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The Strategic Use of Corporate Philanthropy: Evidence from Bank Donations*

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Abstract

This article examines the strategic nature of banks' charitable giving by studying bank donations to local nonprofit organizations. Relying on the application of antitrust rules in bank mergers as an exogenous shock to local deposit market competition, we find that local competition affects banks' local donation decisions. Using county-level natural disaster shocks, we show that banks with disaster exposure reallocate donations away from nonshocked counties, where they operate branches, and toward shocked counties. The reallocation of donations represents an exogenous increase in the local share of donations in nonshocked counties for banks with no disaster exposure and leads to an increase in the local deposit market shares of such banks. Furthermore, banks can potentially earn greater profits from making donations and tend to donate to nonprofits that have the most social impact. Overall, our evidence suggests that banks participate in corporate philanthropy strategically to enhance performance.

Keywords: Corporate philanthropy, banking

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1. Introduction

In the USA, there has been an unprecedented surge in corporate philanthropy in the past decade. According to Giving USA 2019, corporate charitable giving increased by 5.4% in 2018, totaling $20.05 billion. Of this amount, corporate foundation grantmaking constituted $6.88 billion, an increase of 6.5% from 2017. Banks, in particular, are one of the largest donors in corporate philanthropy; seven banks are included in the list of the twenty most generous Fortune 500 companies in terms of cash contributions in 2015.[1] Despite the active engagement of banks in corporate philanthropy, relatively less attention has been paid to their charitable donations. Thus, the objective of our study is to explore why banks engage in local philanthropic activities and whether bank donations impact local performance as measured by deposit market shares.

Our investigation begins with an analysis of the motivation behind banks' donation decisions. Using a sample of the largest banks in the USA that operate branches across multiple counties with varying degrees of local deposit market competition,[2] we hypothesize that the local deposit market competition is a determinant of banks' philanthropic giving activities. In particular, we study donations made to nonprofits located in the same county ("local nonprofits"), where the bank has a branch presence and predict that higher local deposit market competition is associated with more donations to local nonprofits. Our focus on local deposit market competition is motivated by findings that show that firms with local operations benefit the most from corporate social responsibility (CSR) engagements that have a local impact on firms' communities and employees (Cahan *et al.*, 2015; Husted *et al.*, 2016; Byun and Oh, 2018). Specifically, we predict that in counties where bank branches experience a high degree of competition, banks donate more to local nonprofits because such charitable activities have been shown to represent positive signals about banks' reputation (Luo and Bhattacharya, 2009; Elfenbein and McManus, 2010), thereby increasing the local demand for their deposits (Baron, 2001; McWilliams and Siegel, 2001; Bagnoli and Watts, 2003; Siegel and Vitaliano, 2007; Fisman, Heal, and Nair, 2007).

We measure local deposit market competition at the county level using the Herfindahl–Hirschman Index (HHI) based on branch-level deposit data. Our baseline results demonstrate a significant positive relation between local deposit market competition and subsequent donations to local nonprofits. However, since competition is likely to be endogenous with respect to donations, we use a quasi-exogenous source of variation in HHI based on the application of antitrust rules in banking market mergers, to alleviate concerns that unobserved characteristics could be driving a spurious correlation between competition and

1 For example, Goldman Sachs donated 3% of its pre-tax profits in 2015, and Wells Fargo gave 2% of its after-tax profits to charity in 2019.

2 The US banking sector provides a convenient laboratory to study the strategic use of corporate philanthropy. Since banks sell relatively homogeneous products to their customers, corporate philanthropy could potentially be a way to enhance product differentiation (Dick, 2008; Dai and Yuan, 2013). Also, focusing only on the banking industry allows us to investigate the strategic use of corporate donations at the local level and to mitigate a concern on heterogeneous industry characteristics that may drive the relationship between local competition and donations.

donations. For example, there could be omitted variables, such as growth opportunities in the local markets, which are correlated with both a bank's donation decisions and the local deposit market competition. The source of our empirical variation is the quantitative screening process used by bank regulators to determine the approval conditions of bank mergers.[3] When banks plan to merge, regulators take into consideration the effects that the merger could have on the competition in the banking markets where both the acquirer and target banks have branches. Violating the antitrust rule sharply increases the probability of regulatory intervention, in which case merging banks will need to divest branches to restore competition. Thus, these antitrust interventions provide a source of exogenous variation in the local deposit market competition, which we use to study the effects on donations to local nonprofits.

We first validate the identifying assumptions of our identification strategy and then use a difference-in-differences specification to establish that the application of antitrust rules has a significant impact on the level of local deposit market competition. Specifically, we find that after mergers occur, the competition in markets where antitrust rules are applied is relatively greater than that in markets without intervention. Next, we study how bank donation decisions respond to exogenous variation in competition induced by antitrust interventions. We remove the banks directly involved in the mergers and find that nonmerging banks that operate in markets where antitrust interventions are predicted donate more to local nonprofits relative to those operating in markets where mergers are allowed to go through unhindered. Our results are robust to controls for differences in charitable opportunities between rural and urban markets, changes in the nature of competition over time (e.g., the rise of online banking), and using alternative estimation methods such as a regression discontinuity design (RDD).

If donations to local nonprofits help improve reputation and attract additional depositors, then we should observe an increase in donating banks' local performance (Flammer, 2015a; Ferrell, Liang, and Renneboog, 2016; Fernando, Sharfman, and Uysal, 2017; Gong and Grundy, 2019). Since deposit taking is one of the most crucial sources of funding for banking businesses (Egan, Lewellen, and Sunderam, 2022), we measure the performance by using a bank's local deposit market share. In our baseline analysis, we examine the relation between donations to local nonprofits and local deposit market shares and show that bank donations are associated with a subsequent increase in local deposit market share. However, bank donations could be endogenous with respect to deposit market shares in that a bank's decision to donate likely correlates with unobservable bank characteristics that can also affect its deposit market share. For example, it could be that banks donate more to local nonprofits because they are more profitable in those counties as reflected by a high local deposit market share.

Our identification strategy utilizes county-level natural disasters and exploits the inherent branching structure of banks to generate exogenous variation in the local supply of donations through three key steps. First, we examine counties that are hit by natural disasters ("shocked counties"). In these shocked counties, local demand for donations increases because residents need funds to rebuild damaged properties and businesses. We show that

3 Similar quasi-exogenous changes in competition based on the application of antitrust rules have been used in the banking literature to study the effects of competition on market structure (Liebersohn, 2021), transmission of monetary policy (Williams, 2020), and deposit/loan pricing (Granja and Paixao, 2022).

banks with branch presence in shocked counties respond by increasing donations to local nonprofits in these counties. Second, we examine counties where banks operate branches, but are not hit by natural disasters ("connected non-shocked counties"). We show that in order to satisfy the excess demand for donations in shocked counties, banks that operate in both shocked and connected nonshocked counties reallocate donations away from connected nonshocked counties and toward shocked counties. The reallocation of donations is economically sizable. For example, we find that over the 4 years following natural disaster shocks, donations to local nonprofits fall by roughly \$1.60 in connected nonshocked counties per dollar of additional donations stimulated by natural disasters in shocked counties.

In the third step, we show that the reallocation of donations for banks that have branch presence in both shocked and connected nonshocked counties ("exposed banks") leads to an exogenous increase in the local share of donations for banks that have branch presence in only connected nonshocked counties ("non-exposed banks"). Finally, after verifying the validity of our identification strategy in the aforementioned three steps, we focus only on connected nonshocked counties and use the exogenous variation in local donation share to study the effects on the local deposit market share of nonexposed and exposed banks in these connected nonshocked counties. Using a difference-in-differences specification, we find that nonexposed banks experience higher post-disaster local deposit market shares in connected nonshocked counties compared to exposed banks. Our results remain robust after accounting for systematic differences between exposed and nonexposed banks through the use of propensity score matching and weighted-least squares using propensity score-derived weights, as well as controlling for local deposit rates.

In the last set of analysis, we conduct a hypothetical exercise to attribute economic importance to the increase in deposits derived from making donations. Specifically, we show that if a donating bank channels all of the increase in local deposits due to donations into making local retail loans, then it could potentially earn up to \$530,000 more in profits than nondonating banks, controlling for bank and county characteristics. We also document the types of nonprofits that banks prefer to donate to. Recipient nonprofits tend to be larger, have sizable asset bases, and receive more public donations. Thus, banks appear to maximize the salience of their charitable activities by donating to nonprofits that have the most social impact.

We contribute to the literature that examines competition as a determinant of corporate philanthropy. Prior studies have examined how competition shapes firms' CSR activities using variation derived from different competition laws across countries (Ding *et al.*, 2020), international trade tariffs (Flammer, 2015b), and peer firms' adoption of CSR practices (Cao, Liang, and Zhan, 2019). Our article differs in that we exploit local variation in deposit market competition to examine its effects on donations to local nonprofits. We also show that banks' donations to local nonprofits can serve as a type of business strategy to gain a competitive advantage. Lastly, it is often difficult to disentangle how a firm specifically responds to competition based on its aggregate CSR performance because such a measure depends on a host of factors ranging from social to environmental issues. Our article offers insight into how firms use corporate philanthropy, arguably one of the most visible methods to demonstrate a commitment to social causes, to improve their competitive position by donating to local nonprofits.

Our research also contributes to the growing body of literature on the strategic value of corporate philanthropy. Existing studies have shown that corporate philanthropy can be a result of agency problems (Brown, Helland, and Smith, 2006; Yermack, 2009; Masulis and

Reza, 2015), which can arise because corporate giving reflects managers' preferences for using firm resources to increase their own utility through the consumption of private benefits. Recent work has also documented the strategic benefits of corporate philanthropy as an effective tool for political influence and advocacy (Wang and Qian, 2011; Bertrand *et al.*, 2020; Bertrand *et al.*, 2021). However, while these studies focus on corporate philanthropy as a means of securing favorable regulatory treatment, we examine how banks use corporate philanthropy to gain a competitive advantage in deposit product markets through obtaining more local deposit shares. Additionally, understanding how donations to local nonprofits impact local deposit market shares is important because deposit productivity accounts for the majority of bank value (Egan, Lewellen, and Sunderam, 2022).

Finally, we contribute to the literature on bank depositors' behavior and, in particular, their response to banks' involvement in corporate philanthropy. Studies have shown that investors reward firms for their commitment to CSR in the form of lower costs of capital, lower capital constraints, and greater capital inflows (e.g. Heinkel, Kraus, and Zechner, 2001; Sharfman and Fernando, 2008; Hong and Kacperczyk, 2009; El Ghoul *et al.*, 2011; Goss and Roberts, 2011; Chava, 2014; Cheng, Ioannou, and Serafeim, 2014; Hasan *et al.*, 2017; Liu, Cheong, and Zurbruegg, 2020; Freund, Nguyen, and Phan, 2021). In a banking context, studies have focused on how banks are disciplined in response to changes in reputation (Deng, Willis, and Xu, 2014), transparency (Chen *et al.*, 2022), and financial fundamental information (Goldberg and Hudgins, 2002; Martinez Peria and Schmukler, 2001; Maechler and McDill, 2006; Iyer, Puri, and Ryan, 2016), while less attention has been given to the way depositors reward banks for their social performance.[4] By focusing on donations between banks and local nonprofits, we are able to offer new insights on how depositors reward banks for their charitable activities.

2. Related Literature

Our article is related to the growing body of work that examines the determinants of corporate philanthropy. One strand of literature finds that corporate philanthropy arises due to agency problems because it is used to enhance CEOs' personal utility through the consumption of private benefits of control (Brown *et al.*, 2006; Yermack, 2009; Masulis and Reza, 2015). The primary focus of these studies is on the variation of donations driven by agency issues. For example, Brown *et al.* (2006) and Masulis and Reza (2015) find that firms with larger boards and weaker corporate governance, respectively, contribute more funds to their corporate foundations. Yermack (2009) documents large charitable stock gifts made by chairmen and CEOs to their family foundations just before sharp declines in stock prices and attributes such behavior to the CEOs' fraudulent backdating of stock gifts to increase personal income tax benefits. Our study, however, examines the geographical variation of donations distributed from foundations.

The nature of our data is also inherently different from those used in the existing literature on agency motives. Both Brown *et al.* (2006) and Masulis and Reza (2015) use data from the National Directory of Corporate Giving that provides data on the aggregate

4 Homanen (2018) provides evidence of how depositors punish a bank's *lack of* participation in CSR. The author finds that total deposit growth decreases when banks are caught in CSR-related scandals.

amount of direct and indirect donations at the firm–year level.[5] Our study uses more granular data at the nonprofit–firm–year level because we examine donations made through bank foundations, which are publicly observable via foundation disclosures. Although agency motives are arguably more prevalent when examining direct giving because such donations are generally unobservable, they are less of a concern when studying foundation giving because of greater visibility due to the additional layers of disclosure oversight.[6] Another advantage of the granularity of our data is that we are able to exploit geographical variation in donations since we observe the nonprofit recipients. This geographical distribution is key when examining the relation between local competition and donations because we are able to tease out the allocation of donations across different counties with varying levels of competition.

Another strand of literature documents the strategic nature of corporate philanthropy. Bertrand *et al.* (2020) show that firms with corporate foundations strategically donate to nonprofits located in the same congressional district as politicians who are of particular policy relevance to the firm. Bertrand *et al.* (2021) provide evidence that nonprofits that receive donations from corporate foundations are more likely to comment on the same regulation as their donors. Wang and Qian (2011) find that firms that are not government owned or politically well connected benefit the most from corporate philanthropy because it helps firms gain critical political resources. The motivations behind participating in corporate philanthropy depend critically on a firm's operating environment (Ioannou and Serafeim, 2012; Liang and Renneboog, 2017). Thus, while the existing literature has mainly focused on firms engaging in corporate philanthropy to secure preferential regulatory treatment, our study examines banks' use of charitable giving to increase the local consumer demand for deposits. Given that recent studies have highlighted the importance of generating deposits in banking activities (Begenau and Stafford, 2019; Drechsler, Savov, and Schnabl, 2021; Egan, Lewellen, and Sunderam, 2022), our analysis differs from the socio-political focus of the existing studies by examining the strategic aspects of corporate philanthropy derived from local deposit market competition.

Although the market for deposits has gradually become more national through the rise of online and mobile banking, we argue that studying local deposit markets is still important given both anecdotal and empirical evidence that consumers' primary method of banking is still local. For example, surveys conducted by the Federal Deposit Insurance Corporation (FDIC) National Survey of Unbanked and Underbanked Households find that

5 Our study focuses specifically on donations made through corporate foundations (i.e. indirect donations) because reporting requirements (such as the filing of an IRS 990-PF form) allow us to observe the recipients and amounts received from corporate giving. However, the distribution of such funds from the foundation to nonprofits may not occur until a future point in time. Thus, there is also a timing difference between the data used in the studies on agency motives and our paper.

6 Following Cai, Xu, and Yang (2021), we investigate the amount of donations that could potentially be associated with agency motives in our data. Out of the 102 banks that we study, only 35 banks have ever made affiliated donations directed to nonprofits that are affiliated with the firm's independent directors, with the average amount being $0.43 million at the firm–year level for this subsample of banks. The magnitude of affiliated donations in our sample is considerably lower than the average of $1.5 million in Cai *et al.* (2021). More importantly, the total amount of affiliated donations accounts for less than 1% of the total amount of bank donations in our sample. Therefore, our results are less likely to be driven by agency motives.

a substantial portion of the US citizens rely on local banking services.[7] Similarly, the 2019 Survey of Consumer Finances finds that households tend to use banks with branches that are close to their residence. The banking literature shows that deposit markets are primarily local because consumers prefer close geographical proximity to bank branches due to search costs (Honka, Hortaçsu, and Vitorino, 2017) and consider only a limited number of local banking options due to limited consideration bias (Egan, Hortaçsu, and Matvos, 2017; Abrams, 2019). Our focus on county-level deposit markets is also consistent with other papers in the banking literature that use county-level deposit market competition to study various outcomes (Drechsler, Savov, and Schnabl, 2017; Hatfield and Wallen, 2022).

3. Data

In this section, we describe our data sources and provide descriptive statistics for the sample of banks used in our analysis.

3.1 Bank Foundations

We begin by manually searching each bank holding company's website to verify the existence of bank foundations. The search starts with the largest bank and continues until it has covered 94% of the total asset value of the market as of 2010, which yields 148 banks. Out of this amount, there are 102 banks with foundations, which account for 87% of the market, based on bank asset size.[8] Our sample mainly consists of the largest banks in the USA that operate branches across multiple counties. The average bank in our sample operates branches in roughly 57 counties with a standard deviation of 133 counties. Data on charitable donations made by bank foundations are obtained from FoundationSearch, which provides funding information based on IRS Form 990-PF for more than 120,000 active foundations. When a bank does not appear to have a foundation in the aforementioned manual search, we search the bank name in FoundationSearch to check whether there is a foundation that has a similar name as the bank. Lastly, we inspect Schedule B of the 990-PF form for each foundation to confirm that the bank and its subsidiaries are the main donors of the foundation.

Once we establish a link between a bank and its foundation, the donation record is obtained from FoundationSearch. For each grant, FoundationSearch reports the amount, the nonprofit recipient's name, city, and state, as well as a giving category created by the database. We collect a total of 391,715 grants in the sample period from 2000 to 2015.

7 In the 2013 survey, nearly four out of five households used a bank teller in the past 12 months, one in three used bank tellers as their primary method of account access, and 17.5% used bank tellers as their only method of account access. The subsequent surveys up until 2019 report that bank teller use remained prevalent. The 2019 survey finds that although mobile banking usage has increased over time, 83% of the banked households spoke with a teller or other employee in person at a bank branch in 2019. Moreover, branch visits were prevalent even among banked households that used online or mobile banking as their primary method of account access. For example, in 2019, 79.9% of the banked households that used mobile banking as their primary method visited a branch and 18.8% visited ten or more times. The survey also shows that the median distance from a household to their bank's nearest branch is only three miles and 75% of the households use a bank with a branch within 22 miles.

8 When a bank has more than one charitable foundation, we merge them into one.

International observations are dropped, leaving 387,433 observations.[9] We aggregate our donation data at the bank–county level to merge with other bank data. Supplementary Figure IA.1 presents a breakdown of bank donations in each giving category aggregated over time across our sample period. The majority of bank donations with respect to both the frequency and amount of donations are directed toward the social and human services category, followed by the community development and education categories.

3.2 Bank Variables

We obtain consolidated financial bank data from the call reports, which all banks must submit to the Federal Reserve System each quarter. The data provide detailed information on the banks in our sample, including consolidated balance sheet and income statement items, as well as off-balance sheet activities. We use these data to construct bank-level control variables, such as total equity capital divided by total assets (*Equity ratio*); the natural logarithm of total assets (*ln(Size)*); total loans divided by total assets (*Loan ratio*); nonperforming loans divided by total loans (*NPL*); loan loss reserves (*LLR*), defined as reserves for credit losses divided by total loans; loan loss provisions divided by total loans (*LLP*); return on assets (*ROA*), defined as net income divided by total assets; and a binary variable that equals to one if a bank is a multibank holding company and zero otherwise (*MBHC*).

Additionally, we obtain branch-level deposit data from the Summary of Deposits surveys provided by the FDIC. Deposit balances are measured at an annual frequency as of June 30 each year. We use these data to construct the key variables used in this article. In particular, we measure the competitiveness of the local deposit markets using the variable HHI, defined as the sum of squared deposit market shares of all banks that operate branches in a given county in a given year. This variable is constrained between zero and one, with a lower value corresponding to a lower level of deposit market concentration and hence a higher level of competition. We measure a bank's local deposit market share using the variable *Deposit share*, defined as the deposits of a bank in a given county in a given year divided by the total deposits of all banks in the same county and year.

We collect weekly branch-level retail deposit and loan rates from RateWatch. Following Drechsler *et al.* (2017), we use the rates for \$10,000 certificates of deposit with a 12-month maturity, money market accounts of \$10,000, and savings accounts with a \$2,500 minimum balance. For loan rates, we use the most common products in each category of loans. Specifically, we focus on 15-year fixed-rate mortgages of \$175,000, 4-year used auto loans with a 36-month term, and home equity loans of \$20,000, for a loan-to-value ratio of up to 80%, with a 60-month term. We calculate equally weighted average annual deposit rates and loan rates across all branches at the bank–county level. After merging our bank and donation data, we obtain a final sample of 92,523 observations at the bank–county–year level.

9 Around 25% of these observations are missing information regarding the city and/or state where the grant recipients are incorporated. We obtain the precise addresses of nonprofits missing data by matching the recipient name in FoundationSearch to a master list of all nonprofits obtained from the IRS Exempt Organizations Business Master File. The proportion of grant recipients missing city or state information is thus reduced to about 6%.

3.3 Bank Mergers

We obtain data on bank mergers from the National Information Center (NIC) of the Federal Reserve System. This data set contains details on bank merger events and the characteristics of the financial institutions involved. The transformation table of the data set provides information on bank mergers and failures. To construct our sample, we use all merger events, including mergers at the branch, commercial, and bank-holding company levels. We restrict our sample to mergers between domestic banking organizations operating in the USA. In addition, we exclude transformation events that are related to bank failures or government assistance. We also exclude mergers if we do not have geographical information for either the acquiring or target entity. Lastly, we drop intra-bank holding company merger events.

Our analysis using bank mergers is conducted at the banking market level. Regional Federal Reserve Banks define the geographical banking markets, which are used in connection with applications to evaluate effects on competition in the local banking markets. In urban areas, markets often coincide with cities, and in rural areas, they may be single counties. In our sample, an average banking market consists of 2.22 counties with a standard deviation of 2.20 counties. To aggregate our county-level donation data to the banking market level, we obtain data on the definition of banking markets from CASSIDI at the Federal Reserve Bank of St. Louis. We first match our donation data for counties that only appear in one banking market. For those counties that are part of more than one banking market, we narrow the data down further by using city-level information to match the donation data to the relevant banking market.

3.4 Natural Disasters

We use data on natural disasters from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) from 2001 to 2015. This data set provides county-level information on each natural disaster event, including the beginning date, location (county and state), and property damage. We focus on a subset of the SHELDUS data in which the governor declared a state of emergency with a formal Federal Emergency Management Agency (FEMA) declaration. FEMA disaster declarations are made in response to natural disasters that have caused severe damage that is beyond the capabilities of the local or state government to respond. Thus, we focus on relatively large disasters.

3.5 Descriptive Statistics

Table I presents the summary statistics of the variables used in this article at the bank–county–year level. The average bank has a deposit market share of 13%, with a standard deviation of 13.2%. The mean and standard deviation of HHI are 0.207 and 0.122, respectively, indicating that the average county has a moderately competitive deposit market according to the guidelines set by the U.S. Department of Justice (DOJ).[10] There is also significant variation in competition across counties, from a minimum HHI of 0.05 to a maximum of one. Our values are consistent with those of Drechsler *et al.* (2017), who document a mean HHI of 0.24 with a standard deviation of 0.14 at the bank–county level.

In terms of donations, we construct the variable *Donation*, which is a binary variable that equals one if a bank donates to at least one nonprofit in a county where it operates

10 According to the DOJ, values of HHI between 0.15 and 0.25 indicate that the market is moderately concentrated and hence moderately competitive. Markets in which the HHI is in excess of 0.25 are considered to be highly concentrated and hence not very competitive.

Table I. Descriptive statistics

This table provides summary statistics of the variables used in this article. Variable definitions are presented in Appendix Table A.1.

Variable	*N*	Mean	Median	Std. dev.	Min	Max
Bank variables						
Donation	92,523	0.214	0.000	0.410	0.000	1.000
Donation amount (US millions)	92,523	0.227	0.030	1.190	0.000	99.489
Donation share	17,227	0.279	0.018	0.379	0.000	1.000
Disaster donation	28,952	−0.221	0.000	1.416	−96.000	1.000
ΔConnected donation	28,952	−0.197	0.000	5.625	−549.060	1.000
Deposit share	92,523	0.130	0.095	0.132	0.000	1.000
Dep_12mcd10k (%)	73,384	1.063	0.337	1.259	0.010	5.819
Dep_mm10k (%)	71,315	0.382	0.146	0.541	0.010	4.741
Dep_sav2500 (%)	73,334	0.169	0.060	0.262	0.009	4.378
Equity ratio	91,690	0.101	0.099	0.020	0.016	0.404
LLP	91,690	0.009	0.005	0.011	−0.023	0.112
LLR	91,690	0.018	0.016	0.008	0.000	0.086
Loan ratio	91,690	0.603	0.636	0.119	0.027	0.926
MBHC	92,523	0.653	1.000	0.476	0.000	1.000
NPL	91,690	0.023	0.017	0.020	0.000	0.200
ROA	91,690	0.010	0.010	0.007	−0.084	0.057
ln(Size)	91,690	18.980	19.041	1.881	12.010	21.674
Advertising ratio	82,000	0.000	0.000	0.000	0.000	0.013
Deposits (US billions)	91,690	330.195	124.709	406.019	0.104	1,375.180
Deposit ratio	91,690	0.653	0.668	0.105	0.001	0.919
County-level variables						
HHI	92,523	0.207	0.175	0.122	0.050	1.000
ln(Establishments)	83,015	7.803	7.686	1.489	2.639	12.488
ln(New nonprofits)	90,432	4.308	4.263	1.665	0.000	9.424
Disaster	92,523	0.233	0.000	0.423	0.000	1.000
Adj disaster	92,523	0.319	0.000	0.466	0.000	1.000
ln(GDP per capita)	83,812	10.593	10.568	0.425	9.239	14.390
ln(Population)	89,928	11.591	11.497	1.436	6.603	16.129
ln(PI per capita)	89,928	10.470	10.450	0.298	9.455	12.235
ln(HPI)	89,176	4.863	4.843	0.193	4.143	5.959
M&A	92,523	0.007	0.000	0.086	0.000	1.000

branches, and zero otherwise. In our analysis, we use a continuous measure of donations, *ln(Donation amount)*, defined as the natural logarithm of one plus the dollar amount of donations to nonprofits in a given county by a given bank in a given year. The variable *Donation* has a mean of 0.214, implying that banks donate to nonprofits in 21.4% of the counties where they operate branches. The average donation size is approximately \$227,000, with a standard deviation of \$1.19 million at the bank–county–year level, indicating significant variation in bank donation size. The *Disaster* variable has a mean value of 0.233, meaning that almost a quarter of the counties where a bank operates branches are affected by a FEMA-related natural disaster event at least once during our sample period. We also provide summary statistics on a range of control variables based on the bank- and county-level characteristics. A full list of the variables used in this article and their data sources can be found in Appendix Table A.1.

Table II presents additional summary statistics on the natural disaster events in our sample. Panel A describes the property damage at the county level (in 2016 US dollars) across different types of natural disasters. Overall, there are 17,260 natural disaster events at the county–year level over our sample period (or about 1,150 per year). Severe storms/thunderstorms are the most frequent natural disaster type, accounting for approximately 27% of all observations, followed closely by flooding and wind. In terms of average property damage, earthquakes and hurricanes/tropical storms are the most severe, due to their massive scale, although they are not as frequent. Panel B presents the average bank donations in US dollars to nonprofits across different giving categories, sorted by whether the donation is given to a nonprofit located in a county affected by a natural disaster event or not. We find that for the community development, education, environment, and religion categories, banks donate significantly more, on average, to nonprofits located in counties affected by a natural disaster event.

4. Competition and Bank Donations

We begin by exploring the relation between local deposit market competition and bank donations. We first present our baseline regression results, followed by an identification strategy based on the application of antitrust rules in banking market mergers to mitigate issues related to endogenous changes in competition.

4.1 Baseline Results

To examine the relation between local deposit market competition and bank donations, we estimate the following model:

$$ln(Donation\ amount)_{i,c,t+1} = \beta_0 + \beta_1 HHI_{c,t} + \beta_2 X_{c,t} + \gamma_{i,c} + \delta_{i,t} + \varepsilon_{i,c,t+1} \quad (1)$$

for bank i, county c, and year t. The dependent variable is the natural logarithm of one plus the dollar amount of donations to nonprofits in a given county by a given bank in year $t+1$. We control for a variety of county-level characteristics, as represented by $X_{c,t}$, including *ln(GDP per capita)*, *ln(Population)*, *ln(PI per capita)*, *ln(HPI)*, and *M&A*. All of these variables are defined in Appendix Table A.1. We include bank × county fixed effects ($\gamma_{i,c}$) to control for time-invariant pair-specific effects and bank × year-fixed effects ($\delta_{i,t}$) to control for time-varying bank factors. Standard errors are double clustered at the bank- and year levels. If banks increase donations to local nonprofits in response to greater deposit market competition, then we expect a negative coefficient on β_1.

We present the estimation results of Equation (1) in Table III. In Column (1), the coefficient on HHI is negative and statistically significant, implying that increases in local deposit market competition are associated with greater subsequent donations to nonprofits in those counties. Economically, a one-standard deviation decrease in HHI is associated with a 31.89% increase in the dollar value of donations. In Columns (2)–(4), we control for potential county-level growth opportunities by including the number of establishments and new nonprofits in a given county.[11] However, the coefficients on HHI remain negative and statistically significant. Lastly, in Supplementary Figure IA.2, we provide a visual confirmation

11 Growth opportunities can influence both a bank's donation decisions, as well as local deposit market competition, leading to an omitted variable problem.

Table II. Natural disasters and bank donation characteristics

This table provides summary statistics of natural disaster events and bank donation characteristics. Panel A presents summary statistics on the total property damage (in billions of US dollars), average property damage (in millions of US dollars), and the number of unique combinations of County × Disaster across different types of natural disasters. Reported damages are in 2016 dollars. Panel B presents the average bank donations (in US dollars) to nonprofits across different donation categories sorted by whether the donation is given to a nonprofit located in a county affected by a natural disaster event or not. For both panels, the sample starts with all natural disasters as identified by SHELDUS from 2001 to 2015 and includes those in which the governor declared a state of emergency with a formal FEMA declaration. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively.

Panel A: Property damage by types of natural disasters

Hazard type	Total damages (US billions)	Average damage (US millions)	County × Occurrence
Avalanche	0.001	0.120	11
Coastal	1.485	15.627	95
Drought	0.038	0.598	64
Earthquake	4.010	286.406	14
Flooding	74.298	17.623	4,216
Fog	0.002	0.066	28
Hail	1.308	1.353	967
Heat	0.003	0.162	18
Hurricane/tropical storm	141.712	154.707	916
Landslide	1.706	13.539	126
Lightning	0.119	0.155	769
Severe storm/thunder storm	1.272	0.276	4,608
Tornado	19.398	12.653	1,533
Tsunami/Seiche	0.056	8.027	7
Wildfire	6.480	21.528	301
Wind	8.566	3.919	2,186
Winter weather	3.254	2.322	1,401

Panel B: Characteristics of donations by natural disaster

	No disaster		Disaster			
Donation category	*N*	Mean	*N*	Mean	Difference	*p*-value
Arts and culture	15,488	27,600	6,978	28,612	1,012	0.39
Community development	22,446	35,503	9,285	42,584	7,081***	0.00
Education	33,069	36,098	13,409	40,257	4,159**	0.04
Environment	3,576	31,371	1,482	34,582	3,212***	0.00
Health	6,936	23,429	3,384	24,940	1,510	0.36
Miscellaneous	14,686	30,177	6,390	29,563	−614	0.86
Religion	3,514	30,814	1,515	33,778	2,964**	0.04
Social and human services	39,051	30,177	16,586	31,551	1,375	0.53
Sports and recreation	1,036	24,620	475	23,393	−1,227	0.82

Table III. The relation between bank donations and deposit market competition

This table provides the OLS regression results of bank donations on deposit market competition. In all specifications, the dependent variable is the natural logarithm of one plus the dollar amount of donations to nonprofits in a given county by a given bank in year $t+1$. *HHI* is the sum of squared deposit market shares of all banks that operate branches in a given county in a given year. *ln(Establishments)* is the natural logarithm of one plus the number of establishments in a given county in a given year. *ln(New nonprofits)* is the natural logarithm of one plus the number of new nonprofits in a given county in a given year. Control variables include *ln(GDP per capita)*, *ln(Population)*, *ln(PI per capita)*, *ln(HPI)*, and *M&A*. For all specifications, standard errors are robust to heteroscedasticity and double clustered at the bank- and year levels; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Dep. variable: $ln(Donation\ amount)_{t+1}$	(1)	(2)	(3)	(4)
HHI_t	−2.269***	−2.133**	−1.711**	−2.321**
	(−2.74)	(−2.38)	(−1.99)	(−2.30)
$ln(Establishments)_t$		0.628*		0.581
		(1.77)		(1.58)
$ln(New\ nonprofits)_t$			0.025	0.019
			(1.10)	(0.73)
Controls	Yes	Yes	Yes	Yes
Bank × county fixed effects	Yes	Yes	Yes	Yes
Bank × year-fixed effects	Yes	Yes	Yes	Yes
Observations	84,134	76,516	79,166	75,142
Adj R^2	0.01	0.01	0.01	0.01

of the positive relation between local deposit market competition and bank donations by comparing the total amount of bank donations at the county level aggregated over our sample period with the average deposit market competition at the county level. The figure shows that areas with greater deposit market competition generally correspond to those with greater amounts of donations.

Overall, while the baseline results indicate that the local deposit market competition appears to be a main determinant of bank donations, we caution against a causal interpretation since there could be unobservable factors driving local competition. In the next section, we alleviate endogeneity concerns by using a quasi-exogenous change in HHI as a shock to local competition.

4.2 A Quasi-Natural Experiment Using Banking Market Mergers

4.2.a. *Institutional setting*

In the USA, regulators take into account many different laws and regulations when evaluating mergers conducted by banks. In particular, bank regulators assess the antitrust implications of the mergers. According to the guidelines stipulated by the DOJ,[12] bank regulators

12 See the guidelines provided at https://www.federalreserve.gov/bankinforeg/competitive-effects-mergers-acquisitions-faqs.htm and https://www.justice.gov/atr/horizontal-merger-guidelines-08192010.

perform a quantitative screening based on the expected changes in the HHI of each banking market where both the acquiring and target banks have branches. Regulators will intervene and require branch divestitures in any market where the HHI is predicted to rise by at least 0.02 points to a level above 0.18 as a result of the merger. In contrast, regulators do not require branch divestitures if the HHI is predicted to rise by at least 0.02 points to a level below 0.18.

The divested branches are usually the former branches of the target bank and are commonly sold to a nonmerging bank with no prior presence in the banking market. The purpose of these divestitures is to ensure that a high level of competition is maintained in banking markets where mergers could adversely affect competition.[13] Since banks usually operate across multiple banking markets, regulators will only require divestitures in those markets that violate the screening process, while the merger can proceed in all the other markets as planned.[14]

Our empirical strategy exploits the heterogeneity in the application of the antitrust screening process. Specifically, we use realized bank mergers to predict, on an *ex ante* basis, which banking market mergers would plausibly require antitrust intervention and which would not. In an ideal setting, one would use data on regulators' actual *ex post* intervention to classify mergers into those that required divestitures for violating antitrust rules and those that did not. However, such data are not made available by regulators, so our analysis estimates an intention-to-treat effect. In Section 4.2.d, we will provide evidence that supports our empirical design to predict reasonably well the application of antitrust rules.

4.2.b. *Empirical design*

We predict antitrust intervention as follows. For each merger event in a given banking market, we first calculate the pre-merger HHI, which is defined as the HHI of the banking market immediately before the merger. Then, we calculate the predicted post-merger HHI, which is defined as the HHI of the banking market immediately after the merger, assuming no divestitures. Finally, we calculate the difference between the predicted post- and pre-merger HHI values to obtain the predicted change in HHI. For our baseline definition, the treated group is defined as banking markets where the predicted post-merger HHI is between 0.18 and 0.26 and the predicted change in HHI is an increase of at least 0.02 points. Thus, the treated group consists of banking markets where antitrust rules are required to maintain competition. The control group is defined as banking markets where the predicted post-merger HHI is between 0.10 and 0.18, and the predicted change in HHI is an increase of at least 0.02 points. The banks in the markets belonging to the control group are unlikely to undergo divestitures, and hence competition will decrease as a result of the mergers being completed.

13 It is precisely the divestment of these branches and their repurchase by third-party banks that ensure that competition is sustained following mergers that violate antitrust rules. Furthermore, regulators often monitor these divested branches to make sure that they remain competitive after they are sold.

14 Regulators, however, have discretion in mandating divestiture or not. In certain cases, a merger is allowed to go through even if it violates the screening process because of bank survivability issues or concerns of financial stability. Thus, in our analysis, we will confirm that the antitrust screening process actually has a significant effect on banking market competition.

In our definition of the treated and control groups, the predicted post-merger HHI is restricted within a 0.08-point range of the 0.18 cutoff to control for potential differences between markets that are too far above the 0.18 cutoff, which minimizes bank reactions to mergers other than regulator intervention. To ensure that our results are not driven by this particular choice of sample selection rule, we also consider samples that vary the range of markets by using a narrower range of 0.05 points within the 0.18 cutoff, as well as restricting the predicted change in HHI to be between 0.02 and 0.03 points.

To arrive at the final sample of banking market mergers, we impose three restrictions. First, we remove all merger events that occurred during the Global Financial Crisis period of 2007Q3 to 2008Q4 since these mergers may be allowed to complete even if they violate the antitrust rules, given the regulatory discretion on financial stability. Second, we drop all mergers where the acquiring bank has no branch presence in the banking market prior to the merger, so that our sample only consists of mergers where both the acquirer and target banks operate branches in the same banking market. This restriction alleviates concerns, whereby out-of-market acquiring banks may donate more to local nonprofits because they are less known in the community, rather than in response to increases in competition due to antitrust interventions. Third, since a bank's involvement in the merger can impact its future donation decisions, for each merger event, we drop all banks that directly participate in the merger (e.g. the acquirer and target banks). Therefore, our analysis focuses on the response to changes in competition of incumbent banks that do not actually take part in the merger themselves. In summary, our sample consists of 85 banking markets involving 64 unique incumbent banks and 320 merger events, of which 135 (185) belong to the treated (control) group.

We employ a difference-in-differences specification that uses a balanced panel of 3 years on each side of the merger year to compare banks in treated and control markets before and after mergers. We estimate the following model:

$$ln(Donation\ amount)_{i,m,t} = \beta_0 + \beta_1 Treat_m + \beta_2 PostMerger_t + \beta_3 PostMerger_t \times Treat_m + \gamma_{i,m} + \delta_{i,t} + \varepsilon_{i,m,t} \tag{2}$$

for bank i, banking market m, and year t. We aggregate our bank donation data to the banking market level because it is originally constructed at the county level. Thus, the dependent variable is the natural logarithm of one plus the dollar amount of donations to nonprofits in a given banking market by a given bank in a given year. $Treat_m$ is a binary variable that equals to one if a bank operates branches in a banking market where antitrust intervention is predicted, and zero otherwise. $PostMerger_t$ is a binary variable that equals one for the years following a bank merger, and zero otherwise. We include bank $\times$ banking market fixed effects ($\gamma_{i,m}$) and bank $\times$ year-fixed effects ($\delta_{i,t}$).

The key coefficient of interest is β_3, which represents the difference in post-merger donation decisions between banks operating in treated versus control banking markets due to relative differences in competition as a result of the heterogeneous application of antitrust rules. Since bank regulators do not publicly announce antitrust interventions, the interpretation of β_3 is an intention-to-treat effect, which measures differences in donations between banks operating in markets where divestitures are required based on predicted antitrust interventions and markets where they are not required. Our hypothesis predicts a positive coefficient on β_3, indicating that banks increase their donations to nonprofits in banking markets where competition increases due to the application of antitrust rules.

4.2.c. *Identifying assumptions*

In this section, we provide evidence that supports the quasi-random assignment of treatment status based on predicted antitrust interventions. The main threat to identification is that treated and control banking markets may not be directly comparable due to strategic bank behavior in response to antitrust interventions. For example, in the absence of antitrust rules, target banks located in markets with an HHI above the 0.18 threshold may provide better future investment opportunities. However, given that acquiring banks know that such a merger will trigger divestitures, they may forgo these profitable mergers to avoid divestitures. Thus, mergers that occur in banking markets above the 0.18 threshold may differ on important dimensions compared to mergers in markets below the threshold.

We test whether the distribution of predicted post-merger HHI in banking markets where mergers occur is continuous around the 0.18 threshold. Any discontinuity would suggest a nonrandom assignment of treatment status around the threshold as it implies that banks may be strategically participating in mergers to avoid antitrust intervention. Intuitively, it is unlikely that such strategic behavior would be a major concern for our empirical design. The reasoning is that bank mergers usually involve multiple banking markets, and antitrust rules are typically applied in a small subset of violating markets. Therefore, as long as the violating markets are not pivotal markets that influence the bank's overall merger decisions at the national level, it is plausible to assume that such strategic behavior is minimal around the 0.18 threshold.

Figure 1 presents the histogram of predicted post-merger HHIs in banking markets where mergers occur, limited to mergers where the predicted increase in HHI is at least 0.02 points. If mergers were being avoided because of anticipated antitrust interventions, one would expect to see a bunching of mergers just below the 0.18 threshold. However, the figure shows that the distribution of HHIs appears to be smooth and continuous around the threshold. To formally test for the existence of a discontinuous jump in HHIs around the threshold, we plot the density of centered HHIs (by subtracting the threshold of 0.18) in Supplementary Appendix Figure IA.3. Using the density break test following Cattaneo, Jansson, and Ma (2020), we fail to reject the null hypothesis that banks are unable to strategically participate in mergers to be right below the 0.18 threshold ($p = 0.762$).

We also test for preexisting differences between the banks that operate in treated and control markets. If the treatment status based on predicted antitrust interventions is as good as randomized around the 0.18 threshold, then there should be no preexisting differences prior to the merger event. In Supplementary Appendix Table IA.1, we examine the change in a variety of bank characteristics between years $t-2$ and $t-1$, relative to the merger event. There are no statistically significant differences between the changes in bank characteristics for banks in the treatment and control markets.

4.2.d. *Effects of predicted antitrust intervention on HHI*

We now provide evidence that the application of antitrust rules has a material impact on local bank competition. Specifically, we estimate a modified version of Equation (2) at the banking market level where the dependent variable is the banking market HHI. We present the results in Table IV. In Column (1), where we use our baseline definitions of treated and control markets, we see that the HHI increases after mergers in nonintervention markets (positive and significant coefficient on *PostMerger*), but for treated markets, the change in HHI is significantly less than that of nonintervention markets (the coefficient on the difference-in-differences estimator $PostMerger \times Treat_m$ is negative and statistically

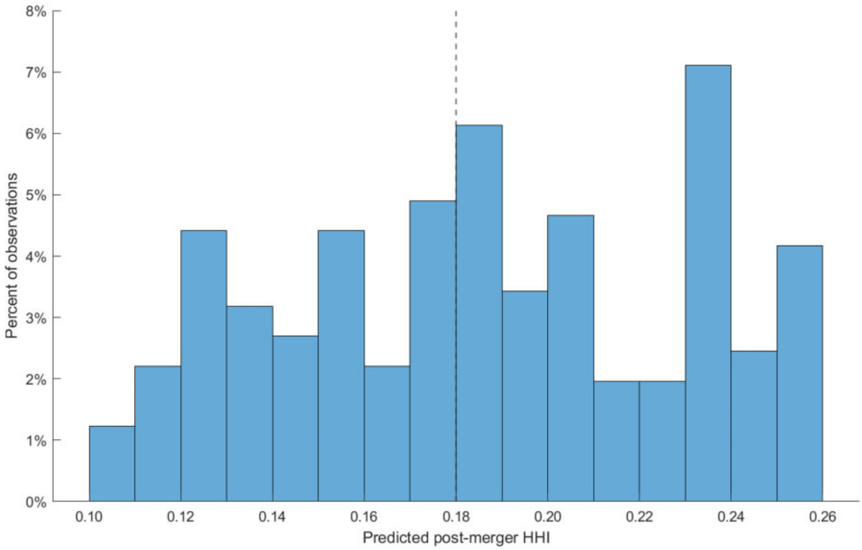

Figure 1. Distribution of predicted post-merger HHI. This figure presents the histogram of predicted post-merger HHI in banking markets where mergers occur. The sample is limited to mergers where the predicted increase in HHI is at least 0.02 points. Mergers with a predicted post-merger HHI between 0.18 and 0.26 (0.10–0.18) are the treated (control) group. The horizontal axis indicates the predicted post-merger HHI of each banking market merger in 0.01 intervals. The vertical axis indicates the percentage of mergers per HHI interval. The dashed vertical line at 0.18 represents the HHI threshold for antitrust intervention.

significant). This result implies that the post-merger competition in markets with predicted antitrust intervention applied is relatively greater than that in markets without intervention. Columns (2) and (3) use alternative definitions for the treated markets and yield similar results.

The absence of pre-trends (differential response in banking market HHI prior to merger events) is a necessary condition for the validity of our difference-in-differences setting. We conduct an event study by using an extended window of 5 years on each side of the merger year to detect any pre-trends. Figure 2 shows how the HHI changes year by year before and after mergers, relative to the year before the merger event, using the specification in Column (1) of Table IV.[15] Prior to the merger event, the HHI in both treated and control markets appears to move in parallel since none of the estimates on $PostMerger(k) \times Treat_m$ is statistically significant. This result lends support for the parallel trends assumption in that there do not appear to be any pre-trends in HHI prior to the merger events. However, after the merger, the HHI decreases in the treated sample relative to that of the control group, which increases confidence in using the application of antitrust rules as an exogenous source of variation in local deposit market competition.

15 The event study figure is created by replacing the *PostMerger* variable with a series of year dummies that represent the years relative to the merger year. These year dummies are denoted *PostMerger(k)*, where *k* ranges from –5 to + 5.

Table IV. The effect of predicted antitrust interventions on deposit market competition

This table provides the difference-in-differences regression estimates of the effect of predicted antitrust interventions on local deposit market competition following banking market mergers. We focus on 3 years before to 3 years after the bank mergers. In Column (1), the treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.26 (0.10–0.18) with a predicted increase in HHI of at least 0.02 points. In Column (2), the treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.23 (0.13–0.18) with a predicted increase in HHI of at least 0.02 points. In Column (3), the treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.26 (0.10–0.18) with a predicted increase in HHI between 0.02 and 0.03 points. The dependent variable, HHI, is the sum of squared deposit market shares of all banks that operate branches in a given banking market in a given year. $Treat_m$ is a binary variable that equals to one for banking markets where antitrust intervention is predicted and zero otherwise. *PostMerger* is a binary variable that equals to one for the years following bank mergers and zero otherwise. For all specifications, standard errors are robust to heteroscedasticity and clustered at the banking market level; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1 .

Dep. variable: HHI_t	0.08-point range, $\Delta HHI \geq 0.02$ (1)	0.05-point range, $\Delta HHI \geq 0.02$ (2)	0.08-point range, $\Delta HHI \in [0.02, 0.03]$ (3)
PostMerger	0.034^{***}	0.064^{***}	0.016^{***}
	(2.62)	(3.25)	(3.51)
$PostMerger \times Treat_m$	-0.042^{***}	-0.058^{***}	-0.031^{**}
	(−2.65)	(−3.73)	(−2.20)
Banking market fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Observations	714	504	311
Adj R^2	0.78	0.87	0.74

As further evidence for the exogeneity of antitrust interventions, we conduct placebo tests to show that there is no effect on banking market HHIs when mergers occur, but antitrust rules do not bind. In Supplementary Appendix Table IA.2, we define the treated sample using placebo definitions of intervention, but no intervention should actually occur. In Column (1), the treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.26 (0.10–0.18) with a predicted change in HHI of less than 0.02 points. In Column (2), the treated (control) banking markets are those where the predicted post-merger HHI is greater than 0.26 (between 0.18 and 0.26) with a predicted increase in HHI of at least 0.02 points. In both cases, there are no statistically significant differences in the HHI between the treated and control samples.

4.2.e. Donation decisions in response to predicted antitrust interventions

Having verified the basic premise of our difference-in-differences setting, we now examine how bank donations respond to increases in competition as a result of antitrust interventions. The estimation results of Equation (2) are presented in Panel A of Table V. We use the baseline definition of treated and control markets in Column (1) and observe a positive

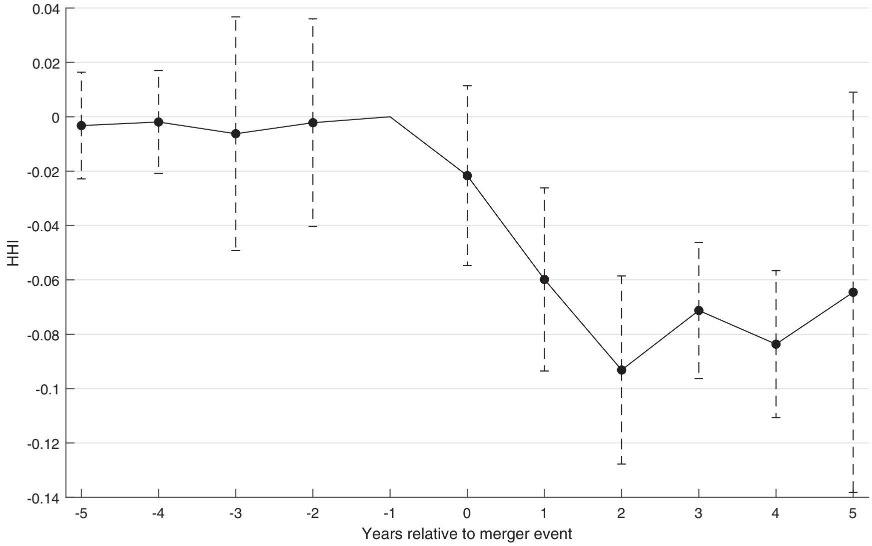

Figure 2. Dynamics of banking market HHI around banking market mergers. This figure shows the point estimates (solid line) and 95% confidence intervals (dashed lines) of the coefficients for the interaction term, *PostMerger*(*k*) $\times$ $Treat_m$, where *k* ranges from –5 to + 5, using the regression specification in Column (1) of Table IV. The treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.26 (0.10–0.18) with a predicted increase in HHI of at least 0.02 points. The year before the merger is the omitted category. The dependent variable, HHI, is the sum of squared deposit market shares of all banks that operate branches in a given banking market in a given year. $Treat_m$ is a binary variable that equals to one for banking markets where antitrust intervention is predicted and zero otherwise. Variable definitions are presented in Appendix Table A.1.

and statistically significant coefficient on *PostMerger* $\times$ $Treat_m$. This result implies that banks operating in markets with predicted antitrust interventions donate more to local nonprofits relative to those operating in markets where mergers are allowed to go through unhindered. Economically, banks operating in markets where competition increases due to the application of antitrust rules donate 11% more in the post-merger period to local nonprofits relative to those in non-intervention markets. Using alternative definitions for the treated markets in Columns (4) and (5) yields similar results.

Meyer (2018) shows that urban banking markets are much more competitive than rural markets. This may lead to a potential omitted variable problem, whereby banks may be more likely to merge in urban markets and subsequently have more charitable opportunities because there are more local nonprofits to donate to in urban areas. To address this concern, in the second column of Panel A of Table V, we include the control variable *MSA (%)*, defined as the proportion of a banking market where a given bank operates branches in counties categorized as an MSA. A given bank with a higher value of *MSA (%)* implies that the bank has a greater branch presence in urban areas. Although the coefficient on *MSA (%)* is positive and statistically significant, it does not subsume the effects on the double interaction term *PostMerger* $\times$ $Treat_m$, as the coefficient of 0.108 is still statistically significant and similar in magnitude when compared to that in Column (1). This result implies that while banks operating branches in urban areas donate more, on average, to local nonprofits, local deposit market competition still affects banks' donation decisions.

Table V. Donation decisions in response to predicted antitrust interventions

This table provides the difference-in-differences (Panel A) and regression discontinuity (Panel B) estimates of the effect of predicted antitrust interventions on local donations following banking market mergers. In Columns (1), (2), (4), and (5) of Panel A, we focus on 3 years before to 3 years after the bank mergers. In Column (3) of Panel A, we use all years of data before and after mergers occur. In Panel B, we focus on the year of the bank merger and examine subsequent year donations. In Columns (1)–(3) of Panel A and Column (1) of Panel B, the treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.26 (0.10–0.18) with a predicted increase in HHI of at least 0.02 points. In Column (4) of Panel A and Column (2) of Panel B, the treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.23 (0.13–0.18) with a predicted increase in HHI of at least 0.02 points. In Column (5) of Panel A and Column (3) of Panel B, the treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.26 (0.10–0.18) with a predicted increase in HHI between 0.02 and 0.03 points. *ln(Donation amount)* is the natural logarithm of one plus the dollar amount of donations to nonprofits in a given banking market by a given bank in a given year. $Treat_m$ is a binary variable that equals to one if a bank operates branches in a banking market where antitrust intervention is predicted and zero otherwise. *PostMerger* is a binary variable that equals to one for the years following bank mergers and zero otherwise. *MSA* (%) is the proportion of a banking market where a given bank operates branches in counties categorized as a MSA. *Period* is a binary variable that equals to one in the year 2011 or later and zero otherwise. For all specifications, standard errors are robust to heteroscedasticity and double clustered at the bank- and year levels; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Panel A: Difference-in-differences estimates

Dep. variable: $ln(Donation\ amount)_t$	0.08-point range, $\Delta HHI \geq 0.02$			0.05-point range, $\Delta HHI \geq 0.02$	0.08-point range, $\Delta HHI \in [0.02, 0.03]$
	(1)	(2)	(3)	(4)	(5)
PostMerger	0.020	0.022	0.049	0.047*	0.065
	(0.95)	(1.17)	(0.83)	(1.84)	(0.59)
$PostMerger \times Treat_m$	0.102***	0.108***	0.163***	0.097***	0.149***
	(3.78)	(3.59)	(3.82)	(3.47)	(4.03)
MSA (%)		1.303***	1.045***		
		(4.47)	(3.65)		
$PostMerger \times Period$			0.013		
			(0.20)		
$Treat_m \times Period$			−0.001		
			(−0.01)		
$PostMerger \times Treat_m \times Period$			−0.072		
			(−1.21)		
Bank × banking market fixed effects	Yes	Yes	Yes	Yes	Yes
Bank × year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	10,327	10,303	25,999	6,126	8,597
Adj R^2	0.97	0.96	0.95	0.96	0.97

Panel B: Regression discontinuity estimates

Dep. variable: $ln(Donation\ amount)_{t+1}$	0.08-point range, $\Delta HHI \geq 0.02$ (1)	0.05-point range, $\Delta HHI \geq 0.02$ (2)	0.08-point range, $\Delta HHI \in [0.02, 0.03]$ (3)
$Treat_m$	0.368***	0.369**	0.579**
	(3.97)	(2.61)	(2.46)

(continued)

Table V. Continued

Panel B: Regression discontinuity estimates			
Dep. variable: *ln(Donation amount)*$_{t+1}$	0.08-point range, $\Delta HHI \geq 0.02$ (1)	0.05-point range, $\Delta HHI \geq 0.02$ (2)	0.08-point range, $\Delta HHI \in [0.02, 0.03]$ (3)
Bank × banking market fixed effects	Yes	Yes	Yes
Bank × year-fixed effects	Yes	Yes	Yes
Observations	2,692	1,339	1,622
Adj R^2	0.97	0.94	0.98

Another important question is whether the local deposit market competition still matters in more recent years as compared to the earlier years in the sample. In particular, the rise of online banking could have weakened the local determinants of donations since the market for deposits has become more national. Thus, in more recent years, banks' donation decisions may be less responsive to local deposit market competition. To allow for changes in the nature of competition over time, we estimate an extension of Equation (2), whereby we add a binary variable, *Period*, which equals to one in the year 2011 or later and zero otherwise. This variable captures the period when the expansion of online banking was rapidly growing. We fully interact *Period* with the *PostMerger* and *Treat* variables. Additionally, we use all years of data before and after mergers occur (rather than restricting the window to be within 3 years before and after the merger) to capture long-run outcomes. We present the results in Column (3) of Panel A of Table V. Although the coefficient on the triple interaction term *PostMerger* × *Treat* × *Period* is negative, indicating that changes in local competition have a weaker effect on donation decisions in the latter period of our sample, it is not statistically distinguishable from zero. More importantly, the overall effect of local competition is given by the sum of the coefficients on *PostMerger* × *Treat* and *PostMerger* × *Treat* × *Period*, which is equal to 0.091 and is both statistically significant with an F-statistic of 4.67 ($p = 0.032$) and economically comparable to the result obtained in Column (1).

The estimation of Equation (2) relies on the parallel trends assumption, which requires that banks' donation decisions in response to mergers would be similar in treated and control markets, absent antitrust interventions. Intuitively, this assumption is likely to hold since interventions are based on exogenous regulatory cutoffs. To provide more concrete evidence, we conduct an event study by replacing *PostMerger* with year dummies, *PostMerger(k)*, ranging from 5 years before ($k = -5$) to 5 years after ($k = +5$) the merger year. The year before the merger is the omitted category so that all changes are relative to this year. Figure 3 shows the event study graph based on Column (1) of Panel A of Table V. As can be seen, pre-trends are parallel before mergers occur, but there is a sharp rise in the amount of donations for banks in markets where antitrust rules are applied coincident with the merger year and the subsequent 3 years.

In the final set of analysis, we use a different methodology based on RDD to estimate the effect of antitrust interventions on banks' donation decisions. Since we do not find evidence that suggests banks engage in mergers strategically to avoid antitrust interventions nor do there appear to be any significant preexisting differences in bank characteristics between treated and control markets, the application of antitrust rules is arguably a random

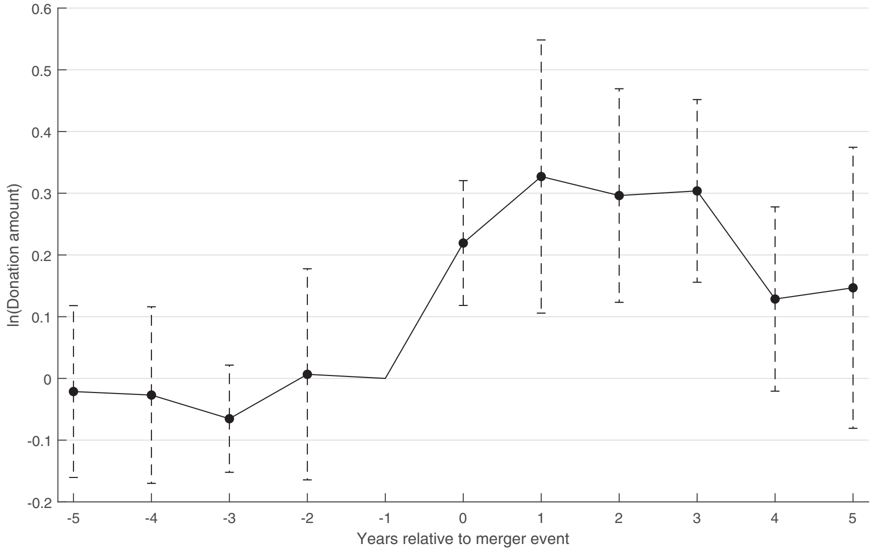

Figure 3. Dynamics of the amount of bank donations around banking market mergers. This figure shows the point estimates (solid line) and 95% confidence intervals (dashed lines) of the coefficients for the interaction term, *PostMerger*(*k*) × *Treat*$_m$, where *k* ranges from –5 to + 5, using the regression specification in Column (1) of Panel A of Table V. The treated (control) banking markets are those where the predicted post-merger HHI is between 0.18 and 0.26 (0.10–0.18) with a predicted increase in HHI of at least 0.02 points. The year before the merger is the omitted category. The dependent variable, ln(Donation amount), is the natural logarithm of one plus the dollar amount of donations to nonprofits in a given banking market by a given bank in a given year. *Treat*$_m$ is a binary variable that equals to one if a bank operates branches in a banking market where antitrust intervention is predicted and zero otherwise. Variable definitions are presented in Appendix Table A.1.

assignment in a small interval around the 0.18 threshold. Using RDD, therefore, captures the discontinuity in banks' donation decisions around the threshold. We estimate the following local linear regression:

$$\begin{aligned} ln(Donation\ amount)_{i,m,t+1} &= \beta_0 + \beta_1 Treat_{m,t} + \beta_2 Dist_{m,t} + \beta_3 Treat_{m,t} \times Dist_{m,t} \\ &+ \gamma_{i,m} + \delta_{i,t} + \varepsilon_{i,m,t+1} \end{aligned} \tag{3}$$

for bank i, banking market m, and year t. We focus on the year of the merger and examine subsequent year donations. $Dist_{m,t}$ is the centered HHI (i.e. the running variable in RDD parlance), defined as the difference between the predicted post-merger HHI and the threshold of 0.18. Positive (negative) values indicate that the market is in violation of (compliance with) the antitrust rules. $Treat_{m,t}$ is a binary variable that equals to one if a bank operates branches in banking market m where antitrust intervention is predicted in year t and zero otherwise. The RDD estimate of the intention-to-treat effect is given by the coefficient β_1.

We present the RDD estimation results in Column (1) of Panel B of Table V. We use the baseline neighborhood of 0.08 points around the threshold so that the sample of banking markets consists of those where the predicted post-merger HHI is between 0.10 and 0.26, with a predicted increase in HHI of at least 0.02 points. The coefficient on *Treat* is positive and significant, indicating that banks operating in markets where mergers result in an HHI that is slightly above the threshold subsequently donate 44% more to local nonprofits than those that operate in markets where mergers result in an HHI that is slightly below the threshold.[16] Similar results are obtained using alternative neighborhoods around the threshold in Columns (2) and (3). Overall, the evidence presented in this section suggests that the local deposit market competition is a determinant of banks' donation decisions.

5. Bank Donations and Deposit Market Shares

In this section, we investigate whether donations to local nonprofits translate into greater local deposit market share. We begin by documenting a robust positive relation between local donations and deposit market shares. We then use an identification strategy based on county-level natural disasters to control for the endogenous nature of bank donations.

5.1 Baseline Evidence on the Relation between Bank Donations and Deposit Market Shares

Our baseline specification examines the relation between bank donations to local nonprofits and subsequent local deposit market shares:

$$Deposit\ share_{i,c,t+1} = \beta_0 + \beta_1 ln(Donation\ amount)_{i,c,t} + \beta_2 X_{c,t} + \gamma_{i,c} + \delta_{i,t} + \varepsilon_{i,c,t+1} \quad (4)$$

for bank i, county c, and year t. We include bank × county fixed effects ($\gamma_{i,c}$) to control for time-invariant donation preferences. We also include bank × year-fixed effects ($\delta_{i,t}$) to control for time-varying bank factors. If donation decisions are strategic and lead to additional benefits in the form of increased deposit shares, then we predict a positive coefficient for β_1.

We present the results in Column (1) of Table VI. The coefficient on *ln(Donation amount)* is positive and statistically significant, indicating that greater donations to local nonprofits are associated with higher future local deposit market share. Economically, for the average bank in our sample, this coefficient implies that a 1% percent increase in the dollar value of local donations is associated with an increase of roughly $34,431 in deposits for the bank in the same county.[17] In Columns (2)–(4), we control for price competition by including controls for local deposit interest rates by averaging the deposit rates on certificates of deposit, money market accounts, and savings accounts, respectively, across all branches of a given bank in a given county (Egan *et al.*, 2017; Dlugosz *et al.*, 2022).[18] However, the results remain qualitatively similar.

16 The results obtained using RDD have a stronger economic significance when compared to those using difference-in-differences, which is consistent with the fact that the majority of branch divestitures due to the application of antitrust rules occur in the following year after mergers according to the DOJ. Thus, the increase in local deposit market competition is strongest in the following year after mergers with predicted antitrust interventions, which arguably elicits the strongest response in banks' donation decisions. Using difference-in-differences, however, estimates the average effect of an increase in local deposit market competition on donations to local nonprofits over the following 3 years after mergers, which results in a relatively smaller economic magnitude since incentives to donate decrease with the passage of time after mergers.

17 The average deposit at the county level in our sample is approximately $3.443 billion. Assuming total county-level deposits do not change, then, a 1% increase in the dollar value of donations leads to an increase of $3.443 billion $\times 0.001/100 \approx$ $34,431 in deposits.

18 We include the controls for deposit rates one by one to avoid multicollinearity because they are highly correlated with each other (correlation coefficients are above 0.70).

Table VI. The relation between local deposit market share and bank donations

This table provides the OLS regression results of county-level bank deposit market share on bank donations. In all specifications, the dependent variable is the deposits of a bank in a given county in a given year divided by the total deposits of all banks in the same county and year. *ln(Donation amount)* is the natural logarithm of one plus the dollar amount of donations to non-profits in a given county by a given bank in a given year. $Dep\_12mcd10k_t$ is the deposit interest rate on a 12-month certificate of deposit of \$10,000 averaged across all branches of a given bank in a given county. Dep_mm10k_t is the deposit interest rate on money market accounts of \$10,000 averaged across all branches of a given bank in a given county. $Dep\_sav2500_t$ is the deposit interest rate on savings account of \$2,500 averaged across all branches of a given bank in a given county. Control variables include *ln(GDP per capita)*, *ln(Population)*, *ln(PI per capita)*, *ln(HPI)*, and *M&A*. For all specifications, standard errors are robust to heteroscedasticity and double clustered at the bank- and year levels; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Dep. variable: $Deposit\ share_{t+1}$	(1)	(2)	(3)	(4)
$ln(Donation\ amount)_t$	0.001***	0.001***	0.001***	0.001***
	(5.56)	(3.53)	(3.13)	(3.58)
$Dep\_12mcd10k_t$		−0.069		
		(−0.48)		
Dep_mm10k_t			−0.183	
			(−1.11)	
$Dep\_sav2500_t$				0.052
				(0.21)
Controls	Yes	Yes	Yes	Yes
Bank × county fixed effects	Yes	Yes	Yes	Yes
Bank × year-fixed effects	Yes	Yes	Yes	Yes
Observations	83,936	66,222	64,537	66,173
Adj R^2	0.93	0.94	0.94	0.94

While our baseline results indicate a positive relation between bank donations and deposit market share, it should not be interpreted as a causal relation since the reverse direction is just as plausible. In the next section, we mitigate endogeneity by using an identification strategy based on county-level natural disaster shocks.

5.2 Identification strategy Using Natural Disasters

Identification of the impact of bank donations on local deposit market shares is subject to a potential endogeneity concern, in that banks with better performance, as reflected by their deposit shares, are more likely to donate than banks with worse performance. Thus, the main econometric challenge is obtaining exogenous variations in the local supply of donations. Our empirical strategy can be split into three key steps and is highlighted in Figure 4.

In the first step, we examine counties that are hit by natural disasters ("shocked counties"). These shocked counties have a higher local demand for donations because residents and businesses in the affected county require funds to repair and rebuild. We show that banks respond to this spike in demand by increasing their donations to nonprofits in

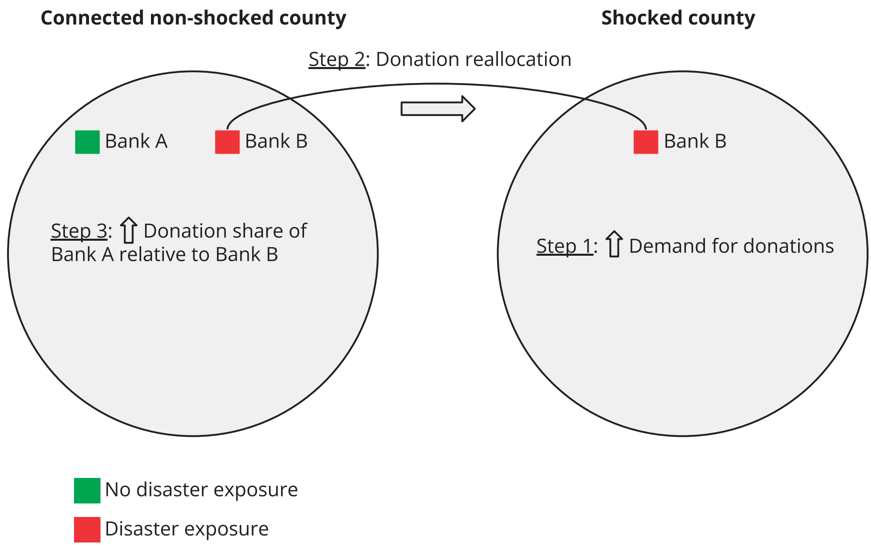

Figure 4. Empirical design using natural disasters. This figure illustrates the basic idea behind the identification strategy using natural disasters to examine the effect of bank donations on local deposit market shares. The empirical design can be split into three key steps. First, a natural disaster shock increases the local demand for donations in shocked counties. Second, banks that are exposed to the natural disaster shock reallocate donations away from connected nonshocked counties and toward shocked counties. Third, in connected nonshocked counties, banks that are not exposed to the natural disaster shock experience an exogenous increase in local donation shares relative to exposed banks.

shocked counties. In the second step, we examine counties where banks operate branches, but are not affected by natural disasters ("connected non-shocked counties"). We show that in order to satisfy the sudden spike in demand for donations in the shocked county, banks that operate in both shocked and connected nonshocked counties (e.g. Bank B) reallocate donations away from connected nonshocked counties and toward shocked counties.

In the third step, we focus our attention only on connected nonshocked counties and examine changes in the local donation share of banks that are not exposed to natural disaster shocks (e.g. Bank A) relative to those that are exposed (e.g. Bank B). In particular, we show that the reallocation of donations for banks that are exposed to natural disaster shocks represents an exogenous increase in the local share of donations in connected nonshocked counties for banks with no disaster exposure. Finally, we use this exogenous variation in local donation share to study the effects on local deposit market share in connected nonshocked counties. Each of the steps in our empirical strategy is explained in more detail below.

5.2.a. *Increase in demand for donations in shocked counties*

Shocked counties have a higher local demand for donations because of the need for disaster-relief funds. While some funds may come from FEMA and insurance payments, there is still likely to be an excess demand for donations in the presence of relatively large disasters. Furthermore, natural disasters incentivize banks to donate to the affected areas because these donations are often highly visible in the local media and/or national broadcasting, improving the banks' public relations.[19] In this section, we show that there is an abnormal increase in bank donations in shocked counties after a natural disaster.

Some preliminary evidence of an increase in donations in shocked counties is documented in Panel B of Table II. On average, donations directed toward nonprofits in counties that are affected by natural disaster shocks are significantly larger. To systematically examine how banks vary their donations year by year around natural disasters, we estimate the following specification:

$$ln(Donation\ amount)_{i,c,t} = a_0 + a_1 Disaster_c + \sum b_k PostShock(k) + \sum \beta_k PostShock(k) \times Disaster_c + a_3 X_{c,t} + \gamma_{i,c} + \delta_{i,t} + \varepsilon_{i,c,t} \tag{5}$$

for bank i, county c, and year t. We focus on 5 years before ($k = -5$) to 5 years after ($k = +5$) the natural disaster shock, where $PostShock(k)$ are year dummies with $k = 0$ representing the year in which the shock itself occurs. The year before the natural disaster shock is the omitted category, implying that changes in donations are relative to this year. $Disaster_c$ is a binary variable that equals to one if a county is hit by a natural disaster shock and zero otherwise.

Figure 5 reports the coefficients of the interaction term $PostShock(k) \times Disaster_c$ along with the 95% confidence intervals for the estimates. These coefficients measure the difference in post-disaster donations between banks operating in shocked counties and those in nonshocked counties. Figure 5 shows that there are no distinguishable differences in donations before the natural disaster shock, consistent with the shock being exogenous and unexpected. However, banks operating in shocked counties significantly increase their donations to local nonprofits during the year of the natural disaster; the increase lasts for several years before dissipating by the fourth year. In summary, our results are consistent with banks increasing their donations in shocked counties in response to an increase in the local demand for donations.

5.2.b. *Reallocation of donations*

A stylized fact of corporate foundations' grantmaking is that their charitable giving remains relatively stable over time even if there are fluctuations in the firms' contributions to their foundations in any given year (Webb, 1994; Petrovits, 2006; Sansing and Yetman, 2006).[20] Thus, to maintain a smooth distribution of donations during a natural disaster, banks may reallocate donations away from connected nonshocked counties and toward shocked counties to satisfy the sudden spike in demand for donations in the shocked counties.

19 As an anecdotal example, JPMorgan Chase announced on September 12 2017, an initiative to donate \$1 million to aid the response to Hurricane Irma. On September 14 2017, a local nonprofit, Hispanic Unity of Florida, voiced its support of the initiative on Twitter. Using our bank donation data, we can confirm that this particular nonprofit received \$350,000 from JPMorgan Chase in 2017. It is clear from this example that natural disaster shocks trigger bank donations, and nonprofits do indeed respond to such donations.

20 Petrovits (2006) showed that firms may use their foundations when engaging in earnings management. Also, the literature has documented multiple reasons as to why foundations smooth their distributions over time including tax-induced incentives (Sansing and Yetman, 2006) and maintaining a steady level of corporate goodwill (Webb, 1994).

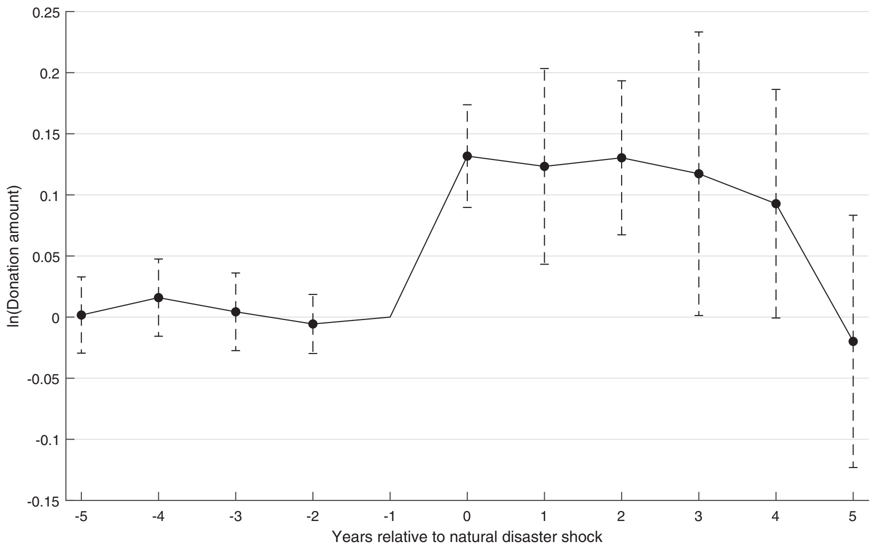

Figure 5. Dynamics of donations at the bank–county–year level around natural disaster shocks. This figure shows the point estimates (solid line) and 95% confidence intervals (dashed lines) of the coefficients for the interaction term, *PostShock(k)* $\times$ *Disaster*$_c$, where *k* ranges from –5 to + 5, using the regression specification in Equation (5). Standard errors are robust to heteroscedasticity and double clustered at the bank- and year levels. The year before the natural disaster shock is the omitted category. The dependent variable, ln(Donation amount), is the natural logarithm of one plus the dollar amount of donations to nonprofits in a given county by a given bank in a given year. *Disaster*$_c$ is a binary variable that equals to one if a county is hit by a natural disaster shock and zero otherwise. Variable definitions are presented in Appendix Table A.1.

To provide evidence of donation reallocation, we construct a panel data set at the bank–county–year level. For each bank–year, we include all of the counties in which that bank donated to nonprofits in the prior calendar year. These counties are assumed to contain the relevant nonprofits for the banks' charitable activities. Once a bank–county enters our data set, we keep it going forward, even if during some years that bank made no donations to nonprofits in that county. We then flag each county as shocked in the year in which that county experienced a natural disaster and keep it labeled as shocked for the next 4 years.[21] We drop these shocked county–years from our sample because our aim is to study how the shock affects donations in connected nonshocked counties.

To measure the incremental donations made by each bank in the shocked county–years stemming from the higher local demand for donations experienced by these banks as a consequence of the natural disaster, we construct the following variable at the bank–year level:

$$\textit{Disaster donation}_{i,t} = \frac{\Delta \textit{Donation in shocked counties}_{i,t}/N_{i,t}}{\sum_c \textit{Donation amount}_{i,c,t}} \tag{6}$$

where i indexes bank, c indexes county, and t indexes year. $\Delta \textit{Donation in shocked counties}_{i,t}$ is equal to the change in the total dollar amount of donations between year t and year $t-1$,

21 Given the results in Figure 5, changes in donation during these 4 years are assumed to stem from the extra local demand for donations due to the shock.

summed across all shocked counties where the bank operates. However, since a given bank operates across many different connected nonshocked counties, we parcel out the additional increase in donations in shocked counties equally across the number of connected nonshocked counties ($N_{i,t}$) to measure the average amount of donations reallocated to shocked counties from nonshocked ones. Finally, we normalize by each bank's total donations summed across all counties so that $Disaster\ donation_{i,t}$ is bounded between –1 and 1. For example, banks' exposure to natural disasters in nonshocked markets is equal to zero if the banks operate in only one market.

Using the constructed data set, we estimate the effect of each bank's additional donations from the demand increase in shocked counties on its donation in connected nonshocked counties as follows:

$$\Delta Connected\ donation_{i,c,t} = \beta_0 + \sum_{k=1}^{4} \beta_k Disaster\ donation_{i,t-k} + \beta_5 X_{i,t} + \beta_6 X_{c,t} + \gamma_{i,c} + \nu_i + \phi_t + \varepsilon_{i,c,t} \tag{7}$$

for bank i, county c, and year t. The dependent variable is measured at the bank–county–year level and is equal to the change in the total dollar amount of donations between year t and year $t-1$ in connected nonshocked counties, normalized by the total dollar amount of donations of the given bank in year t across all counties. We include bank × county fixed effects ($\gamma_{i,c}$) to control for time-invariant donation preferences as in Equation (4). However, we do not include bank × year-fixed effects because they will absorb *Disaster donation*. Instead, we include individual bank fixed effects (ν_i), year-fixed effects (ϕ_t), and control for a variety of bank ($X_{i,t}$) and county ($X_{c,t}$) characteristics. The coefficients of interest are those on the four lags of the *Disaster donation* variable, which capture the extent to which banks reallocate donations from connected nonshocked counties to shocked counties in response to the heightened demand for donations in the 4 years following a natural disaster.

The estimation results of Equation (7) are presented in Column (1) of Panel A of Table VII. We find that the coefficients on the first three lags of *Disaster donation* are all negative and statistically significant, suggesting that banks reallocate donations away from connected nonshocked counties and toward shocked counties. Furthermore, the magnitude of the coefficients decreases monotonically as we move from the first lag to the third lag and eventually becomes statistically insignificant at the fourth lag. This result suggests that the majority of the reallocation occurs in the first year following natural disaster shocks, gradually becomes weaker over time, and eventually dissipates in the fourth year.

The regression in Equation (7) is based on dollar changes in normalized donations divided equally across connected nonshocked counties. Thus, the sum of the coefficients on the lags of *Disaster donation* provides a straightforward economic interpretation on the total effect per dollar of increased donation in shocked counties on the changes in donations in connected nonshocked counties. The sum of all four lags in the first column of Panel A of Table VII is -1.561 and is statistically significant with an F-statistic of 26.91. This result shows that the effect of donation reallocation is economically

Table VII. The effect of natural disasters on the reallocation of donations from connected non-shocked counties to shocked counties

This table provides the regression results involving the reallocation of donations from connected nonshocked counties to satisfy the excess demand for donations in counties hit by a natural disaster shock. Panel A presents the regression of Δ*Connected donation* on four lags of the *Disaster donation* variable. Column (1) uses the full sample of connected nonshocked counties, while Column (2) removes connected nonshocked counties that are adjacent to counties hit by a natural disaster shock. The dependent variable, $\Delta Connected\ donation_{i,c,t}$, is measured at the bank–county–year level and is equal to the change in the total dollar amount of donations between year t and year $t-1$ in connected nonshocked counties, normalized by the total dollar amount of donations of the given bank in year t across all counties. The independent variable, $Disaster\ donation_{i,t}$, is measured at the bank–year level and is equal to the change in the total dollar amount of donations between year t and year $t-1$, summed across all shocked counties and normalized by the total dollar amount of donations of the given bank in year t across all counties; we divide this by the number of connected nonshocked counties associated with the bank in year t. Panel B presents the results of the regression of the natural logarithm of one plus the dollar amount of donations to nonprofits in connected nonshocked counties on *Disaster exposure*, which equals to one for banks that operate in shocked counties for the 3 years following a natural disaster, and a second indicator variable *Pre-disaster exposure*, which equals to one for banks that operate in shocked counties for the 3 years preceding a natural disaster. Control variables include *Equity ratio*, *ln(Size)*, *Loan ratio*, *NPL*, *LLR*, *LLP*, *ROA*, *MBHC*, *ln(GDP per capita)*, *ln(Population)*, *ln(PI per capita)*, *ln(HPI)*, and *M&A*. For all specifications, standard errors are robust to heteroscedasticity and double clustered at the bank- and year levels; t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Panel A: Reallocation of donations

Dep. variable: $\Delta Connected\ donation_{i,c,t}$	All connected nonshocked counties (1)	Drop adjacent to shocked counties (2)
$Disaster\ donation_{i,t-1}$	-0.984^{***}	-0.678^{***}
	(-5.62)	(-3.80)
$Disaster\ donation_{i,t-2}$	-0.416^{***}	-0.453^{***}
	(-3.31)	(-6.89)
$Disaster\ donation_{i,t-3}$	-0.172^{***}	-0.165^{***}
	(-5.53)	(-4.26)
$Disaster\ donation_{i,t-4}$	0.011	0.051
	(0.07)	(0.30)
Controls	Yes	Yes
Coefficient sum	-1.561	-1.244
F(sum of four lags)	26.91	22.30
p-value	0.000	0.001
Bank × county fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes

(continued)

Table VII. Continued

Panel A: Reallocation of donations

Dep. variable: $\Delta Connected\ donation_{i,c,t}$	All connected nonshocked counties (1)	Drop adjacent to shocked counties (2)
Observations	15,977	11,935
Adj R^2	0.35	0.23

Panel B: Testing for reallocation pre-trends

Dep. variable: $ln(Donation\ amount)_{i,c,t}$	(1)	(2)
$Disaster\ exposure_{i,t}$	-0.255^{**}	-0.262^{**}
	(−2.19)	(−2.22)
$Pre-disaster\ exposure_{i,t}$		0.096
		(0.93)
Controls	Yes	Yes
Bank × county fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
Observations	11,935	11,935
Adj R^2	0.77	0.78

sizable as it implies that donations fall by roughly \$1.60 in connected nonshocked counties per dollar of additional donations stimulated by natural disasters in shocked counties.[22]

In Column (2) of Panel A of Table VII, we remove all county–years in which a connected nonshocked county is adjacent to a shocked county to account for spillovers that could introduce noise in our analysis of donation reallocations. For example, banks may shy away from reallocating donations from connected nonshocked counties that are adjacent to shocked counties because these counties might also suffer from the peripheral effects of the shock. However, the results are qualitatively unchanged after dropping these connected nonshocked counties that are adjacent to shocked counties.

To ensure that there are no pre-trends driving the reallocation of donations, we regress the natural logarithm of one plus the dollar amount of donations to nonprofits in connected nonshocked counties on *Disaster exposure*, which equals to one for banks that operate in shocked counties for the 3 years following a natural disaster, and a second indicator variable *Pre-disaster exposure*, which equals to one for banks that operate in shocked counties for the 3 years preceding a natural disaster. Connected nonshocked counties that are adjacent to shocked counties are dropped from the regression to avoid any spillover effects. The

22 A plausible explanation for why the magnitude of the decrease in donations in connected nonshocked counties is greater than the dollar increase in shocked counties is that the average bank in our sample operates more branches in shocked counties than in connected nonshocked counties. Specifically, the average bank operates thirty-three branches in shocked counties compared with twenty-five branches in connected nonshocked counties. Thus, the reallocation toward every additional dollar of donations in shocked counties is "spread" over a less number of connected nonshocked counties.

first column of Panel B of Table VII validates our basic finding that there is a contraction in donations in connected nonshocked counties in response to natural disaster shocks. In Column (2), the coefficient on the *Pre-disaster exposure* variable is statistically insignificant, suggesting that it is unlikely that trends in donations are nonparallel in connected nonshocked counties prior to the natural disaster shocks.

5.2.c. *Exogenous variation in donation share in connected nonshocked counties*

In the last step of our empirical strategy, we show that the reallocation of donations by banks that are exposed to natural disaster shocks leads to an exogenous increase in the local donation share of nonexposed banks in connected nonshocked counties. We focus on 3 years before to 3 years after a natural disaster shock and estimate the following regression using only the sample of connected nonshocked counties:

$$\begin{aligned} \textit{Donation share}_{i,c,t} &= \beta_0 + \beta_1 \textit{No disaster exposure}_i + \beta_2 \textit{PostShock}_t + \beta_3 \textit{PostShock}_t \\ &\times \textit{No disaster exposure}_i + \beta_4 X_{c,t} + \gamma_{i,c} + \delta_{i,t} + \varepsilon_{i,c,t} \end{aligned} \tag{8}$$

for bank i, county c, and year t. The dependent variable is the dollar amount of donations to nonprofits of a given bank in a given connected nonshocked county in a given year divided by the total dollar amount of donations of all banks in the same county and year. *No disaster exposure* is a binary variable that equals to one if a bank operates only in a connected nonshocked county and does not operate any branches in shocked counties during the event window and zero otherwise. *PostShock* is a binary variable that equals to one for the years following the natural disaster shock and zero otherwise. The coefficient of interest is β_3, which represents the difference in post-disaster donation share in connected nonshocked counties between nonexposed and exposed banks.

We present the results in Column (1) of Table VIII. The positive and statistically significant coefficient on *PostShock* × *No disaster exposure* implies that nonexposed banks experience an increase in donation share of 0.014 in connected nonshocked counties relative to exposed banks, corresponding to an increase of 5% relative to the unconditional sample mean. In Column (2), we remove connected nonshocked counties that are adjacent to shocked counties and the results remain qualitatively similar.

A potential concern is that banks that operate in both connected nonshocked counties and shocked counties (i.e. exposed banks) may not be directly comparable to those that operate only in connected nonshocked counties (i.e. nonexposed banks) because they differ on some dimensions. To account for systematic differences between nonexposed and exposed banks, we begin with the same initial sample as in Column (1) of Table VIII, but each bank that is not exposed to a natural disaster shock is matched to a bank that is exposed to the *same* shock using nearest-neighbor propensity score matching with replacement (Roberts and Whited, 2013). We use a probit model and include bank characteristics such as *Equity ratio*, *ln(Size)*, *Loan ratio*, *NPL*, *LLR*, *LLP*, *ROA*, and *MBHC*. Supplementary Appendix Table IA.3 shows that there are no observable differences between nonexposed and exposed banks after the matching.[23] The results of estimating Equation (8) using the matched sample are presented in Column (3). The coefficient on *PostShock* × *No disaster exposure* remains positive and statistically significant.

23 We should note that our matching methodology allows us to control for *observable* systematic differences between banks. A limitation, perhaps unavoidable, lies in the fact that we are unable to control for possible *unobservable* differences, but instead only mitigate their confounding effects.

Table VIII. The effect of reallocation of donations on local donation share in connected nonshocked counties

This table examines how the reallocation of donations affects the local donation share in connected nonshocked counties. We focus on 3 years before to 3 years after a natural disaster shock. The dependent variable is the dollar amount of donations to nonprofits of a given bank in a given connected nonshocked county in a given year divided by the total dollar amount of donations of all banks in the same county and year. Column (1) uses the full sample of connected nonshocked counties, while Column (2) removes connected nonshocked counties that are adjacent to counties hit by a natural disaster shock. Column (3) uses the same initial sample as in Column (1), but each bank that is not exposed to a natural disaster shock (i.e., $No\ disaster\ exposure = 1$) is matched to a bank that is exposed to the same shock (i.e., $No\ disaster\ exposure = 0$) using nearest-neighbor propensity score matching with replacement (Roberts and Whited, 2013). The bank characteristics used in the matching include *Equity ratio*, *ln(Size)*, *Loan ratio*, *NPL*, *LLR*, *LLP*, *ROA*, and *MBHC*. Column (4) uses WLS regression with propensity score-derived weights, as in Caliendo and Kopeinig (2008). *No disaster exposure* is a binary variable that equals to one if a bank operates only in a connected nonshocked county and does not operate any branches in shocked counties during the event window and zero otherwise. *PostShock* is a binary variable that equals to one for the years following the natural disaster shock and zero otherwise. Control variables include *ln(GDP per capita)*, *ln(Population)*, *ln(PI per capita)*, *ln(HPI)*, and *M&A*. For all specifications, standard errors are robust to heteroscedasticity and double clustered at the bank- and year levels; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Dep. variable: $Donation\ share_{i,c,t}$	All connected nonshocked counties (1)	Drop adjacent to shocked counties (2)	Propensity score matched sample (3)	Propensity score WLS (4)
$No\ disaster\ exposure_i$	−0.003	−0.007	−0.019	−0.004
	(−0.70)	(−1.25)	(−0.67)	(−0.77)
PostShock	−0.006**	−0.008***	−0.011	−0.006**
	(−2.28)	(−2.86)	(−0.76)	(−2.37)
$PostShock \times No\ disaster\ exposure_i$	0.014***	0.025***	0.037**	0.012***
	(2.59)	(3.16)	(2.08)	(2.79)
Controls	Yes	Yes	Yes	Yes
Bank × county fixed effects	Yes	Yes	Yes	Yes
Bank × year-fixed effects	Yes	Yes	Yes	Yes
Observations	15,415	12,952	7,634	15,415
Adj R^2	0.65	0.63	0.57	0.67

Rather than discarding the nonmatched observations, we could incorporate all observations by estimating Equation (8) using a weighted least squares (WLS) procedure in which the weights are inversely proportional to the probability of an observation belonging to a nonexposed or exposed bank. Specifically, we follow the procedure in Caliendo and Kopeinig (2008), whereby for each observation, we estimate the propensity score $\hat{p}$ as the conditional probability of the observation belonging to a nonexposed bank, derived from the probit model used in the matching above. An observation with a nonexposed bank receives a weight w so that $w = 1/\hat{p}$, whereas an observation with an exposed bank receives a weight w so that $w = 1/(1-\hat{p})$. Intuitively, propensity score weighting assigns a lower weight to nonexposed bank observations, which are "very different" (in terms of bank characteristics) from exposed bank observations and similarly gives a lower weight to exposed bank observations, which are "very different" from nonexposed bank observations. We present the results in Column (4) of Table VIII and show that the coefficient on *PostShock* × *No disaster exposure* remains unchanged, suggesting that nonexposed banks experience an increase in donation share in connected nonshocked counties relative to exposed banks after accounting for systematic differences in bank characteristics.

5.2.d. ***Disaster exposure and local deposit market share***

Now that we have verified the premise of our identification strategy, we use the exogenous variation in local donation share attributable to disaster exposure to study the effects on local deposit market share. If donations do attract additional deposits, then we expect nonexposed banks to experience an increase in local deposit market share relative to exposed banks. Our specification is similar to Equation (8), in that we use data from 3 years before to 3 years after a natural disaster shock and only use the sample of connected nonshocked counties, except the dependent variable measures local deposit market share:

$$\begin{aligned} Deposit\ share_{i,c,t} &= \beta_0 + \beta_1 No\ disaster\ exposure_i + \beta_2 PostShock_t + \beta_3 PostShock_t \\ &\times No\ disaster\ exposure_i + \beta_4 X_{c,t} + \gamma_{i,c} + \delta_{i,t} + \varepsilon_{i,c,t} \end{aligned} \tag{9}$$

for bank i, county c, and year t. *Deposit share* is the deposits of a given bank in a given connected nonshocked county in a given year divided by the total deposits of all banks in the same county and year. All other variables are defined as previously described. The coefficient of interest is β_3, which represents the difference in post-disaster deposit market share in connected nonshocked counties between banks that are not exposed to natural disaster shocks and those that are exposed.

We present the results in Table IX. Column (1) uses the full sample, while Column (2) removes connected nonshocked counties that are adjacent to shocked counties. Column (3) uses a matched sample of exposed banks using the propensity score matching methodology described in the previous section, and Column (4) uses WLS regression with propensity score-derived weights. Across all four columns, the coefficient on *PostShock* × *No disaster exposure* is positive and statistically significant, suggesting that nonexposed banks experience higher local deposit market shares in connected nonshocked counties compared to exposed banks. Economically, the coefficient estimate in Column (1) corresponds to roughly a 4% increase relative to the unconditional sample mean. In Columns (5)–(7), we control for local deposit interest rates in connected nonshocked counties to account for changes in local deposit market shares that are attributable to changes in deposit rates. However, the coefficients on *PostShock* × *No disaster exposure* remain unchanged.

Figure 6 plots the event study graph based on Column (1) of Table IX by replacing *PostShock* with year dummies. The year before the natural disaster shock is the omitted category. We extend the window from 5 years before to 5 years after a shock to observe if there are any pre-trends in the data and to see how long the gap in deposit shares persists for. In the years leading up to the natural disaster shock, we do not find any evidence of pre-trends in the local deposit market shares in connected nonshocked counties since there is no significant difference in deposit shares between nonexposed and exposed banks.

Table IX. Disaster exposure and local deposit market share in connected nonshocked counties

This table examines the effect of banks' exposure to natural disaster shocks on their local deposit market share in connected nonshocked counties. We focus on 3 years before to 3 years after a natural disaster shock. The dependent variable is the deposits of a given bank in a given connected nonshocked county in a given year divided by the total deposits of all banks in the same county and year. Column (1) uses the full sample of connected nonshocked counties, while Column (2) removes connected nonshocked counties that are adjacent to counties hit by a natural disaster shock. Column (3) uses the same initial sample as in Column (1), but each bank that is not exposed to a natural disaster shock (i.e. *No disaster exposure* = 1) is matched to a bank that is exposed to the same shock (i.e. *No disaster exposure* = 0) using nearest-neighbor propensity score matching with replacement (Roberts and Whited, 2013). The bank characteristics used in the matching include *Equity ratio*, *ln(Size)*, *Loan ratio*, *NPL*, *LLR*, *LLP*, *ROA*, and *MBHC*. Column (4) uses WLS regression with propensity score-derived weights, as in Caliendo and Kopeinig (2008). Columns (5)–(7) use the same sample as in Column (1), but control for local deposit market interest rates. *No disaster exposure* is a binary variable that equals to one if a bank operates only in a connected nonshocked county and does not operate any branches in shocked counties during the event window and zero otherwise. *PostShock* is a binary variable that equals to one for the years following the natural disaster shock and zero otherwise. *Dep_12mcd10k* is the deposit interest rate on a 12-month certificate of deposit of $10,000 averaged across all branches of a given bank in a given county. *Dep_mm10k* is the deposit interest rate on money market accounts of $10,000 averaged across all branches of a given bank in a given county. *Dep_sav2500* is the deposit interest rate on savings account of $2,500 averaged across all branches of a given bank in a given county. Control variables include *ln(GDP per capita)*, *ln(Population)*, *ln(PI per capita)*, *ln(HPI)*, and *M&A*. For all specifications, standard errors are robust to heteroscedasticity and double clustered at the bank- and year levels; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Dep. variable: *Deposit share*$_{i,c,t}$	All connected nonshocked counties	Drop adjacent to shocked counties	Propensity score matched sample	Propensity score WLS	Controls for local deposit rates		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No disaster exposure$_i$	−0.001	−0.001	−0.001	−0.001	−0.001	−0.000	−0.001
	(−0.35)	(−0.67)	(−1.61)	(−0.36)	(−0.31)	(−0.17)	(−0.28)
PostShock	0.000	0.000	−0.002***	0.000	0.000	0.000	0.000
	(0.11)	(0.23)	(−3.82)	(0.07)	(0.30)	(0.08)	(0.29)
PostShock ×*No disaster exposure*$_i$	0.005***	0.006***	0.002**	0.004***	0.006***	0.006***	0.006***
	(3.79)	(3.99)	(1.99)	(3.40)	(2.84)	(2.80)	(2.86)

(continued)

Table IX. Continued

Dep. variable: *Deposit share*$_{i,c,t}$	All connected nonshocked counties	Drop adjacent to shocked counties	Propensity score matched sample	Propensity score WLS	Controls for local deposit rates		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Dep\_12mcd10k_t$					0.164		
					(0.50)		
Dep_mm10k_t						0.808	
						(1.20)	
$Dep\_sav2500_t$							0.599
							(0.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × county fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,415	12,952	7,634	15,415	14,107	13,682	14,106
Adj R^2	0.93	0.94	0.95	0.95	0.93	0.94	0.94

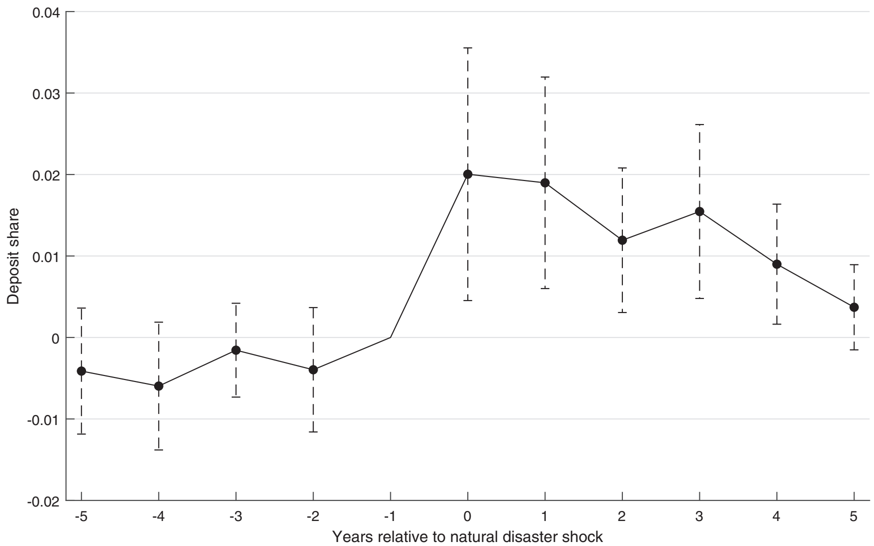

Figure 6. Dynamics of local deposit market share in connected nonshocked counties around natural disaster shocks. This figure shows the point estimates (solid line) and 95% confidence intervals (dashed lines) of the coefficients for the interaction term, *PostShock*(*k*) × *No disaster exposure*$_i$, where *k* ranges from –5 to + 5, using the regression specification in Column (1) of Table IX. The year before the natural disaster shock is the omitted category. The dependent variable, Deposit share, is the deposits of a given bank in a given connected nonshocked county in a given year divided by the total deposits of all banks in the same county and year. *No disaster exposure*$_i$ is a binary variable that equals to one if a bank operates only in a connected nonshocked county and does not operate any branches in shocked counties during the event window and zero otherwise. Variable definitions are presented in Appendix Table A.1.

However, coincident with the start of the natural disaster shock, deposit market shares are higher for nonexposed banks. This gap is maintained for the next few years before dissipating.

6. Profitability and Donation Recipient Characteristics

In the following sections, we conduct a hypothetical exercise to quantify how much of the increase in deposits through donations can potentially translate into profits. Then, we examine the characteristics of the nonprofits that banks prefer to donate to.

6.1 Profitability of Bank Donations

Our goal in this section is to conduct a hypothetical exercise to gage the potential increase in profits attributable to the increase in deposits through donations. This exercise is important since it attributes economic importance to the benefits that banks receive from making donations. For example, Egan, Lewellen, and Sunderam (2022) demonstrate that deposit productivity accounts for the vast majority of the variation in bank value. In our analysis, we formally test for differences in profits between donating and nondonating banks, assuming that a donating bank channels all of the increase in local deposits due to donations into making local loans.[24] Specifically, we decompose this difference in donation impact—which we call, for brevity, a premium—into three components, due to bank characteristics (bank premium), county characteristics (county premium), and most importantly, the fact that the bank makes donations (donation premium), respectively. To measure profits, we first multiply the net interest rate spread (defined as the difference between the local loan and local deposit interest rates) by the yearly change in deposits at the bank–county level. Then, to account for the relationship between deposit productivity and loan productivity, we use the calibration estimates obtained from Egan, Lewellen, and Sunderam (2022) to adjust for deposit productivity.[25] Finally, we subtract the total amount of donations.

We first estimate the total premium, whereby, for each donating bank, we identify a randomly drawn observation from the sample of nondonating banks (Match 1: Random). We then compute the difference between the mean profits for the donating bank sample and for this set of randomly matched nondonating banks. Next, we identify a series of matched observations resembling donating banks in terms of bank characteristics by using propensity score matching. To do so, we estimate a probit model in which the response is the *Donation* variable, which is equal to one if a given bank donates to nonprofits in a given county in a given year and zero otherwise. The set of predictors includes various bank characteristics. The results are presented in Column (1) of Supplementary Appendix Table IA.4. We then compute a probability score by fitting the estimated coefficients to the data set and match, with replacement, the nondonating bank observation with the closest probability score to each donating bank observation. This procedure enables us to identify a sample of nondonating bank observations that is the most similar to the sample of donating bank observations in terms of bank characteristics (Match 2: Bank characteristics). To estimate the premium component attributable to bank characteristics, we subtract the mean profits of Match 1 from that of Match 2. The rationale is that any systematic residual difference in profits between the two samples should be due to bank characteristics.

To compute the premium component attributable to county characteristics, we repeat the aforementioned matching procedure, but we include additional county characteristics in the probit model. The results are presented in Column (2) of Supplementary Table IA.4. This procedure identifies a sample of nondonating banks matched on the basis of bank and county characteristics (Match 3: Bank and county characteristics). To calculate the county premium, we subtract the mean profits of Match 2 from those of Match 3. The intuition is the same: any systematic residual difference in potential profits between the two samples should be due to county characteristics. Finally, to estimate the premium component attributable to donations, we compute the mean difference in profits between the donating bank

24 In reality, however, it is unlikely that a bank would channel all of its deposits into loans. Thus, the results obtained in this section should be interpreted as a hypothetical exercise that places an upper bound on the potential profits that could be earned from donations.

25 Specifically, Egan, Lewellen, and Sunderam (2022) find that a one-standard deviation increase in deposit productivity translates into a 0.26-standard deviation increase in loan productivity. Assuming that the inputs for local deposits and loans do not change, then using the standard deviation estimates from Egan, Lewellen, and Sunderam (2022) implies that a dollar increase in deposits translates to roughly a $0.11 increase in loans.

sample and Match 3; any systematic residual difference (after controlling for bank and county characteristics) is attributable to the donation decisions of the bank.

We present the results of the decomposition in Table X.[26] We use three measures of profit based on different loan rates averaged across all branches of a given bank in a given county: (i) the interest rate on $20,000 home equity loans, up to 80% of the loan to value, with a 60-month maturity; (ii) the interest rate on 4-year used auto loans for a 36-month term; and (iii) the interest rate on 15-year fixed-rate mortgage loans of $175,000. In all specifications, the deposit interest rate is that on a $10,000 certificate of deposit with a 12-month maturity. In all columns, the total premium is positive and statistically significant, indicating that donating banks can earn significantly more profits than those that do not make donations. By decomposing the total premium into its respective components, we can see that, while bank and county characteristics account for a sizable portion of the profit difference, the donation premium is much larger and always statistically significant. For example, in Column (1), the economic interpretation of the donation premium is that if a donating bank takes all of the increase in deposits attributable to donation decisions and uses it to make local home equity loans, then, on average, the donating bank can earn roughly $530,000 more in profits than nondonating banks with similar bank and county characteristics. The difference in profits is economically sizable relative to the unconditional mean donation of $227,000 from Table I.

A natural question to ask is what constitutes the source of these profits. Although a closer investigation is outside the scope of this article, we offer a plausible explanation based on the CSR literature. In particular, studies have shown that engagement in CSR is associated with improved stakeholder relations over the long term (Choi and Wang, 2009; Gregory, Tharyan, and Whittaker, 2014), which leads to better long-run growth prospects (Fatemi, Fooladi, and Tehranian, 2015) and profitability (Eccles, Ioannou, and Serafeim, 2014). In our context, the greater profit potential of donating banks may be a result of their improved reputation due to their charitable activities, which helps attract long-term clients with higher profit margins (Wu and Shen, 2013) and reduce nonperforming loans (Shen *et al.*, 2016).

6.2 Bank Donation Recipients and Nonrecipients

Consumers are often not aware of a firm's engagement in CSR (Sen and Bhattacharya, 2001; Bhattacharya and Sen, 2004; Pomering and Dolnicar, 2009). As a result, consumers are less likely to reward firms for their CSR activities unless they are made aware of such activities, which is usually achieved by increasing advertising intensity (McWilliams and Siegel, 2001; Servaes and Tamayo, 2013). Foundation giving to nonprofits can also serve to increase consumer awareness due to its salient nature and reputation-improving attributes (Barnett, 2007; Brammer and Millington, 2008). Thus, in this section, we analyze the types of nonprofits that banks prefer to donate to by comparing nonprofits that receive bank donations (recipients) to those that do not (nonrecipients). If charitable giving serves to improve banks' reputation and increase customers' awareness of their products, then we expect banks to donate to nonprofits with the biggest social impact to maximize the exposure and visibility of their charitable activities.

26 We only include donating bank observations for which we were able to match observations with nonmissing net interest rate spreads and for which all three sets of matches exist.

Table X. Decomposition of hypothetical bank profits following donations

This table provides the mean hypothetical profits (in thousands of US dollars) at the bank–county–year level, for banks that make donations and for matched samples of banks that do not make donations in the same year. Hypothetical profits are based on three factors: i) the net interest rate spread (defined as the difference between the loan and deposit interest rates) at the bank–county–year level; ii) the change in deposits at the bank–county–year level; and iii) the relationship between deposit productivity and loan productivity obtained from Egan, Lewellen, and Sunderam (2022). In all specifications, the deposit interest rate is the $10,000 certificate of deposit interest rate with a 12-month maturity averaged across all branches of a given bank in a given county. Column (1) uses the loan interest rate on $20,000 home equity loans, up to 80% of the loan to value, with a 60-month maturity, averaged across all branches of a given bank in a given county. Column (2) uses the loan interest rate on 4-year used auto loans for a 36-month term, averaged across all branches of a given bank in a given county. Column (3) uses the loan interest rate on 15-year fixed-rate mortgage loans of $175,000 averaged across all branches of a given bank in a given county. "Donation" is a sample of banks that make donations to non-profits in a given county–year. "Match 1" is a sample of randomly drawn banks that do not make donations in a given county–year. "Match 2" is a sample of banks that do not make donations matched on bank characteristics in the same year. "Match 3" is a sample of banks that do not make donations matched on bank and county characteristics in the same year. Means are tested using standard errors double clustered at the bank- and year levels; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Loan type:	Home equity (1)	Auto (2)	Fixed-rate mortgage (3)
Donation	824.213***	880.842***	891.557***
	(3.98)	(4.11)	(3.71)
Match 1: Random	88.399***	96.029***	78.545***
	(5.45)	(3.49)	(5.30)
Match 2: Bank characteristics	257.583***	268.270***	105.141
	(4.05)	(3.84)	(1.30)
Match 3: Bank and county characteristics	294.862***	353.352**	425.239***
	(3.87)	(2.03)	(4.20)
Total premium (Donation—Match 1)	735.814***	784.812***	813.013***
	(3.55)	(3.70)	(3.51)
Bank premium (Match 2—Match 1)	169.184***	172.240**	26.597
	(2.59)	(2.39)	(0.13)
County premium (Match 3—Match 2)	37.279	85.083	320.098**
	(0.38)	(0.73)	(2.47)
Donation premium (Donation—Match 3)	529.351***	527.490**	466.318**
	(3.12)	(2.00)	(2.35)
Observations	13,137	13,360	13,026

The National Center for Charitable Statistics (NCCS) Core Files provide data on the entire population of active nonprofits annually. We match the nonprofits that receive bank donations in our sample to the sample from NCCS and label them as recipients, and those that are left over as nonrecipients. Panel A of Table XI provides the mean differences across a range of nonprofit characteristics. The total number of recipients is approximately 3% of

Table XI. Nonprofit characteristics of bank donation recipients and nonrecipients

This table examines the characteristics of nonprofits that receive bank donations to those that do not. Panel A presents the mean difference for various nonprofit characteristics between bank donation recipients and nonrecipients. *Expenses*, *Investment income*, *Net assets*, *Program revenues*, *Public donation*, and *Total assets* are denoted in US millions. Panel B presents the regression results for the determinants of whether a nonprofit receives bank donations or not. In all specifications, the dependent variable is a binary variable that equals to one if a nonprofit receives bank donations in a given year and zero otherwise. Control variables include *Compensation ratio*, *Financing*, *Mortgage*, *ln(Program revenues)*, and *ln(Total assets)*, but their coefficients are omitted for brevity. For all specifications, standard errors are robust to heteroscedasticity and clustered by the industry classification of nonprofits; *t*-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Variable definitions are presented in Appendix Table A.1.

Panel A: Mean difference between bank donation recipients and nonrecipients

	Recipients	Nonrecipients	Difference	*p*-value
Star effect	0.120	0.008	0.111***	0.000
Compensation ratio	0.060	0.117	−0.057**	0.039
Expenses	25.434	3.585	21.849***	0.000
Financing	0.105	0.109	−0.004***	0.000
Investment income	0.867	0.079	0.788***	0.000
Mortgage	0.351	0.243	0.108***	0.000
Net assets	53.474	3.684	49.790***	0.000
Program revenues	15.869	2.800	13.069***	0.000
Public donation	9.246	0.751	8.495***	0.000
Total assets	75.491	6.297	69.194***	0.000
Observations	114,984	4,315,195		

Panel B: Determinants of bank donation recipient and nonrecipient status

Dep. variable: 𝟙(Recipient)	(1)	(2)	(3)	(4)	(5)	(6)
ln(Expenses)	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(9.72)	(9.84)	(9.80)	(9.89)	(9.83)	(9.87)
ln(Investment income)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(7.04)	(6.80)	(6.65)	(6.40)	(6.50)	(6.69)
ln(Net assets)	0.001***	0.001***	0.001***	0.001***	0.001**	0.001***
	(3.02)	(3.10)	(3.14)	(3.12)	(2.70)	(3.07)
ln(Public donation)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(3.82)	(3.88)	(3.88)	(3.88)	(3.89)	(3.83)
Star effect		0.071***	−0.393***	0.049***	−0.205***	−0.350***
		(8.72)	(−4.43)	(2.86)	(−6.35)	(−4.79)
Star effect ×*ln(Expenses)*			0.030***			
			(5.06)			
Star effect ×*ln(Investment income)*				0.002**		
				(2.08)		
Star effect ×*ln(Net assets)*					0.018***	
					(8.43)	
Star effect ×*ln(Public donation)*						0.028***

(continued)

Table XI. Continued

Panel B: Determinants of bank donation recipient and nonrecipient status						
Dep. variable: $\mathbb{1}$(Recipient)	(1)	(2)	(3)	(4)	(5)	(6)
						(5.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Nonprofit × county fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Nonprofit fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,537,938	3,537,938	3,537,938	3,537,938	3,537,938	3,537,938
Adj R^2	0.38	0.39	0.39	0.39	0.39	0.38

the universe of nonprofits. Following Lo, Matveyev, and Zeume (2021), we use four variables to proxy for a nonprofit's social impact, including expenses, investment income, funding balance (as measured by net assets), and public donations. On average, recipients have a greater social impact as measured by these four variables. Recipients also tend to have larger program revenues and total assets.

In Panel B of Table XI, we examine the determinants of bank donation recipient status, where the dependent variable takes a value of one if a nonprofit receives bank donations and zero otherwise. To control for the potential clustering of bank donations in certain industries, we include fixed effects based on the industry classification of nonprofits. We also include nonprofit × county fixed effects to control for any time-invariant pair-specific factors. We do not include nonprofit × year-fixed effects because they will absorb the nonprofit characteristics variables. Rather, we include individual nonprofit fixed effects and year-fixed effects, and control for various nonprofit characteristics that could also determine recipient status, such as *Compensation ratio*, *Financing*, *Mortgage*, *ln(Program revenues)*, and *ln(Total assets)*.[27] Column (1) shows that banks are more likely to donate to nonprofits that have greater expenses, investment income, funding balance, and public donations. Thus, recipient nonprofits tend to be larger and have ample funds for daily operations and sizable asset bases to make investments. The results are consistent with the interpretation that banks maximize the exposure of their charitable activities by donating to nonprofits that have the most social impact.

Prior studies have shown that even if consumers are aware of a firm's CSR activities, they may not necessarily reward the firm if they do not *perceive* such activities to be reputable (Schuler and Cording, 2006; Du, Bhattacharya, and Sen, 2010). This gives rise to an omitted variable problem, whereby even if consumers are aware of a bank's charitable giving to nonprofits with broad social impact, these nonprofits may not align with consumers' perceptions of reputability. Thus, we introduce a control variable *Star effect*, which equals to one if a nonprofit is awarded a star rating by Charity Navigator and zero otherwise.[28] Nonprofits with star ratings are those generally perceived by the public as having more accountability and transparency. In Column (2) of Panel B of Table XI, we see that

27 These variables are defined in Appendix Table A.1.

28 Charity Navigator is a nonprofit assessment organization that evaluates the information of other nonprofits and makes it available to the public. In particular, it receives evaluation requests from the general public and produces a star rating based on a multitude of factors.

controlling for *Star effect* does not subsume the effects of the other key variables examined earlier. Furthermore, interacting *Star effect* with measures of nonprofits' social impact in Columns (3)–(6) shows that, conditional on individuals' perceptions of nonprofit reputation, donation recipients still tend to be the ones that generate the most social impact.

7. Conclusion

Charitable donations made by banks represent a significant portion of all corporate philanthropic activities in the USA. However, fundamental issues such as why banks engage in charitable giving and the effects that these donations have on a bank's local deposit market share are underexplored. In this article, we closely examine the strategic aspects of corporate philanthropy by collecting data on donations for a sample of the largest US banks that operate foundations and cover 90% of the total asset value of the market.

In our analysis, we provide systematic evidence that the competitiveness of the local deposit market affects bank donations. These donations then lead to a subsequent increase in the bank's local deposit market share, which can potentially translate into greater profitability. Banks also appear to maximize the salience of their charitable activities by donating to nonprofits that have the most social impact. Our results are consistent with the interpretation that banks strategically use donations as a form of business strategy to gain a competitive advantage.

The findings reported in this article suggest that corporate virtue can be profitable. While many studies have shown that firms can do well by doing good, corporate philanthropy could be a particularly nuanced form of business strategy, given its special merits. Specifically, since charitable foundations enjoy a tax-exempt status and are typically identified as 501(c)(3) organizations for tax purposes, corporate giving can serve as a less costly strategic consideration for managers to enhance their firms' market position and thereby increase profits.

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Data Availability

The data underlying this article were provided by CRSP, Compustat, FoundationSearch, Charity Navigator, SHELDUS, and RateWatch under licence. We further used datasets that are available from sources in the public domain: FDIC Summary of Deposits, Bank Call Reports, NIC, CASSIDI at the Federal Reserve Bank of St. Louis, Federal Housing Finance Agency (FHFA), U.S. Census, FEMA disaster declarations, U.S. Bureau of Economic Analysis, NCCS Core Files. Thus, we do not personally own the data and would not be allowed to make them available to third parties.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

Table A.1. Variable definitions

Variable	Definitions	Data source
Bank variables		
Donation	A binary variable equal to one if a given bank donates to nonprofits in a given county in a given year and zero otherwise	FoundationSearch
Donation amount	The dollar amount of donations to nonprofits in a given county by a given bank in a given year	FoundationSearch
Donation share	The dollar amount of donations to nonprofits of a given bank in a given connected nonshocked county in a given year divided by the total dollar amount of donations of all banks in the same county and year	FoundationSearch
Disaster donation	The change in the total dollar amount of donations between year t and year $t-1$ of a given bank, summed across all shocked counties and normalized by the total dollar amount of donations of the given bank in year t across all counties; we divide this by the number of connected nonshocked counties associated with the bank in year t	FoundationSearch; SHELDUS
Δ*Connected donation*	The change in the total dollar amount of donations between year t and year $t-1$ of a given bank in connected nonshocked counties, normalized by the total dollar amount of donations of the given bank in year t across all counties	FoundationSearch; SHELDUS
Deposit share	The deposits of a given bank in a given county in a given year divided by the total deposits of all banks in the same county and year	FDIC Summary of Deposits
Dep_12mcd10k	Deposit interest rate on a 12-month certificate of deposit of $10,000 averaged across all branches of a given bank in a given county	RateWatch
Dep_mm10k	Deposit interest rate on money market accounts of $10,000 averaged across all branches of a given bank in a given county	RateWatch
Dep_sav2500	Deposit interest rate on savings account of $2,500 averaged across all branches of a given bank in a given county	RateWatch
No disaster exposure	A binary variable that equals to one if a bank operates only in a connected nonshocked county and does not operate any branches in shocked counties during the event window and zero otherwise	SHELDUS
Equity ratio	Total equity capital divided by total assets	Call Report
LLP	Loan loss provisions, defined as loan loss provisions divided by total loans	Call Report
LLR	Loan loss reserves, defined as reserves for credit losses divided by total loans	Call Report
Loan ratio	Total loans divided by total assets	Call Report
MBHC	A binary variable that equals to one if a bank is a multibank holding company and zero otherwise	Call Report

(continued)

Table A.1. Continued

Variable	Definitions	Data source
NPL	Nonperforming loans divided by total loans	Call Report
ROA	Net income divided by total assets	Call Report
Size	Total assets	Call Report
Advertising ratio	Advertising expenses divided by total assets	Call Report
Deposits	Total bank-level deposits	Call Report
Deposit ratio	Total bank-level deposits divided by total assets	Call Report
County-level variables		
HHI	County-level HHI, defined as the sum of squared deposit market shares of all banks that operate branches in a given county in a given year	FDIC Summary of Deposits
Establishments	The number of establishments in a given county in a given year	U.S. Census Bureau
New nonprofits	The number of new nonprofits in a given county in a given year	NCCS
Disaster	A binary variable that equals to one if a county is affected by a FEMA-related natural disaster event identified by SHELDUS and zero otherwise	SHELDUS
Adj disaster	A binary variable that equals to one if an adjacent county is affected by a FEMA-related natural disaster event identified by SHELDUS and zero otherwise	SHELDUS
GDP per capita	County-level real GDP (in 2012 dollars) per capita	U.S. Census Bureau, U.S. Bureau of Economic Analysis
Population	County-level population	U.S. Census Bureau
PI per capita	County-level personal income per capita	U.S. Census Bureau, U.S. Bureau of Economic Analysis
HPI	County-level house price index (relative to year 2000)	FHFA
M&A	A binary variable that equals to one if there is at least one bank-level merger in a county and zero otherwise.	NIC
Nonprofit variables		
Compensation ratio	Total compensation of officers and directors divided by total expenses	NCCS
Expenses	Total expenses that a nonprofit spends on its operations	NCCS
Financing	A binary variable that equals to one if a nonprofit has a loan and zero otherwise	NCCS
Investment income	The amount of income from a nonprofit's investment portfolios	NCCS
Mortgage	A binary variable that equals to one if a nonprofit has a mortgage loan and zero otherwise	NCCS
Net assets	Total assets minus total liabilities	NCCS

(continued)

Table A.1. Continued

Variable	Definitions	Data source
Program revenues	The amount of revenue from a nonprofit's charitable programs	NCCS
Public donation	The amount of donations the nonprofit receives from the general public	NCCS
Star effect	A binary variable that equals to one if a nonprofit is awarded a star rating by Charity Navigator and zero otherwise	Charity Navigator
Total assets	The total amount of assets that a nonprofit possesses	NCCS

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