Growth, Inequality, and Nonprofit Contributions

Elaine Kiiru*

September 22, 2024

Abstract

The nonprofit sector is a small part of the economy that has potentially outsized effects on welfare and has grown in the past 30 years. One important distinction between nonprofit organizations and for-profit firms is that many nonprofits receive charitable contributions. Contributions to nonprofits have risen from 1.2 percent of GDP to around 1.7 percent of GDP, while the income distribution has become more unequal over this period. In a model with non-homothetic preferences for positive charitable contributions and other consumption, increasing GDP produces more than the observed increase in charitable contributions, while increasing inequality slightly decreases charitable contributions.

Keywords: Altruism, Inequality, Nonprofit institutions, Economic Growth

JEL Codes: D63, L31, O40

*I am grateful for the guidance and feedback of my advisors: David Lagakos, Pascual Restrepo, and Stephen Terry.

1 Introduction

Over the past thirty years, charitable contributions have risen faster than GDP, yet few macroeconomic models can address this trend because they lack altruistic agents. I use a general equilibrium model, with non-homothetic preferences for consumption and contributions, to determine which macroeconomic trends contribute to the relative increase in contributions. I find that economic growth plays an important role in the increase in contributions to the nonprofit sector, relative to GDP. Meanwhile, increasing inequality and changes in the tax code have had very little effect on contributions.

Aggregate contributions have been shown to respond to macroeconomic conditions, including business cycles (List and Peysakhovich (2011), Exley, Lehr, and Terry (2023), Meer, Miller, and Wulfsberg (2017)) and catastrophes (Lilley and Slonim (2016), Bergdoll et al. (2019)). This paper relates long-term macroeconomic trends in GDP growth and inequality to charitable contributions. I find that contributions have grown in both absolute and relative terms, from around 1.2 percent of GDP in 1991 to 1.7 percent of GDP in 2017 [1]. Over the same period, GDP almost doubled and the income share at the top of the income distribution increased (Piketty, Saez, and Zucman, 2019; Auten and Splinter, 2022). Historically, charitable giving has been correlated with inequality in the United States (Duquette, 2018). My model allows me to separate the effects of these two trends on contributions.

Trends in inequality and GDP both are the result of aggregating changes in individual level income. Reviews of abundant empirical studies, in microeconomics and other fields, on the relationship between income, wealth, and charitable contributions include Andreoni (2006), Havens, O'Herlihy, and Schervish (2006), List (2011), Wiepking and Bekkers (2012), and Neumayr and Pennerstorfer (2021). Most of the studies reviewed agree that contributions among the lowest income groups are positive and that contributions rise with income over most of the income distribution. This is the case even when controlling for wealth

[1] List (2011) observes this increase through 2011 and also notes that the S&P 500 grew at only half the rate of charitable contributions over this period.

and demographic factors[2] (Meer and Priday, 2021). I complement this literature by providing a macroeconomic perspective on the relationship between income and contributions to nonprofit organizations.

To account for the *relative* increase in contributions, requires a model with non-homothetic preferences. My agents value both consumption and contributions to nonprofit organizations, in accordance with Andreoni (1989) and Andreoni (1990) warm glow preferences. Models of charitable contributions usually implement this using a log-log (Andreoni, 2006) or Stone-Geary utility function (Huang and Ray (1986), Harbaugh (1998)). Stone-Geary preferences imply that households must consume a subsistence level before they begin to donate, however this is not consistent with the data. Like James and Sharpe (2007), I observe that even the households with the lowest levels of consumption donate, and that the percent of expenditures donated increases with expenditures. Thus, I adopt Constant Relative Income Elasticity (CRIE) preferences (Matsuyama, 2023), which allow all households to donate, while richer households donate a larger percentage of their wealth.

Since contributions to nonprofit organizations are a luxury good, the effects from increasing GDP must be positive. However, rising inequality can increase contributions relative to GDP only if the wealthy increase their contributions enough to outweigh decreases in contributions lower in the income distribution. This paper explores whether this has recently been the case in the United States.

I calibrate my model to the US economy in 1991 and 2017 and find that the change in the income distribution actually decreased contributions to nonprofit organizations. Instead, the primary driver of the relative increase in contributions is growth in GDP. The increase in GDP between 1991 and 2017 alone more than doubles contributions as a percent of GDP. This is because income effects raise contributions at every point over the income distribution.

I retain these results even after accounting for the effects of changes in the federal tax code on contributions. This is not surprising because there were no direct changes in the tax

[2]Including age, education, marital status, religion, retired or disabled status, race, and gender.

treatment of charitable contributions between 1984 and 2018. The changes in the tax code were not large enough to affect contributions behavior, especially since only filers who itemize have any tax incentive to make contributions. Furthermore, my model predicts state-level contributions growth rates for 2006-2017 that have a correlation of 0.33 with the untargeted data.

In the next section, I document the rise in contributions to nonprofit organizations over the past thirty years and relate it macroeconomic trends. Then, I incorporate altruistic preferences in a GE model by adding a non-homothetic preference for charitable contributions. Section four calibrates the model and analyzes the resulting effects of a change in GDP, the income distribution, and federal taxes between 1991 and 2017. Driven by the effects of increasing GDP, these three factors overshoot the actual increase in charitable contributions relative to GDP by a factor of three. Section five concludes.

2 Charitable Contributions and Macro Trends

By many measures, the nonprofit sector in the United States has grown over the last three decades[3]. The nonprofit sector consists of tax-exempt organizations that have shown the IRS that they serve a pro-social agenda[4] and make no distributions to shareholders. Due to their pro-social missions, the rise of nonprofit organizations could have an outsized impact on societal welfare. The the real gross value added by nonprofit institutions serving households in chained 2017 dollars has increased from 664.6 to 1063.9 billion dollars between 1991 and 2017, an increase of 60 percent (*Table 1.3.6. Real Gross Value Added by Sector, Chained Dollars* 1991 and 2017). Meanwhile real GDP increased by 95 percent over the same period.

Charitable contributions are a major source of funding for nonprofit organizations, mak-

[3]The value of nonprofit inputs is commonly used as a proxy for nonprofit output because nonprofit output are often provided at discounted or no cost, for the sake of furthering their prosocial missions. This method is used by the Bureau of Economic Analysis (BEA). Self-reported financial data that nonprofit organizations disclose in their tax filings are another source of information on the size of the nonprofit sector. Figure 8 in the appendix shows the rise of the nonprofit sector according to several financial variables from 990 tax filings.

[4]i.e. Nonprofit organizations must engage in charitable, religious, or public health activities.

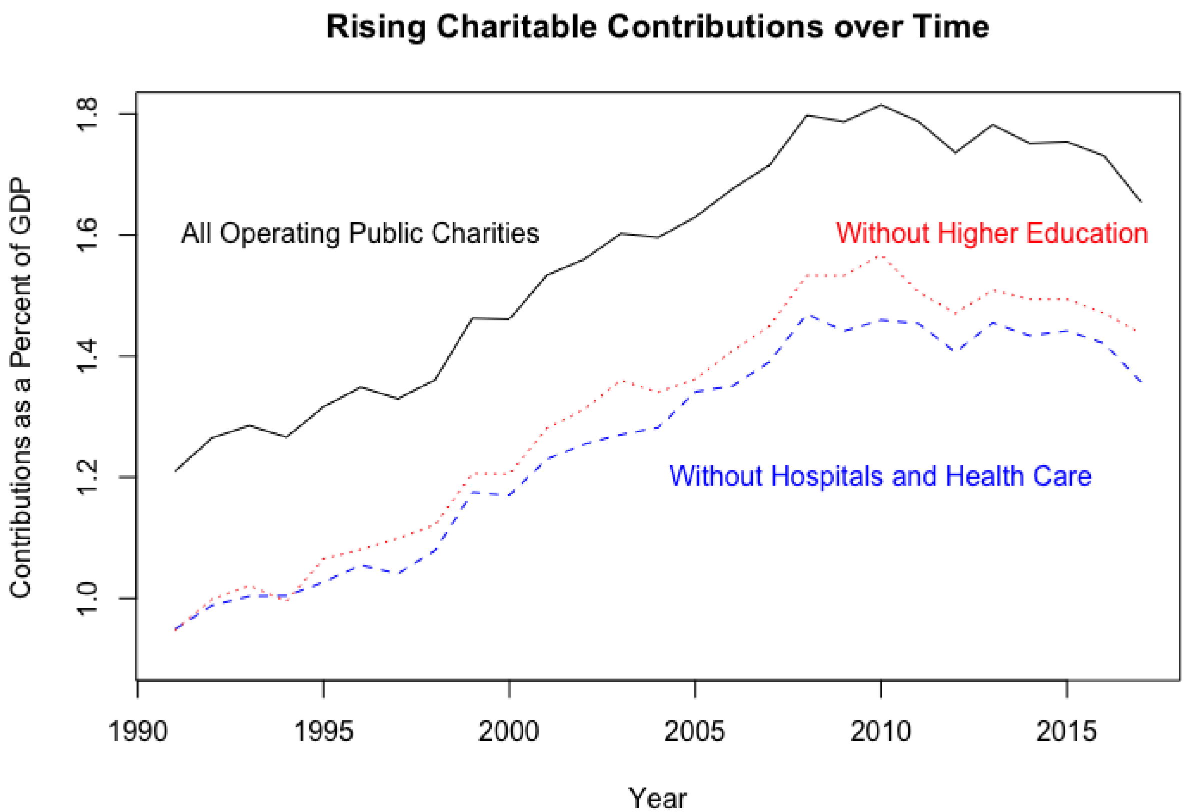


Figure 1: Rising Charitable Contributions over Time
Note: Contributions rose between 1991 and 2017. Contributions consist of total contributions, gifts, and grants reported by operating public charities in the NCCS Core Files, which contain data from nonprofit forms 990, 1023, and 1024, and are filed on an annual basis with the IRS. More details about the data and sample selection can be found in the appendix.

ing up about 20 percent of nonprofit revenue on average, with the rest mainly coming from program revenue. While the nonprofit sector shares some revenue streams with the private sector, tax-deductible contributions are a unique form of revenue for the nonprofit sector in support of the pro-social agendas of nonprofit organizations[5].

One factor that has driven the rise of the nonprofit sector is increased spending on healthcare and higher education. Several factors, including changes in service price and intensity, population growth, and population aging (Dieleman et al., 2017) contributed to the rise in healthcare spending[6], however these are not factors that affect charitable contributions. Similarly, rising tuition increased program revenue for higher education. Figure 1 shows a rise in contributions relative to GDP of about 0.02 percent per year to operating public charities that is consistent regardless of whether hospitals and health care organizations or organizations for higher education are included. The main sample, which includes hospitals and healthcare organizations as well as private, nonprofit universities, increased from 1.2 percent of GDP in 1991 to about 1.7 percent of GDP in 2017, increasing by more than a third.

3 Model

The increase in charitable contributions is of particular interest because this revenue component is unique to the nonprofit sector. I introduce a model with CRIE preferences for positive charitable contributions and other consumption to explore the effects of productivity and the income distribution on charitable contributions.

Various branches of the macroeconomics literature have explored how under non-homothetic preferences, increasing inequality can affect the aggregate consumption of luxury goods. In this paper, charitable giving is an example of such a good. Savings and bequests are another

[5] Program revenue and charitable contributions make up 71.3 percent and 19.0 percent of revenue per year on average, respectively.

[6] The rise in healthcare spending comes primarily from increased program revenue, as seen in figure 10 in the appendix.

example in Campanale (2017), Straub (2019), and Jang, Xu, and Zheng (2022). In Murayama (2022) and Imoto (2022), human capital investment enters a CRIE utility function as a luxury good. There is also an extensive trade literature examining how inequality affects trade flows in economies with non-homothetic preferences. Higher income countries consume more goods with higher income elasticities of demand in trade models with CRIE preferences (Fieler (2011) and Caron, Fally, and Markusen (2014)). Comin, Lashkari, and Mestieri (2021) write about structural change, from agricultural to manufacturing and service-based economies, and arrive at a similar conclusion to this paper: that sectoral reallocation is primarily driven by income effects.

3.1 Firms and Households

The economy has a unit mass of households indexed by i. Homogeneous firms buy household endowments $z(i)$ for a wage of w. The endowments are the only factor of production to make a homogeneous output Y, and firms have a productivity of A. Their production function is

$$Y = A \int z(i) di \tag{1}$$

Households value private consumption, $c \geq 0$ and their material contributions to the nonprofit sector, $g \geq 0$. Let the utility function be given by

$$U_i(c(i), g(i)) = \alpha \frac{(c(i))^{1-\sigma}}{1-\sigma} + (1-\alpha) \frac{(g(i))^{1-\Sigma}}{1-\Sigma} \tag{2}$$

where α represents the weight that the agent puts on private consumption. Notice that these preferences are non-homothetic, so that uility has potentially different elasticity with respect to consumption and contributions, σ and Σ. The differences in these parameters implies that wealthier individuals prefer to donate a different proportion of their income than poorer individuals. For example, if $\Sigma < \sigma$, then the fraction of income donated is increasing in income. [7]

Let $z(i)$ be the household i's endowment so that z is a probability density function, which represents the distribution of endowments. Thus another way to think about this distribution is that $\int z(i)di = 1$, representing the total initial endowment of the economy. $z' > 0$ so that i also represents the individual's percentile in the endowments distribution.

The only use for a household's endowment is to sell it to the firms in exchange for the wage. Hence, the income distribution is proportional to the distribution of endowments.

Households use the wage to buy the output good.

$$wz(i) = y(i) \tag{3}$$

where y(i) represents the portion of the total output afforded by household i.

After households buy as much output good as they can afford, they choose how they will divide their share of the output between consumption, $c(i)$ and donation, $g(i)$. Since a proportion $\theta(i)$ of households itemize their taxes, the sum of consumption and giving must be equal to their share of the output less taxes, where $\tau(i)$ represents the tax rate for individuals with income i.

$$c(i) + g(i) = y(i) - \tau(i)(y(i) - \theta(i)g(i)) \tag{4}$$

Notice that the no-tax case is nested, where $\tau(i) = 0$ for all i. Assume that the proceeds from tax collection confer no additional consumption or utility on agents.

Combining equations 3 and 4, gives the household budget constraint:

$$c(i) = (1 - \tau(i))wz(i) - (1 - \theta(i)\tau(i))g(i) \tag{5}$$

In order to choose how much to donate, each household maximizes $U_i(c(i), g(i))$ subject

[7] While I could have included a subsistence level of consumption, the data was best matched by setting subsistence level of consumption to zero since even the lowest consumption decile contributed almost three percent of the value they spent on other consumption.

to its budget constraint. The first order conditions imply that, assuming an interior solution,

$$c(i) = g(i)^{\frac{\Sigma}{\sigma}} (\frac{1-\alpha}{\alpha(1-(i)\tau(i))})^{-\frac{1}{\sigma}}$$

Market clearing requires that

$$\int_0^1 y(i)di = Y \tag{6}$$

Combining equations 1, 3, and 6 implies that

$$A = w \tag{7}$$

3.2 Solution

I find the optimal level of private consumption and contributions to nonprofits in the case of an interior solution by setting the derivatives with respect to $c(i)$ and $g(i)$ equal to 0.

Plugging this into the budget constraint, I numerically solve for $g(i)$, however, this cannot be done analytically.

$$(1-\tau(i))wz(i) = g(i)^{\frac{\Sigma}{\sigma}} (\frac{(1-\alpha)}{\alpha(1-\theta(i)\tau(i))})^{-\frac{1}{\sigma}} + (1-\tau(i)\theta(i))g(i)$$

In order to solve for the optimal level of private consumption and contributions to nonprofits computationally, I minimized the distance between $(1-\tau(i))Az(i)$ and $g(i)^{\frac{\Sigma}{\sigma}}(\frac{(1-\alpha)}{\alpha(1-\theta(i)\tau(i))})^{-\frac{1}{\sigma}} + (1-\tau(i)\theta(i))g(i)$ for a set of moments i for which data are available. I do this by iterating over points between the zero lower bound for contributions and the maximum contribution of $Az(i)$, which is the agent's income. Finally, I use $g(i)$ and $z(i)$ to calculate $c(i)$, as well as the aggregates G and C.

4 Quantitative Analysis

I compare the total charitable contributions implied by my model for parameter values that have been chosen to represent the US economy. Table 1 summarizes my preferred parameterization. While a parameterization representing 2017 implies an increase in contributions relative to the model's implied contributions for 1991, perturbing GDP and the income distribution individually shows that most of the difference comes from the increase in productivity rather than changes in the income distribution.

4.1 Model Calibration

4.1.1 Productivity

By equation 1 in the model, total output $= A$, since $\int z(i)di = 1$. Thus, I use GDP to calibrate productivity. I normalize GDP in 1991 to 1. According to the US Bureau of Economic Analysis (BEA)(1991 and 2017), real GDP in 2017 dollars was \$10044.2 billion in 1991 and \$19612.1 billion in 2017, an increase of 95 percent. Therefore, for my 2017 calibration I let $A = 1.95$.

4.1.2 Income Distribution

In the model, $z(i)$ is a distribution that describes agents' endowment, for example of skills. The production function implies that the income distribution is proportional to the endowment distribution. I use this fact to parameterize the z distribution.

The CPS reported the number of respondents by income category in 1991 and 2017. I used this data to approximate points in the income distribution, $z(i)$, and the Lorenz curve for each year. Then I used linear interpolation to create a continuous income distribution to use in my model (Carr, 2020). Figure 2 represents the empirical Lorenz curves of the United States in 1991 and 2017. The position of the 1991 Lorenz curve to the left of the 2017 Lorenz curve confirms that the income distribution was more unequal in 2017 than in

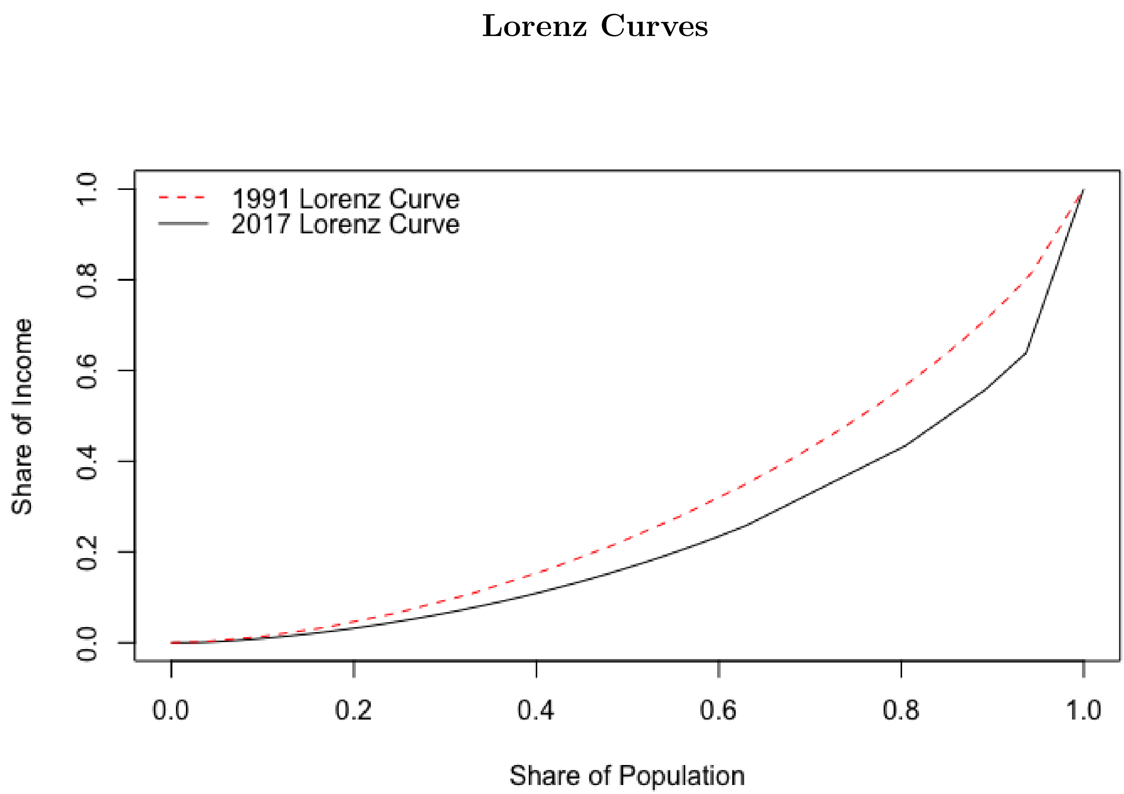


Figure 2: Lorenz curves from 1991 and 2017 show that inequality increased.

1991.

4.1.3 Elasticity of Utility with respect to Consumption and Contributions, and the Private Consumption Weight

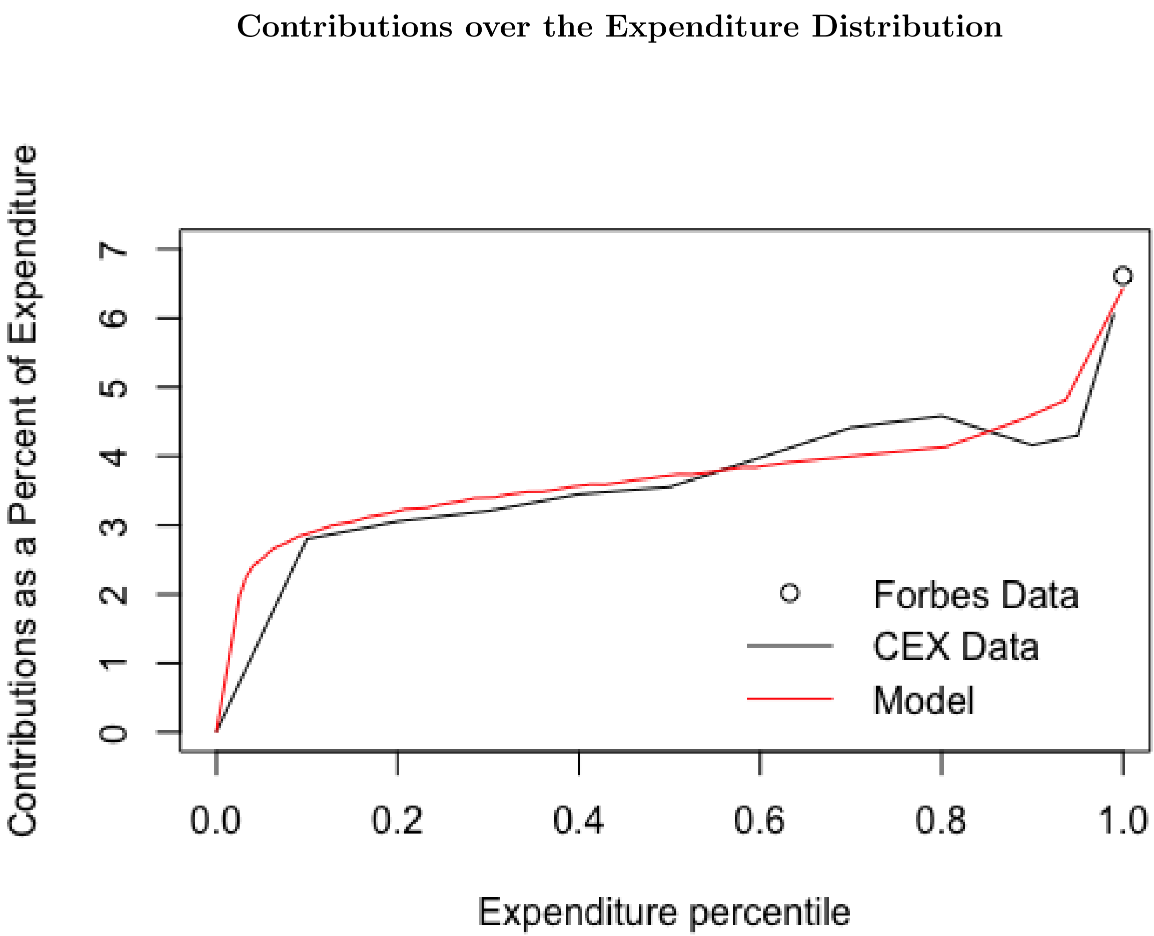


Figure 3: A model with parameters $\alpha = 0.96$ and $\Sigma = 0.81$ best approximates CEX data from 2013-2017.

The assumption that $\sigma = 1$ implies that the utility function is logarithmic with respect to consumption, a condition which can support a balanced growth path. I also assumed previously that $0 < \Sigma \leq \sigma$ so that the fraction of income donated is increasing in income. Furthermore, $0 < \alpha < 1$ since α represents the weight that agents place on private consumption. Thus, I let $\sigma = 1$ and choose the values of Σ and α that minimize the area between the profile of contributions as a percent of expenditures over the expenditure distribution and the contributions policy function from my model. Note that in my model, the expenditure distribution will be the same as the income and endowment distribution.

I calculated contributions as a percent of expenditures over the expenditure distribution using Consumer Expenditure Survey (CEX) data, from 2013 to 2019. The black line in figure 3 represents average donations to religious, charitable, educational, and other organizations as a percent of expenditures by expenditure groups[8]. The income groups are deciles, except for the last decile, which is divided in two. The value for each income group is graphed at its upper bound, except for the highest income group, which is assigned to the 99th percentile. All observations with expenditures below zero were dropped and the value for contributions as a percent of expenditures is assumed to be zero at the zeroth percentile.

The highest expenditure in the CEX data set is \$326,865. Under the assumption that the interest rate for the wealthy is $r = 1.0379$ (Smith, Zidar, and Zwick, 2023) and that the wealthy don't have income, the wealth of this individual is projected at around nine million dollars. Thus the CEX data set does not capture the billionaires at the very top of the income distribution. It may be particularly important to capture the contributions behavior of the wealthiest individuals if they tend to donate significantly more relative to their expenditures than the rest of society[9]. Forbes collected data on the wealth and charitable contributions of billionaires from 2018-2022. There are 1543 observations of billionaires between 21 and 65 years old, 45 percent of which report a range of percentiles into which their charitable contributions fall. The ranges for lifetime giving as a percent of net worth are less than one, one-4.99, 5-9.99, 10-19.99, and more than 20 percent. Assuming that individuals reporting contributions in the bottom four rages gave the median of the range, and individuals in the

[8]These estimates are based on James and Sharpe (2007). However, I exclude political contributions, narrow my sample to households headed by individuals who are between 21 and 65 years old, and use expenditures this quarter times four rather than estimated annual after tax income. The 2013-2019 contributions data is collected on a monthly basis over a three month period, so I assume that annual contributions are equal to four times the aggregate of the monthly contributions for each individual. All estimates are averaged within the income group over all surveys during this time period.

[9]The growing popularity of the Giving Pledge, whereby billionaires publicly commit to give the majority of their wealth to philanthropy, provides evidence that this may be the case.

top range gave twenty five percent of their wealth, the wealth-weighted average giving of billionaires is 6.611, represented by a dot at the 100th percentile in Figure 3.

By definition, individuals at the lowest expenditure percentile, which represents no expenditure, do not donate. But contributions almost immediately jump to over two percent and rise gradually to about four percent up to the 95th percentile. Contributions from the 99th and 100th percentile jump to over six percent. $\Sigma = 0.81$ and $\alpha = 0.96$ best capture the empirical profile of contributions as a percent of expenditures over the expenditures distribution. The red line in Figure 3 represents contributions implied by these parameters over the income distribution.

4.1.4 Taxes

While there were no changes to the charitable deduction for individuals between 1984 and 2018[10], other changes in tax rates and brackets could have indirectly changed incentives to donate. Income tax incentives for charitable contributions only apply to individuals who itemize their taxes. Therefore, in Table 4 in the appendix, I report the percent of filers itemizing (θ) in addition to the average tax rate (τ) for each level of adjusted gross income (AGI) from Prizzi and Curry (1991) and Internal Revenue Service (2019). I assign each individual in the model a tax rate and percent itemizing based on the percent of filings at each level of AGI.

The first panel in figure 4 represents the $\tau(i)$ parameter for tax rates in 1991 and 2017, and the second panel in figure 4 represents the $\theta(i)$ parameter representing the percent of filers itemizing over the income distribution. While the tax rate in 1991 was higher for most individuals in 1991, the percent itemizing was lower. Increasing the tax rate only affects the cost of consumption, so contributions are expected to increase when the tax rate increases. However, only itemizers have tax incentives to make donations, so contributions are expected to fall when the percent of individuals itemizing falls. Hence, these changes would have the

[10]The 2017 Tax Cuts and Jobs Act, which "increased the AGI limit for cash donations made to public charities from 50% to 60%"(Crandall-Hollick, 2020) beginning in 2018.

Federal Taxes over the Income Distribution

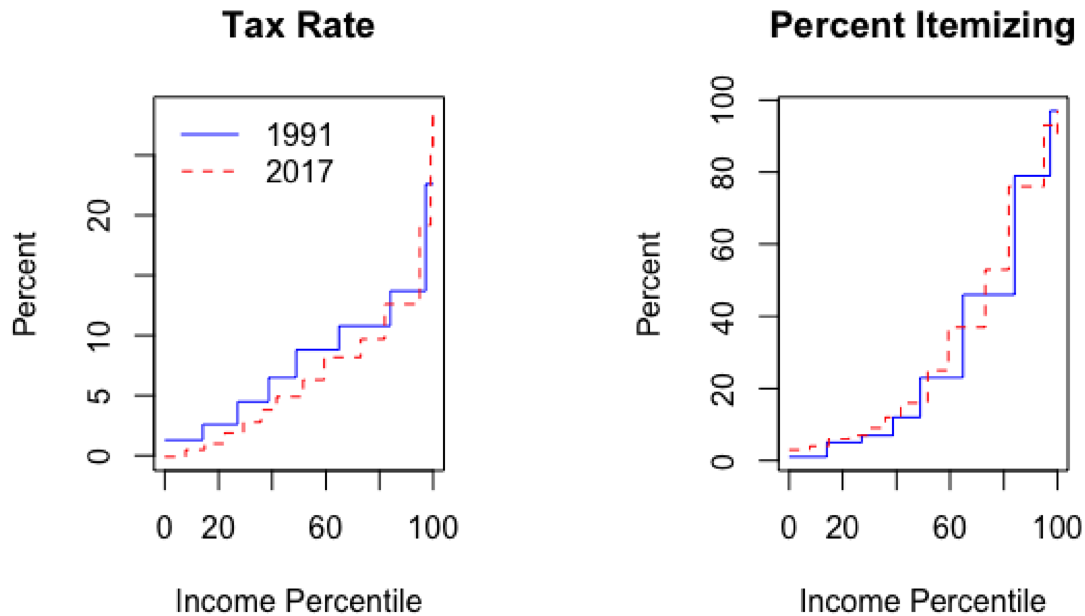


Figure 4: 1991 data from the IRS SOI Table 5 . 2017 data from the IRS SOI Tables 1.1 and 2.1 .

opposite expected effects on contributions.

Table 1: Parameterization

Parameter	Interpretation	Data Source	Value
$\frac{\Sigma}{\sigma}$	Ratio of Income Elasticities with respect to Consumption and Contributions	CEX	0.81
α	Private Consumption Weight	CEX	0.96
A_{1991}	Productivity	BEA	1
A_{2017}	Productivity	BEA	1.95
$z(i)$	Income Distribution	CPS	See Figure 2
$\tau(i)$	Tax Rate	SOI Tables	See Figure 4
$\theta(i)$	Percent Itemizing	SOI Tables	See Figure 4

State Level Contributions and GDP Growth Rates

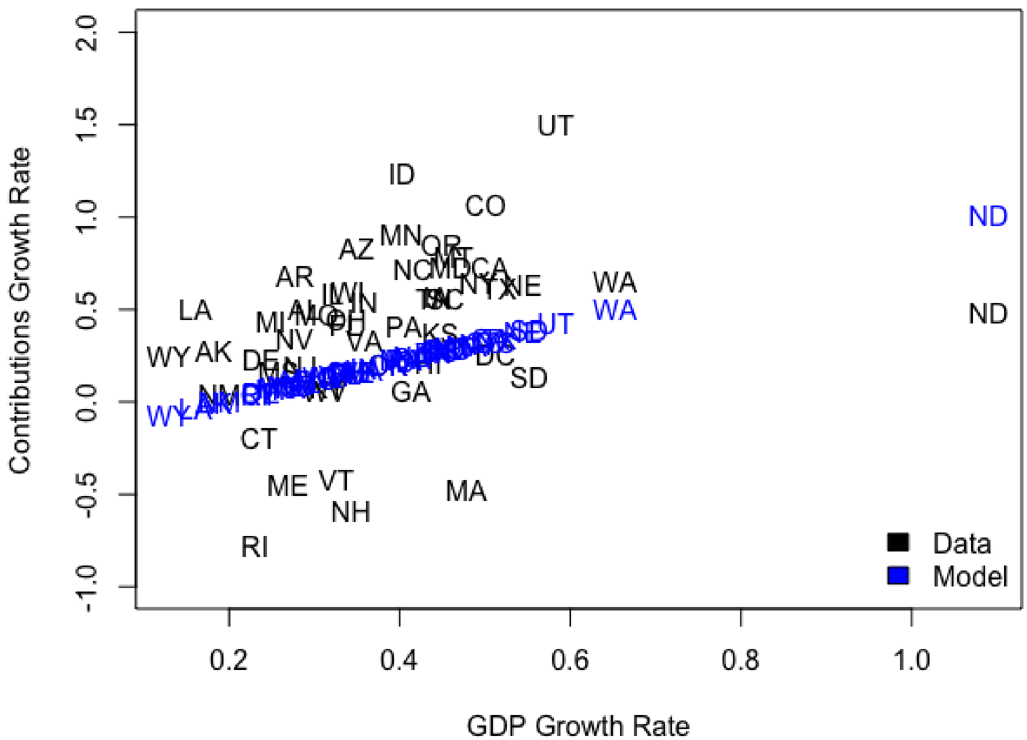


Figure 5: State Level Contributions and GDP Growth Rates between 2006 and 2017. State-level GDP and inequality came from Internal Revenue Service (2008 and 2020). The model calibration was done using no taxes.

4.2 Out-of-sample Prediction

In addition to correlation over time between GDP and contributions as a share of GDP, I also observe a positive relationship between growth rates of contributions and GDP at the state level. Even if changes in GDP cause changes in contributions at the national level, there would not necessarily be correlation between GDP growth and contributions growth at a state level because individuals may donate to organizations outside of their state. Nevertheless, donations tend to display a home bias (Gluckler, 2021) that could cause a positive correlation between GDP growth and the growth of contributions to hold, even at the state level.

When I use my model to predict state-level contributions as a percent of GDP using state-level GDP and inequality for 2006 and 2017 (Internal Revenue Service, 2008 and 2020) and no taxes, the level of my predictions is similar in magnitude to the state-level contributions data. The growth rates of my predictions also have a correlation of 0.33(0.13) with the growth rate of state-level contributions in the data, which is different from zero with 95 percent confidence, even though the sample size is only 51. Figure 5 shows that the growth rate of contributions to nonprofits headquartered within a state, plotted in black, is positively correlated with state-level GDP growth rates. Furthermore, the model results are plotted in blue. Given that these results do not account for cultural or institutional differences between the states, the similarity between my model results and the data is striking.

4.3 Counterfactuals

I calibrate the economy for 1991 and 2017, and then I test the effects of changing the income distribution, GDP, and taxes independently. As shown in Figure 6, rising GDP causes a large increase in contributions between 1991 and 2017, while changes in the income distribution decrease contributions slightly. Changing taxes produces virtually no change in the results.

Figure 7 compares the calibrations for 1991 and 2017 with the counterfactuals. The solid red lines represent the contributions of individuals over the income distribution in 1991.

Total Contributions Under Counterfactuals

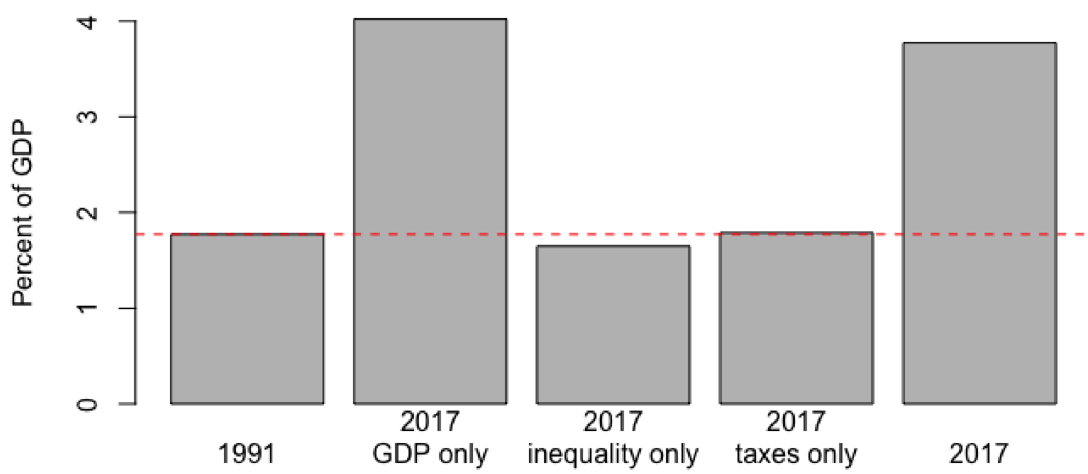


Figure 6: Total Contributions Under Counterfactuals

The median agent donates about 1.7 percent of his or her income, whereas the richest agent donates about 2.5 percent. Total contributions G_{1991} account for 1.77 percent of A_{1991}. The dashed black line represents the contributions of individuals over the income distribution in 2017. The richest agent donates about 6.4 percent of his or her income in 2017, while the median agent donates about 3.7 percent. Total contributions G_{2017} account for about 3.77 percent of A_{2017}.

The dotted blue lines in Figure 7 represent counterfactuals, where one factor is changed to the 2017 calibration while the other two are held constant at the 1991 calibration. The first panel shows that when GDP increases and taxes and inequality are held constant, agents at every point in the income distribution increase their donations relative to the 1991 calibration, leading to an overall increase in contributions to about four percent of GDP. Holding the income distribution constant, raising GDP has a large impact because all individuals have more income and thus donate more.

Theoretically, the direction of the overall change in contributions under the inequality

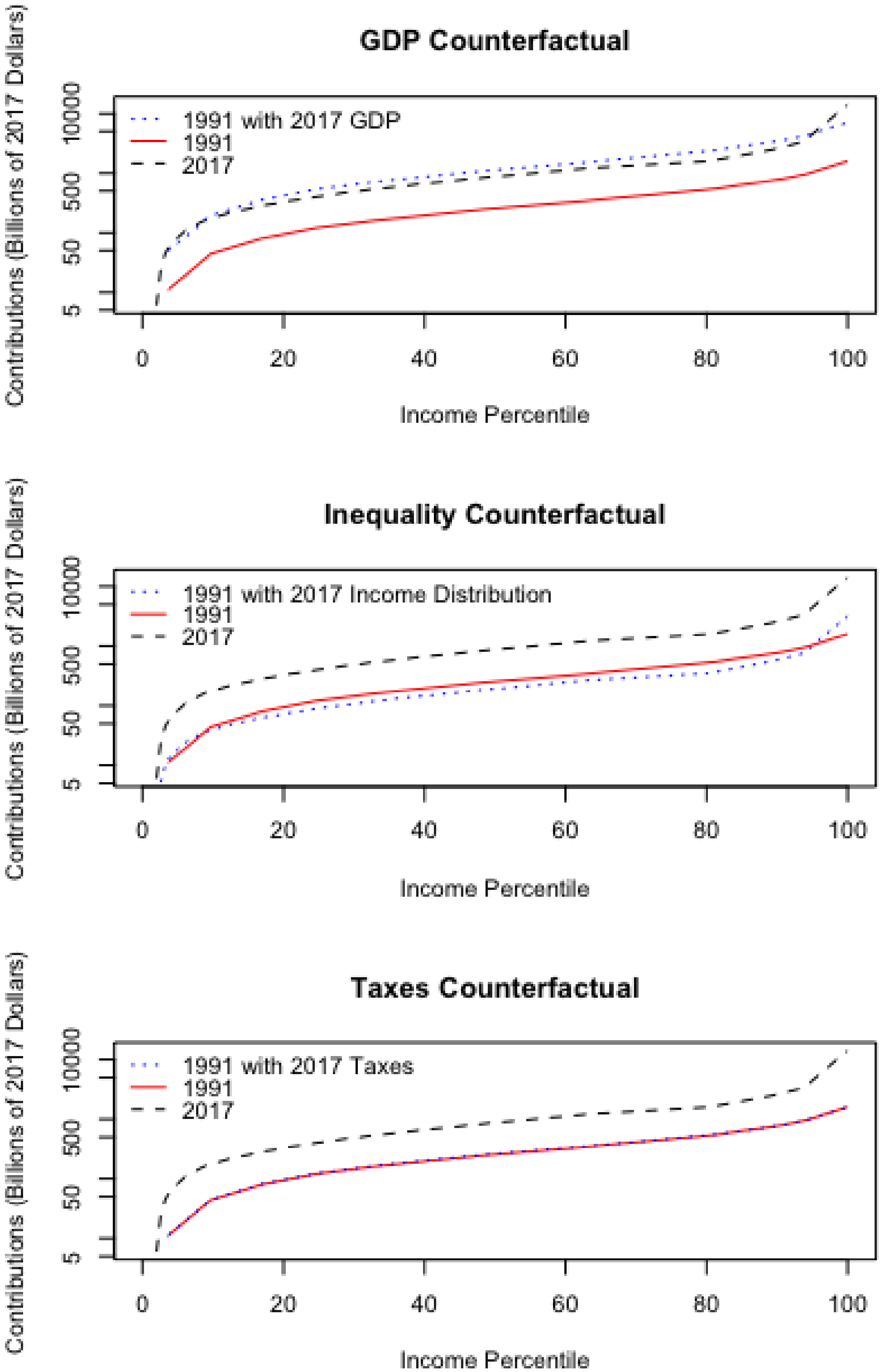


Figure 7: Contributions Policy over the Income Distribution.

counterfactual is ambiguous because contributions at the top of the income distribution must increase, while contributions at the bottom must decrease. However, the relative magnitude of these changes depends on how much of the income distribution is getting wealthier and how much giving increases as a portion of income for the wealthy. The second panel of figure 7 demonstrates that empirically, the decrease in contributions over the bottom 95% of the income distribution does not outweigh the increase in contributions at the top. Hence, overall contributions decrease to about 1.65 percent of GDP.

The last panel of figure 7 shows that essentially no change in contributions occurs at any point in the income distribution when taxes are adjusted to reflect the 2017 tax code. In this counterfactual, the overall contributions remain at 1.79.

The actual increase in contributions, from 1.21 to 1.65 percent of GDP, was smaller than the increase implied by the model. The model implies a 113 percent change in contributions as a percent of GDP, while the change in actual contributions was only 37 percent. While the actual percent change is only about one third of the estimated percent change, my model produces contributions that are reasonable in magnitude relative to GDP and a change in the correct direction. Of the three macroeconomic factors that I explore as explanations for increasing contributions relative to GDP, the main effect comes from the increase in productivity between 1991 and 2017.

Table 2: Donations as a Percent of GDP

Category	1991	2017	% Change
Actual	1.21	1.65	37
Estimated	1.77	3.77	113
Est. as a % of Act.	146	228	305

5 Conclusion

In the last 30 years, the size of the nonprofit sector as a percent of GDP approximately doubled. Contributions accounted for about 20 percent of total revenue for nonprofit organizations. This paper focuses on explaining the increase in charitable contributions because this source of revenue is unique to the nonprofit sector and rose quickly in the 1990's and early 2000's from 1.2 to around 1.7 percent of GDP.

Of the macroeconomic factors that I test using my model, only increasing GDP produces an increase in contributions as a percent of GDP. In fact, increasing GDP in my calibrated model overshoots the actual increase in the data by a factor of three. This is possible due to nonhomothetic preferences. Increasing inequality decreased contributions slightly because a large portion of itemizers in the middle of the distribution were relatively poorer in 2017 than in 1991. Although the rich donate more relative to their expenditures, the difference does not outweigh the decrease in contributions in the middle of the distribution, since the rich make up a very small part of the population. Most tax brackets in the federal tax code saw their tax rate increase and percent itemizing decrease. These changes in the federal tax code resulted in essentially no change in contributions.

Due to the prosocial missions of nonprofit organizations, this sector could have a large impact on welfare relative to its size. While increases in contributions are driven by the preferences of donors in this model, it is likely that contributions have positive externalities such that donor welfare is not the only improvement to overall welfare that contributions affect. Future work on this topic could address changes in the nonprofit sector, itself, that may have increased the utility of donations and thus increased the amount of contributions received.

References

Andreoni, J. (1989) Giving with impure altruism: Applications to charity and Ricardian equivalence. *Journal of Political Economy* 97.6, 1447–1458.

— (1990) Impure altruism and donations to public goods: A theory of warm-glow giving. *The economic journal* 100.401, 464–477.

— (2006) Philanthropy. *Handbook of the economics of giving, altruism and reciprocity* 2, 1201–1269.

Auten, G. & D. Splinter (2022) Income Inequality in the United States: Using Tax Data to Measure Long-Term Trends. *Working Paper*.

Bergdoll, J. et al. (2019) US household disaster giving in 2017 and 2018.

Campanale, C. (2017) Luxury consumption, precautionary savings and wealth inequality. *The BE Journal of Macroeconomics* 18.1, 20150196.

Caron, J., T. Fally & J.R. Markusen (2014) International trade puzzles: A solution linking production and preferences. *The Quarterly Journal of Economics* 129.3, 1501–1552.

Carr, A. (2020) *Tools for Deriving Income Inequality Estimates from Grouped Income Data*.

Comin, D., D. Lashkari & M. Mestieri (2021) Structural change with long-run income and price effects. *Econometrica* 89.1, 311–374.

Core Files (2021). (accessed May 23, 2022). Washington, DC: Urban Institute, National Center for Charitable Statistics.

Crandall-Hollick, M.L. (2020) *The Charitable Deduction for Individuals: A Brief Legislative History*. Congressional Research Service.

Dieleman, J.L. et al. (2017) Factors Associated With Increases in US Health Care Spending, 1996-2013. *Journal of the American Medical Association* 138.17, 1668–1678.

Duquette, N.J. (2018) Inequality and philanthropy: High-income giving in the United States 1917–2012. *Explorations in Economic History* 70, 25–41.

Exley, C.L., N.H. Lehr & S.J. Terry (2023) Nonprofits in good times and bad times. *Journal of Political Economy Microeconomics* 1.1, 42–79.

Fieler, A.C. (2011) Nonhomotheticity and bilateral trade: Evidence and a quantitative explanation. *Econometrica* 79.4, 1069–1101.

Guide to Using NCCS Data (2022). National Center for Charitable Satistics.

Harbaugh, W.T. (1998) The prestige motive for making charitable transfers. *American Economic Review* 88.2, 277–282.

Harrison, T.D. & C.A. Laincz (2008) Entry and exit in the nonprofit sector. *The BE Journal of Economic Analysis Policy* 8.1, 1–40.

Havens, J.J., M.A. O'Herlihy & P.G. Schervish (2006) Charitable giving: How much, by whom, to what, and how. *The nonprofit sector: A research handbook* 2, 542–567.

Huang, W.-C. & S.C. Ray (1986) Labor Supply, Voluntary Work, and Charitable Contributions in a Model of Utility Maximization. *Eastern Economic Journal* 12.3, 257–263.

Imoto, S. (2022) Persistent inequality, Kuznets curve, and evolution of study effort in human capital model. *Kuznets curve, and evolution of study effort in human capital model (February 9, 2022)*.

Internal Revenue Service (2019) *Statistics of Income—2017 Individual Income Tax Returns, Table 1.1.* Washington, D.C.

Internal Revenue Service, S.o.I.D. (2008 and 2020) *Table 1.–Returns with Positive Adjusted Gross Income (AGI): Number of Returns, Shares of AGI and Total Income Tax, AGI Floor on Percentiles, and Average Tax Rates, by Selected Descending Cumulative Percentiles of Returns Based on Income Size Using the Definition of AGI, by State, Tax years 2006 and 2008.*

James, R.N. & D.L. Sharpe (2007) The Nature and Causes of the U-Shaped Charitable Giving Profile. *Nonprofit and Voluntary Sector Quarterly* 36.2, 218–238.

Jang, H.J., Z.Q. Xu & H. Zheng (2022) Optimal Investment, Heterogeneous Consumption, and Best Time for Retirement. *Operations Research.*

Lilley, M. & R. Slonim (2016) Gender differences in altruism: Responses to a natural disaster.

List, J.A. (2011) The Market for Charitable Giving. *Journal of Economic Perspectives* 25.2, 157–180.

List, J.A. & Y. Peysakhovich (2011) Charitable donations are more responsive to stock market booms than busts. *Economics Letters* 110.2, 166–169.

Matsuyama, K. (2023) Non-CES aggregators: a guided tour. *Annual Review of Economics* 15, 235–265.

Meer, J., D. Miller & E. Wulfsberg (2017) The great recession and charitable giving. *Applied Economics Letters* 24.21, 1542–1549.

Meer, J. & B.A. Priday (2021) Generosity across the Income and Wealth Distributions. *National Tax Journal* 74.3, 655–687.

Murayama, Y. (2022) Human Capital Inequality with Subsistence Consumption. *Journal of the Knowledge Economy* 13.3, 2127–2137.

Neumayr, M. & A. Pennerstorfer (2021) The relation between income and donations as a proportion of income revisited: Literature review and empirical application. *Nonprofit and Voluntary Sector Quarterly* 50.3, 551–577.

Piketty, T., E. Saez & G. Zucman (2019) Simplified Distributional National Accounts. *AEA Papers and Proceedings* 109, 289–295.

Prizzi, L.Y. & J.B. Curry (1991) *Individual Income Tax Returns, 1991: Taxpayer Usage Study, Table 5.* Tech. rep. Accessed: 2024-06-29. Internal Revenue Service.

Smith, M., O. Zidar & E. Zwick (2023) Top Wealth in America: New Estimates under Heterogeneous Returns. *Quarterly Journal of Economics* 138.3, 515–573.

Straub, L. (2019) Consumption, Savings, and the Distribution of Permanent Income. *Unpublished Manuscript, Harvard University.*

Table 1.3.6. Real Gross Value Added by Sector, Chained Dollars (1991 and 2017). U.S. Bureau of Economic Analysis.

Wiepking, P. & R. Bekkers (2012) Who gives? A literature review of predictors of charitable giving. Part Two: Gender, family composition and income. *Voluntary Sector Review* 3.2, 217–245.

Appendix

Nonprofit Tax Data and Sample Selection

Throughout this paper, I refer to "nonprofit organizations", by which I mean organizations that are designated by the IRS to be 501(c)(3) organizations that are operating public charities. In order to receive this designation from the IRS, nonprofit organizations must apply for it by filing form 1023 or 1024, which includes information about the nonprofit's purpose. Nonprofits with more than $25,000 in gross receipts that are not religious, political, or government organizations are additionally required to file a version of form 990, which discloses detailed financial information, annually. The IRS publishes data from filings of organizations that were required to file form 990 in the Return Transaction Files (RTF).

The NCCS uses the RTF and information from forms 1023 and 1024 to create the NCCS Core Files, which are the main source of data for this paper (*Core Files* 2021). In addition to combining the two IRS sources of data, the NCCS reviews the RTF for quality and excludes governmental and foreign organizations.

The Core Files cover 1989-2019, however since a substantial percentage of organizations receive filing extensions(*Guide to Using NCCS Data* 2022), the IRS data for a given tax period is not complete until three years later. Hence, while there is data for 2018 and 2019, only tax filings from 2017 are complete enough to use in this analysis. Therefore, I created an unbalanced panel from the including the most recently filed firm-year observation over the 1989-2017 time period.

The NCCS has published the Trend Analysis files to assist in longitudinal studies. However, these files provide complete data for a shorter period than the Core files, 1989-2013, and they contain a smaller number of variables. I compare the panel I created from the Core files to the Trend files for the years that the two datasets overlap. I find that the Core files are missing very little data in the beginning of the period, through 2000. After 2000, no more than 13 percent of the observations from the trend file are missing from the core file panel. Furthermore, no more than 20 percent and mostly less than 8 percent of the value of total expenses, total revenue, or total contributions are missing in the trend files. The Core files panel contains no observations that are missing from the trend files. Therefore, my estimates can be taken as a lower bound on the true values of nonprofit financial variables.

Nearly 90 percent of nonprofit organizations are Public Charities (*Guide to Using NCCS Data* 2022). This means that they use publicly collected funds to directly support their initiatives. The other approximately 10 percent are private foundations, which derive their funds from a single benefactor, usually an individual or a business. Private foundations are mostly created to distribute funds to public charities, and thus to avoid double-counting contributions, I exclude private foundations. I further narrow my sample to include only operating public charities, which function for the benefit of the public in a variety of ways from research to anti-poverty work. These represent about 85 percent of nonprofit organizations in the NCCS sample (*Guide to Using NCCS Data* 2022). Excluded from the public charities category are mutual benefit organizations, which are "essentially providers of private services to paying customers" (Weisbrod, 1988 as cited in the Guide to Using NCCS Data) and supporting public charities, which, like private foundations, function mostly as distributors of funds to operating public charities. Since my sample is restricted to operating public charities (OPCs) with at least $25,000 in gross receipts that are not religious, political, or government organizations, I interpret my estimates of financial aggregates as lower bounds.

The nonprofit sector consists of many types of organizations, which are categorized according to the National Taxonomy of Exempt Entities (NTEE-CC) based on information provided to the IRS in form 1023 or 1024. The twelve major categories of the NTEE-CC are Arts, Education, Environment and Animals, Higher Education, Hospitals, Health Care, Human Services, International, Religion-related, Mutual benefit, Public and societal benefit (other), and Unknown or unclassified.

Nonprofit organizations in the health and hospital categories are unique because program revenue (i.e. individuals and insurance providers paying for medical services) accounts for most of their total revenue. As noted above, many factors that are not related to charitable giving or inequality increased healthcare spending in the United States over the last 30 years.

The data displayed in figures 8 and 10 are the result of aggregating financial variables over my sample by year and dividing them by the BEA's estimates of GDP(*Table 1.3.6. Real Gross Value Added by Sector, Chained Dollars* 1991 and 2017). The variable definitions in table 3 come from the NCCS data dictionaries.

Table 3: Variable Definitions

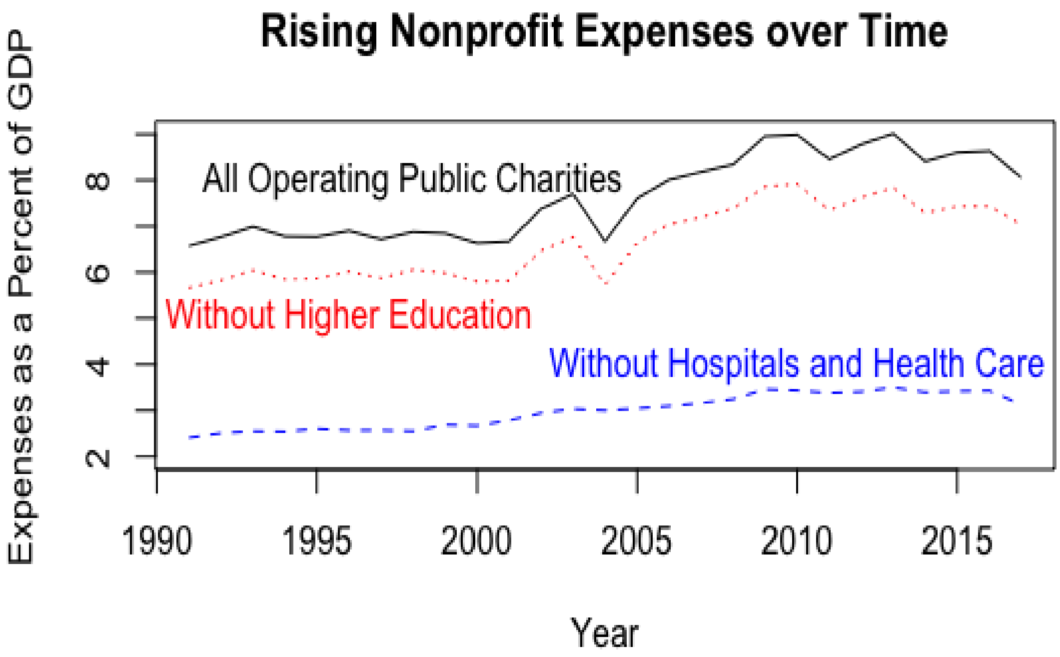
Variable	Abbreviation	Interpretation
Total Expenses	**EXPS**	**Equals the sum of program, fundraising, management, and general expenses, as well as payments to affiliates.**
Total Revenue	**TOTREV**	**Prior to 2008, the sum of total contributions, program service revenue, membership dues and assessments, total investment income, net rental income, net sale of securities, gross sales of other assets, special events net income, inventory gross profit, and other income. In 2008 and later, the sum of total expenses and net income.**
Program Service Revenue	**PROGREV**	**Program service revenue and membership dues and assessments.**
Total Contributions	**CONT**	**Total contributions, gifts, and grants.**

Nonprofit Sector Growth 1991-2017

Nonprofit expenses and revenue increased as a percent of GDP between 1991 and 2017, as shown in Figure 8. In the OPC sample total revenue and expenses both started around 7 percent of GDP and grew to around 8 percent of GDP in 2017. Total expenses and revenue of nonprofits forseeably decrease substantially when hospitals and healthcare organizations are excluded from the sample, and hence so does the percent of GDP accounted for by nonprofit organizations as measured by these variables. Yet, these variables still increase over the sample period. These data provide evidence that not only is the magnitude of the nonprofit sector large enough to affect macroeconomic aggregates, but also that its size has increased substantially over the past 30 years.

Increases in the financial aggregates of the nonprofit sector could have occurred due to either an increase in the size or number of nonprofit organizations. Harrison and Laincz (2008) noted that the number of nonprofits increased between 1991 and 2003. The first panel of Figure 9 shows that this trend has continued, using the OPC sample. The other three panels of Figure 9 show that in spite of there being more operating public charities, average expenditures, revenue, and contributions all increased between 1991 and 2017. Not only is the number of nonprofit organizations increasing, the average size of a nonprofit organization and contributions are also growing.

Figure 10 shows that the ratio of program revenue to GDP increased from 5 to 7 percent between 1991 and 2017 for the OPC sample. Notice that when hospitals and health care nonprofits are excluded from the sample, program revenue falls much more than contributions does in Figure 10. The rate at which program revenue increases as a percent of GDP falls from 0.06 to 0.02 percent per year when hospitals and health care organizations are excluded. In contrast, the rate at which contributions increase as a percent of GDP is similar for both samples, approximately 0.02 percent per year. This is because hospitals and health care organizations tend to rely much more heavily on program revenue than contributions, relative to other types of nonprofit organizations. In this paper, I include hospitals and



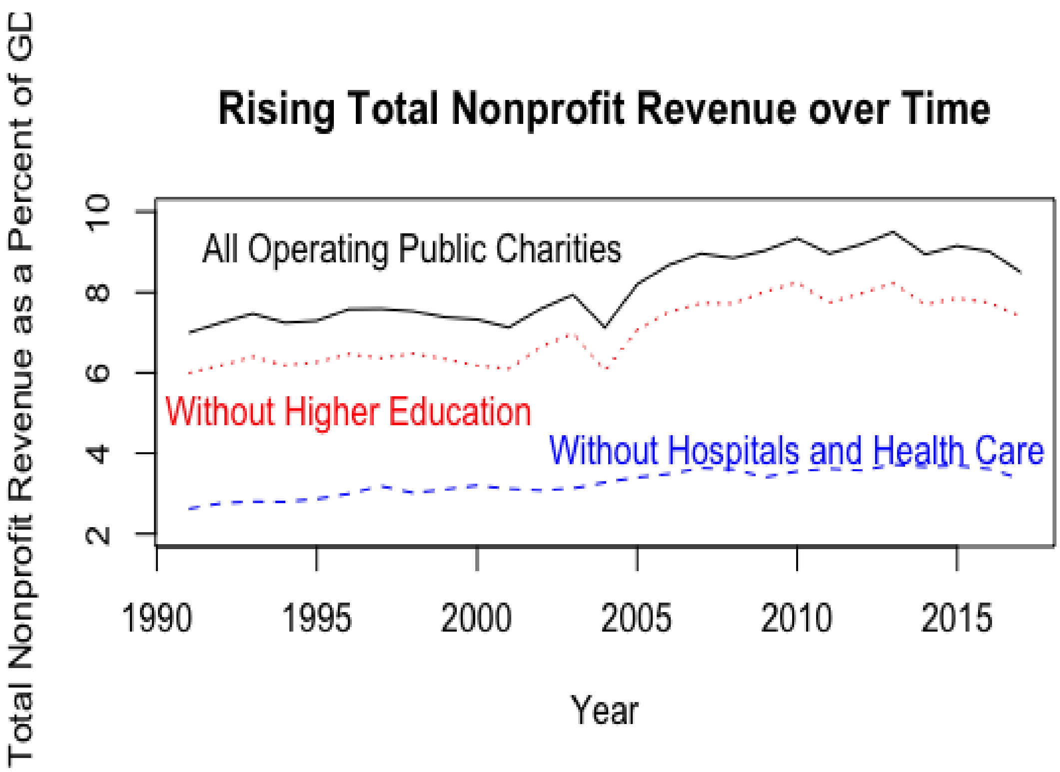


Figure 8: Key financial variables indicate that the Nonprofit Sector grew faster than GDP between 1991 and 2017.

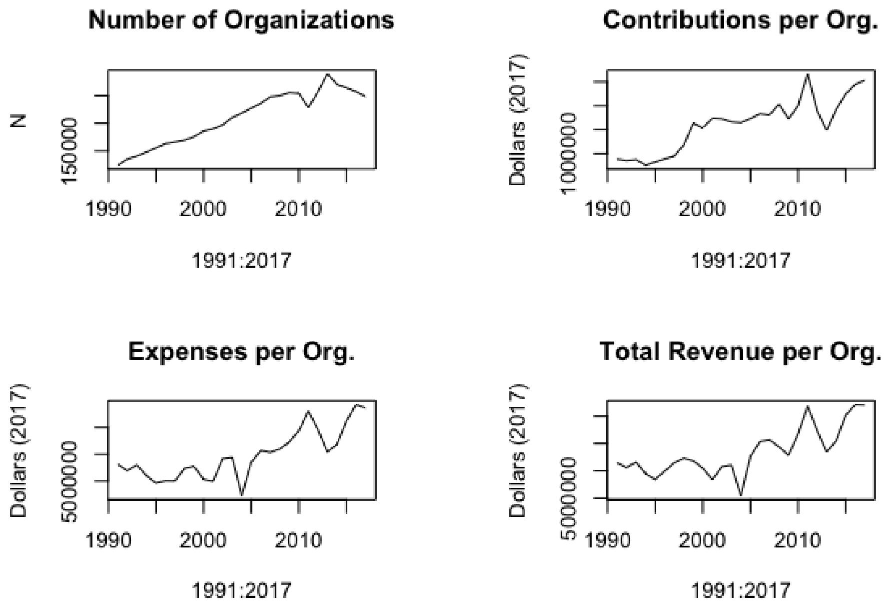


Figure 9: Both the number and size of OPC nonprofit organizations grew between 1991 and 2017.

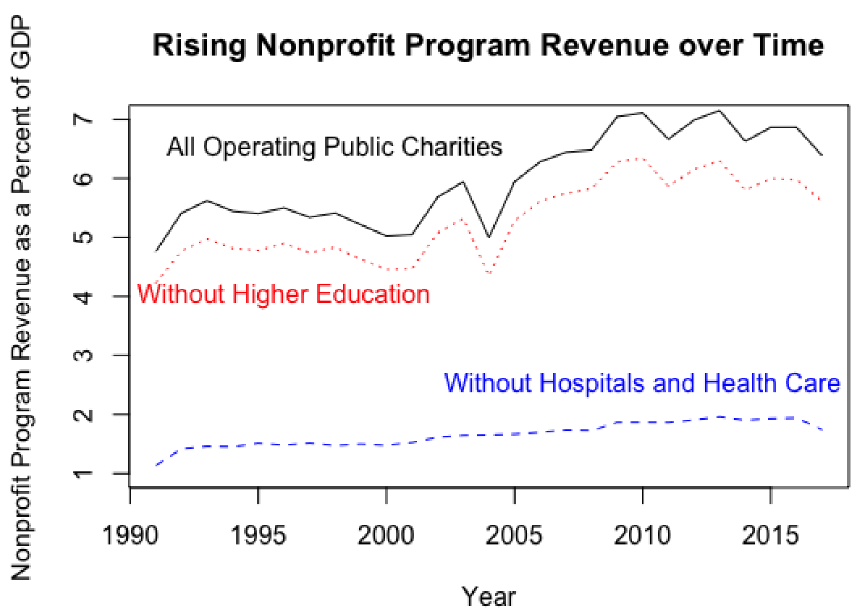


Figure 10: The increase in program revenue between 1991 and 2017 was driven by Hospitals and Health Care Organizations.

health care organizations in nonprofit statistics because contributions to these organizations behave similarly to contributions for the rest of the nonprofit sector.

US Tax Code 1991 vs. 2017

Table 4: US Tax Code 1991 vs. 2017

AGI	Average Tax Rate (τ)	Percent of Filings	Percent Itemizing (θ)
1991 [1]			
\$0	1.3	14.10	1
\$5,000	2.6	12.98	5
\$10,000	4.5	11.63	7
\$15,000	6.5	10.18	12
\$20,000	8.8	15.98	23
\$30,000	10.8	19.16	46
\$50,000	13.7	13.20	79
\$100,000	22.6	2.77	97
2017 [2]			
\$0	-0.1	7.71	3
\$5,000	0.5	7.06	4
\$10,000	1.0	7.58	6
\$15,000	1.9	6.98	7
\$20,000	2.8	6.53	9
\$25,000	3.8	5.77	12
\$30,000	4.9	9.95	16
\$40,000	6.3	7.79	25
\$50,000	8.2	13.71	37
\$75,000	9.7	8.83	53
\$100,000	12.6	13.05	76
\$200,000	19.2	4.06	93
\$500,000	25.4	0.66	93
\$1,000,000	27.6	0.15	91
\$1,500,000	28.3	0.06	91
\$2,000,000	28.7	0.08	91
\$5,000,000	28.3	0.02	95
\$1,000,000	25.6	0.01	97

[1] SOI Table 5 from the IRS [2] SOI Tables 1.1 and 2.1 from the IRS