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# Nonprofits: A Public Policy Tool for the Promotion of Community Subjective Well-being

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## Abstract

Looking to supplement common economic indicators, politicians and policymakers are increasingly interested in how to measure and improve the subjective well-being of communities. Theories about nonprofit organizations suggest that they represent a potential policy-amenable lever to increase community subjective well-being. Using longitudinal cross-lagged panel models with IRS and Twitter data, this study explores whether communities with higher numbers of nonprofits per capita exhibit greater subjective well-being in the form of more expressions of positive emotion, engagement, and relationships. We find associations, robust to sample bias concerns, between most types of nonprofit organizations and decreases in negative emotions, negative sentiments about relationships, and disengagement. We also find an association between nonprofit presence and the proportion of words tweeted in a county that indicate engagement. These findings contribute to our theoretical understanding of why nonprofit organizations matter for community-level outcomes and how they should be considered an important public policy lever.

> Nonprofits provide an enormous range of services, mostly for the purpose of improving aspects of the quality of life—or preventing its deterioration. (Ott and Dicke 2012, xv)

The founding documents of the United States enshrined the "pursuit of happiness" as an inalienable right for government to protect. Several state constitutions go even further to make fostering the general well-being of society and other social rights an explicit duty of government (Marwell and Calabrese 2015). Despite the clear history that caring for the quality of life is an obligation of the state, typically other indicators are used to measure the growth and health of society like gross domestic product (GDP). Recently, though, a push is taking place for government agencies and administrators to make subjective well-being a primary consideration in governing decisions (Dolan and White 2007). National governmental projects such as the Center for Disease Control's *Office of Disease Prevention 2013* initiative and international bodies such as the World Health Organization and the Organization for Economic Cooperation and Development (OECD) have committed to improving global subjective well-being (OECD 2013a). Aside from a duty to improve the happiness or life satisfaction of communities, governments have an interest to do so because, on the individual level, heightened subjective well-being is associated with individual immunity, longevity, and healthier social relationships (Diener and Chan 2011; Howell, Kern, and Lyubomirsky 2007). On a more communal level, greater subjective well-being is also associated with increasing citizen engagement in democratic practices and trust in institutions—helping to strengthen the state in turn (Hudson 2006). A key question remains: what elements of community life might be amenable to policies that promote the subjective well-being of community members?

This study investigates one such feature: the civic infrastructure as indicated by local nonprofit organizations. While recent studies investigate the density and distribution of nonprofits (Lecy and Van Slyke 2013), only recently are scholars trying to understand the influence of these organizations on social outcomes in large-N studies (Cheng 2019). Policies that increase nonprofits represent a possible mechanism for influencing subjective well-being given that local organizations are a key component of healthy communities characterized by high levels of social capital, social cohesion, and strong informal networks (Putnam 1995; Sampson 2012; Tocqueville [1835, 1840] 1972). We test the hypothesis that nonprofit organizations have meaningful consequences for the communities in which they are located by examining the association between nonprofit organizations and community subjective well-being between 2009 and 2012. We measure five dimensions of subjective well-being—engagement, disengagement, positive emotions, negative emotions, and negative relations—using data from Twitter in 1,330 US counties. Since the association between nonprofits and subjective well-being may be interdependent (with nonprofits increasing subjective well-being and the well-being of community members positively influencing the formation and duration of nonprofits), we use cross-lagged panels to explore the potential for reciprocal relationships between nonprofit organizations and community subjective well-being over time. Because Twitter users are a select sample and do not represent the general population, we test the robustness of our results in relation to sampling bias using an approach developed by Frank et al. (2013).

Results suggest that most types of public-oriented, 501(c)3 nonprofit organizations buffer against threats to subjective well-being and some types of nonprofits may generate positive subjective well-being. We conclude with a thorough discussion of these results and their implications for how the interplay between government and nonprofits can help improve subjective well-being.

## Background

There is no consensus on a single definition of well-being (Office of Disease Prevention 2013). Following Diener and Tov (2012, 137), we define subjective well-being as positive evaluations of one's life:

> subjective well-being [...] refers to the various ways in which people evaluate their lives positively. In the emotional realm, it involves positive feelings and experiences in relation to what is happening and few negative or unpleasant experiences [...] Unlike economic indicators, which locate a person's well-being primarily in the material realm of marketplace production and consumption, well-being indicators assess the full range of inputs to the quality of life, from social relationships to spirituality and meaning, from material consumption to feelings of relaxation and security.

This definition encompasses the presence of positive emotions and social relationships and the absence of negative emotions (Keyes 1998; Office of Disease Prevention 2013; Veenhoven 2013).

Following others (Diener, Diener, and Diener 1995; Eichstaedt et al. 2015), our concept of subjective well-being includes three dimensions: emotions, engagement, and relationships. Emotional well-being is an excess of positive over negative feelings (Keyes 1998). A sense of engagement in one's community and the ability to contribute to community life are also fundamental components of subjective well-being (Prilleltensky, Nelson, and Peirson 2001). Beyond general engagement, "quality ties to others are universally endorsed as central to optimal living" (Ryff and Singer 2000, 30; see also Lamu and Olsen 2016). Each of these three dimensions uniquely contributes to overall subjective well-being.

What influences subjective well-being? Subjective well-being depends on people's personal strivings, their ability to achieve their goals, and having fulfilled their goals in the past (Emmons 1986). Thus, researchers hypothesize that public policies and governmental agencies that provide "societal resources that allow people to make progress in achieving their goals should [promote] life satisfaction and affective well-being" (Diener, Diener, and Diener 1995, 851). It is not surprising, therefore, that societies with higher subjective well-being are those that are more economically developed; have effective governments with low levels of corruption and high levels of economic, political, and personal freedom; and can meet citizens' basic needs (Helliwell 2003; Helliwell and Huang 2008; Office of Disease Prevention 2013; Oswald and Wu 2010).

While most studies of subjective well-being link to macro-level conditions that are not easy to manipulate or change, there is also evidence to suggest that the local community context can be instrumental in promoting positive subjective well-being and mitigating negative experiences. Access to well-organized public-serving entities within a country, for example, is associated with increased subjective well-being among the individuals in that country (Helliwell and Huang 2008) and contributes significantly to the correlation between income and subjective well-being (Diener, Diener, and Diener 1995). Although underexplored in existing research because of difficulty obtaining widespread local information, it is precisely this local level which is perhaps the most meaningful to policy makers concerned with what makes a philosophical "good life" for citizens (Castillo et al. 2019). Here, we suggest that nonprofits are an actionable public policy lever that provide social resources to increase subjective well-being.

### Nonprofit Contributions to Subjective Well-being

Nonprofits, specifically 501c(3) nonprofits, are oriented toward social ends and serve the common good by emphasizing community need over profit (Barman 2016; Sanger 2004). As an important component of civic infrastructure, nonprofits should improve a community's subjective well-being through three mechanisms: service provision, advocacy, and the development of social capital.

To begin, nonprofits provide services which improve community members' quality of life (Cheng 2019; Marwell and Calabrese 2015; Mosley and Grogan 2013). Indeed, citizens and government leaders expect the nonprofit sector to produce public services which add social value and therefore afford nonprofits a favored US tax status (Frumkin 2002; Hopkins 2011). Services provided by nonprofits are often direct and tangible: helping residents get jobs, accessing educational resources, providing health care services, and so on (Guo 2012; Salamon 1987; Stanis, Oftedal, and Schneider 2014; Weisbrod 1988). More generally, nonprofits lead to a variety of community goods, such as "better equipped museums, private schools, more active churches, public radio stations, family service centers, hospitals, [and] clinics…" (Wolpert 1999, 237; see also Putnam, Feldstein, and Cohen 2004). These services are the main justification for state subsidization of this sector: the state forgoes tax revenue because the nonprofits "produce greater social value than what the state could have produced on its own" (Reich 2011, 182).

Communities that have access to more nonprofit services should demonstrate higher levels of subjective well-being because these services can improve community members' actual well-being. A review of the social determinants of health literature, for example, highlights how communities with more social services exhibit lower levels of respiratory illness and higher levels of self-reported health, infant health, and good mental health (Andrews and Withey 2012; Currie, Neidell, and Schmieder 2009; Taylor et al. 2016). One reason for these improvements is that nonprofits help to alleviate the most immediate, pressing concerns of people like access to food, shelter, and basic health care (Allard 2008). Even organizations that do not provide direct services can give people access to basic entertainment, recreation, or socialization opportunities which are fundamental drivers of human happiness (Prilleltensky, Nelson, and Peirson 2001). Nonprofit services allow people to divert more resources to achieving their personal goals while providing community members with enjoyable experiences that elicit positive feelings and form positive relationships with others.

Nonprofits also serve as advocacy channels between the general population and the government sector (Chetkovich and Kunreuther 2006; McCarthy and Castelli 2002; Taylor 2010). Although some scholars debate the utility of this advocacy (Almog-Bar and Schmid 2014), such advocacy is usually designed to influence policy outcomes for specific causes or to protect basic civil rights for disadvantaged populations (McCarthy and Castelli 2002). The nonprofit sector, therefore, collectively advocates for groups that may not otherwise have the "resources, opportunities, and motivations" (Boris and Mosher-Williams 1998, 490) to do so, especially if such advocacy requires competing with the resource-rich lobbying of private enterprise (Taylor 2010). Further, nonprofits link residents to larger networks of organizations and government agencies across their locality, state, and even nation, providing them with access to external resources and sources of influence (Bursik and Grasmick 1993; Sampson 2012). Although only some nonprofits explicitly identify as advocacy organizations, and organizations cannot conduct direct political advocacy at high levels and retain tax benefits, all nonprofits engage in some advocacy by representing the needs of communities that go unmet by public or private institutions to the public at large (McCarthy and Castelli 2002).

Communities with more nonprofits, and therefore more organizations advocating for the fulfillment of community members' unmet needs, should have improved subjective well-being because that advocacy actively promotes positive and tangible public policy outcomes toward improved physical or mental health. Through everyday advocacy, nonprofits can push for and create a policy environment that ultimately improves citizens' subjective well-being. In some contexts, organizations that promote positive outcomes for disadvantaged groups, such as children or low-income families, may be even more successful at securing these opportunities than individuals from the communities alone (Mosely and Ros 2011). Good mental health, a key component underlying well-being, has been connected to successful advocacy efforts within the LGBTQ community (Hatzenbuehler et al. 2010). Even if the outcomes are not immediately achieved, having visible representation of marginalized individuals as role models in advocacy positions can be beneficial for other members of that community (Campbell and Wolbrecht 2006; Ellington and Frederick 2010).

Finally, positive community life is "shaped by the structure of formal and informal networks of association" (Bursik and Grasmick 1993, x) and nonprofits can stimulate subjective well-being through creating opportunities for improved social connection and cohesion. By acting as the backbone of civic life, nonprofits of all types, including service and advocacy nonprofits, give people opportunities for fellowship, companionship, sociability, and integration which can lead to increases in the quantity and quality of social capital in a community (Musick and Wilson 2008; Smith 1974; Tocqueville [1835, 1840] 1972). Even nonprofits not typically associated with traditional ideas of local community engagement, like museums, medical research centers, or international relief organizations, add to civic life when they gather individuals with a common interest, engage board members, organize local awareness campaigns, or host fundraising events (e.g., "Run for a Cure" or "Help for Haiti Casino Night") (Higgins and Lauzon 2003; Lindenberg and Bryant 2001; Wood, Snelgrove, and Danylchuk 2010). As Joseph Stiglitz and colleagues point out in addressing effective policy priorities, net of income, "evidence on both the aggregate and individual level suggests that social connections are among the most robust predictors of subjective measures of life satisfaction" (Stiglitz, Sen, and Fitoussi 2010, 183; see also Lamu and Olsen 2016). Through their contributions to the production of social capital alone, nonprofits should be associated with community-level subjective well-being.

Local organizations also promote social cohesion in other ways. They unite neighborhoods (Sampson 2012), act as pathways to social and political participation that increase individual social and political engagement, and facilitate "coordination and cooperation for mutual benefit" (Ott and Dicke 2012; Putnam 1995, 67). As Lester Salamon (1997, 13) explains, nonprofit organizations protect "a sphere of private action through which individuals can take the initiative, express their individuality, and exercise freedom of expression and action." As an aspect of civic infrastructure that promotes social capital and cohesion, a higher number of nonprofits in a community should increase subjective well-being.

### Nonprofits as Buffers

Economists argue nonprofits are a structural response to critical deficits in public goods (Salamon 1987; Weisbrod 1988). Consequently, nonprofits may not only enhance the positive dimensions of well-being, but also buffer or mitigate the *negative* subjective experiences that demand a nonprofit response in the first place.

Market failure theory proposes that the private sector's failure to provide much-needed collective goods, coupled with government's limitations in satisfying the public demand for these goods, leads to the need for a private, voluntary sector to act as a compensatory force filling these voids with volunteered time and charitable contributions (Ott and Dicke 2012; Salamon 1987; Weisbrod 1988). Though market theory can be applied to explain the need for transaction-oriented nonprofits that provide much-needed services at little-to-no costs, the "theory applies not only to the basic, but also to the more elaborate, forms of public goods (e.g., opera, recreational activity, religious worship, and many more)," (Salamon and Toepler 2015, 2160).

Indeed, according to Smith, the voluntary sector can "ease the shocks of social dislocation and rapid social changes of all sorts" (Smith 1974, 390). Nonprofits may combat the modern experience of loneness and isolation (Durkheim [1897] 1984). Certainly, many theorists have explored the role of social bonds in mitigating negative outcomes (Arendt 1973; Habermas 1991; Riesman, Glazer, and Denney 1950). Nonprofits, therefore, can prevent or act as social insurance against deterioration that could harm a community during inhospitable times. These characteristics suggest that nonprofit organizations, both in their entirety and across specific subfields, act as critical buffers against the adverse social and individual consequences of market failure and isolation (Salamon 1987; Weisbrod 1988). In short, a community with more nonprofits may exhibit less negative subjective well-being because the service provision, advocacy, and social capital provided by nonprofits blunts economic or social hardship.

### Reciprocal Effects

Although we have theorized that nonprofits influence subjective well-being, the reverse could be true as well (Cheng 2019). Put simply, communities with higher levels of subjective well-being—those whose residents are more positive and engaged—may be better able to attract and retain nonprofits. Nonprofits are private, often voluntary, and many rely on individual contributions. Prior research demonstrates that the characteristics of communities influence where nonprofits originate and thrive (Bielefeld, Wolfgang, and Murdoch 2004; Corbin 1999; Grønbjerg and Paarlberg 2001; Saxton and Benson 2005; Schnable 2015). Nonprofit organizations are bounded geographically by factors such as donor and volunteer engagement and perceived need (Allard 2008). Further, the characteristics of founders influence where nonprofits choose to locate (Anheier 2005; Rose-Ackerman 1996; Young 1983). Thus, it is sensible to expect the relationship between community subjective well-being and nonprofits to be reciprocal. Importantly, accounting for reciprocal effects in our models ensures that any observed associations between nonprofits and subjective well-being are not biased by nonprofits locating in specific contexts.

## Data and Methods

### Subjective Well-being

Increasing national and international interest in happiness, quality of life, and social well-being (Diener 2000; Kahneman et al. 2004; Stiglitz, Sen, and Fitoussi 2010) corresponds to numerous recent attempts to measure subjective well-being (Land 2001; OECD 2013b; Office of Disease Prevention 2013). Researchers typically obtain population estimates of subjective well-being through the process of aggregating individual survey responses (Helliwell, Huang, and Wang 2014; Land 2001; Lee et al. 2016; OECD 2013a). We follow instead the work of Eichstaedt et al. (2015) and others (Bollen et al. 2011; Schwartz and Ungar 2015) who measure subjective well-being through individuals' own expressions.

We draw from a 10% sample of all tweets between 2009 and 2010 and again between 2012 and 2013 to calculate the proportion of all words tweeted in a county that reflect five dimensions of subjective well-being (for counties with 50,000+ words tweeted). Computers scanned each tweet for key words that corresponded to Linguistic Inquiry and Word Count (LIWC) dictionaries of words that suggest (1) engagement, (2) disengagement, (3) positive emotions, (4) negative emotions, or (5) negative relationships (Pennebaker, Booth, and Francis 2007). The words "interesting" and "learn," for example, are in the engagement dictionary, while "sorry," "mad," and "pissed" are in the negative emotions dictionary. LIWC matches almost exactly with popular theoretical understandings of subjective well-being as having highly correlated hedonistic and eudaimonic dimensions in the three domains of emotions, engagement, and relationships (Deci and Ryan 2008). And, certainly, policy makers are concerned with what makes a philosophical "good life" for citizens. To understand what makes life happy and fulfilling, we need to know not only how well people's basic physical needs are being met objectively, but also how they evaluate their lives subjectively in terms of things like happiness, engagement, and connections.

To give a sense of the meaning of each dictionary, table 1 provides top words tweeted per dictionary in the 2009–10 period as well as sample tweets for each dictionary. Table 1 indicates that the five dictionaries have high face validity, being what a subjective observer "would expect." For example, the top words for positive engagement are "learn," "interesting," and "awake." Words such as "tired," "bored," and "meh" represent disengagement.

The high face validity of the subjective well-being categories is matched by extensive validation processes that went into creating LIWC dictionaries by Pennebaker and colleagues. LIWC is a tool used to assess mental states and psychological characteristics from text. To create dictionaries of words that corresponded to certain psychological traits, such as engagement, teams of 4–8 human judges generated lists of words that conceptually matched a given topic supplemented by standard dictionaries, Roget's Thesaurus, and other documents (Pennebaker et al. 2015; Tausczik and Pennebaker 2010). Extensive and continually updated validation processes established strong psychometric properties, leading to wide adoption in social and psychological research (Bail, Brown, and Mann 2017; Goldberg et al. 2016). The supplementary appendix details additional tests of validity for our sample including whether how the word was categorized matched sentiment holistically within the context of the entire tweet.

We total all words tweeted in each county that appear in each of the dictionaries, excluding retweets but including replies, and divide these values by the total number of words tweeted in that county to create five proportions as dependent variables. To map tweets to counties we use both self-reported location information in user profiles and latitude/longitude coordinates associated with a tweet. If latitude/longitude coordinates are present (available for ~2% of tweets) then we trivially map the tweet to a county. Self-reported location information in user profiles is available from approximately 20% of tweets. The self-reported location information is a free text field and we use a cascading set of rules to map this field to a county. The supplementary appendix describes in detail how location information from tweets and users was used to connect tweets to counties and alternative aggregation strategies.

Growing evidence points to the promising potential of social media data for social research (DiGrazia et al. 2013; Flores 2017; Mislove et al. 2011; Schwartz and Ungar 2015). A national survey of adults conducted in 2016 found that 79% of online Americans use Facebook, a third use Instagram (32%), and a quarter use Twitter (24%). Taking into account that almost 9 out of 10 Americans are online (Anderson and Perrin 2016), this means 68% of all US adults are Facebook users, 28% use Instagram, and 21% use Twitter (Gottfried and Shearer 2016). Stefanidis, Crooks, and Radzikowski (2013, 320) argued that social media data, therefore, "conveys *ambient geospatial information*, [and] harvesting this ambient

**Table 1.** Top Tweeted Words Per Dictionary With Example Tweets

| Dictionary | Top Words | | Example Tweets[a] |
|---|---|---|---|
| Engagement | Learn<br>Interesting<br>Awake | Alive<br>Interested<br>Learning | "I'm properly ***learning*** Chinese from a babys program called Ni Hao, Kai Lan! Ha," November 9, 2009<br><br>"A weekend full of flying, crashing, chatting with flier friends (some super folks) rain winds storm … total excitement… felt so ***alive***," September 15, 2010 |
| Disengagement | Meh<br>Tired<br>Bored | Lazy<br>Blah<br>Sleepy | "Listening to the game on my phone because I can't seem to get myself out of bed to go watch. ***meh***," July 9, 2010<br>"I'm so ***bored*** … literally nothing to do in this town," August 14, 2010 |
| Positive emotions | Great<br>Happy<br>Awesome | Cool<br>Amazing<br>Glad | "Just ate an ***amazing*** salad at the Aroma Café! Mmmmm Sooo Good!" November 12, 2009<br><br>"I'm so ***happy*** right now. My dearest friends just came back from Africa with their new son! He is so adorable! God is so good!:)," November 12, 2009 |
| Negative emotions | Pissed<br>Sad<br>Mad | Terrible<br>Horrible<br>Sorry | "Didn't get to go to Halloween world today … ***pissed***," October 12, 2009<br><br>"Good job making me feel ***horrible***, like i'm worth nothing):," July 14, 2010 |
| Negative relations | Jealous<br>Blame<br>Alone | Hate<br>Evil<br>Rude | "really ***hate*** some men sometimes or maybe I just pick the crap ones lol," August 29, 2009<br><br>"Dealing with an astoundling ***rude*** and unhelpful Spring Store employee," August 29, 2009 |

[a]Although tweets are public, we exclude user Twitter handles.

geospatial information provides a unique opportunity to gain valuable insight on information flow and social networking in society." Moreover, there are recent calls for public administration to embrace the possibilities of text analysis to provide new insights into the field (Hollibaugh 2019).

Although Twitter users are not representative of the US population, recent research has linked aggregated tweets to more traditional measures of subjective well-being. Relevant examples include: Schwartz and colleagues (2013) who used tweets from 1,293 US counties to accurately predict self-reported life satisfaction scores from phone surveys and Mitchell et al. (2013) who link Twitter-based happiness scores to more traditional measures like Gallup Well-Being and America's Health Rankings, finding correlations of .51 and .58, respectively. Quercia, Capra, and Crowcroft (2012) link tweets to subjective well-being across larger geographic contexts. While these studies using surveys of individuals or phone surveys can help validate social media, surveys cannot replace social media data because obtaining adequate sample sizes at the county level is only possible by pooling many years of data (Helliwell 2018). Overall, evidence suggests that Twitter and other social media data can be used to successfully assess ecological context (Ginsberg et al. 2009; Lee, Wakamiya, and Sumiya 2011; Pang and Lee 2008; Stefanidis, Crooks, and Radzikowski 2013). O'Connor and colleagues (2010) used Twitter data to predict consumer confidence and results of public opinion polls with correlations as high as .80. As traditional polling becomes more challenging, researchers are able to use Twitter to accurately predict congressional elections in the United States (DiGrazia et al. 2013) and party vote share in Germany to a high degree of accuracy (Tumasjan et al. 2010).[1]

Theory points to the importance of the community level for understanding subjective well-being, and state-level analyses support a focus on subjective well-being and ecological context, but we have not before had measures of subjective well-being at the community level. That is, prior to widespread availability of social media data, there were no data at the county level, over time, and for the whole United States with which to test associations between subjective well-being and

1 In auxiliary analyses, we correlated the average number of mentally unhealthy days (using data from Behavioral Risk Factor Surveillance Survey [BRFSS]) with disengagement (.30), negative relations (.25), and negative emotions (.15).

anything else. The relevance of our analysis is further supported by the fact that our independent variable, the nonprofit context, is something that is amenable to policy intervention unlike other state-level studies of subjective well-being that investigate aggregated characteristics that do not have clear policy connections (e.g., race/ethnicity or gender). We use these as control variables in our analysis. Collecting and analyzing new county-level data through surveys is prohibitive due to the number of observations needed for small area estimation. Although imperfect in ways we discuss, the ability to leverage millions of social media posts and combine it with administratively obtained tax data has provided us with a heretofore impossible test of important hypotheses at the county level. So too, the fact that different dimensions of subjective well-being can be measured with these data is useful to policy makers. Thus, even if policy makers do not view citizen emotions as particularly important, government long-term investment in the Current Population Survey measures of volunteering and civil society suggest they should still find evidence for engagement and disengagement useful in reference to civic and political participation.

### Nonprofits

The Internal Revenue Service and the National Center for Charitable Statistics (NCCS) provide data on 501(c)3 public charities, private foundations, and other tax-exempt organizations. Our analysis includes only 501(c)3 organizations because these are typically public-serving and associated with the charitable, "public benefit" as theorized above (Boris and Steuerle 2006, 67; Salamon 2011). To become a nonprofit and be listed in the IRS Business Master File (BMF), an organization first applies for an Employer Identification Number and then applies for recognition of exemption. Extracted on a rolling basis, BMF files include the most recent information the IRS has for active organizations (IRS 2014).

Using the IRS/NCCS data, Census data, and a US Housing and Urban Development (HUD) first quarter 2016 crosswalk, we constructed a per capita count of all eligible nonprofits active in a county at the end of 2009 and again at the end of 2012. The county is a familiar unit of analysis for questions of public health (Ahern, Brown, and Dukas 2011; Arnold 1985; Hood et al. 2016), but previous research on nonprofit organizational impact has typically focused on either program-specific evaluations or aggregated to a level that does not reflect practical considerations of community dynamics, such as the state (Flynn and Hodgkinson 2001). The BMF contains the zip code for each nonprofit organization, but zip code is too small a unit to appropriately capture the community context of interest (Sampson 2003). McDougle (2015) analyzes the reliability of a nonprofit's reported location and finds that it is not uncommon for nonprofits to be operating in different parts of a city than their reported zip code. However, within a county there is minimal location error; the author finds that approximately 3%–4% operate outside of their county. Above the level of the county, we could consider the commuting zone, used in studies of marriage and labor markets (Tolbert and Sizer 1996). Although an individual may drive into a nearby urban area over state lines for a job or to find a partner, that geographic unit and any larger aggregations are too big to capture the informal networks and social relations that communities evoke (Collins 2010). We therefore consider the county as the appropriate unit.

There are a few notable exceptions to tax exemption registration with the IRS. Charitable organizations with less than $5,000 in gross receipts are not required to register with the IRS. Neither churches nor their integrated auxiliaries, church conventions, nor associations of churches are required to register for tax exempt status, although those that do are included in our sample and classified as "Religion-Related" organizations.

NCCS classifies nonprofits based on the National Taxonomy of Exempt Entities (NTEE) coding system, which groups similar entities by purpose, type, or major function, such as arts and culture, education, health, or human services. We theorize general pathways through which nonprofits will influence communities, but there may be variation within the nonprofit sector according to field. Disaggregating through major NTEE codes allows us to investigate possible variation in effect size or significance.

To account for population, we construct county-level per capita counts for all nonprofit fields grouped by their major NTEE category. We exclude some categories because more than a fifth of counties had no representative nonprofit organization (Higher Education, Hospitals, International, Mutual Member Benefit, Unknown) resulting in seven categories of nonprofits for our analyses: Arts and Culture, Environment & Animals, Education, Health, Human Services, Public and Societal Benefit, and Religion-Related. The supplementary appendix provides a table with specific examples of nonprofit organizations for each of these categories.

### Control Variables

Aspects of the community other than the presence of nonprofits certainly influence community subjective well-being (DiMaggio 1986; Easterlin 1995; Helliwell and Putnam 2004; Oswald and Wu 2010). For example, inequality decreases the subjective well-being of women and minorities (Argyle 1999; Nolen-Hoeksema and Rusting 1999). Both age and education correlate positively with subjective well-being (Argyle 1999; Diener, Diener, and Diener 1995; Easterlin 1995; Keyes, Shmotkin, and Ryff 2002). Because of these associations between subjective well-being and demographic characteristics, we include several county-level controls from the 2010 ACS. These include proportions of males, high school graduates, college students, and African-Americans, as well as the percentage of the county defined as "rural," the logged median household income, the county's Gini coefficient, and the median age of individuals in the county. We also include the 2010 ACS unemployment rate to address potentially disparate effects of the Great Recession across counties and county-level voting rates in 2008 to address different levels of civic engagement in that presidential election year. Finally, we include state-level fixed-effects to account for any unobserved heterogeneity at the state level. See the supplementary appendix for descriptive statistics of dependent and key independent variables.[2]

### Plan of Analysis

First, across two time points, 2009 and 2012, and 1,330 counties, we model the cross-lagged relationships between nonprofits and our five measures of subjective well-being. Our 1,330 counties contain nearly 90% of the US population in 2010. Cross-lagged panels are a longitudinal design that models change in the independent and dependent variables when they are hypothesized to be contingent on one another over time (Finkel 1995). These models protect against unmeasured, stable confounds and against the potential biasing effects of reverse causation (Allison 2005). We hypothesize that the number of nonprofits per capita in 2009 will influence subjective well-being in 2012. Because of theoretically based hypotheses suggesting reciprocal effects, the cross-lagged panel model likewise evaluates the possibility that subjective well-being in 2009 affects the presence of nonprofit organizations in 2012. These models also estimate stability parameters: nonprofits per capita in 2009 predict nonprofits per capita in 2012, and subjective well-being in 2010 affects subjective well-being in 2012. We also include the full set of control variables and state fixed-effects. We correlate the errors in the equations of nonprofits per capita and subjective well-being in 2012 to reflect possible covariation between nonprofits per capita and subjective well-being that the cross-lagged panels, stability effects, or controls in the model do not capture. Figure 1 illustrates our general model. We test a set of 8 × 5 cross-lagged panels: one for each of the 7 nonprofit fields (+1 for total) and one for each of our five well-being dictionaries. Because we used multiple cross-lagged panels and multiple tests, we use Benjamini and Hochberg's (1995) *p*-value adjustment to control for the Type I error rate, with a conservative false discovery rate (FDR) of .05.

Twitter users are not representative: they skew younger, more diverse, and more urban than the population as a whole (Mislove et al. 2011). How can we handle this threat to external validity? We use a new approach to assessing robustness to sample bias that quantifies precisely how much bias in the design components there must be to invalidate an inference (Frank et al. 2013). Based in Ruben's causal model, the likelihood of the quantity of bias in the real world that the analysis identifies can inform the severity of the threat the nonrepresentativeness of the sample poses to causal inferences. Here, our target population—everybody—contains both those represented in our sample—Twitter users in some counties—as well as those not directly represented by our sample. The Frank et al. (2013) test quantifies how much of our sample would have to be replaced with other cases, under the limiting condition of no effect between nonprofit community organizations and subjective well-being in those cases, to invalidate our inference. Put another way, this test will determine how many counties in our sample would have to be replaced by counties in which there is no association between the number of nonprofits and subjective well-being to invalidate our inferences. Similarly, we can estimate the impact threshold for a confounding variable (ITCV) which quantifies the impact (e.g., bias) of a potential omitted confounding variable on the inference of a regression coefficient (Frank 2000). Through quantifying the magnitude of sampling and confounding variable bias necessary to invalidate inferences for the whole population, this approach allows us to determine the extent to which the nonrepresentative nature of Twitter users and omitted variables exert undue influence on our conclusions.

## Results

Do nonprofits in a community influence community subjective well-being? Table 2 presents the cross-lagged panel coefficients for the associations between our nonprofit variables and our five measures of subjective well-being. As outlined above, in addition to a nonprofit variable, each model also contains all control variables, including logged median household income, the county's Gini coefficient, unemployment rate, voting rate, and the median age of the county's population as well as state fixed-effects. These models also include reciprocal effects, stability effects, and correlated errors. Table 2 presents the standardized coefficients for the nonprofit variable in each (full models

2 A full list of auxiliary models with additional controls including government expenditures, population, and poverty, which yielded similar results, available in the supplementary appendix.

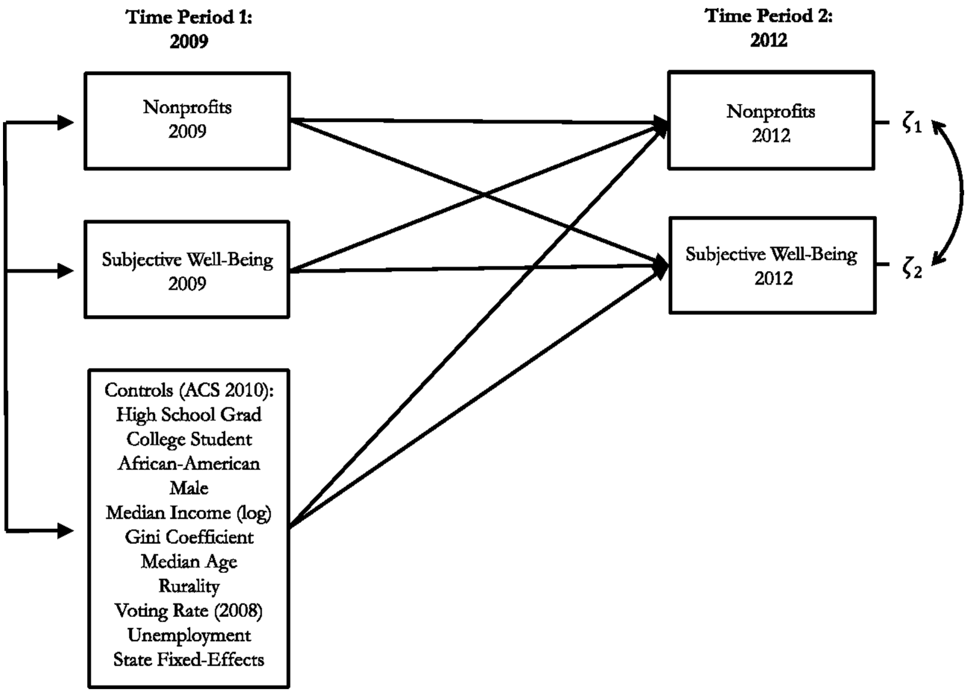


**Figure 1.** Cross-Lagged Panel Model of Nonprofits and Subjective Well-Being

**Table 2.** Standardized Coefficients for Nonprofits Per Capita Predicting Subjective Well-Being From Fully Controlled Cross-Lagged Panels

| | Negative Emotions | | Positive Emotions | | Disengagement | | Engagement | | Negative Relations | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *β* | *p* | *β* | *p* | *β* | *p* | *β* | *p* | *β* | *p* |
| Total Count | −0.137[a] | .000 | 0.015 | .595 | −0.080[a] | .000 | 0.120[a] | .000 | −0.131[a] | .000 |
| Subtype | | | | | | | | | | |
| Arts, Culture & Humanities | −0.161[a] | .000 | 0.034 | .231 | −0.085[a] | .000 | 0.133[a] | .000 | −0.167 | .000 |
| Education | −0.097[a] | .001 | 0.032 | .256 | −0.064[a] | .002 | 0.120[a] | .000 | −0.112[a] | .000 |
| Environment & Animals | −0.147[a] | .000 | 0.038 | .197 | −0.065[a] | .002 | 0.147[a] | .000 | −0.126[a] | .000 |
| Health | −0.143[a] | .000 | -0.001 | .971 | −0.079[a] | .000 | 0.091[a] | .001 | −0.137[a] | .000 |
| Human Services | −0.090[a] | .001 | 0.001 | .983 | −0.035 | .078 | 0.091[a] | .001 | −0.090[a] | .001 |
| Public, Societal Benefit | −0.139[a] | .000 | 0.009 | .751 | −0.091[a] | .000 | 0.102[a] | .000 | −0.129[a] | .000 |
| Religion Related | −0.049 | .049 | -0.01 | .601 | −0.045[a] | .013 | 0.023 | .376 | −0.029 | .223 |

[a]Indicates significance at the false discovery rate of .05.

for the total per capita nonprofit count are available in the supplementary appendix). We star coefficients that were significant at the Benjamini-Hochberg correction FDR of .05.

The first and most apparent trend in table 2 are the numerous negative coefficients concentrated in the three negative subjective well-being categories. The top row illustrates this trend: total nonprofit per capita counts were negatively associated with the three negative measures of subjective well-being. As nonprofits per capita increase, therefore, the proportion of tweeted words that correspond to the negative dictionaries decrease. We interpret this as a buffering or mitigation effect of nonprofits on tweeted indications of negative emotions, disengagement, and negative relationships. Squared multiple correlations indicate that total per capita nonprofits and the control variables account for 38% of the variation in negative emotions, 38% of the variation in engagement, and 68% of the variation in disengagement. Squared multiple correlations for other models are similar in size (average = 46%).

The same buffering effect is apparent when we consider per capita counts of nonprofits by selected NTEE major codes. We find that almost all the major nonprofit fields return significant and sizeable negative coefficients for the negative subjective well-being categories. The fields with the largest average negative standardized effect size are Arts, Culture, & Humanities, Health, Public Societal Benefit, and Environment & Animals. Certainly, the missions of many Arts, Culture, & Humanities nonprofits include reducing disengagement or negative emotions in a community. For example, the mission of the B. B. King Museum and Delta Interpretive Center is "to empower, unite and heal through music, art and education and share with the world the rich cultural heritage of the Mississippi Delta."

Our results indicate that a one standard deviation (SD) increase in Arts, Culture, & Humanities nonprofits per capita in a county is associated with a 0.16 SD decrease in negative emotion words, an 0.08 SD decrease in disengagement words, and a 0.16 decrease in negative relations words in that county's tweets. These results signify that if Arts, Culture, & Humanities nonprofits per capita in a county were to increase by 1 SD, which translates on average to one additional nonprofit per 5,274 people, it would be associated with 1,705 fewer tweeted negative emotion words and 296 fewer disengagement words. Across all counties, the median number of negative emotion words tweeted in 2012 was 1,884 and the median number of disengagement words was 616. For Education, a 1 SD increase in nonprofits per capita, or 1 education nonprofit per 4,897 people, would be associated with 1,033 fewer negative emotion words and 957 fewer negative relation words.

The negative associations we see between nonprofits and negative emotion, disengagement, and negative relation words in tweets support the theory that nonprofits may be particularly effective at preventing negative feelings of subjective well-being from occurring in response to adverse social conditions (Salamon 1987; Smith 1974; Weisbrod 1988). Traditional, survey-based measures of subjective well-being correlate strongly with objective measures of well-being [see Oswald and Wu (2010) for a discussion of subjective well-being and "compensating differentials"]. So nonprofit organizations may improve the tangible but often overlooked experiences of individuals, similar to good air quality or hours of sunshine.

Our models also suggest that nonprofit organizations increase subjective well-being, particularly engagement. Seven of our eight nonprofit per capita counts are significantly and positively associated with engagement. For all nonprofits, for example, a 1 SD per capita increase is associated with a 0.12 SD increase in the proportion of tweeted engagement words. This result translates to an increase of 1 nonprofit per 800 people being associated with an increase of 577 tweeted engagement words. The median engagement words tweeted across counties is 676. Recall from table 1 that the engagement dictionary includes words such as "learn" and "interesting." Once again, Arts, Culture, & Humanities has the largest standardized effect size, and the missions of such nonprofits are often oriented toward eliciting such indicators of engagement. The mission of Southwest Symphony Orchestra, for example, is "…to foster excellence and originality in the presentation and performance of great music; to *enhance the lives* of our citizenry; to *educate* present and future audiences; to *inspire* synergistic cultural partnerships; and to bring distinction to the community as a leader in the arts."

In sum, the preponderance of models indicates that nonprofits of many types can buffer against social ills. Results also indicate that nonprofits may generate positive subjective well-being.

### Reciprocal Associations

It is possible that communities attract or repel nonprofit organizations based on their levels of subjective well-being. Counties with higher levels of engagement, for example, might be better able to attract and maintain community organizations such as nonprofits. On the other side, relatively disengaged communities might have difficulty maintaining nonprofits. Cross-lagged panels of the type we estimated directly test such reciprocal relationships. Here, however, we find no evidence for reciprocal relationships (results reported in supplementary appendix). Overall, we find that community subjective-well-being does not tend to drive the nonprofit landscape beyond other community characteristics, including previous per capita nonprofit counts. Our cross-lagged panel with state fixed effects, as well as other dynamic models, do not include stable unit-specific factors that assure that associations are unconfounded by culture or other differences between counties. Thus, another modeling strategy would be to assess within-county change over time using static models like fixed or random effects models. Such models assume that neither reversed causal direction or x/y feedback exist (Zyphur et al. 2020). We note in the supplementary appendix that in line with research that supports the relatively comparable performance of random and fixed effects models to general cross-lagged panels (Zyphur et al. 2020), our robustness checks with county-level random effects return very similar results and fixed effects similar without significance.

### Robustness of Inference to Sample Bias or Confounds

Following Frank et al. (2013) to assess the vulnerability of our results to sampling bias, we ask what percent of our sample of counties would have to be replaced with counties in which there is no relationship between nonprofits and well-being to invalidate our inferences? To invalidate our significant coefficients in models with the total per capita nonprofit count, we would need to replace 60% of counties in our sample with ones with no association between the number of nonprofits and subjective well-being in the form of negative emotions and relations. The inference for disengagement was only slightly weaker: 49% of counties would have to be replaced, in the limiting condition of no effect, to invalidate the inference. Overall, we would need to replace more than 691 counties in our sample to cause the observed associations between nonprofits and subjective well-being to reduce to insignificance/zero. In other words, sampling bias would have to be so egregious that on average 52% counties would have to have no relationship between nonprofit community organizations and subjective well-being to invalidate the inference.

We also evaluated the ITCV which calculates a "single valued threshold at which the impact of the confound on both the dependent and independent variable would be great enough to alter an inference regarding a regression coefficient" (Frank 2000, 150). Calculated for our model, an omitted variable would have to be correlated from .236 for disengagement to .292 for negative relationships, conditional on covariates. To contextualize this possibility, none of the variables currently in our model reach this threshold.

These generally high thresholds suggest that our results are robust and generalizable. This test also helps validate previous research that finds that while Twitter users are not representative of the national population, their sentiments appear to be (O'Connor et al. 2010).

## Discussion and Conclusion

Nonprofits represent a critical component of service provision in the United States both currently and historically (Reckhow, Downey, and Sapotichne 2020). Over time, the government–nonprofit partnership has come to resemble one of collaboration rather than competition through the development of shared goals and resource interdependency (Gazley and Brudney 2007). Although not all nonprofits rely directly on government grants or contracts, all 501(c)3 nonprofits benefit from a tax structure where the government forgoes taxes to support a third sector that ostensibly provides services better than it could itself (Reich 2011). In 2013, for example, over 1.4 million nonprofit organizations represented 5.3% of the US GDP and almost $906 billion in contributions to the American economy (McKeever 2015; Pettijohn 2013). Indeed, since the 1980s, the convergence of public sector austerity and a burgeoning philanthropic and nonprofit sector has led nonprofit leaders to have an outsized role in guiding public policy, sometimes with limited input from elected officials or citizens (Bryan 2019; Reckhow, Downey, and Sapotichne 2020). Yet, despite nonprofit sector's scope, we still understand little about the usefulness of the sector to improve the lives of individuals beyond the discrete impacts of individual programs (Anheier 2014; DiMaggio 1986; Salamon 2011; Sharkey, Torrats-Espinosa, and Takyar 2017). Our longitudinal cross-lagged panel models assess the ability of nonprofit organizations, a core component of civic infrastructure, to improve subjective well-being while accounting for the possibility of reciprocal effects and variation across major nonprofit fields. We find that areas with more nonprofit organizations appear to experience reduced, or "buffered," negative social expressions in their communities and increases in positive expressions of engagement. These findings support hypotheses that nonprofit organizations shape how individuals interact within a community, bridge social divisions, and help alleviate feelings of isolation or social detachment. Translated to real numbers, an additional Health nonprofit per 9,542 people, for example, would be associated with 1,521 fewer tweeted negative emotion words. The services that nonprofit organizations provide help keep people from feeling "lazy," "mad," or "alone" and help them to feel more "alive" and "awake."

Although our analysis by NTEE field indicates a generally comparable association across organizations, there is some evidence that particular types of services and activities may have stronger ties to community subjective well-being. The organizations that tend to have the largest standardized effect across all measures of subjective well-being; Arts, Culture, & Humanities; Health Care; Education; and Human Services, are predominately concerned with providing cultural or direct service provision. But activity alone does not capture the full diversity of nonprofits, even within field (Fulton 2020), and there remains considerable variation in what nonprofits do within fields. Future research can expand on these findings, for example, by re-categorizing nonprofits according to their organizational identity or the specific programming they provide. In doing so, it will offer a more in-depth examination of our three theorized mechanisms and whether public investment in one type of activity (e.g., advocacy) provides greater returns than another (e.g., direct services). Future work exploring the very particular activities of nonprofits located within service provision fields could help us further specify the mechanisms behind the observed buffering effect (Guo 2012; Stanis, Oftedal, and Schneider 2014). For example, do organizations engaged in direct applications of developmental research, such as in areas of early childhood education and youth programs, promote positive human development and resilience that create long-term protective effects for community subjective well-being (Lerner et al. 2006)?

Reciprocal findings indicate little evidence that existing levels of subjective well-being within a community influence per capita nonprofit counts, but other community characteristics which we include as controls might influence the effectiveness of nonprofit civic infrastructure in the promotion of subjective well-being. For example, results from exploratory analyses suggest that nonprofits may have a stronger influence on subjective well-being in more rural areas. As our main study establishes the existence of an association between subjective well-being and civic infrastructure, future research could theorize and test moderators of this relationship by meaningful community characteristics such as the rurality of the county, the size of the local government, or other sources of diversity. When considering the evidence presented here that the association between nonprofits and subjective well-being varies by field, the potential for theorizing variation in these mechanisms is expansive.

To understand community subjective well-being, this study incorporates a novel measure using Twitter. Surveys no longer hold a monopoly on collecting country-wide data about people's attitudes or behavior. Further, community-level outcomes can be difficult to measure with surveys due to declining survey response rates (National Research Council 2013) and the need for very large samples or complicated statistical techniques (Rao 2003) to provide small-area estimation. Therefore, we must find ways to work with new sources of data, including administrative data and social media data, to augment our understanding of communities. Social media data allow for novel measurement through individuals' own expressions of their lived experiences. And, as we demonstrate here, can be aggregated to the community level. By harvesting geographic information from social media feeds, researchers have monitored earthquakes (Crooks et al. 2013), tracked contagious outbreaks and unusual social events (Christakis and Fowler 2010; Ginsberg et al. 2009; Lee, Wakamiya, and Sumiya 2011), linked public sentiment to current events (Bollen, Pepe, and Mao 2011), and successfully predicted elections and presidential approval ratings (DiGrazia et al. 2013; O'Connor et al. 2010). In general, new research across various computational fields suggests that social media text data will become an ever more important tool for social researchers (Aggarwal and Zhai 2012; Hollibaugh 2019; Lecy and Thornton 2016; Salloum et al. 2017).

The utility of social media data is especially apparent when combined with other social scientific data. In this study, we combine Twitter data with conventional community-level measures from the US Census and administrative data from the IRS/NCCS. Studies working with social media typically keep the analysis within the social media realm. By linking social media back to traditional, "offline" datasets, our analysis demonstrates how these data can be deployed to provide new insights.

Nonetheless, limitations persist. While our cross-lagged panel design accounts for reciprocal relationships and indicates direction of influence, it remains limited in demonstrating causation. We enthusiastically encourage leveraging even more complex longitudinal or experimental methods toward understanding the associations we present here. Another potential limitation is the nonrepresentative nature of Twitter users and how the data is aggregated. But our tests of sample bias suggest that, while Twitter users are not representative of communities, their aggregate subjective well-being may be. Another issue requires acknowledging that members of a community use Twitter, or other social media platforms, to differing degrees. Aggregating the proportion of words tweeted in a county, therefore, risks over-influence of users that tweet at disproportionately high rates. In the supplementary appendix we present an alternative aggregation method that accounts for differential tweet volume by user. Even with a more limited number of counties in that analysis, 691, the observed associations between nonprofit organizations and subjective well-being remained, and were, in fact, stronger in magnitude than the results aggregated by word.

Prior research suggests that nonprofits are a useful site for public investment. Public and nonprofit organizations have converging interests to serve the common good (Barman 2016; Sanger 2004). Nonprofits should be less motivated than for-profits to divert resources from any government investment to pursue their own interests (Brown, Potoski, and Van Slyke 2006; Van Slyke 2007; Witesman and Fernandez 2013). Many nonprofits are locally based and have established relationships with local government officials, improving outcomes (Witesman and Fernandez 2013). And while research show that in many fields outcomes are identical between nonprofits and for-profits, in some fields such as health, nonprofits have better outcomes than for-profits in access, quality, and efficiency (Rosenau and Linder 2003). To these reasons, our analysis suggests that the nonprofit sector is also a useful sector for public investment because, in an era of concern with government fostering well-being (Marwell and Calabrese 2015), such investments should return improvements to communities' subjective well-being.

Policy-makers have several levers to return such improvements. Nonprofits are funded through a combination of program service revenue (e.g., museum admission, tuition), government grants, and donations, each of which is amenable to investment or regulation. For example, acknowledging that some nonprofits are disincentivized in seeking partnerships with governments (Gazley 2010), public administration officials could actively encourage nonprofits to engage in the resource-rich environment of government contracting. When awarding contracts or grants, officials could remind themselves that for-profits can underbid nonprofits and nonprofit programming for sometimes inferior outcomes (Cleveland and Krashinsky 2009). Local and state laws governing nonprofits influence nonprofits' dependence on the mix of service revenues, donations, or government funding. Such state, and especially national, regulations can influence charitable giving and the donations nonprofits receive (Paxton 2020; Reich 2011) which are especially important for nonprofit startups (Lecy, Van Slyke, and Yoon 2016).

Attention by policy-makers could both encourage existing nonprofits to expand or scale up their programming as well as boost the formation of new nonprofits. Although 1%–2% of nonprofits do fail each year, higher numbers of nonprofits enter the sector than exit, and the rate of exit is less than other sectors (Harrison and Laincz 2008). Since new nonprofits innovate at higher rates than other organizations (Bornstein 2007; Fleishman 2007; Smith 1974), are started in response to perceived need instead of business opportunity (Katre and Salipante 2012), and spend less on employee compensation relative to programming (Carman and Nesbit 2013; Lecy, Van Slyke, and Yoon 2016) we might expect them to have special influence on community subjective well-being.

At the same time, a nonprofit lever must be used with care. Like other organizations and institutions, attention to diversity is an important link between nonprofits and well-being. Too much or unbalanced competition for limited resources within a field, for example, can result in fewer, poorly funded, or lower quality nonprofit services (Berrone et al. 2016; Ressler, Paxton, and Velasco 2020). And while nonprofits can provide advocacy for underrepresented communities, an over-reliance on nonprofit organizations in public service provision and decision making can also undermine public democratic participation or silence the voices and experiences of those already on the margins (Arena 2012; INCITE 2007; Reckhow, Downey, and Sapotichne 2020). At the extreme, similar to critiques of social capital (e.g., Foley and Edwards 1997; Gambetta 1988) organizations with nefarious or inequitable missions are unlikely to activate the mechanisms to improve community subjective well-being we explore here. As with any social policy, investments in the nonprofit sector should incorporate an equitable community perspective, with attention to research-based decision making, cultural sensitivity, and analyzing impact for unintended consequences.

Proof of the success of the nonprofit sector too frequently relies "on anecdotal evidence and general good will to argue for its many successes and tax-exempt status" (Flynn and Hodgkinson 2001, 3). Here, we move beyond simple assessment of service delivery (Barman 2016; Reich 2011; Salamon 1987) to evaluate a more intangible community-level benefit that this sector may provide; subjective well-being.

## Supplementary Material

Supplementary data are available at *Journal of Public Administration Research and Theory* online.

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## Data Availability

The data underlying this article are available through Open Science Framework at doi: 10.17605/OSF.IO/3VUHQ.

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