The Source of Nonprofit Risk Aversion: Theory and Evidence from Hospitals*

Cameron M. Ellis† Meghan I. Esson‡ Jingshu Luo§

March 2, 2026

Abstract

We show that donors, not managers, drive risk-averse behavior in nonprofit organizations (NPOs). Theoretically, when donor recognition is tiered (e.g., naming rights vs. thank-you cards), donors concentrate rather than diversify giving, making shadow donation capital costs sensitive to NPO-specific risk. This induces risk-averse actions even without risk-averse managers. We test our theory using hospitals and the staggered adoption of medical liability caps and find that reduced NPO risk increases donations. Effects on substitute bond-financing indicate this increase is supply- (donor-) driven, not demand- (manager-) driven. Liability caps lead nonprofit hospitals to expand risky investments faster than for-profits, improving patient health.

JEL Codes: **L31 · I11 · K13 · G31 · I18 · G22 · G32**
Keywords: Nonprofit Risk Aversion · Donations · Municipal Bonds · Hospital Finance

---

*The authors have no relevant funding sources to disclose. The authors would like to thank Kelly Edmiston, Jon Garfinkel, Taylor Graciano, Fotis Grigoris, Lixiong Guo, Joseph Kalmenovitz, Katharina Lewellen, and the participants at the American Risk and Insurance Association, the CEAR/MRIC Behavioral Insurance Workshop, the Eastern Finance Association, the University of Georgia, the University of Iowa, the University of Mississippi, and the WashU Conference on the Economics and Finance of Healthcare and Medicine.

†Tippie College of Business, Department of Finance, University of Iowa, Iowa City, IA, cameron-ellis@uiowa.edu

‡**Contact Author** Tippie College of Business, Department of Finance, University of Iowa, Iowa City, IA, (319)-467-3142, meghan-esson@uiowa.edu

§Department of Finance, School of Business Administration, University of Mississippi, jluo2@olemiss.edu

1 Introduction

Since Modigliani and Miller (1958) (MM), there has been an extensive literature examining how for-profit companies respond to risk.[1] In contrast, despite contributing $1.4 trillion to US GDP and employing over 12 million workers, we know far less about how nonprofit organizations (NPOs) respond to risk. The limited evidence suggests that NPOs behave more risk-aversely than for-profits (e.g., Fisman and Hubbard, 2005; Chen and Bozeman, 2012; Lo et al., 2025).[2] Most of these empirical studies implicitly attribute nonprofit risk aversion to managers, often on "mission protection" grounds (e.g., Gentry, 2002; Fisman and Hubbard, 2005; Dimmock, 2012; Adelino et al., 2015), while giving little attention to an alternative source: donors. In this paper, we ask: Who drives NPO risk aversion, managers or donors?

We speak to three aspects of this question and provide empirical support from the hospital industry. (1) Why would donor risk aversion influence NPO behavior? We present a novel theoretical model showing that the way NPOs offer "tiered recognition" discourages donors from diversifying and leads to organizational-level risk aversion. We test this theory by examining how NPO hospital donations respond to risk shocks. (2) Which channel matters more: Do donors drive NPO risk aversion or do manager preferences drive donation patterns? We show that the relative strength of each channel can be identified by examining whether donations substitute or complement bond financing in response to changes in risk. (3) Does NPO risk aversion translate into real investment decisions and real outcomes? We compare investments into trauma centers of nonprofit relative to for-profit hospitals when they are exposed to the same risk shock and show how this impacts local traffic fatalities.

[1] Papers in this literature examine why firms hedge when external finance is costly (Froot et al., 1993), the role of agency costs, taxes, and financial distress in hedging decisions (Smith and Stulz, 1985), corporate demand for insurance as risk transfer (Mayers and Smith, 1982), how managerial ownership affects hedging intensity (Tufano, 1996), hedging to increase debt capacity and tax benefits (Graham and Rogers, 2002), and evidence that derivative use reduces firm risk and increases value (Bartram et al., 2011).

[2] Notable exceptions are Hansmann (1980) and Glaeser and Shleifer (2001).

Why would donor risk aversion lead to NPO risk aversion? There is a long and active literature equating donors to shareholders, which implies that donors should be able to diversify their donations and thus not react to idiosyncratic risk.[3] We provide a novel explanation for the lack of donor diversification.[4] Unlike for-profit shareholders who seek financial returns, donors' payoff is through recognition.[5] Hospitals supply this payoff by converting donations into status and visibility (e.g., thank-you cards, donor walls, and naming rights for endowed funds and buildings). However, the inventory of recognition is finite and tiered, with benefits increasing in scarcity (i.e., there are many thank-you cards, but only so many programs and buildings to name). We show that, because the supply of recognition becomes more limited as the tier increases, NPOs optimally set their donation-to-recognition function convexly—donating $1,000,000 to one hospital gets a building named after you, but donating $1,000 to 1,000 hospitals only gets you 1,000 thank you cards—so that donors concentrate their donations to specific NPOs.[6]

This concentration violates MM's costless diversification assumption and makes donors sensitive to organization-specific risks, particularly the risks that damage the NPO's reputation and devalue their recognition. Donor preferences now enter the NPO's objective function: when project risk increases, it becomes harder to attract donations, effectively raising the NPO's cost of capital. Conversely, when risk is lower, donors are more willing to give, reducing NPO's financing costs. This mechanism induces NPOs to behave in a risk-averse

[3]For example, Fama and Jensen (1983); Lakdawalla and Philipson (2006); Wedig (2010); Yermack (2017).

[4]In this paper, we focus on one plausible and prevalent driver behind why donors concentrate. Donation concentration may also arise for other reasons. For instance, generous alumni may perceive a high need for contributions to their alma mater (Diamond and Kashyap, 1997; Weerts and Ronca, 2007). Likewise, individuals who have "a deeply loved pet animal" may be more inclined to give to animal welfare rather than other charitable organizations (Bennett, 2003).

[5]Although altruism may motivate donations, it is often "impure" altruism where donors derive *additional* utility from things such as recognition (Andreoni, 1989). In our case, we assume that donors care more about the "mission outcome" for NPOs that they receive recognition from relative to the ones they do not receive recognition from.

[6]Concentrating donations is consistent with industry evidence. Philanthropic fundraising is heavily driven by major gifts, with capital-campaign handbooks and consultant guides commonly estimating that 90-95% of funds come from 5-10% of donors (Association of Fundraising Professionals, 2018; Creative Fundraising Advisors, 2022).

manner even if managers themselves are risk-neutral, providing a novel micro-foundation for the widely observed conservative investment behavior of NPOs.

We explore the donor channel by examining the response of NPO hospital donations relative to for-profit hospitals following risk shocks. For identification, we exploit the staggered implementation across states of caps on medical malpractice awards, which directly limit hospital risk. We find that donations to NPO hospitals increase by roughly 30% relative to for-profit hospitals after risk caps are implemented, showing a strong relationship between NPO risk exposure and NPO donation financing. This result suggests that donor risk aversion changes the *supply* of donations. However, donor-driven risk aversion is not the only possible explanation for the increased donations. If, instead, managers are risk-averse and donors are not, then reducing risk exposure would increase managerial willingness to scale up capital projects and their *demand* for donations. Both channels, donor and manager, predict an increase in donations.

Which channel dominates? Our theoretical model generates a novel insight which allows us to distinguish these channels empirically through the (a)symmetry of nonprofit hospitals' response to risk shocks in their use of two key substitute capital sources: donations and municipal bonds. Under donor-driven risk aversion, lower risk decreases the cost of securing donations, leading NPOs to shift toward donation financing and away from debt financing. This shift away from debt financing causes issuance to decline and yields to fall more than the direct risk reduction alone would predict. In contrast, under manager-driven risk aversion, when project risk falls a decline in risk prompts risk-averse managers to invest more, increasing demand for *both* financing types. This increased demand for bonds would push yields upward relative to the direct risk impact. These opposing predictions for bond market responses provide a clean test of which channel, donor or manager, dominates.

To test these competing predictions, we examine bond yield spread and bond issuance responses in the healthcare municipal bond market, where nonprofit hospital bonds are actively traded and yield data are readily available, allowing us to observe market pricing of NPO hospital debt.[7] We first estimate how much yields should decline based purely on improved credit quality (i.e., the direct risk effect). If observed bond yields fall beyond this benchmark, it suggests the donor-driven channel: a drop in demand for debt due to the greater supply of donations.

We find that healthcare municipal bond yields fall by 27 basis points following caps on medical malpractice awards, far exceeding the 5 basis points expected from the direct reduction in liability risk alone. This additional 22 basis point decline indicates a substantial shift in the supply-demand equilibrium for NPO hospital bonds. We also find that the size of issued long-term bonds, which are most commonly used for large, long-term investments, declined significantly following the reduction in liability risk.[8] Combined with the simultaneous increase in donations, this pattern precisely matches our predictions of donor-driven risk aversion and demonstrates that the causality runs from donor risk preferences to NPO behavior, and not from manager risk preferences to donor behavior.

Having shown that donor risk aversion drives nonprofit organizations' risk-averse financing behavior, we next ask whether this influence extends to real investment decisions. We focus on trauma centers, which are profitable but carry significant medical liability risk and, unlike aggregated balance-sheet measures, are discrete, observable decisions that directly reflect firm-level risk-taking. We find that caps on non-economic damages lead to a 40% increase in the probability that a NPO hospital operates a trauma center relative to a for-profit hospital.

While we use hospitals and trauma centers as a laboratory for larger questions about NPO behavior, the context is also important in its own right. Trauma centers provide critical emergency care infrastructure, yet many communities lack access. Our findings reveal significant public health benefits from expanded trauma center availability: an 8%

[7]We focus on nonprofit hospital bonds because they are issued within a single state, aligning with our state-level identification strategy. For-profit hospital systems, by contrast, frequently operate across multiple states, so their bonds cannot be cleanly assigned to a single state's tort reform environment.

[8]We also find negative point estimates for the number of bonds issued, but the results are too noisy to establish statistical significance.

reduction in total traffic fatalities in treated states and an 18% reduction in multi-casualty incident fatalities (accidents with two or more fatalities), showing that donor-driven NPO behavior has direct consequences on health outcomes.

We make three primary contributions to the literature. Our novel micro-foundation for NPO risk aversion does not rely on risk-averse managers, which is typically assumed by the literature (Gilbert and Hrdlicka, 2015). Our theory also leads to a new testable prediction that can be used to identify the primary source of risk aversion for NPOs when risk changes. We are also the first to show that nonprofit organizations' risk aversion can be primarily driven by donors' risk aversion (see also, Wedig, 1994). Our findings complement experimental evidence that donors and other stakeholders are risk-averse (Exley, 2016; Brock et al., 2013; Null, 2011; Khan, 2025) and, more importantly, demonstrate how this donor risk aversion shapes real-world nonprofit behavior.

Second, we contribute to the literature on NPO capital structure (e.g., Wedig, 1994; Wedig et al., 1996; Jegers and Verschueren, 2006) and financing costs (e.g., Cornaggia et al., 2024; Gao et al., 2022; Lu and Ye, 2023). Prior studies have focused on how debt and equity financing influence hospital behavior (Aghamolla et al., 2024; Adelino et al., 2022; Rossi and Yun, 2024; Aghamolla et al., 2025), and how external risk shocks influence hospitals' cost of debt capital (Cornaggia et al., 2024; Osborne, 2025). Our results of cross-substitution between financing sources offer a novel perspective on how NPOs adjust their financing mix under changing risk environments. We also add to the recent literature on conditions affecting municipal bonds (e.g., Chava et al., 2024; Jha et al., 2025; Gustafson et al., 2025).

Finally, we contribute to a growing healthcare finance literature examining ownership differences in hospital behavior (e.g., Horwitz and Nichols, 2009; Moon and Shugan, 2020; Cornaggia et al., 2024; Gao et al., 2025a; Gupta et al., 2024; Gao et al., 2025b). Prior work documents differences in healthcare quality and governance across ownership types (e.g., Herpfer et al., 2024; Lewellen et al., 2025). We add to the literature by showing that hospital ownership also influences their responses to risk. Relative to for-profits, nonprofits adjust both financing and investment more strongly following a liability risk shock. Because nonprofits account for roughly half of U.S. hospitals, these ownership-based differences in risk preferences have direct implications for hospitals' willingness to expand and sustain high-risk services, influencing healthcare access.

2 Institutional Background

This section provides the institutional context for our theory and empirical design. We begin with an overview of the U.S. nonprofit hospital sector, focusing on its unique governance structure and the debate over whether donors or managers control major decisions. We then describe the medical malpractice liability environment and explain how state laws of caps on non-economic damages reduce hospitals' liability risk exposure, creating exogenous variation in hospitals' risk environment. Finally, we discuss trauma centers, our primary investment outcome, and explain why they are well-suited for studying how risk preference influences nonprofit hospitals' investment decisions.

2.1 Nonprofit Hospital Governance and Decision-Making

Hospitals are one of the largest components of the U.S. health system. In 2023, healthcare spending accounted for 17.6% of GDP, with hospital care representing 31% of that total (Centers for Medicare & Medicaid Services, 2024). Nonprofit hospitals dominate this sector: of the 4,778 non-government hospitals, over 60% operate as nonprofits (American Hospital Association, 2025). In return for tax exemption, nonprofit hospitals provide community benefits valued at more than $129 billion annually, including uncompensated care and subsidized services (American Hospital Association, 2024).

Unlike for-profits, nonprofit hospitals operate under a nondistribution constraint, which prohibits profits from being distributed to those who control the organization (Hansmann, 1980). Without shareholders, they often draw on donations as a source of external finance

(Fama and Jensen, 1983), creating ambiguity about who ultimately controls major decisions (Lewellen et al., 2025).

One view, donor control theory, argues that hospitals must act in donors' interests to compete for scarce philanthropic resources (Fama and Jensen, 1985; Rose-Ackerman, 1996; Lakdawalla and Philipson, 2006; Petrovits et al., 2011). Donors actively monitor hospital practices such as risk controls (Harris et al., 2015), profitability (Frank et al., 1990), and executive compensation (Balsam et al., 2020), rewarding hospitals that meet expectations with continued support. An alternative view, managerial autonomy, emphasizes that weak governance and the absence of shareholders give nonprofit managers wide discretion to prioritize their own preferences over those of donors (Fisman and Hubbard, 2005; Glaeser and Shleifer, 2001; Glaeser, 2003; Adelino et al., 2015). This tension between donor and managerial influence frames our analysis of how nonprofit hospitals respond to changes in liability risk and who drives such decisions.

2.2 Hospital Malpractice Risk and Non-Economic Damage Caps

Hospitals face substantial financial exposure from medical malpractice, with national liability costs exceeding $55 billion annually and nearly half of physicians over age 55 reporting at least one lawsuit in their career (Mello et al., 2010). While hospitals and physicians typically carry medical malpractice insurance, standard coverage limits of $1-3 million often fall short. Catastrophic cases, such as wrongful death or lifelong disability, can exceed $10 million, with rare awards surpassing $200 million—roughly 50 times the average annual profit of nonprofit hospitals in our sample. When physician coverage is inadequate, hospitals are liable for the remainder. Some hospitals set aside their own funds (self-insure) or use special in-house insurance programs (captives), but these approaches still leave exposure to large claims.[9]

[9]Verdicts exceeding $10 million are often described as "nuclear verdicts. Medical malpractice verdicts account for 20.3% of nuclear verdicts in 2010-2019 (Silverman and Appel, 2022). For example, a Florida jury awarded approximately $216.7 million in a stroke-misdiagnosis medical malpractice case in 2006 (Claims Journal, 2006).

This vulnerability was most acute during the "medical malpractice crisis" of the 1970s-2000s, when claim severity and insurance premiums surged. In response, states enacted tort reforms to reduce liability exposure. Among the most consequential type of tort reform are caps on non-economic damages, which limit jury awards for pain and suffering typically between $250,000 and $750,000.[10] Because pain-and-suffering awards are volatile and unpredictable, these caps directly reduce liability tail risk. Empirical evidence suggests they lower liability costs by 20-30% in adopting states (Born et al., 2009; Paik et al., 2012), giving hospitals both fewer uninsured losses and a predictable ceiling on liability exposure.[11] These reforms provide a natural experiment in how altering external risk shapes hospital financing and investment.

2.3 Trauma Centers as an Investment

We study trauma center openings as a lens on hospital investment decisions. Trauma centers are well-suited for this purpose because they are large, discrete projects with significant ongoing costs, making them comparable to major capital investments in other industries. Establishing a center requires $2-5 million in up-front spending and $3-7 million annually to maintain 24-hour specialist coverage and advanced facilities (Ashley et al., 2015; American College of Surgeons, 2024). These commitments force hospitals to weigh expected returns carefully against substantial risk.

Strategically, trauma centers can strengthen a hospital's finances and prestige. They attract high-acuity patients who generate higher reimbursement through trauma activation fees and complex case-mix classifications (American College of Surgeons, 2024), and they serve as regional hubs for this care. They also enhance institutional reputation and help recruit top physicians. At the same time, trauma centers are especially liability-exposed.

[10] There are two different types of caps: Per plaintiff caps and per case caps. Of our seven treatment states, four capped per plaintiff and three capped per case.

[11] Other tort reforms include caps on punitive damages, collateral source reform, and modifications to joint-and-several liability. We focus on non-economic caps because they most directly reduce tail risk, are considered the most effective reform (Paik et al., 2017), and exhibit sufficient variation in adoption during our study period.

Trauma surgeons are consistently ranked among the highest-risk specialties for malpractice claims (Jena et al., 2011), reflecting the clinically complex nature of trauma care and the likelihood of mass-casualty events where multiple critically injured patients must be treated simultaneously. These features make trauma centers an ideal setting for examining how altering the risk environment influences nonprofit hospitals' investment decisions in a profitable but risky asset.

3 Theoretical Framework

This section develops a model showing how nonprofit recognition systems induce organizational risk-averse behavior even with risk-neutral managers. The key insight is simple: unlike shareholders who can diversify, donors seeking recognition must concentrate their giving. For example, naming rights for a building requires a $1 million donation to one hospital; however, splitting that into $1,000 donations to 1,000 hospitals yields only thank-you cards. The price levels of this tiered recognition structure are endogenously chosen by hospitals to prevent donor diversification, which makes donors sensitive to hospital-specific risk, effectively raising the NPO's cost of capital when risk increases.

We present this intuition in a model where NPOs offer tiered recognition to attract donations while also accessing bond markets.[12] The model generates three testable predictions: (1) donations increase when NPO-specific risk falls, (2) bond yields respond asymmetrically depending on whether donor or manager risk aversion dominates, and (3) NPOs adjust risky investments more than for-profit companies, following risk shocks.

We now formalize this intuition. Consider a market with nonprofit organizations (NPOs) that need to finance projects delivering uncertain mission outcomes (e.g., lives saved from a

[12]To keep the theory transparent, we assume exponential utility (CARA) for donors and managers, normally distributed mission outcomes, and quadratic effort costs. These choices yield a closed-form mean-variance representation of the nonprofit's objective, echoing standard finance models (Arrow, 1965; Pratt, 1964). Recognition is offered in *indivisible* tiers with a pyramid inventory; our convexity results follow from scarcity and do not require screening regularity.

trauma center). Each NPO has access to two sources of capital: charitable donations and municipal bonds.

NPOs compete for donations from a population of donors who value both the mission outcomes and the recognition they receive for giving. Crucially, recognition can only be offered in discrete, indivisible tiers: a donor may receive a thank-you card, a named plaque, or building naming rights, but cannot split or share these goods with others. The supply of recognition follows a pyramid structure: many low-tier items are available, fewer middle tiers, and only a single top-tier prize.

The game unfolds in four stages. At $t = 0$, NPOs choose their investment scale, fundraising effort, and recognition thresholds (e.g., \$1,000 for a plaque, \$100,000 to attend the annual gala, or \$1 million for naming rights for a building). At $t = 1$, donors observe these choices and allocate their donations. At $t = 2$, the NPO issues residual bonds $B_h = K_h - D_h$ and invests. At $t = 3$, uncertainty about the mission outcomes (M_h) resolves, bondholders are repaid, and agents realize utility.

This structure generates our key friction: because recognition is indivisible and tiered, donors cannot diversify their giving portfolios the way shareholders diversify stock holdings. A donor seeking high-tier recognition must concentrate donations at a single NPO, making them sensitive to that organization's specific risk. Lower risk reduces the effective cost of donation financing, while higher risk raises it.

In the subsections that follow, we first introduce the model primitives and derive the donation supply function, showing how concentrated giving makes donations sensitive to NPO-specific risk. We then characterize equilibrium behavior and show how this concentration creates donor-driven risk aversion. Finally, we derive comparative statics that distinguish whether donor or manager risk aversion dominates, generating our empirical predictions for bond yields and investment behavior.

3.1 Donation Supply Function

We first derive characteristics of the donation supply function. NPOs face an investment decision in a project that delivers a mission-related outcome (e.g., lives saved) with distribution $M_h \mid K_h \sim \mathcal{N}\big(\bar{M}_h(K_h), \sigma_h^2(K_h)\big)$. The project outcome is subject to risk captured by its variance $\sigma_h^2(K_h)$, which depends on the chosen investment scale K_h. We write aggregate donations as

$$D_h = D_h\big(e_h,\ \bar{M}_h(K_h),\ \sigma_h^2(K_h)\big),$$

with $\frac{\partial D_h}{\partial \bar{M}_h} > 0$ and $\frac{\partial D_h}{\partial \sigma_h^2} < 0$ almost everywhere under CARA–Normal. Our donation results are local in variance and proceed through the state-dependent aggregator $\widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big)$. Intuitively, $\widehat{\Omega}_h(e_h, \sigma_h^2(K_h))$ collects the mass of donors located at each tier margin, weighted by the square of tier recognition: $\widehat{\Omega}_h = \sum_k R_k^2\, \psi_{h,k}$, where $\psi_{h,k}$ is the (a.e.) density of donors sitting at breakpoint k.

The project costs K_h and must be financed. NPOs have two forms of financing. They can solicit donations D_h or borrow B_h on the municipal bond market at an interest rate $r_B(B_h) = r_0 + \kappa B_h$ for $B_h \geq 0$ with $\kappa > 0$. In order to raise donations, NPOs can offer recognition $R_h(D_{h,i})$ to donors, which is free to the NPO but limited in supply, where $D_{h,i}$ represents the donation from donor i to NPO h. NPOs can also spend effort e_h, which incurs a "shadow cost" to improve their ability to collect donations. We model this shadow cost as quadratic: $C(e_h) = \frac{1}{2} c e_h^2$ with $c > 0$. NPOs set their recognition to donation function $R_h(D_{h,i})$ to maximize the donations received for a given level of shadow cost. Finally, we assume NPO managers value the project as

$$U(x) = -\exp(-\phi x), \qquad \phi \geq 0, \quad x := M_h - r_B(B_h)B_h.$$

Under CARA–Normal, the manager's certainty equivalent given choices (K_h, B_h, e_h) is

$$CE_M(K_h, B_h, e_h) \;=\; \bar{M}_h(K_h) \;-\; \frac{\phi}{2}\,\sigma_h^2(K_h) \;-\; r_B(B_h)\,B_h \;-\; C(e_h),$$

subject to the financing constraint $K_h = D_h + B_h$ with $r_B(B_h) = r_0 + \kappa B_h$. where ϕ denotes the representative NPO manager's risk aversion; fundraising effort enters only through the convex cost $C(e_h) = \frac{1}{2}ce_h^2$.

Donors allocate their wealth w_i to the NPOs and to themselves. Donors have a "mission match" $\mu_{h,i}(e_h)$ which is influenced by NPO effort, sums to 1 over active NPOs, and acts as relative weights on the mission outcomes M_h. The outside good is the numeraire and is not match-weighted.

Mission Match Function Specification. We specify the mission match function using a multinomial logit form:

$$\mu_{h,i}(e_h) = \frac{\exp(\alpha_{h,i} + \beta e_h)}{\sum_{j=1}^{H} \exp(\alpha_{j,i} + \beta e_j)} \tag{1}$$

where $\alpha_{h,i}$ captures the baseline affinity between donor i and NPO h, and $\beta > 0$ measures the effectiveness of fundraising effort in improving donor–NPO matching. This functional form ensures that $\sum_{h=1}^{H} \mu_{h,i}(e_h) = 1$ across NPOs and satisfies our required properties:

- $\frac{\partial \mu_{h,i}}{\partial e_h} = \beta \mu_{h,i}(e_h)[1 - \mu_{h,i}(e_h)] > 0$: fundraising effort increases mission match
- $\frac{\partial^2 \mu_{h,i}}{\partial e_h^2} = \beta^2 \mu_{h,i}(e_h)[1 - \mu_{h,i}(e_h)][1 - 2\mu_{h,i}(e_h)]$: which is negative when $\mu_{h,i}(e_h) > 1/2$, ensuring diminishing returns to effort for the dominant NPO

The logit structure captures competition for donor attention: when one NPO increases effort, it not only raises its own mission match probability but also reduces the match probabilities for all other NPOs. This strategic substitutability in fundraising effort plays a crucial role in establishing equilibrium uniqueness (Proposition 3). We assume that donor i only gains utility from causes they have received recognition from:

$$\begin{aligned} V_h(R_h(D_{h,i}), M_h) &= v\big(R_h(D_{h,i}) \cdot M_h\big) \\ &= -\exp(-\gamma_D R_h(D_{h,i}) \cdot M_h), \qquad \gamma_D > 0 \end{aligned}$$

The exponential form implies that donor utility is positively influenced by how well the mission does given a positive level of recognition. It also implies concavity, which represents that the donors are risk-averse with respect to mission outcomes for causes they have received recognition from. R_k can be interpreted as a weight on how much of the mission outcome the donor 'experiences' via recognition; higher tiers increase this weight. We set the outside good as the numeraire and assume a constant marginal utility of 1. Donors then maximize the weighted sum of their expected donation utility plus the known utility from the outside good.

This assumption of donor risk aversion with respect to mission outcomes is consistent with experimental findings that charitable giving declines in risky environments (Exley, 2016; Brock et al., 2013; Null, 2011). The utility formulation captures both the "warm glow" effect from giving (as in Andreoni (1990)) through the recognition component and the donor's concern about the ultimate impact of their gift through the mission outcome component.

3.1.1 Equilibrium Concept

We characterize the subgame perfect Nash equilibrium (SPNE) of this sequential game. The equilibrium consists of:

- NPO strategies: Each NPO h chooses investment scale $K_h^* \geq 0$ at $t = 0$, fundraising effort $e_h^* \in \mathbb{R}_+$, recognition breakpoints $\bar{D}_h^* = (\bar{D}_{h,1}^*, \ldots, \bar{D}_{h,K-1}^*)$, and issues residual bonds B_h^* at $t = 2$ given realized D_h, to maximize expected utility given anticipated donor responses and bond market pricing.

- Donor strategies: Each donor i chooses donations $\{D_{h,i}^*\}_h$ to maximize expected utility given NPO choices and other donors' strategies.

- Bond market pricing: The interest rate function $r_B(B_h)$ clears the bond market given rational expectations about project outcomes.

The SPNE requires that strategies are mutual best responses at every subgame, ensuring time consistency and ruling out non-credible threats.

3.1.2 Recognition Technology

Recognition tiers. We allow for an arbitrary but finite number $K \geq 2$ of recognition tiers ordered by prestige. Each item is indivisible, and fractional sharing is not allowed.

Recognition inventory. Let R_k denote the k-th recognition tier and $|R_k|$ the number of items available in that tier. We assume a "pyramid" structure such that higher tiers are fewer in number: $|R_{k+1}| < |R_k|$.

Donation break-points. The NPOs' first problem is then to choose donation thresholds $\bar{D} := (\bar{D}_1, \ldots, \bar{D}_{K-1})$ with

$$0 \ = \ \bar{D}_0 < \bar{D}_1 < \cdots < \bar{D}_{K-1} < \bar{D}_K = \infty.$$

that maximizes their donations for a given level of effort.[13]

Donation-to-recognition map. For NPO h and donor i giving $D_{h,i}$, define the recognition tier allocation rule

$$R_h(D_{h,i}) = \sum_{k=1}^{K} R_k \cdot \mathbb{1}\{D_{h,i} \in [\bar{D}_{k-1}, \bar{D}_k)\},$$

where $\mathbb{1}\{\cdot\}$ is the indicator function. This ensures that each donor receives exactly one discrete recognition tier k based on their donation amount falling within the interval $[\bar{D}_{k-1}, \bar{D}_k)$. For the highest tier, we set $\bar{D}_K = \infty$ so that any donation $D_{h,i} \geq \bar{D}_{K-1}$ receives tier K.

[13]Donor wealth has finite support $[0, \bar{w}]$ in primitives; taking $\bar{D}_K \geq \bar{w}$ is without loss. Writing ∞ is shorthand for "exceeds support."

Choosing the break-points. The organization selects $\bar{D}$ by solving

$$\begin{aligned} \arg\max_{\bar{D}} \quad & \sum_i D^*_{h,i}(\bar{D}, e_h) - C_R(R(\bar{D})) \\ \text{s.t.} \quad & \sum_i \mathbb{1}\{R_h(D_{h,i}) = k\} \ \leq \ |R_k| \quad \forall k = 1, \ldots, K. \end{aligned}$$

That is, it maximizes total donations at a given effort level subject to the finite inventory constraint for each tier: the number of donors receiving tier k cannot exceed the available inventory $|R_k|$. The recognition cost function $C_R(R(\bar{D}))$ represents the administrative and opportunity costs associated with the recognition program.[14] The optimal structure emerges endogenously.

Definition (Donor certainty equivalent). Under CARA–Normal, the donor certainty equivalent for tier k is

$$u(R_k) := R_k \bar{M}_h - \tfrac{\gamma_D}{2} R_k^2 \sigma_h^2,$$

which is the cardinal scale we use to compare marginal "recognition per dollar" across tiers. It is linked to expected utility via $v(x) = -\exp(-\gamma_D x)$.

3.1.3 Best-Response Ladder

Lemma 1. *Assume positive upper-tier inventory ($|R_{k+1}| > 0$) for the relevant tiers. For any donor who has reached tier $k \geq 1$ at NPO h, the match-weighted marginal certainty-equivalent per dollar from escalating at h weakly dominates the best entry-tier return elsewhere:*

$$\mu_{h,i}(e_h) \frac{u(R_{k+1}) - u(R_k)}{\bar{D}_{k+1} - \bar{D}_k} \ \geq \ \max_j \ \mu_{j,i}(e_j) \frac{u(R_1) - u(0)}{\bar{D}_1}.$$

[14] These costs encompass organizing donor galas, maintaining donor walls, producing plaques, coordinating naming ceremonies, and the opportunity cost of allocating limited high-prestige recognition items to specific donors.

In a symmetric equilibrium with identical baseline affinities for the marginal donor ($\alpha_{h,i}$ equal across h) and $e_h = e_j$, entry-tier slopes are common across NPOs and the condition reduces to $S_k \geq S_0$ for all $k \geq 1$. Under either (i) a tie-break rule that favors the incumbent on indifference or (ii) an arbitrarily small per-NPO initiation cost $\varepsilon > 0$ (a multi-homing friction), the inequality is strict: $S_k > S_0$.

Notation. Define $S_k := \frac{u(R_{k+1})-u(R_k)}{\bar{D}_{k+1}-\bar{D}_k}$ and $S_0 := \frac{u(R_1)-u(0)}{\bar{D}_1}$. This states that donors compare match-weighted marginal upgrades across NPOs; concentrate locally when the inequality holds; and only initiate Tier 1 elsewhere when it fails.[15] Formally, this yields the following proposition.

Proposition 1 (Donor Non-Diversification)**.** *Under the model primitives and Lemma 1, any donor either gives zero or exactly the breakpoint amount tied to a recognition tier at a single NPO and exhausts all incumbent upgrades before initiating Tier 1 at a new NPO.*

Because recognition items are indivisible and arranged in a pyramid, a donor who has already started giving to a particular hospital receives more recognition per extra dollar by upgrading the existing gift than by initiating a new gift elsewhere. The optimal pattern is therefore to complete all available upgrades at one hospital before making even a modest gift to another. This built–in switching cost concentrates giving and sets the stage for donors to care about that hospital's idiosyncratic risk.

Proposition 2 (Equilibrium Existence)**.** *Under the following conditions, a subgame perfect Nash equilibrium exists:*

1. *The effort cost function $C(e_h)$ is continuous, strictly convex, and satisfies $C(0) = 0$, $C'(0) = 0$, and $\lim_{e\to\infty} C'(e) = \infty$.*

[15] Classic screening a la Mussa and Rosen (1978) derives monotone price schedules from single-crossing and hazard-rate regularity over a continuum of types. Our environment differs fundamentally: recognition is rival and rationed (finite inventory) with discrete breakpoints chosen via KKT, and donors are not being screened for marginal price discrimination. Our step-function analysis centers on marginal certainty-equivalent per dollar at breakpoints $\{\bar{D}_k\}$ rather than curvature of $R_h(\cdot)$.

2. *The mission match function $\mu_{h,i}(e_h)$ is continuous and bounded in $[0,1]$ with $\sum_h \mu_{h,i}(e_h) = 1$.*

3. *The donor wealth distribution has finite support $[0,\bar{w}]$ with continuous density.*

4. *The recognition inventory sets $\{|R_k|\}_{k=1}^{K}$ are finite.*

The existence follows from standard fixed-point arguments. The compactness of strategy spaces (effort is effectively bounded by the cost function, breakpoints by the wealth distribution) combined with continuity of payoffs ensures that best-response correspondences are upper hemicontinuous with non-empty, convex values.

Proposition 3 (Equilibrium Characterization)**.** *In the symmetric case where all NPOs share identical primitives $(\bar{M}_h(\cdot), \sigma_h^2(\cdot))$, identical bond pricing, and identical choice sets for K_h and e_h, and face identical donor populations:*

1. *A symmetric equilibrium exists where all investing NPOs choose identical strategies $(e^*, \bar{D}^*)$.*

2. *If the donation mapping exhibits diminishing returns in own effort and strategic substitutability across rivals (i.e., $D_{ee} \leq 0$ and $D_{e,-h} < 0$ almost everywhere), then the symmetric equilibrium is unique whenever the contraction bound*

$$\sup_{state} \frac{\lambda\,|D_{e,-h}|}{C''(e_h) + \lambda\,(-D_{ee})} \;<\; 1,$$

   holds with $\lambda := r_B(B_h) + \kappa B_h$ and $C''(e_h) > 0$ from $C(e_h) = \frac{1}{2}ce_h^2$.

3. *The equilibrium is characterized by NPOs competing for a fixed pool of donors, with effort levels determined by the first-order condition balancing marginal fundraising benefits against marginal costs.*

Note: Larger κ steepens the bond-pricing schedule $r_B(\cdot)$ (less elastic supply) and increases λ via $\lambda = r_B(B_h) + \kappa B_h$, which tightens the uniqueness bound. If no explicit capacity bound on K_h is assumed, interpret the contraction bound locally at the evaluated symmetric equilibrium; with $K_h \leq \bar{K}$ in primitives, one obtains a global sup-state bound via $\lambda \leq r_0 + 2\kappa\bar{K}$.

The uniqueness result relies on the strategic substitutability of effort choices: when one NPO increases fundraising effort, it reduces the marginal return to effort for competitors through the donor matching process. With a fixed number of NPOs reflecting regulatory and historical constraints on hospital entry, the equilibrium determines optimal fundraising effort and capital structure choices.

Proposition 4 (Step-function recognition and marginal CE ladder)**.** *The recognition map $R_h(\cdot)$ is a step function with jumps at breakpoints $\{\bar{D}_k\}$. In a symmetric equilibrium, the breakpoint marginal certainty-equivalents per dollar $\{S_k\}$ satisfy $S_k \geq S_0$ for all k; under the sufficient conditions in Appendix A (binding inventories, increasing shadow prices, and regular donor masses), adjacent-tier increases $S_k > S_{k-1}$ obtain.*

Viewed through $\{S_k\}$, higher variance reduces the certainty-equivalent value of high tiers more, shrinking aggregate donations; Lemma 2 formalises this elasticity. By Lemma 1 and the indivisible tiers, the donor's within-tier choice is a corner solution, and global behavior follows Proposition 1. This tier-by-tier concentration makes a donor's willingness to give highly sensitive to the hospital's own downside risk, linking liability exposure directly to the cost of external capital.

Lemma 2 (Donation Supply Function)**.** *Aggregate donations to NPO h are increasing in fund-raising effort and decreasing in mission risk: $\partial D_h/\partial e_h > 0$ and $\partial D_h/\partial \sigma_h^2 < 0$.*

Higher effort increases donor match probabilities, while greater mission variance lowers the recognition-weighted certainty equivalent, shrinking donations.

Proposition 5 (Emergent Risk Aversion)**.** *With a risk-neutral manager ($\phi = 0$), the NPO's objective locally (a.e.) includes a variance penalty term $-\lambda \frac{\gamma_D}{2} \widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big)\, \sigma_h^2(K_h)$ with $\lambda = \frac{d\,[r_B(B)B]}{dB} = r_0 + 2\kappa B_h$ (equivalently, $\lambda = r_B(B) + \kappa B$ when $r_B(B) = r_0 + \kappa B$), causing* *the risk-neutral manager to behave* as if *she dislikes variance due solely to donor preferences in a neighborhood of the evaluation point.*

If the manager is formally risk-neutral, the donation elasticity derived above locally embeds a state-dependent variance term $-\lambda \frac{\gamma_D}{2} \widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big)\, \sigma_h^2(K_h)$ in the NPO's objective, causing the manager to behave *as if* she dislikes variance in a neighborhood of the evaluation point. For our empirical example of trauma centers, which are projects with fat left tails from medical malpractice payouts, this means the decision to invest hinges on how liability law shapes $\sigma_h^2(K_h)$. When caps on these potential payouts are adopted, the effective risk premium falls, making investment more attractive even if the expected outcome minimally changes. For-profit hospitals may also respond to risk reduction through managerial risk aversion, but they lack the donation channel. Nonprofit hospitals therefore face an additional variance penalty from donor preferences, predicting a stronger investment response to risk reductions relative to for-profit counterparts.

In our model, caps on non–economic damages are represented as an exogenous reduction in the liability-risk scale parameter ν_h in $\sigma_h^2(K_h) = \nu_h g(K_h)$. This reduction increases the marginal utility of donations for risk-averse donors, effectively encouraging greater giving. The mechanism operates through two channels: directly by reducing the variance $\sigma_h^2(K_h)$ of mission outcomes and indirectly by lowering the shadow cost of donations D_h in the nonprofit's optimization problem.

Proposition 6 (Debt response to a change in mission risk)**.** *Let the bond pricing function be $r_B = r_B(B, \sigma_h^2)$. Then the equilibrium bond-yield response satisfies*

$$\frac{\partial r_B^*}{\partial \sigma_h^2} = \underbrace{\kappa \left(\frac{\partial K_h^*}{\partial \sigma_h^2} - \frac{\partial D_h^*}{\partial \sigma_h^2} \right)}_{\textit{capital-mix channel}} + \underbrace{\left. \frac{\partial r_B}{\partial \sigma_h^2} \right|_{B=B_h^*}}_{\textit{direct credit-risk channel}} .$$

In the baseline analysis, we abstract from the direct term $\partial r_B / \partial \sigma_h^2$ and focus on the capital-mix channel; Online Appendix C quantifies the direct component at about 5 bps in our set-

ting. Here $-\frac{\partial D_h^*}{\partial \sigma_h^2} > 0$ *is the donor channel and* $\frac{\partial K_h^*}{\partial \sigma_h^2}$ *is the manager channel. As a worked linear–quadratic (LQ) example under CARA–Normal with quadratic costs, the comparative static simplifies to*

$$\frac{\partial r_B^*}{\partial \sigma_h^2} = \kappa \cdot \frac{\gamma_D - \phi}{2\mathcal{J}}, \tag{2}$$

where $\mathcal{J} > 0$ *is a positive stability constant. Therefore: if* $\gamma_D > \phi$ *(donor channel dominates), reducing risk lowers yields; if* $\gamma_D < \phi$ *(manager channel dominates), reducing risk raises yields; and if* $\gamma_D = \phi$*, yields are locally unchanged. The special case with fixed investment scale* K_h *is nested via the envelope theorem by setting* $\frac{\partial K_h^*}{\partial \sigma_h^2} = 0$.

The economic intuition is straightforward. If $\gamma_D > \phi$ (donor channel dominates), then a reduction in project risk primarily increases the supply of donations, allowing the NPO to substitute away from costly bond financing. This shift in capital structure toward cheaper donations lowers equilibrium bond yields. Conversely, if $\phi > \gamma_D$ (manager channel dominates), the same risk reduction primarily increases the manager's valuation of the project, leading to greater investment scale and higher demand for all forms of capital, including bonds. This increased bond issuance raises equilibrium yields.

4 Empirical Design

Our theory in Section 3 generates three testable predictions that allow us to identify whether donor or manager risk aversion drives NPO behavior. First, donations should increase when hospital risk falls because concentrated giving makes donors sensitive to NPO-specific risk (Proposition 1, Lemma 2). Second, because hospitals may adjust their financing and investment decisions in response to these risk-averse donors, Proposition 6 shows how to disentangle whether donor or managerial risk aversion drives NPO behavior using the sign of the bond yield response. Finally, Proposition 5 predicts that nonprofit hospitals' investments in risky projects (trauma centers) should respond *more* to risk reductions than those of for-profit hospitals, since nonprofits rely on donors who are sensitive to organizational risk, giving them an additional reason to avoid risky investments that for-profits do not face.

To test these predictions empirically, we need variation in risk exposure for NPO hospitals. For this, we rely on the staggered adoption of caps on non-economic damages across U.S. states between 1991 and 2011.[16,17] These caps, which are a key type of tort reform, place a ceiling (typically \$250,000–\$500,000) on awards for pain and suffering, the most volatile component of malpractice payouts, and are widely regarded as the most effective mechanism for reducing liability risk (Paik et al., 2017). By truncating the right tail of potential awards, caps substantially reduce hospitals' exposure to extreme liability shocks.

This setting is well-suited to our empirical tests for three reasons. First, caps decrease hospital risk directly by lowering exposure to high-damage liability claims. Second, staggered adoption across states and time provides plausibly exogenous variation in risk. Third, because nonprofit and for-profit hospitals operate side by side under the same regulatory changes, we can test whether their responses differ in ways predicted by our theory.

Figure 1 shows the timing of adoption.[18] We classify states into three groups: treated states (purple, green, blue, or pink), which adopted caps during 1991–2011 and neither abolished them nor enacted other tort reforms; control states (white), which made no tort reform changes during this period; and excluded states (gray or beige), which either adopted before 1991, abolished caps, or implemented other types of reforms. In total, seven states comprise the treated group and twelve states form the control group.[19]

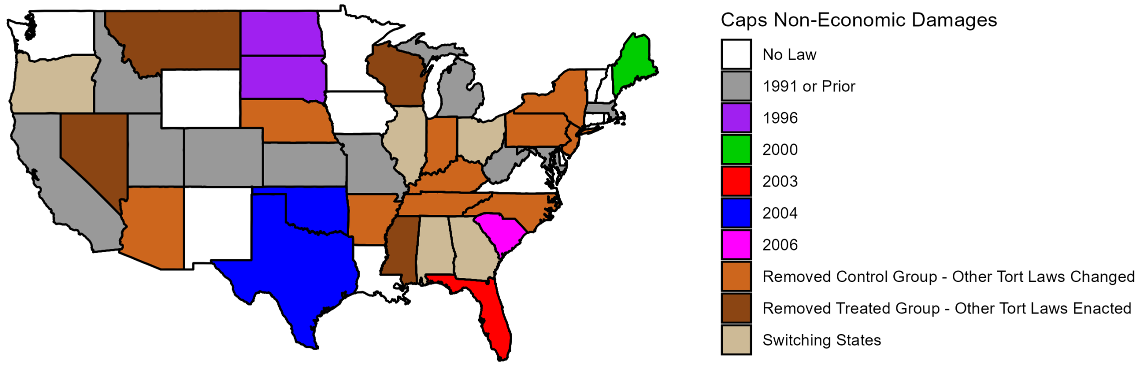
[16]There were 6 other types of tort reform that were adopted during this time frame. However, these reforms do not directly cap risk exposure and Online Appendix E shows they have very limited identifying variation.

[17]We begin in 1991 due to data limitations and end our sample in 2011 as the Affordable Care Act provided funds for hospitals to invest in infrastructure.

[18]Data on tort reform adoption come from the Database of State Tort Law Reforms, Version 7 (DSTLR7) (Avraham, 2021).

[19]Appendix B lists treated and control states by sample window. For analyses restricted to 1996–2011, North Dakota and South Dakota are excluded because their adoption in 1996 leaves no pre-treatment period, reducing the treated group to five states. For the health analysis, Maine is also excluded due to its 2000 adoption, which precludes pre-treatment data.

Figure 1: Tort Reform Adoption: Caps Non-Economic Damages



Note: This figure presents the timing of tort reform adoption by the type of reform. Our analysis relies on the roll-out of tort reform adoption. Control states are those states that did not adopt and had no other law changes. Treatment states are those that adopted after 1991, did not abolish the tort reform during the period, and did not experience other tort reforms.

We exploit this staggered policy rollout to test our theoretical predictions through three complementary analyses. First, we examine whether reduced risk increases charitable donations to nonprofit hospitals relative to for-profit hospitals. Second, we analyze the impact on pricing (yield spreads) and quantities (issuance size and number of bonds) in the healthcare municipal bond market to distinguish between donor- and manager-driven risk aversion. Third, we test real investment responses by studying trauma center operations, where our theory predicts a stronger response by nonprofit hospitals than for-profits. Finally, as a downstream test of whether the expansion of trauma centers translates into improved health outcomes, we examine traffic fatalities. Each outcome requires distinct data and methods, which we describe in the next sections.

5 Data

We draw on three complementary data sources to test our theoretical predictions. First, we use hospital-level financial data to measure changes in donations and government grants. Second, we use municipal bond data to assess borrowing costs and debt financing behavior.

Third, we use hospital infrastructure data to study real investment in a risky asset: trauma centers. Table 1 summarizes the key variables from each dataset. The first two columns provide the mean and standard deviation of the variables, the third column indicates the unit of analysis, and the final column indicates the years of data utilized.

We obtain hospital-level financial data from the Centers for Medicare and Medicaid Services (CMS) Hospital Cost Reports (HCRIS), which contain detailed information on hospital finances, including income from private donations.[20] We begin with a balanced panel of 707 nonprofit and for-profit hospitals observed between 1996 and 2011, ensuring that these hospitals appear in our investment analysis using Medicare provider numbers.[21]

After restricting to the event-time window used in our triple-difference analysis and removing observations that fail imputation validity checks (i.e., no for-profit hospitals in the state), the final panel includes 625 hospitals and 9,112 hospital-year observations. Panel A of Table 1 reports summary statistics. On average, hospitals received roughly $500,000 in annual private donations (about 6% of average profits) and $14.9 million from government grants or appropriations. These hospitals generated about $139 million in operating revenue, with 16% located in rural areas, 20% operating trauma centers, and 21% classified as for-profit. While donations comprise a small share of total revenue, they represent unrestricted capital available for discretionary uses, unlike patient revenues that must cover operating costs.

Second, to analyze changes in hospitals' cost of capital, we use municipal bond data from the Municipal Securities Rulemaking Board (MSRB) Municipal Securities Transaction data, accessed through WRDS. This dataset covers all healthcare bonds issued between 1991 and

[20] While we would ideally examine the direct impact of tail risk on hospital capital assets, reporting requirement changes in the Medicare cost report data during 2000-2005 create identification challenges. As detailed in Online Appendix E, reporting of capital asset purchases became optional for most hospitals from 2000-2004 before being reinstated as mandatory in 2005. This reporting discontinuity coincides with our primary tort reform treatment period, making it difficult to disentangle reporting effects from treatment effects.

[21] The Provider of Services (POS) file maintains greater consistency across years for the Medicare provider number, which is why the balanced panel of hospitals is larger in our POS investment sample than in the HCRIS data.

Table 1: Summary Statistics:

	Mean	St. Dev.	Variable Level	Analysis Years
Panel A: Hospital Financial Data				
Donation Income ($1mill)	0.50	1.49	Hospital	1996-2011
Government Grant Income ($1mill)	14.87	55.47	Hospital	1996-2011
Profit ($1mill)	8.33	34.55	Hospital	1996-2011
Net Patient Revenue ($1mill)	131.93	160.28	Hospital	1996-2011
Operating Revenue ($1mill)	139.09	170.60	Hospital	1996-2011
Rural Hospital (%)	16.12	36.78	Hospital	1996-2011
Has Trauma Unit (%)	19.57	39.67	Hospital	1996-2011
For-Profit Hospital (%)	20.64	40.48	Hospital	1996-2011
Number of Hospitals	625		Hospital	1996-2011
N	9,112		-	-
Panel B: Healthcare Municipal Bond Data				
Yield Spread (bps)	10.20	131.84	Bond	1991-2011
Inflation Adjusted Issue Size ($1mill)	1.41	6.74	Bond	1991-2011
Bonds Mention Refunding (%)	40.63	49.11	Bond	1991-2011
Bond Matures 10Y or Later (%)	49.30	50.00	Bond	1991-2011
N	28,081		-	-
Number of Bonds	72.38	83.09	State	1991-2011
N	388		-	-
Panel C: Hospital Investment Data				
Has Trauma Center (%)	12.65	33.24	Hospital	1991-2011
Number of Beds	148.13	192.24	Hospital	1991-2011
Teaching Hospital (%)	17.40	37.91	Hospital	1991-2011
For-Profit Hospital (%)	15.44	36.14	Hospital	1991-2011
Number of Hospitals	1,897		Hospital	1991-2011
N	29,393		-	-

Note: This table reports summary statistics for the three datasets used in our analysis. Panel A summarizes hospital finances from the CMS Hospital Cost Reports (HCRIS), using the same sample as the donations triple-difference analysis. Panel B covers healthcare municipal bonds from the Municipal Securities Rulemaking Board (MSRB) accessed via WRDS, and Panel C details hospital infrastructure data from the CMS Provider of Services (POS) files, using the same sample as the investment triple-difference analysis. The first two columns report means and standard deviations, the third column indicates the unit of observation, and the final column indicates the years covered. Yield spreads are the difference between the municipal bond's coupon rate and the Treasury yield of the same maturity, reported in basis points (1 bp = 0.01%). All other percentages are reported as shares of hospitals or bonds. Treated and control states for each time frame are defined in Section 4. Table E1 in the Online Appendix provides a breakdown of Panels A and C by hospital ownership type.

2011, with information on bond size, maturity, and refunding status. After excluding bonds with missing issue size, the final sample includes 28,281 healthcare bonds in our treated and control states. Panel B of Table 1 summarizes these data: the average yield spread is about

11.5 basis points, the average inflation-adjusted bond size is \$1.5 million, 40% of bonds mention refunding, and roughly half have maturities of at least ten years.[22] On average, about 72 healthcare bonds are issued in a given state-year.

To capture real investment behavior, we use the CMS Provider of Services (POS) files from 1991–2011, which report hospital characteristics and service offerings as part of the Medicare certification process. We begin with 2,998 short-term general hospitals and then subset to those hospitals that submit an annual cost report to CMS, which yields 2,181 hospitals across our treatment and control states.[23] Panel C of Table 1 summarizes these hospitals: 13% operate a trauma center, 18% are teaching hospitals, and 15% are for-profit.

6 Methods

Our empirical analyses require methods that accommodate staggered treatment timing. Across all settings, we rely on the imputation-based estimator of Borusyak et al. (2024). This approach avoids the negative weighting problems that plague two-way fixed effects estimators in staggered adoption settings (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020).

6.1 The Imputation Method

The imputation estimator proceeds in two stages. In the first stage, we estimate a flexible outcome model using only untreated observations (i.e., units before they are treated or units that are never treated). This model absorbs relevant fixed effects and predicts counterfactual

[22]Bonds are inflation-adjusted using the seasonally adjusted consumer price index for all urban consumers for medical care, using 1982-1984 as the base period. This data can be downloaded here https://www.bls.gov/cpi/data.htm.

[23]Unlike the HCRIS donations sample, we do not restrict the POS investment sample to a balanced panel. The POS data span 1991–2011 (21 years), and our event-time restriction drops observations more than five years after treatment. Balancing after this restriction retains only hospitals observed in all 21 years—mechanically excluding early-treated cohorts that lose late post-treatment years. In practice, this reduces the for-profit comparison group from 382 to just 27 hospitals, making the triple-difference estimator unreliable.

outcomes $\widehat{Y^0}$ for treated observations. In the second stage, we compute residualized outcomes $\tilde{Y} = Y - \widehat{Y^0}$ and regress these on the treatment indicator. The coefficient captures the average treatment effect on the treated (ATT).

We apply this framework to each distinct outcome with a specification tailored to its data structure and identifying variation. For hospital-level outcomes where both nonprofit and for-profit hospitals operate under the same regulatory changes, we employ a triple-difference design. For outcomes where this within-state comparison is not feasible, we use a simple difference-in-differences.[24,25]

For our triple-difference estimations (donations and trauma centers), we are estimating the effect of tort reform on nonprofits *relative to* for-profits. We do not assume that for-profits are entirely unaffected by tort reform, since reduced liability risk may lead for-profits to expand investment as well. Our theory predicts only that nonprofits should respond *more* because they face an additional donor-driven risk aversion channel, whereas for-profits diversified shareholders should discount idiosyncratic tail risk. The triple-difference coefficient therefore captures the *differential* response, not the absolute effect.

6.2 Donations (Triple-Difference)

To measure how donations respond to lower liability risk, we estimate an imputation-based triple-difference. The identifying variation comes from the staggered adoption of caps on non-economic damages across states, combined with the presence of both nonprofit and for-profit hospitals within states.

[24]We do not employ a triple-difference design for bonds because many for-profit hospitals operate within multi-state systems, allowing capital to flow across state lines and undermining the within-state ownership comparison. Multi-state nonprofit hospital systems were uncommon during our sample period. Moreover, donations and trauma center operations are inherently facility-specific outcomes, unlike bond capital which can be reallocated across facilities within a system, so this concern does not similarly affect the triple-difference identification.

[25]For traffic fatalities, a triple-difference is also infeasible because trauma patients are frequently transported outside their local area.

First stage (estimated on untreated observations: pre-reform periods or for-profit hospitals):[26]

$$Y_{it} = \alpha_i + \gamma_{t\times\text{NPO}_i} + \delta_{s(i)\times t} + \epsilon_{it} \tag{3}$$

where Y_{it} is donation income for hospital i in year t; α_i are hospital fixed effects; $\gamma_{t\times\text{NPO}_i}$ are year-by-ownership fixed effects; and $\delta_{s(i)\times t}$ are state-by-year fixed effects. This specification absorbs hospital-specific levels, ownership-specific time trends, and state-specific annual shocks.

Second stage (estimated on all observations):

$$\tilde{Y}_{it} = \beta \cdot \text{Tort}_{st} \times \text{NPO}_i + \nu_{it} \tag{4}$$

where $\tilde{Y}_{it} = Y_{it} - \widehat{Y_{it}^0}$ is the residualized outcome and Tort_{st} is a binary indicator for tort reform. The coefficient β captures the differential effect of tort reform on nonprofit versus for-profit hospitals, specifically, how much *more* nonprofits increase donations compared to for-profits when liability risk falls. Standard errors are clustered at the state-by-ownership level.[27]

6.3 Municipal Bonds (Difference-in-Differences)

Because many for-profit hospitals operate within multi-state systems that can reallocate bond capital across state lines, a triple-difference design is not feasible for the bond market analysis. Instead, we employ a standard imputation-based difference-in-differences. Bond data are observed at the level of individual issuances: each bond enters the dataset at the time of issuance and is not re-observed. The identifying variation comes from the staggered adoption of caps across states.

[26] Note that we are labeling for-profit hospitals as "untreated," which makes the interpretation of our estimation as the causal impact on non-profits *relative* to any impact on for-profits.

[27] We also report staggered synthetic control robustness results in Online Appendix D.1.1.

First stage (estimated on untreated bonds: issued in never-treated states or before reform adoption):

$$Y_{bt} = X_{bt}'\delta + \alpha_{s(b)} + \gamma_t + \epsilon_{bt} \tag{5}$$

where Y_{bt} is the outcome (yield spread or issue size) for bond b issued in state s at time t; X_{bt} includes bond characteristics (refunding status, years to maturity); α_s are state fixed effects; and γ_t are year fixed effects.

Second stage (estimated on all bonds):

$$\tilde{Y}_{bt} = \beta \cdot \text{Tort}_{st} + \nu_{bt} \tag{6}$$

The coefficient β captures the average treatment effect on the treated (ATT). Standard errors are block-bootstrapped at the state level following Abadie et al. (2023), reflecting that treatment is assigned at the state level.

To assess dynamics and check for pre-trends, we also estimate an event-study specification on the imputed residuals:

$$\tilde{Y}_{bt} = \sum_{k\neq -1} \beta_k \mathbf{1}\{t - E_{s(b)} = k\} + \nu_{bt} \tag{7}$$

where $E_{s(b)}$ is the year of reform adoption in bond b's state and k indexes event time. The coefficients β_k trace out dynamic effects, with $k = -1$ normalized as the baseline.

6.4 Trauma Centers (Triple-Difference)

For trauma center provision, we use the same triple-difference structure as donations. The identifying variation again comes from the staggered adoption of caps combined with the presence of both hospital types within states.

First stage (estimated on untreated observations):

$$Y_{it} = \alpha_i + \gamma_{t\times\text{NPO}_i} + \delta_{s(i)\times t} + \epsilon_{it} \tag{8}$$

where $Y_{it} \in \{0,1\}$ indicates whether hospital i operates a trauma center in year t.

Second stage (estimated on all observations):

$$\tilde{Y}_{it} = \beta \cdot \text{Tort}_{st} \times \text{NPO}_i + \nu_{it} \tag{9}$$

The coefficient β measures how much *more* nonprofit hospitals expand trauma provision relative to for-profits following tort reform. This captures the differential investment response predicted by our theory—not the absolute effect on either group. Standard errors are clustered at the state-by-ownership level.[28]

6.5 Traffic Fatalities (Difference-in-Differences)

For health outcomes, we estimate a simple imputed difference-in-differences at the zip code level. Unlike the hospital-level analysis, we do not employ a triple-difference design comparing nonprofit and for-profit areas. In trauma emergencies, patients are often transported outside their home area to reach a trauma center, including airlifting to regional facilities, implying that for-profit areas do not provide a clean within-state control for health outcomes.

The identifying variation comes from the staggered adoption of caps across states, which increases trauma center availability and thereby affects survival from severe injuries.

First stage (estimated on pre-reform observations):

$$Y_{zt} = \alpha_z + \gamma_t + \epsilon_{zt} \tag{10}$$

[28]Staggered synthetic control robustness results appear in Online Appendix D.1.2.

where Y_{zt} is the count of traffic fatalities in zip code z in year t; α_z are zip code fixed effects; and γ_t are year fixed effects.[29]

Second stage (estimated on all observations):

$$\tilde{Y}_{zt} = \beta \cdot \text{Tort}_{st} + \nu_{zt} \tag{11}$$

The coefficient β captures the effect of tort reform on traffic fatalities. Standard errors are obtained via state-level bootstrap (500 iterations).

7 Results

This section presents our empirical findings. We begin with the financing channel, showing that donations to nonprofit hospitals increase relative to for-profit hospitals following reductions in liability risk and that bond yield responses are consistent with donor-driven rather than manager-driven risk aversion. We then turn to real investment outcomes.

7.1 Financing Channels

Our theory predicts that reductions in risk can affect nonprofit financing through two channels. In the donor channel, undiversified donors make donations highly sensitive to hospital-specific risk, and even risk-neutral managers behave as if risk-averse because their cost of capital rises with risk through donor preferences. In the managerial channel, risk-averse managers are more willing to pursue investment when projects become safer, increasing demand for debt financing. To test which channel drives nonprofit behavior, we examine how hospital financing responds to reductions in risk, focusing on both donation flows and the municipal bond market. These responses jointly identify the dominant risk-aversion channel: if donors drive risk aversion, lower risk increases donation supply, allowing NPOs

[29] Time-varying covariates at the zip code level are largely unavailable for this period, so the specification relies on the fixed effects structure to absorb confounders.

to substitute away from bonds, lowering yields by more than the pure reduction in risk (i.e., the direct effect) would imply. If managers drive risk aversion, lower risk increases investment demand, requiring more bonds, lowering yields by less than the direct effect.

7.1.1 Donation Income

Table 2: Hospital Donations: Triple Difference

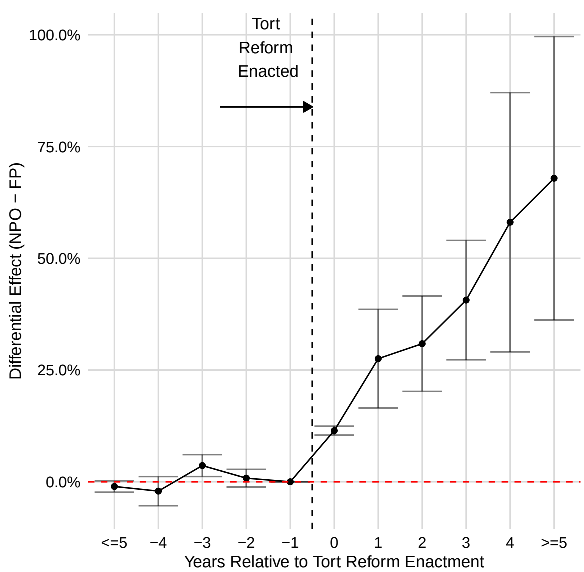
	(1)	(2)	(3)
	% Operating Revenue	% Net Patient Revenue	Raw ($)
Estimated ATT	0.394***	0.433***	75,261**
Std. Error	(0.091)	(0.108)	(33,502)
Pre-Adoption Sample Mean	0.294	0.310	258,161
Pre-Adoption Sample SD	1.311	1.367	754,775
Observations	9,112	9,112	9,112
Hospital FE	Yes	Yes	Yes
Year × Type FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Imputed triple-difference estimates of caps on non-economic damages on private donations. Specification includes hospital and year fixed effects plus year × nonprofit fixed effects; standard errors clustered by state × ownership. Pre-adoption mean and standard deviation reported for nonprofits.

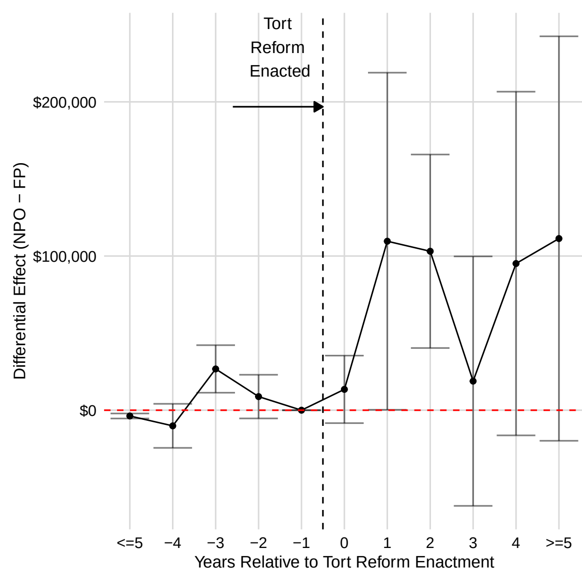
Using the imputation-based triple-difference specification described in Section 6.2, Table 2 reports the resulting ownership-differential effect of tort reform on private donations. Our primary specification scales donations by operating revenue to account for heterogeneity in hospital size. Column (1) shows that when caps on noneconomic damages are enacted, nonprofits increase donations as a share of operating revenue by 0.39 percentage points relative to for-profits, approximately one-third of a standard deviation of the pre-reform nonprofit distribution. Column (2) shows similar results using net patient revenue as the scaling variable. Column (3) confirms our scaled results in raw dollars showing an increase of approximately $75,000 relative to for-profits, roughly a 30% increase relative to the pre-reform nonprofit mean.

Figure 2 presents the corresponding event study with panel (a) showing the scaled specification and (b) the raw dollars. Pre-treatment coefficients show no evidence of differential trending in either specification, supporting parallel trends. Post-reform, both panels show differential increases in donations for nonprofits relative to for-profits. In raw dollars, the effect emerges quickly and stabilizes, while the scaled specification effect also emerges quickly it shows a more gradual increase which is consistent with donors progressively responding to the reduced risk environment.

Figure 2: Event Study: Donation Income (Imputed Triple-Difference)



(a) Donations / Operating Revenue (%)



(b) Raw Donations ($)

Note: This figure presents the imputed triple-difference event-study estimates for charitable donations. The coefficient plotted is the differential effect of tort reform on donation income for nonprofit versus for-profit hospitals at each year relative to treatment. Panel (a) shows donations scaled by operating revenue (as a percent); Panel (b) shows raw donations (in dollars). Year "−1" is the omitted reference period. Error bars represent 90% confidence intervals.

Donations alone cannot distinguish donor-driven from manager-driven risk aversion. We therefore examine the healthcare municipal bond market to test these two competing predictions.

7.1.2 Municipal Bond Level

Building on the donation results, we next test whether it is donor or managerial risk aversion that drives NPO behavior by examining healthcare municipal bond issuance. We exploit the staggered implementation of caps on non-economic damages in a staggered difference-in-differences design, as outlined in Section 6.3.

Table 3 reports results for three bond issuance outcomes: yield spreads (basis points), log issue size, and the number of bonds issued in a state-year. Panel A shows overall results, while Panel B focuses on long-term bonds.[30] Column (1) of Panel A shows that healthcare bonds issued in states that experienced a decrease in risk saw yield spreads fall roughly 27 basis points relative to healthcare bonds in unaffected states. This reduction is substantial: for a \$10 million bond, annual interest payments fall by approximately \$27,000, equal to about 1.3% of median annual profits (\$2.0 million) for nonprofit hospitals in our sample.

Panel B shows that this decrease in yield spread is concentrated among long-term (≥ 10 years maturity) bonds with no statistically significant effects for shorter maturities, consistent with long-term bonds having greater exposure to risk. Figure 3(a) presents the event study for healthcare municipal bond yield spreads for long-term bonds.[31] The pre-treatment coefficients are flat and centered around zero, supporting the parallel trends assumption. Post-reform, yields decline persistently, with the drop emerging after about two years. This timing is consistent with the donor-risk-aversion channel, as substitution away from debt towards donations takes time to materialize.

Although a decline of approximately 5-basis-points in the municipal bond yield spread would be mechanically expected following the direct reduction in risk, the observed 27-basis-point reduction is far larger.[32] Such a substantial decrease in the municipal bond yield spread implies a lower demand for debt and aligns with our theoretical prediction of

[30] Findings for medium-term (5–10 year) and short-term (≤ 5 year) bonds appear in Online Appendix E.0.3.

[31] Event studies and results for all maturity groups, including medium and short-term bonds, can be found in Online Appendix E.0.3.

[32] See Online Appendix C for details on this calculation.

Table 3: Cost of Capital: Municipal Bonds

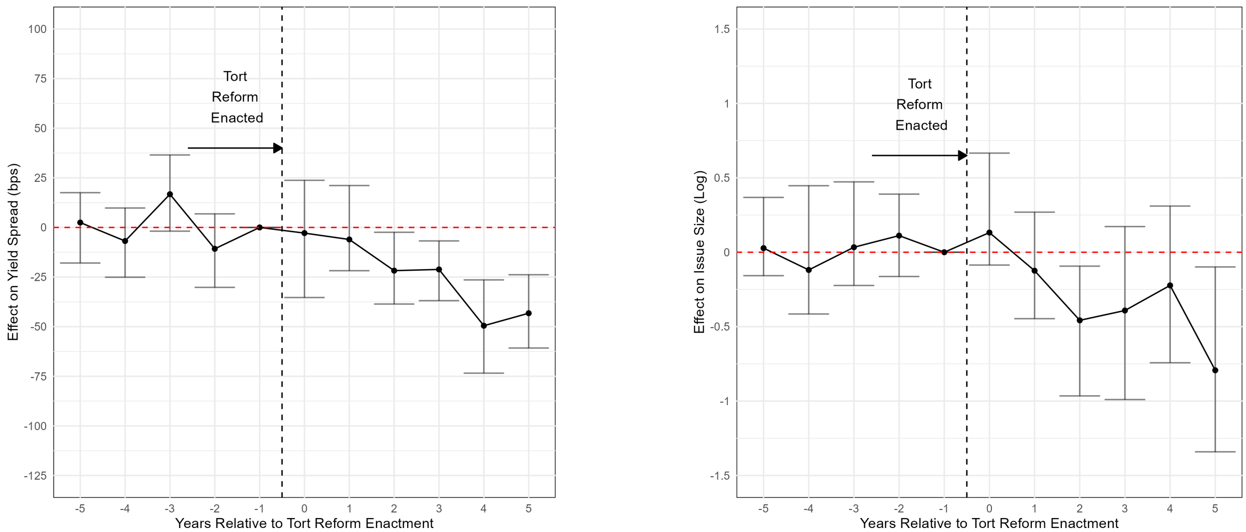
Panel A: All Maturities	Yield Spread (bps)	Issue Size (Log)	Bonds Issued (Total Per State-Year)
	(1)	(2)	(3)
ATT	-27.31^{**}	-0.258	-20.03
90% CI	[-50.14, -4.55]	[-0.499, 0.001]	[-45.53, 21.09]
Pre-Adoption Mean	-34.04	13.103	102.44
N	28,281	28,281	388
Panel B: 10Y and Greater			
ATT	-31.96^{***}	-0.483^{**}	-19.89
90% CI	[-53.83, -10.34]	[-0.999, -0.039]	[-30.89, 12.4]
Pre-Adoption Mean	-32.13	13.849	50.76
N	13,845	13,845	388
Year Fixed Effects?	Yes	Yes	Yes
State Fixed Effects?	Yes	Yes	Yes
State Level Controls?	Yes	Yes	Yes
Bond Characteristic Controls?	Yes	Yes	No

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports staggered difference-in-differences estimates and 90% confidence intervals following Borusyak et al. (2024) for three outcomes in the healthcare municipal bond market: yield spreads (basis points, column 1), inflation-adjusted bond issue size (log, column 2), and the total number of healthcare municipal bonds issued in a state-year (column 3). Panel A shows results for all maturities; Panel B restricts to bonds maturing in 10 years or more. Yield spread and issue size are analyzed at the bond level, while the number of bonds is analyzed at the state-year level. Each panel reports estimated average treatment effects (ATT), 90% confidence intervals, and pre-adoption means. The pre-adoption means for yield spread are negative due to the rising interest rates in the 1990s. All models include year and state fixed effects, as well as state-level controls (population, mean household income, and employment). Bond-level controls (e.g., refunding indicator) are included in the yield spread and issue size specifications but are not applicable to the number of bonds. For column 3, the number of refunding bonds issued in a state-year is included as an additional state-level control. Standard errors are block-bootstrapped at the state level following Abadie et al. (2023). The full table with all maturity groups appears in Online Appendix E.0.3.

donor risk aversion: as risk falls, donors increase giving, allowing NPOs to substitute *away* from debt financing and *towards* cheaper donation funding. By contrast, a managerial-risk-aversion story would raise demand for both donations and debt, which would put upward rather than downward pressure on yields.

However, a decline in yield spreads alone is not sufficient to demonstrate substitution away from debt financing towards cheaper donations. Hospitals could have instead taken advantage of cheaper borrowing by issuing more bonds or increasing their size. Columns 2 and 3 of Table 3 test these margins directly. Across all maturities (Panel A), we find no

Figure 3: Event Study: Municipal Bonds, Maturity $\geq$ 10 Years



(a) Yield Spread (bps) (b) Issue Size (Log)

Note: This figure plots the coefficients and 90 percent confidence intervals for the imputed difference-in-difference estimates for the impact of caps on non-economic damages on bond yield spread (panel (a)) and inflation-adjusted issue size in logs (panel (b)) over time for bonds maturing in 10 years or more. Year "0" refers to the year the state implemented caps on non-economic damages and Year "-1" is the omitted category. Standard errors are block-bootstrapped at the state-level. Municipal bond data comes from the MSRB from 1991 to 2011; Treasury yields used to calculate yield spread come from the US Department of the Treasury. Event studies for other maturity groups and number of bonds issued appear in Online Appendix E.0.3.

evidence that reduced risk increased either issuance frequency or bond size, indicating that overall borrowing did not expand despite lower yields.

Among long-term bonds (Panel B), where yields fell most sharply, average bond size declines by about 0.48 log points (38%), or \$1.3 million relative to the pre-reform mean of \$3.4 million. The number of long-term bonds issued does not rise, and medium- and short-term bonds show no systematic changes for either outcome. The event study in Figure 3 corroborates these findings, showing flat pre-trends and no post-reform expansion in borrowing.

These results suggest that nonprofit hospitals did not exploit cheaper debt by borrowing more. Instead, long-term borrowing contracts even as yields fall, consistent with substitution toward donations and the donor-risk-aversion channel, rather than increased financing demand predicted by managerial risk aversion.

These financing results show that donor risk aversion drives NPO behavior. When liability risk falls, donations increase by roughly $75,000 and bond yields decline by 27 basis points (far exceeding the 5-basis-point direct effect), yet bond issuance contracts rather than expands. This joint pattern of cheaper debt but less borrowing shows NPOs substitute towards increased donation financing after tort reform. Manager risk aversion would generate the opposite pattern: increased demand for all financing sources. Having established that donors drive NPO risk aversion, we next examine whether this affects real investment decisions.

7.2 Investment and Public Health Outcomes

Having established that donor risk aversion is the dominant channel driving NPO financing decisions, we now test whether this affects real investment decisions focusing on trauma centers. We use trauma centers as our primary outcome because they represent discrete, observable investments that are both financially valuable and particularly exposed to medical malpractice risk.[33] We then test whether this altered investment affects public health outcomes by examining traffic fatalities at the zip code level. Traffic fatalities provide a natural outcome because accidents severe enough to result in a fatality are precisely the cases that would be routed to a trauma center when one is available (Nathens et al., 2000; MacKenzie et al., 2006). We measure fatalities using the Fatality Analysis Reporting System (FARS), which records all fatal motor vehicle crashes on U.S. public roads. We restrict to 2001–2011, when accident coordinates allow geocoding to zip codes, and construct a balanced panel of zip codes that experienced at least one fatal accident in every sample year.[34] Table 4 reports results for all three outcomes.

[33]See Section 2.3 for a full description of why trauma centers are financially valuable and why they are uniquely exposed to medical malpractice risk.

[34]Online Appendix F describes the geocoding procedure, panel construction, and summary statistics.

Column (1) reports the differential impact of tort reform on trauma center provision for nonprofit versus for-profit hospitals (imputed triple-difference). Columns (2) and (3) report the impact on traffic fatalities (staggered DiD at the zip code level), with Column (3) focusing on multi-casualty incidents (MCIs), which are accidents with two or more fatalities. Trauma centers specialize in MCIs because their surgical teams and equipment are designed to treat multiple critically injured patients simultaneously, providing the greatest marginal benefit in severe cases.[35]

Table 4: Effect of Tort Reform on Hospital Investment and Public Health Outcomes

	(1) Trauma Centers (pp)	(2) Traffic Fatalities (count)	(3) MCI Fatalities (count)
ATT (Nonprofit × Tort Reform)	4.43^{***}	—	—
	(1.46)	—	—
ATT (Tort Reform)	—	-0.36^{*}	-0.135^{***}
	—	(0.19)	(0.048)
Pre-Adoption Mean	9.92	4.3	0.730
Pre-Adoption SD	29.90	3.0	1.403
Observations	27,973	34,353	34,353
Units	1,494 hospitals	3,137 zips	3,137 zips
Hospital/Zip FE	Yes	Yes	Yes
Year × Type FE	Yes	—	—
State × Year FE	Yes	—	—
Year FE	—	Yes	Yes
Estimator	Imputed 3DiD	Imputed DiD	Imputed DiD

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) uses an imputation-based triple-difference estimator (Borusyak et al., 2024): the first stage is estimated on untreated observations and the second stage regresses the residualized outcome on Tort × Nonprofit with no additional fixed effects; standard errors are clustered by state × ownership type. Columns (2)–(3) use imputation-based staggered DiD at the zip code level with zip code and year fixed effects; standard errors from state-level bootstrap (500 iterations). MCI (multi-casualty incident) is defined as accidents with two or more fatalities.

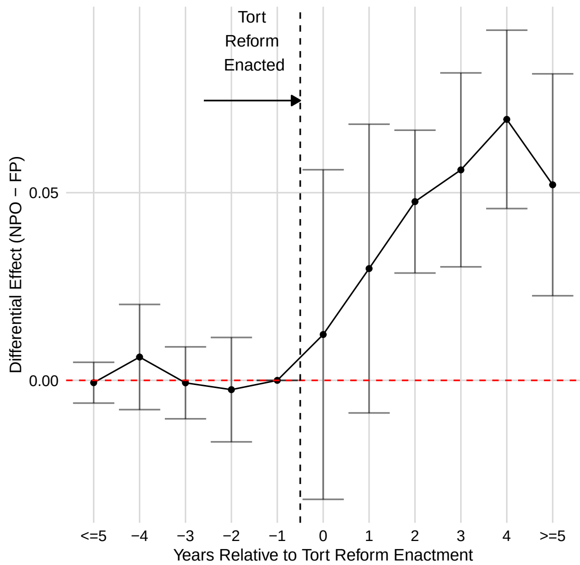
[35]We define MCIs as crashes resulting in two or more fatalities. This threshold is motivated by clinical practice: the CDC's National Guideline for the Field Triage of Injured Patients identifies death of another occupant in the same vehicle as a mechanism-of-injury criterion that triggers transport to a trauma center, reflecting that multi-fatality crashes represent qualitatively more severe events placing distinct demands on emergency medical resources (Sasser et al., 2012; Newgard et al., 2022).

The results indicate that nonprofits expand trauma center provision by about 4 percentage points (roughly 45% of the pre-reform mean) more than for-profits following tort reform. This ownership gap reflects our mechanism: the donor-driven drop in the cost of capital amplifies nonprofit investment. We also find evidence of public health spillovers: treated zip codes experience fewer traffic fatalities. Multi-casualty incidents show the strongest reduction, with fatalities falling by 18% relative to the pre-treatment mean, which is consistent with the importance of trauma centers for severe incidents.

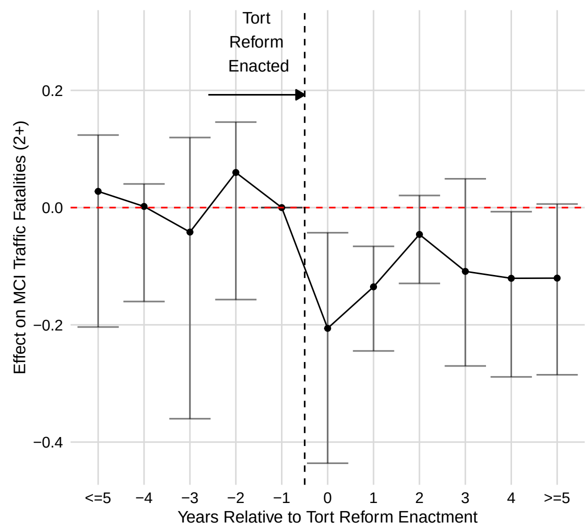
Figure 4 presents event studies for trauma center provision (Panel A) and MCI traffic fatalities (Panel B). Pre-treatment coefficients for both outcomes are centered near zero with no clear trend, supporting parallel trends. After reform, nonprofit hospitals steadily increase trauma center provision relative to for-profits. This effect builds over several years, as trauma centers are large, discrete investments that take time to materialize. MCI fatalities decline in treated zip codes following reform, as trauma centers provide the greatest marginal benefit for the most severe accidents.

Together with the financing results, these investment and health outcome findings trace a complete chain: donor risk aversion shapes nonprofit capital structure, which in turn drives real investment in critical healthcare infrastructure and, ultimately, affects patient survival.

Figure 4: Event Study: Trauma Center Investment and Traffic Fatalities



(a) Trauma Center Provision (NPO vs For-Profit)



(b) MCI Traffic Fatalities (2+, Zip-Code Level)

Note: Panel (a) shows imputed triple-difference event-study estimates for trauma center investment; the coefficient is the differential effect of tort reform on trauma center provision for nonprofit versus for-profit hospitals. Panel (b) shows imputed DiD event-study estimates for MCI traffic fatalities (2+ per accident) at the zip code level. Year "−1" is the omitted reference period. Error bars represent 90% confidence intervals. Pre-treatment coefficients centered near zero support parallel trends for both outcomes.

8 Conclusions

Modigliani and Miller (1958) argue that shareholder risk aversion should not constrain firm behavior because shareholders can diversify. However, nonprofit organizations (NPOs) rely on donors rather than shareholders and on recognition rather than returns. In this paper, we show that donor preferences, not managerial preferences, drive NPO risk aversion. When recognition is tiered and limited, donors concentrate their giving and do not diversify, which makes donation capital sensitive to organization-specific risk. This induces firm-level risk aversion even when managers themselves are risk-neutral. We test this mechanism in the hospital sector, using the staggered adoption of caps on non-economic damages as a shock to liability risk.

We find that reducing malpractice liability risk increases private donations to nonprofit hospitals by 30% relative to for-profits while simultaneously lowering reliance on long-term debt, which decreases municipal bond yields by 27 basis points. This joint response, a shift from borrowing toward gifts, is consistent with donor-driven risk aversion: as projects become safer, donors supply more capital and hospitals substitute away from debt. By contrast, if managerial risk aversion dominated, safer projects would relax internal constraints and increase investment, raising the demand for both donations and debt. This donor-driven reduction in the cost of capital has real consequences for nonprofit investment. Following the reduction in medical malpractice risk, nonprofit hospitals differentially expand investment in a liability-exposed asset: trauma center capacity. This investment, in turn, translates into meaningful public health improvements, with treated areas experiencing 8% fewer traffic fatalities.

Our findings make three contributions to understanding organizational behavior under uncertainty. First, we develop a micro-foundation for nonprofit risk aversion that does not require assuming risk-averse managers. Our theoretical framework shows how the structure of philanthropic markets, in which donors seek recognition and cannot diversify their giving portfolios, generates organizational risk aversion even with risk-neutral management. Second, we provide the first empirical decomposition of nonprofit risk aversion into donor versus manager channels, resolving a fundamental identification challenge in the nonprofit literature. The bond market response uniquely identifies the donor channel: our theory predicts that bond yields fall beyond the direct reduction in credit risk if and only if donor risk aversion exceeds manager risk aversion, and the observed 27-basis-point decline far exceeds the approximately 5-basis-point direct effect. Third, we establish causal evidence that liability risk constrains nonprofit investment in socially valuable but risky projects. Nonprofit hospitals forgo trauma center investments under high liability risk, but expand them once risk is reduced, improving both infrastructure and public health. These findings demonstrate that nonprofit financing frictions, which are driven by how donors respond to risk, can shape not only capital structure but also real investment and patient outcomes.

Several limitations merit acknowledgment. First, our evidence comes from hospitals, which are especially capital-intensive and liability-exposed. While they are central to the nonprofit sector, donor risk aversion may operate differently in nonprofits where capital intensity and risk are less pronounced. Second, we specifically study liability risk, and donors may respond differently to other types of risks, particularly those that are less visible or reputational in nature.

Our findings are particularly relevant in today's policy environment. While we end our sample in 2011 to avoid confounding from the Affordable Care Act, the mechanism we identify for shaping NPO behavior, donor-driven risk aversion, extends beyond that period. Recent federal policy changes have significantly reduced government funding for nonprofits while introducing new tax incentives for private charitable giving, shifting the financing mix further toward donations. As nonprofits become more reliant on donor capital, the constraints imposed by donor risk aversion are likely to intensify, with even greater consequences for investment in socially valuable, high-risk services. Our evidence from hospitals, where reduced liability risk expanded trauma center capacity and lowered fatalities, illustrates the real-world stakes of these financing dynamics. Policymakers should recognize that shifts in funding streams can amplify the role of donor preferences in shaping nonprofit behavior, making donor risk aversion a first-order consideration in the design of future interventions.

Bibliography

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge, "When should you adjust standard errors for clustering?," *The Quarterly Journal of Economics*, 2023, *138* (1), 1–35.

Adelino, Manuel, Katharina Lewellen, and Anant Sundaram, "Investment decisions of nonprofit firms: Evidence from hospitals," *The Journal of Finance*, 2015, *70* (4), 1583–1628.

_ , _ , and W. Ben McCartney, "Hospital financial health and clinical choices: Evidence from the financial crisis," *Management Science*, 2022, *68* (3), 2098–2119.

Aghamolla, Cyrus, Javed Jain, and Richard T. Thakor, "The (going) public option: Equity market financing in the hospital industry," March 2025. Working paper.

_ , Pinar Karaca-Mandic, Xuelin Li, and Richard T. Thakor, "Merchants of death: The effect of credit supply shocks on hospital outcomes," *American Economic Review*, 2024, *114* (11), 3623–3668.

American College of Surgeons, "Statement on Trauma Activation Fees," https://www.facs.org/about-acs/statements/statement-on-trauma-activation-fees/ 2024.

American Hospital Association, "Estimates of the Value of Federal Tax Exemption and Community Benefits Provided by Tax-Exempt Hospitals, 2020," September 2024. Accessed: 2025-08-08.

_ , "Fast Facts on U.S. Hospitals, 2023," 2025. Accessed: 2025-08-08.

American Medical Association, "Medical Liability Reform — NOW! (2025 Update)," Technical Report, American Medical Association 2025.

Andreoni, James, "Giving with impure altruism: Applications to charity and Ricardian equivalence," *Journal of political Economy*, 1989, *97* (6), 1447–1458.

_ , "Impure altruism and donations to public goods: A theory of warm-glow giving," *The Economic Journal*, 1990, *100* (401), 464–477.

Arrow, Kenneth J., *Aspects of the Theory of Risk-Bearing*, Amsterdam: North-Holland, 1965.

Ashley, Dennis W., Robert F. Mullins, Christopher J. Dente, Thomas J. Johns, Laura E. Garlow, Regina S. Medeiros, Elizabeth V. Atkins, Gina Solomon, Dena Abston, and Colville H. Ferdinand, "How much green does it take to be orange? Determining the cost associated with trauma center readiness," *Journal of Trauma and Acute Care Surgery*, 2015, *79* (6), S69–S76.

Association of Fundraising Professionals, "Getting Ready for a Capital Campaign (AFP Ready Reference Series)," https://afpglobal.org/sites/default/files/attachments/2018-12/AFPReadyReferenceCapitalCampaign2018.pdf 2018. Guidance notes that 5–10% of donors typically contribute 90–95% of a campaign's goal.

Avraham, Ronen, "Database of State Tort Law Reforms (7.1)," *U of Texas Law, Law and Econ Research Paper*, 2021, (e555).

Balsam, Steven, Erica E. Harris, and Gregory D. Saxton, "The use and consequences of perquisite types in nonprofit organizations," *Journal of Accounting and Public Policy*, 2020, *39* (4), 106737.

Bartram, Söhnke M., Gregory W. Brown, and Jennifer Conrad, "The Effects of Derivatives on Firm Risk and Value," *Journal of Financial and Quantitative Analysis*, 2011, *46* (4), 967–999.

Ben-Michael, Eli, Avi Feller, and Jesse Rothstein, "Synthetic controls with staggered adoption," *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 2022, *84* (2), 351–381.

Bennett, Roger, "Factors underlying the inclination to donate to particular types of charity," *International Journal of Nonprofit and Voluntary Sector Marketing*, 2003, *8* (1), 12–29.

Born, Patricia, W Kip Viscusi, and Tom Baker, "The effects of tort reform on medical malpractice insurers' ultimate losses," *Journal of Risk and Insurance*, 2009, *76* (1), 197–219.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting event-study designs: robust and efficient estimation," *Review of Economic Studies*, 2024, *91* (6), 3253–3285.

Brock, J. Michelle, Andreas Lange, and Erkut Y. Ozbay, "Dictating the risk: Experimental evidence on giving in risky environments," *American Economic Review*, 2013, *103* (1), 415–437.

Centers for Medicare & Medicaid Services, "National Health Expenditure Data: 2023 Highlights," December 2024. Accessed: 2025-08-08.

Chaisemartin, Clément De and Xavier d'Haultfoeuille, "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, 2020, *110* (9), 2964–96.

Chava, Sudheer, Baridhi Malakar, and Manpreet Singh, "Impact of corporate subsidies on borrowing costs of local governments: Evidence from municipal bonds," *Review of Finance*, 2024, *28* (1), 117–161.

Chen, Chung-An and Barry Bozeman, "Organizational risk aversion: Comparing the public and non-profit sectors," *Public Management Review*, 2012, *14* (3), 377–402.

Claims Journal, "Fla. Jury Awards $217M to Misdiagnosed Stroke Patient," October 2006. Accessed: 2026-02-05.

Congressional Budget Office, "Letter to Senator Orrin G. Hatch: Effects of Proposals to Limit Costs Related to Medical Malpractice," Technical Report, U.S. Congressional Budget Office October 2009.

Cornaggia, Kimberly, Xuelin Li, and Zihan Ye, "Financial effects of remote product delivery: Evidence from hospitals," *The Review of Financial Studies*, 2024, *37* (9), 2817–2854.

Creative Fundraising Advisors, "Capital Campaign Planning Guide," https://creativefundraisingadvisors.com/capital-campaign-planning-guide/ 2022. Advises that 5–10% of donors pledge 90–95% of a campaign goal.

Diamond, William D and Rajiv K Kashyap, "Extending models of prosocial behavior to explain university alumni contributions 1," *Journal of Applied Social Psychology*, 1997, *27* (10), 915–928.

Dimmock, Stephen G., "Background Risk and University Endowment Funds," *Review of Economics and Statistics*, 2012, *94* (3), 789–799.

Exley, Christine L., "Excusing selfishness in charitable giving: The role of risk," *Review of Economic Studies*, 2016, *83* (2), 587–628.

Fama, Eugene F. and Michael C. Jensen, "Agency Problems and Residual Claims," *Journal of Law and Economics*, 1983, *26* (2), 327–349.

_ **and** _ , "Organizational Forms and Investment Decisions," *Journal of Financial Economics*, 1985, *14* (1), 101–119.

Fisman, Raymond and R. Glenn Hubbard, "Precautionary Savings and the Governance of Nonprofit Organizations," *Journal of Public Economics*, 2005, *89* (11–12), 2231–2243.

Frank, Richard G., David S. Salkever, and Jean Mitchell, "Market forces and the public good: competition among hospitals and provision of indigent care," *Advances in Health Economics and Health Services Research*, 1990, *11*, 159–183.

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein, "Risk Management: Coordinating Corporate Investment and Financing Policies," *Journal of Finance*, 1993, *48* (5), 1629–1658.

Gao, Janet, Tim Liu, Shagun Malik, and Merih Sevilir, "Can nonprofits save lives during financial stress? Evidence from the hospital industry," June 2025. Working paper.

_ **, Yongseok Kim, and Merih Sevilir**, "Private equity in the hospital industry," *Journal of Financial Economics*, 2025, *171*, 104107.

Gao, Pengjie, Chang Lee, and Dermot Murphy, "Good for Your Fiscal Health? The Effect of the Affordable Care Act on Healthcare Borrowing Costs," *Journal of Financial Economics*, 2022, *145* (2), 464–488.

Gentry, William M., "Debt, Investment, and Endowment Accumulation: The Case of Not-for-Profit Hospitals," *Journal of Health Economics*, 2002, *21* (5), 845–872.

Gilbert, Thomas and Christopher Hrdlicka, "Why are university endowments large and risky?," *The Review of Financial Studies*, 2015, *28* (9), 2643–2686.

Glaeser, Edward L, "Introduction to" The Governance of Not-for-Profit Organizations"," in "The Governance of Not-For-Profit Organizations," University of Chicago Press, 2003, pp. 1–44.

Glaeser, Edward L. and Andrei Shleifer, "Not-for-Profit Entrepreneurs," *Journal of Public Economics*, 2001, *81* (1), 99–115.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Graham, John R. and Daniel A. Rogers, "Do Firms Hedge in Response to Tax Incentives?," *Journal of Finance*, 2002, *57* (2), 815–839.

Gupta, Atul, Steven L. Howell, Constantine Yannelis, and Aditya Gupta, "Owner Incentives and Performance in Healthcare: Private-Equity Investment in Nursing Homes," *Review of Financial Studies*, 2024, *37* (4), 1029–1077.

Gustafson, Matthew, Peter Haslag, Daniel Weagley, and Zihan Ye, "A flash in the pan (demic)? migration risks and municipal bonds," *Management Science*, 2025.

Hansmann, Henry B., "The Role of Nonprofit Enterprise," *Yale Law Journal*, 1980, *89*, 835–901.

Harris, Erica, Christine M. Petrovits, and Michelle H. Yetman, "The effect of nonprofit governance on donations: Evidence from the revised Form 990," *The Accounting Review*, 2015, *90* (2), 579–610.

Herpfer, Christoph, Jonah Lin, and Gonzalo Maturana, "Corporate behavior when running the firm for stakeholders: Evidence from hospitals," July 2024. Working paper.

Horwitz, Jill R and Austin Nichols, "Hospital ownership and medical services: market mix, spillover effects, and nonprofit objectives," *Journal of health economics*, 2009, *28* (5), 924–937.

Jegers, Marc and Ilse Verschueren, "On the capital structure of non-profit organisations: An empirical study for californian organisations.," *Financial Accountability & Management*, 2006, *22* (4).

Jena, Anupam B, Seth Seabury, Darius Lakdawalla, and Amitabh Chandra, "Malpractice risk according to physician specialty," *New England Journal of Medicine*, 2011, *365* (7), 629–636.

Jha, Akshaya, Stephen A Karolyi, and Nicholas Z Muller, "Polluting Public Funds: The Effect of Environmental Regulations on Municipal Bonds," *Management Science*, 2025.

Khan, Muhammad Yasir, "Mission Motivation and Public Sector Performance: Experimental Evidence from Pakistan," *American Economic Review*, July 2025, *115* (7), 2343–75.

Lakdawalla, Darius and Tomas Philipson, "The Nonprofit Sector and Industry Performance," *Journal of Public Economics*, 2006, *90* (8–9), 1681–1698.

Lewellen, Katharina, Gordon M Phillips, and Giorgo Sertsios, "Control without ownership: Governance of nonprofit hospitals," Technical Report, National Bureau of Economic Research 2025.

Lo, Andrew W, Egor V Matveyev, and Stefan Zeume, "The risk, reward, and asset allocation of nonprofit endowment funds," Technical Report, National Bureau of Economic Research 2025.

Lu, Runjing and Zihan Ye, "Roe v. Rates: Reproductive Healthcare and Public Financing Costs," Technical Report, Center for Open Science 2023.

MacKenzie, Ellen J., Frederick P. Rivara, Gregory J. Jurkovich, Avery B. Nathens, Katherine P. Frey, Brian L. Egleston, David S. Salkever, and Daniel O. Scharfstein, "A National Evaluation of the Effect of Trauma-Center Care on Mortality," *New England Journal of Medicine*, 2006, *354* (4), 366–378.

Mayers, David and Clifford W. Smith, "On the Corporate Demand for Insurance," *Journal of Business*, 1982, *55* (2), 281–296.

Mello, Michelle M, Amitabh Chandra, Atul A Gawande, and David M Studdert, "National costs of the medical liability system," *Health affairs*, 2010, *29* (9), 1569–1577.

Modigliani, Franco and Merton H Miller, "The cost of capital, corporation finance and the theory of investment," *American Economic Review*, 1958, *48* (3), 261–297.

Moody's Investors Service, "US Municipal Bond Defaults and Recoveries, 1970–2022," Technical Report, Moody's Investors Service July 2023.

Moon, Jihwan and Steven M Shugan, "Nonprofit versus for-profit health care competition: How service mix makes nonprofit hospitals more profitable," *Journal of Marketing Research*, 2020, *57* (2), 193–210.

Mussa, Michael and Sherwin Rosen, "Monopoly and product quality," *Journal of Economic theory*, 1978, *18* (2), 301–317.

Nathens, Avery B., Gregory J. Jurkovich, Peter Cummings, Frederick P. Rivara, and Ronald V. Maier, "The Effect of Organized Systems of Trauma Care on Motor Vehicle Crash Mortality," *JAMA*, 2000, *283* (15), 1990–1994.

Newgard, Craig D., Peter E. Fischer, Mark Gestring, Holly N. Michaels, Gregory J. Jurkovich, E. Brooke Lerner, Mary E. Fallat, Theodore R. Delbridge, Joshua B. Brown, and Eileen M. Bulger, "National Guideline for the Field Triage of Injured Patients: Recommendations of the National Expert Panel on Field Triage, 2021," *Journal of Trauma and Acute Care Surgery*, 2022, *93* (2), e49–e60. Writing Group for the 2021 National Expert Panel on Field Triage.

Null, Carys, "Warm glow, information, and inefficient charitable giving," *Journal of Public Economics*, 2011, *95* (5-6), 455–465.

Osborne, Beau, "Data breach information, hospital financing, and patient outcomes," 2025. Working paper, University of Tennessee.

Paik, Myungho, Bernard Black, and David A Hyman, "Damage caps and defensive medicine, revisited," *Journal of Health Economics*, 2017, *51*, 84–97.

_ , Bernard S Black, David A Hyman, William M Sage, and Charles M Silver, "How do the elderly fare in medical malpractice litigation, before and after tort reform? Evidence from Texas," *American law and economics review*, 2012, *14* (2), 561–600.

Pennsylvania Health Care Cost Containment Council, "Hospital Malpractice Expenses — Research Brief #4," Technical Report, PHC4 April 2005.

Petrovits, Christine M., Catherine Shakespeare, and Aimee Shih, "The causes and consequences of internal control problems in nonprofit organizations," *The Accounting Review*, 2011, *86* (1), 325–357.

Pratt, John W., "Risk Aversion in the Small and in the Large," *Econometrica*, 1964, *32* (1/2), 122–136.

Rose-Ackerman, Susan, "Altruism, nonprofits, and economic theory," *Journal of economic literature*, 1996, *34* (2), 701–728.

Rossi, Stefano and Hayong Yun, "Financial reform and public good provision: Municipal bankruptcy law and the financing of hospitals," *Management Science*, 2024, *70* (4), 2209–2235.

Sasser, Scott M., Richard C. Hunt, Mark Faul, David Sugerman, William S. Pearson, Theresa Dulski, Marlena M. Wald, Gregory J. Jurkovich, Craig D. Newgard, E. Brooke Lerner, Arthur Cooper, Stewart C. Wang, Mark C. Henry, Jeffrey P. Salomone, and Robert L. Galli, "Guidelines for Field Triage of Injured Patients: Recommendations of the National Expert Panel on Field Triage, 2011," *MMWR Recommendations and Reports*, 2012, *61* (RR-1), 1–20.

Seabury, Seth A., Eric Helland, and Anupam B. Jena, "Medical Malpractice Reform: Noneconomic Damages Caps Reduced Payments 15 Percent, With Varied Effects by Specialty," *Health Affairs*, 2014, *33* (11), 2048–2056.

Silverman, Carly and Courtney E. Appel, "Nuclear Verdicts: Trends, Causes, and Solutions," September 2022. Accessed: 2026-02-05.

Smith, Clifford W. and René M. Stulz, "The Determinants of Firms' Hedging Policies," *Journal of Financial and Quantitative Analysis*, 1985, *20* (4), 391–405.

Texas Department of Insurance, "Rate Filing Summary: Texas Medical Liability Trust, 2004–2005," 2005.

Tufano, Peter, "Who Manages Risk? An Empirical Examination of Risk Management Practices in the Gold Mining Industry," *Journal of Finance*, 1996, *51* (4), 1097–1137.

Wedig, Gerard, "'De Facto' Residual Claimants and Nonprofit Governance: Who Benefits When Nonprofits Profit?," 2010. SSRN Working Paper.

Wedig, Gerard J, "Risk, leverage, donations and dividends-in-kind: A theory of nonprofit financial behavior," *International Review of Economics & Finance*, 1994, *3* (3), 257–278.

_, Mahmud Hassan, and Michael A Morrisey, "Tax-exempt debt and the capital structure of nonprofit organizations: An application to hospitals," *The Journal of Finance*, 1996, *51* (4), 1247–1283.

Weerts, David J and Justin M Ronca, "Profiles of supportive alumni: Donors, volunteers, and those who "do it all"," *International Journal of Educational Advancement*, 2007, *7* (1), 20–34.

Yermack, David, "Donor governance and financial management in prominent US art museums," *Journal of Cultural Economics*, 2017, *41* (3), 215–235.

Appendix A Proofs

Below we collect the formal proofs omitted from the main text.

Critical Assumptions (Primitives Only)

We collect only the primitives used throughout:

1. **Preferences:** Donors and managers have CARA utilities $v(x) = -\exp(-\gamma_D x)$ and $U(x) = -\exp(-\phi x)$.

2. **Risk and technology:** Mission outcomes are normal conditional on investment scale, $M_h \mid K_h \sim \mathcal{N}\big(\bar{M}_h(K_h), \sigma_h^2(K_h)\big)$. The mean function $\bar{M}_h(\cdot)$ is C^2, increasing, and weakly concave. The variance satisfies $\sigma_h^2(K_h) = \nu_h \, g(K_h)$ where $g(\cdot)$ is C^2 and non–decreasing (weakly convex permitted). Caps on non–economic damages reduce ν_h.

3. **Recognition:** Indivisible tiers with pyramid inventory $|R_{k+1}| < |R_k|$ and breakpoints $0 = \bar{D}_0 < \cdots < \bar{D}_K$.

4. **Diminishing Returns:** Fundraising technology exhibits diminishing returns in the relevant range (e.g., the mission match $\mu_{h,i}(e_h)$ satisfies $\frac{\partial^2 \mu_{h,i}}{\partial e_h^2} < 0$).

5. **Financing and pricing:** Bonds carry $r_B(B_h) = r_0 + \kappa B_h$ with $\kappa > 0$; the financing constraint is $K_h = D_h + B_h$.

6. **Multi-homing friction (tie-breaking):** Donors face an arbitrarily small fixed cost $\varepsilon > 0$ when initiating a donation at a new NPO (or, equivalently, ties are broken in favor of escalating at the incumbent). This delivers strict escalation when marginal returns are equal.

For breakpoint arguments we use $u(R_k)$ as donor certainty equivalent for tier k under CARA–Normal.

Manager Program with Endogenous Scale (CARA–Normal)

Given choices (K_h, B_h, e_h) and $M_h \mid K_h \sim \mathcal{N}\big(\bar{M}_h(K_h), \sigma_h^2(K_h)\big)$, the manager's certainty equivalent is

$$CE_{npo}(K_h, B_h, e_h) \;=\; \bar{M}_h(K_h) \;-\; \frac{\phi}{2}\,\sigma_h^2(K_h) \;-\; r_B(B_h)\,B_h \;-\; C(e_h),$$

subject to $K_h = D_h + B_h$ with $r_B(B_h) = r_0 + \kappa B_h$ and donation mapping $D_h = D_h\big(e_h,\, \bar{M}_h(K_h),\, \sigma_h^2(K_h)\big)$ defined below, with $\frac{\partial D_h}{\partial \bar{M}_h} > 0$ and $\frac{\partial D_h}{\partial \sigma_h^2} < 0$ almost everywhere under CARA–Normal.

Proof of Lemma 1 (Escalate–vs–start condition)

Proof. Donors are atomistic and take $(e_h, \bar{D}_h)$ as given. In a symmetric equilibrium $(e_h = e_j)$, entry-tier slopes are common across NPOs, so denote $S_0 := \frac{u(R_1)-u(0)}{\bar{D}_1}$. Suppose, toward a contradiction, that for some tier $k \geq 1$ at NPO h we had $S_k^h := \frac{u(R_{k+1})-u(R_k)}{\bar{D}_{k+1}-\bar{D}_k} < S_0$. Then any donor at tier k strictly prefers to start Tier 1 at another NPO rather than escalate to $k{+}1$ at h. With atomistic donors and positive upper-tier inventory $|R_{k+1}| > 0$, aggregate escalation cannot fill tier $k{+}1$, contradicting optimality of the announced schedule. Hence $S_k^h \geq S_0$ for all $k \geq 1$; strict inequality follows under arbitrarily small diversification frictions or any taste for variety. □

Proof of Lemma 2 (Donation Supply Function)

Proof. Each donor i maximizes

$$\max_{D_{h,i}\geq 0} \; \mu_{h,i}(e_h)\, E\big[-\exp(-\gamma_D\, R_h(D_{h,i})\, M_h)\big] \;+\; \mu_0\big(w_i - \sum_{j\neq 0} D_{j,i}\big),$$

subject to $\sum_{j\neq 0} D_{j,i} \leq w_i$. Under $M_h \mid K_h \sim \mathcal{N}\big(\bar{M}_h(K_h), \sigma_h^2(K_h)\big)$ and CARA utility,

$$E\big[-\exp(-\gamma_D\, R_k\, M_h)\big] = -\exp\Big(-\gamma_D R_k\, \bar{M}_h(K_h) + \tfrac{\gamma_D^2 R_k^2}{2}\, \sigma_h^2(K_h)\Big),$$

which is strictly increasing in the certainty equivalent CE_k. Because $R_h(\cdot)$ is piecewise constant with breakpoints $\{\bar{D}_k\}_{k=1}^{K-1}$, the optimal donation is bang-bang: donors either give 0 or exactly the amount needed to reach a full tier. Hence aggregate donations can be written as

$$D_h\big(e_h, \sigma_h^2(K_h)\big) \;=\; \sum_i \sum_{k=1}^{K} \bar{D}_k\, \mathbf{1}\{\text{donor } i \text{ optimally selects tier } k\}.$$

Effort e_h enters monotonically via the mission match $\mu_{h,i}(e_h)$, which shifts weight toward NPO h and (weakly) enlarges the set of (i,k) for which selecting a positive tier is optimal. Therefore $\frac{\partial D_h}{\partial e_h} > 0$. By contrast, an increase in variance reduces every tier's certainty equivalent by $\frac{\partial CE_k}{\partial \sigma_h^2} = -\frac{\gamma_D R_k^2}{2} < 0$, shrinking the set of donors for whom a positive tier is optimal, so $\frac{\partial D_h}{\partial \sigma_h^2} < 0$.

Technical note: Since $R_h(\cdot)$ is piecewise constant (jumps at breakpoints), $\partial D_{h,i}^*/\partial \sigma_h^2$ is undefined at the measure-zero set of donors exactly at thresholds under a continuous wealth distribution. Aggregates are nevertheless differentiable almost everywhere, so the comparative static signs stated above are well-defined. □

Proof of Proposition 5 (Emergent Risk Aversion) - Full Derivation

With a risk-neutral manager ($\phi = 0$), the NPO maximizes expected net mission value:

$$\max_{K_h \geq 0,\, B_h,\, e_h} \; E[M_h - r_B(B_h)B_h] - C(e_h) \tag{A1}$$

subject to the financing constraint $K_h = D_h + B_h$. Since $M_h \mid K_h$ is normally distributed with mean $\bar{M}_h(K_h)$ and the manager is risk-neutral, this simplifies to:

$$\max_{K_h \geq 0,\, B_h,\, e_h} \; \bar{M}_h(K_h) - r_B(B_h)B_h - C(e_h) \tag{A2}$$

However, donations D_h depend on mission variance through donor risk aversion and therefore on K_h via $\sigma_h^2(K_h)$.

Donation–variance mapping and local linearization: Each donor i with CARA utility parameter γ_D maximizes:

$$\max_{D_{h,i}} \mu_{h,i}(e_h) \cdot E[-\exp(-\gamma_D R_h(D_{h,i}) M_h)] - D_{h,i} \tag{A3}$$

With $M_h \mid K_h \sim \mathcal{N}\big(\bar{M}_h(K_h), \sigma_h^2(K_h)\big)$, the expected utility from donation tier k is:

$$E[-\exp(-\gamma_D R_k M_h)] = -\exp\left(-\gamma_D R_k \, \bar{M}_h(K_h) + \frac{\gamma_D^2 R_k^2 \, \sigma_h^2(K_h)}{2}\right) \tag{A4}$$

The donor's certainty equivalent for tier k is therefore CE_k. Aggregating across all donors and tiers, total donations become a function $D_h\big(e_h, \sigma_h^2(K_h)\big)$ that is weakly decreasing in $\sigma_h^2(K_h)$. We define the tier-margin density (almost everywhere) and a state-dependent recognition-squared aggregator:

$$\psi_{h,k}\big(e_h, \sigma_h^2(K_h)\big) := -\frac{\partial}{\partial \sigma_h^2} \sum_i \mu_{h,i}(e_h)\, \mathbf{1}\{i \text{ chooses tier } k\}, \tag{A5}$$

$$\widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big) := \sum_{k=1}^{K} R_k^2 \, \psi_{h,k}\big(e_h, \sigma_h^2(K_h)\big). \tag{A6}$$

Then the almost-everywhere derivative of aggregate donations with respect to variance satisfies

$$\frac{\partial D_h}{\partial \sigma_h^2}\big(e_h, \sigma_h^2(K_h)\big) \;=\; -\frac{\gamma_D}{2}\, \widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big), \qquad \text{a.e.} \tag{A7}$$

Equivalently, a first-order (local) approximation around any interior state gives

$$D_h\big(e_h, \sigma_h^2(K_h)\big) \;\approx\; \bar{D}_h(e_h) - \frac{\gamma_D}{2}\, \widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big)\, \sigma_h^2(K_h),$$

where $\widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big)$ depends on effort via the induced tier margins through $\{\psi_{h,k}(e_h, \sigma_h^2(K_h))\}_{k=1}^K$. Using $B_h = K_h - D_h$ and $r_B(B_h) = r_0 + \kappa B_h$, the multiplier on the financing constraint is $\lambda = r_0 + 2\kappa B_h$. Substituting the local mapping for D_h into the NPO's objective, the donor-driven variance term enters scaled by λ as $-\lambda \frac{\gamma_D}{2} \widehat{\Omega}_h\big(e_h, \sigma_h^2(K_h)\big)\, \sigma_h^2(K_h)$. This makes the risk-neutral manager behave *as if* she dislikes variance due solely to donor preferences in a neighborhood of the benchmark.

Proof of Proposition 4 (Step-function recognition and the marginal CE ladder)

Proof. Consider a finite ladder of $K \geq 2$ indivisible recognition tiers with breakpoints $0 = \bar{D}_0 < \bar{D}_1 < \cdots < \bar{D}_K$. Because recognition is tiered and indivisible, the recognition map is a step function,

$$R_h(D) = \sum_{k=1}^{K} R_k \, \mathbf{1}\{D \in [\bar{D}_{k-1}, \, \bar{D}_k)\}.$$

Convexity is therefore expressed in terms of the *discrete* marginal certainty-equivalent-per-dollar ladder $S_k := \frac{u(R_{k+1}) - u(R_k)}{\bar{D}_{k+1} - \bar{D}_k}$ rather than derivatives of $R_h(\cdot)$. In a symmetric equilibrium, Lemma 1 implies $S_k \geq S_0$ for all k (donors escalate before spreading). Under the sufficient conditions detailed in Section A (binding inventories, increasing shadow prices, and regular donor masses), we obtain adjacent-tier strict increases $S_k > S_{k-1}$ for all $k \geq 1$, delivering the stated ladder property without invoking $R_h''(\cdot)$. □

Proof of Proposition 1

Proof. Under CARA utility and normally distributed mission outcomes, the donation decision is mean–variance. Because recognition at a given tier is indivisible and $R_h(\cdot)$ is piecewise constant, the within-tier choice is a corner solution: the donor either gives exactly the next breakpoint amount at a single NPO or gives nothing. Globally, by Lemma 1, donors escalate to complete the next tier at their incumbent NPO before initiating Tier 1 elsewhere unless the concentration inequality fails, in which case they start at another NPO and then continue escalate–then–spread. □

Proof of Proposition 2 (Equilibrium Existence)

Proof. We construct existence by separating the nonatomic-donor side from the NPO subgame. With a continuum of donors, Schmeidler/Aumann guarantees existence of a donation aggregate correspondence mapping $(e, \bar{D})$ to feasible donation aggregates $D \in [0, \bar{w}]$ that is nonempty, convex-valued, and upper hemicontinuous. Using this aggregate, consider the NPO subgame in $(e_h, \bar{D}_h)$ taking the aggregate donation correspondence as given. The NPO strategy space $S_h = [0, \bar{e}] \times \Delta_K$ is nonempty, compact, and convex; payoffs are continuous and quasi-concave in own strategies (by convex costs and the properties of the donation aggregate). Kakutani's fixed-point theorem then yields a fixed point of the NPO best responses against the aggregate donation correspondence, which induces a fixed point in the full game by backward induction. □

Proof of Proposition 3 (Equilibrium Characterization)

Proof. **Part 1 (Symmetric equilibrium existence):** In the symmetric case, we can restrict attention to symmetric strategy profiles. The existence proof above applies directly.

Part 2 (Uniqueness): Let e_h denote NPO h's effort and e_{-h} the vector of rivals' efforts. Using the unified KKT system with multiplier λ on $K_h = D_h + B_h$,

$$\text{(e) } C'(e_h) = \lambda\, D_e, \qquad \text{(B) } \lambda = r_B(B_h) + \kappa B_h, \qquad \text{(K) } \bar{M}_h'(K_h) - \tfrac{\phi}{2}(\sigma_h^2)'(K_h) + \lambda(D_K - 1) = 0,$$

where $D_e := \partial D_h/\partial e_h$, $D_K := \partial D_h/\partial K_h$ and $C''(e_h) > 0$. Totally differentiating (e) with respect to e_{-h} and holding K at its best-response value (so (K) continues to hold) yields the best-response slope

$$\frac{de_h^{BR}}{de_{-h}} = -\frac{\lambda\, D_{e,-h}}{C''(e_h) + \lambda\,(-D_{ee})},$$

using $D_{ee} := \partial^2 D_h/\partial e_h^2 \leq 0$ and $D_{e,-h} := \partial^2 D_h/\partial e_h \partial e_{-h} < 0$ under the multinomial-logit mission-match structure in the main text. Hence best responses are downward sloping (strategic substitutes). A sufficient condition for uniqueness is the global contraction bound

$$\sup_{\text{state}} \frac{\lambda\, |D_{e,-h}|}{C''(e_h) + \lambda\,(-D_{ee})} < 1,$$

with λ given by (B). Since $\lambda = r_0 + 2\kappa B_h$ and $0 \leq B_h \leq K_h$, one can bound λ using primitives and any stated capacity bound on K_h; larger κ steepens $r_B(\cdot)$ and increases λ, tightening the inequality.

Part 3 (Equilibrium characterization): The interior equilibrium effort satisfies $C'(e_h) = \lambda D_e$ with λ from (B). Competition for donors induces $D_{e,-h} < 0$, so each NPO internalizes a reduced marginal return to effort when rivals increase theirs. □

Full Donor Optimization Problem

Donor i solves the following constrained optimization problem:

$$\max_{\{D_{h,i}\}_h} \quad \sum_{h \neq 0} \mu_{h,i}(e_h) \cdot E\left[v(R_h(D_{h,i}) \cdot M_h)\right] + \left(w_i - \sum_{h \neq 0} D_{h,i}\right) \tag{A8}$$

$$\text{s.t.} \quad \sum_{h \neq 0} D_{h,i} \leq w_i \tag{A9}$$

$$D_{h,i} \geq 0 \quad \forall h \tag{A10}$$

The Lagrangian for this problem is:

$$\mathcal{L} = \sum_{h\neq 0} \mu_{h,i}(e_h) \cdot E\left[v(R_h(D_{h,i}) \cdot M_h)\right] + \left(w_i - \sum_{h\neq 0} D_{h,i}\right) + \lambda \left(w_i - \sum_{h\neq 0} D_{h,i}\right) \tag{A11}$$

where $\lambda \geq 0$ is the Lagrange multiplier on the budget constraint.

Taking first-order conditions with respect to $D_{h,i}$:

$$\frac{\partial \mathcal{L}}{\partial D_{h,i}} = \mu_{h,i}(e_h) \cdot R_h'(D_{h,i}) \cdot E[M_h \cdot v'(R_h(D_{h,i}) \cdot M_h)] - 1 - \lambda = 0 \tag{A12}$$

Given the discrete tier structure of recognition, $R_h'(D_{h,i}) = 0$ almost everywhere (except at tier boundaries). This creates a bang-bang solution: donors either give nothing to an NPO or give exactly enough to reach a full tier. Moreover, the convexity of the recognition schedule (Proposition 4) combined with the concavity of $v(\cdot)$ ensures that donors concentrate their giving at a single NPO rather than spreading across multiple organizations. The corner solution emerges naturally from the indivisibility of recognition tiers.

Normalization of the outside good. We normalize the marginal utility of the outside good to $\mu_0 = 1$, which yields the $-1 - \lambda$ term in the donor FOC above and keeps notation consistent with earlier versions that wrote the outside-good marginal utility explicitly as μ_0.

Optimal Breakpoint Characterization

To derive the optimal breakpoints, we set up the Lagrangian:

$$\mathcal{L} = \sum_i D^*_{h,i}(\bar{D}, e_h) \; - \; C_R\big(R(\bar{D})\big) \; + \; \sum_{k=1}^{K} \lambda_k \left[|R_k| - \sum_i \nVdash\{R_h(D^*_{h,i}) = k\} \right] \tag{A13}$$

where $\lambda_k \geq 0$ are the shadow prices on the inventory constraints.

Taking first-order conditions with respect to $\bar{D}_k$ and applying the envelope theorem, we obtain:

$$\frac{\partial \mathcal{L}}{\partial \bar{D}_k} = n_k \cdot \frac{u(R_{k+1}) - u(R_k)}{\bar{D}_{k+1} - \bar{D}_k} - n_{k-1} \cdot \frac{u(R_k) - u(R_{k-1})}{\bar{D}_k - \bar{D}_{k-1}} + \lambda_k - \lambda_{k-1} \; - \; \frac{\partial C_R}{\partial \bar{D}_k} = 0 \tag{A14}$$

where n_k is the measure of donors at tier k.

At an interior optimum with binding constraints ($\lambda_k > 0$) and increasing shadow prices, the breakpoint conditions imply adjacent-tier relations among the slopes $S_k := \frac{u(R_{k+1}) - u(R_k)}{\bar{D}_{k+1} - \bar{D}_k}$. Rearranging the first-order condition above yields the adjacent-tier difference

$$S_k - S_{k-1} \; = \; \left(\frac{n_{k-1}}{n_k} - 1\right) S_{k-1} \; - \; \frac{\lambda_k - \lambda_{k-1}}{n_k} \; + \; \frac{1}{n_k} \frac{\partial C_R}{\partial \bar{D}_k}. \tag{A15}$$

This makes transparent a sufficient condition for a strict increase:

$$\underbrace{(n_{k-1} - n_k)\, S_{k-1} + \frac{\partial C_R}{\partial \bar{D}_k}}_{\text{mass + admin cost gain}} > \underbrace{\lambda_k - \lambda_{k-1}}_{\text{scarcity wedge}} \quad \Longrightarrow \quad S_k > S_{k-1}. \tag{A16}$$

Under regular masses (e.g., log-concave wealth so n_{k-1}/n_k is bounded) and increasing shadow prices on binding inventories, this inequality is economically interpretable and verifiable, delivering the ladder in Proposition 4.

Recognition Cost Function Specification

The function $C_R(R(\bar{D}))$ represents the administrative and opportunity costs associated with the recognition program. These costs include:

$$C_R(R(\bar{D})) = \sum_{k=1}^{K} c_k \cdot \sum_i \mathbb{1}\{R_h(D^*_{h,i}(\bar{D})) = k\} \tag{A17}$$

where c_k is the per-donor cost of providing tier k recognition. These costs encompass organizing donor galas, maintaining donor walls, producing plaques, coordinating naming ceremonies, and the opportunity cost of allocating limited high-prestige recognition items (such as building naming rights) to specific donors. We assume $c_1 < c_2 < \ldots < c_K$, reflecting that higher-tier recognition events require more elaborate arrangements and consume scarcer organizational resources. The shadow price on the inventory constraint λ_k in the optimal breakpoint characterization can be interpreted as the marginal value of expanding tier k's recognition inventory, net of these administrative costs.

Proof of Proposition 6 (Debt Response to Mission Risk) - Full Derivation

Proof. Consider an NPO with risk-averse manager (coefficient ϕ) facing risk-averse donors (coefficient γ_D). The decomposition $\frac{\partial r_B^*}{\partial \sigma_h^2} = \kappa \left(\frac{\partial K_h^*}{\partial \sigma_h^2} - \frac{\partial D_h^*}{\partial \sigma_h^2} \right)$ follows directly from the financing constraint. The manager maximizes expected utility:

$$\max_{K_h \geq 0,\, B_h,\, e_h} \; E\left[-\exp\left(-\phi(M_h - r_B(B_h)B_h)\right)\right] - C(e_h) \tag{A18}$$

With $M_h \mid K_h \sim \mathcal{N}\big(\bar{M}_h(K_h), \sigma_h^2(K_h)\big)$ and CARA utility, this is equivalent to:

$$\max_{K_h \geq 0,\, B_h,\, e_h} \; \bar{M}_h(K_h) - r_B(B_h)B_h - \frac{\phi}{2}\sigma_h^2(K_h) - C(e_h) \tag{A19}$$

Combined with the donation function mapping in equation (A7) and the financing constraint $K_h = D_h + B_h$, consider the Lagrangian with multiplier λ on the constraint:

$$\mathcal{L} = \bar{M}_h(K_h) - r_B(B_h)B_h - \frac{\phi}{2}\,\sigma_h^2(K_h) - C(e_h) + \lambda\left(D_h(e_h, \bar{M}_h(K_h), \sigma_h^2(K_h)) + B_h - K_h\right). \tag{A20}$$

The interior KKT conditions are:

$$\text{(e)}\quad C'(e_h^*) = \lambda^* \cdot \frac{\partial D_h}{\partial e_h}\bigg|_{e_h^*}, \tag{A21}$$

$$\text{(B)}\quad \lambda^* = r_B(B_h^*) + \kappa B_h^*, \tag{A22}$$

$$\text{(K)}\quad \bar{M}_h'(K_h^*) - \frac{\phi}{2}\left(\sigma_h^2\right)'(K_h^*) \;+\; \lambda^*\left(\frac{\partial D_h}{\partial \bar{M}_h}\,\bar{M}_h'(K_h^*) + \frac{\partial D_h}{\partial \sigma_h^2}\left(\sigma_h^2\right)'(K_h^*) - 1\right) = 0. \tag{A23}$$

Equivalently, using the chain rule $\frac{\partial D_h}{\partial K_h} = \frac{\partial D_h}{\partial \bar{M}_h}\,\bar{M}_h'(K_h) + \frac{\partial D_h}{\partial \sigma_h^2}\,(\sigma_h^2)'(K_h)$, condition (K) can be written as

$$\bar{M}_h'(K_h^*) - \frac{\phi}{2}\left(\sigma_h^2\right)'(K_h^*) + \lambda^*\left(\frac{\partial D_h}{\partial K_h}\bigg|_{K_h^*} - 1\right) = 0. \tag{A24}$$

Combining (e) and (B) yields the implementable relation:

$$r_B(B_h^*) + \kappa B_h^* = \frac{C'(e_h^*)}{\frac{\partial D_h}{\partial e_h}\big|_{e_h^*}}. \tag{A25}$$

Differentiating the equilibrium conditions with respect to σ_h^2 yields:

$$\frac{\partial B_h^*}{\partial \sigma_h^2} = \frac{\partial K_h^*}{\partial \sigma_h^2} - \frac{\partial D_h^*}{\partial \sigma_h^2} \tag{A26}$$

The donor channel contributes $-\frac{\partial D_h^*}{\partial \sigma_h^2} = \frac{\gamma_D}{2\mathcal{J}} > 0$ (higher risk reduces donations). The manager channel contributes $\frac{\partial K_h^*}{\partial \sigma_h^2} = -\frac{\phi}{2\mathcal{J}}$ (risk-averse manager reduces scale). Combining:

$$\frac{\partial r_B^*}{\partial \sigma_h^2} = \kappa\frac{\partial B_h^*}{\partial \sigma_h^2} = \kappa \cdot \frac{\gamma_D - \phi}{2\mathcal{J}} \tag{A27}$$

where $\mathcal{J} > 0$ is a positive stability constant ensuring local convergence of the equilibrium system. In this LQ specialization, the recognition-squared aggregator $\widehat{\Omega}_h$ is constant (or normalized) and absorbed into $\mathcal{J}$, which is why it does not appear separately in the compact expression above. □

Note on Inventory Constraints and Donor Competition

Our model assumes limited recognition inventory (e.g., only one building naming opportunity) creates scarcity that drives the convex pricing structure. A natural concern is whether competition among donors for scarce high-tier recognition could generate multiple equilibria or undermine our main results.

We show this concern is unwarranted for three reasons:

1. Atomistic donors: With a continuum of donors, each individual takes the NPO's breakpoint schedule as given. While the shadow prices λ_k on inventory constraints affect the NPO's optimal choice of breakpoints, no single donor can influence these prices. This is analogous to price-taking behavior in competitive markets.

2. Efficient rationing: When tier k inventory binds, the NPO allocates recognition to the highest-value donors—those whose willingness to pay (captured by wealth and mission match) exceeds $\bar{D}_k$. This efficient rationing emerges naturally from the KKT scarcity breakpoint structure derived in Lemma 1 (see the main-text footnote under Lemma 1 clarifying that convexity and rationing arise from scarcity via KKT conditions, not screening).

3. Uniqueness preservation: The inventory constraints tighten the spacing between breakpoints but do not introduce non-convexities in the NPO's objective function. The strategic substitutability in fundraising effort (Proposition 3) continues to ensure a unique equilibrium even with binding inventory constraints.

In essence, inventory constraints strengthen rather than weaken our results by creating the scarcity that makes high-tier recognition valuable and drives donor concentration at individual NPOs.

Appendix B Treated/Control States

Table B1: Treated and Control States by Sample Window

Sample Window	Treated States	Control States
1991–2011	Florida, Maine, North Dakota, Oklahoma, South Carolina, South Dakota, Texas	Connecticut, Delaware, Iowa, Louisiana, Minnesota, New Hampshire, New Mexico, Rhode Island, Vermont, Washington, Wyoming, Virginia
1996–2011[a]	Florida, Maine, Oklahoma, South Carolina, Texas	(same as 1991-2011 sample)
2001–2011[b]	Florida, Oklahoma, South Carolina, Texas	(same as 1991-2011 sample)

[a] North Dakota and South Dakota are excluded because their 1996 adoption leaves no pre-treatment period.

[b] Maine is excluded in the FARS analysis due to its 2000 adoption, which precludes pre-treatment years in the 2001–2011 window.

Note: Excluded states in all windows include those that adopted caps prior to 1991, abolished them during the sample, or experienced other tort reform changes.

Online Appendix C Direct Effect of Risk Reduction

We decompose the total effect of non-economic damage caps on healthcare municipal bond yields into direct and indirect channels. The direct channel captures the mechanical reduction in borrowing costs attributable solely to lower default risk from reduced malpractice liability exposure. We exclude indirect effects operating through changes in service mix, physician staffing, or defensive medicine practices. This calculation establishes that 5 basis points of our observed 27 basis point total effect operates purely through the risk reduction mechanism.

Malpractice Cost Reduction from Damage Caps:

Non-economic damage caps generate substantial reductions in both malpractice payouts and insurance premiums. Empirical evidence from 1985-2010 claims data demonstrates that state-level caps reduce average malpractice payouts by \$42,980 per claim, representing a 15% decline (Seabury et al., 2014). States implementing more restrictive \$250,000 caps achieve even larger reductions, cutting average payments by 20%. These payout reductions translate directly into premium savings for healthcare providers. Physicians in capped states pay 17.3% less for malpractice insurance if they practice internal medicine and 20.7% less if they specialize in general surgery (American Medical Association, 2025). The Congressional Budget Office estimates that a federal reform package featuring a \$250,000 non-economic cap would reduce malpractice premiums by 10% nationally (Congressional Budget Office, 2009).

For nonprofit hospitals specifically, damage caps reduce malpractice liability costs by 10-20%. These savings materialize through three channels: lower commercial insurance premiums, reduced self-insurance reserve requirements, and decreased frequency of catastrophic payouts exceeding policy limits. Texas provides compelling evidence of these effects. Major hospital insurers reduced malpractice rates by 12% in 2004 and an additional 5% in 2005 following the state's damage cap implementation, directly reflecting hospitals' diminished liability exposure (Texas Department of Insurance, 2005).

Effect on Hospital Financial Metrics

Malpractice cost reductions flow directly to hospital operating margins and debt service coverage ratios, thereby reducing default risk. Nonprofit hospitals operate on thin margins averaging 2-3% of revenues, making malpractice expense reductions particularly meaningful for financial stability. During the mid-2000s, malpractice expenses consumed 2.7% of hospital revenues on average. Pennsylvania hospitals faced even higher burdens, with FY2004 malpractice costs equaling 2.67% of net patient revenue – an amount exceeding the entire statewide hospital operating income that year (Pennsylvania Health Care Cost Containment Council, 2005).

A 15% reduction in malpractice expenses saves hospitals approximately 0.4% of revenues (15% of 2.7%). For a hospital with a 2% pre-reform operating margin, this cost reduction increases the margin to 2.4%, representing a 20% relative improvement in profitability.

Pennsylvania's analysis found that a 10% decrease in malpractice costs would raise statewide hospital net income by 7-12%. These margin improvements strengthen debt service coverage ratios proportionally. A hospital maintaining a 2.0× coverage ratio before reform would see this metric rise to approximately 2.1× post-reform. Even modest 0.1-0.2 improvements in coverage ratios meaningfully reduce covenant breach probabilities and signal enhanced repayment capacity to bondholders.

Beyond average cost reductions, damage caps eliminate tail risk by establishing hard ceilings on non-economic awards. This containment of worst-case liability exposure reduces the probability of financial distress from catastrophic verdicts that could otherwise threaten hospital solvency.

Municipal Bond Yield Sensitivity:

Healthcare municipal bond investors price default risk precisely, demanding yield premiums commensurate with credit quality deterioration. Hospital bonds trade at spreads reflecting their underlying financial strength, with coverage ratios, operating margins, and balance sheet metrics driving investor assessments. Credit rating differentials translate into substantial yield differences. The spread between A-rated and BBB-rated hospital bonds of similar maturity ranges from 10 to 50 basis points during normal market conditions, reflecting the default risk premium investors demand for lower credit quality. During stressed market periods, these spreads can exceed 100 basis points.

One-notch rating upgrades generate immediate yield benefits of 10-20 basis points for hospital issuers. In stable markets, 30-year AA-rated hospital bonds trade at spreads of 20-40 basis points above AAA benchmarks, while BBB-rated bonds carry spreads exceeding 100 basis points. These yield differentials demonstrate investor sensitivity to incremental changes in hospital credit metrics. Higher debt service coverage, stronger operating margins, and improved balance sheet liquidity all translate into tighter credit spreads through their impact on default probability assessments.

Estimated Direct Effect on Bond Yields:

Combining the empirical evidence on malpractice cost reductions, financial metric improvements, and bond market pricing yields our estimate of the direct effect. First, damage caps reduce hospital malpractice costs by 15% (the midpoint of our 10-20% range). For hospitals where malpractice represents 2.7% of revenues, this generates savings of 0.4% of annual revenues.

Second, these cost savings flow directly to operating margins. A hospital with a 3.0% initial margin sees this metric rise to 3.4%, a 13% relative improvement in profitability. Debt service coverage ratios improve proportionally – a 2.0× initial ratio increases to approximately 2.1×. These improvements reduce default risk by roughly 10%.

Third, municipal bond yields respond to default risk changes through credit spread adjustments. Consider a single-A hospital revenue bond trading at a 50 basis point spread above top-rated municipals under normal market conditions. A 10% reduction in default risk should compress this risk premium proportionally, reducing the 50 basis point spread by 10%, or 5 basis points.

The relationship between default risk and yield spreads follows:

$$\text{Change in yield} = \text{Initial spread} \times \frac{\text{Reduction in default risk}}{\text{Initial default risk}} \tag{A28}$$

With an initial spread of 50 basis points and a 10% reduction in default risk, the yield spread contracts by 5 basis points (10% of 50 basis points).[36]

Conclusion:

Non-economic damage caps reduce healthcare municipal bond yields by 5 basis points through the direct risk-reduction channel. This mechanical effect operates purely through improved hospital financial metrics and reduced default risk, independent of any behavioral responses or operational changes. While modest relative to our total observed effect of 27 basis points, this 5 basis point direct reduction represents meaningful financing savings – approximately $5,000 annually per $10 million of outstanding debt. The remaining 22 basis points of yield reduction must therefore operate through indirect channels, including the donor risk aversion mechanism we identify as the primary driver of NPO risk aversion.

[36]This standard back-of-the-envelope calculation assumes a linear pricing rule, which simplifies how default risk maps to yield spreads. However, even alternative methods yield similar magnitudes. For example, Moody's estimates a five-year cumulative default rate (CDR) of 0.35% for not-for-profit hospitals (Moody's Investors Service, 2023). Assuming a constant annual default probability and independent defaults across years, the survival probability over five years is $(1-p)^5 = 1 - \text{CDR}$. Solving gives $p = 1-(1-0.0035)^{1/5} \approx 0.0007$, or 7 basis points. Assuming 100% loss given default, this implies an upper bound of 7 basis points on the yield spread attributable to credit risk, which is consistent with the 5 basis point estimate derived under the linear pricing assumption.

Online Appendix D Staggered Synthetic Control: Methods and Results

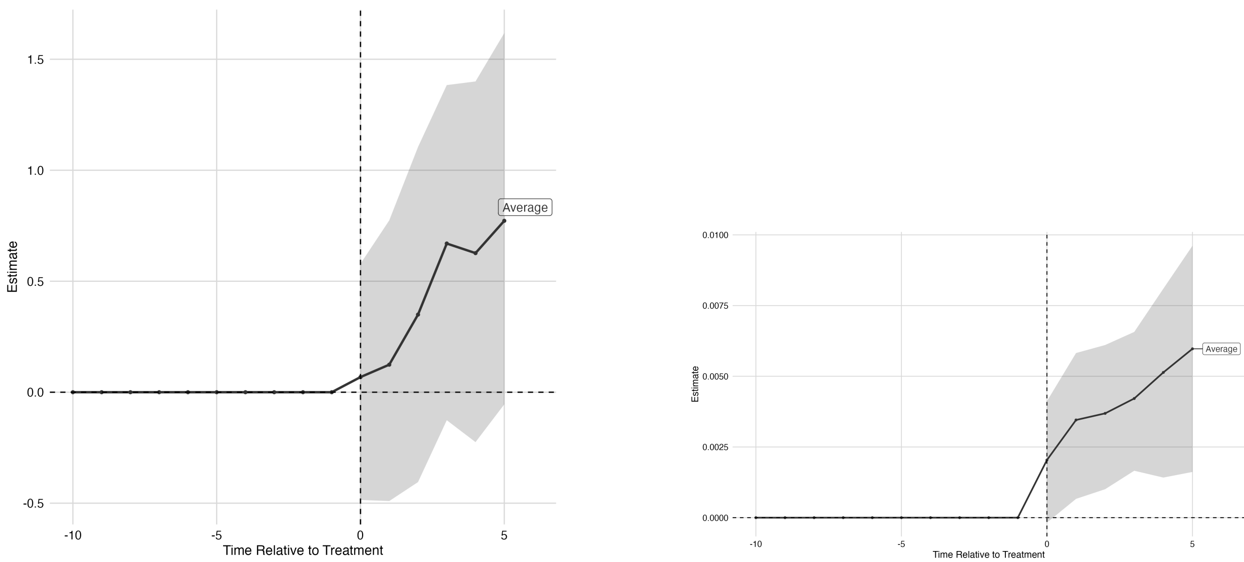
D.1 Staggered Synthetic Control: Methods

We use staggered synthetic control (SSC) analysis to verify the robustness of our hospital-level results. SSC constructs unit-specific counterfactuals by matching treated hospitals to weighted combinations of control hospitals that closely track pre-treatment outcomes.

We implement the partially pooled SCM estimator of Ben-Michael et al. (2022), which blends separate synthetic controls (lower bias) with a pooled synthetic control (lower variance). The pooling weight ν is chosen to minimize pre-treatment imbalance. All estimates use the same sample restrictions as the main analysis.

D.1.1 Donations

Figure D1: Synthetic Control Plots: Private Donations

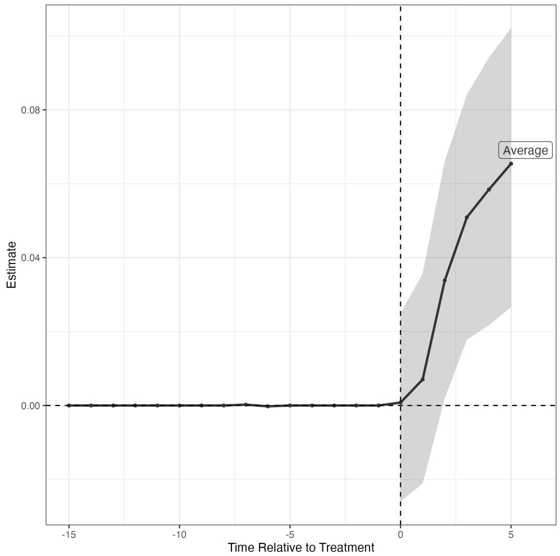


(a) Dollars (b) Per Operating Revenue

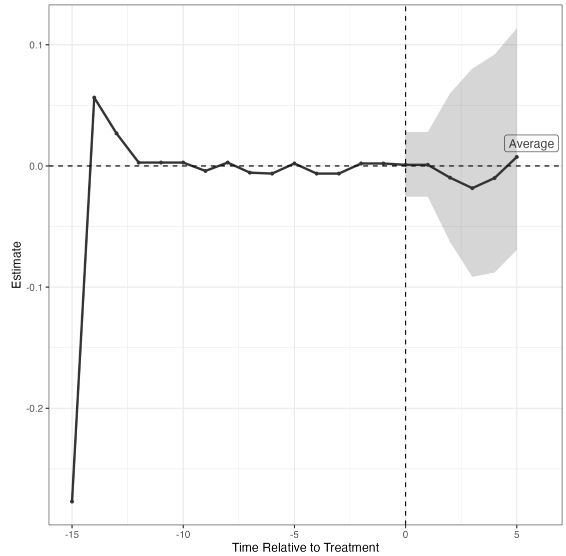
Note: This figure plots partially pooled staggered synthetic control estimates (ν optimally selected following Ben-Michael et al. (2022)) for private donations to nonprofit hospitals after the implementation of caps on non-economic damages. Panel (a) shows donations in dollars (winsorized); panel (b) shows donations scaled by operating revenue. The black line is the treated-minus-synthetic difference; the shaded region shows the 95% confidence interval.

D.1.2 Trauma Center Provision

Figure D2: SSC Plots: Trauma Centers by Ownership Type



(a) Nonprofit Hospitals



(b) For-Profit Hospitals

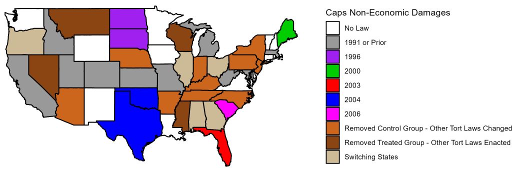
Note: Partially pooled SSC plots for trauma center presence. The black line is the difference between treated hospitals and the weighted synthetic control; shaded area shows 95% confidence interval.

Online Appendix E Financing: Additional Details and Results

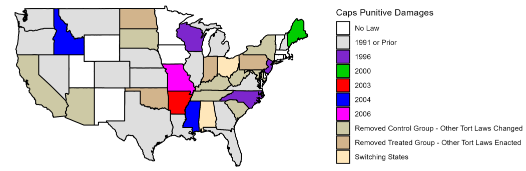
Hospital Level Financials:

E.0.1 Tort Reform Adoption

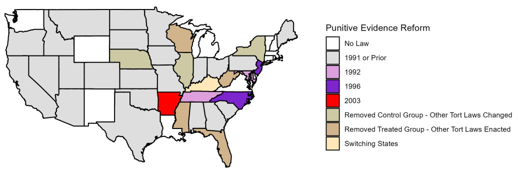
Figure E1: Tort Reform Adoption



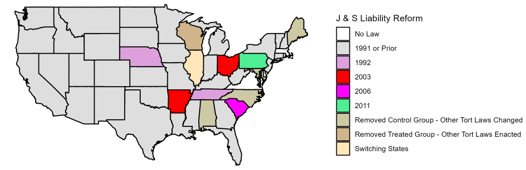
(a) Cap Non-Economic Damages



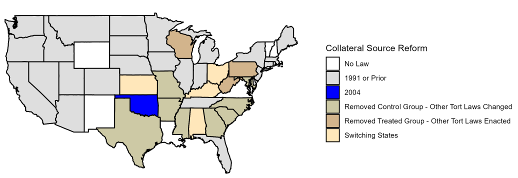
(b) Cap Punitive Damages



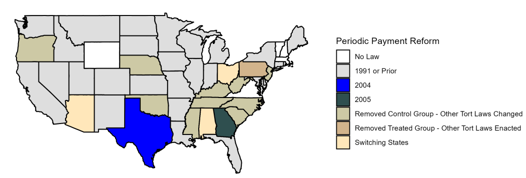
(c) Punitive Evidence Reform



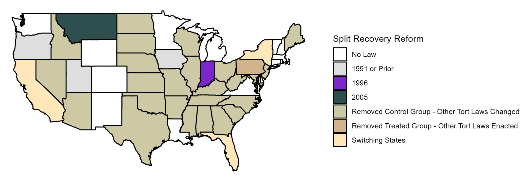
(d) Joint and Several Liability Reform



(e) Collateral Source Reform



(f) Periodic Payment Reform



(g) Split Recovery Reform

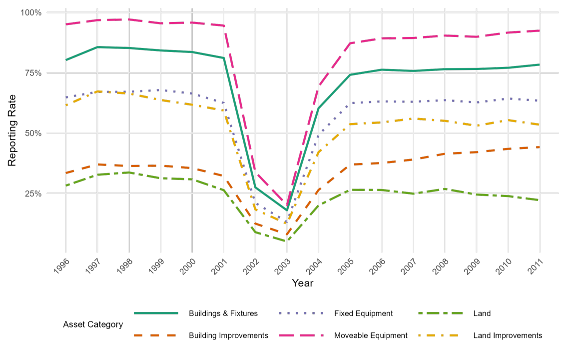
Note: This figure shows the timing of tort reform adoption by reform type. Our analysis relies on the roll-out of these reforms. Control states are states that did not adopt and had no other law changes. Treatment states are states that adopted after 1991, did not abolish the tort reform during the period, and did not experience other tort reforms.

E.0.2 Capital Asset Reporting Rates

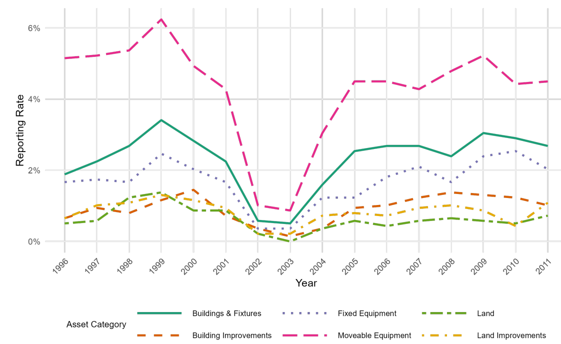
Figure E2 shows the reporting gap for capital assets using the HCRIS starting in 2001 and persisting through 2005. This reporting gap reflects a change in CMS reporting requirements tied to the end of the capital PPS transition period. Under the Form CMS-2552-96 instructions for Worksheet A-7 (Section 3612), hospitals receiving 100 percent federal prospective payment for capital-related costs (i.e., those with Worksheet S-2, column 2, line 36 equal to "Y") were no longer required to complete Parts I through IV of Worksheet A-7, which track purchases, donated assets, disposals, and depreciation of capital assets, for reporting periods beginning on or after October 1, 2001. This exemption coincided with the conclusion of the 10-year capital PPS phase-in, after which most IPPS hospitals transitioned to fully prospective capital payments and no longer needed detailed capital asset reconciliation for Medicare settlement purposes. Because the 10-year capital PPS transition ended for cost reporting periods beginning on or after October 1, 2001 (42 CFR 412.300), nearly all short-term acute care general hospitals, regardless of ownership status, moved to 100 percent federal prospective capital payment and thus qualified for this exemption. The only exceptions were hospitals outside the IPPS, such as Critical Access Hospitals (which are cost-reimbursed), new hospitals in their first two years that elected cost-based capital payment (42 CFR 412.304(c)), and TEFRA-exempt providers (e.g., psychiatric, rehabilitation, and long-term care hospitals). CMS subsequently reinstated mandatory completion of Parts I through IV for all hospitals with cost reporting periods ending on or after February 29, 2004, and further clarified that Parts III and IV must also be completed for periods ending on or after April 30, 2005.[37] This created an approximately three-year window (roughly 2001-2004) during which capital asset data on Worksheet A-7 were systematically underreported, producing the sharp decline and subsequent recovery in reporting rates shown in Figure E2. Because several of our tort reform treatment states adopted caps during this window, disentangling treatment effects from reporting effects on capital asset variables is not feasible, which is why we do not include these variables in our main analysis.

[37] The relevant language appears in Section 3612 of the Form CMS-2552-96 instructions, available at https://www.costreportdata.com/instructions/Instr_A71.pdf. The full Chapter 36 instructions for Form CMS-2552-96 can be downloaded from the CMS Provider Reimbursement Manual, Part 2, available at https://www.hhs.gov/guidance/document/provider-reimbursement-manual-part-2-2-pub-15-2-chapter-36-hospital-and-healthcare-complex.

Figure E2: Capital Asset Reporting Rates

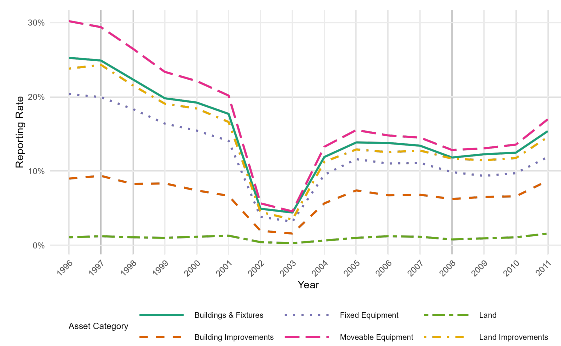


(a) Purchases



(b) Donations

(c) Disposals



(d) Depreciation

Note: This figure plots the response rates for capital assets from the HCRIS Medicare cost reports between 1996-2011 for purchases (panel (a)), donations (panel (b)), disposals (panel (c)), and depreciation (panel (d)). The lines indicate the asset category: buildings and fixtures, fixed equipment, land, building improvements, moveable equipment, and land improvements. This figure illustrates the change in reporting requirements from 2000-2005, which corresponds with the timing of many of our tort reform states (Maine (2000), Florida (2003), Oklahoma (2004), Texas (2004), and South Carolina (2006)).

E.0.3 Summary Statistics by Ownership Type

Table E1: Summary Statistics by Ownership Type

	Nonprofit		For-Profit	
	Mean	St. Dev.	Mean	St. Dev.
Panel A: Hospital Financial Data				
Donation Income ($1mill)	0.52	1.52	0.04	0.16
Government Grant Income ($1mill)	15.20	56.39	5.82	13.10
Profit ($1mill)	7.16	36.78	12.85	23.61
Net Patient Revenue ($1mill)	140.14	170.96	100.35	104.16
Operating Revenue ($1mill)	148.82	182.45	101.70	106.19
Rural Hospital (%)	17.40	37.91	11.22	31.57
Has Trauma Unit (%)	21.99	41.42	10.26	30.35
Number of Hospitals	513		155	
N	7,231		1,881	
Panel B: Hospital Investment Data				
Has Trauma Center (%)	13.99	34.69	5.29	22.38
Number Beds	146.21	201.60	158.60	128.97
Teaching Hospital (%)	19.12	39.33	7.98	27.09
Number of Hospitals	1,557		340	
N	24,854		4,539	

Note: This table reports summary statistics separately for nonprofit and for-profit hospitals. Panel A uses the donations triple-difference sample and Panel B uses the investment triple-difference sample.

Bond Analysis

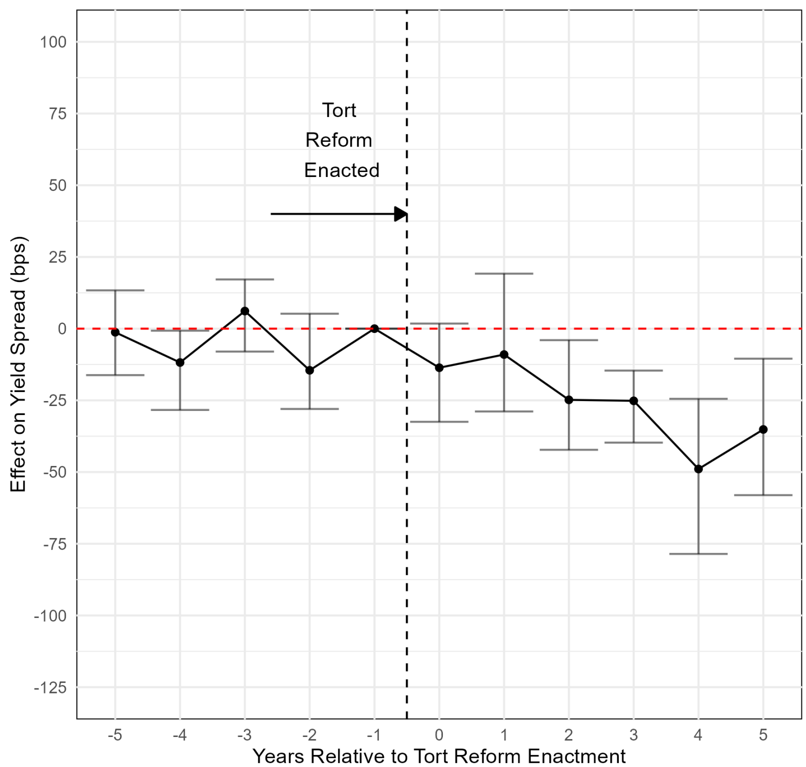
Table E2: Cost of Capital: Municipal Bonds (All Maturity Groups)

Panel A: All Maturities	Yield Spread (bps)	Issue Size (Log)	Bonds Issued (Total Per State-Year)
	(1)	(2)	(3)
ATT	-27.31^{**}	-0.258	-20.03
90% CI	[-50.14, -4.55]	[-0.499, 0.001]	[-45.53, 21.09]
Pre-Adoption Mean	-34.04	13.103	102.44
N	28,281	28,281	388
Panel B: 10Y and Greater			
ATT	-31.96^{***}	-0.483^{**}	-19.89
90% CI	[-53.83, -10.34]	[-0.999, -0.039]	[-30.89, 12.4]
Pre-Adoption Mean	-32.13	13.849	50.76
N	13,845	13,845	388
Panel C: Between 5Y and 10Y			
ATT	-23.02	-0.167	-7.39
90% CI	[-41.9, 0.06]	[-0.322, 0.047]	[-18.07, 15.86]
Pre-Adoption Mean	-36.69	12.870	49.76
N	19,710	19,710	388
Panel D: 5Y and Less			
ATT	-13.87	-0.156	-3.5
90% CI	[-51.71, 18.98]	[-0.351, 0.062]	[-19.29, 9.74]
Pre-Adoption Mean	-28.75	12.265	29.86
N	8,321	8,321	388
Year Fixed Effects?	Yes	Yes	Yes
State Fixed Effects?	Yes	Yes	Yes
State Level Controls?	Yes	Yes	Yes
Bond Characteristic Controls?	Yes	Yes	No

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports staggered difference-in-differences estimates and 90% confidence intervals following Borusyak et al. (2024) for three outcomes in the healthcare municipal bond market: yield spreads (basis points, column 1), inflation-adjusted bond issue size (log, column 2), and the total number of healthcare municipal bonds issued in a state-year (column 3). Results are shown overall and by maturity group, as indicated by the panels. Yield spread and issue size are analyzed at the bond level, while the number of bonds is analyzed at the state-year level. Each panel reports estimated average treatment effects (ATT), 90% confidence intervals, and pre-adoption means. The pre-adoption means for yield spread are negative due to the rising interest rates in the 1990s. All models include year and state fixed effects, as well as state-level controls (population, mean household income, and employment). Bond-level controls (e.g., refunding indicator) are included in the yield spread and issue size specifications but are not applicable to the number of bonds. For column 3, the number of refunding bonds issued in a state-year is included as an additional state-level control. Standard errors are block-bootstrapped at the state level following Abadie et al. (2023).

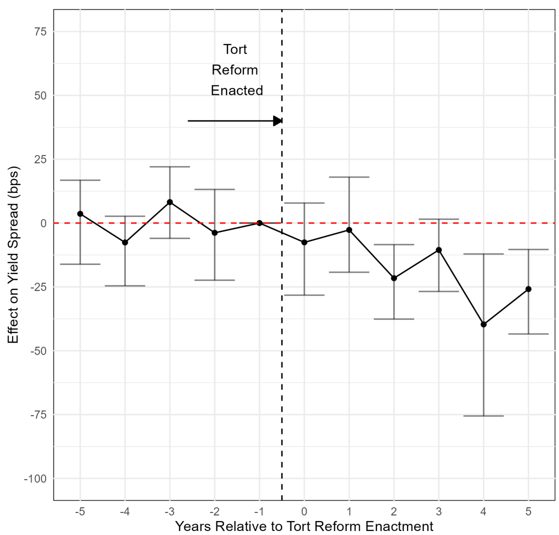
Yield Spread Event Studies

Figure E3: Event Study: Municipal Bond Yield Spread (bps) - All Maturities

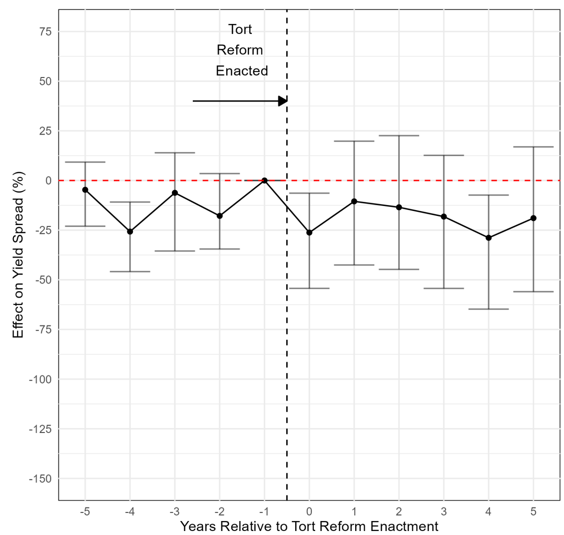


Note: This figure plots the coefficients and 90 percent confidence intervals for the imputed difference-in-difference estimates for the impact of caps on non-economic damages on bond yield spread over time across all maturity levels. Year "0" refers to the year the state implemented caps on non-economic damages and Year "-1" is the omitted category. Standard errors are block-bootstrapped at the state-level. Municipal bond data comes from the MSRB from 1991 to 2011 and Treasury yields, which are used to calculate the yield spread, come from the US Department of the Treasury.

Figure E4: Event Study: Municipal Bond Yield Spread - Medium and Short-Term Maturities



(a) Yield Spread (bps): Maturity 5-10 years

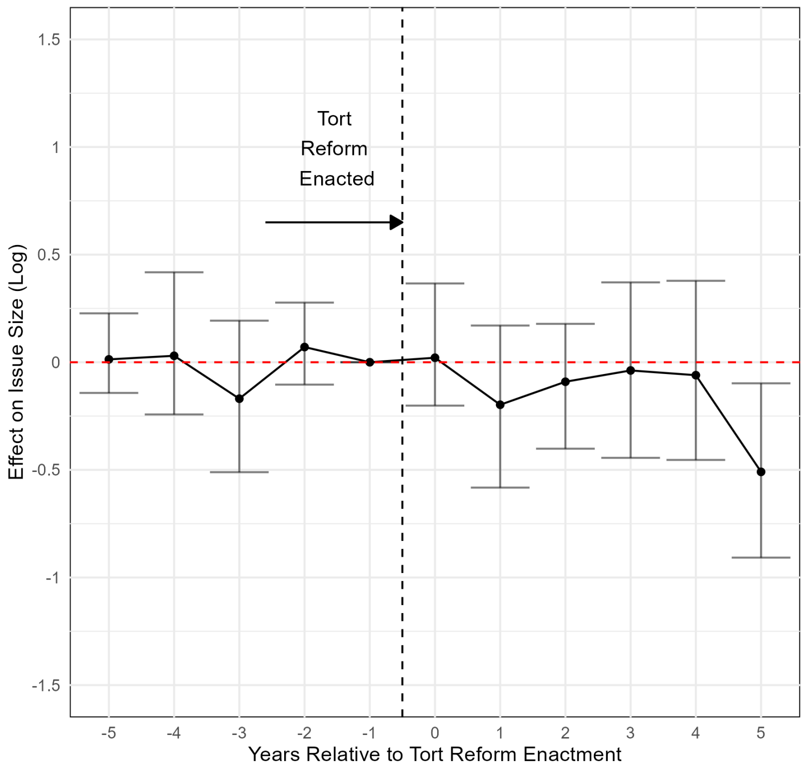


(b) Yield Spread (bps): Maturity $\leq$ 5 years

Note: This figure plots the coefficients and 90 percent confidence intervals for the imputed difference-in-difference estimates for the impact of tort reform on bond yield spread for medium (panel (a)) and short-term (panel (b)) maturity bonds over time. Year "0" refers to the year the state implemented caps on non-economic damages and Year "-1" is the omitted category. Standard errors are block-bootstrapped at the state-level. Municipal bond data comes from the MSRB from 1991 to 2011 and Treasury yields, which are used to calculate the yield spread, come from the US Department of the Treasury.

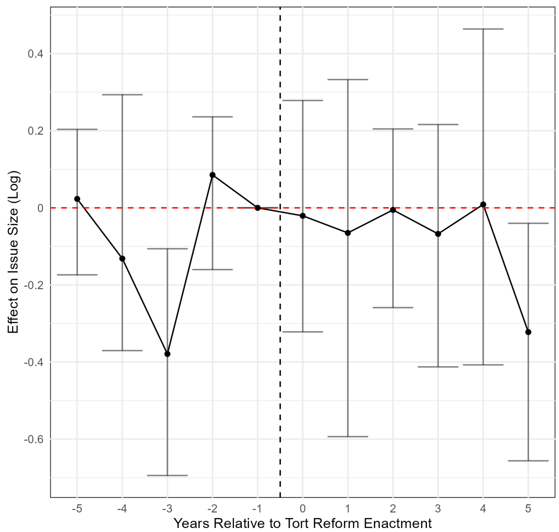
Issue Size Event Studies

Figure E5: Event Study: Municipal Bond Inflation-Adjusted Issue Size (Log) - All Maturities

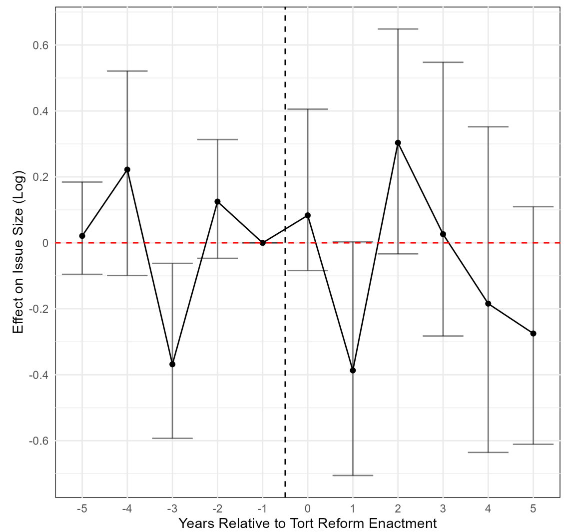


Note: This figure plots the coefficients and 90 percent confidence intervals for the imputed difference-in-difference estimates for the impact of caps on non-economic damages on inflation-adjusted bond issue size (measured in logs) over time across all maturity levels. Year "0" refers to the year the state implemented caps on non-economic damages and Year "-1" is the omitted category. Standard errors are block-bootstrapped at the state-level. Municipal bond data comes from the MSRB from 1991 to 2011.

Figure E6: Event Study: Municipal Bond Inflation-Adjusted Issue Size (Log) - Medium and Short-Term Maturities



(a) Issue Size (Log): Maturity 5-10 years

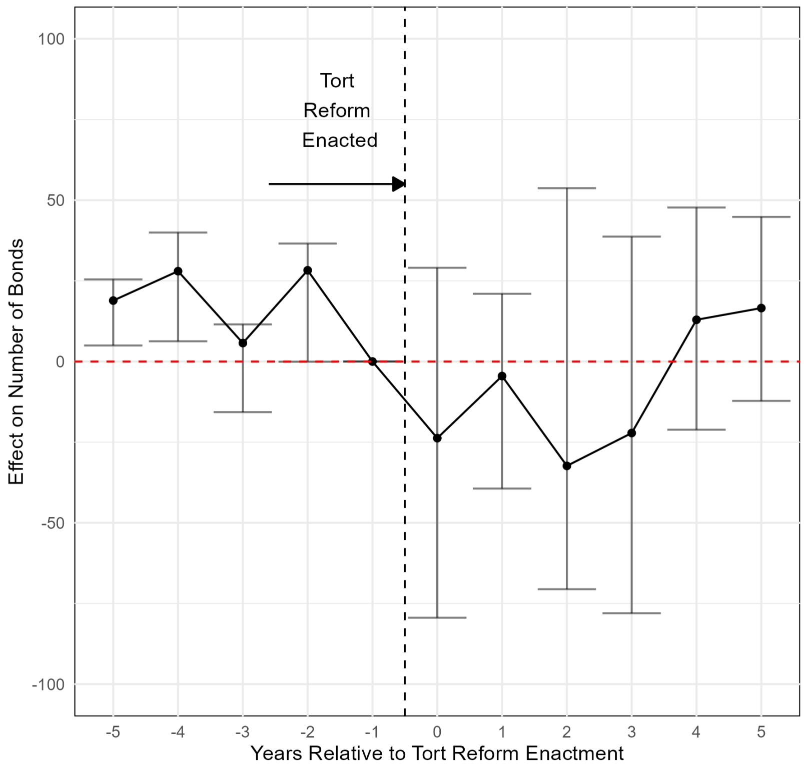


(b) Issue Size (Log): Maturity ≤ 5 years

Note: This figure plots the coefficients and 90 percent confidence intervals for the imputed difference-in-difference estimates for the impact of tort reform on inflation-adjusted bond issue size (measured in logs) for medium (panel (a)) and short-term (panel (b)) maturity bonds over time. Year "0" refers to the year the state implemented caps on non-economic damages and Year "-1" is the omitted category. Standard errors are block-bootstrapped at the state-level. Municipal bond data comes from the MSRB from 1991 to 2011.

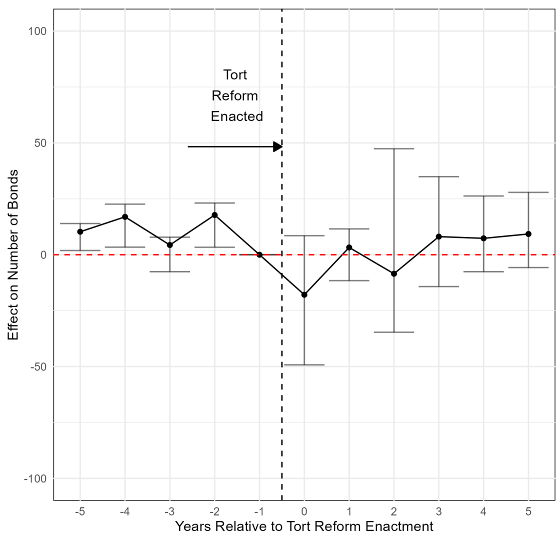
Number of Bonds Issued Event Studies

Figure E7: Event Study: Number of Municipal Bonds - All Maturities

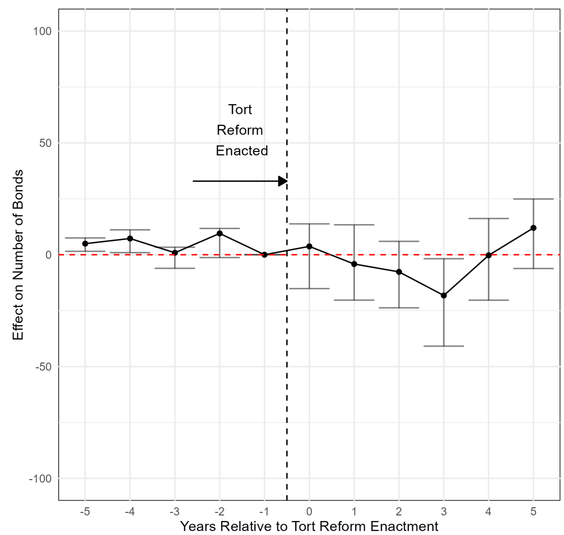


Note: This figure plots the coefficients and 90 percent confidence intervals for the imputed difference-in-difference estimates for the impact of caps on non-economic damages on the number of healthcare municipal bonds issued in a state over time across all maturity levels. Year "0" refers to the year the state implemented caps on non-economic damages and Year "-1" is the omitted category. Standard errors are block-bootstrapped at the state-level. Municipal bond data comes from the MSRB from 1991 to 2011. The maturity breakdowns are shown in the following figure.

Figure E8: Event Study: Number of Municipal Bonds - Medium and Short-Term Maturities



(a) Maturity 5-10 years



(b) Maturity $\leq$ 5 years

Note: This figure plots the coefficients and 90 percent confidence intervals for the imputed difference-in-difference estimates for the impact of caps on non-economic damages on the number of healthcare municipal bonds issued in a state over time. Year "0" refers to the year the state implemented caps on non-economic damages and Year "-1" is the omitted category. Standard errors are block-bootstrapped at the state-level. Municipal bond data comes from the MSRB from 1991 to 2011. Panel (a) shows the event study for bonds with 5-10 year maturities and panel (b) for bonds that mature 5 years or less after issuance.

Online Appendix F Health Outcomes: Additional Details

Data and Methods:

Data on health outcomes comes from the 2001–2011 Fatality Analysis Reporting System (FARS). While FARS data exists from 1991 onward, we utilize only the 2001–2011 data as these years include the latitude/longitude of the accident. This geographic information is necessary to match accidents to specific locations. FARS is a national dataset covering injuries suffered in motor vehicle accidents. For a crash to appear in FARS, two conditions must be met: (1) the accident occurred on a public road, and (2) at least one individual involved in the crash perished within 30 days of the accident. FARS data is well-suited for this analysis, as individuals involved in a car accident severe enough to result in fatalities are likely to require treatment at a trauma facility.

We aggregate FARS data to the zip code level using the following procedure. First, we extract the Zip Code Tabulation Area (ZCTA) for each accident using its longitude and latitude coordinates.[38] We then aggregate fatal accidents by zip code and year, counting the total number of traffic fatalities in each zip code–year cell.

To maintain consistency with the investment analysis, we restrict the sample to states outlined in Section 4.[39] We create a balanced panel by restricting to zip codes that experienced at least one fatal accident in every year of the 2001–2011 period. Our final sample consists of 3,123 balanced zip codes over 11 years, yielding 34,353 observations.

Unlike the hospital-level analysis, we do not employ a triple-difference design. In trauma emergencies, patients are often transported outside their home area to reach a trauma center—including airlifting to regional facilities—so for-profit areas do not provide a clean within-state control for health outcomes. Instead, we estimate a simple imputed difference-in-differences: we use the pre-treatment period (before tort reform adoption) to estimate zip code and year fixed effects, impute counterfactual fatalities for all observations, and then regress the residualized outcome on the tort reform indicator. Standard errors are obtained via 500 bootstrap iterations resampling states with replacement.

[38] For accidents occurring between 2001 and 2009, we extract ZCTAs using the 2000 Census. For accidents in 2010 or later, we use the 2010 Census to determine the ZCTA.

[39] Section 4 outlines that control states are those that did not adopt any types of tort reform between 1991–2011: Connecticut, Delaware, Iowa, Louisiana, Minnesota, New Hampshire, New Mexico, Rhode Island, Vermont, Washington, Wyoming, and Virginia. Treatment states are those that adopted caps on non-economic damages between 1991–2011 and no other tort reform changes during that period: Florida, Maine, North Dakota, Oklahoma, South Carolina, South Dakota, and Texas.

Summary Statistics

Table F1 presents summary statistics for the FARS dataset aggregated at the zip code level. The average zip code in our balanced panel experienced approximately 4.3 traffic fatalities per year during the pre-treatment period, with a standard deviation of 3.0.[40]

Table F1: Health Outcomes: Summary Statistics (Zip Code Level)

	Mean	SD
Traffic Fatalities (per zip-year)	4.33	2.98
MCI Fatalities (per zip-year)	0.73	1.40
Zip Codes	3,123	
Observations	34,353	
Years	2001–2011	

Note: This table presents pre-adoption summary statistics for the balanced panel of zip codes from the 2001–2011 Fatality Analysis Reporting System (FARS). The sample includes zip codes that experienced at least one fatal traffic accident in every year of the sample period. Traffic Fatalities represents the total number of traffic accident fatalities in a zip code per year. MCI (multi-casualty incident) fatalities are fatalities from accidents with two or more deaths.

[40] The balanced panel contains 3,137 zip codes (34,507 observations). Fourteen zip codes in states treated before the FARS sample begins in 2001 have no pre-treatment data, so their zip-code fixed effects cannot be estimated; the imputation step drops these 154 observations, leaving 3,123 zip codes (34,353 observations) in the estimation sample.