than five times the amount granted through the Community Endowment Program. Where governments grants are found to crowd-in additional giving, it is often proposed that they serve as signal of quality. Indeed, Heutel (2014) finds larger levels of crowd in for younger charities. Although, those estimates would also suggest that the grants alone would not have caused contribution levels to more than double.

If the process by which states qualify organizations for CTCs provides additional, positive information to donors, CTCs might induce larger increases in contributions. Vesterlund (2003) provides a model in which early contributions provide signals of quality and produce higher contribution levels; lab experiments (Potters et al., 2005) support the model's conclusions. Discussing universities, Payne (2001) explains that if donors possess imperfect information, government grants can serve to inform potential contributors of research quality and thus crowd-in (increase) contributions. Qualifying for a CTC program may act as a similar signal. Heutel (2014) further posits that the signalling effect should be greater among charities about which less is known and finds (using nonprofit age as a proxy) evidence to support this hypothesis. Unlike traditional charities, community foundations are tasked not only with spending donors' money to produce public goods, but also with investing and managing the donors' money in order to maximize long-term impact. Insofar as this would make foundations less understood by donors than traditional charities (such as the homeless shelters and food pantries), there will be a larger signalling effect produced by Endow Iowa and the County Endowment program than the WPTC.

In Iowa, where the credit program appears to be a success, further research should consider second and third order effects. How are community foundations spending their additional income? Which nonprofits benefit from the growth in grant-making community foundations? Who benefits from their work? Additionally, it is worth further examining the relationship between the proliferation of community foundations and increased donations. Specifically, to what extent are donors drawn to more localized public goods?

It is always difficult to discern the external validity of case-study results. Synthetic Control Methods bring a focus on causal identification and quantitative rigour to case-study methodology. These results represent the first systematic analysis of the effects of charitable tax credits on nonprofits. Further, state-by-state, analysis is necessary. Finding appropriate identification strategies will be difficult, especially for programs that qualify projects rather than organizations. Nevertheless, this research demonstrates how much these charitable tax credit programs differ and points us in the direction of quantifying their failure or success.

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Table 1: Summary of Selected Charitable Tax Credits

Credit	State	Effective	Ended	Issued (2012)	Qualifying Organizations	Pre-Qaulifying Required?	Project Specific?	Peronal/ Business	Percentage	Cap	Refund-able?	Carry-Over?	Reference
Education Tax Credit	AK	1987	–	$3.8 million	Nonprofit or public schools and colleges	No	No	Business	50%*	$5 million	No	No	(Alaska Department of Renue, 2014) (Alaska Deparment of Revenue, 2015)
Working Poor Tax Credit	AZ	1998	–	$21.8 million	Varied	Yes	No	Personal	100%	$400/$800	No	Forward 5 years	(Gene, 2013) (Office of Economic Research and Analysis, 2014)
Neighborhood Assistance Tax Credit	CT	1982	–	$5 million	Varied	Yes	Yes	Business	60%**	$150,000	No	Back 2 years	(Office of Fiscal Analysis, 2012) (R.E. Van Norstrand Neighborhood Assistance Act)
Neighborhood Assistance Tax Credit	DE	2000	–	est. $200,000-$300,000	Varied	Yes	Yes	Business	50%	$100,000	No	Forward 5 years	(Division of Revenue. State of Dele-ware, 1999) (Neighborhood Assistance Tax Credit) (Department of Finance, 2011)
Endow Iowa Tax Credit	IA	2003	–	$5.8 million	Community Foundations	Yes	No	Both	25%	$300,000	No	Forward 5 years	(Gullickson and Tilkes, 2013)
Community Service Tax Credit Program	KS	1994	–	$4.1 million	Community Service, Crime Prevention, and Health Care Nonprofits	Yes	Yes	Both	50%***	$250,000 per Organi-zation	Yes	No	(Kansas Department of Commerce, 2014)
Endow Kentucky	KY	2011	–	$200,000	Community Foundations	Yes****	No	Both	20%	$10,000	No	Forward 5 years	(Governor's Office for Economic Analysis, Office of State Budget Directory, 2011) (Endow Kentucky Tax Credit)
Donations to Resource and Referral Agencies	LA	2008	–	$218,539	Private Agencies with contracts through the Department of Social Services	Yes	No	Business	100%	$5,000	Yes	No	(Louisiana Department of Revenue, 2013) (Louisiana Department of Revenue, 2015)
Homeless Shelter / Food Bank Credit	MI	1992	2011	$20.0 million (2011)	Homeless Shelters and Food Banks			Both	50%	$100/$200 (Individ-uals) $5,000 (Busi-nesses)			(Tax Analysis Devision, Office of Revenue and Tax Analysis, 2014)
Community Foundation / Education Credit	MI	1989	2011	$3.8 million (2011)	Community and Educa-tion Foundations			Both	50%	$100/$200 (Individ-uals) $5,000 (Busi-nesses)	No	No	(Tax Analysis Devision, Office of Revenue and Tax Analysis, 2014)
Youth Opportunities Program	MO	1996	–	$3.8 million	Varied	Yes	Yes	Both	50%	$200,000	No	Forward 5 years	(Missouri Department of Economic Devel-opment, 2015) (Missouri Department of Economic Development, 2013)
Food Pantry Tax Credit	MO	2007	2011	$793,794 (2010)	Food Pantries	No	No	Both	50%	$2,500	No	Forward 3 years	(Oversight Division, 2011)
Qualified Endowment Credit	NE	2006	2009	$150,000 (2008)	Any 501(c)3 with an en-dowment	No	No	Both	15%*****	$5,000	No	No	(Nebraska Department of Revenue Re-search Division, 2008) (Nebraska Depart-ment of Revenue, 2010)
Donations to Biomedical Research Institutes	OK	2005	–	$514,000	Medical Research Insi-tutes	No	No	Both	50%	$1,000	No	Forward 4 years	(The Tax Policy Division of The Oklahoma Tax Commission, 2012) (Qualified Inde-pendent Biomedical Research Institute or Qualified Cancer Research Center Credit)

* Alaska Education Credit is available for up to 50% of annual contributions up to $100,000, 100% of the next $200,000, and 50% of annual contributions beyond $300,000.

** Conneticut provides a 100% credit for energy conservation projects and construction or rehabilitation of low income housing units.

***The Kansas Community Service Program 70% credits for contributions in rural areas.

****Endow Kentucky requires preliminary authorization be requested by the donor rather than the grantee organization.

*****Nebraska's Qualified Endowment Credit provided a 15% credit for individuals, S corporations, partnerships and limited liability companies and a 10% credit for C corporations.

Table 2: Choices of Predictor Variables

	Predictor Variables
1	Annual Per Capita Contributions
2	Average Per Capita Contributions, Program Revenue, and Fundraising Expenditures; Average Per Capita Income, Population, Gini, and Top 1 Percent Share
3	Average, and the values for the first and last years in the pre-intervention period of: Per Capita Contributions, Per Capita Program Revenue, Per Capita Fundraising Expenditures, Per Capita Income, Population, Gini, and Top 1 Percent Share
4	Annual Per Capita Contributions; Average Program Revenue and Fundraising Expenditures; Average Per Capita Income, Population, Gini, and Top 1 Percent Share
5	Annual Per Capita Contributions; Average, and the values for the first and last years in the pre-intervention period of: Per Capita Program Revenue, Per Capita Fundraising Expenditures, Per Capita Income, Population, Gini, and Top 1 Percent Share
6	Average Per Capita Program Revenue and Fundraising Expenditures; Average Per Capita Income, Population, Gini, and Top 1 Percent Share
7	Average, and the values for the first and last years in the pre-intervention period of: Per Capita Program Revenue, Per Capita Fundraising Expenditures, Per Capita Income, Population, Gini, and Top 1 Percent Share
8	Average Per Capita Contributions; Average, and the values for the first and last years in the pre-intervention period of: Per Capita Program Revenue, Per Capita Fundraising Expenditures, Per Capita Income, Population, Gini, and Top 1 Percent Share
9	Average, and the values for the first and last years in the pre-intervention period of Per Capita Contributions; Average Per Capita Fundraising Expenditures and Program Revenue; Average Per Capita Income, Population, Gini, and Top 1 Percent Share
10	Average, and the values for the first and last years in the pre-intervention period of Per Capita Contributions Program Revenue, and Fundraising Expenditures

Notes: In all cases, I use the natural log of population. When estimating the time series of the natural log of per capita contributions, per capita fundraising expenditure, program revenue, and income are also log-transformed.

Table 3: State Level Summary Statistics: Community Foundations

	Iowa		Donor Pool		U.S.	
	Mean	sd	Mean	sd	Mean	sd
Total Per Capita Contributions	18.02	11.69	19.87	28.67	18.72	26.09
Per Capita Program Revenue	0.30	0.64	2.30	12.94	1.85	11.37
Per Capita Fundraising Expenditures	0.10	0.08	0.29	0.52	0.26	0.47
Community Foundations per million people	12.17	3.80	4.27	2.68	5.17	4.16
Population (Millions)	2.95	0.07	6.53	6.82	5.66	6.30
Per Capita Income	30,598	7,678	32,423	9,255	31,974	8,965
Gini Coefficient	0.55	0.01	0.59	0.04	0.59	0.04
Top 1 Percent Income Share	0.14	0.03	0.17	0.04	0.17	0.04

Notes: Standard deviations appear in the columns labelled "sd". All statistics are average levels for the years 1993 to 2012 and measured in 2012 dollars. Contributions, Program Revenue, and Fundraising expenditures for Council Bluffs Community Betterment Foundation are not included in the summary statistics.

Table 4: State Level Summary Statistics: Six National Nonprofit Charities

	Arizona		Donor Pool		U.S.	
	Mean	sd	Mean	sd	Mean	sd
Total Per Capita Contributions	22.12	5.41	23.47	22.31	23.11	20.89
Per Capita Program Revenue	7.50	5.68	7.02	8.04	6.87	7.61
Per Capita Fundraising Expenditures	1.22	0.55	9.98	269.34	8.76	250.18
Population (Millions)	5.24	0.93	5.52	6.59	5.56	6.20
Per Capita Income	26,944	6,909	30,80	9,693	30,285	9,465
Gini Coefficient	0.58	0.02	0.59	0.04	0.58	0.04
Top 1 Percent Income Share	0.16	0.03	0.16	0.04	0.16	0.04

Notes: Standard deviations appear in the columns labelled "sd". All statistics are average levels for the years 1989 to 2012 and measured in 2012 dollars. Contribution, Revenue, and Expenditure statistics are aggregates of all affiliates of Big Brothers Big Sisters, Boys and Girls Clubs, Goodwill Industries, Habitat for Humanity, St. Vincent De Paul Society and the United Way to the state level.

Table 5: Weights for Donor States, Iowa Community Foundations

State	Weight
Arkanas	0.027
Indiana	0.121
Louisiana	0.059
Maryland	0.108
Ohio	0.179
Vermont	0.267
Wisconsin	0.029
West Virginia	0.210

Notes: Table displays donor weights (matrix W). States not listed were either given zero weight or excluded from the donor pool. Weights create a synthetic aggregate of community foundations at the state level.

Table 6: Weights for Donor States, Arizona Affiliates of Six National Nonprofit Charities

State	Weight
Alaska	0.016
Florida	0.005
Georgia	0.493
Idaho	0.038
Oklahoma	0.092
South Carolina	0.039
Texas	0.039
Utah	0.277

Notes: Table displays donor weights (matrix W). States not listed were either given zero weight or excluded from the donor pool. Weights create a synthetic aggregate of Big Brothers Big Sisters, Boys and Girls Clubs, Goodwill Industries, Habitat for Humanity, St. Vincent De Paul Society and the United Way at the state level

Table 7: Estimated Policy Impact on Contributions to Foundations in Iowa

	Gross Change			Net Change		
	treatment	p-values		treatment	p-values	
	effect	DID	Ratio	effect	DID	Ratio
Baseline Estimate	0.81	0.05	0.13	0.49	0.18	0.28
CBCBF not dropped	0.80	0.05	0.21	0.45	0.15	0.59
Predictor Variable List 1	0.50	0.08	0.05	0.47	0.15	0.13
Predictor Variable List 2	0.75	0.05	0.13	0.50	0.15	0.13
Predictor Variable List 3	0.80	0.03	0.08	0.25	0.23	0.05
Predictor Variable List 4	0.50	0.08	0.05	0.32	0.21	0.21
Predictor Variable List 5	0.57	0.08	0.05	0.34	0.26	0.15
Predictor Variable List 6	0.71	0.13	0.10	0.38	0.21	0.13
Predictor Variable List 7	0.73	0.05	0.10	0.45	0.18	0.13
Predictor Variable List 8	0.75	0.03	0.10	0.45	0.18	0.13
Predictor Variable List 10	0.44	0.15	0.26	0.24	0.23	0.51
Arkansas Excluded from Donor Pool	0.80	0.05	0.13	0.48	0.21	0.29
Indiana Excluded	0.80	0.05	0.13	0.47	0.16	0.29
Louisiana Excluded	0.74	0.05	0.16	0.46	0.18	0.37
Maryland Excluded	0.80	0.05	0.13	0.47	0.18	0.21
Ohio Excluded	0.81	0.05	0.16	0.50	0.18	0.29
Vermont Excluded	0.48	0.13	0.37	0.28	0.18	0.76
Wisconsin Excluded	0.77	0.05	0.16	0.47	0.18	0.34
West Virginia Excluded	0.47	0.18	0.74	0.27	0.21	0.84
Using Weights for Fundraising	0.72	0.15	0.57	0.36	0.30	0.93
Restriction to Neighboring States	-0.03	0.60	0.80	-0.13	0.40	0.48
Excluding Population as a Predictor	0.91	0.05	0.18	0.55	0.10	1.19
vs. Average of Neighboring States	0.31	–	–	0.18	3.61	–
vs. National Average	0.35	–	–	0.15	2.95	–
Not Log Transformed	13.60	0.10	0.02	10.09	0.10	0.05
Not Per Capita	0.85	0.05	0.13	0.51	0.21	0.26

Notes: Treatment effect is a difference-in-difference estimate of change in log per capita contributions after intervention. The "Net Change" estimate adds the costs associated with Endow Iowa and the grants distributed by the Community Endowment Program to the counterfactual before calculating the difference-in-differences. Ratio is the ADH (2014) metric described in equation 7. Baseline Estimate follows the methodology described in sections 3.2. Estimates for untransformed per capita contributions follow similar methodology with an expanded donor pool that includes Wyoming and Delaware (which were dropped from the baseline due to years of zero contributions) and predictor set 2. Estimates of log, not per capita contributions use predictor set 9. Unless otherwise specified, the remaining estimates use the same set of predictor variables as the baseline, but create alternative synthetic controls. The p-values displayed are based on the null hypothesis that Endow Iowa increased contributions.

Table 8: Estimated Policy Impact on Contributions to Six National Nonprofit Charities in Arizona

	Gross Change			Net Change		
	treatment	p-values		treatment	p-values	
	effect	DID	Ratio	effect	DID	Ratio
Baseline Estimate	-0.10	0.36	0.36	-0.11	0.33	0.36
Predictor Variable List 1	0.14	0.31	0.58	0.13	0.36	0.58
Predictor Variable List 2	0.16	0.36	0.29	0.15	0.38	0.29
Predictor Variable List 4	0.14	0.31	0.58	0.13	0.36	0.58
Predictor Variable List 5	0.14	0.31	0.58	0.13	0.36	0.58
Predictor Variable List 6	0.18	0.27	0.18	0.16	0.31	0.18
Predictor Variable List 7	0.02	0.49	0.24	0.01	0.49	0.24
Predictor Variable List 8	-0.13	0.33	0.27	-0.14	0.33	0.27
Predictor Variable List 9	0.00	0.51	0.36	-0.01	0.51	0.36
Predictor Variable List 10	-0.24	0.13	0.38	-0.25	0.13	0.38
Including 1989 Data	0.31	0.16	0.62	0.29	0.16	0.62
Excluding Population as a Predictor	0.14	0.31	0.58	0.13	0.36	0.58
Alaska Excluded from Donor Pool	-0.17	0.30	0.34	-0.18	0.27	0.34
Florida Excluded	-0.11	0.30	0.36	-0.12	0.30	0.36
Georgia Excluded	0.23	0.14	0.34	0.22	0.16	0.36
Idaho Excluded	-0.08	0.36	0.34	-0.10	0.32	0.34
Oklahoma Excluded	-0.08	0.39	0.34	-0.09	0.36	0.34
South Carolina	-0.10	0.36	0.36	-0.12	0.32	0.36
Texas Excluded	-0.14	0.30	0.36	-0.15	0.27	0.36
Utah Excluded	-0.13	0.32	0.39	-0.14	0.30	0.36
Restriction to Neighboring States	0.09	0.50	0.50	0.07	0.50	0.50
vs. Neighboring States	0.10	–	–	0.08		–
vs. National Average	-0.11	–	–	0.15		–
Not Log Transformed	0.97	0.47	0.56	0.97	0.47	0.56
Not Per Capita	0.17	0.20	0.58	0.40	0.11	0.29

Notes: Treatment effect is a difference-in-difference estimate of change in log per capita contributions after intervention. The "Net Change" estimate adds the value of credits awarded (for donations to these six nonprofits) under the Working Poor Tax Credit to the counterfactual before calculating the difference-in-differences. The comparison is made between a state-level aggregate of Big Brothers Big Sisters, Boys and Girls Clubs, Goodwill Industries, Habitat for Humanity, St. Vincent De Paul Society and the United Way and its synthetic control. Ratio is the ADH (2014) metric described in equation 7. Baseline Estimate follows the methodology described in sections 3.2. Estimates for untransformed per capita contributions follow similar methodology with an expanded donor pool that includes Wyoming and Delaware (which were dropped from the baseline due to years of zero contributions) and predictor set 9. Estimates of log, not per capita contributions use predictor set 9. Unless otherwise specified, the remaining estimates use the same set of predictor variables as the baseline, but create alternative synthetic controls. Where estimates are positive (negative)The p-values displayed are based on the null hypothesis that WPTC increased (decreased) contributions.

Table 9: Estimated Spillover Effects from Endow Iowa and Arizona's WPTC Program

	treatment	p-values	
	effect	DID	Ratio
Estimates of Spillover from Endow Iowa			
Similar Nonprofits in Iowa	-0.11	0.38	0.55
Public/Societal Benefit Nonprofits in Iowa	0.09	0.20	0.20
Untargeted Nonprofits in Iowa	-0.21	0.08	0.30
Community Foundations in South Dakota	0.63	0.08	0.25
Community Foundations in Minnesota	-0.33	0.22	0.30
Community Foundations in Wisconsin	0.00	0.45	0.38
Community Foundations in Illinois	0.09	0.43	0.98
Community Foundations in Missouri	0.61	0.10	0.90
Estimates of Spillover from WPTC			
Untargeted Nonprofits in Arizona	-0.05	0.42	0.16
Affiliates in California	0.40	0.09	0.93
Affiliates in Nevada	-0.13	0.29	0.58
Affiliates in Utah	-0.25	0.13	0.09
Affiliates in Colorado	0.06	0.42	0.89
Affiliates in New Mexico	-0.03	0.42	0.78

Notes: Treatment effect is a synthetic control-based difference-in-difference estimate of change in log per capita contributions after intervention. The category "Similar Nonprofits in Iowa" includes (Form 990 filing) nonprofit organizations, other than NTEE code T31 community foundations, classified as belonging to either the community improvement and capacity building sub-sector (NTEE code S) or the philanthropy, volunteerism, and grant making sub-sector (NTEE code T). "Public/Social Benefit Nonprofits in Iowa" includes nonprofits, other than community foundations, classified under the broad Public and Societal Benefit Sector (NTEE codes R, S, T, U, V, and W). "Untargeted Nonprofits in Iowa" includes all nonprofits other than community foundations. The remaining spillover estimates for Iowa refer to changes in contributions to community foundations in neighboring states. "Untargeted Nonprofits in Arizona" includes all (Form 990 filing) nonprofit organizations that are not classified under NTEE codes J, L, O, P, and T which would classify them as focusing on areas targeted by the WPTC—Employment, Housing and Shelter, Youth, Human Services, and Philanthropy. Additional spillover estimates in Arizona refer to the change in contributions at affiliates of Big Brothers Big Sisters, Boys and Girls Clubs, Goodwill Industries, Habitat for Humanity, St. Vincent De Paul Society and the United Way in neighboring states. Ratio is the ADH (2014) metric described in equation 7. Baseline Estimate follows the methodology described in sections 3.2.

Table 10: Change in Contributions Per Community Foundation (10 Year Balanced Panel)

	(1)	(2)	(3)	(4)
Treatment	0.268**	0.268**	0.253*	0.287*
	(0.085)	(0.090)	(0.119)	(0.121)
Iowa	-1.439***			
	(0.111)			
Per Capita Income			3.165	3.272
			(1.578)	(1.721)
Populaton			0.612	0.706
			(1.536)	(1.623)
Gini Coefficient			0.027	0.496
			(1.734)	(1.868)
Top 1				
			(1.989)	(2.079)
Fundraising Expenditure				0.022**
				(0.008)
Program Revenue				-0.006
				(0.005)
Year FE	yes	yes	yes	yes
Foundation FE	yes	yes	yes	yes
Observations	2650	2650	2650	2650

* $p< 0.05$ ** $p< 0.01$ *** $p< 0.001$

Standard Errors (in parentheses) are clustered at the state level.

Notes: Contributions, Fundraising Expenditure, Program Revenue, Per Capita Income, and Population are natural log transformed. All dollars are real, 2012 base year.

Table 11: Change in Contributions Per Community Foundation (Sensitivity)

	Balanced			Unbalanced
	1998-2007	2000-2005	1993-2012	
Treatment	0.287*	0.358***	0.729***	0.059
	(0.121)	(0.082)	(0.143)	(0.059)
Per Capita Income	3.272	1.894	2.429	2.118*
	(1.721)	(1.865)	(1.588)	(1.017)
Populaton	0.706	0.023	0.156	0.603*
	(1.623)	(0.119)	(1.174)	(0.277)
Gini Coefficient	0.496	2.543	8.612*	-1.449
	(1.868)	(2.724)	(3.164)	(1.833)
Top 1% Share	-1.954	-2.724	-8.229**	1.100
	(2.079)	(2.365)	(2.806)	(1.477)
Fundraising Expenditure	0.022**	0.019**	0.016**	0.016***
	(0.008)	(0.006)	(0.006)	(0.003)
Program Revenue	-0.006	0.002	-0.012	-0.001
	(0.005)	(0.007)	(0.009)	(0.003)
Year FE	yes	yes	yes	yes
Foundation FE	yes	yes	yes	yes
Observations	2650	2712	1700	13269

* p< 0.05 ** p< 0.01 *** p< 0.001

Standard Errors (in parentheses) are clustered at the state level.

Notes: Contributions, Fundraising Expenditure, Program Revenue, Per Capita Income, and Population are natural log transformed. All dollars are real, 2012 base year.

Table 12: Estimated Policy Impact on the Number of Community Foundations in Iowa

	treatment effect	p-values DID	p-values Ratio
Baseline Estimate	0.25	0.17	0.15
CBCBF included with Iowa Foundations	0.25	0.17	0.15
Predictor Variable List 1	0.25	0.17	0.15
Predictor Variable List 2	0.34	0.10	0.08
Predictor Variable List 3	0.33	0.10	0.03
Predictor Variable List 4	0.25	0.17	0.15
Predictor Variable List 5	0.25	0.17	0.15
Predictor Variable List 6	0.24	0.15	0.22
Predictor Variable List 7	0.23	0.22	0.22
Predictor Variable List 8	0.34	0.10	0.03
Predictor Variable List 10	0.30	0.20	0.15
Indiana Excluded	0.26	0.18	0.23
Oklahoma Excluded	0.24	0.15	0.15
Wisconsin Excluded	0.25	0.18	0.15
Restriction to Neighboring States	0.25	0.17	0.17
Excluding Population as a Predictor	0.30	0.13	0.15
vs. Average of Neighboring States	0.31	–	–
vs. National Average	0.35	–	–
Not Log Transformed	3.62	0.02	0.07
Not Standardized to Per Capita Levels	0.08	0.32	0.85

Notes: Treatment Effect is a difference-in-difference estimate of change in (log) number of foundations per million residents or (log) per capita fundraising expenditures. Post/Pre ratio is the ADH (2014) metric described in equation 7. Baseline Estimate follows the methodology described in section 3.2. Estimates for untransformed measures were made by separately calibrating the list of predictor variables. Unless otherwise specified, the remaining estimates use the same set of predictor variables as the baseline, but create alternative synthetic controls. The p-values displayed are based on the null hypothesis that Endow Iowa increased either number of foundations.

Table 13: Change in Fundraising Expenditure Per Community Foundation

		Balanced		Unbalanced
	1998-2007	2000-2005	1993-2012	
Treatment	-1.710*	-1.102*	-1.167	-0.713* [t]
	2.370	(0.449)	(0.991)	(0.330)
Per Capita Income	(0.766)	-7.588	-12.945	0.227
	(9.119)	(11.825)	(9.455)	(3.600)
Populaton	5.186	-0.801	3.486	-0.516
	(4.954)	(0.785)	(7.602)	(0.645)
Gini Coefficient	-28.118	-25.646	-32.689	-5.684
	(27.578)	(14.687)	(42.215)	(9.828)
Top 1% Share	28.636	32.085*	6.908	8.186
	(24.724)	(15.566)	(34.065)	(9.004)
Year FE	yes	yes	yes	yes
Foundation FE	yes	yes	yes	yes
Observations	2460	2712	1700	13269

* $p< 0.05$ ** $p< 0.01$ *** $p< 0.001$

Standard Errors (in parentheses) are clustered at the state level.

Notes: Contributions, Fundraising Expenditure, Program Revenue, Per Capita Income, and Population are natural log transformed. All dollars are real, 2012 base year.

Table 14: Differential Impacts of Endow Iowa and Community Endowment Fund Program (1998-2007 Balanced Panel)

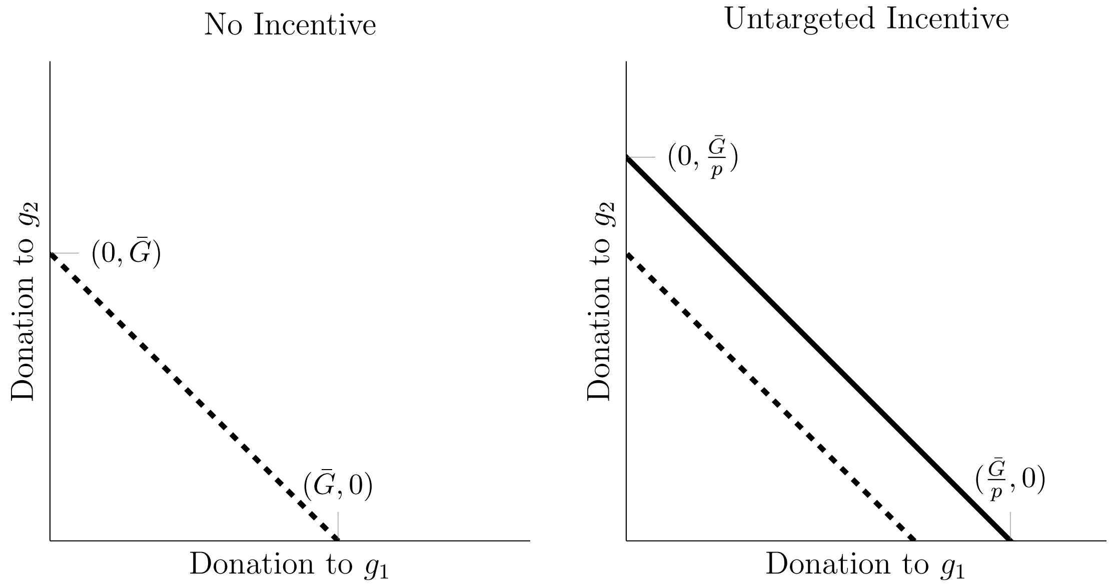
	Contributions		Fundraising	
	(1)	(2)	(3)	(4)
Endow Iowa	0.339**	0.378**	-1.721**	-1.941***
	(0.114)	(0.113)	(0.517)	(0.526)
Community Endowment Fund	-0.146**	-0.155**	0.452	0.524
	(0.048)	(0.050)	(0.290)	(0.314)
Per Capita Income	3.162	3.269	-3.341	-5.710
	(1.584)	(1.728)	(10.186)	(10.655)
Populaton	0.586	0.679	-1.512	-2.593
	(1.531)	(1.619)	(10.920)	(10.777)
Gini Coefficient	-0.039	0.427	-14.250	-16.005
	(1.739)	(1.873)	(17.417)	(17.954)
Top 1% Share	-1.191	-1.898	27.570	29.402
	(1.994)	(2.085)	(20.241)	(20.556)
Fundraising Expenditure		0.022**		
		(0.008)		
Program Revenue		-0.006		0.078
		(0.005)		(0.041)
Contributions				0.625**
				(0.213)
Year FE	yes	yes	yes	yes
Foundation FE	yes	yes	yes	yes
Observations	2650	2650	2650	2650

* p< 0.05   ** p< 0.01   *** p< 0.001

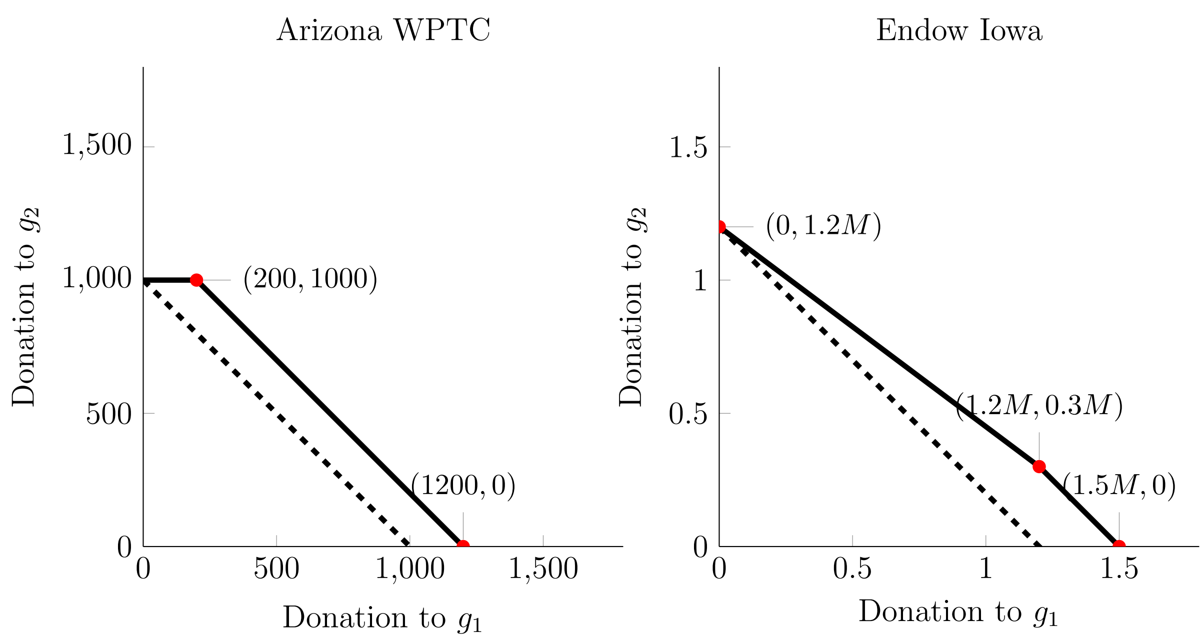
Standard Errors (in parentheses) are clustered at the state level.

Notes: Contributions, Fundraising Expenditure, Program Revenue, Per Capita Income, and Population are natural log transformed. All dollars are real, 2012 base year.

Figure 1: Budget Constraints of Donors in Arizona and Iowa

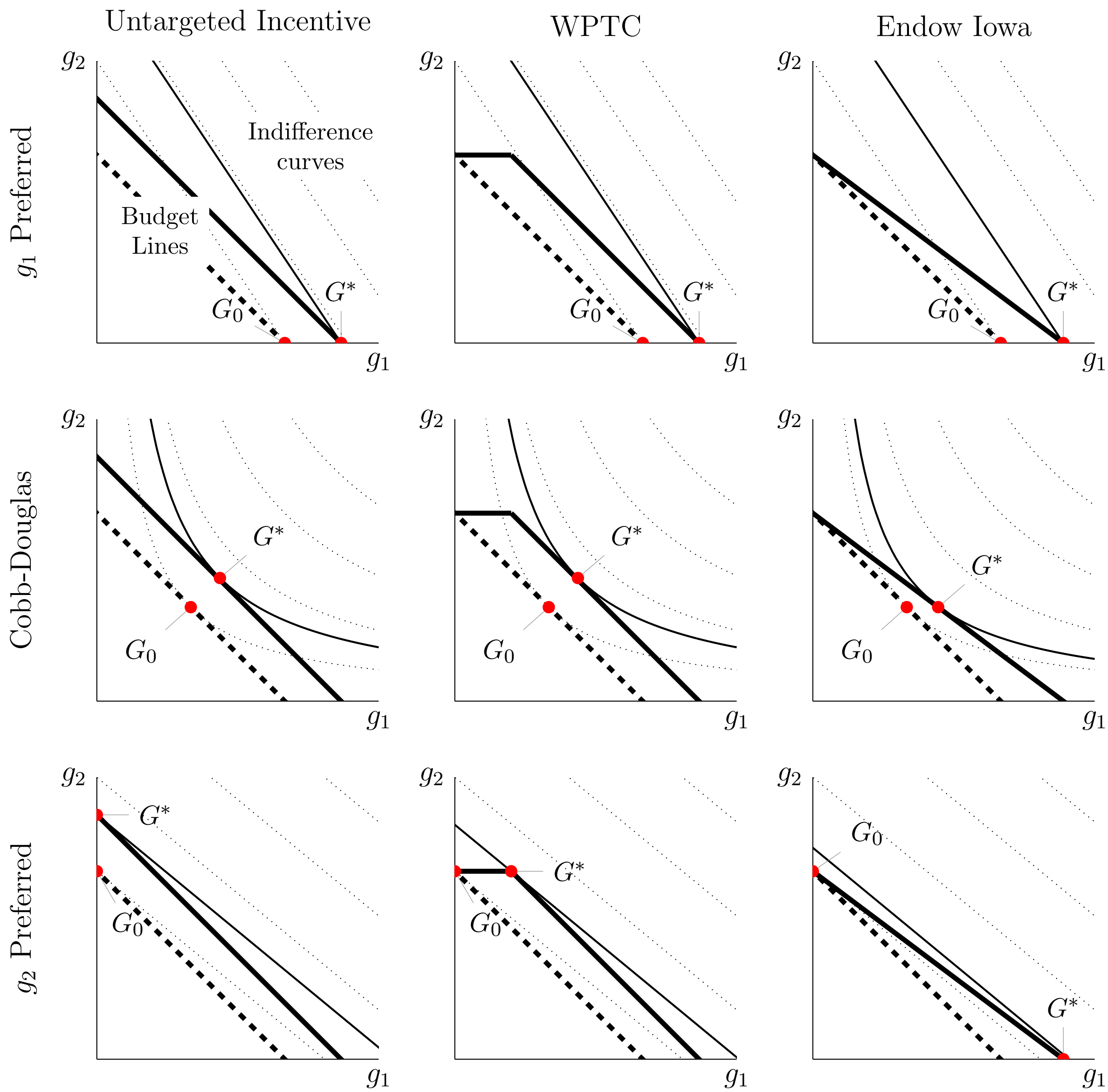


(a) Budget constraints before (dashed) and after (solid)the implementation of an untargeted tax incentive for charitable giving. The budget line shifts outward in proportion to the size of the incentive. The slope of the line is unchanged.



(b) Budget constraints before (dashed) and after (solid)the implementation of an CTC programs in Arizona and Iowa. Kinks in the budget constraint occur when the total subsidy reaches a statutory cap. Note that the budget constraints are not on the same scale. The graphs above include a donor qualifying for Arizona's WPTC spending $1,000 after taxes and a donor qualifying for Endow Iowa spending $1.2 million after taxes. The disparate budgets were chosen to make the kinks in the budget constraints visible in both graphs. In figure 2 the budget constraints are on the same scale.

Figure 2: Consumer Responses to Changes in the Tax Treatment of Charitable Giving



A model of donation with targeted tax incentives. The figure displays the budget constraints before (dashed) and after (solid)the implementation of an untargeted incentive and CTC programs in Arizona (WPTC) and Iowa (Endow Iowa). Indifference curves in the top row assume the charities are substitutes but the targeted charity is preferred. Indifference curves in the middle row assume that donors see charities as neither substitutes nor compliments. Indifference curves in the bottom row assume that the charities are substitutes, that the untargeted charity is preferred in the absence of a subsidy, and that the targeted charity is preferred when it is subsidized.

Figure 3: IRS Form 990

Form **990** | **Return of Organization Exempt From Income Tax** | OMB No. 1545-0047

Under section 501(c), 527, or 4947(a)(1) of the Internal Revenue Code (except black lung benefit trust or private foundation)

▶ The organization may have to use a copy of this return to satisfy state reporting requirements.

Department of the Treasury
Internal Revenue Service

2011
Open to Public Inspection

A For the 2011 calendar year, or tax year beginning , 2011, and ending , 20

B Check if applicable:
- ☐ Address change
- ☐ Name change
- ☐ Initial return
- ☐ Terminated
- ☐ Amended return
- ☐ Application pending

C Name of organization
Doing Business As
Number and street (or P.O. box if mail is not delivered to street address) | Room/suite
City or town, state or country, and ZIP + 4

D Employer identification number
E Telephone number
G Gross receipts $

F Name and address of principal officer:

H(a) Is this a group return for affiliates? ☐ **Yes** ☐ **No**
H(b) Are all affiliates included? ☐ **Yes** ☐ **No**
If "No," attach a list. (see instructions)

I Tax-exempt status: ☐ 501(c)(3) ☐ 501(c) ( ) ◀ (insert no.) ☐ 4947(a)(1) or ☐ 527

J Website: ▶

H(c) Group exemption number ▶

K Form of organization: ☐ Corporation ☐ Trust ☐ Association ☐ Other ▶ | **L** Year of formation: | **M** State of legal domicile:

Part I Summary

Activities & Governance

1 Briefly describe the organization's mission or most significant activities:

2 Check this box ▶☐ if the organization discontinued its operations or disposed of more than 25% of its net assets.

3	Number of voting members of the governing body (Part VI, line 1a)	3	
4	Number of independent voting members of the governing body (Part VI, line 1b)	4	
5	Total number of individuals employed in calendar year 2011 (Part V, line 2a)	5	
6	Total number of volunteers (estimate if necessary)	6	
7a	Total unrelated business revenue from Part VIII, column (C), line 12	7a	
b	Net unrelated business taxable income from Form 990-T, line 34	7b	

			Prior Year	Current Year
Revenue	8	Contributions and grants (Part VIII, line 1h)		
	9	Program service revenue (Part VIII, line 2g)		
	10	Investment income (Part VIII, column (A), lines 3, 4, and 7d)		
	11	Other revenue (Part VIII, column (A), lines 5, 6d, 8c, 9c, 10c, and 11e)		
	12	Total revenue—add lines 8 through 11 (must equal Part VIII, column (A), line 12)		
Expenses	13	Grants and similar amounts paid (Part IX, column (A), lines 1–3)		
	14	Benefits paid to or for members (Part IX, column (A), line 4)		
	15	Salaries, other compensation, employee benefits (Part IX, column (A), lines 5–10)		
	16a	Professional fundraising fees (Part IX, column (A), line 11e)		
	b	Total fundraising expenses (Part IX, column (D), line 25) ▶		
	17	Other expenses (Part IX, column (A), lines 11a–11d, 11f–24e)		
	18	Total expenses. Add lines 13–17 (must equal Part IX, column (A), line 25)		
	19	Revenue less expenses. Subtract line 18 from line 12		
			Beginning of Current Year	**End of Year**
Net Assets or Fund Balances	20	Total assets (Part X, line 16)		
	21	Total liabilities (Part X, line 26)		
	22	Net assets or fund balances. Subtract line 21 from line 20		

Part II Signature Block

Under penalties of perjury, I declare that I have examined this return, including accompanying schedules and statements, and to the best of my knowledge and belief, it is true, correct, and complete. Declaration of preparer (other than officer) is based on all information of which preparer has any knowledge.

Sign Here
Signature of officer | Date
Type or print name and title

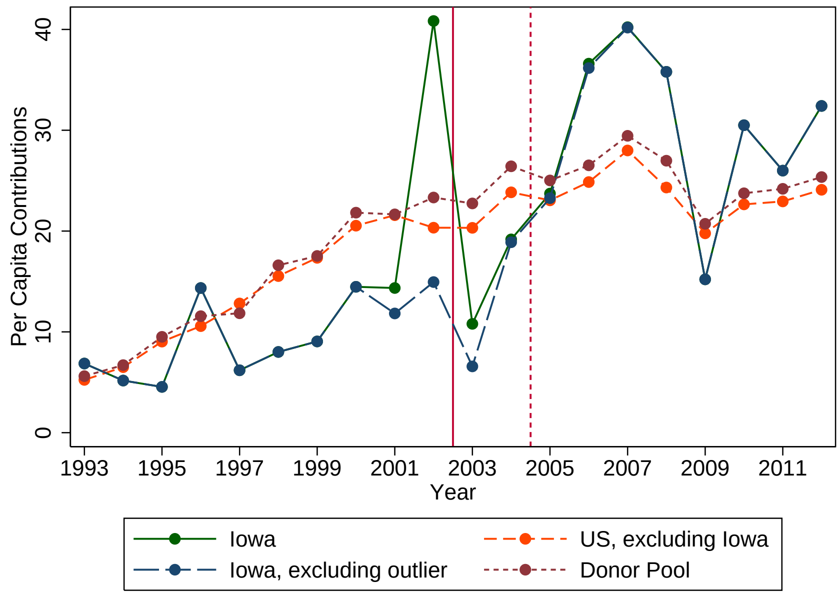
Paid Preparer Use Only
Print/Type preparer's name | Preparer's signature | Date | Check ☐ if self-employed | PTIN
Firm's name ▶ | Firm's EIN ▶
Firm's address ▶ | Phone no.

May the IRS discuss this return with the preparer shown above? (see instructions) ☐ **Yes** ☐ **No**

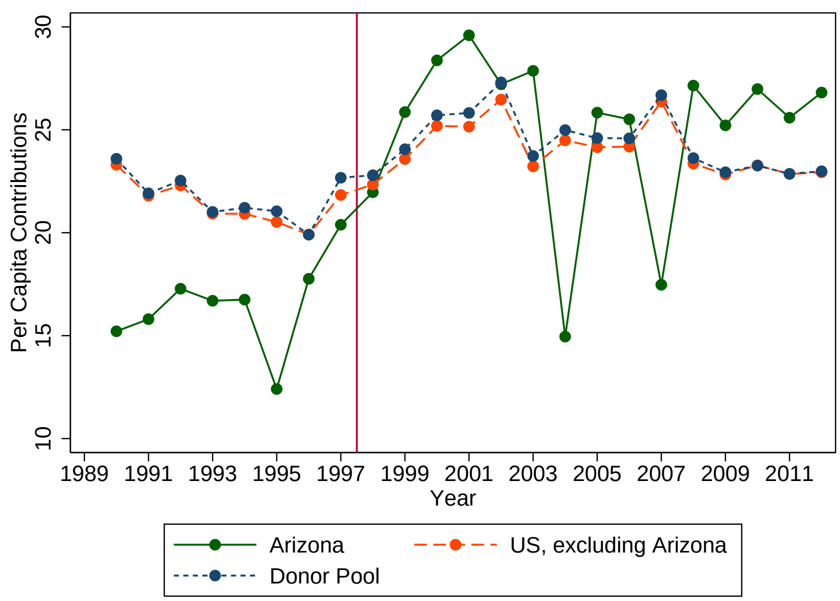
For Paperwork Reduction Act Notice, see the separate instructions. Cat. No. 11282Y Form **990** (2011)

Page 1 of a sample IRS Form 990 downloaded from the IRS website, http://www.irs.gov/pub/irs-prior/f990ez–2011.pdf . Lines 8-12 document sources of revenue. Contributions appear on on line 8.

Figure 4: Per Capita Contributions to Treated Nonprofits and their Donor Pools.



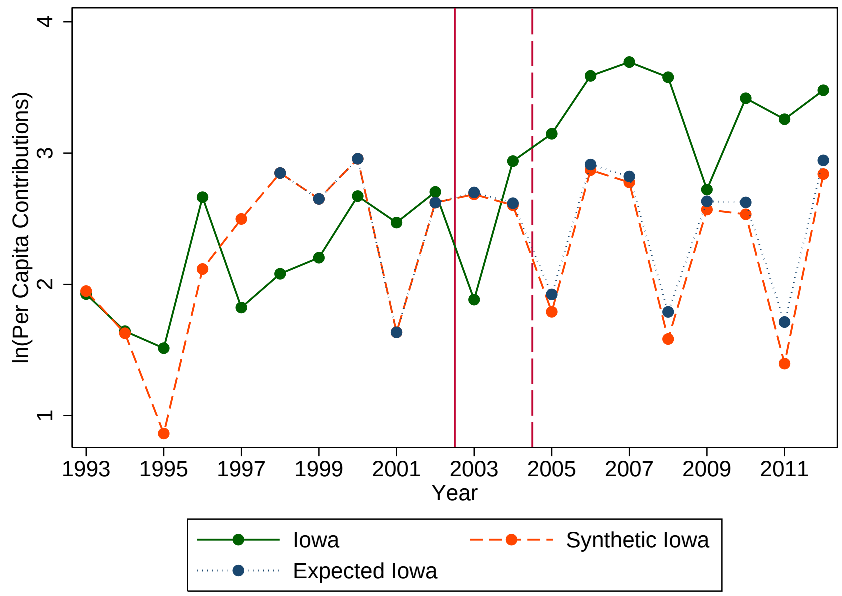
(a) Community Foundations in Iowa, the United States, and the Donor Pool. 1993–2012



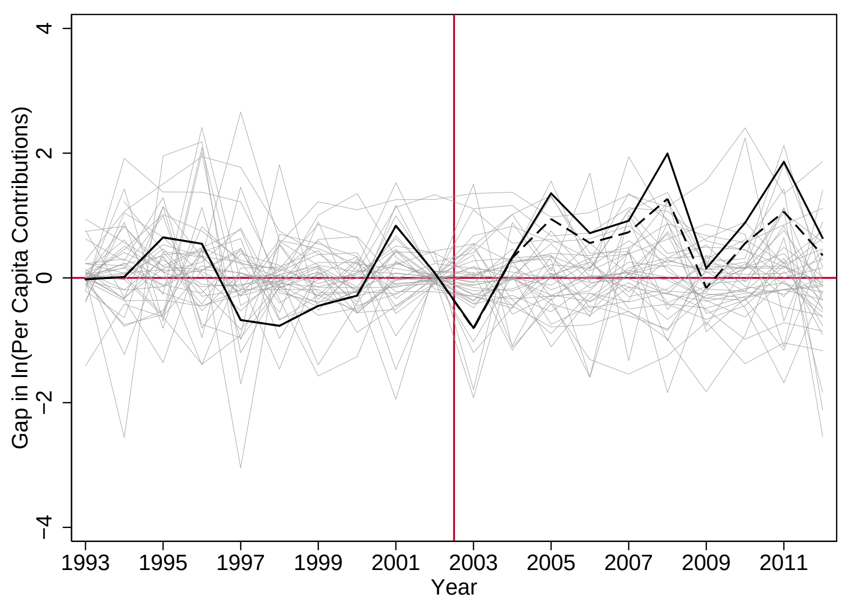
(b) Aggregate of Six National Nonprofits in Arizona, the United States, and the donor pool, 1990–2012

Figures represent total per capita contributions reported by 501(c)3 nonprofit charities on IRS Form 990. Iowa, excluding outlier, removes Council Bluffs Community Betterment Foundation. The Donor Pool for Iowa consists of 39 untreated states. The Donor Pool for Arizona consists of 44 untreated states. Solid vertical lines represent the introduction of the Endow Iowa Tax Credit and Working Poor Tax Credit. The dashed vertical line in panel a represents the first distribution of County Endowment Funds.

Figure 5: Synthetic Control Analysis: Endow Iowa Tax Credit



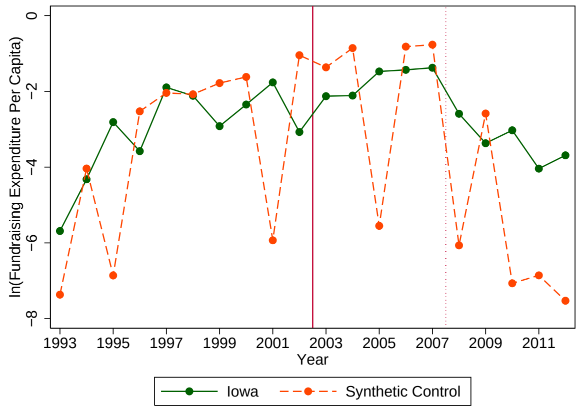
(a) Log Per Capita Contributions to Community Foundations: Iowa and Synthetic Controls



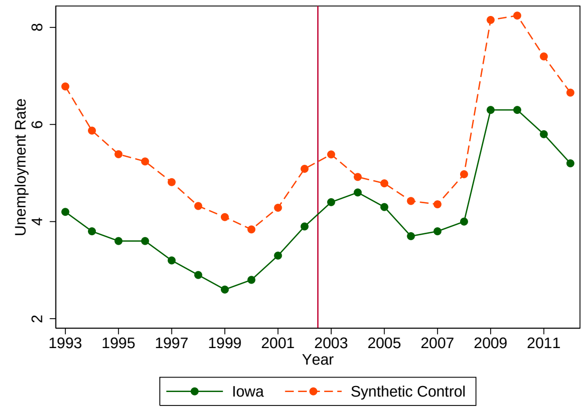
(b) Difference in the Log Per Capita Contributions relative to Synthetic Control, Iowa and Placebos

The Iowa time series in panel (a) represents total per capita contributions reported by community foundations on IRS Form 990. Synthetic Iowa is derived from a donor pool or 39 untreated states. Expected Iowa adds the costs associated with Endow Iowa and the County Endowment Fund program to the synthetic counterfactual. In panel (b) the black solid (dashed) line displays the difference between Iowa and synthetic (expected Iowa). Gray lines represent placebo tests. In both panels, the vertical lines represent the introduction of the Endow Iowa Tax Credit (solid) and the first distribution of County Endowment Funds (dashed).

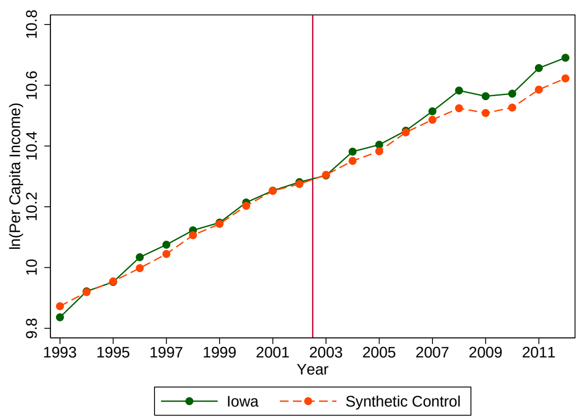
Figure 6: Balance between Iowa and its Synthetic Control: Trends in Fundraising, Income, Inequality, and Unemployment



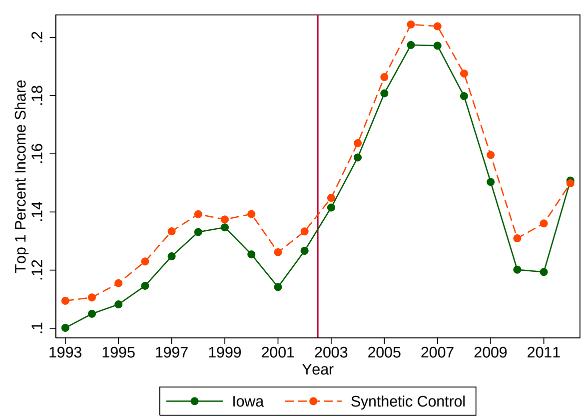
(a) Log Per Capita Fundraising Expenditures



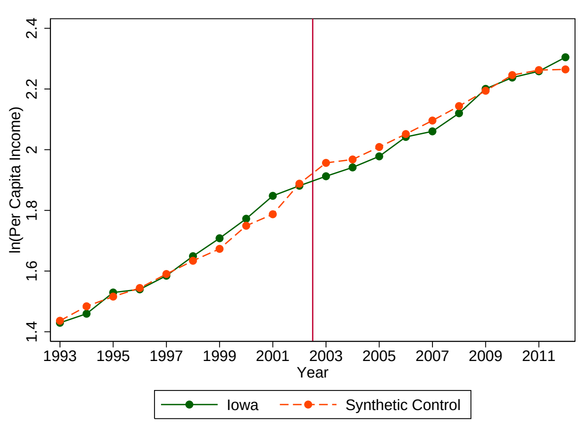
(b) State-wide Unemployment Rate



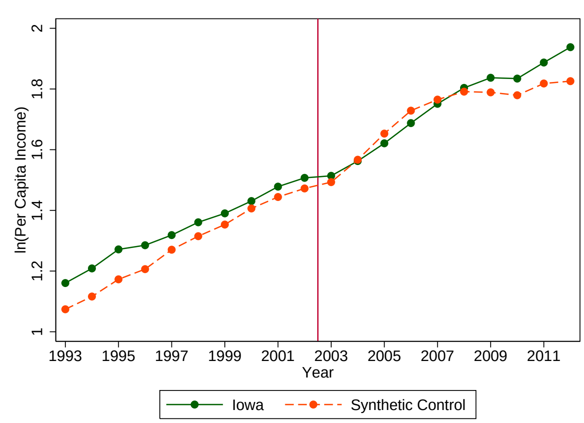
(c) Log Per Capita Income



(d) Inequality: Share of Income to the Top 1 percent



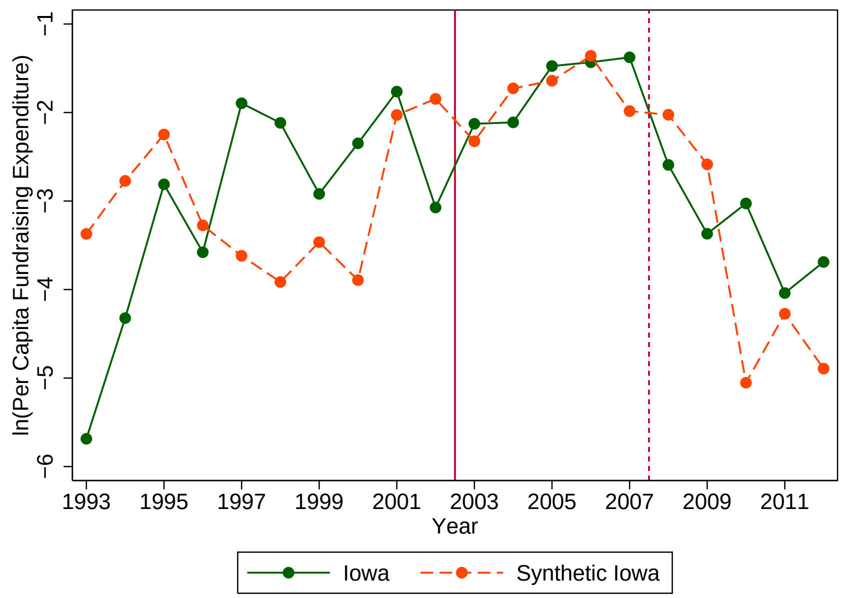
(e) Log State and Municipal Expenditures



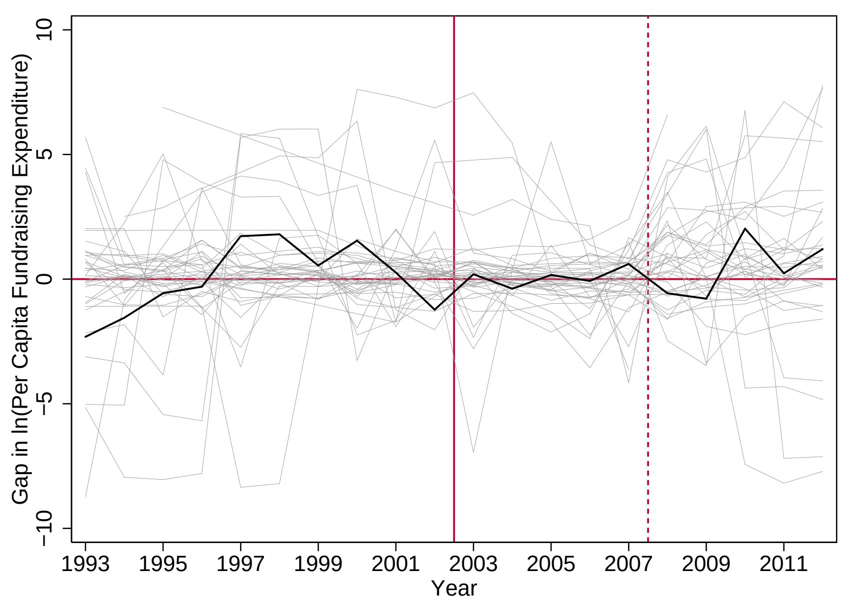
(f) Log State and Municipal Revenues

Note: The figures compare trends in Iowa to those of its baseline Synthetic Control. (That is, the Synthetic Control estimated to fit the trend in Per Capita Contributions in the pre-intervention period shown in figure 5.) Trends in Fundraising, Income, and Inequality were used to fit the synthetic control. Trends in Unemployment were not. The solid vertical line separates pre and post intervention periods. The dashed vertical line marks the first distribution of County Endowment Funds. The dotted line in panel (a) marks the change in the metric for fundraising expenditure.

Figure 7: Synthetic Control Analysis: Endow Iowa Tax Credit (Fundraising)



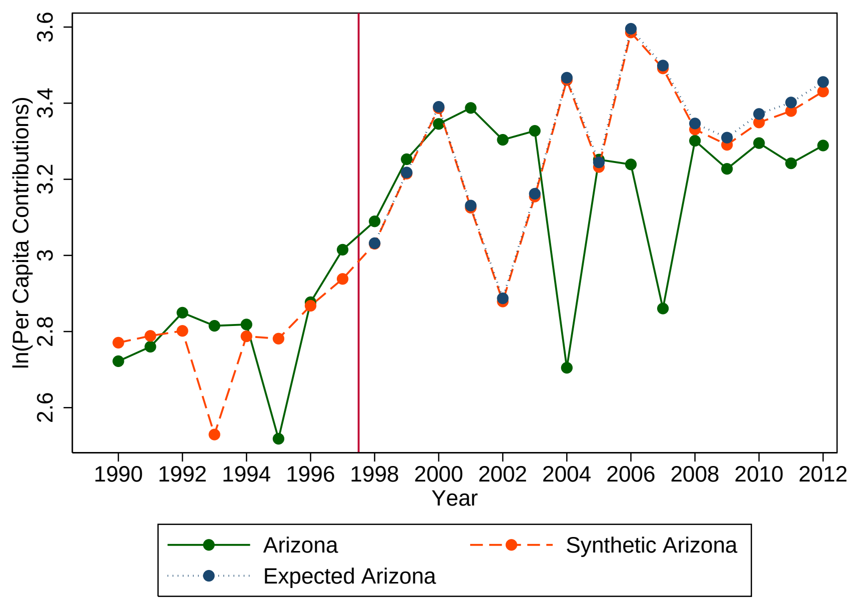
(a) Log Per Capita Fundraising Expenditures by Community Foundations: Iowa and Synthetic Controls



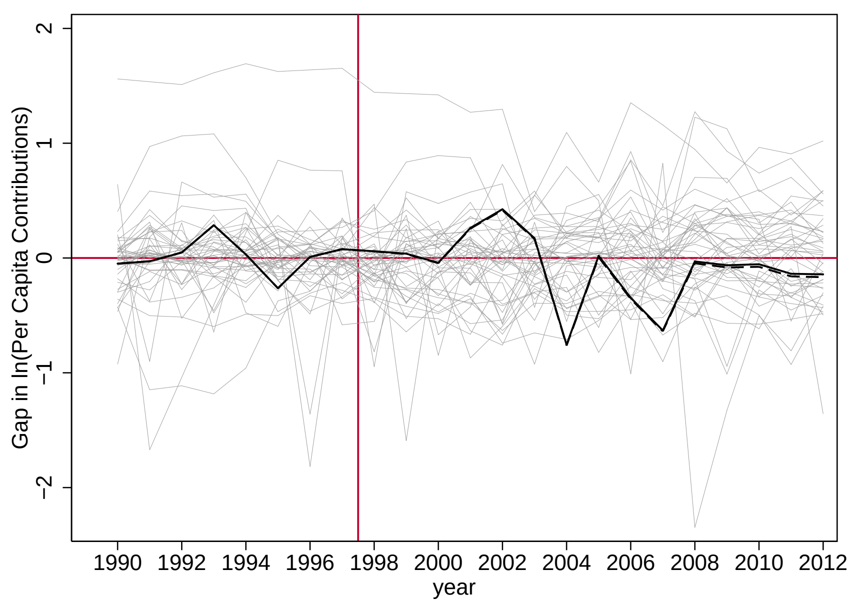
(b) Difference in the Log Per Capita Fundraising Expenditures relative to Synthetic Control, Iowa and Placebos

The Iowa time series in panel (a) represents total per capita fundraising expenditures reported by community foundations on IRS Form 990. Synthetic Iowa is derived from a donor pool or 39 untreated states. In panel (b) the black line displays the difference between Iowa and expected Iowa. Gray lines represent placebo tests. In both panels, the vertical lines represent the introduction of the Endow Iowa Tax Credit (solid) and the change in how fundraising expenditure is reported on IRS Form 990 (dashed).

Figure 8: Synthetic Control Analysis: Arizona's Working Poor Tax Credit



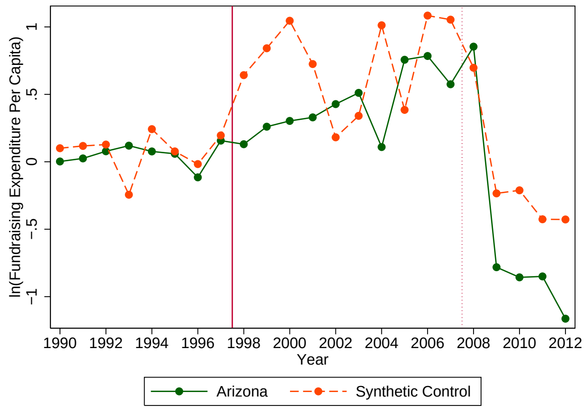
(a) Log Per Capita Contributions to Six National Nonprofits: Arizona and Synthetic Controls



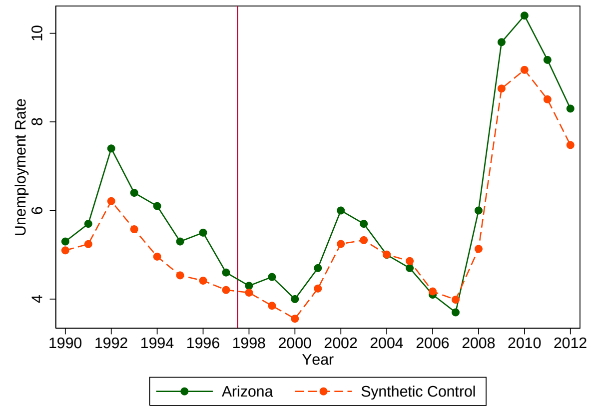
(b) Difference in the Log Per Capita Contributions relative to Synthetic Control, Arizona and Placebos

The Arizona time series in panel (a) represents total per capita contributions reported by six national 501(c)3 nonprofit charities on IRS Form 990. Synthetic Arizona is derived from a donor pool or 43 untreated states. Expected Arizona adds the estimated tax expenditure associated with credits received by donors to the six nonprofits to the synthetic counterfactual. In panel (b) the black line displays the difference between Arizona and expected Arizona. Gray lines represent placebo tests. In both panels, the vertical lines represent the introduction of the Working Poor Tax Credit.

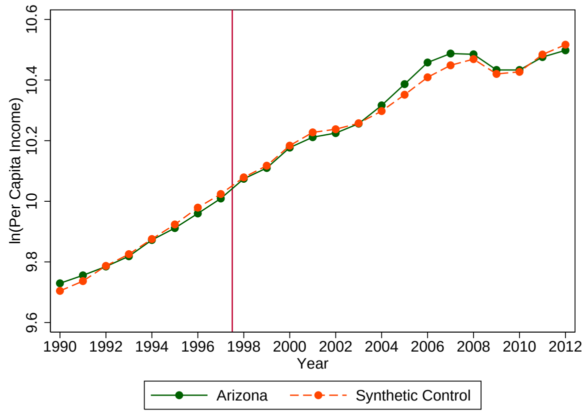
Figure 9: Balance between Arizona and its Synthetic Control: Trends in Fundraising, Income, Inequality, and Unemployment



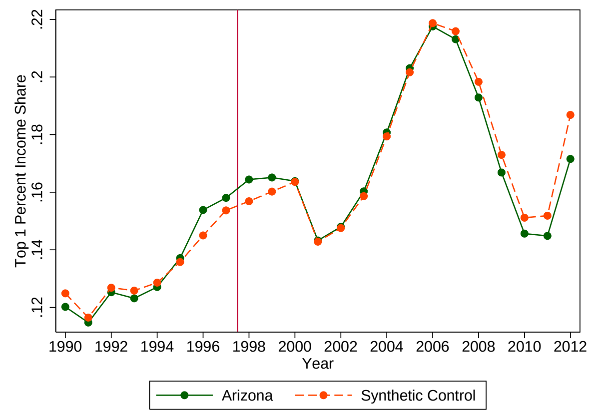
(a) Per Capita Fundraising Expenditures



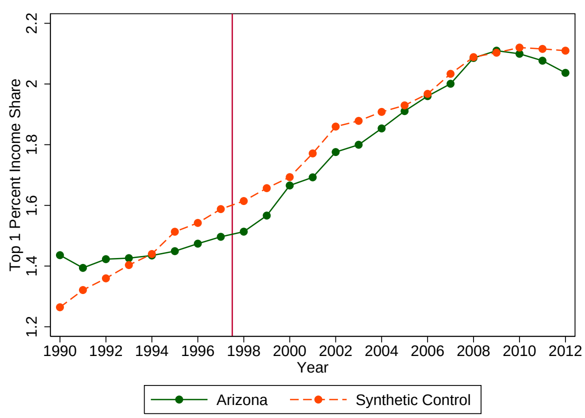
(b) State-wide Unemployment Rate



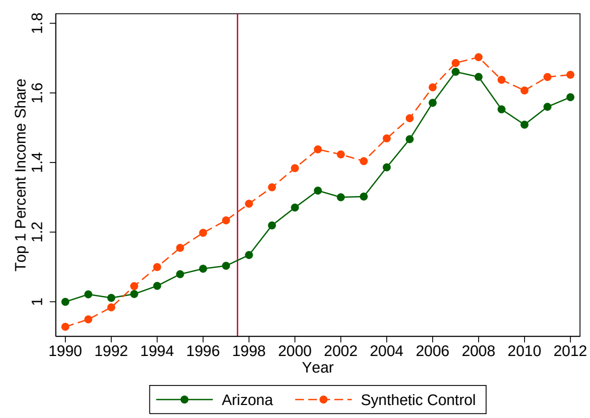
(c) Per Capita Income



(d) Inequality: Share of Income to the Top 1 percent



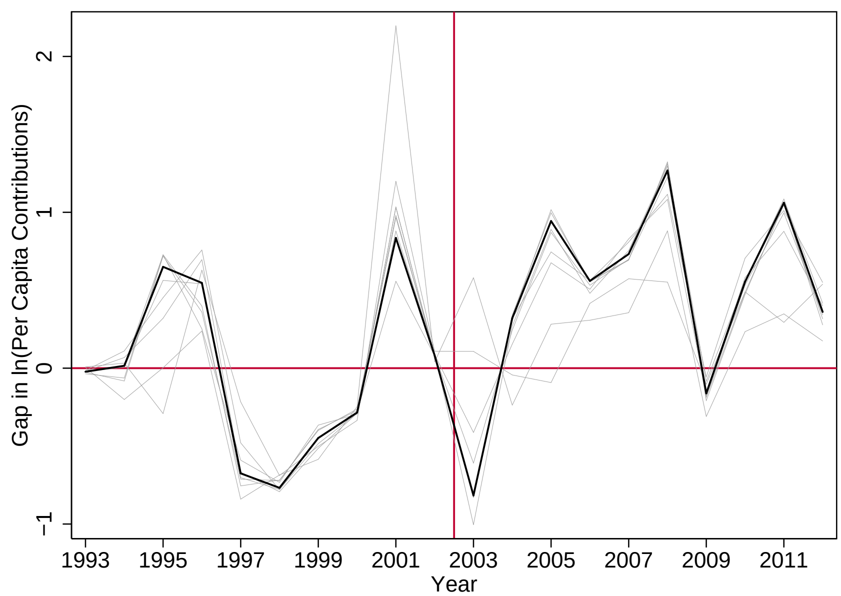
(e) State and Municipal Expenditures



(f) State and Municipal Revenues

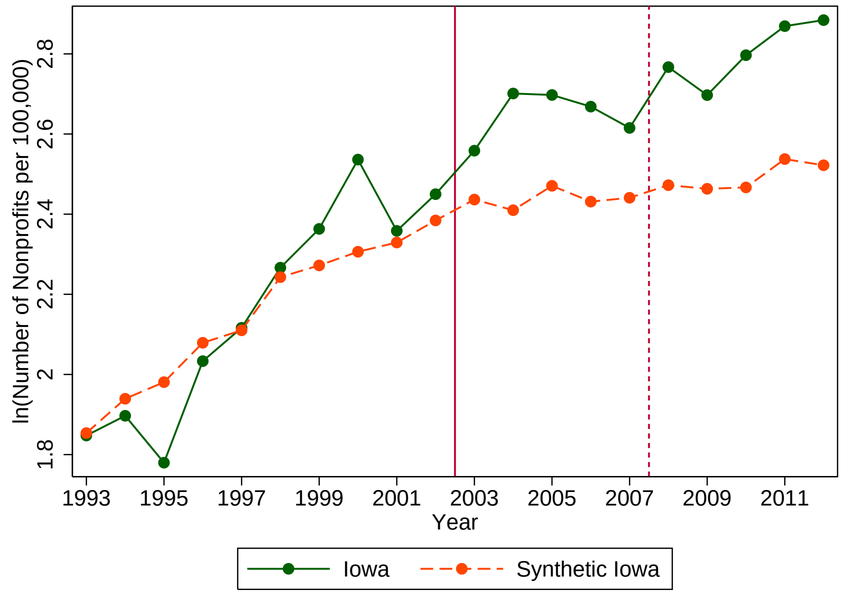
Note: The figures compare trends in Arizona to those of its baseline Synthetic Control. (That is the Synthetic Control estimated to fit the trend in Per Capita Contributions in the pre-intervention period shown in figure 8) Levels of Fundraising, Income, and Inequality were used to fit the synthetic control. Unemployment data was not. The solid vertical line separates pre and post intervention periods. The dashed vertical line in the panel (a) represents the break in the data series between alternative fundraising aggregates.

Figure 10: Leave-One-Out Robustness Check: Endow Iowa

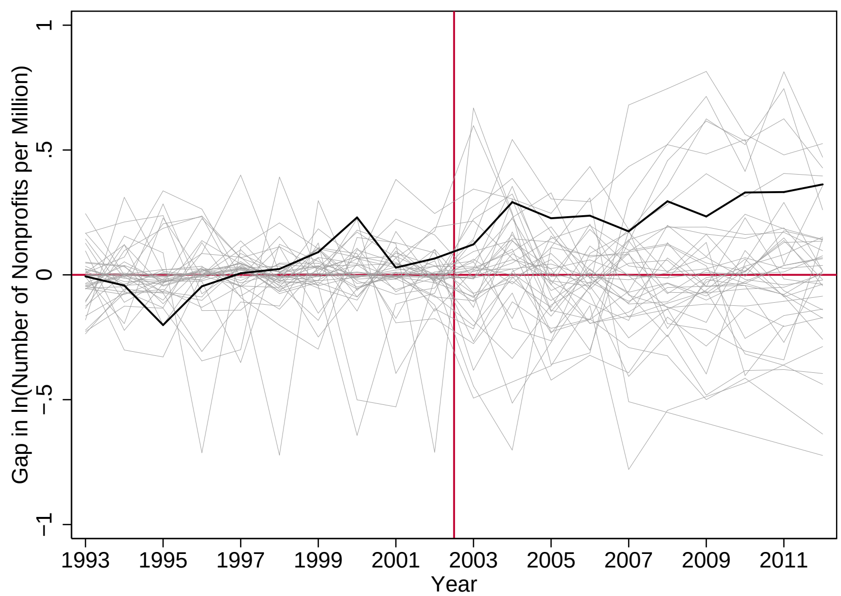


The black line displays the difference between Iowa and expected Iowa. Gray lines represent the difference calculated from alternative synthetic controls in which one of the donor states from the baseline estimate is excluded. The vertical line represents the introduction of the Endow Iowa Tax Credit.

Figure 11: Synthetic Control Analysis: Endow Iowa Tax Credit (Community Foundations)



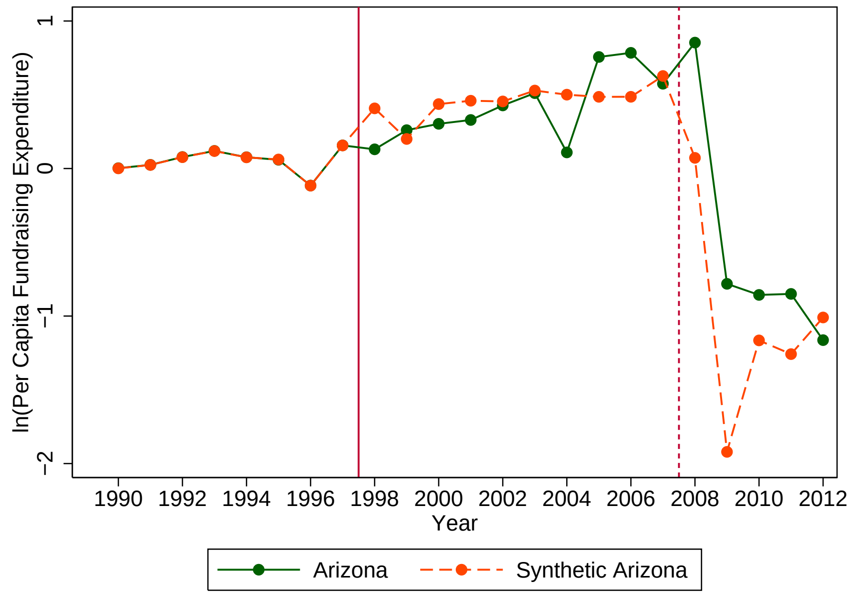
(a) Log of Community Foundations Per Capita: Iowa and Synthetic Controls



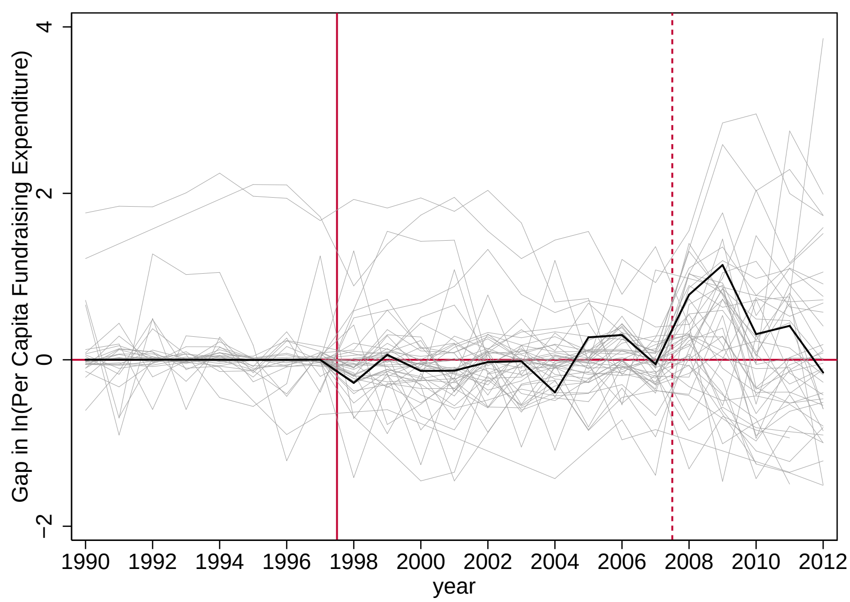
(b) Difference in the Log quantity of Community Foundations Per Capita relative to Synthetic Control, Iowa and Placebos

The Iowa time series in panel (a) the number of community foundations who filed IRS Form 990. Synthetic Iowa is derived from a donor pool or 39 untreated states. In panel (b) the black line displays the difference between Iowa and expected Iowa. Gray lines represent placebo tests. In both panels, the solid vertical line represent the introduction of the Endow Iowa Tax Credit.

Figure 12: Synthetic Control Analysis: Working Poor Tax Credit (Fundraising)



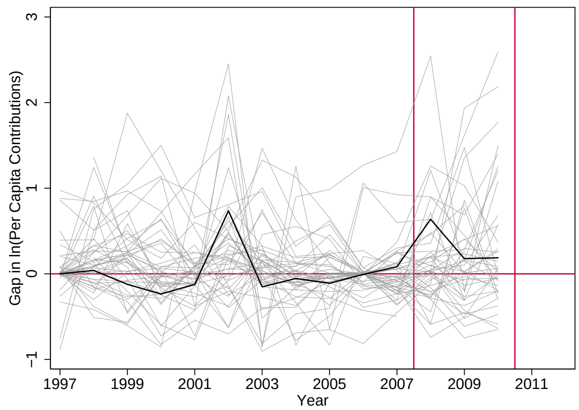
(a) Log of Per Capita Fundraising Expenditure by Six National Nonprofits, in Arizona and its Synthetic Control



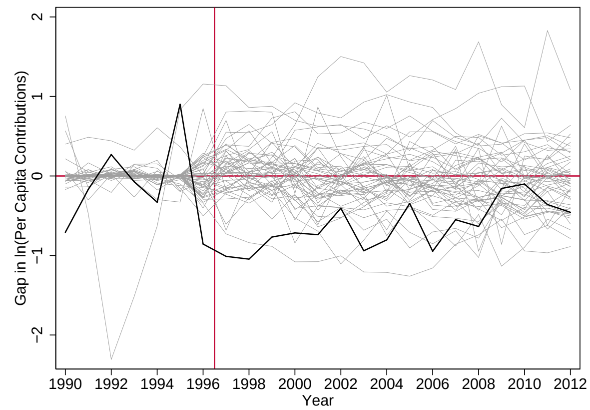
(b) Difference in the Log Per Capita Fundraising Expenditure relative to Synthetic Control, Arizona and Placebos

The Arizona time series in panel (a) represents total per capita fundraising expenditures reported by six national nonprofits. Synthetic Arizona is derived from a donor pool or 43 untreated states. In panel (b) the black line displays the difference between Arizona and expected Arizona. Gray lines represent placebo tests. In both panels, the vertical lines represent the introduction of the WPTC (solid) and the change in how fundraising expenditure is reported on IRS Form 990 (dashed).

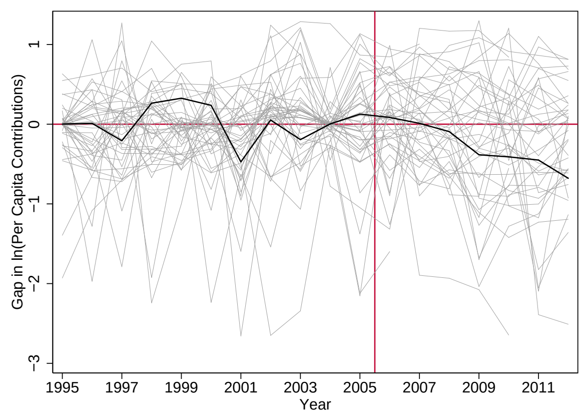
Figure 13: Synthetic Control Analysis: Additional Charitable Tax Credit Programs



(a) Missouri Food Pantry Tax Credit



(b) Missouri Youth Opportunities Program



(c) Oklahoma Tax Credit for Donations to Biomedical Research Institutions

In each panel, the black line displays the difference between log per capita contribution levels to targeted nonprofits in the treated state and its synthetic control. Gray lines represent placebo tests. Vertical lines represent the introduction of the Tax Credit program. The time series for Missouri's Food Pantry Tax Credit is truncated at 2010, the year in which the policy sunset.

Figure 14: Per Capita Contributions to Community Foundations in Michigan, Iowa, the United States, 1993–2012

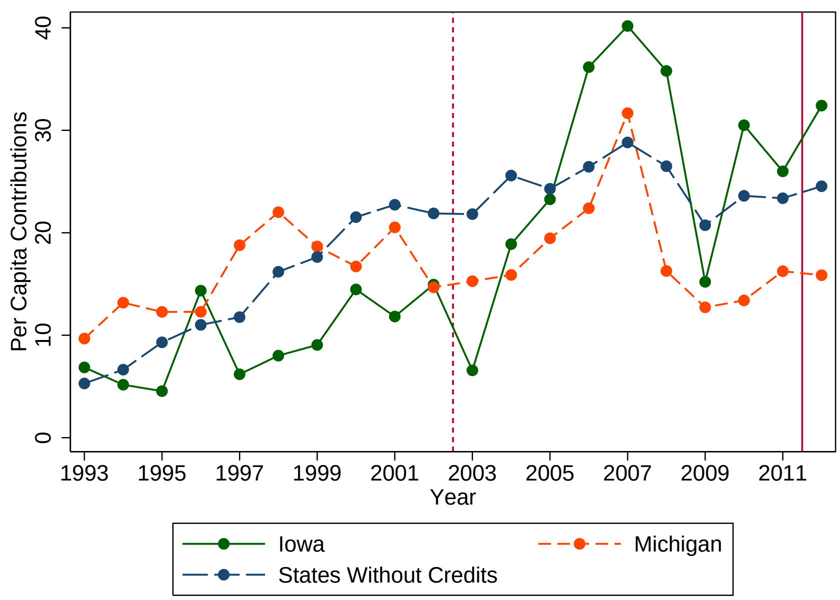


Figure represents total per capita contributions reported by community foundations on IRS Form 990. Vertical lines represent the introduction of the Endow Iowa Tax Credit (dashed) and the repeal of Michigan's tax credit programs (solid).