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Pell Grants and Labor Supply: Evidence from a Regression Kink

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ABSTRACT

A concern in higher education policy is that students are taking longer to graduate. One possible reason for this observation is an increase in off-campus labor market participation among college students. Financial aid may play a role in the labor/study choice of college students—as college becomes more affordable, students my substitute away from work and toward increased study. I use data from the National Postsecondary Student Aid Study (NPSAS) to exploit nonlinearity in the Pell Grant formula to estimate a regression kink and regression discontinuity designs. I find that conditional on receiving the minimum of $550, students reduce their labor supply by 0.4 hours per week, which translates to a 2.4 percent decrease in hours worked. Students who receive the average Pell Grant of $2,250 are 7.6 percentage points (or around 12 percent) less likely to work and, if working, supply 5.10 less hours per week, or around 30.67 percent reduction. I find Pell Grants do increase academic achievement, implying that students substitute study time for work.

JEL Classification Codes: I22, I23, J20

Key Words: Pell Grants, financial aid, regression kink, labor supply

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1 Introduction

A concern in U.S. higher education is the increasing time that it takes the average undergraduate to complete a four-year degree (Bound, Loveheim and Turner, 2010, 2012). One possible reason for this increase is that more students are working off campus than ever before (Scott-Clayton, 2012; Darolia, 2014; Scott-Clayton and Minaya, 2016; Stoddard and Urban, 2019). This change in behavior may be a result of decreasing amounts of per student financial aid at a time when tuition hikes outpace the rate of inflation. If college tuition net of financial aid is increasing, then students may need to work more to fund their college education, especially if they come from lower-income households or are credit constrained.

This paper examines a causal link between the amount of financial aid that a student receives (via the Pell Grant) and student labor supply on both the intensive and extensive margins. I use a regression kink/regression discontinuity design to identify this causal effect. Regression kink is a relatively new technique and was introduced by Card et al. (2015). Turner (2017) first proposed using the regression kink method to exploit kinks and discontinuities in the Pell Grant formula to compare differences in price discrimination from Pell Grants in for-profit versus traditional universities. Turner and Marx (2018) also use this method to identify the causal effect of Pell Grants on student loan debt.[1] This model allows me to study how students change their labor supply decision from a quasi-experimental standpoint by examining those students who are close to the eligibility cutoff (regression discontinuity) and the students who are close to changes in the marginal implicit tax on income because of nonlinearities (regression kink) in the Pell Grant formula.[2]

[1]Researchers have used the regression kink method to identify causal effects in a number of other settings, including the effect of the Earned Income Tax Credit on labor supply (Jones, 2013), the effects of kinks in the tax code on labor supply (Chetty, 2012; Chetty et al., 2011), the effects of an increase in tax returns on college enrollment (Manoli and Turner, 2018), and the effects of unemployment benefits on labor supply (Landais, 2015)

[2]Jeffrey T. Denning and Turner (2019) also use this technique to estimate the effects of Pell Grants on college competition and earnings postgraduation. Evans and Nguyen (2019) use a regression discontinuity to show that Pell Grants reduce student loan balances. Eng and Matsudaira (2021) use a similar methodology

The relationship between student labor supply and college outcomes is unclear, and there is little research that explores why students may choose to work and how employment affects academic outcomes. Some researchers have found that students who allocate more time toward work have lower grades (Kalenkoski and Pabilonia, 2010; Stinebrickner and Stinebrickner, 2003; Liu, 2020) and take longer to graduate (Darolia, 2014; Ehrenberg and Sherman, 1984). However, working a small amount in college, in a field that is connected to the student's major or desired occupation, may be beneficial because it allows the student to gain job experience and establish a professional network (Ruhm, 1997; Light, 2001, 1998).

This paper also adds to the literature by expanding economists' understanding of how transfer payments affect labor supply. Most of the literature has focused on policies designed to help the working poor. Results regarding the effect of cash transfers on labor supply are mixed. For example, Meyer (2002) finds that the changes in the Earned Income Tax Credit (EITC) decreases labor supply on the extensive, but not intensive, margins. However, Jones (2013) finds that workers who face a higher implicit tax because of the loss of EITC do reduce work hours, but this result is only robust for single mothers with one child. Eissa and Hoynes (2004) find that an increase in the implicit tax from the EITC increases male labor supply by a small amount but decreases female labor supply by a greater amount, thus offsetting any gains. Regarding other programs, Hoynes (1996) finds that Aid to Families with Dependent Children-Unemployed Parent Program decreased labor supply greatly for families eligible for the program, Moffitt and Wolfe (1992) find that Medicaid has a large effect on labor supply on all margins, and Depew (2012) finds that mandating dependent health insurance in the Affordable Care Act reduces labor supply of young adults. One possible reason for the disparate results from these studies is that working poor families maximize lifetime consumption and may behave differently given their family makeup and whether the researcher is examining a marginal or average treatment effect. College students are different

to find small effects on college completion rates and earnings.

in that they maximize utility where present consumption is one input in addition to time spent studying and on leisure. Thus, college students may be more sensitive to changes in the amount of scholarship that they receive and reallocate their time toward other pursuits that may differ from the working poor receiving welfare aid.

The effects of financial aid on education outcomes are a popular area for researchers. Previous research shows that financial aid can influence whether a student enrolls in college (Nielsen, Sørensen and Taber, 2010; Cornwell, Mustard and Sridhar, 2006; Leslie and Brinkman, 1987; van der Klaauw, 2002; Dynarski, 2000), the type and prestige of the university that the student attends (Avery and Hoxby, 2004), and the probability a student persists to graduation in a timely matter (Bettinger, 2004; Larry D. Singell, 2004; Alon, 2007; Novak and McKinney, 2011; McKinney and Novak, 2013). Researchers have used a similar regression discontinuity design concerning eligibility for the minimum Pell Grant and found Pell can reduce work and student loans in both four-year (Evans and Nguyen, 2019) and community colleges (Park and Scott-Clayton, 2018). This paper adds to those findings by examining both the minimum Pell Grant via a regression discontinuity, but also additional Pell Grant via a regression kink. While the data I use in this study do not allow me to investigate the effect of student employment on long-term educational outcomes, I can establish a causal link between Pell Grants and student employment, which may then feed back into grades or persistence to graduation.

2 Pell Grants and Nonlinear Eligibility Rules

The Pell Grant program is arguably the largest financial aid program that is a grant as opposed to a loan. The federal government has dramatically expanded the program since its inception in 1965 by increasing both the maximum award and loosening the eligibility requirements. The Department of Education pays Pell Grant dollars directly to the institution, and the federal government does not require that students pay the aid back. However, Pell Grant eligibility is means tested, and a student's academic aptitude, career aspirations, gender, or race do not factor into the decision.

To be eligible for a Pell Grant, students must complete the Free Application for Federal Student Aid (FAFSA).[3] The FAFSA is very complex and is sometimes a deterrent to students who may be unfamiliar with the process or have incorrect ideas about their eligibility; this can result in students forgoing significant amounts of financial aid (Dynarski and Scott-Clayton, 2006; Deming and Dynarski, 2010; Kofoed, 2017).

Once a student completes the FAFSA, the federal government uses information about parent/student income, financial assets and other forms of savings, dependency status,[4] number of siblings (for dependent students), and number of dependents (for independent students). Using this information, the government calculates the expected family contribution (EFC), which measures how much the government believes that the student's parents or the individual student can contribute to his or her college expenses. The student does not know the value of their EFC when they apply for aid or begin the college application process. After the FAFSA deadline the federal government sends the student a notice with their EFC and the amount of aid that the student will receive.

To calculate a student's Pell Grant eligibility, the federal government subtracts the EFC from the maximum Pell Grant that is set by Congress. The maximum Pell Grant has changes over time and currently is \$5,500.[5] Thus the Pell Grant a student receives is equal

[3]There is a long literature about the complexity of the FAFSA and its effects on college enrollment and completion. Kofoed (2017) shows that many families leave thousands of dollars on the table for not completing FAFSA. Bettinger et al. (2012) randomly provided high school students to assistance with FAFSA completion from an H&R Block employee and find that those with help are more likely to enroll and complete college. Dynarski and Scott-Clayton (2006) show that these complexities are regressive and are an obstacle to the equitable distribution of aid.

[4]A student is considered independent if he or she is over the age of 24, has dependents, is married, or is a military veteran; otherwise the student is considered independent. For the purpose of establishing financial need, the government assumes that independent students do not receive parental support.

[5]For the three waves of data that I use in this paper, the maximum Pell Grant is as follows: 2003–2004, \$4,050.00; 2007–2008, \$4,310.00; 2011–2012, \$5,500.00.

to:

$$Pell_{it} = (maxPell_t - EFC_{it}) \times \mathbf{1}[maxPell_t - EFC_{it} \geq minPell_t] + 400 \times \mathbf{1}[maxPell_t - EFC_{it}] \in [200, minPell_t)]. \quad (1)$$

Figure 1 plots the amount of difference between $maxPell_t$ and EFC_{it} against the amount of Pell Grant a student receives in year t. This eligibility formula gives two nonlinearities that are useful for the regression kink/regression discontinuity design. First, any student whose $maxPell_t - EFC_{it}$ is less than \$200 will not receive any aid. Once the difference reaches \$200.00, a student automatically receives \$400.00 in Pell Grants, thus creating a discontinuity. The amount of aid plateaus until the difference between $maxPell_t$ and EFC_{it} reaches \$400.00, where a kink occurs and the student receives one dollar in additional Pell Grant for each dollar increase in the difference. This increase in aid continues until the difference is equal to or greater than $maxPell_t$, where the federal government simply awards the student the maximum Pell Grant and, regardless of the student's need, the student receives no additional grant aid.[6]

The aid formula contains three nonlinearities that produce sources of exogenous identification that I use to identify a causal relationship between financial aid and student labor supply. Turner (2017) first proposed the idea of using the Pell Grant formula with the regression kink technique and showed that universities reduce institutional aid for Pell Grant recipients via price discrimination. Turner and Marx (2018) also use this technique to examine the effect of an increase in Pell Grants and the amount of debt a student incurs.

[6]However, the federal government does begin to offer subsidized student loans to fill the gap up to a maximum point where unsubsidized student loans are used to fill the gap completely.

3 Data and Summary Statistics

3.1 Description of Data

This study uses data from the National Postsecondary Student Aid Survey (NPSAS). The National Center of Education Statistics (NCES), a subsidiary of the U.S. Department of Education, updates the NPSAS with a new cross section every four years. The main purpose of the NPSAS is to better understand how students pay for college. The data contain information such as the amounts of grants, loans, work study program, state lottery programs, and payments from personal accounts. These data also contain information from many sources, including student interviews, student responses to the FAFSA, and surveys completed by college and university administrators about their institutions. For students who do not complete FAFSA, the NCES imputes the values of key numbers such as the EFC from tax records and responses to surveys. Data contained in the NPSAS describe student characteristics such as grades, standardized test scores, and parents' income. NPSAS also identifies the college or university that the student attends and provides data about enrollment size, institutional control, and tuition pricing. All monetary variables are expressed in 2012 dollars.

The NPSAS creates a representative sample of typical college students for each of the 50 states, the District of Columbia, and Puerto Rico. Each institution of higher education that is eligible for federal student aid (i.e., Title IV compliant) is assigned a sampling probability and sampled with replacement so that the NPSAS creates a representative sample of the college student population in each state. Further, to create a nationally representative sample, the following states are oversampled to compensate for their comparative size: California, Georgia, Illinois, Minnesota, New York, and Texas. After the number of observations per institution is determined, NCES randomly samples students such that the sample would represent of the student body with regard to demographic information, types of financial aid, and major selection.

For my sample, I include undergraduate students who attend either a public or traditional university. I also drop students who attend more than one institution in a given year because their Pell Grant eligibility would change midyear. I also drop students who do not complete the FAFSA form. While this may introduce self-selection bias into the results since FAFSA is sufficiently complex and may deter students from completing FAFSA, including nonapplicants may distort the "treatment effect" because of students who otherwise would have been eligible for FAFSA but did not receive a Pell Grant. Including students who do not complete FAFSA would thus sufficiently have noncompliance that it may be difficult to isolate a causal effect given changes in the eligibility criteria.

3.2 Summary Statistics

The advantage of using the NPSAS is that it is representative of the universe of higher education. The data represent all types of students, including working students and community college students, as well as those from regional universities and elite research universities. These data are helpful in understanding student labor supply because they contain information on vulnerable populations and other populations of concern.

Table 1 displays summary statistics for the key variables used in this study. Column (1) shows the overall summary statistics for the entire sample. The average student in my sample works 16.85 hour per week (essentially part time), with 62.2 percent of students working positive hours and participating in the labor force. Also, the average Pell Grant is $1,614.32, with the average EFC being $6,375.99. The Department of Education uses the EFC to determine Pell Grant eligibility and is a key measure of families' and individuals' ability to pay for college. Overall, 60.2 percent of my sample is female, while 18.2 and 15.2 percent are black and Hispanic, respectively. Also, 61.2 percent of the students in my sample are dependents, and 77.7 percent are residents of the same state where their institution is located. Finally, 63.3 percent of my sample attend college full time.

Next, I separate Pell-eligible (column [2]) from non-Pell-eligible (column [3]) students. Between these two groups, there is roughly a third of an hour difference in the numbers of hours worked, with Pell-eligible students working slightly more. However, students not eligible for Pell Grants are more likely to participate in the labor market than students who receive Pell Grants. Unsurprisingly, the average EFC is considerably higher for non-Pell-eligible students. This result is large because it is common for a very poor student to receive an EFC of zero, while there is no upper limit on EFC. There is a higher concentration of female students who receive Pell Grants (64 percent of eligible students versus 57.1 percent of noneligible). Among students who receive Pell Grants, nearly 25 percent are black and 17.4 percent are Hispanic, while the subset of students who are not Pell eligible is 8.5 percent black and 7.8 percent Hispanic. Of students who receive Pell Grants, 41.9 percent are dependent on the parents, which shows that a majority of Pell recipients do not depend on their parents for support and are probably working. Students attending college in state and full-time students are more likely to receive Pell Grants. While the full sample comparison is quite similar, the regression discontinuity focuses on those students around the kink or the cutoff.

Figure 2 shows the average Pell Grant plotted over the distance from eligibility cutoff. Students who are eligible for Pell Grants are on the negative side of the axis (since $EFC_{it} <$ cutoff), while students who are not eligible are on the positive side. I have sorted students into \$100.00 EFC bins and plotted their Pell Grants. This plot shows that conditional on completing financial aid, the amount of Pell Grant that the federal government gives to its students complies closely to the eligibility formula shown in Figure 1. The NPSAS also contains data regarding how much time students spend working. For this study, I do not consider hours spent in the Federal Work Study Program, but am interested in student labor supply off campus. Federal Work Study is also linked to completion of the FAFSA, but the federal government controls how many hours a student can work. Thus, federal work study students may not have as much of an ability to adjust work schedules as those who work off campus.

Finally, I compare students on either side of the cutoff within a tighter bandwidth of plus or minus $3,000 of EFC. Columns (4) and (5) compare these summary statistics. First, it appears that within this bandwidth, similar students who are barely ineligible for Pell Grants work 18.51 hours weekly, while those who barely qualify for a Pell Grant work an average of 16.39 weekly labor hours. These columns also show that 67.7 percent of non-Pell-eligible students work, while 60.3 percent of Pell-eligible students work. Finally, these columns show that the differences demographically between the two groups begin the shrink as the bandwidth tightens.

4 Identification Strategy and Empirical Model

I use regression discontinuity/ kinks in the Pell Grant eligibility formula to identify causally the effect of Pell Grant receipt on college student labor supply. Turner (2017) first developed and used this identification strategy to estimate the reduction in institutional aid caused by Pell Grants. This reduction in aid estimates the degree of price-discriminating behavior by the university.

While regression discontinuity is not necessarily a new technique, regression kink is relatively new, even though it is based on the same principles as the regression discontinuity estimator. While the regression discontinuity design exploits the discontinuity in the first derivative to create exogenous variation needed for identification, the regression kink similarly uses a discontinuity in the second derivative. Regression kink has the potential to increase the number of opportunities for causal inference because sharp changes in policy rules are somewhat common compared to sharp cutoffs. However, similar to the regression discontinuity design, regression kinks require that exogenous variables be smooth around the kink such that agents cannot manipulate their eligibility to perfectly sort into certain outcomes.

Suppose that student labor supply L_S is a function of Pell Grants ($Pell$) and EFC such that

$$L_S = f(Pell, \tau) + g(EFC) + U, \tag{2}$$

where U is a random error term consisting of a vector of unobservables. Identification for the regression kink hinges on the validity of similar assumptions about regression discontinuities (Card et al., 2015). First, in the neighborhood of the kink points, there cannot be any discontinuities in the running variable; thus, there cannot be bunching of observations in EFC around the kink points signifying that agents are "gaming the system" by reducing their incomes such that they become eligible for more Pell Grant funds. This assumption helps to ensure that EFC is independent of the Pell Grant cutoffs and that agents do not have the ability to manipulate their own eligibility. Second, there cannot be any discontinuities in the EFC as it relates to labor force participation and the number of hours worked. This assumption guarantees that the estimated treatment effect (τ) is the same regardless if one decreases or increases the EFC by the same amount. These assumptions are necessary to ensure that (while other factors are obviously influencing labor supply), in the neighborhood of the kinks, the change in Pell Grant eligibility is as good as random to the student. Thus, using both the minimum Pell Grant eligibility and kinks that alter the implicit tax of financial aid on wages identifies the causal effect of Pell Grants on labor supply.

Assuming a linear relationship between Pell Grants and labor supply, then

$$f(Pell, \tau) = \tau_1 Pell, \tag{3}$$

where τ_1 represents the marginal effect of $1.00 of Pell Grant funds on the student's labor force participation and the number of hours worked.

If the previously stated assumptions hold, then I can estimate the treatment effect by using the following regression kink and regression discontinuity estimates:

$$\tau_{RKD} = \frac{\lim_{\epsilon \to 0^+} \frac{dE[L_S|EFC=efc_k+\epsilon]}{dEFC} - \lim_{\epsilon \to 0^-} \frac{dE[L_S|EFC=efc_k+\epsilon]}{dEFC}}{\lim_{\epsilon \to 0^+} \frac{dE[Pell|EFC=efc_k+\epsilon]}{dEFC} - \lim_{\epsilon \to 0^-} \frac{dE[Pell|EFC=efc_k+\epsilon]}{dEFC}} \tag{4}$$

$$\tau_{RKD} = \frac{lim_{\epsilon \to 0^+}[L_S|EFC = efc_d + \epsilon] - lim_{\epsilon \to 0^-}[L_S|EFC = efc_d + \epsilon]}{lim_{\epsilon \to 0^+}[Pell|EFC = efc_d + \epsilon] - lim_{\epsilon \to 0^-}[Pell|EFC = efc_d + \epsilon]}. \tag{5}$$

Since the maximum and minimum Pell Grant amounts change over time, I standardize the running variable so that the dependent variable is the distance from the maximum Pell Grant in a given year ($maxPell_t$) such that $\widetilde{EFC}_{it} = EFC_{it} - efc_d$; where efc_d is the minimum Pell Grant or the discontinuity point. Given this standardization, Pell-eligible students would have a negative $\widetilde{EFC}_{it}$ because $EFC_{itc} < efc_d$.

Using this $\widetilde{EFC}_{it}$ measure, I estimate the following first stage and reduced form estimates to calculate τ_{RDD} and τ_{RKD}:

$$Pell_{it} = \alpha_1 \mathbf{1}[\widetilde{EFC}_{it} < 0] + \alpha_2 \widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0] + \sum_{\rho} [\psi_\rho (\widetilde{EFC}_{it})^\rho] + \nu_{it} \tag{6}$$

$$L_{it} = \beta_1 \mathbf{1}[\widetilde{EFC}_{it} < 0] + \beta_2 \widetilde{EFC}_{it} \times \mathbf{1}[\widetilde{EFC}_{it} < 0] + \sum_{\rho} [\psi_\rho (\widetilde{EFC}_{it})^\rho] + \epsilon_{it}, \tag{7}$$

where ρ is a polynomial that gives the estimation a flexible functional form around the kink and discontinuity, and ν_{it} and ϵ_{it} are error terms. The term $\mathbf{1}[\widetilde{EFC}_{it} < 0]$ indicates whether a student is eligible for a Pell Grant. I calculate the treatment effects by estimating $\hat{\tau}_{RDD} = \frac{\hat{\beta}_1}{\hat{\lambda}_1}$

and $\hat{\tau}_{RKD} = \frac{\hat{\beta}_2}{\hat{\lambda}_2}$.

5 Results

5.1 Internal Validity

The first step to ensure identification is to show that the needed assumptions for the regression discontinuity and regression kink estimators hold. I first sort observations into bins of 100 observations and then plot the variable of interest against the running variable. Figure 3 shows graphs of key covariates and their distributions close to the eligibility cutoff. These variables include distance from Pell Grant eligibility cutoff, the percentage of non-white students, the student's high school GPA, and dependency status of the students.

The plots of these variables are important for different reasons. The first panel shows the distribution of the running variable, distance from the eligibility cutoff, or $\widetilde{EFC}_{it}$. This graph shows that the distribution is somewhat smooth around the cutoff, which is a key assumption for identification. The other three panels show important demographic and academic explanatory variables, including percentage of nonwhite students, high school GPA, and whether the student is considered dependent on the parents. The only dependent variable that seems to not be smooth around the cutoff is high school GPA. This graph shows that high school GPA drops slightly for Pell-eligible students. This finding may be a result of colinearity between a student's high school GPA and demographic information such as race, parents' income, and family education background.

5.2 Graphical Regression Discontinuity and Regression Kink Results

Figure 4 shows a graph of labor force participation, or labor supply on the extensive margin, around the eligibility cutoff. In this figure, I have fit a line through the data just before the Pell Grant eligibility and directly afterward. Recall that an increase in Pell Grant eligibility makes the standardized distance to the cutoff more negative. Thus, as a student or student's family is more able to pay for college, the student receives less Pell Grant funds from the government and increasingly decides to participate in the labor force to cover financial need. However, once students cross the eligibility cutoff and are no longer eligible for a Pell Grant, labor force participation jumps by nearly 7 percentage points and begins to decline again as a student's EFC increases.

Figure 4 shows a graph of the number of hours worked, or labor supply on the extensive margin, around the eligibility cutoff. Again, I fit a line showing trends on either side of the eligibility discontinuity. As a student's Pell Grant is reduced along the regression kink, the number of hours worked each week increases. Once a student is no longer eligible for a Pell Grant, then the weekly number of hours worked increases discontinuously. While they cannot be used for causal inference, these graphs help to visualize both the increase of labor on the extensive and intensive margins while moving along the kink and around the discontinuity.

5.3 Parametric Estimates from Regression Kink and Regression Discontinuity Designs

I estimate Equations 6 and 7 for both whether a student participates in the labor market and the number of hours worked. Using the coefficients from the estimates, I calculate the treatment effect from both the regression discontinuity and the regression kink. To account for possible nonlinearities in the relationship between labor supply and Pell Grants, I use a flexible polynomial function form. I choose the optimal function form using the Akaike information criterion (AIC). For each table, I show the polynomial order and the accompanying AIC statistic. I also use the following variables as demographic controls: race, gender, dependency status, if the student is a resident of the state of the college he or she attends, whether the student attends school part or full time, whether the student is pursuing an associate's or bachelor's degree, and year fixed effects.

5.3.1 Labor Supply on the Extensive Margin

Table 2 shows results for a linear probability model where the dependent variable is whether a student participates in the labor market. I follow Turner (2017) by estimating the model using the following bandwidths: Global [−4,600, 10,000], [−4,000, 4,000], and [−3,000, 3000]. Using the AIC, I find that the optimal polynomial functional form is ρ=3. The parameter estimates, however, are somewhat robust across bandwidths. However, as the bandwidth tightens, the estimates become less precise. However, regarding the tightest bandwidth, I find that, on average, crossing the income eligibility for a Pell Grant increases the student's Pell Grant by \$106.03, and as a student gains an extra dollar of EFC, their Pell Grant increases by nearly \$0.79.

Next, I estimate the effect of increasing \$1.00 of EFC on the propensity of a student deciding to participate in the labor force when they become eligible for the Pell Grant. I find that, using the whole sample, becoming Pell eligible decreases the probability of labor force participation by 3.9 percentage points, or (given a a base of 62.2 percent) 6.27 percent. As I employ a tighter bandwidth, this result is around a 1.2 percentage point decrease, or about two percent. While the tightest bandwidth reduces the sample size and decreases precision, this result is economically significant because the minimum Pell Grant is only \$400.00 in this sample. Thus, students do seem willing to substitute work time when given a Pell Grant.

I show the treatment effects of Pell Grants on labor force participation in the third panel of Table 2. I find that one additional \$1,000 of Pell Grant aid decreases the probability that a student participates in the labor force by 4.73 percentage points. Given that the average Pell Grant is \$2,012.00 this result means that the average Pell Grant decreases probability of employment by 9.52 percentage points or 14.27 percent reduction from a mean of 67.7 percent.

5.3.2 Labor Supply on the Intensive Margin

Table 3 shows results for the weekly number of hours worked or labor supply on the intensive margin. I estimate the model using the following bandwidths: Global, [−4,600, 10,000], [−4,000, 4,000], and [−3,000, 3,000]. I find that as the bandwidth tightens around the discontinuity and the kink, the coefficients decrease in magnitude, but the estimates become more precise. I use these coefficient estimates to calculate the treatment effect of both the discontinuity and kink.

First, I find that the optimal functional form is a polynomial of the order of 3 for each of the bandwidths. As before, I find that, on average, a student who is eligible for a Pell Grant receives \$173.80 of Pell Grant (for the tightest bandwidth). This result is on par with the average minimum Pell Grant, across years and adjusted for inflation. As a student approaches the eligibility cutoff, (i.e., $Pell \times \widetilde{EFC}_{it}$) the treatment effect becomes more positive such that each additional dollar of EFC increases a student's Pell Grant by \$0.067.

I find that as a student receives more Pell Grant around the regression discontinuity, the student's labor supply on the intensive margin decreases. I also find that as students become eligible for a Pell Grant and receive the minimum Pell Grant of \$400.00, their labor supply decreases by 0.001 hours per dollar of grant aid or 0.4 hours per week for the minimum Pell Grant. Since the average student in my sample works 16.63 hours per week, this result indicates that students will reduce their labor supply by 2.4 percent.

Additionally, I find that students around the kink in the eligibility formula decrease their labor hours in response to an increase in the amount of Pell Grant award offered by the federal government. The tightest bandwidth indicates that as a student qualifies for more Pell Grant funding, their labor supply will decrease by 0.002 hours for every dollar. Considering that the average Pell Grant (conditional on being eligible for a Pell Grant) is \$2,547.81, then the average Pell Grant recipient would reduce their labor supply by 5.10 hours per week. Since the average student works 21.15 hours per week, this estimate implies that the average Pell Grant recipient will reduce their weekly labor supply by 30.67 percent.

5.3.3 Effects of Pell Grants on Academic Achievement

Given these results regarding a reduction in labor supply, it would be useful to know if students are using this time to increase their studies or for other less useful activities. To address this question, I use the end of year grade point average (GPA) for each student as a dependent variable. I estimate the same specification across the same bandwidths that I used earlier.

Table 4 displays the results from these specifications. The first panel shows the effects of the eligibility cutoff and kink on Pell Grant receipt. The sample changes slightly from the previous tables because there are less missing variables in GPA than in student labor supply hours. I find that within the \$4,000.00 bandwidth, crossing over the eligibility cutoff increases Pell Grant receipt by \$152.00.

The next panel shows the effect of eligibility rules on a student's GPA. I find that crossing the eligibility increases a students GPA by 0.088 of a GPA point (or about a third of a +/− increase—i.e., moving from a B to a B+). I also find that each additional dollar of EFC increases a student's GPA by 0.005 points. The ratio of these two results is the local average treatment effect and helps scale up the results in dollar terms. The regression discontinuity results imply that an additional dollar of the minimum Pell Grant increases a student's GPA by 0.026 GPA points. Given that the average minimum Pell Grant for the years in my sample was \$400.00, just the minimum Pell Grant receipt increases a student's GPA by 10.4 GPA points (or roughly a third of a $+/-$ grade). The regression kink results show that each additional dollar of Pell Grant increases a student's GPA by 0.006 point. Again, assuming the average Pell Grant of \$2,547.81, then a student's GPA increases by 0.15 points (or roughly half of a $+/-$ average). While these grade results are small, they are statistically significant and suggest that students substitute some of their labor time to increase their studying.

6 Conclusion

With increasing tuition costs, financial aid has become a vital part of the college experience. However, in many cases, aid and parental contributions are not enough to alleviate students' financial need. Thus, many students turn to employment off campus to fill the gap. The literature regarding how students seek outside employment, what factors contribute to their decision, and how it affects education outcomes is sparse. Essentially, working while in college can have both positive and negative effects. First, students who participate in the labor market have less time for other pursuits, especially academic and social. This reallocation of time may affect crucial outcomes such as grades, major choice, and time to graduation. However, if the student is employed in a job related to his or her major, the work experience may complement the academic, and the student may increase the probability of employment because he or she has established a professional network.

Financial aid may affect this decision to work in college similar to how transfer payment programs (e.g., the EITC, unemployment and disability insurance) affect the labor supply. A student who wishes to spend maximum time in the classroom may be very responsive to financial aid as opposed to a worker trying to maximize lifetime earnings. I use the rich data from the National Postsecondary Student Aid Study combined with a discontinuity and kinks in the Pell Grant eligibility formula to study causally the effect of Pell Grant programs and student labor supply on the intensive and extensive margins. I find that students respond to financial aid by decreasing the probability that that they participate in the labor force and the number of hours that a student works if they do choose to work. The policy prescriptions of my study hinges on whether employment is helpful or harmful to academic outcomes. If working does reduce GPAs and increases time to graduation, then perhaps the federal government should consider expanding the Pell Grant program to help deter needy students from working. If employment serves as a complement to academic learning, then the federal government should promote internships and apprenticeships instead of unconditional grant aid as means to encourage students to gain work experience while in college.

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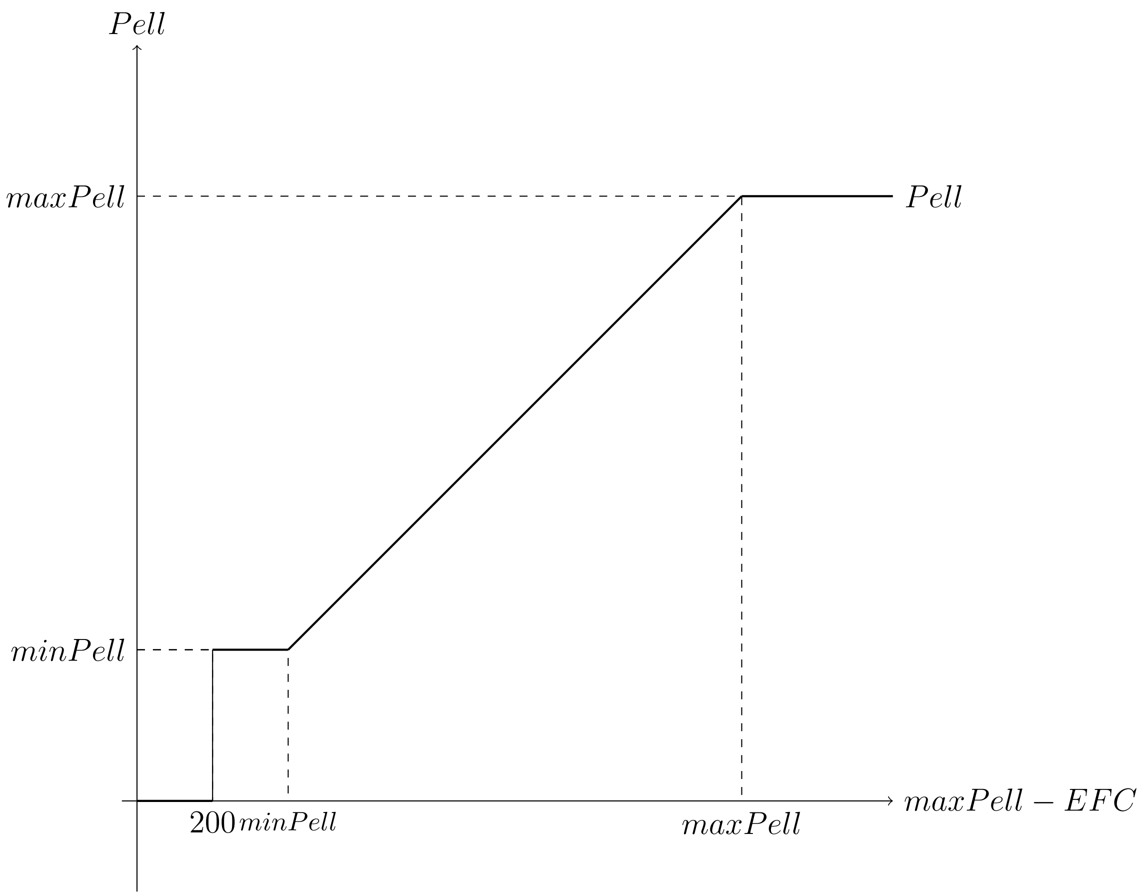

Figure 1: This figure displays the amount of Pell Grant a student receives against a student's eligibility.

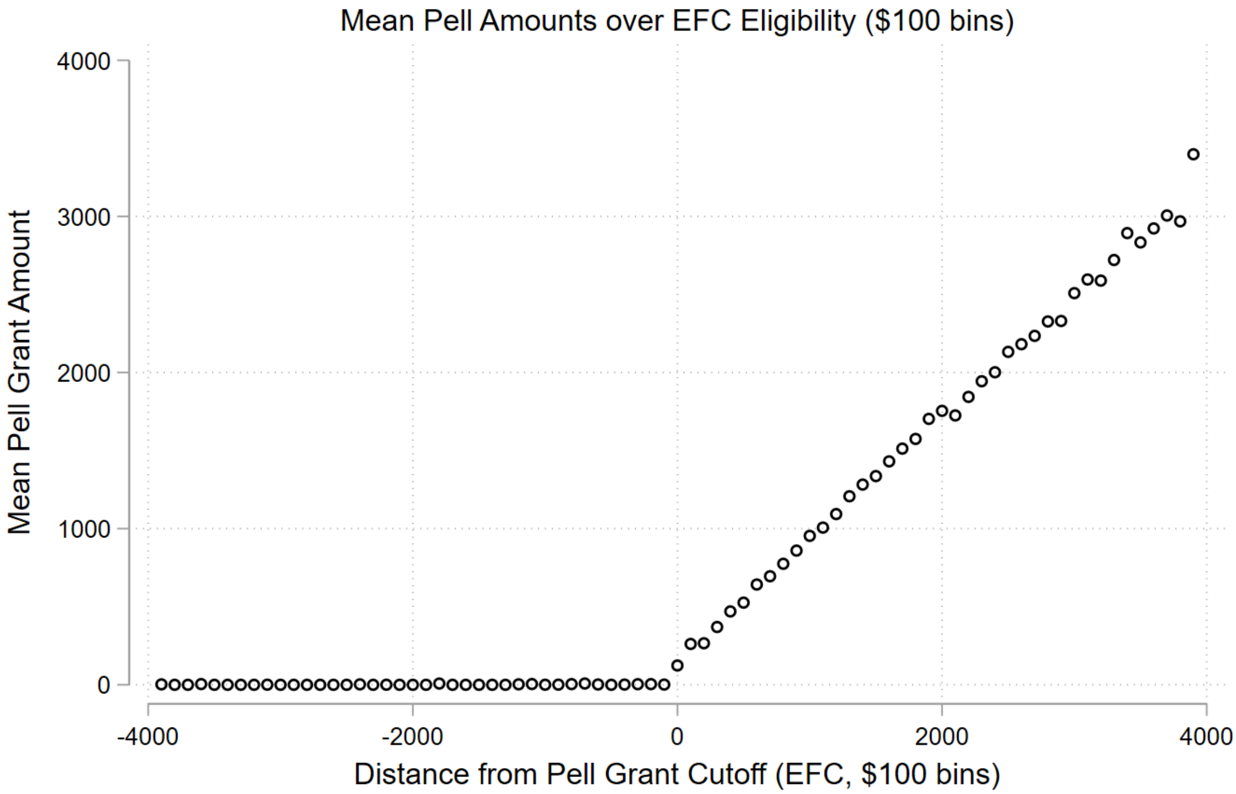

Figure 2: For this figure, I have sorted the data into $100.00 EFC bins to see if the data are compliant with the Pell Eligibility formula presented in the previous figure. Since a student is eligible when EFC_{it} is less than the cutoff, students who are Pell Eligible are located in the negative space, while noneligible students are in positive space. SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011–2012 waves of the National Postsecondary Student Aid Study (NPSAS).

Smoothness of Covariates Around the Cutoff

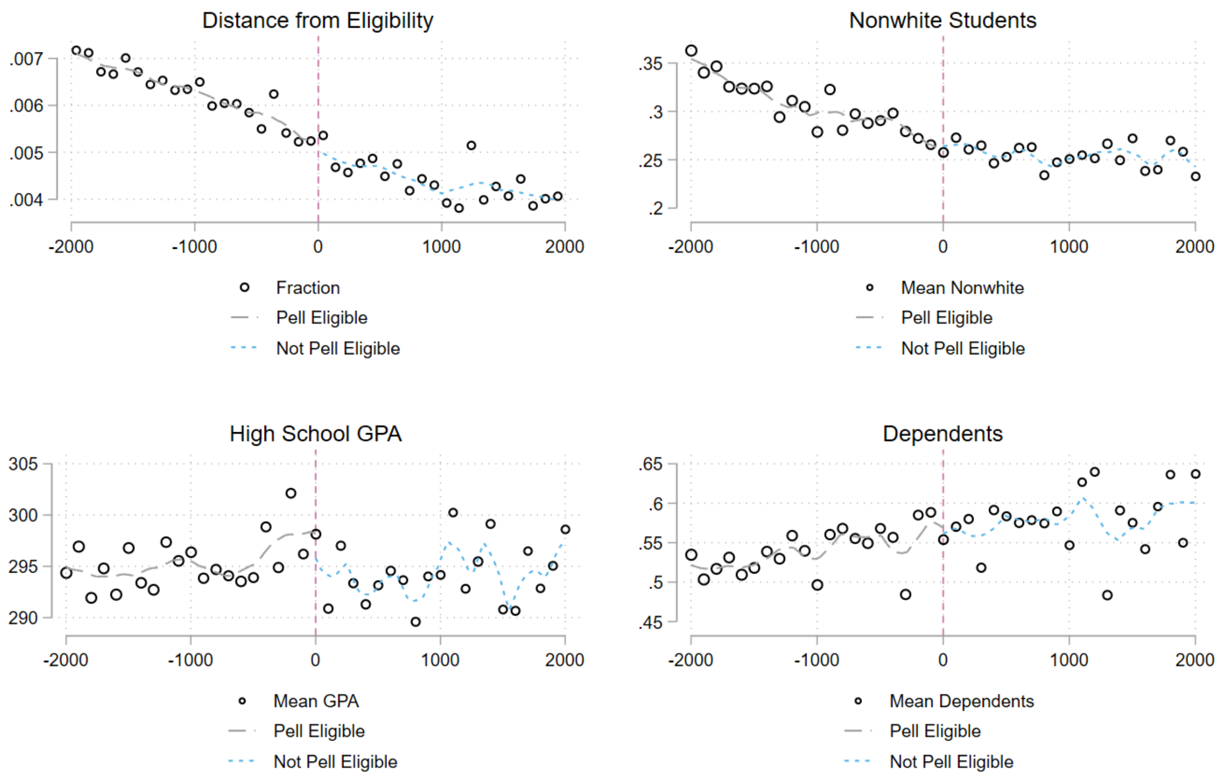

Figure 3: These four panels show evidence for the assumption of smoothness in the neighborhood of the discontinuity. The first shows how the running variable is smooth around the discontinuity as is the percentage of students who are nonwhite and dependent. However, high school GPA shows a slight break around the cutoff. I have sorted the data into $100.00 EFC bins. Since a student is eligible when EFC_{it} is less than the cutoff, students who are Pell eligible are located in the negative space, while noneligible students are in positive space. SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011–2012 waves of the National Postsecondary Student Aid Study (NPSAS).

Student Labor Force Participation around Pell Eligibility Cutoff

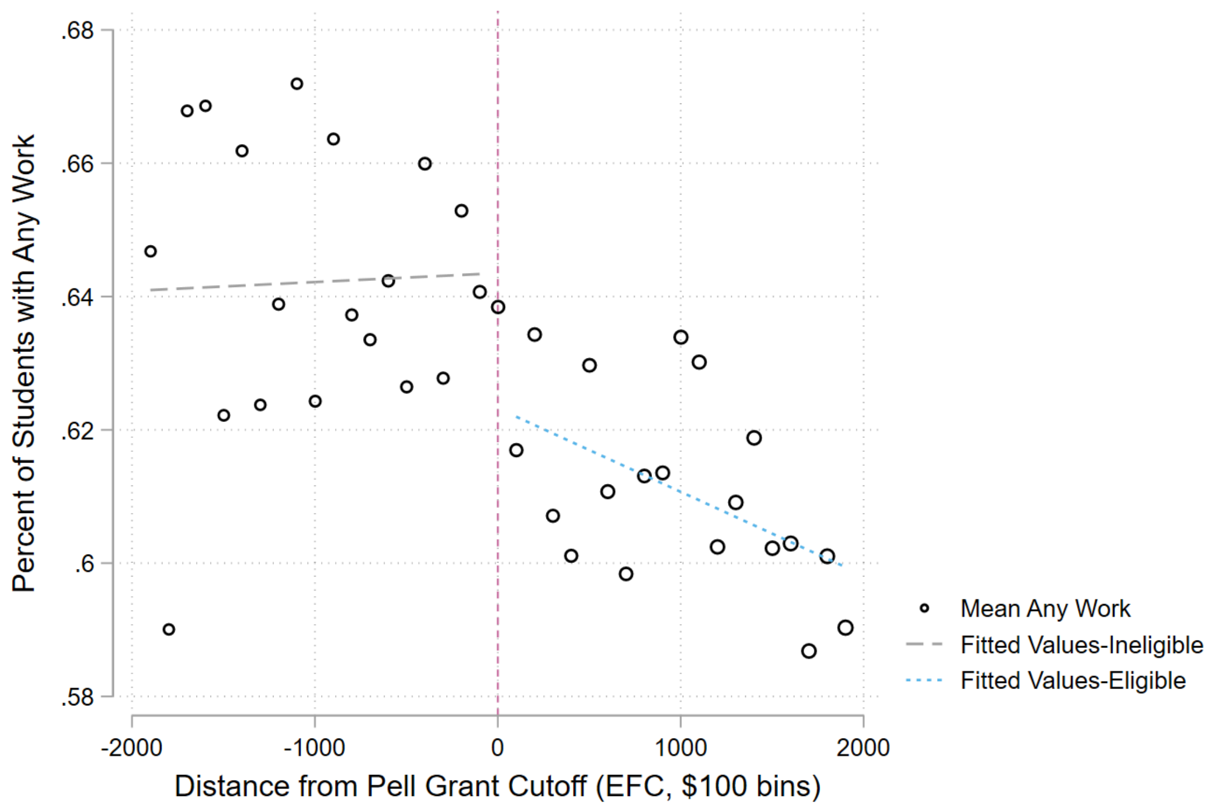

Figure 4: This figure is a plot of the percentage of students who participate in the labor force in each $100.00 EFC bin. Notice that as a student loses Pell Grant funding, the probability of work increase until it jumps at the eligibility cutoff. Since a student is eligible when EFC_{it} is less than the cutoff, students who are Pell eligible are located in the negative space, while noneligible students are in positive space. SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011–2012 waves of the National Postsecondary Student Aid Study (NPSAS).

Student Work Hours around Pell Eligibility Cutoff

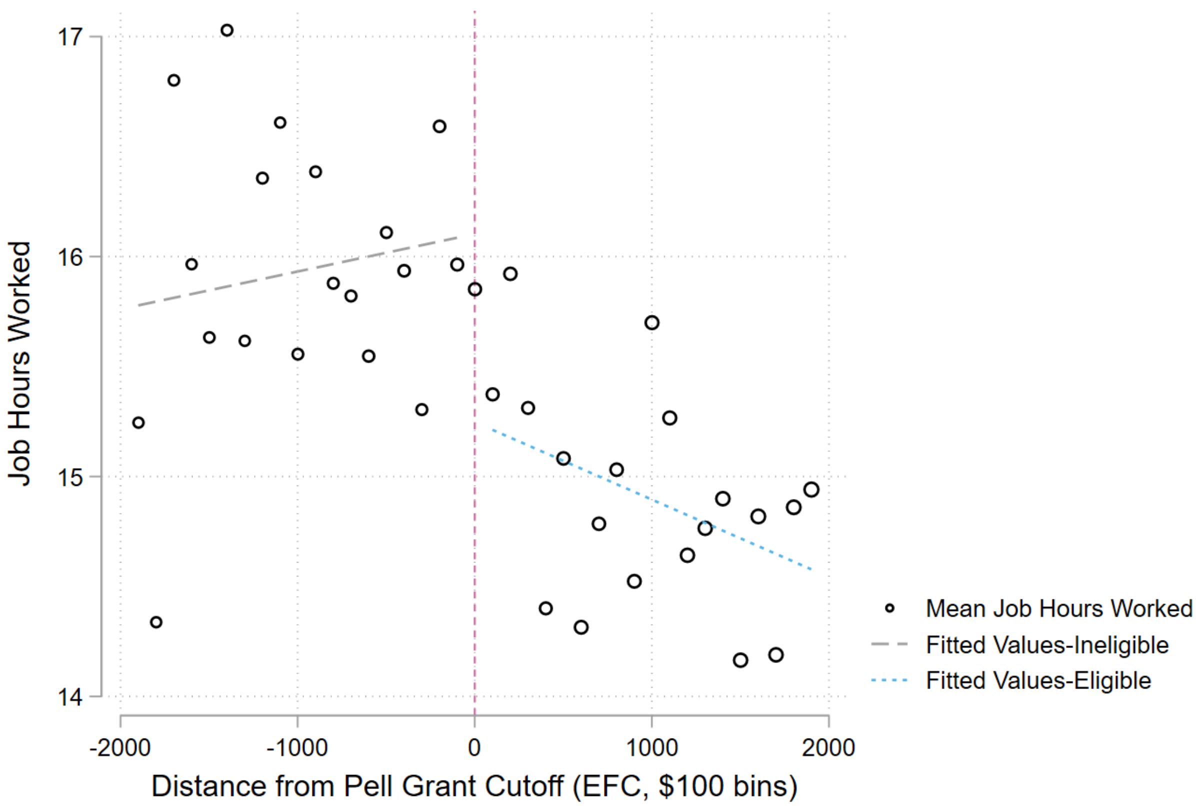

Figure 5: This figure shows a plot of the average weekly hours worked in each $100.00 EFC bin. Notice that as a student loses Pell Grant funding, the average weekly hours worked increases until it jumps at the eligibility cutoff. Since a student is eligible when EFC_{it} is less than the cutoff, students who are Pell eligible are located in the negative space, while noneligible students are in positive space. SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011-2012 waves of the National Postsecondary Student Aid Study (NPSAS).

Table 1: Summary Statistics by Pell Eligibility

	(1)	(2)	(3)	(4)	(5)
		Full Sample		Bandwidth EFC +/− $3,000	
Variable	Overall	Pell Eligible	Not Pell Eligible	Pell Eligible	Not Pell Eligible
Hours worked	16.85	16.98	16.63	16.39	18.51
	(16.70)	(16.96)	(16.25)	(16.69)	(16.65)
Any work	0.622	0.607	0.648	0.603	0.677
	(0.485)	(0.488)	(0.478)	(0.489)	(0.468)
Pell Grant	1,614.32	2,547.81	0.68	1,361.05	1.836
	(1,838.99)	(1,720.48)	(33.10)	(962.37)	(53.20)
Expected family contribution	6,375.99	732.55	16,133.31	1813.36	5,207.58
	(11,906.42)	(1,209.15)	(15,299.79)	(962.37)	(1,400.57)
Female	0.602	0.624	0.564	0.607	0.570
	(0.489)	(0.484)	(0.496)	(0.489)	(0.495)
Black	0.182	0.235	0.091	0.185	0.120
	(0.386)	(0.424)	(0.287)	(0.388)	(0.325)
Hispanic	0.152	0.190	0.088	0.152	0.109
	(0.359)	(0.392)	(0.283)	(0.359)	(0.312)
Dependent	0.612	0.497	0.810	0.690	0.722
	(0.541)	(0.559)	(0.443)	(0.628)	(0.448)
Resident	0.777	0.805	0.730	0.673	0.723
	(0.416)	(0.396)	(0.444)	(0.469)	(0.448)
Full time	0.633	0.612	0.670	0.600	0.638
	(0.482)	(0.487)	(0.470)	(0.490)	(0.481)
Obs.	251,230	159,160	92,060	54,670	25,070

NOTE: Observation totals are rounded to the nearest tenth to comply with security standards for the National Center for Education Statistics (NCES). SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011–2012 waves of the National Postsecondary Student Aid Study (NPSAS).

Table 2: Regression Discontinuity/Regression Kink Results for Labor Force Participation

	(1) Global	(2) [-4600, 10000]	(3) [-4000, 4000]	(4) [-3000, 3000]
Pell Grant				
Pell Elg.	297.50***	155.07***	108.50***	106.03***
	(9.103)	(11.85)	(15.21)	(12.72)
$Pell \times \widetilde{EFC}$	-0.625***	-0.793***	-0.793***	-0.788***
	(0.002)	(0.014)	(0.020)	(0.022)
Any Work				
Pell Elg.	-0.039***	-0.020***	-0.009	-0.012
	(0.004)	(0.006)	(0.008)	(0.009)
$Pell \times \widetilde{EFC}_{it}$	0.00002***	0.00004***	0.00005***	0.0001
	(0.00000)	(0.00000)	(0.00000)	(0.00001)
τ_{RD}	0.0001***	-0.0001	-0.00008	-0.0001
	(0.0000)	(0.00004)	(0.00007)	(0.00009)
τ_{RK}	0.00003***	-0.00005***	-0.000007***	-0.00003
	(0.00000)	(0.00000)	(0.00001)	0.0002)
Optimal ρ	3	3	3	3
AIC	4,544,234	3,033,400	2,317,683	1,352,761
Obs.	251,210	170,840	111,360	79,740

NOTE: This table shows parametric estimates for the effects of Pell Grants on labor force participation given various bandwidths around the discontinuity and kink in Pell Grant eligibility. Exogenous controls include controls for student gender, race, dependency status, attendance status, residency status, and year fixed effects. SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011–2012 waves of the National Postsecondary Student Aid Study (NPSAS).

Table 3: Regression Discontinuity/Regression Kink Results for Hours Worked

	(1) Global	(2) [-4600, 10000]	(3) [-4000, 4000]	(4) [-3000, 3000]
<u>Pell Grant</u>				
Pell Elg.	297.50***	155.07***	108.50***	106.03***
	(9.103)	(11.85)	(15.21)	(12.72)
$Pell \times \widetilde{EFC}$	-0.625***	-0.793***	-0.793***	-0.788***
	(0.002)	(0.014)	(0.020)	(0.022)
<u>Job Hour</u>				
Pell Elg.	-1.837***	-0.899***	-0.531**	-0.112
	(0.135)	(0.204)	(0.281)	(0.317)
$Pell \times \widetilde{EFC}$	0.0006***	0.0007***	0.002***	0.002***
	(0.0000)	(0.0002)	(0.0003)	(0.0006)
$\widehat{\tau}_{RD}$	-0.006***	-0.006***	-0.005*	-0.001
	(0.0005)	(0.001)	(0.003)	(0.003)
$\widehat{\tau}_{RK}$	-0.001***	-0.0009***	-0.002***	-0.002***
	(0.0000)	(0.0003)	(0.0004)	(0.0007)
Optimal ρ	3	3	3	3
AIC	6.312,835	4,241,477	2,888,977	1,914,430
Obs.	251,210	170,840	117,040	79,740

NOTE: This table shows parametric estimates for the effects of Pell Grants on hours worked given various bandwidths around the discontinuity and kink in Pell Grant eligibility. Exogenous controls include controls for student gender, race, dependency status, attendance status, residency status, and year fixed effects. SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011–2012 waves of the National Postsecondary Student Aid Study (NPSAS).

Table 4: The Effects of Pell Grants on Grades

	(1) Global	(2) [-4600, 10000]	(3) [-4000, 4000]	(4) [-3000, 3000]
Pell Grant				
Pell Elg.	290.94***	203.15***	163.51***	147.51***
	(9.044)	(10.72)	(11.75)	(9.711)
$Pell \times \widetilde{EFC}$	-0.635***	-0.693***	-0.841***	-0.801***
	(0.002)	(0.008)	(0.018)	(0.021)
GPA				
Pell Elg.	10.99***	6.397	3.558***	2.530***
	(0.722)	(0.879)	(1.031)	(1.137)
$Pell \times \widetilde{EFC}$	0.007***	-0.0006	-0.004***	-0.004*
	(0.000)	(0.001)	(0.002)	(0.002)
$\widehat{\tau}_{RD}$	0.038***	0.031***	0.022***	0.017***
	(0.003)	(0.005)	(0.005)	(0.008)
$\widehat{\tau}_{RK}$	-0.010***	0.000	0.005***	0.005*
	(0.000)	(0.001)	(0.002)	(0.003)
Optimal ρ	2	2	2	2
AIC	7,085,073	4,713,3323	3,195,754	2,104,374
Obs.	248,720	168,540	114,950	77,710

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTE: This table shows parametric estimates for the effects of Pell Grants on GPA given various bandwidths around the discontinuity and kink in Pell Grant eligibility. Exogenous controls include controls for student gender, race, dependency status, attendance status, residency status, and year fixed effects. SOURCE: The sample consists of the 1995–1996, 1999–2000, 2003–2004, 2007–2008, and 2011–2012 waves of the National Postsecondary Student Aid Study (NPSAS).