Charitable Capital Allocation: Evidence from Private Foundations*

Abstract

We examine how private foundations allocate charitable capital in response to recipient need. Using financial shocks to peer foundations (who fund the same recipients), we isolate exogenous changes in the marginal value of grants. Foundations' cross-sectional allocations respond to need, particularly for scientific causes and longer donor-recipient relationships. In contrast, intertemporal responsiveness is limited, offset by a strong preference for capital preservation. Among governance characteristics, founder involvement most strongly predicts both cross-sectional responsiveness and intertemporal conservatism. Our findings highlight a key tension: founders' charitable intent is critical for effective allocation, but their inclination toward capital preservation can hinder impact maximization.

Keywords: private foundations, nonprofit boards, nonprofit governance, charitable capital allocation, agency costs, 501(c)3
JEL Classifications: D64, G18, G38, H41, L31

"Big philanthropy is often an unaccountable, non-transparent, donor-directed, and perpetual exercise of power." – Robert Reich

1. Introduction

On May 10, 2025, House GOP lawmakers proposed a 10% tax on the investment income of large private foundations, reigniting a contentious debate: are these tax-advantaged entities effectively allocating philanthropic capital, or do they merely serve as tax shelters for disinterested dynasties who neglect their role as charitable capital allocators?[1] Distinguishing these possibilities is challenging. Unlike in for-profit markets, where prices reveal value, nonprofit organizations operate in environments where the effectiveness of capital allocation is difficult to quantify and no universal standard for social value exists.[2] As a result, while the finance literature has long studied capital allocation in for-profit markets, there has been scant evidence regarding the efficiency of capital allocation in the nonprofit sector.

This paper examines one dimension of this efficiency: whether and how private foundations reallocate funds in response to changes in the marginal value of their grants. Importantly, we answer this question using a novel empirical strategy that circumvents the need for a specific definition of social value.

Our key innovation is to exploit exogenous variation in grant recipients' wealth caused by financial shocks to peer foundations (i.e., those that donate to the same charities). Our identification strategy rests on the assumption of decreasing returns to scale: when a recipient experiences an influx of funding due to peer foundations' financial windfalls, the marginal value of further grants should decline. If a focal foundation subsequently reduces its own

[1] Numerous reports detail how ultra-wealthy donors place high-value art and mansions into their own private foundations, collect multimillion-dollar income-tax deductions upfront, yet provide the public little meaningful access to the assets (https://www.propublica.org/article/how-private-nonprofits-ultrawealthy-tax-deductions-museums-foundation-art). Likewise, the rapid growth of donor-advised funds (DAFs) has sparked warnings that these vehicles let donors defer charitable payouts for years while still reaping immediate tax advantages (https://ips-dc.org/wp-content/uploads/2025/04/Independent-Report-on-DAFs-FINAL-04-03-2025.pdf).

[2] See, e.g., Finkelstein and Hendren (2020) and Hendren and Sprung-Keyser (2020) for a formal treatment of the measurement of social marginal utility.

giving to that recipient, this behavior is consistent with efficient capital allocation.

Our approach yields a tractable test of allocative efficiency without taking a stance on the "true" social value of a grant. By isolating foundations' responses to exogenous changes in marginal value, we are able to distinguish economically important competing hypotheses. Specifically, if foundations are unresponsive to changes in marginal value, then grantmaking may be dominated by non-altruistic motives, such as warm glow, visibility, tax optimization, or ideological alignment, which carries significant policy implications. As we explain in detail in Section 3, because foundations' utility function can diverge from the social planner's objective, our approach tests a necessary but not a sufficient condition for efficient charitable capital allocation.[3]

To implement our empirical test, we assemble comprehensive data on the grantmaking behavior of private foundations (henceforth "PFs"), compiled from several sources and ultimately drawing primarily from foundations' IRS Form 990-PF filings.[4] These filings provide detailed, recipient-level grant records, along with annual endowment returns. Because many foundations fund overlapping recipients, we can trace how a focal foundation adjusts its grants in response to variation in peer foundations' giving driven by their investment performance.

We begin by examining PFs' capital allocation across recipients. In simple OLS regressions, we find that changes in a focal foundation's giving are positively and significantly correlated with changes in peer foundations' giving to the same recipient. While this pattern is consistent with the idea that high-impact charities attract more funding from all foundations (e.g., Vesterlund (2003); Karlan and List (2020)), it is not sufficient to demonstrate responsive capital allocation. Coordinated giving could also result from social influence,

[3]Due to this potential divergence, strong responsiveness to changes in marginal value of grants is not a sufficient condition for efficient capital allocation. Nevertheless, as long as the social welfare function is concave, the foundations' tendency to balance out exogeneous peer foundation return shocks is generally socially desirable, since $f(x) \geq Ef(x + \Delta x)$. Note that our test is also of a joint hypothesis: failure to find evidence of reallocative efficiency may reflect either indifference to marginal value or violation of decreasing returns to scale.

[4]Private foundations are predominantly charitable grantmaking institutions (e.g., Rockefeller Foundation, Bill and Melinda Gates Foundation) and are typically funded by a single person or a family. As a result, we exclude corporate private foundations and operating private foundations (i.e., those that actually perform charitable activities).

visibility, reputation, or shared ideology.

To address this, we proceed to our instrumental variable (IV) regression, using peer foundations' endowment returns as an instrument for changes in their giving. In the first-stage regression, we find that endowment returns significantly predict future giving, confirming the instrument's relevance. In the second-stage regression, we find that focal foundations' giving is negatively and significantly correlated with the instrumented changes in peer foundations' giving. This change in the coefficient's sign is consistent with our conjecture that peer foundations' endowment returns are uncorrelated with recipients' perceived quality or with confounding factors such as social influence, visibility, or ideology.

The negative and significant coefficient supports the view that focal foundations adjust their cross-sectional grant allocations in response to changes in the marginal value of donations to recipients. Specifically, a 1% increase in peer foundations' grants to a recipient (driven by exogenous wealth shocks) is associated with a 0.2% to 0.3% decrease in the focal foundation's grants to that recipient. These results thus counter the skeptical view that PFs primarily serve as tax shelters, with their charitable activities being sideshows.[5]

We consider two plausible threats to our identification strategy that could result in the observed responsiveness of private foundations even if they do not genuinely care about recipients' needs. First, foundations might passively react to changes in recipients' fundraising intensity following peer foundation shocks (e.g., Andreoni and Payne (2003)).[6] This passive response channel is concerning if fundraising intensity varies purely because of recipients' self-interested survival needs, rather than in response to the changing marginal value of recipients' ultimate charitable opportunities. Second, foundation staff may aim to maintain a recipient's overall funding level, regardless of direct appeals, as a "safe harbor" strategy to avoid accountability. We first address the self-interested fundraising hypothesis and then turn to examine the organizational incentives.

[5]To be clear, our empirical results do not rule out motives such as tax sheltering, but rather provide the first large-sample, direct evidence that PFs consider the marginal value of their donations—among other motives.

[6]Andreoni and Payne (2011b) and Andreoni and Payne (2011a) document crowding-out effects between government grants and other gifts to charities, and identify the reduced fundraising intensity following grants as the key mechanism behind the negative relationship.

Our first test for the self-interested fundraising channel is to examine whether PFs' grantmaking responsiveness varies across charitable causes. Andreoni and Payne (2003) show that arts (vs. social services) charities display the strongest responsiveness of fundraising following government support, suggesting that PFs' substitution should be strongest within the arts subsample. In contrast, a marginal value channel suggests that responsiveness should vary based on the substitutability of grants across potential recipients, which is plausibly weakest in the arts subsample. Our findings reveal that the substitution effect is weakest in the arts and religion subsamples and strongest in the science subsample, consistent with a marginal value channel.

Second, we investigate how responsiveness varies with the length of relationship between a recipient and a PF. We expect that PFs' active information-gathering ability should grow with the duration of a relationship, while passive reliance on fundraising signals should, if anything, be the strongest early on, when other signals are scarce. Consistent with the active learning channel, we observe a significantly stronger substitution effect for longer relationships.

After documenting private foundations' cross-sectional responsiveness, we turn to their intertemporal responsiveness to changes in recipient needs. Intertemporal responsiveness poses a particular challenge for foundations, as it likely entails increased disbursements precisely when they face negative financial shocks. We use two proxies to capture temporal variation in recipient needs. 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 yields statistically significant evidence that PFs' total spending adjusts to changes in recipient needs.[7]

Furthermore, we find that the time-series variations in foundations' grant making reveals

[7] Our findings on PFs' intertemporal resource allocation corroborate existing empirical evidence of similar procyclical donation behaviors observed in other types of nonprofit organizations (Exley et al. (2023), Dahiya and Yermack (2018)).

a clear capital preservation motive, following the methodology of Brown et al. (2014). Specifically, foundations cut back spending more sharply following negative returns but increase funding more modestly after positive returns.[8]

Finally, we examine how agency considerations – proxied by founder involvement and various governance characteristics – may drive the observed cross-sectional responsiveness to charitable needs and the time-series emphasis on capital preservation. In an environment where board directors face little external discipline,[9] we find that traditional measures of board quality or institutional capacity—such as board size or the foundation's age or asset base—do not significantly affect either the cross-sectional or the intertemporal responsiveness. In contrast, the presence of PF founders or their family members as trustees significantly increases responsiveness to recipient needs and strengthens capital preservation patterns. These results suggest that private foundations' behavior is less about staff agency problems and more about the preferences of founders and their families, whose charitable intent and discretion shapes both the distribution and preservation of philanthropic capital.[10]

This paper provides the first comprehensive analysis of whether and how PFs adjust their charitable capital allocation in response to changes in the marginal value of capital – a key benchmark of allocative efficiency in both for-profit and nonprofit sectors. Private foundations (PFs) are important due to their scale – over \$1.2 trillion in assets and comprising more than 10% of all U.S. charitable donations in 2020 – as well as the substantial public subsidy they receive through tax exemptions (discussed in more detail in Section 2.1). Furthermore, the unique extent of PFs' insulation from product-, capital-, and governance-market discipline presents an opportunity to indirectly evaluate these market forces by examining the consequences of their absence, thus shedding light on the capital allocation efficiency of the

[8]Consistent with prioritization of capital preservation, PFs exhibit a remarkably low annual closure rate of approximately 0.8%.

[9]Unlike for-profit boards, foundation directors are not subject to discipline from the market for corporate control, do not benefit from the information aggregation of equity prices, and need not compete for customers or donors as public charities (e.g., universities, hospitals) must. Directors' egregious misconduct can be disciplined by state attorneys general, but enforcement is "likely to be sporadic, at best" (Blasko et al. (1993)).

[10]Related to 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; see also Lewellen et al. (2023).

broader non-profit charitable capital market.

A growing trend in finance involves the integration of non-financial factors into financial decisions, reflecting their interconnected role in achieving desirable long-term welfare outcomes. Existing literature has identified drivers such as altruism, social pressure, warm glow, tax optimization, and reputational concerns as important drivers in individuals' decision whether or where to donate money.[11] In contrast, institutional philanthropy has received less attention, partly because the experimental methods often used to study individual donors are difficult to apply. Recent studies have identified non-altruistic motives among corporate foundations (Bertrand et al. (2020)) and universities (Brown et al. (2014)), and have explored financial constraints in nonprofit hospitals (Adelino et al. (2015)). Our findings are novel in showing that, while PFs allocate capital in a way that aligns with impact in the cross-section, they prioritize capital preservation when determining overall grant budgets.

2. Institutional Background and 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, private foundations usually receive more than two thirds of their support

[11]See, e.g., Andreoni (1989) on the idea of "warm glow"; Landry et al. (2006), Karlan and List (2007), and Ottoni-Wilhelm et al. (2017) for large-scale experimental evidence regarding givers' motivations, and Andreoni (2006); List (2011); Andreoni and Payne (2013) for comprehensive reviews of the literature on charitable giving.

from a single family or corporation. The most familiar 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.

The tax treatment of private foundations differs slightly from that of public charities. Income tax deductions for contributions to private foundations are limited to 30% of a donor's annual income (vs. 50% for public charities). Private foundations are also subject to a 1.39% net investment income tax on their annual returns, and they face steep penalties if they fail to distribute at least 5% of their assets annually. Because this distribution requirement is tied to the market value of their investments, private foundations are required to report asset values annually.

These preferential tax treatments result in income tax deductions for charitable contributions that may forgo over 50 cents of tax revenue per donated dollar for high-income donors in high-tax jurisdictions like New York City.[12] When foundation assets consist of appreciated stock or are derived from investment returns, this income tax deduction is compounded by large capital gains tax savings: instead of incurring at least 23.8% in taxes on capital gains (20% federal, 3.8% NIIT, plus additional state and local taxes), the foundation pays only a 1.39% excise tax. As a result, almost all potential tax revenue associated with investment gains is effectively lost. Therefore, arguably at least half of private foundations' endowments can be viewed as coming from tax deductions.

[12] The marginal income tax rates combine to exceed 51% (federal 37%, state 10.9%, local 3.88%, as of 2025).

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 typically uses 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.[13] However, SOI only samples a subset of 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.[14] The main drawback of the SOI data for our analysis is its inability to consistently track a private foundation throughout its life cycle.

[13]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 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.

[14]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.

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.[15]

Specifically, we begin with the SOI data between 1994 and 2019.[16] 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 data with NCCS core data, IRS Annual Extract files, XML 990-PF filings, and PDF 990-PF filings, in that order.[17] 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 on a single data source, such as the SOI or the NCCS, our dataset offers the key advantage of including the complete time series for each PF once it appears. This feature of the complete time series avoids the potential survivorship bias due to PFs dropping out

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

[16] 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.

[17] 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.

of the SOI sample after suffering negative financial shocks and is also critical for accurate survival analysis. Appendix A.1 details how we compute returns using this survivorship-bias free dataset.

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 process of manually downloading data from Candid.com, 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 501 unique private foundations.[18]

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.

Our sample of PFs features both a long time series and a large cross-section compared to datasets of other nonprofit organizations 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.

[18]See Appendix A.2 for detailed description of the data collection process.

2.3. 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, rising 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, though the distribution is highly skewed: the median PF-year reflects assets of about \$9 million and the largest PFs are orders of magnitude larger than the median.

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 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.

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.[19] According to Table 1, the grant payout rate is right-skewed, with an average of 8.01% and a median of 4.84%. 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 9.71% and a median of 5.99%. The median value is close to the requirement that the minimum qualifying distributions, which include both grant and operating costs, must be at least 5% of the net value of noncharitable-use assets.[20] In our sample, PFs have

[19]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.

[20]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

a median grant-to-expense ratio of 83%, indicating that for a typical PF, the majority of expenses are allocated towards grants.

We provide summary statistics describing the PF-recipient network in Table 4. Our grant subsample comprises a total of 190,848 grants[21] from 501 unique PFs to 33,133 unique recipients between 2003 and 2019. At the PF-year level, the median PF makes grants to 53 recipients. At the recipient-PF-year level (i.e., the grant-year level), the median number of peer foundations is 4, and the mean is 9.9. The median grant amount is \$115,000, and the mean is \$917,460.

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.[22] The largest foundations are relatively stable, and most names appear consistently across periods. This pattern is the first hint that private foundations are designed to endure.

In Table 3, we list the recipients of the largest grants from private foundations in the subsample for which we collect grant recipient data. For each recipient, we report the grant amount (in billions of dollars) received over three 5-year periods, 2005-2009, 2010-2014, and 2015-2019, as well as 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

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

[21] If a foundation gives multiple grants to the same recipient within the same filing year, we treat the cumulative amount as a single grant.

[22] 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).

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. Conceptual Framework: Social Benefit and Private Benefit

In the for-profit space, assessment of capital allocation effectiveness relies on three simplifying assumptions. First, there exists a universal standard of value: costs and benefits can be measured purely in financial terms. Second, there is broad consensus on how to quantify risk. Third, capital allocation decisions typically focus on risks and rewards to allocators (consistent with the Friedman doctrine of shareholder value maximization), abstracting away from downstream effects on other stakeholders (e.g., employees, customers). In the nonprofit space, none of these simplifying assumptions hold. There is no universal value metric, and downstream effects are central to the very purpose of charitable capital allocation.

Because downstream effects cannot be ignored, assessments of nonprofit activity inherently adopt the perspective of a social planner who can weigh costs and benefits across all stakeholders. However, this planner is a metaphorical construct. The only observable actors are foundations and their recipients.

This raises the central question in our conceptual framework: to what extent can we evaluate the alignment between foundations' observed actions and the social planner's unobserved preferences? In theory, because foundations act to maximize their own utility, a foundation's preferred grant portfolio can diverge from that of a social planner through two broad channels. First, non-altruistic factors—such as warm-glow, visibility, tax considerations, or ideological branding—may shift foundations' objective away from maximizing social welfare. Second, even purely altruistic foundations may hold heterogeneous preferences, reflecting legitimate differences in views about which causes matter most. When aggregated, these preferences implicitly define the social planner's utility function.

One cynical view asserts that the first channel – non-altruistic motives – are the dominant determinant of foundations' behavior. Our analysis takes this cynical view as its null hypothesis and examines whether it can be rejected. Our identification strategy exploits variation in recipients' need that is plausibly orthogonal to these non-altruistic factors. Specifically, our key identifying assumption is that while the marginal value of an incremental grant to a recipient is affected by exogenous return shocks to peer foundations that donate to the same recipient, they do not affect the non-altruistic benefits enjoyed by the focal foundation. We consider two plausible threats to this assumption – recipients' self-interested fundraising efforts and agency-driven concerns – in Sections 4.2 and 6.1, respectively.

While our approach makes progress by testing the cynical null hypothesis, it cannot address the second channel of divergence: the heterogeneity of sincere altruistic preferences. As a result, foundations' reallocation in response to changes in marginal social value may not always move society closer to the planner's optimum. This occurs because the initial grant allocations that satisfy an altruistic foundation's first order condition (equating marginal utilities across potential grant recipients) may not necessarily satisfy a social planner's first order condition. For example, suppose a foundation shifts funds from Recipient A (whose peer grants rose) to Recipient B (whose peer grants fell). From the foundation's standpoint, this is welfare-improving – capital flows from a lower to a higher marginal utility recipient. But if Recipient A is initially underfunded from the planner's perspective, the reallocation does not move society in a welfare-maximizing direction.

Nonetheless, foundations' responsiveness is welfare-improving on average. Under the standard assumption of concave utility, peer-return shocks affect the marginal utility of grants similarly for both the foundation and the social planner due to decreasing returns to scale. A grantmaker who actively rebalances capital – from recipients experiencing positive shocks toward those experiencing negative shocks – aligns funding with shifts in marginal value, thereby enhancing social welfare relative to an allocator who does not. This logic is reinforced by Jensen's inequality: concavity implies that random shocks lower expected welfare, and active rebalancing mitigates this loss. Specifically, for an underfunded recipient, the welfare loss from a negative shock exceeds the gain from an equal positive shock; conversely, for an overfunded recipient, the harm from a positive shock outweighs the benefit of a symmetric negative one. Since return shocks are random, under- and overfunding occur with roughly equal probability, yielding a strictly positive expected payoff to rebalancing.

Taken together, these discussions clarify that our empirical approach tests a necessary condition for efficient charitable capital allocation. Foundations' responsiveness to changes in recipients' need is desirable – even when those "needs" are defined relative to the foundation's own utility function – but it does not demonstrate that private foundations achieve a socially optimal grant allocation. Answering this more difficult question may entail taking a stand on the "true" social value of a grant, which we leave for future research.

4. Cross-Sectional Responsiveness of Charitable Capital Allocation

4.1. Isolating Foundations' Responsiveness to Recipient Needs

We assess foundations' responsiveness to recipient needs by identifying instances where needs likely 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 approach works because, as we demonstrate 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 baseline regression and an instrumented regression. The baseline 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 exogenous component 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.[23]

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

[23]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.

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. Specifically, if the peer PF exogenously increases its grant to the recipient, the focal PF should expect a lower marginal value for each additional dollar given to that recipient, and hence should reallocate their grants towards 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 baseline 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 baseline 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,

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

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 lead to higher grants to their recipient charities. Positive endowment shocks increase the permanent income of the PF, causing it to increase its grantmaking.[24]

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. A 1% increase in peer foundations' grants to recipient j due to endowment shocks is associated with approximately an 0.2% decrease in the focal foundation's grants to that recipient.[25]

[24] In Appendix Section A.3, we perform this analysis on the subset of foundations that are unconstrained by the 5% minimum expenditure rule, and show that the pattern persists even among these unconstrained PFs, suggesting that this grant-return sensitivity is indeed due to a permanent income shift and not mechanically driven by regulatory constraints. In order for endowment returns to impact permanent income, the endowment shock must not be offset by changes in future contributions received by the PF. In Appendix Section A.4, we validate that these shocks are indeed not offset by changes in future contributions received.

[25] 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.

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 adopt the specification without firm fixed effects as the main regression model due to its greater efficiency. The results from the specification with firm fixed effects are provided as a robustness check in the Internet Appendix IA.2.

Our results indicate that PFs' responsiveness to changes in recipient needs dominate one potentially confounding status-based motive. For example, if donors are motivated by public recognition rather 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 want to 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.[26]

4.2. Channels of Responsiveness

The results above are consistent with the idea that PFs' grant allocations respond to changes in the marginal value of grants to recipients. However, two potentially uncharitable explanations could also account for the observed responsiveness of private foundations, even if they do not genuinely care about recipients' needs. First, foundations might passively react to changes in recipients' fundraising intensity following peer foundation shocks. For example, Andreoni and Payne (2003) and Andreoni and Payne (2011a) use recipient-level data to show that charities reduce their fundraising efforts following the receipt of government grants. Because recipients' fundraising may respond in a similar way following changes in peer foundation grants, it is important to assess how a fundraising channel might interact with a marginal value channel. Second, foundation staff may aim to maintain a recipient's overall funding level, even absent changes in recipients' fundraising, as a "safe harbor"

[26]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.

strategy to avoid accountability. In this section, we explore the plausibility of fundraising-based explanations for our findings. We revisit the second class of alternative agency-based explanations in Section 6.1, where we investigate foundation governance.

Regarding the role of a fundraising channel, there are two broad possibilities that are critical to distinguish. First, if a recipient's fundraising effort changes because the marginal social value of grant funds has changed, then PFs' grant adjustments and recipients' fundraising responses are two sides of the same altruistic coin. Recipients with limited staff will trade off time spent raising money against time spent delivering services; when a grant arrives and the marginal value of an extra dollar falls, it is optimal for the recipient to scale back fundraising and for PFs to redirect funds elsewhere. In a for-profit analogy, a private foundation is like a firm's CEO, and the recipients of the foundation's funding are like the CEO's subordinate divisional managers. An effective CEO can allocate capital efficiently either using her own formal analysis, or by engaging with reliable divisional managers who accurately champion projects when they expect the highest returns. That is, if recipients' optimal fundraising intensity and PFs' optimal capital allocation choices reflect the same underlying marginal project value, then they will align.

By contrast, if fundraising varied for recipients' self-interested reasons—e.g., recipients' managerial perks or survival concerns—rather than for value-related reasons, then reliance on fundraising signals would cause capital misallocation. In this second case, PFs that respond passively to those solicitations would exhibit a substitution effect even in the absence of corresponding changes in recipient needs.

We design two tests to distinguish the channels. Our first test, described in Section 4.3, compares foundations' cross-sectional responsiveness conditional on charitable cause type. Our second test, described in Section 4.4, compares how this responsiveness varies with the length of a foundation-recipient relationship. These tests collectively help to distinguish between a passive fundraising channel and a deliberate mechanism where PFs respond to variations in charitable need. The next two subsections describe these tests in detail.

4.3. Variations in Responsiveness across Charitable Causes

Our first test of the fundraising channel is motivated by a result from Andreoni and Payne (2003), who find that recipients' reductions in fundraising efforts following increased government grants arise primarily among art-related recipients. If PFs are passively responding to fundraising intensity alone, we should observe the strongest substitution effects in this subsample. In contrast, if PFs are responding to changes in marginal value, we expect stronger effects in domains where substitution across recipients is more feasible—likely, outside of the art-related recipients.

In order to compare responsiveness across recipient types, 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.[27]

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 baseline regression, we observe no significant 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. This result is telling: prior studies (e.g., Andreoni and Payne (2003)) show that art-related recipients substantially reduce fundraising efforts after receiving increased government grants. If private foundations' responsiveness were driven purely by the fundraising channel, we would expect a significant negative coefficient in the art-related subsample. However, arts and religion initiatives are often viewed as having few meaningful substitutes, which may explain the absence of a significant substitution effect in the data.

To further investigate the drivers of perceived substitutability, we classify gifts based on whether the supported activities relate to a high-priority area for an individual PF. We

[27] 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.

define this high-priority area 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 7, 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 whose favorite area is non-scientific, likely because non-scientific causes are perceived as more unique and harder to substitute.

4.4. Variations in Responsiveness by Relationship Length

Our second test of the fundraising channel investigates how grantmaking responsiveness varies with the duration of the PF-recipient relationship. If PFs' cross-sectional responsiveness is mostly driven by fundraising, one would expect the responsiveness to be stronger early in the relationship when other information is limited. In contrast, if responsiveness reflects an active learning process, it should be greater in longer-standing relationships, when foundations are better informed and more deliberate in their capital allocation.

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 = -3.8) for longer relationships. The difference between these two coefficients is strongly statistically significant. Importantly, the duration of the relationship is not simply proxying for "favorite" recipient status, as the effect of favorite status on responsiveness, shown earlier, has the opposite sign. 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

The marginal value of charitable capital varies not only cross-sectionally, but also over time. A more stringent examination of PFs' responsiveness to changes in recipient needs must consider this intertemporal dimension. Intertemporal responsiveness to changes in recipient needs is likely to be particularly challenging for foundations, because it cannot be satisfied by mere reallocations of a fixed budget across varying recipients. Instead, intertemporal responsiveness requires paying out larger amounts during periods of heightened need – periods that often coincide with broader economic downturns. Faced with negative financial shocks at precisely the time greater disbursements are most valuable, foundations must make a deliberate choice that may compromise their long-term financial sustainability.

Importantly, cross-sectional responsiveness does not imply intertemporal responsiveness. For example, a foundation may prioritize capital preservation when setting its annual spending level, effectively constraining its ability to respond intertemporally. Yet within that constrained budget, it may still reallocate across recipients in a way that appears in cross-sectional analysis. Thus, we proceed to investigate PFs' intertemporal responsiveness.

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, the financial returns of peers to the focal foundation i for recipient j (i.e., $RET_{-i,j,t} = \sum_{i' \neq i} \frac{G_{i',j,t}}{G_{j,t}} RET_{i',t}$) are aggregated to arrive at the weighted average peer return for foundation i ($PeerRET_{i,t} = \sum_{j \in i's \text{ recipients}} RET_{-i,j,t}$). We then use it as an aggregate shock to the focal foundation's marginal value of giving in the following regression.

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

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. The advantage of this test is that it allows us to use all PFs, rather than only those for which we have foundation-recipient level data. If PFs' total spending responds to recipient needs, we should observe a positive loading on the recession dummy. On the other hand, if capital preservation 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.

5.2. Capital Preservation

If PFs do not maximize impact when determining their overall spending levels, what do they prioritize? Following the methodology of Brown et al. (2014), we test the hypothesis that PFs prioritize capital preservation by investigating whether PFs respond more strongly to negative returns than to positive ones, cutting spending aggressively in response to the former but increasing it slowly in response to the latter. We test this asymmetry with the following OLS regressions:

$$\frac{G_{i,t}}{W_{i,t-1}} = \beta_0 + \gamma_i + \gamma_t + \beta_1^+ RET_{i,t}^+ + \beta_1^- RET_{i,t}^- + \left[\beta_2^+ RET_{i,t-1}^+ + \beta_2^- RET_{i,t-1}^-\right] + \eta_{i,t}, \quad (4)$$

where the actual payout is defined as the spending in year t scaled by the beginning-of-year assets.[28] 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 11 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, a 10 percent asset shock raises payout rates by 10 to 16 basis points for positive returns but decreases them by 24 to 32 basis points after negative returns. The asymmetry in responses is thus economically substantial given that the average payout rate is 4.8%.

If PFs prioritize capital preservation and institutional survival when setting their spending level, closure should be rare. We investigate this corollary next. Figure 2 presents hazard rates for private foundations' closure as a function of their age. We measure a foundation's age from the date the IRS approved its application for tax exempt status (its ruledate from the IRS BMF),[29] and define the year of closure 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

[28]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.

[29]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.

filling Form 990-PF.

Young private foundations (<20 years) have a closure probability near 1%. As foundations age, their closure probability falls, reaching a low of around 0.7% around year forty. Between years forty and sixty, there is a second, smaller peak in closure probability, which subsequently declines again. Though our data do not contain information on founder age, we conjecture that this second small peak might reflect closures that occur around or following the death of a foundation's primary donor. To our knowledge, our study is the first to characterize the survival rate of private foundations.

Overall, the average annual closure rate for PFs in our sample is about 0.8%. This extremely low closure rate is consistent with the view that many foundations allocate capital in a way that prioritizes long-term survival. In contrast to this tendency, a handful of prominent foundations explicitly state that their spending levels are not driven by 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."[30]

Private foundations are not the only institutions with a tendency to prioritize capital preservation and institutional continuity. 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 this behavior reflects 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 even more fundamental. In the private foundation context, donors and managers often overlap, suggesting that aligning managers' actions with donors' interests may not be sufficient to ensure alignment with an institution's stated mission. Thus, we now turn to analyze how the governance structure of PFs affects their responsiveness to charitable needs and their emphasis on capital preservation.

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

6. Governance and Responsiveness

In Section 4.2, we discussed two potential alternative explanations for foundations' cross-sectional responsiveness. The second posits that maintaining recipients' overall funding levels might serve as a kind of "safe harbor" that allows foundation staff to avoid blame for their grant allocation choices. To investigate the role of such agency considerations, in this section, we examine the effect of founder influence on foundations' responsiveness. Intuitively, if agency concerns are driving foundation responsiveness, then foundations should be most responsive when principals (i.e., founders) are not involved in decision-making. Conversely, if the most responsive foundations are those with the greatest principal involvement, then responsiveness is more likely to reflect principals' intent and discretion.

In addition to analyzing the role of founder involvement, we also explore whether broader measures of foundation governance influence their responsiveness to changes in recipient need. In principle, it seems reasonable that governance devices like large, independent boards of directors and professional corporate officers should limit founders' consumption of private benefits, including their potentially excessive focus on institutional longevity. On the other hand, these devices may prove ineffective if tools for enforcing governance discipline are relatively constrained – for example, due to 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; the limits to stakeholders' ability to use voice or exit for disciplining trustees or officers; and the absence of market competition that underlies the Friedman Doctrine of shareholder primacy. Given the challenge of quantifying the effectiveness of charitable activities, a governance structure that encourages discretion could promote responsiveness by allowing greater use of private information.

6.1. Governance and Cross-Sectional Responsiveness

Table 12 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 officers and trustees.

Our proxy for founder involvement 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 12 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., follow-

[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 **12**, which are qualitatively similar.

[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.

ing 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 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 need and that agency-based explanations such as "safe harbor" concerns of staff are less likely to explain foundations' cross-sectional responsiveness.

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 12 considers additional foundation characteristics that are indirectly related to governance: foundation size, age, and payout ratio. Columns (1) and (2) report

[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.

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.

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, though the effect of foundation characteristics such as board independence has the expected sign, founders' influence stands out as having the strongest association with foundations' cross-sectional responsiveness. The importance of principals' involvement in foundations' responsiveness suggests that principals' charitable intent, rather than agency channels such as "safe harbor" considerations, are more likely to be primary drivers of the responsiveness we observe.

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

6.2. Governance and Capital Preservation

We then repeat the same capital preservation regression analysis, as used in Table 11, across the same subsamples. 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. We first compare the extent of asymmetric payout response to positive versus negative returns across subsamples, and then compare the magnitude of foundations' spending cuts following negative returns. For brevity, we report the regression with PF fixed effects in Table **13** and the alternative regression with both PF and year fixed effects in Internet Appendix Table **IA2**.[35]

Columns 1 and 2 of Table 13 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

[35] 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 $HighPay$.

differences are not statistically significant at the 5% level. The most notable difference emerges when splitting by payout ratio, where high-payout foundations exhibit a greater tendency toward capital preservation.

Overall, similar to our earlier results on cross-sectional responsiveness, we find that founder influence stands out among foundation characteristics for its strong association with capital preservation. The fact that founder influence is linked to both greater cross-sectional responsiveness and stronger capital preservation suggests that, because recipient needs are difficult to measure and thus efficient allocation is difficult to 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. At the same time, 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.

7. Conclusions

Assessing the efficiency of capital allocation in the nonprofit sector is a challenging and complex question. We take a step towards answering this question by analyzing whether foundations effectively reallocate charitable capital in response to changes in recipient needs. Our approach leverages rich data on the assets and grant-making behavior of private foundations, as well as the network of foundation-recipient relationships. By using financial shocks to peer foundations as a novel source of variation in the marginal value of grants, we isolate the effect of recipient needs on focal foundations' grantmaking from confounding forces.

[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

We document novel evidence that foundations adjust their cross-sectional grant allocations in response to changes in 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. Notably, among various governance characteristics, founder involvement stands out as the strongest predictor of both significant cross-sectional responsiveness and insignificant time-series responsiveness, with the latter reflecting a stronger emphasis on capital preservation.

More broadly, because foundations are insulated from traditional market pressures (such as those from product markets, funding markets, and markets for corporate control), they provide a unique setting to analyze the efficiency of capital allocation when market discipline is minimal. Taken together, our results provide evidence against a purely cynical view of foundation activity in which effectiveness is secondary to non-altruistic motives such as tax optimization, warm glow, visibility, or ideological alignment. However, this efficacy appears fragile, as it relies on a fortuitous alignment between societal needs and the goals of foundation trustees. In the absence of market disciplines that would penalize misalignment, the current regulatory framework is a balancing act: It subsidizes foundation activities in the hope of harnessing foundations' insights into recipient needs, while imposing minimum payout requirements to limit the private benefits of capital preservation.

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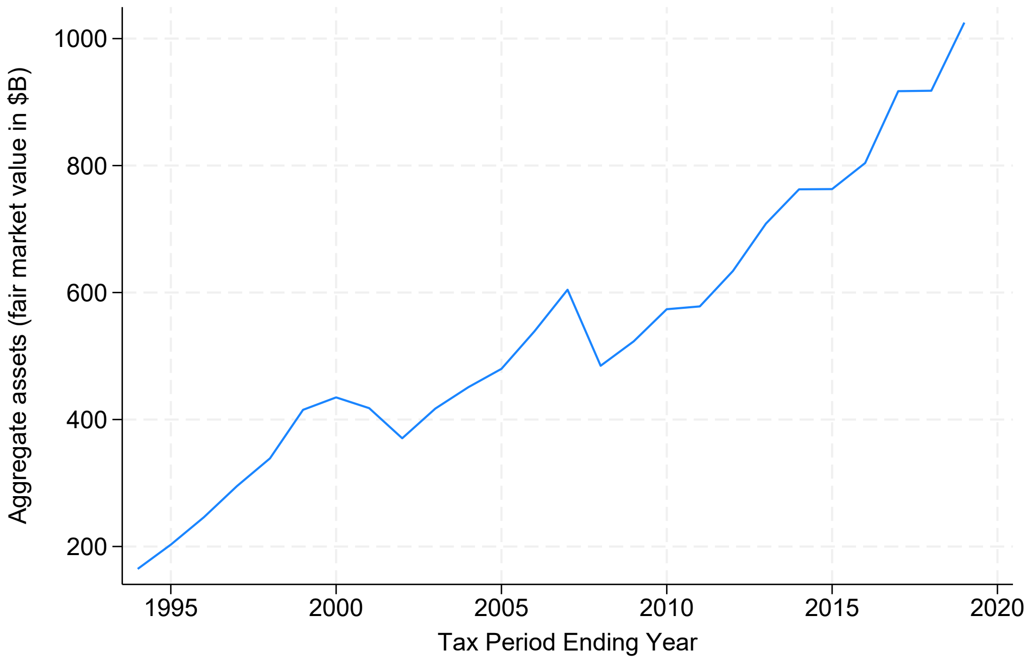
Figure 1: Aggregate Market Value and Spending of Private Foundations, 1994 - 2019

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

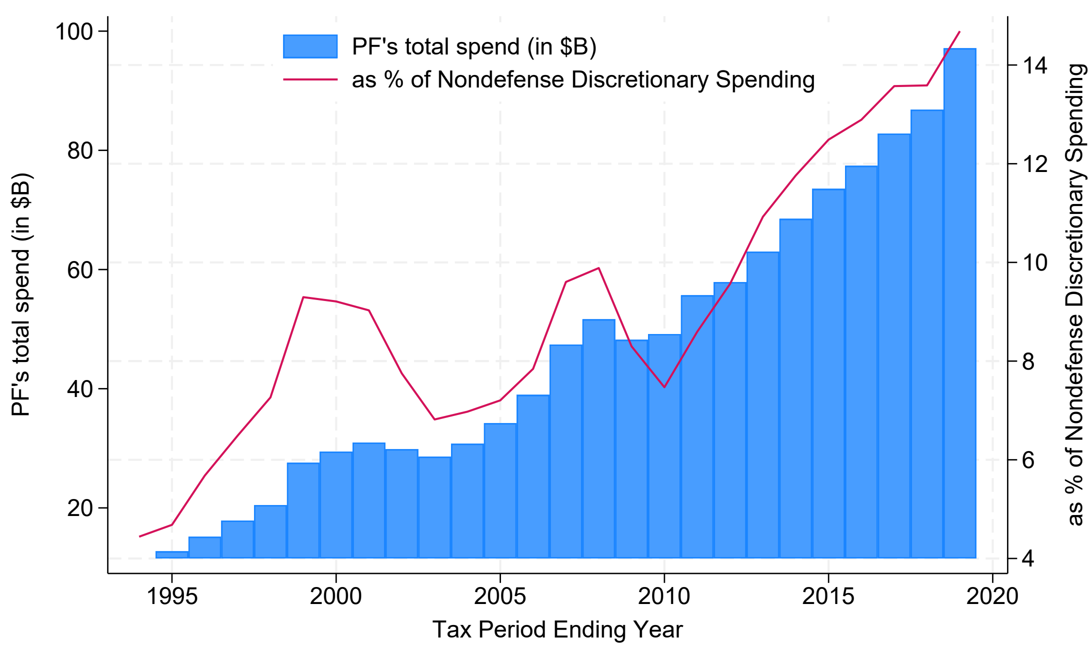


Figure 2: Closure Rate of Private Foundations

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).

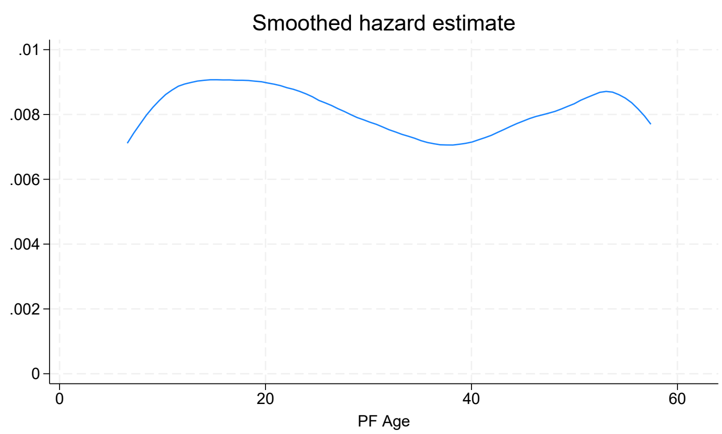


Table 1: Summary Statistics: Assets and Grants

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 recipient-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)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})$	0.03***	0.03***	0.04***			
	(0.01)	(0.00)	(0.01)			
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$				-0.11	-0.29***	-0.21
				(0.07)	(0.08)	(0.14)
$\log(\text{Grant}_{i,j,t})$	-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)
$\log(\text{PeerGrant}_{i,j,t})$	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)
$\log(1+R_{i,t})$	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)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})$	0.04***	0.03***						
	(0.00)	(0.00)						
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$			-0.31***	-0.06	-0.27***	0.11	-0.38***	-0.21
			(0.07)	(0.13)	(0.10)	(0.14)	(0.11)	(0.14)
$\log(\text{Grant}_{i,j,t})$	-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)
$\log(W_{i,t-1})$	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)
$\log(\text{PeerGrant}_{i,j,t})$	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)
$\Delta\log(\text{PeerGrant}_{i,j,t+1})$	0.03***	0.03***	0.04***			
	(0.00)	(0.00)	(0.00)			
$\Delta\log(\text{PeerGrant}_{i,j,t+1})^{inst.}$				0.14	-0.24***	-0.46***
				(0.15)	(0.09)	(0.12)
$\log(\text{Grant}_{i,j,t})$	-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)
$\log(\text{PeerGrant}_{i,j,t})$	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: 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 12: 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 12: 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 13: Capital Preservation: Subsample Analysis (by Foundation Characteristics)

This table presents subsample analysis for the capital preservation regression in Table 11. $Family$ 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

A. Appendix

A.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.

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. The last term, ΔOtherChg, adjusts for changes in the market value of assets that are reported off the income statement, as described later in this section.

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).

Regarding ΔOtherChg, 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.

A.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%.

A.3. Grant-Return Sensitivity and Minimum Spending Constraints

The first stage of our 2SLS analysis in Section 4.1 establishes that foundations' grantmaking responds to their own endowment returns. One 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 A1 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.[37] The subset of private foundations we use in Table A1 contains PFs whose year t qualifying distributions is at least 20% larger than the required distributions

[37]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 $t-4$.

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 $t+3$.

A.4. Responsiveness of Donations Received to Endowment Returns

Foundations potentially have one significant off-balance-sheet asset, comprising future gifts that the foundation expects to receive from its founder. This asset plays an important role in the theoretical framework of Adelino et al. (2015). In their model, an altruistic donor (e.g., a foundation's founder) adjusts future gifts to fully offset the permanent income effect of any nonprofit endowment shock. This occurs because, in a decreasing returns to scale framework, a negative (positive) endowment shock increases (decreases) the marginal utility of additional donations. However, a critical assumption of this model—that financial shocks to nonprofits are uncorrelated with shocks to donors' wealth—is likely violated in our PF setting, where PFs and their donors are likely to hold similar investment portfolios.[38]

In order to understand whether or how this asset interacts with foundations' endowment value, we directly test the conjecture that charitable donors "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

[38] 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.

donations and the amount donated when they occur.[39] Also due to infrequent donation, the coefficients of firm fixed effect regressions can suffer from the 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 A2 run the following logistic regression to examine the extensive margin

$$\text{Logit}P\left(\text{DonationReceived}_{i,t+k}\right) = \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \eta_{i,t+k}, \tag{5}$$

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 A2 run the following OLS regression (conditional on positive $\text{DonationReceived}_{i,t+k}$) to examine the intensive margin

$$\frac{\text{DonationReceived}_{i,t+k}}{W_{i,t-1}} = \gamma_t + \beta_1 RET_{i,t} + \beta_2 logW_{i,t-1} + \eta_{i,t+k}, \tag{6}$$

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.

[39]Our results are robust to using Poisson regression, as reported in Appendix Table A3, which combines the effects of extensive and intensive margins.

B. Appendix Tables

Table A1: 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)	(2)	(3)	(4)	(5)	(6)
	k=1	k=2	k=3	k=1	k=2	k=3
$RET_{i,t}$	0.054***	0.054***	0.046***	0.064***	0.073***	0.075***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
$\log(W_{i,t-1})$	-0.041***	-0.042***	-0.051***	0.002***	0.003***	0.004***
	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)	(0.001)
$Target_{i,t-1}$				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 A2: 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 A3: Cash Flow Sensitivities of Donations Received (Poisson)

This table repeats the analysis in Table A2 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

For Online Publication: Internet Appendix

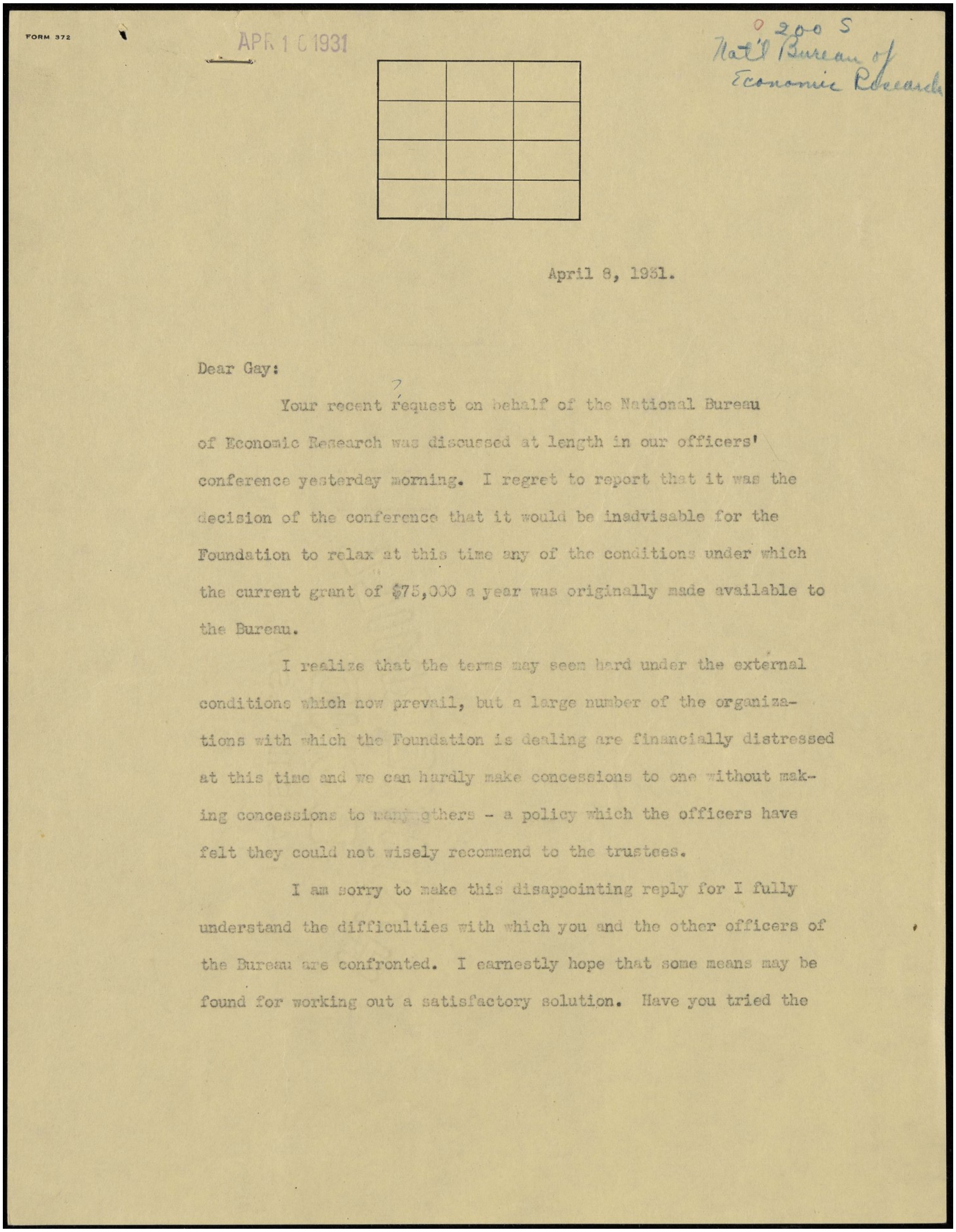
IA.1. Motivating Anecdote: NBER and Private Foundations

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 IA1–IA4 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 IA1: Rockefeller Foundation and the NBER: Funding Request



FORM 372

APR 1 6 1931

0 200 S
Nat'l Bureau of
Economic Research

April 8, 1931.

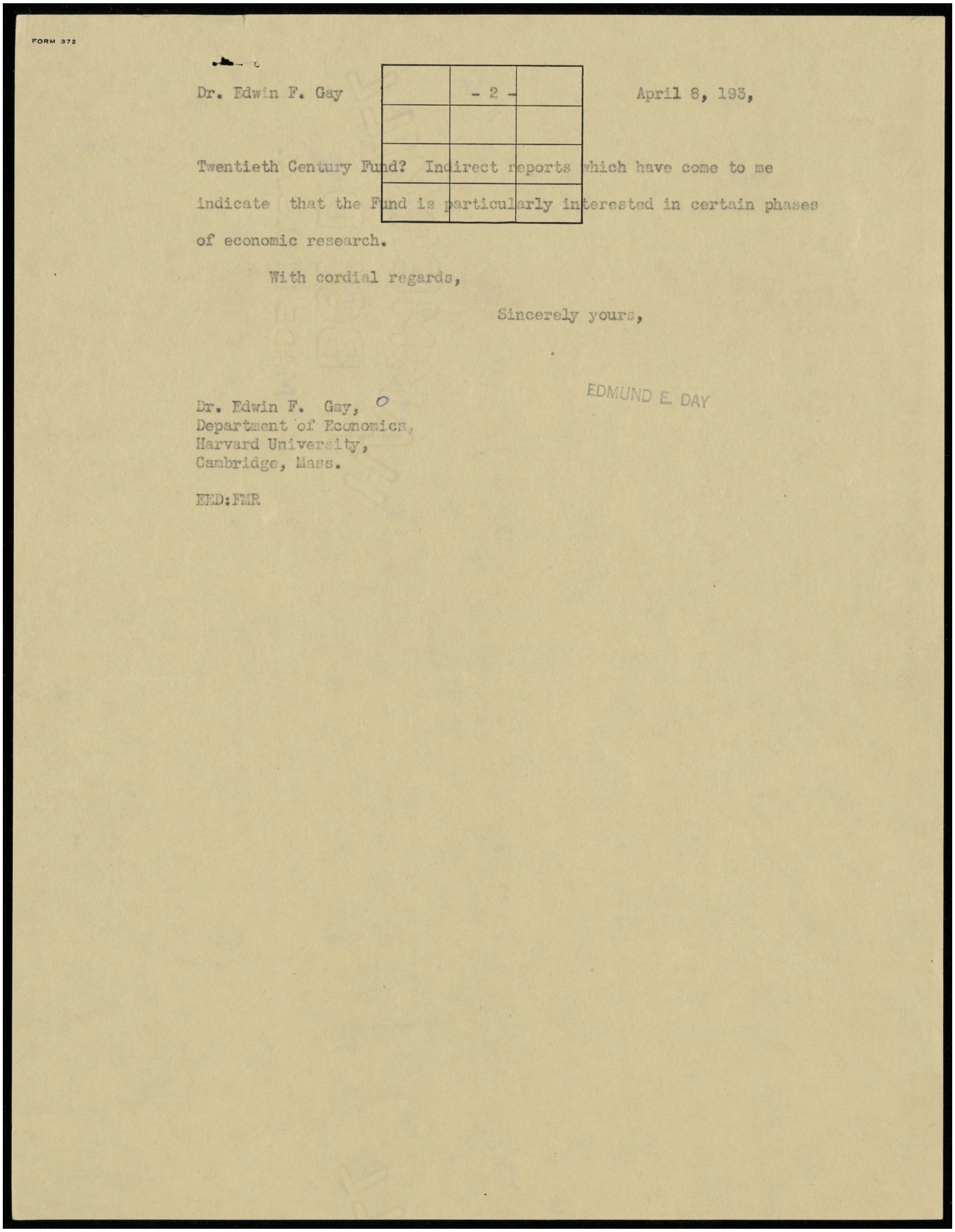
Dear Gay:

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 IA2: 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 IA3: 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.

Finances: 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 IA4: 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.

IA.2. Additional Tables

Table IA1: 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 12 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 IA1: 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 IA1: 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 IA1: 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 IA1: 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 IA2: 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