Charitable Capital Allocation: Evidence from Private Foundations

Abstract

We analyze the responsiveness of private foundations' charitable capital allocation to changes in recipient needs. Using financial shocks to peer foundations as sources of exogenous variation in the marginal value of donations, we find foundations' cross-sectional grant allocations respond to needs. Responsiveness is stronger for scientifically-oriented causes, when donor-recipient relationships are longer, and for foundations under founder control. However, foundations do not respond intertemporally to needs, instead focusing on capital preservation. Our results suggest that in the absence of market discipline, mission-driven discretion can substitute for internal governance to improve charitable capital allocation, but incentive conflicts impede efficient intertemporal allocation.

1. Introduction

The non-profit sector plays a crucial role in the U.S. economy, comprising over 1.8 million organizations with aggregate annual expenditures exceeding $1.94 trillion in 2020 (Faulk et al. (2021)). In the charitable capital market, donors—both individuals and organizations—allocate capital to fund charitable projects. Unlike for-profit capital markets, where value is measured through financial returns and market-clearing prices guide capital to its most efficient uses, the charitable market lacks such mechanisms.[1] This impedes information aggregation and eliminates key sources of market discipline (e.g., shareholder voice, corporate control, and performance-based compensation). Given these challenges, are nonprofits able to effectively allocate charitable capital? In addition to being important in its own right, the nonprofit setting also helps illuminate the role of market forces in capital allocation by allowing us to examine the outcomes that arise in their absence.

In this study, we leverage the unique setting of private foundations to explore three aspects of nonprofit capital allocation. First, we propose a novel test to examine whether capital allocation by private foundations responds to changes in the needs of recipients, in a manner that is not driven by confounding factors such as self-interested donor preferences. Second, we investigate how recipient characteristics and donor-recipient relationships impede or effectuate private foundations' responsiveness to changes in recipient needs. Finally, we examine how characteristics of foundations and their governance structures influence variations in capital allocation efficiency, and explore the reasons behind these differences.

Private foundations (PFs) are a particularly relevant laboratory to investigate nonprofits' capital allocation problem.[2] PFs are predominantly charitable grantmaking institutions

[1] Consistent with this absence, Exley et al. (2023) document that activity in the charitable sector is perversely procyclical, even in domains where participants strongly expect that optimal behavior is countercyclical.

[2] The endowments of U.S. PFs cumulatively exceed $1 trillion, more than any other type of U.S. nonprofits that report asset data to the IRS. For example, the combined value of reporting U.S. non-profit endowments, excluding private foundations, reached approximately $700 billion at the end of 2018 (Dahiya and Yermack (2018)). This figure includes $400 billion from university endowments, a topic that has garnered significant interest in numerous academic studies (e.g., Dahiya and Yermack (2018); Lerner et al. (2008); Lo et al. (2019); Gilbert and Hrdlicka (2015); Barber and Wang (2013); Brown et al. (2010)).

(e.g., Rockefeller Foundation, Bill and Melinda Gates Foundation) and are typically funded by a single person or a family. As a result, the absence of market forces that typically coordinate capital allocation in standard markets is especially pronounced. First, PFs are not subject to product market discipline: unlike for-profit organizations and public charities (e.g., universities or hospitals), they do not need to serve customers, students, or patients to generate revenues. Second, PFs are not subject to capital market discipline, because they do not need to compete for funding. Third, PFs face little governance discipline, as there is no market for corporate control or shareholder oversight. PF trustees answer only to the foundation's charter, which is enforced through the legal system.[3]

While concerns about the efficiency of PFs' capital allocation due to the absence of key market forces are recognized,[4] the literature to date provides no empirical evidence on the optimality of PFs' behavior. Studying this question is inherently challenging: charitable grants rarely produce financial returns, and their impact is not measured in monetary terms. Moreover, it is often difficult to determine whether grants are genuinely responding to recipient needs or simply being driven by other factors, such as visibility in cases like naming rights, or donors' personal preferences in areas like arts, culture, or social rights.

To address these challenges, we propose a quantifiable, albeit narrow, measure of the efficacy of private foundations' (PFs) capital allocation. Specifically, we use variations in recipient need brought about by exogenous endowment shocks to *peer* private foundations donating to the same recipients to cleanly identify focal foundations' responsiveness to recipient need. Our test is based on the principle that the marginal value of incremental donations to a charity should decrease when a charity experiences exogenous increases in its wealth. To illustrate, consider a thought experiment where a focal PF donates to two recipients. The first (second) recipient observes an exogenous decrease (increase) in grants because other peer foundations donating to the first (second) recipient experience a negative (positive) financial shock. If the marginal value of charity is decreasing with scale, ceteris

[3]More specifically, in most jurisdictions within the United States, state Attorneys General are responsible for overseeing and enforcing the charter of private foundations.

[4]For example, reflecting these concerns, the U.S. tax code imposes stricter regulations on the distribution ratio for private foundations than public charities.

paribus, the focal PF should respond by increasing (decreasing) their grants to the first (second) recipient.

We use this novel framework to guide our empirical tests. We collect data on the charitable grantmaking network drawn from private foundations' Form 990-PF filings, which include detailed information about PFs' grants and the identities of their grant recipients. Because these recipients often overlap, we are able to examine the changes in a focal foundation's grants in response to the endowment returns of peer foundations that donate to the same overlapping recipients.

Consistent with effective capital allocation, we find that shocks to peer foundation wealth have a negative and significant substitution effect on the cross-sectional composition of the focal foundation's giving. Specifically, we find that a 1% increase in peer foundations' grants (due to their exogenous wealth shocks) to a recipient is associated with 0.2 to 0.3% decrease in the focal foundation's grants to the same recipient. This result supports the idea that private foundations are responsive to the changing marginal value of additional donations, and rejects the possibility that PFs make decisions based purely on feelings of warm glow or donation appeals or status concerns that do *not* correlate with recipients' marginal need. For instance, this includes cynical scenarios where PFs function purely as tax shelters and the charitable activities of the PFs are mere sideshows. Since focal foundations' grants respond negatively to exogenous changes in peer foundations' grants, this finding also provides evidence against theories of sociality-based giving where givers compete to make the largest donations.

We conduct two sets of tests to further examine PFs' capital allocation across recipients. First, we assess whether the substitution effect varies across charitable causes. Our findings reveal that the substitution effect is weakest in the arts and religion subsample and strongest in the science subsample. These findings indicate that some non-scientific causes are perceived as more unique or harder to substitute. Second, we investigate whether PFs' responsiveness is driven by their active learning or by their passive responses to recipients' fundraising intensity.[5] To assess these channels, we investigate how responsiveness varies

[5]For example, an exogenous decrease in recipients' needs can prompt recipients to reduce fundraising efforts, leading to decreased giving by the focal foundation.

with the length of relationship between a recipient and a PF. Intuitively, PFs' active learning grows with the duration of relationships, while reliance on fundraising signals should be the strongest early on, when knowledge is limited. Consistent with the active learning channel, we find that a statistically stronger substitution effect for longer relationships.

Having examined the effectiveness of PFs' capital allocation across recipients, we then proceed to examine whether PFs' intertemporal capital allocation responds to recipient needs. We find weaker results along this dimension. We conduct two analyses to test PFs' responsiveness to recipient needs over time. First, we use an aggregate version of our foundation-recipient regression, calculating average financial returns of peer foundations for each recipient and treating this as a shock to the focal foundation's marginal value of giving. Second, we use an NBER recession dummy (equal to 1 in 2001, 2008, and 2009) as a proxy for increased recipient needs during economic downturns. Neither analysis provides statistically significant evidence that PFs' total spending adjusts to changes in recipient needs.

In contrast, we find that PFs' total spending responds strongly to the foundation's own return. We show that this positive grant-endowment return sensitivity arises because charitable donors do not "undo" the permanent income effect of endowment returns as predicted by the frictionless model in Adelino et al. (2015) and not because of the mandatory minimal 5% spending rule. Furthermore, we find that the grant-endowment return relationship is significantly more sensitive to contemporaneous negative endowment returns than positive returns: PFs respond more strongly to negative returns by cutting spending aggressively, indicating a powerful capital preservation motive.[6] The focus on capital preservation is consistent with a high PF survival rate. On average, PFs annual income (comprising investment returns plus donations received) equals 9.3% of assets, significantly exceeding their average total spending of 7.8% of assets. This gives rise to a remarkably low annual closure rate for PFs of around 0.8%.

[6]Brown et al. (2014) document a similar asymmetry in the contemporaneous spending responses of universities following shocks to the value of their endowments. Since endowment spending rules do not prescribe this asymmetry, they interpret the pattern as potentially arising from agency costs. Our results show that this asymmetry also appears to arise within private foundations that are relatively insulated from agency costs.

Finally, we explore how foundation characteristics and the governance structure of PFs affect their responsiveness to charitable needs and their focus on capital preservation. We find that the presence of PF founders (or their family members) as foundation trustees leads to significantly higher responsiveness to recipient needs as well as stronger capital preservation. In contrast, measures of board quality or institutional capacity, such as the size of the board or the age or size of the foundation, do not have significant effects on foundation responsiveness. Overall, these results indicate that, in contrast to for-profit corporations, PFs' responsiveness is dependent upon the discretion and charitable intent of trustees rather than the discipline of independent governance. At the same time, the exercise of discretion is also associated with a greater tendency towards the private benefits of capital preservation, indicating that trustees' incentives may not be wholly aligned with their foundations' missions.

Related Literature

Our study builds on two strands of literature that examine the efficiency of resource allocation in the nonprofit sector. One strand of literature shows that the intertemporal resource allocation of nonprofit organizations often deviate from the ideal benchmarks. Exley et al. (2023) show that nonprofit expenditure is strongly procyclical, contracting during economic downturns despite a strong public preference for countercyclical expansion. Similar findings emerge in studies of specific nonprofit organizations. Dahiya and Yermack (2018) show that donors increase contributions to nonprofits during periods of strong endowment returns. Brown et al. (2014) demonstrate that universities' spending deviate from to their stated spending rules by reducing payouts in response to negative, but not positive, endowment returns. Adelino et al. (2015) show that the investment choices of nonprofit hospitals covary positively with their endowment returns. These results suggest that nonprofits fail to smooth expenditures across economic cycles.

The second strand examines how donors optimize charitable giving. Karlan and List (2007) evaluates individuals' propensity to give following changes to the "price" of giving, such as charitable matching, showing that while donors respond to match availability, the match ratio itself has little effect on giving behavior. Andreoni and Payne (2003), Andreoni and Payne (2011), and Ottoni-Wilhelm et al. (2017) show that government grants tend to "crowd out" non-government contributions. And Vesterlund (2003) and Karlan and List (2020) explore the informational content of preceding or contemporaneous contributions to a nonprofit.

We contribute by offering the first comprehensive study on the capital allocation of private foundations (PFs), which is interesting in its own right due to their distinctive characteristics. Our results bridge the two aforementioned strands of literature. By using financial shocks to peer foundations to cleanly identify PFs' responsiveness to recipient need, we isolate exogenous changes in the marginal value of grants from recipient characteristics and non-altruistic motivations such as sociality-based giving. We establish that PFs are responsive to the marginal value of their giving when allocating grants across recipients, demonstrating their consideration of recipient needs; however, when setting overall grantmaking levels, PFs prioritize capital preservation, leading to deviations from ideal intertemporal smoothing. Our results highlight that, in absence of market discipline, mission-driven discretion can act as a substitute for internal governance mechanisms to achieve efficient resource allocation, though this comes with systemic fragility.[7]

Using granular data, we identify factors that influence cross-sectional grant allocation efficiency and connect PFs' deviations from benchmarks to foundation characteristics and governance structure. In doing so, our study also contributes to a broader literature on the motivations underlying charitable giving, which extends beyond economic costs and benefits (e.g., Andreoni (1989), Landry et al. (2006) for non-altruistic motives; and Andreoni (2006); List (2011); Andreoni and Payne (2013) for comprehensive reviews of this literature).

[7]To the extent that market discipline and governance are substitutes (Hart (1983); Giroud and Mueller (2010)), the absence of market discipline for nonprofit organizations may provoke the desire for more restrictive internal governance structures.

However, nonprofits appear to have relatively weak governance in practice (Lewellen et al. (2023)). Strengthening governance can inadvertently undermine the benefits of mission-driven discretion, potentially leading to less effective resource allocation. Consistent with this idea, Herpfer et al. (2024) find that in the hospital context, the introduction of "better" governance via conversion to for-profit status leads to a decline in the quality of patient care.

2. Data

2.1. What Are Private Foundations

In the United States, two broad categories of nonprofit entities receive exemptions from taxation under Section 501(c)(3) of the Internal Revenue Code: public charities and private foundations. The category of public charities comprises charitable organizations that receive more than one third of their contributions from the general public or from exempt function income, as well as charitable organizations whose activities are directed to a specific exempt purpose (mainly schools, hospitals, medical research organizations, churches, and organizations whose purpose is to support the charitable activities of other public charities.)

In contrast, typically, private foundations are charitable organizations which receive more than two thirds of their support not from the general public but from a single family or a single corporation. The most familiar (and common) form of private foundation is a grant-making organization (e.g., the Rockefeller Foundation, the Overdeck Family Foundation, etc.), wherein the organization itself acts essentially as a pass-through, receiving contributions from its high-net-worth founder (either an individual, family, or corporation), and making grants to other charitable organizations as opportunities arise. Less commonly, private foundations may also be operating organizations, which undertake charitable activities directly. Following the Tax Reform Act of 1969, private foundations are formally defined as charitable organizations which *do not* meet the specifically enumerated qualifications for being a public charity. That is, they are charitable organizations for which at least two thirds of their contributions are not from the general public, and which are not schools, hospitals, medical research organizations, or churches.

Private foundations and public charities also differ in terms of the extent of tax advantages available to them: contributions to public charities are tax deductible up to fifty percent of the donor's income, whereas contributions to private foundations have a lower deductibility limit of thirty percent of income. Furthermore, private foundations are subject to 1% to 2% net investment income taxes on the annual investment returns of their endowments, and they face additional excise taxes if they fail to make annual charitable distributions equal to at least five percent of the fair market value of their net assets. Usefully for our analysis, because these requirements are tied to the market value of their investments, private foundations are obliged to report the market value of their investments in their annual filings.

Due to these preferential tax treatments, assuming that donors to private foundations are wealthy individuals who fall into the highest marginal tax bracket, and given that PFs' subsequent investment returns are taxed at an extremely low rate compared to typical capital gains, approximately half of private foundations' endowments can be viewed as coming from tax deductions.

2.2. Sample Construction

Private foundations are required to file Form 990-PF each year with the IRS. These filings contain basic income statement and balance sheet information, alongside information on the charitable activities, investments, and donors of the foundations. Electronic availability of these filings began in 2001. Initially, most e-filings were in PDF format, but since 2013, there has been a notable shift towards XML format, which has become increasingly prevalent in the past five years.

Since earlier filing data are either not available in electronically or only in PDF format, processing these filings to extract the relevant data poses a significant challenge to researchers. Consequently, existing research on private foundations primarily relies on one of two data sources: data processed by the IRS Statistics of Income (SOI) division (as in e.g., Binfare and Zimmerschied (2022)) and data processed the National Center for Charitable Statistics (NCCS) (as in e.g., Allen and McAllister (2018)).

Both datasets have their advantages and disadvantages. The SOI data are highly reliable, as they undergo review by the SOI division staff.[8] However, SOI only samples a subset of

[8]SOI staff make a few adjustments to the data such that the SOI data are not directly comparable to the raw 990-PF data. For example, The Bill & Melinda Gates Foundation was divided into two separate entities in October 2006: the Bill & Melinda Gates Foundation Trust and the Bill & Melinda Gates Foundation. The Foundation Trust oversees the financial assets, while the Foundation distributes funds to grantees. Since the main asset of the Foundation is the interest in net assets of the Foundation Trust, the SOI staff adjust the

foundations. Specifically, it includes all returns from foundations with a fair market asset value of $10 million or more. The rest of the foundation population is randomly selected for the sample at varying rates, ranging from 1 percent to 100 percent, based on asset size. The SOI data are available from 1985–2019.[9] The main drawback of the SOI data for our analysis is its inability to consistently track a private foundation throughout its life cycle. This inconsistency arises because a foundation sampled in one year may not be sampled again if its size falls below the $10 million threshold. In contrast, the NCCS dataset covers all PFs in a year by processing the IRS Business Master File (BMF) and the IRS Form 990-PF filings. The main drawback of the NCCS core dataset is its incomplete time series coverage, with data available only for the years 1989–1992, 1994–2015, and 2019. Additionally, the NCCS data include fewer variables and are slightly less reliable than the SOI data.

We assemble a comprehensive dataset on PFs by first combining the SOI and NCCS core datasets, and then supplementing that combined dataset with three additional data sources. First, we use the IRS Annual Extract files, which cover all PFs but are limited mostly to variables on the first 12 pages of the 990-PF form. These IRS Annual Extract files are only available for 2012–2016 and 2020–2022. Second, we process all the XML 990-PF filings post 2013 (first available year). Third, we fill any remaining missing values by processing the relevant PDF 990-PF filings.[10]

Specifically, we begin with the SOI data between 1994 and 2019.[11] We start tracking a private foundation (PF) once it appears in the SOI data with a market value of asset larger than $1 million and non-zero expenses. We continue to track the PF by augmenting the SOI

market value of the total asset for the Foundation (EIN=562618866) by subtracting the value of its interest in the Foundation Trust to avoid double counting.

[9] The IRS website states that "100 percent of returns filed for foundations with fair market asset value of $10 million or more are included in the samples, since these organizations represent the vast majority of financial activity. The remaining foundation population is randomly selected for the sample at various rates, ranging from 1 percent to 100 percent, depending on asset size." However, while this statement is mostly true, we do find numerous examples in which foundations with fair market asset value more than $10 million are not sampled. For example, Patricia Price Peterson Foundation in 2017 and Laidlaw Foundation in 2009. These observations are captured by the other data sources.

[10] Both the XML 990-PF filings and the PDF 990-PF filings are downloaded from ProPublica.

[11] Our sample begins in 1994 as it marks the first year where we have data from at least two sources. The SOI data end in 2019 as of the first version of this paper.

data with NCCS core data, IRS Annual Extract files, XML 990-PF filings, and PDF 990-PF filings, in that order.[12] We complement this dataset with the IRS Business Master File to identify the last filing of an EIN. Finally, we focus on private foundations set up for the sole purpose of making charitable donations and thus we drop operating private foundations (based Q030 of FORM 990PF) which directly perform charitable activities. Unlike studies that rely solely on a single data source of private foundations, such as the SOI or the NCCS, our dataset has the key advantage of containing the complete time series of a PF once it appears. This feature of the complete time series avoids the potential survivorship bias due to PFs dropping out of the SOI sample after suffering negative financial shocks and is also critical for accurate survival analysis.

We collect detailed data on PFs' grantmaking at the foundation-recipient level from Candid.com, which extracts and processes such information from PFs' 990PF filings. Due to the labor-intensive nature of downloading data from Candid.com, where records can only be retrieved manually, we opt to concentrate on the largest private foundations. Specifically, if a private foundation is among the largest 300 PFs in any year from 2003 (the first year when the Candid data are available) to 2019, it enters our sample, and we collect a complete time series of its recipient data. In total, our analysis below covers 511 unique private foundations.[13]

Finally, we extract the information on foundations' governance structure from Part VIII of the XML 990-PF filings. We compute the board size (i.e., the number of officers, directors, trustees, and foundation managers listed under Part VIII), the number of professional officers (i.e., officers with annual salary exceeding $150,000), and the presence of a founder or a founder's family member as a trustee or officer of the foundation. Since foundations only began gradually filing XML 990-PF forms after 2013, we use the available data to compute the time-series mean of these variables, treating them as foundation-level characteristics.

[12]Since the SOI data sample includes all large foundations and many medium and smaller ones at some point of their life cycle, our sample is very comprehensive. We compare the total market capitalization of the PFs in our sample with the total market capitalization of the PFs in the NCCS core dataset between 1994 and 2015 when the NCCS data is available (the latter includes all PFs), and we find our sample captures 92% of the total market capitalization on average.

[13]See Appendix B for detailed description of the data collection process.

Our sample of PFs has both a long time-series and a large cross-section compared to data on other types of non-profit organizations used in the literature. Brown et al. (2014) study around 200 research universities between 1986 and 2009, Yermack (2017) studies 120 large art museums between 1999 and 2013, and Adelino et al. (2015) study 1,352 non-profit hospitals between 1999 and 2006. Dahiya and Yermack (2018) and Binfare and Zimmerschied (2022) stand as notable exceptions with a sample size comparable to ours, though both focus on the investment side of non-profits.

2.3. Return Computation

Our primary measure of private foundations' annual portfolio returns is generated as follows:

$$\begin{aligned}
\text{Dollar Returns}_t = & W_t - W_{t-1} \\
& - \text{Contribution Received}_t \\
& + \text{Spending}_t \\
& - \Delta\text{Liab}_t \\
& + \Delta\text{OtherChg}
\end{aligned}$$

where W_t is the market value of assets at time t. This is because the changes in the fair market value of a private foundation's assets, henceforth referred to as MV, are the sum of investment returns, money received/paid, and changes in liabilities, minus any expenses. Although private foundations typically do not disclose their portfolio returns, we can estimate the financial returns on their investments through this method. Percentage returns are defined as

$$\text{Percentage Returns}_t = \frac{\text{Dollar Returns}_t}{W_{t-1}}$$

We ensure the returns are measured over 12 month period by using consecutive financial statements that are 12 months apart (based on E010 of FORM 990PF). More details about the return calculation are provided in Appendix A.

3. Descriptive Facts

3.1. The Size and Growth of Private Foundations

Panel A of Figure 1 shows that the total assets of private foundations increase substantially over our sample period, soaring from under $200 billion in 1994 to over $1 trillion by the end of 2019. Giving from private foundations now comprises a meaningful and growing fraction of noncommercial activity in the United States. Our sample covers more than 22,000 unique PFs. As Table 1 shows, the mean market value of assets (across all PF-years) is approximately $43 million, but with a substantial skewness: the median PF-year reflects assets of about $9 million and the largest PFs are orders of magnitude larger than the median.

To provide some examples of the largest foundations and recipients, Table 2 lists the ten largest private foundations during each of five sequential five-year periods: 1995-1999, 2000-2004, 2005-2009, 2010-2014, and 2015-2019. The table also lists each foundation's average total assets and average annual grants paid during each five year period. The Bill and Melinda Gates Foundation (Gates Fnd) is the largest private foundation during four of these five periods, with approximately $45bn in assets during the most recent period.[14] The largest foundations are relatively stable, and most names that appear among the largest foundations in earlier periods continue to appear on the lists in later periods. This pattern is the first hint that private foundations are set up to endure for the long term.

Panel B of Figure 1 plots private foundations' total spending both in billions of dollars as well as expressed as a fraction of U.S. federal government nondefense discretionary

[14] In 2006, the Bill and Melinda Gates Foundation creates a two-entity structure, under which the Bill & Melinda Gates Foundation Trust (EIN=911663695) manages the endowment assets while the Bill & Melinda Gates Foundation is responsible for making grants (EIN=562618866). See https://www.gatesfoundation.org/about/financials/foundation-trust. Therefore, for the Bill and Melinda Gates Foundation, we use the grant making data from the PF filing of EIN=562618866, while using the asset return data from the PF filing of EIN=911663695. We made a similar adjustment to Kellogg Trust (EIN =366030614) and Kellogg Foundation (EIN=381359264).

spending. In 1994, at the beginning of our sample, private foundation spending equaled approximately 5% of contemporaneous nondefense discretionary government spending. By 2019, however, private foundation spending had grown to nearly 15% of contemporaneous nondefense discretionary government spending.[15]

In Table 3, we use our subsample data on grant recipients to list the recipients of the largest grants from private foundations during the periods 2005-2009, 2010-2014, and 2015-2019. These lists are generated using the complete grant making data of the largest 500 PFs (see detailed description in Appendix 8.2). The table also includes summary data on the grant amount (in $B) received over the 5-year period, and also on the number of unique PFs that make grants to the recipient over the same period. Health, climate, and advocacy organizations often appear, and they are more likely to receive very large grants from a relatively small number of individual donor foundations. Universities comprise another prominent recipient type. Universities appear far more likely to have a substantially larger number of individual donor foundations.

3.2. Distribution Rates

Grants paid are a relatively small fraction of assets. We compute the grant payout rate as the grants paid (as stated in Part I, Column (a), line 25 of 990PF) as a percentage of the asset value at the start of the tax year.[16] According Table 1, the grant payout rate is right-skewed, with an average of 7.8 percent and a median of 4.84 percent. Beyond grant payouts, PFs also bear additional expenses, such as employee compensation and operating costs. When these are added, the expense ratio – defined as the sum of grant payouts and operating and administrative expenses paid (Part I, Column (a), line 26 of 990PF) as a percentage of asset value at the beginning of the tax year – increases to an average of 9.32 percent and a median of 5.97 percent. The median value of 5.97% is close to the requirement that the minimum qualifying distributions, which include both grant and operating costs,

[15] Andreoni and Payne (2013) has noted the fast growth of the private foundation segment in their review paper, but ours is the first analysis to assemble comprehensive data on PFs.

[16] We prefer an accrual-based measure over a cash-based one because it more accurately reflects a private foundation's (PF's) grant-making decisions.

must be at least 5% of the net value of noncharitable-use assets.[17] In our sample, PFs have a median grant-to-expense ratio of 83%, indicating that for a typical PF, the majority of expenses are allocated towards grants.

3.3. Survival Rates

Given that Table 1 shows that the average expense ratio surpasses the average annual return of PFs, one might expect PFs to have a relatively short lifespan. However, the annual closure rate for PFs is only around 0.8% in our sample. This is because the donation rate — defined as donations received (Part I, Column (a), Line 1 of 990PF) as a percentage of asset value at the beginning of the tax year — averages 5.91% (Table 1). While infrequent, these donations are often substantial in magnitude relative to existing assets. Consequently, the combined average annual investment return of 7.98% and donation rate of 5.91% significantly exceeds the average expense ratio of 9.31%, supporting the high survival rate of PFs.

Figure 2 presents hazard rates for private foundations' closure as a function of their age.[18] Young private foundations (those less than twenty years of age) have closure probabilities near 1%. As foundations age, their closure probability falls, reaching a low of around 0.7% around year forty. Between forty and sixty, there is a second, smaller peak in closure prob-

[17]Under current rules, qualifying distributions in excess of the minimum can be carried forward for up to five years, while shortfalls in year t can be made up in year $t+1$ without penalty. Shortfalls that are not made up by $t+2$ trigger a 30% excise tax on the undistributed shortfall, and under IRS rules, "[p]ayment of the excise tax is required in addition to, rather than instead of, making required distributions of undistributed income." Shortfalls that are not made up by $t+3$ trigger a 100% tax on any remaining undistributed amount. For further details, see: https://www.irs.gov/charities-non-profits/private-foundations/taxes-on-private-foundation-failure-to-distribute-income

[18]We generally measure a foundation's age from the date the IRS approved its application for tax exempt status (its ruledate from the IRS BMF). In cases where the date of a foundation's first 990-PF filing precedes its ruledate by no more than two years, we measure age from the date of first filing (since foundations may file 990-PF forms while their applications are pending). For foundations whose first filing precedes their ruledate by more than two years, we do not compute age for these foundations due to the lack of reliable data. Because Section 501(c) of the Internal Revenue Code (and hence the assignment of ruledates for tax exempt status) dates to the Revenue Act of 1954, reported ruledates before 1955 are unreliable measures of foundations' ages; if a foundation's reported ruledate is earlier than 1955, we assign it a ruledate of 1955 for this hazard analysis. Thus, ruledates for foundations founded prior to 1955 will underestimate their age, but ruledates after 1955 are a relatively reliable proxy for foundation age. We define the year of death as the year after which PFs no longer appear in our dataset or the IRS Business Master File, which essentially occurs when the PF stops filling Form 990-PF.

ability, which subsequently declines again. Though our data do not contain information on founder age, we conjecture that for some foundations, this second peak might occur around or following the death of a foundation's primary donor. To our knowledge, our study is the first to characterize the exit pattern of private foundations.

4. The Cross-Sectional Responsiveness of Charitable Capital Allocation

4.1. Isolating Foundations' Responsiveness to Recipient Needs

We measure foundations' responsiveness to recipient needs by identifying instances where needs arguably change. Our analysis is based on the principle that the marginal value of an incremental grant to a charity should decrease when that charity experiences exogenous increases in its wealth. To illustrate, consider a thought experiment where a private foundation donates to two recipients. If the first recipient observes an *exogenous* decrease in its wealth while the second experiences an increase, then all else equal, a PF that is responsive to recipient needs should reallocate their ongoing grants: it should increase its grant to the first recipient and decrease its grant to the second.

Identifying episodes where grant recipients' wealth changes exogenously is a challenge. We address this by using data on the grantmaking network. Specifically, we examine scenarios where multiple private foundations donate to the same recipient. In this empirical setting, we can control for financial shocks to the focal foundation, which as we discuss later can affect cost of charitable capital. We then use the financial shocks to peer foundations that donate to the same recipient as a source of exogenous variation in the marginal value of donations to the recipient. This is because, as we document later, following financial shocks to their endowment values, PFs' adjust their grants to recipients, thus generating the desired uninformative variation in the wealth of grant recipients.

We perform two variants of our peer foundation analysis: a naive regression and an instrumented regression. The naive variant regresses changes in the focal foundation's grants on changes in peer foundations' grants, as follows

$$\begin{aligned}\Delta log\left(Grant_{i,j,t+1}\right) =& c+\gamma_j+\delta^{'}Control+\beta_1 log\left(1+RET_{i,t}\right)\\ &+\beta_2\Delta log\left(PeerGrant_{i,j,t+1}\right)+\eta_{i,j,t+1}.\end{aligned} \tag{1}$$

where $Grant_{i,j,t}$ is the grant amount private foundation i makes to recipient j in year t, $RET_{i,t}$ is the return to the endowment of foundation i, and $PeerGrant_{i,j,t} = \sum_{i'\neq i} G_{i',j,t}$. The control variables include $log\left(Grant_{i,j,t}\right)$, $log\left(PeerGrant_{i,j,t}\right)$, and $logW_{i,t-1}$. The instrumented regression uses the average returns of peer foundations that donate to recipient j, $log\left(1+RET_{-i,j,t}\right) = log\left(1+\sum_{i'\neq i}\frac{G_{i',j,t}}{G_{j,t}}RET_{i',t}\right)$, as an instrument for $\Delta log\left(PeerGrant_{i,j,t+1}\right)$. To the extent that the financial returns of donors are exogenous to changes in the quality, actual or perceived, of the recipients of their grants, we can isolate the uninformative part of changes in grants from peer foundations. We condition on foundation i giving a nonzero amount to recipient j in both year t and $t+1$, so our results capture the percentage (log) point change in grants along the intensive margin from a foundation to a recipient due to the foundation's endowment shock.[19]

The parameter of interest is the loading on the additional term, $\Delta log\left(PeerGrant_{i,j,t+1}\right)$. Specifically, we predict that β_2 should be negative when $\Delta log\left(PeerGrant_{i,j,t+1}\right)$ is uninformative.The intuition follows from the thought experiment described above, in combination with the principle of decreasing returns to scale: If one of the focal PF's recipient charities also receives grants from a peer PF, then the marginal value of additional donations to the recipient will be a function of both the focal PF's grant size and the peer PF's grant size. In particular, if the peer PF exogenously increases the magnitude of their grant to the recipient, then all else equal, the focal PF should expect a lower marginal value of an incremental dollar given to that particular recipient, and hence should reallocate their grants towards

[19]We focus on the intensive margin because peer foundation returns are unlikely to be the main driver of the focal foundation's decision to terminate a gift program. While our results are robust to using the level regression, we prefer the log regression because the level regression can be dominated by grants in the right tail of the distribution.

other recipients in its portfolio. We refer to this reallocation as the *substitution mechanism*, because the focal foundation adjusts its grantmaking to substitute for the grant shocks of peer foundations. Thus, in a regression of the focal foundation's grant to recipient j on peer foundations' grants to recipient j, the substitution mechanism would prescribe a negative coefficient on changes in peer foundations' grants.

To identify the substitution mechanism, the changes in peer foundation grants should be uncorrelated with the quality of the recipient, actual or perceived. In contrast, for the naive variant, two confounding mechanisms can lead to a positive β_2. First, private foundations' interest in donating to a charity might vary over time, either for substantive reasons (i.e., the efficacy of its charitable programs has changed) or for superficial ones (e.g., changes in the recipient's prestige, or fashion), both of which may attract grants from multiple private foundations simultaneously, leading to a positive β_2. Second, unlike in a competitive market where the price serves as a good signal of quality, the quality of charity is relatively more opaque. Therefore, changes in one foundation's grant making to recipient j might serve as a signal for the quality of the charity, which may attract other private foundations to donate to the same recipient (Vesterlund (2003); Karlan and List (2020)). Column 1 reports the naive regression. We indeed find a positive and significant β_2. This positive association between grants from peer foundations and the focal foundation suggest that the confounding mechanisms dominate the substitution mechanism.

To conduct the IV regression, we first verify the first stage that a positive cash flows to a foundation leads to higher grantmaking through giving larger grants to existing recipients. Specifically, we run the following regression,

$$\Delta log\left(\mathrm{Grant}_{i,j,t+1}\right) = c + \gamma_j + \delta^{'} Control + \beta log\left(1 + \mathrm{RET}_{i,t}\right) + \eta_{i,j,t+1} \tag{2}$$

Column 2 of Table 5 shows a positive and highly significant effect of $RET_{i,t}$, suggesting that positive endowment shocks to a PF indeed leads to higher grants to their recipient charities. Intuitively, positive endowment shocks increase the permanent income of the PF, causing it to increase its grantmaking.[20]

We then run the following 2-stage least square (2SLS) regression to isolate the substitution channel using $log\left(1 + RET_{-i,j,t}\right) = log\left(1 + \sum_{i' \neq i} \frac{G_{i',j,t}}{G_{j,t}} RET_{i',t}\right)$ as an instrument for $\Delta log\left(PeerGrant_{i,j,t+1}\right)$ in Eq (1). Results are presented in Column 3 of Table 5. The F-statistics for the first stage regression exceeds the threshold of ten, suggesting that our instrument is unlikely to be weak (Staiger and Stock (1997)).

The IV regression reveals a negative coefficient β_2 of -0.23 that is significant at the 1% level, supporting the idea that private foundations are, as a whole, responding to the changing marginal value of *additional* donations due to peer foundations' donations. That is, a 1% increase in peer foundations' grants to recipient j due to endowment wealth shocks is associated with approximately an 0.2% decrease in the focal foundation's grants to that same recipient j.[21] In Columns 4–6 of Table 5, we present robustness tests of the analyses described above in Columns 1–3, but controlling for the fixed effects of PFs. In all instances, the magnitude of β_2 is essentially unchanged and remains statistically significant. These results are consistent with the notion that our instrument, peer returns, is exogenous to characteristics of the focal foundations. Accordingly, we will use the specification without firm fixed effects as the main specification due to its greater efficiency. The results from the specification with firm fixed effects will be provided as a robustness check in the appendix.

Our results indicate that the altruistic motive dominates the potentially confounding sociality-based motives. For example, if donors are motivated by public recognition rather

[20] This will occur as long as the effect of the endowment shock is not offset by changes in future contributions received by the PF. In Table 11, we validate that these shocks are indeed not offset by changes in contributions received.

[21] One might interpret these magnitudes as being consistent with partial substitution. However, note that even if the focal foundation perfectly responds to the marginal value of recipients' needs, as modeled in Adelino et al. (2015), we might not observe identical percentage substitution between the donations of the focal foundation and those of peer foundations for two reasons. First, the focal foundation might optimize by considering the potential substitution effects among foundations when it observes shocks to one peer foundation. For example, in a simplified scenario where all foundations are independently and identically distributed, this strategic consideration implies that a one-dollar exogenous shock to a PF's donation to a recipient would result in a one-dollar reduction in the total donation from the remaining $N-1$ PFs, which means only a $\frac{1}{N-1}$ dollar reduction for each of these PFs. Second, overlapping donations to the same recipient may be directed to different programs. Therefore, to the extent that capital is not perfectly shared across the different programs within the recipient, the substitution (either in dollar or percentage terms) is likely not one-to-one.

than (or in addition to) altruism and desire to be leading benefactors of a particular recipient (e.g., due to social status), focal foundations may increase their donations to compete for the leading position at times when other donors increase donations to the same recipient, leading to a positive β_2.[22]

4.2. Variations in Responsiveness across Charitable Causes

To further understand foundations' responsiveness to changes in recipient needs, we evaluate whether the substitution effect is similar across charitable causes. We consider two types of gift characteristics. First, we classify gifts based on Candid's Philanthropy Classification System (PCS) categories (an expanded system of the National Taxonomy of Exempt Entities). We aggregate these categories into three groups: science, arts and religion, and the rest.[23] Foundations' responsiveness may naturally vary across these charitable causes. For example, if a PF is supporting a specific religious organization or arts program, it may not consider alternative religious organizations or arts initiatives as meaningful substitutes for that particular recipient. Additionally, the significance of public recognition or social status could differ across categories—for example, serving on the board of a prestigious institution like the Metropolitan Museum of Art may hold unique value that cannot easily be replicated elsewhere.

In Table 6, we repeat the same pooled OLS regressions as reported in Table 5, but applied to subsamples "Sci", "Art/Religion", and "Rest". For the naive regression, we do not see a noticeable difference in the regression coefficients on the changes in peer grants. For the 2SLS regressions, we observe the weakest substitution effect among the "Art/Religion" subsample, and the strongest substitution effect in the "Sci" subsample. These results show that the

[22]Focusing on peer shocks also makes our test more robust to various forms of impure-altruism preferences (Andreoni (1989)). Under impure altruism, the overall level of giving may not be perfectly responsive to financial shocks, but the allocation of those grants *across* recipients should still respond to changes in need.

[23]See https://taxonomy.candid.org/subjects. Science group includes 5 subjects: Agriculture, fishing and forestry, Education, Health, Science, Social sciences; arts and religion group includes 2 subjects: Arts and culture, and Religion; the rest includes the remaining 11 subjects:Community and economic development, Environment, Human rights, Human services, Information and communications, International relations, Philanthropy, Public affairs, Public safety, Sports and recreation, Unknown or not classified.

responsiveness does vary across charitable causes and support the notion that foundations view art and religion (science) recipients to be less (more) substitutable.

Second, we classify gifts based on whether the supported activities fall within the area of focus to the PF. We define this area of focus at the PF-year level as the PCS subject in which the PF has allocated the largest dollar amount of grants over the past three years. We refer to this as the PF's "favorite" area.

Ex ante, it is plausible that PFs could exhibit either greater or lesser responsiveness to changes in recipient needs within their favorite area. On one hand, PFs might be more responsive if they dedicate significant effort to understanding and addressing the needs of recipients in this area. On the other hand, they could be less responsive if they perceive recipients in their favorite area as less interchangeable, which may reduce their willingness to make adjustments or substitutions.

In Table 6, we repeat the same analysis in the favorite vs. non-favorite subsamples. We find the negative regression coefficient on the instrumented changes in peer grants is statistically significant in the non-favorite subsample, but insignificant in the favorite subsample. This stronger responsiveness among non-favorites suggests that the second force—reluctance to view favorite recipients as interchangeable—is more influential than the first.

To further explore this reluctance, we examine the interaction between the favorite area and the type of charitable causes. Specifically, we divide the sample into four subsamples using a 2x2 classification: whether the supported activities fall within the favorite area or not, and whether they pertain to the science subject or not. Our findings reveal that the diminishing substitution effects associated with the favorite area are substantially greater when the area is non-scientific compared to when it is scientific. Notably, the difference in substitution effects due to the favorite area is not statistically significant within the science subsample but is highly significant within the non-science subsample. Thus, the non-responsiveness of favorites is arising mostly from foundations where their favorite category is non-scientific, likely because non-scientific causes are perceived as more unique or harder to substitute compared to scientific ones.

4.3. Information Channels

There are two potential information channels that could contribute to foundations' responsiveness to changes in recipient needs. The first involves active learning by the focal PF, either through direct communication with the recipient or via its connections with peer PFs. The second channel reflects a reaction to the recipient's fundraising efforts. For example, recipients often have finite staff capacity that must be allocated between fundraising and implementing charitable projects. When a recipient receives larger grants from a peer foundation, the urgency of fund raising decreases, and its staff may shift their focus toward project implementation. This shift could influence the focal PF's perception of the recipient's needs and affect PFs grant allocation.[24]

While PFs play a more active role in the first channel, both channels predict that PFs reduce their grants when a recipient secures larger grants from peer foundations. Under the assumptions of decreasing returns to scale and ex ante optimal allocation, both channels align with an adjustment that reflects the social planner's preferred response. A useful comparison can be drawn with a for-profit firm allocating capital across projects. In such cases, some of the capital allocation may result from the CEO's direct analysis of the projects. However, part of the process can also be driven by lower-level employees championing their projects, advocating more strongly when the projects are expected to be more profitable. Even if a firm's effective capital allocation occurs primarily through the second channel, the CEO still allocates capital efficiently.

Yet these two information channels carry distinct implications. The active learning channel highlights the foundation's proactive role in gathering and analyzing information to assess recipient needs accurately. In contrast, the recipient-driven channel suggests that the focal PF's adjustments are limited by how well the recipient's fundraising intensity reflects its true needs. If variations in fundraising efforts do not align with variations in actual needs, PFs' adjustments may improperly reallocate capital. We thus design to a test to distinguish

[24] This substitution effect is similar to the crowding out effect of the government funding considered by Andreoni and Payne (2011).

between these information channels by examining how the length of relationship between a PF and a recipient affects PFs' responsiveness. Intuitively, PFs' active learning about a recipient improves as the tenure of their relationship lengthens. In contrast, the sensitivity of PFs' grants to fundraising efforts is likely highest at the beginning of the relationship, when the PF relies more on external signals like fundraising intensity due to limited knowledge of the recipient. Therefore, the active learning channel would predict a stronger substitution effect for longer relationships, whereas the recipient-driven channel would predict a stronger substitution effect for shorter relationships.

In Table 8, we group recipients of a PF into three subsamples based on the duration of their relationship with the PF, measured by the number of years the PF has been making grants to the recipients (Nyear categorized as Low, Middle, and High). We find that the substitution effect, indicated by the regression coefficient on the instrumented changes in peer grants, strengthens monotonically as the relationship lengthens. Specifically, the coefficient progresses from 0.14 (t-stat = 0.9) for shorter relationships to -0.46 (t-stat = -0.38) for longer relationships. The difference between these two coefficients is strongly statistically significant. These findings provide evidence consistent with the active learning channel, as longer relationships appear to enable PFs to better respond to changes in recipients' needs.

Further supporting the existence of an active learning channel strengthened by closer PF-recipient relationships, PFs in longer relationships with their recipients also appear better at distinguishing informative changes in peer grants from uninformative changes in peer grants. Specifically, to the extent that changes in peer grants in the naïve variant of the regression carry information about the quality of recipients, the active learning channel predicts that PFs would respond more strongly to these quality signals as the relationship lengthens. Columns 1 to 3 of Table 8 provide evidence supporting this hypothesis, with the positive coefficient on changes in peer grants being largest in the high-Nyear subsample. Furthermore, the difference in coefficients between the low-Nyear and high-Nyear subsamples is statistically significant. Collectively, these findings suggest that PFs themselves play an active role in determining their optimal capital allocation across recipients.

5. Intertemporal Responsiveness of Charitable Capital Allocation

Our analysis in the previous section suggests that PFs reallocate their donation portfolio in the face of changing recipient need. However, since the analysis focuses on cross-sectional reallocation, it could occur without any intertemporal responsiveness. For example, suppose that when a foundation sets its annual spending, capital preservation concerns supersede altruistic motives. A foundation subject to this hard capital preservation constraint can still reallocate across recipients within a given year and appear responsive to recipient needs based on the foundation-recipient level regression.

The extremely low closure rate of PFs, as documented earlier, indicates that many foundations allocate capital in a way that ensures long-term sustainability. As a result, some prominent foundations have to explicitly clarify that their spending levels are driven by recipient needs rather than capital preservation. For example, following the 2008 financial crisis, the Bill and Melinda Gates Foundation responded by increasing their grant making. As Bill Gates wrote in the Foundation's 2009 annual letter, "Our spending in 2008 was $3.3 billion. In 2009, instead of reducing this amount, we are choosing to increase it to $3.8 billion, which is about 7 percent of our assets."[25] We thus empirically investigate whether PFs' intertemporal responsiveness is dominated by altruistic motives or capital preservation concerns.

5.1. Intertemporal Responsiveness to Needs

We perform two analyses to test PFs' intertemporal responsiveness to recipient need. Our first analysis is an aggregate variant of our earlier foundation-recipient regression analysis. Specifically, we calculate the financial returns of peer foundations for each recipient of the focal foundation, aggregate these returns over the focal foundation's recipients, and use this average peer foundation return as an aggregate shock to the focal foundation's marginal

[25] See: https://www.gatesfoundation.org/Ideas/Annual%20Letters

value of giving.

$$\frac{Grant_{i,t+k}}{W_{i,t-1}} = \gamma_i + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \beta_3 PeerRET_{i,t} + \eta_{i,t+k}, k = 1, 2, \text{or } 3. \quad (3)$$

The coefficient of interest is on $PeerRET$. If PFs are responsive to exogenous variations in the marginal value of giving to a recipient, they should cut back their overall spending levels in the face of positive aggregate peer foundation returns, and increase their spending following negative peer foundation returns, giving a negative coefficient on $PeerRET$.

We present results in Table 9. Contrary to the prediction of intertemporal responsiveness to needs, Columns 1-3 find a statistically insignificant coefficient on $PeerRET$ across k =1, 2, and 3. For robustness, we also run an alternative regression specification controlling for time-varying target payout ratio, and we again find a statistically insignificant coefficient on $PeerRET$ in Columns 4 to 6. Thus, in contrast to the cross-sectional allocation result, we do not find significant evidence that recipient needs causally affect the foundation's total spending.

In our second analysis, we replace $PeerRET$ with an NBER recession dummy—equal to 1 for the years 2001, 2008, and 2009—as a proxy for a plausible increase in recipient needs in macroeconomic downturn. If PFs' total spending responds to recipient needs, we should observe a positive loading on the recession dummy. On the other hand, if the capital preservation concern is more important, we would not expect PFs to increase spending during recessions. Table 10 shows that there is no statistically significant evidence for a positive loading on the recession dummy across all specifications, and if anything, we find a negative loading with mixed significance.

In contrast to this insignificant intertemporal responses to proxies for recipients' needs, we observe a positive and statistically significant coefficient on the foundation's own returns across regression specifications. These results are consistent with the first stage of our 2SLS analysis above, suggesting that PFs' charitable spending increases (decreases) when they experience positive (negative) exogenous cash flow shocks. We now turn to investigate why this is the case.

5.2. Intertemporal Responsiveness to Own Returns

We analyze PFs' intertemporal response to cash flow shocks via the theoretical framework of Adelino et al. (2015). In Adelino et al. (2015)'s idealized, altruistic framework, PFs would not respond to endowment shocks, because the PFs' founders would adjust their additional future donations to the PF to exactly offset the permanent income effect of any endowment shock. More specifically, if PFs' founders equate the marginal utility from their consumption with the social benefits of their charitable giving,[26] then due to the concavity of utility (hence decreasing return to scale), charities' positive (negative) cash flow shocks should reduce (increase) the marginal value of charity, causing donors to substitute away from (towards) charity and towards (away from) personal consumption, which offsetts any effect of endowment returns on the permanent income of charities as described above. A critical assumption in this model is that financial shocks to nonprofits are uncorrelated with shocks to donors' wealth, and this assumption is likely violated in our PF setting given that PFs and their donors are likely to hold similar portfolios.[27]

We thus directly test the model prediction that charitable donors would "undo" the permanent income effect of endowment returns by adjusting their donations in an offsetting manner. Given that donations are infrequent, we run separate regressions to examine both the likelihood of donations and the amount donated when they occur.[28] Also due to infrequent donation, the coefficients of firm fixed effect regressions can suffer from the

[26]The hypothesis that donors are altruistically-driven – i.e., that they receive utility proportional to the social benefits of the charity they provide – is one traditional potential motivation explored in the literature. For discussions of various potential competing motives, see, e.g., Fama and Jensen (1985); Rose-Ackerman (1996); Fisman and Hubbard (2005).

[27]In the case of PFs founded and managed by nonfinancial founders, this overlap may simply reflect similar allocations across asset classes. For PFs with founders from the finance sector, the overlap may be even greater, especially if hedge fund founders invest their PF endowments in their own hedge funds. One suggestive anecdote: according to its 2019 Form 990-PF, the endowment of the Overdeck Family Foundation (the private foundation of hedge fund Two Sigma's cofounder John Overdeck) appears to have nearly all of its assets invested in a vehicle named Thompson Strategies. Little information about this vehicle is publicly available, but according to a 2014 SEC Notice of Exempt Offering of Securities, Thompson Strategies is a hedge fund whose place of business is identical to that of Two Sigma, suggesting that Overdeck's personal wealth and his foundation endowment both maintain substantial exposures to his hedge fund.

[28]Our results are robust to using Poisson regression, as reported in Appendix Table A2, which combines the effects of extensive and intensive margins.

finite-sample bias due to few observations per firm (Stambaugh (1999)) and thus we follow Lewellen and Lewellen (2016) to control for year fixed effects only. Columns 1 - 3 of Table 11 run the following logistic regression to examine the extensive margin

$$\text{Logit}P\left(\text{DonationReceived}_{i,t+k}\right) = \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \eta_{i,t+k}, \tag{4}$$

where k =1, 2, or 3. We find that the regression coefficient β_1 is not statistically different from zero in any of the regressions.

Columns 4 - 6 of Table 11 run the following OLS regression (conditional on positive $\text{DonationReceived}_{i,t+k}$) to examine the intensive margin

$$\frac{\text{DonationReceived}_{i,t+k}}{W_{i,t-1}} = \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \eta_{i,t+k}, \tag{5}$$

where k =1, 2, or 3. We again find that the regression coefficient β_1 is not statistically different from zero in any of the regressions. Therefore, cash flow shocks at time t do not predict future donation probability nor the magnitude of donation provided a donation is made, confirming the conjecture that PFs endowment returns would impact foundations' permanent income. These results are consistent with the existence of a positive correlation between the foundation's cash flow shock and the donor's own wealth shock. For example, consider a positive shock to foundation wealth that decreases the marginal value of future donations to the foundation. If shocks to foundation wealth are positively correlated with shocks to the founder's wealth (e.g., if the foundation and the founder hold similar financial portfolios), a positive wealth shock will lead to both a decrease in the marginal value of future donations and an offsetting decrease in the marginal cost in terms of donors' forgone consumption, weakening the substitution mechanism.

Another potential explanation for PFs' positive grant-endowment return sensitivities is that PFs constrained by the mandatory minimal 5% spending rule are simply obliged to increase their spending when their financial assets grow. We thus examine the spending-cash flow sensitivities for a subsample of PFs whose spending is far above the required minimum spending. If the positive cash flow sensitivity was driven wholly by the regulatory constraint, we should observe zero sensitivity among these PFs.

Table 12 shows the regression analysis of the grant-cash flow sensitivity among the subset of private foundations whose annual grantmaking substantially exceeds the required 5% level. Under current rules, qualifying distributions in excess of the minimum can be carried forward for up to five years. Thus, we first compute the difference between qualifying distributions (Line 4 of Part XII) and the required distributions (one-year lagged value of Line 7 of Part XI). We then compute the sum of the difference from year $t-4$ to year t, and refer to it as the 5-year carry forward.[29] The subset of private foundations we use in Table 12 contains PFs whose year t qualifying distributions is at least 20% larger than the required distributions and whose 5-year carry forward is positive. The spending of these PFs in year $t+1$ is thus virtually unconstrained by the regulation, not only because these PFs can make up any spending shortfall in the following year (year $t+2$), but also because spending shortfall can be offset by their positive carry forward. Contrary to the explanation based on the required minimum spending, we find that the grant-cash flow sensitivities are more positive in this subsample of high payout PFs, with the coefficients remaining positive and highly significant for not only year $t+1$ but also year $t+2$ and $t+3$.

5.3. Capital Preservation

If PFs' overall spending level simply fluctuates with their permanent income, it should comove equally with both positive and negative cash flow shocks. However, if PFs prioritize capital preservation, we would expect them to respond more strongly to negative returns by cutting spending aggressively. Motivated by the findings in Brown et al. (2014), we test this asymmetric response using the following OLS regressions:

$$\frac{G_{i,t}}{W_{i,t-1}} = \beta_0 + \gamma_i + \gamma_t + \beta_1^+ RET_{i,t}^+ + \beta_1^- RET_{i,t}^- + \left[\beta_2^+ RET_{i,t-1}^+ + \beta_2^- RET_{i,t-1}^-\right] + \eta_{i,t}, \quad (6)$$

[29] We further adjust the 5-year carry forward by the difference between qualifying distributions and the required distributions in year $t-5$ if the difference is negative because shortfalls in year $t-5$ needs to be made up in year $t-4$.

where the actual payout is defined as the spending in year t scaled by the beginning-of-year assets.[30] In the main regression, we do not control for the lagged returns to the PF's assets, whereas in the alternative regression specification we do.

Columns 1 and 2 in Table 13 show that the loading on negative returns is more positive than that on positive returns, indicating that the payout rates respond more strongly to negative contemporaneous returns in our PF sample. We formally test this asymmetric response and find that the null hypothesis that $\beta_1^+ = \beta_1^{-1}$ can be rejected at the conventional statistical significance level. Columns 3 and 4 show that these results are robust to controlling for the time-varying target payout ratio instead of the PF fixed effects. In terms of economic magnitude, in the event of a financial shock equivalent to 10 percent of an endowment's beginning-of-year asset value, the average PF's payout rate increases by 10 to 16 basis points for positive returns but decreases by 24 to 32 basis points for negative returns. The asymmetry in responses is thus economically substantial given that the average payout rate is 4.8%.

Brown et al. (2014) document a similar asymmetric response in the spending of universities, indicating that capital preservation is prioritized over the stated policy goals of the institution. Brown et al. (2014) argue that, in the university context, this entails an agency problem between donors (who are presumed to prioritize the institution's interests) and managers (who may have career-related concerns). Our findings suggest that this agency problem may be deeper. In the private foundation context, donors and managers often overlap, suggesting that aligning managers' actions with donors' interests alone may not be sufficient to ensure alignment with an institution's mission as laid forth in the institution's charter.

[30] Brown et al. (2014) documents a stronger response to negative cash flow shocks in university endowment payout behavior and attributes this to managers' desire to preserve capital.

6. Responsiveness and Governance

6.1. Governance and Cross-Sectional Responsiveness to Need

We have established that PFs are responsive to changes in recipient needs when allocating grants but deviate from ideal responsiveness in ways consistent with a more dominant focus on capital preservation when determining their overall spending level. We now proceed to investigate how the governance structure of PFs affects their responsiveness to charitable needs and their focus on capital preservation.

Specifically, we are interested in whether factors typically associated with good governance among for-profit firms are also associated with greater focus on recipient needs and less on capital preservation among PFs. Ex ante, the expected relationship is potentially ambiguous. On one hand, it seems reasonable to assume that governance devices like large, independent boards of directors and professional corporate officers would lead to positive outcomes. On the other hand, these devices may prove ineffective given that the tools available to PFs for exerting governance discipline are relatively constrained (e.g., by the lack of a share price and the consequent limits to compensation schemes that align officers' incentives with the spirit of a PF's charter; by the limits of stakeholders' ability to use voice or exit for disciplining trustees or officers; and by the absence of market competition and the lack of a legible equivalent to the Friedman Doctrine of shareholder primacy). Given the potential illegibility of well-executed charitable activities, in the sense of Scott (1998), a governance structure that encourages (rather than constrains) PFs' managerial discretion and use of private signals may allow for greater responsiveness.

Table 14 repeats our IV regressions of PFs' responsiveness to recipient needs, as in Table 5, in a series of subsamples split on governance and foundation characteristics.[31] Panel A considers characteristics related to a foundation's board: the presence of a founder or founder's family member on the board, the size of the board, and the compensation of

[31]For brevity, we focus on the results for the main regression specification in Table 5 and report the results for the alternative regression specification in Appendix Table **14**, which are qualitatively similar.

officers and trustees.

Our proxy for founder influence is the presence of a founder or a founder's family member as a trustee or officer of the foundation. We identify founder-family trustees in two ways. First, we identify family trustees by examining cases where a trustee's last name appears in the name of the foundation (e.g., the Overdeck Family Foundation's 2022 filing lists two trustees with the last name Overdeck.) Second, we identify cases where the foundation is named after a company owned by a trustee. Specifically, we use SEC Form ADV and Form D to identify investment companies owned by foundation trustees and examine whether the company name appears in the foundation name. We define the indicator variable $Family$ to equal H for a foundation if at least one foundation trustee or officer is identified by these two methods above. In total, using this methodology, about half of foundation-year filings contain a founder-family trustee.

Column (1) of Table 14 presents the subsample analysis results for foundations with $Family = L$, and Column (2) presents the analysis for foundations with $Family = H$, as well as testing the difference in responsiveness across subsamples. Following the discussion above, a board influenced by the founder (or founder's family) may lead to more responsive charitable grantmaking. This is because founders can be more passionate or astute in assessing recipient needs than board directors who are not disciplined by the usual governance forces available to for-profits.[32] Even having assessed these needs, if signals of need are based on soft information, responding to them may require the exercise of discretion. In contrast, when a legacy foundation board exercises control of a foundation – e.g., following the retirement or death of the foundation's primary donor – trustees' convictions about the foundation's mission may be less powerful.[33] Consistent with this hypothesis, we find

[32]Founders often have a deep, personal commitment to the foundation's mission and a nuanced understanding of its goals and beneficiaries, which can drive more effective and responsive decision-making.

[33]This tendency is noted by billionaire philanthropist John Arnold "[d]ead people's influence should decrease as time passes...it would be more efficient if those big legacy foundations, that they brought forward their giving and let the next generation of givers be more influential in the next generation." See: https://www.vox.com/recode/2019/7/25/8891899/john-arnold-billionaire-criticism-donor-advised-funds-silicon-valley-philanthropic-loophole. McAllister and Allen (2017) finds that foundations with the founder on board tend to have relatively larger grant expense and less administrative expense, a measure of foundation efficiency.

that foundations with founding family influence are significantly more responsive to instrumented changes in recipients' needs (due to exogenous changes in peer foundations' grants). Interestingly, the coefficient on instrumented changes in recipients' needs is negative and statistically insignificant for foundations that are not under founder-family influence. This result suggests that the presence of founder-family trustees plays a crucial role in maintaining responsiveness to recipient needs, and without their influence, the responsiveness becomes insignificant.

Next, we consider two other governance factors: board size and the compensation of officers and directors employed by a PF. Columns (3) and (4) consider board size. Column (3) reports results for foundations with $LargeBoard = L$; i.e., for which a foundation's board size is below the cross-sectional median; and Column (4) reports results for the complementary group $LargeBoard = H$. The difference in coefficients of responsiveness across the two subsamples is statistically insignificant, suggesting that board size does not play a major role in foundations' responsiveness to need. However, the negative sign of the difference is directionally consistent with the finding in the broader governance literature that large boards are associated with better performance (see, e.g., Adams and Mehran (2012)).

Columns (5) and (6) consider the compensation of professional officers. We define professional officers as highly paid officers (i.e., annual salary exceeds $150,000), and the indicator variable $HighPay$ is 1 if the number of professional officers is above the cross-sectional median. Foundations with more professional officers are more responsive to changes in recipient need, with the difference being significant at the 5% level.

Panel B of Table 14 considers foundation characteristics: foundation size, age, and payout ratio. Columns (1) and (2) report responsiveness for subsamples split on foundation size. The indicator variable $Large$ is H if the foundation size is above the 70th percentile (inclusive) of the cross-sectional size distribution.[34] Large foundations are directionally more responsive, but the difference in responsiveness between large and small foundations is not statistically significant.

[34] Large foundations tend to have more grant recipients. We choose the 70th percentile to make the split samples balanced in foundation-recipient pairs.

Columns (3) and (4) report subsamples split on foundation age. The indicator variable $Young$ is L if the foundation's age (measured by its ruledate; i.e., the date upon which it was granted nonprofit status) is greater than 40 years, thus Column (3) presents results for older foundations and Column (4) for younger ones. Foundation age can have mixed effects on responsiveness. Older foundations may become less responsive due to organizational stasis or institutional capture following their founders' death or retirement. On the other hand, they may become more responsive due to accumulated expertise in the charitable sector. We find that the former force is weakly stronger: directionally, young foundations are more responsive, though again the difference in responsiveness is not statistically significant.

Finally, Columns (5) and (6) report subsamples split on foundation payout ratio. Intuitively, higher payout ratios can be associated with greater commitment to the mission of the foundation. The indicator variable $HighPayout$ is H for private foundations with payout ratios above the cross-sectional median payout ratio. Columns 5 and 6 show that high payout foundations are indeed associated with stronger substitution effects, with the difference being statistically significant. The stronger responsiveness of higher payout foundations supports the notion that these foundations are more committed to advancing their mission.

Overall, founders' influence appears to be more important than board independence in promoting foundations' responsiveness to recipient need. While foundation age and size do not have significant effects on foundation responsiveness, payout rates do, suggesting that factors that proxy for institutional motivation are more relevant for responsiveness than factors that proxy for institutional capacity. However, unconstrained discretion can potentially allow for greater private benefits, especially if effective grantmaking and the enjoyment of private benefits are hard to distinguish from one another. Thus, in our next subsample analysis, we explore how the same factors affect PFs' tendency towards capital preservation.

6.2. Governance and Capital Preservation

We repeat the same capital preservation regression analysis, as used in Table 13, across the above subsamples.[35] As described in the prior section, if the capital preservation motive is an important driver of PFs' total grantmaking, then PFs would plausibly respond more aggressively to negative returns by cutting grantmaking. Hence, we first compare the extent of asymmetric payout response to positive versus negative returns across two subsamples; and second, we compare the magnitude of the spending cut following negative returns.

Columns 1 and 2 of Table 15 present results for subsamples split on having a founder-family trustee. The positive coefficient on negative returns is about 40% (300%) larger in magnitude than the coefficient on positive returns with $Family = L$ ($Family = H$). When we formally test the difference, we find the asymmetric response to be significantly larger for PFs with a founder-family trustee, suggesting that PFs under founder-family influence ($Family = H$) exhibit substantially greater asymmetric response to negative returns. Furthermore, comparing the coefficient on negative returns between Column (1) vs. Column (2), we observe that following negative returns, PFs with founder influence cut their spending by 80% more than PFs without founder influence. Both comparisons suggest that PFs with founder influence are more focused on capital preservation.

Columns 3 and 4 present results for the sample split based on board size. We observe a smaller symmetric response to negative returns among foundations with larger boards, though the difference is only marginally significant (p-value = 6%). This finding is consistent with prior literature suggesting that larger boards impose greater constraints on managers' ability to pursue private benefits.

For the sample splits based on foundation characteristics (Columns 5-10), we find that older and larger foundations show less tendency toward capital preservation, though the differences are not statistically significant at the 5% level. The most notable difference

[35] For brevity, we focus on the results for the main regression specification in Table A3 and report the results for the alternative regression specification in Appendix Table **14**, which are qualitatively similar. Since this analysis is performed on all PFs and only 2% of foundations (mostly large foundations) have any officers who earn more than \$150k, we do not perform a subsample split based on $HighPay$.

emerges when splitting by payout ratio, where high-payout foundations exhibit a greater tendency toward capital preservation.

Overall, when we contrast the capital preservation subsample results with those of cross-sectional responsiveness, we find that founder-family influence and high-payout status are linked to both greater cross-sectional responsiveness and a stronger tendency toward capital preservation. These findings suggest that, because responsiveness to recipient needs is difficult to measure and thus monitor and contract upon – and given the limited governance tools available to non-profits – a foundation's responsiveness depends more on the discretion and charitable intent of trustees than on the discipline of independent governance. However, the exercise of discretion is also associated with a greater tendency towards capital preservation. While some prominent foundations such as the Bill & Melinda Gates Foundation and the Laura & John Arnold Foundation have explicit plans to spend down their endowments within 10 to 20 years after their founders' death, our analysis indicates that such cases are not representative of the typical foundation.[36] Therefore, regulatory mandates for a minimum spending ratio likely play an important role in curbing deviations from efficient grantmaking due to capital preservation motives; and further research is needed to understand the private benefits underlying such motives.

7. Conclusions

Using a comprehensive dataset on the assets, network characteristics, and grant making behavior of private foundations (PFs), we analyze how effectively these foundations allocate charitable capital in response to changes in recipient needs. Our test exploits rich data on the network of foundation-recipient relationships and uses financial shocks to peer foundations as a novel source of variation to the marginal value of donation, enabling us to isolate the effect of recipient needs on focal foundations' grantmaking from confounding forces.

We document novel evidence showing that foundations adjust their cross-sectional grant

[36] "Because Bill and Melinda believe the right approach is to focus the foundation's work in the 21st century, we will spend all of our resources within 20 years after Bill's and Melinda's deaths." https://www.gatesfoundation.org/about/financials/foundation-trust

allocations in response to recipient needs. This responsiveness is stronger for scientifically-oriented cause areas, longer-standing donor-recipient relationships, and foundations under the influence of founding families. However, we find that foundations show limited intertemporal responsiveness to changing needs, instead prioritizing capital preservation. Moreover, foundations influenced by founding families and those with high payout ratios exhibit both greater cross-sectional responsiveness and a stronger tendency toward capital preservation.

More broadly, the charitable capital allocation of private foundations offers insight into the role of market mechanisms in the broader economy. Because foundations are insulated from these mechanisms (e.g., the discipline imposed by product markets, funding markets, and markets for corporate control), we are able to indirectly evaluate the importance of these market mechanisms by examining the consequences of their absence. Our results highlight that, under certain ideal circumstances, foundations can allocate capital effectively despite the absence of market discipline. However, this efficacy is fragile, likely because it depends upon fortuitous alignment between the societal needs and the goals of foundation trustees, rather than being driven by the incentive alignment enforced through market mechanisms. Any deviation from this alignment – whether due to the opacity of information channels between foundations and recipients, the perceived uniqueness of certain causes, the absence of a motivated founder, or the private benefits from capital preservation – can undermine the responsiveness of charitable capital allocation. In this light, the current regulatory framework is a balancing act. It subsidizes PFs activities in hope of harnessing foundations' insights into recipient needs, while simultaneously mandating minimum spending to limit the private benefits of capital preservation.

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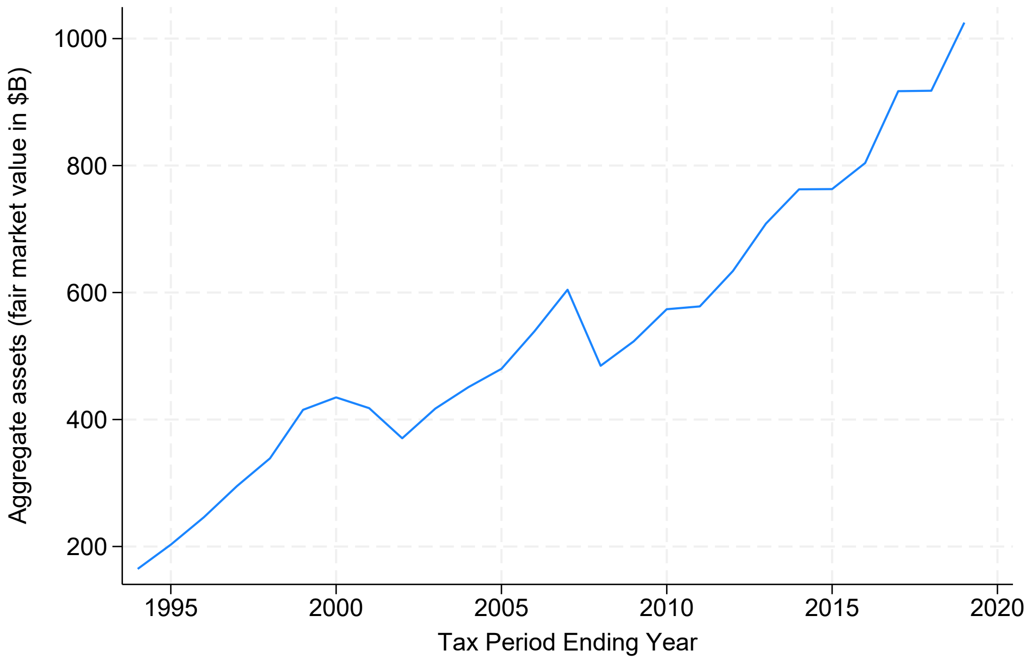
Figure 1: Aggregate Market Value and Spending of Private Foundations, 1994 - 2019

Panel A plots the aggregate market value of assets of PFs in our sample. Panel B plots the aggregate spending both in billions of dollars and as a percentage of the federal non-defense discretionary spending.

Panel A



Panel B

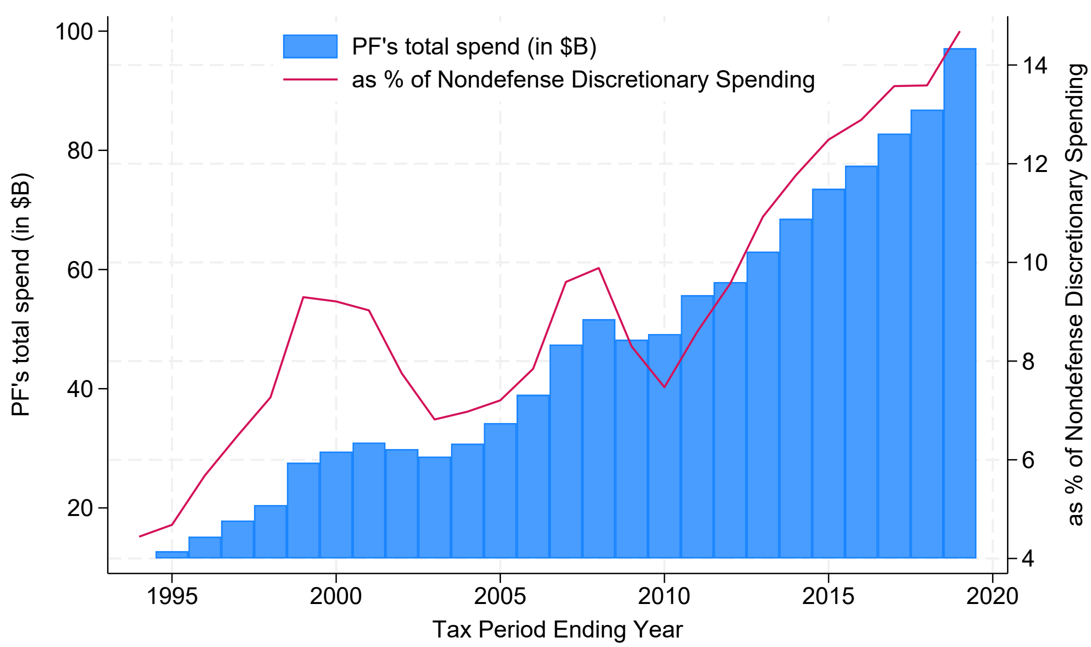


Figure 2: Closure Rate of Private Foundations

This figure plots the annual hazard rates for closing probabilities of private foundations as a function of their age. We generally measure a foundation's age from the date the IRS approved its application for tax exempt status (its ruledate from the IRS BMF). In cases where the date of a foundation's first 990-PF filing precedes its ruledate by no more than two years, we measure age from the date of first filing (since foundations may file 990-PF forms while their applications are pending.) For foundations whose first filing precedes their ruledate by more than two years, we do not compute age for these foundations due to the lack of reliable data. Because Section 501(c) of the Internal Revenue Code (and hence the assignment of ruledates for tax exempt status) dates to the Revenue Act of 1954, reported ruledates before 1955 are unreliable measures of foundations' ages; if a foundation's reported ruledate is earlier than 1955, we assign it a ruledate of 1955 for this hazard analysis. Thus, ruledates for foundations founded prior to 1955 will underestimate their age, but ruledates after 1955 are a relatively reliable proxy for foundation age. We define the year of death as the year after which PFs no longer appear in our dataset or the IRS Business Master File, which essentially occurs when the PF stops filling Form 990-PF. The indicator Hit50M is equal to 1 for all years after a PF's asset exceeds 50 million dollars (even if the assets fall below this threshold in the subsequent years).

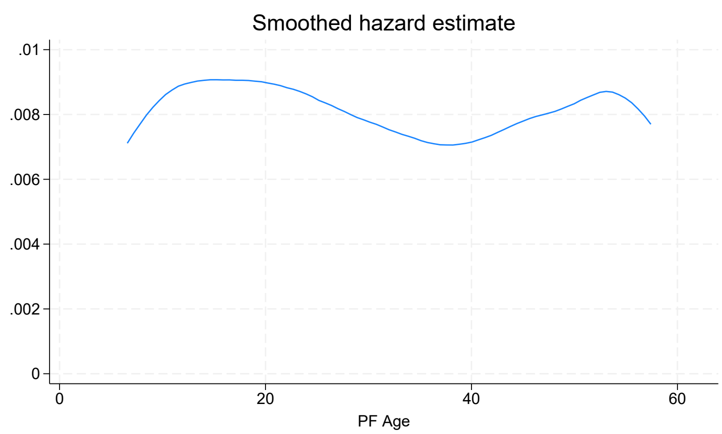


Table 1: Summary Statistics: Assets and Grants

This table reports the summary statistics at the PF-year level over the sample period from 1994 to 2019.

	N	Mean	SD	P5	P25	P50	P75	P95
Assets (MV in $M)	282696	42.94	411.31	1.01	2.70	9.04	22.07	114.64
Dollar grants paid (in $M)	282735	2.64	34.40	0.04	0.13	0.47	1.28	7.57
Grant payout rate (in %)	281825	8.01	15.55	1.67	4.06	4.84	6.24	23.25
Expense rate (in %)	281774	9.71	65.35	3.21	5.16	5.99	7.84	26.03
Grant-to-expense ratio	282533	0.84	22.02	0.42	0.74	0.83	0.92	0.99
Donation rate (in %)	281825	5.91	73.03	0.00	0.00	0.00	0.07	24.05
Return (in %)	281611	7.96	71.11	-16.18	0.55	7.79	14.48	27.12

Table 2: Top 10 PFs by Market Value

This tables shows the largest 10 PFs over 5-year periods. Column "A" reports the average market value of assets and Column "G" reports the average annual grants made by the PFs, both of which are in billion dollars.

1995-1999			2000-2004			2005-2009			2010-2014			2015-2019		
Name	A	G	Name	A	G	Name	A	G	Name	A	G	Name	A	G
Lilly Endwmt	9.4	0.3	Gates Fnd	26.7	1.2	Gates Fnd	32.8	2.8	Gates Fnd	38.2	3.9	Gates Fnd	45.5	5.4
Ford Fnd	9.4	0.4	Lilly Endwmt	11.6	0.5	Ford Fnd	11.8	0.5	Ford Fnd	11.4	0.5	Ford Fnd	13.2	0.6
Packard Fnd	8.3	0.6	Ford Fnd	11.1	0.6	RW Johnson	9.2	0.4	RW Johnson	9.7	0.3	Lilly Endwmt	13.2	0.5
RW Johnson	6.8	0.3	RW Johnson	8.6	0.3	Hewlett Fnd	7.8	0.4	Hewlett Fnd	8.0	0.3	RW Johnson	11.1	0.4
Kellogg Fnd	5.8	0.3	Packard Fnd	6.4	0.4	Kellogg Fnd	7.2	0.3	Lilly Endwmt	7.2	0.3	Open Society	9.9	0.5
Macarthur	3.9	0.2	Hewlett Fnd	5.5	0.2	Lilly Endwmt	6.9	0.3	Kellogg Fnd	7.2	0.3	Hewlett Fnd	9.7	0.4
Casey Fnd	3.6	0.1	Kellogg Fnd	5.3	0.3	Packard Fnd	5.8	0.2	Packard Fnd	6.4	0.3	Bloomberg	8.3	0.6
Mellon Fnd	3.3	0.1	Moore Fnd	5.0	0.2	Macarthur	5.8	0.2	Macarthur	6.0	0.2	Kellogg Fnd	8.0	0.4
Woodruff Fnd	3.2	0.1	Mellon Fnd	4.5	0.2	Mellon Fnd	5.5	0.2	Moore Fnd	5.9	0.2	Packard Fnd	7.5	0.3
Rockefeller	3.1	0.1	Macarthur	4.4	0.2	Moore Fnd	5.5	0.3	Mellon Fnd	5.8	0.2	Moore Fnd	6.7	0.3

Table 3: Top 15 Recipient by Grant Amount

This list is generated using the grant making data of largest PFs (see description in the main text). Column "G" reports the total grant amount (in $B) received by a recipient from these PFs over the 5-year period and Column "N" reports the number of unique PFs that make grants to the recipient over the same period.

2005-2009			2010-2014			2015-2019		
Name	G	N	Name	G	N	Name	G	N
PAT Health	0.7	17	GA Vaccines & Immun.	1.2	1	GA Vaccines & Immun.	1.6	2
World Health Org	0.7	11	World Health Org	1.1	9	World Health Org	1.5	9
ClimateWorks Fnd	0.6	2	The Global Fund	0.8	1	The Global Fund	0.9	4
The Global Fund	0.5	3	PAT Health	0.5	14	PAT Health	0.8	17
Duke University	0.4	68	NYU	0.4	149	Johns Hopkins Univ	0.8	85
Univ of Washington	0.4	50	Broad Institute	0.4	14	Harvard University	0.8	108
GA Vaccines & Immun.	0.4	1	Rotary Foundation	0.4	6	Broad Institute	0.7	15
AGR Africa	0.4	2	Emory University	0.4	59	Univ of Washington	0.7	65
Columbia University	0.3	102	UNICEF	0.4	28	UNICEF	0.6	32
Johns Hopkins Univ	0.3	75	Open Society	0.4	1	UC SF	0.6	84
Harvard University	0.3	92	Columbia University	0.4	124	New Venture Fund	0.5	46
Cornell University	0.3	60	Duke University	0.4	76	Rotary Foundation	0.5	5
NYU	0.3	119	Johns Hopkins Univ	0.4	82	NYU	0.5	163
UCLA	0.3	72	ClimateWorks Fnd	0.4	5	Adelson Fnd	0.5	1
UC Berkeley	0.3	73	Stanford University	0.3	108	Stanford University	0.5	121

Table 4: Summary Statistics: Detailed Grant Subsample

This table reports the summary statistics in the Candid sample used to estimate the cross-sectional responsiveness of PFs' grant allocation to recipient needs. The sample include 501 unique PFs and 33,133 unique recipients from 2003 to 2019. The total number of the reicipient-PF-year observations used in the analysis is 190,848.

Panel A: Distribution Across PF-Year Obs

	Mean	SD	P5	P25	P50	P75	P95
Number of Recipients (PF-Year level)	82.46	92.11	4.00	22.00	53.00	109.00	267.00

Panel B: Distribution Across Recipient-Year Obs

	Mean	SD	P5	P25	P50	P75	P95
Grants Received from PFs (Recipient-Year level, in 000s)	917.46	6285.76	5.00	35.00	115.00	409.50	3054.08
Number of Granting PFs (Recipient-Year level)	2.43	3.10	1.00	1.00	2.00	3.00	6.00

Panel C: Distribution Across Recipient-PF-Year Obs

	Mean	SD	P5	P25	P50	P75	P95
PeerRet (per PF-recipient-year, in p.a.)	5.34	8.09	-7.44	0.77	5.11	10.64	16.91
Number of Peer Foundations (PF-Recipient-Year level)	9.92	16.29	2.00	2.00	4.00	9.00	40.00

Table 5: Cross-Sectional Responsiveness of Grant Allocations to Need

We present the regression results for the following OLS regression in Columns (1)

$$\begin{aligned}\Delta log\left(Grant_{i,j,t+1}\right) &= c+\gamma_i+\beta_1 log\left(1+RET_{i,t}\right)+\delta_1 log\left(Grant_{i,j,t}\right)+\delta_2 log\left(W_{i,t-1}\right)\\ &+\beta_2\Delta log\left(PeerGrant_{i,j,t+1}\right)+\delta_3 log\left(PeerGrant_{i,j,t}\right)+\eta_{i,j,t+1},\end{aligned}$$

where $Grant_{i,j,t+1}$ is the grant amount from foundation i to recipient j in year $t+1$ and $PeerGrant_{i,j,t} = \sum_{i'\neq i} G_{i',j,t}$. Column 2 reports the first stage regression results

$$\Delta log\left(Grant_{i,j,t+1}\right) = c+\gamma_i+\beta_1 log\left(1+RET_{i,t}\right)+\delta_1 log\left(Grant_{i,j,t}\right)+\delta_2 log\left(W_{i,t-1}\right)+\eta_{i,j,t+1}$$

Column 3 reports the 2SLS regressions using $log(1+RET_{-i,j,t}) = log(1+\sum_{i'\neq i}\frac{G_{i',j,t}}{G_{j,t}}RET_{i',t})$ as an instrument for $\Delta log\left(PeerGrant_{i,j,t+1}\right)$. Columns 4 through 6 repeat the analyses from Columns 1–3, respectively, but with the addition of PF fixed effects. This sample contains only PFs for which we have collected grant recipient data as described in the main text.

	(1)	(2)	(3)	(4)	(5)	(6)
log(1+R$_{i,t}$)	0.29***	0.29***	0.40***	0.29***	0.28***	0.39***
	(0.06)	(0.06)	(0.09)	(0.06)	(0.06)	(0.08)
Δlog(PeerGrant$_{i,j,t+1}$)	0.03***			0.03***		
	(0.00)			(0.00)		
Δlog(PeerGrant$_{i,j,t+1}$)$^{inst.}$			-0.23***			-0.22**
			(0.07)			(0.08)
log(Grant$_{i,j,t}$)	-0.23***	-0.20***	-0.21***	-0.28***	-0.26***	-0.26***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
log(W$_{i,t-1}$)	0.12***	0.12***	0.12***	0.05*	0.06**	0.05*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
log(PeerGrant$_{i,j,t}$)	0.05***		0.01	0.06***		0.01
	(0.00)		(0.01)	(0.00)		(0.02)
FE	None	None	None	Firm	Firm	Firm
Observations	143740	190848	143740	143735	190842	143735
F-Stat for Weak IV Test			12			12

Table 6: Cross-Sectional Responsiveness of Grant Allocations to Need (by Recipient Type)

This table presents the same pooled OLS regressions as reported in Columns (1) and (3) of Table 5, but applied to different subsamples. The "Sci" subsample includes all gifts made by private foundations in the following areas: Agriculture, Fishing and Forestry, Education, Health, Science, and Social Sciences. The "Art/Religion" subsample comprises gifts made by private foundations in the areas of Arts and Culture and Religion. Finally, the "Rest" subsample encompasses all gifts made by private foundations in the remaining areas.

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.36***	0.32***	0.24***	0.41***	0.47***	0.32***
	(0.05)	(0.07)	(0.07)	(0.07)	(0.11)	(0.10)
$\Delta\log(PeerGrant_{i,j,t+1})$	0.03***	0.03***	0.04***			
	(0.01)	(0.00)	(0.01)			
$\Delta\log(PeerGrant_{i,j,t+1})^{inst.}$				-0.11	-0.29***	-0.21
				(0.07)	(0.08)	(0.14)
$\log(Grant_{i,j,t})$	-0.22***	-0.22***	-0.24***	-0.21***	-0.20***	-0.22***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.11***	0.12***	0.11***	0.12***	0.12***	0.13***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
$\log(PeerGrant_{i,j,t})$	0.05***	0.05***	0.05***	0.02	0.00	0.00
	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.03)
Sample	Art/Religion	Sci	Rest	Art/Religion	Sci	Rest
Observations	23555	55289	64896	23555	55289	64896
F-Stat for Weak IV Test				17.7	11.5	9.1
Dif(Sci - Art/Religion)	-0.003			-0.178		
p(Sci - Art/Religion)	0.601			0.020		

Table 7: Cross-Sectional Responsiveness of Grant Allocations to Need (by PF Primary Area)

This table presents the same pooled OLS regressions as reported in Table 5, but applied to different subsamples. Favorite (H) subsample includes all gifts in a PF's primary area, defined as the area in which the PF has allocated the largest dollar amount of grants over the past three years. Favorite (L) subsample includes the remaining gifts. The "Sci" areas are defined in the previous table and "NonSci" subsample includes all the other areas.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(1+\mathrm{R}_{i,t})$	0.26***	0.36***	0.40***	0.40***	0.37***	0.25**	0.44***	0.54***
	(0.06)	(0.06)	(0.11)	(0.09)	(0.11)	(0.11)	(0.12)	(0.13)
$\Delta\log(\mathrm{PeerGrant}_{i,j,t+1})$	0.04***	0.03***						
	(0.00)	(0.00)						
$\Delta\log(\mathrm{PeerGrant}_{i,j,t+1})^{inst.}$			-0.31***	-0.06	-0.27***	0.11	-0.38***	-0.21
			(0.07)	(0.13)	(0.10)	(0.14)	(0.11)	(0.14)
$\log(\mathrm{Grant}_{i,j,t})$	-0.23***	-0.23***	-0.21***	-0.22***	-0.21***	-0.26***	-0.21***	-0.20***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\log(\mathrm{W}_{i,t-1})$	0.12***	0.11***	0.13***	0.12***	0.13***	0.10***	0.13***	0.12***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
$\log(\mathrm{PeerGrant}_{i,j,t})$	0.06***	0.05***	-0.01	0.03	-0.01	0.07**	-0.01	0.01
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Sample	Fav(L)	Fav(H)	Fav(L)	Fav(H)	Fav(L)/NonSci	Fav(H)/NonSci	Fav(L)/Sci	Fav(H)/Sci
Observations	99033	44707	99033	44707	70222	18229	28811	26478
F-Stat for Weak IV Test			11.4	12.6	9.2	18.0	16.1	7.9
Dif(H-L)		-0.012		0.251		0.385		0.170
p(H-L)		0.038		0.059		0.006		0.336

Table 8: Cross-Sectional Responsiveness of Grant Allocations to Need (by Relationship Length)

This table presents the same pooled OLS regressions as reported in Table 5, but applied to different subsamples. For each PF-year, recipients of a PF are grouped into three subsamples based on the number of years the PF has been making grants to the same recipient: Nyear (Low/Medium/High).

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.16*	0.21***	0.48***	0.12	0.33***	0.65***
	(0.09)	(0.04)	(0.09)	(0.12)	(0.07)	(0.13)
$\Delta\log(PeerGrant_{i,j,t+1})$	0.03***	0.03***	0.04***			
	(0.00)	(0.00)	(0.00)			
$\Delta\log(PeerGrant_{i,j,t+1})^{inst.}$				0.14	-0.24***	-0.46***
				(0.15)	(0.09)	(0.12)
$\log(Grant_{i,j,t})$	-0.17***	-0.22***	-0.28***	-0.18***	-0.21***	-0.25***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.09***	0.10***	0.15***	0.09***	0.11***	0.17***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
$\log(PeerGrant_{i,j,t})$	0.05***	0.04***	0.07***	0.07**	-0.00	-0.01
	(0.01)	(0.00)	(0.00)	(0.03)	(0.02)	(0.02)
Sample	Nyear(L)	Nyear(M)	Nyear(H)	Nyear(L)	Nyear(M)	Nyear(H)
Observations	40928	47584	55228	40928	47584	55228
F-Stat for Weak IV Test				19.4	9.0	7.7
Dif(H-L)			0.011			-0.598
p(H-L)			0.037			0.008

Table 9: Intertemporal Responsiveness of Grants to Aggregate Peer Returns

Columns 1 - 3 report results for the following regression

$$\frac{Grant_{i,t+k}}{W_{i,t-1}} = \gamma_i + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \beta_3 PeerRET_{i,t} + \eta_{i,t+k}$$

Columns 4 - 6 report the regression results controlling for the time-varying target payout ratio instead of the PF fixed effects. $PeerRET$ is the weighted average of peer foundation returns. The two-way clustered standard errors reported in parentheses are clustered at the year and foundation levels. This sample contains only PFs for which we have collected grant recipient data as described in the main text.

	(1) k=1	(2) k=2	(3) k=3	(4) k=1	(5) k=2	(6) k=3
RET	0.029***	0.020*	0.021	0.043***	0.040***	0.048***
	(0.007)	(0.010)	(0.013)	(0.006)	(0.009)	(0.009)
Size	-0.025***	-0.038***	-0.053***	-0.003**	-0.004**	-0.008**
	(0.004)	(0.005)	(0.003)	(0.001)	(0.002)	(0.003)
PeerRET	0.010	0.033	-0.011	0.029	0.033	0.038
	(0.031)	(0.043)	(0.019)	(0.024)	(0.039)	(0.033)
Target				0.734***	0.753***	0.796***
				(0.069)	(0.046)	(0.064)
Constant	0.553***	0.805***	1.120***	0.068**	0.102**	0.176***
	(0.076)	(0.095)	(0.066)	(0.023)	(0.034)	(0.052)
FE	Firm	Firm	Firm	No	No	No
S.E.	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	4704	4305	3963	4461	4089	3763
Within Adj.R^2	0.068	0.099	0.149	0.359	0.309	0.269

Table 10: Intertemporal Responsiveness of Grants to Recessions

Columns 1 - 3 report results for the following regression

$$\frac{Grant_{i,t+k}}{W_{i,t-1}} = \gamma_i + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \beta_3 \text{Recession}_t + \eta_{i,t+k}$$

Columns 4 - 6 report the results controlling for the time-varying target payout ratio instead of the PF fixed effects. Recession is the dummy variable equal to 1 for the years 2001, 2008, and 2009 and zero otherwise. The two-way clustered standard errors reported in parentheses are clustered at the year and foundation levels.

	(1) k=1	(2) k=2	(3) k=3	(4) k=1	(5) k=2	(6) k=3
RET	0.028***	0.036***	0.028***	0.040***	0.049***	0.048***
	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Size	-0.021***	-0.028***	-0.038***	0.001***	0.001***	0.002***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Recession	-0.003*	-0.003*	-0.003*	0.000	-0.000	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Target				0.726***	0.668***	0.639***
				(0.011)	(0.011)	(0.011)
Constant	0.409***	0.512***	0.676***	-0.000	-0.001	-0.003
	(0.017)	(0.024)	(0.032)	(0.002)	(0.003)	(0.003)
FE	Firm	Firm	Firm	No	No	No
S.E.	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way
Observations	250895	231177	213289	191654	175163	159940
Within Adj. R^2	0.031	0.046	0.062	0.392	0.319	0.265

Table 11: Cash Flow Sensitivities of Donations Received

This analysis directly evaluates the theoretical channel underlying the idealized irrelevance of cash flow shocks under the substitution hypothesis. Specifically, the substitution hypothesis posits that cash flow shocks do not influence the permanent income of a foundation because they are offset by changes in donations. If true, the β_1 loading on RET should be negative. Columns 1 - 3 report results for the following regressions

$$\text{Logit}P\left(\text{DonationReceived}_{i,t+k}\right) = \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \eta_{i,t+k}$$

Columns 4 - 6 report results for the following regressions

$$\frac{\text{DonationReceived}_{i,t+k}}{W_{i,t-1}} = \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \eta_{i,t+k}$$

The two-way clustered standard errors reported in parentheses are clustered at the year and foundation levels. All continuous variables are trimmed at the 1% and 99% levels.

	(1) k=1	(2) k=2	(3) k=3	(4) k=1	(5) k=2	(6) k=3
$\text{RET}_{i,t}$	0.075	0.039	-0.020	-0.017	-0.010	0.002
	(0.164)	(0.174)	(0.167)	(0.018)	(0.021)	(0.025)
$\log(\text{W}_{i,t-1})$	0.225***	0.216***	0.208***	-0.014***	-0.014***	-0.014***
	(0.015)	(0.015)	(0.015)	(0.001)	(0.001)	(0.001)
Constant	-4.416***	-4.227***	-4.213***	0.336***	0.344***	0.352***
	(0.227)	(0.232)	(0.236)	(0.016)	(0.018)	(0.019)
FE	Year	Year	Year	Year	Year	Year
Observations	254713	234557	216404	68726	61702	55821

Table 12: Cash Flow Sensitivities of Grant Spending (High Payout PFs)

This table reports estimates of private foundations' grant-cash flow sensitivity among the subset of private foundations whose annual grantmaking substantially exceeds the required 5% minimal spending level. The coefficient of interest is β_1. Columns 1 - 3 report results for the following regressions

$$\frac{Grant_{i,t+k}}{W_{i,t-1}} = \gamma_i + \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \eta_{i,t+k}$$

where $Grant_{i,t+k}$ is the grant amount made by foundation i at year $t+k$, and $W_{i,t-1}$ represents the lagged total market value of assets. Columns 4 - 6 report results for the following regressions

$$\frac{Grant_{i,t+k}}{W_{i,t-1}} = \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \beta_3 Target_{i,t-1} + \eta_{i,t+k}.$$

	(1) k=1	(2) k=2	(3) k=3	(4) k=1	(5) k=2	(6) k=3
$\text{RET}_{i,t}$	0.054***	0.054***	0.046***	0.064***	0.073***	0.075***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
$\log(\text{W}_{i,t-1})$	-0.041***	-0.042***	-0.051***	0.002***	0.003***	0.004***
	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)	(0.001)
$\text{Target}_{i,t-1}$				0.747***	0.685***	0.656***
				(0.014)	(0.016)	(0.019)
Constant	0.770***	0.788***	0.928***	-0.006	-0.017**	-0.035***
	(0.031)	(0.033)	(0.043)	(0.005)	(0.006)	(0.009)
FE	Firm/Year	Firm/Year	Firm/Year	Year	Year	Year
Observations	74156	68375	63194	58616	53819	49422
Within Adj.R^2	0.053	0.051	0.061	0.403	0.331	0.279

Table 13: Testing Capital Preservation Motives: Asymmetric Response of Payout Rate to Cash Flow Shocks

This table reports the following regression

$$\frac{G_{i,t}}{W_{i,t-1}} = \beta_0 + \gamma_i + \gamma_t + \beta_1^+ RET_{i,t}^+ + \beta_1^- RET_{i,t}^- + \left[\beta_2^+ RET_{i,t-1}^+ + \beta_2^- RET_{i,t-1}^-\right] + \eta_{i,t}$$

Columns 1 and 2 controls for the PF fixed effects, while Columns 3 and 4 additionally control for the year fixed effects. The two-way clustered standard errors reported in parentheses are clustered at the year and foundation levels. The left hand-side variable is multiplied by 100 and in percentage points.

	(1)	(2)	(3)	(4)
max{RET,0}	1.42***	1.06***	1.65***	1.35***
	(0.49)	(0.36)	(0.27)	(0.29)
min{RET,0}	3.13***	3.23***	3.89***	3.66***
	(0.55)	(0.61)	(0.40)	(0.34)
Lagged max{RET,0}		-2.49***		-2.05***
		(0.32)		(0.17)
Lagged min{RET,0}		-1.14**		-1.21***
		(0.45)		(0.36)
Constant	6.66***	6.88***	6.66***	6.82***
	(0.05)	(0.06)	(0.03)	(0.04)
FE	Firm	Firm	Firm/Year	Firm/Year
S.E.	Two-way	Two-way	Two-way	Two-way
Observations	269567	243542	269567	243542
Within Adj.R^2	0.00	0.00	0.00	0.00
p-value of Wald Test for $\beta_1^+ = \beta_1^-$	0.04	0.01	0.00	0.00

Table 14: Cross-Sectional Responsiveness of Grant Allocations to Need (by Foundation Characteristics)

This table presents subsample analysis of the main responsiveness IV regression in Table 5. $Family$ is H if a foundation has at least one founder or founder family member as trustee or officer. $LargeBoard$ is H for PFs for which the number of trustees or officers is greater than the cross-sectional median. $HighPay$ is H for PFs for which the number of trustees or officers that earn a salary of more than $150k is greater than the cross-sectional median. $Large$ is H for PFs with size in the top 30% of the cross-sectional distribution. $Young$ is H for PFs with age below 40 years. $HighPayout$ is H for PFs for which the past payout ratio is above the cross-sectional median. The past payout ratio for a PF in year t is computed as the ratio of the average grants paid (X140) between $t-3$ and $t-1$ over the average market value of assets (A400) between $t-3$ and $t-1$. Size is based on the lagged market value of assets (A400) in year $t-1$. This sample contains only PFs for which we have collected detailed recipient data as described in the main text. The two-way clustered standard errors reported in parentheses are clustered at the year and foundation levels.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.36***	0.44***	0.37***	0.42***	0.30***	0.50***
	(0.07)	(0.13)	(0.12)	(0.10)	(0.10)	(0.10)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$	-0.04	-0.40***	-0.19*	-0.26**	-0.10	-0.34***
	(0.13)	(0.09)	(0.10)	(0.13)	(0.10)	(0.08)
$\log(\text{Grant}_{i,j,t})$	-0.23***	-0.20***	-0.17***	-0.25***	-0.17***	-0.24***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.12***	0.12***	0.09***	0.16***	0.09***	0.16***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
$\log(\text{PeerGrant}_{i,j,t})$	0.04*	-0.02	0.01	0.01	0.02	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Sample	Family(L)	Family(H)	LargeBoard(L)	LargeBoard(H)	Highpay(L)	Highpay(H)
Observations	67233	76507	64659	79081	66073	77667
F-Stat for Weak IV Test	10.0	13.5	11.5	11.9	15.5	10.4
Dif(H-L)		-0.363		-0.071		-0.237
p(H-L)		0.021		0.698		0.030

Table 14: Cross-Sectional Responsiveness of Grant Allocations to Need (by Foundation Characteristics) - continued

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.28***	0.48***	0.40***	0.44***	0.43***	0.46***
	(0.08)	(0.12)	(0.06)	(0.14)	(0.08)	(0.16)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$	-0.15	-0.29***	-0.15	-0.33***	-0.20***	-0.35***
	(0.09)	(0.11)	(0.10)	(0.09)	(0.07)	(0.10)
$\log(\text{Grant}_{i,j,t})$	-0.16***	-0.26***	-0.25***	-0.18***	-0.26***	-0.17***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.03	0.19***	0.18***	0.09***	0.18***	0.10***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
$\log(\text{PeerGrant}_{i,j,t})$	0.00	0.01	0.02	-0.01	0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Sample	Large(L)	Large(H)	Young(L)	Young(H)	HighPayout(L)	HighPayout(H)
Observations	68972	74188	74462	69046	68718	70608
F-Stat for Weak IV Test	12.7	9.9	16.0	6.8	17.2	8.4
Dif(H-L)		-0.141		-0.180		-0.151
p(H-L)		0.280		0.189		0.011

Table 15: Capital Preservation: Subsample Analysis (by Foundation Characteristics)

This table presents subsample analysis for the capital preservation regression in Table 13. $Family$ is H if a foundation has at least one founder or founder family member as trustee or officer. $LargeBoard$ is H for PFs for which the number of trustees or officers is greater than the cross-sectional median. $HighPay$ is H for PFs for which the number of trustees or officers that earn a salary of more than $150k is greater than the cross-sectional median. $Large$ is H for PFs with size in the top 30% of the cross-sectional distribution. $Young$ is H for PFs with age below 40 years. $HighPayout$ is H for PFs for which the past payout ratio is above the cross-sectional median. The two-way clustered standard errors reported in parentheses are clustered at the year and foundation level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
max{RET,0}	1.60***	1.29**	1.62***	1.84***	1.70***	1.66***	1.42**	1.39***	1.80***	2.77***
	(0.49)	(0.53)	(0.44)	(0.52)	(0.45)	(0.48)	(0.54)	(0.49)	(0.33)	(0.57)
min{RET,0}	2.29***	3.75***	3.90***	2.49***	2.22***	3.93***	3.19***	2.67***	0.20	4.55***
	(0.33)	(0.79)	(0.76)	(0.44)	(0.38)	(0.78)	(0.64)	(0.48)	(0.25)	(0.64)
FE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Sample	Family(L)	Family(H)	LargeBoard(L)	LargeBoard(H)	Young(L)	Young(H)	Large(L)	Large(H)	HighPayout(L)	HighPayout(H)
Observations	116108	153459	111435	97372	121348	126400	133073	134942	102283	101046
β_1^- - β_1^+	0.69	2.45	2.28	0.65	0.53	2.27	1.78	1.28	-1.60	1.78
Dif in β_1^- - β_1^+ (H-L)		1.8		-1.6		1.7		-0.5		3.4
p(H-L)		0.05		0.06		0.10		0.56		0.00

8. For Online Publication: Internet Appendix

8.1. Details on Return Calculation

The accuracy of our return measure depends on the reliability of the reported market value in the 990-PF filings. There are at least two regulatory constraints that ensure foundations report the market value accurately. First, private foundations must pay a 1 percent (or 2 percent) excise tax on their investment returns, so they are required to correctly calculate market value in order to correctly calculate this tax. Second, to address concerns that donors to private foundations are receiving immediate tax benefits for their donations while can potentially indefinitely defer their contributions to the ultimate operating charitable organizations, private foundations are required to pay out at least 5 percent of the net value of non-charitable-use assets. Accurate reporting of the market value of their holdings (not just the book value) is essential for calculating this mandatory payout.

Still, one significant challenge in return calculation that has not been brought up in the literature is that the fair market value of assets can change without a corresponding entry in the income statement. For example, a merger of one private foundation into another or a transfer of assets between foundations are not captured by any line items in Part I of Form 990-PF. These changes are instead included in the Other Increases and Other Decreases (Lines 3 and 5 of Part III). This is the reason why our return calculation differs from the literature by adjusting for these other changes. Complicating this adjustment is that other types of changes that do not affect the fair market value (e.g., changes in the book values) are also recorded in Other Increases and Other Decreases. To address this, we develop a targeted keyword list to identify specific line items in this section that affect fair market values: transf bequest rescis recis check merger recover refund.

While our adjustment mentioned above facilitates a more accurate calculation of returns, the adjustment does not perfectly address all measurement errors. We thus implement two categories of data filters to exclude observations with a relatively small market value that are more susceptible to measurement errors. The first category excludes private foundations

(PFs) with disproportionately small financial assets relative to their operating expenses. This includes those whose total expenses exceed twice their Market Value (MV) from the previous year, and those whose non-charitable-use assets are less than 10 percent of the prior year's total asset fair market value. This filter eliminates about 8 percent of the PF-year observations, representing 9.5 percent of the aggregate MV. The second category of filters exclude small PFs, defined as those with a lagged MV of less than 0.5 million dollars or a negative lagged net book value of total assets or a lagged MV less than 10 percent of the previous year's book value of total assets, or those whose adjusted other increases/decreases exceed their lagged MV. To prevent any look-ahead bias in our return calculation, all data filters are based exclusively on lagged MV. The second category of filters further exclude 1.4 percent of PF-year observations, accounting for 0.3 percent of the aggregate MV. Importantly, all these data filters are only applied for return calculation (i.e., returns are set to be missing for these observations). In other words, all analyses that do not require returns (e.g., the survival analysis) include the complete time series for each foundation.

8.2. Grant Recipient Data

We gather data on private foundations' (PFs) grants and recipients from Candid.com, which extracts and processes such information from PFs' 990PF filings. These data encompass the recipient's name, location, grant amount, subject, and a detailed description of the grant's usage. Due to the labor-intensive nature of downloading data from Candid.com, where only 100 records can be downloaded at a time, we opt to concentrate on the top 300 private foundations for each year from 2003 (the first year when the Candid data are available) to 2019.

A few foundations predominantly donate to a closely affiliated foundation, which in turn makes the grant making decisions. We treat these pairs of foundations as one foundation, e.g., Bill & Melinda Gates Foundation and Bill & Melinda Gates Foundation Trust are treated as one foundation. We exclude corporate foundations, whose donations often reflect employee rather than the founder's preference. For similar reasons, we drop grants related to employee grant matching programs. Finally, we drop donor advised funds.

We assess the data quality by computing the coverage ratio, defined as the total dollar value of grants recorded by Candid to that reported on the 990-PF filing (Line 25 of Part I) for each EIN-year. We find that the median coverage ratio is 93% across EIN-year observations, which indicate the data quality is relatively high. Still, there are errors in the Candid data; for example, the Ford Foundation (EIN=131684331) has too few grants in 2012 and too many in 2014. Based on our conversations with the data provider, they are performing ongoing updates to the data, so these errors may be corrected in the future. Consequently, we conduct a few data cleaning steps. First, we drop grants that exceed the total grant amount reported on the 990-PF filing, which is an error that is likely due to OCR issues when dealing with numbers following the decimal point. Second, we drop 32 EINs for which more than 50% of the EIN-Year observations are outside the range of 50% and 120%. Finally, we drop EIN-Year observations for which the coverage ratio is outside of the range of 20% and 150%.

8.3. Motivating Anecdote: NBER and Private Foundations

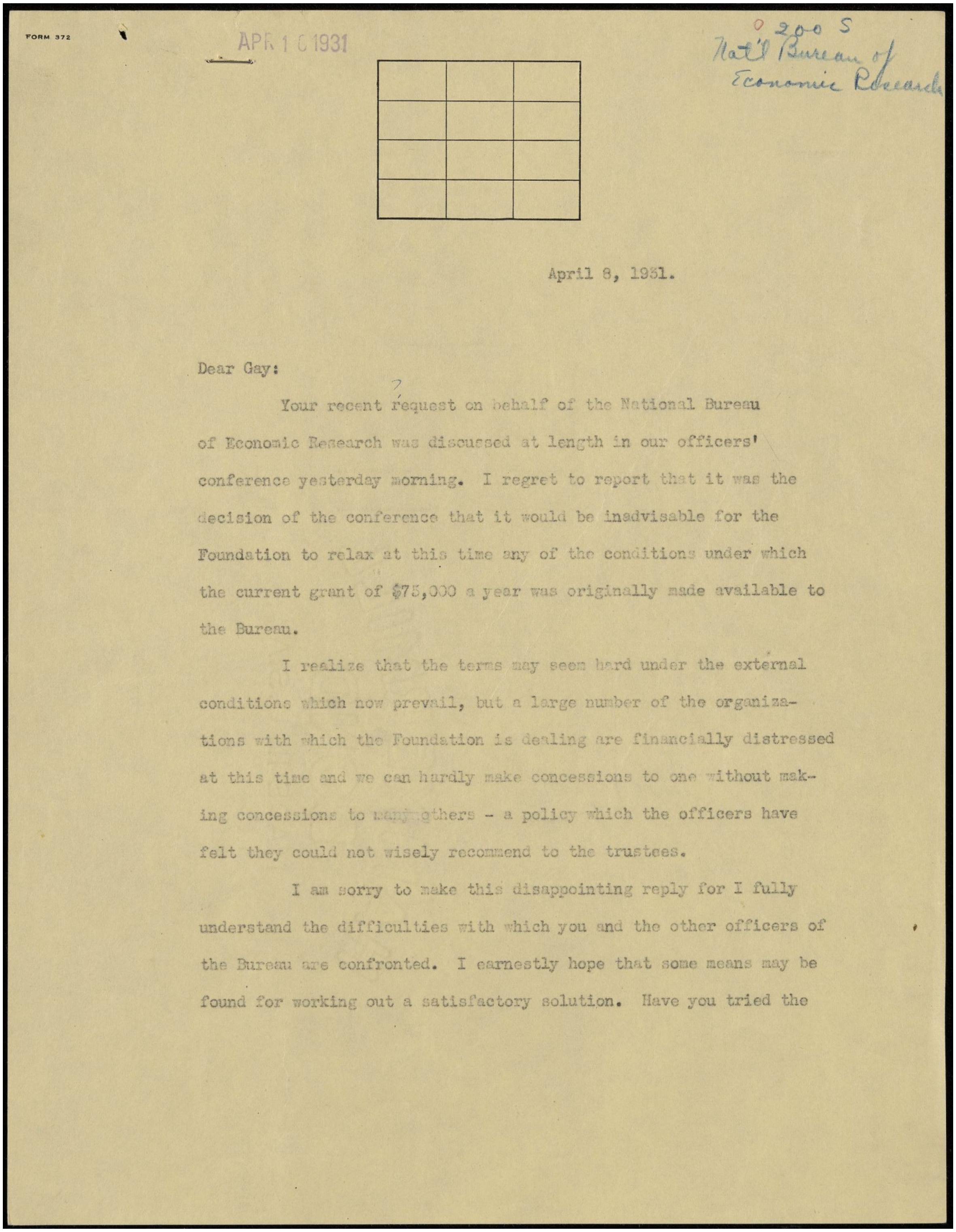
When the National Bureau of Economic Research (NBER) was facing financial distress in the early years of the Great Depression, they turned to their longtime supporters at a prominent private foundation, the Rockefeller Foundation. The Foundation was initially reluctant to increase their support. Responding to the NBER's initial request for additional support, Rockefeller's Director for the Social Sciences, Edmund Day, explained: "a large number of the organizations with which the Foundation is dealing are financially distressed at this time and we can hardly make concessions to one without making concessions to many others."

But after reconsidering, they and their close affiliates agreed to fund the majority of the NBER's budget throughout the Great Depression. See Figures A1–A4 for source documents; via Rockefeller Archives: record on National Bureau of Economic Research; 1932-1942; Projects (Grants), United States - Social Sciences, Subseries 200.S; Rockefeller Archive

Center; https://dimes.rockarch.org/objects/avnT26XeDtMLapaMfvovgg

With the benefit of hindsight, this support ensured the survival of a valuable research institution. And yet Rockefeller's actions hinged on the reversal of their original refusal, and came amidst declining support from other grant-making institutions. Given the apparent difficulty of determining appropriate support ex ante, and in the absence of a market mechanism to aggregate information about recipient need, a natural question emerges: are private foundations collectively effective in pursuing their charitable goals?

Figure A1: Rockefeller Foundation and the NBER: Funding Request



FORM 372

APR 16 1931

0 200 S
Nat'l Bureau of
Economic Research

April 8, 1931.

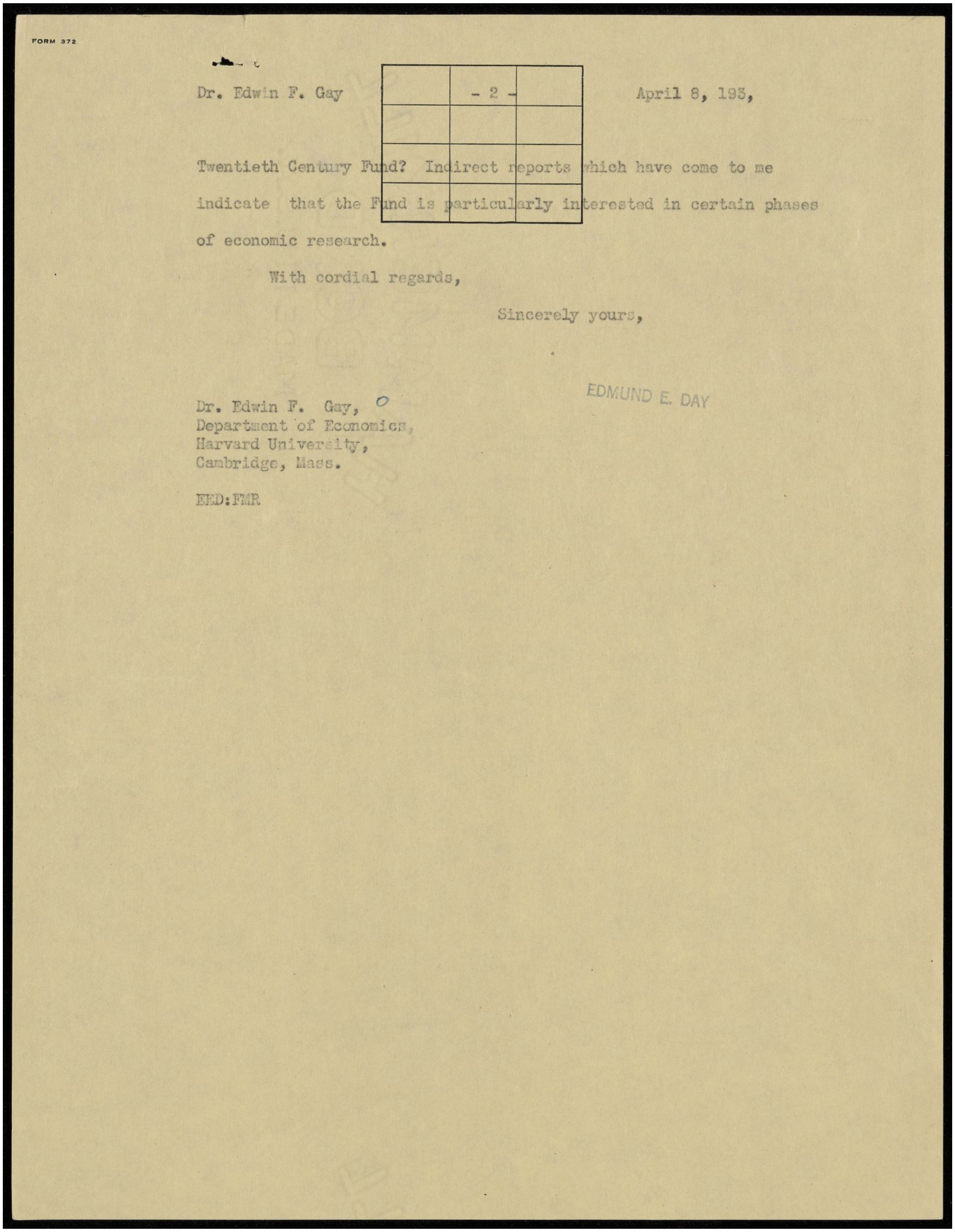
Dear Gay:

Your recent request on behalf of the National Bureau of Economic Research was discussed at length in our officers' conference yesterday morning. I regret to report that it was the decision of the conference that it would be inadvisable for the Foundation to relax at this time any of the conditions under which the current grant of $75,000 a year was originally made available to the Bureau.

I realize that the terms may seem hard under the external conditions which now prevail, but a large number of the organizations with which the Foundation is dealing are financially distressed at this time and we can hardly make concessions to one without making concessions to many others - a policy which the officers have felt they could not wisely recommend to the trustees.

I am sorry to make this disappointing reply for I fully understand the difficulties with which you and the other officers of the Bureau are confronted. I earnestly hope that some means may be found for working out a satisfactory solution. Have you tried the

Figure A2: Rockefeller Foundation and the NBER: Funding Request



FORM 372

Dr. Edwin F. Gay - 2 - April 8, 193,

Twentieth Century Fund? Indirect reports which have come to me indicate that the Fund is particularly interested in certain phases of economic research.

With cordial regards,

Sincerely yours,

EDMUND E. DAY

Dr. Edwin F. Gay,
Department of Economics,
Harvard University,
Cambridge, Mass.

EED:FMR

Figure A3: Rockefeller Foundation and the NBER through the Depression

4/5/39 39150

NATIONAL BUREAU OF ECONOMIC RESEARCH (Continued)

Its Board is composed of men of widely differing points of view and interest - including representatives of nine universities. Its staff is at present composed of faculty members from various universities. Its publications include 40 major titles and 73 bulletins.

The program of the National Bureau is addressed to the inductive study of the basic processes and interrelations of our economic life. Production, changing productivity, and the factors which affect it, national income and its distribution, wages, profits, and professional incomes, the proportions of national income which go for consumption and for savings, gross and net capital formation and obsolescence, the behavior of prices and of credit, especially (at present) consumer credit, bond yields and bond prices, the ebb and flow of trade unionism - and, underlying all, the fluctuations of prosperity and depression - such central economic subjects as these are the concern of the National Bureau.

The program of the Bureau thus involves continuing study of the dynamics of economic change. It does not consist of a series of unrelated inquiries but of well-integrated studies of fundamental issues. This program, which has been slowly but cumulatively developing over a period of nineteen years, has reached a significant harvest time.

The National Bureau plays another role than that of an independent research agency. It is rapidly becoming the co-ordinating agency of national economic research. Since 1935, it has, by special direction of its Board of Directors, put more and more emphasis on its role as an axis for inter-institutional co-operation in economic research. This policy was adopted to lessen the danger of the Bureau's developing as a competitor of universities and to draw university faculty members together in common attack on living problems that often transcend the resources of a single institution acting alone. The initiative of the Bureau in this direction has been freely accepted by universities, by government, and by business. Through the Conference on National Income and Wealth, the Conference on Financial Research, the Committee on Fiscal Policy, and in other ways, the faculty members of many universities and specialists from government and from business have been drawn into active co-operation in the Bureau program.

<u>Finances:</u> The tentative budget for 1939 has been approved by the Board of the Bureau for a little over $250,000. This is a minimum budget, the actual budget being expected to be in excess of this figure. Of the total approved budget Foundation funds will constitute approximately forty-three per cent.

The National Bureau has been successful in broadening the base of its financial support, as evidenced by the following budget totals during the past four years:

Figure A4: Rockefeller Foundation and the NBER through the Depression

4/5/39 39151

NATIONAL BUREAU OF ECONOMIC RESEARCH (Continued)

Year	Total	RF Contribution
1935	$118,219.24	$ 73,918.02
1936	$162,203.96	$ 96,700.18
1937	$135,070.38	$ 85,911.02
1938	$268,721.09	$116,004.84

Since the establishment of the Bureau in 1920 and up to the end of 1938, its sources of financial support with their respective shares have been as follows:

	Amount	Per cent of total
Rockefeller Foundation	$ 733,975.81	32.6
Individuals and corporations	331,457.71	14.6
Carnegie Corporation	310,000.00	13.7
Laura Spelman Rockefeller Memorial	230,000.00	10.2
Social Science Research Council	206,311.37	9.1
Committee on Recent Economic Changes	195,000.00	8.6
Banking Research Fund - Association of Reserve City Bankers	69,780.51	3.1
Commonwealth Fund	45,000.00	2.0
Falk Foundation	45,000.00	2.0
Twentieth Century Fund	10,000.00	0.4
Miscellaneous	85,784.88	3.7
Total	$2,262,310.28	100.0

Of particular interest has been the growth of individual and corporation contributions to the Bureau. These include $5 contributions, $25 contributions, and corporation contributions of various sizes. Within the past year, the following corporations have given or pledged $2,500 each:

American Telephone and Telegraph Company
United States Steel Corporation
Standard Oil Company of New Jersey
General Motors Corporation
Chrysler Corporation
International Nickel Company

Contributions by individuals and corporations are estimated at $25,000 for 1939. It is expected that support of this kind will continue slowly to grow.

Future Implications: The granting to the Bureau of the sums recommended in this statement will not preclude the presentation by the Bureau of further applications for specific purposes that seem to be important.

8.4. Appendix Tables

Table A1: Cross-Sectional Responsiveness of Grant Allocations to Need (Robustness)

This table repeats the subsample analysis for the cross-sectional responsiveness to recipient needs in Tables 6 to 8 and Table 14 with the additional inclusion of PF fixed effects.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.32***	0.33***	0.24***	0.37***	0.49***	0.32***
	(0.07)	(0.07)	(0.07)	(0.09)	(0.11)	(0.08)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})$	0.04***	0.03***	0.04***			
	(0.01)	(0.00)	(0.01)			
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$				-0.06	-0.30***	-0.22
				(0.09)	(0.09)	(0.15)
$\log(\text{Grant}_{i,j,t})$	-0.30***	-0.29***	-0.30***	-0.29***	-0.27***	-0.28***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.06	0.05	0.04*	0.06	0.05	0.05*
	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)	(0.02)
$\log(\text{PeerGrant}_{i,j,t})$	0.06***	0.06***	0.05***	0.04	-0.00	-0.00
	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)	(0.03)
Sample	Art/Religion	Sci	Rest	Art/Religion	Sci	Rest
Observations	23526	55275	64886	23526	55275	64886
F-Stat for Weak IV Test				13.1	13.9	7.8
Dif(Sci - Art/Religion)	-0.002			-0.145		
p(Sci - Art/Religion)	0.688			0.049		

Table A1: Cross-Sectional Responsiveness of Grant Allocations to Need (Robustness) - continued

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(1+R_{i,t})$	0.24***	0.39***	0.38***	0.43***	0.37***	0.29**	0.42**	0.59***
	(0.07)	(0.08)	(0.10)	(0.08)	(0.10)	(0.11)	(0.14)	(0.11)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})$	0.04***	0.03***						
	(0.00)	(0.00)						
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$			-0.30***	-0.06	-0.26**	0.15	-0.38***	-0.20
			(0.07)	(0.12)	(0.10)	(0.16)	(0.12)	(0.13)
$\log(\text{Grant}_{i,j,t})$	-0.29***	-0.29***	-0.27***	-0.29***	-0.28***	-0.32***	-0.28***	-0.27***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
$\log(W_{i,t-1})$	0.04*	0.05	0.05	0.05	0.06**	0.04	0.04	0.08
	(0.02)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.05)	(0.08)
$\log(\text{PeerGrant}_{i,j,t})$	0.06***	0.05***	-0.01	0.04	-0.01	0.09*	-0.02	0.01
	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)
Sample	Fav(L)	Fav(H)	Fav(L)	Fav(H)	Fav(L)/NonSci	Fav(H)/NonSci	Fav(L)/Sci	Fav(H)/Sci
Observations	99026	44693	99026	44693	70214	18206	28789	26463
F-Stat for Weak IV Test			10.7	12.7	8.1	11.6	15.5	10.0
Dif(H-L)		-0.012		0.207		0.291		0.206
p(H-L)		0.052		0.178		0.044		0.367

Table A1: Cross-Sectional Responsiveness of Grant Allocations to Need (Robustness) - continued

Panel C

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.19*	0.18***	0.45***	0.14	0.29***	0.64***
	(0.10)	(0.05)	(0.10)	(0.13)	(0.06)	(0.15)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})$	0.03***	0.03***	0.04***			
	(0.00)	(0.01)	(0.00)			
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$				0.16	-0.19*	-0.45***
				(0.13)	(0.09)	(0.12)
$\log(\text{Grant}_{i,j,t})$	-0.24***	-0.29***	-0.34***	-0.25***	-0.28***	-0.31***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.01	0.04	0.08***	0.01	0.04	0.10**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
$\log(\text{PeerGrant}_{i,j,t})$	0.05***	0.05***	0.07***	0.08**	0.00	-0.02
	(0.01)	(0.00)	(0.00)	(0.03)	(0.02)	(0.02)
Sample	Nyear(L)	Nyear(M)	Nyear(H)	Nyear(L)	Nyear(M)	Nyear(H)
Observations	40916	47568	55218	40916	47568	55218
F-Stat for Weak IV Test				22.5	7.3	7.8
Dif(H-L)			0.015			-0.596
p(H-L)			0.011			0.028

Table A1: Cross-Sectional Responsiveness of Grant Allocations to Need (Robustness) - continued

Panel D

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.36***	0.41***	0.34***	0.49***	0.34***	0.44***
	(0.07)	(0.12)	(0.10)	(0.10)	(0.10)	(0.11)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$	-0.04	-0.37***	-0.17	-0.28**	-0.11	-0.30***
	(0.14)	(0.09)	(0.10)	(0.12)	(0.12)	(0.07)
$\log(\text{Grant}_{i,j,t})$	-0.30***	-0.24***	-0.22***	-0.30***	-0.23***	-0.30***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.05	0.05	0.01	0.13**	0.04	0.07
	(0.03)	(0.04)	(0.02)	(0.05)	(0.03)	(0.04)
$\log(\text{PeerGrant}_{i,j,t})$	0.04	-0.02	0.01	-0.00	0.02	-0.00
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
Sample	Family(L)	Family(H)	LargeBoard(L)	LargeBoard(H)	Highpay(L)	Highpay(H)
Observations	67230	76505	64655	79080	66067	77667
F-Stat for Weak IV Test	12.2	11.6	11.8	11.0	13.9	10.4
Dif(H-L)		-0.327		-0.094		-0.187
p(H-L)		0.075		0.550		0.118

Table A1: Cross-Sectional Responsiveness of Grant Allocations to Need (Robustness) - continued

Panel E

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R_{i,t})$	0.27***	0.52***	0.45***	0.41***	0.39***	0.46***
	(0.04)	(0.14)	(0.09)	(0.11)	(0.06)	(0.14)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$	-0.12	-0.34***	-0.19	-0.26***	-0.17	-0.32**
	(0.09)	(0.11)	(0.13)	(0.08)	(0.10)	(0.11)
$\log(\text{Grant}_{i,j,t})$	-0.22***	-0.30***	-0.30***	-0.24***	-0.32***	-0.22***
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
$\log(W_{i,t-1})$	0.02	0.09	0.17***	0.01	0.12**	0.03
	(0.02)	(0.09)	(0.04)	(0.03)	(0.05)	(0.04)
$\log(\text{PeerGrant}_{i,j,t})$	0.01	-0.00	0.01	0.00	0.02	-0.02
	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
Sample	Large(L)	Large(H)	Young(L)	Young(H)	HighPayout(L)	HighPayout(H)
Observations	68966	74185	74462	69041	68712	70602
F-Stat for Weak IV Test	14.1	9.4	13.0	9.9	13.5	9.1
Dif(H-L)		-0.220		-0.083		-0.132
p(H-L)		0.131		0.638		0.235

Table A2: Cash Flow Sensitivities of Donations Received (Poisson)

This table repeats the analysis in Table 11 using the Poisson regression, which combines the intensive and extensive effects, as a robustness check. The substitution hypothesis posits that cash flow shocks do not influence the permanent income of a foundation because they are offset by changes in donations. If true, the loading on RET should be negative. The two-way clustered standard errors reported in parentheses are clustered at the year and foundation levels. All continuous variables are trimmed at the 1% and 99% levels.

	(1) k=1	(2) k=2	(3) k=3
RET	0.306	-0.103	-0.017
	(0.453)	(0.322)	(0.342)
Size	0.943***	0.050***	0.046***
	(0.083)	(0.016)	(0.016)
Constant	-2.479	-4.262***	-4.195***
	(1.529)	(0.256)	(0.249)
FE	Year	Year	Year
S.E.	Two-way	Two-way	Two-way
Observations	252258	232261	214307

Table A3: Capital Preservation: Subsample Analysis (Robustness)

This table repeats the subsample analysis for the capital preservation regression in Table 13 with PF and year fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
max{RET,0}	1.83***	1.51***	1.73***	1.96***	2.11***	1.67***	1.44***	1.85***	1.75***	2.42***
	(0.37)	(0.30)	(0.36)	(0.35)	(0.36)	(0.27)	(0.33)	(0.30)	(0.24)	(0.50)
min{RET,0}	2.64***	4.78***	4.33***	3.37***	3.40***	4.16***	3.95***	3.30***	1.21**	5.55***
	(0.45)	(0.49)	(0.59)	(0.59)	(0.63)	(0.62)	(0.47)	(0.55)	(0.44)	(0.40)
Sample	Family(L)	Family(H)	LargeBoard(L)	LargeBoard(H)	Young(L)	Young(H)	Large(L)	Large(H)	HighPayout(L)	HighPayout(H)
Observations	116108	153459	111435	97372	121348	126400	133073	134942	102283	101046
β_1^- - β_1^+	0.82	3.27	2.61	1.41	1.29	2.49	2.50	1.45	-0.53	3.13
Dif in β_1^- - β_1^+ (H-L)		2.5		-1.2		1.2		-1.1		3.7
p(H-L)		0.00		0.24		0.31		0.30		0.00