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

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January 2012*

JOB MARKET PAPER

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 institutions capture 17 percent of all Pell Grant aid. However, the extent and pattern of capture 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 effective prices for recipients, 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 17 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 selective nonprofit institutions capture over 60 percent. 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 in fact *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 the 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 schools' ability to capture Pell Grant aid quickly overtakes their willingness to pay for needy students. My results suggest that, on average, Pell Grant recipients receive an additional \$300 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. Selective nonprofit and public schools demonstrate a willingness to pay for students categorized as Pell Grant recipients. However, in selective nonprofit institutions, these transfers are almost immediately overtaken by capture of additional Pell Grant aid. Overall, selective nonprofit institutions appropriate 66 percent of their students' Pell Grants, suggesting these schools have considerable market power. 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.

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). These schools disproportionately serve federal aid recipients, suggesting the potential for extensive capture of Pell Grants. However, I find that for-profit institutions behave no differently than nonselective nonprofit schools and, combined, these schools appropriate only 22 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 (2011) suggests that institutions capture other sources of financial aid via reductions in institutional discounts. 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 total incidence of Pell Grant aid in Section 6 and 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

[1] Rothstein (2008) shows that since Earned Income Tax Credit (EITC) induced increases in labor supply drive down wages, firms receive over half of the benefit of EITC payments. Hastings and Washington (2010) show that grocery stores capture 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).

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 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). In 2010, the maximum Pell Grant represented 42 percent of average tuition and fees at public institutions and 17 percent at private schools (National Center for Education Statistics, 2011).

A student's Pell 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. 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 FAFSA and EFC are then provided to schools which, in turn, calculate students' 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.

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

$$Pell_{it} = \max\{(maxPell_t - EFC_{it}), 0\} \quad (1)$$

Where $maxPell_t$ is the maximum Pell award available in year *t* (Figure 1) and EFC_{it} is the expected family contribution of student *i* in year *t*. Pell awards are rounded up to the next $100 and students qualifying for an award between \$399 and \$200 receive \$400.[3] 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.[4] Figure 2 displays the Pell Grant award schedule in 1996, 2000, 2004, and 2008.[5]

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, 2009). If low-income students lack information about the Pell Grant Program, increases in Pell Grant generosity may not significantly 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. (2009) show that information on the availability of financial aid and assistance with the FAFSA application process increase the likelihood of enrollment.

The relatively weak response of student demand to Pell Grant aid suggests the potential for schools to capture 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; likewise, 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.

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[3] 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 at \$400.

[4] The formula used to determine Pell Grant aid for part-time students is $Pell_{it} = \max\{(0.5 * maxPell_t - EFC_{it}), 0\}$; thus, 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.

[5] A student's EFC also affects her eligibility for other sources of federal aid (e.g., Supplemental Educational Opportunity Grants (SEOG), Stafford loans, work study). However, the Pell Grant Program is the only federal entitlement program.

Raising tuition is only one method schools may use to capture Pell Grant aid. 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.[6]

Two studies explicitly examine whether schools respond to student aid by reducing 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.

Schools' response to the HOPE program suggests that the economic incidence of the Pell Grant Program may vary by institutional control. Traditionally, the market for higher education has been primarily served by public and nonprofit schools. However, the last decade has seen substantial growth in the for-profit sector of higher education. 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).[7] These schools charge significantly higher tuition than comparable public schools, but students do not appear to receive a greater return to their investment (Cellini and Chaudhary, 2010).[8] Influenced by these concerns, "gainful employment" legislation will specifically regulate programs primarily offered by for-profit schools beginning in 2012.[9]

[6] E.g., housing (Yinger, 1998), loans (Charles et al., 2008), and vehicles (Langer, 2009).
[7] In 2009, the federal student loan cohort default rate 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, see: http://www2.ed.gov/finaid/prof/resources/data/pell-data.html). Conversely, the share of all students at for-profit schools grew from 4 to 11 percent (Deming et al., forthcoming).
[8] In 2010, public school students paid $5,000 on average; 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).

2. Data and Descriptive Statistics

The National Postsecondary Student Aid Study (NPSAS) is a restricted-use, nationally representative, repeated cross-section of college students. I observe each student's EFC, demographic characteristics, FAFSA (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. Finally, I exclude all students attending schools that only offer sub-associate certificate programs since many of these institutions are not eligible to distribute federal aid. My final sample includes approximately 180,560 undergraduate students attending 2,270 unique institutions. Due to NCES confidentiality requirements, all NPSAS sample sizes are rounded to the nearest 10.

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 also 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.

I classify schools by selectivity and control, distinguishing between public, nonprofit, and for-profit institutions that are selective and nonselective. I categorize institutions as either selective or nonselective using the IPEDS, which contains annual data on acceptance rates, and the Barrons' College Guide, which 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 an institution lists that it is "inclusive" (i.e., open admissions) in the IPEDS, 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.[10]

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).[11] 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. Students receive Pell Grant aid across all sectors of higher education. Over half of all for-profit students receive Pell Grants, while around one third of students attending public and nonprofit non-selective schools receive grants. Students attending selective institutions are the least likely to receive Pell Grant aid. However, conditional on receiving a Pell Grant, award amounts are similar across sectors; approximately three quarters of Pell Grant recipients receive less than the maximum award. Schools in all sectors use institutional aid to provide discounts from the list price, although students attending for-profit and nonprofit nonselective institutions are least likely to receive these discounts.

Table 1 also displays student demographic characteristics. On average, for-profit students are more likely to be non-white and are older than students in other sectors. Students attending nonselective institutions are more disadvantaged, on average, and are also more likely to be classified as independent, a status given to students who are married, have dependents, are veterans, or are older than 24. Finally, Table 2 displays institutional revenue and expenditures for each sector using IPEDS data. For-profit schools are the only institutions that receive a substantial portion of revenue from the Pell Grant Program (14 percent). Pell Grants contribute

[10] On average, selective public institutions admit 61 percent of applicants and selective nonprofits admit 56 percent. Only 3 percent of the public institutions and 12 percent of nonprofit institutions in my selective category are classified as "most selective" by the Barrons' Guide.
[11] 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).

to only 6 percent of public nonselective schools' revenue, 3 percent of revenue in private nonselective schools, and only 1 percent for more selective institutions.

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 (Figure 2). 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 in a given school and year, where *U* is unobservable and determined prior to Pell Grant aid. 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):

$$f(Pell, \tau) = \tau_1 Pell \tag{2}$$

In this case, τ_1 can be though of as the pass-through of each additional dollar of outside aid from students to schools. If the required identifying assumptions hold, the RK estimator identifies this parameter:

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

Where efc_0 represents the eligibility threshold for the Pell Grant Program.[12] Since the Pell Grant Program's schedule also contains a discontinuity in the *level* of aid at the eligibility threshold, I

[12] With heterogeneous treatment effects, the RK design estimates the average treatment effect weighted by the probability that an individual is close to the kink: $E[y_1(Pell(efc_0), efc_0, U) \mid EFC = efc_0]$. This is the treatment on the

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 will also identify τ_1 :

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

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.[13] Additionally, variables in the NPSAS contain measurement error induced by random perturbations to preserve respondent confidentiality. Since the location of the eligibility threshold changes over time, I create a standardized measure of EFC: $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the cut-off for Pell Grant eligibility in year t and all students with $\widetilde{EFC}_{it} \geq 0$ are ineligible for Pell Grant aid.[14] Figure 3 displays the empirical distribution of Pell Grant aid by standardized EFC, where $\widetilde{EFC}_{it} = 0$ represents the Pell Grant Program's eligibility threshold.[15]

Consider the following first stage and reduced form equations:

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

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

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 $\mathbf{1}\{\widetilde{EFC}_{it} < 0\}$ is an indicator for Pell Grant eligibility while ρ indexes the degree of polynomial in the assignment variable, $\widetilde{EFC}_{it}$. I include year and school fixed effects to

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treated parameter of Florens et al. (2009), evaluated at $Pell(efc_0)$ and $EFC = efc_0$ (where y_1 is the derivative of the outcome with respect to Pell Grant aid).

[13] Results are robust to eliminating students who do not submit a FAFSA.

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

[15] In a given year, the kink and discontinuity in the relationship between Pell Grant aid and EFC occur at slightly different values of EFC. However, the distance between these points is quite small and only a small fraction of students have an EFC falling on this "plateau" (Figures 3). For the remainder of the paper, 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).

reduce residual variation; these terms are not necessary for identification.[16] The ratio of the reduced form and first-stage coefficients for the interaction between $\mathbf{1}\{\widetilde{EFC}_{it} < 0\}$ and the linear term in $\widetilde{EFC}_{it}$, $\hat{\tau}_{RK} = \frac{\hat{\gamma}}{\hat{\lambda}}$, 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 4A and 4B 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 4A), 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 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 4B illustrates full capture. 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 capture. 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 capture 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

[16] I include a vector of student characteristics to reduce residual variation including gender, race, citizenship, level (e.g., whether the student is a first year, second year, etc.), a quadratic in age, indicators for full time and full year enrollment, and whether the student qualified as in jurisdiction for tuition purposes

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.

Nonetheless, I test for continuity and smoothness in the density of EFC to rule out the possibility that students perfectly manipulate their EFCs. Figure 5 displays the unconditional density of EFC, plotting the proportion of students in each \$100 EFC interval. The x-axis measures the distance from the cut-off for Pell Grant eligibility. I limit the sample to students with $\widetilde{EFC} \in [-2100, 2100]$ because of the large mass of individuals with an EFC of zero.[17] In 1996, a zero EFC corresponds to $\widetilde{EFC} = -2140$, 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:

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

Where b indexes bins, N_b is the number of students in bin b, ρ is a second order polynomial, $\widetilde{EFC}_b$ is the distance from the eligibility threshold, and a test of $\gamma = 0$ estimates

[17] 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.

whether the density function is smooth. Figure 5 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 also examine the distribution of predetermined student characteristics around the eligibility threshold and test for discontinuities in both the slope and level of race, gender, dependency status, attendance intensity, age, level, averaged math and verbal SAT scores, and Adjusted Gross Income (Figures 6A through 6G). I estimate equation (7), where N_b is replaced by X_b, the mean of characteristic X in bin b. I examine the distribution of characteristics up to $10,000 above the cut-off for Pell Grant eligibility; here bins represent $200 EFC intervals. In all cases, I find no evidence of discontinuous changes in slopes or levels and these test statistics are displayed in the respective figures.

Finally, I plot the density of EFC by institutional control and selectivity (Figure 7A through 7E). I find no evidence of a discontinuity in the density or its first derivative among nonselective institutions. Conversely, there is a discontinuous increase in the density of EFC among for selective nonprofit and public schools. This increase is only significant for selective nonprofit institutions. However, the increase in the number of students in selective institutions is offset by an equal reduction in students attending nonselective public schools (Appendix Figures A1A through A1E). Because nonselective public schools enroll a greater number of low-income students, overall, this reduction does not significantly alter the density of EFC near the Pell Grant eligibility threshold in this sector. In other words, students appear to sort into more selective schools in response to Pell Grant eligibility, but this is an outcome of Pell Grant receipt rather than an indication of EFC manipulation, and the degree of such sorting is relatively small. If this sorting is driven by selective admissions, where selective nonprofit and public schools are more likely to accept barely eligible students relative to their barely ineligible counterparts, a rejected application could be viewed as an extreme form of price discrimination.[18]

[18] Unfortunately, the NPSAS only contains information for accepted students who choose to enroll in a specific school, and I cannot determine whether the density of EFC is smooth and continuous among all selective institution applicants. In future work, I plan to use different data to analyze student sorting across sectors in response to the Pell Grant Program. Appendix Figures A1A through A1D show some evidence of discontinuities in the characteristics of students attending selective institutions. The fraction of male students is slightly higher (although very imprecisely estimated) to the left of the eligibility cut-off in selective nonprofit schools, and the average SAT scores are slightly higher among barely eligible Pell Grant recipients attending selective schools

4. Results

4.1 Graphical analysis

Figure 8 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.[19] 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 Pell eligible students.

Figure 9 displays the key parameters for estimating the incidence of Pell Grant aid using RK and RD designs. At the eligibility threshold, the slope of the empirical Pell Grant distribution changes from 0 to -0.50, while the slope of the financial aid function changes from -0.07 to 0.14, resulting in an overall change of 0.21. The ratio of these kinks is analogous to the fuzzy RK estimate of the impact of Pell Grant generosity on institutional aid, suggesting that schools capture around 40 cents of every Pell Grant dollar through a reduction in institutional aid in the neighborhood of the eligibility cut-off. Conversely, the discontinuity in institutional aid is positive at the cut-off for Pell Grant eligibility. Combined with the discontinuous increase in Pell Grant aid at this same point, this finding suggests that institutions *increase* institutional discounts in response to Pell Grant aid.

I replicate this exercise by sector (Figures 10A through 10C). 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 section, suggest that schools within each of these groups respond similarly to need-based aid).

[19] Appendix Figure A2 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 qualitatively similar.

The incidence of Pell Grant aid varies substantially between public and private schools, with public institutions appearing to drive the surprising RD estimate that schools supplement Pell Grants with increased institutional aid.[20] 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 no evidence of a discontinuous change in the level of aid among nonselective private schools (Figure 10B). There is a small, insignificant jump in institutional aid for selective nonprofit schools, but the kink in the institutional aid schedule clearly dominates (Figure 10C).

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 represent the first stage and reduced form estimates. Columns 3 and 4 present separate RK and RD instrument variables estimates. Results are consistent with Figure 9 – RK estimates suggest that institutions capture around 20 cents of every Pell Grant dollar through a reduction in institutional aid while the RD estimator results in a point estimate of 0.48, suggesting schools *increase* institutional aid by close to 50 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 discounts 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 $\widetilde{EFC} \in [-3000, 3000]$.[21] 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

[20] 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.
[21] 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.

degree of polynomial. For all but the largest window, a linear term in standardized EFC provides 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 $p_i = c\mu_i$, 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 $s < c \;\forall i$. Thus, the change in the final price paid by students in group i will be:

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

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).[22] 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.

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 this pattern is only present in certain sectors, while the observable characteristics of students near the Pell Grant eligibility threshold are quite similar across sectors.

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 comes 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 elasticity as well as the weight placed on the group in the schools objective function (α_i) and the

[22] 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 $\frac{dp_i}{ds} = -\frac{da_i}{ds}$.

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:

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

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):

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

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: $p_i = \tau_0 \mathbf{1}[s_i > 0] + \tau_1 s_i + u_i$.[23] 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 increasing school-wide diversity or maximizing (weighted) student welfare. Schools might solve

[23] 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.

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 capture 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 and the kink in the relationship between EFC and Pell Grant aid in a specific school and year:

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

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 $\tau_{RD} = \frac{\tau_0}{400} + \tau_1$, 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 are misleading as to the magnitude and sign of either dimension.

The RK estimator is consistent for 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:

$$\begin{aligned} &\hat{\tau}_1 = \hat{\tau}_{RK} \\ &\hat{\tau}_0 = \left(\hat{\tau}_{RD} - \hat{\tau}_{RK}\right) \cdot 400 \end{aligned} \tag{11}$$

Where $\hat{\tau}_{RD}$ 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, the pass-through of Pell Grant aid is approximately 0.22, suggesting institutions capture 22 cents of every additional dollar of Pell Grant aid. However, due to schools' willingness to pay for Pell Grant recipients, these students experience a $300 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 16 percent increase in the expected value of institutional aid. However, only Pell Grant recipients near the eligibility threshold benefit from these transfers, and these students make up less than 30 percent 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 10A through 10C suggest that capture of 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. Nonselective private institutions are the only schools that do not demonstrate a willingness to pay for Pell Grant recipients. These schools capture 12 to 16 cents from every dollar of Pell Grant aid from students near the eligibility threshold. Conversely, public schools and selective nonprofit schools increase institutional aid for recipients by $200 to $440 in public schools and $340 in selective private institutions. Due to large standard errors, I cannot reject equality of this parameter across public and selective private institutions, although for the latter schools, this estimate is only marginally significant.

While public schools capture between 16 and 19 cents of every Pell Grant dollar, pass-through of Pell Grant aid is the largest among selective nonprofit institutions. These schools capture 64 cents every Pell Grant dollar, and these schools' willingness to pay for Pell Grant recipients is quickly overtaken by schools' ability to capture outside aid. Very few Pell Grant recipients in this sector benefit from schools' willingness to pay for needy students. This result suggests that while public and selective nonprofit schools put equal weight on serving Pell Grant recipients, selective nonprofits either serve students with less elastic demand near the eligibility threshold or have greater market power.

5.2 Heterogeneity by student and market characteristics

To determine whether differences in student demand 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 selective nonprofit institutions' greater degree of capture stems from serving students with less elastic demand. I group public schools and nonselective nonprofit institutions to increase power.

Across all student groups, capture of Pell Grant aid is significantly greater for students attending selective nonprofit institutions except in the case of independent students, where differences in capture are not significant. Across all sectors of higher education, significantly less Pell Grant aid is captured from independent students compared to other groups, suggesting these students have more elastic demand. Schools demonstrate a positive willingness to pay for Pell Grant recipients across all groups in the public sector and all groups besides independent students attending selective nonprofit schools. These results suggest that differences in the types of students served cannot explain selective nonprofit institutions' large degree of capture.

Measuring schools' market power is a more difficult task. If institutions are more likely to enter less competitive markets, estimates of market concentration will be endogenous. I create a proxy for the *ex ante* degree of competition in a school's market to address this concern. 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). Although many 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. From the 1990 decennial census, I measure the number of college-aged adults – those between 18 and 34 years of age. I create a simple measure of the *ex ante* tightness of a market by calculating the number of institutions per 1,000 college-aged adults within a given county in 1990.

I find no evidence that capture or willingness to pay for Pell recipients varies in any sector by this measure of competition using both a dichotomous indicator for markets that are *ex ante* more competitive or with a more flexible interaction (results available upon request). However, my measure of market power is admittedly blunt; for instance, it is not clear whether selective nonprofit institutions compete with for-profit schools in their county for Pell Grant recipients. Additionally, Bresnahan and Reiss (1991) show there are large nonlinearities in number of competitors and resulting behavior in other markets. However, the market for higher education also has substantial barriers to entry, since schools face large fixed costs (e.g., investments in facilities). 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.

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 increases in student aid lead to increases in for-profit entry. If for-profit institutions retain captured Pell Grant aid as profits, my results provide a rationale for this response. In Appendix C, I present suggestive evidence of institutions' use of captured Pell Grant aid indicating schools retain these funds as profits rather than increasing expenditures on instruction, student services, or other activities (Tables C2 and C3). Unless barriers to entry or other market imperfections lead to persistent rents, 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. Although I find no difference in capture according to schools' *ex ante* market power, future work will further investigate the longer-run incidence of Pell Grant and other federal aid.

6. Total Incidence

So far, I have only focused on estimating the incidence of need-based 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 total incidence of the Pell Grant program, or the average treatment effect 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 11 provides an illustration of my approach. The shaded area under the Pell Grant curve represents the increase in consumer surplus due to the Pell Grant Program (ΔCS). 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, $\frac{A-B}{\Delta CS}$, 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, institutions capture 17 percent of Pell Grant aid through price discrimination (Table 7). Nonselective private institutions, a category encompassing nonprofit and for-profit schools, capture 22 percent of Pell Grant aid while selective nonprofit institutions capture 66 percent. This latter result is consistent with the estimated capture parameter (Table 5), suggesting that transfers to Pell Grant recipients, due to selective nonprofit institutions' willingness to pay for needy students, are very small relative to overall capture. In the public sector, net capture of Pell Grant aid is zero. The point estimate is small and negative. 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 10A).

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 17 percent of all Pell Grant aid. However, this result masks important variation in capture 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.[24] 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 by showing how schools' responses to Pell Grant aid illustrates differences in schools' objectives and market power across sectors. Both selective nonprofit and public schools demonstrate a positive willingness to pay for Pell Grant recipients. However, students attending selective nonprofit institutions see these transfers almost immediately overtaken by capture of additional Pell Grant aid. Overall, selective nonprofit institutions capture 66 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 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. Finally, I find no evidence that for-profit institutions behave differently than other nonselective schools in the private sector with respect to price discrimination, and combined schools in this sector capture 22 percent of all Pell Grant aid.

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 17 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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[24] 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.

References

Angrist, J. D. (1993) "The Effect of Veterans Benefits on Education and Earnings," Industrial and Labor Relations Review 46(4): 637-52.

Angrist, J. D. and Lavy, V. (1999) "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement," Quarterly Journal of Economics 114(2): 533-75.

Bettinger, E. (2004) "How Financial Aid Affects Persistence," in College Choices: The Economics of Where to Go, When to Go, and How to Pay for it, Hoxby, C. (Ed), NBER.

Bettinger, E., Long, B. T., Oreopoulos, P., and Sanbonmatsu, L. (2009) "The Role of Simplification and Information in College Decisions: Results from the H&R Block FAFSA Experiment," NBER Working Paper 15361.

Bound, J. and Turner, S. (2002) "Going to War and Going to College: Did World War II and the G.I. Bill Increase Educational Attainment for Returning Veterans?" Journal of Labor Economics, 20(4): 784-815.

Bresnahan, T. F. and Reiss, P. C. (1991) "Entry and Competition in Concentrated Markets," Journal of Political Economy 99(5): 977-1009.

Bulow, J. I. and Pfleiderer, P. (1983) "A Note on the Effect of Cost Changes on Price," Journal of Political Economy 91(1): 182-5.

Card, D. (1999) "The Causal Effect of Education on Earnings," in Handbook of Labor Economics Volume 3, Ashenfelter, O. and Card, D. (Eds), Elsevier: Amsterdam.

Card, D., Lee, D. S., and Pei, Z. (2009) "Quasi-Experimental Identification and Estimation in the Regression Kink Design," Princeton University Industrial Relations Section Working Paper 553.

Cellini, S. R. (2010) "Financial Aid and For-Profit Colleges: Does Aid Encourage Entry?" Journal of Policy Analysis and Management 29(3): 526-52.

Cellini, S. R. and Chaudhary, L. (2011) "The Labor Market Returns to a Private Two-Year College Education," working paper.

Charles, K. K., Hurst, E., and Stephens, M. (2008) "Rates for Vehicle Loans: Race and Loan Source," American Economic Review 98(2): 315-20.

Dee, T. S. "Are there Civic Returns to Education?" Journal of Public Economics 88: 1697-1720.

Deming, D. and Dynarski, S. (forthcoming) "Into College, Out of Poverty? Policies to Increase the Postsecondary Attainment of the Poor," in Targeting Investments in Children: Fighting Poverty When Resources are Limited, Levine, P. and Zimmerman, D. (Eds.) University of Chicago Press.

Deming, D., Goldin, C., and Katz, L. F. (forthcoming) “The For-Profit Post Secondary School Sector,” Journal of Economic Perspectives.

Dynarski, S. (2003) “Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion,” American Economic Review, 93(1): 279-88.

Dynarski, S. and Scott-Clayton, J. (2008) “Complexity and Targeting in Federal Student Aid: A Quantitative Analysis,” in Tax Policy and the Economy, Volume 22, Poterba, J. (Ed), NBER: Cambridge, MA.

Florens, J. P., Heckman, J. J., Meghir, C., and Vytlacil E. (2008) “Identification of Treatment Effects using Control Functions in Models with Continuous Endogenous Treatment and Heterogeneous Effects,” Econometrica 76(5): 1191-1206.

Fullerton, D. and Metcalf, G. (2002) "Tax incidence," Handbook of Public Economics, in: Auerbach, A. J. and Feldstein, M. (Eds.), Handbook of Public Economics 1(4): 1787-1872.

Hahn, J., Todd, P., and Van der Klauuw, W. (2001) “Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design,” Econometrica 69(1): 201-209.

Hansmann, H. B. (1980) “The Role of the Nonprofit Enterprise,” Yale Law Review 89: 835-901.

Hastings, J. and Washington E. (2010) “The First of the Month Effect: Consumer Behavior and Store Response,” American Economic Journal: Economic Policy 2(2): 142-62.

Horn, L. and Nevill, S. (2006) “Profile of Undergraduates in U.S. Postsecondary Education Institutions: 2003-04: With a Special Analysis of Community College Students,” NCES 2006-184. U.S. Department of Education, Washington, DC: NCES.

Hoxby, C. (2000) “The Effects of Class Size on Student Achievement: New Evidence from Population Variation,” Quarterly Journal of Economics 115(4): 1239-85.

Kane, T. (1995) “Rising Public Tuition and College Entry: How Well Do Public Subsidies Promote Access to College?” NBER Working Paper 5164.

Lazear, E. (2001) “Educational Production,” Quarterly Journal of Economics 116(3): 777-803.

Lee, D. S. (2008) “Randomized Experiments from Non-random Selection in U.S. House Elections,” Journal of Econometrics 142(2): 675-97.

Lee, D. S., and Lemieux, T. (2010) “Regression Discontinuity Designs in Economics,” Journal of Economic Literature 48(2): 281-355.

Long, B. (2004) “How do Financial Aid Policies Affect Colleges? The Institutional Impact of the Georgia HOPE Scholarship,” Journal of Human Resources 39(4): 1045-66.

Lochner, L. and Moretti, E. (2004) "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports," American Economic Review 94(1): 155-89.

McPherson, M. and Schapiro, M. (1991) Keeping College Affordable: Government and Educational Opportunity. Washington, DC: Brookings Institution.

Moretti, E. (2004) "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions," American Economic Review 94(3): 656-90.

National Center for Education Statistics (2011). "Digest of Education Statistics, 2010." Washington DC: U.S. Department of Education.

Nielsen, H. S., Sorensen, T., and Taber, C. (2010) "Estimating the Effect of Student Aid on College Enrollment: Evidence from a Government Grant Policy Reform," American Economic Journal: Economic Policy 2(2): 185-215.

Rothstein, J. (2008) "The Unintended Consequences of Encouraging Work: Tax Incidence and the EITC," Princeton University Center for Economic Policy Studies Working Paper 165.

Rothstein, J. and Rouse, C. E. (2011) "Constrained After College: Student Loans and Early-Career Occupational Choices," Journal of Public Economics 95: 149-63.

Seftor, N. and Turner, S. (2002) "Back to School: Federal Student Aid Policy and Adult College Enrollment," Journal of Human Resources, 37(2): 336-52.

Singell, L. and Stone, J. (2007) "For Whom the Pell Tolls: The Response of University Tuition to Federal Grants-in-Aid," Economics of Education Review 26: 285-95.

Turner, N. (2011) "Who Benefits from Student Aid: The Economic Incidence of Tax-Based Student Aid," working paper.

Urquiola, M. (2006) "Identifying Class Size Effects in Developing Countries: Evidence from Rural Bolivia," Review of Economics and Statistics 88(1): 171-77.

U.S. Department of Education (2006). The EFC Formula Guide 2006-2007. Washington, DC.

U.S. Government Accountability Office (2010). For-Profit Colleges: Undercover Testing Finds Colleges Encouraged Fraud and Engaged in Deceptive and Questionable Marketing Practices (Publication No. GAO-10-948T). Washington, DC.

Weyl, E. G. and Fabinger, M. (2011) "A Restatement of the Theory of Monopoly," working paper.

Yinger, J. (1998) "Evidence on Discrimination in Consumer Markets," Journal of Economic Perspectives 12(2): 23-40.

Figure 1: Time Series Variation in Maximum Pell Grant Award

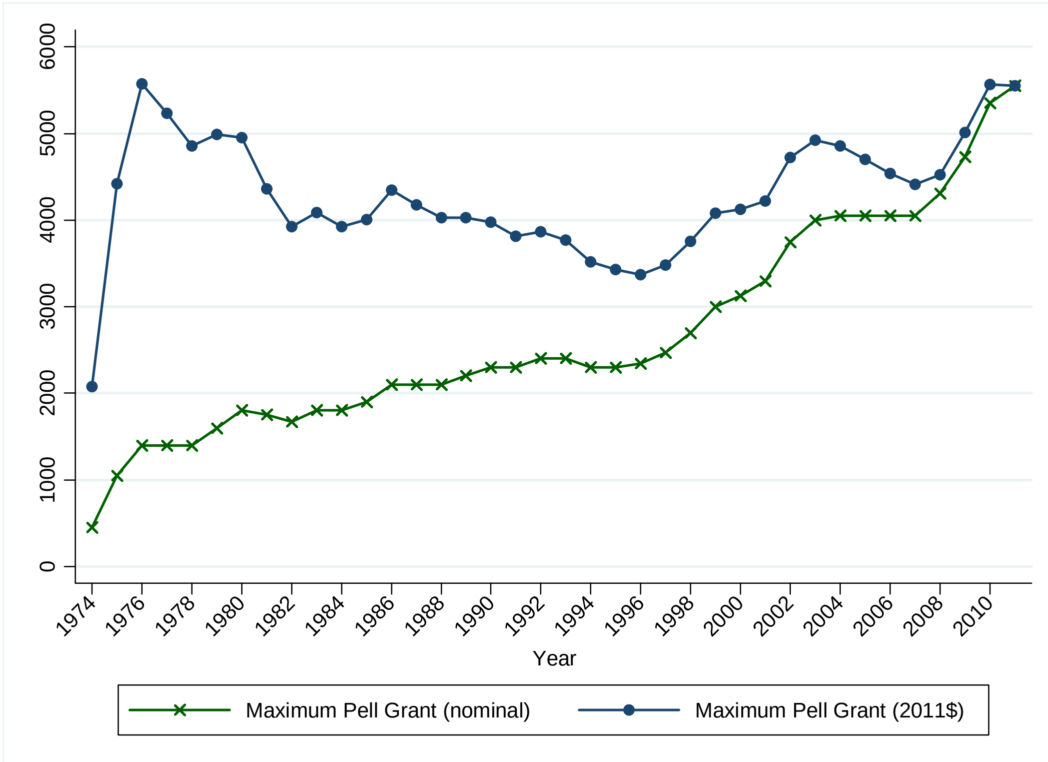
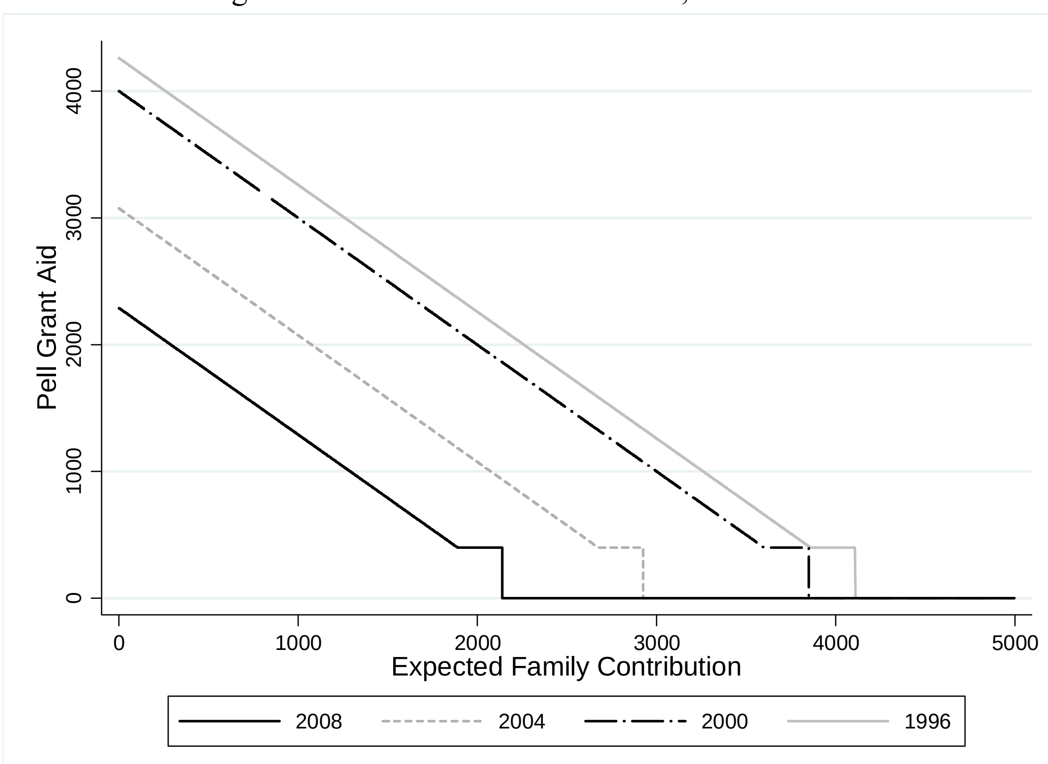
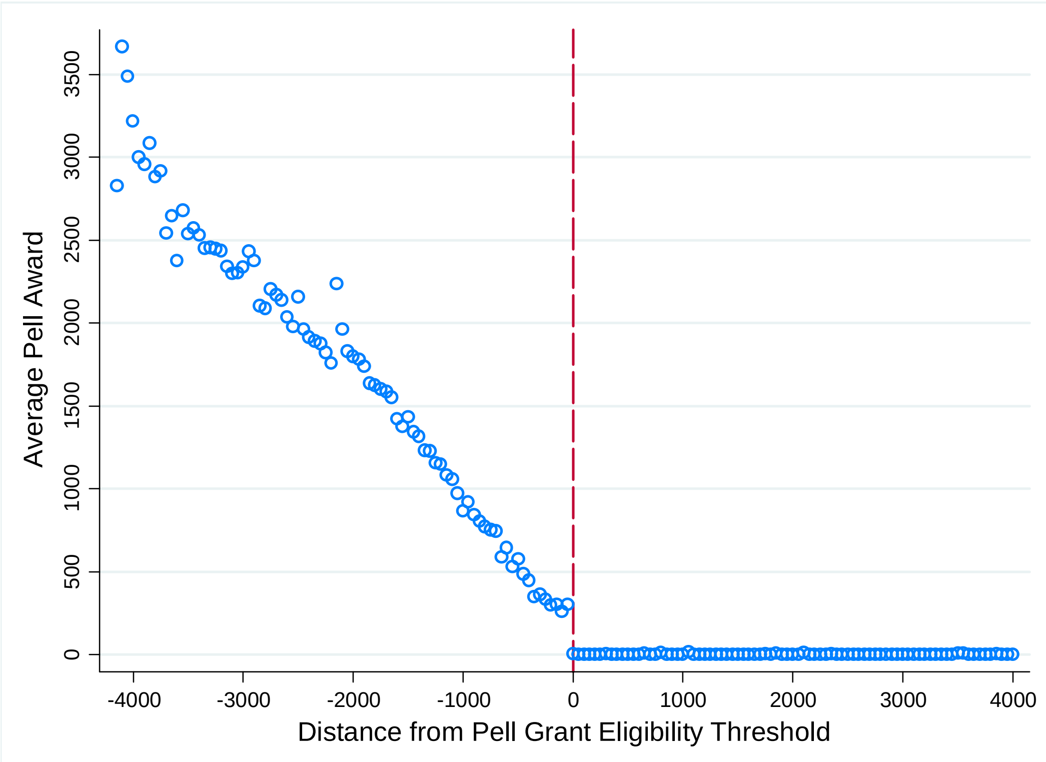


Figure 2: Pell Grant Award Schedule, 1996 – 2008



Note: All dollar amounts are nominal. Pell awards are for full-time, full-year students.

Figure 3: The Empirical Distribution of Pell Grant Aid



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

Figure 4: Conceptual Framework, RK/RD Design

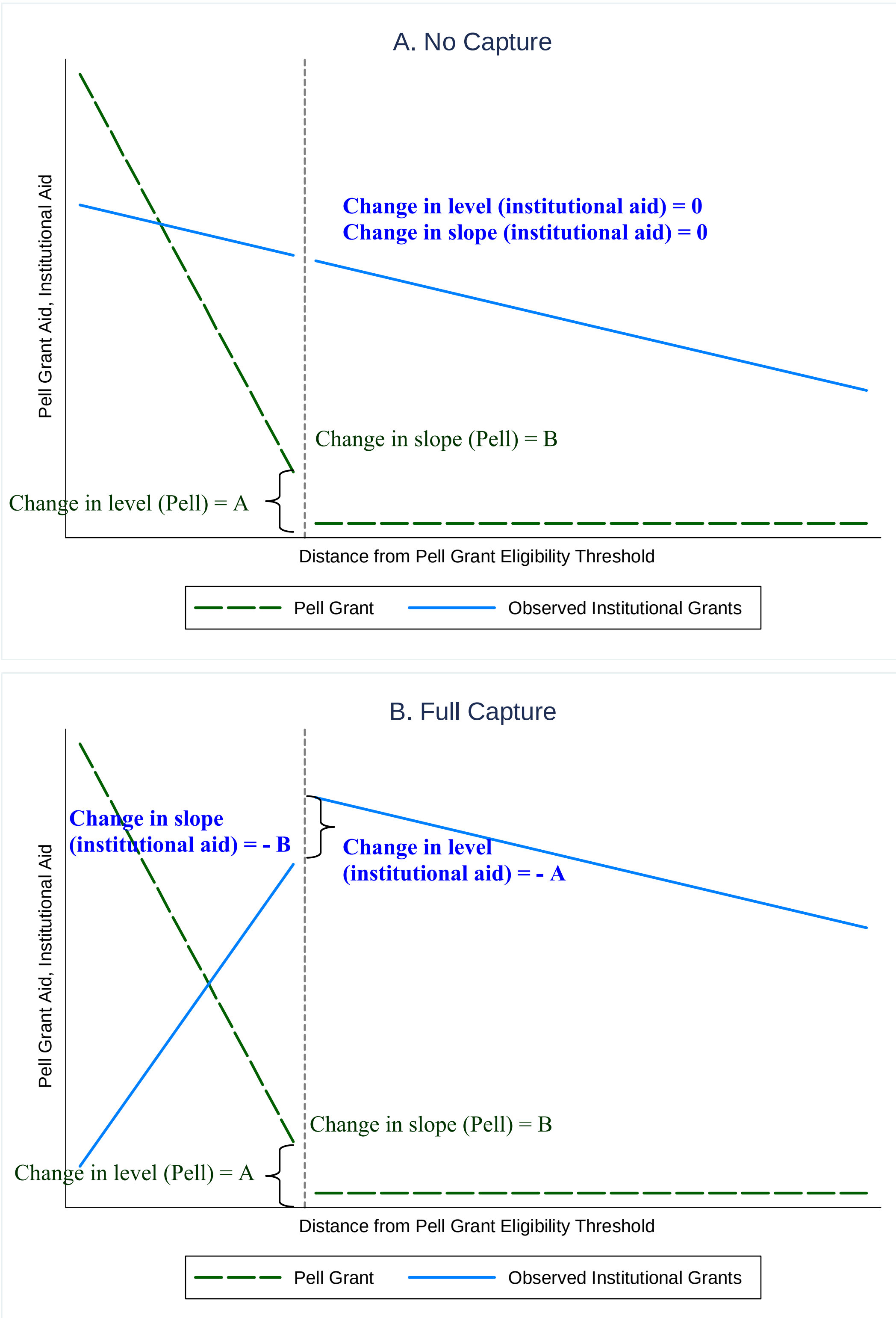
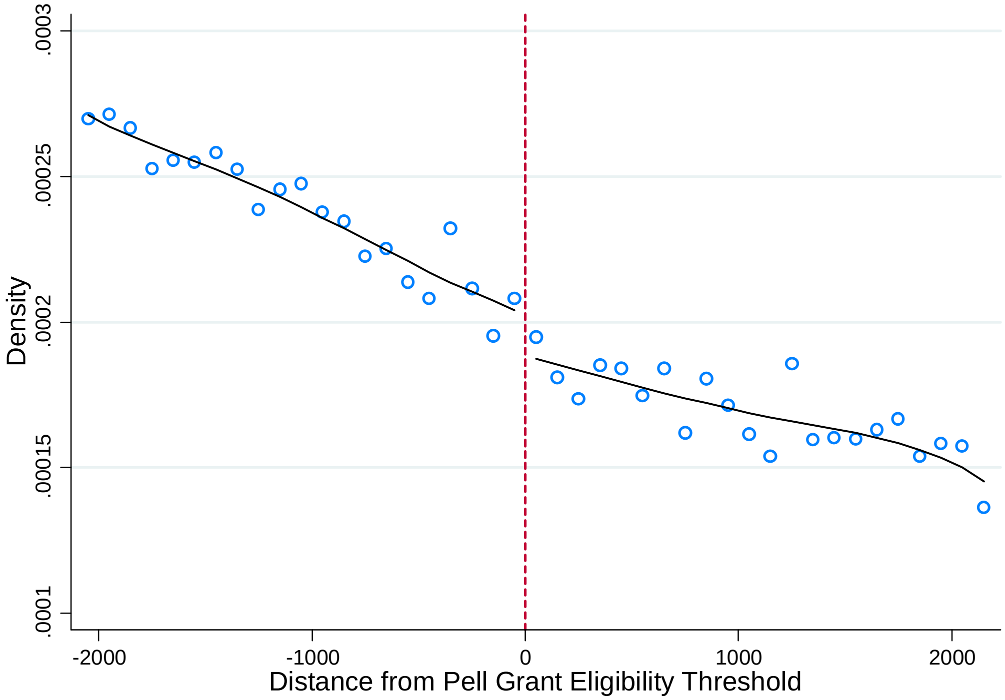


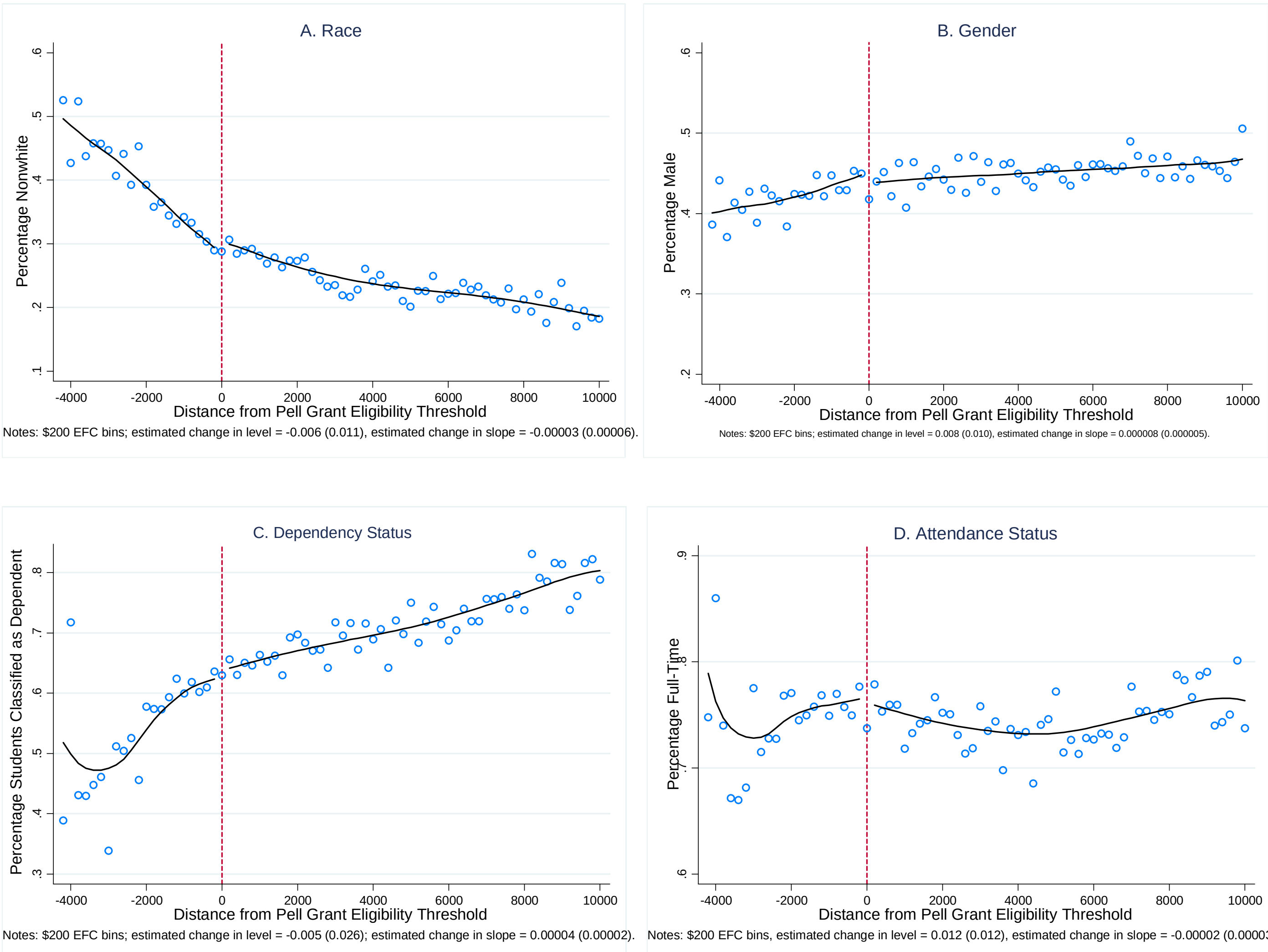
Figure 5: The Density of EFC at the Pell Grant Eligibility Cut-Off

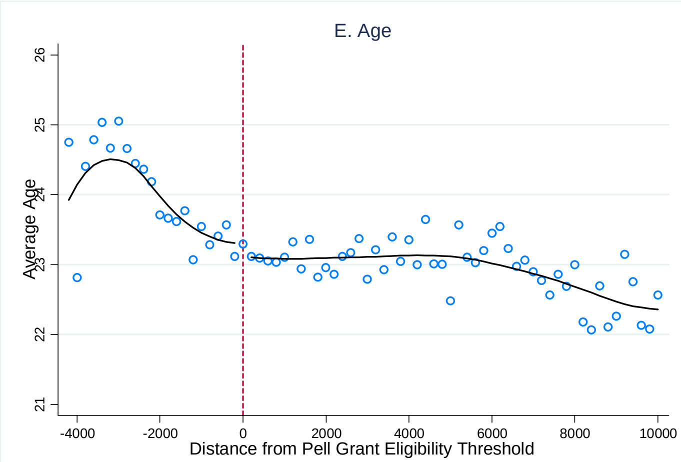


Notes: $100 EFC bins; discontinuity test stat = 0.039 (0.049); estimated change in slope = -0.097 (0.074).

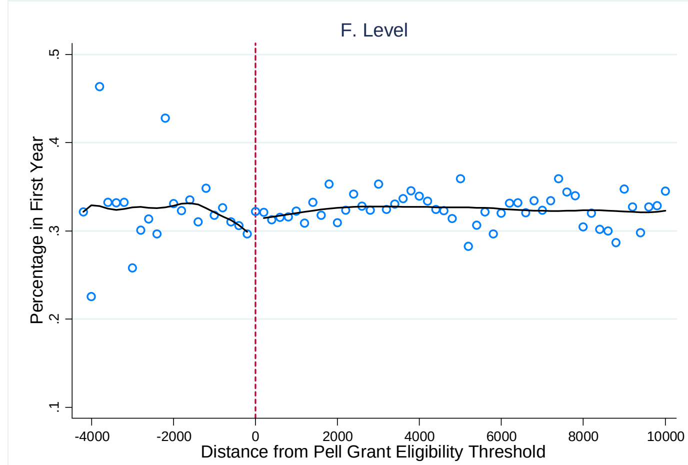
Figure 6: The Distribution of Baseline Covariates

Note: The black solid lines represent local linear regression estimates of demographic characteristics on EFC, estimated separately on each side of the cut-off.

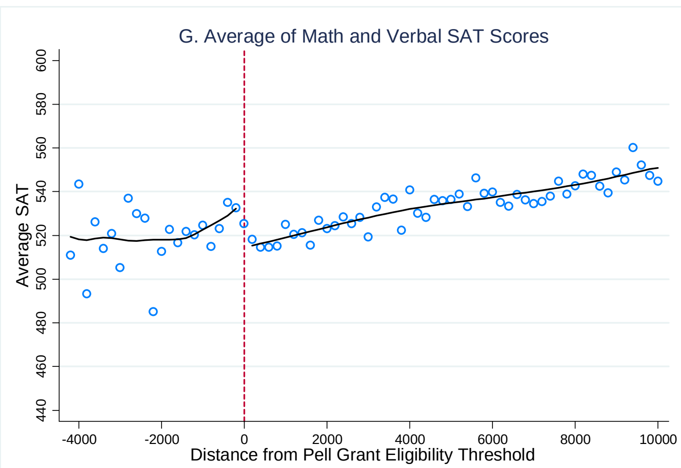




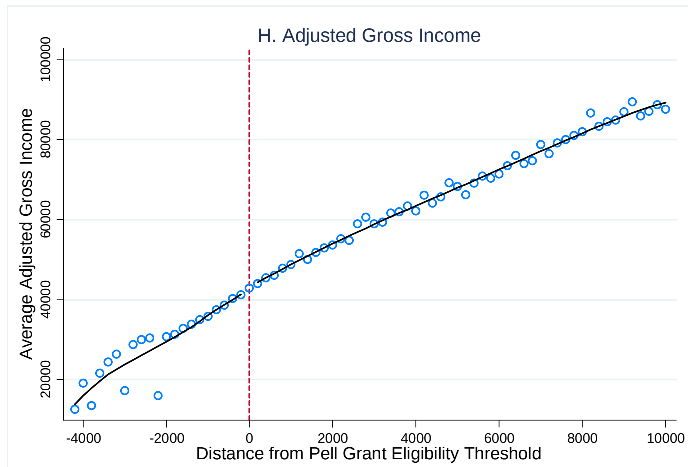
Notes: $200 EFC bins, estimated change in level = 0.152 (0.218), estimated change in slope = -0.0006 (0.0001)



Notes: $200 EFC bins, estimated change in level = -0.003 (0.018), estimated change in slope = -0.000007 (0.000009).



Notes: $200 EFC bins, estimated change in level = 7.20 (4.94), estimated change in slope = -0.002 (0.003).



Notes: $200 EFC bins;Estimated change in level = -1326.91 (1420.26); estimated change in slope = 0.806 (0.782).

Figure 7: The Density of EFC at the Pell Grant Eligibility Cut-off, by Sector

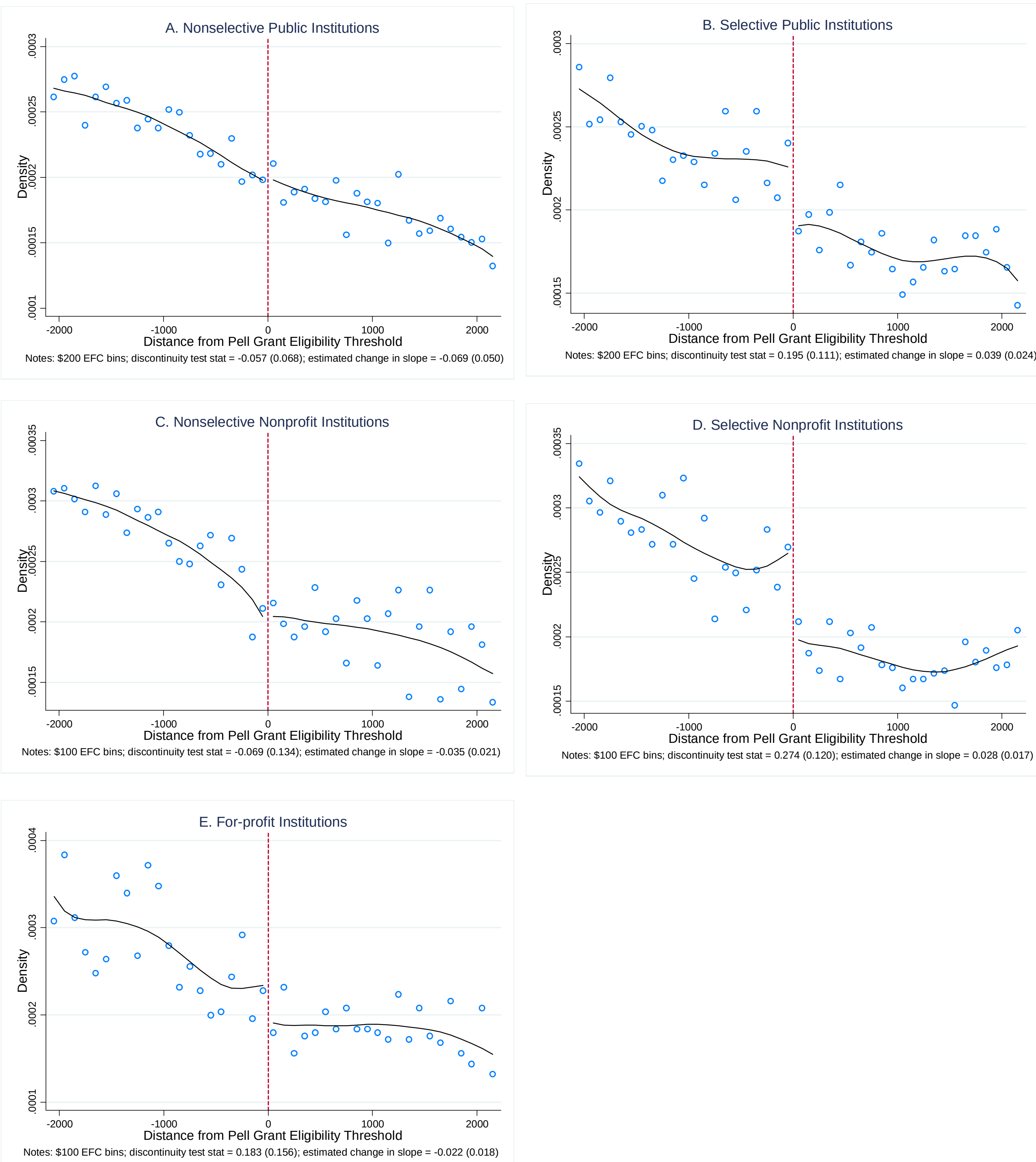
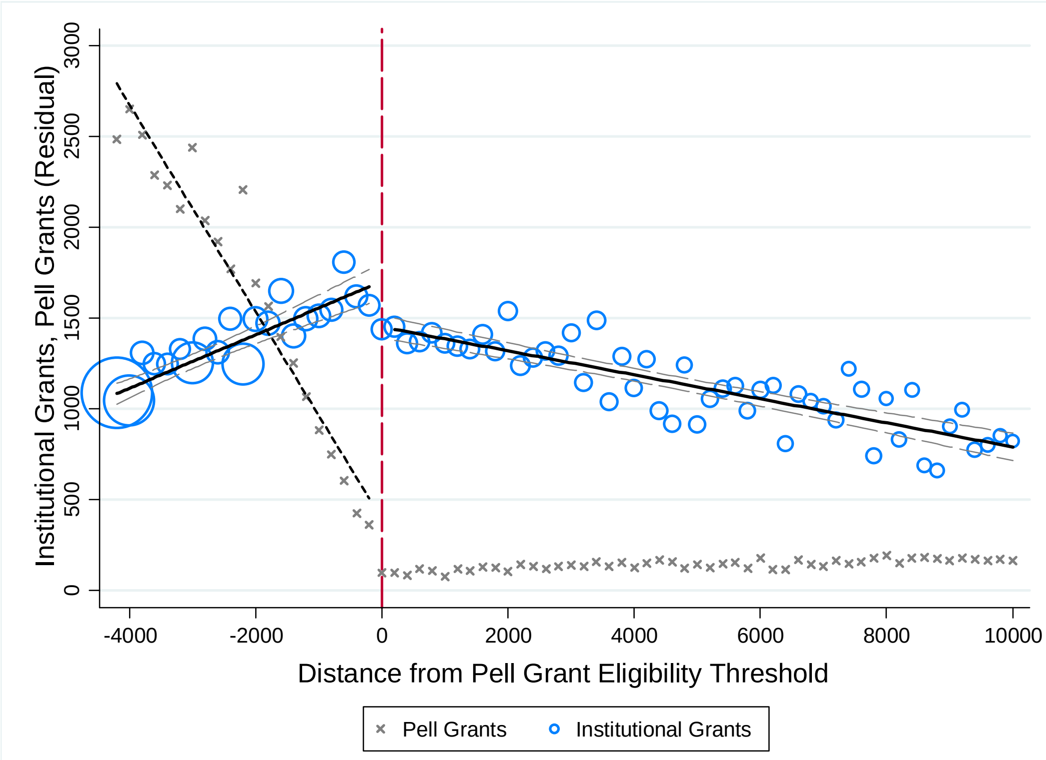
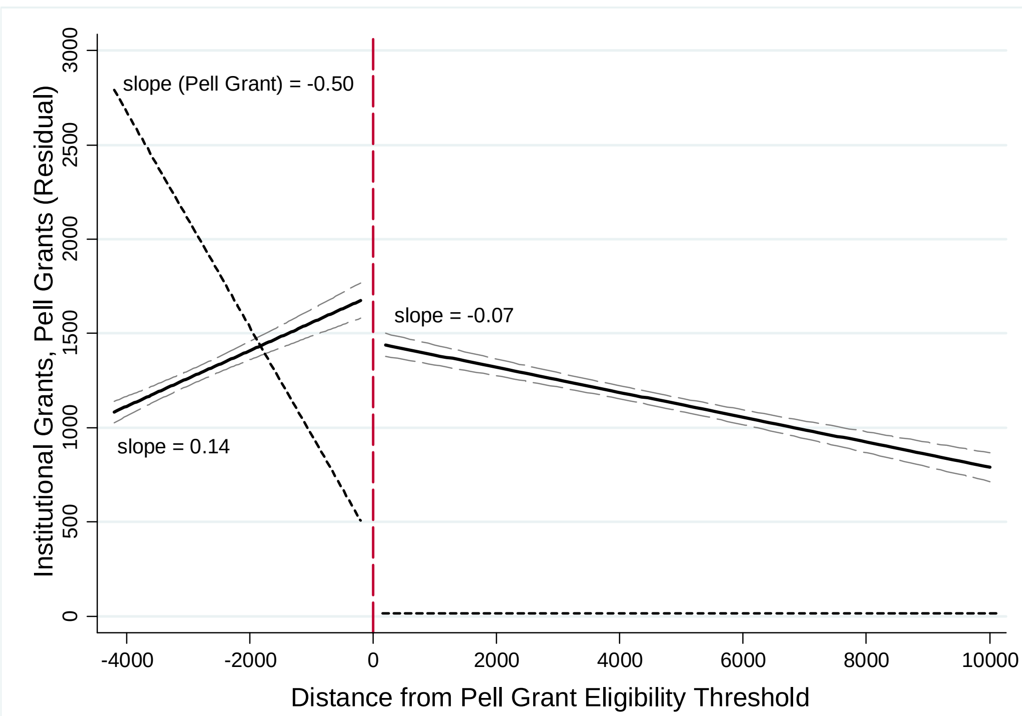


Figure 8: Pell Grant Generosity and Institutional Aid by EFC



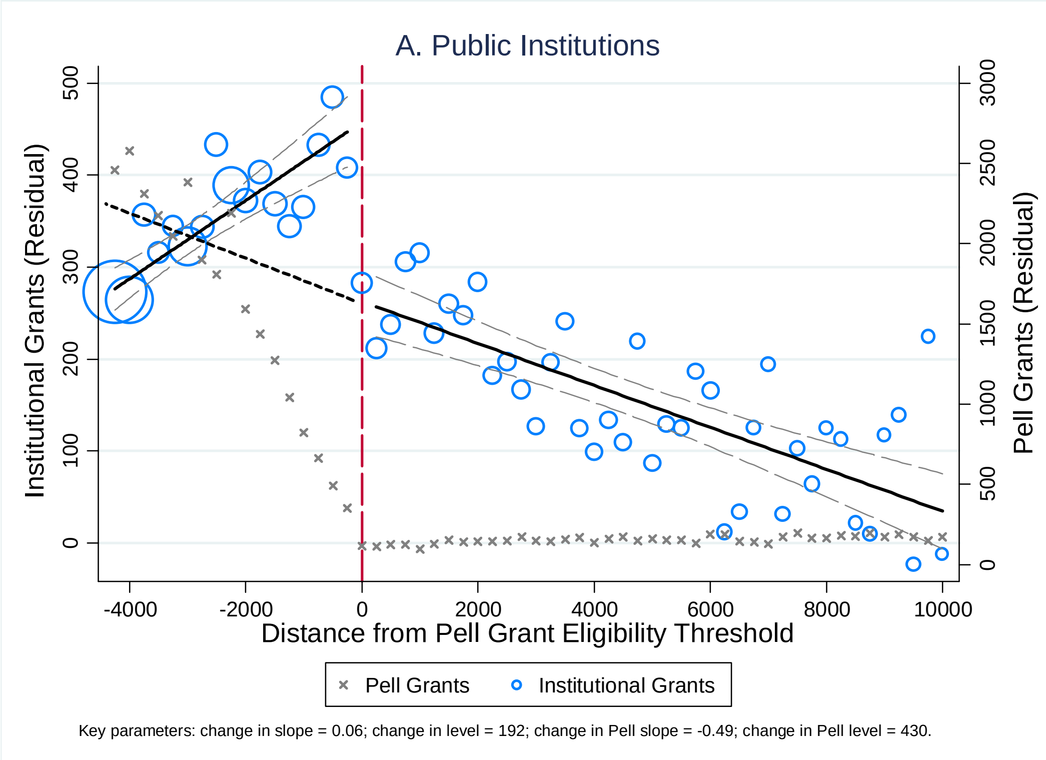
Note: $200 EFC bins. The black solid line represents a linear fit of institutional aid on EFC, estimated separately on each side of the cut-off; gray dashed lines are 95 percent confidence intervals. The black dashed line represents a linear fit of Pell Grant aid on EFC.

Figure 9: Key Parameters

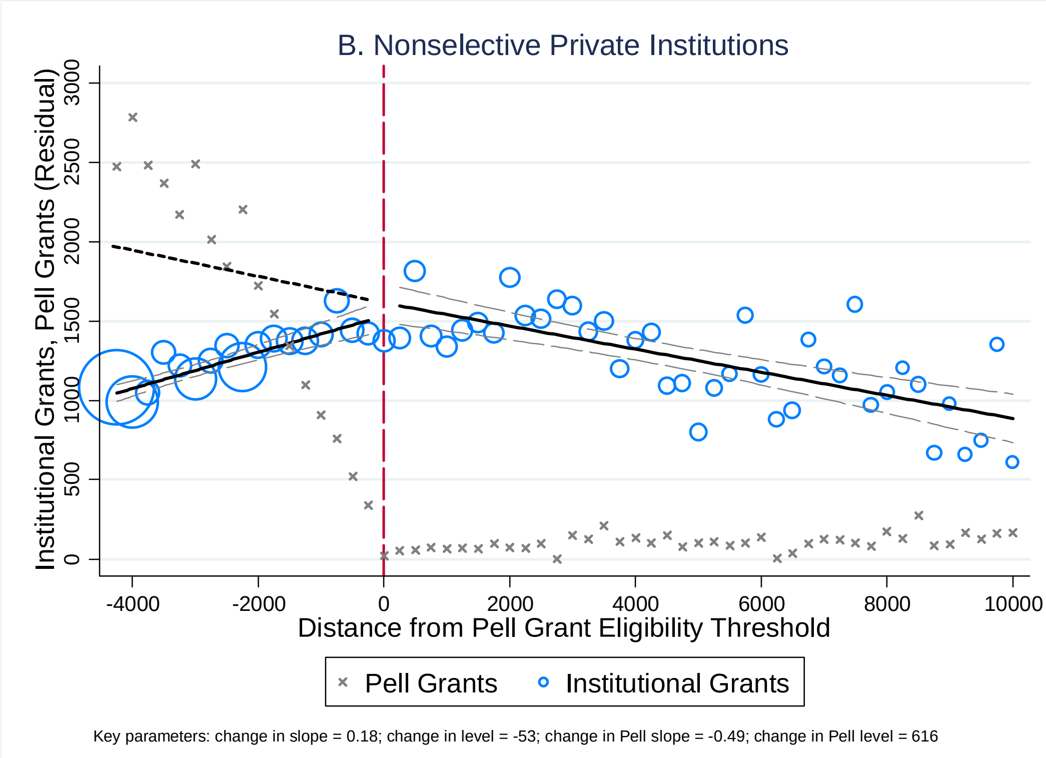


Note: Change in Pell Grant level = 561; change in institutional aid level = 247.

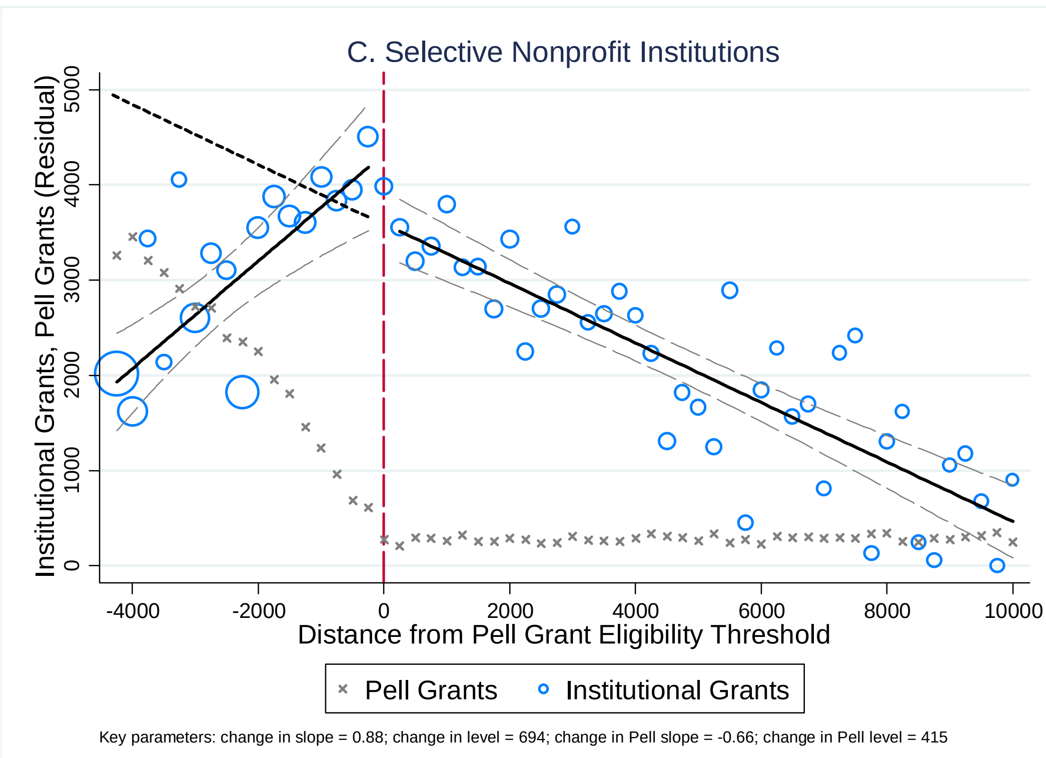
Figure 10: Pell Grant Incidence by Sector:



Notes: $250 EFC bins. The black solid line represents a linear fit of institutional 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.

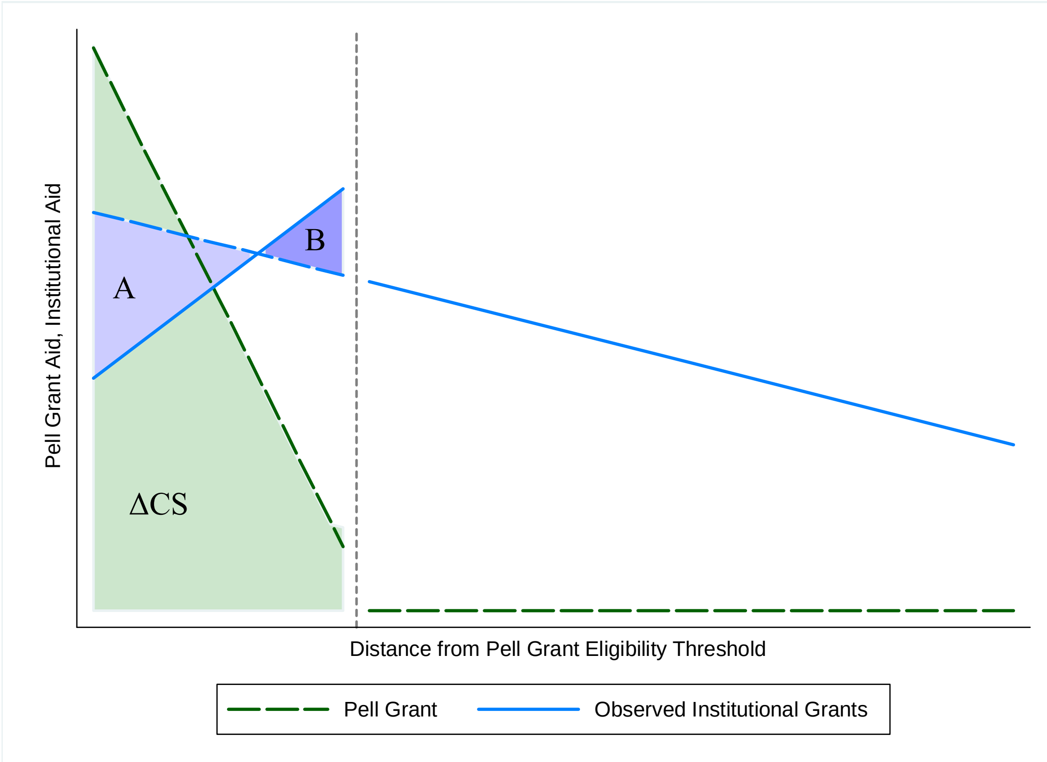


Notes: See Figure 10A notes.



Notes: See Figure 10A notes.

Figure 11: Framework for Estimating the Total Incidence of Pell Grant Aid



Notes: The area labeled ΔCS represents the total increase in consumer surplus due to Pell Grant aid. The areas A and B represent the difference between the area below the counterfactual Pell Grant-EFC relationship (represented by the dashed line) and the actual Pell Grant-EFC relationship for Pell eligible students (represented by the solid line); A-B represents the amount of institutional aid students did not receive due to the Pell Grant Program. See Section 6.

Table 1: Characteristics of Schools and Students

	Nonselective Institutions			Selective Institutions		All Schools
	Public	Nonprofit	For-profit	Public	Nonprofit	
Number of Students	69,820	16,110	14,780	51,060	28,790	180,560
Number of Unique Schools	860	320	340	280	460	2,270
Student Financial Aid						
Percentage receiving Pell Grants	0.36	0.39	0.54	0.30	0.27	0.34
Pell Grant aid (nonzero)	$2,782	$2,931	$2,930	$2,935	$2,900	$2,868
Percentage receiving institutional aid	0.12	0.43	0.10	0.25	0.64	0.27
Institutional aid (nonzero)	$1,942	$6,251	$2,955	$3,619	$10,645	$6,377
Net Tuition (tuition - institutional aid)	$2,363	$9,910	$11,942	$5,186	$15,432	$6,703
Student Demographic Characteristics						
Non-white	0.37	0.36	0.50	0.26	0.24	0.33
Male	0.42	0.40	0.43	0.46	0.43	0.43
Classified as dependent	0.52	0.54	0.35	0.75	0.80	0.62
Age	25	25	26	22	22	24
Expected Family Contribution	$7,355	$8,219	$5,405	$10,774	$13,218	$9,174
Student Attendance Status						
Full-time	0.59	0.78	0.73	0.87	0.91	0.75
Months of enrollment	10.3	10.1	9.8	10.8	10.5	10.4
First-year/freshman	0.37	0.28	0.35	0.20	0.24	0.29

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 who attended multiple institutions during the academic year, students that were not enrolled during the fall semester, athletic scholarship recipients, noncitizens, and students attending nondegree granting institutions, theological seminaries, and faith-based institutions.

Table 2: Institutional Revenue and Expenditures

	Nonselective Institutions			Selective Institutions		All Schools
	Public	Nonprofit	For-profit	Public	Nonprofit	
Average Undergraduate FTE Students	6,730	5,250	2,610	12,390	3,450	6,460
Number of Unique Schools[1]	770	260	270	260	430	2,000
Total Revenue ($100k)	$1,795	$1,879	$6,070	$9,115	$8,554	$5,361
Total Expenditures ($100K)	$2,052	$1,634	$3,881	$11,867	$9,198	$6,399
Revenue - Expenditures ($100K)	-$257	$245	$2,189	-$2,752	-$644	-$1,038
Pell Grants ($100k)	$114	$47	$839	$131	$43	$135
Pell Grants as a % of Total Revenue	0.06	0.03	0.14	0.01	0.01	0.03

Notes: Data: 2000, 2004, 2008 NPSAS and IPEDS. 1. Number of observations rounded to nearest 10; All dollar amounts in 2011$. Sample includes schools serving students described in Table 1 with 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	-0.717	0.161		
	(0.007)**	(0.031)**		
Change in levels	368.100	185.035		
	(12.043)**	(44.263)**		
Pell Grant Aid			-0.224	0.503
			(0.043)**	(0.120)**
F-test of excluded instrument(s)			8772	1028
Over-id test (p-value)			0.000	
Observations	138170	138170	138170	138170

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 awards 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, attendance status, enrollment length, year of college attendance, dependency status, out-of-state student, and a quadratic in student expected family contribution (EFC). In column 3, $\mathbf{1}\{EFC<k_t\}$ instruments for Pell Grant Aid. In column 4, $(EFC - k_t)*\mathbf{1}\{EFC<k_t\}$ instruments for Pell Grant Aid. Students with EFC greater than 10,000 from Pell Grant cut-off are excluded. Regressions are unweighted.

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

	Polynomial of Order:	IV (RK) (1)	IV (RD) (2)
($EFC-k_t$) in [-4100,10000]	One	-0.288	0.509
		(0.023)**	(0.129)**
	Two	-0.224	0.503
		(0.043)**	(0.120)**
	Three	-0.053	0.596
		(0.070)	(0.196)**
Optimal Degree		2	2
Observations		138170	138170
($EFC-k_t$) in [-4000,4000]	One	-0.178	0.525
		(0.030)**	(0.202)**
	Two	-0.182	0.593
		(0.107)+	(0.229)**
	Three	-0.190	0.997
		(0.110)+	(0.530)+
Optimal Degree		1	1
Observations		89990	89990
($EFC-k_t$) in [-3000, 3000]	One	-0.189	0.736
		(0.047)**	(0.309)*
	Two	-0.279	0.844
		(0.137)*	(0.346)*
	Three	-0.301	2.099
		(0.145)*	(1.195)+
Optimal Degree		1	1
Observations		64360	64360

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 awards 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, attendance status, enrollment length, year of college attendance, dependency status, out-of-state student, and a quadratic in student expected family contribution (EFC). In column 1, $\mathbf{1}\{EFC<k_t\}$ instruments for Pell Grant Aid. In column 2, $(EFC - k_t)*\mathbf{1}\{EFC<k_t\}$ instruments for Pell Grant Aid. Optimal degree of polynomial for each bandwidth determine using the minimum Akaike Information Criteria. Regressions are unweighted.

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

	Capture	Willingness to Pay
A. All institutions	-0.224	290.7
	(0.043)**	(48.2)**
Observations	138170	
B. By sector		
Public Nonselective	-0.189	428.9
	(0.017)**	(63.1)**
Public Selective	-0.158	461.7
	(0.031)**	(91.1)**
Nonprofit Nonselective	-0.160	-236.9
	(0.070)*	(186.8)
Nonprofit Selective	-0.639	339.8
	(0.092)**	(217.7)
For-profit	-0.115	35.7
	(0.030)**	(67.5)
Observations	138170	

Notes: Each 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 awards 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, attendance status, enrollment length, year of college attendance, 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. Regressions are unweighted. 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						
Capture	-0.203	-0.178	-0.054	-0.233	-0.212	-0.183
	(0.030)**	(0.022)**	(0.016)**	(0.024)**	(0.021)**	(0.025)**
Willingness to pay	638.1	329.2	409.12	438.24	387.5	500.0
	(108.0)**	(53.7)**	(151.0)**	(67.3)**	(55.2)**	(94.4)**
Private Nonselective						
Capture	-0.100	-0.191	0.001	-0.191	-0.149	-0.169
	(0.048)*	(0.054)**	(0.031)	(0.064)**	(0.051)**	(0.053)**
Willingness to pay	-75.3	-83.5	-217.9	-203.2	-35.5	-162.7
	(137.9)	(137.0)	(106.4)*	(160.2)	(138.3)	(141.1)
Nonprofit Selective						
Capture	-0.453	-0.853	0.068	-0.531	-0.641	-0.627
	(0.158)**	(0.120)**	(0.144)	(0.098)**	(0.115)**	(0.144)**
Willingness to pay	-113.4	504.0	-572.0	246.5	122.0	618.4
	(563.6)	(223.9)*	(534.4)	(260.6)	(301.7)	(333.4)+
Observations	51060	87110	61500	76660	80180	57990

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 awards 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, attendance status, enrollment length, year of college attendance, dependency status, out-of-state student, and a linear term in student expected family contribution (EFC). Students with EFC greater than 10,000 from Pell Grant cut-off are excluded. Regressions are unweighted. See text for definitions of capture and willingness to pay parameters.

Table 7: Total Incidence of Pell Grant Aid

	Percent Captured	95% CI
All Institutions	0.166	[0.095, 0.247]
Public Institutions	-0.001	[-0.004, 0.041]
Nonselective Private Institutions	0.216	[0.035,0.396]
Selective Nonprofit Institutions	0.664	[0.345,0.982]

Notes: These estimates assume the 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 (Section 6).

Appendix A: Supplemental Figures

Figure A1: The Distribution of Select Baseline Covariates, by Sector

Note: Black solid lines represent local linear regression estimates of demographic characteristics on EFC, estimated separately on each side of the cut-off.

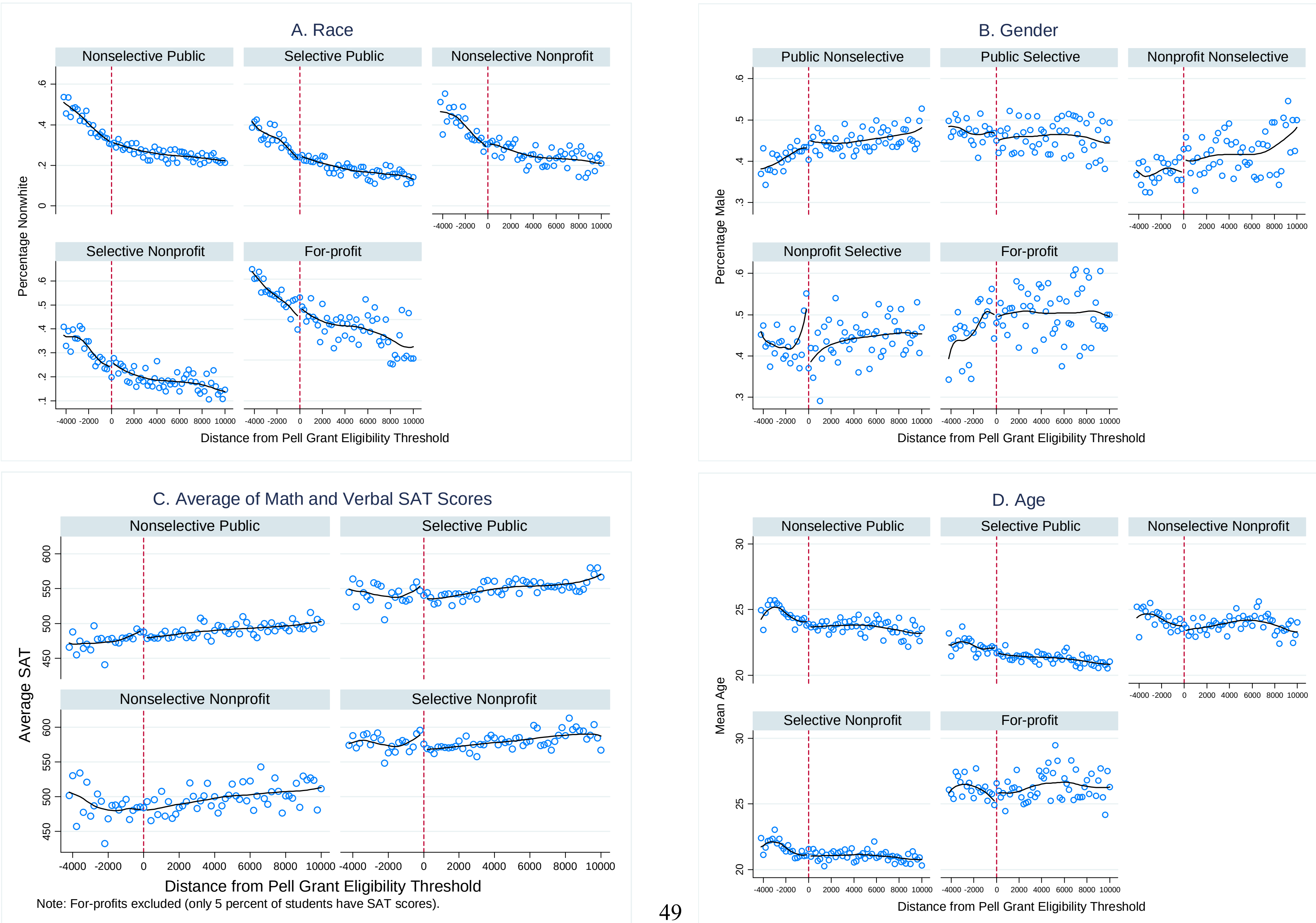


Figure A2: The Distribution of Students by Sector

Note: Black solid lines represent local linear regression estimates the percentage of students in a given sector, estimated separately on each side of the eligibility threshold.

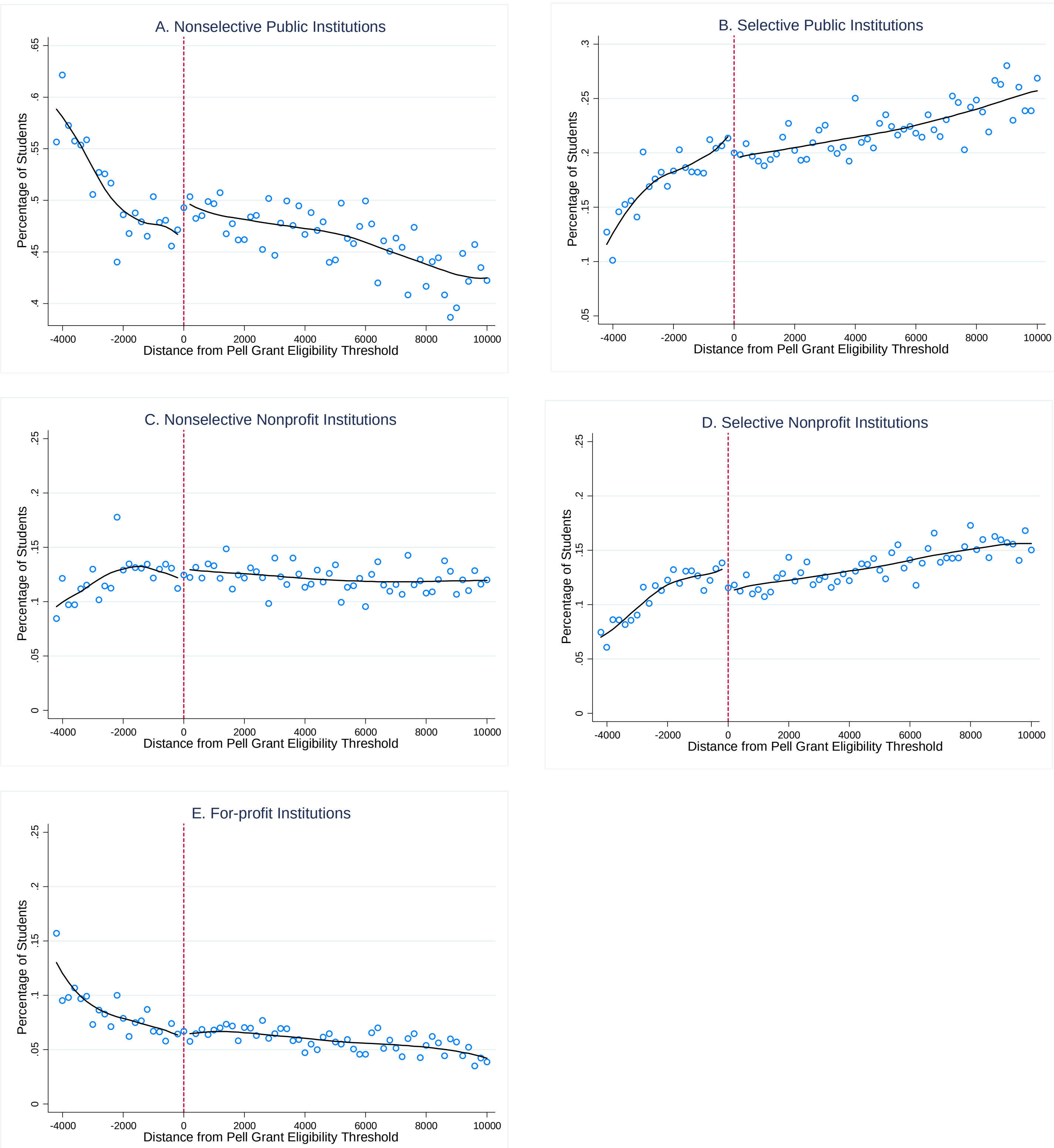
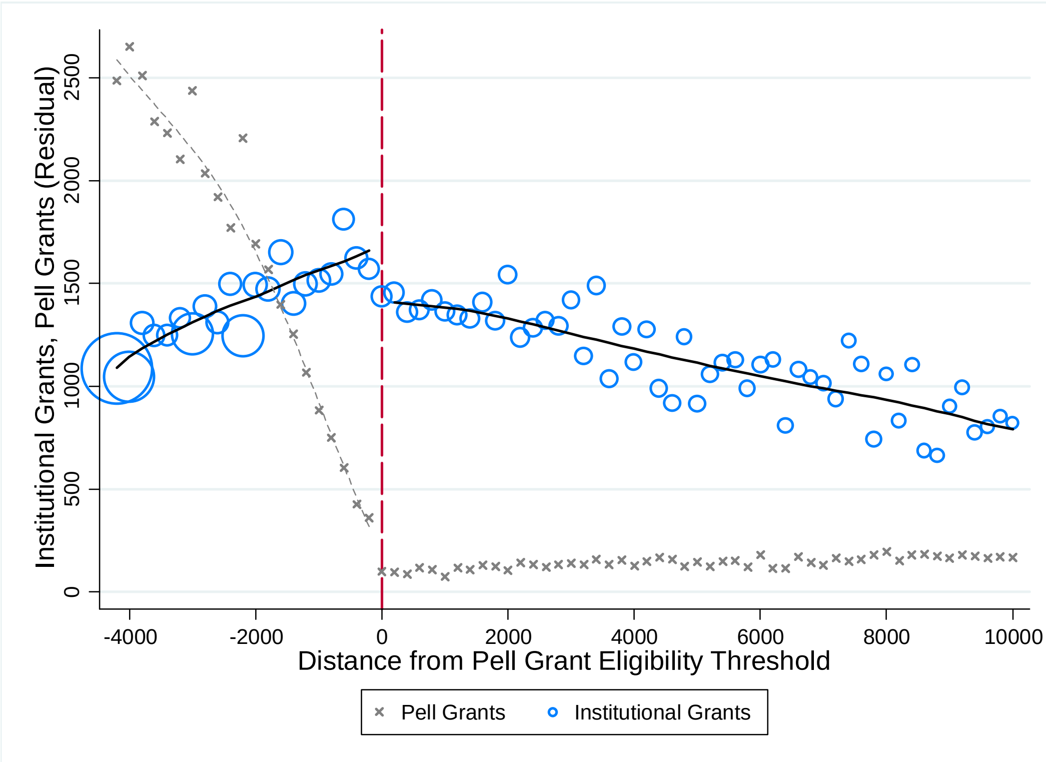


Figure A3: Main Results, Local Linear Regression



Note: $200 EFC bins. See Figure 8 notes.

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:

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

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

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

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

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

Then the RD estimator is equal to:

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

Where

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

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

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 $\tau_0 = (\tau_{RD} - \tau_{RK}) \cdot 400$.

Appendix C: How do Institutions Use Captured Pell Grant Funds?

My results suggest that colleges capture 17 percent of targeted need-based student aid through price discrimination. However, how institutions ultimately use these funds has important implications for student welfare. Student-level regressions suggest some scope for redistribution in public schools. However, on an aggregate level, there is also room for transfers to other students, since schools may use captured funds to improve student services, hire additional instructors, or expand the number of student slots. Conversely, institutions may simply keep these funds as profits, which would be a transfer to the school's controlling body or shareholders. Although my estimates suggest that the behavior across private-sector schools is similar, regardless of control, the ultimate destination of these funds may vary substantially.

C.1 Estimation

Since institutional expenditures do not vary across students, I must rely on time-series variation in the maximum Pell Award to investigate institutional-level responses to Pell Grant generosity. I use data from the IPEDS, which contains the universe of Title IV eligible schools, and focus on the set of degree-granting schools.[3] Unfortunately, the majority of for-profit institutions only report expenditure information after 1999. Therefore, I focus on the decade spanning 2000 through 2009.

Ideally, I would regress tuition and expenditures on exogenous Pell Grant revenue. In practice, Pell Grant revenue is clearly endogenous, since it is correlated with institutional characteristics that affect the number of students who receive Pell Awards. Since the IPEDS is a panel, I can include an institution-specific fixed effect to account for time-invariant institution-specific unobservable characteristics.

Annual institutional choices may affect tuition, expenditures, and Pell Grant revenue jointly. For instance, a school may choose to increase the number of students it serves in a given year while also increasing tuition. To address this concern, I calculate tuition, expenditures, and Pell Grant revenue per FTE students and also instrument Pell grants per FTE with the program's

[3] Table A3 presents information on revenue and expenditures for schools in the IPEDS sample in 2008. Schools in the IPEDS sample had similar characteristics compared to schools in the NPSAS sample (Table 2).

maximum award, which is determined by the federal government.[4] This means estimates will not capture impacts of Pell Grant funding on expansions in the number of students served.

Finally, changes in the maximum award may still correlated with to national trends. Between 2000 and 2009, real tuition continued to increase, following trend from prior decade. Over this time period, maximum Pell awards also followed a generally upward trend. These two trends may lead to an overestimate of the correlation between institutional Pell Grant funds and outcomes, such as average tuition per FTE. Thus, I include a set of either state-specific, or institution-specific linear time trends. Identification comes from breaks in the trend of the dependent variable that occur in years when maximum Pell awards trends also changed (i.e., between 2002 and 2006 when the maximum award decreased in real terms). I estimate:

$$y_{jt} = \beta PellRevenue_{jt} + \mathbf{X}_{\mathbf{j}t}\boldsymbol{\gamma} + \delta_j + \lambda_s t_s + \varepsilon_{jt} \tag{C1}$$

Where y_{jt} is the outcome of interest for school j in year t, such as instructors per student, $PellRevenue_{jt}$ is revenue from the Pell Grant program per FTE student, X_{jt} is a vector of time-varying school characteristics including other sources of revenue per FTE and annual county unemployment rates, δ_j are institution fixed effects, $\lambda_s t_s$ is a state or institution-specific linear time trend, and ε_{jt} is an idiosyncratic error term.[5]

C.2 Correlations between Tuition, Institutional Grants, Expenditures, and Pell Grants per FTE

I focus on nonselective degree granting institutions and present results from separate regressions for public, nonprofit, and for-profit schools.[6] Only for-profit schools receive over 10 percent of their revenue from Pell Grant awards. Pell Grant awards only made up 7 percent and 3 percent of revenue in public and nonprofit school in the nonselective sector. This suggests that changes in Pell Grant generosity will have a smaller impact on school-wide decisions for these

[4] To calculate the number of FTE undergraduate students, I use information on the total number of credit or contact hours provided during the 12 month academic year. For schools operating on a quarter system, the number of FTE undergraduates is equal to $\frac{credithours}{45} + \frac{contacthours}{900}$. For schools operating on a semester, trimester, or other calendar system, the number of FTE undergraduates is equal to $\frac{credithours}{30} + \frac{contacthours}{900}$

[5] Due to Hurricane Katrina, several counties in Louisiana are missing information on unemployment rates between September 2005 and June 2006. I use the average monthly unemployment rate between January 2005 and August 2005 and between July 2006 and December 2006 to impute annual unemployment rates for these counties in 2005 and 2006.

[6] Results are robust to the inclusion of non-degree-granting institutions and when focus on a balanced panel of schools (available upon request).

schools than in the case of for-profit schools. Pell Grant revenue only comprises 1 percent or less of total revenue in selective schools.

Table C1 presents estimates of the impact on tuition and institutional grants for nonselective institutions. I find substantial differences in responses to Pell Grant generosity across sectors. Public institutions decrease tuition by an estimated $30 for every $100 increase in per student Pell Grants. Similar to my student-level estimates, public institutions also decrease institutional grants. The magnitude of the response is larger – approximately $60 for every $100 in Pell Grant funding – but is not statistically distinguishable. Taken together, these results suggest that public institutions may be redistributing captured Pell Grant funds to ineligible students in the form of lower tuition (or smaller increases in tuition than would have otherwise been implemented).

Conversely, nonprofit and for-profit institutions increase tuition more than dollar for dollar with increases in Pell Grant awards. Surprisingly, my estimates suggest nonprofits also increase institutional aid approximately dollar for dollar with Pell Grant increases, a result at odds with my student level estimates. These results are offsetting and student tuition, net of institutional aid, does not significantly increase with Pell Grant generosity in nonprofit institutions. However, for-profit schools both increase tuition and decrease institutional aid. Taken together, the estimates suggest that for-profit institutions increase their revenue from student tuition by $320 for every $100 increase in Pell Grant generosity.

In Table C2, I examine whether these increased profits lead to increases in expenditures per FTE student on instruction, research and public service, academic and student support services, or on a broad category of other expenditures that includes auxiliary enterprises, hospitals, independent operations, sales and services of education activities, interest, and operations and maintenance. Unfortunately, I cannot separate expenditures on facilities and investments in a school's physical plant from the other types of expenses in this category. I find no significant impact on for-profit expenditures on any of these categories, although instruction related expenditures are positive and marginally significant, providing suggestive evidence that revenue captured from Pell Grant awards is retained as profits.

Appendix Table C1: Institution-level analyses of the correlation between Pell Grant Aid, Tuition, and Institutional Grants per FTE, Nonselective Institutions

	Public Institutions		Nonprofit Institutions		For-profit Institutions	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:						
Tuition	-0.265	-0.345	4.314	2.621	1.997	2.972
	(0.149)+	(0.150)*	(1.037)**	(1.648)	(0.939)*	(1.557)+
Institutional Grants	-0.723	-0.600	1.504	1.182	-0.025	-0.228
	(0.127)**	(0.124)**	(0.383)**	(0.471)*	(0.074)	(0.080)**
First Stage	0.313	0.303	0.341	0.340	0.501	0.436
	(0.016)**	(0.018)**	(0.039)**	(0.053)**	(0.117)**	(0.142)**
Number of Observations	13,002	13,002	5,530	5,530	10,629	10,629
Institution linear time trends		X		X		X

Source: IPEDS 2000-2009. Notes: Each cell represents a separate regression. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1; all amounts in constant 2011$; all regressions include instititution fixed effects, county annual unemployment rates, and controls for other sources of revenue per FTE student (federal, state/local, private/investment/endowment, and other). Columns 1,3, and 5 also include linear state time trends; columns 2, 4 and 6 include institution-specific linear time trends. All regressions instrument for Pell Grants/FTE with the annual maximum Pell Grant award (Figure 1). Regressions are weighted by number of FTE undergraduate students.

Appendix Table C2: Institutional-level analyses of the correlation between Pell Grant Aid and Expenditures per FTE, Nonselective Institutions

	Public Institutions		Nonprofit Institutions		For-profit Institutions	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:						
Instruction expenditures	0.177	0.009	1.223	0.395	0.262	0.640
	(0.133)	(0.146)	(0.633)+	(0.838)	(0.271)	(0.397)
Research & public service expenditures	-0.052	-0.042	0.400	0.179	0.028	0.023
	(0.076)	(0.103)	(0.190)*	(0.181)	(0.036)	(0.051)
Academic/student support expenditures	-0.232	-0.227	1.767	0.581	-0.190	0.241
	(0.167)	(0.149)	(0.967)+	(0.906)	(0.726)	(0.863)
Other expenditures	1.156	1.085	1.549	1.039	-0.234	-0.035
	(0.203)**	(0.221)**	(0.611)*	(0.747)	(0.432)	(0.688)
Number of Observations	13,002	13,002	5,530	5,530	10,629	10,629
Institution linear time trends		X		X		X

Source: IPEDS 2000-2009. Notes: Each cell represents a separate regression. Standard errors clustered at institution level in parentheses; ** p<0.01, * p<0.05, + p<0.1; all amounts in constant 2011$; all regressions include institituion fixed effects, county annual unemployment rates, and controls for other sources of revenue per FTE student (federal, state/local, private/investment/endowment, and other). Columns 1,3, and 5 also include linear state time trends; columns 2, 4 and 6 include institution-specific linear time trends. All regressions instrument for Pell Grants/FTE with the annual maximum Pell Grant award (Figure 1). Regressions are weighted by number of FTE undergraduate students.