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NONPROFITS IN GOOD TIMES AND BAD TIMES

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ABSTRACT

Need fluctuates over the business cycle. We conduct a survey revealing a desire for nonprofit activities to countercyclically expand during downturns. We then demonstrate, using comprehensive US nonprofit data drawn from millions of tax returns, that the public's hopes are disappointed. Nonprofit expenditure, revenue, and balance sheets fluctuate procyclically: contracting during national and local downturns. This finding is evident even for a narrow group of nonprofits the public most wishes would expand during downturns, e.g., those providing critical needs like food or housing. Our new facts contribute to the charitable giving, nonprofit, and business cycle literatures.

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A data appendix is available at http://www.nber.org/data-appendix/w29630
A nonprofit DCR survey ranking is available at https://sites.google.com/site/clexley/dcr

1 Introduction

The needs of vulnerable individuals in the US fluctuate over the business cycle, with measures such as food insecurity, poverty, and homelessness rates increasing during bad times (Sard, 2009; Kneebone and Holmes, 2016; Lombe et al., 2018). The public at large expresses a desire for countercyclicality in US nonprofits, hoping that nonprofits will expand their activities during downturns in the face of rising need.[1] This hope motivates the rich literature on the drivers of giving to nonprofits. Yet there is little comprehensive evidence on whether nonprofits—particularly nonprofits that the public especially hopes will expand during bad times—are indeed countercyclical.

In this paper we establish a set of key facts about nonprofits in good and bad times which demonstrate that the public's hopes are disappointed. The expenditure, revenue, and balance sheet size of US nonprofits are procyclical, declining rather than expanding during downturns at the national and local levels. We uncover procyclicality not only among all nonprofits but also among a select group of charities—such as food banks and housing assistance organizations—for which the public most intensely reports a desire for countercyclicality.

We build our analysis on micro data drawn from millions of tax returns of nonprofit organizations in the US from 1990 to 2013—covering the near universe of nonprofits in the US for all but the smallest organizations. While US nonprofits are exempt from taxation, Internal Revenue Service (IRS) guidelines generally require the filing of annual returns to maintain tax-exempt status. This legally mandated disclosure offers a useful window into financials across the distribution of nonprofit activity.[2] Crucially, the returns of tax-exempt organizations include information on revenue and expenditure, in addition to a wide range of data on the characteristics and type of each organization. This tax return database offers substantial advantages for the study of nonprofits, primarily through its measurement of a nonprofit's full financial position and because of its impressive coverage of this large and growing sector of the economy. Indeed, from 2000 to 2013, nonprofits in our data grew from 5% to 8% of US businesses while their revenue grew from 10% to 13% of US GDP.[3]

[1] 66% of survey respondents said yes when asked "Should charities expand their programs and services during economic downturns (e.g., recessions)?" (Google Consumer Survey run by the authors, August 2020, with 500 respondents). Elected officials sometimes express similar desires (Lee, 2013). This hope is particularly strong for certain types of nonprofits (see Section 2.2).

[2] In political economy applications, Bertrand et al. (2020a) and Bertrand et al. (2020b) have used related tax return data to link nonprofits to corporate contributions and lobbying.

[3] These figures are from author calculations. The 5% and 8% numbers are the ratio of the number of nonprofit organizations in IRS data to the total number of nonprofit and for-profit organizations from the US Census Statistics of US Businesses. The 10% and 13% revenue shares are the ratio of total nonprofit revenue from IRS tax returns to US nominal GDP from the Bureau of Economic Analysis' NIPA Accounts.

Nonprofits vary widely in purpose and type, ranging from hospitals and universities to golf clubs and soup kitchens. The National Taxonomy of Exempt Entities (NTEE)—used by researchers and by the IRS for classification—includes over 600 detailed codes grouping nonprofits. While these classifications are informative for a range of purposes, NTEE codes themselves do not provide a direct mapping to the "type" of nonprofit that may provide a public safety net during bad times. For example, wineries and food banks are both subgroups of the "Food, Agriculture & Nutrition" NTEE major group.

Given our desire to comprehensively examine whether nonprofits countercyclically expand during bad times—while still being able to narrow in on the aforementioned types of nonprofits—we build a novel classification scheme which organizes nonprofits according to the degree to which the public hopes they expand their programs and services during bad times. We recruited thousands of individuals to complete an online survey. In this survey, after respondents are presented with a randomly selected NTEE code and corresponding description, they indicate—on a scale from 1 (Strongly Disagree) to 7 (Strongly Agree)—whether they believe nonprofits with that detailed NTEE code should expand their programs and services during economic downturns. We then construct an average desired countercyclicality rating (DCR) for each NTEE code. Quite intuitively, the highest DCR nonprofits provide critical assistance such as food, housing, or medical care to indigent populations, while the lowest DCR nonprofits include organizations such as nonprofit golf clubs. Indeed, rather than food banks and wineries being grouped similarly because they both fall under the same NTEE major group, food banks secure the second-highest DCR whereas wineries are ranked 631 out of 655. Not only does the DCR measure allow us to distinguish between nonprofits within the same major groups, the DCR measure also allows us to link nonprofits with vastly different NTEE codes. The top ranked DCR—just above food banks (K31)—is emergency assistance (P60), defined as "organizations that provide food clothing, household goods, cash and other forms of short-term emergency assistance." Our construction of the DCR measure uniquely positions our paper to provide comprehensive insight into the cyclicality of the types of nonprofits which the public hopes to see expand to provide more services during bad times.

We organize our empirical analysis around five main questions. We frame each question in a manner that sheds light on our key motivation. Do nonprofits weather adverse economic conditions as the public hopes, expanding during downturns? Or do they instead contract during bad times? We first ask whether nonprofits adjust their spending in bad times by increasing their expenditure (Q1) or by reallocating their expenditure towards core programs

(Q2). We then investigate the sources and uses of nonprofit financial resources in bad times, asking whether their revenue increases (Q3), whether their assets decline (Q4), and whether their liabilities increase (Q5). Leveraging our comprehensive data on nonprofits, the resulting facts, i.e., answers to these questions, describe cyclicality at nonprofits in the face of nationwide business cycles and local economic fluctuations. We emphasize at the outset that each of our facts are descriptive rather than causal in nature, with our analysis purposefully targeted towards the documentation of observed behavior.

In Q1 we ask whether nonprofit expenditure is countercyclical. To answer this question—as well as the following four questions—we employ cyclicality regressions measuring the elasticity of nonprofit outcomes to income at the national and local level. We find that the answer to Q1 is no. Instead of expanding during economic downturns as desired by the public, we instead observe procyclicality in nonprofit expenditure with an elasticity of around 0.5 to local income. Even the "high DCR" nonprofits—those with a DCR in the top decile—cut their expenditure during downturns with an elasticity of 0.4 to local income.

After documenting a reduction in nonprofit expenditure during downturns, in Q2 we ask whether nonprofits reallocate their (lower) expenditure during bad times. We are motivated by a debate in the nonprofit sector about the importance of spending on two categories: core programs and services versus overhead costs. Historically, there has been a push for nonprofits to spend little on overhead costs under the belief that high overhead costs are indicative of waste and not instrumental to achieving their mission. Under this belief, if nonprofit expenditure falls, it would be less harmful, perhaps even helpful, for such reductions to be disproportionately borne by lower administrative expenditure. We find little to no reallocation in the data. While there is some evidence that high DCR nonprofits reallocate their expenditures towards core programs during national downturns, we do not find similar shifts for high DCR nonprofits during local downturns, and we find no cyclical shifts for all nonprofits. Overall, the answer to Q2 is no: the share of spending on core programs and services is mostly acyclical and does not shift over the business cycle. We note, however, that our result need not be viewed as a "failure" of the nonprofit sector. Business leaders and academics have reasonably argued that, as detailed in Gregory and Howard (2009), a focus on decreasing the share of spending on overhead costs can lead to a "nonprofit starvation cycle" in which charities lack the necessary talent or infrastructure to implement their goals.[4]

Motivated by evidence that nonprofit outlays or expenditure decline in bad times, we then

[4]For a range of other work on overhead costs and charity performance metrics, see Gneezy et al. (2014); Karlan and Wood (2017); Meer (2014); Brown et al. (2016); Yörük (2016); Coffman (2017); Exley (2020).

move to an analysis of nonprofit financial resources. In Q3 we ask whether nonprofits secure higher revenue during bad times. We find that the answer to Q3 is no. Revenue for nonprofits is procyclical, declining during bad times and increasing during good times for both the nationwide and local economies. We estimate an elasticity of revenue to local income of 1.1 for all nonprofits and 0.7 for high DCR nonprofits. We also document the procyclicality of various revenue streams, including donation-based revenue and non-donation-based revenue. While prior work similarly finds procyclicality of donation-based revenue (List, 2011), our investigation of non-donation-based revenue—facilitated by tracking organization-level rather than donor-level outcomes—is informative since the average nonprofit in our data receives more than 80% of its revenue from non-donation sources including the sales of products (e.g., discounted clothes) and fees associated with services (e.g., job training or medical care).

Declining revenue during economic downturns motivates our next two questions on nonprofit finances or balance sheets: Do nonprofit assets decline during bad times (Q4)? Do nonprofit liabilities increases during bad times (Q5)? The answer to Q4 is yes: nonprofits do in fact experience declines in their assets during economic downturns with a cyclical elasticity of assets to local income of 0.5 for all nonprofits and the same for the high DCR group. The answer to Q5 is no: nonprofit liabilities decline during bad times with a cyclical elasticity of liabilities to local income of 0.2 for all nonprofits and the same for the high DCR group. Our findings of procyclicality for both assets and liabilities imply that the size of nonprofit balance sheets shrinks during economic downturns. These patterns are consistent with the idea that financial constraints may impact nonprofit decision-making.[5]

Taken together, our empirical facts reveal that the public's desire for countercyclicality is disappointed in practice, both for the nonprofit sector as a whole and even in the highest DCR nonprofits such as food banks or homeless shelters which all fluctuate procyclically. The pronounced disconnect between hopes and empirical outcomes makes it important to conduct a set of comprehensive robustness checks, subsample analyses, and extensions of our baseline analysis. In a series of these checks we ask whether our findings differ by the exact DCR level, by size, by broad NTEE categories, by nonprofit legal structure, by Census region, by local urbanization level, by revenue streams, by measure of economic fluctuations, and under alternative specifications of our cyclicality regressions. We also compare nonprofit cyclicality to that of for-profit businesses.[6] These exercise uncover some

[5]We revisit this possibility in our discussion of charity size in Section 4.2. Theories of firm financial frictions (Ottonello and Winberry, 2020; Crouzet and Mehrotra, 2018) often imply that only firms facing few financial constraints can afford to expand their balance sheets in the face of investment opportunities. For nonprofits, increased need during downturns may provide a similar opportunity.

[6]This question is relevant given a movement within the nonprofit sector to become more "business-like,"

interesting heterogeneity across groups of nonprofits in the magnitude of their cyclicality. But in no case do we uncover evidence of the nonprofit countercyclicality desired by the public: procyclicality among US nonprofits is a robust phenomenon.

Our results complement the rich literature on charitable giving. See Vesterlund (2006), List (2011), Andreoni and Payne (2013), and Gee and Meer (2020) for excellent reviews of that work. Much of this literature focuses on the manner in which micro conditions influence individual giving decisions, e.g., how donations are influenced by social pressure (Ariely et al., 2009; DellaVigna et al., 2012, 2013; Andreoni et al., 2016), by matching donations (Eckel and Grossman, 2003; Karlan and List, 2007; Meier, 2007), by seed money or lead donors (List and Lucking-Reiley, 2002; Karlan and List, 2020), by household income (Randolph, 1995; Auten et al., 2002; List, 2011; Kessler et al., 2019; Meer and Priday, 2020b), and by tax policy (Duquette, 2016, 2019; Meer and Priday, 2020). A smaller set of studies focuses on the relationship between macro conditions and giving, such as papers relating to giving after large, tragic events (Lilley and Slonim, 2016; Bergdoll et al., 2019) and work relating to redistribution and fairness views at the societal level (Almås et al., 2020).[7] An even smaller but important and emerging body of literature seeks to understand aggregate giving in response to nationwide economic fluctuations.[8] This existing body of research compellingly documents the procyclicality of giving in relation to nationwide economic fluctuations (List, 2011; Reich and Wimer, 2012; Meer et al., 2017) and includes evidence that such procyclicality is smoothed during recessions (List and Peysakhovich, 2011). Relative to this prior work on procyclicality, we differ by focusing on the behavior of nonprofits themselves rather than individuals giving to nonprofits. Not only does this approach allow us to investigate the cyclicality of total nonprofit revenue (combining both donations and non-donation sources), our data allows us to investigate other nonprofit outcomes such as the cyclicality of nonprofit expenditure, which we view as useful to understanding whether nonprofits expand their programs and services during bad times. For all of our cyclicality analyses—on expenditure, program expenditure share, revenue and its subcomponents, assets, and liabilities—we start

e.g., by adopting strategic plans (Hwang and Powell, 2009). See also McConnell et al. (2016); Bloom et al. (2015); Tsai et al. (2015) for evidence on formal management practices and hospital performance.

[7]This literature typically finds that giving increases after natural disasters, which are likely times of increased need (although this is not always the case, see e.g., Eckel et al. (2007)). While one could view this result as running counter to findings which report decreased giving during economic downturns, there are many reasons for such differences (e.g., natural disasters may involve more targeted-need). For work that dives into the role of nonprofit strategy in response to the financial crisis, see Horvath et al. (2018).

[8]Even work on aggregate giving more generally is limited. As discussed in Gee and Meer (2020), while prior work often focuses on the drivers of a single giving decision, there has been a recent movement to consider more aggregated giving outcomes, e.g., substitution effects across charities.

by investigating nationwide economic fluctuations, like this prior literature on the cyclicality of donations. But, in addition, we further examine local economic fluctuations. These local economic fluctuations are larger in magnitude than nationwide cycles, providing substantially more variation in our data and crucially linking our notion of "good versus bad times" more closely to the lived experiences of individuals in a given local area.

Our results also complement a nonprofits literature that uses nonprofit tax return data similar to ours or relies on related surveys. One stream (Froelich, 1999; Carroll and Stater, 2009; Duquette, 2017) studies the sources of nonprofit revenue and emphasizes differences between volatile revenue sources, such as contributions, versus other sources of income. A second stream of work (Tuckman and Chang, 1991; Greenlee and Trussel, 2000; Trussel, 2002) studies nonprofit financial vulnerability, finding wide heterogeneity across organizations in their ability to withstand financial shocks. Most closely related to our paper, a third stream of work (Salamon et al., 2009; Brown et al., 2013; Lin and Wang, 2015) directly examines fluctuations in nonprofit outcomes during the Great Recession and often focuses on a small sample or survey of nonprofits. This work typically finds meaningful declines in revenue and financial resources during the Great Recession. Relative to this prior work, we broaden the scope beyond the nationwide Great Recession by studying a longer time period with multiple economic cycles, by analyzing local rather than only nationwide economic fluctuations, and by studying a comprehensive sample of the near universe of tax returns across nonprofits.

We also highlight that this prior work on nonprofits often focuses on a small subset of organizations precisely because those studies correctly recognize the diversity of nonprofits of different types. This diversity—and indeed the associated challenge in classifying whether nonprofits are more "like food banks" which the public might hope will expand during bad times or more "like wineries"—is exactly what motivates our construction of the novel DCR measure as well as many heterogeneity analyses in our paper. Our constructed DCR measure—for all 655 detailed NTEE codes—is publicly available online.[9] We hope this ranking will prove to be a useful methodological resource for research on nonprofits. Indeed, we broadly view the study of nonprofits as an important, underexplored area of work, particularly in economics. We hope that the set of descriptive facts we establish about nonprofit behavior encourages more work that focuses on nonprofits themselves. Growing a literature in economics on nonprofits themselves—to complement the existing, rich, but distinct literature that focuses instead on giving to nonprofits—would substantially improve our understanding of this large and diverse sector of the economy.

[9]For DCR data, see Christine Exley's website (https://sites.google.com/site/clexley/dcr).

Finally, our results also complement a literature on the cyclicality of for-profit firms. One stream of papers focuses on documenting the relative cyclicality of sales at small versus large firms with respect to macro fluctuations (Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2018). Another set of studies analyzes firm growth and selection patterns around recessions (Moreira, 2017; Kehrig, 2015; Bloom et al., 2018). A third body of work measures the observed volatility and sensitivity of outcomes at for-profit firms in the face of various disaggregated shocks (Davis et al., 2006; Decker et al., 2014, 2020). A fourth set of research examines the cyclicality or responses to economic policy at the local level (Nakamura and Steinsson, 2014). Relative to each of these sets of work, the contribution of our paper is to extend the knowledge of cyclicality and sensitivity patterns at for-profit firms to the large, qualitatively distinct, context of nonprofit organizations.

Section 2 describes our data. Section 3 presents our results. Section 4 reports our heterogeneity and robustness checks. Section 5 concludes. Online appendices provide more detail on our data, additional results, and our DCR survey.

2 Data

2.1 Nonprofit Data

Our definition of a nonprofit includes organizations deemed tax-exempt by the IRS. Throughout the paper, we have referred and will refer to these entities interchangeably as "nonprofits," "organizations," or "charities." Generally, the IRS requires nonprofits to file a tax return—Form 990—each year (Internal Revenue Service, 2020).[10] Unlike private businesses, whose tax returns are in general confidential in the US, nonprofit tax returns are a matter of public record. We utilize a database of individual nonprofit tax returns compiled by the National Center for Charitable Statistics (NCCS) covering essentially the universe of nonprofit Form 990 data in the US for all but the smallest organizations.[11,12] Our *main dataset* built on the NCCS core fiscal year trend files includes over 8.5 million organization-years

[10] Various variants of Form 990, such as Form 990-EZ, Form 990-N, or Form 990-PF, exist for small nonprofits or nonprofits organized in specific legal forms. Our data includes all such variants. Also, most religious organizations are not required to submit tax returns to the IRS.

[11] The data covers nonprofits which are required to file Form 990. Organizations with fewer than $25,000 in revenue are not included. This threshold rises to $50,000 in 2010. There are two reasons that our results are not driven by this shift. First, we examine regressions with time effects accounting for any induced common shifts in nonprofit financials at the year level. And second, in heterogeneity analysis we also verify that our results obtain among the largest nonprofits for which filing thresholds are irrelevant.

[12] Note that charities are not required to report in-kind contributions in Form 990. Thus, all statements made in this paper about nonprofit revenue and contributions are strictly limited to monetary values.

drawn from about nine hundred thousand nonprofits from 1990 to 2013. While this dataset is comprehensive in terms of organization-years, it lacks some detailed line items that we rely on in robustness checks and in one of our facts. For these analyses we instead employ our *supplemental dataset*, which is built on the IRS Statistics of Income (SOI) files. The latter dataset is more comprehensive in terms of available line items but covers about 5% of the observations in our main dataset.

The bulk of our analysis centers on four outcomes measured in our main data at the organization-year level: 1) expenditure, including spending on all activities by the nonprofit 2) revenue, including income from both contributions as well as the sale of goods and services, 3) assets, including the value of both financial as well as physical resources held by nonprofits, and 4) liabilities, the value of total debt or obligations owed by a charity to outside entities. We also examine subcategories within some of these variables when relevant.

The nonprofit sector accounts for a sizable portion of economic activity, organizations, and assets in the US. In 2013, almost 10% of US business-type entities were nonprofits, and their revenue totaled around 13% of US GDP. Compared in the same year to two commonly studied groupings of for-profit firms—manufacturers and publicly traded companies—the nonprofit sector also appears sizable. Total revenue (assets) of nonprofits were around 17% (34%) of those of all publicly listed firms. And total revenue (assets) of nonprofits were 43% (75%) of those of all listed manufacturing firms. As noted in the introduction, the sector has also grown relative to the rest of the economy since 2000.

See data Appendix A for more information on our nonprofit sample construction and data. In Appendix A, we also provide more details on our construction of a sample of financial information on US for-profit public firms from the Compustat database. See Table A.4 for descriptive statistics on each of the main variables used in our analysis.

2.2 The Desired Countercyclicality Rating (DCR) Measure

A key motivating question for us is whether nonprofit organizations which the public reports "should" be countercyclical are indeed countercyclical. To examine this question we constructed a novel desired countercyclicality rating (DCR) for each type of nonprofit.

As a first step, we constructed a list of 655 types of nonprofits—resulting from the letter and two-digit number code classification provided by the National Taxonomy of Exempt Entities (NTEE) developed by NCCS.[13] Some context on the NTEE classification system is useful. The purpose of NTEE codes—which are also used in IRS classifications of nonprofits—is

[13] See here for a full listing: https://nccs.urban.org/publication/irs-activity-codes.

similar to broader statistical classification schemes such as NAICS industry codes assigned to for-profit businesses. The breadth of NTEE codes reflects substantial heterogeneity in purpose across the nonprofit sector, ranging from organizations focused on providing direct charitable services to individuals to very different nonprofits such as large universities, museums, or hospitals. As an example, K31 is refers to "Food Banks & Pantries" and is described as "Organizations that gather, store and distribute food to indigents at no charge or at low cost." As a second step, with this list of descriptions for each NTEE code in hand, we asked survey respondents to rate whether they believe nonprofits of that type should expand their programs and services during economic downturns.

In October 2021, we recruited 2002 individuals from Prolific, a commonly used online platform for academic surveys.[14] Each respondent answered ratings questions for 40 randomly selected types of nonprofits, resulting in 92-158 submitted ratings for each type of nonprofit. Specifically, after being informed of the classification name and description for a type of nonprofit, the participant answered the ratings question about that nonprofit type. Respondents were randomly assigned to answer all 40 ratings questions in one of two versions. In the *Self Belief* version, respondents were asked "Please indicate your agreement with the following statement: The nonprofit organizations described above should expand their programs and services during economic downturns (e.g., recessions)." In the *Modal Belief* version, rather than being asked to indicate their own agreement with the following statement, respondents were asked "When other Prolific participants are asked to indicate their agreement with the following statement, what answer do you think is most commonly chosen?" In the *Modal Belief* version, respondents also knew that they would receive an additional bonus payment of $1 if they correctly answered one randomly selected ratings question. The purpose of the *Modal Belief* version is to demonstrate that our results are robust to incentivizing respondents to pay attention, although evidence for attention is also evident from the fact that 98% of respondents pass attention checks in both versions.[15] The ratings questions permitted answers that ranged from 1 (Strongly Disagree) to 7 (Strongly Agree). Thus, a higher DCR indicates stronger agreement with the statement that the relevant nonprofit type should expand their programs and services during economic downturns.

[14] Eligible individuals must have previously completed at least 100 tasks on Prolific with an approval rating of 95% of better. Respondents received $2 for completing this 10-minute survey.

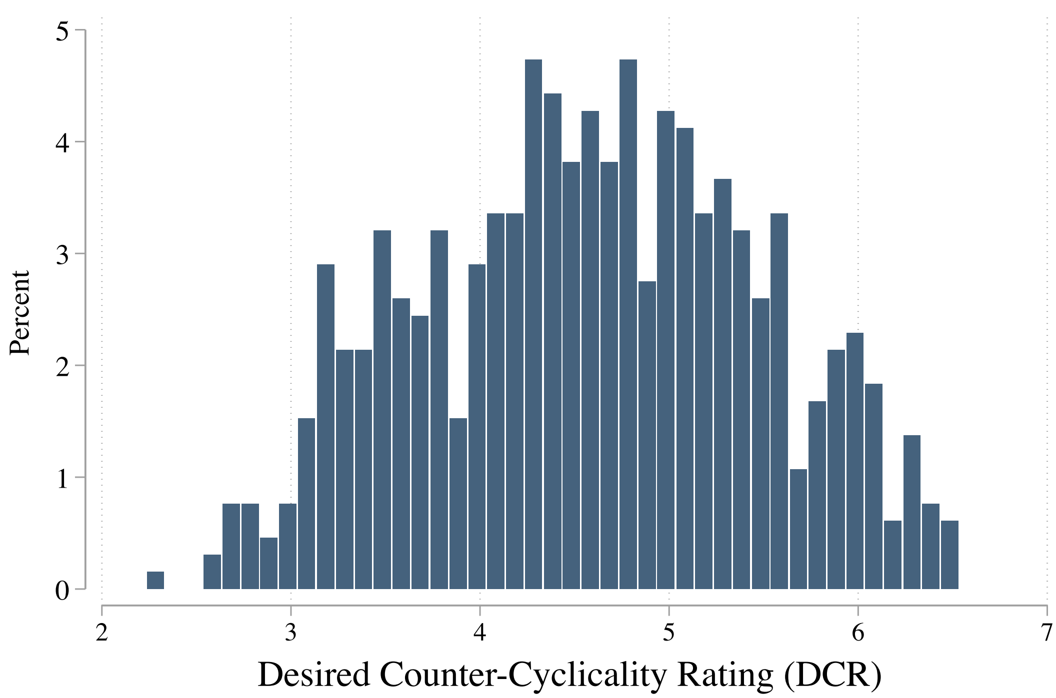
[15] After respondents completed the ratings questions, they complete a short unincentivized follow-up survey. They pass our attention check if they correctly select the button furthest to the left when asked to do so in one of those questions and instead select the button furthest to the right when asked to do so in another question. Evidence for respondents paying attentions is further evident via the very sensible desired countercyclicality ratings we observe across the 655 nonprofit types (see Footnote 9 for reference).

See Appendix C for the survey materials.

As expected, the ratings from the *Self Belief* version and the *Modal Belief* version are highly correlated: $\rho = 0.95$ ($p < 0.01$). Moreover, the difference between the average ratings across these versions is small. The average ratings are 4.64 and 4.52 in the *Self Belief* and *Modal Belief* version, respectively, and 89% of the 655 nonprofit types fall within 0.5 points of each other across these two versions. Thus, to construct the DCR for each nonprofit type, we calculate the average rating of that nonprofit type when pooling across both study versions. Plotting the distribution of DCRs in Figure 1 makes it clear that there is meaningful variation across nonprofit types in terms of their DCR.

Table 1 lists the 10 nonprofit types with the highest DCRs. Appendix Tables C.1 - C.5 lists the nonprofit types with top 10% highest DCRs. The full list of DCRs is available online.[16] Quite encouragingly, the categories of nonprofits with the highest DCRs are what one might expect—largely consisting of organizations providing direct assistance to indigent individuals with critical needs such as food or housing.

Figure 1: Distribution of Desired Countercyclicality Ratings (DCR)



Note: This figure plots the distribution of DCRs across 655 two-digit nonprofit NTEE codes.

[16]See Footnote 9 for details on accessing our DCR data.

Table 1: Top 10 Desired Countercyclicality Ratings (DCR)

Rank	DCR	NTEE classification: Major Group–Description (Code): Definition
1	6.52	**Human Services–Emergency Assistance** (P60): Organizations that provide food, clothing, household goods, cash and other forms of short-term emergency assistance for indigent individuals and families who have insufficient resources to meet their basic needs.
2	6.52	**Food, Agriculture & Nutrition–Food Banks & Pantries** (K31): Organizations that gather, store and distribute food to indigents at no charge or at low cost.
3	6.5	**Housing & Shelter–Homeless Shelters** (L41): Organizations that provide a temporary place to stay for people who have no permanent housing.
4	6.49	**Food, Agriculture & Nutrition–Meals on Wheels** (K36): Organizations that prepare and deliver regular hot meals to elderly individuals, people with disabilities or people with AIDS or other targeted conditions who are unable to shop and/or prepare food for themselves or to travel to a site where a meal is being served. Also known as home delivered meals.
5	6.38	**Human Services–Homeless Centers** (P85): Organizations that provide supportive services for individuals and families who are homeless or which work with people who are at risk for homelessness in an effort to prevent them from losing their permanent residence.
6	6.37	**Employment–Employment Preparation & Procurement** (J20): Organizations that help people prepare for, find, secure and retain suitable employment. Use this code for organizations that provide a wide range of employment services or those that offer employment-related services not specified below. Includes: Employment placement agencies; Job development organizations including those for youth and people with disabilities; Retraining; and Senior Community Service Employment Programs
7	6.37	**Food, Agriculture & Nutrition–Soup Kitchens** (K35): Organizations that provide meals in a central location for indigent people.
8	6.34	**Housing & Shelter–Housing Search Assistance** (L30): Organizations that assist people to find available purchasable or rental housing which meets their individual needs.
9	6.34	**Mental Health & Crisis Intervention–Hot Lines & Crisis Intervention** (F40): Organizations that provide in-person or telephone assistance for people who are in acute emotional distress; who are a danger to themselves or to others; who are having suicidal feelings; or who are hysterical, frightened or otherwise unable to cope with a problem that requires immediate action. Use this code for crisis intervention services or hotlines not specified below or for organizations that offer multiple types of crisis intervention, hotline services.
10	6.33	**Housing & Shelter–Housing Support** (L80): Organizations that provide supportive services which help people obtain and remain in suitable housing. Use this code for organizations that provide multiple supportive services or for supportive services specified below.

Note: For each of the 10 nonprofit types with the highest DCRs, this table lists its rank according to the DCR measure, DCR measure, NTEE code, title, and description.

3 Results

Our survey reveals a public desire for US nonprofits, especially those with high DCRs such as food banks or housing assistance organizations, to increase their activities during bad times. This section reports our key findings using transparent cyclicality regressions varying across multiple nonprofit financial measures (e.g., expenditure, revenue, etc.), multiple measures of economic fluctuations (defined at the national and local levels), and multiple groups of nonprofits (all organizations and only those with the highest DCRs). We employ baseline specifications of the form

$$\Delta Y_{j,t} = \alpha + \beta \Delta X_{a,t} + \varepsilon_{j,t}, \tag{1}$$

where $\Delta Y_{j,t}$ is the growth rate of a series of interest Y, e.g., expenditure, for nonprofit j in year t, and $\Delta X_{a,t}$ is the growth rate of total personal income in area a surrounding j in the same year t.[17] The coefficient of interest, β, reveals the cyclicality or the association of nonprofit outcome Y with personal income X in elasticity units. When $X_{a,t}$ is noted as Nat. Income, we examine national cyclicality by setting a equal to the national level. When $X_{a,t}$ is noted as CZ Income, we examine local cyclicality by setting a equal to a commuting zone (CZ). CZ's are defined by the US government and typically between a county and state in size. We examine local areas based on CZ's for comparability with other research on local economic dynamics (Autor et al., 2013). In addition to Equation 1, we also report estimates of β allowing for year fixed effects, exploiting only relative fluctuations in local economic conditions after discarding common nationwide income fluctuations. Estimating Equation 1 in growth rates follows standard procedure in the regional shocks literature (Autor et al., 2013), conservatively accounting for permanent unobserved heterogeneity across nonprofits and CZ's. However, the choice is immaterial for our purposes since we also later report similar results from less conservative estimation of our regressions in levels (see Section 4.9).

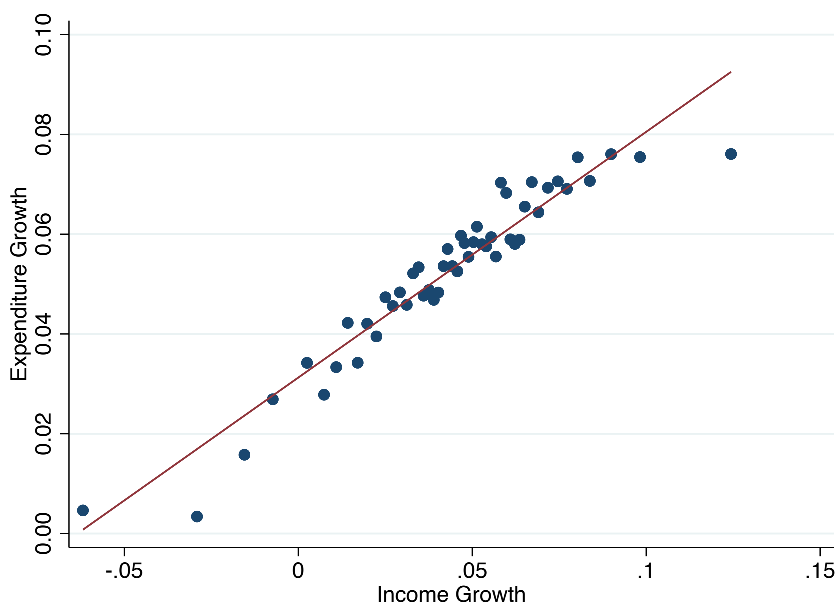
In each Subsection 3.1 - 3.5 we examine the cyclicality of a single outcome for nonprofits, framing our results for rhetorical purposes as the answer to one of our motivating questions from the introduction. We view these descriptive facts as a step towards improving our understanding of how the large nonprofit sector operates. We also hope that, as discussed in Section 5, these facts will motivate future work including work that seeks to identify a particular treatment effect or a particular causal mechanism of interest relating to nonprofits.

[17] Throughout, we define the growth rate of $Y_{j,t}$ for nonprofit j at time t as $\Delta Y_{jt} \equiv 2 \times \frac{Y_{j,t} - Y_{j,t-1}}{|Y_{j,t}| + |Y_{j,t-1}|}$. This formula safeguards against outliers without the need for censoring or winsorization and follows common practice in the firm dynamics literature (Davis et al., 1996).

3.1 Do nonprofits increase their spending during downturns?

In our survey, the public reports a desire for US nonprofits to countercyclically expand their activities and provide a form of insurance against downturns. Relative to other observable outcomes such as revenue, we view expenditure as a closer proxy for nonprofit activities, and a strength of our dataset is the separate measurement of charity spending versus revenue. So we first ask whether nonprofits do in fact expand their expenditure during downturns. To provide some preliminary visual insight, Figure 2 plots a binscatter of expenditure growth at the nonprofit level against CZ-level income growth. The horizontal axis displays quantiles of CZ income growth, and the vertical axis displays the corresponding mean of nonprofit expenditure growth. The positive correlation in the figure reveals that the answer to our first question is no: spending growth at nonprofits does not increase during local economic downturns. Instead, spending is procyclical.

Figure 2: Nonprofit Expenditure and Economic Fluctuations



Note: This binscatter plots displays quantiles of CZ income growth on the horizontal axis against the corresponding mean of nonprofit expenditure growth rates. The trend line depicts the best linear fit. See Appendix A for more data details.

Table 2 presents a related series of cyclicality regressions for nonprofit expenditure. The first three columns estimate cyclicality for our sample of all nonprofits. We see in column (1) that when national income growth falls by one standard deviation or 2.5 percentage points, expenditure growth for nonprofits declines by an average of $0.69 \times 2.5 \approx 1.7$ percentage points. Column (2) shows that when local CZ income growth falls by one standard deviation or 3.2 percentage points, expenditure growth for nonprofits in that area falls by an average of $0.49 \times 3.2 \approx 1.6$ percentage points. We then include time effects and rely on narrower, relative variation. Column (3) reports that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—expenditure growth for nonprofits in that area falls by an average of $0.22 \times 3.2 \approx 0.7$ percentage points relative to the average growth in expenditure across all nonprofits in that year.

Table 2: Cyclicality Regressions for Expenditure

	All nonprofits			High DCR nonprofits		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Nat. income	0.69***			0.47***		
	(0.02)			(0.03)		
Δ CZ income		0.49***	0.22***		0.37***	0.20***
		(0.03)	(0.02)		(0.04)	(0.03)
N	8625639	8625639	8625639	1110550	1110550	1110550
Year FE	no	no	yes	no	no	yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state level. This table reports coefficient estimates from OLS on Equation 1 when $\Delta Y_{j,t}$ is the growth rate of expenditure for nonprofit j in year t. Columns (1)-(3) include all nonprofits in our main dataset, while Columns (4)-(6) are restricted to high DCR nonprofits. See Appendix A for more data details.

The next three columns narrow to a group of nonprofits in the top decile of our DCR measure, i.e., the group of charities which our survey respondents most strongly feel should increase their activities during downturns. We refer to this group as "high DCR" nonprofits, which are fully described in Appendix Tables C.1 - C.5. Column (4) shows that when national income growth falls by one standard deviation or 2.5 percentage points, expenditure growth for high DCR nonprofits declines by an average of $0.47 \times 2.5 \approx 1.2$ percentage points. We see in column (5) that when local CZ income growth falls by one standard deviation or 3.2 percentage points, expenditure growth for high DCR nonprofits in that area falls by an average of $0.37 \times 3.2 \approx 1.2$ percentage points. Finally, column (6) implies that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—expenditure growth for high DCR nonprofits in that area falls by an average of $0.20 \times 3.2 \approx 0.6$ percentage points relative to the average growth in expenditure across high DCR nonprofits in that year. That nonprofit expenditure grows *less* during bad times is consistent with a misalignment between fluctuations in need and nonprofit activities in practice, suggesting a path forward for future research into the underlying drivers of nonprofit activities.

> **Fact 1 (Nonprofit Expenditure)**: Nonprofit expenditure is procyclical, falling during bad times and increasing during good times. The elasticity of nonprofit expenditure to local personal income is 0.5 for all nonprofits and 0.4 for high DCR nonprofits.

3.2 Do nonprofits reallocate their expenditure during downturns?

In principle, expenditure reductions during bad times might be cushioned if nonprofits strategically reallocate their expenditure in ways that allow them to maintain key activities during bad times. Relatedly, nonprofits often highlight how much of their expenditure is allocated to 1) core programs and services, versus 2) administrative or overhead costs. Indeed, well known organizations, such as Charity Navigator, commonly evaluate nonprofits positively based on the size of their program spending and negatively based on the size of their administrative overhead expenses (Charity Navigator, 2020). Such metrics are controversial, since cuts to spending on overhead categories, such as the salaries of skilled workers or facility maintenance, might prove damaging for service provision in practice (Gregory and Howard, 2009). Nevertheless, the core program spending share remains widely discussed and tracked in the nonprofit sector, making it a metric worth understanding better.

While we do not observe nonprofit expenditure on programs and services specifically in our main dataset, we can construct a measure of the share of spending on core programs in our supplemental dataset. We remind the reader that the latter is comprised of a subset of organizations for which the IRS has released more detailed tax return information, implying that our supplemental data involves about 5% of the observations included in our main data (although it still amounts to nearly 400,000 observations). Table 3 measures the cyclicality of the core program expenditure share. Columns (1) - (3) reveal that among all nonprofits the answer to our second question is no: during downturns in national income, local CZ income, or local CZ income controlling for common shifts, nonprofits do not reallocate their spending towards or away from core programs. Paired with the overall spending declines reported in Fact 1, the acyclicality result from Table 3 for all nonprofits suggests near uniform declines in nonprofit expenditure across multiple categories. Indeed, we verify in Appendix Table B.1 that both core program and administrative spending individually decline during bad times at the national and local levels.

By contrast, we see in column (4) that among high DCR nonprofits there is a reallocation of spending towards core programs and away from administrative expenditure during downturns in national income. When national income growth falls by one standard deviation or 2.5 percentage points, the share of spending on core program expenditure for high DCR nonprofits increases by an average of $1.36 \times 2.5 \approx 3.4$ percentage points. But despite this shift during national downturns, columns (5) - (6) reveal that among high DCR nonprofits there is no such reallocation during downturns in local CZ income. This lack of reallocation of expenditure during local downturns is particularly remarkable given the larger magnitude of local relative to national fluctuations and highlights the importance of separately examining local versus national cyclicality. We also verify in Appendix Table B.1 that both program expenditure and administrative spending are individually procyclical for high DCR nonprofits, declining during bad times at the national and local levels.

Fact 2 (Core Program Spending Share): The share of nonprofit spending on core programs relative to administrative expenditure is acyclical for all nonprofits and in response to local fluctuations, reflecting common shifts in both categories of spending over the economic cycle. Countercyclicality is only observed among high DCR nonprofits in response to national fluctuations.

Table 3: Cyclicality Regressions for Program Expenditure Share

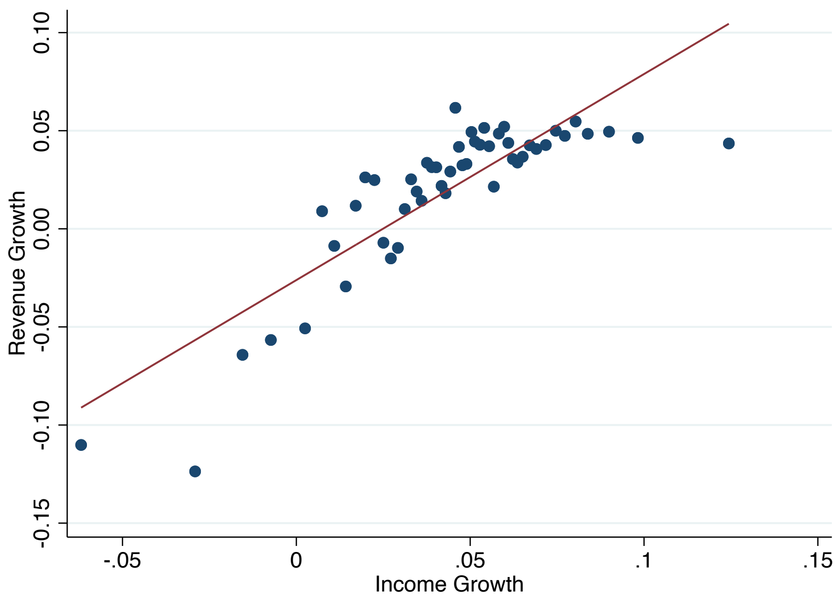
	All nonprofits			High DCR nonprofits		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Nat. income	-0.31			-1.36***		
	(0.32)			(0.48)		
Δ CZ income		0.02	0.43		-0.50	0.26
		(0.24)	(0.31)		(0.52)	(0.67)
N	393160	393160	393160	87416	87416	87416
Year FE	no	no	yes	no	no	yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state level.This table reports coefficient estimates from OLS on Equation 1 when $\Delta Y_{j,t}$ is the change in the share of expenditure on core programs for nonprofit j in year t. Columns (1)-(3) include all nonprofits in our supplemental dataset, while Columns (4)-(6) are restricted to nonprofits in our supplemental dataset with NTEE codes in the top 10 percentile of desired countercyclicality ratings. See Appendix A for more data details.

3.3 Do nonprofits secure higher revenue during downturns?

We now shift from our first two questions directly examining spending on the activities of nonprofits to an analysis of the cyclicality of nonprofit funding sources. In our third question, we ask whether nonprofits secure higher revenue during economic downturns. Figure 3 plots a binscatter of revenue growth at the nonprofit level against CZ-level personal income growth and reveals that the answer to this question is no: revenue growth at nonprofits does not increase during local economic downturns. Instead, revenue appears procyclical.

Figure 3: Nonprofit Revenue and Economic Fluctuations



Note: This binscatter plots displays quantiles of CZ income growth on the horizontal axis against the corresponding mean of nonprofit revenue growth rates. The trend line depicts the best linear fit. See Appendix A for more data details.

Table 4 presents a related series of cyclicality regressions for nonprofit revenue. The first three columns estimate cyclicality for our full sample including all types of nonprofits. We see in column (1) that when national income growth falls by one standard deviation or 2.5 percentage points, revenue growth for nonprofits declines by an average of $1.63 \times 2.5 \approx 4.1$ percentage points. Column (2) shows that when local CZ income growth falls by one standard deviation or 3.2 percentage points, revenue growth for nonprofits in that area falls by an average of $1.05 \times 3.2 \approx 3.4$ percentage points. We then include time effects and rely on narrower, relative variation. Column (3) reports that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—revenue growth for nonprofits in that area falls by an average of $0.31 \times 3.2 \approx 1.0$ percentage points relative to the average growth in revenue across all nonprofits in that year.

The next three columns narrow to the sample of high DCR nonprofits. We see in column (4) that when national income growth falls by one standard deviation or 2.5 percentage points, revenue growth for high DCR nonprofits declines by an average of $1.15 \times 2.5 \approx 2.9$ percentage points. Column (5) shows that when local CZ income growth falls by one standard deviation or 3.2 percentage points, revenue growth for high DCR nonprofits in that area falls by an average of $0.73 \times 3.2 \approx 2.3$ percentage points. Finally, column (6) implies that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—revenue growth for high DCR nonprofits in that area falls by an average of $0.24 \times 3.2 \approx 0.8$ percentage points relative to the average growth in revenue across high DCR nonprofits in that year.

> **Fact 3 (Nonprofit Revenue)**: Nonprofit revenue is procyclical, falling during bad times and increasing during good times. The elasticity of nonprofit revenue to local personal income is 1.1 for all nonprofits and 0.7 for high DCR nonprofits.

Table 4: Cyclicality Regressions for Revenue

	All nonprofits			High DCR nonprofits		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Nat. income	1.63***			1.15***		
	(0.06)			(0.06)		
Δ CZ income		1.05***	0.31***		0.73***	0.24***
		(0.08)	(0.05)		(0.06)	(0.04)
N	8625639	8625639	8625639	1110550	1110550	1110550
Year FE	no	no	yes	no	no	yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state level. This table reports coefficient estimates from OLS on Equation 1 when $\Delta Y_{j,t}$ is the growth rate of revenue for nonprofit j in year t. Columns (1)-(3) include all nonprofits in our main dataset, while Columns (4)-(6) are restricted to high DCR nonprofits. See Appendix A for more data details.

To further investigate the procyclicality of nonprofit revenue (Fact 3), we examine the cyclicality of different types of nonprofit revenue. Specifically, motivated by prior work that documents the procyclicality of donations (List, 2011; List and Peysakhovich, 2011; Reich and Wimer, 2012; Meer et al., 2017), we investigate whether we can replicate the procyclicality of broad revenue within categories such as donations and non-donation revenue.

In our main dataset, with over eight million observations, we can break nonprofit revenue into two categories: contributions and non-contribution revenue. Contributions, accounting for approximately 20% of total revenue, include donation support from the public and support from government grants.[18] Thus, focusing on contributions provides an overestimate of donation revenue. Meanwhile, non-contribution revenue, accounting for approximately 80% of total revenue, includes revenue from programs and services, financial income, profits from special events or sales, and other miscellaneous sources. Examples of non-contribution revenue include the sales of products such as discounted clothes, fees associated with affordable housing, job training, medical clinics, or college tuition, and earnings from non-mission-related activities such as ticket sales for special events, rental fees for their space, or the sale of paraphernalia. Appendix Table B.2 shows the cyclicality of contributions and non-contribution revenue. Both types of revenue are procyclical, with similar patterns for all nonprofits and high DCR nonprofits. Non-contribution revenue exhibits more procyclicality with an elasticity to local income of 1.3 for all nonprofits, while the elasticity of contributions revenue to local income is lower at 0.3 for all nonprofits.

In our supplemental dataset, which includes about 5% of the observations in our main data, we observe government grant revenue allowing us to measure donations as contributions less government grants. We find that 7.8% of total revenue arises from donations while 92.2% arises from other sources.[19] We also confirm our main conclusions with this narrow donation measure. Both donation and non-donation revenue are procyclical. Appendix Table B.3 shows that the cyclical elasticity of donations to local income is around 0.6 for all nonprofits, while the cyclical elasticity of non-donation revenue is 0.2 for the same group. Among high DCR nonprofits, our estimates are more muted for donations and around the same for non-donation revenue.

We conclude with some comments on the procyclicality of total revenue (Fact 3) and these additional results. First, we highlight that within our data we replicate the procyclicality of donations in response to nationwide economic fluctuations documented in prior work (List, 2011; List and Peysakhovich, 2011; Reich and Wimer, 2012; Meer et al., 2017). Second, we show that this finding extends to larger, local economic fluctuations. Third, we document the procyclicality of two additional outcomes: non-donation sources of revenue and total revenue. These latter findings are not implied by procyclicality of donations in response to nationwide economic fluctuations. However, it turns out to be clear in the data that revenue procyclicality is quite pervasive across sources and economic fluctations.

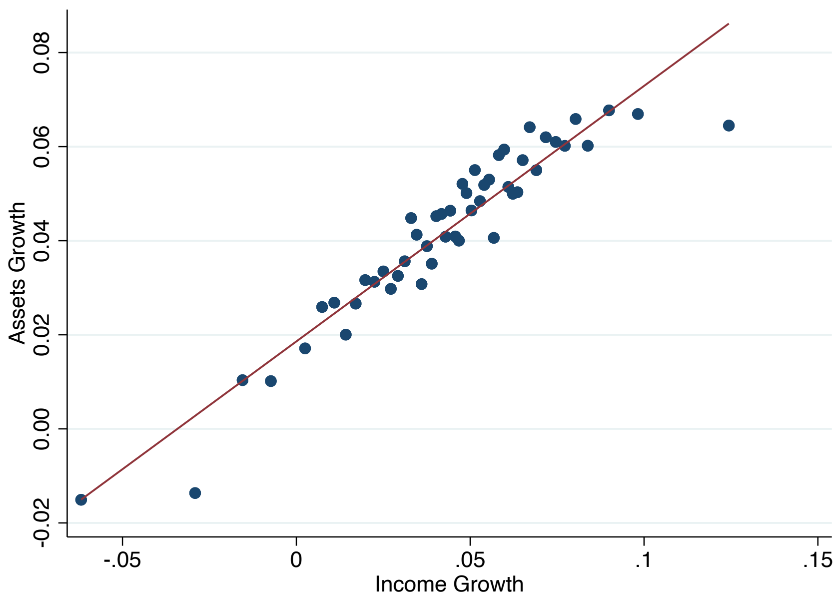
[18]Before 2008, contributions were defined as including direct public support, indirect public support, and government contributions. In 2008 and later, contributions were defined as including federated campaigns, membership dues, fundraising events, related organizations, government grants, and other contributions.

[19]We find that contributions account for 13.4% of total revenue, and we arrive at 7.8% after subtracting out government grants that account for 5.6%. Note that contributions account for 13.4% of total revenue in our supplemental dataset compared to 20% in our main dataset, a moderate difference across samples.

3.4 Do nonprofit assets decline during downturns?

An organization's own accumulated assets can in principle provide a buffer when faced with revenue declines. In our fourth question, we ask whether nonprofit assets decline during economic downturns. Figure 4 plots a binscatter of asset growth at the nonprofit level against CZ-level personal income growth and reveals that the answer to this question is yes: asset growth at nonprofits is procyclical and declines during local economic downturns.

Figure 4: Nonprofit Assets and Economic Fluctuations



Note: This binscatter plots displays quantiles of CZ income growth on the horizontal axis against the corresponding mean of nonprofit asset growth rates. The trend line depicts the best linear fit. See Appendix A for more data details.

Table 5 presents a related series of cyclicality regressions for nonprofit assets. The first three columns estimate cyclicality for our full sample including all types of nonprofits. We see in column (1) that when national income growth falls by one standard deviation or 2.5 percentage points, asset growth for nonprofits declines by an average of $0.73 \times 2.5 \approx 1.8$ percentage points. Column (2) shows that when local CZ income growth falls by one standard deviation or 3.2 percentage points, asset growth for nonprofits in that area falls by an average of $0.54 \times 3.2 \approx 1.7$ percentage points. We then include time effects and rely on narrower, relative variation. Column (3) reports that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—asset growth for nonprofits in that area falls by an average of $0.29 \times 3.2 \approx 0.9$ percentage points relative to the average growth in assets across all nonprofits in that year.

The next three columns narrow to the sample of high DCR nonprofits. We see in column (4) that when national income growth falls by one standard deviation or 2.5 percentage points, asset growth for high DCR nonprofits declines by an average of $0.61 \times 2.5 \approx 1.5$ percentage points. Column (5) shows that when local CZ income growth falls by one standard deviation or 3.2 percentage points, asset growth for high DCR nonprofits in that area falls by an average of $0.46 \times 3.2 \approx 1.5$ percentage points. Finally, column (6) implies that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—asset growth for high DCR nonprofits in that area falls by an average of $0.27 \times 3.2 \approx 0.9$ percentage points relative to the average growth in assets across high DCR nonprofits in that year.

> **Fact 4 (Nonprofit Assets)**: Nonprofit assets are procyclical, falling during bad times and increasing during good times. The elasticity of nonprofit assets to local personal income is 0.5 for all nonprofits and 0.5 for high DCR nonprofits.

Table 5: Cyclicality Regressions for Assets

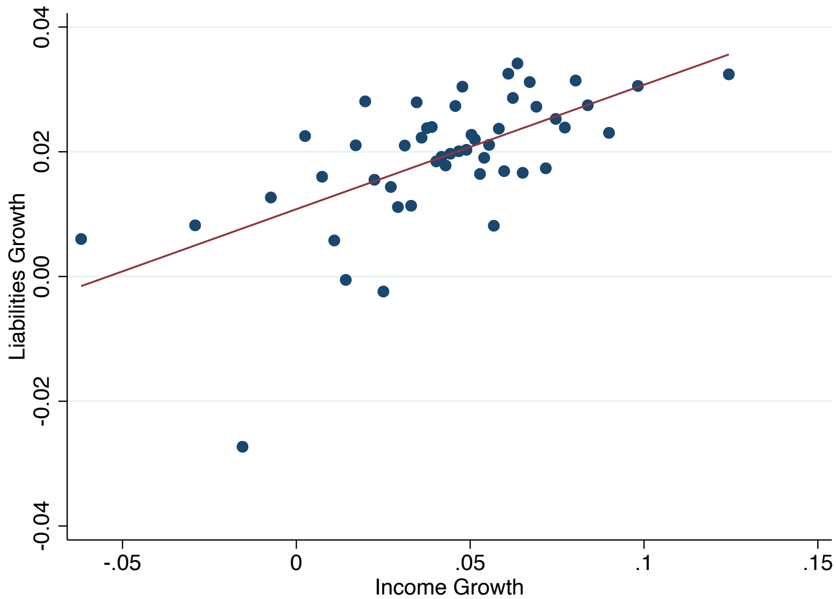
	All nonprofits			High DCR nonprofits		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Nat. income	0.73^{***}			0.61^{***}		
	(0.02)			(0.03)		
Δ CZ income		0.54^{***}	0.29^{***}		0.46^{***}	0.27^{***}
		(0.03)	(0.02)		(0.03)	(0.03)
N	8625639	8625639	8625639	1110550	1110550	1110550
Year FE	no	no	yes	no	no	yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state level. This table reports coefficient estimates from OLS on Equation 1 when $\Delta Y_{j,t}$ is the growth rate of assets for nonprofit j in year t. Columns 1-3 include all nonprofits in our main dataset, while Columns 4-6 are restricted to high DCR nonprofits. See Appendix A for more data details.

3.5 Do nonprofits increase their liabilities during downturns?

In addition to relying on their internal resources, nonprofit organizations might also turn to external resources to support spending by increasing their liabilities in bad times. In our fifth question, we ask whether nonprofits make use of this external funding source—by increasing their own liabilities—during economic downturns. Figure 5 plots a binscatter of liability growth at the nonprofit level against CZ-level personal income growth and reveals that the answer to this question is no: liability growth at nonprofits is procyclical and declines during local economic downturns.

Figure 5: Nonprofit Liabilities and Economic Fluctuations



Note: This binscatter plots displays quantiles of CZ income growth on the horizontal axis against the corresponding mean of nonprofit liability growth rates. The trend line depicts the best linear fit. See Appendix A for more data details.

Table 6 presents a related series of cyclicality regressions for nonprofit liabilities. The first three columns estimate cyclicality for our full sample including all types of nonprofits. We see in column (1) that when national income growth falls by one standard deviation or 2.5 percentage points, liability growth for nonprofits declines by an average of $0.23 \times 2.5 \approx 0.6$ percentage points. Column (2) shows that when local CZ income growth falls by one standard deviation or 3.2 percentage points, liability growth for nonprofits in that area falls by an average of $0.20 \times 3.2 \approx 0.6$ percentage points. We then include time effects and rely on narrower, relative variation. Column (3) reports that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—liability growth for nonprofits in that area falls by an average of $0.14 \times 3.2 \approx 0.4$ percentage points relative to the average growth in liabilities across all nonprofits in that year.

The next three columns narrow to the sample of high DCR nonprofits. We see in column (4) that when national income growth falls by one standard deviation or 2.5 percentage points, liability growth for high DCR nonprofits declines by an average of 0.30 × 2.5 ≈ 0.8 percentage points. Column (5) shows that when local CZ income growth falls by one standard deviation or 3.2 percentage points, liability growth for high DCR nonprofits in that area falls by an average of 0.21 × 3.2 ≈ 0.7 percentage points. Finally, column (6) implies that when local CZ income growth falls by one standard deviation or 3.2 percentage points in a particular area—relative to the average growth in income across all CZ's in that year—liability growth for high DCR nonprofits in that area falls by an average of 0.09 × 3.2 ≈ 0.3 percentage points relative to the average growth in liabilities across high DCR nonprofits in that year.

> **Fact 5 (Nonprofit Liabilities)**: Nonprofit liabilities are procyclical, falling during bad times and increasing during good times. The elasticity of nonprofit liabilities to local personal income is 0.2 for all nonprofits and 0.2 for high DCR nonprofits.

Since both nonprofits assets (in Fact 4 in Section 3.4) and liabilities (Fact 5 in this section) are procyclical, we conclude that the total size of nonprofit balance sheets at all organizations and high DCR nonprofits also declines during downturns. These patterns are broadly consistent with financial constraints, such as a lack of access to external financing, playing a role in determining nonprofit behavior during downturns.

Table 6: Cyclicality Regressions for Liabilities

	All nonprofits			High DCR nonprofits		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Nat. income	0.23***			0.30***		
	(0.02)			(0.03)		
Δ CZ income		0.20***	0.14***		0.21***	0.09***
		(0.04)	(0.05)		(0.03)	(0.03)
N	8625639	8625639	8625639	1110550	1110550	1110550
Firm FE	no	no	yes	no	no	yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state level. This table reports coefficient estimates from OLS on Equation 1 when $\Delta Y_{j,t}$ is the growth rate of liabilities for nonprofit j in year t. Columns (1)-(3) include all nonprofits in our main dataset, while Columns (4)-(6) are restricted to high DCR nonprofits. See Appendix A for more data details.

4 Robustness and Extensions

We explore whether there is substantial heterogeneity in our findings of broad procyclicality by deciles of nonprofit DCRs in Section 4.1, by nonprofit size in Section 4.2, by nonprofit purpose in Section 4.3, by nonprofit legal structure in Section 4.4, by Census region in Section 4.5, by local urbanization levels in Section 4.6, by revenue stream in Section 4.7, by economic measures of cyclicality in Section 4.8, in levels specifications rather than growth rates in Section 4.9, and in for-profit firms in Section 4.10. We focus on the empirical findings from our main dataset, i.e., Facts 1, 3, 4, and 5 linked to the cyclicality of nonprofit financials, and we focus on the local cyclicality results but note that similar results follow if we instead consider national cyclicality.[20] Although these robustness checks and extensions uncover interesting heterogeneity in some cases, our findings are quite robust. In no subgrouping or sample split or extension do we find evidence of the sort of nonprofit expansion during downturns desired by our survey respondents.

4.1 Do our facts differ across the distribution of nonprofit DCRs?

Appendix Table B.4 explores whether there is substantial heterogeneity in the cyclicality estimates—focusing on the growth rate of expenditure, revenue, assets, and liabilities in Panels A, B, C, and D respectively—varying with a nonprofit's DCR. Column (1) includes an interaction of the demeaned DCR with the growth rate of CZ income as well as a control for the level of the demeaned DCR. The negative and statistically significant coefficient estimates on this interaction in Panels A, B, and C reveal that nonprofits with higher DCRs, e.g., food banks and housing assistance organizations, tend to be slightly less procyclical in terms of their revenue, assets, and expenditure. The positive and statistically significant coefficient estimate on this interaction in Panel D reveals the opposite for liabilities.

Columns (2)-(11) separately consider nonprofits within each decile of the distribution of DCRs. These results suggest some nonmonotonicity or a hump shape in the cyclicality. Nonprofits with the lowest (decile = 1) or highest (decile = 10) DCRs are the least cyclical, while organizations with middling DCRs are the most cyclical.[21] That said, our uniformly

[20] Since we present these results via a series of sample splits, we also focus on the specifications without year fixed effects to ease interpretation. For example, if we include year fixed effects when separately running regressions on samples of the smallest and largest nonprofit organizations, size could spuriously appear to substantially affect local cyclicality simply because that local cyclicality is measured relative to different nationwide fluctuations in small versus large nonprofits.

[21] Clearly, cyclicality is nonlinear in DCR. This nonlinearity could be due to any number of reasons, such as a potential correlation between financial constraints and DCR. We return to results potentially linked to financial constraints, more specifically to nonprofit size, in Section 4.2.

positive or procyclical estimates of elasticities reveal that—contrary to the stated desires of our survey respondents—there is no group of DCR ratings in which nonprofits expand during downturns.[22] Our findings of nonprofit procyclicality remain robust across DCRs.

4.2 Do our facts differ by nonprofit size?

Cyclicality could change with nonprofit size for multiple reasons. One possibility is that the importance nonprofits place on various objectives—such as their stability, survival, or expansion during bad times—may differ by nonprofit size. Another possibility, not mutually exclusive, is that financial constraints may differ by nonprofit size. Indeed, empirical and theoretical research suggests that financial frictions—such as difficulty in accessing external finance, information asymmetries, etc.—are more prevalent among smaller firms (Midrigan and Xu, 2014; Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).

Figure 6 shows a distribution of nonprofits in 2010 by their size defined as total assets in 2010. Appendix Table B.5 explores whether there is heterogeneity in nonprofit cyclicality across each decile of this measure of nonprofit size. These results reveal that financial outcomes at larger nonprofit organizations tend to be more procyclical. Interestingly, the strength of this pattern varies across measures, with a local income elasticity of 0.4 for the revenue of the smallest (decile = 1) organizations rising by about a factor of 4 in the largest (decile = 10) while expenditure cyclicality rises only by a factor of around 2 over the same groups. But these results also make clear that nonprofits in any decile of size exhibit substantial and significant procyclicality in their expenditure, revenue, assets, and liabilities—implying that our empirical facts remain qualitatively similar across nonprofit size.[23] Contrary to the stated desires of our survey respondents, there is no size grouping of nonprofits which expand during downturns.

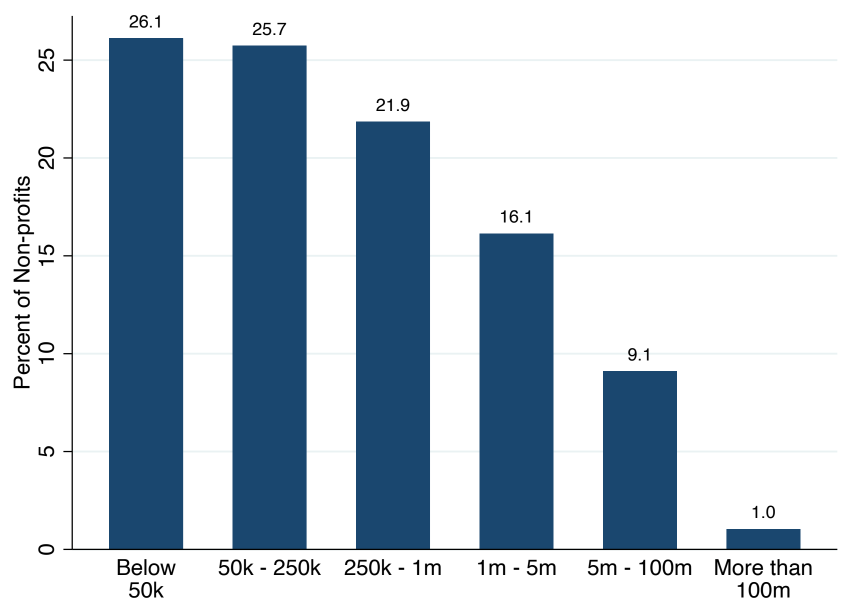
Appendix Table B.6 pushes further. For each decile of nonprofit size, we estimate the elasticity of nonprofit financial outcomes with respect to local CZ income. We also interact a nonprofit's demeaned DCR with the growth rate of CZ income as well as a control for the level of the demeaned DCR. For the smallest nonprofits—approximately those in size deciles 1 to 5—the insignificant or small estimated interaction terms reveal that cyclicality does not vary meaningfully with a nonprofit's DCR. By contrast, the strongly negative and precise

[22] Out of the 40 estimates in Columns (2)-(11) of Panels A-D in Appendix Table B.4, only one estimated elasticity is not statistically significant. This single exception is an imprecisely estimated strongly positive point estimate for liabilities in decile 6. In no case do we precisely estimate countercyclicality.

[23] Out of the 40 estimates in Columns 1-10 of Panels A-D in Appendix Table B.5, only two estimates are not statistically significantly positive. In no case do we precisely estimate countercyclicality.

interaction terms reveal that cyclicality at the largest nonprofits is meaningfully smaller when those organizations have high DCRs.[24] Intuitively, these results imply that—among small nonprofits—outcomes like expenditure decline during downturns at roughly similar rates for high DCR nonprofits (like small food banks) and low DCR nonprofits (like small golf clubs). By contrast, among larger nonprofits, high DCR organizations (like large food banks) reduce their activities more modestly during downturns than low DCR nonprofits (like large golf clubs). Although individual metrics such as size provide notoriously imprecise proxies for underlying financial constraints, our findings in Table B.6 are consistent with the idea that only the largest nonprofits in high DCR categories such as food and housing assistance are able to overcome financial constraints and reduce the magnitude of the decline in their activities during downturns.

Figure 6: Nonprofits by Size in 2010



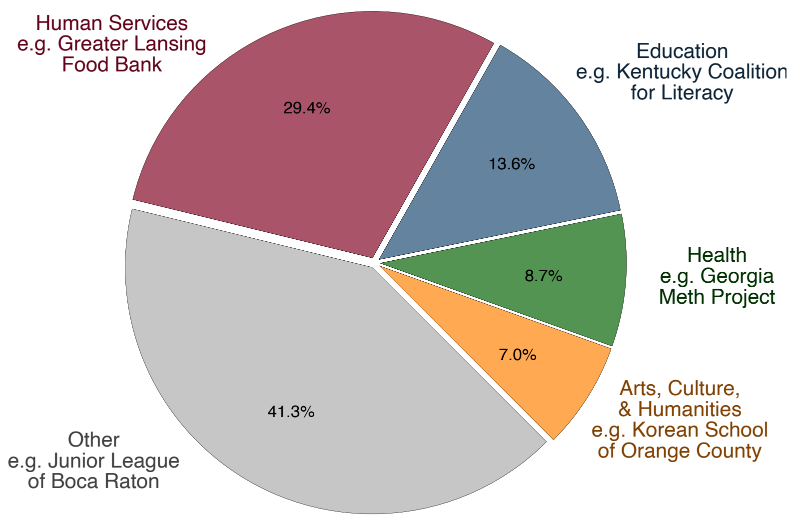
Note: We divide the distribution of nonprofits in 2010 in our main dataset into six categories or bins based on the total value of their financial assets in that year. This figure displays the share of nonprofits in our main dataset within each size bin.

[24]The exception to this pattern—which holds for revenue, assets, and expenditure—is liabilities for which we uncover only small, unstable, and imprecise interactions of local CZ income growth with charity DCR ratings. Combined with our finding of less cyclicality for asset growth at the largest high DCR charities, we conclude that nonprofit balance sheets contract in size more moderately during downturns for the largest, high DCR organizations, consistent with our discussion of potential financial constraints.

4.3 Do our facts differ according to nonprofit purpose?

To construct nonprofit DCRs, we exploited highly disaggregated NTEE codes to categorize nonprofits. In this section, we ignore our charity DCR ratings and instead ask more broadly whether nonprofit cyclicality varies by NTEE category. For context, Figure 7 displays the 2010 cross-section of organizations across five NTEE major code groups, together with examples of organizations drawn from each category. Note that the NTEE also identifies a total of 11 sizable subgroups of these major categories, each accounting for the following fractions of nonprofits in 2010: Human Services (29.4%), Education–Higher Education (0.4%), Education–Other (13.2%), Health–Hospitals (0.8%), Health–Other (7.9%), Arts, Culture, & Humanities (7%), Other–Religion (3.9%), Other–Environment (3.2%), Other–Mutual Benefit (2.8%), Other–Public or Societal Benefit (29.9%), and Other–International (1.3%).

Figure 7: Nonprofits by Nonprofit Purpose in 2010



Note: This figure displays the share of nonprofits by organizational type in 2010 in our main dataset. Organizations are grouped by the NCCS using the NTEE classification scheme's "major codes" corresponding to a total of five categories.

In Appendix Table B.7, we estimate each of our cyclicality regressions for the 11 NTEE nonprofit subgroupings above.[25] We uniformly estimate that expenditure, revenue, assets, and liabilities are procyclical across all categories. The magnitude of the procyclicality, and the precision of our estimated elasticities, varies across nonprofit NTEE groupings in

[25]We thank Bob Slonim and Marta Serra-Garcia for the suggestion to examine nonprofit cyclicality by this more detailed set of 11 NTEE categories.

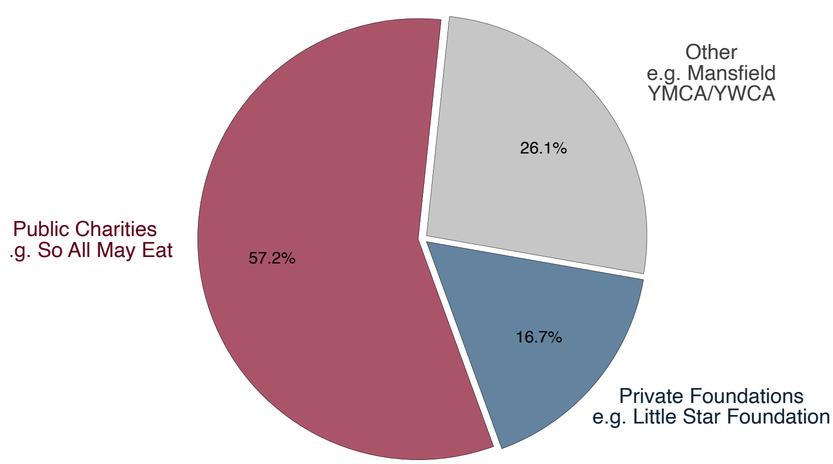
potentially interesting ways. But for our purposes we emphasize that in no NTEE group is there evidence of countercyclicality or expansion during bad times. Our empirical findings of nonprofit procyclicality are robust across NTEE groups.

4.4 Do our facts differ by nonprofit legal structure?

Nonprofits differ in legal structure. Figure 8 plots the 2010 proportion of nonprofits which are 1) public charities, 2) private foundations, or 3) organized in other legal ways. Public charities, accounting for the dominant share of nonprofits at slightly below 60%, collect contributions from the general public. Private foundations, a smaller share at around 15% , obtain contributions primarily from a single entity such as a family or business. Other legal forms span various special purpose categories—clubs or organized labor, for example—and account for around a quarter of nonprofits.

In Appendix Table B.8, we estimate each of our cyclicality regressions for these three nonprofit legal structures. We uniformly estimate that expenditure, revenue, assets, and liabilities are procyclical across all nonprofit legal forms. The exact magnitude of cyclicality, and the precision of our estimated elasticities, varies somewhat across types, but in no case do we find significant evidence of expansion during bad times for any legal form of nonprofits. Our empirical findings of nonprofit procyclicality are robust across nonprofit legal structure.

Figure 8: Nonprofits by Legal Structure in 2010



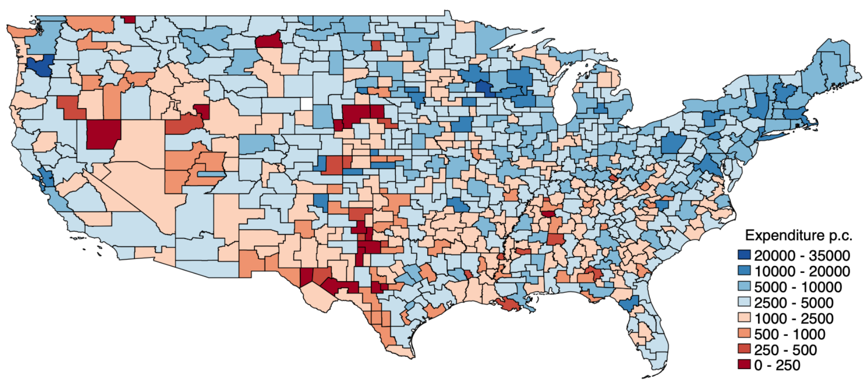
Note: This figure displays the share of nonprofits by legal structure in 2010 in our main dataset. Organizations are classified as public charities, private foundations, or other based on the nature of their tax filings with the IRS.

4.5 Do our facts differ by region?

Figure 9 displays variation in nonprofit expenditure per capita across the over 700 CZ's in the continental US.[26] Nonprofit spending varies considerably, with values higher than $10,000 per person near Boston, Massachusetts compared to just above $1,000 per person in the Rio Grande Valley in Texas.

In Appendix Table B.9, we find potentially interesting quantitative heterogeneity in cyclicality by broad Census region—with Northeastern nonprofits being more procyclical, particularly in their revenue and balance sheets. Even so, across all regions, nonprofits exhibit substantial and significant procyclicality in expenditure, revenue, assets, and liabilities. Our empirical findings of nonprofit procyclicality are robust across regions.

Figure 9: Nonprofit Spending across US Commuting Zones in 2010



Note: This figure shows average nonprofit expenditure per capita in each CZ within the continental US in 2010 in our main dataset. Total nonprofit expenditure within a CZ is computed by summing across the expenditures of all nonprofits in that CZ. The population data is from county-level US Census tabulations aggregated to the CZ level.

4.6 Do our facts differ by urbanization level?

The local areas or CZ's in which nonprofits are located differ substantially in urbanization levels. Our measure of urbanization at the local CZ level is given by the Census Bureau's

[26] We locate nonprofits within CZ's according to their IRS Form 990 address, i.e., their mailing address for tax purposes. This tax address may, of course, not reflect the full span of a nonprofits operations which may spill across multiple CZ's. There is little we can do with this tax return dataset to directly improve upon this location measure. However, there are three reasons to believe that our results are not driven by deficiencies in this method of assigning location. First, our local cyclicality results suggest that local economic fluctuations in the CZ where an organization's tax address is located are in fact strongly predictive of their total activities. Second, our national cyclicality results are of course not subject to this concern given their nationwide scope. And third, in our heterogeneity analysis, we show that the smallest nonprofits—organizations which we would least expect to span multiple CZ's with their operations—also exhibit local cyclicality.

estimate of the fraction of the population in land which is urban or densely settled within the CZ. We group CZ's into three equally sized categories: rural (lowest urbanization), intermediate (moderate urbanization), and urban (highest urbanization). Appendix Table B.10 reports our cyclicality results by urbanization level. In urban, intermediate, and rural areas, nonprofits exhibit substantial and significant procyclicality in their expenditure, revenue, assets, and liabilities. Our empirical findings of nonprofit procyclicality are robust across urbanization levels.

4.7 Do our facts differ by the extent to which contributions account for nonprofit revenue?

Nonprofits differ vastly in the composition of their revenue streams, which—as previously discussed in Section 3.3—we can break in our main dataset into two categories: contributions revenue (accounting for donation support and government grants) and non-contribution revenue (accounting for revenue from programs and services, financial income, etc.). Prior work on the sources of nonprofit funding (Carroll and Stater, 2009; Duquette, 2017) documents that contributions tend to be the least stable or predictable source of nonprofit funding. Motivated by those findings, Appendix Table B.11 investigates whether our measure of cyclicality differs by an organization's "contribution intensity" defined as the ratio of contributions to total revenue. We report our cyclicality regressions by decile of contribution intensity.[27] Across the entire distribution of contribution intensity, nonprofits exhibit substantial procyclicality in their expenditure, revenue, assets, and liabilities. Our empirical findings of nonprofit procyclicality are robust across the distribution of nonprofit contribution intensity.

Consistent with the prior work emphasizing that contributions are volatile or unstable, we also find that more contribution-dependent nonprofits exhibit more procyclicality. Future work might investigate whether these cyclicality patterns are explained by the nature of an organization's fundraising strategies.

4.8 Do our facts differ with alternative measures of economic fluctuations?

Our baseline cyclicality regressions following Equation 1 measure local economic fluctuations with personal income growth. We now examine if our results are robust to alternative measures of economic fluctuations that focus more narrowly on the labor market.

[27] We thank Dean Karlan and Jonathan Meer for originally pointing us towards this line of investigation.

Appendix Table B.12 reports the results. Column (1) duplicates our baseline results based on CZ personal income growth. Column (2) exploits CZ employment growth. Column (3) examines CZ per-capita wage growth. Column (4) relies upon the CZ unemployment rate, left in levels because the unemployment rate already measures labor market flows. The results reveal that—regardless of whether local downturns are measured by declining personal income, declining employment, lower wages per worker, or higher unemployment—nonprofits exhibit substantial and significant procyclicality in expenditure, revenue, assets, and liabilities.[28] Our empirical findings of nonprofit procyclicality are robust to alternative measures of economic fluctuations.

4.9 Why do we use growth rates?

Our baseline cyclicality analysis relies on specifications in first differences or growth rates as in Equation 1. Our approach is standard in the literature on local economic shocks (Autor et al., 2013) for a natural reason. As the highly dispersed distribution of nonprofit size in Figure 6 reveals, nonprofits are very different from one another. If there are permanent differences across nonprofits in scale, and if nonprofits in CZ's with persistently high income happen to be among the largest, it is easy to conflate this type of cross-sectional sorting in levels with procyclical fluctuations. By estimating specifications in growth rates or first differences, however, we can avoid this conflation because growth rates take out organization- and CZ-level fixed effects and therefore identify elasticities solely off of within-nonprofit and within-CZ changes. We also flexibly account for trend inflation in nominal quantities, which is absorbed in the constant term of our cyclicality regressions.

Nevertheless, Appendix Table B.13 reports estimates of our regressions for nonprofit cyclicality, replacing growth rates with log levels. Whether considering our full sample or restricting to high DCR nonprofits, we continue to uncover evidence consistent with nonprofit procyclicality.[29] For example, column (2) reveals that in CZ's with income levels one standard deviation or 167% higher, nonprofit expenditure is about $167 \times 0.07 \approx 11.7$ percentage points higher on average for the full sample. Importantly, in no cases do we estimate

[28]The single exception to this pattern is liabilities, for which we still estimate a small and imprecise negative elasticity against local wage growth. Against all other cyclical proxies, we precisely estimate procyclicality of liabilities. We note that the combination of procyclical assets and acyclical liabilities continues to imply a reduction in nonprofit balance sheet sizes during downturns according to the wage growth measure. We also not that—while the adjusted R-squared in unsurprisingly small (< 0.01 in all specifications)—it is the highest or second-highest when we use CZ personal income growth.

[29]There is one slight exception. When restricting to the set of nonprofits with high desired countercyclicality ratings, we estimate a statistically insignificant countercyclical response for specifications involving nonprofit assets.

negative elasticities consistent with the idea that nonprofits expand during downturns, so our empirical findings of nonprofit procyclicality are robust.

4.10 Do nonprofits behave differently from for-profit firms?

In our final step we ask whether cyclicality of for-profit businesses differs from nonprofits. We gather data on US publicly listed firms, a group of for-profit businesses accounting for a large share of output and employment. We draw revenue, assets, and liabilities directly from financial statements reported in the standard data source, Compustat, and we compute total expenditure as revenue less operating cashflows. We assign firms to CZ's based on headquarters location. See Appendix A for more details on our sample and variable construction.

Using the direct for-profit equivalents of the nonprofit cyclicality specifications in Equation 1, Appendix Table B.14 reports cyclicality estimates for expenditure, revenue, assets, and liabilities among for-profit firms which are unsurprisingly high and positive. Panel A shows that the elasticity of expenditure to local personal income is 1.48 / 0.49 $\approx$ 3.0 times as high for US public firms than for nonprofits. In Panel B, we see that the elasticity of revenue to local personal income is 1.39 / 1.05 $\approx$ 1.3 times as large for for-profit firms than nonprofits. Panel C reveals that the elasticity of assets to local personal income is 1.16 / 0.54 $\approx$ 2.1 times larger for for-profit firms. Panel D shows that the elasticity of liabilities to local personal income is 1.25 / 0.20 $\approx$ 6.25 times higher in the for-profit sector. Broadly, these estimates reveal higher sensitivity to economic fluctuations in the for-profit sector than for nonprofits, although the exact magnitude of these differences varies by measure.

5 Conclusion

Our survey evidence reveals a public hope that US nonprofits, especially those assisting with critical needs such as food or housing, will expand during economic downturns. Using data from millions of nonprofit tax returns, we lay out a series of facts about nonprofit behavior in the face of nationwide and local economic fluctuations. We find that—far from increasing their scope as the public hopes—nonprofits exhibit robust procyclicality with their expenditure, revenue, assets, and liabilities declining in bad times.

By providing descriptive facts on nonprofit outcomes in good times and bad times, this paper seeks to improve our understanding of the nonprofit sector and to motivate further work on it. In light of our descriptive facts, at least two avenues for further research into the nonprofit sector suggest themselves. As is often the case following the establishment of descriptive facts, these avenues are motivated by a desire to narrow in on a particular mechanism or a particular counterfactual question that requires different analyses than in this paper, e.g., causal identification or structural modeling.

First, many questions remain open around the counterfactual impact of policy on the nonprofit sector. The existing level of government subsidies to nonprofits during economic downturns does not prevent their revenue from declining, because our revenue measure includes government grants. But one might reasonably speculate that—and future work could investigate through explicitly causal analysis whether—government subsidies to nonprofits during bad times might cause nonprofits to expand their services or to, at least, contract less.

Second, we note that cuts to nonprofit expenditure during bad times could in principle stem from multiple sources including but not limited to manager preferences or financial constraints. As one example, if the leaders of charities were biased on average towards organizational survival rather than maintenance of service provision, or if managers were averse to expansion, then the natural implication would be a failure of charities to expand during times of increased need. In the for-profit sector, evidence exists that such motives might be widespread (Bertrand and Mullainathan, 2003; Pugsley and Hurst, 2011). As another example, nonprofit managers may hold beliefs which are not accurate about their optimal strategies during bad times. See, for example, inaccurate beliefs about fundraising strategies documented in Samek and Longfield (2019).[30] Exploring the extent to which these alternative explanations contribute to the procyclicality of nonprofit expenditure is a natural avenue for future work.

[30]DellaVigna and Pope (2018a) and DellaVigna and Pope (2018b) also show that academics frequently hold inaccurate beliefs about the impact of leveraging social preferences.

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