

# Essays on Charitable Organizations and Public Policy

Benjamin M. Marx

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## **ABSTRACT**

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The dissertation analyzes public policies of subsidization and regulation in three contexts. Chapter 1 develops a dynamic bunching empirical design and uses it to estimate the compliance cost that IRS reporting requirements impose on public charities. Chapter 2 estimates the effects of tax and enforcement provisions of the Tax Reform Act of 1969 on charitable foundations and their donors. Chapter 3 estimates the impact of Pell Grant aid on student attainment and borrowing.

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## DEDICATION

*To Joy, for everything (including baking my way into my classmates' and advisors' good graces).*

# 1 Regulatory Hurdles and Growth of Charitable Organizations: Evidence From a Dynamic Bunching Design

## Abstract

Taxes and regulations, such as labor laws and reporting requirements, often exempt small firms, creating incentives to stay small or delay growth. Firms' responses to such size thresholds provide an opportunity to empirically assess consequences of regulations and firms' willingness to pay to avoid them. This paper presents a new dynamic research design to estimate income responses to thresholds and analyzes an income notch at which IRS reporting requirements for charitable organizations become more onerous. I estimate that the average charity will reduce reported income by \$600 to \$1000 to "bunch" with those below the notch. In addition, a significant share of charities fail to file when first required to report more information. There is some evidence of retiming of income to delay growing above the notch, but a long-run reduction in the share that grow above the notch provides evidence of real responses as well. Relatively low-expense and low-asset charities are most likely to reduce reported income to stay below the notch, while charities with past receipts above the notch do not manipulate income to get below it, suggesting the report imposes an adjustment cost on new filers. The results highlight the benefits of the dynamic approach, which isolates responses at the time the threshold is encountered by conditioning on past income and growth, for clarifying heterogeneity in responses and estimating extensive-margin responses and long-run effects.

## 1.1 Introduction

Price discrimination, income eligibility limits, and other policies create “notches” – discontinuities in budget constraints (Slemrod, 2010). Notches create incentives that can distort behavior. A pervasive example is a notch at which expenses rise discretely with income, creating incentives for agents to reduce (reported) income. Such income notches can be found in policies that provide benefits to low-income individuals, such as Medicaid (Yelowitz, 1995), or that restrict government attention to high-income firms, as have elements of the Sarbanes-Oxley Act (Iliev, 2010), the Americans With Disabilities Act (Acemoglu and Angrist, 2001) and Affordable Care Act, and some countries’ payroll tax systems (Dixon et al., 2004). Income notches produce deadweight loss if they affect income.

In this paper I show that an Internal Revenue Service reporting notch reduces the incomes of public charities in both the short and the long run. The notch is an income eligibility limit for using simplified IRS reporting forms. The distribution of income exhibits “bunching” of charities at income levels just below the notch. I estimate the number of extra charities below the notch using the techniques of a growing literature that infers behavioral parameters from bunching at kinks and notches. With this approach I estimate that the number of extra charities equals the total number that should be observed with incomes in a range up to \$600 above the notch, implying an average willingness to pay \$600 to avoid filing the lengthier form. The estimated reduction in the number charities with incomes above the notch, however, is even larger than the excess number below the notch. Because it is difficult to account for attrition or heterogeneity with existing techniques, I develop a new dynamic bunching research design that conditions on past income and income growth. With this new design I affirm the static estimates and show that extensive-margin responses (in this context failure to file the IRS return on time) account for the extra reduction in the number of charities above the notch. In addition, I find that the notch permanently reduces the growth of charities and that smaller charities (in terms of assets or expenses) are the most likely to hold their incomes below the notch. Both ordinary least squares and maximum likelihood estimates show that bunching is confined to charities that were previously below the notch and therefore eligible to file the simplified IRS form, providing evidence that much of the compliance cost imposed by the long form is a one-time adjustment cost to establish the requisite knowledge or financial management infrastructure.

The reporting notch for public charities provides a useful setting for thinking about optimal regulation, particularly as it relates to the large and active charitable sector. In the United States, the charitable sector accounts for 9.2 percent of all wages and salaries (Roeger et al., 2012). Example charities of the size studied in this paper include arts organizations, athletic leagues, economic and social development programs, and youth organizations. The IRS exempts public charities from corporate income taxes in exchange for their

commitments to provide social benefits and not distribute profits.<sup>1</sup> Tax exemptions for charities, and tax deductions for donors, create opportunities for tax avoidance and evasion. About a third of each annual IRS “Dirty Dozen” list of tax evasion schemes involves public charities. To enable monitoring by the government and other stakeholders, charities of sufficient size must annually file IRS Form 990, an information return. For most of the last two decades, those with gross receipts below \$100,000 and year-end assets below \$250,000 were eligible to file the simpler Form 990-EZ, creating a reporting notch in both receipts and assets. The optimal design of such a regulatory notch depends on the extent of social benefits obtained by monitoring charities and costs that monitoring imposes. Recent increases in IRS monitoring of the nonprofit sector and ongoing Congressional hearings demonstrate renewed interest in the optimal regulation of charitable organizations.<sup>2</sup> The optimal design of the monitoring notch for public charities reflects trade-offs that arise in regulation more broadly and is useful for thinking about notches that impose heterogeneous costs.

One contribution of this paper is to extend the methodology of bunching estimation used in a growing body of empirical work. Saez (2010) showed that the extent of bunching (i.e. excess mass) in the distribution of income around a tax schedule kink reveals the tax price elasticity of income. Bunching has since been estimated at kinks in the tax schedule (Chetty et al. (2011)) and at notches in taxes (Kleven and Waseem, 2012) and regulatory schedules (Sallee and Slemrod, 2010).<sup>3</sup> The identifying assumption in bunching estimation is that the distribution of income would be smooth if not for the threshold (whether a notch or kink). The researcher can therefore use observations away from the threshold to construct a counterfactual income distribution. The difference between the mass observed near the threshold and the mass predicted by the counterfactual provides an estimate of the share of agents who bunch.

To supplement the standard approach I develop a dynamic version of bunching estimation. As in static estimation, the goal is to quantify distortions in what would otherwise be a smooth distribution of income. Rather than restricting attention to the univariate distribution of current income, the dynamic approach exploits panel data to identify distortions in the joint distribution of income in multiple periods. To implement the dynamic approach I estimate distributions of growth conditional on current income, comparing charities

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<sup>1</sup>The “nondistribution requirement” prohibits nonprofits from paying operating profits to individuals who exercise control over the organization. Excise taxes can be imposed on “excess benefit transactions” including compensation packages deemed to be excessive. Nonprofits include foundations, churches, political groups, and labor organizations in addition to the public charities studied in this paper. State laws vary but frequently exempt charities from income and sales taxes.

<sup>2</sup>Reforms since 2007 include requiring individuals to maintain receipts for noncash donations, revising the 990 forms for fiscal years 2008 and after to require more information from each organization, and in 2011 revoking the tax-exempt status of more than a quarter-million organizations that had not filed in the past three years. In an October 6, 2011 letter to the IRS Commissioner, House of Representatives Committee on Ways and Means Chairman of the Subcommittee on Oversight Charles Boustany wrote that members of both the Oversight and Health Subcommittees “have expressed concern that other tax-exempt organizations may not be complying with the letter or the spirit of the tax-exempt regime, yet continue to enjoy the benefits of tax exemption.” In 2012 the Subcommittee Chairman called a series of hearings to elicit testimony from the IRS and experts on the nonprofit sector, and the IRS will be holding a public hearing on proposed regulations or charitable hospitals.

<sup>3</sup>Other recent papers estimating bunching include Bastani and Selin (2012), Carillo et al. (2012), Kopczuk and Munroe (2012), Ramnath (2012), and Weber (2012). Kleven and Waseem (2012) also build on the theoretical work of Saez (2010), deriving formulas relating the taxable income elasticity to bunching at tax notches and kinks when the bunching is limited by optimization frictions.

approaching the notch to charities with similar growth rates but different current income. I first bin the joint distribution to obtain transparent ordinary least squares estimates of income and other responses, testing for heterogeneous responses and for long-run effects on growth. I then use a maximum likelihood approach to precisely estimate the extent of income manipulation and extensive-margin responses.

Dynamic bunching estimation offers several potential benefits. First, conditioning on current income and other variables as in my dynamic approach makes it easier to distinguish which variables predict income responses and which respond concurrently with income. By comparing a treatment group that approaches the notch to control groups with similar growth rates but different initial income, the researcher can identify the effect of approaching the notch on a charity's behavior and test for heterogeneity. Second, it is possible to directly identify long-run effects of a notch on income growth. Third, one can estimate extensive-margin responses or other sources of sample selection related to the threshold. Fourth, identification relies on assumptions that are arguably more plausible than those of the static approach, particularly for responses to a notch that agents face repeatedly. Repeated bunching or persistence of income from year to year could generate growing distortions in the cross-sectional income distribution used in static estimation, but my approach accounts for such dynamics by conditioning on income in the year prior to the year that a charity approaches the notch and identifying distortions in the distribution of growth rates.

A few papers have studied dynamic aspects of bunching. For example, thresholds in time may induce bunching in intertemporal decisions such as the choice of when to claim retirement (Manoli and Weber, 2011), but these one-time decisions will not generate the repeated bunching or long-run effects identified here. Gelber et al. (2012) examine whether bunching persisted after elimination of the Social Security earnings test but not how the policy affected earnings dynamics while it was in place. Kleven and Waseem (2012) use panel data to estimate the share of taxpayers remaining just above or below tax notches. I present a version of such analysis, taking the additional step of estimating a counterfactual probability of remaining in place, as an example of how panel data can be used to explore heterogeneity within the static framework. More similar to my dynamic design is the work of Schivardi and Torrini (2007), who look for distortions in growth rates around a 15-employee notch in Italian labor law. They estimate that the probability of positive growth is reduced by 2 percent for firms in a bin just below the notch, assume these firms would grow to the bin just above the notch, and construct a counterfactual size distribution by solving for the steady-state of an adjusted one-year transition matrix between employment levels. My design follows a similar logic but enables analysis of a continuous variable, estimates bunching and the counterfactual distribution of growth from each level of current receipts, and provides tests for heterogeneity and threshold-related attrition.

The findings of this study provide new information about the behavior of charities and more broadly about the growth of firms and threshold policies. Just as fiscal policy instruments may affect the long-run

distribution of wealth, regulatory instruments may affect the firm size distribution and its evolution. The responses of charitable organizations to the IRS filing threshold produce clear distortions in the distribution of reported income. Average income is reduced by several hundred dollars per charity in a neighborhood of the notch, and the share growing income to a point above the notch is significantly reduced for a decade or more. Moreover, policy effects interact with measures of organizational capacity similar to those that have been shown to influence the evolution of the for-profit firm size distribution (Cabral and Mata (2003); Angelini and Generale (2008)). Controlling for current income, a one percent increase in a charity's expenses or assets is associated with a 2.5 percent reduction in the probability of manipulating receipts when approaching the notch in the next year.

This paper also contributes to the literature on firm compliance costs by providing evidence that charities manipulate income to avoid incurring the adjustment cost of complying with new reporting requirements. Tax and regulatory compliance costs made up close to three percent of the revenue of the 1300 largest firms in 1992 (Slemrod and Blumenthal, 1993). Compliance costs appear to have an important fixed component because their burden is proportionately heavier on smaller businesses (Slemrod and Venkatesh, 2002). The estimates in these papers preceded the Sarbanes-Oxley Act, which greatly increased reporting requirements. Public charities also face scale economies in compliance, which consumes 7 percent of the annual budgets of surveyed charities with revenue below \$100,000 (Blumenthal and Kalambokidis, 2006). Consistent with these findings, I provide evidence that adjustment is an important component of total compliance cost. I find that charities whose incomes in the prior year necessitated filing a long form showed no propensity to reduce current income by even a small amount to avoid filing again.

The benefit of imposing reporting costs is that firms must disclose information for use by the government and individuals. Investors in for-profit firms appear to value mandatory disclosure of financial information (Greenstone et al., 2006), and the same is likely true of donors to nonprofit firms. The reporting notch therefore reflects a trade-off between imposing additional compliance costs on charities and obtaining additional information from them, much like the calculus of weighing compliance and administrative costs against tax revenues when setting a VAT tax that excludes small firms (Keen and Mintz (2004), Dharmapala et al. (2011)). It is known that income responses must be considered in such situations, and I derive a formula for welfare effects of setting regulatory notches when responses include avoidance and evasion.

The paper proceeds as follows. Section 1.2 describes the empirical setting of an IRS filing notch for public charities and provides a simple welfare model that motivates estimation of the bunching ratio. In Section 1.3 I replicate the static approach in the literature and discuss prospects for exploiting panel information within the static design. Section 1.4 describes the general concept of dynamic bunching estimation. Section 1.5 presents a reduced-form dynamic approach to estimating responses to notches and testing for heterogeneity



in the degree and kind of responses. Section 1.6 demonstrates a maximum likelihood estimation strategy to precisely estimate the extent of the response and allow for attrition that may be endogenous to the notch. Section 1.7 concludes.

## 1.2 The Setting: Nonprofit Information Returns

This section describes the context of a reporting notch for U.S. charities, the data on these firms, and a simple model for determining the government's optimal notch policy. The importance of the sector, the existence of longitudinal data, and the current interest in regulation of charities make this setting an attractive application for dynamic bunching estimation.

### 1.2.1 Background on the Reporting of Charities

The charitable organization reporting notch provides an excellent application for dynamic bunching estimation because: (1) IRS forms create a clear notch in compliance costs, (2) charitable firms face the notch year after year, (3) there is roughly twenty years of longitudinal data on these organizations, and (4) regulatory hurdles will reduce welfare if they discourage these firms from growing to serve their social missions.

I examine IRS reporting notches for public charities. Public charities are organizations granted income and sales tax exemption under section 501(c)(3) of the Internal Revenue Code. All public charities with gross receipts over \$25,000 (except religious congregations) must annually file information returns with the IRS using Form 990 or Form 990-EZ. For fiscal years starting before 2008, charities with gross receipts exceeding \$100,000 or year-end total assets above \$250,000 were required to file the lengthier Form 990.<sup>4</sup>

Form 990 requires charities to access and report more financial data than Form 990-EZ. Table 1 presents a comparison of 990-EZ and 990 for fiscal years beginning in 2007 or earlier. The two forms require nearly all the same categories of information, but Form 990 requires much greater detail. Form 990 contains more lines in most sections and requires a detailed statement of functional expenses. Estimates under the Paperwork Reduction Act for the time required for completion and filing are 164 hours for Form 990-EZ and 260 hours for Form 990 (Internal Revenue Service, 2007). The time estimates include the required Schedules A and B and include time required to perform the necessary recordkeeping (the majority of the difference between the two forms), to learn about the forms, and to prepare and assemble them. The raw difference of roughly 100 hours (a 59% increase), if accurate for the marginal charity near the notch, would imply that an organization with receipts above \$100,000 by less than 100 times the hourly wage could forgo enough receipts to stay

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<sup>4</sup>The IRS also provides simplified individual income tax forms for filers with incomes below a notch, but it turns out this notch is not sufficiently relevant to observe bunching in the distribution of individual incomes. While eligibility for filing Form 1040-EZ is restricted to taxable incomes below \$100,000, other restrictions on age, types of income, and filing status restrict its use among filers even if their incomes are below the notch. Inspection of the distribution of incomes among filers in the IRS Tax Model data reveals very few 1040-EZ filers with income near the notch.

below the notch and have more net resources as a result. Blumenthal and Kalambokidis (2006) asked for the titles and qualifications of individuals responsible for filings and imputed hourly wages between \$13.09 and \$51.77. If all charities faced a marginal cost of filing Form 990 equal to 100 hours at a rate of \$13 per hour then none should report receipts between \$100,000 and \$101,300. Realistically, the marginal cost of filing would vary with the amount of recordkeeping already being performed, implying variation in the amount of receipts charities would forgo to avoid filing. Blumenthal and Kalambokidis (2006) also find that after controlling for size and other factors, those filing Form 990 report spending about 45% more on professional advisory fees than those filing Form 990-EZ.

Form 990 may also impose a disclosure cost on charities that do not want to reveal certain information. For example, charities filing Form 990 must check a box if any officers or key employees are related to each other and must list any former officers that were compensated during the year. However, most potentially-sensitive information is required of both types of filers: compensation of current officers and employees must be listed on each form, and the rule for completing Schedule B (Schedule of Contributors) is the same for both forms.<sup>5</sup> Moreover, charities near the eligibility notch at \$100,000 of gross income are unlikely to be able to pay large salaries. It will not be possible to fully test for disclosure costs, but I look for suggestive evidence by relating income manipulation to ex-post values of items appearing only on Form 990.

Income threshold policies may create incentives for entities to reorganize as multiple smaller organizations (Onji, 2009). In the present context this incentive is likely to be weak because exempt status would have to be applied for and obtained for each organization and because economies of scale are likely to be considerable at sizes small enough to make organizations eligible to file Form 990-EZ. I therefore treat each charity as an individual unit.

### 1.2.2 Panel Data on Charities

This study uses IRS data from the Core files of the National Center for Charitable Statistics (NCCS), a division of the Urban Institute. IRS databases offer the most comprehensive standardized data on tax-exempt organizations in the U.S. The IRS produces a Business Master File of descriptive information from each filing and Return Transaction Files of financial information. The NCCS Core files contain data from the IRS databases on all 501(c)(3) organizations that were required to file a Form 990 or Form 990-EZ and complied in a timely manner.<sup>6</sup> Analyses “show the IRS 990 Returns to be a generally reliable source of

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<sup>5</sup>Public charities must file Schedule B if they received any individual contributions of more than \$5000. Those meeting the “public support test” of receiving more than a third of their support from general, public sources must also file Schedule B if they receive an individual contribution greater than 2% of total contributions. Amounts and descriptions from a public charity’s Schedule B are made available for public inspection, but information identifying contributors is not.

<sup>6</sup>To create the Core file, NCCS cross-checks and cleans data from the various IRS databases and from organizations’ 990s when necessary. NCCS carries out a variety of procedures to check and clean the data. A detailed description of the Core Files and other data is available from the National Center for Charitable Statistics (2006).

financial data,” although inattention by filers adds noise to the data and purposeful expense shifting may inflate program-related expenses relative to administrative expenses (Froelich and Knoepfle, 1996). This study makes limited use of expense categories and explicitly examines manipulation of revenue around the Form 990 reporting notch.

Several financial variables from each form appear in the data. In this paper I focus on gross receipts. “Contributions, gifts, grants, and similar amounts received” make up the largest component of gross receipts. The other components are program service revenue, membership dues, investment income, gross sales of inventory, gross sales of other assets, and other revenue, all of which appear in the data. Total assets, liabilities, and expenses are each available for both types of filing. While both forms require listing all officers, directors, and trustees and the compensation paid to each, compensation only appears in the data for organizations that filed Form 990.<sup>7</sup> Other variables populated for all filings include the date at which tax-exempt status was granted, reasons for 501(c)(3) status, and codes describing the type of organization and services provided. I do not use the limited set of variables collected from Schedule A, which includes lobbying and other political expenses that equal zero for a large majority of organizations.

I analyze public charities in filing years 1990 to 2010, the years for which data on public charities are currently available. Marx (2012a) compiled data on private charitable foundations going back to the 1960s, but private foundations file Form 990-PF and hence do not face the same notch as public charities. Data for each NCCS file year comprise the most recent return filed by each organization. Unfortunately, the variable indicating whether organizations filed Form 990 or 990-EZ is not available for file years preceding 2006. I use the Form 990 variable to show that the receipts notch is a binding constraint for many charities in 2007 but use observations from the earlier years throughout the analysis.

Table 2 provides summary statistics showing the prevalence of small charities. The \$100,000 receipts notch (which has been defined nominally and not adjusted for inflation) falls between the lower quartile and median of gross receipts. Expenses are highly correlated with gross receipts, while assets exhibit greater variation. Of the more than four million observations in the data, over 20,000 have receipts in a region around the notch. The IRS and NCCS classify charities according to the National Taxonomy of Exempt Entities, which groups charities into major and minor categories. Education is the most common major category among organizations near the notch, of which many fall into minor categories indicating organizations that support schools. Other charities of this size include religious groups, arts organizations, and athletic leagues.

Figures 1 and 2 show that the filing notch binds, and charities bunch below the notch. Figure 1 shows that, for charities with fiscal years that begin in 2007, the probability of filing Form 990 is discontinuous

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<sup>7</sup>Form 990 contains separate lines for compensation of current officers and directors, former officers and directors, and other employees, while Form 990-EZ contains just one line for “Salaries, other compensation, and employee benefits.”

at the receipts notch. Just under half of organizations with receipts just below the \$100,000 notch file Form 990-EZ. About 17% of firms in this region must file the longer form because their assets are above the \$250,000 notch. The others to file Form 990 by choice, perhaps to satisfy donors or because they had filed it in the past. The fact that some firms choose to voluntarily file Form 990 suggests heterogeneity in organizations' cost structures or preferences. Since recordkeeping accounts for much of the estimated cost difference between the two types of filing, organizations that have already made the necessary investment in their administrative capacity would find it less costly to switch to the longer form. Among those with 2007 current receipts below the notch and 2006 receipts above, nearly 80 percent continue to file Form 990. In the empirical analysis I present further evidence that adjustment is a primary component of the compliance cost, with organizations that have previously filed the long form showing little propensity to bunch below the notch. The fact that a considerable share of organizations file Form 990 before reaching the notch should be kept in mind when interpreting results but does not affect the analysis except for the fact that it will not be possible to identify a strictly dominated income region as in the work of Kleven and Waseem (2012).<sup>8</sup>

This study analyzes income responses to the notch.<sup>9</sup> Figure 2 shows a histogram of receipts. The distribution of receipts is smooth except for an excess of mass just below the notch. This excess of mass of bunchers is the object of interest, as supported by the model in the next section. Charities must also file Form 990 if their assets exceed \$250,000, but bunching at this asset notch is less conspicuous. Tests suggest a small discontinuity in the density of assets with statistical significance that is sensitive to the choice of bin width. The asset notch is binding for fewer organizations, since roughly 72% of charities with assets between \$200,000 and \$250,000 have receipts over \$100,000, and an additional 15% in this range file the full Form 990 by choice. I therefore focus on the receipts notch in the model and empirical analysis.

### 1.2.3 A Simple Model of Welfare Effects of a Notch Policy

This section presents a welfare analysis to provide a conceptual framework for evaluating bunching estimates. The model demonstrates that the optimal location of the notch depends on the counterfactual density near the notch and the excess bunching mass below it, quantities estimated in other bunching studies to measure the taxable income elasticity. In the model, policy design weighs the social value of obtaining information through reporting requirements against the costs these requirements impose, including the avoidance costs of organizations that bunch.

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<sup>8</sup>Charities filing Form 990 by choice are relatively young, rapidly growing, high-expense, and with most receipts in the category "Contributions, gifts, grants, and similar amounts received." Variation across states shows no clear pattern; Illinois, Maine, and Pennsylvania have auditing requirements that apply to charities with contributions at levels below \$100,000 but do not have a significantly higher share of Form 990 filers.

<sup>9</sup>If the level of receipts was exogenously determined then Figure 1 could represent the first stage in a fuzzy regression discontinuity study of the effect of Form 990 on, say, donations received. Since organizations can manipulate their receipts by varying fundraising expenditures or shifting receipts across years, regression discontinuity is not appropriate.

## The Charity

A charity seeks to maximize expendable net income  $x$ . The charity earns receipts (income)  $y$  and reports receipts  $r := y - a$  to the government, where the amount  $a$  is kept hidden by tax avoidance or evasion. The total cost to the charity is the sum of the cost  $A(y, a, \gamma, \omega)$  of avoidance and the cost  $B(y, \omega)$  of earning the amount  $y$  in receipts, where  $\gamma$  is a vector of parameters describing heterogeneity and  $\omega$  is a parameter describing heterogeneity in fundraising ability that is unrelated to (but perhaps correlated with) the cost of avoidance. Assume the cost functions are nondecreasing and convex in  $y$  and  $a$  and that  $A_y(y, 0, \gamma, \omega) = 0$ . This formulation is in keeping with the “general model of behavioral response to taxation” of Slemrod (2001); the cost of avoidance includes both direct psychic or financial costs as well as changes to the expected cost of an audit, and avoidance opportunities may vary with income. The organization must also pay filing cost  $\phi(\gamma, \omega)$  if  $r > \rho$ , the filing threshold. The budget constraint is thus  $x \leq y - A(y, a, \gamma, \omega) - B(y, \omega) - \phi(\gamma, \omega) \cdot 1\{r > \rho\}$ , and the firm’s problem is

$$\max_{y, a} \{y - A(y, a, \gamma, \omega) - B(y, \omega) - \phi(\gamma, \omega) \cdot 1\{y - a > \rho\}\}$$

If the filing constraint does not bind then optimal avoidance is zero, and the first-order condition  $B_y(y, \omega) = 1$  defines the optimal value of receipts  $\bar{y}(\omega)$  as that level of fundraising at which the marginal cost of raising one dollar has reached one dollar. Because  $\bar{y}(\omega)$  plays an important role throughout the analysis, from this point I simply describe fundraising heterogeneity in terms of  $\bar{y}$ . There will be a one-to-one relationship between  $\bar{y}$  and  $\omega$  if  $\frac{d\bar{y}}{d\omega} = -\frac{B_{y\omega}(y, \omega)}{B_{yy}(y, \omega)} > 0$ , implying that the inverse function  $\omega(\bar{y})$ . I therefore rewrite  $\phi(\gamma, \omega)$  as  $\phi(\gamma, \bar{y})$  and define  $C(y, a, \gamma, \bar{y}) = A(y, a, \gamma, \omega(\bar{y})) + B(y, \omega(\bar{y}))$ .

If the filing constraint does bind, i.e. optimal reported income is  $r = \rho$ , then  $y - a = \rho$ , and the problem becomes

$$\max_y \{y - C(y, y - \rho, \gamma, \bar{y})\}$$

In this case the first-order condition gives  $C_y(y, a, \gamma, \bar{y}) = 1 - C_a(y, a, \gamma, \bar{y})$ . Receipts fall short of  $\bar{y}$  because marginal earnings increase the necessary amount (and therefore cost) of avoidance. Call the level of receipts that satisfies this condition  $\hat{y}(\gamma, \bar{y})$ , which I will generally write simply as  $\hat{y}$ .

When will the charity bunch at the reporting threshold? If  $\bar{y} \leq \rho$  there is no need to misreport. If  $\bar{y} > \rho$  then the charity obtains  $\hat{y} - C(\hat{y}, \hat{y} - \rho, \gamma, \bar{y})$  if it reports  $r = \rho$  and  $\bar{y} - C(\bar{y}, 0, \gamma, \bar{y}) - \phi(\gamma, \bar{y})$  if it does not. The charity will therefore bunch if and only if  $\phi(\gamma, \bar{y}) \geq (\bar{y} - \hat{y}) - [C(\bar{y}, 0, \gamma, \bar{y}) - C(\hat{y}, \hat{y} - \rho, \gamma, \bar{y})]$ . Because costs are convex we can define  $\delta(\rho, \phi, \gamma, \bar{y})$  as the maximum difference (possibly zero) between  $\bar{y}$

and  $\rho$  from which the organization would be willing to choose  $r = \rho$ . That is, a charity bunches at the notch if  $\rho < \bar{y} \leq \rho + \delta$  ( $\rho, \phi, \gamma, \bar{y}$ ). Again simplifying notation, I will suppress the arguments of  $\delta$ .

Reported receipts are

$$r = \begin{cases} \bar{y} & \bar{y} \leq \rho \\ \rho & \rho < \bar{y} \leq \rho + \delta \\ \bar{y} & \bar{y} > \rho + \delta \end{cases}$$

The charity obtains indirect utility

$$V(\rho, \phi, \gamma, \bar{y}) = \begin{cases} \bar{y} - C(\bar{y}, 0, \gamma, \bar{y}) & \bar{y} \leq \rho \\ \hat{y} - C(\hat{y}, \hat{y} - \rho, \gamma, \bar{y}) & \rho < \bar{y} \leq \rho + \delta \\ \bar{y} - C(\bar{y}, 0, \gamma, \bar{y}) - \phi & \bar{y} > \rho + \delta \end{cases}$$

Note that  $\rho$  enters directly for bunchers but not others. This implies that changes to the location of the threshold will have first-order effects on the utility of inframarginal bunchers (but not others).

## The Government

The government's problem is to maximize the net value of the reporting regime. Social welfare includes the indirect utility of charities as well as the (external) social benefit obtained from reporting. The social benefit of an organization's disclosure spending, net of the administrative cost to the government, is  $\pi(\phi, \gamma, \bar{y})$ . Potential income is distributed with cumulative distribution function  $F(\bar{y})$  and probability density function (pdf)  $f(\bar{y})$ . The heterogeneity parameter  $\gamma$  has pdf  $g(\gamma)$ . Social welfare per firm<sup>10</sup> is

$$\begin{aligned} W &= \int \left[ \int_0^\infty V(\rho, \phi, \gamma, \bar{y}) f(\bar{y}) d\bar{y} + \int_{\rho+\delta}^\infty \pi(\phi, \gamma, \bar{y}) f(\bar{y}) d\bar{y} \right] g(\gamma) d\gamma \\ &= \int \left[ \int_0^\infty (\bar{y} - C(\bar{y}, 0, \gamma, \bar{y})) f(\bar{y}) d\bar{y} + \int_{\rho+\delta}^\infty (\pi(\phi, \gamma, \bar{y})) f(\bar{y}) d\bar{y} \right. \\ &\quad \left. - \int_{\rho+\delta}^\infty \phi(\gamma, \bar{y}) f(\bar{y}) d\bar{y} + \int_\rho^{\rho+\delta} [\hat{y} - \bar{y} - (C(\hat{y}, \hat{y} - \rho, \gamma, \bar{y}) - C(\bar{y}, 0, \gamma, \bar{y}))] f(\bar{y}) d\bar{y} \right] g(\gamma) d\gamma \end{aligned}$$

With the social welfare function written as the sum of these four terms, one can immediately see how policy will affect social welfare. Policy-makers can influence two parameters, the location of the notch and

<sup>10</sup> Donor utility is excluded from the social welfare function, as recommended in research on optimal taxation of charitable giving (e.g., Andreoni (2006), Diamond (2006)). In addition to their arguments there is evidence that fundraising reduces the utility of the average prospect (DellaVigna et al., 2012).

the cost of reporting. Increasing the amount or complexity of information reported on the long form will increase  $\phi$ . From terms two and three one sees that this will directly increase welfare to the extent that this new information is of net social benefit but will reduce the number of number of charities filing the long form. The choice of how much detail to require in financial reports is therefore similar to optimal screening of social benefits under imperfect takeup because greater complexity has direct benefits but may reduce participation (Kleven and Kopczuk, 2011). I will not attempt to estimate the social value of reporting.<sup>11</sup> It turns out, however, that the optimal location of the threshold depends on estimable quantities analogous to those studied in the tax bunching literature. Marginal changes to  $\rho$  will affect all but the first term in the social welfare function, but marginal bunchers (with  $\bar{y} = \rho + \delta$ ) experience no first-order utility changes due to the indifference condition  $\phi(\gamma, \bar{y}) = ((\rho + \delta) - \hat{y}(\rho + \delta)) - [C(\rho + \delta, 0, \gamma, \bar{y}) - C(\hat{y}(\rho + \delta), \hat{y}(\rho + \delta) - \rho, \gamma, \bar{y})]$  and indifference for those with  $\bar{y} = \rho$ . After using the indifference conditions to cancel terms,

$$\frac{dW}{d\rho} = \int \left[ \int_{\rho}^{\rho+\delta} C_a(\hat{y}(\bar{y}), \hat{y}(\bar{y}) - \rho, \gamma, \bar{y}) f(\bar{y}) d\bar{y} \right] g(\gamma) d\gamma - \int (1 + \delta_{\rho}) \pi(\rho + \delta, \phi, \gamma, \bar{y}) f(\rho + \delta) g(\gamma) d\gamma$$

Raising the threshold has two counteracting effects. First, charities that were bunching achieve some savings because they no longer have to avoid reporting as much income. Second, raising the threshold reduces the amount of information available to the extent that previously-indifferent charities now bunch at the threshold.

The expression for the welfare effect of moving the notch becomes simpler when written in terms of averages in the region from which bunching occurs. The main identifying assumption in bunching estimation is that bunching is local and there exists some  $\bar{\delta} = \max(\delta(\rho, \phi, \gamma, \bar{y}))$ . The localness assumption restricts the degree of heterogeneity and would hold, for example, if there is an  $M > 0$  such that for all  $\gamma, \bar{y}$  and  $y$  we have  $C_a(y, 0, \gamma, \bar{y}) \geq M$ . Denote the excess mass observed below the notch as  $B := \int \left[ \int_{\rho}^{\rho+\delta} f(\bar{y}) d\bar{y} \right] g(\gamma) d\gamma = b(F(\rho + \bar{\delta}) - F(\rho))$ , where  $b$  is the share of organizations that choose to bunch. Assume that  $\frac{db}{d\rho} \approx 0$ ,  $\frac{d\bar{\delta}}{d\rho} \approx 0$ , and  $\exists \bar{\pi} : \forall \gamma, \bar{y} \in [\rho, \rho + \delta], \pi(\phi, \gamma, \rho + \delta) \approx \bar{\pi}$ . In words, slight movements of the notch have little effect on the share of organizations that bunch, the maximum amount by which they will reduce income, or the social value of the average buncher's report. The first two assumptions are effectively the same as the simplifications common in the taxable income bunching literature, while the third is useful here due to the potential heterogeneity in the social value of reporting.

The simplifying assumptions make it possible to rewrite the term describing the welfare effect of lost

<sup>11</sup>Potential benefits would include reductions in avoidance/evasion on other margins. Examinations of tax-exempt organizations in 1998 through 2005 resulted in recommended additional tax payments (for taxable transactions including payroll and unrelated business income) averaging \$106 million per year (Internal Revenue Service, 1998-2005). I have found no sources that present enforcement statistics by form filed.

reports as  $-\bar{\pi} [bf(\rho + \bar{\delta}) + (1 - b)f(\rho)]$ .<sup>12</sup> That is, the value of long forms lost is the product of their average value and the change in the share of charities that bunch. Under the simplifying assumption that bunching is proportional to mass in the reduced range, the change in the share of charities that bunch is the weighted average of the values taken by the underlying density at the top and bottom of the reduced range. The welfare criterion for the optimal location of the notch is thus

$$\frac{dW}{d\rho} \geq 0 \Leftrightarrow \frac{\bar{\pi}}{E[C_a(\hat{y}, \hat{y} - \rho, \gamma, \bar{y}) | \rho < \bar{y} \leq \rho + \bar{\delta}]} \leq \frac{(F(\rho + \bar{\delta}) - F(\rho))}{(bf(\rho + \bar{\delta}) + (1 - b)f(\rho))}$$

The expression for the welfare effects of moving a regulatory notch includes factors comparable to those arising from the choices of marginal income tax and VAT rates studied in the literature. When administrative costs increase with the number of covered firms, the optimal income exemption threshold for a value-added tax will induce bunching if the revenue effects are small (Dharmapala et al., 2011). The net benefit of reporting  $\bar{\pi}$  plays a role similar to that of tax revenue, although this benefit varies across organizations (as reflected in the fact that only larger organizations are required to file the long form). The regulatory problem is similar to setting a minimum wage or tax rates at low incomes, where extensive-margin responses are likely more important than intensive-margin responses (Saez, 2002). The expression on the right-hand side of the inequality is a version of the ratio that arises in other bunching studies that are motivated by the problem of setting marginal tax rates. The existing literature uses the relationship  $b(F(\rho + \bar{\delta}) - F(\rho)) = B \approx b\bar{\delta}f(\rho)$  to back out an estimate of  $\bar{\delta}$  from estimates of the counterfactual distribution and excess mass. Kleven and Waseem (2012) estimate a parameter similar to  $b$  by using the known amount of a tax to identify a strictly dominated region just above the notch, taking those that remain in this region as the share that cannot bunch. I do not observe the exact reporting costs, which I expect to exhibit heterogeneity, and will instead use dynamic techniques to estimate  $b$ . Because  $b$  is small, and in keeping with other bunching studies, I will report the bunching ratio as the ratio of excess mass to the value of the counterfactual distribution at the notch (rather than the weighted average).

Naturally, it is far more difficult to estimate the marginal cost  $C_a(\hat{y}, \hat{y} - \rho, \gamma, \bar{y})$ . The distribution of reported income reveals income responses, but the cost of these responses is not identified without another source of variation. Though the marginal benefits of real and avoidance responses are equated (per the first-order condition) and have the same implications in the model (as is generally true unless externalities or other considerations are incorporated), evidence of avoidance is useful in at least two respects. First, relative to a world in which avoidance was prohibitively costly, evidence of avoidance would indicate a lower

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<sup>12</sup>  $-\int [(1 + \delta_\rho)\pi(\phi, \gamma, \rho + \delta)f(\rho + \delta)]g(\gamma)d\gamma \approx -\bar{\pi}\int [(1 + \delta_\rho)f(\rho + \delta)]g(\gamma)d\gamma = \bar{\pi}\frac{d}{d\rho}\int [f_{\rho+\delta}^\infty(\bar{y})d\bar{y}]g(\gamma)d\gamma = \bar{\pi}\frac{d}{d\rho}[1 - b(F(\rho + \bar{\delta}) - F(\rho)) - F(\rho)] \approx \bar{\pi}[-b(f(\rho + \bar{\delta}) - f(\rho)) - f(\rho)] = -\bar{\pi}[bf(\rho + \bar{\delta}) + (1 - b)f(\rho)]$ .



total cost of manipulating income to stay below the notch, making it less desirable to raise the notch to a higher level of receipts. Second, the extent of avoidance affects inference of the preferences of charities. The amount by which a charity reduces reported receipts in order to bunch provides an upper bound on willingness to pay to avoid reporting because avoidance allows the organization to pay less than the full amount of this reported income reduction. The bound approaches the true value of willingness to pay as the marginal cost of avoidance approaches one. I obtain some evidence of the extent of avoidance by comparing short-run and long-run responses.

The theory in this section motivates the estimation of the excess mass  $B$ , the bunching share  $b$ , and the counterfactual density at the notch  $f(\rho)$ . I now turn to estimation of these parameters using static and then dynamic techniques.

### 1.3 Benchmark Static Techniques For Estimating Bunching

Before presenting the dynamic bunching research design I follow the static approach used in the literature. I describe the technique for the unfamiliar reader, display the results for public charities, then explore what insights can be obtained within this framework by incorporating other variables, including those requiring panel data.

#### 1.3.1 The Static Methodology for Estimating Bunching

Bunching empirics exploit distortions in distributions around thresholds at which income or prices change discretely. By estimating the excess mass around a threshold one can obtain reduced-form estimates of policy-relevant behavioral elasticities. Saez (2010) introduced this insight by showing how kinks in marginal tax rates produce a pattern of bunching in the income distribution that reveals the taxable income elasticity without the need to specify a particular utility function. Individuals with incomes above a kink that raises the marginal tax rate have an incentive to reduce reported income, and the greater the income elasticity the more bunching will be observed in the distribution around the kink. Bunching estimation, both at kinks and at notches, quantifies the extent of bunching by comparing the observed distribution to an estimate of the smooth counterfactual that would be expected in the absence of the threshold.

The key to bunching estimation is to construct the counterfactual distribution of income. Static bunching estimates use parts of the density above and below a threshold to construct a counterfactual for the amount of mass that should be at the threshold. Figure 3 provides an example of the static procedure as applied to the Form 990 filing notch. Most studies approach the distribution as a histogram, constructing bins and plotting the count of observations in each bin as depicted by the circles in Figure 3. The number of observations

within some number of bins of the threshold is compared to a counterfactual constructed using bins further away from the threshold. That is, the researcher estimates the counterfactual density by omitting a certain number of bins around the threshold (the “omitted region”) and then estimating a smooth function through the values of the other bins. Figure 3 displays the estimated counterfactual as the smooth curve through the data. Some authors construct the counterfactual by taking a simple average of the bin just above the omitted region and the bin just below it, an appropriate counterfactual under the assumption of local linearity of the distribution. Others use a wider range of the distribution and fit polynomials to the bin counts in this range (except for the omitted region around the threshold). In Figure 3 I provide an example using charities with receipts of \$50-200,000 and a polynomial of degree 3, which minimizes the Akaike information criterion.

Kinks and notches offer slightly different implications. In the case of a kink, incomes may bunch on either side of the threshold, so the bunching estimate is the sum of all excess mass observed in the omitted region. In the case of a notch, observations that should be on one side of the threshold will instead bunch on the other. For a notch at which costs increase there will be excess mass in the bunching range below the notch and reduced mass in the reduced range above the notch.<sup>13</sup> Both the excess mass and reduced mass can be estimated by comparing the observed density to the counterfactual. Estimation of bunching at kinks requires the further step of raising or lowering the counterfactual distribution on the side of the kink where prices are affected, but this step is not necessary for a notch at which fixed costs are imposed because other than income effects there should be no responses far from the threshold.

### 1.3.2 Static Estimation Results

Using the static approach, I estimate significant bunching of public charities at the reporting notch. In the pooled sample a significant excess share of charities appears below the notch and the reduction in the share above the notch is even larger. Annual results show the response of charities to removal of the notch.

Static bunching estimates for the pooled sample appear in Table 3. I use the sample of charities in years up to 2007 that also appear in the prior year (for maximum comparability with the dynamic estimates that follow). The first row of the table shows estimates of excess mass below the notch, the numerator  $B$  of the bunching ratio. An estimate of .1 would indicate .1 percent of all charities in that year’s sample are below the notch and should be above it. The results from the basic specification, a cubic counterfactual as depicted in Figure 3, indicate that the share of charities appearing below the notch is .148 percentage points greater than predicted by the counterfactual. In the second row this number is divided by the value of the density at the notch to give the bunching ratio that is derived from theory in this and other settings. The bunching

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<sup>13</sup>I use “reduced” in place of the term “missing” that appears in the literature to maintain a distinction between organizations that shift receipts and those that go missing from the data.

ratio reveals that the number of bunching charities is roughly equal to the number of charities that should be above the notch by up to \$600 ( $=\$100,000 \cdot .00592$ ). If all income responses are real, this estimate would imply the average charity is willing to pay \$600 to file Form 990-EZ instead of Form 990. The third row displays estimated reduction of mass above the notch, which is .25 percent of the sample.

The estimates in Table 3 raise the question of why the reduction in the number of charities above the notch is significantly larger than the addition below the notch. The basic specification suggests the excess is only about 60% of the reduction, and the size of the reduction suggests charities may be willing to pay as much as \$1000 to avoid Form 990. The difference between the estimated excess and reduction could arise due to attrition because, say, Form 990 is more difficult to complete on time and hence more data are missing above the notch. It is not clear how we would test the static specification or whether we should require the excess to equal the reduction. The second and third columns present the results of more flexible specifications that do not reconcile the two results. Allowing for a discontinuity at the notch reduces the estimate on both sides by a very small amount, leaving the asymmetry in the estimates. Estimating a separate polynomial on each side of the notch gives a similar point estimate of the excess but a much larger standard error, and the lack of curvature in the distribution above the reduced range yields an insignificant estimate of the reduced mass. With the dynamic design I will provide support for the basic specification of the static estimate. I will use the distribution of receipt growth to show that the reduction above is greater than the addition below because charities that should be crossing the notch instead drop out of the sample.

Annual static estimates raise another potential question. Figure 4 displays annual cross-sectional estimates of the excess bunching mass.<sup>14</sup> Point estimates are generally around .15, the estimate for the pooled sample, with some variation from year to year. Surprisingly, excess mass remained at incomes just below \$100,000 even after the notch was moved to \$1,000,000 in 2008. The estimate of .150 for 2008 (with standard error .039) is among the upper half of all the static estimates and significantly different from zero. Gelber et al. (2012) find similar delays in the adjustment of some individuals' earnings to removal of the Social Security earnings test. One potential explanation would be that the extra charities remaining in the bunching region were former bunchers who were unable to raise their receipts rapidly when the notch was moved. An alternative possibility is that the staff of charitable organizations did not understand that the notch had moved and that they continued to actively keep income below \$100,000.<sup>15</sup> The dynamic approach offers a way to distinguish between these possibilities by looking for distortions in the 2008 receipts of charities that were below the notch in 2007. Estimates obtained from the dynamic methodology described in Section

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<sup>14</sup>For the presented annual results I reduce the allowed bunching range to just \$90-100,000, which yields more-tightly-grouped estimates with smaller standard errors.

<sup>15</sup>The revised form for fiscal years starting in 2008 was released in June of 2007, and 99.9 percent of organizations in the NCCS data filed the correct 2008 form for their 2008 fiscal year. While the income eligibility level for the 990-EZ is stated near the top of the form, it is possible that uninformed filers did not look closely and misread the \$1,000,000 as the usual \$100,000.

1.6 support the notion that charities continued to manipulate income in 2008. According to the dynamic approach, an estimated .088 percent of charities (with standard error .041) had receipts below \$100,000 in 2007 and chose the remain below \$100,000 when they could have crossed. An additional .098 percent (with standard error .035) would have moved to the region just above the notch but instead left the sample.

### 1.3.3 Exploring Heterogeneity in the Static Framework

Other variables can provide additional information about heterogeneity in the income response. I show that the static bunching design can exploit panel data to determine whether total bunching is widespread or attributable to a small number of repeated bunchers. I then present growth rates by level of receipts as an example of correlation between income bunching and another variable. These examples indicate some difficulties in interpreting correlations when agents face the same notch repeatedly, which motivates the use of dynamic bunching estimation.

Testing for repeated bunching is straightforward. Repeated bunching is the act of remaining below the notch for more years than expected, so the goal is to estimate the share of charities that would remain near current receipts if the notch did not exist. To estimate repeated bunching I construct bins of current receipts and estimate the probability that in  $h$  years the organization remains in its current bin. That is, I partition receipts into bins of width  $bw$  and estimate

$$(1) \quad D(bin_i)_{i,t+h} = \beta \cdot bunchbin + \sum_{k=1}^K \alpha_k r_{it}^k + \gamma_t$$

where  $D(bin_i)_{i,t+h} = 1 \{r_{i,t+h} \in bin_i \cap r_{i,t} \in bin_i\}$  is an indicator for remaining in the same bin  $h$  years in the future,  $bunchbin = 1 \{r_{it} \in [notch - bw, notch)\}$  is an indicator for having current receipts in the bunching range,  $\sum_{k=1}^K \alpha_k r_{it}^k$  is a polynomial in receipts that provides the counterfactual for the bunching range, and  $\gamma_t$  is a vector of year dummies.<sup>16</sup>

I find that charities bunch at the reporting notch for many years. Figure 5 shows the probability of remaining within a \$5000 receipts bin three years into the future. This probability varies smoothly with receipts except just below the notch. Among observations in the bin just below the notch, about 5.7 percent remain in the same bin, compared to a counterfactual prediction of only 5 percent.

Table 4 reports the results from estimating regression (1) for horizons up to 10 years. Observations in the bin just below the notch are about 1.55 percentage points more likely to remain there the following year

<sup>16</sup>Since crossing the notch requires a positive growth rate, one could alternatively nonparametrically regress the probability of positive growth on current receipts and estimate any discontinuity at the notch. Such an approach might work well if agents are able to bunch precisely at the exact value of the notch but would underestimate bunching if manipulation is imprecise and bunchers' receipts move around within the bunching range. Manipulation indeed appears to be imprecise around the Form 990 notch, and the choice of bin width should reflect the range of incomes that appear to exhibit bunching. In this setting, similar results obtain for different bin widths and Probit specifications.

than would be predicted by surrounding observations. This excess probability of staying in the same range of income declines over time but remains significantly positive for at least five years. Bunching is persistent, suggesting the proclivity to bunch is much stronger in some organizations (the repeat bunchers) than others.

In principle, heterogeneity can be described in the static setting by plotting any other variable as a function of income. Figure 6 presents another example using panel data. The outcome is the growth of log receipts from the previous year to the current year. The average growth rate is discontinuous in receipts, with charities just below the notch having significantly higher growth rates than charities just above. Graphs of this sort may offer a clear interpretation in some cases, but caution is warranted. Here there is an issue of simultaneity: bunching is itself a manipulation of the growth rate, but the growth rate may affect the propensity to bunch. At the same time, plotting variables that are distorted against current income may not reveal the distortion in these variables. Income, for example, would obviously show no discontinuity in itself. Similarly, if expenses are always proportional to reported income then these will also appear undistorted despite responding to the notch in proportion to the income response. In general it will be difficult to tell cause from effect or to disentangle simultaneous responses in multiple variables without making strong assumptions about functional forms.

The static approach provides clear evidence of income responses. Exploiting panel data within the static framework we can also see that observations stay in the bunching region for many years and that growth is distorted at the notch, providing immediate evidence that bunching is a dynamic process in which past income is relevant. I now model the dynamic bunching process explicitly.

## 1.4 Introduction to Dynamic Bunching Estimation

Here I describe a dynamic approach to bunching analysis. The idea is to look for distortions not just in the univariate distribution of current income but also in the joint distribution of income in multiple periods. My implementation of dynamic bunching estimation tests for manipulation in the joint distribution of current and future income. Income manipulation is identified under smoothness assumptions about the distribution of growth conditional on current receipts.

When agents face notches repeatedly their choices over time may reveal more information than is captured in the cross section. Because notches and kinks are often fixed in real or nominal terms, they may affect the same agents year after year. These agents therefore face a notch both in current income and future income. With panel data it is possible to observe agents' choices in multiple years and estimate the joint distribution of income over these years.

The intuition of static bunching estimation extends naturally to the multivariate distribution of current

and future incomes. For each year in the data, some agents whose incomes should be just above the notch will instead be observed just below the notch. Thus, in the joint distribution of this year’s income and next year’s income, for example, we should therefore observe bunching of both current incomes and future incomes below the notch and perhaps some interaction between the two periods. To estimate these distortions one must again construct a counterfactual distribution in a neighborhood of the now-multi-dimensional notch.

Relative to the univariate distribution of current income, the joint distribution of current and future income offers the researcher more options. A straightforward option appearing in the literature is to ignore intertemporal correlations and simply pool years as repeated cross sections and perform static estimation. More generally, one could simply estimate the entire multivariate density of income in each year. Allowing such generality, however, would be computationally expensive. To simplify the analysis while retaining potentially valuable correlations the researcher could transform, segment, or collapse the distribution. For example, the univariate procedure could be applied to the subsequent income of agents with current incomes in a range of interest. Regardless of the implementation choice, the the empirical strategy will seek to estimate distortions around the notch in the relevant dimensions.

I perform dynamic estimation in terms of the distribution of log current receipts and growth to the next year’s log current receipts. The joint distribution of current receipts and growth is isomorphic to the joint distribution of current and future receipts: labeling current log receipts  $r_t$ , growth  $g_t = r_{t+1} - r_t$ , and the notch in future income *notch* implies that conditional on current receipts there is a unique level of growth ( $g_t = \textit{notch} - \log r_t$ ) that puts receipts at the notch in the next year. Bunching will manifest in the distribution of growth from current income as an excess share of organizations growing at rates just below that which brings them to the notch and a reduced share growing to just above it. Future bunching can be estimated conditional on any level of current receipts by constructing a counterfactual distribution of conditional growth rates.

Distortions in the distribution of growth rates can be identified if this distribution does not change sharply as current income varies. Figure 7 conveys the idea behind the identification strategy in this form of dynamic bunching estimation. Panel A shows the distribution of income in the next year for three illustrative ranges of current income. Each conditional distribution of future receipts is centered around the level of current receipts. For each group, the distribution of future income is distorted around the notch, with excess mass just to the left and reduced mass just to the right. Panel B shows the distribution of growth rates for each group, a simple translation of the group’s future income. Charities with different levels of current receipts have similarly-shaped growth distributions, except that each has a bunching distortion wherever the notch lies in its distribution (in bold). Local responses to the notch will not affect the growth distribution away from the notch. Each group’s growth distribution has a similar shape for most levels of growth and

distortions at different levels of the growth than other groups. The extent of the distortions can therefore be estimated by comparing the shape of one group’s growth distribution around its notch to the corresponding, undistorted section of the growth distribution among charities that are a different distance from the notch.

The dynamic approach estimates the same measures of income distortions as the static estimates but relies on arguably more attractive assumptions of smoothness of conditional rather than unconditional distributions. The static approach assumes that (1) the distribution of current receipts would be continuous and smooth in the absence of the notch and that (2) deviations from this counterfactual distribution all occur within a neighborhood of the notch. What is required for consistent dynamic estimation of bunching using my approach is that (1’) in the absence of the notch the distribution of growth conditional on current receipts would vary smoothly with growth and current receipts, so that one can use the distribution of growth at other income levels as a counterfactual, and that (2’) the manipulations of conditional growth all occur within a neighborhood of the notch. It is possible for either pair of assumptions to hold while the other fails, though plausible behavioral patterns seem more likely to violate the static assumptions. In Appendix A I discuss examples of behavior that would yield biased static estimates but consistent dynamic estimates.

I implement the dynamic estimation strategy in two ways. First, in Section 1.5, I construct bins of the joint distribution of current (log) receipts and conditional growth to the next year’s (log) receipts and perform OLS and IV regressions. This reduced-form procedure provides a novel but intuitive means of comparing “treated” charities approaching the notch to “control” charities with similar growth rates but different starting points and hence future receipts away from the notch. With the reduced-form regressions I describe distortions close to the notch and test for heterogeneous responses and long-run effects. In Section 1.6 I use maximum likelihood to obtain precise estimates of the extent of income manipulation and extensive-margin responses.

## **1.5 Dynamic Estimation of Bunching Characteristics**

Using a dynamic approach to bunching estimation I present an easily-implemented method for characterizing the manipulation of income around a notch and testing the importance of various factors that might relate to this manipulation. I estimate the propensity to bunch within a neighborhood of the notch, the amount by which income is manipulated within this neighborhood, and the traits that predict whether a charity will bunch.

### **1.5.1 Methodology for Describing Bunching**

Dynamic estimation provides an opportunity to describe the propensity to bunch, the means by which agents bunch, and heterogeneity in each. The idea is to compare those whose growth will bring them near a notch

to a counterfactual constructed using those with similar growth rates but different levels of current income. Here I implement this approach by binning the bivariate distribution of current receipts and growth rates, which allows for convenient graphical illustration and analysis of heterogeneity. The binning approach in this section will provide transparent evidence of whether, conditional on current income, those approaching the notch will move to lower income levels than predicted in order to stay below the notch. In this framework it is straightforward to test which traits predict manipulation of future income.

I now argue that if responses to a notch are local then it is possible to construct treatment groups and control groups that are not selected on the basis of whether they bunch. Consider a range of growth rates, say growth of 10 to 20 percent. Charities with current receipts 20 percent below the notch will be especially likely to have growth in this range, which would put them in the bunching range in the next year. Charities 10 percent below the notch will be especially unlikely to have growth in this range, which would put them in the reduced range in the next year. The group of charities growing 10 to 20 percent from either of these starting points will therefore contain a selected group with too many or too few bunchers. However, there is an intermediate range of current receipts for which the growth range of 10 to 20 percent gives a range of future receipts that spans the notch. Call charities in this intermediate range of current receipts the treatment group. If responses to the notch are local then, for charities with current receipts in the treatment group, the growth range of 10 to 20 percent will include both bunchers and nonbunchers. That is, if we choose a wide enough range of growth rates to include both the bunching and reduced regions then the bunching response should not affect the total share of organizations growing at a rate within this range. For different ranges of growth rates we can identify different treatment groups that grow to a point *near* the notch and construct estimate counterfactual growth rates within this range using organizations with growth in the same range but higher or lower levels of current receipts.

Details of my implementation of the dynamic OLS estimates appear in Appendix A. The goal is to include a set of controls in current receipts and growth that will provide an accurate counterfactual for the group approaching the notch. Here I will simply provide visual evidence that my construction of treatment and control groups is reasonable. Figure 8 displays the probability of being in a particular growth range (growth of log receipts by .1 to .2) as a function of current receipts. The filled circle with confidence intervals indicates the probability among the treatment group of charities for whom this growth rate puts them near the notch in the next year. The probability of being *somewhere* in this growth bin is not distorted for these charities because the bins are wide enough to include both the bunching range and the reduced range. As expected, the share in the growth bin *is* distorted for charities just to either side of the “Near Notch” group (represented by light gray markers in Figure 8) because growth in this range puts these observations squarely in one of the distorted regions on either side of the notch. These charities are excluded from estimation of



the counterfactual. These results can be shown for any growth bin  $x$ . I define  $near\ notch_{xit}$  as an indicator for the treatment group of charities in this growth bin that will be near the notch in the next period and  $near\ notch_{it} = \sum_x (near\ notch_{xit} * 1_{\{x \leq growth_{it} < x+.1\}})$  for treated charities in any growth bin.

With this strategy of identifying treatment and control groups it remains only to define the outcomes of interest that will characterize responses. The primary outcome in which we should see responses is receipts growth, which should be reduced among charities nearing the notch. One can also examine the growth of other financial variables, including total revenues, expenses, and assets, to determine whether these are affected along with income. Finally, it will be useful to construct an indicator  $cross_{xit}$  for growth above the observation-specific rate corresponding to crossing the notch. For each observation in the treatment bin, the growth rate that will bring it to the notch is a simple function of location in the bin.<sup>17</sup> This same function can be applied to all observations, regardless of bin, to obtain the growth rate that *would* correspond to the notch if the observation were in the treatment bin. For growth rate range  $x$  to  $(x + .1)$ , I define  $cross_{xit}$  as an indicator for whether the charity grows by more than this rate. I will say an observation “crosses” if  $cross_{xit} = 1$ . Because  $cross_{xit}$  only has significance for the treatment bin, the relative probability of  $cross_{xit}$  will be reduced in the bin of interest by the share of charities that bunch and not affected for other bins. As with the treatment variable  $near\ notch_{it}$  we can stack regressions for all growth rate ranges if we define  $cross_{it} = \sum_x (cross_{xit} * 1_{\{x \leq growth_{it} < x+.1\}})$ . We can also examine long-run effects by defining  $cross_{it+s}$  using the growth rate over the next  $s$  years and estimate whether the probability of being across the notch  $s$  years is reduced in the future. Finally, interactions of  $near\ notch_{it}$  with other variables describing a charity offer straightforward tests for heterogeneity in the bunching response.

### 1.5.2 Estimation and Results Describing the Bunching of Charities

I now employ the dynamic design to describe the bunching of charities. Measures of income manipulation are highly significant for charities moving to a bin surrounding the notch. Manipulation occurs only among those not already filing Form 990 and is less common among larger charities. Short-run income manipulation by charities with administrative staff provides suggestive evidence of avoidance behavior, but the notch also has long-run effects on growth.

Before presenting regression results using multiple growth bins I provide a visual example using charities growing by .1 to .2 log points. Figure 9 plots the constructed variable  $cross_{.1it}$  as a function of current income. The filled circle with standard error bands shows the share that cross the notch among those for

<sup>17</sup>For a growth rate range of  $x$  to  $(x + .1)$  and bunching range of width  $Bwidth$ , the treatment bin has minimum value  $binmin_{it} = notch - Bwidth - x$ . Observations with receipts at the minimum of this bin will cross the notch if they grow by  $x + Bwidth$ . Other charities in the bin will cross the notch if growth is greater than  $x + Bwidth - (r_{it} - binmin_{it})$ .  $cross_{xit} = 1_{\{growth_{it} > x + Bwidth - (r_{it} - binmin_{it})\}}$ .

which  $near\ notch_{.1it} = 1$ , while empty circles and the quadratic fit display the outcome for charities with higher or lower current receipts. The counterfactual implies that over 40 percent of the charities nearing the notch should have crossed it, but instead less than 35 percent do so. These findings extend to charities in the other growth rate ranges that I now combine in estimation.

Regression analysis shows highly significant manipulation of receipts. In column (1) of Table 5 we see that receipt growth of charities that near the notch is lowered by .0017 log points. The average reduction is therefore about 0.17% of \$100,000, or \$170. The average is taken over all charities nearing the notch, whether they bunch or not. In column (2) we see that the probability of achieving growth that would imply crossing the notch is reduced by 4 percentage points. This regression of  $cross_{it}$  on  $near\ notch_{it}$  and controls is also the first stage of an instrumental variables estimate of receipt manipulation by bunchers themselves, the second stage of which is presented in column (3). The identifying assumption of the IV specification is that receipt growth of charities in the group approaching the notch only deviates from the counterfactual due to their responses to keep receipts below the notch. The IV results show that the average buncher reduces reported receipts by .0423 log points, or about \$4500. Unfortunately, the expense and asset growth outcomes that might signal the extent of avoidance are not precisely estimated; standard errors are larger than the direct effect of the notch on receipts, and underlying growth rates for these variables are similar to that of receipts. Such regressions may prove more informative in settings where more data are available or growth rates are less variable.

Next I estimate the effect of the notch on long-run growth. Table 6 displays the results of 12 regressions for the probability of crossing the notch in  $t$  years. The results show that the notch reduces crossing by about 1.5 percentage points for over a decade. The reduction in crossing is relative to the counterfactual share that should cross (not shown), which grows from 40 percent in year one to a bit over 75 percent in year ten.

In addition to these average responses, the dynamic estimation strategy provides illuminating tests for heterogeneity in responsiveness. Table 7 shows that smaller organizations are more likely to reduce income to stay below the notch. The outcome for each regression is the indicator variable  $cross_{it}$ . Interactions of total revenue, expenses, and assets (all in logs) with  $near\ notch_{it}$  reveal that larger charities are more likely to cross the notch when approaching it, i.e. less likely to reduce income to avoid crossing. The magnitude of the coefficients implies that a one percent increase in a charity's expenses or assets is associated with about a 1.5 percentage point (2.5 percent) reduction in the probability of manipulating receipts when approaching the notch in the next year. Including all of these variables and their interactions eliminates the predictive power of total revenue but leaves expenses and assets as highly significant determinants of bunching. The fact that large organizations are less likely to bunch supports the idea that the long form imposes administrative

expenses, some of which are likely related to transitioning to an accounting infrastructure that facilitates detailed financial reporting.

The first four columns of Table 7 show that size is predictive of income manipulation but may have more than one interpretation. Since most years of the NCCS data do not include a variable indicating which form was filed, it could be that larger organizations respond less because they are already filing Form 990 or because they adopt the form more quickly when reaching the notch, regardless of which form they filed before. To address this questions I incorporate data from the IRS Statistics of Income files for a random sample of 990-EZ filers. Columns (5) and (6) report results of regressions that only include observations moving to the notch if they appear in the IRS Statistics of Income 990-EZ sample. Column (5) of Table 7 shows that 990-EZ filers are less likely to cross the notch, consistent with an adjustment cost. The interaction terms in column (6) are no longer significant due to the reduced sample of organizations nearing the notch, but the point estimates are quite similar to those in other columns. It appears, therefore, that large charities are not just more likely to file Form 990 before required but are less likely to manipulate income to stay below the notch even if they previously filed Form 990-EZ.

The final dimension of heterogeneity for which I present results is staffing. Charities with paid staff may be less willing to file Form 990 and more able to manipulate income to avoid filing the longer form. Unfortunately, the data do not include the staffing line item for charities filing Form 990-EZ. To examine heterogeneity by future staffing I restrict attention to charities that have receipts above the notch at some point in the sample. The data include Form 990 staffing variables “Compensation” (for officers and directors), “Other Salary” (for others), and “Payroll Taxes.”<sup>18</sup> The regression results in Table 8 reveal how staffing variables and their interactions with  $near\ notch_{it}$  predict manipulation according to the outcome  $cross_{it}$ . Charities with paid administrative staff, whether measured by “Other Salary” or “Payroll Taxes,” are less likely to cross the notch when they first approach it. This result provides suggestive evidence that while the notch was found to have permanent effects on some charities’ growth it also leads to some temporary avoidance. I deem these results “suggestive” because the notch was shown to have permanent effects on the share crossing, which implies that the sample of charities that eventually cross may be selected based on characteristics related to the staffing variables.

A few other covariates suggest variation in the incentives or ability to bunch. These results are available by request. First, if assets are above \$250,000 then the organization must file Form 990 regardless of receipts level. Only charities below the asset notch would be expected to bunch, and this is confirmed in regression analysis (though this does not eliminate the size effects presented in Table 7). Other financial variables that

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<sup>18</sup>Just under half of the estimation sample has “Other Salary” when above the notch, and median Other Salary is between \$30,000 and \$35,000.

appear with the same wording on both forms include fundraising event income and inventory sales, neither of which predicts bunching. It is also possible to test for disclosure costs, albeit imperfectly, by examining whether some information that appears on Form 990 and not Form 990-EZ predicts bunching. As with the staffing variables, these measures must be defined in years that charities file the long form. Using the value of each variable in the first year after a charity crosses the notch, I find no evidence that charities avoid filing in order to conceal fundraising expenses or sources of business income unrelated to the charitable purpose. The cost of disclosing other variables appearing on the long form, including personal benefit contracts and controlled entities, could not be tested because these variables are not captured in the data.

In summary of the OLS and IV results, I find significant manipulation of income when nearing the notch. Consistent with adjustment costs, large charities and those that filed Form 990 previously are less likely to avoid being above the notch. Short-term manipulation by charities with administrative staff suggests avoidance, but the notch also has significant effects on growth in the long run. I do not find evidence that charities reduce income to avoid disclosing other information but do not have sufficient data to completely rule out this possibility.

## **1.6 Dynamic Estimation of the Quantity of Bunching**

Having described characteristics of bunching, I now turn to estimation of the extent of bunching. As before, the goal is to quantify distortions in the joint distribution of current and future receipts. I construct a maximum likelihood estimator that identifies the entire counterfactual distribution of growth conditional on current receipts by comparing observations that differ in current receipts and hence in the level of growth that would bring them to the notch. Bunching is estimated as the difference between the observed share moving to a region just below the notch and the share predicted by the counterfactual distribution of conditional growth. The approach can account for notch-related attrition due to extensive margin responses or other features specific to the empirical setting.

### **1.6.1 Methodology of Dynamic Estimation of the Quantity of Bunching**

Distortions in the joint distribution of an agent's income in different years identify bunching in dynamic settings. While the tools presented in the previous section can provide estimates of the quantity of bunching, a maximum likelihood approach offers advantages in terms of efficiency and clarity of assumptions. For example, it is straightforward to define parts of the growth distribution from which agents may not be observed in the next year's data and test for these systematic deviations from a random sample. The counterfactual conditional growth distribution is estimated as a smooth but flexible function with form that

is identified by observations throughout the distribution of current receipts.

Maximum likelihood estimation provides an efficient way to perform joint estimation of the prevalence of attrition and income responses. Dynamic OLS bunching estimates offer potential advantages over static estimates but retain some drawbacks. Without further adjustments, OLS may not provide a consistent estimate of the bunching propensity if organizations are more likely to go missing from the data when their receipts exceed the notch. Even if they are consistent, the OLS estimates may not be efficient because binning the data by current receipts and growth rate treats observations within a bin as equivalent, and the choice of bin widths and locations is necessarily ad-hoc when the data are continuous. These issues can be addressed with a maximum likelihood estimator.

The reasoning behind the MLE approach is the same as that for the OLS estimator: the level of growth that will take an organization to the Form 990 notch depends on current receipts. It would be possible to estimate the entire joint distribution of current income and future income, but focusing on the distribution of growth conditional on current receipts provides computational benefits and isolates the desired variation in the growth distribution rather than trying to simultaneously recover the static income distribution. I therefore estimate the conditional cdf of counterfactual growth,  $F(g|r)$ .<sup>19</sup>

The maximum likelihood estimate can be implemented by defining and estimating the parameters of a flexible function for the conditional distribution of growth. Growth  $g$  is defined as the change in an organization’s log receipts from the current value of  $r$  to its value one year later. I first define the latent cdf  $F(g|r)$  that would be observed if no observations were bunching or going missing, then incorporate these responses into the distribution  $F^*(g|r)$  that is fit to the data. To parametrize the counterfactual growth distribution I assume it falls within a flexible class of widely-used functions. Because the data have fat tails and a kink at zero growth, the Laplace distribution provides a natural choice. Laplace (or “double exponential”) distributions have been used extensively to model financial data and “are rapidly becoming distributions of first choice whenever ‘something’ with heavier than Gaussian tails is observed in the data” (Kotz et al., 2001).<sup>20</sup> The Laplace distribution describes the difference between two independent exponentially-distributed random variables. While the distribution of charities’ reported receipts appears to be approximately exponential, an organization’s future receipts are certainly not independent of current receipts, providing one important reason to allow for flexibility in the conditional growth distribution. I estimate a modification of the Laplace cdf by allowing for flexible functions  $P_l(g, r, \theta)$  and  $P_u(g, r, \theta)$  to

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<sup>19</sup>The joint density of growth and receipts can be estimated by maximizing  $\sum_i \log(f(g_i, r_i)) = \sum_i \log(f_g(g_i|r_i) \cdot f_r(r_i)) = \sum_i [\log(f_g(g_i|r_i)) + \log(f_r(r_i))] = \sum_i \log(f_r(r_i)) + \sum_i \log(f_g(g_i|r_i))$ . Maximizing only the second term will provide consistent estimates of the parameters of the conditional growth density but may be less efficient than maximizing the joint density if all years are included such that current receipts in one year also enter the growth rate for the previous year.

<sup>20</sup>See Kozubowski and Nadarajah (2010) for other recent applications.

enter the lower and upper pieces of the distribution:<sup>21</sup>

$$F(g|r) = \begin{cases} \exp(P_l(g, r, \theta)) & g < \theta(r) \\ 1 - \exp(P_u(g, r, \theta)) & g \geq \theta(r) \end{cases}$$

I describe the main points of the maximum likelihood estimation here and provide details in Appendix C. Using the latent density of log receipt growth I then specify the form of the observed density to account for bunching and for missing data. To adjust for bunching I define a conditional omitted region of growth rates that take each current level of receipts to a region around the notch. I count observations that grow to the omitted region so that they are not treated as missing, but I exclude them from estimation of the shape of the latent distribution. Next I account for attrition, which could be due to late filing, earning receipts below the level at which filing is required, shutting down, merging, or simply non-compliance. I estimate three types of attrition. First, I include terms that are constant or linear in current receipts to capture basic, random attrition. Second, I adjust the observed conditional growth densities to account for truncation of the sample due to the fact that organizations with receipts below \$25,000 do not have to report. Third, I use the latent cdf to determine the share of observations that should cross the notch from each level of current receipts and allow a heightened probability that charities that should cross the notch instead go missing. This last parameter estimates the extra share of organizations that go missing because the requirement to file the longer form for the first time induces late filing or nonfiling. This last parameter is identified by the way in which attrition varies with current receipts, because the share that should cross the notch increases as current receipts approach the notch.

I will report estimates describing the bunching response and missing observations. The first parameter of interest is the bunching propensity or bunching share ( $b$  in the discussion of theory Section 1.2), which reveals the share of bunchers among the total number that should move to the reduced region. is identified by comparing the observed distribution of growth rates to the counterfactual distribution. I allow this bunching parameter to take a different value for charities coming from below the notch than for charities already above the notch. I use the estimated bunching shares and the counterfactual distribution of growth to calculate the excess mass that is observed in the bunching range in the next year and the reduction in the mass above the notch. I also report estimates of excess attrition among those below the notch and those crossing it, where the latter is identified by variation across current receipts in the counterfactual share with growth that would put them above the notch.

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<sup>21</sup>The symmetric Laplace distribution with location parameter  $\theta$  and scale parameter  $\sigma$  has this form with  $P_l(g, r, \theta) = P_u(g, r, \theta) = \left| \frac{g-\theta}{\sigma} \right| - \log(2)$ .

### 1.6.2 Results of Dynamic Estimation of the Quantity of Bunching

Now I turn to the maximum likelihood estimates of the amount of bunching. Results are broadly consistent with the bunching measures obtained from static estimation and the ordinary least squares dynamic estimation. Roughly ten percent of the charities that should cross the notch by a small amount in each year will instead remain below it. Extensive-margin responses are significant and explain the difference between the static estimates of the excess mass below the notch and the reduced mass above the notch.

Table 9 displays the results of MLE estimation of the extent of bunching and systematic attrition. The first parameter estimate in each column gives the bunching propensity among charities that have current receipts below the notch. In the basic specification, 9.3 percent of such charities that should have future receipts just above the notch will instead reduce reported receipts to stay below the notch. The second row shows the bunching propensity for those with current receipts above the notch, which is always estimated to be less than 0.14 percent and never significantly different from zero. Charities coming from above have already filed Form 990 and have less incentive to bunch if the marginal cost of filing is largely a one-time adjustment cost. The lack of bunching by charities coming from above the notch is consistent with (unreported) results from the reduced-form estimation strategy of Section 1.4.

Attrition is significantly related to current receipts. Columns (1) through (3) of Table 10 display results for different specifications of attrition as a function of current and future receipts. Adding a simple constant term for charities currently below the notch as in column (2) reveals that these charities are about 1.3 percentage points more likely to go missing in the next year but has little effect on the bunching propensity estimates. The estimated bunching propensity decreases, however, when allowing for greater attrition among charities that would have crossed the notch, as in column 3. Failure to account for these extensive margin responses leaves only the bunching estimate to account for the full reduction of mass above the notch, whereas the flexible approach distinguishes the response of manipulating income from the response of leaving the sample. The flexible model minimizes the Akaike Information Criterion, reinforcing the importance of systematic attrition.

The final rows of Table 9 reveal the estimated excess share of charities below the notch and reduction in the share above it. The excess and reduction are found by aggregating the bunching and attrition propensities across all observations according to their counterfactual probability of moving to the reduced region. In the baseline specification, .183 percent of all organizations will manipulate income to bunch in the next year. By construction, the excess and reduced mass are equal. The estimate of .183 lies in between the static estimates of the excess and the reduction, as reported in the last column. Allowing for excess attrition below the notch has a minor impact on the excess estimate, but allowing for extensive-margin responses gives

estimates quite similar to those of the static approach. The dynamic approach therefore confirms the static estimate that about .15 percent of charities manipulate income and provides evidence that the additional .1 percent reduction in the mass of charities above the notch is due to extensive-margin responses.

Table 10 shows robustness of the baseline dynamic estimates to the choice of width for the bunching and reduced ranges. The baseline dynamic regression, with an omitted region of \$80-130,000, corresponds to column (3) in Table 9. The dynamic estimates vary with the omitted range as one would expect. If the researcher overly restricts the omitted range so that it does not cover the full range over which income is manipulated then bunching will be underestimated. Accordingly, the dynamic estimates capture more bunching as the reduced range used in the estimation is expanded from \$10,000 in width to about \$30,000. Further widening does not affect the estimate much because all bunching has been captured. The static estimates are also fairly robust for sufficiently wide omitted ranges. The main difference between the patterns of dynamic and static estimates is that the static estimate of the excess grows rather than shrinks when the reduced range is overly restricted because observations in the true reduced range are used to estimate the counterfactual, causing it to be biased downwards. In practice there should be no problem so long as the reduced range is made sufficiently wide.

## 1.7 Conclusion

This study provides new evidence on the behavior of charities and responses to threshold policies. The IRS income threshold for filing simplified returns produces a clear distortion in the distribution of reported income. The average charity is willing to reduce income by \$600 to \$1000 to avoid reporting more information, but this average masks considerable heterogeneity, and the fact that small charities who had previously filed the simplified form were most likely to manipulate income provides evidence that much of the compliance cost is a one-time adjustment. Responses appear to consist of both short-run manipulation of income and permanent distortions of income growth.

The results of this study highlight several benefits of incorporating dynamics into bunching estimation. Conditioning on past income provides a different identification strategy and provides new opportunities to describe behavior by estimating extensive-margin responses, preference heterogeneity, long-run effects, and the extent of avoidance. Dynamic bunching techniques could be used to analyze responses to thresholds in many other settings, including social welfare programs with income-eligibility limits, tolls and security checkpoints, product pricing with quantity discounts, or rewards programs for charitable giving.



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## Figures and Tables

Table 1.1: Comparison of Information Provided on IRS Forms for Charities

	Form 990-EZ	Form 990
Pages	3	9+
Revenues	15 lines	25 lines
Expenses	8 lines	5 lines
Statement of Functional Expenses		~80 cells
Balance Sheets	8 lines	40 lines
Reconciliation with Audited Financials		if $\exists$ audited financials
Officers, Directors, Trustees, & Employees	Compensation	Compensation, # of relations
Compensated Former Officers, Directors, etc.		✓
Income Lines By Related vs. Unrelated		✓
Form 990-T if Unrelated Income > \$1000	✓	✓
Controlled Entities		✓
Hours to Complete (Paperwork Reduction Act)	164	260



Table 1.2: Summary Statistics

All Public Charities, All Years (N=4,299,984)			
	Lower Quartile	Median	Upper Quartile
Gross Receipts (\$ Thousands)	72	200	825
Expenses (\$ Thousands)	51	153	647
Assets (\$ Thousands, Year-End Total)	36	180	996

Charities With Receipts of \$80-130,000, FY2007 (N=36,173)			
Major NTEE Category	Share	Minor NTEE Category	Share
Education	19.4%	Parent Teacher Group	6.5%
Arts, Culture, and Humanities	12.4%	Education - Single Organization Support	4.1%
Recreation, Sports, Leisure, Athletics	12.1%	Religion - Christian	3.9%
Human Services - Multipurpose and Other	9.6%	Baseball, Softball (Includes Little Leagues)	3.1%
Religion Related, Spiritual Development	7.8%	Fire Prevention/Protection/Control	1.9%
Community Improvement, Capacity Building	5.1%	Animal Protection and Welfare	1.8%
Housing, Shelter	4.1%	Education - Scholarships, Student Financial Aid, Awards	1.7%
Health	3.7%	Community/Neighborhood Development, Improvement	1.6%
Philanthropy, Voluntarism, Grantmaking Foundations	3.5%	Amateur Sports Clubs, Leagues	1.3%
Public Safety	2.5%	Theater	1.2%
Animal-Related	2.4%	Soccer Clubs/Leagues	1.1%
Environmental Quality, Protection, and Beautification	2.3%	Community Service Clubs	1.1%

Table 1.3: Static Bunching Estimates: Distortions of the Income Distribution in the Pooled Sample

	Basic	Discontinuous	Two-Sided
Excess mass below the notch (*100)	.148*** (.020)	.135*** (.029)	.152 (.093)
Bunching ratio (*100)	.592*** (.096)	.537*** (.123)	.608* (.312)
Reduction in mass above the notch (*100)	.250*** (.026)	.223*** (.049)	-.055 (.066)

*Notes:* The table shows deviations of the binned income distribution from a counterfactual estimated in the range of \$50-200,000. In the Basic specification, the counterfactual is a cubic in gross receipts. The Discontinuous specification allows for a discontinuity at the notch, and the Two-Sided specification allows for a separate quadratic on each side of the notch. The excess mass shows the estimated extra share of charities with incomes below the notch relative to the counterfactual, the bunching ratio is the ratio of the excess mass to the counterfactual density at the notch, and the reduction above the notch is the difference between the counterfactual and actual share above. The Basic specification indicates that .148 percent of charities appear below the notch when they shouldn't, which is roughly equal to the number of charities that should be above the notch by up to \$600 ( $=\$100,000 \times .00592$ ). The reduction in the number of charities above the notch is significantly larger than the addition below the notch, suggesting either misspecification or missing observations, and the flexible specifications do not reconcile the two results. The sample includes observations in years up to 2007 for charities also appear in the prior year (for comparability with the dynamic estimates). Bin width = \$250. N = 969,842 in the range used for estimation and 2,907,476 total.

Table 1.4: Repeated Bunching: Charities Remain Just Below the Notch for Years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
bunchbin	1.55*** (0.37)	1.15*** (0.30)	0.68*** (0.24)	0.63*** (0.21)	0.44* (0.24)	0.20 (0.20)	0.31** (0.15)	0.29** (0.14)	0.11 (0.12)	0.14 (0.14)

*Notes:* The table shows the results of regressing a dummy for remaining in the same log receipts bin (t) years in the future on a dummy for being in the bin just below the notch, with controls for year and a quadratic function of log receipts. The coefficients, which are multiplied by 100, show the heightened probability that charities just below the notch remain where they are. The sample includes charities within one log point of the notch in any starting year from 1990 to 1997. Standard errors are clustered by state. Bin width = .05. N=595,478.

Table 1.5: The Effect of Approaching the Notch on Organizational Finances

	(1)	(2)	(3)	(4)	(5)	(6)
	Receipts	Cross	IV: Receipts	Revenue	Expenses	Assets
Near Notch	-0.0017*** (0.0002)	-0.0408*** (0.0033)		0.0021 (0.0022)	0.0016 (0.0032)	-0.0009 (0.0037)
crosslead1			0.0423*** (0.0031)			
N	1,076,302	1,076,302	1,076,302	1,070,904	1,069,204	1,064,645
Adj. R-Squared	0.999	0.001	1.000	0.383	0.078	0.037

*Notes:* The table shows the results of regressing financial variables on a dummy ("Near Notch") for bins that straddle the notch in future receipts, controlling for bins of growth rate (of width .1) each interacted with a quadratic function of current receipts. The negative relationships for growth of log receipts (1) and crossing the notch (2) reflect downward distortions of receipt growth in the neighborhood of the notch. Using the "Near Notch" dummy as an instrument for crossing (3) shows receipt growth is reduced by an average of .45 log points among charities induced not to cross. Effects on the growth of total revenue (4), expenses (5), and assets (6), all in logs, is not precisely estimated. The sample includes all charities growing by 0 to 1 log points. Standard errors are clustered by state.

Table 1.6: The Effect of Approaching the Notch on the Probability of Further Growth Years Ahead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Near Notch	-0.053*** (0.009)	-0.021*** (0.007)	-0.018** (0.007)	-0.015** (0.007)	-0.016** (0.007)	-0.017*** (0.006)	-0.016** (0.008)	-0.015** (0.006)	-0.017*** (0.005)	-0.022*** (0.006)	-0.012* (0.007)	-0.014*** (0.005)
N	307,526	260,209	261,771	256,548	252,669	247,364	245,228	240,193	234,728	231,303	225,570	221,296

*Notes:* The table shows the results of regressing a dummy for crossing the level of growth corresponding to the notch ("Cross" as defined in the text) (t) years in the future on the "Near Notch" dummy for bins that straddle the notch in the next year, controlling for bins of growth rate (of width .1) and a quadratic function of current receipts. The coefficients show charities a significant reduction of at least one percentage point in the probability of crossing the notch at all horizons. The sample includes charities within one log point of the notch in any starting year from 1990 to 1997 and growing by 0 to 1 log points. Standard errors are clustered by state.

Table 1.7: Heterogeneity in Share Crossing the Notch, by Size

	(1)	(2)	(3)	(4)	(5)	(6)
Near Notch	-.260*** (0.073)	-.197*** (0.042)	-.178*** (.024)	-.371*** (.077)		
Log Total Revenue * Near Notch	.020*** (0.007)			-.0001 (.012)		.082 (.150)
Log Total Revenue	-.002 (0.0101)			.005** (.002)		.005*** (.002)
Log Expenses * Near Notch		.014*** (0.004)		.018*** (.007)		.206 (.151)
Log Expenses		-.007*** (0.002)		-.009*** (.001)		-.009*** (.001)
Log Assets * Near Notch			.013*** (0.002)	.013*** (.002)		.033 (.033)
Log Assets			-.005*** (0.001)	-.005*** (.001)		-.005*** (.001)
990-EZ * Near Notch					-.129*** (0.042)	-3.619*** (1.320)
990-EZ					.008 (0.012)	.009 (0.060)
N	1,071,602	1,070,546	1,068,105	1,059,710	1,053,004	1,036,868

*Notes:* The table shows the results of regressing a dummy for crossing the level of growth corresponding to the notch ("Cross" as defined in the text) on a dummy ("Near Notch") for bins that straddle the notch in future receipts, interacted with various measures of size, and controlling for bins of growth rate (of width .1), each interacted with a quadratic function of current receipts. The positive coefficients on the interaction terms indicate that larger charities are less likely to reduce income to stay below the notch when first approaching it. Columns (5) and (6) report results of regressions that only include observations moving to the notch if they appear in the IRS Statistics of Income 990-EZ sample, thereby excluding those already filing Form 990. The restriction renders the interaction terms insignificant but has little effect on point estimates. The sample for all regressions includes charities growing by 0 to 1 log points. Standard errors clustered by state.

Table 1.8: Heterogeneity in Share Crossing the Notch in the Short Run, by Staffing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Has "Compensation" * Near Notch	-0.0257*** (0.0079)	-0.0247** (0.0115)		-0.0090 (0.0112)		-0.0015 (0.0114)	-0.0035 (0.0115)
Has "Compensation"	0.0132*** (0.0013)	0.0089*** (0.0024)		0.0113*** (0.0024)		0.0117*** (0.0025)	0.0115*** (0.0026)
Has "Other Salary" * Near Notch			-0.0509*** (0.0118)	-0.0483*** (0.0117)			-0.0366** (0.0174)
Has "Other Salary"			-0.0043** (0.0019)	-0.0076*** (0.0019)			-0.0071** (0.0027)
Has Payroll Tax * Near Notch					-0.0468*** (0.0101)	-0.0460*** (0.0097)	-0.0185 (0.0152)
Has Payroll Tax					-0.0007 (0.0019)	-0.0058*** (0.0019)	-0.0007 (0.0028)
N	989,706	355,810	355,810	355,810	355,810	355,810	355,810
Adj. R-Squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001

*Notes:* The table shows the results of regressing a dummy for crossing the level of growth corresponding to the notch ("Cross" as defined in the text) on a dummy ("Near Notch") for bins that straddle the notch in future receipts, interacted with dummies for different types of staffing. Staffing is only known for filers of Form-990 and is defined for each charity in its first year with receipts above the notch. The negative coefficients on the interaction terms indicate that charities with administrative staff are less likely to cross the notch when first approaching it. Controls include dummies for bins of growth rate (of width .1) each interacted with a quadratic function of current receipts. The sample includes all charities with current growth between 0 to 1 log points that ever appear above the notch. Regressions (2) through (7) include only charities that first appear above the notch in or after 1997, the year in which "Other Salary" and "Payroll Tax" first appear in the data. Standard errors are clustered by state.

Table 1.9: MLE Estimates of Propensities to Manipulate Income Or Leave the Sample

	Dynamic (1)	Dynamic (2)	Dynamic (3)	Static
Share bunching from below notch	0.087*** (0.003)	0.090*** (0.003)	0.079*** (0.005)	
Share bunching from above notch	0.001 (0.002)	0.000 (0.000)	0.000 (0.000)	
Extra share from below going missing		0.013*** (0.001)	0.009*** (0.002)	
Extra share missing instead of crossing			0.017*** (0.004)	
Excess mass below the notch (*100)	.183*** (.030)	.184*** (.026)	.159*** (.010)	.148*** (.020)
Additional reduction above the notch (*100)	.183*** (.030)	.184*** (.026)	.246*** (.018)	.250*** (.026)
AIC	5,531,280	5,530,760	2,765,374	

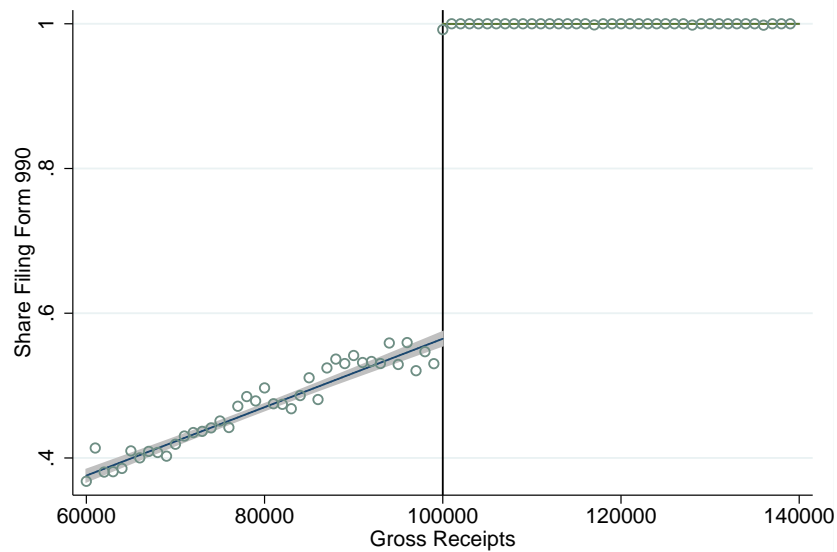
*Notes:* The table shows the results of maximum likelihood estimation of the bunching propensities of charities approaching the notch next year from current receipts below or above the notch, with and without adjusting the likelihood function for an increased share of charities with current receipts below the notch leaving the data (either in total or in proportion to how frequently they should cross over the notch). The top two parameter estimates indicate that charities that approach the notch from below are significantly more likely to manipulate receipts to remain below the notch in the next year. Allowing more attrition among observations below the notch slightly reduces the bunching propensity estimate and lowers the excess mass in the bunching region in the next year. The estimates in columns (2) and (3) require the excess mass below the notch to equal the reduction above the notch and hence obtain estimates in between the static estimates of these two values, whereas the dynamic estimates allowing for extensive-margin responses of those who would have crossed gives similar results to the static estimate. All regressions allow for attrition that is linear in current receipts and manipulation of receipts in the range \$80-130,000. Standard errors calculated using the Delta Method. N=2,907,476.

Table 1.10: Robustness of Bunching Estimates To Omitted Range

	Dynamic	Static
Reduced Range: \$100-\$110K	.111*** (.007)	.208*** (.018)
Reduced Range: \$100-\$120K	.151*** (.011)	.169*** (.019)
Reduced Range: \$100-\$130K	.159*** (.010)	.148*** (.020)
Reduced Range: \$100-\$140K	.170*** (.010)	.136*** (.022)
Reduced Range: \$100-\$150K	.164*** (.011)	.146*** (.024)

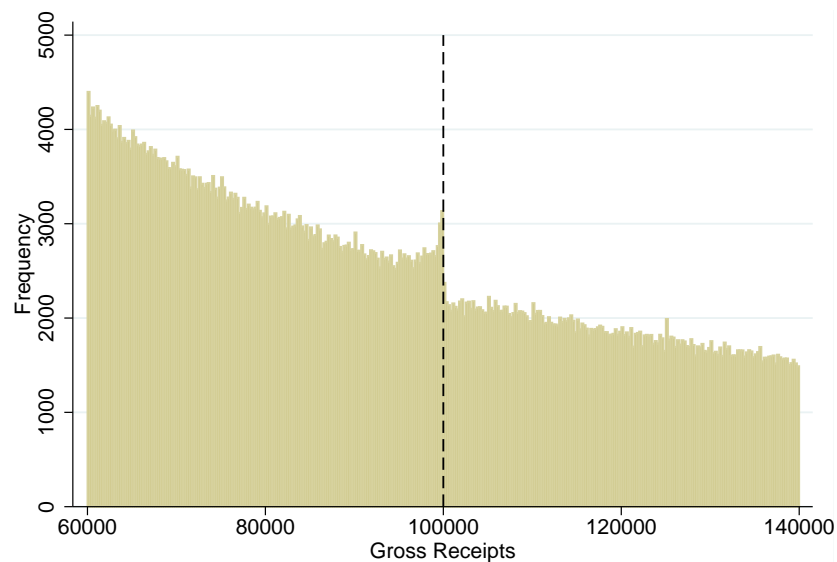
*Notes:* The table shows the results of maximum likelihood dynamic estimation and static estimation of (100 times) the excess mass in the \$80-100,000 bunching region for various widths of the reduced region from which this mass has moved. According to the dynamic approach, the number of extra charities in the bunching region is about .2 percent of all charities in the sample. The dynamic estimates have the expected pattern: bunching is underestimated when the reduced range from which charities bunch is not sufficiently large, but estimates are stable as this range is widened. Static estimates are large when the specified reduced region is too small because the counterfactual is underestimated but also stabilize when the range is widened. For comparability, static estimation is performed on the sample of organizations that appeared in the previous year. The reduced range is \$100-130,000 for all regressions. Standard errors calculated using the Delta Method. N=2,907,476.

Figure 1.1: Probability of Filing Form 990 Around the Receipts Notch



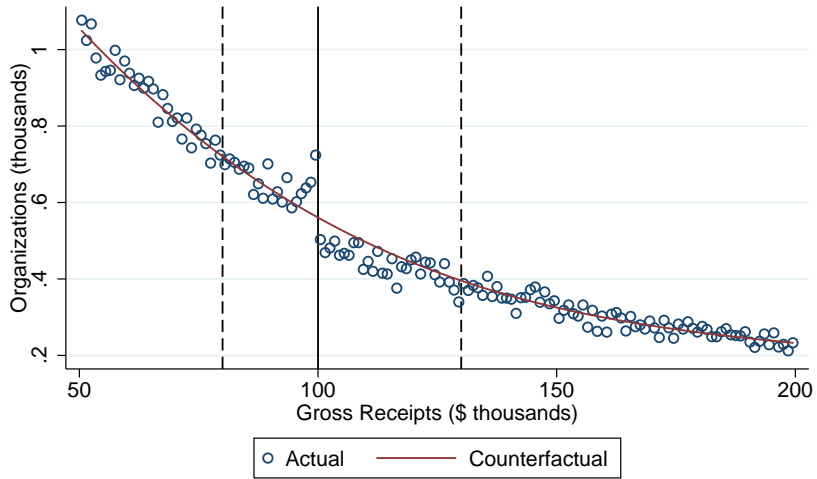
*Notes:* The figure shows the results of regressing a dummy for those filing Form 990 (vs. 990-EZ) in 2007 on quadratics in gross receipts below and above the \$100,000 notch at which charities lose eligibility to instead file Form 990-EZ. Curves with standard error bands show the results of these regressions and circles show the mean within a \$1000 receipts bin. The share of organizations filing the longer form is increasing in receipts up to the notch, with nearly 100% compliance above the notch. N=72,354.

Figure 1.2: Bunching Just Below the Form 990 Receipts Notch



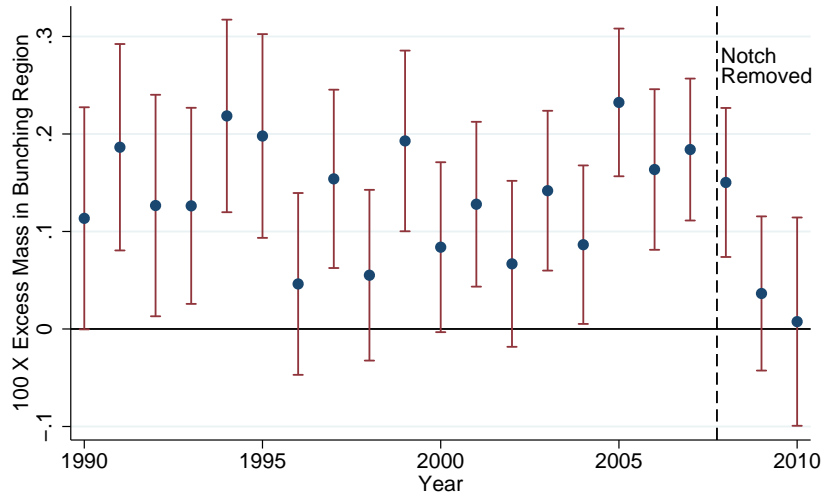
*Notes:* The figure is a histogram of gross receipts. An excess of charities just below the \$100,000 notch appears as bunching in what is otherwise a smooth distribution. N=810,869. Bin width=\$250. Years 1999-2007 pooled.

Figure 1.3: Distribution of Receipts in 2006 vs. Smooth Counterfactual



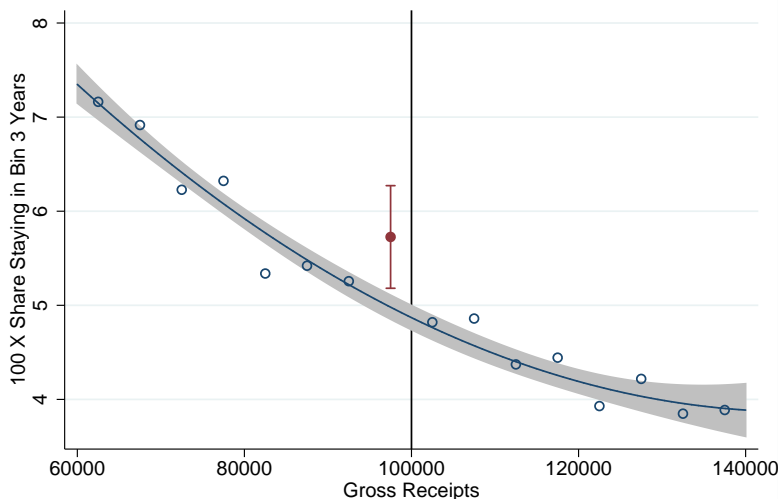
*Notes:* The figure shows the deviation of the 2006 distribution, represented by a histogram in blue circles, from a smooth counterfactual. Each bin is treated as an observation. Bin counts are regressed on a polynomial of degree 3, which estimates the counterfactual distribution, and a dummy variable for each bin in the omitted range of \$80-130,000 indicated by the dashed lines. Excess “bunching” mass is calculated as the sum of coefficients on dummy variables for each bin in the bunching region between the dashed line at \$80,000 and the solid at the the \$100,000 notch. Similarly, the estimated reduction in mass above the notch is the sum of coefficients on dummies for each bin up to \$130,000. N(graph)=92,791. N(2006)=264,770. Bin width=\$1000.

Figure 1.4: Annual Static Estimates of Share Bunching Below the Notch



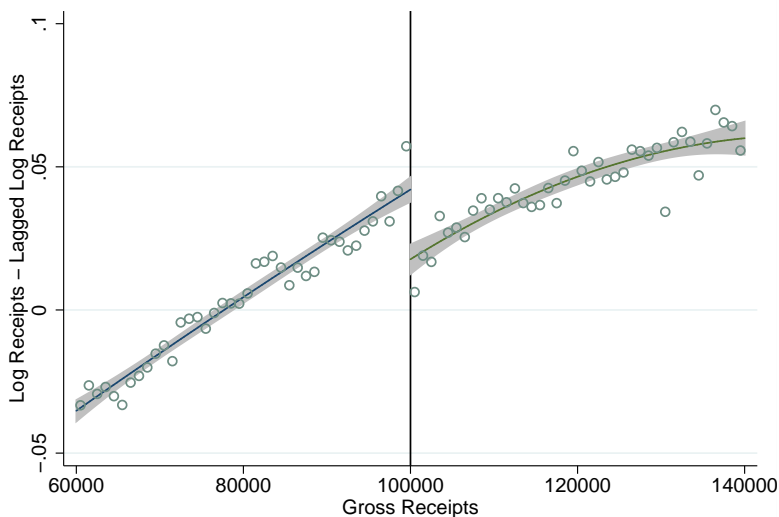
*Notes:* The figure shows the excess mass of charities below the notch in each year, as estimated using the static approach described in the text and Figure 3. Circles indicate the estimates and lines show 95-percent confidence intervals. Estimates fluctuate somewhat around the pooled estimate of .148. There is significant bunching below \$100,000 for one year after the notch was raised to \$1,000,000 (where new bunching forms), suggesting slow adjustment or lack of understanding that the notch had moved. The counterfactual for each year is a polynomial of degree 3 estimated on observations with receipts of \$50-200,000 but outside of an omitted region of \$90-130,000. Year is the calendar year in which the charities’ fiscal years begin. The sample consists of charities that appear in the prior year (for comparability to other estimates in the paper). N=2,907,476.

Figure 1.5: Repeated Bunching: Share Staying Within Bin For 3 Years



*Notes:* The figure shows the results of regressing a dummy for remaining in the same \$5000 receipts bin 3 years after the current year on a quadratic in gross receipts and a dummy for the bin just below the notch. The marker with a 95-percent confidence interval shows that organizations in the bunching region just below the notch are especially likely to remain where they are for several years. Standard errors clustered by state. N=329,448. Bin width=\$5000.

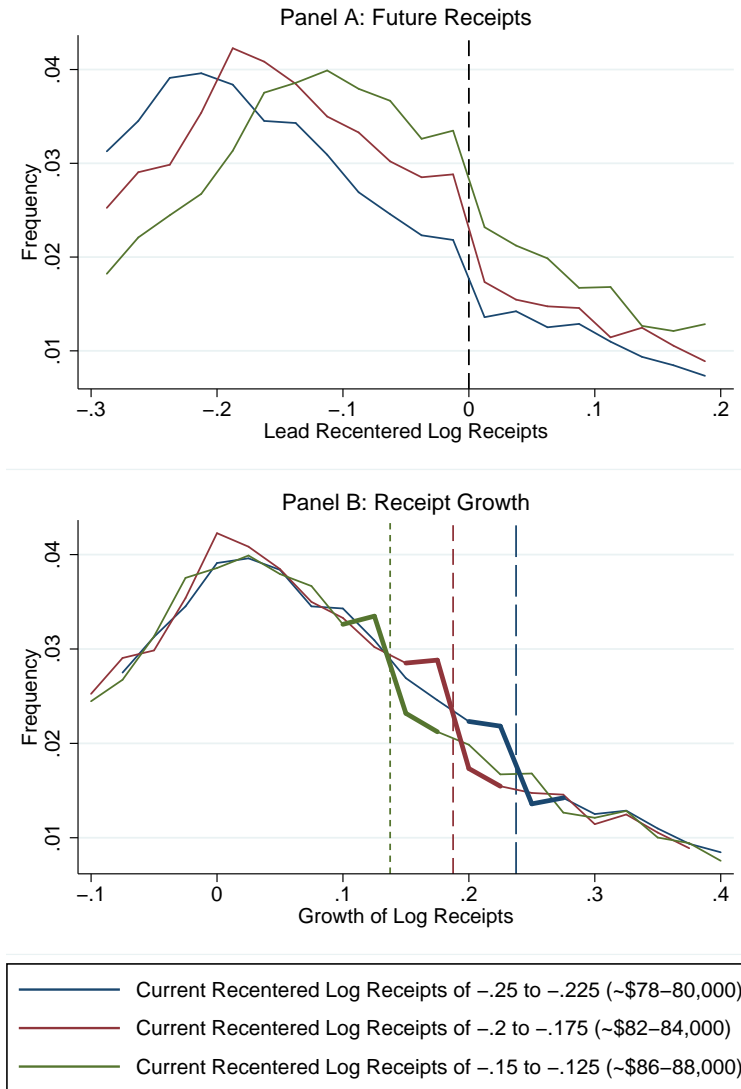
Figure 1.6: Mean Past Growth Is One Characteristic That Varies Discontinuously Around the Notch



*Notes:* The figure shows the results of regressing growth of log receipts (from the previous year to the current year) on quadratics in gross receipts below and above the \$100,000 notch. Curves with standard error bands show the results of these regressions and circles show the mean within a \$1000 receipts bin. Mean growth is a discontinuous function of current receipts, so traits of charities that correlate with past income may also appear distorted in current income. This figure motivates conditioning on past income when describing and measuring income manipulation around the notch. N=688,948.

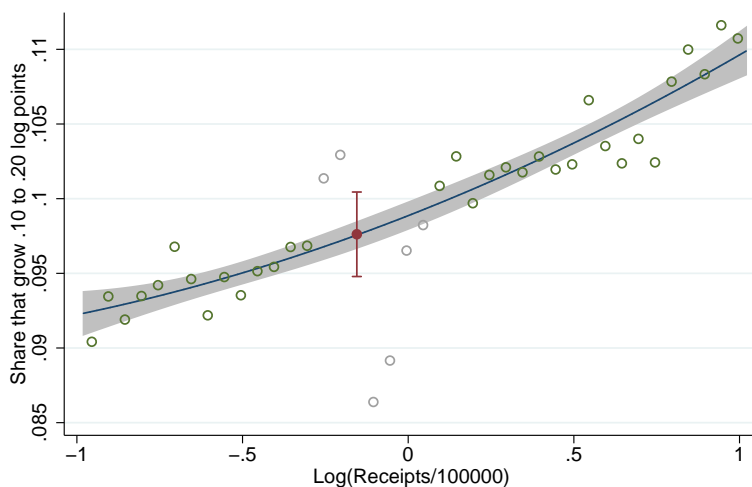


Figure 1.7: Distorted and Undistorted Sections of Conditional Distributions of Future Receipts/Growth



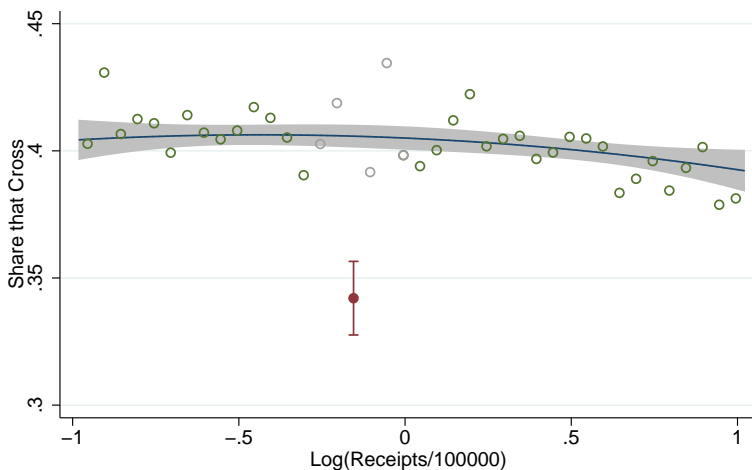
*Notes:* The figure shows the distribution of future receipts (Panel A) and growth to future receipts (Panel B) for charities in three sample bins of current receipts. The distributions for each group exhibit a spike at incomes just below the notch and a depression just above it, indicating manipulation of future income in order to stay below the notch. The growth distribution of each group is similar except around the notch, which appears in a different part of each distribution. Because the growth distribution does not vary too much with current income, the extent of distortion in the rates of growth that bring charities with one level of current receipts to the notch can be identified using the likelihood of such growth rates among charities with a different level of current receipts.  $N=92,242$ . Bin width = .025.

Figure 1.8: Share Growing To a Range That Spans the Notch is Unaffected



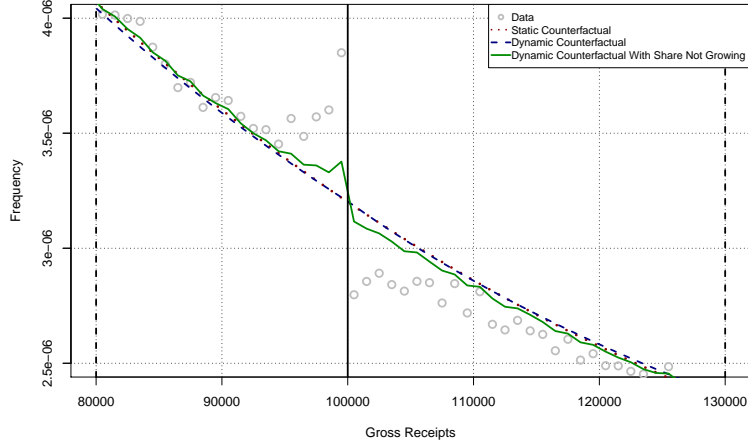
*Notes:* The figure shows the results of regressing the probability of growing log receipts by .1 to .2 (from the current year to the next) on a quadratic in current recentered log receipts and a dummy ("Near Notch") for the bin for which future receipts lie in the "omitted range" straddling the notch. The marker with a confidence interval represents the average among the "Near Notch" bin. Because growth of .1 to .2 log points from this bin leads to receipts on both sides of the notch it includes both those who manipulate and those who don't and so the overall probability of growth in this range is unaffected. Charities in the "Near Notch" bin can therefore be compared to counterfactuals constructed using charities in the same growth range but with higher and lower current receipts. Comparisons should exclude charities in bins represented by light markers because manipulation of income from one side of the notch to the other alters the sample with growth of .1 to .2 from these bins. The same arguments apply to other growth ranges. N=152,191. Omitted range is -.08 to .07. Bin width = .05.

Figure 1.9: Share Crossing the Notch vs. Counterfactual



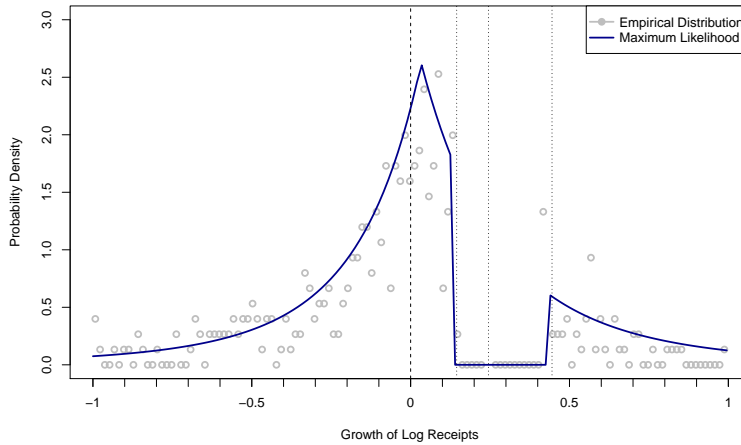
*Notes:* The figure shows the results of regressing the probability of crossing the growth rate corresponding to the notch (the "Cross" dummy described in the text) on a quadratic in current recentered log receipts and a dummy ("Near Notch") for the bin for which future receipts lie in the "omitted range" straddling the notch. The marker with confidence intervals represents the average among the "Near Notch" bin. Charities that move to a range near the notch reduce their income to stay below it and are therefore less likely to cross it than predicted by the estimated counterfactual represented by the curve. The figure sample consists of organizations growing .1 to .2 log points, and the same result obtains for other ranges of positive growth. N=152,191. Omitted range is -.08 to .07. Bin width = .05.

Figure A.1: Smooth and Non-smooth Counterfactual Distributions of Income



*Notes:* The figure shows the distribution of gross receipts and some potential counterfactual distributions. The dotted and dashed lines show the estimated counterfactual using the static and dynamic approaches, which give similar results. The solid line shows a counterfactual in which 80 percent of charities grow according to the conditional distribution estimated by maximum likelihood and 20 percent have no growth. When a share of charities don't grow the counterfactual is not smooth around the notch, implying different estimates and interpretation of the excess mass observed in the data. Details of the dynamic estimates are provided in Appendix C. The plot includes observations that appear in a prior year, the static counterfactual is estimated directly from this data, and the dynamic counterfactuals apply the estimated distribution of growth conditional current income to the distribution of incomes in the prior year.

Figure C.1: Estimation of the Distribution of Growth Rates



*Notes:* The figure shows the distribution of growth in log receipts. The curve shows the fit of the maximum likelihood estimate of this distribution to the data represented by the histogram in circular markers. The sample consists of organizations .24 to .25 log points below the notch, implying that growth of about .245 puts these charities near the notch in the next year, as represented by the middle dashed vertical line. Observations in the omitted region around the notch, marked by the surrounding dashed lines, have been omitted from estimation of the shape. These observations are only used to compare the number of organizations just above and below the notch to the numbers implied by the counterfactual to get estimates of the share bunching or missing. N=12,637.

## Appendix 1A - Discussion of the Relationship Between Dynamic and Static Bunching Estimates

Dynamic bunching estimation offers several benefits as a complement to static estimation in settings for which panel data is available. The dynamic estimates can illuminate the nature of heterogeneity in responses, as seen in Section 4, and can test for attrition that is endogenous to a notch, as in Section 5. Here I argue that, in addition, the identifying assumptions of dynamic bunching estimation are arguably more plausible than those used in static estimation, particularly for settings where agents face a notch repeatedly.

Repeated bunching may lead to a violation of the identifying assumptions of the static approach. Consider, for example, agents that grow income at a constant rate every year unless they approach a notch, in which case they never cross. In the current setting, this might describe a charity with a low growth rate and a high discount factor. Even if the charity is fully forward-looking, it may not deem future growth to be of sufficient value to compensate for the cost of crossing the notch. Conditional on current income, then, the charity makes a rational decision of the kind motivating bunching analysis, in which bunching in the next period is preferred to income in a range just above the notch. In the long-run, however, the constant growth this charity would have achieved in the absence of the notch would raise its income far above the notch. In this case, the static counterfactual will underestimate the number of agents that should be above the notch no matter how wide the researcher allows the omitted region to be. If the distribution is only affected above the notch then it might be possible to estimate the counterfactual using only observations below the notch and projecting the results to higher incomes. However, projection may be unreliable in practice, as was shown in Table 3, and the distribution may also be affected below the notch if agents that get “stuck” at the notch then experience negative income shocks.

Income that exhibits a high degree of serial correlation could also pose a concern for static bunching estimates. To see that serial correlation may violate the smoothness assumption, consider the extreme case in which the conditional distribution of income in the next period is discrete-continuous with strictly positive mass at today’s income level. Say that income has observed distribution  $f_t(y_t)$  in the current year, and the pre-bunching (counterfactual) cumulative distribution function (cdf) for the following year is given by  $F_{t+1}(y_{t+1}) = \int G_{t+1}(y_{t+1}|y_t) f_t(y_t) dy$ , with  $G_t(y_{t+1}|y_t) = \alpha \cdot 1_{\{y_{t+1} \geq y_t\}} + (1 - \alpha) H_t(y_{t+1}|y_t)$  for some constant  $\alpha \in (0, 1)$  and continuous cdf  $H_t(y_{t+1}|y_t)$ . Say there is a notch at  $y_t = n$  and bunching at the notch in current year. Then

$$\lim_{y_{t+1} \rightarrow n^+} F_{t+1}(y_{t+1}) - \lim_{y_{t+1} \rightarrow n^-} F_{t+1}(y_{t+1})$$

$$\begin{aligned}
&= \lim_{y_{t+1} \rightarrow n^+} \int [\alpha \cdot 1_{\{y_{t+1} \geq y_t\}} + (1 - \alpha) H_t(y_{t+1}|y_t)] f_t(y_t) dy \\
&- \lim_{y_{t+1} \rightarrow n^-} \int [\alpha \cdot 1_{\{y_{t+1} \geq y_t\}} + (1 - \alpha) H_t(y_{t+1}|y_t)] f_t(y_t) dy \\
&= \alpha \left[ \lim_{y_{t+1} \rightarrow n^+} F_t(y_{t+1}) - \lim_{y_{t+1} \rightarrow n^-} F_t(y_{t+1}) \right]
\end{aligned}$$

$$\neq 0$$

The difference between these limits is not zero because current bunching implies the current income distribution is discontinuous at the notch. Because income is highly persistent, the discontinuity at the notch will remain in the future even without further bunching. To create problems in practice, the distribution of growth need not truly be discrete-continuous, but simply concentrated around a particular growth rate (such as zero).

Figure A.1 provides an illustration of how serially correlated income could affect estimation. The figure shows projected counterfactuals using the static methodology and the methodology presented in Section 6. The dashed line depicting the dynamic estimate of the counterfactual distribution coincides nearly exactly with the dotted line depicting the static estimate. The similarity of the dynamic and static counterfactuals highlights the equivalence of the two approaches in this setting. The solid line, however, describes the counterfactual if 10 percent have zero growth and 90 percent of charities follow the dynamic estimate of the growth distribution conditional on their receipts in the prior year. In this case, even the counterfactual is discontinuous simply because there are more charities below the notch in the prior year. If many agents have income growth close to zero, the income distribution would exhibit bunching even if the notch was removed and agents had no further propensity to bunch. While the notch is in place, mass may accumulate over time in the bunching range, leading to biased estimates of the propensity to bunch in any particular year. These issues may arise, for example, in the context of individual incomes at an inflation-indexed notch if cost-of-living adjustments to wages are also indexed to inflation.

The growth distribution of charitable organizations is sufficiently disperse that the dynamic estimates of the bunching quantity closely follow the static estimates, but there is some evidence the growth distribution has become increasingly distorted around the notch. Annual estimates show that the discontinuity in the density of receipts at the notch has grown steadily over most of the sample period. Among charities in the NCCS data, the overall share with receipts above \$100,000 has steadily declined from over 66% in 1989 to less

than 62% in 2002. Using entry rates and a simple binary transition matrix estimated over the full sample, I calculate a stationary distribution in which fewer than 42% of charities have receipts above \$100,000. A continuation of this trend might have lead to sufficient accumulation that significant excess mass would remain for some amount of time after the removal of the notch, but there had not been sufficient accumulation by the time the Form 990 notch was moved. Future research can apply the methodology developed in this paper to assess the importance of dynamics in other settings.

## Appendix 1B - Details of Dynamic Ordinary Least Squares Estimation

Section 5 introduced a reduced-form approach to dynamic bunching estimation to characterize heterogeneity and long-run effects. This appendix details the implementation in this paper, including the estimating equation, sample selection and bin construction, choice and test of omitted range, an instrumental variables specification, and a test for long-run effects.

Estimating outcome  $Y_{it+1}$  in the dynamic ordinary least squares approach involves stacking multiple growth rate ranges and estimating equations of the form

$$(2) \quad Y_{it+1} = \beta \cdot \text{near notch}_{it} + \sum_{j=1}^J \alpha_j r_{it}^j + \sum_{k=0}^K \sum_{a=1}^A \gamma_{ka} r_{it}^k D(f(a), f(a+1))_{it+1}$$

where  $r_{it}$  is current recentered log gross receipts and  $D(f(a), f(a+1))_{it+1} = 1 \{r_{it+1} - r_{it} \in [f(a), f(a+1))\}$  is an indicator for growth falling within a particular range. The estimating equation allows for specifying greater or lesser flexibility in the controls, as desired. The double sum contains an interaction term that allows for a separate pattern of variation across receipts within each growth rate range. The expression encompasses the simple case of growth rate dummies not interacted with current receipts ( $K=0$ ). Results are highly robust to different specifications. I present specifications with a full set of growth range dummies and the interactions of each growth rate bin with a quadratic function of receipts (so that  $J = 2$  and  $K = 2$  in the estimating equation). Potential outcomes of interest include growth of receipts, expenses, and assets. Bunching would imply that receipts would grow by less among the *near notch*<sub>*it*</sub> treatment group. If this reduction represents real income losses (rather than avoidance) then this group should exhibit concurrent reductions in expenses or assets.

Throughout I use the sample of observations with  $r_{it} \in [-1, 2)$  and consider growth rate ranges of the form  $[x, x + .1)$  with  $x \in [0, .9)$ . I show results only for positive growth rates because, as shown in Section 6, essentially all responses are due to charities with current incomes below the notch. Similar results obtain when excluding the bin of lowest growth rates ( $x = 0$ ), for which *near notch*<sub>*xit*</sub> indicates charities with current receipts already in the neighborhood of the omitted region. Statistical testing confirms the visual evidence that observations are binned in such a way that there is no net distortion to the share of charities in the treatment bins moving to a neighborhood of the notch. Running a regression for each growth rate range, I perform a Wald test of the hypothesis that  $\forall x, \text{near notch}_{xit}$  has no effect on the probability of growth in range  $x$ . The test fails to reject, with p value .1361. That the probability of growing to the omitted region is not significantly different from the counterfactual provides evidence that the specified omitted region includes a sufficient range to include organizations whether or not they bunch.

As described in the text, *near notch*<sub>*it*</sub> is a dummy for charities moving to an omitted region that straddles

the notch. I present results for current log receipt bins of width .05, log growth bins of width .1, and an omitted region of  $r_{it+1} \in [-.08, .07)$ . Estimates are qualitatively similar when using receipt bins of width .03 or .1 and growth rate bins of width .05 or .15. Widening the omitted region increases the number of bunchers in the treatment group, which should increase the precision of estimated responses. Because responses are local, widening the omitted region increases the total number in the group by even more than it increases the number of included bunchers, so that for a given level of precision it becomes necessary for bunchers' responses to be larger to distinguish the average response from zero. Such tradeoffs suggest an opportunity to develop an econometric procedure for optimally constructing the bins, but I leave this for future research.

Because the regressions estimate an average response among those that respond and those that do not, it is also useful to estimate the amount by which the bunching charities manipulate their income. To calculate the receipt reductions of bunchers one can relate the reductions of receipts that is estimated with equation (2) and relate this reduction to the share of charities that bunch, which is estimated by equation (2) when the outcome is  $cross_{it}$ . It is natural, then, to perform Two Stage Least Squares estimation with receipt growth as the outcome and  $near\ notch_{it}$  as an instrument for  $cross_{it}$ . The exclusion restriction would require that charities nearing the notch only reduce their receipts in order to stay below the notch, a reasonable assumption given that these charities are spread through the distribution of current receipts and are compared to other charities with growth rates in the same range as theirs. The coefficient on  $cross_{it}$  in the second stage provides a measure of bunchers' average reduction of reported income to avoid filing Form 990.

Lastly, tests for long-run effects merit a brief note on sample selection. I examine long-run effects using the outcome  $cross_{xit+s}$  for  $s$  ranging from 1 to 12. The specification requires that year zero falls in 1997 or earlier so that each organization can be observed for all twelve years. The sample size generally decreases with the horizon as organizations go missing from the data. Restriction of the sample to charities that appear in all twelve subsequent years would reduce the sample by a prohibitive 90 percent.



## Appendix 1C - Details of Dynamic Maximum Likelihood Estimation

Section 6 introduced the dynamic estimation of bunching by maximum likelihood. The details of this approach follow. I describe the observed distribution as a function of the latent distribution and of parameters governing bunching and attrition.

It is possible to perform maximum likelihood estimation by estimating a flexible function for the pdf and constraining it to integrate to unity, but starting from the cdf offers several advantages. First, it is desirable to estimate excess attrition among those who cross above the notch or below the point of sample truncation, and the cdf gives the probabilities of these occurrences. Second, the cdf makes it straightforward to constrain the reduced mass to equal the bunching mass (except for differences due to systematic attrition). Third, truncation requires integration of the likelihood between limits that vary with the level of current receipts, a practical issue for multidimensional integration programs. A disadvantage of specifying the cdf is the need for functions that appear more arbitrary than their derivatives. For example, I include inverse tangents to allow for curvature at growth rates close to zero because the derivative of  $\arctan(x)$  is  $\frac{1}{1+x^2}$ .

The latent cdf of conditional growth is given by

$$F(g|r) = \begin{cases} \exp(P_l(g, r, \theta)) & g < \theta(r) \\ 1 - \exp(P_u(g, r, \theta)) & g \geq \theta(r) \end{cases}$$

$$P_l(g, r, \theta) = \pi_0^l + \tau_0^l r + (\pi_1^l + \tau_1^l r)(g - \theta) + (\pi_2^l + \tau_2^l r)[\exp(g - \theta) - 1]$$

$$P_u(g, r, \theta) = \pi_0^u + \tau_0^u r + (\pi_1^u + \tau_1^u r)(g - \theta) + (\pi_2^u + \tau_2^u r)[\exp(-(g - \theta)) - 1] \\ + (\pi_3^u + \tau_3^u r)[\exp(-(g - \theta)^2) - 1] + (\pi_4^u + \tau_4^u r) \arctan((\pi_4^u + \tau_4^u r)(g - \theta))$$

I now list and impose as needed the conditions that ensure  $F(g|r)$  is a cdf. First, the function must have infimum 0 and supremum 1. The appropriate limits can be achieved by two restrictions on the parameters:

1.  $(\pi_1^l + \tau_1^l r) < 0 \Rightarrow \lim_{g \rightarrow -\infty} P_l(g, r, \theta) = -\infty \Leftrightarrow \lim_{g \rightarrow -\infty} F(g|r) = 0$
2.  $(\pi_1^u + \tau_1^u r) < 0 \Rightarrow \lim_{g \rightarrow \infty} P_u(g, r, \theta) = -\infty \Leftrightarrow \lim_{g \rightarrow \infty} F(g|r) = 1$

Both constraints are easily implemented by using exponentiated coefficients in the numerical maximization.

Second,  $F(g|r)$  must be nondecreasing. Because the posited functional form has one point of nondifferentiability at  $g = \theta$ , the nondecreasing property requires  $\lim_{g \rightarrow \theta^-} F(g|r) \leq \lim_{g \rightarrow \theta^+} F(g|r)$ . I require this relation to hold with equality, giving continuity of the cdf and ruling out point mass at zero growth. This gives

$$\exp(P_l(\theta, r, \theta)) = 1 - \exp(P_u(\theta, r, \theta))$$

$$\exp(\pi_0^l + \tau_0^l r) = 1 - \exp(\pi_0^u + \tau_0^u r)$$

$$3. \pi_0^l + \tau_0^l r = \log(1 - \exp(\pi_0^u + \tau_0^u r))$$

The implied latent density is

$$f(g|r) = \begin{cases} P'_l(g, r, \theta) \exp(P_l(g, r, \theta)) & g < \theta(r) \\ -P'_u(g, r, \theta) \exp(P_u(g, r, \theta)) & g \geq \theta(r) \end{cases}$$

where  $P'_l(g, r, \theta)$  and  $P'_u(g, r, \theta)$  are derivatives with respect to  $g$ . These derivatives can be assured of the correct sign by exponentiating each of the relevant coefficients, but this would impose more than is required because nonnegativity of the density does not necessitate that *all* the coefficients have the same sign. Instead I simply impose a prohibitive penalty on the value of the likelihood function if the pdf is negative for any observations. Similarly, I do not impose conditions 1 and 2, which arise naturally during the optimization, but I do impose condition 3, which has the added benefit of reducing the number of parameters to be estimated.

To measure bunching I estimate  $b$ , the share of mass from the reduced region that instead appears in the bunching region. I specify a vector for  $b$ , allowing the bunching propensity to depend on whether current receipts are above the notch, but in either case require the bunching mass to equal the reduced mass. I define  $notch := \log(100,000)$  as the Form 990 receipts notch and allow organizations to shift receipts from a region of width  $Rwidth$  to a region of width  $Bwidth$ . Thus, there is excess mass  $B$  in the bunching region  $g + r \in [notch - Bwidth, notch)$  that would otherwise lie in the reduced region  $g + r \in [notch, notch + Rwidth)$ . Combining these ranges gives an omitted region of  $g + r \in [notch - Bwidth, notch + Rwidth)$ . I do not use charities moving to the omitted region to identify the shape of the latent distribution. However, I incorporate these observations to estimate bunching and attrition parameters. To do this I generate a variable  $g^*$  equal to  $(notch + Rwidth - r)$  for charities moving to the reduced range,  $(notch - r)$  for charities moving to the bunching range, and  $g$  for other charities. The fact that  $g^*$  is assigned as such is then incorporated into the likelihood function.<sup>22</sup> Since the empirical distribution has fat tails, with observed growth rates of absolute value greater than 10 log points, I allow for infinite support.

The other observations that do not follow the latent distribution are those that go missing in the next

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<sup>22</sup>Missing and bunching observations could be assigned to any value of  $g^*$ . Identification uses the count of missing and the count of omitted and not the location of either.

year. I allow for 3 channels through which these organizations go unobserved. First, organizations do not file any information return if log receipts are below  $\log(25,000)$ . I drop the few observations with reported receipts below  $rmin := \log(25,000)$  and set the share of truncated observations equal to the value taken by the latent conditional cdf at  $rmin - r$ .<sup>23</sup> Second, some share  $\lambda$  of current filers will not appear in the next year's data file regardless of their receipts, either because they miss the filing deadline or because their data is lost in some stage of the collection process. Third, I allow that an additional share  $\delta$  go missing when crossing *notch*. In each case growth is unobserved, so for these observations I set the value of  $g^*$  equal to the minimum observable growth ( $rmin - r$ ).

Finally, I set  $\theta = 0$  after obtaining nonparametric mode estimates between 0 and 0.005 for all years. The observed conditional cdf is therefore

$$F^*(g^*|r) = \begin{cases} 0 \\ \lambda + (1 - \lambda) F(rmin - r|r) + \delta(1 - F(notch - r|r)) \\ \lambda + (1 - \lambda) F(g^*|r) + \delta(1 - F(notch - r|r)) \\ \lambda + (1 - \lambda) F(notch - Bwidth - r|r) + \delta(1 - F(notch - r|r)) \\ (1 - \lambda) [F(notch - r + Rwidth|r) - F(notch - r - Bwidth|r)] \\ \quad + b(1 - \lambda - \delta) [F(notch - r + Rwidth|r) - F(notch - r|r)] \\ (1 - b)(1 - \lambda - \delta) [F(notch - r + Rwidth|r) - F(notch - r|r)] \\ \lambda + \delta + (1 - \lambda - \delta) (F(g^*|r)) \end{cases}$$

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<sup>23</sup>Results are robust to further truncation of the sample at  $\log(100,000) - 1 \approx 37,000$ , which would avoid any potential concerns about selective entry just above the truncation point. One could also exclude observations with current receipts in the omitted region or allow the density to be discontinuous in current receipts at  $r$ , in keeping with the potential concern that even the upper counterfactual region has been affected by repeated bunching at the notch, as discussed in Appendix A. In practice these adjustments also appear to have little effect on the estimates.

$$\left\{ \begin{array}{l} \text{for } g^* < rmin - r \\ \text{for } g^* = rmin - r \\ \text{for } rmin - r < g^* < notch - r - Bwidth \\ \text{for } notch - r - Bwidth \leq g^* < notch - r \\ \text{for } g^* = notch - r \\ \\ \text{for } g^* = notch - r + Mwidth \\ \text{for } notch - r + Mwidth < g^* \end{array} \right.$$

Maximizing the likelihood function  $\sum_{i=1}^N \log [f^*(g_i^*|r_i)]$ , where  $f^*(g_i^*|r_i)$  is the discrete-continuous implementation of the conditional likelihood implied by  $F^*(g_i^*|r_i)$ , gives an estimate of the value of each parameter. For any value of  $r$  one can then obtain counterfactual growth estimates by plugging the desired value(s) of  $g$  into the estimated distribution function(s). Integrating over  $r$  gives the total counterfactual mass for the next year. I perform the estimation on observations with  $r < 14 \approx notch + 2.5$  to reduce computation time and keep the results from being influenced too heavily by charities far above the notch. I rescale the resulting estimates of excess and reduced mass to represent shares of the full population in the next year (for comparison with static estimates).

Figure C.1 shows the fit of the model to the data for a sample of charities with log gross receipts below the notch by .24 to .25. Data for the omitted region has been dropped, and this is reflected in the MLE prediction. Otherwise the distribution is simply fit to the data as is.

## 2 Tax Avoidance and Compliance-Cost-Sensitivity of Donations: Evidence From Regulation of Charitable Foundations

### Abstract

To curb tax avoidance and evasion through charitable foundations, the Tax Reform Act of 1969 imposed regulatory requirements similar to those that would be included in the Sarbanes-Oxley Act over 30 years later. I have compiled the first longitudinal data set spanning the introduction of the new regulations by digitizing directories that included both affected and unaffected foundations. The reform nearly halved the number of foundations receiving gifts, and entry dropped precipitously. Consistent with a deterrent effect, declines were greatest among donors who managed their own foundations and in states that had not required foundations to file financial reports. At the same time, about half of the decline in giving can be explained by the increased cost of running a foundation. The results indicate that donors care about the cost of providing charity and that the compliance cost of regulation may be reducing charity by more than it is reducing the use of charities for tax evasion.

## 2.1 Introduction

U.S. tax law allows donors to claim deductions from their taxable income when they donate to a charitable organization. Internal Revenue Code section 501(c)3 defines two types of tax-exempt charitable organizations: public charities, such as the Red Cross and many universities, and private foundations. Public charities engage in continual fundraising to cover the costs of providing charitable goods or services, whereas most U.S. foundations are “private,” i.e. they are funded by a small number of individuals or companies, and “non-operating” in that they primarily make grants to public charities rather than providing services directly. Wealthy families and companies give a large share of their charitable donations to foundations.

Donors’ ability to control their private foundations raises concerns for tax enforcement. Managers of public charities that misuse one donor’s gift will have difficulty attracting other donors, but the management of a private foundation is generally determined by the only donors it will ever have.<sup>24</sup> As a result, foundation donors and managers have more opportunity to direct funds for their own benefit instead of the charitable uses for which the federal tax subsidy is provided. To prevent abuse of the charitable deduction, new rules regulating the behavior of private non-operating foundations and their donors were incorporated into the Tax Reform Act of 1969 (TRA69), “the most far-reaching legislation affecting private philanthropy in our two hundred year history” (Worthy, 1975). This paper presents evidence that the regulation of charitable foundations, which has remained largely unaltered since 1969, reduced misuse of foundations but also imposed compliance costs that greatly reduced charitable giving.

To analyze foundation donations and responses to regulation I have compiled a new electronic data set. To my knowledge this is the first panel of charitable foundations that includes multiple years prior to 1969. I produced the database from hard copies of the Foundation Directory, a regular publication of the Foundation Center that provides financial and grantmaking data on the foundations large enough to account for over 90 percent of U.S. foundation assets.

This study first provides difference-in-differences estimates of the overall impact of TRA69. The numerous provisions of TRA69 included documentation and reporting requirements, prohibition of certain types of transactions, a tax on investment returns, and the requirement to spend a minimum percentage of the foundation’s assets each year. It is believed that TRA69 had a negative effect on foundations, but the economic decline that followed the reform and a lack of data have made it difficult to measure the impact of the law. I estimate the overall effect on entry, exit, giving, and expenses by comparing changes among regulated foundations to changes among unaffected community foundations (geographically-based grantmakers that receive funds from many donors) and operating foundations (endowed organizations that provide services

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<sup>24</sup>Warren Buffet’s gift to the Bill and Melinda Gates Foundation garnered attention in part because such gifts to others’ foundations are rare.

directly). I find that TRA69 reduced the entry rate of private non-operating foundations by more than 10 percentage points, reduced the share of regulated foundations receiving donations by about 50 percent (30 percentage points), and more than doubled administrative expenses without significantly affecting total spending.

With the foundation data I am also able to estimate the sources of overall decline in gifts to distinguish deterrence of abuse from adverse effects of compliance costs on charitable giving. First I define two proxies for misuse of foundations: donors who manage their own foundations, and states that did not require the type of public financial reporting that was mandated nationally by TRA69. Difference-in-difference estimates comparing such foundations to the other private non-operating foundations indicate that both factors predicted significant drops in reported gifts when TRA69 was enacted, and the interaction of the two shows that gifts fell most for donor-managers that were not subject to state reporting. Next I analyze how donors respond to administrative expenses. Expenses are endogenous to donor choices and generally increase with gifts and assets, but the sudden rise in administrative expenses after TRA69 was greatest among formerly-low-admin foundations, as would be the case if compliance entailed significant fixed costs. To obtain causal estimates of the effects of compliance costs on gifts to foundations I instrument for a foundation's administrative expense growth using the level of administrative expenses before the reform. I estimate that a 1 percent increase in administrative expenses lowers the probability of donation by about .05 percentage points (about .15 percent of the post-reform average). A decomposition of the results indicates that the increase in administrative expenses explains nearly 60 percent of the decline in gifts, and the two proxies for malfeasance explain much of the remaining 40 percent.

This paper contributes to a long literature on the elasticity of charitable giving with respect to (tax) price. Since donations can be deducted from income and estate taxes, the cost of providing a dollar of support to charity is decreasing in the donor's marginal tax rate. Particular emphasis has been given to the question of whether the tax price elasticity is less than -1, which would indicate that a dollar of subsidy produces more than a dollar of donations (Andreoni, 2006). Randolph (1995) found large temporary effects and small permanent effects, but subsequent research has found permanent elasticities less than -1 (Auten et al. 2002, (Bakija and Heim, 2011)). Though the tax price elasticity of giving offers an intuitive interpretation, it is only a sufficient statistic for welfare analysis under strong assumptions about the nature of tax avoidance and donor preferences.

Private foundations offer a unique opportunity to test for a form of donor altruism, which has important welfare implications. Optimal subsidization of charitable giving depends on whether donors care about recipients' utility or simply the amount they give, even if the "warm glow" a donor might obtain from the amount of the gift is not included in the social welfare function (Diamond, 2006). Variation in foundations'

administrative expenses enables a test for pure warm glow because administrative expenses create a wedge between a donor's gifts and the amount that is passed along to recipients. Several empirical studies of giving to public charities have included recipient organizations' administrative expense ratio in the donor's price of giving have calculated the tax price as  $\frac{1-t}{1-a}$ , where  $t$  is the marginal tax rate and  $a$  is the percentage of assets spent on administrative expenses (for example Khanna et al. (1995) and Okten and Weisbrod (2000)). However, donors may respond to public charities' expense ratios due to signalling effects, concern about agency problems such as excessive use of organizational resources by management, preferences for charitable programs that are more costly to administer, or a desire to help young organizations achieve greater economies of scale. Even the compliance costs of seemingly-exogenous federal reporting requirements for public charities are gamed by charities manipulating income to remain below eligibility thresholds for simplified reporting (Marx, 2012b). Whereas the strategic interplay between the donors and managers of public charities cloud the interpretation of behavior, donations to private foundations controlled by the donor provide a setting in which donative behavior can be taken to reveal preferences rather than strategy. My finding of strong donor responses to administrative expenses provides evidence that donors care about the degree to which their donation goes to charitable recipients, indicating that donors are not motivated entirely by warm glow.

The rest of the paper is organized as follows. Section 2 describes the policy reforms affecting private non-operating foundations and the data compiled for the analysis. Section 3 provides estimates of the overall effect of TRA69 that compare regulated foundations to community foundations and operating foundations. Section 4 explores the determinants of the fall in giving by comparing the responses of different types of foundations. Section 5 concludes.

## **2.2 Policy Background and Data**

In this section I describe the regulations affecting private non-operating foundations as well as the Foundation Directory data that was compiled for this analysis. The Tax Reform Act of 1969 induced a sea change in the regulation of charitable foundations, and the digitized Foundation Directory data enables a detailed examination of the effects of the reform.

### **2.2.1 Private Foundations and the Tax Reform Act of 1969**

Statistics from the nonprofit Foundation Center describe the foundation sector in 2010 as comprising roughly 76,000 foundations holding \$622 billion in assets and making \$46 billion in grants to individuals and charitable organizations (Lawrence and Mukai, 2011). These foundations accounted for over 15 percent of the \$291 billion in U.S. charitable giving in that year (Bond, 2009). Private foundations make up an even larger



percentage of charitable bequests. Tabulations from 1995 IRS Statistics of Income data put giving to charitable foundations at 36 percent of charitable bequests, 60 percent among bequests of married men and close to 75 percent among estates worth \$20 million or more (Auten et al., 2000). In tax returns from 1996-1998 the percentage of bequests going to foundations is over 60 percent for estates worth more than \$10 million and close to 95 percent for estates worth over \$50 million (Joulfaian, 2000).<sup>25</sup>

The desirability of charitable tax deductions decreases if individuals can abuse them to obtain subsidies for non-charitable activity, and privately-controlled foundations may offer particularly good opportunities for such abuse. CEOs' gifts of company stock to their private foundations often occur just before declines in share prices, suggesting CEOs use insider information or even illegal backdating to maximize their tax deductions (Yermack, 2009). Moreover, assets within foundations have not always been used for charitable purposes. Before TRA69, a donor was able to give corporate stock to his foundation, claim a tax deduction, then instruct the foundation to hold the stock in perpetuity and vote according to his preferences. Congressional investigations in the 1950s and 1960s discovered donors enriching themselves by having their foundations purchase their assets or extend them loans on favorable terms (Smith and Chiechi, 1974). The commissions performing these investigations argued that foundations represented a small network accumulating wealth and power that interfered with markets and politics, and their numerous recommendations included prohibiting certain foundation activities and limiting the life of a foundation to 25 years (Liles and Blum, 1975). A 1965 report by the Treasury Department concluded that fears of accumulating influence were unfounded but that malfeasance had occurred. The report also concluded that while the 1950 Revenue Act contained vague admonitions against accumulating too much income before making grants to charities it had not prevented some foundations from doing so, leading to lengthy delays between the granting of tax deductions and the benefits to charities (Smith and Chiechi, 1974).<sup>26</sup>

Congressional efforts to prevent misuse of foundations culminated in the Tax Reform Act of 1969, which placed restrictions on private non-operating foundations and their donors and gave the federal government new authority to regulate and fine charitable organizations beyond the blunt tool of rescinding tax-exempt status. TRA69 prohibited political activity and "self-dealing" transactions that would benefit "related parties" including the donor, managers, and directors. It placed a 4 percent tax on the investment returns of private non-operating foundations.<sup>27</sup> It required them to document due diligence in confirming that grants went towards charitable purposes, including showing that all grants to individuals were allocated according to a

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<sup>25</sup>Descriptive statistics on charitable foundations are provided in Clotfelter (1985), Margo (1992), Meckstroth and Arnsberger (1996), and Whitten (2001).

<sup>26</sup>The simple model in Appendix ?? provides a conceptual framework for the government's problem of jointly determining how much to subsidize charitable giving and the level of enforcement to identify and prevent misuse of the deduction for noncharitable purposes.

<sup>27</sup>In 1978 the tax rate was lowered to 2 percent, and starting in 1984 a foundation could qualify for a 1 percent rate in a particular year if its spending rate in that year was high relative to its spending rate in the 5 preceding years.

competitive application process. It capped foundations' voting shares of companies' stock and taxed any holdings above the permitted amount. It required all charitable organizations to file more informative returns with the IRS (using new Form 990-PF) and make annual reports publicly available. It raised the maximum deduction an individual could claim for charitable contributions to public charities from 30 percent to 50 percent of the individual's income but kept the limit at 20 percent of income for gifts to private foundations. It reduced the allowable deduction for gifts of appreciated property by half the value of the appreciation. Finally, it established the "payout rule" requiring foundations to spend a minimum percentage of assets on non-investment expenses each year, with the minimum initially set at 6 percent.<sup>28</sup>

While the foundation provisions of TRA69 were intended to reduce perceived and documented abuses, some would impose costs on all foundations. The investment returns excise tax, the first income tax ever imposed on U.S. charitable organizations, was included on the basis that it would pay for heightened IRS enforcement. Perhaps even more costly for small foundations were the new reporting requirements, necessitated in part to ensure compliance with the payout rule. Prior to TRA69, foundations filed the two-page Form 990-A, which included a basic statement of income and expenses and a basic balance sheet. After TRA69, private foundations were required to file the thirteen-page Form 990-PF, which includes significantly more detailed versions of the sections from the 990-A, as well as sections for listing capital gains, calculating the investment income tax, describing program activities (some of which require completion of additional forms), naming and listing compensation of key employees and contractors, calculating the required spending amount and qualifying distributions, tabulating income produced by activities and their connection to the foundation's charitable purpose, listing transactions with other exempt organizations, and providing other "supplementary information."

Existing empirical analysis suggests TRA69 reduced giving and increased expenses. Charitable deductions claimed by individuals in the 99.9th percentile of the income distribution, those most likely to give to foundations, declined by roughly 30 percent relative to those of the 90th percentile (Fack and Landais, 2009). Time series aggregates from the Foundation Directory reveal that the average ratio of administrative expenses to grants never exceeded 9.9 percent in periods before 1970 but was never below 14.9 percent thereafter (Margo, 1992). Foundations surveyed after TRA69 reported average legal and accounting fees more than 50 percent greater than those reported for 1968, and the share of respondents with such fees totaling less than \$2000 for the fiscal year fell from 52 percent to 29 percent. 46 of 350 respondents added their first executive after 1968, and reported staffing increased by 25 percent (Council on Foundations, Inc., 1977). Past estimates of the effects of TRA69 using foundation data have relied on simple differences of

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<sup>28</sup>For a comprehensive history of the tax treatment of charity up to 1969 see Liles and Blum (1975). For details on the foundation-related sections of TRA69 see Smith and Chiechi (1974), and for subsequent adjustments to the regulation of foundations see Deep and Frumkin (2001) and Gravelle (2003).

averages between a changing sample of foundations across two time periods with very different economic conditions.<sup>29</sup> Moreover, there has been no attempt in past research to link the changes in administrative costs to changes in gifts received or to distinguish between desirable and undesirable giving. Until now there has been no electronic data that could be used to measure within-foundation changes.

### 2.2.2 Data

For this analysis I have compiled a multi-year panel database from the Foundation Directory (Foundation Center, The, 1960-1986). The Directory allows grant seekers to find likely funders and provides information about the foundations' grants and finances. The Foundation Center has published an edition of the Foundation Directory at least once every three years since 1960. The Directory samples the largest foundations, capturing those that make up 90 percent or more of all foundation assets in the period covered by each edition. Foundations are included if grants or assets exceed a time-varying truncation point.

The Foundation Center collected the data from a combination of surveys and public records. The Center contacted each foundation multiple times to complete its survey, then provided IRS data for non-respondents. Much of the data was publicly available because the Revenue Act of 1950 required foundations to file annual information returns that include the financial variables of interest (Liles and Blum, 1975). Observations from 1974 and after report whether data were retrieved from public records. The foreword to the first edition of the Directory aptly described foundations' incentives for providing information:

We recognized that some foundations would prefer anonymity, and would not supply any information. For this position they may have cogent reasons, including the fear that listing will increase the flood of appeals, which they are ill-equipped to handle. However, the fact is that anonymity is already impossible; by federal law the information returns of all tax-exempt foundations are open to public inspection, and address lists are on sale by commercial organizations. Under these circumstance an adequate description, including geographical and other limitation, may reduce—though it will not eliminate—the inappropriate appeals foundations receive (Foundation Center, The, 1960).

The Foundation Center published several editions of the Directory before TRA69, but their contents were never compiled electronically. Research on foundations has therefore relied heavily on the IRS Form 990-PF that foundations have been required to file annually since TRA69 was passed. To create a panel database

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<sup>29</sup>Labovitz (1974) compares the traits of 388 foundations in 1967 to the traits in 1970 of the 275 of those who remained in existence and whose data could be obtained. The Council on Foundations, Inc. (1977) sent a single questionnaire to 2248 foundations and received 566 responses, of which 433 reported expenses in the most recent year and 360 reported expenses in 1968. The criteria for inclusion in the Foundation Directory, and hence the aggregates reported by Margo (1992), used to construct these aggregates changed over time, particularly in the 1960s.

spanning TRA69 I scanned hard copies of the first 15 editions of the Foundation Directory, converted the images to text using ABBYY FineReader optical character recognition software, wrote Python code with Regular Expressions to organize the text by variable name and extract information to populate a data table, and merged editions in Stata. Further details of this process are provided in Appendix 2.5.

The database includes a wealth of information about foundations. Key financial variables include gifts received by the foundation during the fiscal year (for editions after the first), assets accumulated, and expenses incurred. Expenses are broken down into several categories, including grants made to charitable organizations, grants made to individuals, scholarships awarded, loans made, in-kind gifts, matching gifts, and programs. The Directory does not explicitly list administrative expenses but does provide total expenses. I define “charitable spending” as the sum of outlays in the aforementioned charitable categories and “administrative expenses” as the difference between this amount and the amount of total spending. The Foundation Center, The (1975) uses the same formulation but cautions that accounting practices differ between foundations, a source of measurement error that should be mitigated by using foundation fixed effects to estimate within-foundation changes. Donors are listed throughout, and all editions but the first indicate if a donor is deceased. I am able to identify company donors by the existence of terms such as “Company,” “Companies,” “Ltd.,” “Inc.,” “Corp” and major industries among donor names. The words “Community foundation” and “Operating Foundation” in the name and purpose fields identify foundations in the control group.<sup>30</sup> Because each edition includes data for multiple years, with nonrandom timing of foundation responses within edition, I use edition as the time variable rather than year.

I make three major sample restrictions for this study. First, I remove unusually small foundations. The Directory includes foundations that have enough assets *or* enough grants, but I exclude foundations that qualify only based on grants so that the sample is determined entirely by asset size. Second, I use only the first eight editions, thus centering the sample around the 1969 reforms and excluding years after the major tax reforms of 1981. Third, I exclude Edition 4, which covers just before as well as just after the reform, when some provisions had not been fully implemented.

Table 2.1 provides summary statistics for the full sample, the balanced panel, the treatment group in the balanced panel, and two types of (treated) foundation. Foundations in the balanced panel are larger, as expected, but comparable to the full sample with regard to the number of donor-managers and family managers. Within the balanced panel, the vast majority of foundations are treated, and these treated private non-operating foundations are slightly smaller along each dimension than the control group of community and operating foundations. Among regulated foundations in the balanced panel, roughly one quarter had

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<sup>30</sup>The Foundation Directory did not include a “Foundation Type” field until the 6th edition, after the passage of TRA69. I exclude the very small number of foundations identified explicitly as community or operating in editions of the Foundation Directory that follow those included in the current analysis.

donor-managers before TRA69 and two thirds were in states with no financial reporting law. Foundations whose donors served as managers had more assets and spent more despite receiving somewhat smaller gifts. Foundations subject to no state reporting law were about five percent larger than the average among regulated foundations but had similar numbers of donor-managers and family managers.

## 2.3 Total Effect of TRA69: Private Non-Operating vs. Other Foundations

I first estimate the total effect of TRA69 on charitable foundations by comparing changes among regulated private non-operating foundations to changes among unaffected community and operating foundations. Results indicate that the law reduced the number of foundations receiving gifts and greatly increased the administrative expenses of the average foundation.

### 2.3.1 Effects on Entry and Exit

#### Empirical Strategy

To estimate effects on entry and exit I compare changes in the hazard rates among the regulated foundations to the changes among unregulated foundations. A difference-in-difference estimator will be consistent if the hazard rates for the two groups would have evolved similarly in the absence of the reform. Focusing on the subsample of foundations with assets greater than \$1 million (1974) in order to set a consistent size threshold across time, I estimate

$$E_{it} = \beta * post_t * private_i + \gamma * private_i + \phi * new_{it} + \delta_t + \epsilon_{it}$$

where  $E_{it}$  is an indicator for the foundation's first appearance in the subsample (entry) or its last (exit),  $post_t$  is an indicator for years after TRA69,  $private_i$  is an indicator for private non-operating foundations (those subject to the new regulations),  $new_{it}$  is an indicator for entering foundations that is included in the exit regression to account to the preponderance of foundations that only appear for one period, and  $\delta_t$  is a vector of dummies for editions of the Foundation Directory. The coefficient of interest,  $\beta$ , identifies the effect of the reform on the entry and exit hazard rates.

#### Results

Most striking is the reduction in the entry rate of private non-operating foundations. Figure 2.1 depicts the entry rates of these regulated foundations and of community and operating foundations in each edition of the Foundation Directory after the first. The entry rate of regulated foundations falls from around 35 percent before the reform to less than 10 percent after. The entry rate of community and operating foundations

also falls between Foundation Directory Editions 5 and 6, reflecting the fall in the stock market and poor economic conditions. The decline among community and operating foundations is significantly smaller, however. One can also see that entry of private non-operating foundations begins to fall immediately after the reform, whereas unregulated foundations continue to enter at a relatively high rate until the adverse economic conditions. While it was difficult to determine from previously-available data whether the reform or economic conditions were responsible for declines among private foundations, it is clear in Figure 2.1 that private foundation entry declined before market conditions turned.

Figure 2.2 depicts the exit rates of each type of foundation in each period. In contrast to past studies, there is no evidence of exit by newly-regulated foundations. If anything, the rate of exit declined once the market decline played out. The requirement to deliver the assets of any dissolving charitable foundation to another charitable organization suggests little incentive to dissolve well-endowed foundations, even those used for private gain. Past findings of a high degree of exit immediately after TRA69 may therefore reflect dissolution of low-asset foundations that would not appear in the Foundation Directory sample.<sup>31</sup>

Table 2.2 provides regression results for entry and exit. Whether one uses a linear probability model (column 1) or a probit model (column 2), there is a significant adverse effect on the entry rate of private non-operating foundations. The effect on exit is also insignificant, regardless of the empirical model. The results suggest a reduction in churning rather than exodus of newly-regulated foundations. Appendix Figure 2C.1 shows that it was newer private foundations that were exiting at a higher exit rate before the reform. Appendix Figure 2C.2 shows that small foundations (just above the threshold for inclusion in the data) were especially likely to exit during the stock market decline between ed Editions 5 and 6, and Appendix Table 2C.1 shows that the types of private foundations studied in the paper showed no differential propensity to exit at this time. Since only asset size predicts exit by existing foundations, I turn to analysis of a balanced panel to study the effects of TRA69 on existing foundations.

### 2.3.2 Effects on Balanced Panel

#### Empirical Strategy

To estimate the impact of TRA69 on existing foundations that continued operations I estimate the equation

$$Y_{it} = \beta * post_t * private_i + \phi' X_{it} + \gamma_i + \delta_t + \gamma_i * t + \epsilon_{it}$$

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<sup>31</sup>A 1970s report of the Council on Foundations showed a sharp increase in exit among private foundations in twelve states (Council on Foundations, Inc., 1977). The methodology and identities of the twelve states were not reported. The report attributes the results to earlier work by the firm Caplin & Drysdale and the Foundation Center. Staff of the Council on Foundations, Caplin & Drysdale, the Foundation Center, the Philanthropy Archives at IUPUI University Library, and the Rockefeller Archive Center all graciously attempted to locate the earlier study or its analysis but were unsuccessful.

where the outcomes  $Y_{it}$  are various measures of gifts and expenses, while  $post_t$ ,  $private_i$ ,  $\gamma_i$ , and  $\delta_t$  are defined as in the previous section. The time-varying characteristics  $X_{it}$  are dummies for 1 or more deceased donors, 2 or more deceased donors, and an unknown number of deceased donors.<sup>32</sup> Linear time trends for each foundation,  $\gamma_i * t$ , are included to allow for differential trends. Standard errors are always clustered by the U.S. state in which a foundation is first observed.

## Results

I first show results for the effect of TRA69 on gifts to foundations. Figure 2.3 shows log gifts to foundations in each edition of the Foundation Directory for which gifts were reported.<sup>33</sup> Trends for the two groups appear very similar before and after the reform, but the regulated foundations exhibit a large decline at the time TRA69 is enacted. The decline in the average gift size is driven by a reduction in the probability of receiving any gift at all. Figure 2.4 shows the share of foundations receiving a gift in each edition. The share of private non-operating foundations receiving gifts fell from over 55 percent before TRA69 to about 30 percent after. In contrast, community and operating foundations maintain a steady upward trend. While the difference between the two groups' trends is not statistically significant, foundation time trends reduce the estimated impacts on the share receiving gifts and are included in the primary specification to provide conservative estimates.

The regression results in Table 2.3 confirm the graphical evidence of impacts on existing foundations. The first three columns present impacts on measures of gifts received by foundations: the log of gifts plus 1000, the log of gifts plus 1, and an indicator for any gift. In each case, the relative reduction among newly-regulated foundations is highly significant. Because separate analysis (not shown) reveals little effect on the size of gifts made, I focus throughout the rest of the paper on results for the probability of any gift being received. Column 3 shows that the probability of receiving a gift dropped by nearly 30 percentage points when TRA69 was passed. Although the reform included a payout rule to increase foundations' current spending on charitable causes, column 4 reveals that the effect on spending was insignificant. Administrative expenses, however, increased by about a full log point, whether one excludes zeros (column 5) or includes them (column 6). In other words, the administrative expenses of private non-operating foundations more than doubled relative to those of community and operating foundations.<sup>34</sup> In Figure 2.5 one can see that while administrative expenses of community and operating foundations rose at a slightly lesser rate in the

<sup>32</sup>Results are robust to inclusion of lagged financial variables as well as interactions of  $post_t$  with financial variables, age, and deceased donor variables.

<sup>33</sup>While the logarithmic specification is often employed for its convenient interpretation as an approximate percentage change, the logarithm is undefined when gifts are zero. Because the majority of foundations receive no gifts in any particular year, I add 1000 (the fourth-smallest of the 2080 observed gifts and the smallest amount observed more than once) before taking the log.

<sup>34</sup>Appendix table 2C.2 shows similar but stronger results for all variables when foundation time trends are not included.

1970s than in the 1960s, private non-operating foundations experienced a sharp increase in administrative expenses when TRA69 was passed.

The evidence strongly suggests that TRA69 had a negative impact on the foundations it affected. The question, then, is whether the decline among private non-operating foundations should be interpreted in a positive or negative light. If donors were mostly turned off by the increased cost of administration then the reforms introduced socially costly distortions. On the other hand, we would consider the reforms a success if they mostly prevented tax deductions for “donations” that were not going towards charitable purposes. I next estimate the extent to which different factors influenced donors’ decisions to stop giving to private, non-operating foundations.

## **2.4 Heterogeneous Responses By Donor Type, State Law, and Administrative Expenses**

In this section I estimate instrumental variables, difference-in-difference, and triple-difference regressions to analyze heterogeneity in the reduction of gifts to private foundations. Results indicate that TRA69 had some expected effects but also reduced giving significantly by increasing compliance costs.

### **2.4.1 Empirical Strategy**

One observable form of heterogeneity is the characteristics of donors. Foundations may be formed by companies or by individuals, and the mandated increase in spending rates might have disproportionately affected foundations started by individuals with a preference for a foundation that exists in perpetuity. Among human donors, those who managed their own foundations would have had the most opportunity to obtain private benefits, and so the number of donor-managers, as measured by matching donor names to management names, offers a proxy for the type of “self-dealing” transactions for which the law strengthened enforcement. Matching simply on last names reveals whether the foundation is run by kin of the donor(s), an alternative proxy for impropriety, though one that would be weakened by the existence of family foundations that exist for generations beyond the death of the donor(s).

A second set of observable differences can be found in state laws governing foundations. Some states required that foundations file regular financial reports to the attorney general or other state officials. In all but a few states, attorneys general had the power to dissolve a charitable corporation. Fremont-Smith (1965) provides the reporting and other requirements across states, a copy of the federal Form 990-A, and examples of (more detailed) state reporting forms. I take the lack of a state financial reporting law as an additional proxy for foundation malfeasance. If more donors gave more to non-reporting foundations in order to obtain



private benefits then gifts to such foundations should fall by more upon enactment of TRA69.

The influence of both donor characteristics and state laws can be identified in a simple difference-in-differences framework similar to that of the previous section. I drop community and operating foundations and estimate

$$gift_{it} = \beta * post_t * W_i + \phi' X_{it} + \gamma_i + \delta_t + \gamma_i * t + \epsilon_{it}$$

where  $gift_{it}$  is an indicator for receiving a gift, and the new variable  $W_i$  is the foundation's maximum pre-TRA69 value of: (1) an indicator for having human donors (rather than companies), (2) managers with last names matching those of donors', (3) donor-managers, and (4) an indicator for the state having no financial reporting law for this type of foundation. Because most foundations are incorporated and because the minority that are organized as trusts are subject to varying laws depending on the timing of the gift relative to the donor's death, I include specifications that include only incorporated foundations, for which the reporting law variable is likely to be measured with less error.<sup>35</sup> I also present triple-difference specifications that interact the donor-managers variable with state reporting laws to assess whether donor-managers are particularly sensitive to the public reporting regime.

Next I examine the influence of compliance costs. Four components of the law increased administrative duties: the public reporting requirement, the grantee due diligence requirement, the investment tax, and the need to calculate and meet the minimum spending ratio. Adherence to the new rules necessitated a certain amount of compliance cost spending, increasing the administrative expenses most among those foundations that had been operated with little overhead prior to the reform. I use the pre-TRA69 level of administrative expenses as an instrument for expense growth to test whether the foundations experiencing the largest increases in administrative expenses were also more likely to see a decline in gifts. Estimating equations are of the following form:

$$gift_{it} = \beta * \hat{cost}_{it} + \alpha * post_t * W_i + \phi' X_{it} + \gamma_i + \delta_t + \gamma_i * t + \epsilon_{it}$$

$$\hat{cost}_{it} = \alpha * post_t * Z_i + \pi * post_t * W_i + \nu' X_{it} + \mu_i + \theta_t + \omega_i * t + u_{it}$$

In the first stage regressions, the instrument  $Z_i$  predicts greater cost growth among certain foundations when TRA69 is imposed. I use the maximum value of administrative expenses before the reform as the instrument and hence expect a negative value for the coefficient  $\alpha$ . In the second stage regressions, the

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<sup>35</sup>Statistical tests indicate no significant effect of state reporting laws on a foundation's probability of incorporating or moving between states.

coefficient  $\beta$  on predicted administrative costs shows the impact of imposed costs on giving.

Lastly, I present a decomposition of the effects between the different factors examined. I take the post-TRA69 means of the predicted change in administrative costs and the  $W_i$  variables of interest, then multiply these means by the respective coefficients to obtain the effect on gifts that is explain by each variable. I then divide each variable's effect by the total change in gifts, as estimated by a simple difference allowing for time trend but no edition dummies, to obtain the share of the total effect that is explained by each variable.

## 2.4.2 Results

### Donor Type and State Reporting Laws

Table 2.4 shows the decline in the probability of receiving a gift for several types of foundation. TRA69 had the strongest effect on the giving of donor-managers. The heightened response of donor-managers does not reflect a general difference between companies and individuals; the indicator for having human donors has no significant predictive power, and neither does the number of donor family members appearing among management. State reporting laws, however, are significantly predictive, with foundations in nonreporting states showing a greater decline in giving. This last result is robust to the inclusion of  $post*state$  interactions (not shown), which can be separately identified because reporting laws for trusts and those for incorporated foundations are not collinear across states. These findings indicate that giving declined most among donors in position to benefit from their own foundations and in states where foundations did not have to provide public financial reports, suggesting that the reform was effective in reducing misuse of foundations for private benefits.

Table 2.5 further explores these responses by examing results according to state law. Interaction of the donor-managers variable with the state law variable reveals that it was donor-managers in non-reporting states who most reduced their giving. Restricting the sample to incorporated foundations isolates the reporting variable that has less measurement error, and the coefficient on this variable's interaction with  $post_t$  is significant at the .05 level. The main result is the same: Gifts decreased significantly among donor-managers that didn't have to provide public financial reports before the reform.

### Administrative Expenses

Figure 2.6 compares current administrative expenses to the level in Edition 1 of the Foundation Directory, many years before the reform. When TRA69 was passed, administrative expenses grew the most among foundations that were previously low-expense, such that these foundations nearly caught up to the level of the highest-expense foundations. The lower panel of Figure 2.6 shows giving before and after the reform

as a function of the same Edition-1 administrative expenses. The decline in gifts was greatest among the low-expense foundations that experienced the greatest increase in their administrative expenses. Controlling for assets and charitable expenses does not alter this finding.

Table 2.6 shows the results of IV regressions for administrative expenses. In the first stage, high administrative expenses strongly predict a smaller increase at the time of the reform. This is true, and if anything strengthened, when size controls are interacted with  $post_t$ . In the second stage, donors are seen to react negatively to the increase in administrative expenses. The coefficients imply that a one percent increase in log administrative expenses reduces the probability of receiving a gift by .05 to .06 percentage points.

### Decomposition of the Response

Table 2.7 presents a decomposition of the decline in giving. The growth of administrative expenses among previously-low-cost foundations explains nearly 60 percent of the decline in gifts. Donor-managers and state reporting laws explain about 12 and 15 percent, respectively, so that the three variables together explain over 95 percent of the decline in giving.<sup>36</sup> While there is significant evidence of successful deterrence of non-charitable behavior, the reform may well have done more harm than good by imposing compliance costs that deterred legitimate charitable giving.

## 2.5 Conclusion

I study how regulations in the Tax Reform Act of 1969 affected private foundations and their donors. At the time of the reform, gifts to private foundations dropped precipitously, and the administrative expenses of foundations rose just as quickly. The analysis suggests that these simultaneous responses were not coincidental; donors are highly responsive to the cost of running a foundation. The result suggests that giving to foundations is not purely driven by warm glow. While enforcement is undoubtedly necessary to prevent misuse of foundations for specious tax benefits, simplifying the rules could reduce the cost of running a foundation and increase charitable donations.

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<sup>36</sup> Appendix Table 2C.3 provides the same decomposition among incorporated foundations, revealing that the better-measured reporting law explains a larger share of the decline in gifts.

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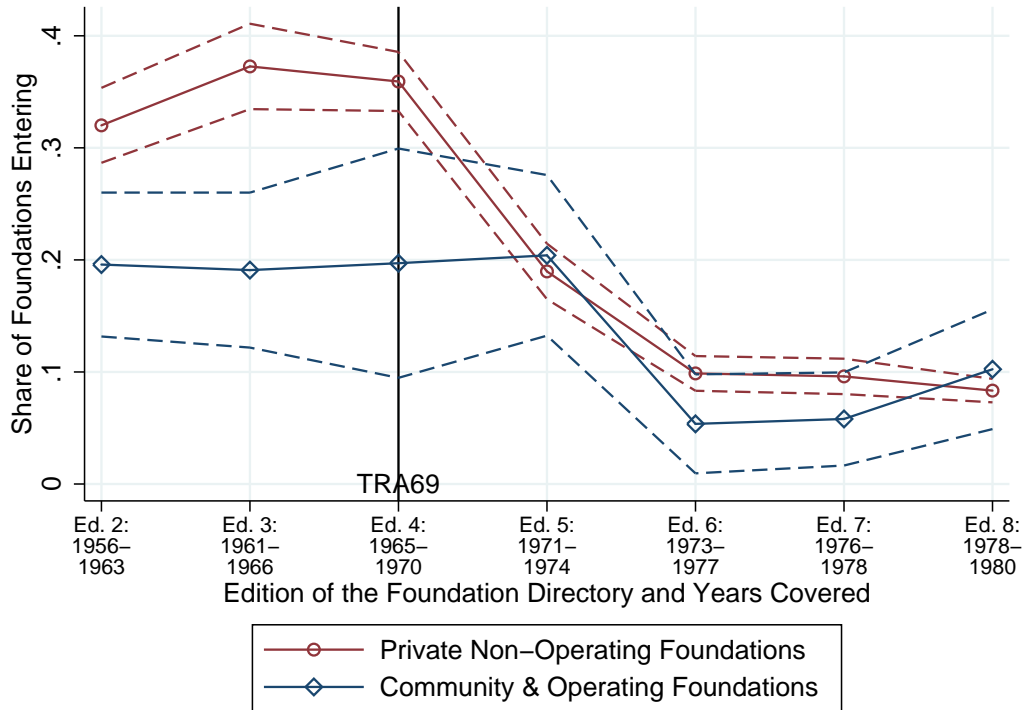
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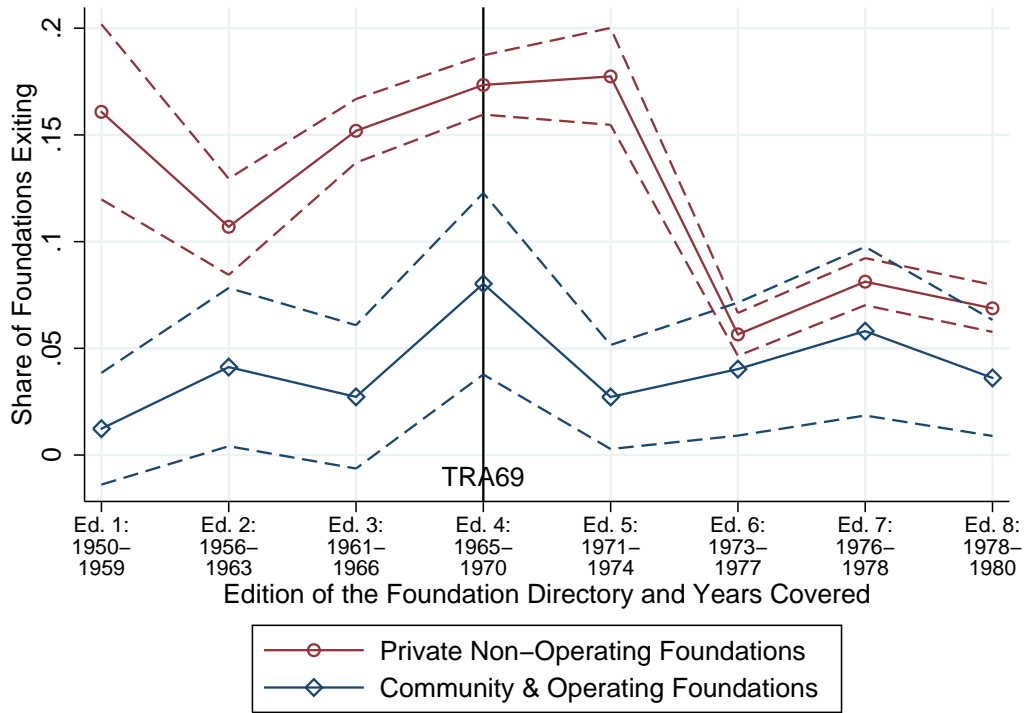
## Figures and Tables

Figure 2.1: Decline In Entry by Private Foundations



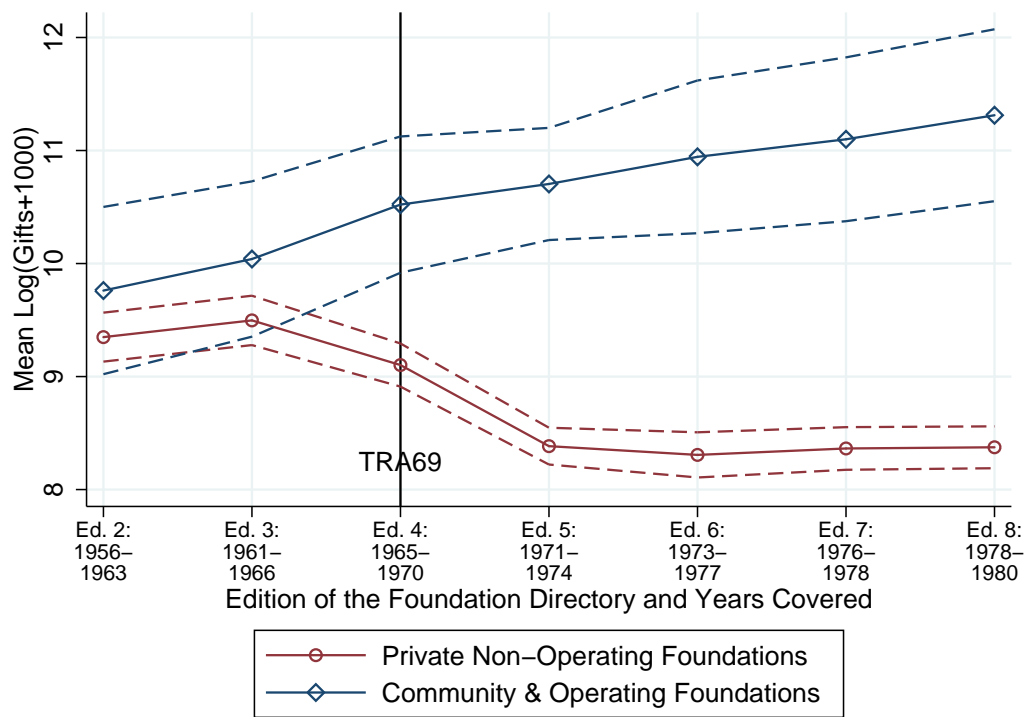
*Notes:* The figure displays the number of foundations first appearing with assets over \$1 million (1974) as a share of the total number of the same type in each edition of the Foundation Directory. Each edition includes one observation per foundation in a span of a few years, with most foundations' data pertaining to the listed modal year. TRA69 was enacted towards the end of 1969, during the period spanned by Edition 4. Entry by newly-regulated private non-operating foundations fell immediately after the reform, while entry of unaffected community and operating foundations did not decline until the market decline from 1973 to 1975. N=14,318.

Figure 2.2: No Increase In Exit by Private Foundations



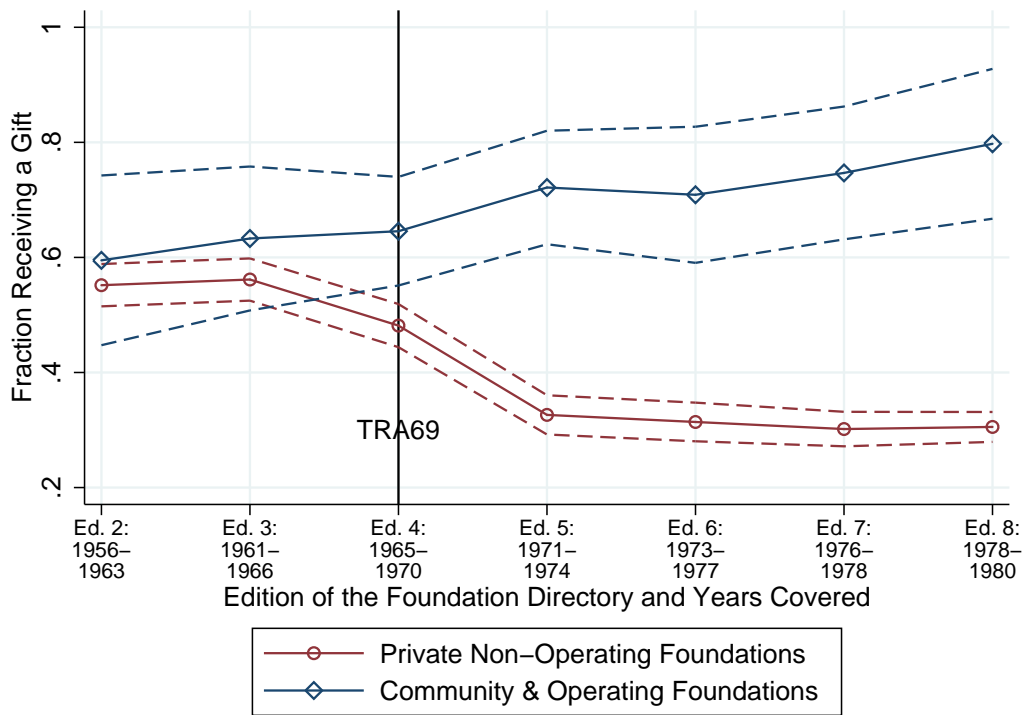
*Notes:* The figure displays the number of foundations appearing for the last time with assets over \$1 million (1974) as a share of the total number of the same type in each edition of the Foundation Directory. Exit by private non-operating foundations was somewhat greater than exit by community and operating foundations until the market decline from 1973 to 1975. TRA69 did not increase the exit rate of large private foundations and may have reduced it, consistent with a reduction in churning. N=14,318.

Figure 2.3: Decline in Gifts Received by Private Foundations



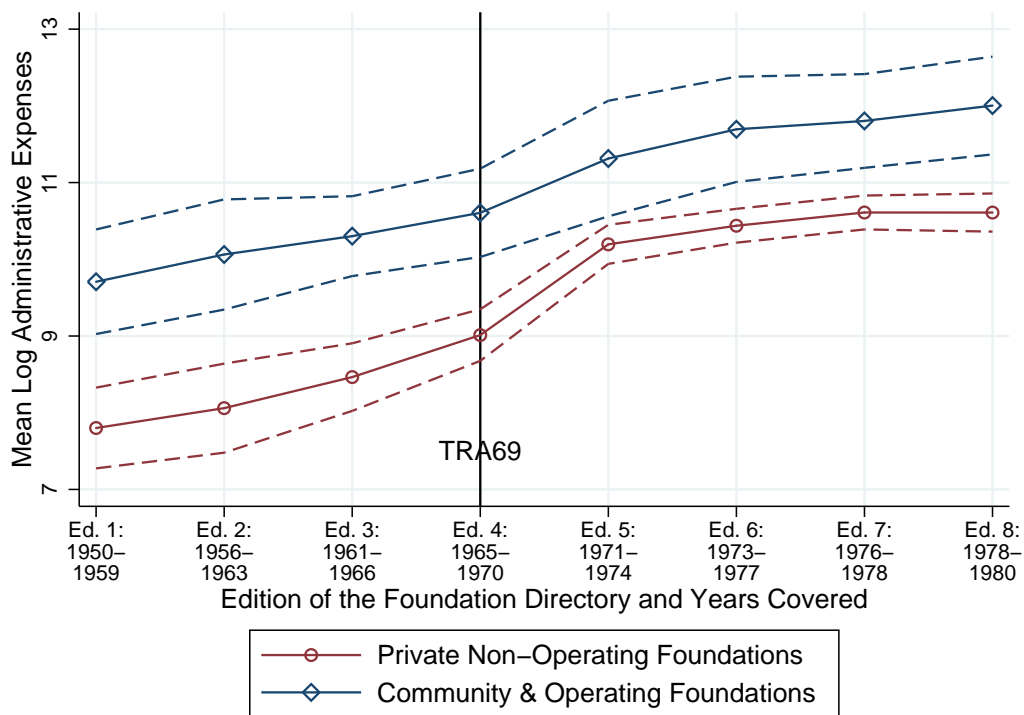
*Notes:* The figure displays the mean level of gifts received by each type of foundation in each edition of the Foundation Directory. The measure of gifts is  $\log(\text{gifts}+1000)$  so that zeros are included. Gifts to regulated private non-operating foundations follow a trend similar to that of community and operating foundations except for a large decline upon the enactment of TRA69. N=5803.

Figure 2.4: Decline in Share of Private Foundations Receiving a Gift



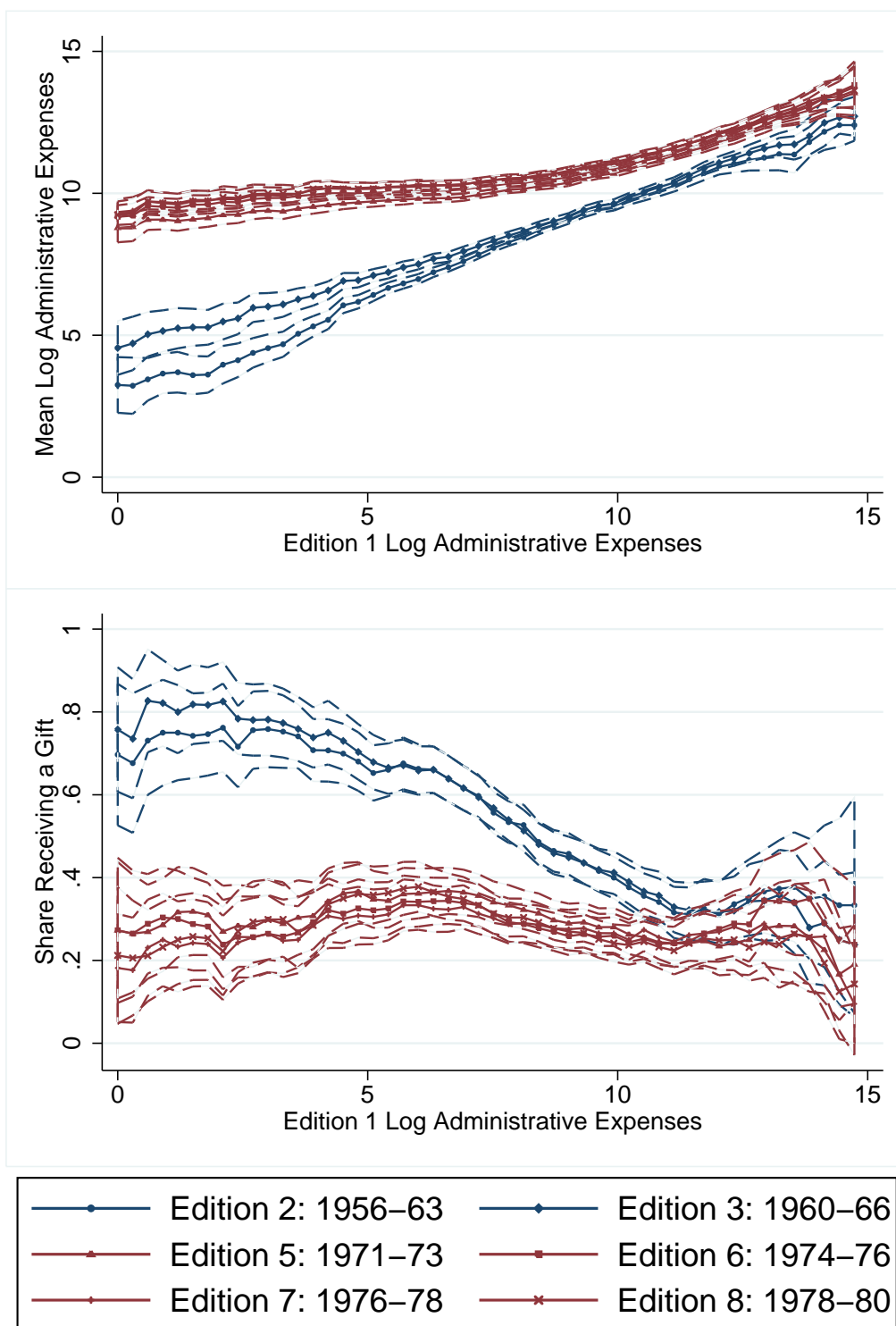
*Notes:* The figure displays the mean level of gifts received by each type of foundation in each edition of the Foundation Directory. The measure of gifts is an indicator for nonzero gifts received. Gifts to regulated private non-operating foundations follow a trend similar to that of community and operating foundations except for a large decline upon the enactment of TRA69. N=5803.

Figure 2.5: Rise in Administrative Costs of Private Foundations



*Notes:* The figure displays the mean level of log administrative expenses each type of foundation in each edition of the Foundation Directory. Administrative expenses of private non-operating foundations follow a trend similar to that of community and operating foundations except for a large increase upon the enactment of TRA69. N=5803.

Figure 2.6: Heterogeneity by Initial Administrative Expenses



*Notes:* The figures display the evolution of log administrative expenses and gifts for foundations with different levels of initial administrative expenses. Both subfigures plot local polynomial smooth by Edition 1 log administrative expenses. The upper panel shows log administrative expenses in each edition before TRA69 (blue) and after (red). The pattern indicates that administrative expenses rose sharply at the time of the reform, with the largest increase occurring among foundations with the lowest initial level, consistent with the imposition of fixed costs. The lower panel shows the share of observations with a nonzero gift, averaged before the reform (blue) and after (red). Giving fell the most among foundations with the lowest initial level of administrative expenses. Standard error bands in both panels show differences between editions are generally only statistically significant when comparing editions before and after the reform. <sup>84</sup> N=5803.

Table 2.1: Summary Statistics

	Full Sample	Balanced Panel	Private Non-Operating	Has Donor-Managers	No State Report
Number of Foundations	22,505	5,803	5,509	1,477	3,619
Mean Assets (M)	6.6	15.7	15.6	24.9	16.3
Share With Gifts	0.46	0.42	0.40	0.44	0.41
Mean Gifts (K)	246	294	279	242	300
Mean Expenses (K)	416	881	875	1,295	923
Mean Administrative Expenses (K)	54	115	105	161	120
Mean Donor-Managers pre-TRA69	0.3	0.4	0.4	1.5	0.4
Mean Managers of Donors' Family pre-TRA69	0.6	0.8	0.9	1.4	0.9

*Notes:* Summary statistics are provided for the full sample in the first column and subsamples in the other columns. Foundations in the second column appear in Foundation Directory Editions 1 through 3 and 5 through 8. Of these, foundations whose donors managed the foundation at some time before TRA69 are included in the statistics in column 3, while the statistics in column 4 include foundations that were not subject to state financial reporting requirements as of Edition 3, the last edition fully before TRA69.

Table 2.2: Stronger Effects on Entry Than Exit of Private Foundations

	(1) Entering - LPM	(2) Entering - Probit	(3) Exiting - LPM	(4) Exiting - Probit
Post * Private Foundation	-0.121*** (0.043)	-0.344** (0.141)	-0.034 (0.023)	-0.180 (0.187)
Private Foundation	0.125** (0.047)	0.367** (0.152)	0.076*** (0.025)	0.451** (0.203)
Constant	0.200*** (0.043)	-0.823*** (0.141)	0.036 (0.025)	-1.671*** (0.206)
N	11,878	11,878	11,878	11,878

*Notes:* The table displays the results of regressions estimating relative changes in the entry and exit rates of newly-regulated foundations after TRA69. Post is an indicator for Editions 5-8 of the foundation directory, which covered years after TRA69, and Private is an indicator for the private non-operating foundations subject to the new rules in the law. The outcome is a dummy for a foundation's first (columns 1-2) or last (columns 3-4) appearance in the sample with assts over \$1 million (1974). Columns 1 and 3 provide results from a linear probability model, while columns 2 and 4 contain results from a probit model. The first row of results indicates that regulated foundations were less likely to enter after the reform, but the relative change in exit rates was not significant. Regressions include edition (time) dummies and are estimated using all observations from Editions 2-3 (pre-TRA69) or 5-8 (post TRA69) with assts over \$1 million (1974). Standard errors are clustered by the state in which a foundation first appears.



Table 2.3: Effects of TRA69 On Private Foundation Gifts and Expenses

	(1)	(2)	(3)	(4)	(5)	(6)
	log(gifts+1000)	log(gifts+1)	any gift	log exps	log admin	log(admin+1)
Post * Private Foundation	-1.879*** (0.379)	-3.935*** (0.937)	-0.297*** (0.087)	0.138 (0.159)	1.230*** (0.288)	0.848 (0.726)
N	4,974	4,974	4,974	5,797	5,530	5,803
Adj. R-Squared	0.289	0.319	0.321	0.752	0.760	0.715

*Notes:* The table displays the results of regressions estimating relative changes in the finances of newly-regulated foundations after TRA69. Post is an indicator for Editions 5-8 of the foundation directory, which covered years after TRA69, and Private is an indicator for the private non-operating foundations subject to the new rules in the law. The estimation sample is the balanced panel of foundations that appear in Editions 1-3 and Editions 5-8. Each column represents a regression with a different outcome, showing that newly-regulated foundations experienced a relative decline in gifts received (1-3), insignificant change in total expenses (4), and increase in administrative expenses (5-6). Sample size varies across regressions because gifts are not observed in Edition 1, 7 observations have zero total expenses, and 273 observations have zero administrative expenses. Regressions include edition (time) dummies and foundation linear time trends. Standard errors are clustered by the state in which a foundation first appears.

Table 2.4: Decline in the Probability of Receiving a Gift by Foundation Type

	(1)	(2)	(3)	(4)	(5)
Post * Donor-Managers	-0.083*** (0.030)				-0.094*** (0.030)
Post * Managers in Donors' Family		0.004 (0.022)			0.010 (0.023)
Post * Has Human Donors			0.038 (0.045)		0.078 (0.057)
Post * No State Reporting Law				-0.093** (0.043)	-0.084* (0.045)
N	4,722	4,722	4,722	4,722	4,722
Adj. R-Squared	0.322	0.320	0.320	0.321	0.323

*Notes:* The table displays the results of regressions estimating post-TRA69 relative changes in the share of different types of regulated foundations receiving gifts. Post is an indicator for editions after TRA69, Donor-Managers is the count of managers with both first and last name matching a donor, Managers in Donors' Family is the count of managers with only the last name matching a donor's, Has Human Donors is an indicator for donors that are people (not companies), and No State Reporting Law is a dummy indicating that just before TRA69 the foundation was in a U.S. state that did not require it to file financial reports. The estimation sample is the balanced panel of private non-operating foundations that appear in Editions 1-3 and Editions 5-8. Results indicate that gifts decreased most among donor-managers (though not other human donors) and foundations for which reporting requirements were new. Regressions include edition (time) dummies and foundation linear time trends. Standard errors are clustered by the state in which a foundation first appears.

Table 2.5: Decline in the Probability of Receiving a Gift by State Reporting Law

	(1)	(2)	(3)	(4)
	All Fdns	All Fdns	Incorp Only	Incorp Only
Post * Donor-Managers	-0.087*** (0.029)	0.005 (0.050)	-0.088*** (0.028)	-0.009 (0.031)
Post * No State Reporting Law	-0.080* (0.042)	-0.039 (0.047)		
Post * Donor-Managers * No State Reporting		-0.122** (0.053)		
Post * No State Report for Incorporated			-0.098** (0.043)	-0.056 (0.051)
Post * Donor-Managers * No State Report for Incorporated				-0.102** (0.043)
N	4,722	4,722	3,504	3,504
Adj. R-Squared	0.323	0.323	0.312	0.312

*Notes:* The table displays the results of regressions estimating post-TRA69 relative changes in the share of different types of regulated foundations receiving gifts. Post is an indicator for editions after TRA69, Donor-Mangers is the count of managers with both first and last name matching a donor, No State Reporting Law is a dummy indicating that just before TRA69 the foundation was in a U.S. state that did not require it to file financial reports, and No State Report for Incorporated is a dummy indicating that the state did not require financial reports from incorporated foundations, which may be measured with less error than the No State Reporting Law that includes laws for living trusts. The estimation sample is the balanced panel of private non-operating foundations that appear in Editions 1-3 and Editions 5-8, with the additional restriction to incorporated foundations in regressions (3) and (4). Results indicate that gifts decreased most among donor-managers for whom reporting requirements were new. Regressions include edition (time) dummies and foundation linear time trends. Standard errors are clustered by the state in which a foundation first appears.

Table 2.6: IV Estimation of Administrative Expenses and Effect on Giving

(a) First Stage - Growth of Administrative Expenses Decreases With Pre-TRA69 Level

	(1)	(2)	(3)	(4)	(5)
Post * Log Admin Expenses	-0.499*** (0.050)	-0.496*** (0.051)	-0.503*** (0.050)	-0.656*** (0.051)	-0.657*** (0.051)
Post * Donor-Managers		0.096** (0.046)	0.102** (0.046)	0.100** (0.047)	0.098* (0.049)
Post * No State Reporting Law		-0.115 (0.102)	-0.100 (0.105)	-0.186 (0.115)	-0.178 (0.115)
N	3,960	3,960	3,960	3,960	3,960
Adj. R-Squared	0.002	0.003	0.003	0.033	0.034
Kleibergen-Paap F Stat	98.4	95.7	101.3	164.7	167.6
Post * Year Established			X	X	X
Post * Log Assets and Charity Before TRA69				X	X
Post * Cubics in Log Assets and Charity Before TRA69					X

(b) Second Stage - Administrative Expenses Reduce Probability of a Gift

	(1)	(2)	(3)	(4)	(5)
Log Admin Expenses	-0.057** (0.027)	-0.061** (0.028)	-0.059** (0.029)	-0.052* (0.027)	-0.051** (0.026)
Post * Donor-Managers		-0.049 (0.031)	-0.048 (0.032)	-0.049 (0.031)	-0.051 (0.031)
Post * No State Reporting Law		-0.104* (0.054)	-0.102* (0.055)	-0.103* (0.055)	-0.099* (0.054)
N	3,960	3,960	3,960	3,960	3,960
Adj. R-Squared	-0.487	-0.489	-0.487	-0.481	-0.481
Post * Year Established			X	X	X
Post * Log Assets and Charity Before TRA69				X	X
Post * Cubics in Log Assets and Charity Before TRA69					X

*Notes:* The table displays the results of regressions estimating the change in log administrative expenses upon enactment of TRA69 and the effect of this change on the probability of receiving a nonzero gift. Post is an indicator for editions after TRA69, Post \* Log Admin Expenses is the interaction of this variable with the foundation's maximum level of log administrative expenses observed before TRA69, Donor-Managers is the count of managers with both first and last name matching a donor, No State Reporting Law is a dummy indicating that just before TRA69 the foundation was in a U.S. state that did not require it to file financial reports. The estimation sample is the balanced panel of private non-operating foundations that appear in Editions 1-3 and Editions 5-8, have nonzero log administrative expenses in all periods, and have year of establishment and all financial variables observed before TRA69. The first stage F statistic shows that the instrument Post \* Log Admin Expenses is a strong predictor of log administrative expenses because these expenses rose most among previously-low-cost foundations. In the second stage, a one percent increase in administrative expenses general leads to statistically significant decrease of .05 to .06 percent in the probability of receiving a gift. Robustness to the listed covariates supports the argument that changes relate to initial expenses rather than size. All regressions include edition (time) dummies, foundation linear time trends, dummies for deceased donors, and the interaction of Post with the deceased donor dummies. Standard errors are clustered by the state in which a foundation first appears.

Table 2.7: Decomposition of the Decline in the Probability of Receiving a Gift

	(1)	(2)	Post-TRA69 Variable Mean	Effect	Share of Total Effect
Post	-0.222*** (0.028)				
Post * Change in Mean(Log(Admin+1))		-0.041** (0.012)	3.192	-0.129	58.2
Post * Donor-Managers		-0.069*** (0.026)	0.389	-0.027	12.1
Post * No State Reporting Law		-0.085* (0.045)	0.657	-0.056	25.0
N	4,722	4,722			

*Notes:* The table displays the results of regressions estimating the determinants of the decline in the probability of receiving a nonzero gift after TRA69. Post is an indicator for editions after TRA69, Change in Mean(Log(Admin+1)) is a foundation's average administrative expenses after TRA69 less its average expenses before TRA69, Donor-Managers is the count of managers with both first and last name matching a donor, and No State Reporting Law is a dummy indicating that just before TRA69 the foundation was in a U.S. state that did not require it to file financial reports. The estimation sample is the balanced panel of private non-operating foundations that appear in Editions 1-3 and Editions 5-8. Regression (1) includes linear foundation time trends but no edition dummies, providing a simple-difference estimate of a 22.2 percentage point drop in the share receiving gifts. Column (2) shows the second stage of a regression in which the level of administrative expenses before TRA69 is used to instrument for the change occurring after the reform. Each coefficient is multiplied by its post-TRA69 mean (column 3) to get the effect of that variable on gifts (column 4), which is then expressed as a percentage of the total effect (column 5). Results indicate that the growth of administrative expenses explains nearly 60 percent of the decline in gifts, while reporting laws and donor-managers explain much of the remaining 40 percent. Regressions include edition (time) dummies and foundation linear time trends. Standard errors are clustered by the state in which a foundation first appears.

## Appendix 2A - Model: Subsidy and Enforcement of Charitable Gifts

Following the notation of Fack and Landais (2009), individuals and companies make charitable gifts  $g$  as well as “cheating” gifts  $g^c$ , gifts made for avoidance or evasion purposes that are not counted in social welfare. Since the two types of gift cannot be distinguished, both are subsidized at rate  $\tau$ , which in the U.S. is currently equal to the marginal tax rate. I introduce a level of enforcement  $e \in [0, 1]$ , conducted by the government at cost  $C(e)$ , which could represent the probability or amount of a fine for cheating gifts or the amount of information that organizations are required to report publicly. Enforcement deters both cheating and charitable contributions.<sup>37</sup> The government maximizes the value of true, charitable gifts net of the costs of subsidy and enforcement:

$$\max_{\tau, e} W = g(\tau, e) - \tau g(\tau, e) - \tau g^c(\tau, e) - C(e)$$

The first-order conditions can be written as:

$$\frac{dW}{d\tau} = -(g + g^c) - (1 - \tau) \frac{\partial g}{\partial(1 - \tau)} + \tau \frac{\partial g^c}{\partial(1 - \tau)} \quad (1)$$

$$\frac{dW}{de} = (1 - \tau) \frac{\partial g}{\partial e} - \tau \frac{\partial g^c}{\partial e} - \frac{\partial C}{\partial e} \quad (2)$$

Equation 1 is the same as that in Fack and Landais (2009). When  $g^c = 0$  it reduces to the well-known unit elasticity rule  $\frac{dW}{d\tau} \geq 0 \Leftrightarrow 1 \leq |\varepsilon_{g, 1-\tau}| = \left| \frac{(1-\tau)}{g} \frac{\partial g}{\partial(1-\tau)} \right|$ .

By equation 2,  $\frac{dW}{de} \geq 0 \Leftrightarrow -\tau \frac{\partial g^c}{\partial e} \geq \frac{\partial C}{\partial e} + -(1 - \tau) \frac{\partial g}{\partial e}$ . An increase in enforcement directly improves welfare if savings from subsidizing fewer cheating contributions is greater than the sum of direct expenses and lost net charitable gifts.

Did the increased enforcement of the Tax Reform Act of 1969 raise welfare? The direct cost of increased auditing was passed on to foundations through the investment tax, so essentially  $\frac{\partial C}{\partial e} = 0$ . Increased administrative expenses can explain about half of the decrease in gifts, so suppose that on average (over a large change in  $e$ ),  $-\frac{\partial g^c}{\partial e} = -\frac{\partial g}{\partial e}$ . Plugging these values into equation 2,  $\tau \geq .5 \Rightarrow \frac{dW}{de} \geq 0$ . Unfortunately, we do not know donors’ marginal tax rates. The top rates at the time exceeded 70 percent, and donors most likely made gifts when their incomes and hence marginal tax rates were high, suggesting a positive effect on  $W$ . On the other hand, much of these donors incomes may have come from capital gains, which were always taxed at rates below 40 percent. What is clear is that continued enforcement at the current level

<sup>37</sup>In theory enforcement could encourage genuine charitable contributions by increasing the social rewards to giving. Charitable contributions would be deterred if targeting of cheating gifts was imperfect or if enforcement imposed broad compliance costs, as observed empirically of TRA69.

would not pass a direct cost-benefit analysis at today's lower income tax rates unless current gifts are much less responsive to enforcement or current cheating is much more responsive.

Even if enforcement is not set optimally it may allow social welfare to become closer to its maximum than it could be in the absence of enforcement. This is because the optimal subsidy rate will in general depend on the level of enforcement, and enforcement that is excessive may at least have the benefit that it enables the government to further subsidize and promote truly charitable gifts. Differentiating equation (1) gives

$$\frac{d^2W}{d\tau de} = \frac{-\partial g}{\partial e} + \frac{-\partial g^c}{\partial e} - (1 - \tau) \frac{\partial^2 g}{\partial(1 - \tau) \partial e} + \tau \frac{\partial^2 g^c}{\partial(1 - \tau) \partial e}.$$

As stated above, we expect the first two terms to be positive. These terms reflect the fact that raising the subsidy rate increases the cost of subsidizing either type of gift, and this cost is reduced when enforcement reduces either type. The cross partial derivative terms reflect the effects of enforcement on the tax price elasticity of each type of gift. Increasing the subsidy rate is good if it has a large effect on charitable gifts and a small effect on cheating ones, and enforcement may increase the extent to which this is true. If, for example, enforcement completely prevents all cheating (making it completely inelastic, so that the cross partial is zero) while imposing a fixed cost on true gifts that lowers their level but makes them more price sensitive, then enforcement would increase the marginal benefit of subsidy. In general, enforcement will increase the optimal subsidy rate so long as it does not make cheating gifts much more price-elastic than charitable gifts. The lack of income and tax data on the donors to foundations prevents estimation of these cross-partial derivatives, which I leave to future work.

## Appendix 2B - Data Collection

Data were collected from the Foundation Directory, a publication of the nonprofit Foundation Center. All files, editing procedures, and code used in the collection process are available by request.

To begin the data collection process I purchased hard copies of Editions 1-15 (actually named Editions 1-12 and Editions 1991-1993) of the Foundation Directory, removed all pages, and scanned them at 400dpi using ABBYY FineReader 7.0. I then used ABBYY's optical character recognition software to convert these image files to Rich Text format. Images were recognized as text using ABBYY FineReader 9.0, which had the highest recognition accuracy of the FineReader products available (but was not used for scanning on the advice of a frequent user). The user can train FineReader to recognize unusual characters, which allowed me to capture the Directory's symbols for deceased donors, publicly supplied information, and initial appearance in the Directory.

Text recognition was generally accurate, but a number of errors were made on a regular basis. For example, FineReader often used the wrong case for the letters i and j, misread parentheses as the letter j and slashes as the number 1, converted "E" into "£", and failed to recognize roman numerals and the trained symbols. Moreover, FineReader failed to replicate the blank lines between paragraphs that separated foundations in the Directory, combined separate lines of text onto one line, and inserted line breaks into the text at seemingly random locations. The rich text files therefore demanded assiduous cleaning and reformatting. I was able to automate a number of tasks using Visual Basic macros. For example, I used the bolding of foundation names to recreate the spaces between each foundation's entry so that a blank line of text would mark the end of one observation and beginning of another. I manually performed wildcard searches that could not be made sufficiently specific to isolate errors without finding some legitimate text, such as the searches for adjoining text and numbers that I used to remove headings and page numbers that had been combined with surrounding text. This work was obviously time-consuming, and I strongly encourage researchers planning to use optical character recognition software to test multiple programs on their source material to find the option that minimizes the length of this cleaning phase.

After cleaning the Rich Text files I saved them as plain text to be manipulated by Python script. Python offers a Regular Expressions module that enables the complex matching needed to convert text into data. I wrote one Python script that reorganized the text to facilitate line-by-line reading and another Python script to convert each line of text into data for the database. The first script deals with FineReader's poor recognition of line breaks by starting new lines when markers such as "**Donor:** " or "**Donors:** " appear, and it combines subsequent lines until the next marker is found. This ensures that each line of text corresponds to exactly one of the data fields supplied in the Directory. The second script uses more advanced Regular

Expressions to search each data field for text patterns that correspond to desired variables. For instance, a search for “\\$( [0-9,]+ ) in ([0-9]+ ) \*grants” would capture the phrases “\$1000 in grants” or “\$10,000 in 15 grants” and use the numbers in parentheses to populate the grant-amount and grant-number variables for that observation. The flexibility of Regular Expressions was necessary for such work because wording and formatting were not consistent throughout the text. I incorporated extensive error reporting in the code to point out when such inconsistencies were found and to reveal recognition flaws that escaped detection during the initial file cleaning.

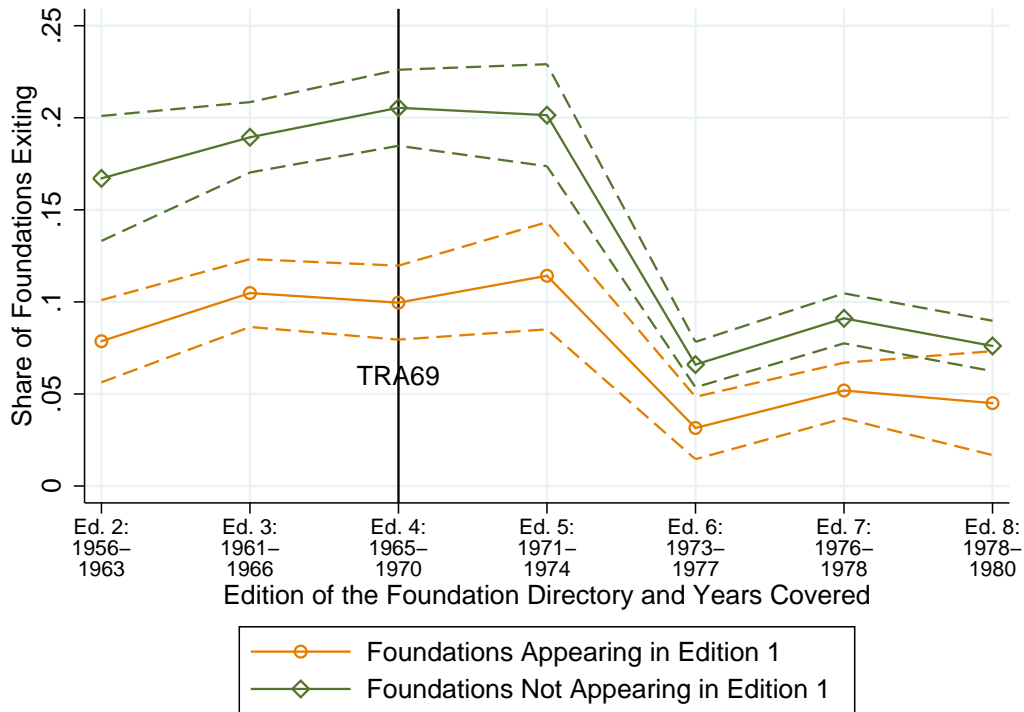
All financial records and names of foundations, donors, officers, and managers have been verified to have been correctly read from the hard copies. I have verified the accuracy of the extraction for Edition 1 by reconciling the data with the Directory’s state-by-state tabulations of assets, gifts, grants, and expenses. I did not repeat this process for other editions because the Directory’s tabulations themselves contained rounding errors and quirky (unlisted) exclusions. Instead I repeated the recognition process for all editions using OmniPage Professional optical character recognition software and checking all discrepancies in the fields of interest.

Last, I merged editions to make the data longitudinal. Data extracted from each edition of the Directory were written to a tab-delimited file that could be uploaded in Stata. Having obtained 15 cross sections, I then used time-invariant foundation characteristics to construct a panel with unique foundation ID numbers using Johannes Schmieder’s sequential merge Stata code seqmerge.ado (available at <http://sites.google.com/site/johannesschmieder/stata>). A foundation was matched to one in an earlier edition if they shared the same name as well as either the state, establishment year and state, director names, donor names, or address. I dropped observations that were exact duplicates of those in a prior edition, which mostly occurred in 1991 when the Foundation Center first began publishing the Directory on an annual basis (well after the period included in this study).



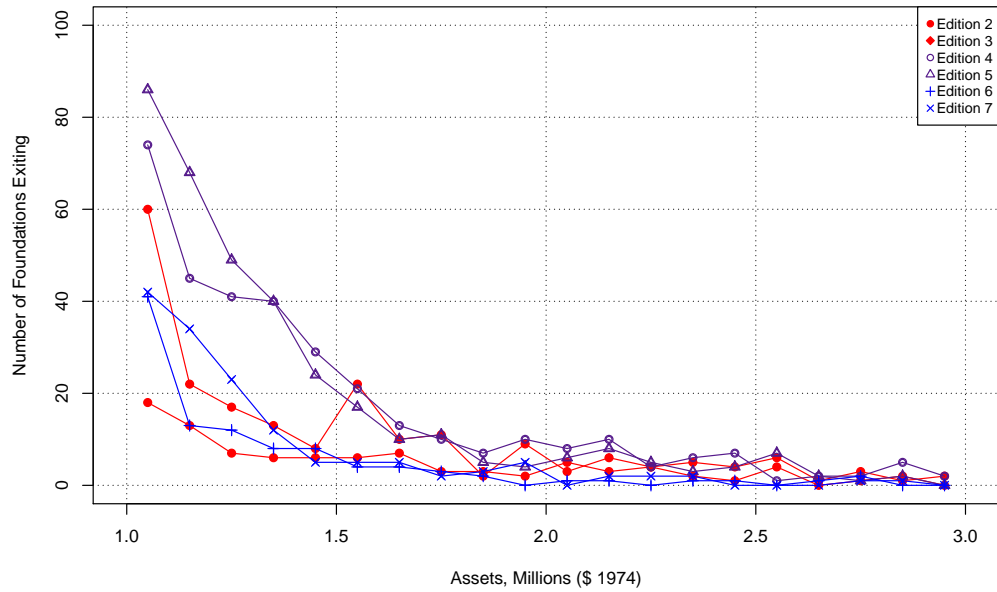
## Appendix 2C - Additional Figures and Tables

Figure 2C.1: Heightened Exit Among Newer Foundations Before Reform



*Notes:* The figure displays the number of private non-operating foundations appearing for the last time with assets over \$1 million (1974) as a share of the total number of the same type in each edition of the Foundation Directory. The observed decline in exit occurred primarily among new foundations that did not appear in the first edition of the Foundation Directory, consistent with a reduction in churning. N=14,487.

Figure 2C.2: Exit By Small Foundations During Market Decline From 1973 to 1975



*Notes:* The figure displays the distribution of real assets among foundations exiting from the sample with assets over \$1 million (1974) in each edition of the Foundation Directory. Lines are provided for editions before TRA69 (red), during and immediately after the reform (purple), and several years later (blue). During the reform years, exit is heightened among the smallest foundations. The result suggests that poor investment performance in the early 1970s drove exit rates at the time of TRA69. Standard errors are clustered by the state in which a foundation first appears. N=21,825.

Table 2C.1: Lack of Differential Exit In Edition 5 (After TRA69) By Foundation Type

	(1)	(2)	(3)	(4)	(5)
Edition 5 * Has Human Donors	0.031 (0.022)				
Edition 5 * Blank Donors		0.018 (0.030)			
Edition 5 * Donor's Family Managers			0.007 (0.005)		
Edition 5 * Donor-Managers				0.017 (0.015)	
Edition 5 * Managers on Board of Directors					-0.004 (0.004)
N	11,980	11,980	11,980	11,980	11,980
Adj. R-Squared	0.080	0.078	0.080	0.080	0.079

*Notes:* The table displays the results of linear probability model regressions estimating the share of foundations exiting from the sample with assets over \$1 million (1974) just after TRA69. Edition 5 is an indicator for Edition 5 of the Foundation Directory, the first full edition after TRA69, Has Human Donors is an indicator for donors that are people (not companies), Blank Donors is an indicator for foundations whose donors were not listed in the Foundation Directory before TRA69, Donors' Family Managers is the count of managers with only the last name matching a donor's, Donor-Managers is the count of managers with both first and last name matching a donor, and Managers on Board of Directors is a count of the managers with both first and last name matching a member of the foundation's board of directors. Results indicate that none of the foundation types of interest were significantly more or less likely to exit after TRA69 was enacted. Regressions include edition (time) dummies. Standard errors are clustered by the state in which a foundation first appears.

Table 2C.2: Effects of TRA69 On Private Foundation Gifts and Expenses, No Time Trends

	(1)	(2)	(3)	(4)	(5)	(6)
	log(gifts+1000)	log(gifts+1)	any gift	log exps	log admin	log(admin+1)
Post * Private Foundation	-2.382*** (0.290)	-5.468*** (0.607)	-0.447*** (0.052)	-0.191* (0.113)	0.742*** (0.183)	0.614* (0.345)
N	4,974	4,974	4,974	5,797	5,530	5,803
Adj. R-Squared	0.080	0.102	0.106	0.550	0.509	0.476

*Notes:* The table displays the results of regressions estimating relative changes in the finances of newly-regulated foundations after TRA69, the analog of Table for estimates excluding foundation time trends. Post is an indicator for Editions 5-8 of the foundation directory, which covered years after TRA69, and Private is an indicator for the private non-operating foundations subject to the new rules in the law. The estimation sample is the balanced panel of foundations that appear in Editions 1-3 and Editions 5-8. Each column represents a regression with a different outcome, showing that newly-regulated foundations experienced a relative decline in gifts received (1-3), insignificant change in total expenses (4), and increase in administrative expenses (5-6). Sample size varies across regressions because gifts are not observed in Edition 1, 7 observations have zero total expenses, and 273 observations have zero administrative expenses. Regressions include edition (time) dummies. Standard errors are clustered by the state in which a foundation first appears.

Table 2C.3: Decomposition of the Decline in the Probability of Receiving a Gift, Incorporated Foundations

	(1)	(2)	Post-TRA69 Variable Mean	Effect	Share of Total Effect
Post	-0.216*** (0.031)				
Post * Change in Mean(Log(Admin+1))		-0.030** (0.012)	3.322	-0.100	46.5
Post * Donor-Managers		-0.080*** (0.024)	0.449	-0.036	16.5
Post * No State Reporting Law for Incorporated Foundations		-0.099** (0.041)	0.726	-0.072	33.3
N	3,504	3,504			

*Notes:* The table displays the results of regressions estimating the determinants of the decline in the probability of receiving a nonzero gift after TRA69, the analog of Table restricted to incorporated foundations. Post is an indicator for editions after TRA69, Change in Mean(Log(Admin+1)) is a foundation's average administrative expenses after TRA69 less its average expenses before TRA69, Donor-Managers is the count of managers with both first and last name matching a donor, and No State Reporting Law for Incorporated Foundations is a dummy indicating that just before TRA69 the foundation was in a U.S. state that did not require incorporated foundations to file financial reports. The estimation sample is the balanced panel of private non-operating foundations that appear in Editions 1-3 and Editions 5-8. Regression (1) includes linear foundation time trends but no edition dummies, providing a simple-difference estimate of a 21.6 percentage point drop in the share receiving gifts. Column (2) shows the second stage of a regression in which the level of administrative expenses before TRA69 is used to instrument for the change occurring after the reform. Each coefficient is multiplied by its post-TRA69 mean (column 3) to get the effect of that variable on gifts (column 4), which is then expressed as a percentage of the total effect (column 5). Results indicate that the growth of administrative expenses explains over 45 percent of the decline in gifts, while reporting laws and donor-managers explain much of the remaining 55 percent. Regressions include edition (time) dummies and foundation linear time trends. Standard errors are clustered by the state in which a foundation first appears.

### 3 Student Loans, the Cost of Borrowing, and Implications for the Effectiveness of Need-Based Grant Aid(with Lesley J. Turner<sup>38</sup>)

#### Abstract

In this paper, we estimate the impact of need-based grant aid on City University of New York (CUNY) students' educational investment decisions, taking advantage of the the nonlinearities in the Pell Grant Program's formula. Pell Grant aid reduces borrowing: on average, an additional dollar of Pell Grant aid leads to \$0.37 reduction in federal loans. Among borrowers, a dollar of Pell Grant aid crowds-out over \$1.50 of loans, suggesting that students face a fixed cost of incurring debt. Access to federal loan aid in the CUNY system differs from other schools along one key dimension: the default loan offer in the CUNY system is \$0, while most other institutions offer eligible students nonzero loan awards. CUNY students must opt into borrowing rather than opting out, which generates a substantial fixed cost for students who wish to take-up federal loans. Our estimates suggest that relaxing this cost would increase borrowing rates by over 200 percent among Pell Grant eligible CUNY students.

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<sup>38</sup>Department of Economics, University of Maryland, 3115E Tydings Hall College Park, MD 20742.

### 3.1 Introduction

In the United States, federal and state governments provide substantial subsidies to college students, with the intention of increasing low-income individuals' educational attainment. During the 2011-12 academic year, the U.S. Department of Education provided \$34 billion in Pell Grant aid and \$68 billion in federal direct loans to college students (?).<sup>39</sup> Although many students are eligible for both Pell Grants and federal loan aid, little is known about how these programs interact and how need-based grant aid affects students' borrowing decisions.

In this paper, we take advantage of the nonlinearities in the formula for the Pell Grant Program to identify the impact of need-based grant aid on college students' educational investment decisions. We study City University of New York (CUNY) students who are eligible or nearly eligible for a Pell Grant. Pell Grant aid has large, negative, and statistically significant impacts on borrowing. We estimate that a dollar increase in Pell Grant aid induces first-year students to reduce borrowing by \$0.37. Furthermore, we show that Pell Grant aid crowds out over 100 percent of loan aid among borrowers – with an additional dollar of Pell Grant aid inducing these students to reduce borrowing by over \$1.50 – a result at odds with traditional models of human capital investment under credit constraints.

Crowd-out in excess of 100 percent can result when preferences or budget sets are discontinuous, as in the case of a fixed cost of borrowing. CUNY students do not face a monetary fixed cost of borrowing. Access to federal loan aid in the CUNY system differs from other schools along one key dimension: the default loan offer in the CUNY system is \$0, while most other schools offer eligible students nonzero loan awards. CUNY students must opt into borrowing rather than opting out, which generates a substantial fixed cost for students who wish to take-up federal loans. Our estimates suggest that relaxing this cost would increase borrowing rates by 215 percent among Pell Grant eligible CUNY students.

Our identification strategy uses the Pell Grant Program's formula to estimate causal effects of grant aid on borrowing and other educational investment decisions. A naive regression of outcomes on grant aid will conflate the effect of aid with the effect of unobserved factors that are correlated with aid, such as motivation or family support. To overcome this concern, we use regression discontinuity (RD) and regression kink (RK) designs to identify the causal impact of need-based aid on borrowing and educational attainment (Hahn et al. 2001; Card et al. 2009). While a student's Pell Grant aid depends on the federal government's measure of need, this relationship is discontinuous at the Pell Grant eligibility threshold, causing students with similar characteristics to receive significantly different amounts of aid (Turner 2012).

Empirically, we find little evidence that Pell Grant aid increases educational attainment. With a simple

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<sup>39</sup>Total student loan disbursements calculated from Title IV Program Volume Reports, available at: <http://studentaid.ed.gov/about/data-center/student/title-iv>.

model of students' joint borrowing and schooling decisions, we show how the impact of grant aid on educational attainment depends on a student's financial circumstances. A marginal increase in grant aid only increases the educational attainment of students at a borrowing threshold such as a credit constraint (e.g., Becker 1975; Cameron and Taber 2004; Lochner and Monge-Naranjo 2011). We show that students whose borrowing decisions are affected by discontinuities in the price of borrowing caused by a kinked interest rate schedule should behave much like traditionally constrained students who fully exhaust their loan eligibility. However, once we incorporate a fixed cost of incurring student loan debt, our model generates ambiguous predictions for the average impact of Pell Grant aid on educational outcomes. A small increase in grant aid may *reduce* the educational attainment of students whose optimal debt is shifted to a level at which the fixed cost binds.

Our results are consistent with the literature showing the importance of default options. For example, ? examines an increase in the number of free score reports ACT test-takers can send to colleges. She estimates that reducing the price of the fourth ACT score report from \$6 to \$0 had substantial impacts on the quality of college attended by low-income students. ? studies an experiment conducted by New York University's law school, where prospective students were randomly assigned to receive either debt forgiveness or a tuition waiver tied to taking a job in the public sector. Although both options had the same present discounted value, tuition waiver recipients were significantly more likely to enter into a public sector career. ?, ?, and ? show that default options matter for decisions related to investment, saving, and 401(k) participation.

Our paper also contributes to the large literature on the effectiveness of financial aid programs in promoting educational attainment. Existing estimates suggest that increases in grant aid have the same impact on college attendance as tuition decreases of a similar magnitude, as long as the grant application process is relatively simple. In general, a \$1000 increase in financial aid (or decrease in tuition) increases the probability of college attendance by approximately 4 percent (Deming and Dynarski 2010).<sup>40</sup> Students targeted by the Pell Grant Program are especially needy - among first-year, Pell Grant-eligible CUNY students, the average award (\$3,898) represents 18 percent of family adjusted gross income (AGI).<sup>41</sup> Despite the program's generosity, Pell Grant aid does not appear to increase the probability of college enrollment for most low-income students, although there is some evidence that additional Pell Grant aid increases persistence (Kane 1995;

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<sup>40</sup>Fewer studies examine how grant aid affects attainment conditional on enrollment. Angrist et al. (2009) study a program where students attending a nonselective Canadian public university were randomly assigned to earn aid based on maintaining a minimum GPA and course load. Male students were not affected, but the program had a small impact on the GPAs of female students that were also assigned to receive additional services, such as peer advising and study groups. Scott-Clayton (2011) finds that a conditional merit-aid program in West Virginia, where recipients were required to meet minimum GPA and credit requirements to receive aid, increased educational attainment and graduation rates. Castleman and Long (2012) examine the impact of Florida's need-based grant program on college enrollment and educational attainment, and find that first year eligibility for grant aid increases credits earned and degree completion. Bettinger (2004) finds positive impacts of Pell Grant aid on persistence.

<sup>41</sup> Nationwide, the average Pell Grant award represented 17 percent of average annual income in 2012 (?).

Bettinger 2004).<sup>42</sup>

We show that while grant programs may increase educational attainment in settings where few students are constrained by borrowing limits, grant aid may also reduce the attainment of students facing a fixed cost of borrowing. The overall educational impacts of programs like the Pell Grant are likely to vary considerably with the degree to which students can smoothly adjust their borrowing.

The remainder of our paper proceeds as follows: in Section 3.2, we describe the CUNY system. Section 3.3 outlines a simple conceptual framework allowing for discontinuous borrowing costs, which generates testable predictions for how borrowing should respond to increases in grant aid in the presence of fixed costs. We describe our data and sample in Section 3.4. In Section 3.5, we discuss our empirical approach, while in Section 3.6, we present reduced form estimates of the impact Pell Grant aid on student loan aid and characterize the fixed cost CUNY students incur when borrowing. We present estimates of the impact of Pell Grant aid on educational attainment in Section 3.7 and Section 3.8 concludes.

### 3.2 The CUNY System and Need-Based Student Aid

The City University of New York (CUNY) is the largest urban public university system in the country, encompassing 17 two- and four-year colleges that serve over 250,000 undergraduate students in a given year. CUNY institutions have low tuition and operate in a state with generous need-based grant aid.<sup>43</sup> A substantial portion of CUNY undergraduates also receive federal grant aid. For example, 81 percent of the 2009-2010 fall cohort of first-time freshmen students received a Pell Grant. Similar to other urban public institutions, CUNY schools have low retention and graduation rates. Among first-time freshmen who enrolled in fall 2006, only 15 percent of students pursuing an associate's degree graduated in four years and only 41 percent of students in a bachelor's degree program graduated within six years.

A centralized application system determines eligibility for federal need-based financial aid. To apply for federal aid, current and prospective students must submit a Free Application for Federal Student Aid (FAFSA) to the U.S. Department of Education. FAFSA inputs include a detailed set of financial and demographic information, such as income, untaxed benefits, assets, family size and structure, and number of siblings in college. The federal government calculates a student's "Expected Family Contribution" (EFC) using a complicated, non-linear function of these inputs. Eligibility for Pell Grant aid, subsidized federal student loans, and campus-based aid (e.g., work-study) are determined by a student's EFC and cost of attendance (COA), which includes tuition, fees, and living expenses (e.g., books and supplies, room and

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<sup>42</sup>Bettinger et al. (forthcoming) provide evidence that the complexity of the federal student aid application process substantially reduces the impact of Pell Grant eligibility on college-going.

<sup>43</sup>Tuition at CUNY four-year schools was \$4000 per year in 2008 and 2009 and \$4600 per year in 2010. Two-year schools charged full-time students \$2800 in tuition in 2008 and 2009 and \$3150 in 2010. Over this period, fees at four-year CUNY schools ranged from \$291 to \$477 per year, while two-year schools' charged \$268 to \$355 per year in fees.



board, transportation expenses).

For most students, Pell Grant aid is solely determined by EFC.<sup>44</sup> Students with EFC below a set threshold are eligible to receive the minimum Pell Grant award.<sup>45</sup> Additionally, among Pell eligible students, every \$1 decrease in EFC leads to a \$1 increase in (statutory) Pell Grant aid, up to the maximum Pell Grant award.

Low- and middle-income students in New York received \$920 million of grant aid through the state's Tuition Assistance Program (TAP) in 2012.<sup>46</sup> New York State residents must complete a supplemental application for the TAP program, as TAP aid depends on New York State taxable income, which cannot be calculated from FAFSA inputs alone. TAP provides grants to students much higher in the income distribution than the Pell Grant Program - up to \$80,000 in New York State taxable income for dependent students.<sup>47</sup>

In addition to federal and state grant aid, CUNY students are eligible to borrow through the federal Direct Loan Program.<sup>48</sup> The terms of federal loan aid depend on a student's course load, tenure, and remaining need. Specifically, a student's remaining need, equal to the total cost of attendance (tuition, fees, and a cost of living allowance) minus EFC and grants, determines her eligibility for subsidized federal loans. First-year students are eligible for subsidized loan aid equal to the lesser of remaining need and \$3,500. Dependent first-year students can borrow an additional \$2,000 in unsubsidized loans while independent students can borrow an additional \$6,000.<sup>49</sup> All students are eligible for unsubsidized loans and even students that do not qualify for subsidized loan aid can still borrow up to the overall maximum in unsubsidized loans (\$5,500 for first-year dependent students and \$9,500 for first-year independent students). Subsidized loans do not accrue interest until six months after a student leaves school; after this period, students face an interest rate of 3.4 percent.<sup>50</sup> The cohorts of students we examine could borrow unsubsidized federal loans at an interest

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<sup>44</sup>As long as a student's COA is greater than her statutory Pell Grant, Pell Grant aid only depends on EFC. For most students, this constraint is not binding. The lowest COA faced by full-time, full-year CUNY students was \$8,700 in 2007-08, \$8,800 in 2008-09, and \$9,300 in 2009-10. In comparison, the maximum Pell Grant award was \$4310 in 2007-08, \$4732 in 2008-09, and \$5350 in 2009-10.

<sup>45</sup>The minimum Pell Grant award was \$400 during the 2007-08 academic year, \$890 during 2008-09, and \$976 during 2009-10.

<sup>46</sup>See the National Association of State Student Grant and Aid Programs State Data Quick Check (available at: [http://www.nassgap.org/survey/state\\_data\\_check.asp](http://www.nassgap.org/survey/state_data_check.asp)).

<sup>47</sup>In the years we examine, the maximum TAP award equals the lesser of \$5,000 and tuition and fees.

<sup>48</sup>Prior to 2010, schools participated in one of two parallel federal lending programs: the William D. Ford Federal Direct Loan Program and the Federal Family Education Loan (FFEL) Program, through which the federal government guaranteed loans originated by private lenders. The 2010 Health Care and Education Reconciliation Act abolished the FFEL program. However, since CUNY schools participated in Direct Loan Program prior to 2010, the legislation did not affect federal lending to CUNY students.

<sup>49</sup>Students who are considered to be in their second year for federal loan eligibility purposes (i.e., those who have accumulated between 30 and 59 credits) with unmet need can borrow up to \$4,500 in subsidized loans, while students in their third year and above (i.e., those who have accumulated at least 60 credits) who have unmet need can borrow up to \$5,500. Regardless of credits accumulated, students in two-year degree programs are never considered to be third year students for federal borrowing purposes. The overall borrowing limits dependent students face are \$6,500 in their second year and \$7,500 as upper years, while independent students can borrow up to \$10,500 in their second year and \$12,500 in their third year and beyond. Students are limited in the total amount of federal debt they can incur during their undergraduate education. Dependent students can borrow up to \$31,000 overall (\$23,000 subsidized) and independent students can borrow up to \$57,500 (\$23,000 subsidized). See [studentaid.ed.gov/types/loans](http://studentaid.ed.gov/types/loans) for additional details.

<sup>50</sup>Cadena and Keys (forthcoming) estimate that eligible students would receive a subsidy from the federal government worth \$1500 if they borrowed the maximum allowed subsidized amount for four years.

rate of 6.8 percent.<sup>51</sup> Despite low tuition and generous state grant aid, most CUNY students remain eligible to borrow the maximum allowed subsidized federal loans.<sup>52</sup>

The timing of the school and financial aid application processes lends credibility to the use of the Pell Grant formula as a quasi-experiment for estimating effects of grant aid on borrowing and educational investment. Prospective students generally apply to CUNY schools in advance of completing a FAFSA. CUNY schools admit prospective students on a rolling basis, but students must submit an application by February 1st to be guaranteed consideration. Prospective students list up to six two- or four-year colleges within the system they would like to attend, in order of preference, as well as their planned attendance intensity (i.e., full-time or part-time). Because the FAFSA requires information on prior-year taxable income, prospective students generally wait to complete the FAFSA until after their family has filed their tax return (at best, early February).<sup>53</sup> Students are notified of their EFC by the Department of Education shortly after submitting a FAFSA but do not learn of their financial aid eligibility until after they have been admitted to a college. Upon admission, the college provides the student with a financial aid package which specifies grant aid (federal, state, and institutional).<sup>54</sup> During the months leading up to the fall semester, the student decides whether to accept the admissions offer and how much (if any) federal loan debt to incur.

Schools must offer students their full federal grant aid entitlement, but they have discretion over federal loan aid packaging (?). In the CUNY system, the default amount of offered loan aid is \$0. While most institutions include suggested federal loan awards as part of a student's financial aid package, CUNY institutions require students to submit a separate application and specify both their desired amount of federal loan aid and whether they are willing to take on unsubsidized debt.<sup>55</sup> The requirement of an additional application for federal loan aid may contribute to the cost of obtaining student loans. Students may also face a cost of deviating from the default loan offer of \$0.

### 3.3 Conceptual Framework

In this section, we outline our model of students' human capital investment decisions, which we tailor to match the actual structure of the federal student aid programs.<sup>56</sup> An individual lives for two periods. In the first period, she chooses schooling  $s$  and debt  $d$  to maximize lifetime utility,  $U = u(c_0) + \beta u(c_1)$ , where

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<sup>51</sup>Current federal law caps the interest rate for direct loans at 8.25 percent.

<sup>52</sup>In general, private lenders and some institutions offer student loans. CUNY schools do not offer loans, and we find that no CUNY students borrow through private lenders, most likely due to the superior terms on federal loans.

<sup>53</sup>Individuals are allowed to estimate their prior year taxable income if they wish to submit the FAFSA before their family's tax return is submitted, and update the FAFSA information at a later date, but few choose to do so.

<sup>54</sup>Appendix Figure 3A.1 displays a sample of a CUNY financial aid award letter. Grant and loan aid is first used to pay direct costs (tuition and fees), with the student receiving any remaining aid directly.

<sup>55</sup>Appendix Figure 3A.2 displays a sample of the additional loan application required by Hunter College.

<sup>56</sup>The institutional detail incorporated here is intended to distinguish groups of students in different circumstances and highlight the expected responses of different groups of students to changes in grant aid. A more parsimonious model, as in Lochner and Monge-Naranjo (2011), provides similar conclusions.

subscripts indicate the period,  $\beta \in (0, 1)$  is the time discount factor, and  $u(\cdot)$  follows standard assumptions for instantaneous utility (strictly increasing, strictly concave, and twice continuously differentiable). In the first period, the student receives exogenous grants  $g$  from the government and has resources equal to her expected family contribution  $EFC$  and exogenous income  $\omega$ , where  $\omega$  represents the error term in the federal government's estimation of family resources, and can be positive or negative. The student faces costs  $C(s)$  associated with her first period educational investment, which encompass both direct costs  $C_t(s)$  (e.g., such as tuition and fees) and opportunity costs  $C_i(s)$  (e.g., foregone earnings).  $C(s)$  is twice continuously differential, with  $C'_t(s) \geq 0$ ,  $C'(s) > 0$  and  $C''(s) \geq 0$ .<sup>57</sup> In the second period, the student receives earnings  $w(s)$  where  $w' > 0$  and  $w'' \leq 0$ .

Borrowing is subject to multiple interest rates and potential constraints. The student can borrow an amount  $d$ , which can be less than zero if the student prefers to save. The gross market interest rate is  $R_m < \frac{1}{\beta}$ , but the government subsidizes some student loans by charging the rate  $R_s < R_m$ .<sup>58</sup> The student receives the subsidized interest rate on all loans up to a limiting amount  $d_s^{max} = \min\{\bar{d}, C_t(s) - g - EFC\}$ , where  $\bar{d}$  is a constant. This formulation captures the structure of the federal subsidized Direct Loan Program, which can be used to cover "unmet need" up to a fixed limit. Additionally, the student can borrow up to a set limit  $\bar{\bar{d}} > d_s^{max}$ , where loans in excess of  $d_s^{max}$  are unsubsidized and subject to the market interest rate.

The student also pays a fixed borrowing cost  $\gamma$  if she chooses any  $d > 0$ , which represents discrete monetary, time, and psychic costs of incurring debt.<sup>59</sup> For notational convenience, we define indicator functions  $\kappa_0 = \mathbf{1}\{d > 0\}$  (incurring positive debt),  $\kappa_s = \mathbf{1}\{d > d_s^{max}\}$  (incurring positive unsubsidized debt), and  $\xi = \mathbf{1}\{C_t(s) - g - EFC < \bar{d}\} = \mathbf{1}\{d_s^{max} = C_t(s) - g - EFC\}$  (being bound by the endogenous subsidized borrowing limit) to distinguish between cases.

The student faces budget constraints  $c_0 \leq \omega + EFC + g + d - C(s) - \gamma \cdot \kappa_0$  in the first period and  $c_1 \leq w(s) - R_s d - \kappa_s (R_m - R_s) (d - \bar{d} - \xi (C_t(s) - g - EFC - \bar{d}))$  in the second period.<sup>60</sup> Assigning the variable  $\lambda$  for the Lagrange multiplier on the maximum-loan constraint, the student solves:

<sup>57</sup>We could also allow for heterogeneous costs of schooling effort by letting  $s$  enter directly into the period utility functions (as in Cameron and Taber (2004)) or by allowing ability to vary across students (as in Lochner and Monge-Naranjo (2011)).

<sup>58</sup>In practice, if students were able to earn  $R_m$  on their savings, all students should either chose not to borrow, or borrow at or above the subsidized limit. This is because for subsidized loans, students can borrow at  $R_s$  and earn  $R_m > R_s$  by saving. However, in the years we examine, market interest rates were quite low and students faced a 1 percent origination fee on all loans, resulting in  $R_s$  being approximately equal to the market rate. While the interest rate on unsubsidized debt was higher than the market rate in our setting, we only include two terms for gross interest rates, rather than a third term representing the market rate for savings - omitting this additional term does not affect our predictions.

<sup>59</sup>Students pay an origination fee when taking out federal loan aid, but this fee is continuous in the amount borrowed (i.e., 1 percent) and thus, would not represent the fixed cost we model.

<sup>60</sup>We assume the regularity condition  $w''(s) \leq -R_m C''_t(s)$  for all  $s$  to ensure global concavity of the problem. We deem this condition reasonable because direct costs are linear or concave in schooling, depending on a student's course load: tuition is linear in credits attempted for part-time students, while full-time students (attempting 12 to 18 credits) are charged a flat rate. Additionally, we show in Appendix 3.8 that a weaker condition would suffice.

$$\max_{s,d} \left\{ u(\omega + EFC + g + d - C(s) - \gamma \cdot \kappa_0) + \beta u(w(s) - R_s d - \kappa_s (R_m - R_s) (d - \bar{d} - \xi (C_t(s) - g - EFC - \bar{d}))) + \lambda (\bar{d} - d) \right\}$$

Optimal schooling  $s^*$  and debt  $d^*$  will satisfy some combination of the first order conditions:

$$u'(c_0) = \beta (R_s + \kappa_s (R_m - R_s)) u'(c_1) + \lambda \quad (3)$$

$$C'(s) u'(c_0) = \beta (w'(s) - \xi \kappa_s (R_m - R_s) C'_t(s)) u'(c_1) \quad (4)$$

$$d = \bar{d} \quad (5)$$

Which subset of the first-order conditions applies depends on which case the student falls into. For example, if the maximum loan constraint is not binding ( $\lambda = 0$ ), the student's remaining need is greater than the subsidized loan limit ( $\xi = 0$ ), and optimal borrowing is nonzero ( $d^* \neq 0$ ) then conditions (3) and (4) hold, implying that  $C'(s^*) = (R_s + \kappa_s (R_m - R_s))^{-1} w'(s^*)$ . In such cases,  $s^*$  equates the present discounted values of the marginal costs and benefits of schooling. Optimal schooling does not depend on income or consumption in either period, implying that schooling will not respond to a marginal increase in grant aid. This result is standard: students who are not do not face borrowing constraints will not increase their schooling in response to a marginal increase in grant aid.

For a given level of  $EFC$ , students can be ordered in terms of additional resources  $\omega$ . A partition of this spectrum defines the different cases a student may fall into, which we label groups A through F. The chart below summarizes students' choices of debt and responses to grant aid in each potential case. Group A is made up of students with resources great enough that they choose to save (i.e.,  $d^* < 0$ ). Group F describes students who have so few resources that they would prefer to borrow more than the maximum allowable government loan  $\bar{d}$  but cannot. For groups between these extreme cases, the optimal level of debt is weakly decreasing in resources.<sup>61</sup> As long as  $\gamma > 0$ , there will be some minimum level of debt that students are unwilling to take on, which we denote as  $\underline{d}$ .

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<sup>61</sup>See Appendix 3.8 for proofs.

Optimal Borrowing and Educational Investment Decisions by Level of Exogenous Resources

Group	A (highest resources)	B	C	D	E	F (lowest resources)
$d^*$	$(-\infty, 0)$	0	$(\underline{d}, d_s^{max})$	$d_s^{max}$	$(d_s^{max}, \bar{d})$	$\bar{d}$
$\frac{\partial d^*}{\partial g}$	$(-1, 0)$	0	$(-1, 0)$	$\xi \left( \frac{\partial s^*}{\partial g} C_t'(s^*) - 1 \right)$	$(-1, 0)$	0
$\frac{\partial s^*}{\partial g}$	0	$(0, \infty)$	0	$(0, \infty)$	0	$(0, \infty)$

Notes: Groups are listed in decreasing order of exogenous resources  $\omega$  (lower resources are associated with weakly greater debt). Observed debt is bounded from below by 0.

Though we distinguish six distinct groups of students, the groups fall into two general types: those choosing corner solutions for debt, – who we label “threshold borrowers” – and those choosing interior solutions for debt. Groups A, C, and E choose interior levels of debt, and the amount they borrow therefore responds to the amount of grant aid they receive. Grant aid does not increase the educational attainment of students in these three groups. Threshold borrowers, however, arrive at a corner solution for borrowing due to the presence of fixed costs (Group B), kinks in the interest rate schedule (Group D), and credit constraints (Group F). These students respond to an increase in grant aid by completing more schooling in order to raise the ratio of future income to current income. Students choosing zero loans due to the fixed cost (Group B), a subsidized loan at the exogenous limit  $\bar{d}$  (Group D when  $\xi = 0$ ), or maximum available loans  $\bar{d}$  (Group F) will not adjust debt in response to changes in grant aid.<sup>62</sup>

Figure 3.1 provides an illustration of the impact of Pell Grant aid on the borrowing decisions of students in a given group. In Panel B, students whose optimal debt is close to  $\underline{d}$  may be induced to switch to  $d^* = 0$  by small increases in grant aid. Those who would have taken small loans in the absence of the fixed cost will instead choose not to borrow. For these students,  $\frac{\partial d^*}{\partial g} < -1$ , and a dollar of Pell Grant aid crowds-out more than a dollar of student loan aid. Holding all else constant, a larger fixed cost implies a larger response (in absolute magnitude) to changes in Pell Grant aid.

### 3.3.1 Empirical Predictions

Our framework leads to two main predictions concerning how overall borrowing and educational investment respond to changes in grant aid in the presence of a fixed cost of borrowing:

1. *If the fixed cost of borrowing  $\gamma > 0$  then  $\underline{d} > 0$ , and an increase in grant aid may lead to a greater than \$1 for \$1 reduction in loans for borrowers.* This result allows for crowd-out to exceed 100 percent. If students have loan debt close to  $\underline{d}$ , a small increase in grants will cause a discrete drop in (observed) borrowing to zero. With no fixed borrowing cost, the amount of crowd-out is strictly bounded above

<sup>62</sup>In cases where unmet need is less than the exogenous limit on subsidized loans ( $\xi = 1$ ), Group D students adjust loans so as to remain at the kink – grants directly affect their unmet need, but the kink in the marginal cost of borrowing at this limit will still induce them to increase schooling, in addition to reducing borrowing, as grant aid rises.

by 100 percent because  $\frac{\partial d^*}{\partial g}$  is bounded from below by  $-1$  for all groups and there would be no groups between which there would be a discontinuity in optimal borrowing.

2. *Grants only increase educational attainment of threshold borrowers.* Students facing a straightforward borrowing choice (Groups A, C, and E) choose the level of schooling that equates current marginal cost with discounted future marginal benefit and then use debt to smooth income between periods (e.g., Figure 3.1, Panel C). An increase in grant aid has no impact on educational attainment; it only induces these students to borrow less (save more). On the other hand, threshold borrowers (Groups B, D, and F) are limited in their ability to offset small changes in grant aid by altering their borrowing. Only these groups respond by increasing schooling (e.g., Figure 3.1, Panels A and D). Finally, students induced to switch from Group C to Group B will respond to a marginal increase in grant aid by reducing schooling.

### 3.4 Data and sample

In order to take advantage of the nonlinearities in the Pell Grant Program's schedule, we need data that contains information on the underlying assignment variable (EFC), our outcomes of interest (borrowing and educational investment), and a sufficient number of observations to focus on the outcomes of students on either side the discontinuities the Pell Grant formula. We use administrative data from the CUNY system that contains the universe of students from multiple cohorts. This data provides extensive information on students' EFC, student grant and loan aid, and measures of educational attainment (GPA, and credits attempted and earned for semesters between entry and spring 2011).

Our primary sample includes five cohorts of first-time, degree-seeking freshmen who entered a CUNY institution in the fall of the 2005-06 through 2009-10 academic years (hereafter 2006 through 2010 academic years). Unfortunately, we only observe students' FAFSA information (most importantly EFC) in 2008, 2009, 2010. Thus, we observe up to three years of financial aid outcomes for the 2008 cohort, two years for the 2007 and 2009 cohorts, and one year for the 2006 and 2010 cohorts. We differentiate students by entry cohort and level, where level corresponds to years since college entry. We restrict our sample to only include US citizens or permanent residents.<sup>63</sup> Finally, we eliminate students with sufficiently low or high need - those with an EFC more than \$4,000 from the threshold for Pell Grant eligibility. This window excludes students with an EFC equal to zero, who are eligible for the maximum Pell Grant award.<sup>64</sup>

<sup>63</sup>Non-citizens that are not permanent residents are ineligible for most federal and state grant aid and make up less than 1 percent of students in these cohorts.

<sup>64</sup>For the 2008 and 2009 academic years, dependent students and independent students with children would automatically receive a \$0 EFC if their family income fell below \$20,000 and their parents either received means tested benefits during the year or were eligible to file a simplified tax return (indicating low assets). In 2010, the income limit was raised to \$30,000. See [studentaid.ed.gov/types/loanshttp://www.ifap.ed.gov/eannouncements/attachments/0708EFCFormulaGuide.pdf](http://studentaid.ed.gov/types/loanshttp://www.ifap.ed.gov/eannouncements/attachments/0708EFCFormulaGuide.pdf)

Table 3.1 displays the characteristics of students in their first year by Pell Grant eligibility. Pell Grant eligible students receive more TAP and other grant aid (including aid from smaller state and federal grant programs, as well as institutional aid) than ineligible students, while ineligible students take on greater debt. On average, both eligible and ineligible students borrow at low rates; only 11 percent of the sample takes on any debt in their first year, despite, on average, having substantial need and remaining eligibility for subsidized loans. Less than 1 percent of our sample exhausts their total federal loan eligibility in their first year. Pell-ineligible students are more likely to borrow, with 24 percent taking on some debt. Finally, Pell Grant eligible students have different demographic characteristics than ineligible students - they are more likely to be nonwhite, have lower SAT scores, and are less likely to have a college educated parent. These differences in observable characteristics between Pell Grant recipient students and ineligible students motivate our use of RD and RK designs to identify the causal impact of grant aid on student outcomes.

### 3.4.1 Are CUNY Pell Grant recipients representative of the national population?

In Table 3.2, we compare the demographic characteristics, cost of attendance, and financial aid for the 2008 cohort of first-year, degree-seeking, CUNY Pell Grant recipients to a nationally representative sample using data from the 2008 National Postsecondary Student Aid Study (NPSAS).<sup>65</sup> We compare CUNY recipients to both the full NPSAS sample and to public school NPSAS students.<sup>66</sup>

CUNY Pell Grant recipients have greater need than the average Pell Grant recipient enrolled in a public institution, and slightly higher, but comparable need relative to Pell Grant recipients enrolled in public and private schools (Table 3.2, Panel A). CUNY students also receive more grant aid. After taking into account federal, state, and institutional grant aid, CUNY students have around \$5,000 in unmet need compared to \$5,700 for the full nationally representative sample and approximately \$3,700 for public school students.

CUNY Pell Grant recipients borrow at much lower rates than the average Pell Grant recipient, despite having similar levels of remaining need after accounting for grant aid and EFC. While on average, 36 percent of public school Pell Grant recipients borrow, only 4 percent of CUNY students incur any student loan debt in their first year.<sup>67</sup>

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and <http://www.ifap.ed.gov/efcformulaguide/attachments/111408EFCFormulaGuide0910.pdf> for further details.

<sup>65</sup>The NPSAS is a nationally representative, restricted-use, repeated cross-section of college students. A stratified random sample of Title IV-eligible institutions is first drawn, and from these institutions, degree-seeking students are selected into the NPSAS. The Department of Education's National Center for Education Statistics (NCES) collects NPSAS data on a three to four year cycle, with the last publicly available data covering the 2008 academic year. I use the publicly available NCES Data Analysis System (DAS) to generate aggregate statistics from this underlying sample (see <http://nces.ed.gov/das/index.asp> for further details).

<sup>66</sup>In 2008, 64 percent of all Pell Grant recipients were enrolled in public schools (U.S. Department of Education 2009).

<sup>67</sup>In general, CUNY students borrow at much lower rates than other public college students. For instance, 35 percent of 2008 full-time degree seeking students attending four-year public schools received federal loan aid while only 5 percent of full-time, bachelor's degree seeking CUNY students took out federal loans in 2008 (National Center for Education Statistics 2013). Similarly, 5 percent of 2008 full-time associate's degree seeking CUNY students took out federal loans while 19 percent of full-time, degree-seeking two-year students borrowed. Finally, Cadena and Keys (forthcoming) examine a nationally representative

In terms of their demographic characteristics (Panel B), on average, CUNY Pell Grant recipients are younger, more likely to be classified as dependent students, and are more likely to be nonwhite. CUNY students' SAT performance is comparable to that of the average Pell Grant recipient. Finally, CUNY Pell Grant recipients are more likely to be first- or second-generation immigrants, reflecting the fact that the majority of CUNY students attended New York City public schools.

### 3.5 Empirical Framework

We use the variation induced by the kink and discontinuity in the Pell Grant Program's formula to identify the impact of Pell Grant aid on educational investment. The kink occurs where the slope of the statutory  $Pell(EFC)$  schedule changes from 0 to -1, while the discontinuity is driven by the increase in Pell Grant aid from \$0 to the minimum Pell Grant award at the eligibility threshold. Since the eligibility threshold occurs at different EFC values in different years, we standardize our measure of EFC to represent distance from the year-specific threshold. Figure 3.2 displays the empirical distribution of Pell Grant aid, pooling first-, second-, and third-year students.<sup>68</sup>

Let  $Y = \tau Pell + g(EFC) + U$  represent the causal relationship between educational investment,  $Y$ , and Pell Grant aid,  $Pell = Pell(EFC)$ , where  $U$  is a random vector of unobservable, predetermined characteristics. The required identifying assumptions for the RK design are: (1) the direct marginal impact of EFC on  $Y$  is continuous (e.g., around the eligibility threshold, there are no discontinuities in the direct relationship between  $EFC$  and  $Y$ ) and (2) the conditional density of  $EFC$  (with respect to  $U$ ) is continuously differentiable at the threshold for Pell Grant eligibility (Card et al. (2009)). These assumptions encompass those required for identification using the RD design (Hahn et al. 2001). As long as the relationship between unobservable factors and  $EFC$  evolves continuously across the Pell Grant eligibility threshold, the RK design approximates random assignment in the neighborhood of the kink. Additionally, as in the case of the RD design, the second assumption generates testable predictions concerning how the density of EFC and the distribution of observable characteristics should behave in the neighborhood of the eligibility threshold.

If these conditions hold, then both the RK estimator,  $\tau_{RK}$ , and the RD estimator,  $\tau_{RD}$ , will identify the causal impact of Pell Grant aid:

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sample of full-time four-year students attending public and private nonprofit institutions, and estimate that 83 percent of students eligible for subsidized borrowing take advantage of federal loan aid. In comparison, only 8 percent of full-time, bachelor's degree-seeking CUNY students that are eligible for subsidized borrowing take out student loans.

<sup>68</sup>Appendix Figure 3A.3 displays the empirical distribution of Pell Grant aid by level of attendance.



$$\tau_{RK} = \frac{\lim_{\varepsilon \uparrow 0} \left[ \frac{\partial Y|EFC=efc_0+\varepsilon}{\partial efc} \right] - \lim_{\varepsilon \downarrow 0} \left[ \frac{\partial Y|EFC=efc_0+\varepsilon}{\partial efc} \right]}{\lim_{\varepsilon \uparrow 0} \left[ \frac{\partial Pell|EFC=efc_0+\varepsilon}{\partial efc} \right] - \lim_{\varepsilon \downarrow 0} \left[ \frac{\partial Pell|EFC=efc_0+\varepsilon}{\partial efc} \right]} = \tau \quad (6)$$

$$\tau_{RD} = \frac{\lim_{\varepsilon \uparrow 0} [Y|EFC = efc_0 + \varepsilon] - \lim_{\varepsilon \downarrow 0} [Y|EFC = efc_0 + \varepsilon]}{\lim_{\varepsilon \uparrow 0} [Pell|EFC = efc_0 + \varepsilon] - \lim_{\varepsilon \downarrow 0} [Pell|EFC = efc_0 + \varepsilon]} = \tau \quad (7)$$

Where  $efc_0$  represents the Pell Grant eligibility threshold. Since not all students complete a full year of college,  $EFC$  will imperfectly predict students' Pell Grant aid. Therefore, in practice, our estimation strategy involves fuzzy RD/RK. Specifically, we use an instrumental variables approach to estimate  $\tau_{RK}$  and  $\tau_{RD}$ . Since the eligibility threshold changes as the size of the maximum Pell award increases, we first create a standardized measure of the distance a student's EFC falls from the Pell Grant eligibility threshold:  $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$ .

Consider the following first stage and reduced form equations, where  $i$  indicates students,  $t$  indicates year,  $c$  indicates cohorts, and  $s$  indicates colleges,  $f(\cdot)$  and  $g(\cdot)$  are flexible functions of  $\widetilde{EFC}$  that we allow to vary depending on the side of the eligibility threshold on which a student falls, and  $\mathbf{X}$  is a vector of demographic characteristics:

$$Pell_{ist} = f(\widetilde{EFC}_{it}) + \beta_1 \mathbf{1}[\widetilde{EFC}_{it} < 0] + \beta_2 \widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0] + \gamma \mathbf{X}_{it} + \delta_s + \delta_c + \nu_{ist} \quad (8)$$

$$Y_{ist} = g(\widetilde{EFC}_{it}) + \pi_1 \mathbf{1}[\widetilde{EFC}_{it} < 0] + \pi_2 \widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0] + \lambda \mathbf{X}_{it} + \alpha_s + \alpha_c + \epsilon_{ist} \quad (9)$$

In this framework,  $\hat{\tau}_{RK} = \frac{\hat{\pi}_2}{\hat{\beta}_2}$  and  $\hat{\tau}_{RD} = \frac{\hat{\pi}_1}{\hat{\beta}_1}$ . In practice, we use both the kink and the discontinuity for identification.<sup>69</sup>

Table 3.3 displays first stage estimates of the impact of the kink and discontinuity on Pell Grant aid by student level, where  $f(\cdot)$  and  $g(\cdot)$  are quadratic functions of  $\widetilde{EFC}$ , estimated separately on either side of the eligibility threshold. On average, barely-eligible first-year Pell Grant recipients receive a \$450 in Pell Grant aid, and for every dollar decrease in  $EFC$ , their Pell Grant increases by approximately \$0.80. Point estimates for second and third year students are similar.

We are also interested in estimating whether Pell Grant aid has persistent impacts on educational investment. To do so, we regress the period  $t + n$  outcome on Pell Grant aid received in period  $t$ , and estimate

<sup>69</sup>In practice, we estimate these models by level of attendance (first-year, second-year, etc.), allowing all of the coefficients to vary by student level.

2SLS models where the second stage takes the form:

$$Y_{ist} = \tau_n \widehat{Pell}_{it-n} + g_n \left( \widehat{EFC}_{it-n} \right) + \lambda \mathbf{X}_{it} + \alpha_s + \alpha_c + \epsilon_{istn} \quad (10)$$

Here,  $\tau_n$  represents the impact of \$1000 additional Pell Grant aid in period  $t-n$  on the period  $t$  outcome, *vis-à-vis* all other intermediate outcomes affected by Pell Grant aid (including future disbursements of grants). Both the kink and discontinuity in period  $t-n$  serve as excluded instruments for  $Pell_{it-n}$ .<sup>70</sup>

### 3.5.1 Evaluating the RD and RK Identifying Assumptions

We evaluate the RD/RK identifying assumptions by examining the density of students on either side of the Pell Grant eligibility threshold (Figure 3.3) and the distribution of observable characteristics, including gender, race, math and verbal SAT scores (when available), parental education, and dependency status (Figure 3.4). We find no evidence of a discontinuous change in the level or slope of the density or in observable characteristics, the sole exception being the probability of being classified as a dependent student. We examine the density of students on either side of the eligibility threshold and find no evidence that students are manipulating their EFCs - the level and slope of the density function are continuous through the threshold.<sup>71</sup>

## 3.6 Pell Grant Aid Reduces Borrowing

Our model suggests that Pell Grant aid will reduce borrowing by unconstrained students. We first present graphical evidence of the reduced form impacts of Pell Grant eligibility and generosity on borrowing. Figure 3.5 displays mean student loan aid by distance from the Pell Grant eligibility threshold, pooling students across all years of attendance.<sup>72</sup> Average loan aid falls discontinuously at the Pell Grant eligibility threshold, and the relationship between loan aid and EFC changes discontinuously, indicating that (on average) students reduce borrowing upon receiving additional grant aid. These impacts are driven by a reduction in subsidized borrowing (Figure 3.6), which is composed of both a reduction in the probability of any borrowing at the threshold and a reduction in the size of loans conditional on taking on any debt (Figure 3.7).

To quantify the contemporaneous impact of Pell Grant aid on borrowing, we estimate equation (9) separately for first-year students and students still enrolled two and three years after entry (Table 3.4).

<sup>70</sup>This is a version of the ITT estimator proposed by Cellini et al. (2010).

<sup>71</sup>Focusing only on first year students (Appendix Figure 3A.4), this exercise is also a weak test of whether Pell Grant generosity increases the probability of enrollment (within the CUNY system), which would produce additional mass to the left of the threshold. Unfortunately, we currently do not observe the universe of applicants to CUNY schools. Once we obtain this data, we will be able to construct a more definitive test of the impact of Pell Grant aid on enrollment (conditional on applying for college).

<sup>72</sup>We present disaggregated results for each year of schooling in Appendix 3.8 and report 2SLS point estimates separately by year when we turn to our parametric specification.

Panel A presents reduced form impacts of Pell Grant eligibility and generosity on student loan aid. Panel B displays 2SLS estimates of the impact of Pell Grant aid on debt using both the kink and discontinuity as instruments for Pell Grant aid. An additional dollar of Pell Grant aid induces first-year students to reduce borrowing by approximately \$0.37. Students in their second and third years also reduce borrowing in response to Pell Grant generosity, although the point estimates become noisy as the sample size falls due to students not returning to college.<sup>73</sup>

Panel C displays estimates of the impact of an additional dollar of Pell Grant aid in a student's first year on cumulative student loan debt two and three years after entry, regardless of whether a student persists or leaves college. Cumulative borrowing patterns show that grant aid has persistent effects on borrowing. An additional \$1000 of Pell Grant aid in a student's first year reduces cumulative debt by over \$500, an approximately 50 percent decrease from the sample mean.

We also examine the impact of Pell Grant aid on other sources of grant aid (state and institutional) and total financial aid. Panel A of Table 3.5 presents 2SLS estimates of the contemporaneous impact of Pell Grant aid on grant aid from the New York State Tuition Assistance Program (TAP). A student's TAP grant is determined by her New York State Taxable Income, which does not have a one-to-one correspondence with EFC. Thus, this exercise serves as a placebo test since we should not expect to find a relationship between two sources of aid that are independently determined. As expected, we find no evidence of a relationship between TAP and Pell Grant aid.

In Panel B of Table 3.5, we display the estimated impact of Pell Grant aid on other sources of grant aid including institutional, federal, and non-TAP New York State aid. We find a positive relationship between Pell Grant aid and aid from other grants for first- and second-year students, although this relationship is only statistically significant among first-year students, who receive an additional \$0.09 in other grant aid for every dollar of Pell Grant aid. Some sources of grant aid are directly tied to Pell Grant eligibility (e.g., federal Academic Competitiveness Grant aid) while others may be endogenously chosen by the institution after Pell Grant aid is revealed (e.g., Turner 2012). Unfortunately, we cannot separate out the category of "other grant aid" into aid from specific sources. However, we estimate that over 40 percent of the increase in other grant aid at the Pell Grant eligibility threshold can be explained by the federal Academic Competitiveness Grant, which provided an average of \$133 in additional grant aid to first and second year Pell Grant eligible CUNY students that completed a rigorous high school curriculum.<sup>74</sup> Finally, we quantify the impact of Pell Grant aid on total aid from grants and loans in Panel C. On net, a \$1 increase in Pell Grant aid leads to an

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<sup>73</sup>Appendix Tables 3A.1 and 3A.2 examine impacts on subsidized borrowing and unsubsidized borrowing, respectively.

<sup>74</sup>See <http://www2.ed.gov/about/offices/list/ope/ac-smart-families.html> for details in 2008, 2009, and 2010 (authors' calculations, available upon request). The remainder of increase in other grant aid that Pell Grant recipients experience could come from the federal Supplemental Educational Opportunity Grant (SEOG) or institutional aid.

approximately \$0.90 increase in total aid received by first-year students and a \$0.83 increase for second-year students. Among third-year students, a dollar of Pell Grant leads to an insignificant \$0.32 increase in total aid.

Consistent with our fixed-cost borrowing model, grant aid crowd-out of loans exceeds 100 percent among borrowers. Less than 24 percent of Pell-ineligible students borrow (Panel A of Figure 3.7), yet \$1 increase in Pell Grant aid reduces average loan aid across all first year students by \$0.37 (Table 3.4), suggesting borrowing falls by more than \$1.50 among borrowers and would-be borrowers. We examine this result in greater detail by characterizing and estimating the fixed cost of borrowing after documenting the robustness of our borrowing crowd-out results.

### 3.6.1 Robustness of the Estimated Impact of Pell Grant aid on Borrowing

Before concluding that CUNY students' borrowing decisions are influenced by a fixed cost of taking on debt, we need to rule out the possibility that our estimates are driven by our choice of bandwidth or polynomial in  $\widetilde{EFC}$ . We estimate 2SLS models in which we focus on students with EFCs within \$3000, \$2000, and \$1000 of the Pell Grant eligibility threshold, and within each window around the eligibility threshold, we allow for up to a fifth degree polynomial in the running variable. For each window, we determine the optimal degree of polynomial in  $\widetilde{EFC}$  using the Akaike Information Criterion. Finally, we employ the goodness-of-fit test suggested by ?, by testing the joint significance of \$100  $\widetilde{EFC}$  bin dummies added to our main specification (brackets contain p-values from this test). This exercise also directly tests for discontinuities in borrowing away from the Pell Grant eligibility threshold.

Table 3.6 displays impacts on first-year students' borrowing (impacts on second- and third-year students' borrowing and cumulative debt are available upon request). Estimates are robust to smaller windows and higher order polynomials; for every window, second degree polynomial has best fit and our point estimates increase in magnitude when we include higher degree polynomials in  $\widetilde{EFC}$  or limit our sample to students closer to the Pell Grant eligibility threshold. For instance, when we limit our sample to students with EFCs within \$1000 of the threshold and allow for a quadratic in  $\widetilde{EFC}$ , we estimate that every dollar of Pell Grant aid leads to a \$0.65 reduction in loans, which represents a \$2.70 decrease for borrowers. In fact, when scaled by the percentage of Pell Grant ineligible students who borrow, all but one of the point estimates suggest that crowd-out of borrowing in response to Pell Grant increases exceeds 100 percent.

Table 3.7 displays results from additional robustness tests. In Panel A, we present separate IV-RD and IV-RK estimates of the impact of Pell Grant aid on borrowing. Point estimates using only the discontinuity as an instrument for Pell Grant are larger in magnitude than estimates obtained from instrumenting with only the kink, but IV-RK estimates still predict crowd-out exceeding 100 percent. In Panel B, we take into

account the increase in total grant aid that results from a \$1 Pell Grant increase. We estimate (9) but replace the endogenous regressor with the sum of Pell Grant aid and other grant aid and find results consistent with those generated by our main specification.

In Panel C, we address the concern that increases in Pell Grant aid may mechanically decrease borrowing by reducing some students eligibility for subsidized loans.<sup>75</sup> We show that our main results are robust to limiting our sample to students whose subsidized loan eligibility is not affected by Pell Grant aid, although standard errors grow due to the loss of observations. Finally, in Panel D, we show that estimates from models that exclude all covariates besides the quadratic in  $\widetilde{EFC}$  are consistent with our main results.

### 3.6.2 Characterizing the Fixed Cost of Borrowing

A fixed-cost of borrowing can explain our finding that an additional dollar of grant aid induces some students to reduce student loans by more than a dollar. In the canonical model, a student equates current and future marginal utility from loans and therefore saves only a portion of the marginal grant dollar for the future by reducing debt. When borrowing entails a fixed cost, however, the receipt of an additional dollar of grant aid may cause a student to switch from borrowing hundreds or thousands of dollars to borrowing nothing. Large shifts in borrowing are possible because there is a range  $(0, \underline{d})$  in which the amount of debt that would solve the first-order condition (3) would produce only a small utility gain over zero borrowing and hence would not be worth paying the fixed cost. As a result, few students should borrow in small amounts and we expect crowd-out would be greatest among students who would take-up small positive loans in the absence of Pell Grant aid. We provide evidence for both implications, then outline a strategy for estimating the impact of eliminating the fixed cost on borrowing rates and debt.

As shown in Figure 3.8, which displays the distribution of loans among first-year borrowers with a subsidized loan limit of \$3500, students are unlikely to take up small amounts of debt. The density of loans is generally upward sloping between zero and \$2000, as would be the case if students exhibit heterogeneous fixed borrowing costs. These simple histograms, however, do not rule out the possibility that the distribution of desired loan amounts simply does not often take on small positive values.

Estimates of the quantile treatment effects of grant aid on loans reinforce the fixed cost interpretation by showing that the impact of Pell Grant eligibility on borrowing is larger for quantiles corresponding to small positive amounts of debt. Figure 3.9 provides inverse CDFs of loan amounts for first-year (Panel A) and all students (Panel B) with EFCs within \$1000 of Pell Grant eligibility threshold. The vertical distance between

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<sup>75</sup>For instance, increases in Pell Grant aid will directly affect subsidized loan eligibility for students with less than \$3500 in unmet need. Specifically, suppose a student has \$2000 in unmet need, and therefore, is eligible to borrow up to \$2000 in subsidized loans. The discrete increase in Pell Grant aid that occurs at the eligibility threshold, from \$0 to the minimum Pell award, will reduce her eligibility for subsidized loans to  $\$2000 - \min Pell$ . However, her overall eligibility for student loan aid remains unchanged.

the curves provides a reduced-form estimate of the quantile treatment effects of Pell Grant eligibility. In the pooled sample, Pell Grant eligibility does not affect borrowing below the 72nd quantile because 72 percent of students borrow nothing irrespective of their eligibility for Pell Grant aid. Differences in borrowing between eligible and ineligible students are also small at the highest quantiles, but at intermediate quantiles, a Pell Grant of less than \$1000 reduces borrowing by close to \$2000. The patterns for quantiles in which ineligible students borrow but eligible students do not suggest heterogeneous values of  $\underline{d}$  that may reach into the thousands of dollars. These patterns are suggestive, but cannot provide an unbiased estimate of  $\underline{d}$  if Pell Grants induce students to switch quantiles (i.e., if the assumption of rank-invariance is violated).<sup>76</sup>

To quantify the impact of the fixed cost of taking on debt that CUNY students face, we estimate the impact of eliminating this cost on borrowing rates and student loan debt. We consider a simplified version of our model in which students choose some amount of subsidized loans less than the maximum allowable amount:

$$\max_{s,d} U = u(\omega + EFC + g + d - C(s) - \gamma \cdot \kappa_0) + \beta u(w(s) - Rd)$$

Let  $\underline{U}$  and  $U_0$  represent the solutions when  $d^* = \underline{d}$  and  $d^* = 0$ , respectively. Indifference between the solutions implies  $\underline{U} = U_0$ :

$$\gamma = \omega + EFC + g + \underline{d} - C(\underline{s}) - u^{-1}(u(\omega + EFC + g - C(s_0)) - \beta u(w(s_0)) + \beta u(w(\underline{s}) - R\underline{d})) \quad (11)$$

Furthermore, we assume a constant-relative-risk-aversion (CRRA) utility function, where  $u(c) = \frac{1}{1-\eta} (c^{1-\eta} - 1)$ :

$$\gamma = \omega + EFC + g + \underline{d} - C(\underline{s}) - \left[ (\omega + EFC + g - C(s_0))^{1-\eta} - \beta (w(s_0))^{1-\eta} + \beta (w(\underline{s}) - R\underline{d})^{1-\eta} \right]^{\frac{1}{1-\eta}} \quad (12)$$

Given  $\beta$  and  $R$ , we can write  $\eta$  as a function of loan crowd-out (among individuals that arrive at an interior solution for borrowing):

$$\eta = \frac{\log \alpha}{\log R - \log \left( 1 + \frac{\partial d}{\partial g} \right) + \log \left( -\frac{\partial d}{\partial g} \right)} \quad (13)$$

<sup>76</sup>We also examine whether Pell Grant aid crowds-out loan aid in the nationally representative 2008 NPSAS sample. As shown in Appendix Figure 3A.6, we do not observe a discontinuous decrease in average federal loan aid at the Pell Grant eligibility threshold.

Where  $\alpha = R\beta$ .<sup>77</sup>

Observed borrowing, when positive, indicates a student's optimal student loan debt:

$$d^{observed} = -\frac{\alpha^{\frac{1}{\eta}}}{\left(R + \alpha^{\frac{1}{\eta}}\right)}g + \frac{1}{\left(R + \alpha^{\frac{1}{\eta}}\right)}\left[\alpha^{\frac{1}{\eta}}(\gamma + C(s) - \omega - EFC) - w(s)\right] \quad (14)$$

A student's preferred debt is a function of the net cost of college attendance (including the fixed cost of borrowing) and (expected) labor market returns.<sup>78</sup> For students in the neighborhood of the Pell Grant eligibility threshold, the right- and left-sided limits of the expectations of  $EFC$  and  $C_t(s)$  are equal and changing at equal rates. By definition,  $EFC$  is continuous through the eligibility threshold, and we find no evidence of a discontinuity in the level or slope of direct costs (available upon request). Under the RD and RK identifying assumptions, the same holds true for  $C_t(s)$  and  $w(s)$ . Similarly, we assume that there are no discontinuous changes in the level or first derivative of  $\gamma$  at the Pell Grant eligibility threshold.

We observe borrowing when  $d^* > \underline{d}$ . Holding other terms in equation (14) constant, a dollar increase in grant aid will lead a student to decrease borrowing by  $-\frac{\alpha^{\frac{1}{\eta}}}{\left(R + \alpha^{\frac{1}{\eta}}\right)} \in (-1, 0)$  unless  $d - \frac{\alpha^{\frac{1}{\eta}}}{\left(R + \alpha^{\frac{1}{\eta}}\right)} < \underline{d}$ . When  $d - \frac{\alpha^{\frac{1}{\eta}}}{\left(R + \alpha^{\frac{1}{\eta}}\right)} \leq \underline{d}$ , observed debt falls to zero. However, we can estimate a lower bound for  $\underline{d}$  by first predicting what Pell Grant eligible students would have borrowed had they not received Pell Grant aid, and then allowing their predicted debt to decrease by  $\frac{\alpha^{\frac{1}{\eta}}}{\left(R + \alpha^{\frac{1}{\eta}}\right)}$  for every dollar of Pell Grant aid. This exercise provides us with a counterfactual distribution of debt that includes both  $d \geq \underline{d}$  and  $d \in (0, \underline{d})$ . By comparing our counterfactual distribution of borrowing to the actual distribution of borrowing for Pell Grant eligible students, we can estimate  $E[d|d \in (0, \underline{d})]$ , which provides a lower bound for  $E[\underline{d}]$ . Additionally, we can approximate the impact of removing the fixed cost of borrowing on total debt and the probability of borrowing among Pell Grant eligible CUNY students.

We use the relationship between  $\widetilde{EFC}$  and borrowing among Pell-ineligible students as a counterfactual for eligible students would have borrowed in the absence of Pell Grant aid. We then allow borrowing to adjust by  $\frac{\alpha^{\frac{1}{\eta}}}{\left(R + \alpha^{\frac{1}{\eta}}\right)} \times g$ , deriving  $\eta$  according to equation (13), where  $\frac{\partial d}{\partial g}$  is estimated from students arriving at an interior solution for borrowing. Finally, we assume  $\beta = 0.95$  and  $R = 1.034$ .<sup>79</sup>

<sup>77</sup>Given an interior solution, the impact of grant aid on debt is given by:  $\frac{\partial d}{\partial g} = \frac{-u''(c_1)}{u''(c_1) + R^2 \beta u''(c_2)}$ . With CRRA utility, equation (3), the first-order-condition with respect to debt, can be written as:  $c_1^{-\eta} = R\beta c_2^{-\eta}$ . Therefore,  $\frac{\partial d}{\partial g} = \frac{-c_1^{-1-\eta}}{c_1^{-1-\eta} + R \frac{1}{\eta} \frac{-1}{\beta} c_1^{-1-\eta}}$ .

<sup>78</sup>With CRRA utility, equation (3) can be written as:  $(\omega + EFC + g + d - C(s) - \gamma)^{-\eta} = R\beta(w(s) - Rd)^{-\eta}$ .  
<sup>79</sup>In practice, we estimate the counterfactual distribution of loans for Pell Grant eligible students in four steps. First, we generate  $\delta = \frac{\partial d_i}{\partial g}$  from a 2SLS regression of  $d_i$  on  $Pell_i$ , conditioning on  $d_i \in (0, d_s^{max}) \cup (d_s^{max}, \bar{d})$ , and instrumenting for  $Pell_i$  with both the discontinuity and kink. Second, we estimate  $\hat{\eta}$  and generate standard errors via the delta method and third, we predict counterfactual borrowing for Pell Grant eligible students using the observed relationship between borrowing and  $\widetilde{EFC}$

The estimation methodology and approximate results can be visualized using a simple figure. Figure 3.10 displays average loans as a function of  $\widetilde{EFC}$  (light blue circles) and predicted borrowing among Pell-eligible students in the absence of a fixed cost (dark blue circles). Actual borrowing falls sharply when a student becomes eligible for a Pell Grant, while in the absence of a fixed cost of incurring debt, changes in borrowing at the eligibility threshold are much smaller. The difference between the predicted and observed values of borrowing for eligible students represents our estimate of the impact of the fixed cost on total debt. Similarly, we can compare the predicted change in the probability of borrowing to the actual change in the probability of borrowing (not pictured). At the Pell Grant eligibility threshold, predicted borrowing falls by less than 1 percentage point (4 percent); actual borrowing falls by approximately 4 percentage points (17 percent).

### 3.6.3 Estimation Results

The results of our fixed cost estimation appear in Table 3.8. We estimate an intensive-margin response ( $\delta = \frac{\partial d_i}{\partial g}$ ) equal to -0.81 for first-year students and -0.71 for first, second, and third-year student, implying that a marginal dollar of grant aid would reduce loans by approximately 70 to 80 cents if all students borrowed and none faced a fixed borrowing cost. Curvature of the utility function ( $\eta$ ) is not precisely estimated, and although first-year students appear much less risk averse, the estimates are not statistically distinguishable and do not translate into sizable differences in the quantities of interest. We are most interested in  $E[d|d \in (0, \underline{d})]$  – our lower-bound estimate of  $E[\underline{d}]$  – which equals total predicted debt minus total actual debt divided by percentage of additional borrowers. We find that the average student who chooses to forgo debt would have borrowed about \$2400 in the absence of the Pell grant.

In Panel B of Table 3.8, we compare predicted and actual borrowing among Pell Grant eligible CUNY students. If not for the fixed cost, 24 percent of all students would borrow, a 215 percent increase over the observed share of 7.5 percent. These results indicate the economic importance of fixed borrowing costs, which explain about 50 percent of the difference between CUNY students' borrowing rates and the average rate borrowing among Pell Grant recipients attending public schools. The effect on the amount of new debt is also quite large. Mean borrowing across all Pell Grant eligible students, including non-borrowers, would increase from \$254 to \$648, a difference of over \$14 million across the 9 cohort-years we study.

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among ineligible students. Finally, we allow predicted borrowing to adjust by  $-\frac{\alpha^{\frac{1}{\eta}}}{(R+\alpha^{\frac{1}{\eta}})}$  for every dollar increase in predicted Pell Grant aid. By estimating one parameter for  $\frac{\partial d_i}{\partial g}$  we implicitly assume that it is constant across individuals (and hence uncorrelated with  $\underline{d}_i$ ), which allows us to make the comparisons across students necessitated by the fact that some borrow and some do not.



### 3.7 The Impact of Pell Grant Aid on Educational Attainment

When the cost of borrowing is continuous in loan aid, grants increase the attainment of credit-constrained students but do not alter the schooling decisions of students at interior solutions for borrowing. We show that in the presence of a fixed cost of incurring debt, grant aid has ambiguous impacts on average educational attainment. Grants induce a subset of students to stop borrowing to avoid this fixed cost, leading to a decrease in educational attainment. As a result, the aggregate effect of grants on attainment is ambiguous and likely to depend on the population studied.

Table 3.9 displays 2SLS estimates of the impact of an additional \$1000 in Pell Grant aid on contemporaneous and longer-run educational outcomes, including persistence (measured by the probability remaining enrolled in the following semester), effort (measured by credits attempted), attainment (measured by credits earned), and performance (measured by GPA).<sup>80</sup> Overall, additional Pell Grant aid does not appear to increase attainment or performance. Pell Grant aid has small, marginally significant impacts on credits attempted by first year students. Specifically, an additional \$1000 of Pell Grant aid induces first-year students to take an additional 0.5 credits (an approximately 3 percent increase at the sample mean). However, this effect does not translate into an increase in credits earned by first-years.

Ultimately, we are interested in whether Pell Grant aid has longer-run impacts on attainment. The fourth column of Table 3.9 displays estimates of first-year Pell Grant aid on enrollment, cumulative credits attempted, and cumulative credits earned three years after entry. An additional \$1000 of Pell Grant aid in a student's first year leads to an insignificant 0.4 increase in cumulative credits. Furthermore, we can rule out impacts on cumulative credits that are larger than a 3 credit (7 percent) gain three years after entry, suggesting that, on average, Pell Grant aid does little to increase the educational attainment of CUNY students.

The fact that the average impact of Pell Grant aid on educational attainment is not significantly different from zero is also consistent with heterogeneous treatment effects. Our model predicts that only students arriving at a corner solution for borrowing ("threshold borrowers") will respond to increases in Pell Grant aid by increasing schooling, while those at interior solutions will not respond, and those who cease borrowing will decrease schooling. We check for heterogeneous treatment effects by estimating effects on the quantiles of cumulative credits earned 3 years after entry but find no statistically significant point estimates at any quantile (available upon request).

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<sup>80</sup> Appendix Figure 3A.7 displays graphical evidence of the reduced form, contemporaneous relationship between Pell Grant eligibility and generosity and educational attainment, pooling first, second, and third year students.

### 3.8 Conclusion

In this paper, we take advantage of the nonlinearities in the Pell Grant Program's formula to estimate the impact of need-based grant aid on educational attainment and borrowing. Our main results - that Pell Grant aid reduces borrowing and has no lasting impact on educational outcomes - is consistent with traditional models of educational investment under credit constraints. Very few CUNY students face borrowing constraints due to low tuition, generous state grant aid, and universal eligibility for federal student loans.

However, among students who borrow, an additional \$1 of Pell Grant aid leads to borrowers reducing loans by more than \$1, which is inconsistent with traditional models of credit constraints where the marginal cost of borrowing is continuous in debt. To explain this irregularity, we extend the traditional credit constraints framework to allow for discontinuities in the price of borrowing caused by a fixed cost of borrowing. We estimate that this cost induces 16 percent of Pell Grant eligible students to forgo borrowing in a given year. Our model predicts that Pell Grant aid actually reduces the educational effort of these students, offsetting the expected improvements among students constrained by loan limits and perhaps explaining our finding of no aggregate effects on educational effort or attainment.

In 2013, outstanding student loan debt exceeded \$960 billion (?). Our results suggest that the choice of the default loan offered to low income students has large impacts on borrowing. Theoretically, we show that imposing a fixed cost by requiring an additional application for loan aid will reduce educational attainment. While ? estimates that access to federal loan aid increases educational attainment of low-income community college students, in general there is limited evidence concerning the impact of federal loan aid on student outcomes.<sup>81</sup> Furthermore, while estimated returns to higher education suggest that borrowing to finance college is optimal (?), student loan debt may impose costs that alter students' behavior when they enter the labor force or while students are still making educational investments (e.g., ?;Rothstein and Rouse 2011). Imposing a fixed borrowing cost may enhance welfare if student debt distorts future decisions. We leave welfare analysis and estimation of these interesting parameters to future work.

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<sup>81</sup>? provide evidence that high ability students respond similarly to offered loans and offered grants when deciding between colleges.

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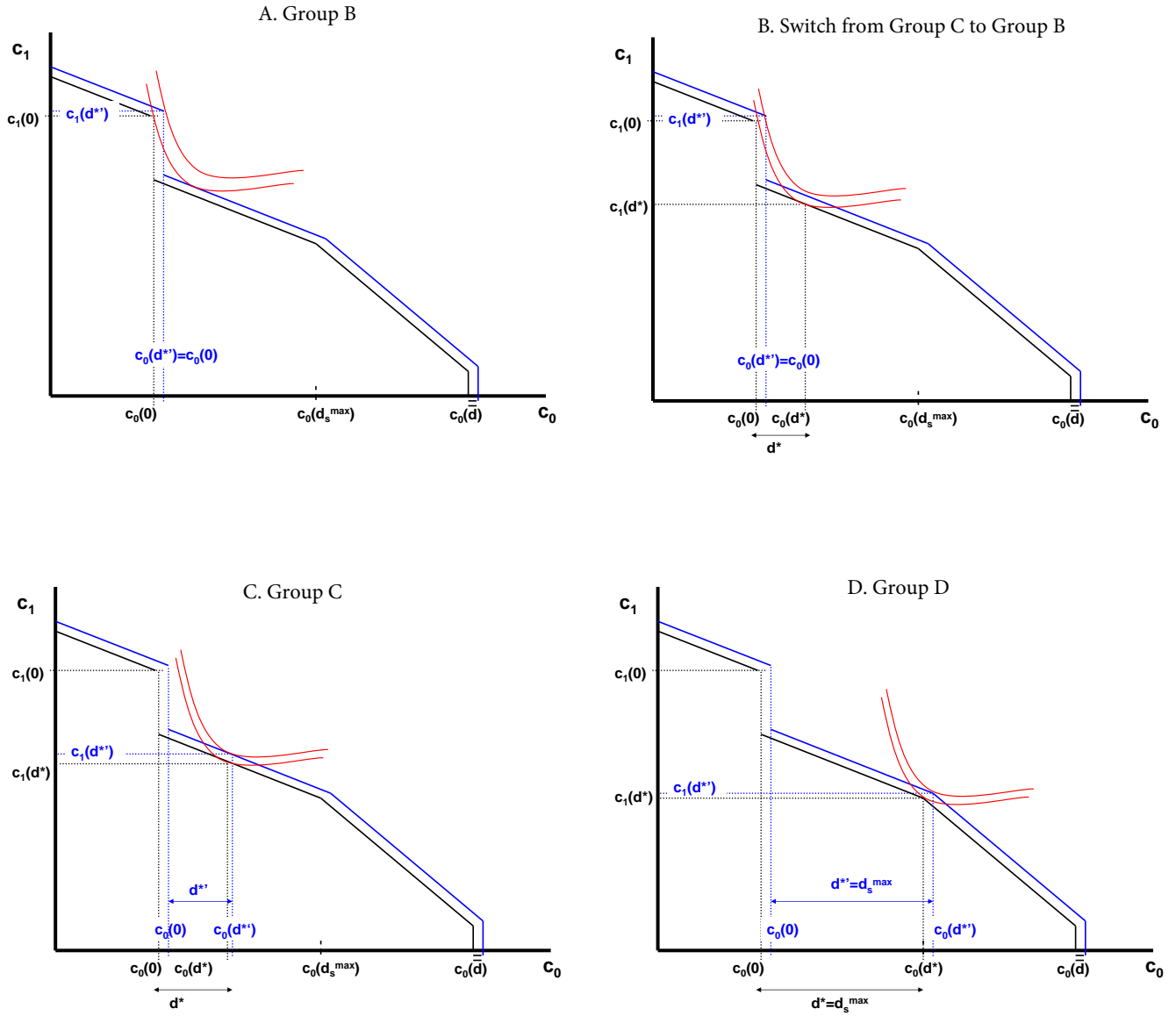
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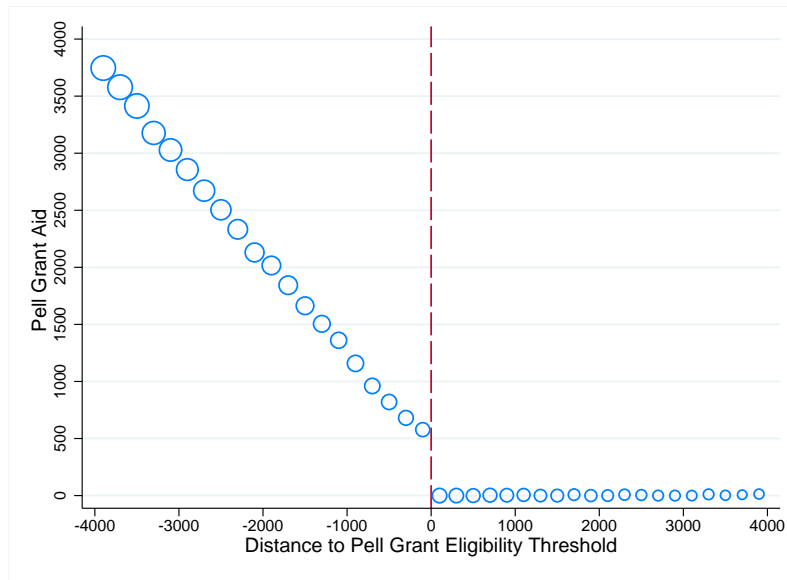
# Figures and Tables

Figure 3.1: The Impact of Pell Grant Aid on Debt by Level of Exogenous Resources



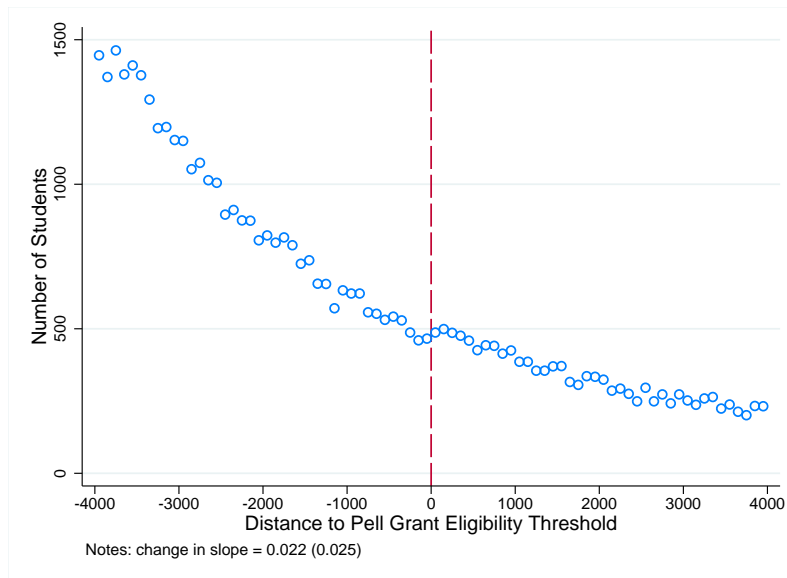
Notes: The black line represents the student's budget constraint in the absence of grant aid, the blue line represents the student's budget constraint upon the receipt of grant aid,  $c_0$  is consumption in the first period, while  $c_1$  is consumption in the second period. See Section 3.3 for descriptions of groups. Panel A and Panel D -  $\frac{\partial d}{\partial g} = 0$  and  $\frac{\partial s}{\partial g} > 0$ . Panel B -  $\frac{\partial d}{\partial g} < -1$  and  $\frac{\partial s}{\partial g} < 0$ . Panel C -  $\frac{\partial d}{\partial g} \in (-1, 0)$  and  $\frac{\partial s}{\partial g} = 0$ .

Figure 3.2: The Empirical Distribution of Pell Grant Aid by Distance to Eligibility Threshold



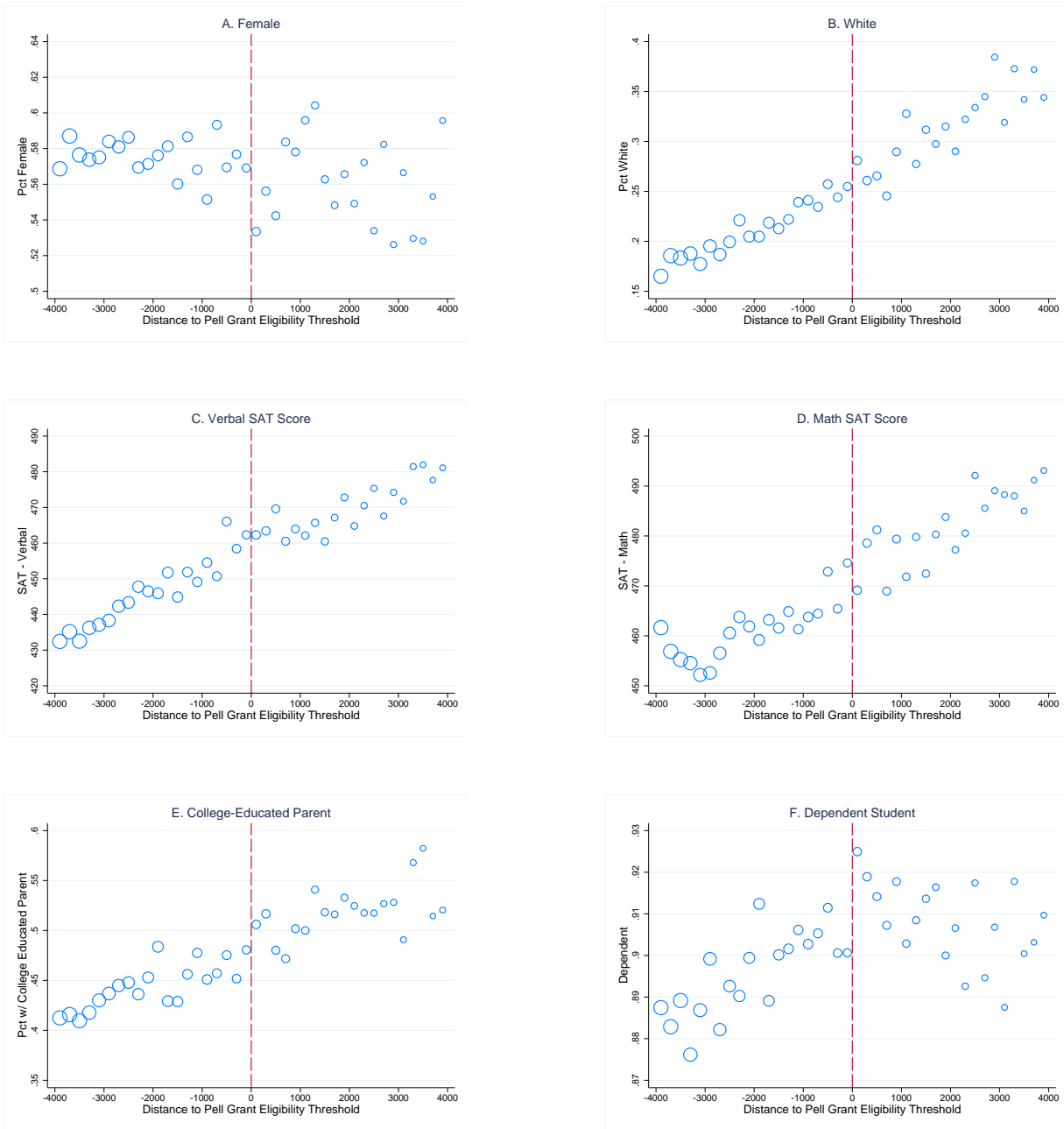
Notes: First, second, and third year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. \$200 EFC bins. Each circle represents the average Pell Grant aid received by students in the bin. Larger circles represent a larger underlying sample size. All dollar amounts adjusted to represent constant 2012\$.

Figure 3.3: The Density of EFC at the Pell Grant Eligibility Threshold



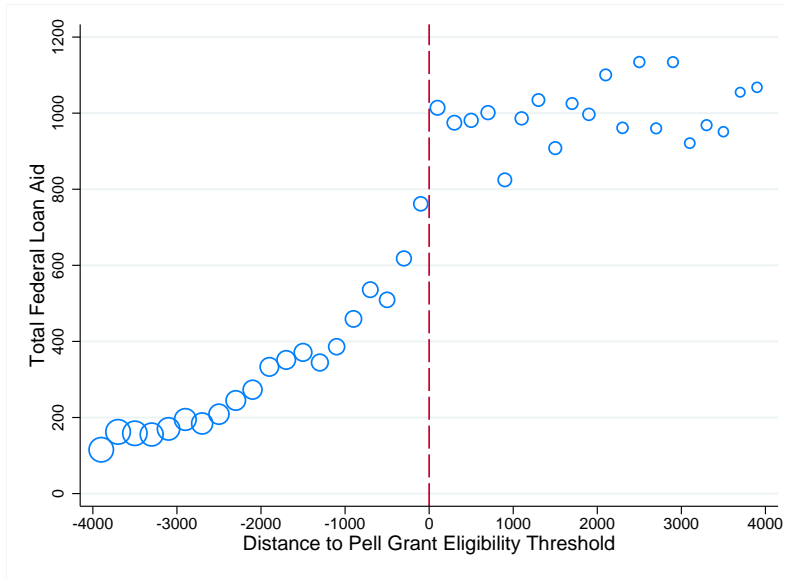
Notes: First, second, and third year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. \$100 EFC bins. Each circle represents the total number of students in the bin. All dollar amounts adjusted to represent constant 2012\$.

Figure 3.4: The Distribution of Baseline Characteristics



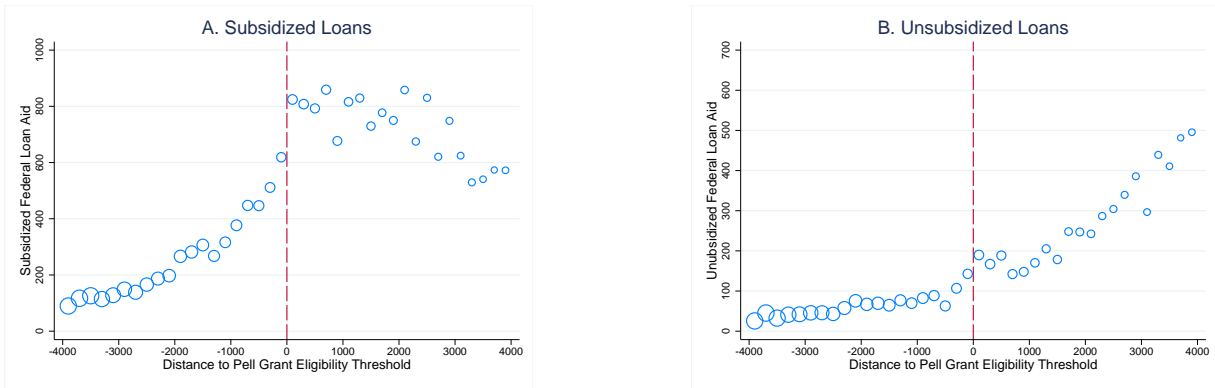
Notes: First, second, and third year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. \$200 EFC bins. Each circle represents the average characteristic of students in the bin. Larger circles represent a larger underlying sample size. All dollar amounts adjusted to represent constant 2012\$.

Figure 3.5: The Reduced Form Impact of Pell Grant Eligibility and Generosity on Total Borrowing



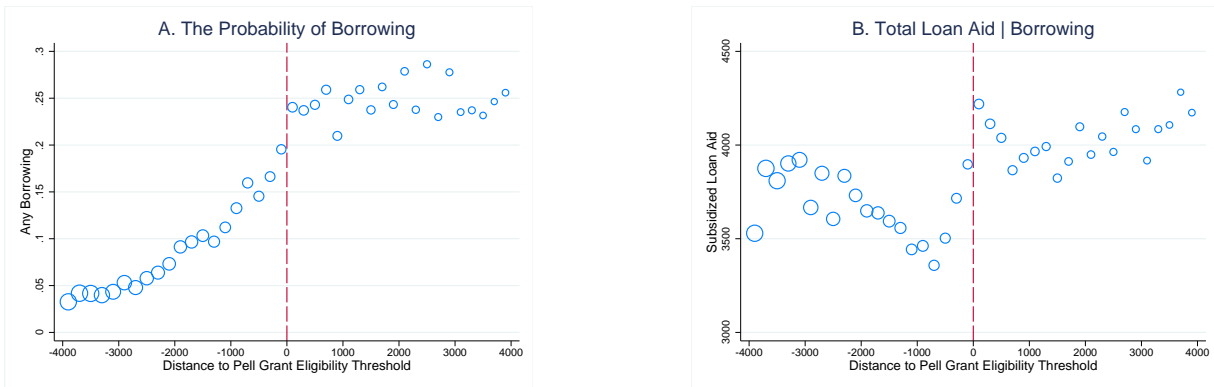
Notes: First, second, and third year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. \$200 EFC bins. Each circle represents average loan aid (subsidized + unsubsidized Federal Direct Loans) received by students in the bin. Larger circles represent a larger underlying sample size. All dollar amounts adjusted to represent constant 2012\$.

Figure 3.6: Impacts on Overall Borrowing Driven by a Reduction in Subsidized Borrowing



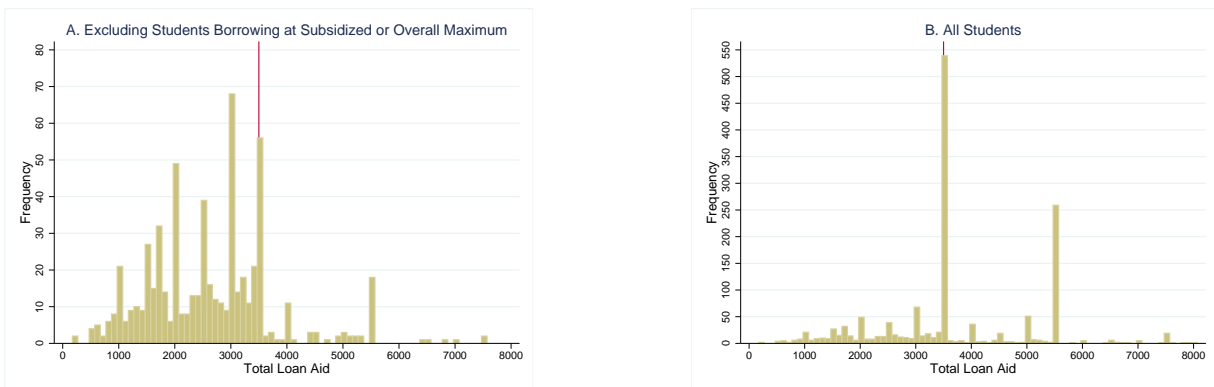
Notes: First, second, and third year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. \$200 EFC bins. Each circle represents average subsidized (A) or unsubsidized (B) Federal Direct Loan aid received by students in the bin. Larger circles represent a larger underlying sample size. All dollar amounts adjusted to represent constant 2012\$.

Figure 3.7: Both the Probability of Borrowing and the Size of Loan Aid Conditional on Any Borrowing Responds to Pell Grant Eligibility and Generosity



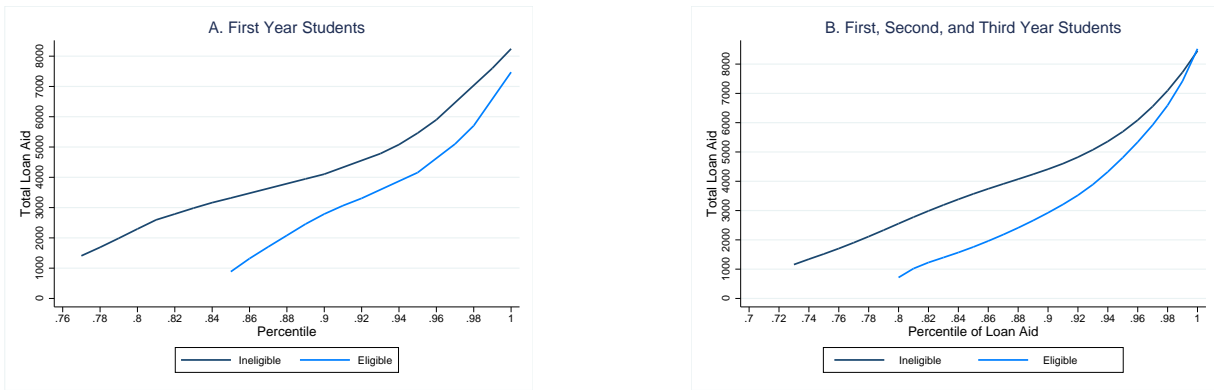
Notes: First, second, and third year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. \$200 EFC bins. Each circle represents average probability of borrowing (A) or subsidized Federal Direct Loan aid received by borrowers (B) in the bin. Larger circles represent a larger underlying sample size. All dollar amounts adjusted to represent constant 2012\$.

Figure 3.8: The Distribution of Loans - 1st Year Borrowers Subject to Exogenous Subsidized Borrowing Limit



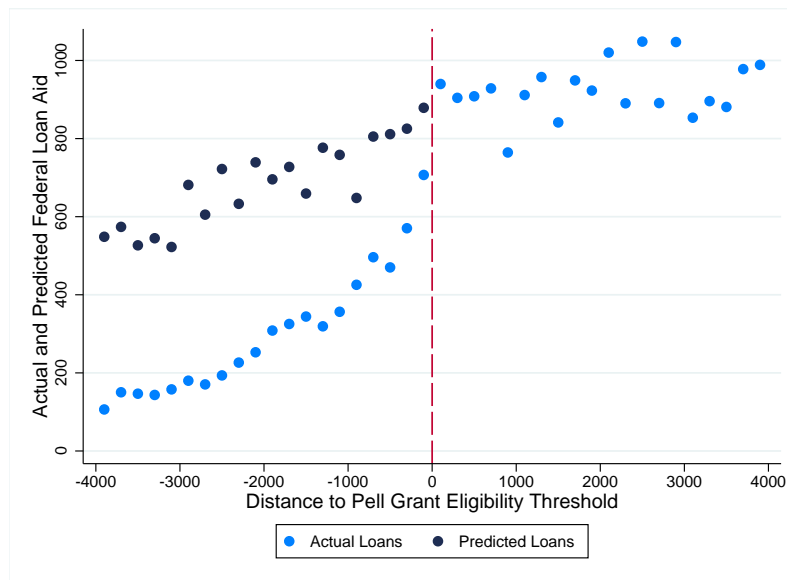
Notes: First year CUNY undergraduate degree-seeking students; 2008 through 2010 cohorts. \$100 bins. Dollar amounts in nominal terms.

Figure 3.9: Quantiles of Student Loans by Pell Grant Eligibility



Notes: Panel A: first year students CUNY undergraduate degree seeking students; 2008 through 2010 cohorts. Panel B: first, second, and third-year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. Students in percentiles that are not listed take on \$0 debt. Limited to students with an EFC less than \$1000 to the Pell Grant eligibility threshold. All dollar amounts adjusted to represent constant 2012\$.

Figure 3.10: Actual and Predicted Borrowing



Notes: CUNY undergraduate degree seeking students; 2006 through 2010 cohorts. \$200 EFC bins. Lighter circles indicate average loan aid received by students in the bin; dark circles indicate average predicted loan aid received by students in the bin. All dollar amounts adjusted to represent constant 2012\$.

Table 3.1: Characteristics of Schools and Students by Pell Grant Eligibility

	Ineligible	Eligible	Full Sample
Number of Students	6,406	17,700	24,106
A. Cost of Attendance and Financial Aid			
Expected family contribution	\$6,312	\$2,166	\$3,268
Total need (=COA-EFC)	\$6,917	\$10,508	\$9,554
Parent AGI	\$58,579	\$38,754	\$44,054
Parent savings	\$6,120	\$3,359	\$4,092
Student AGI	\$4,087	\$2,832	\$3,165
Student savings	\$446	\$293	\$333
Total Grant aid	\$1,050	\$5,055	\$5,932
Pell Grant aid	\$5	\$2,489	\$1,829
TAP Grant aid	\$768	\$1,571	\$1,358
Any borrowing?	0.24	0.07	0.11
Subsidized loan aid	\$693	\$189	\$323
Unsubsidized loan aid	\$241	\$48	\$99
Subsidized borrowing limit	\$2,810	\$2,889	\$2,868
% subject to endogenous limit	0.36	0.36	0.36
% borrowing at subsidized limit	0.17	0.04	0.07
% Need met with grants	0.20	0.47	0.40
B. Student Demographic Characteristics			
Female	0.54	0.56	0.55
Dependent student	0.91	0.90	0.91
API	0.12	0.13	0.13
Black	0.31	0.34	0.33
Hispanic	0.27	0.34	0.32
White	0.29	0.19	0.22
SAT verbal score	467	440	448
Percentile	0.39	0.32	0.34
SAT math score	476	453	460
Percentile	0.38	0.32	0.34
Foreign-born	0.15	0.19	0.18
Foreign-born parent(s)	0.47	0.53	0.53
Parents' highest education			
Less than high school	0.04	0.06	0.06
High school	0.37	0.41	0.40
College	0.52	0.43	0.46
Initial Degree Program = BA	0.44	0.35	0.37

*Notes:* First year CUNY undergraduate degree seeking students; 2008 through 2010 cohorts. COA represents the total cost of attendance, which is equal to tuition and fees, books and supplies, and living expenses. A student's total need is equal to the total cost of attendance minus her EFC. AGI = adjusted gross income. Race and parental education categories may not sum to one due to missing values. Students with EFC greater than \$4,000 from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted to represent constant 2012\$.

Table 3.2: Comparing CUNY Students with a Nationally Representative Sample:  
First-Year, Degree Seeking, Fall 2007 Entering Students who Received Pell Grants

	1. CUNY	2. NPSAS - All Sectors	3. NPSAS - Public Schools
<b>A. Cost of Attendance and Financial Aid</b>			
Expected family contribution	\$586	\$747	\$796
Total need (=COA-EFC)	\$10,585	\$13,067	\$9,533
Total grant aid	\$5,989	\$4,357	\$3,932
Pell Grant aid	\$3,328	\$2,396	\$2,390
Unmet need after grants	\$4,683	\$8,710	\$5,601
Any borrowing?	0.04	0.53	0.36
Federal subsidized loans	\$95	\$1,360	\$924
Federal unsubsidized loans	\$13	\$816	\$342
Private loans	\$0	\$732	\$178
<b>B. Student Demographic Characteristics</b>			
Female	0.58	0.65	0.63
Dependent student	0.88	0.47	0.54
Age	19	25	24
Race/ethnicity			
Asian/Pacific Islander	0.18	0.04	0.05
Black	0.29	0.26	0.26
Hispanic	0.39	0.20	0.20
White	0.14	0.45	0.45
SAT verbal score	422	444	440
SAT math score	446	442	438
Parents' highest education			
Less than high school	0.12	0.19	0.18
High school	0.48	0.32	0.33
College	0.39	0.49	0.49
First generation immigrant	0.26	0.12	0.13
Second generation immigrant	0.27	0.10	0.10
AGI	\$18,910	\$18,804	\$19,549
Initial Degree Program = BA	0.35	0.33	0.28

*Notes:* Column 1: first year CUNY undergraduate degree seeking Pell Grant recipients. Columns 2: first-year undergraduate degree-seeking Pell Grant recipients from 2008 National Postsecondary Student Aid Study (NPSAS). NPSAS statistics generated using the National Center for Education Statistics Data Analysis System (DAS). Column 2 includes NPSAS students attending schools in all sectors of higher education; column 3 includes NPSAS students attending public institutions. AGI equals parental adjusted gross income for dependent students and student AGI for independent students. COA represents the total cost of attendance, which is equal to tuition and fees, books and supplies, and living expenses. Measures of parental education exclude observations with missing values. Measures of race exclude students with missing race. First generation immigrants are students who were not born in the United States. Second generation immigrants are students who were born in the United States with parents that were foreign-born. Dollar amounts in nominal terms (2008\$).



Table 3.3: The Impact of Pell Grant Eligibility and Generosity on Pell Grant Aid

	Year 1	Year 2	Year 3
<i>A. OLS Estimates: Impacts on Contemporaneous Pell Grant Aid</i>			
Pell Grant eligible	451.98 (26.84)**	473.05 (33.36)**	474.72 (20.78)**
× Distance from threshold	-0.785 (0.024)**	-0.756 (0.033)**	-0.828 (0.039)**
Observations	24,106	14,706	9,849
<i>B. 2SLS Estimates: Impacts on Cumulative Pell Grant Aid</i>			
First year Pell Grant aid	-- --	1.101 (0.060)**	1.152 (0.130)**
Mean	\$1,829	\$3,364	\$4,551
Observations	24,106	24,106	24,106

*Notes:* Panel A: First, second, and third-year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. Panel B: CUNY undergraduate degree seeking students; 2008 through 2010 cohorts. Each column within a panel represents a separate regression. Standard errors clustered at institution level in parentheses; \*\*  $p < 0.01$ , \*  $p < 0.05$ , +  $p < 0.1$ . All regressions include controls for age, family AGI, college fixed effects, and indicators for race (white versus nonwhite), dependency status (dependent versus independent), parents' highest level of education (college, high school, or less than high school), cohort of entry, level of attendance (for federal loan eligibility purposes), and a quadratic in student expected family contribution ( $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$ , where  $efc_{0t}$  is the threshold for Pell Grant eligibility in year  $t$ ), allowed to vary on either side of the eligibility threshold. Panel B displays 2SLS estimates of the impact of an additional dollar of Pell Grant aid in a student's first year on cumulative Pell Grant aid two and three years after entry; excluded instruments are  $\mathbf{1}[\widetilde{EFC}_{it} < 0]$  and  $\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$ . Students with EFC greater than \$4,000 from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted to represent constant 2012\$.

Table 3.4: The Impact of Pell Grant Aid on Borrowing

	Year 1	Year 2	Year 3
<i>A. OLS Estimates: Impacts on Contemporaneous Borrowing</i>			
Pell Grant Eligible	-248.74 (54.71)**	-236.52 (66.05)**	-326.07 (83.64)**
× Distance from Threshold	0.232 (0.082)*	0.091 (0.096)	0.607 (0.162)**
Observations	24,106	14,706	9,849
<i>B. 2SLS Estimates: Impacts on Contemporaneous Borrowing</i>			
Pell Grant Aid	-0.365 (0.093)**	-0.241 (0.110)*	-0.720 (0.152)**
Observations	24,106	14,706	9,849
<i>C. 2SLS Estimates: Impacts on Cumulative Borrowing</i>			
First year Pell Grant Aid	-- --	-0.507 (0.168)**	-0.520 (0.263)*
Mean	\$423	\$757	\$1,082
Observations	24,106	24,106	24,106

*Notes:* Panels A and B: First, second, and third-year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. Panel C: CUNY undergraduate degree seeking students; 2008 through 2010 cohorts. Each column within a panel represents a separate regression. Standard errors clustered at institution level in parentheses; \*\*  $p < 0.01$ , \*  $p < 0.05$ , +  $p < 0.1$ . All regressions include controls for age, family AGI, college fixed effects, and indicators for race (white versus nonwhite), dependency status (dependent versus independent), parents' highest level of education (college, high school, or less than high school), cohort of entry, level of attendance (for federal loan eligibility purposes), and a quadratic in student expected family contribution ( $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$ , where  $efc_{0t}$  is the threshold for Pell Grant eligibility in year  $t$ ), allowed to vary on either side of the eligibility threshold. Panel B displays 2SLS estimates of the impact of an additional dollar of Pell Grant aid on contemporaneous borrowing and Panel C displays 2SLS estimates of the impact of an additional dollar of Pell Grant aid in a student's first year on cumulative borrowing two and three years after entry; excluded instruments are  $\mathbf{1}[\widetilde{EFC}_{it} < 0]$  and  $\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$ . F-stat from test of significance of excluded instruments: 856 (Year 1), 569 (Year 2), 590 (Year 3). Students with EFC greater than \$4,000 from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted to represent constant 2012\$.

Table 3.5: Contemporaneous Impacts of Pell Grant Aid on Other Sources of Financial Aid

	Year 1	Year 2	Year 3
<i>A. 2SLS Estimates: Impacts on TAP Grant Aid</i>			
Pell Grant Aid	0.017 (0.059)	0.018 (0.063)	0.070 (0.074)
Observations	24,106	14,706	9,849
<i>B. 2SLS Estimates: Impacts on Other Grant Aid</i>			
Pell Grant Aid	0.089 (0.032)**	0.078 (0.050)	-0.117 (0.106)
Observations	24,106	14,706	9,849
<i>C. 2SLS Estimates: Impacts on Total Aid</i>			
Pell Grant Aid	0.827 (0.158)**	0.831 (0.171)**	0.321 (0.258)
Observations	24,106	14,706	9,849

*Notes:* First, second, and third-year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. Other grant aid includes grant aid from all sources (excluding TAP and Pell Grant aid). Each column within a panel represents a separate regression. Standard errors clustered at institution level in parentheses; \*\*  $p < 0.01$ , \*  $p < 0.05$ , +  $p < 0.1$ . All regressions include controls for age, family AGI, college fixed effects, and indicators for race (white versus nonwhite), dependency status (dependent versus independent), parents' highest level of education (college, high school, or less than high school), cohort of entry, level of attendance (for federal loan eligibility purposes), and a quadratic in student expected family contribution ( $\widehat{EFC}_{it} = EFC_{it} - efc_{0t}$ , where  $efc_{0t}$  is the threshold for Pell Grant eligibility in year  $t$ ), allowed to vary on either side of the eligibility threshold. Excluded instruments are  $\mathbf{1}[\widehat{EFC}_{it} < 0]$  and  $\widehat{EFC}_{it} \times \mathbf{1}[\widehat{EFC}_{it} < 0]$ . F-stat from test of significance of excluded instruments: 856 (Year 1), 569 (Year 2), 590 (Year 3). Students with EFC greater than \$4,000 from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted to represent constant 2012\$.

Table 3.6: The Impact of Pell Grant Aid on First Year Students' Borrowing:

Robustness to Varying Bandwidths and Polynomials				
Bandwidth:	\$4,000	\$3,000	\$2,000	\$1,000
Polynomial of order:				
One	-0.124 (0.032)** [0.000]	-0.673 (0.207)** [0.054]	-0.703 (0.276)* [0.716]	-0.928 (0.333)** [0.825]
Two	-0.365 (0.093)** [0.477]	-0.562 (0.123)** [0.991]	-0.681 (0.167)** [0.994]	-0.651 (0.220)** [0.782]
Three	-0.631 (0.160)** [0.545]	-0.730 (0.232)** [0.997]	-0.688 (0.254)** [0.992]	-0.714 (0.342)* [0.806]
Four	-0.813 (0.255)** [0.699]	-0.659 (0.213)** [0.994]	-0.710 (0.279)* [0.996]	-0.974 (0.348)** [0.724]
Five	-0.812 (0.250)** [0.944]	-0.673 (0.207)** [0.999]	-0.703 (0.276)* [0.938]	-0.928 (0.333)** [0.781]
Optimal Order	2	2	2	2
Observations	24,106	16,231	9,992	4,852

*Notes:* First-year CUNY undergraduate degree-seeking students; 2008 through 2010 cohorts. Each cell represents a separate regression. Standard errors clustered at institution level in parentheses; \*\* p<0.01, \* p<0.05, + p<0.1. All regressions include controls for age, family AGI, college fixed effects, and indicators for race (white versus nonwhite), dependency status (dependent versus independent), parents' highest level of education (college, high school, or less than high school), cohort of entry, level of attendance (for federal loan eligibility purposes), and a polynomial in student expected family contribution ( $\widehat{EFC}_{it} = EFC_{it} - efc_{0t}$ , where  $efc_{0t}$  is the threshold for Pell Grant eligibility in year  $t$ ), allowed to vary on either side of the eligibility threshold. Degree of polynomial is indicated in the first column. Optimal order of polynomial chosen using Akaike Information Criterion. Square brackets include p-values from test of joint significance of \$100 EFC bin dummies included as additional regressors. Excluded instruments are  $\mathbf{1}[\widehat{EFC}_{it} < 0]$  and  $\widehat{EFC}_{it} \times \mathbf{1}[\widehat{EFC}_{it} < 0]$ . Students with EFC greater than the indicated distance from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted to represent constant 2012\$.

Table 3.7: The Impact of Pell Grant Aid on Borrowing:

Other Robustness Tests				
	Year 1	Year 2	Year 3	Year 3 Cumulative
<i>A. Separate RD and RK</i>				
Pell Grant Aid (RD)	-0.550 (0.130)**	-0.500 (0.155)**	-0.687 (0.167)**	-0.463 (0.342)
Pell Grant Aid (RK)	-0.295 (0.100)**	-0.120 (0.124)	-0.733 (0.179)**	-0.541 (0.280)+
Test of equality (pval)	0.065	0.045	0.670	0.815
Observations	24,106	14,706	9,849	24,106
<i>B. Accounting for Other Grant Aid</i>				
Pell + Other Grant Aid	-0.369 (0.092)**	-0.282 (0.099)**	-0.807 (0.184)**	-0.428 (0.227)+
Observations	24,106	14,706	9,849	24,106
<i>C. Eliminate Mechanical Effect on Subsidized Loan Eligibility</i>				
Pell Grant Aid	-0.337 (0.159)*	-0.283 (0.231)	-0.829 (0.255)**	-0.423 (0.386)
Observations	14,582	8,497	4,886	14,582
<i>D. Excluding covariates</i>				
Pell Grant Aid	-0.347 (0.097)**	-0.282 (0.116)*	-0.779 (0.164)**	-0.512 (0.193)**
Observations	24,106	14,706	9,850	48,662

*Notes:* First, second, and third-year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. Cumulative borrowing regressions restricted to CUNY undergraduate degree seeking students; 2008 through 2010 cohorts. Panel C sample is limited to Pell Grant eligible students with unmet need greater than the exogenous subsidized borrowing limit and Pell Grant ineligible students with unmet need greater than the sum of the exogenous subsidized borrowing limit and the minimum Pell Grant award. Each column within a represents a separate regression. Standard errors clustered at institution level in parentheses; \*\*  $p < 0.01$ , \*  $p < 0.05$ , +  $p < 0.1$ . Panel A through C regressions include controls for age, family AGI, college fixed effects, and indicators for race (white versus nonwhite), dependency status (dependent versus independent), parents' highest level of education (college, high school, or less than high school), cohort of entry, level of attendance (for federal loan eligibility purposes). All regressions include a quadratic in student expected family contribution ( $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$ , where  $efc_{0t}$  is the threshold for Pell Grant eligibility in year  $t$ ), allowed to vary on either side of the eligibility threshold. Excluded instruments are  $\mathbf{1}[\widetilde{EFC}_{it} < 0]$  and  $\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$  except as indicated in Panel A. Students with EFC greater than \$4,000 from Pell Grant eligibility threshold in their first year are excluded. All dollar amounts adjusted to represent constant 2012\$.

Table 3.8: Characterizing the Fixed Cost of Borrowing

	First-Year Students	All Years
<i>A. Parameters</i>		
$\delta$	-0.809 (0.227)**	-0.711 (0.144)**
$\eta$	0.895 (1.455)	0.365 (0.699)
$E[d \mid d\epsilon(0, \underline{d})]$	2404.38	2452.73
<i>B. Impact of removing fixed cost on borrowing outcomes</i>		
Actual borrowing rate	0.067	0.075
Predicted borrowing rate	0.227	0.236
Actual average debt	219.55	253.51
Predicted average debt	604.25	648.40
Observations	17,700	35,480

*Notes:* First, second, and third-year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. See Section 3.6 for description of parameters and estimation. Students with EFC greater than \$4,000 from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted to represent constant 2012\$.


Table 3.9: The Impact of Pell Grant Aid on Persistence and Educational Attainment

	Year 1	Year 2	Year 3	Year 3 Cumulative
<i>A. Persistence</i>				
Pell Grant Aid (\$1k)	-0.002 (0.023)	0.038 (0.027)	0.010 (0.023)	-0.011 (0.022)
Mean	0.78	0.81	0.83	0.64
Observations	24,106	14,706	9,849	24,106
<i>B. Credits Attempted</i>				
Pell Grant Aid (\$1k)	0.575 (0.311)+	-0.320 (0.520)	1.030 (0.543)+	0.576 (1.179)
Mean	19.1	21.3	21.7	47.7
Observations	24,106	14,706	9,849	24,106
<i>C. Credits Earned</i>				
Pell Grant Aid (\$1k)	0.264 (0.373)	-0.164 (0.477)	0.105 (0.586)	0.383 (1.243)
Mean	16.3	18.9	19.7	41.8
Observations	24,106	14,706	9,849	24,106
<i>D. GPA</i>				
Pell Grant Aid (\$1k)	-0.030 (0.040)	-0.013 (0.067)	0.017 (0.043)	--
Mean	2.55	2.61	2.75	--
Observations	21,651	13,804	9,435	--

*Notes:* First, second, and third-year CUNY undergraduate degree-seeking students; 2006 through 2010 cohorts. Cumulative attainment regressions restricted to CUNY undergraduate degree seeking students; 2008 through 2010 cohorts. Each column within a panel represents estimates from a separate regression. Standard errors clustered at institution level in parentheses; \*\*  $p < 0.01$ , \*  $p < 0.05$ , +  $p < 0.1$ . Persistence indicates the probability of re-enrolling the following year. All regressions include controls for age, family AGI, college fixed effects, and indicators for race (white versus nonwhite), dependency status (dependent versus independent), parents' highest level of education (college, high school, or less than high school), cohort of entry, level of attendance (for federal loan eligibility purposes), and a quadratic in student expected family contribution ( $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$ , where  $efc_{0t}$  is the threshold for Pell Grant eligibility in year  $t$ ), allowed to vary on either side of the eligibility threshold. Excluded instruments are  $\mathbf{1}[\widetilde{EFC}_{it} < 0]$  and  $\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$ . Students with EFC greater than \$4,000 from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted to represent constant 2012\$.

# Appendix 3A - Additional Figures and Tables

Figure 3A.1: Sample CUNY Financial Aid Award Letter



**The City University of New York - Baruch College**  
Chris Dempsey, 5555

7/8/1988

**Costs in the 2013-14 year**

**Estimated Cost of Attendance** **\$X,XXX / yr**

Tuition and fees .....	\$ X,XXX
Housing and meals .....	X,XXX
Books and supplies .....	X,XXX
Transportation .....	X,XXX
Other education costs .....	X,XXX

**Grants and scholarships to pay for college**

**Total Grants and Scholarships** (Gift Aid; no repayment needed) **\$X,XXX / yr**

Grants from your school .....	\$ X,XXX
Federal Pell Grant .....	X,XXX
Grants from your state .....	X,XXX
Other scholarships you can use .....	X,XXX

**What will you pay for college**

**Net Costs** **\$X,XXX / yr**

(Cost of attendance minus total grants and scholarships)

**Options to pay net costs**

**Work options**

Work-Study (Federal, state, or institutional) ..... \$ X,XXX

**Loan Options\***

Federal Perkins Loans	\$ X,XXX
Federal Direct Subsidized Loan	X,XXX
Federal Direct Unsubsidized Loan	X,XXX

\*Recommended amounts shown here. You may be eligible for a different amount. Contact your financial aid office.


**Other options**

**Family Contribution** **\$X,XXX / yr**

(As calculated by the institution using information reported on the FAFSA or to your institution.)

- Payment plan offered by the institution
- Military and/or National Service benefits
- Parent PLUS Loan
- Non-Federal private education loan


**Institutional 1st Year Retention Percentage of Full Time Freshman**



89.3%

Low
Medium
High

**Degrees Awarded 2011-2012: 2,716**




**Loan Default Rate**

Percentage of borrowers entering repayment and defaulting on their loan

3.2%

This Institution




9.8%

National

**Median Borrowing**

Students at Baruch College typically borrow \$9,309 in Federal loans for their undergraduate study. The Federal loan payment over 10 years for this amount is approximately \$107.13 per month. Your borrowing may be different.



**Repaying your loans**

To learn about loan repayment choices and work out your Federal Loan monthly payment, go to:  
<http://studentaid.ed.gov/repay-loans/understand/plans>

**For more information and next steps:**

**Baruch College  
Financial Aid Office**

151 E 25th Street, Room 880  
New York, NY 10010  
Telephone: (646) 312-1360  
E-mail: [financialaid@baruch.cuny.edu](mailto:financialaid@baruch.cuny.edu)

The above awards are estimated and based upon the data provided on the FAFSA. For federal loan eligibility, consult with the Office of Financial Aid to understand the rights and responsibilities of borrowing. Be sure to respond timely to financial aid requests for missing information. For more details, visit <http://www.cuny.edu/admissions/financial-aid.html>



Figure 3A.2: Sample CUNY Loan Application Form

**Academic Year: 2013-2014**

**HUNTER**  
City University of New York  
695 Park Avenue, New York, NY 10065  
Office of Financial Aid  
Room 241 North  
Tele.: 212-772-4820

Summer 2013  
Fall 2013  
Spring 2014

## WILLIAM D. FORD FEDERAL DIRECT STAFFORD LOAN APPLICATION

(Please **print clearly** in BLACK or BLUE ink)  
\*Incomplete applications will not be processed\*

**Student's Information:**

Last Name: \_\_\_\_\_ First Name: \_\_\_\_\_ Middle Initial: \_\_\_\_\_

SS#: \_\_\_\_\_ / \_\_\_\_\_ / \_\_\_\_\_ Date of Birth: \_\_\_\_\_ / \_\_\_\_\_ / \_\_\_\_\_

Permanent Address: (\*P.O. boxes or dorm addresses CANNOT be used as a permanent address)

Street: \_\_\_\_\_ Apt#: \_\_\_\_\_

City, State: \_\_\_\_\_ Zip Code: \_\_\_\_\_

Mailing Address, if different from permanent address:

Street: \_\_\_\_\_ Apt#: \_\_\_\_\_

City, State: \_\_\_\_\_ Zip Code: \_\_\_\_\_

Phone #: ( \_\_\_\_\_ ) \_\_\_\_\_ Hunter E-mail Address: \_\_\_\_\_ @hunter.cuny.edu

All loans will be disbursed in two (2) equal payments, Fall 2013 and Spring 2014. If the student is eligible for a Summer 2013 loan and he/she indicates that they would like to be considered for a Summer disbursement, the loan will be disbursed in three (3) payments, instead of two.  
\*\*One (1) semester loans will only be processed for graduating students.

I am registered for at least 6 credits during the Summer 2013 semester.	<input type="checkbox"/> Yes <input type="checkbox"/> No	** Undergraduates Only: I would like this loan for Summer 2013 only, because I am anticipating Financial Aid for Fall 2013 & Spring 2014.	<input type="checkbox"/> Yes <input type="checkbox"/> No
If yes: I would like to be considered for a Summer loan disbursement.	<input type="checkbox"/> Yes <input type="checkbox"/> No		

I am graduating at the end of the following semester:  Summer 2013  Fall 2013  Spring 2014  
 I am not graduating during the 2013 - 2014 academic year

**Total loan amount requested for the 2013-2014 academic year:** \$ .00

You must round the amount to the nearest whole dollar.

<p><b>Undergraduates:</b> I understand that I will be considered for a SUBSIDIZED loan first. <input checked="" type="checkbox"/> Yes If I am not eligible for a subsidized loan, I authorize the Office of Financial Aid to process an UNSUBSIDIZED loan. <input type="checkbox"/> Yes <input type="checkbox"/> No</p>	<p><b>Graduates:</b> I understand that Graduate students are no longer eligible for subsidized loans. I authorize the Office of Financial Aid to process an UNSUBSIDIZED loan. <input type="checkbox"/> Yes</p>
---	---

\*\* UNDERGRADUATE STUDENTS: Will you be pursuing your first Bachelor's degree during the 2013-14 academic year?  Yes  No

**Borrower's Certification:** My signature below certifies that I am aware I must be making Satisfactory Academic Progress in order to receive the Federal Direct Stafford Loan(s) I am applying for. I must complete and sign a Master Promissory Note, if I am required to do so. I also understand that if I have not completed the required steps listed on the right of this application, my loan will not be processed. I understand that it is my responsibility to follow up on the status of my loan application if I do not receive notification. I am also aware that my attendance must be verified by the Office of Financial Aid, before a disbursement is made in accordance with the Financial Aid 'Schedule of Payments'.

Applicant's signature: \_\_\_\_\_ Date: \_\_\_\_\_

OFFICE USE ONLY			Undergraduate Annual Loan Limits and Rates			Graduate Annual Loan Limits and Rates		
UG	G		Creds Completed	Dependent	Independent			
			0 - 29.9	\$5,500 (Max. Subsidized= \$3,500)	\$9,500 (Max. Subsidized= \$3,500)			
			30 - 59.9	\$6,500 (Max. Subsidized= \$4,500)	\$10,500 (Max. Subsidized= \$4,500)			
			60+	\$7,500 (Max. Subsidized= \$5,500)	\$12,500 (Max. Subsidized= \$5,500)			
			<b>Subsidized</b> interest rate: 6.8% fixed (disbursed on or after July 1 <sup>st</sup> , 2013 and prior to July 1 <sup>st</sup> , 2014)					
			<b>Unsubsidized</b> interest rate: 6.8% fixed (disbursed on or after July 1 <sup>st</sup> , 2006)					

**REQUIREMENTS:**  
The following 4 criteria are REQUIRED in order for the Office of Financial Aid to process your loan within 15 business days. When your application is reviewed and the 4 criteria have not been completed, your application will not be processed. The Office of Financial Aid will NOT return any incomplete applications. Check with the Office of Financial Aid after 15 business days to follow up on your application status.

- Have a valid 2013-2014 FAFSA Application ([www.FAFSA.ED.GOV](http://www.FAFSA.ED.GOV))
- Must be a matriculated student, registered for at least 6 credits, within your grade level, per semester during the 2013-2014 academic year
- Complete an 'Entrance Counseling' quiz\*\* ([www.STUDENTLOANS.GOV](http://www.STUDENTLOANS.GOV))  
\* You must attach the confirmation page
- Complete a Master Promissory Note (MPN) \*\* ([www.STUDENTLOANS.GOV](http://www.STUDENTLOANS.GOV))

\*\*Your loan request will be applied to your CUNYfirst account within 15 business days or less.

**LOAN ELIGIBILITY DETERMINATION:**  
The approved loan amount will be determined by CUNY's Cost of Attendance (COA), minus the Expected Family Contribution (EFC), which is determined by your FAFSA application for 2013-2014. Any financial aid and scholarships you are awarded will be deducted from your COA.

**NOTIFICATION:**  
Once your loan is processed you should receive an award notification, by mail, from CUNY's University Application Processing Center. If there are any discrepancies on your award notification, you must contact the Office of Financial Aid immediately. Once a disbursement has occurred, you will receive a disclosure statement from the loan servicing agency.

**REFUND:**  
Check Hunter College's 'Schedule of Payments' for loan disbursement dates. Refunds are mailed by check or you can sign up for Direct Deposit, visit [www.hunter.cuny.edu/finaid](http://www.hunter.cuny.edu/finaid) to print the form. **Direct Deposit is strongly encouraged** because you will get your funds on the same day of disbursement. If your check is mailed, you will get it 3 or 5 days later depending on your local post office. If checks are lost via mail it will take about 4 weeks or longer for you to get a replacement check.

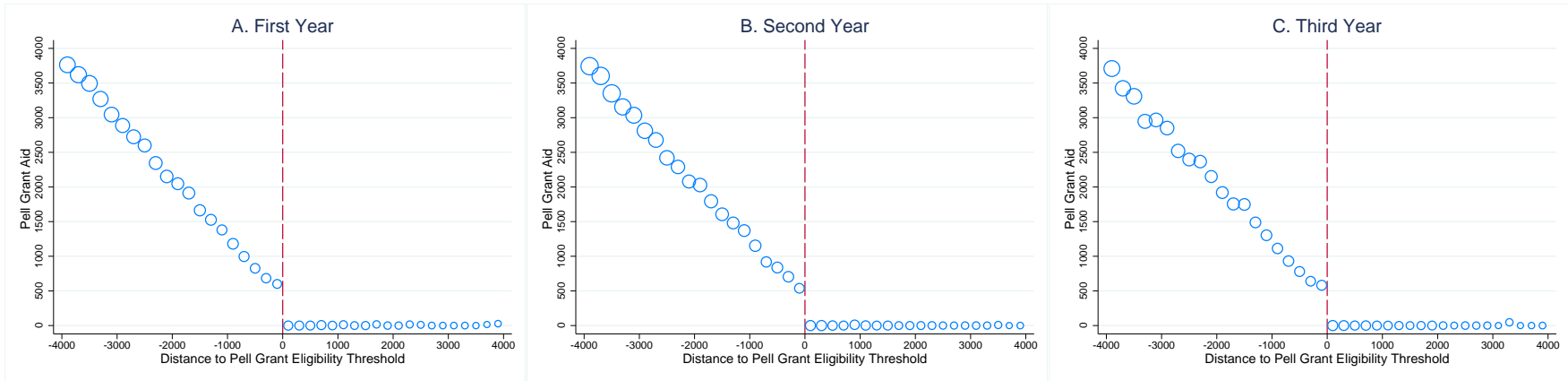
**\*\* Note to Transfer Students:** Your 2013-2014 annual loan limit may be affected if you borrowed loans at another institution for Summer 2013 and/or Fall 2013.

**OFFICE USE ONLY**

UG	G
	SSW
U	F S

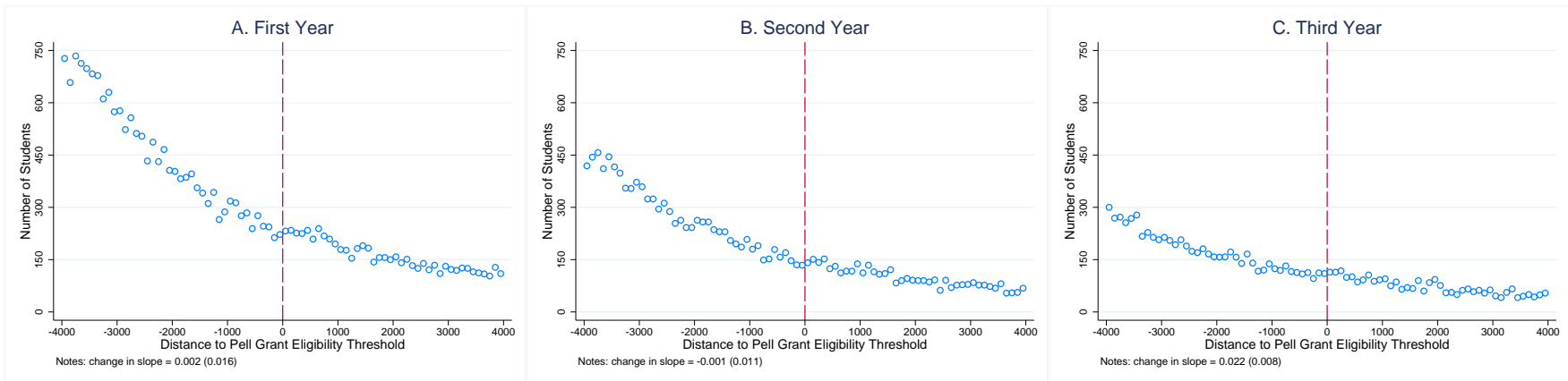
Notes: Available at <http://www.hunter.cuny.edu/onestop/finances/financial-aid/>.

Figure 3A.3: The Empirical Distribution of Pell Grant Aid by Distance to Eligibility Threshold and Level



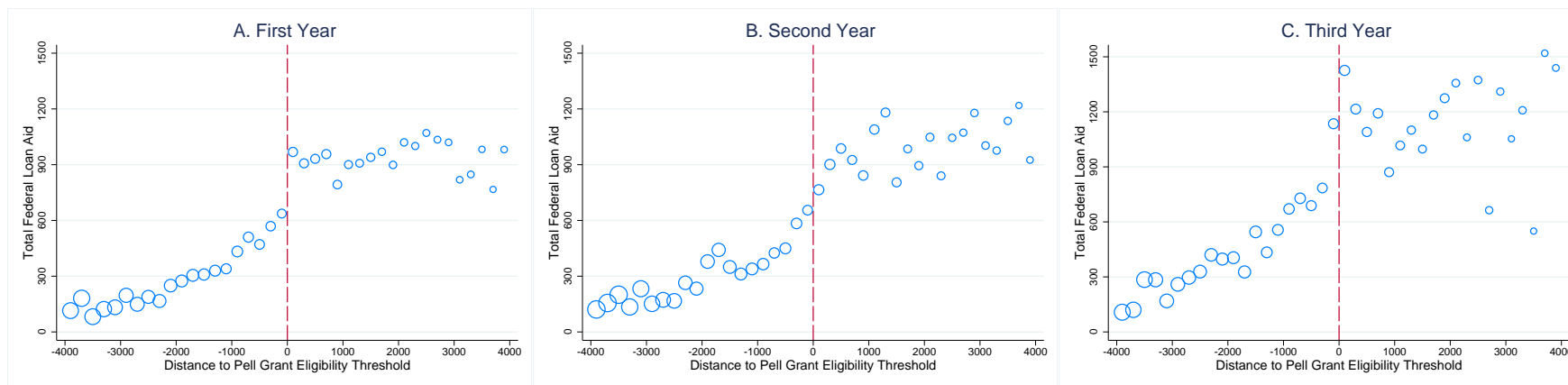
Notes: See Figure 3.2 notes.

Figure 3A.4: The Density of EFC at the Pell Grant Eligibility Threshold by Level



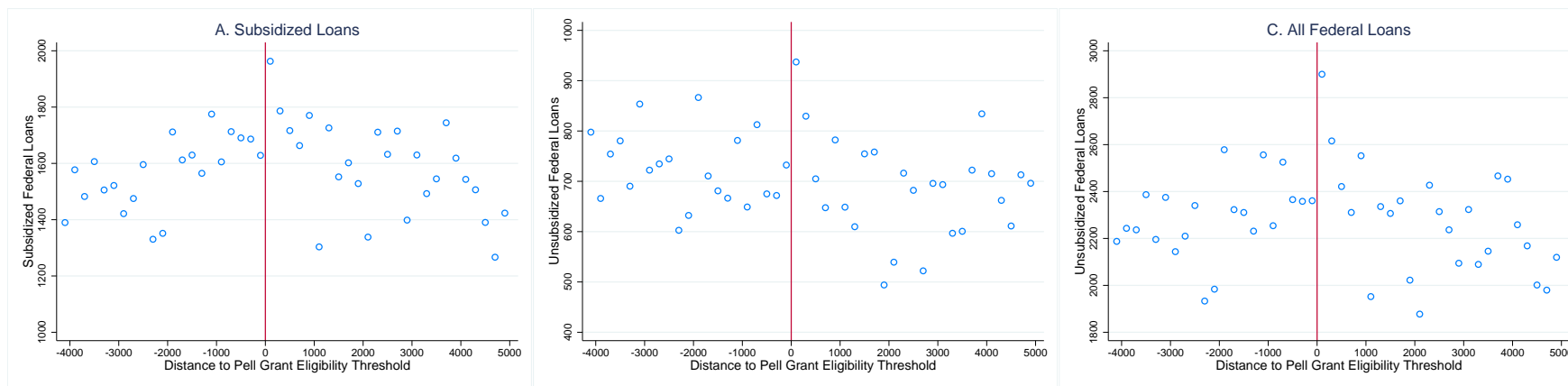
Notes: See Figure 3.3 notes.

Figure 3A.5: The Reduced Form Impact of Pell Grant Eligibility and Generosity on Total Borrowing by Level



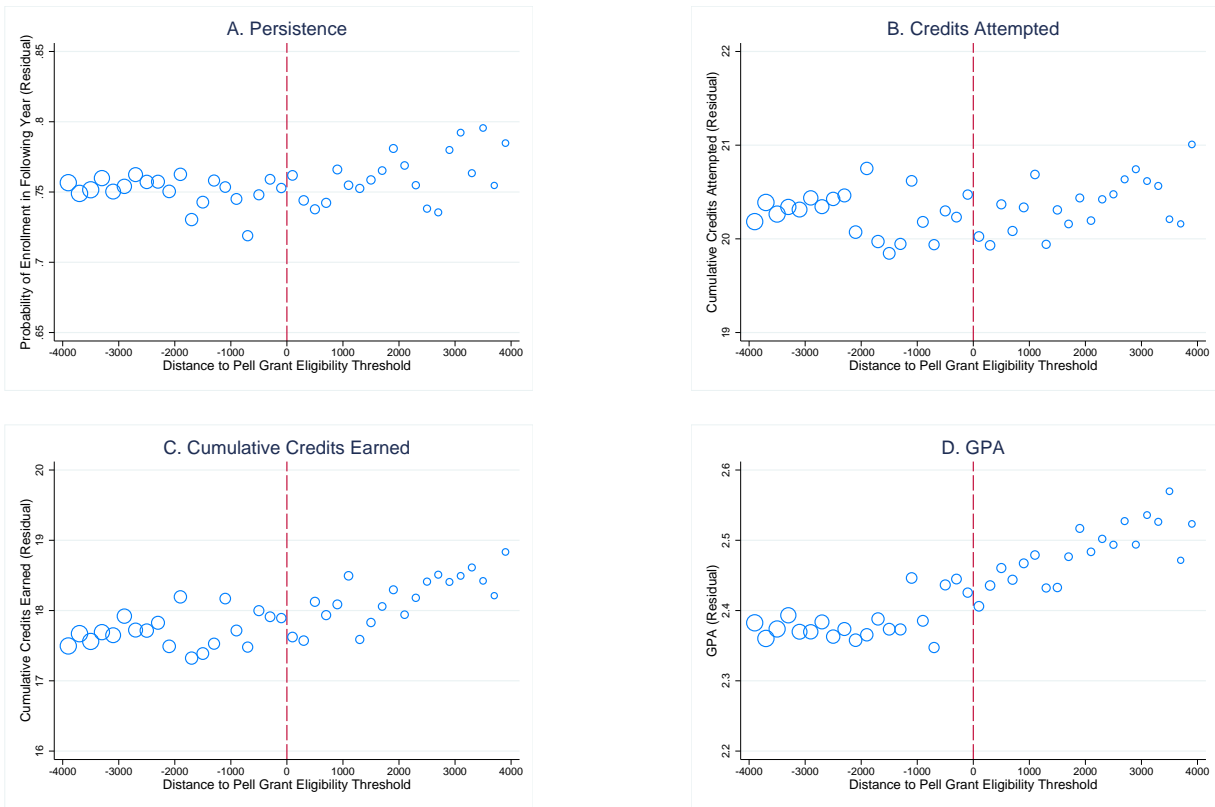
Notes: See Figure 3.5 notes.

Figure 3A.6: No Evidence of Crowd-out in Nationally Representative Sample



Notes: First, second, and third year undergraduate degree-seeking students in 2008 National Postsecondary Student Aid Study (NPSAS). \$200 EFC bins. Each circle represents the average subsidized (A), unsubsidized (B), and total (C) federal loans received by students in the bin. All dollar amounts in nominal terms.

Figure 3A.7: Reduced Form Impacts of Pell Grant Aid on Educational Outcomes



*Notes:* \$200 EFC bins. Each circle represents the average probability of enrolling in the following year (A), average credits attempted (B), average credits earned (C), and average GPA (D) for first, second, and third year students (all conditional on current enrollment). Recentered residuals from a regression on school, cohort, and semester fixed effects. Larger circles represent a larger underlying sample size.

Table 3A.1: The Impact of Pell Grant Aid on Subsidized Borrowing

	Year 1	Year 2	Year 3
<i>A. OLS Estimates: Impacts on Subsidized Loans</i>			
Pell Grant eligible	-185.08 (47.59)**	-190.90 (58.32)**	-270.90 (64.68)**
× Distance from threshold	0.198 (0.055)**	0.094 (0.099)	0.451 (0.105)**
Observations	24,106	14,706	9,849
<i>B. 2SLS Estimates: Impacts on Subsidized Loans</i>			
Pell Grant aid	-0.296 (0.062)**	-0.213 (0.114)+	-0.552 (0.102)**
Observations	24,106	14,706	9,849
<i>C. 2SLS Estimates: Impacts on Cumulative Subsidized Loans</i>			
First year Pell Grant aid	-- --	-0.407 (0.089)**	-0.395 (0.145)**
Mean	\$323	\$539	\$753
Observations	24,106	24,106	24,106

Notes: See Table 3.4 notes.

Table 3A.2: The Impact of Pell Grant Aid on Unsubsidized Borrowing

	Year 1	Year 2	Year 3
<i>A. OLS Estimates: Impacts on Unsubsidized Loans</i>			
Pell Grant eligible	-63.66 (25.85)*	-45.62 (29.20)	-55.16 (28.02)+
× Distance from threshold	0.033 (0.036)	-0.003 (0.035)	0.156 (0.076)+
Observations	24,106	14,706	9,849
<i>B. 2SLS Estimates: Impacts on Unsubsidized Loans</i>			
Pell Grant aid	-0.069 (0.044)	-0.028 (0.040)	-0.168 (0.071)*
Observations	24,106	14,706	9,849
<i>C. 2SLS Estimates: Impacts on Cumulative Unsubsidized Loans</i>			
First year Pell Grant aid	-- --	-0.101 (0.086)	-0.125 (0.129)
Mean	\$99	\$219	\$329
Observations	24,106	24,106	24,106

Notes: See Table 3.4 notes.

## Appendix 3B - Proofs

In this appendix we demonstrate that the solution has the form described in Section 3.3. Proofs of the predictions in Section 3.3.1 follow directly.

First, the student's problem has between one and two optima. The strict concavity of  $u(\cdot)$  and  $w(\cdot)$  and convexity of  $C(\cdot)$ , along with piecewise linearity of the cost of borrowing and the regularity condition  $w''(s) \leq -R_m C_t''(s)$ , imply that the problem is strictly concave in both  $d$  and  $s$  where differentiable. The proof is trivial except to note that the regularity condition is sufficient because

$$\begin{aligned} \frac{\partial^2}{\partial s^2} u(c_1) &= \frac{\partial^2}{\partial s^2} u(w(s) - R_s d - \kappa_s (R_m - R_s) (d - \bar{d} - \xi(C_t(s) - g - EFC - \bar{d}))) \\ &= \frac{\partial}{\partial s} (w'(s) + \kappa_s \xi (R_m - R_s) C_t'(s)) u'(c_1) \\ &= (w''(s) + \kappa_s \xi (R_m - R_s) C_t''(s)) u'(c_1) + (w'(s) + \kappa_s \xi (R_m - R_s) C_t'(s))^2 u''(c_1) \end{aligned}$$

and

$$w''(s) \leq -R_m C_t''(s) \Rightarrow w''(s) + \kappa_s \xi (R_m - R_s) C_t''(s) \leq 0 \Rightarrow \frac{\partial^2}{\partial s^2} u(c_1)$$

Therefore, the problem is concave except for the discontinuity at  $d = 0$ . The domain of  $s$  is bounded by assumption, which therefore places bounds on  $d$  because consumption cannot be negative. Hence, there is at least one solution. The solution will not include  $d$  at the lower bound that makes  $c_0 = 0$  because  $c_1 > 0 = c_0 \Rightarrow \frac{\partial u(0)}{\partial d} \geq \frac{\partial u(c_1)}{\partial d} \geq \frac{\partial \beta u(c_1)}{\partial d}$ , which implies that total utility would be increased by raising  $d$  above this level. Similarly,  $s$  is bounded from above by non-negativity of  $c_0$  and the fact that  $d$  is bounded above by  $\bar{d}$ , and the upper bound for  $s$  will not be optimal. Any solution for observed students (for whom the lower bound  $s = 0$  is revealed to be suboptimal) satisfies the first order condition with respect to  $s$  (3), and either the first order condition with respect to  $d$  given by equation (4),  $d = 0$ , or  $d = \bar{d}$  (5).

Second, the solution is unique with probability one. Because the entire problem would be concave if not for the discontinuity, and because the discontinuity reduces utility for values of  $d$  greater than zero, any solution with  $d < 0$  is unique. It may be, however, that an allocation with  $d > 0$  gives the same utility as one with  $d = 0$ . If two solutions exist for a given level of EFC we denote the positive debt amount chosen in one solution by  $\underline{d}$ . Because student resources are continuously distributed,  $\underline{d}$  is optimal with probability zero.

Third, the solution takes the monotonically ranked form described in Section 3.3. The empirical size (possibly zero) of each group will depend on the parameter values and the distribution of resources among

students. Here we establish the theoretical existence of each group of students and their ranking by resources.

Consider schooling level  $\bar{s}$  satisfying the equation  $R_s C'(\bar{s}) = w'(\bar{s})$  and  $\omega = u^{-1}(R_s \beta u(w(\bar{s}) + \epsilon)) + C(\bar{s}) - EFC - g$  for some  $\epsilon > 0$ . If debt is zero, this allocation gives  $u(c_0) = R_s \beta u(w(\bar{s}) + \epsilon) > R_s \beta u(w(\bar{s})) = u(c_1)$ . Raising  $s$  would increase total utility, but lowering  $d$  by an amount that causes the same reduction in  $c_0$  would cause a greater rise in  $c_1$ , implying that a negative value of debt must be optimal.

Since  $d^* < 0$ ,  $\kappa_0 = \kappa_s = \lambda = 0$ . 3 and 4 hold, and combining them gives  $R_s C'(s^*) = w'(s^*)$ .  $\frac{\partial s^*}{\partial g} = 0$ , while differentiation of 4 gives  $\frac{\partial d^*}{\partial g} = -\frac{u''(c_0)}{u''(c_0) + R_s^2 \beta u''(c_1)} \in (-1, 0)$ . Note that  $g$  and  $\omega$  are interchangeable in the problem, the optimal allocation responds to  $\omega$  in the same way that it responds to  $g$ : Higher values of  $\omega$  reduce  $d^*$  and have no effect on  $s^*$ . The conditions hold until  $\omega$  becomes low enough that  $d^* = 0$ . We label those with resources high enough to induce negative borrowing (i.e. net saving) Group A.

At  $d^* = 0$ ,  $\frac{\partial d^*}{\partial g} = 0$  and of the first-order conditions only 4 holds. We label the mass of students with exactly zero debt as Group B. Differentiation gives

$$\frac{\partial s^*}{\partial g} = -\frac{C'(s^*) u''(c_0)}{C''(s^*) u'(c_0) - C'(s^*)^2 u''(c_0) - w''(s^*) u'(c_0) - w'(s^*)^2 u''(c_0)} > 0$$

Denote the optimal schooling choice when  $d^* = 0$  as  $s_0^*$  (suppressing the arguments of this function to simplify notation). If the fixed cost of borrower is not too large there will be additional groups with positive debt. Students in Group B obtain utility  $u(\omega + EFC + g - C(s_0^*)) + \beta u(w(s_0^*))$ . Students with positive debt obtain utility  $u(\omega + EFC + g - C(s^*) - \gamma) + \beta u(w(s) - R_s d - \kappa_s (R_m - R_s) (d - \bar{d} - \xi (C_t(s^*) - g - EFC - \bar{d})))$ . The level of debt for which the two utilities are equivalent is  $\underline{d}$ . If  $\underline{d} < \bar{d}$  there will be a Group C for which  $d \in (\underline{d}, \bar{d})$  and both 3 and 4 hold. As with Group A,  $R_s C'(s^*) = w'(s^*)$ ,  $\frac{\partial s^*}{\partial g} = 0$ , and  $\frac{\partial d^*}{\partial g} = -\frac{u''(c_0)}{u''(c_0) + R_s^2 \beta u''(c_1)} \in (-1, 0)$ . The optimal  $d^*$  is strictly decreasing with  $\omega$  except in the region for which small positive amounts of debt are dominated by zero debt as a result of the fixed cost of borrowing.

As resources continue to fall,  $d^*$  may rise to the level of  $d_s^{max}$ . For Group D,  $d^* = d_s^{max} = \bar{d} + \xi (C_t(s^*) - g - EFC - \bar{d}) \Rightarrow \frac{\partial d^*}{\partial g} = \xi \left( C_t'(s^*) \frac{\partial s^*}{\partial g} - 1 \right)$ , and because 4 holds,  $\frac{\partial s^*}{\partial g} > 0$  as was the case for Group B. The conditions and properties of Groups E and F follow those of Groups A and B, respectively.

Derivation of the listed implications follows. Denote  $\omega_X$  as the highest value of in each Group X and  $F(\omega)$  the cumulative distribution function for  $\omega$ , conditional on  $g$  and  $EFC$ . The monotonicity of the policy implies that Group F has mass  $F(\omega_F)$ , Group E has mass  $F(\omega_E) - F(\omega_F)$ , Group D has mass  $F(\omega_D) - F(\omega_E)$ , etc. Because the policy function is discontinuous, implications are shown for a discrete change  $\epsilon$  in the amount of grant aid received.

1. If the fixed cost  $\gamma > 0$  then  $\underline{d} > 0$  and an increase in grant aid may lead to a greater than \$1 for \$1



*reduction in loans for borrowers.*

Consider a number  $\delta \in (0, \gamma)$  and let  $s^*(\gamma - \delta)$  denote optimal schooling when  $d^* = \gamma - \delta$ . The choice of  $d = 0$  and  $s = s^*(\gamma - \delta)$  gives strictly greater utility than  $d = \gamma - \delta$  and  $s = s^*(\gamma - \delta)$ . This implies a strictly dominated range of debt values between zero and some  $\underline{d} > \gamma > 0$ . Now suppose *all* students have  $\omega = \omega_C$  and  $d = \underline{d}$ . An increase in grant aid from  $g$  to  $g + \delta/2$  induces these students to stop borrowing. Crowd-out is  $\frac{\Delta d}{\Delta g} = \frac{\delta}{\delta/2} = 2 > 1$ .

*2. Grants only increase schooling for students facing some form of borrowing constraint.*

This implication follows directly from the schooling policy functions.