The Incidence of Student Financial Aid: Evidence from the Pell Grant Program

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Abstract

The federal Pell Grant Program provides billions of dollars in subsidies to low-income college students to increase affordability and access to higher education. I estimate the economic incidence of these subsidies using regression discontinuity (RD) and regression kink (RK) designs. I show that 16 percent of all Pell Grant aid is passed-through to schools in the form of higher effective prices. However, the extent and pattern of pass-through vary by institutional control and selectivity. While RK estimates suggest that schools capture Pell Grant aid through price discrimination, RD estimates imply the opposite result, that schools supplement Pell Grants with *increases* in institutional aid. I reconcile these disparate findings through a framework in which the treatment of Pell Grant aid is multidimensional: students receive an additional dollar of Pell Grant aid and are also labeled as Pell Grant recipients. RD estimates confound the effects of these dimensions, which have opposite impacts on schools' pricing decisions. I develop a combined RD/RK approach, which allows me to separately identify schools' willingness to pay for students categorized as needy and the pricing response to outside subsidies.

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The federal government provides billions of dollars in targeted need-based aid to low-income college students every year. Although students are the statutory recipients of this aid, its economic incidence may fall partially on schools (Fullerton and Metcalf, 2002). Specifically, schools may strategically increase recipients' effective prices, crowding out federal aid by reducing discounts provided through institutional aid. Concurrent tuition and student aid increases combined with substantial growth in the for-profit sector of higher education underscore the importance of evaluating federal aid crowd out.

In this paper, I estimate the economic incidence of the federal Pell Grant Program, the largest source of need-based student aid in the United States, using detailed student-level data from the National Postsecondary Student Aid Study. I show that institutions capture 16 percent of all Pell Grant aid – approximately $6 billion in 2011 – through price discrimination. Furthermore, I illustrate that the extent and pattern of capture vary substantially by institutional control and selectivity. For example, on average, public schools do not capture any Pell Grant aid, while among students attending selective nonprofit schools, decreases in institutional aid crowd out over 50 percent of the value of Pell Grant aid. Additionally, the incidence of the Pell Grant Program also varies across students within some sectors. For instance, among public school students near the Pell Grant eligibility threshold, Pell Grant aid appears to *crowd in* rather than crowd out institutional aid.

I identify these impacts using discontinuities in the relationship between Pell Grant aid and the federal government's measure of student need. Specifically, the Pell Grant Program's schedule contains discontinuities in both the level and in the slope of aid, resulting in students with very similar levels of need receiving significantly different grants. This variation allows me to use both regression discontinuity (RD) and regression kink (RK) designs (Angrist and Lavy, 1999; Hahn et al., 2001; Card et al., 2009; Nielsen et al., 2010). My analysis illustrates the relationship between these two methods and provides an example of circumstances under which RD and RK designs will yield significantly different conclusions.

The RK approach relates the change in the slope of the Pell Grant schedule at the eligibility cut-off with the change in the slope of the institutional aid schedule at this same point. RK estimates imply that, on average, schools capture a portion of Pell Grant aid through price discrimination. In contrast, the RD approach relates the change in the level of Pell Grant aid at the eligibility cut-off with the change in the level of institutional aid at this same point. RD estimates imply that, on average, schools *increase* institutional aid for Pell Grant recipients.

I reconcile these disparate estimates using a framework in which the "treatment" of Pell Grant receipt is multidimensional. Specifically, students at the margin of Pell Grant eligibility receive an extra dollar of outside aid but are also given the label of being a Pell Grant recipient, which may change some institutions' willingness to direct resources towards them. I show that it is possible to identify both schools' willingness to pay for students categorized as Pell Grant recipients and their pricing response to outside subsidies using a combined RD/RK approach.

RD estimates only identify the combined impact of these dimensions, and near the Pell Grant eligibility threshold, a greater willingness to pay dominates the pass-through of outside aid from students to schools. This result is misleading, however, since using my combined RD/RK approach, I estimate that fewer than one third of Pell Grant recipients benefit from these transfers. This is because the pass-through of each additional dollar of Pell Grant quickly overtakes these schools' willingness to pay for needy students. My results suggest that, on average, Pell Grant recipients receive an additional $260 in institutional aid due to schools' willingness to pay for needy students, but every additional dollar of Pell Grant aid is crowded out by a 22 cent reduction in institutional aid.

My paper is one of the first to combine these two identification strategies and the first to explicitly show how a multidimensional treatment affects RD estimates. Although the Pell Grant Program provides an especially stark example of how a multidimensional treatment affects RD estimates, in other circumstances where both a discontinuity and a kink are present, my results suggest that additional information can potentially be gained from using my combined RD/RK approach.

Little is known about how institutions compete for students or the objectives of public and nonprofit schools. This paper provides insight into the industrial organization of higher education by showing how variation in schools' response to Pell Grant aid relates to differences in schools' objectives and market power across sectors. Public schools demonstrate a willingness to pay for students categorized as Pell Grant recipients. Although the net capture of Pell Grants in the public sector is close to zero, increases in institutional aid for recipients near the eligibility threshold come at the expense of the neediest Pell recipients. Conversely, selective nonprofit institutions appropriate 79 percent of their students' Pell Grants, suggesting these schools have considerable market power.

The for-profit sector of higher education has grown substantially over the last decade and in recent years, has been criticized for unethical marketing practices and financial aid fraud (U.S. Government Accountability Office, 2010). Although these schools disproportionately serve federal aid recipients, I find that for-profit institutions behave no differently than nonselective nonprofit schools and, combined, these schools appropriate only 18 percent of their students' Pell Grants.

Finally, this paper contributes to a broader literature on the effectiveness of targeted subsidies and the importance of considering impacts on the behavior of both consumers and firms.[1] Research by Long (2004) and Turner (2012) suggests that other sources of financial aid crowd out institutional discounts by as much as 100 percent. However, previous studies specifically focusing on the Pell Grant Program estimate a positive correlation between prices and Pell Grant generosity. These impacts are identified using time-series variation in the maximum award, variation that is likely correlated with unobservable year specific shocks to the economy (e.g., McPherson and Schapiro, 1991; Singell and Stone, 2007).

The remainder of this paper proceeds as follows: the next section describes the Pell Grant program and previous estimates of the impact of student aid on prices. Section 2 discusses the NPSAS data and presents descriptive statistics, while Section 3 describes the regression kink design and my estimation strategy. Section 4 presents results from RD and RK estimates and Section 5 provides a conceptual framework that reconciles differences between these estimates. I estimate the overall incidence of the Pell Grant Program in Section 6, while Section 7 concludes.

1. The Pell Grant Program and Need-based Student Aid

An extensive literature estimates large private returns to higher education and positive externalities associated with a highly educated population.[2] Between 1979 and 2009, real tuition and fees increased by close to 200 percent, outpacing growth in income and student aid (National Center for Education Statistics, 2011). If some individuals face credit constraints and cannot

[1] For example, Rothstein (2008) shows that Earned Income Tax Credit (EITC) induced increases in labor supply drive down wages, and firms receive over half of the benefit of EITC payments. Hastings and Washington (2010) show that grocery stores benefit from public assistance via cyclical pricing in response to recipients' impatience.
[2] For example, see Card (1999), Moretti (2004), Lochner and Moretti (2004), and Dee (2004).

borrow against future income to finance college attendance, education levels may be inefficiently low. For these reasons, the United States federal and state governments provide substantial subsidies to low-income college students.

Established to promote access to postsecondary education, the Pell Grant Program is the largest source of need-based student aid in the United States. In 2011, the program provided 9.5 million low-income students with subsidies totaling $35 billion. The maximum Pell Grant award has grown in generosity from $452 during the 1973-1974 school year (hereafter, 1974) to $5,550 in 2011, a 62 percent increase in real terms (Figure 1). However, over this period the purchasing power of the maximum Pell Grant award declined (Appendix Figure A1). In 2010, the maximum Pell Grant represented 42 percent of average tuition and fees at public institutions and only 17 percent at private schools (National Center for Education Statistics, 2011).

A student's Pell Grant award depends both on the annual maximum award and upon her expected family contribution (EFC), the federal government's measure of need. Students are required to complete a Free Application for Federal Student Aid (FAFSA) to qualify for Pell Grants and other federal student aid (e.g., loans, work-study). 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. When filing the FAFSA, students also must specify up to (but no more than) six schools they are considering attending.[3] The federal government calculates a student's EFC using a complicated, non-linear function of these inputs (e.g., U.S. Department of Education, 2006). The federal government provides the listed schools with the student's EFC and FAFSA inputs, and these schools calculate federal (and in some cases state) grants and loans. With this information in hand, schools choose how institutional aid will be distributed across students. Thus, a school observes the student's FAFSA, EFC, and outside aid before deciding the level of its own discount, which it provides via institutional aid. Students receive a financial aid package from each school specifying federal, state, and institutional grant aid and loans. Students do not observe their Pell Grant award until this point, where it is included as a component of the final price displayed in their financial aid package.

A full-time, full-year student i in year t qualifies for a Pell award equal to:

$$(1) \quad Pell_{it} = \left(maxPell_t - EFC_{it}\right) \cdot \mathbf{1}\left[maxPell_t - EFC_{it} \geq 400\right] + 400 \cdot \mathbf{1}\left[maxPell_t - EFC_{it} \in \left(400, 200\right]\right]$$

[3] Beginning in 2009, students could specify up to 10 schools that would receive their FAFSA information.

Where $maxPell_t$ is the maximum Pell award available in year t (Figure 1), EFC_{it} is the expected family contribution of student i in year t, and $\mathbf{1}[\cdot]$ is the logical indicator function. Pell Grant awards are rounded up to the next \$100 and students qualifying for an award between \$399 and \$200 receive \$400.[4] Students who qualify for less than \$200 in aid do not receive a Pell Grant. The Pell Grant formula generates two sources of variation that I use for identification. First, crossing the Pell Grant eligibility threshold leads to a discrete increase in a student's statutory award, from \$0 to \$400, which enables me to use a regression discontinuity design. Second, the variation created by the change in the slope of the Pell Grant-EFC function, from 0 to -1, allows me to use a regression kink design.[5] Appendix Figure A2 displays the Pell Grant award schedule in 1996, 2000, 2004, and 2008.[6]

1.1 Previous estimates of the impact of Pell Grant aid on college enrollment and prices

Tuition and financial aid influence important outcomes, from the decision to enroll in college, to persistence and degree completion (Angrist, 1993; Bound and Turner, 2002; Dynarski, 2003; Bettinger, 2004). Although the Pell Grant Program aims to increase low-income students' access to higher education, past research finds little impact on college enrollment except for older, non-traditional students (Kane, 1995; Seftor and Turner, 2002, Deming and Dynarski, forthcoming). Students only receive information concerning the level of their Pell Grant after they have submitted a FAFSA, and this information is provided as part of a school's financial aid package, where the final price (tuition net of state, federal, and institutional grants) is likely the most salient feature. If low-income students lack information about the Pell Grant Program, Pell Grant aid may not increase college enrollment. The complexity of the FAFSA form imposes a large cost on potential students (Dynarski and Scott-Clayton, 2008) and Bettinger et al. (forthcoming) show that information on the availability of financial aid and assistance with the FAFSA application process increase the likelihood of enrollment.

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[4] The minimum Pell Grant award increased to \$890 in 2009, \$976 in 2010, and \$1176 in 2011. However, over the years I examine, the minimum award remained \$400.

[5] The Pell Grant formula for part-time students is $Pell_{it} = \max\{(0.5 * maxPell_t - EFC_{it}), 0\}$; the change in the slope of the relationship between EFC and Pell Grant aid is -0.5. The minimum Pell Grant does not depend on attendance intensity. Part-year students receive a prorated Pell Grant.

[6] Eligibility for other types of federal aid (e.g., Supplemental Educational Opportunity Grants, Stafford loans, work study) also depends on the EFC. However, the Pell Grant Program is the only federal entitlement program.

The relatively weak response of student demand to Pell Grant aid suggests the potential for schools to appropriate student aid through price increases. However, previous studies show no conclusive evidence that increases in Pell Grant generosity cause schools to raise prices. McPherson and Schapiro (1991) show that overall institutional aid levels are positively correlated with Pell Grant generosity; Singell and Stone (2007) find a positive correlation between published tuition and Pell Grant generosity among private institutions. In both cases, identification comes from time-series variation in the maximum Pell Grant.

Raising tuition is only one method schools may use to benefit from Pell Grant generosity. Schools can also adjust students' prices through price discrimination by reducing institutional aid. The practice of price discrimination, or offering a schedule of prices that varies according to consumer demand elasticities, has been documented in a variety of imperfectly competitive markets and the market for higher education is unique in the extensive amount of customer information schools observe, including a measure of students' ability to pay.[7]

Two studies explicitly examine whether student aid crowds out institutional aid. Turner (2011) estimates the incidence of education tax credits, which primarily benefit middle-income students, and finds that schools reduce institutional aid dollar for dollar as tax-based aid increases. Long (2004) examines the implementation of the Georgia HOPE scholarship program, which provides substantial assistance to students in Georgia who achieve a 3.0 GPA. Public schools responded to the HOPE program by increasing fees, capturing 10 percent of HOPE aid, while private nonprofit institutions captured 30 percent of HOPE aid by increasing tuition and fees and reducing institutional aid. Additionally, using administrative Pell Grant data and a simulated instrumental variables approach, Li (1999) finds a positive relationship between Pell Grant aid and both listed tuition and net tuition per student. By comparing the impact of Pell Grant aid on net tuition per student and listed tuition per student, it is possible to infer whether schools also alter institutional aid. Results suggest that four-year institutions both increase tuition and reduce institutional aid in response to Pell Grant generosity

Schools' response to the HOPE program suggests that the economic incidence of the Pell Grant Program may vary by institutional control. Traditionally, public and nonprofit schools primarily serve the market for higher education. However, the last decade has seen substantial

[7] E.g., housing (Yinger, 1998), loans (Charles et al., 2008), and vehicles (Langer, 2009).

growth in the for-profit sector. For-profit institutions increasingly serve low-income students and have been criticized for high student loan default rates and deceptive recruiting practices (U.S. Government Accountability Office, 2010) and charge significantly higher tuition than comparable public schools.[8] Influenced by these concerns, "gainful employment" legislation will specifically regulate programs primarily offered by for-profit schools beginning in 2012.[9]

2. Data and Descriptive Statistics

The National Postsecondary Student Aid Study (NPSAS) is a restricted-use, nationally representative, repeated cross-section of college students.[10] I observe each student's EFC, demographic characteristics, FAFSA inputs (e.g., family income and assets), and financial aid provided by the federal government and other sources. My sample includes students present in the 1996, 2000, 2004, and 2008 NPSAS waves. I eliminate graduate and first-professional students as well as noncitizens and non-permanent residents, as these students are ineligible for Pell Grant aid. Additionally, I exclude students who attended multiple schools in the survey year, received athletic scholarships, and were not enrolled in the fall semester[11]

I exclude all students attending schools that only offer sub-associate certificate programs, theological seminaries, and other faith-based institutions, since many of these schools are not eligible to distribute federal aid. Finally, I focus on students whose EFC is within $10,000 of the Pell Grant eligibility threshold, although in a subset of analyses, I look at students within narrower windows around this threshold. My final sample includes approximately 133,270 undergraduate students attending 1,800 unique institutions. Due to NCES confidentiality requirements, all NPSAS sample sizes are rounded to the nearest 10.

[8] The share of Pell Grant recipients attending for-profit schools increased from 13 to 25 percent between 2000 and 2010 (Pell Grant End of Year Reports). Conversely, the share of all students at for-profit schools grew from 4 to 11 percent (Deming et al., forthcoming). The 2009, 15 percent of former for-profit students defaulted on their student loans within two years of exiting college. The rates for public and non-profit institutions were 7 and 5 percent, respectively. In 2010, average public school tuition was $5,000; for-profit students paid $15,700 (NCES, 2011).
[9] The legislation requires that for-profit institutions and certificate programs in other sectors prepare students for "gainful employment" to qualify for federal student aid (76 FR 34386).
[10] After the original 2008 NPSAS sample was drawn, additional observations of National Science and Mathematics Access to Retain Talent (SMART) Grant recipients were added. For my main set of estimates, I drop oversampled SMART Grant recipients. My results are robust to using the NPSAS sample weights and retaining SMART Grant recipients or excluding observations from 2008, the first year of the NPSAS in which students eligible for SMART Grants could potentially be sampled (results available upon request).

My sample includes new and continuing students. Although upper-year students likely have less elastic demand than first year students, EFC and institutional aid are highly correlated over time. Schools award multi-year institutional aid packages and for many students, one of the primary components of EFC – family income – does not vary substantially over time.

I classify schools by selectivity and control, distinguishing between public, nonprofit, and for-profit institutions that are either selective or nonselective. I use the IPEDS and Barrons' Guide to determine an institution's selectivity. The IPEDS contains annual data on acceptance rates and the Barrons' College Guide classifies four-year public and nonprofit institutions into six categories of selectivity based on acceptance rates, college entrance exam performance, and the minimum class rank and grade point average required for admission. First, I classify all for-profit and institutions offering two-year programs as non-selective. If the IPEDS lists an institution as "inclusive" (i.e., open admissions), I also classify it as nonselective. Finally, I classify remaining institutions as nonselective if either the Barrons' Guide lists them as less competitive or non-competitive or they are missing Barrons' rankings and admit more than 75% of applicants. Under this scheme, schools I classify as "selective" are not highly selective. Rather, these schools reject some portion of applicants.[12]

Public schools are either operated by publicly elected or appointed officials or receive the majority of their funding from public sources. Conversely, private institutions receive the majority of funding from private sources and are run by privately appointed individuals. Nonprofit institutions are exempt from federal taxes but are subject to the "non-distribution constraint" which prohibits a school from distributing revenue to its controlling body in excess of regular wages and other operating expenses (Hansmann, 1980).[13] For-profit schools pay corporate income taxes, but may also distribute profits to owners or shareholders.

2.1 Characteristics of students and schools

Table 1 displays summary statistics by sector. In my sample, for-profit students are the most likely to receive Pell Grant aid, while students attending selective institutions are the least likely to receive Pell Grants. However, conditional on receiving a Pell Grant, award amounts are similar across sectors and approximately three quarters of Pell Grant recipients receive less than

[12] On average, selective public institutions admit 61 percent of applicants and selective nonprofits admit 56 percent.
[13] Internal Revenue Code (IRC) section 501(c)(3). Income from activities unrelated to the provision of education is subject to taxation (IRC sections 511-514).

the maximum award. Schools in all sectors use institutional aid to provide discounts from the list price, although students attending for-profit and nonselective public institutions are the least likely to receive these discounts. On average, for-profit students are more likely to be non-white and are older than students in other sectors. Students attending nonselective schools are more likely to be classified as independent, a status given to students who are married, have dependents, are veterans, or are older than 24.

I use information from the Integrated Postsecondary Student Data System (IPEDS) to examine overall revenue and expenditures for schools in my sample. The IPEDS contains the universe of institutions that receive federal student aid and the U.S. Department of Education collects detailed information on school characteristics, enrollment, faculty and staff, and finances through annual surveys. Table 2 displays institutional revenue and expenditures for each sector using data from the IPEDS. For-profit schools are the only institutions that receive a substantial portion of revenue from the Pell Grant Program (14 percent). Pell Grants represent only 7 percent of public nonselective schools' revenue, 4 percent of revenue in private nonselective schools, and only 1 to 2 percent for more selective institutions. With the exception of for-profit institutions, these calculations suggest that relative to other sources of revenue, even if institutions responded to Pell Grant increases by raising overall tuition, the potential gains would be quite small.

3. Empirical Framework

Previous studies identify the impact of Pell Grant aid on prices using time series variation in the maximum award. However, if aid generosity is correlated with unobservable time-varying shocks, these estimates will suffer from omitted variables bias. Since Pell Grant generosity also varies across students within a given year, it is possible to separate the impact of Pell Grant aid from year-specific shocks under the assumption that, conditional on observables, Pell Grant aid is not correlated with unobservable student characteristics. This is a strong assumption. Pell Grant generosity is increasing in need, and while I can explicitly control for EFC, the specific functional form of the relationship between EFC and unobservable heterogeneity is unknown.

To overcome concerns of omitted variables bias, I take advantage of the relationship between Pell Grant aid and EFC. Specifically, I identify the impact of Pell Grant aid on student prices using variation induced by the kink and the discontinuity in the relationship between Pell

Grant and EFC. The kink occurs where the slope of the $Pell(efc)$ schedule changes from 0 to -1, while the discontinuity is driven by the increase from in Pell Grant aid from \$0 to \$400 at the eligibility threshold, due to the rounding-up of awards scheduled to fall between \$200 and \$400. This variation allows me to use both a regression discontinuity (Angrist and Lavy, 1999; Lee and Lemieux, 2010) and a regression kink design (Card et al., 2009; Nielsen et al., 2010). Like the regression discontinuity design, the regression kink estimator identifies the average treatment effect for individuals near the eligibility cut-off under specific conditions.

3.1 Regression kink and regression discontinuity designs

Similar to the regression discontinuity (RD) design, the regression kink (RK) design allows for identification of the impact of an endogenous regressor that is a known function of an observable assignment variable (Card et al., 2009). Here, the endogenous regressor is Pell Grant aid, while EFC is the assignment variable. The RK design uses variation induced by a change in the slope of the relationship between Pell Grant aid and EFC as the eligibility threshold is approached from above and below. Like the RD design, the RK design will be invalidated if individuals are able to sort perfectly in the neighborhood of the kink.

Let $Y = f(Pell, \tau) + g(EFC) + U$ represent the causal relationship between institutional aid, *Y*, and Pell Grant aid, $Pell = Pell(EFC)$, in a given school and year, where *U* is random vector of unobservable, predetermined characteristics. Given the existence of a kink in the Pell Grant schedule, the required identifying assumptions are: (1) the direct marginal impact of EFC on institutional aid is continuous 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 a RD design, which requires institutional aid to be continuous (rather than continuously differentiable) in EFC and that the conditional density of EFC be continuous (rather than continuously differentiable). Essentially, even if many other factors affect college pricing decisions, as long as there are no discontinuities in the relationship between these factors and EFC at the eligibility threshold, the RK estimator 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 cut-off.

Assume that each additional dollar of Pell Grant aid has the same marginal effect on schools' pricing decisions (at least in the neighborhood of the eligibility threshold):

(2) $$f(Pell, \tau) = \tau_1 Pell$$

In this case, τ_1 represents the pass-through of each additional dollar of Pell Grant aid from students to schools.

If the required identifying assumptions hold, the RK estimator identifies:

(3) $$\tau_{RK} = \frac{\lim_{\varepsilon \uparrow 0} \frac{\partial E[Y \mid EFC = efc_0 + \varepsilon]}{\partial efc} - \lim_{\varepsilon \downarrow 0} \frac{\partial E[Y \mid EFC = efc_0 + \varepsilon]}{\partial efc}}{\lim_{\varepsilon \uparrow 0} \frac{\partial E[Pell \mid EFC = efc_0 + \varepsilon)]}{\partial efc} - \lim_{\varepsilon \downarrow 0} \frac{\partial E[Pell \mid EFC = efc_0 + \varepsilon)]}{\partial efc}} = \tau_1$$

Where efc_0 represents the eligibility threshold for the Pell Grant Program. Since the Pell Grant Program's schedule also contains a discontinuity in the *level* of aid at the eligibility threshold, I can also identify the impact of Pell Grant aid on college pricing decisions using a RD design. As long as equation (2) describes the relationship between Pell Grant aid and colleges' pricing decisions, the RD estimator also identifies τ_1:

(4) $$\tau_{RD} = \frac{\lim_{\varepsilon \uparrow 0} E[Y \mid EFC = efc_0 + \varepsilon] - \lim_{\varepsilon \downarrow 0} \partial E[Y \mid EFC = efc_0 + \varepsilon]}{\lim_{\varepsilon \uparrow 0} E[Pell \mid EFC = efc_0 + \varepsilon)] - \lim_{\varepsilon \downarrow 0} E[Pell \mid EFC = efc_0 + \varepsilon)]} = \tau_1$$

In practice, my estimation strategy involves "fuzzy" RD/RK. Some eligible students do not apply for federal aid and thus, do not receive Pell Grants.[14] Additionally, variables in the NPSAS contain measurement error induced by random perturbations to preserve respondent confidentiality. Since the location of the Pell Grant Program's eligibility threshold changes as the maximum award increases, I create a standardized measure of the distance of a student's EFC from the year-specific EFC representing the eligibility threshold: $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the cut-off for Pell Grant eligibility in year *t* and all students with $\widetilde{EFC}_{it} \geq 0$ are

[14] Results are robust to eliminating students who do not submit a FAFSA (available upon request).

ineligible for Pell Grant aid.[15] Figure 2 displays the empirical distribution of Pell Grant aid for students in my sample by standardized EFC.[16]

Consider the following first stage and reduced form equations:

$$(5) \qquad Pell_{it} = \eta \cdot \mathbf{1}\left[\tilde{EFC}_{it} < 0\right] + \lambda \cdot \mathbf{1}\left[\tilde{EFC}_{it} < 0\right] \cdot \left(\tilde{EFC}_{it}\right) + \sum_{\rho} [\psi_{\rho} \cdot \left(\tilde{EFC}_{it}\right)^{\rho}] + \theta_j + \theta_t + \upsilon_{ijt}$$

$$(6) \qquad y_{ijt} = \beta \cdot \mathbf{1}\left[\tilde{EFC}_{it} < 0\right] + \gamma \cdot \mathbf{1}\left[\tilde{EFC}_{it} < 0\right] \cdot \left(\tilde{EFC}_{it}\right) + \sum_{\rho} [\pi_{\rho} \cdot \left(\tilde{EFC}_{it}\right)^{\rho}] + \delta_j + \delta_t + \varepsilon_{ijt}$$

Here, i indexes students, j indexes institutions, and t indexes years. $Pell_{it}$ is the Pell Grant award received by student i in year t, while y_{ijt} represents the institutional aid provided by school j to this student. The term $\mathbf{1}\left[\tilde{EFC}_{it} < 0\right]$ is an indicator for Pell Grant eligibility while ρ indexes the degree of polynomial in the assignment variable, $\tilde{EFC}_{it}$. I include year and school fixed effects as well as a vector of student characteristic to reduce residual variation; these terms are not necessary for identification.[17] The ratio of the reduced form and first-stage coefficients for the interaction between $\mathbf{1}\left[\tilde{EFC}_{it} < 0\right]$ and the linear term in $\tilde{EFC}_{it}$, $\hat{\tau}_{RK} = \frac{\hat{\gamma}}{\hat{\lambda}}$, represents the RK estimate of the impact of Pell Grant aid on institutional aid. Likewise, the ratio of the reduced form and first-stage coefficients for Pell Grant eligibility, $\hat{\tau}_{RD} = \frac{\hat{\beta}}{\hat{\eta}}$, represents the RD estimate of the impact of Pell Grant aid on institutional aid.

To further illustrate the mechanics of this framework, Figures 3A and 3B illustrate potential behavior of the relationship between institutional aid and EFC near the eligibility threshold (i.e., potential values for γ and β) and corresponding implications for RK and RD estimates. In the first case (Figure 3A), there is no discontinuity or kink in the relationship between institutional aid and EFC near the eligibility cut-off – the change in the level and the

[15] For the years I examine, efc_{0t} equals \$2140 (1996), \$2925 (2000), \$3850 (2004), and \$4110 (2008).

[16] In a given year, the kink and discontinuity in the relationship between Pell Grant aid and EFC occur at slightly different values of EFC (see Appendix Figure A2). However, the distance between these points is quite small and only a small fraction of students have an EFC falling on this "plateau". I treat both the slope and the level of Pell Grant funding changes as occurring at the eligibility cut-off. My results are robust to removing students whose EFC falls on the plateau (forcing the discontinuity and kink to occur at the same value of EFC).

[17] These characteristics include indicators for gender, race, fall attendance intensity, enrollment length, level (e.g., whether the student is a first year, second year, etc.), out-of-state student, and a quadratic in age.

slope of institutional aid are both equal to zero – indicating students receive the full benefit of Pell Grant aid. In this case, the RD and RK estimators both yield an estimate of zero. Conversely, Figure 3B illustrates the case where Pell Grant aid fully crowds out institutional aid. The change in the level of institution aid is equal (in absolute value) to the change in the level in Pell Grant aid, suggesting the RD approach will yield an estimate of -1, or full pass-through of Pell Grant aid from students to institutions. The change in the slope of institutional aid at the eligibility threshold is likewise equal (in absolute value) to the change in the slope of the Pell Grant schedule at this same point, also resulting in an estimate of -1. As in the first example, both RD and RK designs produce the same estimate; in this case, suggesting schools appropriate 100 percent of Pell Grant aid.

3.2 Evaluating the RD and RK identifying assumptions

Identification using the RK or RD design hinges on the assumption that students cannot exactly sort to obtain a more advantageous EFC. Students and their parents likely act to reduce their estimated need, but as long as they cannot chose an exact value of EFC, the RK and RD estimators will be consistent (Lee, 2008). Although online calculators and guides help families predict their potential EFC, these guides are based on prior year Pell Grant schedules and the relationship between income and EFC is complicated and non-linear. In the years I examine, the maximum Pell Grant awards are set by amendments to the Higher Education Act. However, this legislation only specifies *authorized* annual maximum awards. The *appropriated* maximum award, which determines the actual Pell Grant schedule, is generally smaller than the authorized amount. Furthermore, the Department of Education releases the Pell Grant schedule after the end of calendar year, making it impossible for families to make real adjustments to most of the inputs used to determine EFC (e.g., adjusted gross income). Families might still misreport EFC inputs; however, many of these inputs are also reported to the IRS (e.g., adjusted gross income, number of dependents) and over one-third of all FAFSA applications are audited through the Department of Education's verification process.[18]

[18] The NPSAS contains an additional year of FAFSA information for continuing students who applied for federal aid for the following academic year. For these students, I test whether barely missing the eligibility threshold in the current year is correlated with any evidence of strategic behavior for the following year (e.g., bunching to the left of the new threshold). I find no evidence of this behavior (results available upon request).

Nonetheless, I test for continuity and smoothness in the density of EFC to rule out the possibility that students perfectly manipulate their EFCs. Figure 4 displays the unconditional density of EFC, plotting the proportion of students in each \$100 EFC interval. The x-axis measures the standardized distance from the Pell Grant eligibility cut-off. I limit the sample to students with $\tilde{EFC} \in [-2100, 2100]$ because of the large mass of individuals with an EFC of zero.[19] In 1996, a zero EFC corresponds to $\tilde{EFC} = -2140$, thus, this window prevents my estimates from being driven by the large increase in density at $EFC = 0$. Due to the smaller window, I use smaller bins (\$100) than in other graphical analyses.

I use the McCrary (2008) test to determine whether the density of EFC is continuous across the threshold for Pell Grant eligibility. My method for testing continuity in the derivative around the cut-off is less precise, since there is presently no analog to the McCrary test statistic for the RK design. I follow Card et al. (2009), collapse the data into \$100 EFC bins, and run the following regression:

$$N_b = \alpha + \beta \cdot \mathbf{1}\left[\tilde{EFC}_b < 0\right] + \gamma \cdot \mathbf{1}\left[\tilde{EFC}_b < 0\right] \cdot \left(\tilde{EFC}_b\right) + \sum_{\rho} [\lambda_\rho \cdot \left(\tilde{EFC}_b\right)^\rho] + \xi_b \tag{7}$$

Where b indexes bins, N_b is the number of students in bin b, ρ is a second order polynomial, $\tilde{EFC}_b$ is the distance from the eligibility threshold, and a test of $\gamma = 0$ estimates whether the density function is smooth. Figure 4 displays $\hat{\gamma}$ and the McCrary test statistic as well as the corresponding standard errors. I find no evidence that the level or the slope of the density changes discontinuously at the eligibility threshold.

I examine the distribution of predetermined student characteristics around the eligibility threshold, including race, gender, dependency status, average SAT score (first-year students only), and age; here bins represent \$200 EFC intervals (Figures 5A through 5E). I also estimate equation (6), with up to a fifth degree polynomial in EFC, and test for discontinuous changes in the slope or level of baseline characteristic at the eligibility threshold. I display results from the specification using the optimal degree of polynomial (determined via the Akaike Information Criterion) for three different windows around the eligibility threshold in Appendix Table A1. For

[19] In the years I examine, dependent students and independent students with dependents other than a spouse received an automatic zero EFC if (1) anyone in their household receive means tested benefits or their household was not required to file IRS Form 1040, and (2) their household income was less than \$20,000.

the majority of specifications, estimated coefficients are insignificant and all coefficients are quite small in magnitude.

Finally, I plot the density of EFC by institutional control and selectivity (Figures 6A through 6E). I find no evidence of a discontinuity in the density or its first derivative among public and nonselective private institutions. There is a positive increase in the density of EFC to the right of the Pell Grant eligibility threshold among selective nonprofit institutions, but the magnitude of the change in density is small and insignificant.[20]

4. Results

4.1 Graphical analysis

Figure 7 previews my main results. I pool observations from all schools across years and plot the relationship between Pell Grant aid, institutional aid, and standardized EFC (e.g., -$200 indicates a student's EFC is $200 below the cut-off for Pell Grant eligibility). I collapse my data into $200 EFC bins and plot average institutional aid and average Pell aid by distance from the threshold for Pell Grant eligibility, where both institutional aid and Pell aid are residuals from a regression on year and institution fixed effects. Institutional aid is represented by hollow circles, with larger circles representing a greater number of students. Average Pell Grant aid is represented by the gray "X" markers. The black lines represent the linear fit of institutional aid on EFC, estimated separately on either side of the eligibility threshold and weighted by the number of students in the bin.[21] The dashed gray lines represent the 95 percent confidence intervals for these estimates. Finally, the dashed black line represents the linear fit of average Pell Grant aid on EFC for eligible students. At the eligibility threshold, there is both discontinuous change in the relationship between EFC and institutional grant aid. For students who are ineligible for Pell Grants, there is a positive relationship between need and institutional aid, while for students who are eligible for Pell Grant aid, institutional aid is decreasing in need.

I replicate this exercise by sector (Figures 8A through 8C). Due to sample size constraints, I pool selective and nonselective public schools into a single category and likewise group nonselective nonprofit schools (parametric regression estimates, presented in the next

[20] Unfortunately, the NPSAS only contains information for accepted students who choose to enroll in a specific school, making it impossible to determine whether the density of EFC is smooth and continuous for all applicants.
[21] Appendix Figure A3 replicates this figure allowing for a more flexible fit of the relationship between institutional aid and EFC with a local linear regression. The resulting discontinuity and kink are very similar.

section, suggest that schools within each of these groups respond similarly to need-based aid). The incidence of Pell Grant aid varies substantially between public and private schools, with public institutions appearing to supplement Pell Grants with increased institutional aid.[22] Private institutions' response to Pell Grant aid is more straightforward. There is a clear discontinuity in the slope of institutional aid to the left of the Pell Grant eligibility threshold and a negative, but insignificant change in the level of aid among nonselective private schools (Figure 8B). There is a small, insignificant jump in institutional aid for selective nonprofit schools, but the kink in the institutional aid schedule clearly dominates (Figure 8C).

4.2 Parametric RD and RK estimates

Table 3 presents OLS and 2SLS estimates of equations (5) and (6) with a second degree polynomial in $\widetilde{EFC}$. The first two columns display the first stage and reduced form estimates, respectively. Columns 3 and 4 present separate RK and RD instrument variables estimates. Results are consistent with Figure 7 – RK estimates suggest that institutions capture around 22 cents of every Pell Grant dollar through a reduction in institutional aid while the RD estimator results in a point estimate of 0.32, suggesting schools *increase* institutional aid by over 30 cents for every dollar of Pell Grant aid. The test of equality of the RD and RK coefficients confirms that these estimated impact is statistically different. The test of equality also serves as a formal test of whether the impact of the Pell Grant Program on institutional pricing varies with EFC.

Before further investigating the surprising result suggested by the RD estimator – that schools respond to each additional dollar of Pell Grant aid by increasing institutional aid – I test how robust my main results are to difference specifications by varying the window and polynomial in $\widetilde{EFC}$ to confirm that this result is not an artifact of a particular specification (Table 4). I use three windows of standardized ECF: $\widetilde{EFC} < 10{,}000$, $\widetilde{EFC} \in [-4000, 4000]$, and $\widetilde{EFC} \in [-3000, 3000]$.[23] For each window, I include up to a third degree polynomial in standardized EFC and use the Aikake Information Criterion (AIC) to determine the optimal degree of polynomial. For all but the largest window, a linear term in standardized EFC provides

[22] To better illustrate the behavior of institutional aid around the eligibility threshold in the public sector, the left axis measures institutional aid while the right axis represents Pell aid.
[23] The largest window encompasses students with an AGI ranging from $0 to approximately $90,000, the second window includes families whose AGI falls between $20,000 and $60,000, and the smallest window restricts the analysis to families with an AGI between $25,000 and $50,000.

the best fit to the data. Results are consistent across windows and polynomials in $\widetilde{EFC}$.

5. A Framework for Understanding Differences in RK and RD Estimates

Would a profit-maximizing firm ever pass-through more than 100 percent of a subsidy to consumers? When firms have market power, the economic incidence of a tax or subsidy may exceed 100 percent, but a simple model suggests that my result would not occur without very specific patterns of student demand or a departure from profit-maximization. First, suppose a profit-maximizing monopolist serving N distinct student groups solves:

$$\max_{p_1,\ldots,p_N} \pi = \sum_{i=1}^{N} Q_i(p_i)(p_i - c)$$

where Q_i is the demand of students in group i and c is the marginal cost of serving an additional student. For simplicity, I assume marginal costs are constant, both in the number of students served and across student groups, which is reasonable if instruction and facilities make up the majority of expenses. The school charges students in group i a price that is equal to overall tuition (which does not vary across groups) minus institutional aid (which may vary across groups). Groups are defined by students observable characteristics (e.g., demographic characteristics, EFC), and schools use these characteristics to practice price discrimination. This is a static problem, where a school's behavior in the current period does not affect cost or demand in future periods.

A profit-maximizing monopolist charges group i students price $p_i = c\mu_i$, where $\mu_i = \left(\frac{e_i}{e_i + 1}\right)$ and e_i is the price elasticity of demand for students in group i. When federal need-based aid (s) is introduced, the school charges $p_i = (c - s)\mu_i$, where $s < c \;\forall i$. The change in the final price paid by students in group i in response to the subsidy will be:

(8) $$\frac{dp_i}{ds} = -\mu_i + (c - s)\frac{d\mu_i}{ds}$$

For instance, $\frac{dp_i}{ds} = 0$ indicates that the school fully captures every additional dollar of the subsidy, while $\frac{dp_i}{ds} = -1$ indicates subsidies are fully passed-through to students. The sign of $\frac{dp_i}{ds}$

depends on both the elasticity and the curvature of the demand function for students in group i (Bulow and Pfleiderer, 1983; Weyl and Fabinger, 2011). If demand is log-concave, $\frac{dp_i}{ds} > -1$, and schools capture a portion of students' Pell Grant aid by increasing prices (decreasing institutional aid).[24] If demand is log-convex, $\frac{dp_i}{ds} < -1$, and schools respond to Pell Grant aid by decreasing prices (increasing institutional aid), the result suggested by the RD estimator.[25]

However, the increase in institutional aid combined with the change in the slope of the institutional aid-EFC schedule at the threshold, with institutional transfers decreasing with every additional dollar of Pell Grant aid, is more surprising. If student demand is log-convex, then institutional transfers should increase as Pell Grant aid increases. There would have to be sharp changes in the demand functions of students near the eligibility threshold to account for the patterns of institutional aid provision I observe. Specifically, the initial $400 Pell Grant award would have to move students from a log-concave portion of the demand curve to a log-convex portion, requiring the existence of an inflection point. This is unlikely, since the eligibility threshold for Pell Grant aid changes over time, while pricing patterns are persistent (results available upon request).

Conversely, suppose a subset of schools have a different objective function, and maximize weighted student enrollment, where weights vary across student groups:

$$\max_{p_1,\ldots,p_N} W = \sum_{i=1}^{N} \alpha_i Q_i(p_i) \qquad \text{s.t.} \qquad \sum_{i=1}^{N} Q_i(p_i)(p_i - c) \geq 0$$

The constraint stems from the requirement that in a static model, expenditures cannot exceed revenue. If the constraint is binding, schools will offer a schedule of prices that vary by demand

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[24] The price set by a school has two components: tuition and institutional aid: $p_i = t - a_i$. Since schools set tuition before Pell Grant awards are announced, only institutional aid responds to Pell Grant awards, thus $\frac{dp_i}{ds} = -\frac{da_i}{ds}$.

[25] In the short-run, this model can be easily generalized to represent institutional pricing with monopolistically competitive firms offering differentiated products. In this case, student demand will depend not only on an institution's price but the prices offered by competitors, $Q_i = Q_i(p_i, p_{j \neq i})$, and pricing will also depend on the cross-price elasticities of demand. Pass-through will be decreasing in the number of competitors in the market and the degree of substitutability between programs offered by institutions. In the long-run, incidence will depend on the ease of entry into a specific market. Additionally, a substantial minority of institutions are monopolists. In 2009, 17 percent of all institutions eligible to disburse federal aid were the only institution in their county.

elasticity as well as the weight placed on the group in the schools objective function (α_i) and the marginal "utility" of revenue (represented by the Lagrange multiplier): $p_i = (c - \tilde{\alpha}_i)\mu_i$, where $\tilde{\alpha}_i$ is the weight on students in group *i* divided by the Lagrange multiplier. If being labeled as a Pell Grant recipient this weight, schools' pricing response to subsidy *s* is now:

$$\frac{dp_i}{ds} = -\left(\frac{d\tilde{\alpha}_i}{ds} + 1\right)\mu_i + \left(c - \tilde{\alpha}_i(s) - s\right)\frac{d\mu_i}{ds} \tag{9}$$

Equation (9) implies that if Pell Grant recipients receive a positive weight in the school's objective function (e.g., $\tilde{\alpha}_i(s) > 0$), the second term will be smaller than in the case of static profit maximization. Furthermore, if Pell Grant recipients' weights are larger than those of observationally similar students who do not qualify for Pell Grant aid (e.g., $\frac{d\tilde{\alpha}_i}{ds} > 0$), the first term will be larger. If either of these terms is positive, these schools will capture a smaller portion of Pell Grant aid. Furthermore, rearranging equation (9):

$$\frac{dp_i}{ds} = \left\{-\mu_i + (c - s)\frac{d\mu_i}{ds}\right\} - \left\{\mu_i \frac{d\tilde{\alpha}_i}{ds} + \tilde{\alpha}_i(s)\frac{d\mu_i}{ds}\right\} \tag{10}$$

Here the first term represents the pass-through of outside student aid due to profit maximization (or cost minimization), while the second term accounts for a school's willingness to pay for Pell Grant recipients. If, in the neighborhood of the cut-off for Pell Grant eligibility, $\frac{d\tilde{\alpha}_i}{ds}$ does not vary with *s* for Pell Grant recipients (e.g., if being a Pell Grant recipient increases your weight in the school's objective function by a constant amount), the relationship between the prices for group *i* students and Pell Grant aid can be approximated by: $p_i = \tau_0 \mathbf{1}[s_i > 0] + \tau_1 s_i + u_i$.[26] Here, p_i is the final price faced by students in group *i*, τ_0 and τ_1 represent willingness to pay for Pell Grant recipients and pass-through of each additional dollar of Pell Grant aid, respectively, and u_i is an idiosyncratic error term.

There are a number of reasons why schools might treat Pell Grant recipients differently than other students. First, schools might have objectives beyond profit maximization, such as

[26] This approximation also assumes that in the neighborhood of the Pell Grant eligibility threshold, each additional dollar of Pell Grant aid does not lead to large changes in the log-curvature of demand.

increasing school-wide diversity or maximizing (weighted) student welfare. Schools might solve a dynamic problem where additional Pell Grant recipients in the current period increase the expected value of the stream of future revenue (or reduce the expected value of the stream of future costs). For example, schools that serve a larger number of Pell Grant recipients might receive more funding from state legislatures in the long-run or experience an increase in student demand. For instance, in recent years, the U.S. News and World Report began incorporating a measure of Pell Grant receipt in its school ranking calculations. For the purposes of this paper, I remain agnostic as to the reasons schools might treat Pell Grant recipients differently from students who barely miss the cut-off for eligibility.

5.1 RD, RK, and estimating the multiple treatment dimensions of Pell Grant receipt

Equation (10) suggests that the "treatment" of receiving a Pell Grant affects prices through two dimensions: a school's willingness to pay for Pell Grant recipients (τ_0) and ability to appropriate outside aid due to the pass-through of cost decreases (τ_1). To see how these two dimensions are related to RD and RK estimates, consider a simplified version of equation (6), the reduced form impact of Pell Grant eligibility on institutional aid for a specific school and year:

$$y_i = \beta \cdot \mathbf{1}\left[E\tilde{F}C_i < 0\right] + \gamma \cdot \mathbf{1}\left[E\tilde{F}C_i < 0\right] \cdot \left(E\tilde{F}C_i\right) + \pi\left(E\tilde{F}C_i\right) + \varepsilon_i$$

Furthermore, assume that all eligible students receive a Pell Grant, where the minimum award is \$400 (e.g., "sharp" RD/RK).

The RD design provides a reduced form estimate of the "treatment" of Pell Grant receipt, where $\beta = \tau_0 + \tau_1 \cdot 400$ and $\tau_{RD} = \dfrac{\tau_0}{400} + \tau_1$, which confounds the school's ability to capture an additional dollar of outside aid with its willingness to pay for students labeled as Pell Grant recipients (see Appendix B). When these two dimensions have opposite signs, RD estimates will not identify the magnitude and sign of either dimension.

The RK design will consistently estimate the pass-through of an additional dollar of outside aid, under the assumption that τ_1 is constant in the neighborhood of the cut-off for Pell Grant eligibility (see Appendix B). Since $\tau_{RK} = \tau_1$ and the RK/RD design is fuzzy:

(11)
$$\hat{\tau}_1 = \hat{\tau}_{RK}$$
$$\hat{\tau}_0 = (\hat{\tau}_{RD} - \hat{\tau}_{RK}) \cdot Pell(efc_0)$$

Where $Pell(efc_0)$ is the minimum Pell Grant award, $\hat{\tau}_{RD}$ and $\hat{\tau}_{RK}$ are the RD and RK estimators, respectively, $\hat{\tau}_0$ is the estimated willingness to pay for Pell Grant recipients, and $\hat{\tau}_1$ is the pass-through of Pell Grant aid from the student to the school. Appendix B provides further details for the derivation of these parameters.

Table 5 presents estimates of the capture and willingness to pay parameters for the pooled sample (Panel A) and by sector (Panel B). I use the delta method to calculate standard errors. Across all institutions, estimated pass-through is 0.22, suggesting institutions receive 22 cents of every additional dollar of Pell Grant aid. However, due to schools' willingness to pay for Pell Grant recipients, Pell Grant recipients experience a $260 increase in institutional aid. Since students ineligible for Pell Grants received $1,800 in institutional aid on average (including students that did not receive any institutional aid), this transfer represents a 14 percent increase in the expected value of institutional aid.[27] However, only Pell Grant recipients near the eligibility threshold benefit from these transfers, and these students make up less than a third of all recipients. For the remainder of Pell Grant recipients, schools' ability to capture Pell Grant aid outweighs willingness to pay for needy students.

Figures 8A through 8C suggest that pass-through Pell Grant aid and willingness to pay for Pell Grant recipients vary across sectors. I test for differences in behavior by fully interacting $Pell_{it}$ with a vector of indicators for the different sectors of higher education. Private institutions do not demonstrate a willingness to pay for Pell Grant recipients and 13 to 15 cents of every Pell Grant dollar is passed-through from students to nonselective institutions. Conversely, public schools increase institutional aid for recipients by $300 to $600 in public schools. The difference in willingness to pay between selective and nonselective public schools is only marginally significant. This additional aid represents a 140 percent increase in the expected value of institutional grants among nonselective public school students and a 90 percent increase for selective public school students.[28]

[27] This calculation includes students within $10,000 of the Pell Grant eligibility threshold. However, if I limit the distance to be $4,000, estimated institutional aid is quite similar ($1850).
[28] On average, Pell ineligible students receive approximately $230 in institutional aid from nonselective public schools and $700 from selective public schools.

While public schools appropriate 17 to 18 cents of every Pell Grant dollar, pass-through of Pell Grant aid is the largest among selective nonprofit institutions. These schools capture 69 cents every Pell Grant dollar, while any willingness to pay for Pell Grant recipients is quickly overtaken. This result suggests that selective nonprofits either serve students with less elastic demand or have greater market power.

5.2 Heterogeneity by student and market characteristics

To determine whether differences in student demand can explain differences in pass-through between sectors, I examine heterogeneity in pass-through and schools willingness to pay for Pell Grant recipients across three student demographic groups, defined by race (white versus nonwhite), dependency status, and gender (Table 6). If students with similar characteristics have relatively similar demand elasticities, this analysis provides a test of whether the greater degree of pass-through in the selective nonprofit sector stems from differences in the demand of the students these schools serve. Specifically, if selective nonprofits serve a segment of the market is with less elastic demand, pass-through will be greater without any differences in these schools' underlying objectives.

I find that across all demographic groups, pass-through of Pell Grant aid in the selective nonprofit sector is significantly greater than in other sectors, except in the case of independent students.[29] Additionally, public schools display a willingness to pay for Pell Grant recipients across all groups. These results suggest that differences in the characteristics of students served cannot fully explain selective nonprofit institutions' large degree of capture or public schools' valuation of students receiving Pell Grant aid.

Measuring schools' market power is a more difficult task. I measure the *ex ante* degree of competition in a school's market using a Herfindahl index of institutional shares of the undergraduate population during the prior academic year. I define the market served by a particular institution to be the county in which it is located, since the median distance a student travels to attend a nonselective institution is 15 miles (Horn and Nevill, 2006), and use data from the IPEDS to measure the total number of undergraduate full-time equivalent (FTE) students in a

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[29] In independent students in all sectors experience the smallest degree of crowd-out, suggesting these students have more elastic demand than dependent students.

county and institutional shares for NPSAS and non-NPSAS schools.[30] Although some selective schools effectively serve a national market, I find evidence that Pell Grant receipt causes some students to switch from attending nonselective schools to selective institutions, suggesting students may be evaluating their choices in their local market.

To test whether pass-through varies by market structure, I create a dichotomous measure of concentration based on the index (H>0.25) and estimate equation (11), fully interacting $Pell_{it}$, $\mathbf{1}\left[\widetilde{EFC}_{it} < 0\right]$, and $\mathbf{1}\left[\widetilde{EFC}_{it} < 0\right]\left(\widetilde{EFC}_{i}\right)$ with this measure. Appendix Table A2 displays these results (estimates of willingness to pay by market concentration are available upon request). In column 2, I consider all other institutions when constructing the index; in column 3, I only consider institutions with similar selectivity (e.g., assuming that selective nonprofit schools do not compete with for-profit schools for students). I find some evidence that selective nonprofit institutions respond to competitors – in markets with few similarly selective schools, these institutions capture 79 cents of every Pell Grant dollar, while in more competitive markets, only 44 cents of every Pell dollar are passed through. However, my measure of market power is blunt and does not account for endogenous entry decisions.

My results represent the short-run incidence of Pell Grant aid. In the long-run, increases in competition may limit schools' ability to capture student aid. Although the supply of public institutions is relatively fixed, Cellini (2010) shows that student aid increases lead to for-profit entry. If for-profit institutions retain captured Pell Grant aid as profits, my results provide a rationale for this response. An increase in number of schools should reduce the ability of schools to capture Pell Grant aid and in the long-run, institutional capture should be driven to zero. Incidence analysis in this case is complicated by the fact that captured Pell Grant funds in the present period ultimately lead to an expansion provision of higher education. Although current Pell recipients lose out, new students, who would not have otherwise attended college, will gain from the ability of schools to capture Pell aid. However, the market for higher education also has substantial barriers to entry, since schools face large fixed costs (e.g., investments in facilities).

[30] Unfortunately, prior to 2000, the IPEDS data files do not accurately represent the presence of for-profit institutions among the set of schools eligible to disburse federal student aid. However, as shown in column 1 of Appendix Table A3, estimates of pass-through are quite similar for this truncated sample.

Schools also must gain accreditation and demonstrate a sufficiently high level of enrollment for two years before their students are eligible for Pell Grant aid.

5.3 Evaluating alternate explanations for institutional pricing

Thus far, I have attributed differences in institutional pricing responses to Pell Grant aid to differences in institutional objectives and market power. However, there are other potential explanations for this behavior. First, differences in unmet need and institutional policies across sectors could potentially explain differences in estimated crowd-out. For instance, since public schools charge significantly lower prices than private institutions, institutional aid may mechanically fall if increases in Pell Grant aid reduce students' unmet need to zero. State need-based aid may be distributed differently across sectors, also contributing to this effect. Appendix Figures A4 and A5 explore this possibility and plot the percentage of students with any unmet need and average unmet need and by EFC and sector, where unmet need is defined as the difference between a student's cost of attendance and her expected family contribution, Pell Grant and other federal grant aid, and state grant aid. Across all sectors, over 90 percent of students near the Pell Grant eligibility threshold had remaining unmet need, and on average, these students faced an additional $10,000 in expected education-related expenses that are not covered by federal or state grant aid. Even students attending nonselective public institutions – schools with the lowest cost of attendance – had substantial remaining need.

Second, students may respond to Pell Grant generosity by upgrading to a higher quality institution. In this case, price increases would be expected, as students are receiving a more valuable product. Although I find some evidence of sorting across sectors at the eligibility threshold – with a small, discrete increase in the probability of attending a selective institution as the eligibility threshold is crossed – there is no evidence of a kink. Since selectivity is just one dimension of school quality, I also test for evidence of quality upgrading by examining institutional revenue, expenditures, and the outcomes of former students. I use information from the IPEDS linked to NPSAS institutions to create measures of revenue and expenditures, including tuition and total revenue per full-time equivalent (FTE) student and institutional grants, instruction-related expenditures, and expenditures on student services per FTE.[31] Finally, I use

[31] I use prior-year revenue and expenditure data to create these measures. Unfortunately, the IPEDS only began collected revenue and expenditure data for the majority of schools in 2000, thus, when examining these measures of quality, my sample is limited to students attending institutions in 2004 and 2008.

the Department of Education's official cohort default rate, which measures the proportion of individuals defaulting on their federal loans within the two years, to measure the outcomes of former students.

I little evidence of upgrading along any of these measures of school quality and in many cases, find evidence of a negative relationship between Pell Grant generosity and school quality (Appendix Table A3). I estimate a positive relationship between Pell Grant aid and expenditures on institutional grants and instruction for students attending public schools, but the magnitudes of these effects are quite small. A $1000 increase in Pell Grant aid is correlated with a $14 (1 percent) increase in institutional grants/FTE offered by nonselective public schools. For selective public schools, a $1000 increase in Pell Grant aid is correlated with a $22 (1 percent) increase in institutional aid and a $132 (2 percent) increase in instruction-related expenditures for students attending selective public schools. Pell Grant aid is negatively correlated with student loan default rates in the for-profit sector, where a $1000 increase in Pell Grant aid is correlated with a 0.9 percentage point reduction in the default rate of graduating students. However, among students attending selective nonprofit institutions – the sector which shows the highest degree of crowd-out – there is no evidence of quality upgrading.

6. Incidence across all Pell Grant Recipients

So far, I have only focused on estimating the incidence of Pell Grant aid in the neighborhood of the cut-off for Pell Grant eligibility. With stronger assumptions, I can use the observable relationship between institutional aid and EFC for ineligible students to estimate the incidence of the Pell Grant program across all students. Specifically, I assume that the relationship between institutional aid and EFC for ineligible students provides a valid counterfactual for what the relationship between institutional aid and EFC would have been for Pell Grant recipients in the absence of the Pell Grant Program. For this approach to work, heterogeneous treatment effects must be linear. Specifically, the pass-through of Pell Grant aid and schools' willingness to pay for Pell Grant recipients must be constant in the amount of Pell Grant aid

Figure 9 provides an illustration of my approach. The shaded area under the Pell Grant curve represents the total amount of aid directed towards Pell Grant recipients by the federal government. The solid lines represent the observed relationship between institutional aid and

EFC for eligible and ineligible students, while the dashed line represents counterfactual institutional aid for eligible students in the absence of the Pell Grant Program. In other words, each point along this line represents the amount of institutional aid a student with a particular EFC would have received had the Pell Grant Program not existed. The difference between the area under the first curve (counterfactual institutional aid) and the second curve (actual institutional aid) represents institutional capture ($A - B$). The ratio of total capture to total Pell aid, $\frac{A-B}{Total\ Pell}$, represents the percentage of Pell Grant aid captured by institutions, and is also the average treatment effect of Pell Grants on institutional aid.

Across all sectors, every dollar of Pell Grant aid reduces students' effective prices by 84 cents, with institutions appropriating the remaining 16 cents through price discrimination (Table 7). Nonselective private institutions, a category encompassing nonprofit and for-profit schools, receive 18 cents of every Pell Grant dollar while selective nonprofit institutions capture 79 cents. In the public sector, net crowd-out of Pell Grant aid is close to zero; the point estimate is small and only marginally insignificant. However, this result masks important heterogeneity – transfers to students close to the eligibility threshold are offset by decreases in institutional aid for the neediest Pell Grant recipients (Figure 8A).

7. Conclusions

Although low-income students are the statutory recipients of Pell Grant aid, they do not receive the full benefit of these subsidies. Using a combined regression discontinuity and regression kink approach, I estimate the impact of Pell Grants on institutional aid and show that schools strategically respond to changes in need-based aid by systematically altering institutional aid. Overall, I estimate that institutions capture 16 percent of all Pell Grant aid. However, this result masks important variation in pass-through across sectors and across students with different levels of need.

RK and RD designs yield conflicting estimates of the impact of Pell Grant aid on college pricing, with RK estimates suggesting schools capture Pell Grant aid and the RD estimator implying schools supplement Pell Grants with *increased* institutional aid. I show that these disparate estimates can be reconciled using a framework in which schools place different weights on students with different characteristics. In this case, the "treatment" of Pell Grant aid has two dimensions: the additional dollar of outside aid that the school would like to capture and the school's willingness to pay for Pell Grant recipients.

Through a combined RD/RK approach, I separately identify schools' willingness to pay for students categorized as needy and the pricing response to outside subsidies. The RD design only identifies the reduced form impact of these two dimensions, and for RD estimates, schools' willingness to pay dominates their ability to capture outside aid. Using the combined RD/RK approach, I estimate that less than one third of Pell Grant recipients benefit from these transfers, since schools' ability to capture Pell Grant aid quickly overtakes their willingness to pay for needy students. My paper is the first to combine RD and RK estimators to distinguish between different treatment dimensions.

The Pell Grant Program provides an especially stark example of how a multidimensional treatment affects RD estimates. However, in other circumstances where both a discontinuity and a kink are present, my results suggest that additional information is present in the kink, and this information may provide insight into the channels through which the "treatment" of interest works. In a number of the studies cited by Lee and Lemieux's (2010) survey on the RD design that examine the impact of a continuous endogenous regressor, the deterministic relationship between the endogenous regressor and assignment variable leads to both a discontinuity and a kink. For instance, in cases where a minimum class size rule leads to a discontinuous relationship between total enrollment and class size (e.g., Angrist and Lavy, 1999; Hoxby, 2000; Urquiola, 2006), this rule creates both a discontinuity and a kink.[32] If, for instance, the creation of an additional classroom leads to smaller classes *and* sorting of children by achievement, behavior, or some other dimension (e.g., Lazear, 2001), the discontinuity and the kink could potentially be used to separately analyze the influence of these dimensions on educational outcomes.

My paper also provides insight into the industrial organization of higher education. I show how schools' responses to Pell Grant aid illustrate differences in schools' objectives and market power across sectors. Public schools demonstrate a positive willingness to pay for Pell

[32] For example, if the rule mandates a maximum class size of $\overline{N}$, when enrollment reaches $\overline{N}+1$, average class size changes discontinuously from $\overline{N}$ to $\frac{\overline{N}+1}{2}$. This rule also leads to a kink in the relationship between average class size and total enrollment. When enrollment is less than $\overline{N}$, the slope of relationship between class size and total enrollment is 1. When class size is greater than $\overline{N}$, but less than $2\overline{N}$, the slope of the relationship between class size and total enrollment is 0.5.

Grant recipients. Overall, selective nonprofit institutions capture close to 80 percent of their students' Pell Grants. Across different student demographic groups, I estimate a similar degree of capture students attending selective nonprofits, suggesting these schools' extensive ability to appropriate Pell Grant aid stems from a greater degree of market power rather than differences in student demand. Although the net crowd-out of Pell Grants in the public sector is close to zero, increases in institutional aid for recipients near the eligibility threshold come at the expense of the neediest Pell recipients.

Finally, I find no evidence that for-profit institutions behave differently than other nonselective schools in the private sector in their response to Pell Grant aid, and combined, schools in this sector capture just 17 percent of their students' Pell Grant aid. However, in many for-profit institutions, the majority of students receive Pell Grants. It may be easiest for these institutions to benefit from Pell Grant generosity by raising the list price of tuition. Consistent with this view, Cellini and Goldin (2012) show that in the for-profit sector, schools eligible to distribute federal student aid charge a list price that is 75 percent higher than ineligible schools with similar characteristics.

Under the stronger assumption that the distribution of institutional aid to ineligible students near the threshold provides a valid counterfactual for the distribution of institutional aid in the absence of the Pell Grant Program, I calculate that schools capture 16 percent of all Pell Grant aid. In 2011, the federal government distributed $35 billion in Pell Grants to 9.5 million students. My results suggest that institutions captured $6 billion of this aid.

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Figure 1: Time Series Variation in Maximum Pell Grant Award

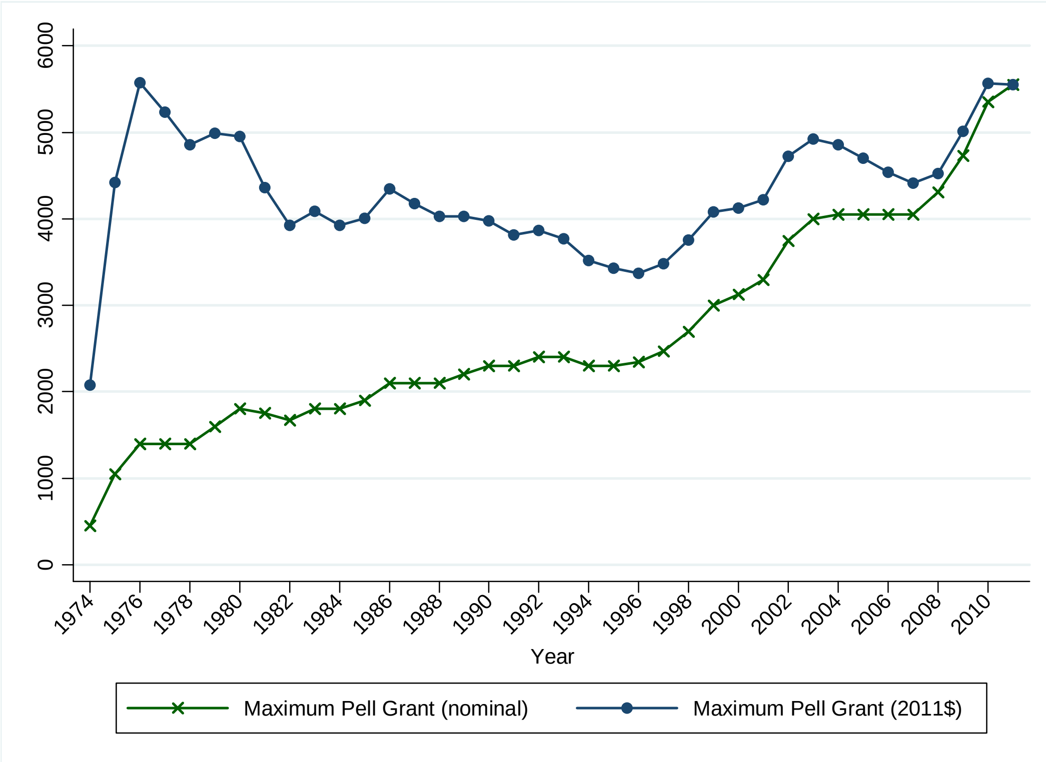
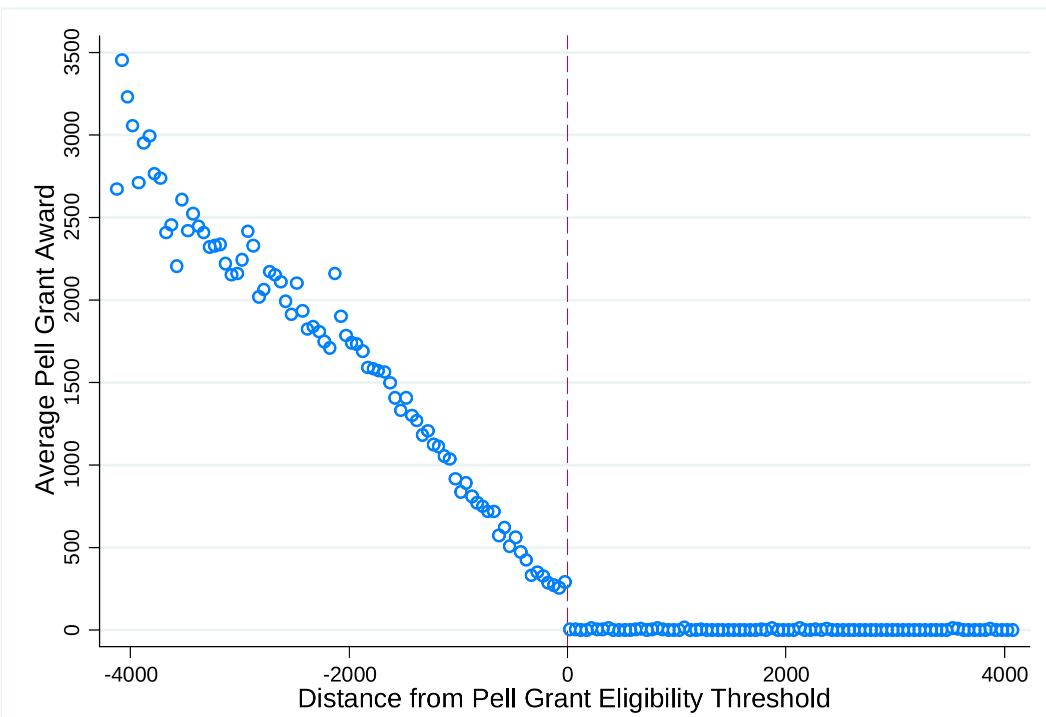


Figure 2: The Empirical Distribution of Pell Grant Aid



Notes: $50 EFC bins. Each marker represents the average Pell Grant received by students in the bin.

Figure 3: Conceptual Framework, RK/RD Design

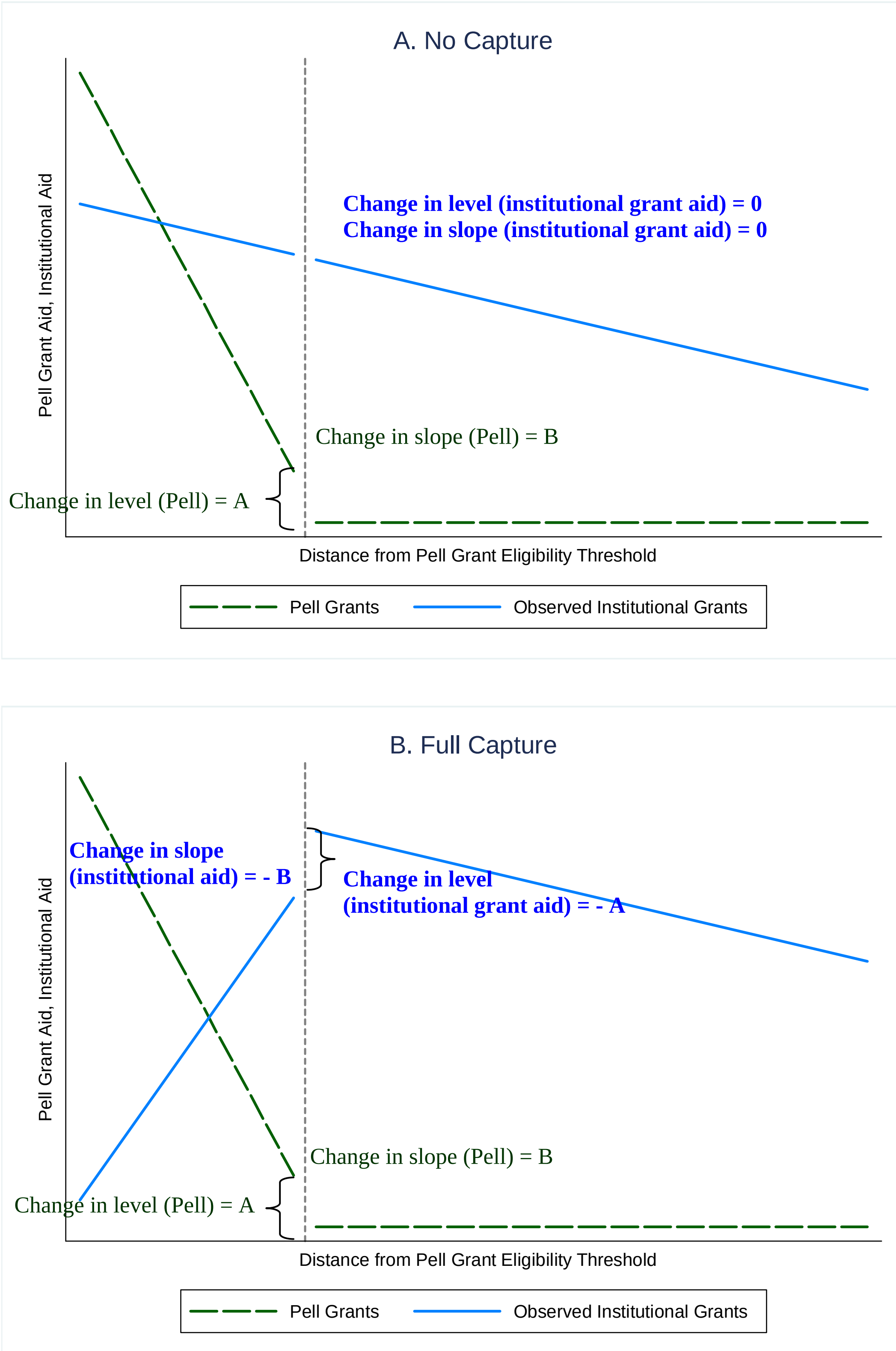
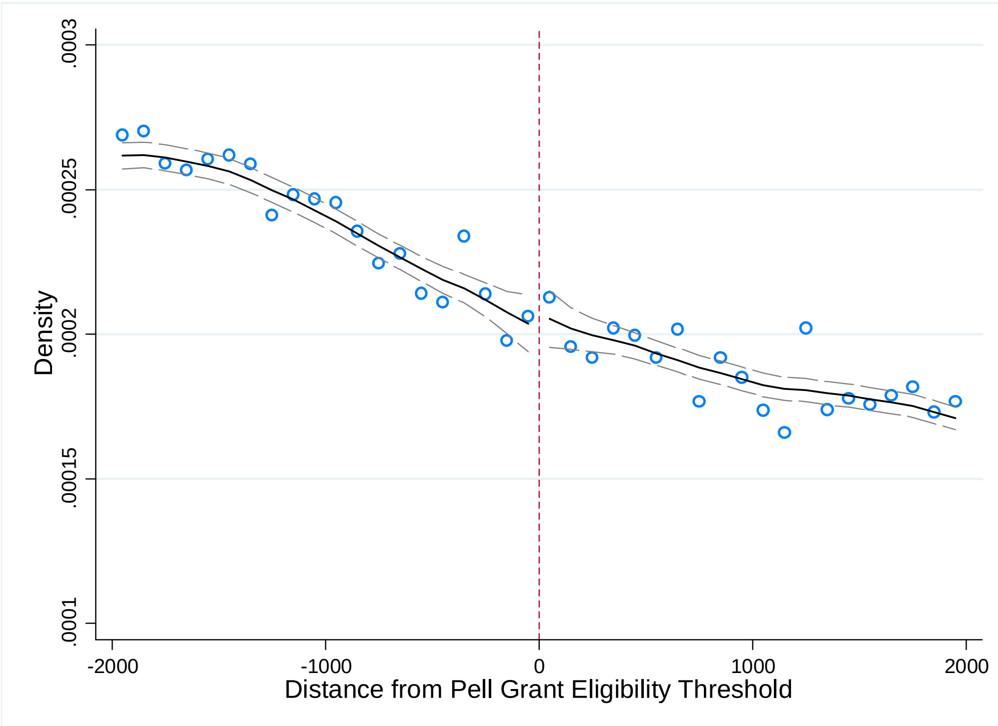
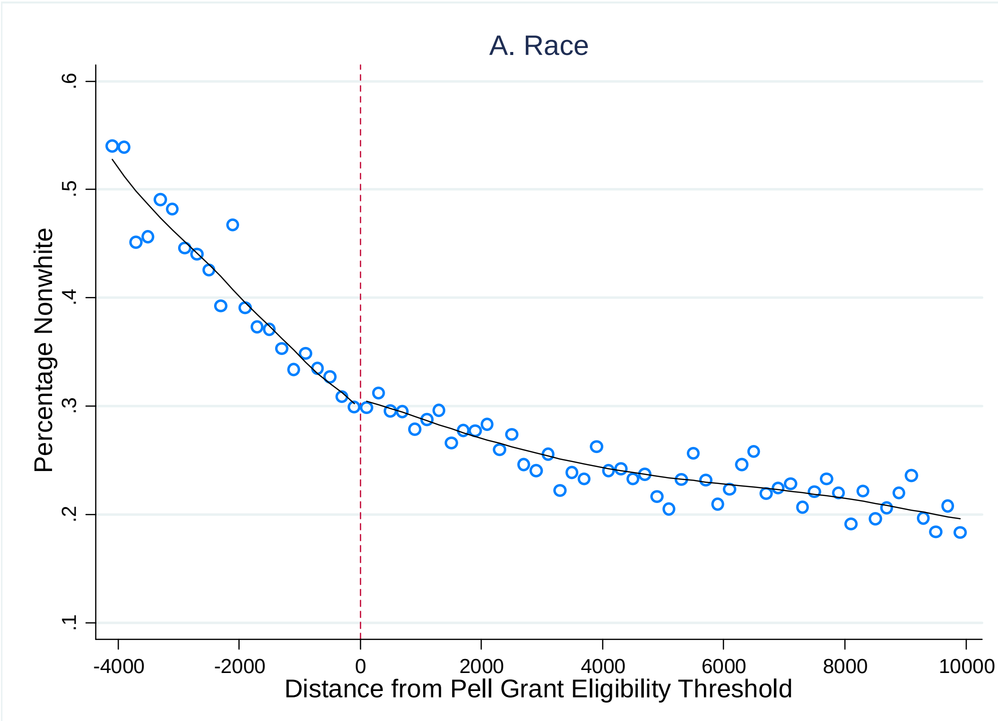


Figure 4: The Density of EFC at the Pell Grant Eligibility Threshold



Notes: \$100 EFC bins. Estimated discontinuity (McCrary test) = 0.028 (0.041). Estimated change in slope = -0.113 (0.083).

Figure 5: The Distribution of Baseline Covariates



Notes: \$200 EFC bins.

Figure 5: The Distribution of Baseline Covariates, cont.
Notes: $200 EFC bins.

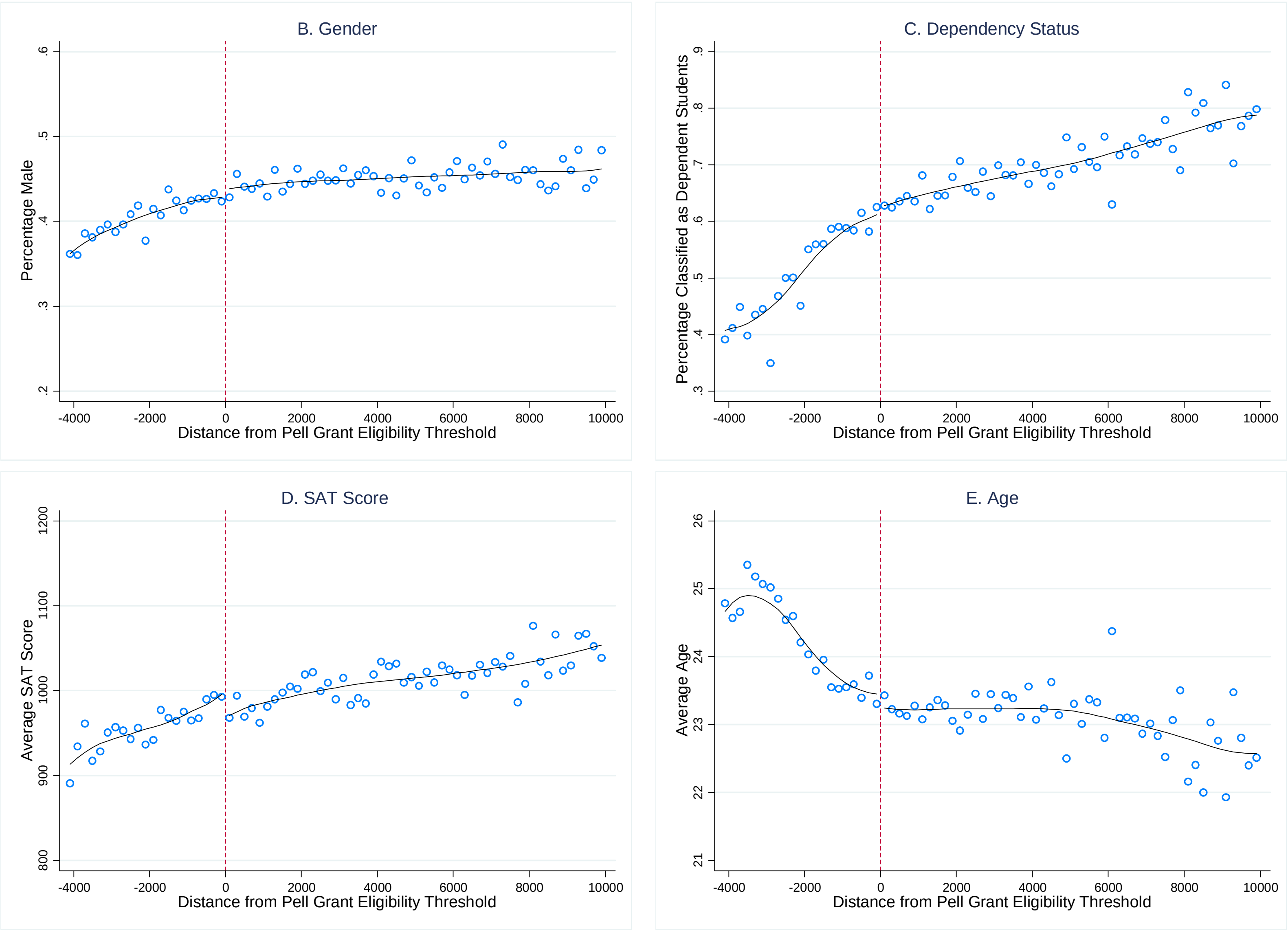


Figure 6: The Density of EFC at the Pell Grant Eligibility Cut-off, by Sector

Notes: $100 EFC bins. SAT scores for first-year students only.

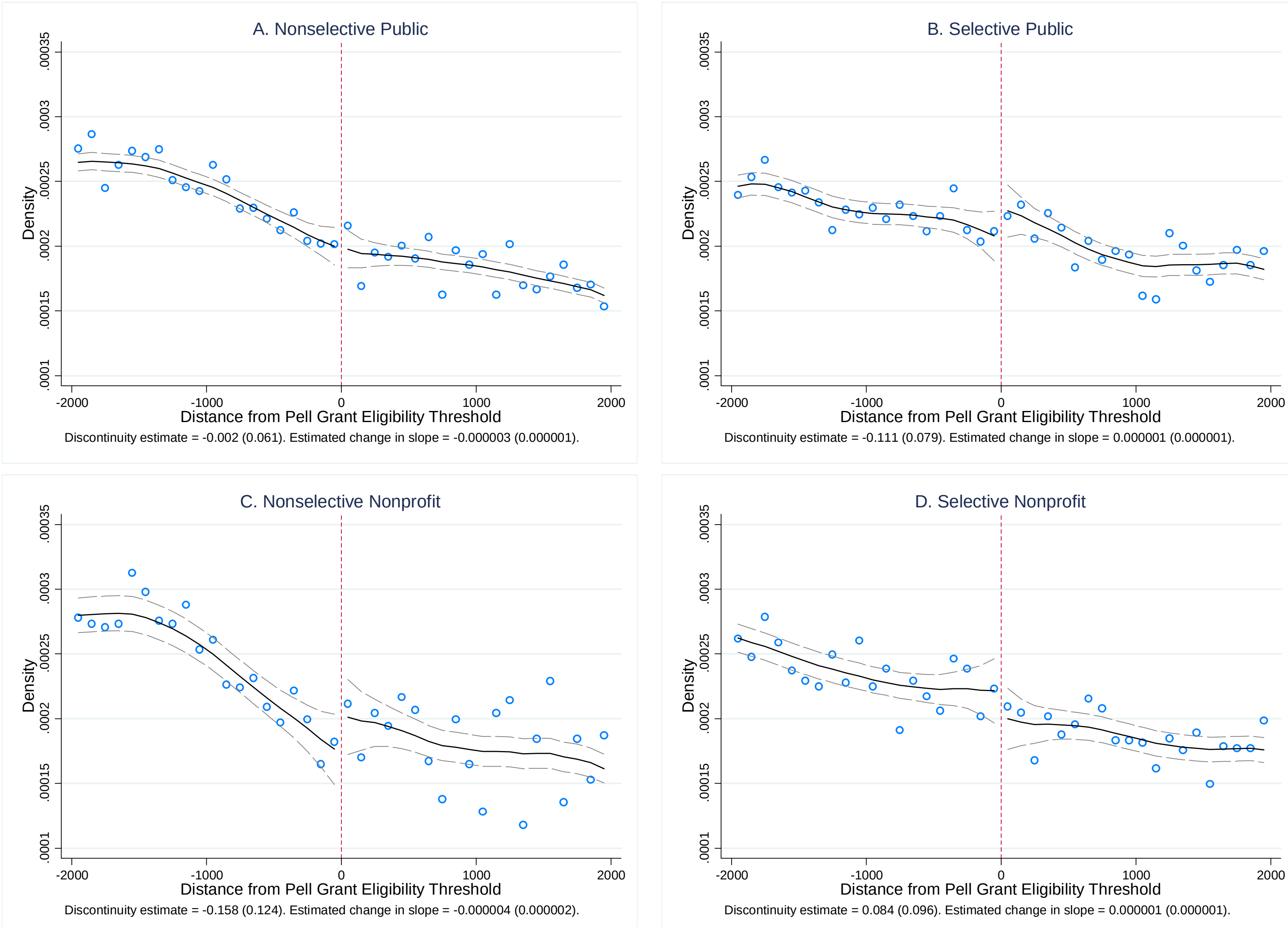
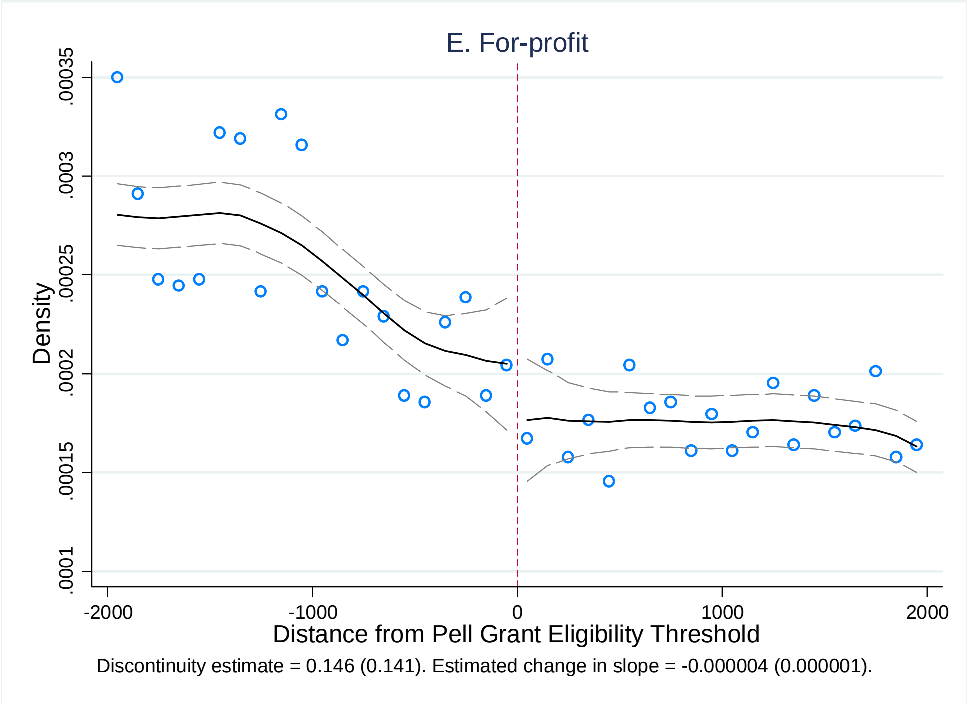
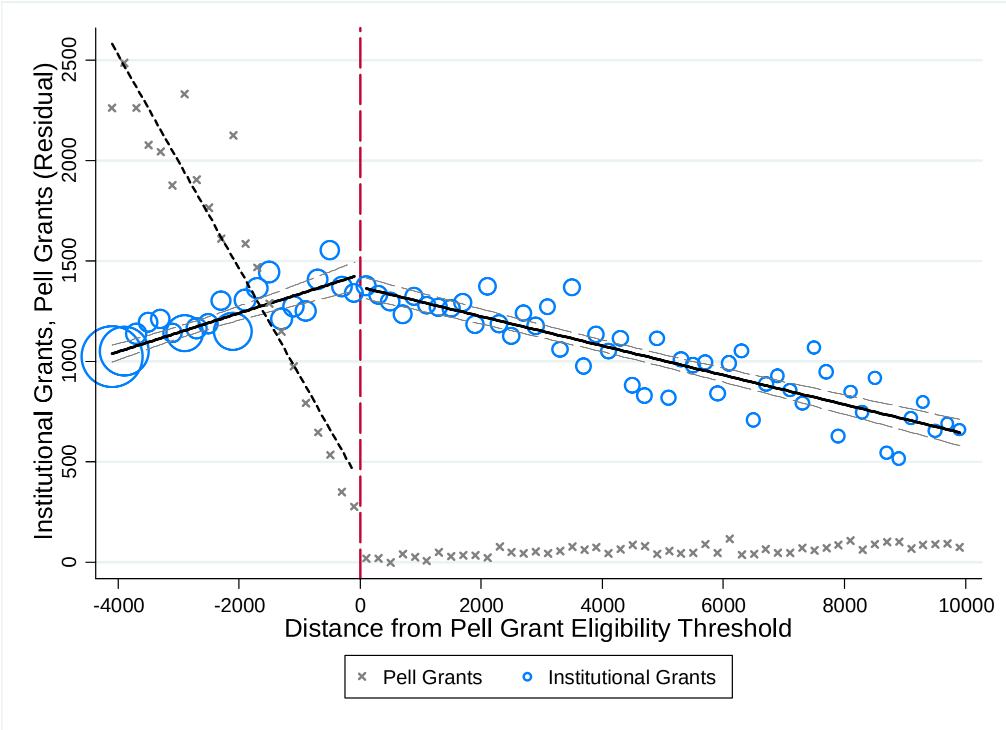


Figure 6: The Density of EFC at the Pell Grant Eligibility Cut-off by Sector, continued



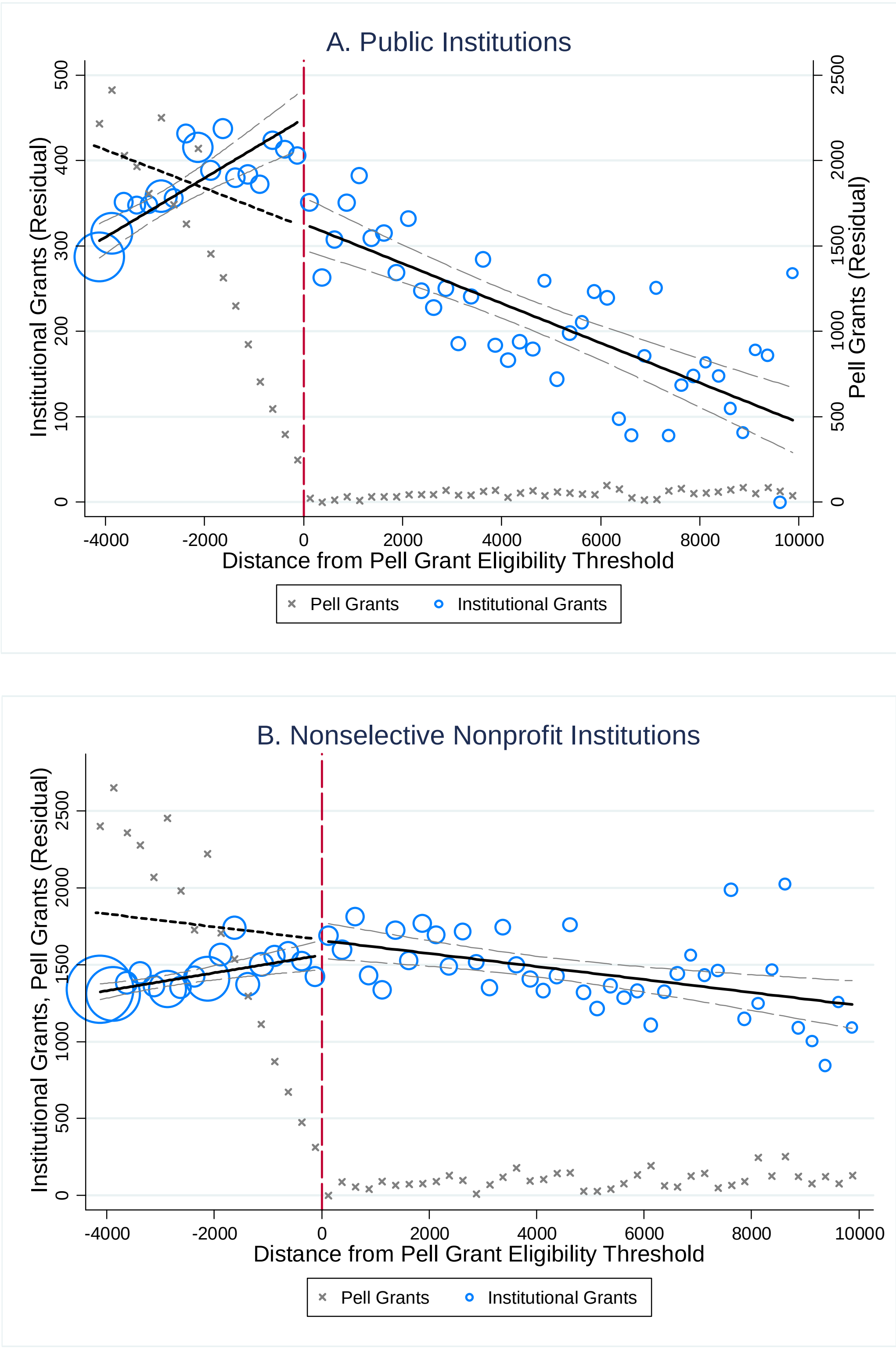
Notes: $100 EFC bins.

Figure 7: Pell Grant Generosity and Institutional Aid by EFC



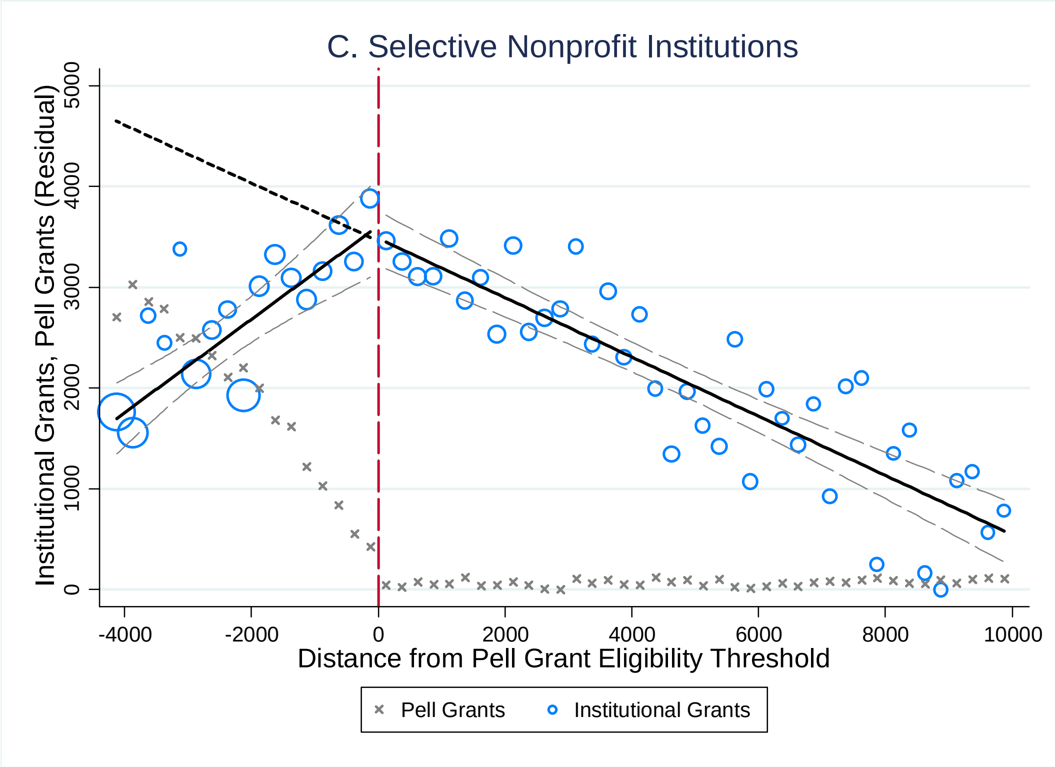
Notes: $200 EFC bins. The black solid line represents a linear fit of institutional grant aid on EFC, estimated separately on each side of the cut-off; gray dashed lines are 95 percent confidence intervals. The thin black dashed line is a linear fit of Pell Grant aid on EFC. Larger circles indicate a larger number of students within the EFC bin.

Figure 8: Pell Grant Generosity and Institutional Aid by Sector



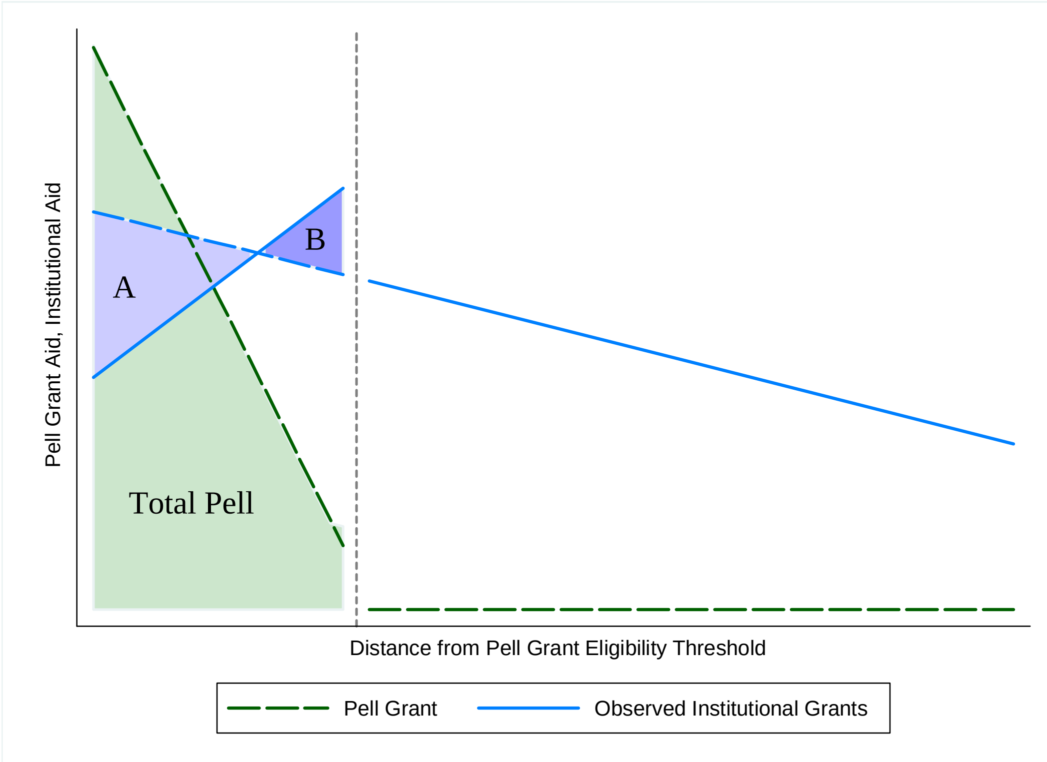
Notes: $250 EFC bins. The black solid line represents a linear fit of institutional grant aid on EFC, estimated separately on each side of the cut-off; gray dashed lines are 95 percent confidence intervals. The black dashed line is an extension of the linear fit of Pell Grant aid on EFC for Pell ineligible students. Larger circles indicate a larger number of students.

Figure 8: Pell Grant Incidence by Sector, continued



Notes: $250 EFC bins. The black solid line represents a linear fit of institutional grant aid on EFC, estimated separately on each side of the cut-off; gray dashed lines are 95 percent confidence intervals. The black dashed line is an extension of the linear fit of Pell Grant aid on EFC for Pell ineligible students. Larger circles indicate a larger number of students.

Figure 9: Framework for Estimating the Economic Incidence of the Pell Grant Program



Notes: The area labeled Total Pell represents the total amount of Pell Grant aid disbursed to students. The areas A and B represent the difference between the area below the counterfactual institutional grant aid-EFC relationship (represented by the dashed line) and the actual institutional grant aid-EFC relationship for Pell eligible students (represented by the solid line); A-B represents the amount of institutional grant aid students failed to receive due to the Pell Grant Program. See Section 6 for details.

Table 1: Characteristics of Schools and Students

	Nonselective Institutions			Selective Institutions		All Schools
	Public	Nonprofit	For-profit	Public	Nonprofit	
Number of Students	55,420	12,350	12,620	34,710	18,160	133,270
Number of Unique Schools	700	260	270	240	340	1,800
Student Financial Aid						
Percentage receiving Pell Grants	0.43	0.50	0.62	0.37	0.38	0.43
Pell Grant aid (nonzero)	$2,768	$2,927	$2,902	$2,899	$2,865	$2,844
Percentage receiving institutional aid	0.13	0.43	0.10	0.26	0.68	0.26
Institutional aid (nonzero)	$1,763	$5,567	$2,865	$3,304	$10,776	$5,949
Net Tuition (tuition - institutional aid)	$2,231	$9,044	$11,607	$4,639	$13,301	$5,887
Student Demographic Characteristics						
Non-white	0.40	0.42	0.52	0.30	0.27	0.37
Male	0.40	0.38	0.42	0.45	0.41	0.41
Dependent student	0.48	0.50	0.32	0.69	0.75	0.56
Age	25	25	26	22	22	24
Expected Family Contribution	$3,368	$3,330	$2,574	$4,267	$4,503	$3,678
Student Attendance Status						
Full-time	0.59	0.79	0.77	0.85	0.89	0.73
Months of enrollment	10.3	10.1	9.7	10.7	10.4	10.3
First-year/freshman	0.48	0.41	0.48	0.25	0.30	0.39

Data: 1996, 2000, 2004, and 2008 NPSAS. **Notes:** Number of observations rounded to nearest 10. All dollar amounts in 2011$. See text for definitions of sectors (public, nonprofit, for-profit, selective, and nonselective). Sample excludes graduate and professional students, students attending multiple institutions during the academic year, students not enrolled in the fall semester, athletic scholarship recipients, noncitizens, and students attending nondegree granting institutions, theological seminaries, or other faith-based institutions.

Table 2: Institutional Revenue and Expenditures

	Nonselective Institutions			Selective Institutions		All Schools
	Public	Nonprofit	For-profit	Public	Nonprofit	
Average FTE Students Enrolled	5,590	1,810	1,950	11,390	2,830	4,880
Number of Unique Schools	770	240	290	290	470	2,060
Total Revenue ($100k)	$1,171	$1,042	$3,562	$7,320	$5,681	$3,944
Total Expenditures ($100K)	$1,364	$1,139	$2,308	$9,506	$6,262	$5,681
Revenue - Expenditures ($100K)	-$193	-$97	$1,254	-$2,186	-$581	-$1,737
Pell Grants ($100k)	$87	$44	$488	$113	$29	$106
Pell Grants as a % of Total Revenue	0.07	0.04	0.14	0.02	0.01	0.03

Data: 2000, 2004, 2008 NPSAS and IPEDS. **Notes:** Number of observations rounded to nearest 10; All dollar amounts in 2011$. Sample includes schools serving students described in Table 1 with IPEDS revenue and expenditure data available for 2000, 2004, and 2008.

Table 3: RK and RD Estimates of the Impact of Pell Grant Generosity on Institutional Aid

	First Stage	Reduced Form	IV (RK)	IV (RD)
	(1)	(2)	(3)	(4)
Change in slope	-0.699	0.153		
	(0.007)**	(0.031)**		
Change in level	397.74	128.45		
	(12.52)**	(42.55)**		
Pell Grant Aid			-0.219	0.323
			(0.044)**	(0.106)**
F-test of excluded instrument(s)			7928	1132
Over-id test (p-value)			0.000	
Observations	133,270	133,270	133,270	133,270

Data: 1996, 2000, 2004, and 2008 NPSAS. **Notes:** Each column represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1; Pell Grants and instituional grants in constant 2011$. All regressions include year and school fixed effects, linear and quadratic terms in age, and indicators for gender, race, fall attendance status, enrollment length, level, dependency status, out-of-state student, and a quadratic in student expected family contribution (EFC - k_t, where k_t is the threshold for Pell Grant eligibility in year *t*). In column 3, **1**[EFC < k_t**]** instruments for Pell Grant Aid. In column 4, (EFC - k_t)***1[**EFC<k_t**]** instruments for Pell Grant Aid. Students with EFC greater than 10,000 from Pell Grant eligibility thresold are excluded.

Table 4: Robustness of RK and RD Estimates of the Impact of Pell Grant Generosity on Institutional Aid to Varying Bandwidths and Polynomials

	Polynomial of Order:	IV (RK) (1)	IV (RD) (2)
A. (EFC - k_t) in [-4100,10000]	One	-0.294	0.298
		(0.024)**	(0.109)**
	Two	-0.219	0.323
		(0.044)**	(0.106)**
	Three	-0.028	0.315
		(0.070)	(0.174)+
Optimal Degree		2	2
Observations		133,270	133,270
B. (EFC-k_t) in [-4000,4000]	One	-0.173	0.307
		(0.031)**	(0.184)+
	Two	-0.135	0.337
		(0.107)	(0.209)
	Three	-0.153	0.438
		(0.110)	(0.475)
Optimal Degree		1	1
Observations		87,290	87,290
C. (EFC-k_t) in [-3000, 3000]	One	-0.183	0.383
		(0.047)**	(0.289)
	Two	-0.188	0.435
		(0.134)	(0.323)
	Three	-0.208	0.973
		(0.142)	(1.147)
Optimal Degree		1	1
Observations		62,420	62,420

Data: 1996, 2000, 2004, and 2008 NPSAS. **Notes:** Each cell represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1; Pell Grants and instituional grants in constant 2011$. All regressions include year and school fixed effects, linear and quadratic terms in age, and indicators for gender, race, fall attendance status, enrollment length, level, dependency status, out-of-state student, and a up to a third degree polynominal in student expected family contribution (EFC - k_t, where k_t is the threshold for Pell Grant eligibility in year t). The optimal degree of polynomial for each bandwidth is determined using the minimum Akaike Information Criteria. RD estimates instrument for Pell Grant aid with **1[**EFC < k_t**];** RK estimates instrument with (EFC - k_t)***1[**EFC < k_t**].**

Table 5: The Impact of Pell Grant Generosity on Institutional Aid, Treatment Dimensions

	Pass-Through	Willingness to Pay
A. All institutions	-0.219	260.5
	(0.044)**	(50.06)**
Observations	133,270	
B. By sector		
Public Nonselective	-0.179	318.3
	(0.017)**	(63.31)**
Public Selective	-0.173	618.9
	(0.032)**	(101.5)**
Nonprofit Nonselective	-0.154	-193.3
	(0.060)*	(216.6)
Nonprofit Selective	-0.687	97.23
	(0.101)**	(248.3)
For-profit	-0.133	84.67
	(0.029)**	(80.84)
Observations	133,270	

Data: 1996, 2000, 2004, and 2008 NPSAS. **Notes:** Each column within a panel represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1. Pell Grants and instituional grants in constant 2011$. All regressions include year and school fixed effects, linear and quadratic terms in age, and indicators for gender, race, fall attendance intensity, enrollment length, level, dependency status, out-of-state student, and a linear term in student expected family contribution. Panel A also includes a quadratic in EFC. Students with EFC greater than 10,000 from Pell Grant cut-off are excluded. See text for definitions of treatment dimensions.

Table 6: Heterogeneity in the Impact of Pell Grant Generosity on Institutional Aid by Sector & Demographics

	Nonwhite	White	Independent	Dependent	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Public						
Pass-through	-0.207	-0.183	-0.073	-0.232	-0.208	-0.195
	(0.031)**	(0.021)**	(0.013)**	(0.024)**	(0.021)**	(0.027)**
Willingness to pay	670.6	338.6	361.8	471.5	452.7	465.2
	(115.9)**	(50.19)**	(88.61)**	(74.89)**	(61.01)**	(79.16)**
Private Nonselective						
Pass-through	-0.134	-0.150	-0.009	-0.171	-0.145	-0.165
	(0.047)**	(0.0500)**	(0.030)	(0.053)**	(0.044)**	(0.049)**
Willingness to pay	-27.17	-68.76	-147.3	-185.3	-11.58	-136.1
	(159.0)	(142.0)	(116.5)	(196.2)	(139.6)	(164.6)
Nonprofit Selective						
Pass-through	-0.438	-0.982	0.144	-0.609	-0.665	-0.716
	(0.163)**	(0.138)**	(0.128)	(0.115)**	(0.131)**	(0.146)**
Willingness to pay	-704.5	441.5	-505.2	18.36	-117.2	373.9
	(704.6)	(256.6)+	(375.6)	(309.7)	(339.6)	(367.3)
Observations	49,360	83,910	59,090	74,180	78,140	55,130

Data: 1996, 2000, 2004, and 2008 NPSAS. **Notes:** Each column represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1. Pell Grants and instituional grants in constant 2011$. All regressions include year and school fixed effects, linear and quadratic terms in age, and indicators for gender, race, fall attendance status, enrollment length, level, dependency status, out-of-state student, and a linear term in student expected family contribution. Students with EFC greater than 10,000 from Pell Grant cut-off are excluded. See text for definitions of treatment dimensions.

Table 7: The Incidence of Pell Grant Aid across all Recipients

	Percent Captured	95% CI
All Institutions	0.163	[0.114, 0.212]
Public Institutions	0.031	[0.002, 0.060]
Nonselective Private Institutions	0.176	[0.062, 0.290]
Selective Nonprofit Institutions	0.787	[0.563, 1.011]

Data: 1996, 2000, 2004, and 2008 NPSAS. **Notes:** These estimates assume the observed institutional aid-EFC relationship for Pell ineligible students is a valid counterfactual for Pell eligible students in the absence of the Pell Grant Program. The overall percentage of Pell Grant aid captured by institutions is equal to the ratio of the difference between the area below the counterfactual Pell Grant-EFC curve and the actual Pell Grant-EFC curve and the overall transfer of Pell Grant aid to eligible students (refer to section 6 for details).

Appendix A: Supplemental Figures and Tables

Figure A1: The Maximum Pell Grant Award as a Percentage of the Average Cost of Attendance

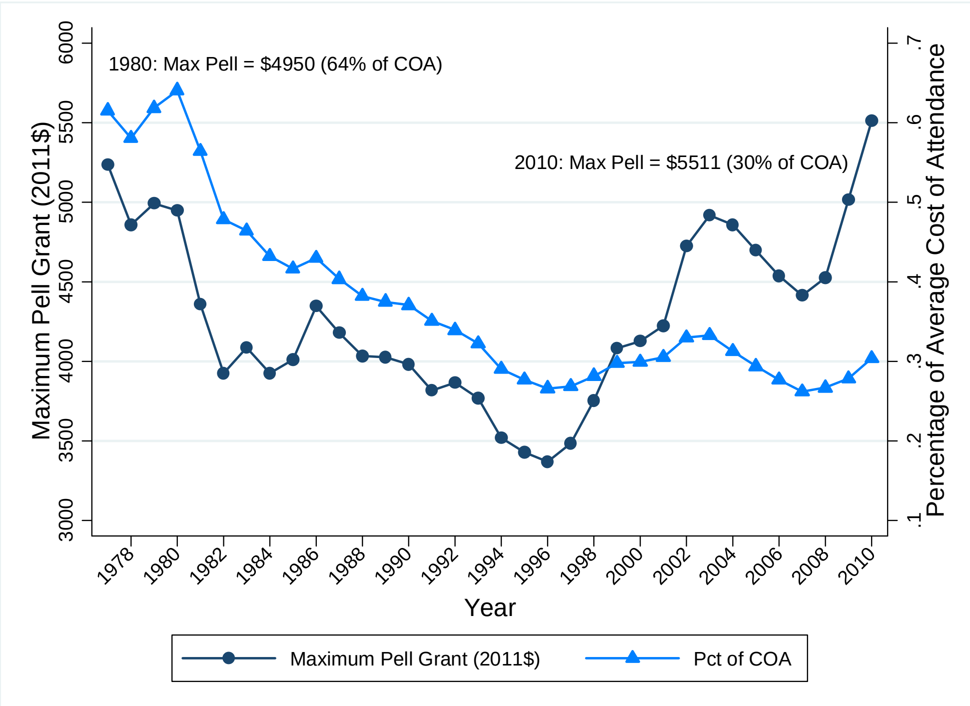
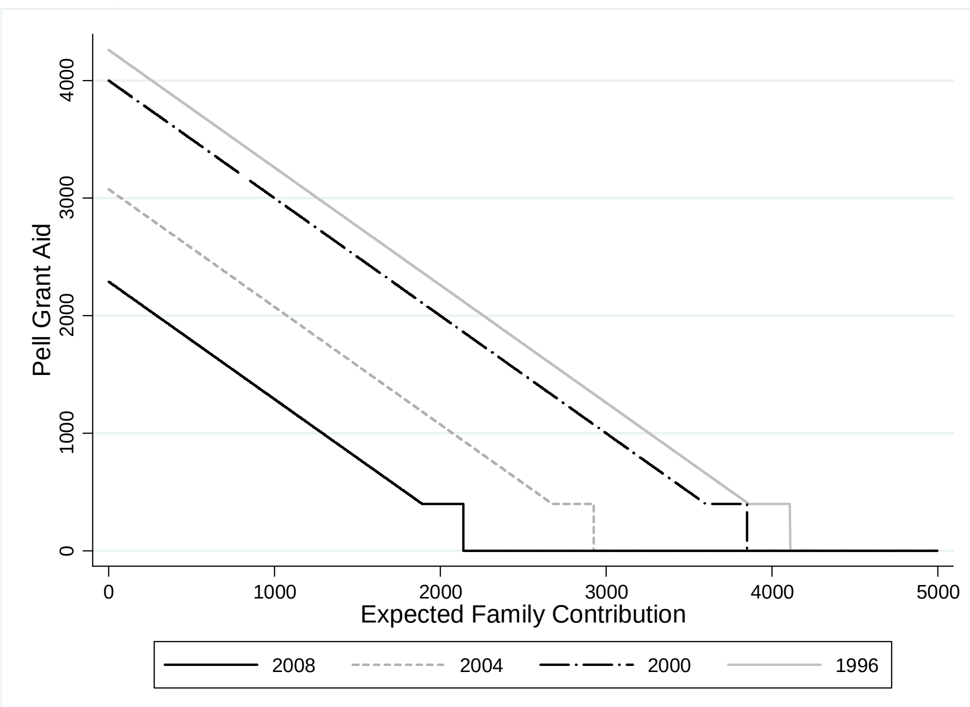
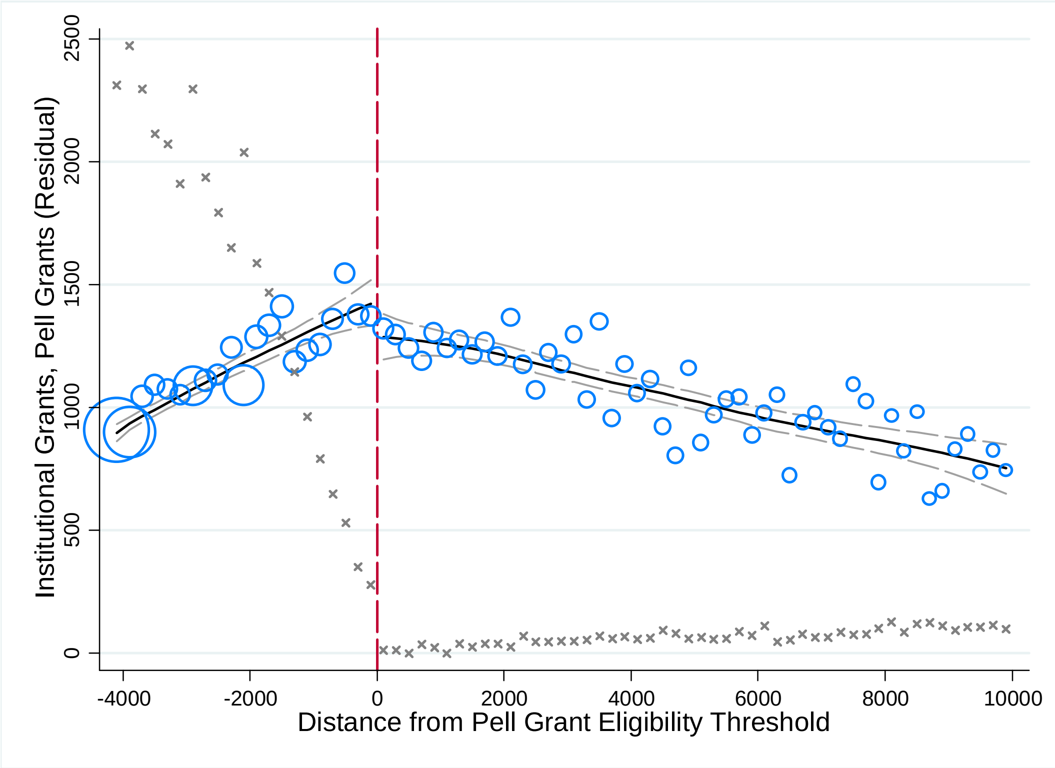


Figure A2: Pell Grant Award Schedules, NPSAS Sample Years



Notes: Each line represents the statutory Pell Grant award a full-time, full-year student with a given EFC would receive in the years covered by the NPSAS. All dollar amounts are nominal.

Figure A3: Main Results, Local Linear Regression



Notes: $250 EFC bins. The black solid line represents a local linear fit of institutional grant aid on EFC, estimated separately on each side of the cut-off; gray dashed lines are 95 percent confidence intervals. Larger circles indicate a larger number of students within the EFC bin.

Figure A4: Percentage of Students with any Unmet Need

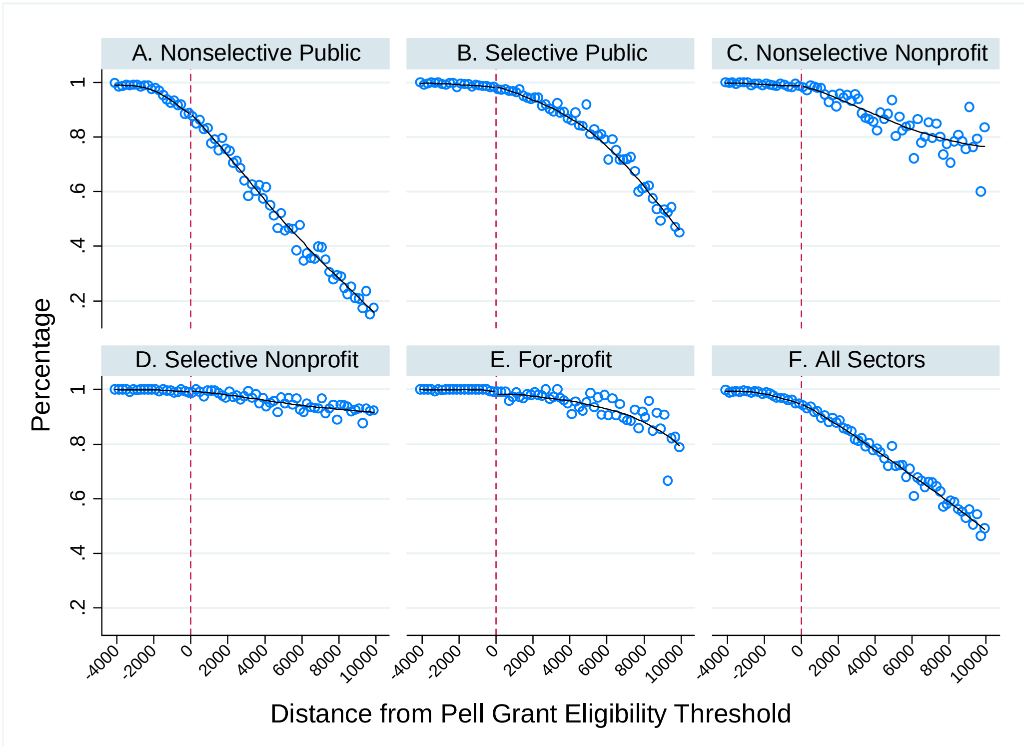
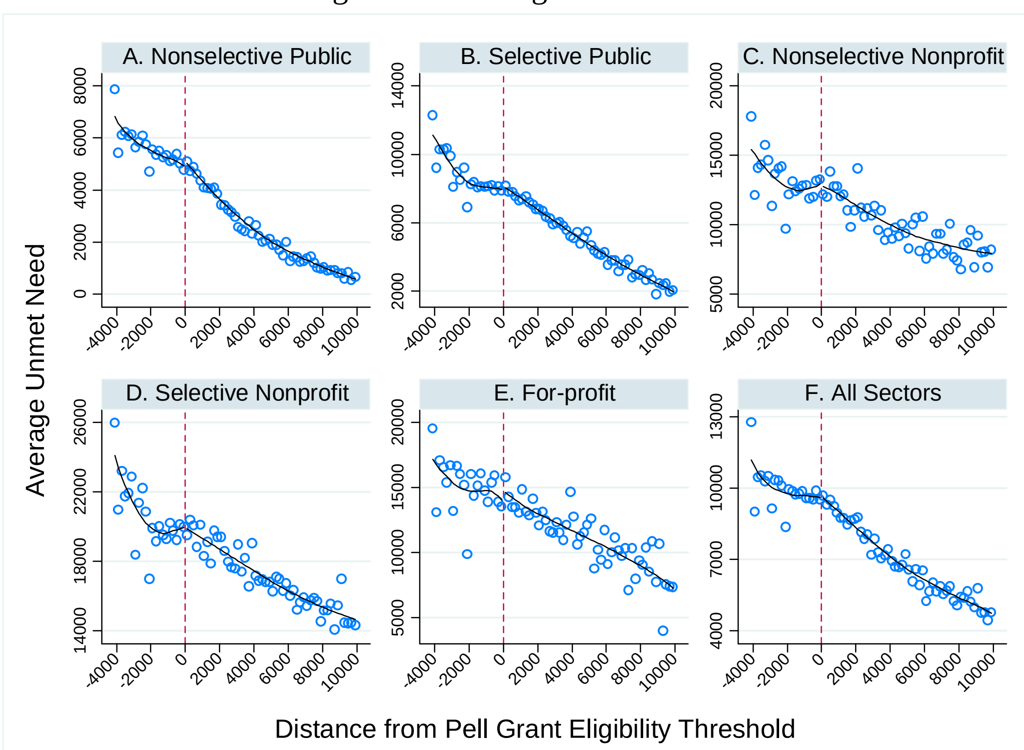


Figure A5: Average Unmet Need



Notes: Unmet need equals a student's cost of attendance minus her EFC, Pell Grant and other federal grant aid, and state grant aid.

Table A1: Baseline Characteristics, Varying Bandwidths and Polynomials

	1. White		2. Male		3. Dependent		4. SAT Score		5. Age	
	level	derivative	level	derivative	level	derivative	level	derivative	level	derivative
($EFC-k_t$) in [-4100,10000]	0.007	0.00004	-0.004	0.00001	0.032	-0.000001	11.57	0.012	-0.260	0.00002
	(0.007)	(0.0001)	(0.006)	(0.00002)	(0.008)**	(0.00001)	(8.17)	(0.009)	(0.104)*	(0.0002)
Optimal Degree of Polynomial	5		1		5		4		5	
Observations	133270		133270		133270		17080		133270	
($EFC-k_t$) in [-4000,4000]	0.002	0.00004	-0.006	-0.000003	-0.013	-0.0001	9.73	0.043	0.129	0.001
	(0.008)	(0.0001)	(0.010)	(0.00001)	(0.011)	(0.0001)	(9.96)	(0.027)	(0.114)	(0.003)
Optimal Degree of Polynomial	3		3		5		4		5	
Observations	87310		87310		87310		10240		87310	
($EFC-k_t$) in [-3000, 3000]	-0.002	-0.00003	-0.0002	0.00001	-0.009	-0.0001	5.09	0.006	-0.006	0.0002
	(0.009)	(0.00003)	(0.009)	(0.00001)	(0.010)	(0.0002)	(9.09)	(0.005)	(0.102)	(0.0002)
Optimal Degree of Polynomial	4		1		3		1		2	
Observations	62480		62480		62480		7830		62480	

Data: 1996, 2000, 2004, and 2008 NPSAS. **Notes:** Each cell represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1; Pell Grants in constant 2011$. All regressions include year and school fixed effects, and a up to a fifth degree polynominal in student expected family contribution (EFC). Optimal degree of polynomial for each bandwidth determine using the minimum Akaike Information Criterion. SAT scores for first-year students only.

Table A2: Heterogeneity in Pass-Through by Market Concentration

	(1) Baseline	(2) All Competitors		(3) Direct Competitors	
		Unconcentrated	Concentrated	Unconcentrated	Concentrated
A. All institutions	-0.189	-0.227	-0.169	-0.187	-0.188
	(0.047)**	(0.057)**	(0.046)**	(0.065)**	(0.046)**
Test of equality (p-value)		*0.129*		*0.987*	
Observations	108,400	108,400		108,400	
B. By sector					
Public	-0.106	-0.150	-0.087	-0.157	-0.094
	(0.048)*	(0.052)**	(0.048)+	(0.057)**	(0.047)*
Nonselective Private	-0.112	-0.109	-0.116	-0.117	-0.109
	(0.053)*	(0.058)+	(0.068)+	(0.060)+	(0.064)+
Selective Nonprofit	-0.719	-0.699	-0.747	-0.442	-0.794
	(0.112)**	(0.175)**	(0.130)**	(0.247)+	(0.118)**
Test of equality (p-value):					
Public		*0.011*		*0.039*	
Nonselective Private		*0.918*		*0.901*	
Selective Nonprofit		*0.812*		*0.169*	
Observations	108,400	108,400		108,400	

Data: 2004 and 2008 NPSAS, 2003 and 2007 IPEDS. **Notes:** Each column within a panel represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1. Pell Grants and instituional grants in constant 2011$. All regressions include year and school fixed effects, linear and quadratic terms in age, and indicators for gender, race, fall attendance status, enrollment length, level, dependency status, out-of-state student, and a linear term in student expected family contribution (EFC). Panel A also includes a quadratic in EFC. Students with EFC greater than 10,000 from Pell Grant cut-off are excluded. A school's market is considered concentrated if the Herfindahl index of institutional FTE undergraduate student shares is greater than 0.25. In column 2, schools in all sectors in a given market are considered competitors. In column 3, only schools with similar selectivity in a market are considered competitors.

Table A3: RK Estimates of the Impact of Pell Grant Aid on Institution Quality

	Tuition/FTE	Revenue/FTE	Institutional Expenditures/FTE on: Grants	Instruction	Student Services	CDR
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Sectors						
Mean of depvar	$10,619	$19,038	$1,061	$6,214	$5,748	6.55
* Pell Grant Aid	-0.027	-0.030	0.004	-0.035	0.008	0.0003
	(0.142)	(0.198)	(0.015)	(0.060)	(0.072)	(0.0001)**
Observations	66,950	77,470	66,940	83,810	84,630	128,800
B. By Sector						
Nonselective Public						
Mean of depvar	$5,160	$13,629	$1,086	$5,051	$3,828	8.2
* Pell Grant Aid	-0.089	-0.153	0.014	-0.023	-0.047	-0.0001
	(0.040)*	(0.074)*	(0.008)+	(0.024)	(0.025)+	(0.00007)
Selective Public						
Mean of depvar	$7,839	$25,364	$1,495	$8,412	$5,503	4.5
* Pell Grant Aid	0.082	0.070	0.022	0.139	0.034	0.0003
	(0.059)	(0.170)	(0.013)+	(0.064)*	(0.036)	(0.0001)**
Nonselective Nonprofit						
Mean of depvar	$15,247	$22,260	$799	$6,138	$7,872	7.1
* Pell Grant Aid	-0.043	0.120	0.033	0.008	0.116	0.0001
	(0.155)	(0.259)	(0.030)	(0.088)	(0.093)	(0.0004)
Selective Nonprofit						
Mean of depvar	$22,449	$32,393	$1,500	$9,489	$10,288	3.2
* Pell Grant Aid	0.088	0.071	0.038	-0.038	0.064	0.0003
	(0.175)	(0.288)	(0.051)	(0.097)	(0.112)	(0.0001)**
For Profit						
Mean of depvar	$14,409	$15,860	$353	$3,522	$8,545	10.1
* Pell Grant Aid	-0.231	-0.277	-0.006	0.022	-0.228	-0.001
	(0.133)+	(0.161)+	(0.013)	(0.057)	(0.156)	(0.0003)**
Observations	66,950	77,470	66,940	83,810	84,630	128,800

Data: 1996, 2000, 2004, and 2008 NPSAS, 2003 and 2007 IPEDS, Department of Education Official Cohort Default Rates. **Notes:** 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. Columns 1 through 6 include students attending institutions in 2004 and 2008 with revenue or expenditure information available in prior year IPEDS. Column 6 includes students attending institutions in all years with information on two-year cohort default rates. Number of observations rounded to nearest 10. Regressions include year fixed effects and a linear term in student expected family contribution (EFC). Panel A also includes a quadratic in EFC.

Appendix B: Regression Discontinuity Estimation with a Multidimensional Treatment

In this appendix, I provide a general example of how a multidimensional treatment will affect regression discontinuity (RD) design estimates. Additionally, I show how using a regression kink (RK) design, in combination with a RD design, allows estimation of more than one treatment dimension. Finally, I show how this approach is applied in the case of the Pell Grant Program.

Let Y be the outcome of interest, where $Y = y(T, X, U)$ and *T* is the "treatment" of interest and is continuous and potentially endogenous. *X* and *U* are covariates, where *X* is observable, *U* is unobservable, and both are determined prior to *T*. Finally, *T* is a deterministic function of *X*, $T = t(X)$, and the data generating processes for *Y* and *T* are:

(B1) $$Y = f(T, \tau) + g(X) + U$$

(B2) $$T = \beta_0 1[X \leq x_0] + \beta_1 X \cdot 1[X \leq x_0] + h(X)$$

Where $h(X)$ is continuously differentiable in the neighborhood of x_0. In this case, the deterministic relationship between *T* and *X* leads to both a change in the level and in the first derivative of *T* at x_0.[1] Finally, $F_U(u)$ is the cdf of *U* and $F_{X|U}(x \mid u)$ is the conditional cdf of *X*.

Under the following identifying assumptions, the RD estimator will approximate random assignment (Hahn et al., 2001; Lee and Lemieux, 2010).

RD1 (Regularity): $y(t, x, u)$ is continuous in *x* in the neighborhood of x_0 and $f_U(x_0) > 0$.

RD2 (First Stage): *T* is a known function, continuous on $(-\infty, x_0)$ and (x_0, ∞), but $\lim_{\varepsilon \uparrow 0} E[T \mid X = x_0 + \varepsilon] \neq \lim_{\varepsilon \downarrow 0} E[T \mid X = x_0 + \varepsilon]$.

RD3 (Continuous conditional density of the assignment variable): $f_{X|U}(x \mid u)$ is continuous in *x* in the neighborhood of x_0 for every *u*. This condition means that observations have imperfect control over *X* and rules out sorting in response to the treatment.

Consider two different forms of $f(T, \tau)$:

[1] In the following discussion, I assume that treatment effects do not vary with *X* or *U*, but this assumption could be relaxed without affecting my main conclusions.

(B3) $$f(T,\tau)=\tau_1 T$$

(B4) $$f(T,\tau)=\tau_0 1[T>0]+\tau_1 T$$

If equation (B3) describes $f(T,\tau)$, "treatment" has a single dimension, as is generally assumed in RD designs, the RD estimator equals:

$$\tau_{RD}=\frac{\lim_{\varepsilon\uparrow 0} E[Y \mid X=x_0+\varepsilon]-\lim_{\varepsilon\downarrow 0} E[Y \mid X=x_0+\varepsilon]}{\lim_{\varepsilon\uparrow 0} E[T \mid X=x_0+\varepsilon]-\lim_{\varepsilon\downarrow 0} E[T \mid X=x_0+\varepsilon]}=\tau_1$$

If instead, T is multidimensional and equation (B4) describes $f(T,\tau)$, the RD estimator will equal $\tau_{RD}=\tau_1+\frac{\tau_0}{T(x_0)}$. To see this, note that the numerator of the RD estimator equals:

$$\lim_{\varepsilon\uparrow 0} E[\tau_0 1[T>0]+\tau_1 T+g(X)+U \mid X=x_0+\varepsilon]-\lim_{\varepsilon\downarrow 0} E[\tau_0 1[T>0]+\tau_1 T+g(X)+U \mid X=x_0+\varepsilon]$$

Assumptions RD1 and RD3 imply: $\lim_{\varepsilon\uparrow 0} E[g(X)+U \mid X=x_0+\varepsilon]=\lim_{\varepsilon\downarrow 0} E[g(X)+U \mid X=x_0+\varepsilon]$.

Since $\lim_{\varepsilon\uparrow 0} E[h(X) \mid X=x_0+\varepsilon]=\lim_{\varepsilon\downarrow 0} E[h(X) \mid X=x_0+\varepsilon]$ by assumption, the RD numerator is equal to $\tau_0+\tau_1(\beta_0+\beta_1 x_0)$ and the RD estimator equals:

(B5) $$\tau_{RD}=\tau_1+\frac{\tau_0}{\beta_0+\beta_1 x_0}=\tau_1+\frac{\tau_0}{T(x_0)}$$

Thus, when the treatment has more than one dimension, the RD estimator only recovers the reduced form impact of these dimensions. In this case, with the RD design alone, it is not possible to separately identify τ_0 and τ_1. However, since the deterministic relationship between T and X leads to both a discontinuous change in the level and a discontinuous change in the slope of T at x_0, it is possible to separately identify these dimensions using a combined RD and RK approach.

In addition to the RD identifying assumptions, the RK design requires the following additional assumptions (Card et al., 2009):

RK1 (Regularity): $\frac{\partial y(t,x,u)}{\partial x}$ is continuous in x in the neighborhood of x_0.[2]

RK2 (First Stage): T is continuously differentiable on $(-\infty, x_0)$ and (x_0, ∞), but $\lim_{\varepsilon \uparrow 0} \frac{\partial E[T \mid X = x_0 + \varepsilon]}{\partial x} \neq \lim_{\varepsilon \downarrow 0} \frac{\partial E[T \mid X = x_0 + \varepsilon]}{\partial x}$.

RD3 (Continuously differentiable conditional density of the assignment variable): $f_{X|U}(x \mid u)$ is continuously differentiable in x in the neighborhood of x_0 for every *u.*

If these conditions are met, regardless of whether $f(T,\tau)$ is represented by equation (B3) or (B4), the RK estimator will equal:

$$\tau_{RK} = \frac{\lim_{\varepsilon \uparrow 0} \frac{\partial E[Y \mid X = x_0 + \varepsilon]}{\partial x} - \lim_{\varepsilon \downarrow 0} \frac{\partial E[Y \mid X = x_0 + \varepsilon]}{\partial x}}{\lim_{\varepsilon \uparrow 0} \frac{\partial E[T \mid X = x_0 + \varepsilon]}{\partial x} - \lim_{\varepsilon \downarrow 0} \frac{\partial E[T \mid X = x_0 + \varepsilon]}{\partial x}} = \tau_1$$

To see this, first note that the numerator equals:

$$\lim_{\varepsilon \uparrow 0} \frac{\partial E[\tau_0 1[T > 0] + \tau_1 T + g(X) + U \mid X = x_0 + \varepsilon \mid X = x_0 + \varepsilon]}{\partial x} - \lim_{\varepsilon \downarrow 0} \frac{\partial E[\tau_0 1[T > 0] + \tau_1 T + g(X) + U \mid X = x_0 + \varepsilon \mid X = x_0 + \varepsilon]}{\partial x}$$

By assumptions RK1 and RK3, $\lim_{\varepsilon \uparrow 0} \frac{\partial E[g(X) + U \mid X = x_0 + \varepsilon]}{\partial x} = \lim_{\varepsilon \downarrow 0} \frac{\partial E[g(X) + U \mid X = x_0 + \varepsilon]}{\partial x}$

$\lim_{\varepsilon \uparrow 0} \frac{\partial E[1[T > 0] \mid X = x_0 + \varepsilon]}{\partial x} = \lim_{\varepsilon \downarrow 0} \frac{\partial E[1[T > 0] \mid X = x_0 + \varepsilon]}{\partial x} = 0$ regardless of the value of τ_0, and

$\lim_{\varepsilon \uparrow 0} \frac{\partial E[h(X) \mid X = x_0 + \varepsilon]}{\partial x} = \lim_{\varepsilon \downarrow 0} \frac{\partial E[h(X) \mid X = x_0 + \varepsilon]}{\partial x}$ by assumption. Thus, the RK numerator

equals $\tau_1 \left(\lim_{\varepsilon \uparrow 0} \frac{\partial E[T \mid X = x_0 + \varepsilon]}{\partial x} - \lim_{\varepsilon \downarrow 0} \frac{\partial E[T \mid X = x_0 + \varepsilon]}{\partial x} \right)$ and the RK estimator equals:

(B6) $$\tau_{RK} = \tau_1$$

[2] Card et al. (2009) include the additional assumption that $\frac{\partial y(t,x,u)}{\partial t}$ is continuous in *t*. If treatment is multidimensional, this condition is violated. Comparisons of RD and RK estimators allows for a test of whether this condition is met.

Furthermore, if the treatment has two dimensions, as described in equation (B4), the RD and RK estimators can be combined to identify both τ_0 and τ_1. The RK estimator identifies τ_1, and combining (B5) and (B6) allows for identification of the second treatment dimension:

(B7) $$\tau_0 = (\tau_{RD} - \tau_{RK})T(x_0)$$

If $f(T,\tau)$ has higher order terms, then $\tau_{RD} = \frac{\tau_0}{T(x_0)} + \tau_1 + \tau_2 T(x_0) + ... + \tau_p T(x_0)^{p-1}$ and $\tau_{RK} = \tau_1 + \tau_2 T(x_0) + ... + \tau_p T(x_0)^{p-1}$ where *p* is the order of the polynomial in *T*. Thus, using a combined RD/RK approach, it is always possible to identify τ_0, or the discrete change in the outcome that occurs when $T > 0$, but it is not possible to separately recover higher order terms without discontinuities in higher order derivatives of *T*.

B.1 Identification of multiple treatment dimensions in the case of the Pell Grant Program

In the case of the Pell Grant Program, $Y = y(Pell, EFC, U)$ represents institutional aid. Since not every student submits an application for federal aid, Pell Grant aid is not completely determined by a student's EFC, and the RD/RK designs will be fuzzy. The data generating processes for *Y* and *Pell* are:

(B8) $$Y = f(Pell,\tau) + g(EFC) + U$$

(B9) $$Pell = \pi \cdot \mathbf{1}[EFC < efc_0](400 - (EFC - efc_0))$$

Where efc_0 is the cut-off for Pell Grant eligibility, and $\pi \in \{0,1\}$ (e.g., the probability a student applies for federal aid) is a random variable where $E[\pi] > 0 \,\forall efc$. Although π may also depend on *EFC*, since the decision to apply is determined prior to an individual receives their Pell Grant award, I assume that $\pi = \pi(EFC)$ is continuous and smooth in the neighborhood of efc_0.

My model suggests that Pell Grant aid may affect institutional aid provision through two dimensions: by altering a school's willingness to pay (τ_0) and through schools' ability to capture outside aid due to the pass-through of demand increases (τ_1):

(B10) $$f(Pell,\tau) = \tau_0 \mathbf{1}[Pell > 0] + \tau_1 Pell$$

The numerator of the RD estimator will be equal to:

$$\lim_{\varepsilon \uparrow 0} E\left[f(Pell,\tau)+g(EFC)+U \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[f(Pell,\tau)+g(EFC)+U \mid EFC = efc_0 + \varepsilon\right]$$

Since $\lim_{\varepsilon \uparrow 0} E\left[g(EFC)+U \mid EFC = efc_0 + \varepsilon\right] = \lim_{\varepsilon \downarrow 0} E\left[g(EFC)+U \mid EFC = efc_0 + \varepsilon\right]$ by assumptions RD1 and RD3, the RD numerator is equal to:

$$\lim_{\varepsilon \uparrow 0} E\left[\tau_0 \mathbf{1}[Pell > 0] + \tau_1 Pell \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[\tau_0 \mathbf{1}[Pell > 0] + \tau_1 Pell \mid EFC = efc_0 + \varepsilon\right]$$

$$= \tau_0 \left(\lim_{\varepsilon \uparrow 0} E\left[\mathbf{1}[Pell > 0] \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[\mathbf{1}[Pell > 0] \mid EFC = efc_0 + \varepsilon\right]\right)$$
$$+ \tau_1 \left(\lim_{\varepsilon \uparrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right]\right)$$

$$= \tau_0 \left(\lim_{\varepsilon \uparrow 0} E\left[\mathbf{1}[Pell > 0] \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[\mathbf{1}[Pell > 0] \mid EFC = efc_0 + \varepsilon\right]\right)$$
$$+ \tau_1 \left(\lim_{\varepsilon \uparrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right]\right)$$

Then the RD estimator is equal to:

$$\tau_{RD} = \tau_1 + \tau_0 \left(\frac{\lim_{\varepsilon \uparrow 0} E\left[\mathbf{1}[Pell > 0] \mid EFC = efc_0 + \varepsilon\right]}{\lim_{\varepsilon \uparrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right]} \right)$$

Where

$$\frac{\lim_{\varepsilon \uparrow 0} E\left[\mathbf{1}[Pell > 0] \mid EFC = efc_0 + \varepsilon\right]}{\lim_{\varepsilon \uparrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right] - \lim_{\varepsilon \downarrow 0} E\left[Pell \mid EFC = efc_0 + \varepsilon\right]} = \frac{\lim_{\varepsilon \uparrow 0} \Pr\left[\pi = 1 \mid EFC = efc_0 + \varepsilon\right]}{\lim_{\varepsilon \uparrow 0} E\left[\pi \cdot \left(400 - (EFC - efc_0)\right) \mid EFC = efc_0 + \varepsilon\right]}$$

$$= \frac{\lim_{\varepsilon \uparrow 0} \Pr\left[\pi = 1 \mid EFC = efc_0 + \varepsilon\right]}{400 \lim_{\varepsilon \uparrow 0} \Pr\left[\pi = 1 \mid EFC = efc_0 + \varepsilon\right]} = \frac{1}{400}$$

Thus, as in the sharp case, $\tau_{RD} = \tau_1 + \dfrac{\tau_0}{Pell(efc_0)}$, where $Pell(efc_0) = 400$. Following the arguments presented in the previous section, and assuming that $f(Pell,\tau)$ does not include any higher order terms, the regression kink estimator is equal to τ_1 and $\tau_0 = (\tau_{RD} - \tau_{RK}) \cdot 400$.