The Road to Pell is Paved with Good Intentions: The Economic Incidence of Federal Student Grant Aid

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Abstract

The federal Pell Grant Program provides billions of dollars in subsidies to low-income college students to increase affordability and access to higher education. I estimate the economic incidence of these subsidies using regression discontinuity (RD) and regression kink (RK) designs. RK estimates suggest that schools capture Pell Grant aid through price discrimination, while RD estimates imply the opposite result, that schools supplement Pell Grants with increased 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. Taking into account both dimensions, I estimate that 12 percent of all Pell Grant aid is passed-through to schools. JEL: H22, I21, I23.

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1 Introduction

The federal government provides billions of dollars in targeted need-based aid to low-income college students every year. Although students are the statutory recipients of this aid, its economic incidence may fall partially on schools (Fullerton and Metcalf, 2002). Specifically, schools may strategically increase recipients' effective prices, crowding out federal aid by reducing discounts provided through institutional grants and scholarships. 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 measure the economic incidence of the federal Pell Grant Program, the largest source of need-based grant aid in the United States, using student-level data from the National Postsecondary Student Aid Study. I estimate that institutions capture 12 percent of their students' Pell Grant aid through price discrimination. Furthermore, I illustrate that the extent and pattern of capture vary substantially by institutional control and selectivity. For example, public schools capture less than 5 percent of their students' Pell Grant aid, on average, while among students attending selective nonprofit schools, decreases in institutional grant aid crowd out two-thirds of Pell Grant aid. Incidence 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* institutional aid.

I identify these impacts using discontinuities in the relationship between Pell Grant aid and the federal government's measure of 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 (Hahn, Todd and der Klauuw, 2001; Nielsen, Sørensen and Taber, 2010; Card et al., 2012). 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 schools capture 17 percent 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 schools *increase* institutional aid by close to 40 cents for every dollar of Pell Grant aid. These estimates, and the statistically significant difference between RD and RK estimates, are robust to a variety of specifications.

I reconcile these disparate estimates using a framework in which the "treatment" of Pell Grant receipt is multidimensional. Students at the margin of Pell Grant eligibility receive an extra dollar of outside aid but are also labeled as Pell Grant recipients, 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 Pell Grant recipients and their pricing response to outside subsidies using a combined RD/RK approach.

The RD estimator only identifies the combined impact of these dimensions, and near the Pell Grant eligibility threshold, a greater willingness to pay for Pell Grant recipients dominates pass-through of outside grant aid. This result is misleading, however, since using my combined RD/RK approach, I estimate that only one-fifth of Pell Grant recipients benefit from these transfers; the pass-through of each additional dollar of Pell Grant aid quickly overtakes schools' willingness to pay for needy students. On average, Pell Grant recipients receive an additional $284 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 17 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, 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.

My findings also contribute to the literature on the market for higher education and the objectives of higher education institutions (e.g., Rothschild and White, 1995; Hoxby, 1997; Winston, 1999; Epple, Romano and Sieg, 2006). I show how variation in schools' response to Pell Grant aid relates to differences in schools' objectives and market power across sectors. Public schools demonstrate a willingness to pay for students categorized as Pell Grant recipients. Although in the public sector, net pass-through of Pell Grants is close to zero, increases in institutional aid for recipients near the eligibility threshold come at the expense of the neediest Pell recipients. Conversely, more selective nonprofit institutions appropriate over two-thirds of their students' Pell Grant aid, suggesting these schools have considerable market power.

The for-profit sector of higher education has grown substantially over the last decade (Deming, Goldin and Katz, 2012) and in recent years, has been criticized for unethical marketing practices and financial aid fraud (U.S. Government Accountability Office, 2010). My estimates, which suggest that for-profit institutions appropriate only 6 percent of their students' Pell Grant aid via price discrimination, complementing recent findings by Cellini and Goldin (forthcoming), who estimate that for-profit institutions capture the majority of federal student aid by raising tuition.

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 (e.g., Rothstein, 2008; Hastings and Washington, 2010). Research by Long (2004) and Turner (2012) suggests that other sources of federal and state financial aid crowd out institutional discounts by as much as 100 percent. Previous studies that specifically focus on the Pell Grant Program find a positive correlation between prices and Pell Grant generosity (e.g., McPherson and Schapiro, 1991; Singell and Stone, 2007). However, these impacts are identified using time-series variation in the maximum Pell Grant award, variation that is likely correlated with unobservable year specific shocks to the economy. My empirical approach overcomes this limitation taking advantage of variation in Pell Grant aid across within a given school and year.

The remainder of this paper proceeds as follows: the next section describes the Pell Grant program. Section 3 discusses my data and sample and presents descriptive statistics, while Section 4 describes the RK design and my estimation strategy. Section 5 presents RD and RK estimates and Section 6 provides a conceptual framework that reconciles differences between these estimates. I estimate the global incidence of the Pell Grant Program in Section 7 and Section 8 concludes.

2 The Pell Grant Program

Established to promote access to postsecondary education, the federal Pell Grant Program is the largest source of need-based student aid in the United States. In 2013, over 8.9 million low-income received Pell Grant subsidies totaling $34 billion (U.S. Department of Education, 2014). The maximum Pell Grant has grown in generosity from $1,400 during the 1975-1976 school year (hereafter, 1976) to $5,550 in 2013, a 4 percent decrease in real terms (Figure 1).[1] Over this period, the purchasing power of the maximum Pell Grant has fallen from 67 percent to 27 percent of the average cost of college attendance.[2]

A student's Pell Grant depends on both the annual maximum award and her expected family contribution (EFC), the federal government's measure of need. Students must complete a Free Application for Federal Student Aid (FAFSA) to qualify for Pell Grants and other sources of federal student aid. The FAFSA requires detailed 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.[3] Students specify up to six schools (ten schools after 2008) they are considering attending. The federal government provides each of these schools with the student's EFC and FAFSA inputs and these schools calculate the student's eligibility for federal and state grants. With this information in hand, schools distribute institutional grant aid across students. Thus, a school observes a student's FAFSA, EFC, and outside aid before deciding the level of its own discount from listed tuition. Students receive a financial aid package from each school specifying federal, state, and

[1] Although Pell Grant aid was first disbursed 1974, the program was fully implemented in 1976.

[2] Appendix Figure C.1 displays the purchasing power of the maximum Pell Grant relative to the average cost of attendance and average tuition and fees between 1976 and 2013.

[3] The Department of Education's 36 page *EFC Formula Guide* (available at: http://ifap.ed.gov/efcformulaguide/attachments/082511EFCFormul provides a detailed explanation of the formula used to calculate a student's EFC.

institutional grant aid and loans. Students do not observe their Pell Grant award until this point, where it is included as a component of the final price displayed in their financial aid package.

A full-time, full-year student is eligible for a Pell Grant award equal to:

$$\begin{aligned} Pell_{it} = (maxPell_t - EFC_{it}) \times \mathbf{1}\left[maxPell_t - EFC_{it} \geq 400\right] \\ + 400 \times \mathbf{1}\left[maxPell_t - EFC_{it} \in [200, 400)\right] \end{aligned} \tag{1}$$

Where $maxPell_t$ is the maximum Pell Grant in year t, EFC_{it} is the expected family contribution of student i in year t, and $\mathbf{1}[\cdot]$ is the logical indicator function. Pell Grant awards are rounded up to the nearest \$100. Students qualifying for an award between \$399 and \$200 receive \$400, while students who qualify for less than \$200 do not receive a Pell Grant.[4]

The Pell Grant formula generates two sources of variation that I use for identification. First, crossing the Pell Grant eligibility threshold leads to a discrete increase in a student's statutory award, from \$0 to \$400, which enables me to use a regression discontinuity design. Second, the variation created by the change in the slope of the Pell Grant-EFC function, from 0 to -1, allows me to use a regression kink design.[5]

Students only learn about the level of their Pell Grant after they have submitted a FAFSA, and this information is provided as part of a school's financial aid package, where the final price (tuition net of state, federal, and institutional grants) is likely the most salient feature. Past research finds little impact of Pell Grant aid on college enrollment except for older, non-traditional students (Kane, 1995; Seftor and Turner, 2002; Deming and Dynarski, 2010). Pell Grant aid may not increase college enrollment if low-income students lack information about their eligibility for aid. Bettinger et al. (2012) show that information and assistance with the FAFSA application process raises the likelihood of college enrollment for low-income students, providing a potential explanation for earlier findings of no enrollment response. Most prospective students do not "shop around" for the best price: among incoming students with EFCs near the Pell Grant eligibility threshold, only 28 percent listed more than one school on their FAFSA applications.[6]

The weak response of student demand to Pell Grant aid suggests the potential for schools to appropriate

[4]The minimum Pell Grant award increased to \$890 in 2009, \$976 in 2010, and \$1,176 in 2011, and then lowered to \$555 in 2012. Although eligibility for other forms of federal aid (e.g., subsidized loans, work study) also may depend on a student's EFC, the Pell Grant eligibility threshold does not correspond to changes in eligibility for any other federal programs except for the short-lived Academic Competitiveness Grant (ACG) and National Science and Mathematics Access to Retain Talent (SMART) Grant programs. The ACG program targeted first- and second-year Pell Grant recipients that had completed a rigorous secondary school program with up to \$1,300 in grant aid per year. Third- and fourth-year students enrolled in a qualifying degree program (e.g., STEM fields, critical foreign language studies) were selected by their institution to receive a SMART Grant of up to \$4,000. Funds from these programs were first released in fall of 2006 and discontinued in 2011. Other federal grants include the Supplemental Educational Opportunity Grant (SEOG) and and smaller programs that target specific students or careers (e.g., TEACH Grants for students that intend to become teachers in high-need fields and will work in low-income areas). Schools have discretion over the allocation of SEOG grants as long funds are directed to needy students.

[5]The minimum award for half-time students is the same as that received by full-time students, while the slope of the relationship between Pell Grant aid and EFC is 0.5. Part-year students receive a prorated grant.

[6]Appendix Figure C.2 displays the share of first-year students in a given \$200 EFC bin, by distance from the Pell Grant eligibility threshold, that listed more than one school on their FAFSA.

these subsidies by increasing prices. Singell and Stone (2007) find a positive correlation between Pell Grant generosity and private institutions' published tuition. However, they identify these impacts using time-series variation in the maximum Pell Grant, which is likely correlated with unobservable year specific shocks. Additionally, as Hoxby (1997) argues, few public and nonprofit schools enroll a sufficiently large population of Pell Grant recipients for tuition increases to yield a substantial increase in revenue and many public schools lack control over tuition setting. The for-profit sector represents an exception to both of these arguments. On average, 66 percent of for-profit students received Pell Grants in 2012 and most for-profit schools set tuition at the program-level.[7] Cellini and Goldin (forthcoming) show that for-profit institutions that are eligible to disburse federal student aid charge 78 percent more for associate's degree and certificate programs than schools that do not offer federal aid, an amount that is approximately equal to the value of federal subsidies received by students.

Raising tuition is only one method schools may use to capture Pell Grant aid. Schools can also adjust students' prices by altering the institutional aid provided to Pell Grant recipients. 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. Long (2004) and Turner (2012) find evidence that schools respond to other sources of financial aid by decreasing institutional grants.[8] Epple et al. (2013) model the impact of federal grant aid increases on enrollment and prices using a general equilibrium model of the market for higher education and predict that reductions in institutional aid would crowd out close to 60 percent of simulated federal aid increases provided to nonprofit students. However, the two studies that explicitly examine whether Pell Grant aid crowds out institutional aid provide conflicting results (McPherson and Schapiro, 1991; Li, 1999).[9]

[7] In 2012, total enrollment in degree-granting for-profit institutions was 3.1 million in and of these students, 2.1 million received Pell Grant aid, suggesting that on average, 66 percent of for-profit students were Pell Grant recipients (2013 Digest of Education Statistics, Table 308.20; U.S. Department of Education, 2013). In comparison, approximately 31 percent of the 20.3 million students enrolled in degree-granting public schools and 25 percent of the 4.8 million nonprofit students received Pell Grant aid in 2012.

[8] 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 and finds that private nonprofit institutions captured 30 percent of HOPE aid by increasing tuition and fees and reducing institutional aid. Turner (2012) focuses on tax-based aid, which primarily benefits middle class students, and finds that schools reduce institutional aid dollar for dollar with estimated education tax benefits.

[9] Using time-series variation in the maximum Pell Grant award, McPherson and Schapiro (1991) find a positive correlation between Pell Grant generosity and overall institutional aid levels. Li (1999) uses administrative Pell Grant data and a simulated instrumental variables approach, and finds a positive relationship between Pell Grant aid and both listed tuition and per-student net tuition. By comparing the impact of Pell Grant aid on per-student net and listed tuition, she estimates that four-year institutions increase tuition and reduce institutional aid.

3 Data and Descriptive Statistics

I primarily use data from the National Postsecondary Student Aid Study (NPSAS), a nationally representative, restricted-use, repeated cross-section of college students.[10] My sample includes students from the 1996, 2000, 2004, 2008, and 2012 NPSAS waves. I observe each student's EFC, demographic characteristics, FAFSA inputs, and financial aid from all sources. I eliminate graduate and first-professional students as well as noncitizens and non-permanent residents, as these students are ineligible for federal student aid. 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 military academies, tribal institutions, schools that only offer sub-associate certificate programs, theological seminaries, and other faith-based institutions, since many of these schools are not eligible to distribute federal student aid.

I focus on students with EFCs that are no greater than 5,500 from the Pell Grant eligibility threshold. However, I show that my results are robust to larger and narrower windows around this threshold. My main analysis sample includes approximately 152,500 undergraduate students attending 2,600 unique institutions.

I classify schools by selectivity and control, distinguishing between public, nonprofit, and for-profit institutions that are either nonselective or "more selective".[11] I use the Integrated Postsecondary Education Data System (IPEDS) and Barron's College Guide to determine an institution's selectivity. The IPEDS contains annual data on acceptance rates and the Barron's Guide groups four-year public and nonprofit schools into six categories of selectivity based on acceptance rates, college entrance exam scores, and the minimum class rank and grade point average required for admission. I classify all for-profit and other institutions offering two-year programs as nonselective. If the IPEDS lists an institution as open admissions, I also classify it as nonselective. Finally, I classify remaining institutions as nonselective if either the Barron's Guide lists them as "less competitive" or "non-competitive" or they are missing Barron's Guide rankings and admit over 75 percent of applicants. Appendix B provides additional details on the data and sample construction.

Table 1 displays the characteristics of students in my sample by Pell Grant receipt, illustrating why a naïve comparison of prices charged to recipients and non-recipients would be problematic. Although Pell Grant recipients are more likely to receive institutional aid, they also have lower income, greater need (lower EFC) and are more likely to be non-white.[12]

[10] After the original 2008 NPSAS sample was drawn, additional observations of National Science and Mathematics Access to Retain Talent (SMART) Grant recipients were added. For my main set of estimates, I drop oversampled SMART Grant recipients. My results are robust to using the NPSAS sampling weights and retaining SMART Grant recipients or excluding observations from 2008, the first year of the NPSAS in which students eligible for SMART Grants could be sampled.

[11] To be clear, "more selective" public and nonprofit institutions in my sample are largely *not* highly selective. Only 2 percent of schools (representing 1 percent of students in my primary sample), are classified by the Barron's Guide as being the most selective, a category that encompasses the set of schools that are traditionally labeled as "selective".

[12] Appendix Table C.1 reports sample characteristics by Pell Grant receipt and sector.

4 Empirical Framework: RK and RD Designs

I identify the impact of Pell Grant aid on college pricing using variation induced by the kink and the discontinuity in the relationship between Pell Grant and EFC at the threshold for Pell Grant eligibility. The kink occurs where the slope of the Pell Grant schedule changes from 0 to -1, while the discontinuity is driven by the increase from in Pell Grant aid from $0 to the minimum Pell Grant at the eligibility threshold. This variation allows me to use both a regression discontinuity (Hahn, Todd and der Klauuw 2001; Lee and Lemieux 2010) and a regression kink design (Nielsen, Sørensen and Taber, 2010; Card et al., 2012).

Similar to the RD design, the RK design allows for identification of the impact of an endogenous regressor (i.e., Pell Grant aid) that is a known function of an observable assignment variable (i.e., EFC). 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 (Card et al., 2012).

Let $Y = f(Pell, \tau) + g(EFC) + U$ represent the causal relationship between institutional aid, Y, and Pell Grant aid, $Pell = Pell(EFC)$, for a given school and year; U is a random vector of unobservable, predetermined characteristics. The key identifying assumptions for inference using the RK design are (1) in the neighborhood of the eligibility threshold, there are no discontinuities in the direct impact of EFC on institutional aid and (2) the conditional density of EFC (with respect to U) is continuously differentiable at the threshold for Pell Grant eligibility (Card et al., 2012). These assumptions encompass those required for identification using a RD design. Essentially, even if many other factors affect college pricing decisions, as long as the relationship between these factors and EFC evolves continuously across the Pell Grant eligibility threshold, RK and RD designs will approximate random assignment in the neighborhood of the kink. Additionally, as with the RD design, the second assumption generates testable predictions concerning how the density of EFC and the distribution of observable characteristics should behave in the neighborhood of the eligibility threshold.

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

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

In this case, τ_1 represents the pass-through of each additional dollar of Pell Grant aid from students to schools.[13] If the required identifying assumptions hold, the RK estimator identifies:

$$\tau_{RK} = \frac{\lim_{\varepsilon \uparrow 0} \left[\frac{\partial Y | EFC = efc_0 + \varepsilon}{\partial efc} \right] - \lim_{\varepsilon \downarrow 0} \left[\frac{\partial Y | EFC = efc_0 + \varepsilon}{\partial efc} \right]}{\lim_{\varepsilon \uparrow 0} \left[\frac{\partial Pell | EFC = efc_0 + \varepsilon}{\partial efc} \right] - \lim_{\varepsilon \downarrow 0} \left[\frac{\partial Pell | EFC = efc_0 + \varepsilon}{\partial efc} \right]} = \tau_1 \tag{3}$$

Where efc_0 represents the eligibility threshold. Since the Pell Grant Program's schedule also contains a discontinuity in the level of aid, I can also identify the impact of Pell Grant aid on college pricing decisions using a RD design:

$$\tau_{RD} = \frac{\lim_{\varepsilon \uparrow 0} [Y | EFC = efc_0 + \varepsilon] - \lim_{\varepsilon \downarrow 0} [Y | EFC = efc_0 + \varepsilon]}{\lim_{\varepsilon \uparrow 0} [Pell | EFC = efc_0 + \varepsilon] - \lim_{\varepsilon \downarrow 0} [Pell | EFC = efc_0 + \varepsilon]} = \tau_1 \tag{4}$$

In practice, my estimation strategy involves "fuzzy" RD/RK. Some students do not apply for federal aid and thus, do not receive Pell Grants. Additionally, some NPSAS variables contain measurement error induced by random perturbations to preserve respondent confidentiality.

Since the location of the Pell Grant Program's eligibility threshold changes as the maximum award increases, I create a standardized measure of the distance of a student's EFC from the year-specific eligibility threshold: $\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the cut-off for Pell Grant eligibility in year t and all students with $\widetilde{EFC}_{it} \geq 0$ are ineligible for Pell Grant aid. Figure 2 displays the empirical distribution of Pell Grant aid for students in my sample by standardized EFC.[14]

Consider the following first stage and reduced form equations:

$$Pell_{it} = \eta \mathbf{1} \left[\widetilde{EFC}_{it} < 0 \right] + \delta \widetilde{EFC}_{it} \times \mathbf{1} \left[\widetilde{EFC}_{it} < 0 \right] + \psi_t \widetilde{EFC}_{it} + \theta_{jt} + \nu_{ijt} \tag{5}$$

$$y_{ijt} = \beta \mathbf{1} \left[\widetilde{EFC}_{it} < 0 \right] + \gamma \widetilde{EFC}_{it} \times \mathbf{1} \left[\widetilde{EFC}_{it} < 0 \right] + \lambda_t \widetilde{EFC}_{it} + \xi_{jt} + \epsilon_{ijt} \tag{6}$$

Where $Pell_{it}$ is the Pell Grant received by student i in year t and y_{ijt} represents institutional grant aid provided by school j. The term $\mathbf{1} \left[\widetilde{EFC}_{it} < 0 \right]$ indicates Pell Grant eligibility and θ_{jt} and ξ_{jt} represent school by year fixed effects. My main specification includes only a linear term in $\widetilde{EFC}$, the degree of polynomial that minimizes the Akaike Information Criterion (AIC). Since my data spans the 16 year period between 1996 and 2012, I allow the polynomial in $\widetilde{EFC}$ to vary by survey year. I also include a vector of

[13] With heterogeneous treatment effects, similar to the RD case, the RK estimator represents the weighted average of marginal treatment effects across all individuals, where weights represent relative likelihood individual is close to the Pell Grant eligibility threshold (Lee, 2008; Lee and Lemieux, 2010; Card et al., 2012).

[14] The kink and discontinuity in the relationship between Pell Grant aid and EFC occur at slightly different values of EFC (e.g., Appendix Figure C.3). However, the distance between these points is quite small and only a small fraction of students have an EFC falling on this "plateau". I treat both the slope and the level of Pell Grant funding changes as occurring at the eligibility cut-off. My results are robust to removing students whose EFC falls on the plateau (forcing the discontinuity and kink to occur at the same value of EFC).

student characteristics to reduce residual variation, but these terms are not necessary for identification.[15] The ratio of the reduced form and first-stage coefficients for the interaction between $\mathbf{1}\left[\widetilde{EFC}_{it} < 0\right]$ and the linear term in $\widetilde{EFC}_{it}$, $\hat{\tau}_{RK} = \frac{\hat{\gamma}}{\hat{\delta}}$, 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.

4.1 Evaluating the RD and RK identifying assumptions

Identification with RD and RK designs hinges on the assumption that students and their families lack complete control over their EFCs. Students and their parents likely act to increase 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 can help families predict their potential EFC, these guides are based on prior year Pell Grant schedules. 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. Moreover, in most years, 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 after the end of the calendar year but many of these inputs are also reported to the IRS and over one-third of all FAFSA applications are audited through the Department of Education's verification process. As the NPSAS contains an additional year of FAFSA information for continuing students who reapply for federal aid, I test for evidence of strategic behavior by examining whether a given student's $\widetilde{EFC}$ in year $t+1$ is continuous and smooth at the Pell Grant eligibility threshold in year t. As shown in Appendix Figure C.4, I find no evidence of manipulation.[16]

Nonetheless, I formally test the continuity and smoothness of the distribution of students at the Pell Grant eligibility threshold. Figure 3 displays the unconditional density of $\widetilde{EFC}$, plotting the proportion of students in each \$200 $\widetilde{EFC}$ bin, up to \$10,000 above the Pell Grant eligibility threshold, a window larger than that used in my preferred specification for the purpose of exposition. To test for discontinuities in the level and slope of the density of $\widetilde{EFC}$ at the Pell Grant eligibility threshold, I follow Card et al. (2012),

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

[16] I also examine the density of observations that submit a FAFSA in year t and $t+1$ by distance to the Pell Grant eligibility threshold, to determine if receiving a Pell Grant increases the probability a given study will reapply for student aid in the following year, and find no evidence of a discontinuity in the level or slope of the density (available upon request).

collapse the data into \$200 $\widetilde{EFC}$ bins, and estimate:

$$N_b = \alpha + \beta \mathbf{1}\left[\widetilde{EFC}_b < 0\right] + \gamma \widetilde{EFC}_b \times \mathbf{1}\left[\widetilde{EFC}_b < 0\right] + \sum_{\rho}\left[\pi_\rho \left(\widetilde{EFC}_b\right)^\rho\right] + \epsilon_b \tag{7}$$

Where N_b represents the number of students in bin b, students with an $\widetilde{EFC}$ more than \$5,500 above the eligibility threshold excluded, and $\rho = 12$ is chosen to minimize the AIC.[17] I find no evidence that the level or the slope of the density change discontinuously at the eligibility threshold; with $\hat{\beta} = -51.13\,(82.60)$, $\hat{\gamma} = -0.186\,(0.436)$, and $p = 0.648$ from an F-test of joint equality.[18]

Finally, I examine the distribution of predetermined student characteristics around the eligibility threshold, including race, gender, dependency status, average SAT score (first-year students only), age, and adjusted gross income (AGI). Figure 4 displays recentered residuals from a regression on school by year fixed effects, where bins again represent \$200 $\widetilde{EFC}$ intervals. Again, I use a window that is larger than the bandwidth for my preferred specification for expositional purposes. Using my preferred bandwidth, which excludes students more than \$5,500 from the Pell Grant eligibility threshold, I estimate equation (7), where N_b is replaced with the corresponding mean characteristic among students in bin b. I find no evidence of discontinuities in the slope or level of the distribution of these characteristics, except in the case of age and AGI, where I find a statistically significant but economically small change in the slope of these characteristics at the Pell Grant eligibility threshold.[19] For instance, the estimated change in the slope of age, equal to -0.0001, suggests a difference of half a year in the age between students who received the maximum Pell Grant and those with an EFC at the Pell Grant eligibility threshold.

5 Results

Figure 5 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. I collapse the data into \$200 $\widetilde{EFC}$ bins and plot average institutional aid and average Pell Grant aid by distance from the threshold for Pell Grant eligibility. For expositional purposes, I use a window around the Pell Grant eligibility threshold that is approximately twice as large as the window used to generate point estimates (\$10,000 versus \$5,500). Institutional aid is represented by hollow circles, with larger circles representing a greater number of students in

[17] Figure (3) excludes students with a zero EFC for the purpose of exposition, but I include these observations when estimating equation (7). 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.

[18] I also perform the McCrary (2008) density test, which yields similar conclusions, with a test statistic of -0.069 and standard error of 0.028.

[19] The estimated change in the slope and level of the full set of characteristics are provided in the notes of Figure 4.

the bin. Average Pell Grant aid is represented by the gray "X" markers. The black lines represent the linear fit of institutional aid on $\widetilde{EFC}$, estimated separately on either side of the eligibility threshold and weighted by the number of students in the bin. The dashed gray lines represent the 95 percent confidence intervals for these estimates. Finally, the diagonal dashed black line represents the linear fit of Pell Grant aid on $\widetilde{EFC}$.

For Pell Grant-ineligible students, institutional aid is increasing in need (decreasing in EFC). At the eligibility threshold, the relationship between $\widetilde{EFC}$ and institutional grant aid and the level of institutional grant aid changes discontinuously. For eligible students, institutional aid is decreasing in need, although barely eligible students experience a net increase in institutional aid. As shown in Appendix Figure C.5, the relationship between institutional grant aid and $\widetilde{EFC}$ remains linear over the full support of the running variable.

I replicate this exercise by sector (Figure 6). Due to sample size constraints, I pool selective and nonselective public schools into a single category and likewise group nonselective nonprofit schools; bins represent \$250 $\widetilde{EFC}$ intervals. Public and private institutions respond differently to Pell Grant aid, with public institutions appearing to supplement Pell Grants with increased institutional grant aid. Private institutions' response to Pell Grant aid is more straightforward. There is a clear discontinuity in the slope of institutional aid to the left of the Pell Grant eligibility threshold and a negative, but insignificant change in the level of aid among nonselective private schools. There is a small, insignificant jump in institutional aid for students attending selective nonprofit schools, but the kink in the institutional aid-$\widetilde{EFC}$ schedule clearly dominates.

5.1 Impacts of Pell Grant eligibility and generosity on institutional aid

Table 2 presents OLS and IV estimates of equations (5) and (6), focusing on students within the \$5,500 $\widetilde{EFC}$ window around the Pell Grant eligibility threshold. The first two columns display the first stage and reduced form estimates, respectively. Estimates from equation (5), suggests that Pell Grant eligibility leads to a \$212 increase in Pell Grant aid and, for every dollar increase in need (decrease in EFC), eligible students experience a \$0.61 increase in Pell Grant aid. Estimates from (6) suggest that Pell Grant eligibility results in a marginally significant \$82 increase in institutional grant aid, but for every dollar increase in need (decrease in EFC), eligible students experience a \$0.11 reduction in institutionally provided grant aid.

Columns 3 and 4 present RK and RD instrumental variables estimates, which are consistent with Figure 5. IV-RK estimates suggest that, on average, institutions capture 17 cents of every Pell Grant dollar provided to students near the eligibility threshold through reductions in institutional aid. Conversely, the IV-RD estimator results in a point estimate of 0.39, suggesting schools increase institutional aid by approximately 40 cents for every dollar of Pell Grant aid received by students near the Pell Grant eligibility threshold.

The test of equality of the RD and RK coefficients confirms that the difference in coefficients is statistically significant at $p < 0.01$.[20]

5.2 Robustness and Placebo Tests

Before further investigating why the RK and RD estimators produce significantly different estimates, I explore the robustness of my results to a variety of different specifications. First, I estimate local linear regression models with a rectangular kernel and the bandwidth chosen following Imbens and Kalyanaraman (2012) (Table 3, Panel A) or the Fan and Gijbels (1996) rule of thumb (Table 3, Panel B). These models only include school by year fixed effects and for IV estimates, I use the bandwidths chosen in the reduced form models. In both cases, my first stage estimates of the impact of the discontinuity and kink on Pell Grant aid are similar to those presented in Table 2, albeit with larger standard errors, most likely due to smaller bandwidths. With institutional grant aid as the dependent variable, the Fan and Gijbels (1996) rule-of-thumb bandwidth is larger and the Imbens and Kalyanaraman (2012) bandwidth is smaller than my preferred bandwidth (\$5,652 and \$4,705, respectively). IV-RK estimates are negative, statistically significant, and larger in magnitude than my main results in both cases, suggesting that, on average, institutions reduce their own grant aid by \$0.21 to \$0.30 for every dollar of Pell Grant aid. Likewise, IV-RD estimates are positive and statistically significant, suggesting that, on average, institutions increase grant aid by \$0.21 to \$0.46 for every dollar of Pell Grant aid. I can reject the equality of IV-RD and IV-RK coefficients with $p < 0.001$ in both cases.

To illustrate that my findings are consistent across a large range of bandwidths, the first four panels of Figure 7 display IV-RK and IV-RD point estimates and the corresponding 95 percent confidence intervals from specifications that include my full set of controls and a linear or quadratic term in $\widetilde{EFC}$ over most of the range of the running variable.[21] Estimates from models with bandwidths larger than \$30,000 are quite similar to those from models with bandwidths between \$10,000 and \$30,000 (available upon request).[22] An F-test of the equality of point estimates for each bandwidth suggests that differences in the IV-RD and IV-RK estimates are statistically significant at $p < 0.05$ for bandwidths above 4200 and at $p < 0.1$ for bandwidths above \$3,700 in models with a linear term in $\widetilde{EFC}$.[23]

[20] In Appendix Table C.2, I present results from models that allow for heterogeneity in the impact of Pell Grant aid by by sector. IV-RD point estimates are positive in the case of public and more selective nonprofits, but only statistically significant among more selective public and nonprofit institutions. IV-RK point estimates are negative and statistically significant across all sectors, ranging from -0.06 (for-profit institutions) to -0.76 (more selective nonprofit institutions).

[21] For bandwidths between \$3,100 and \$12,000, a first degree polynomial in $\widetilde{EFC}$ minimizes the AIC. For bandwidths between \$2,300 and \$3,000, a third degree polynomial minimizes the AIC, and for bandwidths between \$900 and \$2200, a linear term in $\widetilde{EFC}$ again provides the best fit. For bandwidths above \$12,000, the degree of polynomial that minimizes the AIC is either 1 or 2.

[22] Appendix Figure C.6 contains the corresponding kink and discontinuity estimates from first stage and reduced form models that include my full set of controls and a linear term in $\widetilde{EFC}$.

[23] For models with a quadratic term in $\widetilde{EFC}$, differences between the IV-RD and IV-RK estimates are statistically significant

As shown in Panel E of Figure 7, the share of institutions that are represented for a given bandwidth begins to decline below $4,000. For instance, while approximately 96 percent of NPSAS institution by year observations are represented in a bandwidth of $4,000, 94 percent are represented in a bandwidth of $3,000, and only 85 percent are represented in a bandwidth of $2,000. Furthermore, declines in representation are uneven across sectors (Panel F). Within a bandwidth of $4,000, 99 percent of public institutions and around 94 percent of private institutions are represented, while within a $2,000 bandwidth, 91 percent of nonselective public institutions, 98 percent of more selective public schools, 78 percent of nonselective private schools, and 75 percent of more selective private schools are represented.

Table 4 presents results from additional robustness tests. In Panel A, I replace Pell Grant aid with the sum of Pell, state, and other federal grant aid to account for the possibility that my estimates of crowd out are driven by changes in these other funding sources at the Pell Grant eligibility threshold.[24] Both IV-RD and IV-RK estimates from this model are consistent with my main results, suggesting that a dollar of Pell Grant aid leads to a 0.17 decrease in institutional aid, in the case of the IV-RK, and a 0.21 increase in institutional aid in the case of the IV-RD. In Panel B, I drop students in institutions that have pledged to meet "full need" in the study year. Since students in these schools have no unmet need, increases in Pell Grant aid will lead to a mechanical decrease in institutional aid.[25] Approximately 23,600 students in my sample (15 percent) attend these institutions. However, this specification produces point estimates that are very close to my main results: the RK estimate suggests that a dollar of Pell Grant aid leads to a 19 cent reduction in institutional aid, while the RD estimate suggests that schools increase their own aid by 44 cents for ever dollar of Pell Grant aid. In Panel C, I report results from models that drop institutions that never provide institutional aid over the sample period. Only 1,250 students are dropped, and point estimates are quite similar to those reported in Table 2.

The Panel D specification uses the NPSAS sampling weights. While still positive, the IV-RD point estimate of 0.42 is insignificant due an increase in the corresponding standard error. Finally, the specifications in Panels E and F present estimates from models that exclude covariates and school and year fixed effects, respectively. Omitting covariates leads to a loss of precision, but does not affect the IV-RD or IV-RK point

at $p < 0.05$ for bandwidths above 4600 and at $p < 0.1$ for bandwidths above 3700.

[24]Bettinger and Williams (forthcoming) examine the interaction between state and federal grant aid, and show that in Ohio, increases in Pell Grant generosity were met with decreases in state grant aid for students with the greatest need. However, as shown in Appendix Figure C.8, I find no evidence of a discontinuous change in the level or slope of state grant aid at the Pell Grant eligibility threshold.

[25]The Project on Student Debt provides a list of schools that have pledged to meet full need and the corresponding pledge details (available at: http://projectonstudentdebt.org/pc_institution.php). In 2008, less than 2 percent of all Pell Grant recipients (representing 2 percent of expenditures) attended schools that had an ongoing pledge relating to meeting need (calculations using Pell Grant administrative data, available upon request). Many of these schools only guaranteed full need being met for a subset of students, such as those with a zero EFC (e.g., University of Illinois at Urbana-Champaign, University of Maryland at College Park, and University of Michigan) while others met need using loans and work-study (e.g., Brown University, University of Virginia, Rice University, and others).

estimates. Excluding institution by year fixed effects also leads to an increase in both standard errors and the magnitude of both RK and RD estimates (to -0.21 and 1.52, respectively), suggesting that school by year fixed effects capture substantial heterogeneity in schools' responses to Pell Grant aid.

Finally, I perform the permutation test proposed by Ganong and Jäger (2014) by estimating placebo regressions using observations away from the actual Pell Grant eligibility threshold. To do so, I draw 500 placebo thresholds uniformly distributed over $\widetilde{EFC} \in [11304, 100000]$, with the lower bound representing 200 percent of the Fan and Gijbels (1996) rule of thumb bandwidth chosen using the true eligibility threshold.[26] For each placebo threshold, I calculate the Fan and Gijbels (1996) rule of thumb bandwidth and run local linear regressions of institutional grant aid on the running variable and school by year fixed effects, and retain the estimated change in the level and slope of institutional grant aid. Appendix Figure C.7 displays the cumulative distribution of these estimates. Consistent with the asymptotic standard errors in Table 3, less than 1 percent of the placebo kink estimates are larger than the estimated kink at actual Pell Grant eligibility threshold. However, approximately 27 percent of placebo discontinuity estimates are larger than estimated discontinuity at actual threshold.

6 A Framework for Understanding 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 pure profit-maximization. First, suppose a profit-maximizing monopolist serving N distinct student groups solves:

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

Where Q_i is the demand function for students in group i and c is the school's 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

[26]Only 0.3 percent of NPSAS observations have an $\widetilde{EFC}$ above \$100,000 and the following results are robust to using higher or lower upper bounds for the distribution of placebo thresholds.

not affect cost or demand in future periods.[27]

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

$$\frac{dp_i}{ds_i} = -\mu_i + (c - s_i)\,\frac{d\mu_i}{ds_i} \tag{8}$$

If schools fully capture every additional dollar of the subsidy, $\frac{dp_i}{ds_i} = 0$, while $\frac{dp_i}{ds_i} = -1$ indicates that the subsidy is fully passed-through to students.[28] The sign of $\frac{dp_i}{ds_i}$ depends on both the elasticity and the curvature of student demand (Bulow and Pfleiderer 1983; Weyl and Fabinger, 2013). If demand is log-concave, $\frac{dp_i}{ds_i} > -1$ and schools capture a portion of students' Pell Grant aid by increasing prices (decreasing institutional aid), the result suggested by the RK estimator. If demand is log-convex, $\frac{dp_i}{ds_i} < -1$, and schools respond to Pell Grant aid by decreasing effective prices (increasing institutional aid), the result suggested by the RD estimator.[29]

However, my estimates are not consistent with either of these cases. With log-convex student demand, institutional transfers should increase as Pell Grant aid increases, suggesting that we should observe a positive relationship between need and institutional aid for Pell Grant eligible students. 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 their demand curve to a log-convex portion, requiring the existence of an inflection point in log demand. This is unlikely, since the eligibility threshold for Pell Grant aid changes over time, while pricing patterns are persistent over the years I examine (Appendix Table C.3).

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

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

[27] Additionally, this model assumes that schools are not capacity constrained or that capacity constraints are not binding. However, allowing for a binding capacity constraint would only increase pass-through of Pell Grant aid and cannot explain crowd in.

[28] 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 $\frac{dp_i}{ds_i} = -\frac{da_i}{ds_i}$.

[29] This model can be generalized to represent institutional pricing with monopolistically competitive firms offering differentiated products in the short-run. In this case, student demand will depend not only on an institution's price but the prices offered by competitors, $Q_i = Q_i(p_i, p_{-i})$, and pricing will also depend on the cross-price elasticities of demand. Pass-through will be decreasing in the number of competitors in the market and the degree of substitutability between programs offered by institutions. In the long-run, incidence will depend on the ease of entry into a specific market. A substantial minority of institutions are monopolists. In 2012, 12 percent of all institutions eligible to disburse federal aid were the only institution in their county (calculations using Department of Education data on Pell Grant disbursements).

The constraint stems from the requirement that in a static model, expenditures cannot exceed revenue. If the constraint is binding, schools will offer a schedule of prices that vary according to students' demand elasticity, the weight placed on the group in the schools objective function (α_i), and the marginal "utility" of revenue (represented by the Lagrange multiplier): $p_i = (c - \tilde{\alpha}_i)\, \mu_i$, where $\tilde{\alpha}_i$ is the weight placed on students in group i divided by the Lagrange multiplier.[30] If being labeled as a Pell Grant recipient affects a student's weight in the school's objective function, the school' pricing response to subsidy s_i is now:

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

Comparing equation (9) to equation (8) suggests that if Pell Grant recipients receive a positive weight in the school's objective function (i.e., $\tilde{\alpha}_i\left(s_i\right) > 0$), 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., $\frac{\tilde{\alpha}_i(s_i)}{ds_i} > 0$), the first term will be larger. If either of these terms is positive, these schools will capture a smaller portion of Pell Grant aid relative to profit maximizing schools. Furthermore, rearranging equation (9) yields:

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

Here the first term is equivalent to equation (8), and represents the pass-through of outside student aid due to profit maximization (cost minimization). The second term represents the school's willingness to pay for Pell Grant recipients. If, in the neighborhood of the cut-off for Pell Grant eligibility, $\frac{d\tilde{\alpha}_i}{ds_i}$ does not vary with s for Pell Grant recipients (e.g., if being a Pell Grant recipient increases a student's weight in the school's objective function by a constant amount), the relationship between the prices and Pell Grant aid can be approximated by: $p_i = \tau_0 \mathbf{1}\left[s_i > 0\right] + \tau_1 s_i + u_i$. Here, τ_0 and τ_1 represent willingness to pay for Pell Grant recipients and the pass-through of each additional dollar of Pell Grant aid, and u_i is an idiosyncratic error term.

Schools might treat Pell Grant recipients differently than other students for a number of reasons. First, schools might have objectives beyond profit maximization, such as increasing school-wide diversity or maximizing (weighted) student welfare. Schools might solve a dynamic problem where additional Pell Grant recipients in the current period increase the expected value of the stream of future revenue. For example, schools that serve a larger number of Pell Grant recipients might receive more funding from state legislatures

[30] This general framework, in which schools maximize weighted student enrollment, is consistent with Rothschild and White (1995), where weights depend on students' contributions to the education production function, Epple, Romano and Sieg (2006), in which institutions choose prices to maximize "quality" (student income and ability), and Steinberg and Weisbrod (2005), where a nonprofit firm produces a merit good and chooses a schedule of prices for its customers to maximize consumer surplus.

in the long-run or experience an increase in student demand.[31] For the purposes of this paper, I remain agnostic as to the reasons schools might treat Pell Grant recipients differently.

6.1 Treatment dimension estimation

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

$$y_i = \beta \mathbf{1}\left[\widetilde{EFC}_i < 0\right] + \gamma \widetilde{EFC}_i \times \mathbf{1}\left[\widetilde{EFC}_i < 0\right] + \lambda \widetilde{EFC}_i + \epsilon_i$$

Furthermore, assume that all eligible students receive a Pell Grant, and let $Pell\left(efc_0\right)$ represent the minimum Pell Grant. Then, the RD design will provide a reduced form estimate of the "treatment" of Pell Grant receipt, where $\beta = \tau_0 + \tau_1 \cdot Pell\left(efc_0\right)$ and $\tau_{RD} = \frac{\tau_0}{Pell(efc_0)} + \tau_1$, and will confound the school's ability to capture an additional dollar of outside aid with its willingness to pay for students labeled as Pell Grant recipients. When these two dimensions have opposite signs, RD estimates will not identify the magnitude *or* the sign of either dimension.

Conversely, the RK design will consistently estimate the pass-through of an additional dollar of outside aid, under the assumption that τ_0 is constant in the neighborhood of the cut-off for Pell Grant eligibility. Since $\tau_{RK} = \tau_1$:

$$\begin{aligned} \hat{\tau}_1 &= \hat{\tau}_{RK} \\ \hat{\tau}_0 &= \left(\hat{\tau}_{RD} - \hat{\tau}_{RK}\right) \times Pell\left(efc_0\right) \end{aligned} \tag{11}$$

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 estimated pass-through of Pell Grant aid from students to schools.[32]

Table 5 presents estimates of pass-through and willingness to pay for the pooled sample (Panel A) and by sector (Panel B) via equation (11). To do so, I jointly estimate equations (5) and (6) and calculate standard errors using the delta method. When examining heterogeneity in treatment dimensions across sectors, I allow $\widetilde{EFC}$ and the kink and discontinuity terms to vary by sector.

Estimated pass-through is 0.17, implying that students benefit from 83 cents of a given dollar of Pell

[31] A 2003 Century Foundation issue brief by Donald E. Heller provided information on the share of students that were Pell Grant recipients in highly selective nonprofit and public institutions and in 2008, the U.S. News and World Report began incorporating a measure of Pell Grant receipt in its school ranking calculations (Heller 2003).

[32] Appendix A provides further details on the derivation of these parameters in both the general case of a multidimensional treatment and the specific case of the Pell Grant Program.

Grant aid. However, due to schools' willingness to pay for Pell Grant recipients, these students also receive \$283 additional institutional grant aid. Since on average, non-recipients received \$1,436 in institutional grant aid, this transfer represents an 20 percent increase in the expected value of institutional aid. However, only Pell Grant recipients near the eligibility threshold benefit from schools willingness to pay, and these students make up only 20 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. The "switching point" – where Pell Grant recipients shift from experiencing a net increase in institutional aid to a net decrease – corresponds to an EFC that is approximately 1,700 below the eligibility threshold and an average AGI of approximately \$32,000.

As shown in Panel B of Table 5, nonselective private institutions demonstrate no willingness to pay for Pell Grant recipients. Among nonselective nonprofit institutions, 22 cents of every Pell Grant dollar is passed-through to schools via reductions in institutional aid. Pass-through in the for-profit sector is only 6 cents of every Pell Grant dollar. Conversely, nonselective and selective public schools increase institutional aid for recipients by \$191 and \$421, respectively, although only the latter estimate is statistically significant. This additional aid represents a 99 percent increase in the expected value of institutional grants among nonselective public school students and a 53 percent increase for selective public school students. Public schools appropriate 6 to 10 cents of every Pell Grant dollar.[33]

Pass-through of Pell Grant aid is the largest among selective nonprofit institutions. These schools capture 76 cents every Pell Grant dollar. This result suggests that selective nonprofits either serve students with less elastic demand or have greater market power.[34] These schools demonstrate the largest willingness to pay for Pell Grant recipients (\$1013), representing a 13 percent increase relative to average institutional aid received by non-recipients.[35]

Next, I investigate whether differences in pass-through and willingness to pay for Pell Grant recipients across sectors relate to differences in student characteristics (Table 6, Panels A and B) and level of attendance (Panel C). I examine heterogeneity in pass-through and willingness to pay by student race (white versus nonwhite), gender, and years since entry (first-year versus other students). If student demand elasticities

[33] Approximately 54 percent of nonselective public school Pell Grant recipients experience a net increase in institutional grant aid. The switching point in this sector corresponds to an EFC that is 4,200 below the Pell Grant eligibility threshold (where average AGI is approximately \$25,000). Approximately 70 percent of Pell Grant recipients attending more selective public schools experience a net increase in institutional grant aid and the switching point in this sector corresponds to an EFC that is 4,600 below the Pell Grant eligibility threshold (where AGI is approximately \$12,500).

[34] In the Epple et al. (2013) model, students receive idiosyncratic preference shocks for schools in their choice sets, which explains the high degree of crowd out in the private nonprofit sector even when schools do not appear to have substantial market power.

[35] Due to the high rate of pass-through, only 17 percent of Pell Grant recipients attending more selective nonprofit institutions benefit from an increase in institutional grant aid. The switching point at which pass-through outweighs willingness to pay in this sector corresponds to an EFC that is 1200 below the Pell Grant eligibility threshold (where average AGI is approximately \$36,500).

vary across different demographic groups and students from these groups differentially select into different sectors, differences in pass-through and willingness to pay should be attributed to these trends rather than differences in school objectives. Furthermore, upper year students may be less responsive to price increases, and the extent to which these students are more likely to enrolled in selective institutions due to higher rates of persistence, my estimates may be driven by differences in student demand elasticities rather than institutional objectives. However, I find that pass-through of Pell Grant aid is significantly greater in selective nonprofit institutions and public schools display a willingness to pay for Pell Grant recipients across the four demographic groups and find no evidence of increased crowd out for upper year students compared to those in their first year.

6.2 Evaluating alternative explanations for pricing patterns

Up until this point, I have attributed differences in institutional pricing responses to Pell Grant aid to differences in institutional objectives and market power. However, there are other potential explanations for this behavior. Since public schools charge lower prices than private institutions, institutional aid may mechanically fall if increases in Pell Grant aid drive students' remaining need to zero. State need-based aid may be distributed differently across sectors, also contributing to this effect.

As shown in Table 1, 95 percent of students near the Pell Grant eligibility threshold had remaining need after accounting for their EFC and federal, state, and institutional grant aid.[36] On average, students faced \$11,000 in unmet need. Even students attending nonselective public institutions – schools with the lowest cost of attendance – had over \$6,500 in unmet need, on average.[37]

Second, students may respond to Pell Grant generosity by upgrading to a higher quality institution. In this case, price increases would be expected, as students are receiving a more valuable product. I test for evidence of quality upgrading by examining the impact of Pell Grant aid on institutional revenue (tuition and total revenue per full-time equivalent (FTE) student), expenditures (institutional grants, instruction-related

[36] I define a student's unmet need to equal her total cost of attendance (COA) less EFC and aid from all grants. This differs from the federal definition in that the federal definition considers work-study and federal loan aid to contribute towards meeting need. However, since these sources of aid are applied after all grant aid is accounted for, they are less relevant for determining whether a student has remaining need for the purposes of providing institutional grant aid. A student's COA differs from tuition and fees in that it also includes living expense (e.g., books and supplies, room and board, transportation). Although in many cases, tuition and fees may be fully covered by grant aid, often a student's COA is more than double this amount. According to the 2013 Digest of Education Statistics (Table 330.10), in 2013, average tuition, fees, room, and board for full-time undergraduate students equaled \$20,234, approximately 90 percent higher than average tuition and fees (\$10,683). Since the former amount does not include the cost of transportation or books and supplies, the average total cost of attendance is likely at least double that of average tuition and fees. Among public institutions, average tuition represented 39 percent of average tuition, fees, room, and board (\$15,022). Among nonprofit institutions, average tuition and fees represented 73 percent of average tuition, fees, room, and board (\$39,173) and among for-profit institutions, average tuition and fees represented 59 percent of average tuition, fees, room, and board (\$23,158).

[37] Appendix Table C.1 contains information on EFC, federal, state, and institutional grant aid as well as unmet need by sector and Pell Grant receipt. Appendix Figures C2 and C3 plot the percentage of students with any unmet need and average unmet need and by EFC and sector, where unmet need is defined as the difference between a student's cost of attendance and her expected family contribution, Pell Grant and other federal grant aid, and state grant aid.

expenditures, and expenditures on student services per FTE), and the outcomes of former students (federal loan default rates) using data from the IPEDS and the Department of Education's official cohort default rate calculations. I find little evidence of economically meaningful upgrading, and in many cases, observe a negative relationship between Pell Grant aid and school quality (Appendix Table C.4).[38]

7 Global Incidence

Thus far, I have focused on estimating the incidence of Pell Grant aid in the neighborhood of the eligibility threshold. With stronger assumptions, I can use the observable relationship between institutional aid and EFC for ineligible students to estimate the global incidence of the Pell Grant program, or the average amount of Pell Grant aid pass-through from all recipients to schools. 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. I can partially test this assumption, since the location of the Pell Grant eligibility threshold moves as the maximum Pell Grant changes. By using data from earlier NPSAS waves, I can trace out the counterfactual institutional aid-EFC relationship for students that are eligible for Pell Grant aid in the current year. Results suggest that, at least over the range of EFC where students gained Pell Grant eligibility, this relationship is linear (Panel A, Figure 8).

Panel B of Figure 8 provides an illustration of my approach to estimating the global incidence of the Pell Grant Program. The shaded area under the Pell Grant schedule ($Total\,Pell$) represents the total amount of aid intended for Pell Grant recipients by the federal government. The solid lines represent the observed relationship between institutional aid and $\widetilde{EFC}$ for eligible and ineligible students, while the light diagonal dashed line represents counterfactual institutional aid for Pell Grant eligible students. In other words, each point along this line represents the predicted amount of institutional aid a student with a particular $\widetilde{EFC}$ 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 total pass-through of Pell Grant aid (A–B). The ratio of total pass-through to total Pell Grants, $\frac{A-B}{Total\,Pell}$, represents the percentage of Pell Grant aid captured by institutions.

[38]One exception is the case of expenditures on institutional grants for students attending more selective public schools: the IV-RD estimate suggests that a \$1000 increase in Pell Grant aid is correlated with a \$132 (19 percent) increase in institutional aid per FTE. Conversely, the IV-RD estimator suggests that a similar increase in Pell Grant aid is correlated with a 1 percentage point (24 percent) increase in cohort default rates. Among students attending selective nonprofit institutions – the sector which shows the highest degree of crowd out – there is no evidence of quality upgrading.

To estimate the counterfactual institutional aid-$\widetilde{EFC}$ relationship, I restrict the sample to Pell ineligible students and regress institutional aid on $\widetilde{EFC}$ and school and year fixed effects, allowing the relationship between $\widetilde{EFC}$ and institutional aid to vary by sector. The $\widetilde{EFC}$ coefficient and corresponding confidence interval provide estimates of the counterfactual institutional aid Pell Grant recipients would have received if the program did not exist.

Overall, every dollar of Pell Grant aid reduces students' effective prices by 87 cents (Table 7). Nonselective nonprofit institutions receive 35 cents of every Pell Grant dollar while more selective nonprofit institutions capture 67 cents. In the public sector, net crowd out of Pell Grant aid is less than 5 percent. Finally, among for-profit institutions, net crowd out is not statistically distinguishable from zero.

These results should be interpreted with two important caveats. First, schools might also raise or lower listed tuition in response to changes in Pell Grant generosity. However, the majority of Pell Grant recipients attend public schools and, in most states, public institutions lack the ability to raise tuition without approval from their governing body (Turner, 2012).[39] On average, more selective private institutions serve few Pell Grant recipients, making it unlikely that these schools would raise tuition for all students to appropriate federal aid provided to a small number of individuals. However, in the case of for-profit institutions, Cellini and Goldin (forthcoming) provide evidence that these schools may respond to federal aid eligibility by increasing tuition, which would suggest my estimates represent a lower bound of the global incidence of Pell Grant aid. If instead, I also incorporate the Cellini and Goldin (forthcoming) estimate of close to 100 percent pass-through of federal aid via tuition increases among for-profits with the distribution of Pell Grant recipients across sectors in 2013, back-of-the-envelope estimates suggest an upper bound of 31 percent pass-through.

Second, my results represent the short-run incidence of Pell Grant aid. In the long-run, increased competition may limit schools' ability to capture student aid.[40] Although the supply of public institutions is relatively fixed, Cellini (2010) shows that student aid increases lead to for-profit entry. If for-profit institutions retain captured Pell Grant aid as profits, my results provide a rationale for this response. An increase in competition should reduce institutions' ability to capture Pell Grant aid; in the long-run, institutional rents may be driven to zero. Welfare analysis is complicated by the fact that captured Pell Grant funds may ultimately lead to an expansion in the provision of higher education. However, the market for higher education also has substantial barriers to entry, since schools face large fixed costs (e.g., investments in facilities) and must gain accreditation and demonstrate a sufficiently high level of enrollment for two years

[39] In the years I examine, 69 percent of Pell Grant recipients attended public schools (calculations using Department of Education data on Pell Grant disbursements).

[40] I do find some evidence of declining crowd out among more selective nonprofits between 1996 and 2012 (Appendix Table C.3).

before their students are eligible for Pell Grant aid. Thus, I leave the analysis of the long-run incidence of the Pell Grant Program to future work.

8 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 RD/RK approach, I estimate the impact of Pell Grants on institutional aid and show that schools strategically respond to changes in federal grant aid by systematically altering institutional aid. Overall, I estimate that institutions capture 12 percent of all Pell Grant aid.

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. 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 (2010), the deterministic relationship between the continuous endogenous regressor and assignment variable leads to both a discontinuity and a kink.

My paper also provides insight into the industrial organization of higher education. I show how schools' responses to Pell Grant aid illustrate differences in schools' objectives and market power across sectors. 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 12 percent of all Pell Grant aid. In 2013, the federal government distributed $32 billion in Pell Grants to 8.9 million students. My results suggest that institutions captured at least 3.8 billion of this aid.

A RD Estimation with a Multidimensional Treatment

This appendix provides a general example of how a multidimensional treatment affects RD estimates. Additionally, I show how using a combined RD/RK design allows for estimation of more than one treatment dimension. Finally, I illustrate how this approach is applied in the case of the Pell Grant Program.

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

$$Y = f(T, \tau) + g(X) + U \tag{A.1}$$

$$T = \beta_0 \mathbf{1}[X \leq x_0] + \beta_1 X \cdot \mathbf{1}[X \leq x_0] + h(X) \tag{A.2}$$

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 at x_0.[41] Finally, $F_U(u)$ is the cdf of U and $F_{X|U}(x|u)$ is the conditional cdf of X.

Under the following identifying assumptions, the RD estimator approximates random assignment in the neighborhood of x_0 (Hahn, Todd and der Klauuw 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 $\lim_{\varepsilon \uparrow 0} \mathrm{E}[T|X = x_0 + \varepsilon] \neq \lim_{\varepsilon \downarrow 0} \mathrm{E}[T|X = x_0 + \varepsilon]$.

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

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

$$f(T, \tau) = \tau_1 T \tag{A.3}$$

$$f(T, \tau) = \tau_0 \mathbf{1}[T > 0] + \tau_1 T \tag{A.4}$$

If equation (A.3) describes $f(T, \tau)$, the "treatment" has only one dimension and the RD estimator identifies τ_1:

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

[41] 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.

If instead, the treatment is multidimensional and equation (A.4) describes $f(T,\tau)$, the RD estimator equals $\tau_1 + \frac{\tau_0}{T(x_0)}$.[42]

When the treatment has two dimensions, the RD estimator only recovers the reduced form impact of these dimensions and it is not possible to separately identify τ_1 and τ_0. However, since the deterministic relationship between T and X also results in a discontinuous change in the slope of $T(X)$ at x_0, these dimensions can be identified using a combined RD/RK approach. In addition to **RD1** through **RD3**, the RK design requires the following identifying assumptions (Card et al., 2012):

RK1 (Regularity): $\frac{\partial y(t,x,u)}{\partial x}$ is continuous in x in the neighborhood of x_0.[43]

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

RK3 (Continuously differentiable conditional density of the assignment variable): $f_{X|U}(x|u)$ is continuously differentiable in x in the neighborhood of x_0 $\forall u$.

If these conditions are met, regardless of whether $f(T,\tau)$ takes the form of equation (A.3) or equation (A.4), the RK estimator will identify τ_1:[44]

$$\tau_{RK} = \frac{\lim\limits_{\varepsilon\uparrow 0}\left[\frac{\partial \mathrm{E}[Y|X=x_0+\varepsilon]}{\partial x}\right] - \lim\limits_{\varepsilon\downarrow 0}\left[\frac{\partial \mathrm{E}[Y|X=x_0+\varepsilon]}{\partial x}\right]}{\lim\limits_{\varepsilon\uparrow 0}\left[\frac{\partial \mathrm{E}[T|X=x_0+\varepsilon]}{\partial x}\right] - \lim\limits_{\varepsilon\downarrow 0}\left[\frac{\partial \mathrm{E}[T|X=x_0+\varepsilon]}{\partial x}\right]} = \tau_1$$

Furthermore, if the treatment has two dimensions, as described in equation (A.4), the RD and RK estimators can be combined to identify both τ_0 and τ_1. The RK estimator identifies τ_1, and $\tau_{RD} = \tau_1 + \frac{\tau_0}{T(x_0)}$.

[42] To see this, note that numerator of the RD estimator equals:

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

Given **RD1** and **RD3**, $\lim\limits_{\varepsilon\uparrow 0}\ \mathrm{E}[g(X)+U] = \lim\limits_{\varepsilon\downarrow 0}\ \mathrm{E}[g(X)+U]$. By assumption, $\lim\limits_{\varepsilon\uparrow 0}\mathrm{E}[h(X)] = \lim\limits_{\varepsilon\downarrow 0}\mathrm{E}[h(X)]$. Therefore, the RD numerator can be written as:

$$\tau_0\left[\lim_{\varepsilon\uparrow 0}\ \mathrm{E}[\mathbf{1}[T>0]|X=x_0+\varepsilon] - \lim_{\varepsilon\downarrow 0}\ \mathrm{E}[\mathbf{1}[T>0]|X=x_0+\varepsilon]\right] + \tau_1\left[\lim_{\varepsilon\uparrow 0}\ \mathrm{E}[T|X=x_0+\varepsilon] - \lim_{\varepsilon\downarrow 0}\ \mathrm{E}[T|X=x_0+\varepsilon]\right]$$

And the RD estimator equals: $\tau_1 + \frac{\tau_0}{\lim\limits_{\varepsilon\uparrow 0}\mathrm{E}[T|X=x_0+\varepsilon] - \lim\limits_{\varepsilon\downarrow 0}\mathrm{E}[T|X=x_0+\varepsilon]} = \tau_1 + \frac{\tau_0}{\beta_0+\beta_1 x_0} = \tau_1 + \frac{\tau_0}{T(x_0)}$

[43] Card et al. (2012) include the additional assumption that $\frac{\partial y(t,x,u)}{\partial t}$ is continuous in t. If the treatment is multidimensional, this condition may not hold. Comparisons of RD and RK estimators allows for a test of whether this condition is met.

[44] To see this, first note that the RK numerator equals:

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

By assumptions **RK1** and **RK3**, $\lim\limits_{\varepsilon\uparrow 0}\left[\frac{\partial \mathrm{E}[g(X)+U|X=x_0+\varepsilon]}{\partial x}\right] = \lim\limits_{\varepsilon\downarrow 0}\left[\frac{\partial \mathrm{E}[g(X)+U|X=x_0+\varepsilon]}{\partial x}\right]$. Furthermore, $\lim\limits_{\varepsilon\uparrow 0}\left[\frac{\partial \mathrm{E}[\mathbf{1}[T>0]|X=x_0+\varepsilon]}{\partial x}\right] = \lim\limits_{\varepsilon\downarrow 0}\left[\frac{\partial \mathrm{E}[\mathbf{1}[T>0]|X=x_0+\varepsilon]}{\partial x}\right] = 0$ and by assumption, $\lim\limits_{\varepsilon\uparrow 0}\left[\frac{\partial \mathrm{E}[h(X)|X=x_0+\varepsilon]}{\partial x}\right] = \lim\limits_{\varepsilon\downarrow 0}\left[\frac{\partial \mathrm{E}[h(X)|X=x_0+\varepsilon]}{\partial x}\right]$. Therefore, the RK numerator equals: $\tau_1\left(\lim\limits_{\varepsilon\uparrow 0}\left[\frac{\partial \mathrm{E}[T|X=x_0+\varepsilon]}{\partial x}\right] - \lim\limits_{\varepsilon\downarrow 0}\left[\frac{\partial \mathrm{E}[T|X=x_0+\varepsilon]}{\partial x}\right]\right)$, and the RK estimator equals: $\tau_{RK} = \tau_1$.

Combining these two terms allows for identification of τ_0:

$$\tau_0 = (\tau_{RD} - \tau_{RK}) \cdot T(x_0) \tag{A.5}$$

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 $\tau_{RK} = \tau_1 + \tau_2 T(x_0) + ... + \tau_p T(x)^{p-1}$ where p is the order of polynomial in T. Thus, using a combined RD/RK approach, it is always possible to identify τ_0 - 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.

A.1 Multiple treatment dimensions: 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:

$$Y = f(Pell, \tau) + g(EFC) + U \tag{A.6}$$

$$Pell = \pi(400 - (EFC - efc_0)) \times \mathbf{1}[EFC < efc_0] \tag{A.7}$$

Where efc_0 is the cut-off for Pell Grant eligibility, $\pi \in \{0,1\}$is a random variable, and $\mathrm{E}[\pi] > 0$ (i.e., π represents the probability a student applies for federal aid). Although π may depend on EFC, since the decision to apply for for financial aid is determined prior to Pell Grant receipt, I assume $\pi = \pi(EFC)$ 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): $f(Pell,\tau) = \tau_0 \mathbf{1}[Pell > 0] + \tau_1 Pell$. The RD estimator is equal to:

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

Since $\frac{\lim_{\varepsilon \uparrow 0} \mathrm{E}[\mathbf{1}[Pell>0]|EFC=efc_0+\varepsilon]}{\lim_{\varepsilon \uparrow 0} \mathrm{E}[Pell|EFC=efc_0+\varepsilon] - \lim_{\varepsilon \downarrow 0} \mathrm{E}[Pell|EFC=efc_0+\varepsilon]} = \frac{\lim_{\varepsilon \uparrow 0} \Pr[\pi=1|EFC=efc_0+\varepsilon]}{\lim_{\varepsilon \uparrow 0} \mathrm{E}[\pi(400-(EFC-efc_0))|EFC=efc_0+\varepsilon]} = \frac{1}{400}$, as in the sharp case, $\tau_{RD} = \tau_1 + \frac{\tau_0}{Pell(efc_0)}$, 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 identifies τ_1 and $\tau_0 = (\tau_{RD} - \tau_{RK}) \cdot 400$.

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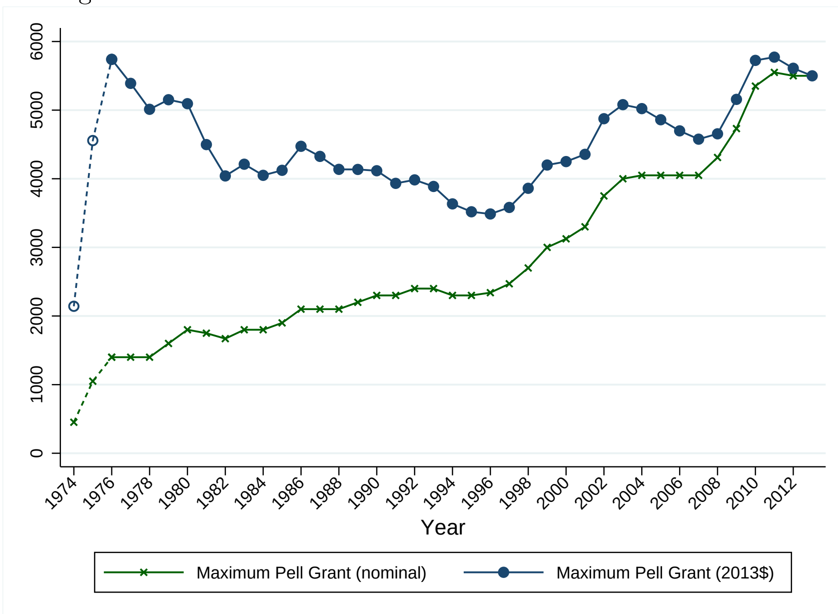
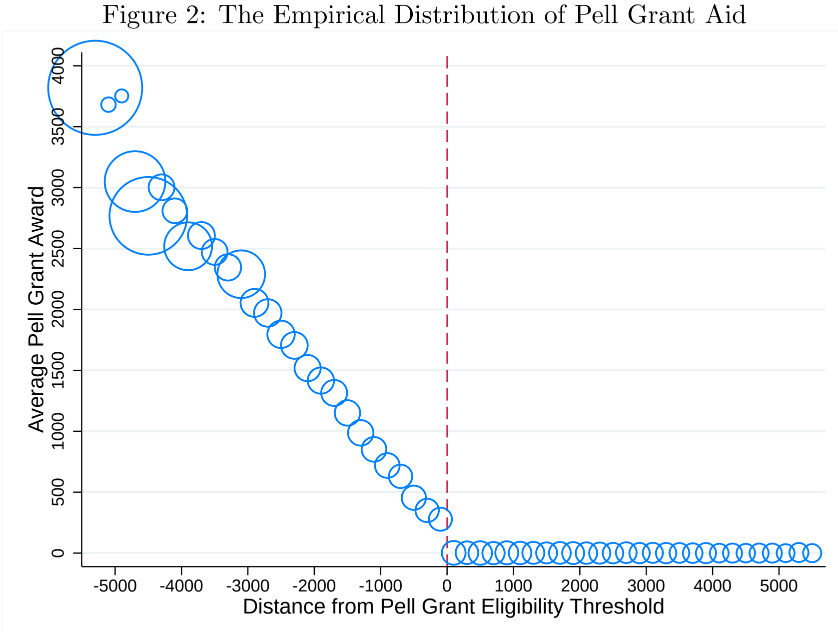
Figures and Tables

Figure 1: Time Series Variation in Maximum Pell Grant Award



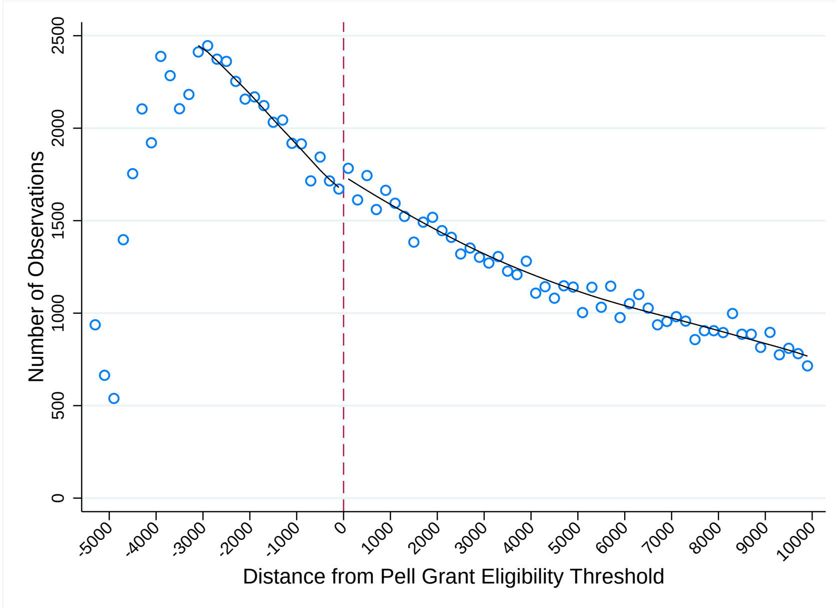
Source: U.S. Department of Education (2014). *Notes:* Dashed lines indicate years in which the Pell Grant Program was partially implemented (1974 and 1975).

Figure 2: The Empirical Distribution of Pell Grant Aid



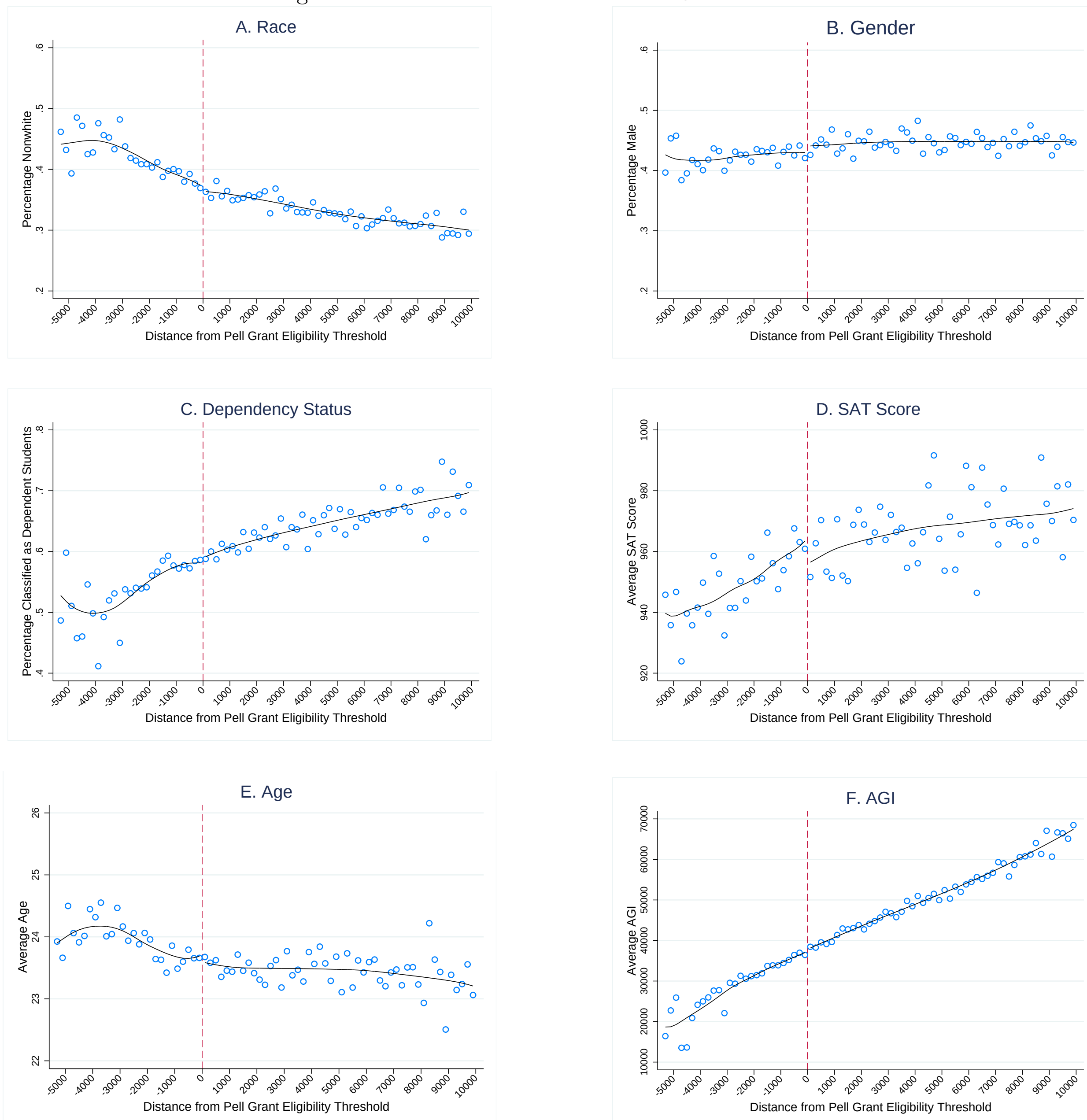
Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes:* Each circle represents the average Pell Grant received by students with standardized expected family contribution ($\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the threshold for Pell Grant eligibility in year t) within a given \$200 bin. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Figure 3: The Density of EFC at the Pell Grant Eligibility Threshold



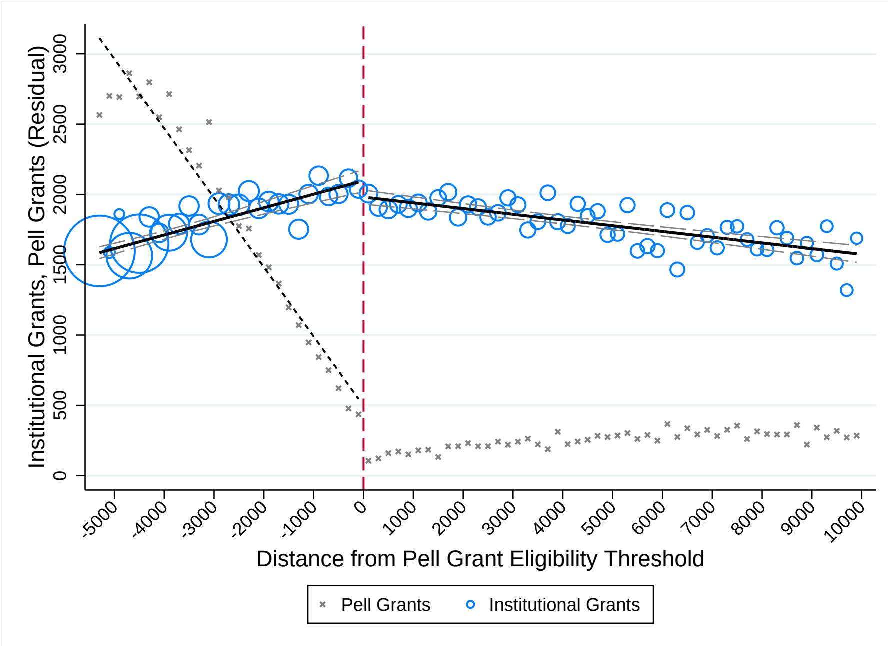
Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: \$200 $\widetilde{EFC}$ bins; each circle represents the number of students in the bin. The black line represents the predicted density from a local linear regression of the number of students in a given bin on $\widetilde{EFC}$, allowed to vary on either side of the Pell Grant eligibility threshold. Estimated level change from equation (7)with $\rho = 12$ (see Section 4 for additional details), $\hat{\beta} = -51.13\,(82.60)$; estimated slope change, $\hat{\gamma} = -0.186\,(0.436)$; $p = 0.648$ from F-test of joint significance of coefficients. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Figure 4: The Distribution of Baseline Characteristics



Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: \$200 $\widetilde{EFC}$ bins; each circle represents the mean characteristic for students in the bin (recentered residuals from a regression on school and year fixed effects). The black line represents the predicted density from a local linear regression of the mean characteristic of students in a given bin on $\widetilde{EFC}$, allowed to vary on either side of the Pell Grant eligibility threshold. Panel A (probability nonwhite): $\rho = 4$, $\hat{\beta} = -0.001\,(0.008)$, $\hat{\gamma} = -0.00001\,(0.00002)$, and $p = 0.789$ from F-test of joint significance of coefficients. Panel B (probability male): $\rho = 3$, $\hat{\beta} = -0.003\,(0.009)$, $\hat{\gamma} = -0.000002\,(0.00001)$, and $p = 0.934$ from F-test of joint significance of coefficients. Panel C (probability dependent student): $\rho = 15$, $\hat{\beta} = -0.015\,(0.014)$, $\hat{\gamma} = -0.00006\,(0.0001)$, and $p = 0.555$ from F-test of joint significance of coefficients. Panel D (SAT score): $\rho = 1$, $\hat{\beta} = 2.89\,(4.19)$, $\hat{\gamma} = 0.003\,(0.002)$, and $p = 0.618$ from F-test of joint significance of coefficients. Panel E (age): $\rho = 1$, $\hat{\beta} = 0.131\,(0.098)$, $\hat{\gamma} = -0.0001\,(0.00004)^{**}$, and $p = 0.006$ from F-test of joint significance of coefficients. Panel F (Adjusted Gross Income): $\rho = 1$, $\hat{\beta} = 336.95\,(781.70)$, $\hat{\gamma} = 1.14\,(0.45)^{*}$, and $p = 0.009$ from F-test of joint significance of coefficients. Degree of polynomial ρ chosen to minimize AIC from a regression of the mean characteristic on $\widetilde{EFC}$, allowing for a kink and a slope, using equation (7). All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Figure 5: Pell Grant Generosity and Institutional Aid by EFC



Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: \$200 EFC bins. The black solid line represents a linear fit of average institutional grant aid (recentered residuals from a regression with school and year fixed effects) on $\widetilde{EFC}$, estimated separately on each side of the Pell Grant eligibility threshold; gray dashed lines are 95 percent confidence intervals. The thin black dashed line is a linear fit of Pell Grant aid (residuals from a regression on school and year fixed effects) on EFC. Larger circles indicate a larger number of students. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Figure 6: Pell Grant Generosity and Institutional Aid by Sector

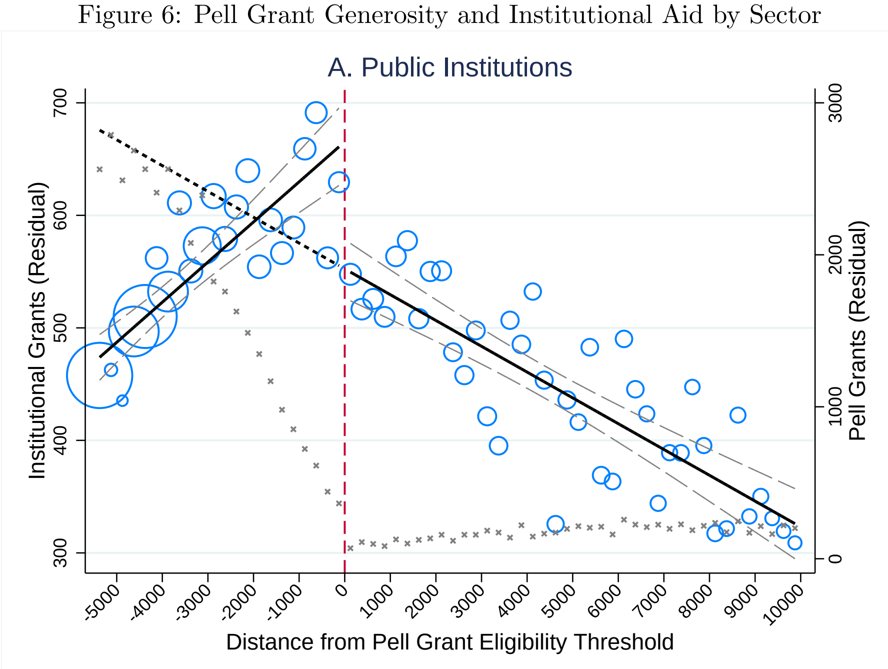
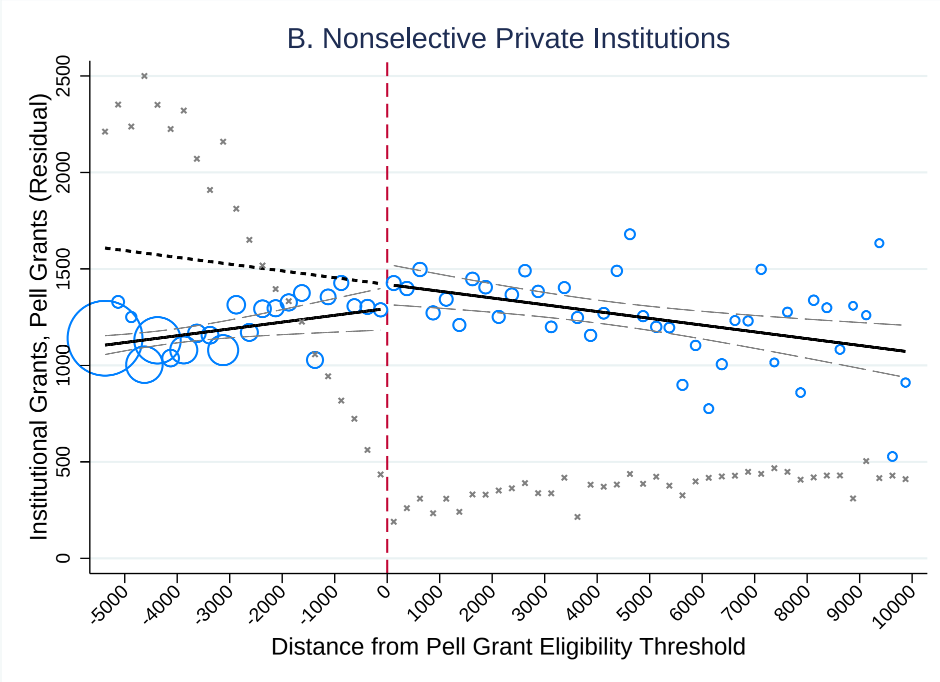
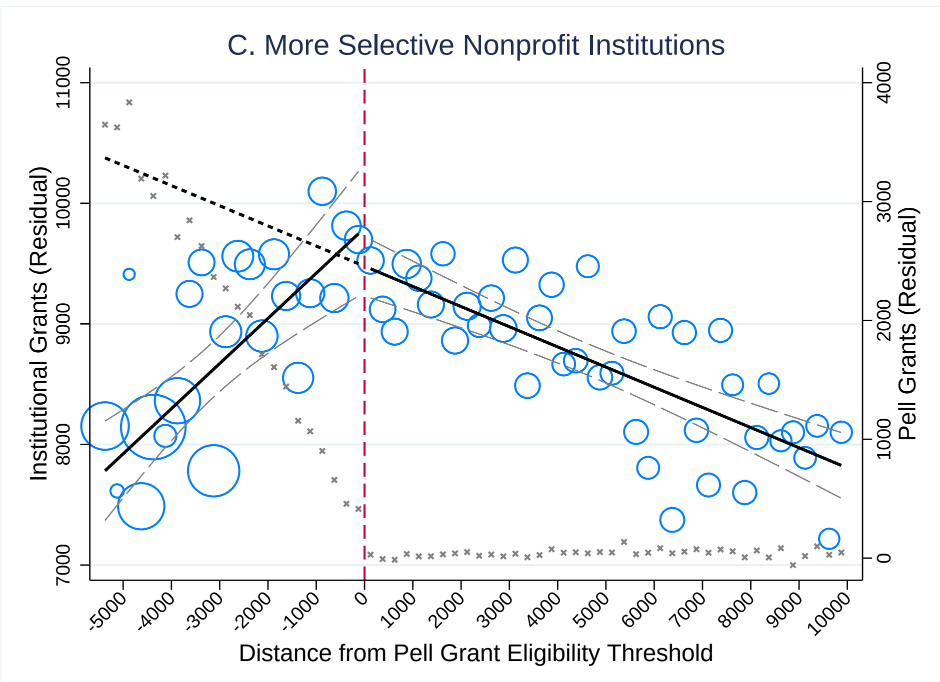


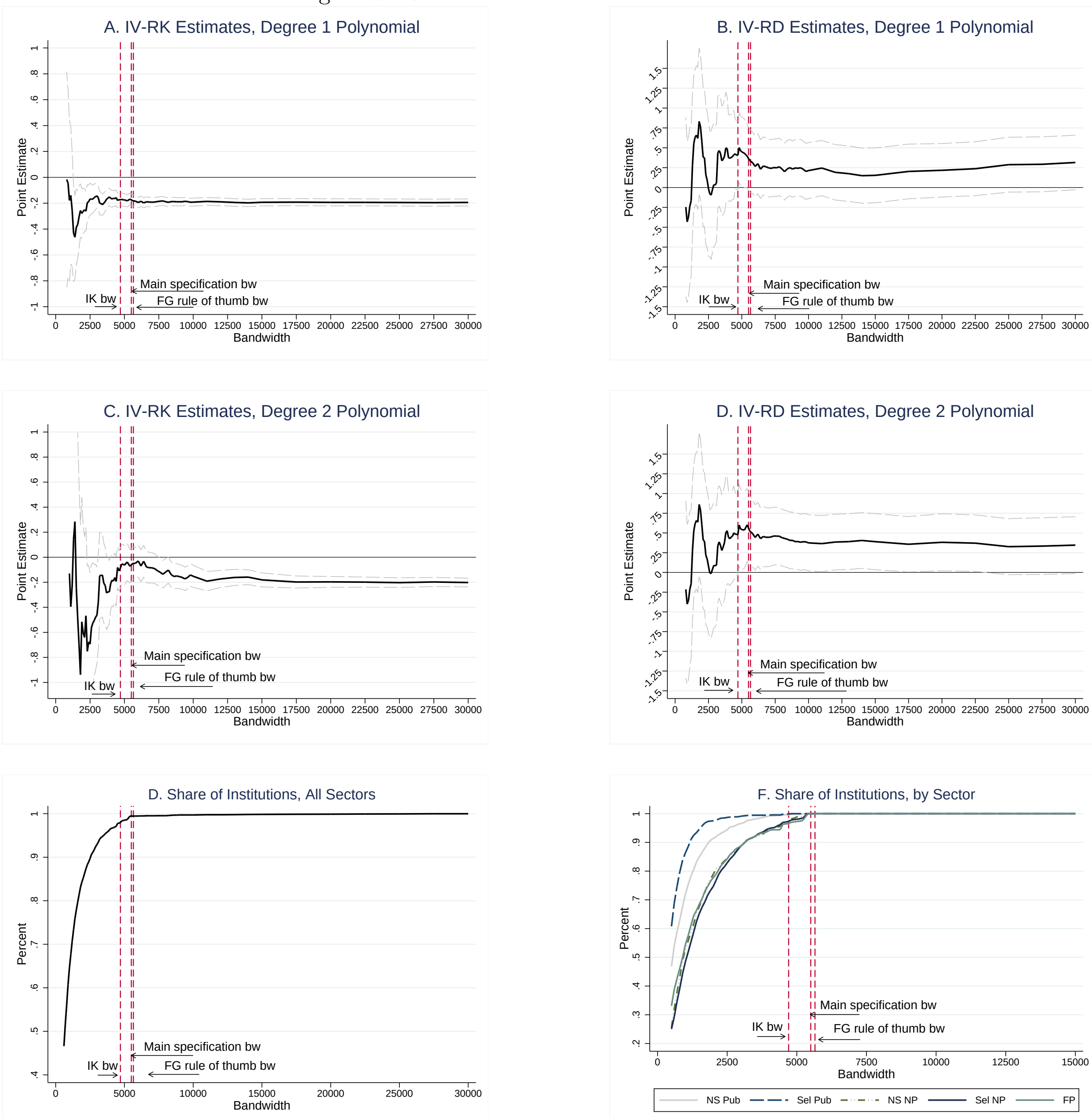
Figure 6, continued





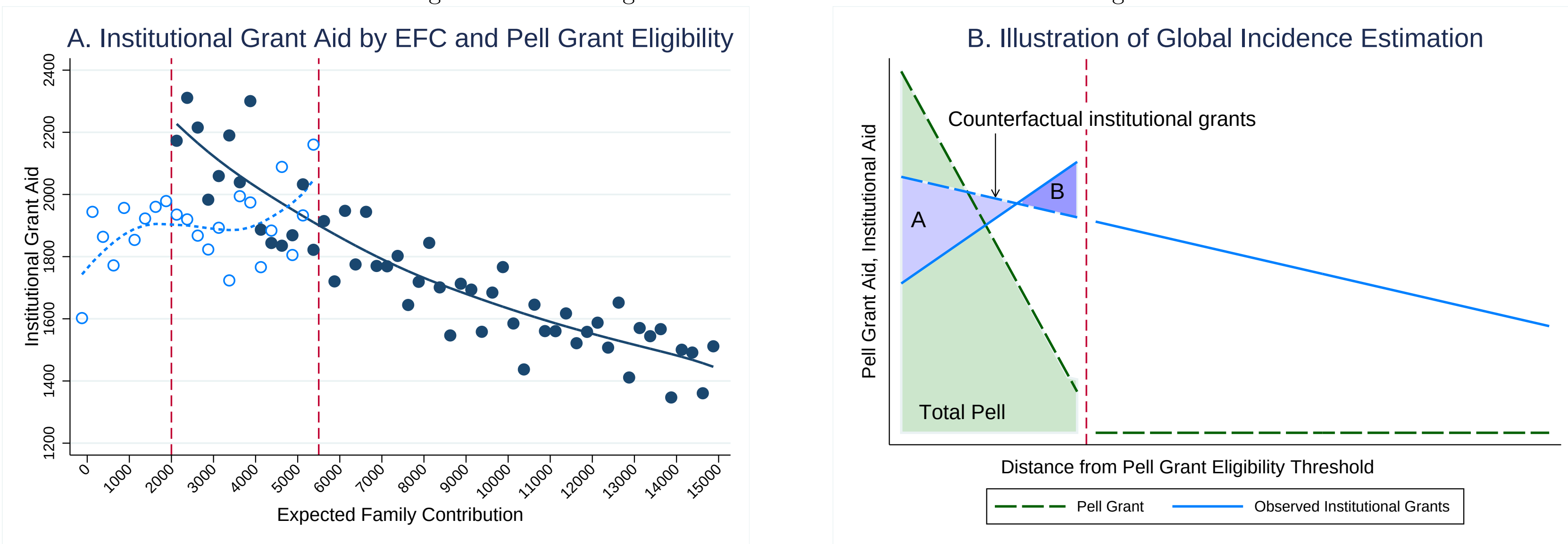
Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: \$250 EFC bins. The black solid line represents a linear fit of average institutional grant aid (recentered residuals from a regression with school and year fixed effects) on $\widetilde{EFC}$, estimated separately on each side of the Pell Grant eligibility threshold; gray dashed lines are 95 percent confidence intervals. The thin black dashed line represents predicted institutional grant aid using the relationship between institutional grant aid and EFC for Pell Grant ineligible students. Larger circles indicate a larger number of students. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Figure 7: Robustness of Estimates to Bandwidth



Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: Panels A through D display IV estimates from a regression of institutional grant aid on Pell Grant aid using varying windows around the Pell Grant eligibility threshold (e.g., a bandwidth of 5000 only includes students with an $\widetilde{EFC}$ within 5,500 of this threshold); the black solid line represents point estimates for each bandwidth and the light gray dashed lines represent the corresponding 95 percent confidence intervals. All regressions include linear and quadratic terms in age, and indicators for gender, race, fall attendance status, enrollment length, level, dependency status, out-of-state student, the specified polynomial in student expected family contribution allowed to vary by survey year ($\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the threshold for Pell Grant eligibility in year t), an indicator for Pell Grant eligibility ($\mathbf{1}[\widetilde{EFC}_{it} < 0]$), and the interaction between Pell Grant eligibility and distance from the eligibility threshold ($\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$). In IV-RK regressions, $\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$ serves as the excluded instrument for Pell Grant aid; in IV-RD regressions, the excluded instrument is $\mathbf{1}[\widetilde{EFC}_{it} < 0]$. Panels E and F display the share of all NPSAS institution by year observations that are included in a given bandwidth, both across all sectors (Panel E) and by sector (Panel F). All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Figure 8: Estimating the Global Incidence of the Pell Grant Program



Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: Panel A – each circle represents the institutional grant aid received by students within a given $200 EFC bin, with dark solid circles representing Pell Grant ineligible students and light hollow circles representing Pell Grant eligible students. The vertical dashed lines represent the range of EFC within which students gained Pell Grant eligibility between 1996 and 2012. The dark solid line represents predicted institutional grant aid from a local linear regression of institutional grant aid on EFC among Pell Grant ineligible students; the light dashed line represents the same for Pell Grant eligible students. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars. Panel B – the area labeled Total Pell represents the total amount of Pell Grant aid disbursed to students. The areas A and B represent the difference between the area below the counterfactual institutional grant aid-EFC relationship (represented by the dashed line) and the actual institutional grant aid-EFC relationship for Pell eligible students (represented by the solid line); A-B represents the amount of institutional grant aid students failed to receive due to the Pell Grant Program. See Section 7 for details.

Table 1: Characteristics of Schools and Students by Pell Grant Receipt

	(1) Pell Grant Recipients	(2) Nonrecipients	(3) Full Sample
A. Cost of Attendance and Financial Aid			
Expected family contribution	$741	$3,979	$2,034
Cost of attendance	$18,993	$16,072	$17,827
Pell Grant aid	$3,256	$0	$1,956
State grant aid	$1,020	$450	$792
Other federal grant aid	$259	$19	$163
Institutional grant aid	$1,377	$1,436	$1,400
Percent receiving institutional aid	0.23	0.21	0.23
Unmet need	$11,952	$9,792	$11,090
Percent with unmet need	0.99	0.90	0.95
B. Student Demographic Characteristics			
White	0.49	0.67	0.57
Male	0.39	0.46	0.42
Dependent student	0.49	0.56	0.52
Age	24	24	24
In-state	0.88	0.87	0.88
Adjusted gross income	$19,257	$37,128	$26,105
C. Student Attendance Status			
Full-time	0.77	0.67	0.73
Months of enrollment	11	10	10
D. Institution Selectivity and Control			
Nonselective public	0.43	0.47	0.45
Nonselective nonprofit	0.08	0.07	0.08
For-profit	0.23	0.09	0.18
More selective public	0.17	0.24	0.20
More selective nonprofit	0.09	0.12	0.10
Number of students	91,620	60,880	152,500

Source: 1996, 2000, 2004, and 2008 NPSAS. *Notes*: Number of observations rounded to nearest 10. See Section 3 for definitions of selectivity and control. Sample excludes graduate and professional students, students attending multiple institutions during the academic year, students not enrolled in the fall semester, athletic scholarship recipients, noncitizens, and students attending nondegree granting institutions, theological seminaries, or other faith-based institutions. See Online Appendix B for further details. Cost of attendance equals tuition and fees, books and supplies, and room and board, transportation, and other living expenses. Total need equals $max\{(COA - EFC), 0\}$. Unmet need equals total need minus EFC, state, federal, and institutional grants. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Table 2: RK and RD Estimates of the Impact of Pell Grant Aid on Institutional Aid

	OLS		IV	
	(1) FS	(2) RF	(3) RK	(4) RD
Change in slope	-0.614	0.105		
	(0.005)**	(0.014)**		
Change in level	212.16	81.58		
	(11.01)**	(42.52)+		
Pell Grant Aid			-0.171	0.385
			(0.023)**	(0.202)+
F-test of excluded instrument			17600	372
Test of equality (p -value)			0.005	
Observations	152,500	152,500	152,500	152,500

Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: Each column represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution by year level in parentheses; ** p<0.01, * p<0.05, + p<0.1. All regressions include school by year fixed effects, linear and quadratic terms in age, and indicators for gender, race, fall attendance status, enrollment length, level, dependency status, out-of-state student, and student expected family contribution allowed to vary by survey year ($\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the threshold for Pell Grant eligibility in year t), an indicator for Pell Grant eligibility ($\mathbf{1}[\widetilde{EFC}_{it} < 0]$), and the interaction between Pell Grant eligibility and distance from the eligibility threshold ($\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$). In column 3, $\mathbf{1}[\widetilde{EFC}_{it} < 0]$ serves as the excluded instrument for Pell Grant Aid. In column 4, $\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$ serves as the excluded instrument for Pell Grant Aid. Students with EFC greater than 5,500 from Pell Grant eligibility threshold are excluded. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Table 3: Local Linear Regression Estimates

	OLS		IV	
	(1) FS	(2) RF	(3) RK	(4) RD
A. Imbens-Kalyanaraman Bandwidth				
Change in slope	-0.592	0.119		
	(0.034)**	(0.016)**		
Change in level	234.75	145.2		
	(21.33)**	(47.22)**		
Pell Grant Aid			-0.209	0.464
			(0.029)**	(0.151)**
Test of equality (*p* -value)			<0.001	
Bandwidth	1154	4705	4705	4705
Percent of institutions	0.87	0.99	0.99	0.99
Observations	19,880	108,440	108,440	108,440
B. Fan-Gijbels Rule of Thumb Bandwidth				
Change in slope	-0.614	0.132		
	(0.027)**	(0.011)**		
Change in level	226.97	131.29		
	(20.85)**	(36.13)**		
Pell Grant Aid			-0.304	0.213
			(0.031)**	(0.069)**
Test of equality (*p* -value)			<0.001	
Bandwidth	1324	5652	5652	5652
Percent of institutions	0.89	1.00	1.00	1.00
Observations	22,940	153,400	153,400	153,400

Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: Each cell represents a separate regression. Number of observations rounded to nearest 10. Students above bandwidth chosen using the Imbens and Kalyanaraman (2012) method (Panel A) or the Fan and Gijbels (1996) rule of thumb bandwidth (Panel B) are excluded. Standard errors clustered at institution by year level in parentheses; ** p<0.01, * p<0.05, + p<0.1. All regressions include school by year fixed effects, student expected family contribution allowed to vary by survey year ($\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the threshold for Pell Grant eligibility in year t), an indicator for Pell Grant eligibility ($\mathbf{1}[\widetilde{EFC}_{it} < 0]$), and the interaction between Pell Grant eligibility and distance from the eligibility threshold ($\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$). RD estimates instrument for Pell Grant aid with $\mathbf{1}[\widetilde{EFC}_{it} < 0]$; RK estimates instrument with $\widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0]$. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Table 4: RK and RD Estimates: Additional Robustness Tests

	(1) IV (RK)		(2) IV (RD)
A. Accounting for other grant aid			
Federal and state grant aid	-0.172		0.212
	(0.023)**		(0.110)+
Test of equality (*p* -value)		0.001	
Observations	152,500		152,500
B. Dropping institutions that meet full need			
Pell Grant Aid	-0.190		0.441
	(0.025)**		(0.219)*
Test of equality (*p* -value)		0.004	
Observations	128,910		128,910
C. Dropping institutions that do not give out institutional aid			
Pell Grant Aid	-0.169		0.343
	(0.022)**		(0.200)+
Test of equality (*p* -value)		0.009	
Observations	151,250		151,250
D. Using sampling weights			
Pell Grant Aid	-0.143		0.416
	(0.026)**		(0.270)
Test of equality (*p* -value)		0.039	
Observations	152,500		152,500
E. Excluding covariates			
Pell Grant Aid	-0.170		0.361
	(0.022)**		(0.216)+
Test of equality (*p* -value)		0.013	
Observations	152,500		152,500
F. Excluding fixed effects			
Pell Grant Aid	-0.212		1.517
	(0.033)**		(0.289)**
Test of equality (*p* -value)		<0.001	
Observations	152,500		152,500

Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: Each column represents a separate regression. Number of observations rounded to nearest 10. Standard errors clustered at institution by year level in parentheses; ** p<0.01, * p<0.05, + p<0.1. See Table 2 notes for discussion of control variables and instruments. In Panel A, Pell Grant aid is replaced with the sum of federal and state grant aid. In Panel B, students attending institutions that have pledged to meet full need in the survey year are excluded (see Section 5 for details). In Panel C, students attending institutions that do not provide institutional aid in any of the NPSAS waves are excluded. Panel D models are weighted with the NPSAS sampling weights. Panel E models only include school by year fixed effects and a linear term in $\widetilde{EFC}$ that is allowed to vary by survey year, while Panel F models only include $\widetilde{EFC}$ (allowed to vary by survey year).

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

	Pass-Through	Willingness to Pay
A. All institutions	-0.171	283.90
	(0.023)**	(101.86)**
Observations	152,500	
B. By sector		
Nonselective Public	-0.056	191.85
	(0.012)**	(131.14)
More Selective Public	-0.098	421.94
	(0.031)**	(135.53)**
Nonselective Nonprofit	-0.220	-218.23
	(0.085)*	(498.41)
More Selective Nonprofit	-0.748	1044.67
	(0.133)**	(414.23)*
For-profit	-0.059	-1.46
	(0.029)*	(76.37)
Observations	152,500	

Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: Each panel represents estimates from separate models. Number of observations rounded to nearest 10. Standard errors clustered at institution by year level in parentheses; ** p<0.01, * p<0.05, + p<0.1. All models include school by year fixed effects, linear and quadratic terms in age, and indicators for gender, race, fall attendance intensity, enrollment length, level, dependency status, out-of-state student, and a linear term in student expected family contribution allowed to vary by survey year ($\widetilde{EFC}_{it} = EFC_{it} - efc_{0t}$, where efc_{0t} is the threshold for Pell Grant eligibility in year t). Panel B also includes interactions between sector dummies and $\widetilde{EFC}$, discontinuity, and kink. Students with an $\widetilde{EFC}$ greater than \$5,500 from Pell Grant cut-off are excluded. See Section 6 for definitions and estimation of treatment dimensions. See Section 3 for definitions of sectors. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.

Table 6: Heterogeneity in the Impact of Pell Grant Aid on Institutional Aid by Sector and Demographic Characteristics

	(1) Race			(2) Gender			(3) Class Level		
	White	Nonwhite	Test of equality	Female	Male	Test of equality	First year	Upper year	Test of equality
Public Institutions									
Pass-through	-0.075	-0.069	[0.837]	-0.074	-0.083	[0.735]	-0.070	-0.091	[0.452]
	(0.018)**	(0.027)*		(0.019)**	(0.022)**		(0.019)**	(0.020)**	
WTP	147.52	634.23	[0.078]	249.04	305.16	[0.773]	230.88	433.94	[0.215]
	(79.04)+	(279.65)*		(105.68)*	(129.25)*		(123.30)+	(124.17)**	
Nonselective Private Institutions									
Pass-through	-0.074	-0.183	[0.211]	-0.112	-0.135	[0.755]	-0.094	-0.133	[0.600]
	(0.059)	(0.064)**		(0.062)+	(0.056)*		(0.052)+	(0.055)*	
WTP	-77.98	-87.09	[0.996]	-27.39	-216.17	[0.486]	-169.62	-267.44	[0.797]
	(175.57)	(235.30)		(227.01)	(202.79)		(141.19)	(352.42)	
Selective Nonprofit Institutions									
Pass-through	-0.849	-0.709	[0.628]	-0.669	-0.882	[0.400]	-0.743	-0.770	[0.916]
	(0.152)**	(0.278)*		(0.184)**	(0.193)**		(0.235)**	(0.158)**	
WTP	1143.48	363.64	[0.568]	443.06	1807.76	[0.073]	774.10	840.65	[0.939]
	(367.35)**	(1377.60)		(511.59)	(610.93)**		(731.71)	(502.86)+	
Observations	152,500			152,500			152,500		
Test of equality (*p*- value):									
Pass-through	<0.001	0.022		0.005	<0.001		0.016	<0.001	
WTP	0.008	0.130		0.481	0.002		0.063	0.111	

Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: Each panel represents a estimates from separate models. Number of observations rounded to nearest 10. Standard errors clustered at institution by year level in parentheses; ** p<0.01, * p<0.05, + p<0.1. See Table 5 notes for additional details on controls and treatment dimensions.

Table 7: The Incidence of Pell Grant Aid

	Percent Captured	95% Confidence Interval
All Institutions	0.118	[0.08, 0.15]
By Sector:		
Public Institutions	0.049	[0.03, 0.07]
Nonselective Private Institutions	0.349	[0.22, 0.47]
More Selective Nonprofit Institutions	0.663	[0.48, 0.84]
For-profit Institutions	0.011	[-0.03, 0.05]

Source: 1996, 2000, 2004, 2008, and 2012 NPSAS. See Online Appendix B for sample construction details. *Notes*: These estimates assume the observed institutional aid-EFC relationship for Pell ineligible students is a valid counterfactual for Pell eligible students in the absence of the Pell Grant Program. The overall percentage of Pell Grant aid captured by institutions is equal to the ratio of the difference between the area below the counterfactual Pell Grant-EFC curve and the actual Pell Grant-EFC curve and the overall transfer of Pell Grant aid to eligible students (see Section 7 for details). Number of observations rounded to nearest 10. All dollar amounts adjusted for inflation using the CPI-U and reported in 2013 dollars.