FLORIDA GULF COAST UNIVERSITY

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Selection Committee,

I am pleased to submit my application for Review of Economics and Statistics Fellowship for the NBER Summer Institute. If I am selected, I would be interested in attending the Education or Labor Economics session. These areas are most aligned to my research interest and current working papers.

Please find enclosed: (i) my current research pipeline (ii) curriculum vitae, and (iii) a recent research publication at the Journal of Development Economics.

Biography

Nicholas A. Wright is an Assistant Professor of Economics at Florida Gulf Coast University. He holds a Ph.D. in Economics from Georgia State University and a Master of Science and Bachelor in Economics from the University of the West Indies. His research utilizes quasi-experimental methods to study issues in education and public health, with a primary focus on higher education policies, college financing, and college-level interventions. His most recent research projects have focused on need-based financing policies, performance standards, public recognition, academic coaching, and non-cognitive skills. His work has been funded by several agencies including the National Academy of Education and he has published in various notable journals such as Labour Economics and the Journal of Development Economics.

Abstract of Working Papers

Wright, N. & Arora, P. "What Are My Chances? Incomplete Information and College Students' Effort".

Abstract: Students form beliefs about their expected performance based on incomplete information. This may lead students to make sub-optimal effort decisions and ultimately have a negative effect on their actual performance. In this study, we examine the impact of providing students with complete information about their likelihood of success on their actual performance. This is accomplished using a field experiment that randomly exposes students to instructor-level information about the past distribution of grades. We find that treated students are more likely to be successful in the course. The results further indicated that low-ability students, students who expected to obtain an A, and those who underestimate the difficulty of the course benefited most from the intervention.

Anderson, P & Wright, N. "Teacher Quality and High School Performance: Evidence from a Math Specialist Intervention".

Students' performance in STEM courses is a topical issue facing policy makers in developing countries. Several attempts have been made to address this issue, especially under-performance in mathematics. At the heart of many countries' STEM initiatives and reforms are the development of effective STEM teaching methods, teacher training, and curricula development. Our paper examines the impact of an intervention that utilizes math specialists to coach existing math teachers on High School students performance in math. We utilize the universe of high school students and several quasi-experimental designs to estimate the causal effect of the program. The main results show that the intervention increased the number of students sitting the examinations, but had no impact on the average pass rate in math.

Wright, N. & Sinclair, S. "Non-Cognitive Skills, Academic Coaching, and Students' Performance".

In this paper, we examine the extent to which targeted coaching can improve the non-cognitive skills and academic outcomes of college students. To explore this issue, we create a non-cognitive skills profile for incoming students at a southwestern public university. Using a field experiment, we randomly assign students to one of three groups: (i) a control group, (ii) a passive intervention group, and (iii) an active intervention group. The students belonging to the passive intervention group are exposed to information about their non-cognitive skills profile and the challenges they are likely to face in college because of deficits in their non-cognitive skills. In addition to receiving this information, students in the active intervention group are also directed to various services at the university to help them address any deficits in their non-cognitive skills profile that may hinder their academic success. We examine the impact of each treatment on students short- and long-term academic outcomes.

Wright, N. & Dorilas, E. "Focus as You Drive and Arrive Alive: The Impact of Handheld Laws on Traffic Fatalities".

Distracted driving is one of the leading causes of fatal motor vehicle accidents in the United States. Policymakers in several states have responded to this phenomenon by implementing laws aimed at restricting the use of handheld devices while operating a vehicle. In this paper, we utilize the regression discontinuity design to estimate the impact of state-level handheld mandates on traffic fatalities. We find robust evidence that introducing a law that restricts the use of handheld devices while driving reduces daily traffic fatalities by 26% and daily average fatalities by 0.63 in the short term. The results further indicate that the magnitude of the impact is smaller in the long term, but this policy is still effective at curbing traffic fatalities.

Wright, N. & Lee, L. "Alcohol-Related Laws and Alcohol-Induced Fatalities".

In the United States, about 28 lives are lost daily in motor vehicle accidents that involve an alcohol-impaired driver. While most states have enacted traffic-safety laws to address this phenomenon, little consensus exists on the causal impact of these laws in reducing alcohol-induced fatalities. This paper exploits quasi-random variation in state-level laws to estimate the causal effect of alcohol-related traffic laws on the frequency of fatal accidents. This is identified from the discontinuities in traffic laws among homogeneous contiguous-counties that are separated by a shared state border. We present robust empirical evidence that the conventional approaches that are typically utilized in the literature may erroneously estimate the effectiveness of several alcohol-related laws.

Work in Progress: Drafts Expected in 12 Months

Wright, N. & Solanki, S. "The Right Formula To Predict Success? Admission Scores and College Student Outcomes".

Wright, N. & Neto, A. "Opportunity Zones and Local Labor Market Outcomes: An Early Impact Assessment".

Wright, N. & Denteh, A. "HIV Criminalization Laws and Risky Behavior".

Wright, N. & Alvin, H. "Oil Price Fluctuations and Labor Market Outcomes".

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EMPLOYMENT

ASSISTANT PROFESSOR OF ECONOMICS

- Florida Gulf Coast University, Lutgert College of Business — Jul 2019 – Present

RESEARCH & TEACHING ASSISTANT

- Georgia State University, Economics Dept — Aug 2014 – May 2019
  - Taught Econ 4350: *Econ of Poverty and Public Policy*, Spring 2017
  - Taught Econ 4950: *Econometrics and Applications*, Fall 2016
- Federal Reserve Bank of Atlanta — May 2016 – May 2018

EDUCATION

GEORGIA STATE UNIVERSITY

- Ph.D. in Economics — Aug 2014 – May 2019
  - Focus: Labor, Education, & Public Economics
  - Adviser: Prof. Tom Mroz

THE UNIVERSITY OF THE WEST INDIES

- M.Sc. in Economics — Sep 2012 – Jul 2014
- B.Sc. in Political Science & Economics — Sep 2009 – Aug 2012

PUBLICATIONS

[1] Wright, N. (2021). Need-Based Financing Policies, College Decision-Making, and Labor Market Behavior. *Journal of Development Economics*, 102617.

[2] Wright, N. (2020). Perform Better, or Else: Academic Probation, Public Praise, and Students Decision-Making. *Labour Economics*, 62:101773.

WORKING PAPERS

[1] Wright, N. & Arora, P. "What Are My Chances? Incomplete Information and College Students' Effort".

[2] Anderson, P & Wright, N. "Teacher Quality and High School Performance: Evidence from a Math Specialist Intervention".

[3] Wright, N. & Solanki, S. "The Right Formula To Predict Success? Admission Scores and College Student Outcomes".

[4] Wright, N. & Dorilas, E. "Focus as You Drive and Arrive Alive: The Impact of Handheld Laws on Traffic Fatalities".

[5] Wright, N. & Sinclair, S. "Non-Cognitive Skills, Academic Coaching, and Students' Performance".

GRANTS & FELLOWSHIPS

- Co-Principal Investigator, Native American Agriculture Fund (NAAF) ($230,190) — 2020 – 2022
- Principal Investigator, National Academy of Education/Spencer Dissertation Fellowship ($27500) — 2018 – 2019
- Bank of Jamaica, G. Author Brown Memorial Scholarship ($8000) — 2012 – 2014
- Ambassador Sue Cobb Scholarship ($3000) — 2011 – 2012

AWARDS

- Best Research Paper Award (FGCU) ($1500) — 2021
- Top Tier Research Award (FGCU) ($750) — 2020
- AEFP New Scholar Award ($500) — 2019
- Jack Blicksilver Award ($1000) — 2019
- Outstanding Graduate Research Assistant Award ($11,275) — 2019
- Quantitative Economics Award ($1000) — 2016
- Bernard B. and Eugenia A. Ramsey Chair of Private Enterprise Grant ($2000) — 2015
- The Top Graduate Student Award — 2014
- The Economics Theory Prize — 2014
- Prime Minister Youth Award for Excellence in Academics — 2014
- Alfred A. Francis Economics Award — 2013
- Nethersole Award — 2013
- Top Undergraduate Student in Social Sciences — 2013
- Conference Travel Grants — 2016 – 2018
  - Federal Reserve Bank, 2017 ($1000)
  - W.J. Usery Chair of the American Workplace (GSU), 2016-18 ($2500)
  - Bernard B. and Eugenia A. Ramsey Chair of Private Enterprise, 2018 ($6250)

CONFERENCES

- AEFP 46^{th} Annual Conference (Chair & Presenter) — Mar 2021
- AEFP 45^{th} Annual Conference (Chair & Presenter) — Mar 2020
- Missouri Valley Economic Association 55^{th} Annual Meeting — Nov 2018
- AEFP 43^{rd} Annual Conference — Mar 2018
- West Indies Economic Conference — Mar 2018
- 87^{th} Annual Meeting of the Southern Economic Association — Nov 2017
- FRB CHCS Annual Employment Conference: Labor Supply, Sorting, and Wages — Sep 2017
- 86^{th} Annual Meeting of the Southern Economic Association — Nov 2016

SEMINARS & INVITED PRESENTATIONS

- University of Kentucky, Martin School — Apr 2021
- Indiana University, Health Policy Workshop — Dec 2020
- University of West Indies, Department of Economics — Nov 2018
- Federal Reserve Bank of Atlanta, Research Department — Nov 2018
- West Virginia University, Department of Economics — Oct 2018
- WEAI Graduate Student Workshop — Jun 2018
- GSU Summer Labor Economics Brown Bag Workshop Series — Jul 2018

PROFESSIONAL AFFILIATION

REFEREE

- Education Finance and Policy (EFP)
- Journal of Policy Analysis and Management (JPAM)
- Contemporary Economic Policy (CEP)
- Economics of Education Review (EER)
- Southern Economic Journal (SEJ)

MEMBERSHIP

- American Economic Association
- Royal Economic Society
- Association for Education Finance and Policy
- American Educational Research Association
- Southern Economic Association

SERVICE

- Reviewer: AERA 2021 Annual Meeting
- Reviewer: AERA 2020 Annual Meeting

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Regular Article

Need-based financing policies, college decision-making, and labor market behavior: Evidence from Jamaica☆

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ABSTRACT

Designing an effective framework for financing higher education is a key objective of policymakers in developed and developing countries. While we have a good understanding of how college financing options affect students' college outcomes in developed countries, less is known about the impact of these programs in developing countries. In this paper, I employ several quasi-experimental designs and novel administrative data from Jamaica to estimate the effect of need-based grants and student loan funding on students' academic achievement and labor market outcomes. The results indicate that the students who benefited from either program had a higher GPA, graduated at higher rates, and were more likely to remain in college beyond their second year. While both programs induce treated students to reduce their engagement in the labor market during college, I find that each program had an opposing impact on students' earnings in the early years after their expected graduation date.

1. Introduction

Higher education plays an essential role in reducing poverty and promoting upward economic mobility (Chetty et al., 2017; David and Dynarski, 2009; Hershbein et al., 2020). Although the cost of attending college has consistently increased, a growing number of low-income students have sought to capitalize on the net benefits that a college education promises (Johnstone and Marcucci, 2010).[1] In low- and middle-income countries, tertiary enrollment among college-aged students has increased from about 9% in 1990 to 34% in 2019 and this upward trend is expected to continue over the next two decades (Calderon, 2018; Pandey and Indrakanti, 2017; World Bank, 2020b). This significant growth in demand has placed a greater financial burden on the scarce public resources in developing countries and has prompted several countries to revise their framework for financing higher education.[2] Many countries have adopted a cost-sharing model where a significant fraction of the cost of higher education is shifted from the government to students and their families. Because cost-sharing could lock out low-income students from pursuing higher education opportunities, governments have also launched subsidized loan and grant pro-

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[1] In Colombia, for example, Marta Ferreyra et al. (2017) found that low-income students accounted for 71% of the overall growth in higher education enrollment between 2000 and 09.

[2] College attendance is heavily subsidized in many developing countries. Low- and middle-income countries now allocate about 20% of total government education spending to the higher education sector (World Bank, 2020a). See Johnstone and Marcucci (2010) for an extensive discussion of the main approaches used to finance higher education in developed and developing countries. In addition, Barro and Lee (2013), Freeman (2009), Johnstone and Marcucci (2010), and Marta Ferreyra et al. (2017) provide a description of how tuition cost and the demand for higher education have changed over time.

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grams to provide access to credit-constrained students who do not possess the financial means to pay (Hutchings, 2017; Johnstone and Marcucci, 2010; Oketch, 2003).[3] Despite the increased demand for higher education in developing countries, and the corresponding changes in college financing, there is limited research that evaluates the impact of financial assistance programs on student outcomes, both in college and in the labor market.

In this paper, I evaluate a national student loan and grant assistance program that targets low-income college students in Jamaica. This is an upper-middle-income developing country where about 40% of students rely on publicly-financed tuition loans and grant subsidies to pursue higher education.[4] This study examines how the receipt of these benefits influence students' college credit hours, academic performance, graduation prospects, and labor market outcomes during and immediately after college. The analysis uses a novel individual-level panel data set that is constructed using educational and financial administrative records from multiple public institutions.

Evaluating the impact of a need-based financial aid program is challenging because there are many unobserved differences between the students who are eligible to receive benefits and those who are excluded from them. Given that these unobserved attributes are likely to be correlated with student outcomes, a naive comparison of program participants and non-participants will yield a biased estimate of the true treatment effect. To account for these unobserved differences, this paper exploits quasi-random variation in program participation to identify the causal effect of interest.

I utilize two quasi-experimental designs to evaluate the impact of the grant program. The first empirical approach is a regression discontinuity (RD) design, which exploits the means-test score that is used to determine students' eligibility for the grant program. This model compares the students who are marginally eligible for grant funding to otherwise similar students who are marginally ineligible. The second estimation strategy, a difference-in-difference (DID) design nested within an instrumental variables (IV) model, relies on the exogenous variation in grant eligibility created by a policy change that modified the rules governing students on welfare. Each approach identifies the local average treatment effect of the grant program, but for marginal students at different points of the income distribution. Finally, I utilize the instrumental variables (IV) method to evaluate the loan program. This approach exploits an intervention that exposed potential college applicants to information about the student loan program. This information campaign creates an exogenous change in the likelihood that college-goers utilize a student loan to pay for college. Together, these estimates can help policymakers to assess how need-based loan and grant funding programs impact the outcomes of the marginal students who receive them.

Economic theory predicts that student loan and grant funding have a substantive impact on the outcomes of disadvantaged college students who possess limited access to credit markets. Both types of financial support produce an income effect that enables recipients to purchase the educational inputs they need to perform well, and may also induce them to reduce the time they allocate to paid work during college. Therefore, these programs may improve students' academic achievement and their subsequent outcomes in the labor market (Bettinger et al., 2019; Denning et al., 2019).

While grants do not have to be repaid, student loans create a debt obligation that recipients must start paying back shortly after graduation. This future obligation may induce marginal students to exert more effort in their studies (Rau et al., 2013). Moreover, the loan granting agency may require the student to maintain a certain standard of performance to be eligible for continued funding (Schudde and Scott-Clayton, 2016). These conditions also cause student loan recipients to perform better than their peers during college. However, among new graduates, the students who utilized a loan may be willing to accept a lower wage than those who did not (Gervais and Ziebarth, 2019; Gibson and Johnson, 2017; Ji, 2020). This is because these students must begin repaying their debt quickly to avoid added interest, penalties, and default. Strict repayment conditions also increase the search cost and reduce the bargaining position of new graduates, and this may cause them to accept wages that are below their productive capacity. Therefore, theory predicts that both loan and grant financing improve students' academic outcomes, and that grant funding yields positive returns in the labor market, but it also predicts that the impact of loan funding on students' labor market outcomes is ambiguous.

The results indicate that both the tuition loan and grant funding programs improved students' academic performance and persistence during college. The treated students maintain a better grade point average (GPA), are more likely to remain in college beyond their second year, and graduate at a higher rate. The results also suggest that each program induced treated students to lower their labor market engagement during their college years. However, while grant funding improved the earnings of treated students in the early years after college, the loan recipients had lower earnings during these years. Consistent with theory, I find that one plausible mechanism that can explain this distinction is that the loan program induces students to accept job offers that pay below their productive characteristics. This is likely because students are required to start repayment within six months after graduation, and thus they are more willing to accept an early offer than to hold out for an opportunity that better matches their productive characteristics. I present several falsification checks that support this conclusion. These findings have two main implications. First, need-based assistance can be used as an effective tool to improve the academic and labor market outcomes of low-income students. Second, as an unintended consequence, imposing strict repayment conditions on student loan borrowers may significantly penalize them as new college graduates entering the labor market. These insights are very important for policymakers who endeavor to improve the long-term outcomes of low-income college students by designing efficient funding programs.

This paper contributes to an emerging strand of the college financing literature that examines the impact of financial aid on student outcomes in developing countries.[5] The previous studies in this literature have evaluated the extent to which credit access affects college enrollment, persistence, and educational attainment. For instance, studying loan programs in Chile, Solis (2017) found that access to credit eliminated the gap in college enrollment across income quintiles and Card and Solis (2020) showed that loan programs increased the likelihood of completing college. Similar positive results have been found for com-

[3] Government-backed student loan and grant programs have been implemented in many developing countries around the world. See Albrecht and Ziderman (1991), Marta Ferreyra et al. (2017), and Shen and Ziderman (2009) for a review of some of these programs.

[4] Within Latin America and the Caribbean, similar programs exist in Brazil, Chile, Colombia, Costa Rica, and Mexico (Canton and Blom, 2010; Marta Ferreyra et al., 2017).

[5] There are many factors that may cause college students in developing countries to respond differently than those in developed countries to the same exogenous change in income. First, developing countries have a higher share of students from low-income households who lack the financial resources to pay for college and face significant liquidity constraints (Solis, 2017). Second, these countries experience higher default rates due to institutional inefficiencies and the lack of political will to punish defaulters (Oketch, 2003). Third, the financing programs in developing countries may impose more restrictive conditions on recipients. For example, many developed countries utilize an income-contingent student loan repayment system, while loan repayment conditions in developing countries do not typically offer this kind of flexibility. Finally, differences in the skill distribution and institutional framework between developed and developing countries may lead to different college wage premiums (Patrinos et al., 2006; Peet et al., 2015). These are just a few reasons why it is crucial that we evaluate the impact of financial aid programs in developing countries.

parable loan programs in Colombia, Mexico, and South Africa (Canton and Blom, 2010; Gurgand et al., 2011; Londoño-Vélez et al., 2020; Melguizo et al., 2016).[6] A unique feature of this paper is that it evaluates a national tuition loan program that considers need as the sole eligibility criterion and covers the full tuition cost of all approved students up to graduation. This financial support enables more low-income and low-ability students, groups that are most at risk of succeeding in college, to access higher education. This design feature provides a rare opportunity to assess the net impact of student loan financing when funding eligibility is independent of students' prior academic performance and where all eligible borrowers receive full tuition support.[7] This paper also extends the previous literature by examining the marginal effect of awarding a need-based grant to students whose college fees are already fully covered by a tuition loan. This interaction effect is interesting because the marginal impact of grant funding may vary based on the baseline level of financial resources students have available to them. Consequently, this study fills a significant gap in the literature and may offer some useful insights about the efficacy of these programs when certain design conditions are met.

This paper also contributes to a growing body of research that assesses the impact of financial aid on students' labor market outcomes (Denning et al., 2019; Gervais and Ziebarth, 2019; Ji, 2020; Rau et al., 2013). In general, past research shows that student loans and grant funding can affect students' earnings after college. However, most of the applied work in this area has focused on programs in the United States. For example, using administrative data, Denning et al. (2019) showed that being eligible for additional grant aid increased students' post-college earnings in Texas. Similarly, Gervais and Ziebarth (2019) concluded that student loan debt has a non-negative effect on the earnings of U.S. students after graduation. I contribute to this literature by evaluating the impact of need-based loan and grant funding on students' labor market engagement during and immediately after college in a developing country. In addition, the findings in this study suggest that the loan repayment conditions borrowers face may influence how student loan debt affects the labor market outcomes of new college graduates. This result sheds light on the unintended consequences of imposing stringent repayment conditions on student loan borrowers.

The remainder of this paper is organized as follows: Section II provides a description of the institutional details and data utilized in this study. Section III describes the empirical models and identification strategies, and Section IV presents the main results. Section V outlines some concluding remarks and discusses the main policy implications of the study.

2. Data and institutional background

This paper combines administrative person-level data from five institutions in Jamaica. These are the Students' Loan Bureau (SLB), the Tax Administration of Jamaica (TAJ), Ministry of Education (MOE), The University of the West Indies (UWI) and the University of Technology (UTECH).

2.1. Student loan & grant financing in Jamaica

College financing data is collected from the Students' Loan Bureau (SLB). This is an independent statutory body that is invested with the sole responsibility of providing tuition loans and grant funding to low-income students who are unable to self-finance college. The institution is publicly financed and caters to students attending one of the 45 approved tertiary educational institutions (universities, teachers' colleges, and community colleges) in the Caribbean.

The Students' Loan Bureau became operational in 1970 and was re-structured in 1996 through a US$28.5 million loan from the World Bank. The loan facility was developed as a revolving loan fund, such that future loan disbursements would be primarily financed through the repayment flows from past loan beneficiaries. However, due to a high degree of non-repayment of past loans, 55% of the loan disbursements in 2014 was supported by supplemental funding from public sources (SLB, 2015). These included education taxes or government subvention (46%), grants earmarked for particular loan types (6%), and injections from the Ministry of Finance (3%). This has sparked a national debate about the sustainability of the Bureau and the net value that recipients derive from their interactions with the institution.

The SLB provides three loan facilities: Targeted Loan, Pay As You Study (PAYS), and Post-Graduate Loan.[8] The Targeted Loan is a need-based program that determines eligibility using a mean-test assessment. To qualify for this loan, the applicant must establish financial need and submit proof of their acceptance at an approved tertiary institution. The beneficiaries of the program are given 15 years to repay the loan at an interest rate of 9%, and repayment must begin within six months after graduation. The PAYS loan program provides financial support to working students who have been employed for at least one year and whose place of employment facilitates salary deduction. This loan has an interest rate of 6%, and repayment (salary deduction) begins immediately after the loan is disbursed. While the Targeted and Pay As You Study loan programs are both earmarked for undergraduate students, the Post-Graduate loan program offers tuition financing exclusively to graduate students. The loan carries an interest rate of 9.5%, and applicants must be employed and agree to salary deductions to take advantage of this facility.[9]

The Targeted Loan program is the main focus of this study. This program accounts for approximately 99% of the total loans disbursed by the SLB in the 2015–2016 academic year (SLB, 2015). For new applicants, the student loan application process typically begins in February and ends in May of the same year. All applicants are required to complete a comprehensive online form that collects information about their personal details, demographic and background characteristics, major choice, and the college institution they will attend. In addition, the applicant is required to provide a detailed record of their household's resources, savings, and welfare assistance, as well as the employment history and educational attainment of each household member and the details of two individuals who will sign as guarantors for the loan.

Once a student submits the online application form, a means-test score is calculated using the self-reported information. This score is used to determine the applicant's eligibility for the Targeted Loan program. Each applicant and their guarantors must also attend an in-person

[6] There is an extensive literature that examines the way various college financing programs affect student outcomes in developed countries. See, for example, Arendt (2013), Carruthers and Özek (2016), Castleman and Long (2016), Dearden et al. (2014), Denning et al. (2019), Dynarski (2000, 2002, 2003), Glocker (2011), Page et al. (2019), Scott-Clayton (2011), Singell (2004), Solis (2017), and Welch (2014). These studies find that eligibility for need-based grant or loan funding positively impacts college enrollment and degree attainment (Castleman and Long, 2016; Dearden et al., 2014; Denning et al., 2019; Kane, 2003). However, the evidence on academic performance and credit investment is inconclusive (Castleman and Long, 2016; Denning et al., 2019). The financial aid programs in this context are typically more generous relative to the ones that exist in developing countries (Solis, 2017).

[7] The student loan programs in Brazil, Chile, Colombia, and Mexico are both merit- and need-based. In each of these countries, students must attain a minimum standardized test score, in addition to a demonstrated financial need, to qualify for these loans (Canton and Blom, 2010; Marta Ferreyra et al., 2017).

[8] Each of these programs is unsecured, requires two guarantors, and is only available to Jamaican nationals.

[9] The SLB is the main college financing option for low-income families in Jamaica. This is because the institution provides unsecured loans that are more cost-effective and flexible than the competing options in the private market. For instance, while the Targeted Loan has an interest rate of 9%, the average lending rate for installment, mortgage, personal, and commercial credit in Jamaica between 2010 and 2016 was 18%.

interview with the SLB to ensure that they did not misrepresent any information on their application form, to submit supporting documents, and for guarantors to sign the contractual agreement. The institution does a good job of authenticating the applicants' self-reported information. During the interviews, applicants are required to submit supporting documents such as their identification cards, college acceptance letters, pay stubs or employment letters, bank statements, and welfare benefit cards. Approved applicants are subjected to a second round of review to determine their eligibility for a need-based grant.

The means-test score (I_i) is determined as follows:

$$I_i = F(W_h, N, L, R_i(E, H)) \quad (1)$$

where N is household size; W_h is the total household wealth; L is the cost of living in the applicant's locality of residence; and R is the perceived risk of repayment. The risk of repayment is a function of the earning potential of the selected degree (E) and the payment histories of past loan recipients who chose that degree (H).[10]

Once I_i is calculated, individuals are ordered and their scores are compared to the loan and grant eligibility threshold. Each applicant is then presented with one of three possible results: (i) the loan is approved and a grant is awarded, (ii) the loan is approved, or (iii) the loan is denied. As such, loan applicants from needy families may also be selected for a grant if I_i is sufficiently small relative to the grant eligibility threshold. The non-repayable grant assistance, about US$500 each year, aims to subsidize the cost of books and living expenses for college students who are most in need. Over the sample period, about 25% of applicants who received a student loan from the Bureau also qualified for grant funding.

Each individual is advised in writing of the status of their loan application within three weeks of the online submission. Once the applicant submits the supporting documents and the guarantor signs the required paperwork, the loan is disbursed directly to the students' chosen college. Returning applicants are required to submit a status report each year. Starting in 2015, continuing students were also required to submit their transcripts to prove that they have made satisfactory progress in their existing program of study by maintaining a minimum GPA of 1.5.

Approximately 67% of all loans are allocated to students attending Jamaica's two leading tertiary institutions, namely the University of Technology and the University of the West Indies. Since the loan program's approval rate is about 98% and students must be accepted into college before they are eligible to apply to the SLB, the outcome of the application process should have no direct impact on students' university choice or enrollment decisions. Similarly, it is unlikely that the result of the grant selection process would influence these outcomes, because the SLB does not advertise the grant program and students are generally unaware of the grant when they apply for the loan program. Moreover, students are not notified about their selection to receive the grant until several weeks into their first semester. Consequently, this study focuses on the outcomes that best characterize college success and labor market engagement for students who attend these two elite institutions.

2.2. Data

The core population of interest is comprised of students enrolled at the two most selective colleges in Jamaica (UWI and UTECH). For this study, the academic records of these students are merged with their SLB, high school, and labor market records.

On average, these two colleges jointly account for about two-thirds of all student loans disbursed by the SLB (SLB, 2015). The expected duration of a bachelor's degree ranges from three to five years across both institutions. At both colleges, courses are offered in the fall, spring, and summer semesters. New cohorts are admitted at the start of the academic year in September. Each institution determines tuition based on the degree program and the number of credit hours taken by the student. Therefore, there is significant heterogeneity in tuition cost and loan amount across degree programs and institutions.

Students' pre-treatment academic performance is obtained from the Ministry of Education (MOE). This is the public entity responsible for administering education policies that govern public schools in Jamaica. This institution also supervises the standardized high school exit examinations. These exams include the Caribbean Secondary Education Certificate (CSEC) and the Caribbean Advanced Proficiency Examinations (CAPE). Students attempt about eight CSEC examinations in various subject areas upon completing five years of secondary school. Qualifying students can then opt to complete two more years of advanced secondary studies; those who do are typically advised to sit for two to four CAPE examinations each year. To qualify for entry to university, students must typically complete at least five CSEC examinations and four CAPE units.[11] The academic records obtained from the MOE offer meaningful details on the high school academic performance of students. These pre-treatment characteristics are utilized as a useful control for students' academic ability.

Finally, to assess formal sector labor market outcomes, employment and earnings records are obtained from the Tax Administration of Jamaica. This institution is responsible for tax collection in Jamaica and hosts the employment records (annual earnings, contributions, and taxes) of all workers in the formal sector. To calculate a measure of labor market intensity, records on individuals' mandatory weekly national insurance contributions are utilized. Each employer in the formal sector is required to deduct a mandatory share of their employee's salary that is paid into a national social security scheme. This scheme offers some financial protection for the taxpayer in the event of a loss of earnings through employment-related shocks. In a given year, the number of weeks the employer contributes on behalf of the employee can be used as a good measure of the number of weeks for which the taxpayer was employed.

The records obtained from the various entities are merged using each person's date of birth, sex, first, middle, and last names. Since loan or grant eligibility is independent of the matching characteristics, any errors in the matching process are likely random.[12] Each individual in the sample is observed as they move from high school into college and ultimately the labor market. Together, these records form a comprehensive panel of students' high school performance, demographic and household details, family financial information, college records, loan repayment data, and labor market outcomes between 2006 and 2016. The key advantage of using this data is that it contains very detailed person-level characteristics and an extensive time horizon. The post-secondary and labor market variables of interest include cumulative GPA, attempted credits, on-time graduation, likelihood of graduating, drop-out, employment, tax, and earnings. Students' labor market outcomes are examined while they are enrolled in college and within three

[10] Loans and grants are issued subject to budgetary allocations. The details of the means-test score are not publicly available. Access to this information is typically restricted to a limited number of officials, but was granted for the purpose of this study. Consequently, to protect the confidentiality of the SLB's operation, information on the mechanics of the scoring procedure will be divulged on a need-to-know basis in this paper.

[11] Both exams are taken by students across the entire Caribbean region. There are over 30 subjects offered by the regional examination body, covering the core areas of arts, business, and science, technology, engineering, and mathematics (STEM). All colleges strongly recommend that students complete CSEC Mathematics and English with a passing grade. The CSEC examinations are graded on a discrete scale ranging from 1 to 6, with 1 being the highest score and 3 being the minimum passing score. Similarly, the score for CAPE exams range from 1 to 7, with 5 being the minimum passing score. For both exams, colleges only accept passing scores for admission.

[12] University ID numbers are available for about 10% of loan applicants. This allows their academic records to be uniquely matched to their SLB records. Among these applicants, the matching criteria employed in this study yields a match rate of over 95%.

years after their expected graduation date.

The sample is restricted to Jamaican college students between the ages of 17 and 44. Students with missing values for any of the outcomes of interest are also omitted.[13] The first cohort of students examined in this study entered university or submitted a student loan application starting in 2006. Since degree programs have an expected duration of three to five years, the last entering cohort examined started their program in 2014. The core sample includes 48,329 new students who are followed for at least six semesters in college. Of this sample, 23,798 are enrolled at the UWI and 24,531 at the UTECH. The descriptive statistics for the entering cohort at each institution are presented in Tables 1 and 2. At both institutions, the treated group utilizing the loan or grant has a larger share of females and of full-time students; the students utilizing loans or grants are also younger on average and had better mean scores on the standardized high school exit examination.

Over the sample period, about 43% of students in the entering class at UWI used a loan from the SLB to cover tuition expenses, compared to 38.5% of the entering class at the UTECH. Similarly, the SLB awarded grants to about 11% and 9.3% of the UWI and UTECH entering class, respectively.[14] As such, a substantial share of the undergraduate population at the two largest universities have much of their college expenditures covered by the SLB and are directly affected by its policies. The annual average tuition fee is about US$1300 at the UWI and $1400 at the UTECH.[15] In the sample, the students who only received the loan have an annual per capita family income of about $2700, while recipients of both a loan and a grant had an annual per capita family income of about $1000 dollars. The annual grant amount is $500 per year, which is approximately one-half of the per capita family income of eligible students. As such, the grant is a sizable addition to the budget of treated students.

3. Identification strategy and empirical specification

The students that utilize the loan facilities at the SLB are different from those that finance their studies through scholarships or using their own resources. These differences arise due to a systematic sorting into the loan application process and because of the need-based criteria the SLB uses to approve loans and select grant recipients. The unobserved differences between these groups can induce bias in the estimated parameters in a way that cannot be fully anticipated.

On the one hand, many of the factors that positively affect college outcomes and persistence in college are negatively correlated with loan use and grant approval. On the other hand, the factors on which students positively select into the student loan application pool may also enable them to perform well in college. For example, students with higher family wealth and available resources are less likely to select into the loan applicant pool, but they can also afford better inputs to improve their performance at the college level. But it is also possible that the students who are responsible, motivated, or have a better high school preparation may be more likely to apply for a student loan (conditional on income), and that these students are better equipped to perform well at the college level. Some of these selection mechanisms are observed in the descriptive statistics and must be addressed through models that directly control for the potential selection bias.

This section outlines the various empirical models employed and details the identifying assumptions underpinning each model.

3.1. Regression discontinuity

The funding criteria utilized by the SLB creates a discontinuity in the financial resources available to needy students. These eligibility rules can be exploited to estimate the impact of the need-based grant program on students' academic and labor market outcomes.[16]

Loan recipients are also selected for the grant program if they possess a means-test score that is lower than the grant eligibility threshold. Some of these students may choose not to participate in the program if they are awarded need- or merit-based financial support from an alternative source. In contrast, some of the students who are ineligible for the grant program based on their score may still receive support if their university recommends them as a student facing hardship, or after an applicant's appeal and subsequent extensive review.[17]

Consequently, the probability of treatment falls discontinuously as the means-test score increases and crosses the grant eligibility threshold. However, because the score does not perfectly predict students' grant award status, the fuzzy regression discontinuity design is the most suitable to estimate the treatment effect in this context. This approach estimates the impact of grant assistance on the group of students who comply with their assigned grant award status. The empirical model is depicted in equations (2) and (3) below:

$$D_i = \gamma_0 + \gamma_1 \mathbb{1}[I_i < c_G] + P_D(I_i - c_G, I_i < c_G) + X_i\omega + \varepsilon_i \tag{2}$$

$$Y_{it} = \pi_0 + \pi_1 \widehat{D}_i + P_Y(I_i - c_G, I_i < c_G) + X_i\mu + u_{it} \tag{3}$$

where $(I_i - c_G)$ is the means-test score of student i net of the grant eligibility threshold; D_i takes the value 1 if student i utilized a grant irrespective of their assignment by the means-test score; Y_{it} is the academic and labor market outcomes of interest; $P_D(I_i - c_G, I_i < c_G)$ and $P_Y(I_i - c_G, I_i < c_G)$ are polynomial terms in the means-test score and its interaction with grant assignment status; X_i are background and demographic covariates; and ε_i and u_{it} are unobserved mean-zero random error terms. $\mathbb{1}[I_i < c_G]$ is the rule utilized by the SLB to determine which students are eligible for grant funding. Therefore, if $I_i < c_G$ is satisfied, the student is selected for a grant-in-aid and $500 in grant funding is disbursed upon acceptance of the loan amount. The actual treatment status, D_i, differs from assignment for non-compliant students. Consequently, the first-stage regression in equation (3) isolates the variation in grant use (D_i) that is explained by grant assignment using the means-test score.

The parameter of interest, π_1, captures the local average treatment effect (LATE) of the grant program. The main estimates correct for the bias in the conventional non-parametric polynomial approach as recommended by Calonico et al. (2014). Additionally, all RD specifications refrain from the use of higher-order polynomials as suggested in Gelman and Imbens (2019). In particular, a linear specification is used in the baseline estimates.[18] Triangular weights are utilized.

Finally, I utilize the mean squared error (MSE)-optimal bandwidth selection procedure proposed in Calonico et al. (2019) to select the bandwidth size for the baseline estimates. However, I show that the results are robust across much of the bandwidth distribution. The band-

[13] The only explanatory variable that had missing observations was the previous high school that students at UTECH attended. This record was incomplete from the university records and could not be completed using the MOE data. This variable was only utilized in the high school by cohort FE model that is presented in Online Appendix B. Since this approach relies on within high school by year of birth variation in financing status, this data limitation is not very concerning.

[14] Roughly 25% of loan beneficiaries at each university receive a grant.

[15] All monetary values in this study are reported in US dollars.

[16] In employing the RD design, I focus exclusively on the grant program. Only 2% of loan applicants are denied because of their means-test score. Therefore, the density of students above the loan cutoff is inadequate to identify the effect of the program. In contrast, about 25% of loan recipients are awarded grant funding.

[17] The SLB administrators note that there are only a few appeal cases each year. Therefore, grant appeals should not violate the identification assumptions.

[18] The results are robust to the inclusion of quadratic local polynomials.

width choices considered belong to the interval $|I_i - C_G| \in [2, 16]$.[19]

3.1.1. Local randomization assumption

The regression discontinuity estimates have a causal interpretation when the sufficient assumptions are satisfied. These key assumptions are documented in Imbens and Lemieux (2008), McCrary (2008), and Lee (2008).

The first is that, crossing the eligibility cutoff from either direction, there is a discontinuous change in the likelihood of treatment. In the current context, this requires that students with the lowest family income have a higher probability of being selected for grant funding. This criterion is satisfied by design because the SLB adheres to its policy of using the means-test score to determine applicant's eligibility for the grant program.[20] Figs. 1 and 2 show that at each college, the students who are eligible for the grant have a 40–47% higher likelihood of utilizing a grant at the margin, relative to ineligible students.

The second assumption is that in the neighborhood around the treatment cutoff, there are no systematic differences in the observable and unobservable characteristics of the treated and untreated groups. Table 3 shows that, on average, the observed differences in students' age, sex, attendance status, city of residence, commuting status, high school performance, family size, and welfare participation status is not statistically significant between the treated and untreated groups. Therefore, there are no systematic differences between the treated and untreated marginal students at the grant eligibility threshold.

Lastly, since the SLB incorporates self-reported information in determining the means-test score of each applicant, there is a concern that students may manipulate their information to become eligible for grant assignment. In the absence of verification and with perfect knowledge of the assignment variable and cutoff, the strictly dominant strategy of each applicant is to report family characteristics that places them below the cutoff for each programs. However, there are three main reasons the applicant is unable to manipulate their eligibility in this study. First, the general public is unaware of the means-test formula and the cutoff utilized to determine grant eligibility. Secondly, the SLB requests proof of income and other supporting documentation for all successful applicants.[21] Finally, many applicants are unaware of the grant program when they submit their loan applications.

While manipulation of the means-test score is unlikely because of the reasons stated above, this study uses the non-parametric local polynomial density plots and test statistics proposed in Cattaneo et al. (2016) to explicitly test for manipulation. The test evaluates the null hypothesis of no manipulation at the cutoff, $H_0 : \lim_{x \uparrow \bar{x}} f(x) = \lim_{x \downarrow \bar{x}} f(x)$ for $x = I_i - C_G$. Figs. 3 and 4 show that there is no statistical difference in the density of the means-test score around the grant eligibility cutoff. The p-value ($p = 0.51$) from Cattaneo et al. (2016) suggests that the break in the density is not statistically significant at all conventional levels, and that there is no manipulation at the cutoff. This indicates that the RD design can be credibly employed to estimate the treatment effect of grant funding on students' academic and labor market outcomes.

[19] To the right of the cutoff, as $I_i - C_G$ increases, families with more monetary resources are included in the analysis. Similarly, to the left of the cutoff, as $I_i - C_G$ decreases, families with fewer monetary resources are included. Consequently, as $|I_i - C_G|$ increases, the analysis contains students that are less homogeneous in terms of household wealth.

[20] While there are students who are non-compliant with their assignment to treatment, this does not invalidate this assumption.

[21] However, households can still be selective in what they report to the SLB. There is no auditing of the supporting documentation and no attempts are made to verify the veracity of the documentation provided. However, the SLB advertises strict penalties for willful misrepresentation on the application form. The penalties include loan cancellation and the immediate collection of any disbursed funds.

3.2. Instrumental variables approach

Two separate policy interventions are utilized to evaluate the impact of each funding program. This section describes the way each of these natural experiments changes the likelihood of loan and grant eligibility for affected students.

3.2.1. Welfare and Grant Reform

The SLB and the Ministry of Labor and Social Security (MLSS) entered into a technical assistance and information sharing partnership in 2012. This agreement led to three main changes to the financing program at the SLB. First, the agreement allowed the SLB to verify each applicant's welfare benefits using the MLSS beneficiary database.[22] Second, the means-test funding formula was modified to incorporate information on household consumption. Third, the number of guarantors and the application cost of the Targeted Loan was significantly reduced for students on welfare. Thus, the new system improved the SLB's ability to target low-income students. In addition, the policy changes made it easier for welfare recipients to complete the loan application process and increased the likelihood that these students would be selected for the need-based grant program. However, since only 2% of loan applications are declined, the reform had a negligible impact on loan approval.

These policy discussions were conducted privately, and there were no press releases about the changes. Therefore, there is no reason to expect that the reform had any direct influence on students' subsequent outcomes. However, the reform created an exogenous variation in grant eligibility rules, which can be utilized to examine the impact of grant use on students' academic and post-college outcomes. To exploit this policy change, this study employs a two-stage least squares (2SLS) approach, where the first stage is augmented with a Difference-in-Difference (DID) design. The empirical model is shown in equations (4) and (5) below:

$$D_{grant_i} = \gamma_1 + \gamma_2 WELFARE_i + \gamma_3 WELFARE_i * POST_t^{2012} + X_i\pi + \tau_t + \varepsilon_i \tag{4}$$

$$Y_{it} = \alpha_0 + \alpha_1 \hat{D}_{grant_i} + X_i\beta + \tau_t + \eta_{it} \tag{5}$$

where D_{grant_i} takes the value 1 if the student receives a grant; $WELFARE_i$ takes the value 1 for applicants who are welfare recipients; $POST_t^{2012}$ takes the value 1 in all time period following the policy change in 2012; Y_{it} is the academic and labor market outcomes of interest; τ_t are time fixed-effects, and X_i is comprised of household-level and individual-level covariates. These variables include gender, age, household income, high school outcomes, location fixed effects, tuition, and various degree characteristics. The parameter γ_3 captures the effect of the reform on the likelihood that welfare recipients are awarded a need-based grant. For a causal interpretation, conditional on X_i, the policy change must be independent of η_{it}. Since the reform was mainly an administrative change in the eligibility rules and these changes were not announced publicly, conditional on the background variables from the application form, it is unlikely that the policy change had a direct impact on students' academic and labor market outcomes. The parameter of interest, α_1, shows the effect of the grant on the outcomes of students who were selected for the grant program because of the policy changes in 2012.[23]

Panel A of Table 4shows that the reform increased grant awards for students on welfare by 12% and 17% at the UWI and UTECH,

[22] Social welfare benefits are provided through a means-tested conditional cash transfer program (the Programme of Advancement Through Health and Education [PATH]). This program uses a screening interview and home visits to assess the need of potential recipients.

[23] The sample is comprised of the applicants who received the Targeted Loan.

respectively. This temporal variation in grant assignment across welfare and non-welfare households is caused by the changes in grant eligibility rules. Causal identification requires that these amendments to the grant award rules do not alter the trends in the reported characteristics of applicants from welfare and non-welfare households. Therefore, the observed trends in need-based attributes (household consumption, income, and labor supply) should be unchanged before and after the reform.

I perform several robustness checks to show that the temporal variation in grant assignment across welfare status is exogenous. First, Panel A of Table 4 shows that the first-stage DID point estimates do not change when a detailed list of background covariates is included in the model. Second, when the sample is restricted to the pre-intervention period and a placebo date for the policy change is created, the model finds no impact on grant assignment. In Fig. 5, the date of the policy change is assigned to various years in the pre-intervention period. The horizontal axis depicts the year of the placebo policy change and the vertical axis shows the impact of the false policy change on the likelihood that welfare recipients are selected for grant funding. For example, the first point on the graph shows the DID estimate for a placebo policy change that begins in 2007 and continued through to 2011. The resulting point estimates from each of these models are statistically insignificant.

This result is further strengthened by Fig. 6A, which shows that there is a parallel trend in grant awards for welfare and non-welfare applicants in the pre-intervention period. Similarly, the event study presented in Fig. 6B shows that, relative to the last year in the pre-intervention period (base year = 2011), the treatment-control differential in grant assignment is statistically insignificant in all pre-intervention years. However, because of the policy change, grant awards to welfare recipients increased by at least seven percentage points in the post-intervention period. Together, these results support the claim that grant assignment trends are parallel across welfare and non-welfare households in the pre-intervention period.

Lastly, I examine the impact of the reform on several household-level covariates that are highly correlated with grant eligibility. These variables are household income, the number of employed members in the household, durable consumption, and economic well-being. To create indices for durable consumption and economic well-being, I use several mandatory questions on the application form that collect information about the applicant's asset holdings and housing conditions. This includes home ownership status, housing type, housing material, type of toilet facilities, source of drinking water, and ownership of various durable consumption goods.[24] The Principal Component Analysis (PCA) technique is leveraged to create proxies for each index. This approach takes several linear combinations of the reported variables and loads them into various uncorrelated indices that retain most of the underlying variation. This data reduction tool is widely utilized in applied research to reduce a large set of correlated variables into a smaller set of components. For the consumption and economic well-being indices, the leading component of the PCA is reported in Table 5.[25] The DID estimates show that the policy change had no statistical impact on reported household income, the number of employed members in the household, durable consumption, or the economic well-being of applicants.

Jointly, the various robustness checks suggest that the instrument likely satisfies both the exogeneity and relevance IV conditions. The estimates from the second stage are discussed in the results section.

[24] Appendix B shows the mandatory questions that are asked on the application form and provides a detailed description of the way each index is created.

[25] In Appendix B, I show that similar results are obtained when the scree plot and Kaiser rule are utilized to select the number of components. In general, these results are also robust to alternative approaches of creating the indices (such as adding or averaging the various binary variables). Those results can be provided upon request.

3.2.2. High school visits and loan use

Over the years, the SLB has used high school visits as a medium to expose potential applicants to information about the loan facilities it offers. Generally, SLB administrators believe that there is an information gap in high school students' knowledge about the program, as well as misconceptions about the terms of the services offered. Conducting high school visits is one avenue through which the Bureau attempts to close that information gap and offer greater transparency in the application process. The schools targeted for intervention are largely those located in geographical areas that were under-represented in the application pool in previous years.

The information disseminated to treated high schools may induce some students to apply for a tuition loan to continue their studies. The students who are induced into the application process are those who are interested in seeking a college education, are eligible for entry, and were previously unaware of the services offered by the SLB. These students would not have applied for a loan in the absence of the intervention. This information campaign provides a good source of exogenous variation in loan financing because it aims to increase the number of loan applications, and it has no direct impact on students' academic and labor market outcomes (conditional on observed covariates). However, because 98% of loan applications are approved, the intervention may also increase the number of students who utilize the loan program for college.

The high schools visited change each year, according to the priorities of the institution and available resources. By matching students to their likely exposure to the SLB's high school visits, I exploit the variation in loan use that is created by the information intervention. Using high school visits as an instrument, the two-stage least squares (2SLS) model is estimated using:

$$D_{loan_i} = \delta_0 + \delta_1 VISIT_i + W_i\psi + \tau_t + u_i \tag{6}$$

$$Y_{it} = \upsilon_0 + \upsilon_1 \widehat{D}_{loan_i} + W_i\theta + \tau_t + \xi_{it} \tag{7}$$

where D_{loan_i} takes the value 1 if the student uses a loan and 0 if they did not apply or were denied; $VISIT_i$ is an indicator variable that takes the value 1 if the student was potentially exposed to an information session during their senior year of high school; Y_{it} is the academic and labor market outcomes of interest; τ_t are admitted year fixed effects; and W is a vector of individual level background covariates such as gender, age, high school performance, and location fixed effects. The high school information campaign had no plausible direct impact on students' outcomes, except through its effect on their likely college financing options. Causal identification requires that, conditional on the geographic and background variables in W, the students were exogenously exposed to the loan details by the information intervention. The results in Table 4 show that, conditional on W, the school visit campaign increased loan use by about 10–12 percent.[26]

The parameter of interest, υ_1, shows the impact of the loan program on the college and labor market outcomes of students induced into utilizing loan financing by the school visit campaign. This model offers the best estimate of the impact of student loan financing on the academic and labor market outcomes of affected students.

4. Empirical results

Using various quasi-experimental designs, this study finds robust evidence that beneficiaries of the need-based tuition loan and grant financing programs experienced better outcomes during college. The participants in both programs had better GPAs, higher graduation rates,

[26] Figs. 17 and 18 show the variation in loan use and high school visits over the sample period. Alternative estimates that rely on within high school and across cohort variation in loan use yield similar results to the main specification.

and were more likely to remain in school beyond their second year, relative to non-participants. In addition, the results suggest that each program reduced the labor market earnings of some treated students during college. However, this study found that, in the early years after college, while the grant program increased the earnings of recipients, the participants of the loan program were induced into accepting starting jobs (and earnings) that were below their productive capacity.[27]

The results for the grant and loan programs are discussed in Sections 4.1 and 4.2, respectively. The estimated treatment effects are consistent across research sites. Therefore, I focus on the impact of each program for students attending the University of the West Indies and then briefly discuss the areas where the conclusions are similar and different for the UTECH sample.

4.1. Impact of the grant program

The main results for the grant program are presented in Tables 6 and 7. While the regression discontinuity design estimates the impact of grant funding on students who were marginally selected for the program, the instrumental variables design estimates the impact of the funding on students who were induced into the program by the policy change in 2012. Both models provide credible estimates of the local average treatment effect of the grant program at different points in the income distribution.

Table 6A shows the effect of the grant program on the academic outcomes of students attending the University of the West Indies. Columns 1–6 displays the estimated impact on first semester GPA, first semester attempted credits, on-time graduation rates, the likelihood of graduating, degree GPA at graduation, and the probability of dropping out prior to the third year of study.[28] The coefficient estimates, corresponding standard errors, and the control group's mean are provided for each estimation approach and outcome of interest.

The RD estimates indicate that the students who were marginally eligible for the grant funding invested in fewer credit hours and had a higher GPA of 0.48 points in their first semester. They were also 21 percentage points more likely to graduate on time, and graduated with a higher GPA of 0.27 points relative to ineligible students. However, at this margin, the grant program had a small impact on persistence and the overall likelihood of graduating from college. On the other hand, for students who were induced into the grant program by the 2012 policy change, the IV-DID estimates suggest that the funding reduced the probability of drop-out by 10 percentage points and increased their on-time graduation rate by 11 percentage points. The treated students at this margin also had a higher GPA in their first semester and a higher GPA of 0.21 points at graduation.

Table 6B shows the impact of the grant program on students' labor market outcomes during and after college in the UWI sample. Columns 1 to 3 illustrate the impact on the likelihood of being employed, the number of weeks employed, and annual earnings during college. Similarly, the outcomes in columns 4 to 7 are the likelihood of being employed, the number of weeks worked, annual earnings, and total tax contributions within the first three years after students are expected to graduate. The remaining features of the table are equivalent to Table 6A. The RD estimates show that the students who were marginally eligible for the grant worked and earned the same during college as the students who were marginally ineligible. After college, however, the grant recipients earned nearly $1020 more in their starting job and paid about $337 more in taxes each year. In contrast, the IV-DID estimates suggest that the students who were induced into the grant program by the reform earned about $115 less each year during college. This reduction is primarily due to treated students adjusting their labor supply at the intensive margin. These students were also three percentage points more likely to be employed in the early years after college, but at the same annual salary as comparable untreated students.[29]

Tables 7A and 7B shows the impact of the grant program on students attending the University of Technology. Table 7A indicates that grant funding improved the academic performance, likelihood of remaining in college, and on-time graduation rate of treated students.[30] The RD estimates in Table 7B show that marginally eligible students earned approximately $1092 more and contributed about $350 more in taxes each year after completing their degree program at this university.

The point estimates in the UTECH sample are typically within the 95% confidence interval of those obtained from the UWI sample, and the qualitative conclusion across the two research sites is highly consistent. To formally assess whether the corresponding point estimates from the two samples are statistically equivalent ($H_0 : \widehat{\beta}_{UTECH} = \widehat{\beta}_{UWI}$), I utilize the independent samples T-Test. The standard error of the difference in the coefficients is calculated using $SE(\widehat{\beta}_{UTECH} - \widehat{\beta}_{UWI}) = \sqrt{SE(\widehat{\beta}_{UTECH})^2 + SE(\widehat{\beta}_{UWI})^2}$ (Clogg et al., 1995; Paternoster et al., 1998). In all cases, the test failed to reject the null hypothesis that the point estimates in the UTECH sample are statistically different from those found for the UWI sample at all conventional levels of significance. As such, the estimated parameters across the two research sites are statistically equivalent.[31]

Jointly, the findings above suggest that a small grant improves the academic and labor market outcomes of low-income college students. Therefore, this is one avenue that policymakers can utilize to enhance the long-term outcomes of disadvantaged students who possess limited access to credit markets.

4.1.1. Heterogeneous impact of the grant program

The margin at which the grant program is evaluated is an important consideration in appraising its effectiveness. While the RD and IV-DID estimates are mostly consistent in terms of direction, the magnitude of the impact varies across the two designs. This is likely due to the fact that these two estimators identify different local average treatment effects and highlight varying responses to the program at different points in the income distribution. This heterogeneous response to a single policy intervention is documented in the literature (Heckman and Vytlacil, 2005; Lamadrid-Figueroa et al., 2010). As discussed in Section 3, the changes that were implemented in 2012 improved the SLB's ability to target low-income students. Therefore, it is likely that the students

[27] In Online Appendix B, I assess the impact of each program using an alternative model specification that relies on within high school cohort variations in loan use. The results are very consistent with those discussed in this section.

[28] In the worst-case scenario, the college-level estimates discussed in this study will exhibit a downward bias if the grant or loan programs systematically impact students' enrollment decision. This is because, at the margin, lower-ability grant recipients would be more likely to enroll. In contrast, it is the most motivated, persistent, and higher-ability non-grant recipients who would find a way to enroll in college. However, first semester GPA and attempted credits are unlikely to be affected by this selection bias. As outlined above, this is because students are not notified about their grant selection until several weeks into the semester and loan approval does not have any plausible impact on college choice or enrollment. On the other hand, the results for degree GPA at graduation are correlational because each program may affect the likelihood of staying in college. However, the estimate for this variable is also likely a lower bound, since lower-ability students are more likely to stay in college because of each program.

[29] In the main estimates presented in Tables 6B and 7B, a value of zero is assigned for the annual earnings and weeks worked outcome variables if the individual is not observed in the formal sector. Alternative estimates that condition on employment are presented in Table 7C of Online Appendix A. Restricting the sample to employed individuals does not change the conclusion, but these alternative results are more prone to selection bias.

[30] The RD estimates in Table 7A are notably less precise than the corresponding results in Table 6A.

[31] These calculations are available upon request.

who are induced into treatment by the policy change (IV-DID) are more in need of financial assistance than those who are marginally eligible (RD) for treatment. The empirical results are consistent with this conjecture.

A simple thought experiment may explain this heterogeneous response across the two empirical designs. Consider two groups: one that is comprised of low-income students, and the other containing high-income students. In each group, a grant is randomly assigned to half the population of students. Ceteris paribus, the grant should be more effective in preventing the low-income students from dropping out of college for financial reasons, relative to its impact on the high-income students. Similarly, the grant should affect the work decisions of the wealthier students to a lesser degree than its impact on poorer students. This thought experiment is consistent with the main results. While the IV-DID findings show that the grant program induced treated students to persist in college longer and to reduce their earnings during this period, the RD results suggest that these effects are significantly lower on marginal students. In addition, since treated students are more likely to remain in college at the IV-DID margin, it is not surprising that the grant would have a lower positive impact on their college outcomes and post-college earnings relative to students at the RD cutoff.[32]

In comparing the findings at the two margins, it is not clear what role employment during college plays in the observed improvement in students' academic performance. While students at the RD margin do not reduce their work engagement during college, the grant had a greater positive impact on their likelihood of graduating on time and their graduating GPA compared to the students induced by the reform. However, this analysis is complicated by the differences in family income and the impact of the program on remaining in college at each margin.

4.1.2. Robustness of grant program estimates

To evaluate the sensitivity of the RD estimates, I re-estimate this model using various bandwidth sizes for both research sites. The main objective of this exercise is to show that the grant estimates are robust to the bandwidth selection procedure. The sensitivity analysis also provides some insight into the likely direction of the bias as the bandwidth size increases. In the baseline results presented in Tables 6 and 7, the bandwidth size is selected using the mean squared error (MSE)-optimal bandwidth selection procedure proposed in Calonico et al. (2019). Given that $|I_i - C_G|$ belongs to the interval [0,16], this analysis examines how the baseline estimates change when larger bandwidth intervals are utilized.

The results are presented in Figs. 7–16. Each figure plots the bandwidth size, $|I_i - C_G|$, along the horizontal axis and the resulting estimates along the vertical axis. The point estimates presented in Tables 6 and 7 are represented by squares on each graph, while the other estimates are depicted with diamonds. The confidence interval is also presented as bands around each estimate. The figures show that the qualitative conclusion for each outcome does not change as the size of the bandwidth increases. As expected, using bandwidth sizes further away from the cutoff produces estimates that are biased towards zero, but with tighter confidence intervals. Jointly, these figures show that the main conclusions are robust to the bandwidth size utilized in the baseline specification.

4.2. Impact of the tuition loan program

Tables 8A and 8B shows the impact of the loan program on the students attending the University of the West Indies. The outcome variables in both tables correspond to those discussed in Tables 6 and 7 above. The IV results in Table 8A suggest that the recipients of the loan program were 22 percentage points more likely to remain in college until their third year, 19 percentage point more likely to graduate on time, and 49 percentage points more likely to graduate from college. In addition, loan recipients had a higher GPA of about 0.36 points at graduation relative to similar students that did not utilize the loan. Consequently, the students that were induced into the loan program persisted longer in college and were also more likely to complete. The estimates in Table 8B indicate that loan recipients were less likely to be employed and earned about $713 less each year during college. This reduction is large, as it represents about one-half of the annual cost of tuition. After college, the students induced into the loan program earned approximately $1800 less and paid about $440 dollars less in taxes each year.

Similarly, at the University of Technology, loan recipients performed better, were more likely to remain in college, and were more likely to graduate than non-recipients. Treated students also earned less during college and had a lower earnings of about $1630 each year after college. Therefore, the treated students at UTECH also outperformed their peers in college, but accepted lower-paying jobs after completing college.[33] Similar to results for the grant program discussed above, for all outcomes, the independent samples T-Test suggests that the estimated coefficients for the loan program are not statistically different across the UWI and UTECH samples.

At first glance, the estimated impact of the loan program on students' college and post-college outcomes may appear inconsistent. The program enables participants to improve their college outcomes, but these higher quality outcomes appear to yield a negative return in their starting jobs. One potential explanation for the post-college labor market findings is that the loan recipients are incentivized to take up early employment offers that pay them less than their productive capacity. This explanation is plausible, since the loan agreement stipulates that students must start repaying their debt about six months after completing their degree program. I assess the feasibility of this explanation using several additional checks below.[34]

4.2.1. Loan program mechanism

It may seem paradoxical that loan recipients perform better in college, but earn a lower starting wage when they graduate and enter the labor market. One potential explanation for this inconsistency is that treated students have an incentive to accept job offers that pay them less than their productive characteristics, because the short moratorium on repayment restricts their job search. To test the veracity of this explanation, I estimate the impact of the loan program on: (i) students' labor market outcomes in professions that are given a longer moratorium on loan repayment, (ii) employment and earnings each year after students' expected graduation date, and (iii) graduate school enrollment.

The first check examines whether a longer moratorium on repayment influences students' employment prospects and starting salary after college. Because students from licensed occupations cannot gain employment in their field of study until they have obtained their professional license, the SLB gives them a moratorium that is about eight months longer than that of students in other fields. Therefore, I create a

[32] The students that self-select out of college are those that would have been most likely to perform poorly had they remained. At the IV-DID margin, more low-performing grant recipients remain in college than low-performing non-recipients. In contrast, at the RD margin, poor performing grant recipients drop-out at the same rate as non-recipients. Consequently, it is reasonable to expect that the IV-DID treatment effect on college performance would be lower.

[33] For both research sites, alternative estimates that condition on employment are presented in Table 8C of Online Appendix A.

[34] Following multiple conversations with program administrators, this explanation was seen as the most plausible. Administrators refer to the employment of loan recipients in the business process outsourcing (BPO) industry as one example. These jobs are widely available and have a continuous hiring process, but they offer compensation packages that are below the average earnings of a college graduate.

sub-sample comprised of individuals in occupations with a grace period of 14 months (e.g. nursing and pharmacology) to evaluate the plausibility of this mechanism. The result of this analysis is shown in Table 10. The findings suggest that the recipients of the loan program are more likely to be employed after college, but their earnings are equivalent to those of students who did not utilize the loan. This finding lends weak support to the proposed explanation.[35]

The second check presented in Tables 11 and 12 indicates that in the first full year after graduating from college, the students who received the loan are about 15 percentage points more likely to be employed, but they earn a lower salary in their starting job relative to untreated students. This early disparity in employment and earnings supports the theory that treated students are induced into lower-paying jobs in order to fulfill their repayment obligation within six months of degree completion. Both tables also show that the disparity in employment and earnings persist for a few years after graduation.

The third check addresses the concern that, in the early years after graduation, there may be a negative selection of lower-quality loan recipients into the labor market. This would occur if high-performing treated students are more likely to enroll in graduate school, while low-performing treated students enter the labor force. The last column of Table 11 shows that the students who utilized the loan were less likely to enter graduate school by 21 percentage points. Therefore, under the assumption that higher-performing students are more likely to enter graduate school, the estimated effect of the loan on earnings may actually understate the detrimental impact of the loan program.[36] This result also supports the proposed explanation.

Jointly, these additional checks support the theory that the students who utilized the loan may be induced into accepting job offers that pay them less than their productive characteristics because of the short moratorium on loan repayment to the SLB.

5. Conclusion and policy discussion

This paper utilizes several quasi-experimental designs to evaluate a national student loan and grant assistance program that targets low-income college students in Jamaica. The study focuses on how these benefits impact students' academic outcomes, paid work during college, and labor market outcomes in the early years after college completion. The analysis uses a novel individual-level panel data set that is constructed using educational and financial administrative records from multiple public institutions in Jamaica. This paper contributes to an emerging strand of the college financing literature that evaluates the impact of loan and grant funding programs on students' academic outcomes in developing countries. The paper also contributes to a growing body of research that assesses the impact of financial aid on students' work-study trade-off and post-college labor market outcomes.

I found robust evidence that grant funding had a large, positive, and statistically significant impact on students' persistence in college, degree GPA, and likelihood of on-time graduation. In addition, the grant recipients were engaged in less paid work during college, but earned a higher starting salary after completing their degree program. Similarly, the results indicate that loan recipients had a lower drop-out rate, a higher GPA throughout college, and were more likely to graduate on time compared to their untreated counterparts. Furthermore, the students who received loan funding engaged in less paid work during college. However, while treated students were more likely to be employed after college, they also earned a lower wage in their starting job. Several additional checks suggest that the negative impact of the loan program on post-college earnings may be driven by the short moratorium on loan repayment. Therefore, affected students are willing to accept lower salary offers to meet this obligation.

Estimating the economic return of each program is challenging. One approach is to assess whether each program has achieved its primary policy objective of improving college outcomes and the prospects of economic mobility for needy students. In this respect, each program has had significant successes. Looking across the IV and RD margins in both schools, each additional year of grant funding ($500) improves the likelihood of on-time graduation by five to nine percentage points and graduating GPA between 0.09 and 0.12 points. Similarly, each $1000 in loan funding improves the likelihood of graduating on time by roughly one to four percentage points and reduces the likelihood of dropping out before the third year by two to four percentage points. In each sample, since one in every eight college students benefited from the grant program and two in every five received a loan, these improvements are large and practically meaningful for aggregate college-level outcomes.[37]

A second approach is to weigh the budgetary cost of each program against their public returns (taxes, educational attainment, crime, health, welfare). This is not very feasible in the short-term, given that most of the returns to education are realized over a long-term horizon. Over the period 2008–2016, the total budgetary cost of the grant and loan programs were US$8.92 and US$221 million, respectively. The corresponding per-recipient value is roughly $1150 and $4700. It is promising that in the early years after expected graduation, some grant recipients paid an average of $350 dollars more in taxes each year. In present discounted value, these marginal students would have repaid the grant through higher tax contributions in about four years. In a decade, if these differences persist, the average treated student would cumulatively contribute about $2250 more in taxes, enough to repay their subsidy and fund the grant amount for an incoming student.

A similar argument cannot be made about the loan program from evidence in the short-term. For this program, the puzzle facing policymakers is how to ensure consistent and timely repayment while also encouraging students to meet their full potential in the job market. While finding a good job match may be time-consuming, a longer job search may yield better wages and higher tax contributions. In addition, students also need an incentive to find a job and begin loan repayment. In theory, adjusting the length of the moratorium on loan repayment and formally incorporating income-based repayment may be a good place to start (Akers and Chingos, 2018; Dynarski and Kreisman, 2013). The evidence for licensed occupations supports this conclusion.

Evaluating the social return of both programs will require more analysis over a longer time horizon. This will provide more concrete

[35] Students determine their majors before they apply to the SLB. Therefore, the loan should not have any direct effect on the students who select into licensed occupations. However, the extent to which these results are externally valid is an open question.

[36] One may be similarly concerned that the better-trained loan recipients are more likely to migrate. For this to be a major concern, overseas migration would have to be higher for the talented loan recipients than the talented non-loan population. While this selection concern is legitimate and cannot be directly ruled out, the fact that the loan population has fewer resources available to them makes it less likely that they would migrate overseas. Furthermore, a simple descriptive analysis of the labor market suggests that selective migration cannot plausibly explain the results. About 35 percent of students in the sample complete college on time. Among these students, 12 percent are observed in graduate school and 33 percent find a job in the formal sector within one to three years. Consequently, 45 percent of the students that graduate on time can be directly tracked in the early years after college. Given that the estimated size of the informal sector in Jamaica is 35–44 percent (Peters, 2017) and the youth unemployment rate is roughly 30 percent, it is likely that the migration rate during one to three years after expected graduation is minute.

[37] The average grant recipient received $1150, or 2.3 years of grant funding, and the average loan recipient borrowed about $4700. The coefficients presented in Tables 6A–9B represents the total impact of the average per-person funding. To approximate the value of one year of grant funding ($500), I employ the simple formula: $\frac{500}{1150} \times \beta_{grant}$, where β_{grant} is the estimated impact of the grant on college outcomes. Similarly, the value of $1000 in loan funding is given by $\frac{1000}{4700} \times \beta_{loan}$.

evidence on the successes and failures of each program. There are several important implications of this research for designing loan and grant programs in Jamaica. First, since the grant program generates net revenue for the government, it may be useful to raise the program's eligibility threshold to improve students' on-time graduation and academic performance. Second, the short moratorium on repayment appears to be forcing loan recipients to accept a lower-paying job rather than continue searching for a job that matches their productive characteristics. While there is yet little evidence that a longer moratorium will improve labor market outcomes, the Student Loan Bureau should potentially experiment along this margin. This is certainly a question that future studies should continue to explore.

Author statement

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Data availability

The authors do not have permission to share data.

Appendix A. Main Tables and Figures

Table 1
Entering Students Descriptive Statistics, University of the West Indies

Fin Stat	Male	Age	FT	Tuition	Loan	Entry Score	CSEC
DNA	0.33	20.66	0.76	1216.78	0.00	36.29	7.72
	0.47	4.63	0.43	1289.42	0.00	15.29	1.57
Denied	0.27	19.54	0.85	1522.26	0.00	39.78	7.91
	0.45	3.00	0.36	1617.78	0.00	13.25	1.51
Loan	0.28	19.55	0.89	1431.37	1357.08	41.07	8.02
	0.45	2.79	0.31	1380.54	691.07	13.53	1.48
Loan & Grant	0.26	19.54	0.95	1316.19	1303.22	41.16	7.96
	0.44	2.29	0.21	1037.26	588.05	12.95	1.42
Total	0.30	20.16	0.83	1301.21	573.86	38.40	7.85
	0.46	3.92	0.38	1304.72	794.55	14.66	1.53

Note: The mean and standard deviations are presented within each financial status. The first group consists of students that did not apply (DNA) for a student loan and instead paid their tuition with personal funds or scholarships. The remaining groups include the unsuccessful loan applicants, the applicants approved for only loan funding, and applicants approved for both loan and grant funding. There are 13211, 420, 7555, and 2612 students in each of these groups, respectively.

Table 2
Entering Students Descriptive Statistics, The University of Technology

Fin Stat	Male	Age	FT	Tuition	Loan	HS GPA	CSEC
DNA	0.48	21.43	0.67	1450.82	0.00	1.68	5.13
	0.50	5.33	0.47	1406.30	0.00	0.99	3.40
Denied	0.37	20.80	0.71	1243.08	0.00	1.64	4.90
	0.48	4.04	0.46	1288.64	0.00	0.97	3.11
Loan	0.40	20.38	0.78	1378.99	1567.20	1.81	5.62
	0.49	3.42	0.41	1371.76	385.18	1.04	3.71
Loan & Grant	0.35	20.36	0.84	1410.84	1510.10	1.81	5.59
	0.48	3.04	0.37	1398.20	385.63	1.03	3.64
Total	0.44	21.02	0.72	1423.80	599.33	1.73	5.32
	0.50	4.68	0.45	1394.71	793.32	1.01	3.52

Note: The mean and standard deviations are presented within each financial status. The first group consists of students that did not apply (DNA) for a student loan and instead paid their tuition with personal funds or scholarships. The remaining groups include the unsuccessful loan applicants, the applicants approved for only loan funding, and applicants approved for both loan and grant funding. There are 14842, 225, 7189, and 2275 students in each of these groups, respectively.

Table 3
Local Randomization Within Bandwidth

	Age	Male	FT	City	Commute	HS GPA	Fam Size	Welfare	Treatment
UWI	−0.35	0.11	0.003	0.05	−0.09	0.20	−0.08	−0.02	0.47***
	(0.95)	(0.16)	(0.11)	(0.09)	(0.12)	(0.20)	(0.43)	(0.05)	(0.06)
Obs	1735	1899	1737	1823	1686	1140	1768	1301	1588
UTECH	0.96	−0.03	0.06	−0.03		0.45	−0.63	0.05	0.40***
	(0.82)	(0.27)	(0.20)	(0.16)		(0.72)	(0.51)	(0.07)	(0.05)
Obs	1603	1036	825	920		975	1358	1019	1327

Note: Standard errors are clustered within year of entry and presented below each estimate. The high school (HS) performance measure differs across university. Therefore, it is normalized for comparability. For each model, the bandwidth size is chosen using the MSE-optimal bandwidth selection procedure proposed in Calonico et al. (2019). The outcomes in columns 1 to 9 are: age, gender, full-time status, city of residence, commuting status, high school performance, family size, welfare participation status, and a grant use indicator.

Table 4
IV First-Stage Results

	UWI	UTECH	Controls
Panel A: Grant			
WELFARE*POST	0.12***	0.17***	Yes
	(0.03)	(0.03)	
WELFARE*POST	0.12***	0.16***	No
	(0.03)	(0.04)	
Obs	10,003	8916	
Panel B: Loan			
HS VISIT	0.12***	0.10***	Yes
	(0.01)	(0.02)	
HS VISIT	0.18***	0.16***	No
	(0.01)	(0.02)	
Obs	23,432	16,720	

Panel A Instrument: Welfare Reform.
Panel B Instrument: HS Visit.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, family income (grant), high school performance, field of study fixed effects, and admitted year indicators.

Table 5
Trends in Household-Level Variables

	Log HH Income	# of Employed HH Members	Consumption	Economic Well-Being
Treatment Effect	0.01	0.001	0.01	0.04
	(0.20)	(0.02)	(0.20)	(0.05)
Mean	7.19	1.37	0.00	0.00

IV Instrument: Welfare and Grant Reform.
Note: Each model includes controls for gender, age, high school performance, location fixed effects, and admitted year indicators. The outcomes in columns 1 to 4 are: household income, number of employed household members, a durable consumption index, and a economic well-being index. The indices in columns 3 and 4 are created using the principal component analysis (PCA) and the leading components are utilized.

Table 6A
The Impact of the Grant Program on College Outcomes

	GPA	Credit Hrs	Ontime Grad	Any Grad	Grad GPA	Exit (3rd Year)
RD	0.48**	−1.15***	0.21***	0.03	0.27**	−0.02
	(0.22)	(0.37)	(0.08)	(0.15)	(0.13)	(0.08)
Mean	2.16	15.16	0.49	0.71	2.82	0.32
Obs.	1333	1557	1681	1197	655	1651
IV-DID	0.19**	0.26	0.11**	0.08*	0.21***	−0.10**
	(0.09)	(0.21)	(0.04)	(0.05)	(0.07)	(0.04)
Mean	2.13	15.04	0.38	0.66	2.71	0.19
Obs	10,003	10,003	10,003	7176	6041	10,003

IV Instrument: Welfare and Grant Reform, UWI SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, family income, high school performance, field of study fixed effects, and admitted year indicators. The outcome variables in columns 1 to 6 are: first-semester GPA, first-semester credit hours, on-time graduation, any graduation, degree GPA at graduation, and a drop-out indicator that takes the value 1 if the student exited college by the start of their third semester.

Table 6B
The Impact of the Grant Program on Labor Market Outcomes

	Emp	Weeks	Earnings	Emp	Weeks	Earnings	Taxes
RD	0.01	−0.41	150.86	−0.10	−2.34	1018.2***	336.50***
	(0.06)	(1.31)	(179.40)	(0.11)	(3.33)	(346.67)	(107.77)
Mean	0.08	1.39	184.2	.26	8.16	1558.66	377.81
Obs	4161	3093	3531	3516	4212	3891	3756
IV-DID	0.003	−1.35**	−114.5**	0.03**	−0.59	−11.05	32.32
	(0.02)	(0.52)	(45.88)	(0.013)	(0.52)	(226.40)	(61.10)
Mean	.13	2.45	308.17	.24	7.50	1559.18	378.31
Obs	30,009	30,009	30,009	25,383	25,383	25,383	25,383

IV Instrument: Welfare and Grant Reform, UWI SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, family income, high school performance, field of study fixed effects, and admitted year indicators. The dependent variables in columns 1 to 3 are the labor market outcomes observed during college: an employment indicator, weeks worked, and earnings. Similarly, columns 4 to 7 show the labor market outcomes observed within the first three years after students are expected to complete college: an employment indicator, weeks worked, earnings, and tax contribution. All monetary values are reported in US dollars.

Table 7A
The Impact of the Grant Program on College Outcomes

	GPA	Credit Hrs	Ontime Grad	Any Grad	Grad GPA	Exit (3rd Year)
RD	0.22	−0.13	0.17	0.08	−0.07	−0.09***
	(0.21)	(1.09)	(0.25)	(0.19)	(0.18)	(0.03)
Mean	2.35	14.93	0.52	0.68	2.77	0.094
Obs	1184	881	871	810	745	1058
IV-DID	0.34***	0.03	0.05	0.11*	0.34***	−0.10**
	(0.08)	(0.33)	(0.04)	(0.06)	(0.10)	(0.04)
Mean	2.25	14.25	0.33	0.59	2.72	0.143
Obs	8916	8916	8916	6632	4124	8916

IV Instrument: Welfare and Grant Reform, UTECH SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, family income, high school performance, field of study fixed effects, and admitted year indicators. The outcome variables in columns 1 to 6 are: first-semester GPA, first-semester credit hours, on-time graduation, any graduation, degree GPA at graduation, and a drop-out indicator that takes the value 1 if the student exited college by the start of their third semester.

Table 7B
The Impact of the Grant Program on Labor Market Outcomes

	Emp	Weeks	Earnings	Emp	Weeks	Earnings	Taxes
RD	0.05	0.88	365	−0.06	6.85	1092***	356.02**
	(0.09)	(2.95)	(392)	(0.18)	(6.89)	(430.30)	(178)
Mean	0.08	1.84	227	0.36	13.10	2838.05	732.59
Obs	2940	3528	3123	1742	1509	2125	2250
IV-DID	−0.01	−0.63	−174.60	−0.09	−3.93	−73.96	−191.30
	(0.04)	(1.22)	(189.70)	(0.09)	(2.48)	(589.20)	(285.60)
Mean	0.12	3.02	428.93	0.33	11.52	2507.60	632.60
Obs	26,748	26,748	26,748	11,295	11,295	11,295	11,295

IV Instrument: Welfare and Grant Reform, UTECH SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, family income, high school performance, field of study fixed effects, and admitted year indicators. The dependent variables in columns 1 to 3 are the labor market outcomes observed during college: an employment indicator, weeks worked, and earnings. Similarly, columns 4 to 7 show the labor market outcomes observed within the first three years after students are expected to complete college: an employment indicator, weeks worked, earnings, and tax contribution. All monetary values are reported in US dollars.

Table 8A
The Impact of the Loan Program on College Outcomes

	GPA	Credits	Ontime Grad	Any Grad	Grad GPA	Exit (3rd Year)
IV	0.42***	0.15	0.19***	0.49**	0.36*	−0.22***
	(0.15)	(0.67)	(0.07)	(0.22)	(0.20)	(0.08)
Mean	2.04	14.48	0.35	0.60	2.72	0.26
Obs	23,432	23,432	23,432	17,241	13,288	23,432

IV Instrument: High School Visits, UWI SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, high school performance, field of study fixed effects, and admitted year indicators. The outcome variables in columns 1 to 6 are: first-semester GPA, first-semester credit hours, on-time graduation, any graduation, degree GPA at graduation, and a drop-out indicator that takes the value 1 if the student exited college by the start of their third semester.

Table 8B
The Impact of the Loan Program on Labor Market Outcomes

	Emp	Weeks	Earnings	Emp	Weeks	Earnings	Taxes
IV	−0.02	−2.36	−712.5***	0.073	2.00	−1791.31**	−441.34**
	(0.047)	(2.13)	(243.6)	(0.06)	(2.69)	(663.13)	(200.84)
Mean	0.13	3.23	571.32	0.25	7.67	1759.55	450.40
Obs	70,296	70,296	70,296	60,294	60,294	60,294	60,294

IV Instrument: High School Visits, UWI SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, high school performance, field of study fixed effects, and admitted year indicators. The dependent variables in columns 1 to 3 are the labor market outcomes observed during college: an employment indicator, weeks worked, and earnings. Similarly, columns 4 to 7 show the labor market outcomes observed within the first three years after students are expected to complete college: an employment indicator, weeks worked, earnings, and tax contribution. All monetary values are reported in US dollars.

Table 9A
The Impact of the Loan Program on College Outcomes

	GPA	Credits	Ontime Grad	Any Grad	Grad GPA	Exit (3rd Year)
IV	0.42***	1.12	0.02	0.16	−0.008	−0.27***
	(0.12)	(1.19)	(0.09)	(0.16)	(0.13)	(0.081)
Mean	2.13	13.63	0.27	0.52	2.69	0.23
Obs	16,635	16,635	16,635	11919	6718	16,635

IV Instrument: High School Visits, UTECH SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, high school performance, field of study fixed effects, and admitted year indicators. The outcome variables in columns 1 to 6 are: first-semester GPA, first-semester credit hours, on-time graduation, any graduation, degree GPA at graduation, and a drop-out indicator that takes the value 1 if the student exited college by the start of their third semester.

Table 9B
The Impact of the Loan Program on Labor Market Outcomes

	Emp	Weeks	Earnings	Emp	Weeks	Earnings	Taxes
IV	−0.18***	−5.70***	−779.3**	−0.014	1.87	−1630.43**	−532.90**
	(0.028)	(1.00)	(306.6)	(0.092)	(4.11)	(795.68)	(234.69)
Mean	0.12	3.42	634.78	0.31	11.12	2725.98	699.15
Obs	49,905	49,905	49,905	18,109	18,109	18,109	18,109

IV Instrument: High School Visits, UTECH SAMPLE.
Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, high school performance, field of study fixed effects, and admitted year indicators. The dependent variables in columns 1 to 3 are the labor market outcomes observed during college: an employment indicator, weeks worked, and earnings. Similarly, columns 4 to 7 show the labor market outcomes observed within the first three years after students are expected to complete college: an employment indicator, weeks worked, earnings, and tax contribution. All monetary values are reported in US dollars.

Table 10
Impact of the Loan Program in Licensed Occupations

	Emp	Earnings
IV	0.31*	−140.1
	(0.18)	(478.6)
Obs	2999	2999

Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, high school performance, field of study fixed effects, and admitted year indicators. The dependent variables are employment and earnings in occupations that require an occupational license. All monetary values are reported in US dollars.

Table 11
Disaggregated Impact of the Loan Program on Post-College Employment

	First Yr Employment	Second Yr Employment	Third Year Employment
UWI			
IV	0.15(0.10)	0.09(0.16)	0.17*(0.10)
Mean	0.24	0.28	0.32
Obs	20,056	17,241	14,212
UTECH			
IV	0.16(0.13)	−0.05(0.15)	-.03(0.19)
Mean	0.32	0.35	0.36
Obs	6437	5273	4112

Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, high school performance, field of study fixed effects, and admitted year indicators. The dependent variables in columns 1 to 3 captures employment in the first, second, and third year after students are expected to complete college.

Table 12
Disaggregated Impact of the Loan Program on Post-College Earnings

	First Yr Earnings	Second Yr Earnings	Third Year Earnings	Grad School
UWI				
IV	−1402.44*	−1124.75	−3052.78**	−0.21***
	(834.20)	(876.52)	(1472.27)	(0.03)
Mean	1928	2683	3426	0.07
Obs	20,056	17,241	14,212	23,432
UTECH				
IV	−770.40	−2261.60**	−3224.91**	0.01
	(882.50)	(1118.12)	(1381.80)	(0.04)
Mean	3223.90	4077.81	4729.80	0.02
Obs	6437	5273	4112	16,635

Note: Standard errors are clustered within year of entry and presented below each estimate. Control variables include: gender, age, full-time status, location fixed effects, high school performance, field of study fixed effects, and admitted year indicators. The dependent variables in columns 1 to 3 captures earnings in the first, second, and third year after students are expected to complete college, and the outcome in column 4 is a graduate school indicator. All monetary values are reported in US dollars.

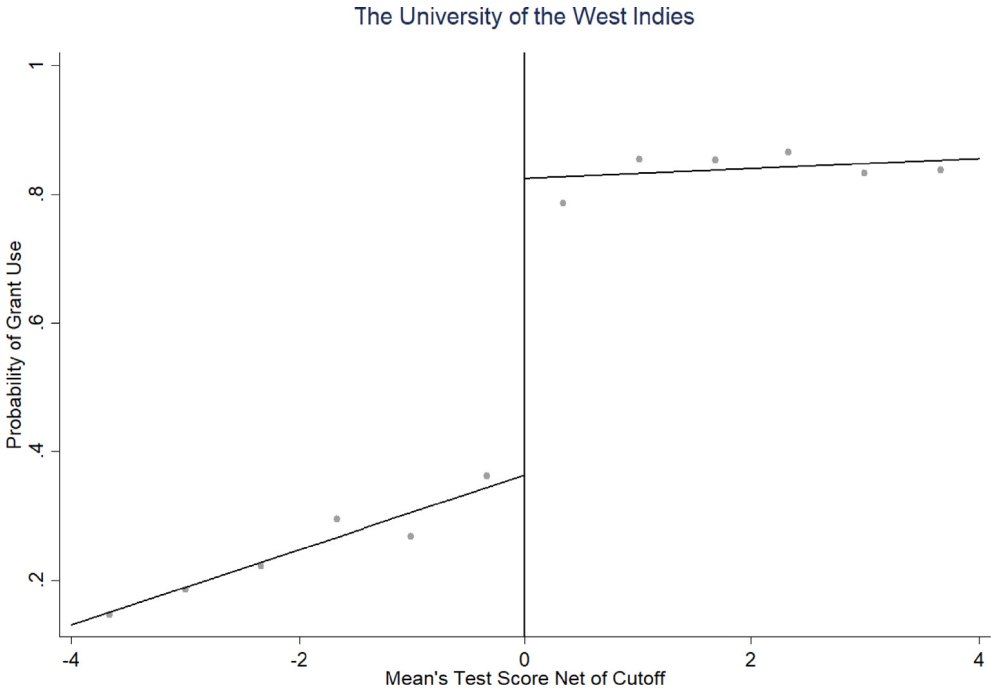


Fig. 1 Probability of Grant Use Within Bandwidth (UWI).

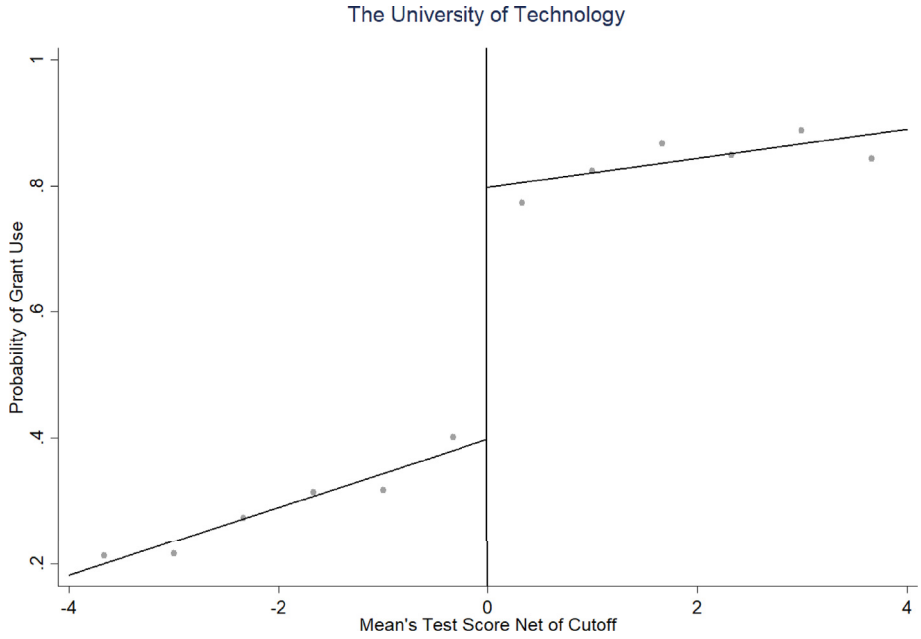


Fig. 2 Probability of Grant Use Within Bandwidth (UTECH).

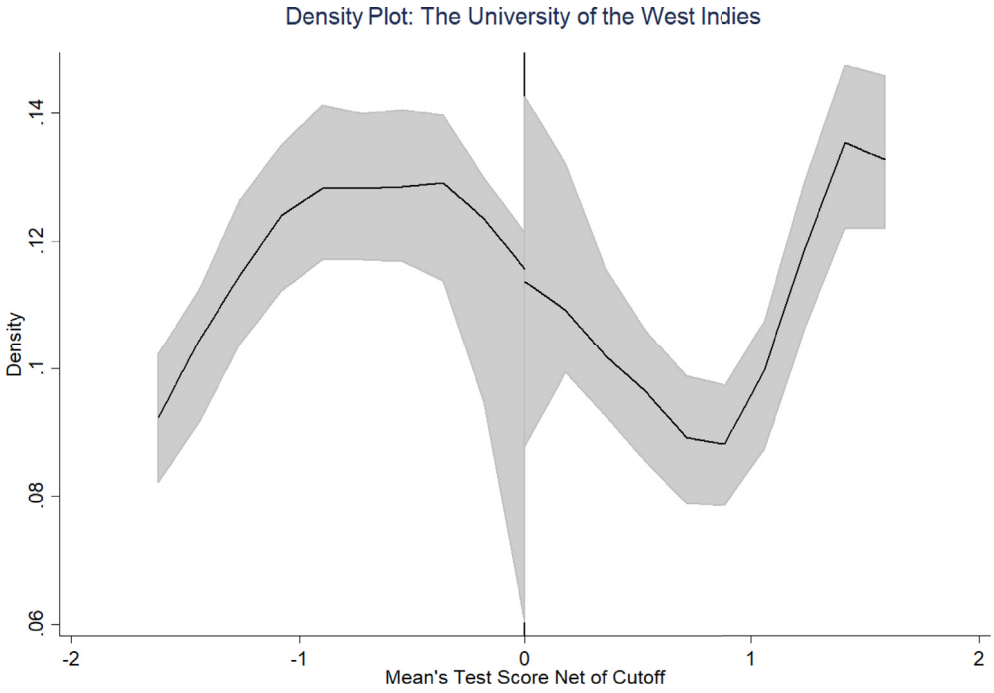


Fig. 3 Assignment Score Density Plot (UWI).

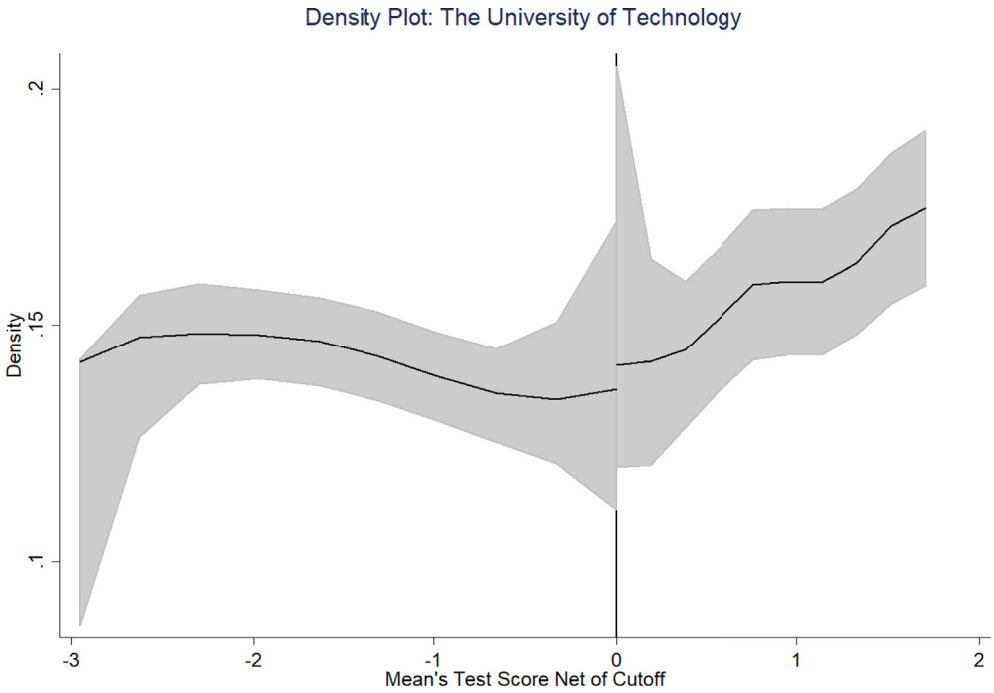


Fig. 4 Assignment Score Density Plot (UTECH).

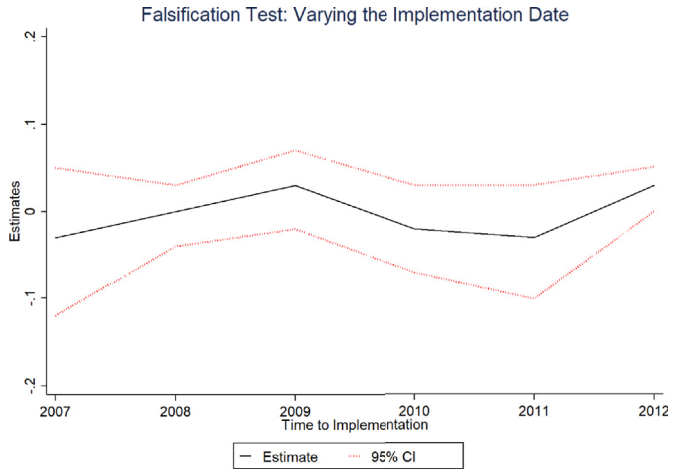
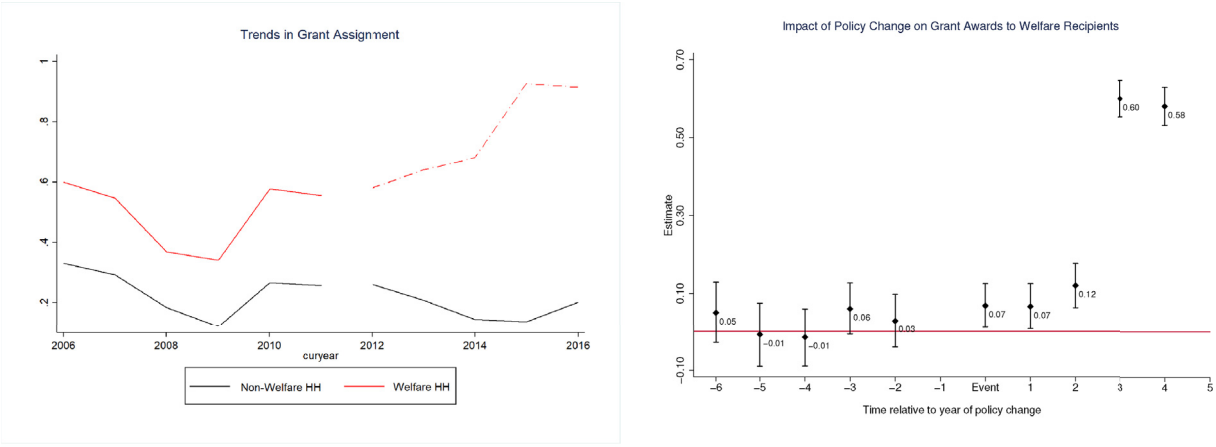


Fig. 5 Changing the Implementation Date.



(a) Parallel Pre-Trend Assumption (b) Event Study

Fig. 6 (A) Parallel Pre-Trend Assumption. (B) Event Study.

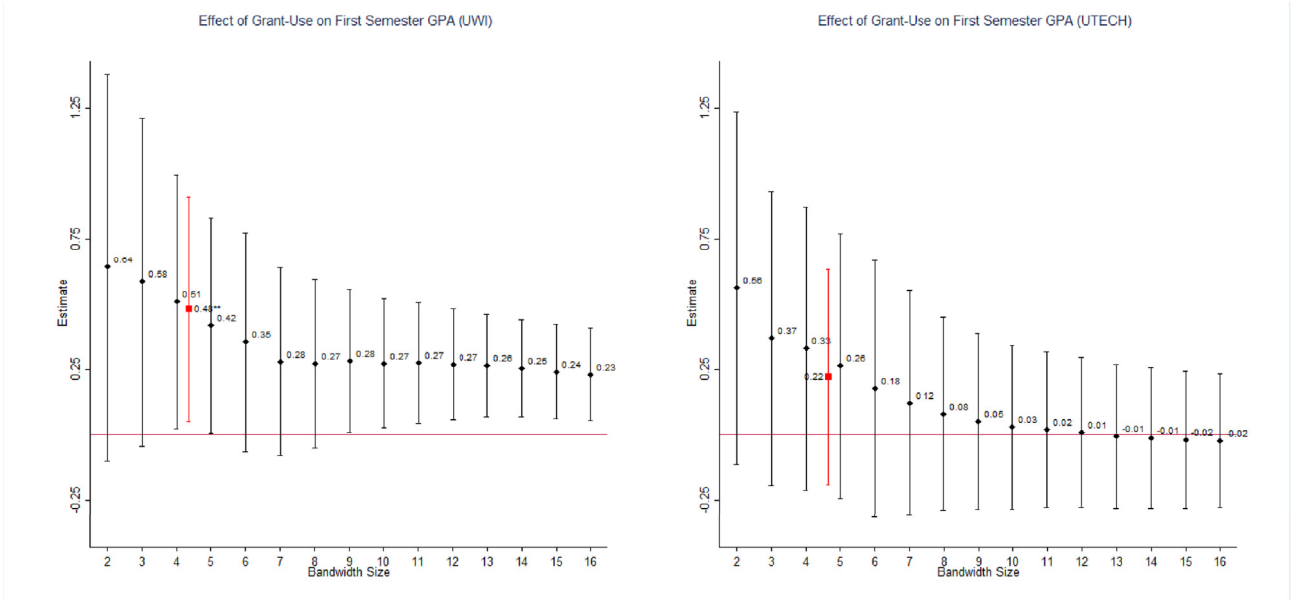


Fig. 7 RD Sensitivity Analysis, GPA.

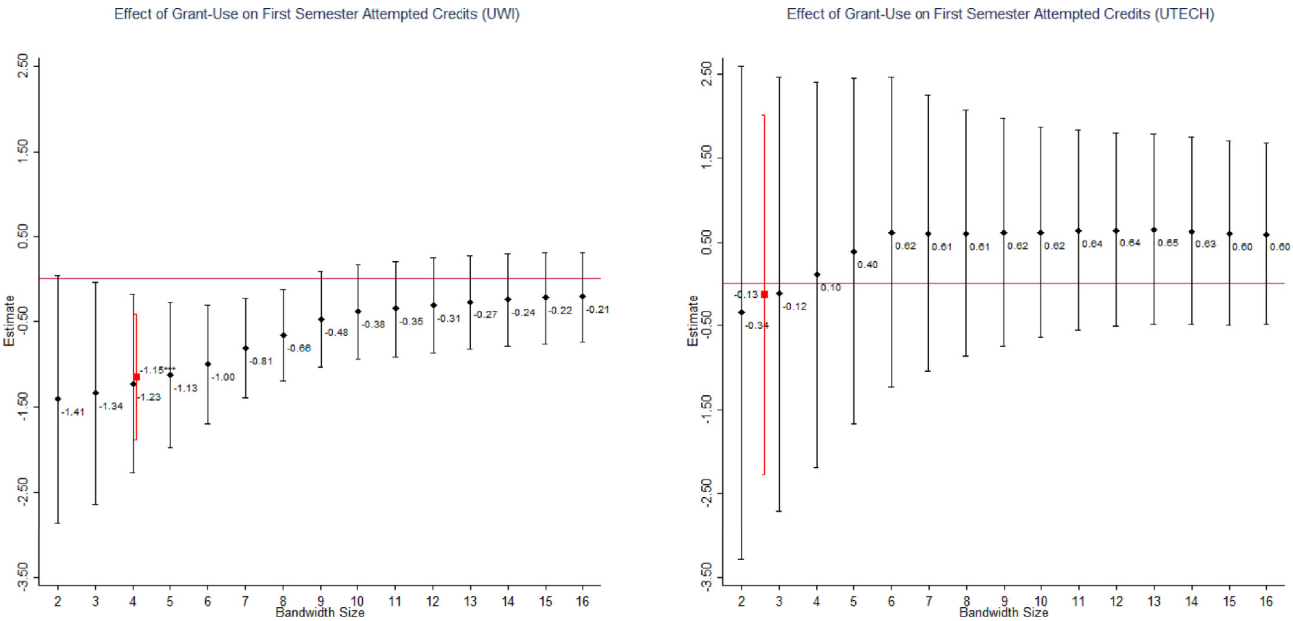


Fig. 8 RD Sensitivity Analysis, Attempted Credits.

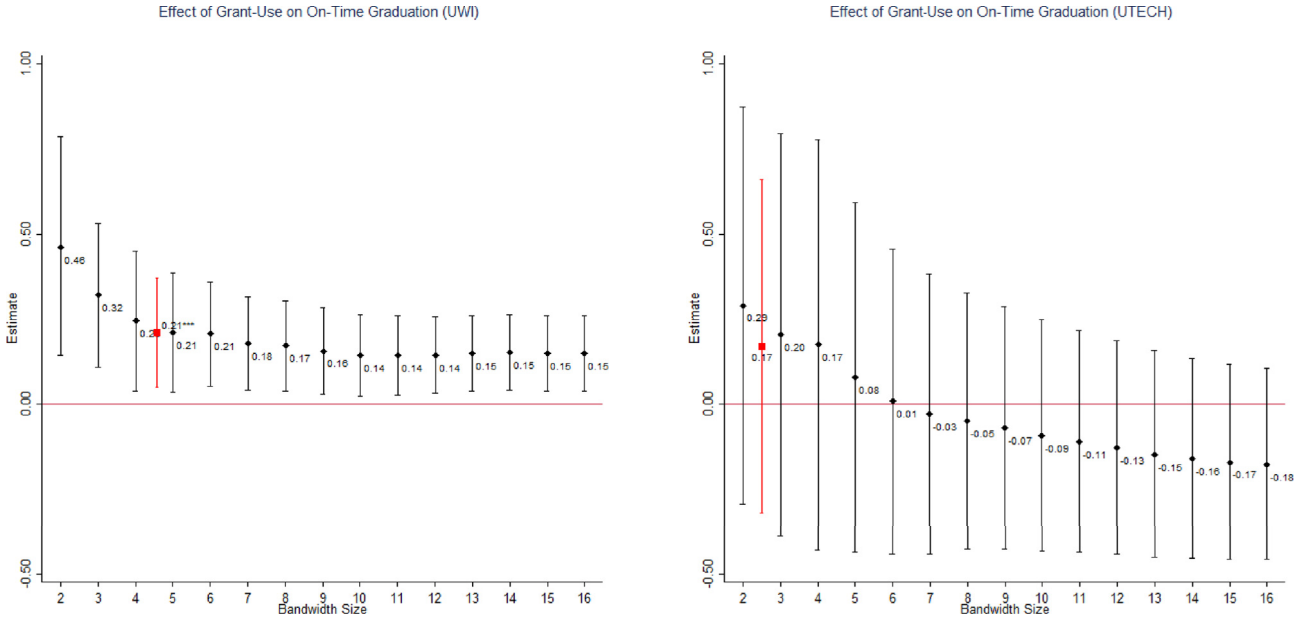


Fig. 9 RD Sensitivity Analysis, On-time Graduation.

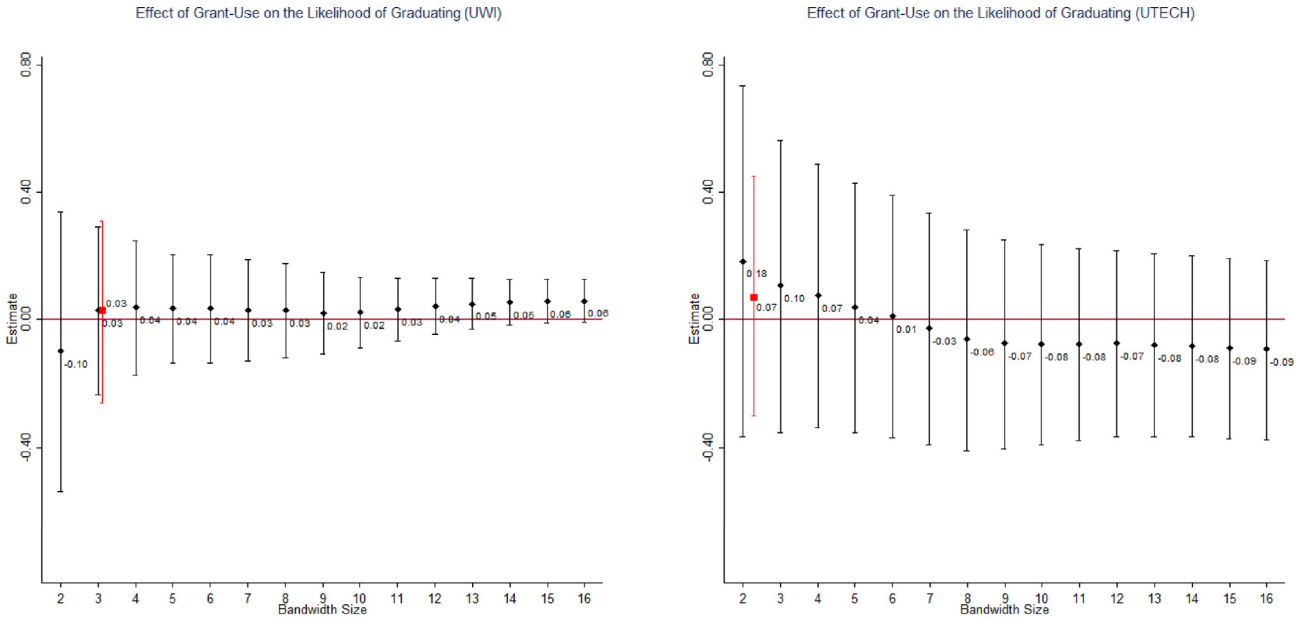


Fig. 10 RD Sensitivity Analysis, Any Graduation.

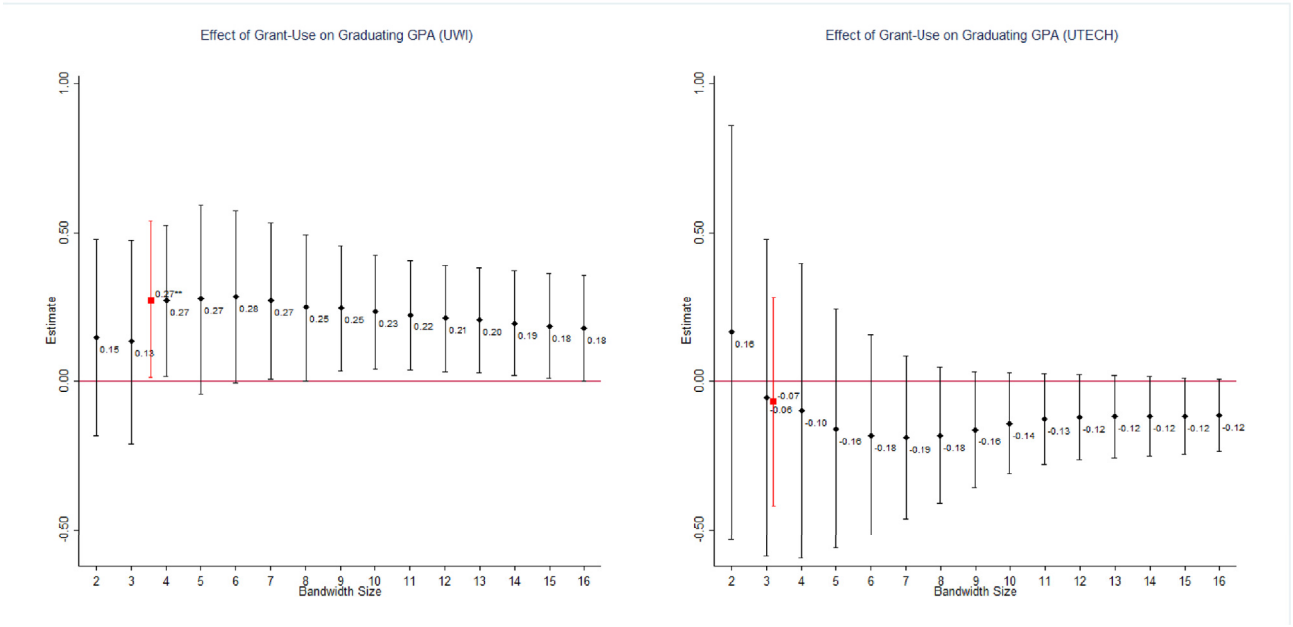


Fig. 11 RD Sensitivity Analysis, Grad GPA.

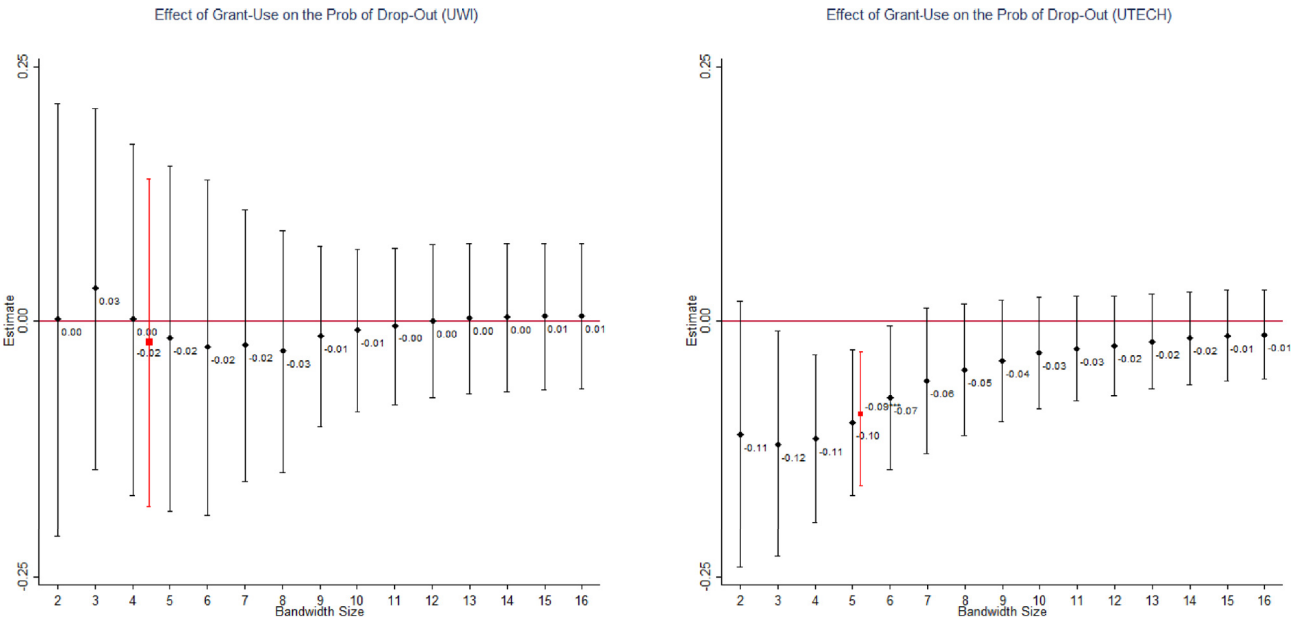


Fig. 12 RD Sensitivity Analysis, Drop-out.

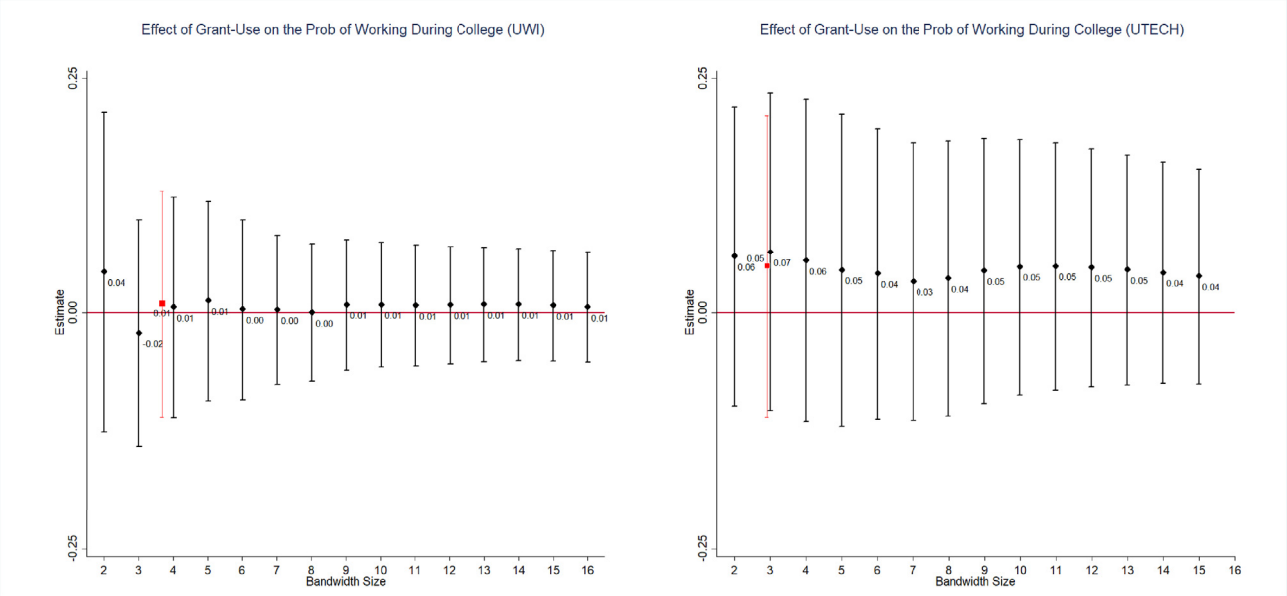


Fig. 13 RD Sensitivity Analysis, Employment in College.

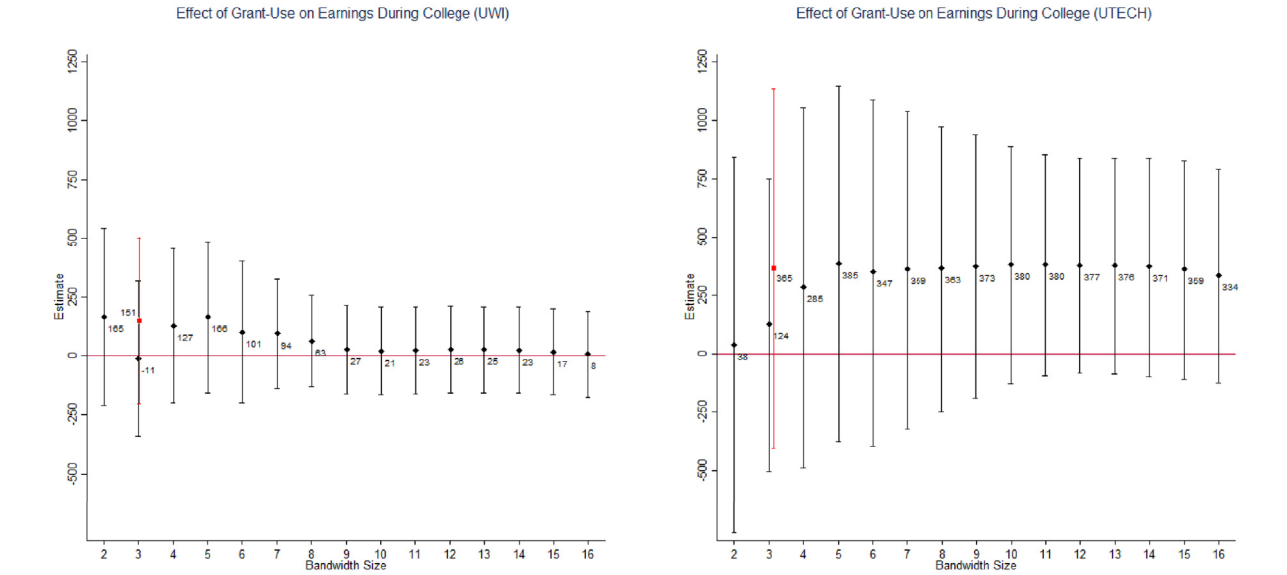


Fig. 14 RD Sensitivity Analysis, Earnings in College.

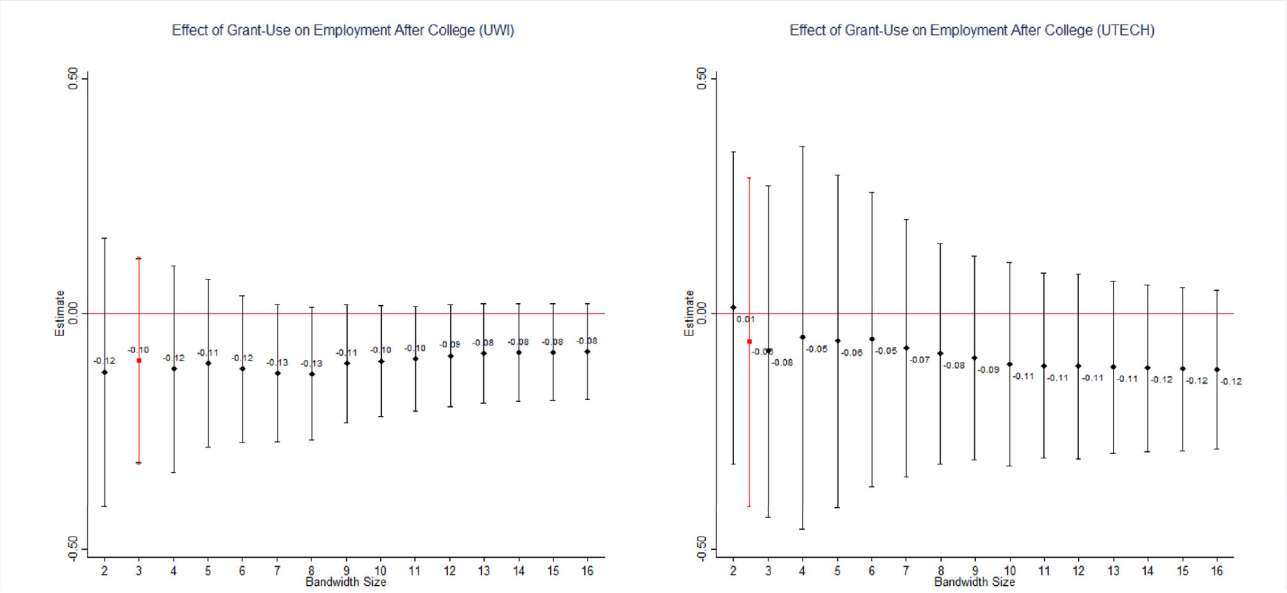


Fig. 15 RD Sensitivity Analysis, Employment After College.

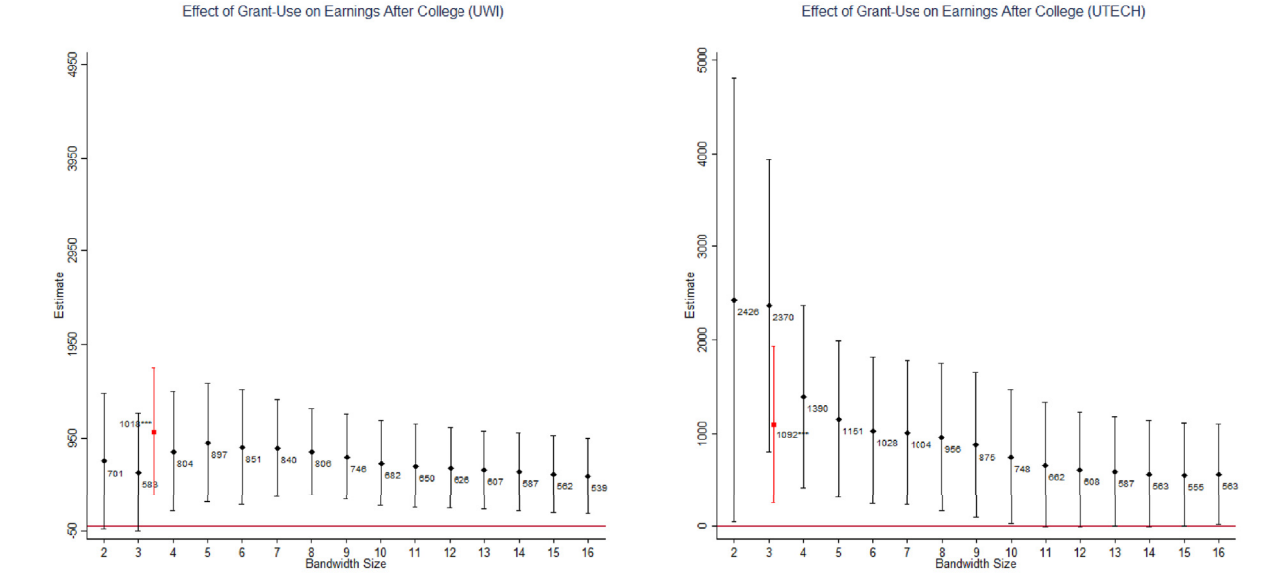


Fig. 16 RD Sensitivity Analysis, Earnings After College.



Fig. 17 Average Loan Use by Parish.



Fig. 18 Average Exposure to High School Visits by Parish.

Appendix B. Principal Component Analysis

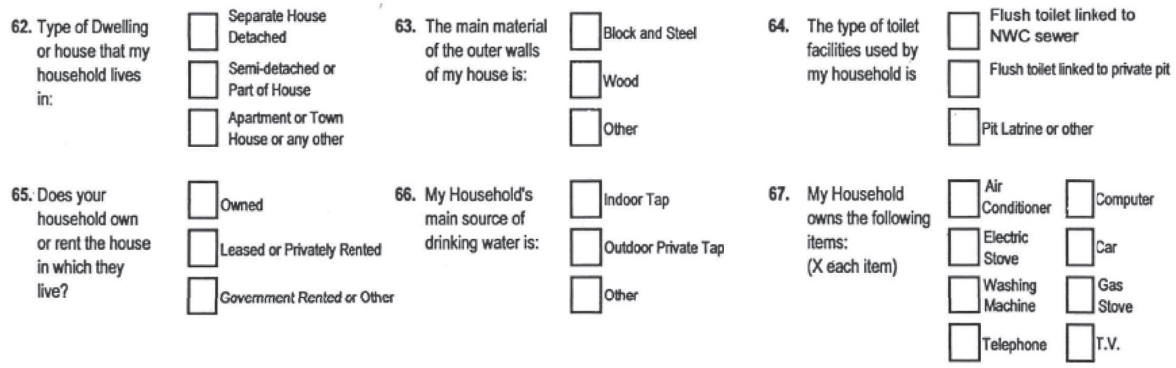


Fig. 19 Application Form: Consumption and Housing Conditions.

The figure above shows the consumption and housing condition questions that are asked on the student loan application form. Over the sample period, all applicants were required to answer these questions. The household items listed in Question 67 are used to create the index for durable consumption. This includes the binary ownership of a car, computer, gas or electric stove, washing machine, television, or air conditioner. To create the index for economic well-being, I combine several binary variables for home ownership, housing type, housing material, type of toilet facilities, main source of drinking water, and household items owned.

Principal component analysis (PCA) is utilized to create the consumption and economic well-being indices. To determine the number of components to be retained for each index, I examined the scree plot and retained the components whose eigenvalues are above a straight line fit through the smaller values. The literature suggests that this approach works well across multiple settings (Zwick and Velicer, 1986). The scree plot shown in Fig. 20 indicates that the two leading components of each index have eigenvalues that are well above 1 and are clearly distinguishable from the other components. Therefore, the first two components are retained for each index.

Table 1B shows the way selected components load onto the household-level variables of interest and the percent of the total variation that each component explains. For example, in roughly equal magnitude, the first component loads positively on each durable consumption good. Similarly, the second component for economic well-being (column 4) has a higher positive loading on the variables that are strong indicators of household wealth. Similar to the main results, the bottom panel of Table 1B shows that the policy change did not have an impact on the various household-level measures.

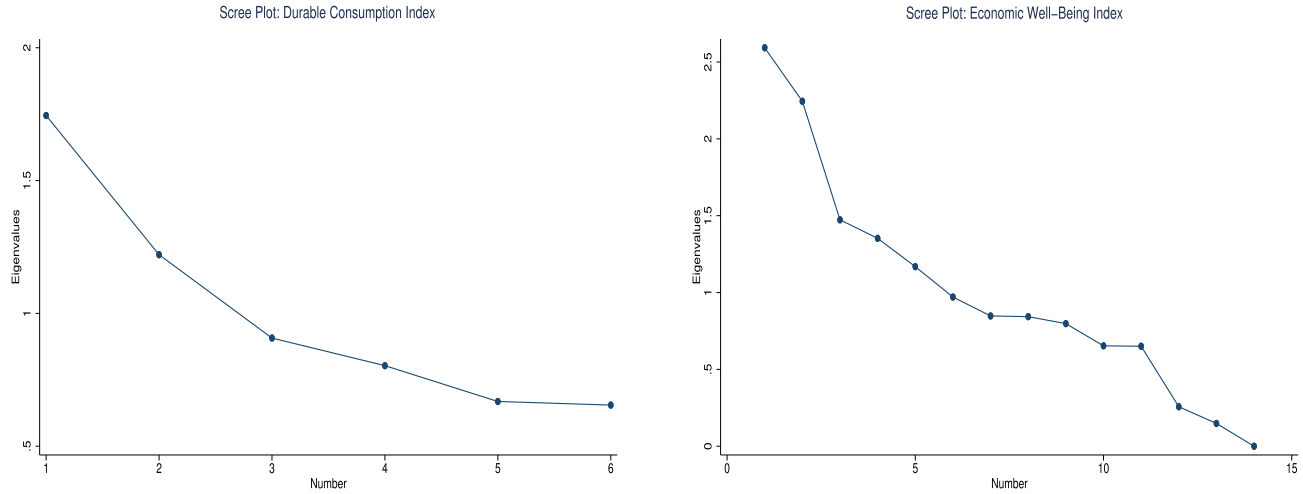


Fig. 20 Scree Plots.

Table 1B
Trends in Household-Level Variables

	Consumption 1	Consumption 2	Economic Well-being 1	Economic Well-Being 2
Car	0.49	−0.30	0.13	0.34
Computer	0.42	−0.19	0.05	0.34
Washing Machine	0.51	−0.22	0.07	0.40
Gas/Electric Stove	0.36	0.59	0.12	0.21
Air Conditioner	0.28	−0.32	0.04	0.19
TV	0.35	0.61	0.13	0.19
Home Ownership			0.51	0.07
Detached Home			0.39	−0.03
Semi-Detached Home			−0.35	0.01
Block and Steel			0.04	0.30
Private Water Source			−0.07	0.29
Flush Toilet (Sewer)			−0.25	0.46
Flush Toilet (Pit)			0.27	−0.30
Explained Variation	29%	21%	19%	16%
Treatment Effect	0.01	0.001	0.04	−0.07
	(0.20)	(0.02)	(0.05)	(0.06)

Online Appendix

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2020.102617.

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