Life-cycle Effects of Income-Driven Repayment on Credit Outcomes, Future Student Loan Borrowing, and Labor Market Outcomes*

Laura Boisten[†], Annemarie Schweinert[‡], Dalie Jimenez[§]

January 1, 2025

Click here for latest version

Abstract

In this paper, we examine how income driven repayment (IDR) impacts future student loan take-up and the implications for other lines of credit and occupational choices. Given selection into IDR plans, we instrument for IDR enrollment using randomly assigned student loan servicers. Using a 2% sample of all individuals with credit in the US from the University of California Consumer Credit Panel (UC-CCP), we find individuals on IDR are more likely to re-enter enrollment and take out a future student loan. Additionally, we examine whether the additional student loans lead to larger balances and whether individuals are paying off a larger subset of their debt after returning to receive more education; we find that while initially IDR is associated with growing balances, IDR keeps individuals current and eventually leads to balances being paid down faster. We examine whether individuals are more responsive to more generous plans and whether certain groups are more responsive to IDR. Lastly, we look at how changes in human capital investments may impact other wealth-generating lines of credit such as small business loans and mortgages. We find IDR causes an increase in mortgages and a small increase in small business loans.

*We thank Carter Braxton, Rasmus Lentz, Chris Taber, and Jeff Smith for their feedback and guidance. Any views expressed here and any errors contained in this paper are solely those of the authors and not of the data provider, California Policy Lab, or the Regents of the University of California. We thank the California Policy Lab for hosting, documenting, and facilitating access to the University of California Consumer Credit Panel.

[†]University of Wisconsin-Madison; E-mail: boisten@wisc.edu

[‡]University of Wisconsin-Madison; E-mail: schweinert@wisc.edu

[§]University of California-Irvine; E-mail: djimenez@law.uci.edu

1 Introduction

With the price of college increasing by nearly 40% between 2002 and 2022, a growing body of literature looks at the impacts of growing student loan debt balances on the labor market and credit outcomes (e.g., Black, Denning, Dettling, Goodman, and Turner (2023)). The debate over how to address the consequences of mounting student debt has often focused on comparisons between free education models and debt-financed education, yielding valuable insights into these approaches' broader societal and economic effects. However, how the repayment of these large student loan balances affects the economy, particularly through income-driven repayment (IDR) plans, remains an understudied but critical area in the literature on the economics of higher education financing. This paper seeks to address this gap.

Specifically, we analyze how IDR[1] influences decisions related to educational attainment and broader financial behaviors. In the U.S., income-driven repayment has been proposed as an alternative tool—alongside grants and free tuition—to address growing student loan debt. Before 2010, most student loans were repaid in 120 fixed payments over ten years; instead, IDR ties student loan payments to a percentage of disposable income. By tying student loan repayments to borrowers' income levels, IDR plans can shape credit outcomes by insuring against income shocks that would otherwise not allow the borrower to make on-time full payments. Previous research, such as Boutros, Clara, and Gomes (2024), demonstrates that IDR plans can improve borrower credit outcomes. Countries like Australia and the UK, where IDR is the primary repayment method, offer valuable insights; however, research in these contexts has largely focused on adverse labor market outcomes and occupational selection. These studies often rely on small variations within IDR systems and do not compare mortgage-style repayment with income-driven repayment directly (Britton and Gruber (2020), Chapman and Leigh (2009), Chapman and Doris (2019)), while studies like Beyer, Hastings, Neilson, and Zimmerman (2015) on Chili's 2014 reform emphasize repayment assurance but are less applicable to the U.S. context.

This paper answers the following four sets of questions regarding IDR in the United States. First, does IDR encourage additional student loan borrowing, and if so, to what extent? Second, does IDR increase student loan balances over time? Third, does income-driven repayment affect occupational choices, particularly for those in teaching or healthcare professions and other credit outcomes? If so, to what extent? Fourth, does IDR have other economic impacts for individuals, such as affecting lines of credit, credit health, or mortgage takeup? If so, to what extent? Lastly, we examine the effects of heterogeneous treatment.

[1] IDR is the umbrella term for all different types of income-driven repayment plans, such as IBR.

Do the effects of IDR vary based on the generosity of the repayment plan or the type of institution attended?

This paper makes three main contributions. First, to our knowledge, we are the first to identify student loan repayment plans in large credit data. Empirical studies on the causal impacts of IDR remain limited, primarily due to limited data availability and quality, often relying on survey data (i.e.: Weidner (2016)). We overcome this challenge by using the University of California Credit Panel (UC-CCP) to answer our questions with causal evidence. This data set provides us with a 2% random sample of individuals with credit records from one of the three largest credit bureaus. We have information on every credit tradeline and its characteristics, such as the date it was opened and the payments that were agreed upon. It allows us to identify borrowers with federal direct student loans and their repayment plans. Using tradeline characteristics, in this dataset, we are the first to identify tradelines that are likely federal tradelines and then separately identify whether the tradeline is in an income-driven repayment plan or a mortgage-style repayment plan. Most importantly for our results, the dataset includes information on borrowers' student loan servicers, allowing for a causal interpretation of our results.

Our second contribution is being the first to use student loan servicer data to estimate the causal impacts of IDR on additional borrowing and occupational persistence. To estimate causal effects on U.S. credit markets, we use randomly assigned student loan servicers as an instrument for IDR take-up, while other's have looked at impacts fo IDR take up using variation within one servicer (Herbst (2023), Yannelis and Tracey (2022)), we leverage variation across all student loan servicers. Since IDR positively selects individuals with low income, OLS would be biased to estimate the effects of IDR on credit or labor market outcomes. Using a 2SLS design with a randomly assigned student loan servicer as an instrument, we causally estimate the local average treatment effect (LATE) of IDR on future human capital investments and credit. When borrowers take out a federal direct loan, they are randomly assigned a student loan servicer, making it a valid instrument. Student loan servicers primarily record payments and recommend alternative payment plans when borrowers struggle to make payments. However, not all servicers are equal. Several court cases have alleged servicers of steering borrowers for profit. When we examine servicers in the UC-CCP, we find a wide dispersion in the likelihood they recommend IDR after controlling for the borrowers' observables. In line with recent literature on judge IVs, we construct a jackknife instrument using the randomly assigned student loan servicer.

Our third contribution adds to the growing literature on student loans, which is well summarized in Yannelis and Tracey (2022). We add to the discussion on the optimal IDR plan and how sensitive the results are to relative IDR generosity. We are the first to leverage heterogeneity between existing repayment plans to add to the current policy discussion regarding the SAVE plan. Furthermore, we add new insights using causal estimates on occupational choices that complement those in Rothstein and Rouse (2011) and Luo and Mongey (2019), who start the discussion of debt and job choices. We examine the impacts of IDR on occupational licensing. We examine whether IDR increases the likelihood a borrower stays licensed in either healthcare or teaching occupations, as both fields have a forgiveness incentive.

This paper provides short- to medium-run casual estimates of how increased access to IDR impacts credit outcomes, future human capital investments, and occupational choices. Our OLS estimated impact of IDR on future student loan borrowing is significant but near zero. If an individual is on IDR, OLS estimates suggest they are .2 percentage points more likely to take out a student loan that quarter as well. We find that our instrumented IDR status shows an increase of three percentage points, which is quite substantial given that about three percent of the sample has an additional student loan 12 quarters into repayment. We see this initial effect only becomes stronger throughout the life-cycle as estimated effects increase from roughly three percentage points to as high as seven percentage points. This result suggests that IDR does substantially impact the market for student loans.

In order to evaluate whether additional student loans are a net positive or negative, we estimate the medium-run impact of IDR on balances. When we naively estimate IDR with OLS, we find balances tend to be growing on IDR–consistent with other descriptive statistics. However, once we instrument for IDR, we find that balances initially increase early on but eventually fall. After 5 years of repayment, IDR leads to lower balances of nearly $3,000. While this may be counterintuitive, we examine repayment histories for individuals with IDR. Individuals with IDR are 20- 35% less likely to ever be behind on a payment.

The previous results allude to IDR either fixing credit markets or creating a moral hazard in borrowing; while we cannot directly test either mechanism, we provide suggestive evidence by comparing the treatment effects for different groups. To evaluate whether moral hazard is a driving factor, we separately estimate the effects of IDR for groups with 10% IDR plans and 15% IDR plans. Groups eligible for repayment as low as 10% of disposable income are similar in their likelihood of taking out additional student loans to groups with repayment as low as 15% of their disposable income. Next, we separately estimate the treatment effects by which quartile of borrowing a student was in relative to other students within their state and year. We find that students in the lowest quartile initially are the most likely to be positively influenced by IDR. For groups in the lowest quartile, IDR increases the likelihood that a student takes out a future student loan by five percentage points. Jointly, these results suggest IDR helps with incomplete credit markets.

To evaluate whether the additional student loans are a net negative or positive for the economy, we evaluate the impact of IDR on other lines of credit. We start with examining mortgages and small business loans to see if additional student loan debt crowds out other wealth-generating lines of credit. We find that IDR increases mortgage take-up by 8-17 percentage points. Similar to the effects of whether an individual takes out an additional student loan, the effects are stronger the longer an individual has been in repayment. We find relatively small effects for personally guaranteed small business loans.

In addition to credit market outcomes, we examine occupational choices as IDR may either encourage reskilling since new degrees are cheaper; it may also allow individuals to stay in low-paying occupations if student loan payments are more affordable under IDR than under standard-based repayment plans. To examine the changes to occupational persistence, we estimate the effect of IDR on whether an individual is in a teaching or healthcare occupation. We find null effects initially; however, the effects appear stronger at the end of the five-year period–when student loan forgiveness may be expected. With IDR, we see nearly a one percentage point increase in the likelihood an individual is licensed as a teacher or in health care four years after starting repayment.

We perform a series of robustness checks to validate the instrument. We perform a balance test to test whether borrowers are randomly assigned servicers; additionally, we test the monotonicity assumption by seeing if the first stage is relatively similar for different subgroups such as borrowers on different repayment plans, by age, by gender, and by initial amount borrowed. Lastly, in the appendices, we perform several robustness checks–the testing judge fixed effects and a test on the exclusion restriction. We cannot reject the null for the judge fixed effects test, which is consistent with our earlier tests. Lastly, for the exclusion restriction, we test our instrument with an instrument constructed similarly to Welch (2024). In Welch (2024), the author argues that servicers directly affect default but not other lines of credit. Our instrumented IDR has a very small correlation with instrumented default and our results are relatively robust to the inclusion of instrumented default.

The following section briefly summarizes important details regarding direct student loans, servicers, and timing (Section 2). We then briefly describe our data in Section 3, before diving into our estimation in Section 4 and our results in Section 5. Lastly, discuss some potential mechanisms in Section 7 and discuss other economic impacts in Section 8 before concluding in Section 9.

2 Background

2.1 Introduction of Student Loan System

In this section, we briefly overview the components of the student loan system from 2010-2019. In the following subsections, we detail the types of loans borrowers may choose to take out, discuss servicer assignments and repayment, and explain how a servicer may impact borrowers' ability to repay their student loans. In Table 1, we depict a sample timeline of when a student makes decisions regarding each type of student loan and subsequent repayment.

2.2 Direct Student Loans for Undergraduates

Since July 2010, most student loans have originated through the William D. Ford Direct Student Loan program. Every student who applies for a Federal direct student loan is approved for a set amount of loans at a federally mandated interest rate, provided they are enrolled in an accredited institution and complete the FAFSA application. Interest rates and amounts on Federal Direct loans are independent of a borrower's characteristics and risk.

Every Federal Direct loan disbursed within the same academic year will have the same interest rate and maximum borrowing limit. For example, a student who accepted a Federal Direct loan between July 2011 and June 2013 would have an interest rate of 3.4%. Borrowing amounts are fixed based on accumulated credits and dependency status. If a student is listed as a first year, enrolled full time, and dependent on their parents, they can borrow up to $5,500 for one full academic year. Under similar circumstances but with second-year standing, the student can borrow $6,500 for one full academic year. Lastly, if a student is a third or fourth year, the student can borrow $7,500. If students are independent of their parents, these amounts are increased by $4,000. In extraordinary circumstances where a dependent student cannot receive additional funding through a Parent Plus loan, additional unsubsidized Direct loans may be available. Total borrowing for dependent undergraduates cannot exceed $31,000, and for independent undergraduates $57,500.

Based on a student's financial need, their Direct loans may be eligible for an interest subsidy in deferment or income-driven repayment. Subsidized Direct loans are eligible for an interest subsidy while in deferment or income-driven repayment, while unsubsidized Direct loans are not. During deferment, unsubsidized loans accrue interest, capitalized at the end of the qualifying deferment period. The Stafford program has limits on the amount of subsidized loans for students. For example, of the $5,500 available to a dependent first-year college student enrolled full-time in an accredited institution, no more than $3,500 of the total amount can be subsidized.

2.3 Direct Student Loans for Graduates

Similar to undergraduates, graduate students are also eligible for direct student loans at a capped amount and a fixed interest rate. Annual borrowing is capped at $20,500, and the interest rate is set by Congress. Unlike undergraduate loans, graduate students cannot take out subsidized loans; the interest rate is also slightly higher.

2.4 Direct Student Loan Repayment: Assignment to Servicer and Repayment Options

When students leave school with Direct student loans (graduate or undergraduate), they enter into a six-month grace period followed by repayment, during which they interact with their loan servicer. Loan servicers are private entities that contract with the Department of Education to collect student loan payments. The loan servicing companies receive a fixed number of borrowers based on their prior performance; borrowers are randomly assigned a loan servicer and cannot change loan servicers except in a few limited instances. The loan servicer's primary job is to assist the borrower in repayment.

When students begin repayment, they have several plan options: fixed payments, income-driven repayments, and periods of non-payment followed by fixed payments. Borrowers are typically initially assigned non-income sensitive plans such as graduated repayment and standard-based repayment. The standard-based repayment plan is a fixed payment over 120 months; graduated repayment is similar to the standard-based repayment plan but starts off with smaller payments and grows over 120 months in repayment.

If a borrower struggles to make payments, loan servicers can suggest deferment, forbearance, or moving to an income-driven repayment plan. Deferment and forbearance are brief periods of non-payment followed by a fixed payment plan. Deferment and forbearance essentially reallocate a borrower's payment from today to the future. There are federally mandated reasons for offering deferment—such as economic hardship, medical hardship, or military service, to name a few—along with discretionary deferment by each servicer. Deferment and forbearance for economic hardship are limited to 6 to 12-month periods with a lifetime limit of 36 months. During these periods, loans without an interest subsidy accrue interest, which is capitalized at the end of the deferment period. Since the repayment was moved from the present period to a future period, the monthly payment once out of deferment will be larger, with capitalized interest from the deferment period.

Instead of deferment, servicers can suggest that individuals demonstrating "partial financial hardship" apply for income-driven repayment plans. Income-driven repayment reduces the payment to 10-20% of an individual's disposable income (gross income minus 150% of the Federal Poverty Line); however, it will also elongate the time of repayment to 20-25 years. Payments may be as low as zero if the borrower makes only 150% of the FPL. After 20-25 years, any unpaid balance is forgiven. However, if the borrower makes 120 payments while working in a qualifying institution, balances may be forgiven after 10 years. To stay on income-driven repayment, individuals must re-certify their income yearly to show "partial financial hardship."

Besides IDR, deferment, and forbearance, servicers can suggest loan consolidation. Generally, individuals with exclusively direct student loans would lose benefits such as grace periods, interest subsidies, and some IDR plans under loan consolidation. On the other hand, loans previously ineligible for IDR may become eligible through loan consolidation. These loans may include Parent Plus, FFELP, and Perkins loans. When a loan is consolidated, all payments are made on one line of credit, individuals may move all their loans to one servicer, and the loan is moved to a fixed rate if it was previously at a variable rate.

To summarize, servicers have limited actions: providing information on repayment options, collecting repayments, and consolidating. Even in the case of consolidation, servicers are not making initial loan disbursement decisions or setting interest rates for borrowers as the initial amounts, eligible payment plans, and rules regarding consolidation are set by the Federal government. Additionally, they are not providing nudges before repayment, such as information on major choices or encouraging borrowers to take out additional student loans. Servicers have been shown to provide nudges into different repayment plans through E-sign as shown in Mueller and Yannelis (2019) and Herbst (2023), calls to delinquent borrowers in Herbst (2023), and through company-wide policies to encourage deferment or forbearance as described in Bureau (2017).

2.5 Other Federal Student Loans: FFEL, Perkins, and Plus Loans

In addition to the Federal Direct Loan program, there are other federal loan programs to help finance college. However, these federal loan programs differ substantially in both the groups they target and the total cost to the student. We briefly summarize each program.

Prior the William D. Ford Direct Loan Program becoming the main method of financing student loans, federal student loans were primarily disbursed through the Federal Family Education Loan Program (FFELP). While the federal government directly funds Direct loans, FFELP loans were provided by private lenders. From 1993-2006, FFELP loans had a variable interest rate. From 2006 to 2010, FFELP loans had a fixed interest rate similar to that of direct loans. Before 2008, annual federal limits on loan amounts were less. From June 2007 to July 2008, annual limits were increased, so a dependent freshman with full-time status went from being able to borrow $2,625 to $5,000 annually. FFELP loans were last disbursed in 2010.

Repayment plan options for FFELP loans are more limited than repayment plan options for Federal Direct Loans. Borrowers can pay a fixed payment, consolidate into a Federal Direct Loan, or pay under an income-driven repayment plan. Most loans start in a fixed payment plan like the standard-based repayment plan, where the time horizon varies based on the total amount borrowed. A borrower may be interested in income-driven repayment plans if they have a low income. Most FFELP loans are only eligible for income-based repayment (IBR) if consolidated into a Direct Consolidation Loan. If borrowers consolidate, they are potentially eligible for ICR, SAVE (formerly REPAYE), PAYE, and IBR. Additionally, consolidated FFELP loans are eligible for PSLF provided the borrower makes 120 qualifying payments while working in a qualifying institution. Since repayment for FFELP loans can change drastically with consolidation, interest rates can vary before 2006, and time horizons can differ depending on the total amount borrowed, we do not focus on loans originating before 2010. Identifying repayment for these loans is a part of our future work.

From 1957 through 2017, students with "exceptional financial need" could borrow through the Federal Perkins Loan program. Perkins loans were subsidized loans with a 5% interest rate and were limited to $5,500 per year for a student. Perkins loans are subject to an interest subsidy, similar to subsidized Direct loans. Like FFELP loans, Perkins loans were subject to different repayment options than Direct loans. Unlike Direct Loans, Perkins Loans were only eligible for Income-Driven Repayment through Federal Direct Loan consolidation. Forgiveness for Perkins Loans was more generous than FFELP and Direct loans. If the borrower worked in a qualifying institution, they could have some percentage of their Perkins loans canceled based on the number of years of service served, with 100% of the loan forgiven by the fifth year of qualifying service. Perkins loans are intertwined in our sample, and we identify whether the loan is a standard repayment or IDR plan.

With rising tuition costs, students and parents may take out additional loans through the Plus program. The Plus program directly covers graduate students; undergraduates are not able to borrow directly through the Plus program. Instead, parents borrow on their children's behalf and carry the loan's responsibility. Plus loans are subject to a slightly higher interest rate than the Direct loans but still have a fixed interest rate for all who apply. There is no interest subsidy for Plus loans. Unlike Direct loans, there is no limit on the amount borrowed, except it cannot exceed the estimated cost of attendance each year. Unlike Direct loans, not all individuals who apply for Plus loans are eligible. Individuals are subject to a credit check and cannot have an adverse credit outcome—such as bankruptcy discharge, foreclosure, etc—within the last five years.

Like FFELP loans, PLUS loans have more limited repayment options. Most parent plus and graduate plus loans start with a standard repayment plan with 120 fixed payments. Borrowers can repay Plus loans through income-based repayment through ICR or another IDR plan through Direct Loan Consolidation. One thing to note with Parent Plus is that the repayment liability is often with the parent. Any income-driven repayment plan would be tied to the parent's income, not the student's. In the appendix, we extend our sample to include graduate plus loans; however, our main analysis does not focus on these. Parent Plus loans are largely underrepresented in our sample, given the age restrictions we impose and the fact that we only focus on loans of which the student is designated as the owner.

2.6 Private loans

Unlike the previous loans, private loans are not provided through the Department of Education and involve separate applications. Private loans vary in interest rates and can be fixed or variable. The dispersed loan amount and interest rate are often dependent on the expected risk of the borrower based on many different metrics, such as parental income and credit score. Repayment for private loans is also very different from federal student loans, with payment plans varying by creditor. Private loans are not subject to the same regulation regarding income-driven repayment or qualifying periods of deferment. In our sample, we do not exclude students with private loans; however, we do not focus on the repayment process of private loans.

3 Data

We use data from from the University of California - Consumer Credit Panel (UC-CCP). The UC-CCP is a quarterly longitudinal credit panel at the tradeline level, which follows approximately 60 million individuals. Since the panel is at the tradeline level instead of the individual level, the panel follows each line of credit a consumer has over time.[2] Each tradeline has information on lines of credit, payment histories, and agreement terms. The UC-CCP data provides credit scores, general demographics, and geographic information; a subset of the UC-CCP also has occupational information from state agencies, occupational licenses, and self-reports.

[2]Definition of a tradeline: A tradeline is an account that appears in your credit report. Examples include credit cards, mortgages, personal loans, and auto loans.

3.1 Sample Selection

Within the UC-CCP, we focus on a subset of consumers who likely borrowed at least one federal direct undergraduate student loan. We use similar restrictions as Black, Denning, Dettling, Goodman, and Turner (2023). We restrict our treated student loans to those disbursed after 2010; and due to the Covid-19 pandemic and the payment pause during it, the last quarter we use is quarter 4 of 2019. Furthermore, we restrict to those loans with a kind of business code related to education. Additionally, the final original disbursed amount before the in-school deferment ends must be lower than the federally mandated amounts for independent undergraduate students. Our final restriction differs from Black, Denning, Dettling, Goodman, and Turner (2023) to limit the number of loans with multiple disbursements, which would send the final disbursement amount above the federally mandated maximum. Lastly, individuals must be no older than 25 when we observe them taking out a student loan. Our restrictions all aim to identify federal student loans likely for an undergraduate education cleanly.

Our federal loan sample identifies individuals in IDR if one of their federal loans is in IDR. A loan is in IDR if the scheduled payments do not match the hypothetical scheduled repayment amount given the origination date, interest rate, and origination amount of the loan at the end of the previous deferment spell. Additionally, the non-standard payment cannot be accompanied by deferment, forbearance, or rehabilitation codes.

After our selection criteria are satisfied, we are left with our analysis sample. Our sample has similar levels of IDR as in Herbst (2023); our sample is slightly younger but also does not face as much attrition due to individuals paying off loans early.

A summary of our sample from the 12$^{\text{th}}$ quarter (3 years) after leaving school can be found in Table 2, where we show summary statistics for both groups combined, those in IDR and those not, as well as, separate statistics for each group in Table 3. In our sample, we see borrowers on IDR are similar in terms of age, sex, and year they left school. In terms of need, they are more likely to have a subsidized loan and a larger undergraduate balance. Age is reported every quarter. Male and female are binary indicators; there is some subset of the data where the sex of the borrower is unknown. The end of first deferment is based on a stata quarterly variable and is interpreted as (213/4)+1960. Therefore the mean borrower leaves school at the end of 2013.

We note that leaving school does not necessarily mean the individual received a degree, as we cannot observe graduation but simply when loans are no longer in in-school deferment–meaning the borrower is either graduated, left without a degree, or is below half-time enrollment. Unsubsidized loans are a binary variable where they are identified as loans which do accrue interest while in deferment; subsidized loans is a binary variable and is one if the loan does not accrue interest while in deferment. As described in the background section, these loans are not mutually exclusive and students may have one of each. IDR determination is described in Appendix A.

3.2 Summary Statistics

In Table 2 and 3, we show summary statistics for the whole sample, and broken down by payment plan, respectively. Table 2 shows summary statistics for individuals measured in the 12$^{\text{th}}$ quarter (3 years) after their first deferment spell ended. Table 3 breaks down the summary statistics of individuals on IDR compared to individuals not on IDR in our sample. Lastly, Table 4 shows characteristics for individuals in our sample who have different eligibility for the PAYE IDR plan.

Our primary outcome of interest is whether an individual took out an additional student loan to pay for additional schooling. Our indicator is formally defined by whether a new federal student loan tradeline was generated after we see the student had entered into repayment; we also require the student to be in deferment when the new tradeline is generated. The deferment requirement excludes consolidations and loan refinancing, which may not indicate additional schooling. We additionally add a requirement that the total loan amounts must be increasing by more than $500; this substantially cuts back on the part of our sample, which has a new continuing education loan.

Our indicator for additional student loan debt may indicate graduate student loans or undergraduate student loans. If a student were to withdraw after a semester, enter into repayment, and return to complete their undergraduate, we would indicate continued education if a second deferment spell with a new student loan occurs. If a student were to enroll in graduate school after entering repayment on their undergraduate student loans and take out an additional student loan, we would also indicate continued education.

We do note our measure for new student loan activity is conservative. If a student were to continue on to graduate education but not take a gap, then we would not indicate additional schooling. If a student were to enter into graduate school or continue undergraduate after the end of a deferment period but not take out an additional student loan, we again would mark them as not taking out an additional student loan. Our indicator may underestimate the impact of IDR on future student loan take-up if individuals make decisions based pre-existing knowledge of IDR and labor market outcomes. However, previous literature such as Wiswall and Zafar (2015) suggest students may not have complete information when making decisions in college; in their paper, students on average over-estimated the returns to their college major at age 30 prior to receiving more information. We also are aiming at capturing the effect of IDR on future student loan activity. In the case of Federal Direct student loans, students are often not contacted by their servicer until repayment begins. If we believe students lack information on repayment until they are contacted by a servicer, our indicator captures student loan decisions made after students are given information on repayment.

In addition to whether an individual took out an additional student loan, we construct indicators for whether the individual ever had a student loan fall behind in repayment. Ever behind in a payment is binary and indicates whether a borrower is ever 30, 60, 90, or 120 days past due on their federal student loan or delinquent; this span the entire payment history of the loan. Current is if the borrower is current over the whole history of the loan. Currently current is only the given quarter and past due is whether the loan is behind in the given quarter. We see a large percentage of borrowers do fall behind at some point during their repayment.

We also construct indicators for whether the individual took out additional lines of credit and the balances on the lines of credit. We separate these indicators into mortgages, small business loans with a personal guarantee, auto loans, and credit cards.

Lastly, using merged in occupational codes, we construct indicators for whether an individual was in health or social services, a teaching occupation, or a licensed occupation. Our occupation data is constructed by merging in occupational licensing data in addition to some self reported occupations. Due to potential non-random missingness, we only create indicators for occupations that were likely to be collected administratively through occupational licensing data.

Additionally, Table 2 displays summary statistics for our credit outcomes and current labor market outcomes. Federal student loan balance takes all undergraduate loans which fit our criteria. Mortgage indicates whether the borrower has a primary mortgage line. Small business loan indicates whether the borrower has a small business loan with a personal guarantee. Credit card spending is the month to month change across all credit cards along with any payments. Total student loan balance includes graduate loans and private student loans. Car balance is the balance on an auto tradeline. Average credit score is the credit score over the quarter. Migration indicates whether the borrower changed zip codes in the past year. In health or social services indicates whether a borrower has an occupational license in a health field or is marked in social services. Teacher or health indicates whether the borrower has a teaching license; licensed occupation indicates whether the borrower is likely in a licensed occupation. Lastly, number of sid is the number of servicer ids we use in the estimation.

In Table 3, we show how individuals differ based on their repayment plans. We can see individuals in IDR tend to have graduated later, have higher loan balance, and take out fewer future educational loans. They are more likely to be current on their student loans, especially in the current period.

4 Estimation: 2SLS

4.1 Estimation

In this paper, we are interested in the impact of individual i being on IDR in year t after their first deferment spell ended, IDR_{it}, on the binary indicator of whether an individual takes out a future student, Y_{it}. The model we would like to estimate is as follows,

$$Y_{it} = \beta_{0t} + \beta_{1t} IDR_{it} + X_{it}'\gamma + \epsilon_{it}. \tag{1}$$

However, estimating Equation (1) without an instrument would lead to biased results due to unobserved factors and reverse causality. First, high-income individuals would not be eligible for IDR. Second, unobservables such as unemployment risk, innate ability, and financial literacy may correlate with IDR enrollment and future student loan take-up. For example, if an individual is facing higher unemployment risk, they may enroll in IDR. They may also choose to re-enroll in schooling based on their expected lifetime earnings when considering unemployment risk. This would bias the effect of IDR on future enrollment upwards.

Therefore, we leverage random assignment to student loan servicers; we construct a leave-one-out measure for the likelihood an individual is on IDR. Our approach is similar to a judge-IV estimation; in the standard judge IV, conditionally randomly assigned judges are used to instrument for leniency or likelihood of incarceration. Instead of leniency, we use the likelihood of a servicer nudging a borrower into an IDR plan. Student loan servicers can only influence borrowers by providing information on government-approved repayment plans and evaluating whether an individual is qualified for a plan. Given that conditionally randomly assigned servicers have different propensities to suggest an IDR plan, we can estimate a local average treatment effect where the difference in IDR residuals causally changes the likelihood a borrower takes out a future student loan.

4.2 2SLS using Servicer IV

Following the literature on judge IV (e.g., Kling (2006), Frandsen, Lefgren, and Leslie (2023)), we construct a leave-one-out estimator for individual i assigned to servicer s at time t. While the assignment is mostly random, some bulking at different institutions is possible. In our data, this bulking does appear at the state level, with some states displaying a higher concentration of one servicer; however, no state has a complete concentration of one servicer. Additionally, the Department of Education loan contracts with servicers can change yearly; the pool of available servicers depends on which year the student had their first direct student loan disbursed. We construct our instrument as a jackknife instrument, removing all the observations from each individual's loans.

The following equation shows how we estimate the residualized IDR values for individual i at time t.

$$IDR^*_{it} = IDR_{it} - X'_{it}\delta = Z_{st} + \eta_{it} \tag{2}$$

Our X_{it} contains dummies for the first observed state and year in which the first federal student loan was disbursed. We also include a variable for the final amount borrowed *before* the individual entered into repayment for the first time. We include both the amount borrowed and a dummy for which quartile of borrowing the initial amount borrowed falls into for the state and year. While we cannot see the institution, we use these bins to approximate which type of institution the individual attended by grouping individuals by loan amounts in their state and year. We would expect the lower bins to be compromised of more individuals in community colleges while the upper bins may have more students at four-year degree-granting universities. We include this to capture if all students at a state university in year t are more likely to be assigned to a given servicer s. We denote the likelihood of a servicer enrolling an individual in IDR by Z_{st} for servicer s in time t.

We construct our leave-one-out measure in the following way. For each in individual i, we compute

$$Z_{ist} = \frac{1}{n_{st} - n_{sit}} \left(\sum_{k=0}^{n_{st}} IDR^*_{it} - \sum_{c=0}^{n_{sit}} IDR^*_{it}\right) \tag{3}$$

where n_{st} is the number of cases by servicer s in year t and n_{sit} is the number of cases by servicer s for individual i in year t. We remove all other credit observations of individual i as they may be correlated with individual i's outcomes.

4.3 Description of Servicer Selection

To construct the servicer IV, we identify servicers who were randomly assigned federal student loans with sufficient caseloads. Over our sample, we have at least 21 unique servicers[3]

[3] See https://fsapartners.ed.gov/knowledge-center/library/electronic-announcements/2011-09-23/loans-subject-loan-servicing-information-new-servicers-join-federal-loan-servicer-team-octo for a full list of servicers who were operating in 2011 and entering with new loans 2011-2014.

who serviced student loans; however, students are not necessarily given only one servicer. Therefore, students are treated by a servicer combination if more than one servicer is noted since we cannot separately identify which servicer may nudge a student into IDR or the standard plan. We select servicers with at least 50 borrowers who are in repayment by 2016. This leaves us with 54 unique servicer combinations.

In Figure 1, we show the variation in IDR enrollment by servicer for our cohorts; we calculate what percent of borrowers were in IDR in each year by servicer and plot a histogram of the variation.[4] Our servicers range from none of the borrowers being in IDR to all borrowers being in IDR. On average, about 19% of borrowers are in IDR. We note that this does not control for the characteristics of the borrower.

In Figure 2, we present a descriptive graph of our servicer treatment effects after controlling for borrower characteristics such as the borrower's age, the initial amount borrowed before entering repayment, and gender. Even after controlling for observables, we see heterogeneity in how servicers enroll their borrowers in IDR plans. We note again from our previous figure that each bar does not necessarily represent one servicer but can represent any servicer with similar treatment probabilities.

Servicers could strategically nudge borrowers into repayment plans to maximize the new contracts they would receive. Based on the servicer's allocation contract, each servicer has incentives to keep borrowers in good standing but elongate repayment for as long as possible to obtain a larger share of future borrowers. The share of new borrowers for each servicer is determined by each servicer's score relative to the other servicers in the market.[5] The Department of Education allocated new loans to servicers based on the following formula:

$$\text{New Loans} = \frac{\text{Loan Servicer Score}_i}{\sum_{i=1}^{n} \text{Loan Servicer Score}_i} * (\text{Number of New Borrowers}) \tag{4}$$

Due to servicer incentives, we use the first assigned servicer or servicers in some cases. Servicers can nudge borrowers into different types of repayment plans by reaching out to their borrowers. In the law suit against Navient, the attorney general alleged that Navient steered borrowers into deferments and forbearances instead of income-driven repayments. Overall, the servicer's objective is to keep borrowers in good standing while keeping the contract open.

[4] We note that each bar does not represent one servicer but what fraction of the student loan population is assigned to a servicer with that given percent of individuals in IDR. If two servicers have the same propensity to put their borrowers into IDR, they would be grouped in this graph.

[5] Formula found on page 63 of Great Lakes contract with the Department of Education https://www2.ed.gov/policy/gen/leg/foia/contract/greatlakes-061709.

4.4 Servicer IV details

For the instrument to be valid and provide a local average treatment effect (LATE), we must satisfy the three assumptions listed in Angrist and Imbens (1994). Each assumption can be tested as described in Frandsen, Lefgren, and Leslie (2023).

The first assumption is that student loan servicers are randomly assigned. Based on contract agreements from the Federal Student Aid (FSA) website, we see loan servicers are given an allotment of new contracts each year; per a conversation with an expert, these contracts may be bulked by geography but are otherwise randomly assigned. These contracts are randomly assigned once we control for geography by year-fixed effects. In our data, we examine the share of servicers in each state and find that every state has more than one servicer present.

Furthermore, to test assumption one, we perform a balance test to check whether any covariates can predict IDR treatment in Table 7. We test whether individuals are more likely to have a higher IDR score if they were female, had a higher amount borrowed, were observed in a different quarter, maxed out their federal loans, or entered repayment in a different period. Our coefficients are insignificant and zero. Our balance test suggests that individuals are randomly assigned to a servicer based on the observable characteristics we see.

The second assumption assumes that treatment vary by servicer and are non-trivial. We note our earlier figures, Figure 1 and 2, where we show that treatment effects do vary by servicer even after we control for our observables. We can see treatment vary from nearly -0.2 to 0.4. Additionally, we test that servicers directly affect credit outcomes through IDR and not other mechanisms such as default in Appendix C.

The third assumption is monotonicity, where if a student loan borrower moved from one servicer with a lower propensity to treat to one with a higher propensity to treat and they were treated at the previous servicer, they would continue to be treated at the next one. There are a variety of methods to test monotonicity.

We provide several abbreviated versions of monotonicity tests to give evidence that assumption three holds in two different ways. Table 6 shows these results. This top panel provides estimates of the first stage by different groupings. In particular, we see if the instrument's effect depends on the types of IDR offered. We estimate the first stage separately for each group. In each panel, regardless of group, the treatment does appear to be highly correlated with the likelihood an individual is assigned to an IDR plan. [6]

[6] We also test for monotonicity and the sc restriction through the judge fixed effects monotonicity test outlined in Frandsen, Lefgren, and Leslie (2023), TESTJFE. We provide abbreviated results from TESTJFE. We note that these results are run separately for each outcome variable and each time horizon. Generally

4.5 First-stage Results

In our first stage, we estimate how well our instrument Z_{it} predicts IDR status. For each year t after the end of the first disbursement spell, we use a leave one out estimator–removing the individual's own IDR status–with servicer S_{it} to predict the likelihood an individual was on IDR. We control for state and time-fixed effects to account for the possibility of servicer assignment by year and region. We cluster our standard errors by the first observed state of residence and the first year we see a student loan disbursed.

$$IDR_{it} = \alpha_{0t} + \alpha_{2SLS,t} Z_{it} + X_{it}^{\prime} \psi + \epsilon_{it} \tag{5}$$

We control for individual characteristics (X_{it}) such as gender, current age, state of first disbursement, year of first disbursement, the total amount disbursed before repayment started, and year observed.

Table 5 shows these results from the first stage for each quarter with the given controls. The table displays the coefficient of the IV, the number of observations in each regression, the F-statistic on the instrument, and Anderson-Rubin test results. Our F-statistic is above the 104.67 threshold described in Lee et al. (2023). Therefore, our confidence intervals are computed using standard methods instead of the tF adjustment.

The leave-one-out estimator strongly predicts whether an individual is on IDR. Our estimated α_{2sls} is near one in each column. A one standard deviation in servicer score increases an individual's likelihood of being on IDR by nearly seven percentage points. We note most controls do not have a considerable influence on our predictor.

5 Main Results

In the following results section, we detail our OLS and 2SLS results. We report our results quarterly.[7] All regressions are conditioned on the individual's sex, age, initial student loan balance, initial reported state of residence, graduation year, assignment year, current year, and whether any student loans are subsidized.

speaking, we cannot reject the null hypothesis of monotonicity and the exclusion restriction. Due to the sheer amount of results, these tests are available upon request.

[7] We note that we have estimated our results quarterly. In our annual regressions, we take all 4 observations for the individual and cluster standard errors by individual. Annual results are available upon request and the overall results do not change much.

5.1 Future Student Loan Borrowing: OLS

In Table 8, we estimate the likelihood an individual takes out an additional student loan given their IDR status. In part 1 of the table, we show the estimated coefficients given current IDR status. In Table 9, we present estimated coefficients given a six month lag on IDR status. In both cases, the estimated coefficients suggest individuals currently on IDR are less likely to take out a future student loan.

The negative OLS estimates are driven by two separate factors: the mechanical construction of the estimator and bias arising from unobservable factors that correlate with both IDR enrollment and schooling decisions. Mechanically, an individual cannot be enrolled in IDR while also attending school, as borrowers enrolled in school are classified as being in "in-school deferment" rather than "currently repaying". Therefore, we do expect either null results or negative estimated coefficients in Table 8. To address this concern, Table 9 uses lagged IDR status. The coefficients on the lagged IDR status are still negative or null; this may be due to downward bias. This bias arises because borrowers enrolled in IDR are more likely to have lower disposable income, given the eligibility requirements for IDR enrollment. If we expect wages to be a sign of ability, then individuals with lower disposable income will be less likely to go back to school and, therefore, less likely to apply for future loans. In order to address these issues and to isolate the causal effect of IDR enrollment on future schooling decisions, we turn to our results using our instrumental variable approach in the following section.

5.2 Future Student Loan Borrowing: 2SLS

Using our 2SLS framework described in Section 4.2, we estimate the likelihood that the borrower takes out an additional student loan given their instrumented IDR status.

In Table 10, we examine whether IDR induces individuals to take out an additional student loan using our preferred estimation strategy, two stage least squares. In our sample, approximately 3% of our borrowers start a second deferment spell and take out an additional student loan below the graduate student loan limit. We find relatively large results with a one percentage point increase if we increase IDR take-up by one standard deviation.

Whether this result is desirable is ambiguous without considering whether borrowers are paying off their loans faster after their second educational spell ends and whether borrowers are less likely to default after their second educational spell. Are balances adjusting due to IDR fixing incomplete markets or are IDR balances increasing due to moral hazard? If we see balances are falling for our sample, this would suggest that IDR may be rectifying incomplete educational markets. If balances are rising over the entire repayment cycle, this may suggest moral hazard in repayment. We also include Table 11 for completion as we included it in Section 5.1 and we do not find any evidence that it matters whether we used lagged IDR status or not in our 2SLS estimation.

5.3 Federal Student Loan Balances and Loan Status

To evaluate whether IDR is solving an incomplete markets problem or increasing moral hazard, we estimate the effect of IDR on student loan balances and the loan's status. In Table 12 and 13, we present the estimated effect on federal student loan balances both using OLS and 2SLS, respectively. We find that IDR is indeed associated initially with growing student loan balances. However, at the end of our sample, IDR is associated with declining student loan balances. This would be more consistent with growing balances due to increased educational attainment and increased earnings later in the life cycle.

6 Treatment Effect by IDR Plan Availability

6.1 By Payment Plan Availability

In addition to estimating the general effect of IDR, we investigate the importance of the generosity of the repayment plan. In particular, using the dates of origination on the student loans and the repayment start date, we identify whether borrowers were eligible for repayment as low as either 10% or 15%. The difference between PAYE and other plans is outlined in Table 14, PAYE allowed for the lowest percentage of repayment, 10%, while others are either 15% or 20%.

In Table 4, we show summary statistics for the three sets of borrowers who have a different menu of IDR plans. The first group is the oldest set of borrowers, who cannot have a student loan after 2012 and may have unpaid student loans originating before 2007. This group is eligible for older IBR plans but not for PAYE; practically, this means the best IDR plan available prior to 2020 had income indexed to 15% of income. The second group has student loans disbursed after 2012 but also has a pre-existing loan from before 2014. This group is eligible for both PAYE and the older IBR plan; the best option for this group would have loan repayments indexed to 10% of income. The third group only has new borrowers as of 2014 with no pre-existing loans when the newest loan was disbursed during or after 2014. This group is eligible for the new IBR plan and PAYE.

To identify effects of different treatment plan, we specifically estimate the following equation,

$$Y_{it} = \beta_{0t} + \beta_{1t} IDR^{*}_{it} P_{it} + \Gamma X_{it} + \eta_i + \lambda_i + \alpha_i + \epsilon_{it}. \tag{6}$$

Just as in Equation (1), the outcome of interest is Y_{it}, the likelihood of returning to school. We also include the same controls, first observed state of residence, η_i, first year of student loan disbursement, λ_i, interaction between state of residence and year of disbursement, α_i, and individual characteristics, X_{it} (sex, year in which they ended their first deferment spell, number of previous IDR spells each individual has had, had a subsidized loan, the initial amount borrowed at the end of first deferment spell).

Table 15 shows the estimated effect of IDR on the probability of the borrower taking out another student loan by plan, P_{it}. We do not see any statistically significant effect between IDR for individuals with the PAYE IDR plan and individuals without access to the PAYE IDR plan, suggesting that the difference in repayment plan in terms of the percent of disposable income that needs to be repaid does not significantly impact student loan take-up.

This result may be surprising if one expects moral hazard to drive the additional loan take-up. If anything, we would expect individuals with more generous repayment plans to be slightly more likely to take-up additional education; student loan repayment expectations may be driving the difference. We note the date different repayment plans debuted in Table 14. The oldest borrowers applied for their student loans and chose their majors before new, more generous IDR plans were announced. Individuals eligible for PAYE may have made major and job decisions, knowing that more generous IDR plans would be enacted. In other papers such as Dinerstein et al. (2024), student loan expectations can be quite important in driving borrowing behavior.

6.2 By Original Amount Borrowed

In order for policymakers to fully understand who is affected by IDR, we need to understand to what extent different groups benefit from it, including some of the unintended consequences, such as going back to school and taking on more debt. Understanding this would allow policymakers to target groups accordingly.

To help identify who is driving the increase in new student loans and student loan balances, we interact our IDR indicator with bins for the initial amount borrowed, B_{it}. In particular, we take the initial amount borrowed for each student and identify which quartile the student's initial amount falls within our sample of borrowers within that state and year. Specifically, we estimate the following,

$$Y_{it} = \beta_{0t} + \beta_{1t} IDR^{*}_{it} B_{it} + \Gamma X_{it} + \eta_i + \lambda_i + \alpha_i + \epsilon_{it}. \tag{7}$$

Just as in Equation (1), the outcome of interest is Y_{it}, the likelihood of returning to school; we also include the same controls. The lowest bin, on average, has about \$4,000 in federal student loans, the second quartile has roughly $10,000 in student loans, the third lowest bin has $19,000 in student loans, and the fourth bin has $56,000 in student loans.

We find that increased likelihood of IDR enrollment is more effective for those with lower total student loans borrowed, meaning those who have lower amounts borrowed are more likely to enroll in further education than those with larger amounts borrowed, as seen in Table 16. This seems plausible; individuals with less borrowed money may return to school as they have not finished school, while those with larger amounts most likely have taken on more years of schooling. This suggests that IDR could play a big role in expanding access to education amongst populations who would otherwise be deterred and not finish their schooling. For higher-debt borrowers, the absolute burden of loans is larger. Still, they may already perceive IDR as a "safety net" that makes the marginal incentive to take on additional student loans less pronounced.

7 Mechanisms

In this section, we consider why IDR may impact future student loan attendance and think about how certain mechanisms may interact.

7.1 Loan status

Using our 2SLS framework, we estimate the likelihood the borrower has an adverse credit history after being on IDR in a given year post-educational enrollment. Our first regression measures whether the individual is ever behind on their federal undergraduate student loans where the outcome is binary if the loan is reported as ever behind.

Figure **??** shows the effect of being always current on IDR; our estimates are statistically significant and negative. Our effects suggest that IDR may be associated with more positive credit outcomes or null effects on credit status. The current estimates are relatively large, likely due to the lack of variation in borrowers' status while on IDR.

Our results differ from those of Herbst (2023), which shows an immediate effect of IDR in decreasing negative credit outcomes.First, borrowers in Herbst (2023) are selected from a pool of borrowers that receive a delinquency call, while our borrowers are representative of the entire student loan borrower population in the US. For the marginal borrower going into IDR may not be as beneficial as for borrowers that are about to go delinquent. Second, our estimation is about being on IDR that period and may include individuals who are ending their IDR spell. Previous literature such as Herbst (2023) has shown low re-certification rates, especially for individuals with IDR payments near zero. In separate preliminary work, we show the hazard rates for IDR within our sample, which supports the claim that many individuals fail to re-certify. We would expect IDR to have a larger effect when students have lower incomes at the beginning of their careers.

In Tables 13 and 12, we examine the impact of IDR on student loan balances; while OLS shows significant positive effects over the entire life-cycle, IDR shows initial positive effects on student loan balances followed by negative effects. We note that OLS would be biased upwards. The Appendix shows that IDR individuals are likely to receive zero payment, which could lead to either interest capitalization or a slower pace of paying off the loan. While deferment and forbearance also have zero payments, these are often for much shorter periods. However, the 2SLS estimation shows balances rising initially, followed by balances falling at a faster rate. The previous tables showed IDR individuals were less likely to fall behind or default, which suggests that even if they are paying off balances slower, the balances are being paid.

While moral hazard may impact future student loan take-up, eligibility requirements for FAFSA may also impact future student loan take-up. If students default on their existing student loans, they cannot enroll in FAFSA until the loans are rehabilitated through six months of qualifying payments, loan consolidation, or the Fresh Start program. We do find evidence that IDR helps students maintain FAFSA eligibility while in repayment by reducing the negative marks on a credit report.

7.2 Occupational Choice

Another potential impact of IDR is that it may influence major and occupation choices. Certain majors or occupations may require additional schooling to advance career-wise. Early forgiveness promised under IDR may encourage students to pursue these careers, given that the total debt disbursed is not what they expect to repay. In Tables 19 and 20, we show the impact of being on IDR on whether individuals are licensed in health care or teaching occupations. The OLS estimates show a largely null effect; meanwhile, the 2SLS estimates show a null effect which eventually becomes positive towards years 4 and 5. Our evidence is suggestive that loan forgiveness may induce individuals to stay in occupations that promise forgiveness.

8 Other Economic Impacts

In this section, we look at the impact of IDR on different credit outcomes. In particular, we examine whether there is a causal effect of IDR on credit scores, mortgage debt, and small business loans, y_{it} using the same estimation as outlined in Section 4.2.

With other lines of credit, there are several reasons for these to be impacted by IDR. The first is IDR could impact approval odds through changes to debt obligations and credit scores. In Appendix Figures 8 and 7, IDR individuals are more likely to see growing or non-changing balances while on IDR. Additionally, we see growing student loan debt from additional loans being taken out.

IDR may influence career selection and earnings trajectories as it alters the risks of entering into small business ownership. One upside of IDR is that it provides insurance if businesses fail. Individuals working in licensed occupations such as medical professionals with private practices may rely on small business loans. IDR may allow individuals with high debt loads to avoid licensure suspension from student loan default. On the other hand, the downside of IDR may be higher payments if a business is successful. While IDR provides insurance against negative income shocks, IDR plans such as ICR and REPAYE are not capped at the maximum standard repayment amount. Changing plans to a standard plan for good income would cause the consumer additional hassle and costs.

8.1 Credit score

To see the overall cumulative effect on credit (credit score), we examine how IDR interacts with credit score in Table 18. This would capture the likelihood a borrower would have a delinquency on their account, changes in balances, and any payment history. We estimate IDR is associated with a 48 to 61-point increase in credit score over the life-cycle. We find that IDR tends to positively impact credit scores, which likely captures the lower likelihood of negative credit events such as delinquency. We note the impacts on credit scores may be wide-reaching onto other lines of credit like mortgages and small business loans.

8.2 Mortgages

In Table 21 and Table 22, we show the effect of IDR on mortgage uptake both using our OLS and 2SLS estimation. We find that IDR has a positive impact on mortgages, with an eight percentage point increase in mortgages initially and eventually point estimates as high as seventeen percentage points. In the case of owning a mortgage, we see large positive coefficients which are larger in the 2SLS estimation. Our OLS estimates are biased downwards likely due to IDR enrollees having less disposable income. However, when we instrument, the estimates are even more positive.

IDR increases mortgages due to increased liquidity, insurance, and positive effects on credit score. When applying for mortgages, individuals have to list their other debts, and

IDR reduces these obligations, albeit by less than what they are actually paying in some cases. Additionally, we see significant increases in the likelihood an individual has a mortgage at the later stages in the life-cycle. While insurance value may play a larger role early in individuals' careers, the increasing magnitude of the coefficients suggests individuals are able to accumulate additional liquidity by years 4 and 5 to open a mortgage, or positive credit impacts increase approval odds.

8.3 Small Business Lines of Credit

In Table 23 and Table 24, we show IDR's effect on mortgage uptake using our OLS and 2SLS estimation. We find that the impact of IDR on taking out a small business loan. With small business lines of credit, we note largely null results. We note that small business loans are likely to be reported if they have a personal guarantee in this case.

In Tables 23 and 24, we estimate the effect of small business loans on IDR and find IDR generally increases small business loan take-up. We find the IDR impacts are largely positive in the OLS estimates; this could be expected if business owners have higher financial literacy and are more likely to switch to an IDR plan to lower their debt obligations. In the 2SLS estimates, we find initially positive and significant coefficients which then tend towards zero. Since the effect is initially positive, we can hypothesize that IDR is more important for early on in the life-cycle when individuals are starting new businesses.

Lastly, we want to note this result has limited scope. To estimate small business loans, we can only see the loans if they appear on the individual's credit report. If the individual is able to open a small business separate from their own credit, we do not capture it. Some evidence has shown that small business loans are more likely to be reported on a consumer credit report when the line is delinquent; overall, our IDR results suggest IDR helps reduce delinquency, so we are likely underreporting the number of individuals on IDR with small business loans.

9 Conclusion

In this paper, we utilize the University of California Consumer Credit Panel to examine how IDR impacts borrowers through credit and labor market outcomes for up to five years after they leave post-secondary education. To deal with the endogeneity of who selects into IDR, we use random assignment to student loan servicers as an instrument for whether an individual is on IDR. We note this instrument is similar to Welch (2024), and we test for how our instrument and data compare in Appendix C.

We examine whether IDR leads to moral hazard in the student loan market. We document that IDR leads to an increase in individuals taking out additional student loans. Worries about additional student loans often worry about individuals at expensive, low-quality institutions. We find that while borrowers with a larger amount of student loans to start with have a higher baseline likelihood of taking additional student loans, IDR has the highest impact on borrowers with a low initial amount of student loans. Consistent with descriptive statistics, we see that IDR can causally leave balances higher over time for individuals at the beginning of the life-cycle. There are several potential reasons for balances to increase. One is that borrowers are slower at paying off existing balances. Second, borrowers may have interest capitalization. Third, we find that borrowers who are more likely to experience an IDR spell are more likely to take out a future student loan. We note that our results are just the beginning to understand the impacts of IDR on aggregate welfare. However, later in the life-cycle, we find that IDR leads to faster repayment of student loans; one caveat to faster repayment is whether individuals end up repaying the entire loan or whether the loan is forgiven.

In our heterogeneity analysis, we also examine if additional student loans are driven by borrowers with more generous repayment options. We do not see heterogeneity in borrowing based on the generosity of the plan, which suggests that the insurance value of IDR and IDR expectations may play a larger role than the actual liquidity generated by IDR. We do note, consistent with other literature, that student loan expectations are possibly an important channel in repayment and borrowing behavior.

While the declining student loan balances and increased human capital accumulation largely suggest positive outcomes from IDR, we have an additional caveat with forgiveness. While IDR largely encourages student loan borrowing that enables better repayment outcomes, individuals on IDR are more likely to stay in occupations that promise early forgiveness. While the current study only evaluates up to 5 years of repayment, there may be large balances forgiven, which we are not accounting for in our five-year analysis. We note these results are more limited without actual employment data as this does not state whether these individuals are working or non-employed. It simply states whether they are licensed or not.

Concerning credit outcomes, we find that IDR has largely positive outcomes on credit and largely encourages additional borrowing. IDR spells are more likely to keep borrowers current on their obligations while on IDR, which leads to positive effects on credit scores. Additionally, access to IDR may increase borrower uptake of other forms of wealth-generating credit. Borrowers with higher access to IDR are more likely to have a business loan or a mortgage. These effects are the composite of borrower incentives and other lender incentives.

In particular, borrowers may be more likely to take on risky credit when given the insurance value of IDR; however, lenders may be less likely to extend credit when borrower student loan obligations are high or when credit scores are lower. We cannot say whether these increases are due to effects on licensing, increased approval odds or liquidity. The estimated impacts suggest IDR may have larger implications for the dynamics of housing markets and small business owners.

In terms of future work, there is a considerable amount of future work regarding the impacts of IDR on credit markets and the labor market. There are questions of what percent of disposable income is optimal and whether IDR has large impacts in labor effort.

10 Tables and Figures

Table 1: Potential Student Loan Timeline

Time	Student's Action
T-6	Student applies for college
T-3	Student is accepted to college
T-3	Student uses FAFSA to apply for Federal Student Aid
T-3	Federal Student Aid awarded, all applicants receive direct loans
T-2	Student may apply for additional loans through the private market or Plus loans
T -1	High School Graduation
T	Student enrolls in college
T	Student loans are disbursed and loan servicer is assigned
T+12	Repeat FAFSA, loans awarded, and disbursement, note interest accruing if not subsidized
T+24	Repeat FAFSA, loans awarded, and disbursement, note interest accruing if not subsidized
T+36	Repeat FAFSA, loans awarded, and disbursement, note interest accruing if not subsidized
T+48	Graduates
T+48	6 month grace period, no repayment during this period
T+54	grace period ends, make payments to loan servicer, everyone initially in standard repayment plans
T+54+X*	Unemployed: Servicer can nudge to IDR or forbearance/ deferment
T+54+12+X*	Still facing hardship: renew IDR or forbearance or deferment

This example student takes out loans 4 years and leaves college in 4 years. One period is a mo

This table includes summary statistics for the 12^{th} quarter (3 years) after the end of the first first deferment spell spell for any individual in our sample.

Table 2: Summary Statistics for Our Sample

Variables	N	Mean	Standard Deviation
Age	158,098	27.70	4.77
Male	158,098	0.40	0.49
Female	158,098	0.52	0.50
End of first deferment	158,098	213.12	5.40
Unsubsidized Loan Indicator	158,098	0.76	0.43
Subsidized Loan Indicator	158,098	0.28	0.45
In IDR	158,098	0.19	0.40
IDR residualized treatment	158,098	0.00	0.07
Ever behind in payment	158,098	0.45	0.50
Current	158,098	0.52	0.50
Currently Current	158,098	0.72	0.45
Past Due	158,098	0.24	0.43
Total Federal Student Loan Balance	158,098	22,922.82	34,374.27
Has mortgage	158,098	0.10	0.31
Has small business loan	158,098	0.04	0.19
Takes out a future student loan	158,098	0.03	0.17
Total Credit Card Spending	158,098	2,070.97	6,338.02
Total Student Loan Balance	158,098	23,417.11	35,043.24
Average Credit Score	158,098	591.68	94.74
Migration	24,017.00	0.17	0.37
In Health or Social Services	158,098	0.02	0.12
Licensed Occupation	158,098	0.04	0.20
Teacher or Health occupation	158,098	0.02	0.14
Treatment Group	158,098	1.61	0.54
Number of sid	14	14	14

This table includes summary statistics for the 12$^{\text{th}}$ quarter (3 years) after the end of the first first deferment spell spell for any individual in our sample.

Table 3: Summary Statistics by Repayment Plan: IDR vs Standard Repayment

	Not in IDR		In IDR	
Variables	Mean	SD	Mean	SD
Age	27.62	4.80	28.04	4.63
Male	0.40	0.49	0.40	0.49
Female	0.52	0.50	0.53	0.50
End of first deferment	212.89	5.44	214.06	5.10
Unsubsidized Loan Indicator	0.73	0.44	0.89	0.31
Indicator for has subsidized loans	0.27	0.44	0.30	0.46
Residualized IDR Treatment	-0.01	0.05	0.03	0.11
Ever Behind	0.49	0.50	0.28	0.45
Always Current	0.47	0.50	0.72	0.45
Currently Current	0.67	0.47	0.95	0.21
Currently Past Due	0.29	0.45	0.04	0.21
Has mortgage	0.09	0.29	0.15	0.35
Has small business loan	0.04	0.19	0.05	0.22
Takes out a future student loan	0.03	0.17	0.03	0.16
Total Credit Card Spending	1,772.08	5,880.82	3,312.67	7,840.11
Total Student Loans	20,088.49	29,494.27	37,245.22	49,785.32
Total Auto Balance	5,139.14	9,860.09	7,035.91	11,122.00
Average Credit Score	583.60	95.55	625.22	83.30
Migration	0.17	0.38	0.15	0.36
In Health or Social Services	0.02	0.12	0.02	0.13
Licensed	0.04	0.20	0.05	0.21
Teacher or Health Services	0.02	0.12	0.02	0.14
total Federal Student Loan Balance	19,622.95	28,784.49	36,631.48	49,144.15
Treatment Groups	1.61	0.55	1.62	0.55
N	127,425		30,673	

This table includes summary statistics for the 12^{th} quarter (3 years) after the end of the first first deferment spell spell for any individual in our sample.

Table 4: Summary Statistics by Income Drive Repayment Plan Availability

	Not PAYE Eligible		PAYE Eligible, Old IBR		Paye Eligible, New IBR eligible	
Variables	Mean	SD	Mean	SD		
Age	28.37	4.80	27.96	4.36	27.12	4.91
In IDR	0.15	0.36	0.16	0.37	0.14	0.34
End of first deferment	2012.88		2013.45		2014.77	
Residualized IDR Treatment	-0.00	0.06	-0.00	0.07	0.00	0.08
Ever Behind	0.51	0.50	0.44	0.50	0.48	0.50
Always Current	0.43	0.50	0.52	0.50	0.44	0.50
Currently Current	0.62	0.48	0.71	0.45	0.59	0.49
Currently Past Due	0.31	0.46	0.24	0.43	0.33	0.47
Has mortgage	0.12	0.33	0.12	0.32	0.07	0.25
Has small business loan	0.04	0.20	0.04	0.20	0.02	0.14
Takes out a future student loan	0.04	0.20	0.03	0.17	0.02	0.14
Total Credit Card Spending	2,134.57	6,073.42	2,265.26	6,543.46	1,399.84	4,085.02
Total Student Loans	13,055.19	15,135.88	16,086.50	15,650.68	7,309.24	9,240.76
Total Auto Balance	5,830.09	10,535.72	6,222.03	10,789.04	5,109.56	9,807.75
Average Credit Score	585.91	99.31	595.57	91.16	558.42	93.81
Migration	0.12	0.33	0.11	0.33	0.16	0.37
In Health, Social Services, or Teaching	0.02	0.13	0.02	0.12	0.01	0.10
Licensed	0.04	0.20	0.04	0.19	0.03	0.17
Total Federal Student Loan Balance	12,723.05	14,547.82	15,780.65	15,106.69	7,193.49	8,756.29
N	57,133		76,671		5,292	

This table includes summary statistics for 12^{th} quarters (3 years) after the end of the first first deferment spell spell for any individual in our sample.

Table 5: First Stage Estimates

Quarter	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR Instrument	1.26***	1.22***	1.20***	1.15***	1.13***	1.11***	1.07***	1.02***	0.97***	0.94***	0.91***	0.87***	0.83***	0.81***	0.79***	0.74***	0.70***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	154726	154481	156359	157811	158123	156122	155953	156100	154034	152936	151902	150838	149693	140740	125621	116131	109241
Instrument F-stat	7764.76	7393.33	7178.33	6719.44	6420.93	6262.53	5962.40	5515.17	5115.52	4873.36	4633.91	4374.71	4012.52	3620.43	2945.32	2309.96	1937.81

Note: Standard errors, clustered by servicer id, are in parentheses. * $p < 0.05$,** $p < 0.01$,*** $p < 0.001$

Table 6: Monotonicity

Quarter	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR IV for borrowers eligible for IBR and ICR, no PAYE	1.25***	1.23***	1.20***	1.16***	1.13***	1.11***	1.10***	1.05***	1.00***	0.96***	0.93***	0.90***	0.88***	0.83***	0.81***	0.74***	0.68***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
N	63588	63875	65237	66634	66944	66386	66237	66703	64771	64398	64077	63843	63564	60362	55679	52581	50404
Instrument F-stat	2632.96	2541.42	2469.38	2370.19	2245.33	2183.34	2175.99	2022.92	1860.71	1770.80	1706.67	1614.45	1590.06	1330.65	1111.20	869.72	706.54
IDR IV for borrowers eligible for ICR,PAYE, AND IBR	1.24***	1.20***	1.17***	1.13***	1.11***	1.10***	1.04***	0.99***	0.95***	0.91***	0.88***	0.85***	0.79***	0.79***	0.77***	0.74***	0.71***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
N	86104	85540	86023	86005	85935	84478	84423	84034	83880	83174	82539	81781	80956	76132	67264	61780	57797
Instrument F-stat	4603.48	4349.28	4207.01	3891.30	3746.83	3692.63	3389.73	3139.58	2918.42	2752.10	2591.58	2456.83	2149.39	2046.96	1668.10	1343.31	1162.39

Figure 1: IDR enrollment by servicer group

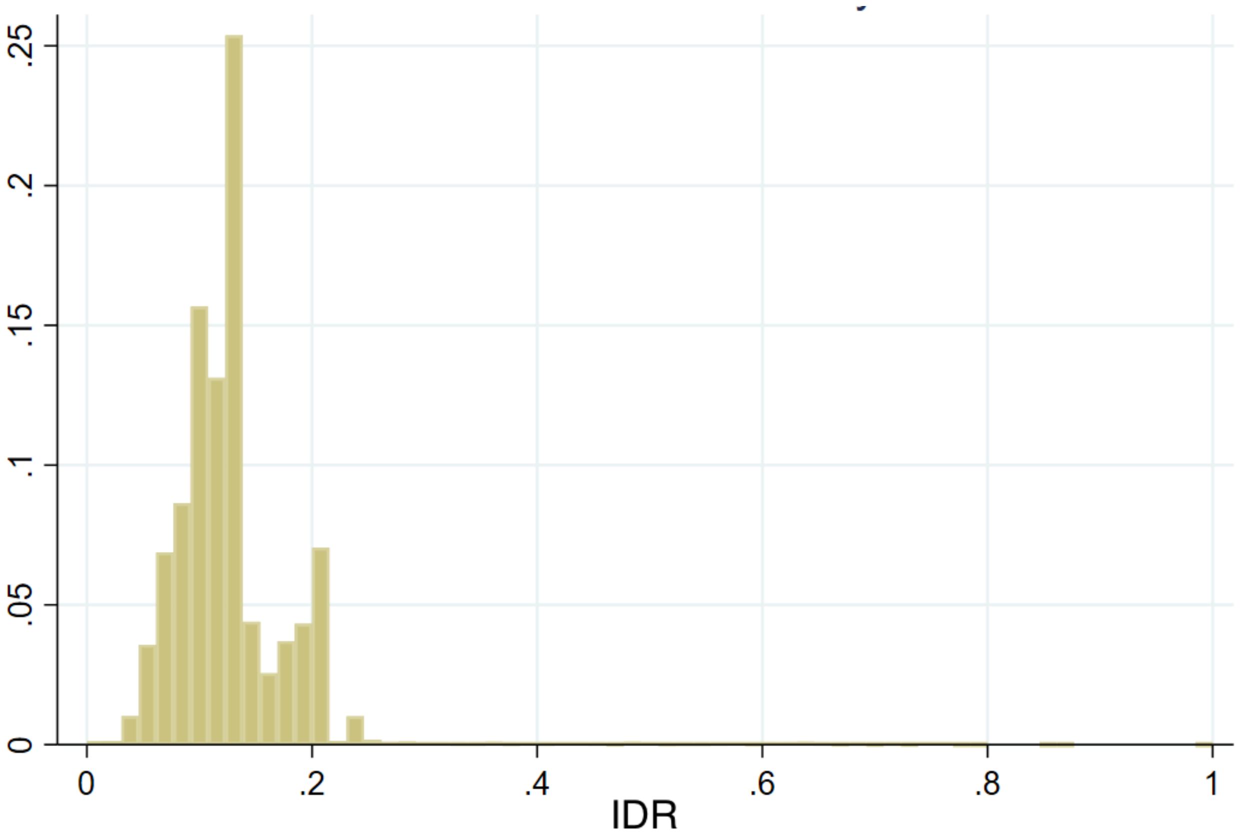


Figure 2: Treatment Variation

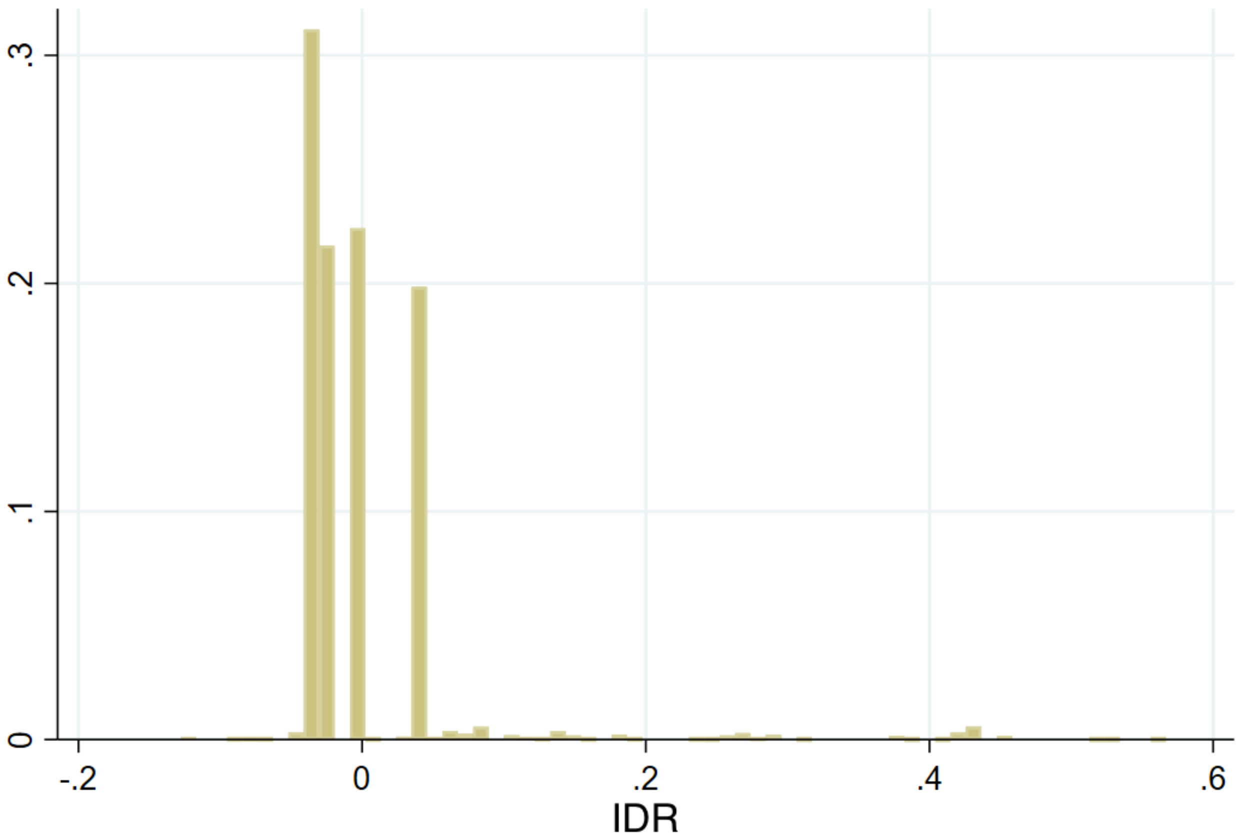


Table 7: Balance Test

	IDR Treatment 4 Quarters	IDR Treatment 8 Quarters	IDR Treatment 12 Quarters	IDR Treatment 16 Quarters	IDR Treatment 20 Quarters
Indicator for female	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Indicator for entered repayment in 2011	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Indicator for entered repayment in 2012	-0.01	-0.01	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Indicator for entered repayment in 2013	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Indicator for entered repayment in 2014	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Indicator for entered repayment in 2015	-0.00	-0.00	-0.01	-0.01	
	(0.01)	(0.01)	(0.01)	(0.01)	
2nd quarter	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3rd quarter	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4th quarter	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Initial Amount Borrowed	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Second Quartile Borrowing	-0.00	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Third Quartile Borrowing	-0.00	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fourth Quartile Borrowing (highest)	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Indicator for maxed out federal loans	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	121639	125980	123158	119913	88596

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: OLS Estimates: Additional Student Loan on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR	0.002**	0.003**	0.004***	0.004***	0.004**	0.004**	0.004**	0.003*	0.004*	0.004**	0.006***	0.004*	-0.001	-0.000	0.007**	0.010***	0.007**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
N	121645	121799	123685	125315	125983	124552	124482	124736	123162	122235	121471	120749	119918	113302	101501	93858	88598

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 9: OLS Estimates: Additional Student Loan on 2 Quarter Lagged IDR status

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Two quarters lagged IDR	-0.004***	-0.005***	-0.001	0.002	0.001	0.001	0.002	0.003*	0.003*	0.003	0.003	0.001	-0.000	-0.000	-0.000	0.004	0.005*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	121205	121784	123668	125302	125975	124539	124475	124732	123158	122234	121467	120747	119916	113301	101498	93857	88595

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 10: 2SLS Estimates: Additional Student Loan on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR*	0.025***	0.030***	0.036***	0.038***	0.040***	0.040***	0.046***	0.051***	0.052***	0.058***	0.057***	0.058***	0.050***	0.061***	0.075***	0.056***	0.046*
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)	(0.013)	(0.014)	(0.016)	(0.019)
N	121639	121795	123682	125312	125980	124549	124479	124732	123158	122231	121467	120744	119913	113297	101497	93857	88596

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 11: 2SLS: Additional Student Loan on 2 Quarters Lagged IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Two Quarter Lagged IDR*	0.025***	0.029***	0.032***	0.033***	0.037***	0.039***	0.044***	0.047***	0.046***	0.053***	0.053***	0.053***	0.045***	0.055***	0.068***	0.046**	0.035*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)	(0.011)	(0.012)	(0.013)	(0.014)	(0.016)
N	113479	114195	116019	118200	119952	119864	121064	121942	120787	120309	119792	119106	118274	111768	100107	92574	87391

Note: $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 12: OLS: Student Loan Balances on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR	1163.060***	1496.441***	1313.210***	1199.106***	1231.096***	1316.965***	1375.887***	1498.742***	1621.858***	1727.474***	1859.145***	2025.338***	2152.936***	2357.969***	2708.982***	3004.299***	3272.805***
	(38.641)	(42.194)	(45.549)	(46.900)	(49.436)	(53.152)	(58.000)	(62.446)	(67.541)	(73.557)	(80.485)	(87.341)	(94.257)	(103.365)	(105.012)	(112.975)	(126.682)
N	121645	121799	123685	125315	125983	124552	124482	124736	123162	122235	121471	120749	119918	113302	101501	93858	88598

Note:* $p < 0.05$,** $p < 0.01$,*** $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 13: 2SLS: Federal Student Loan Balances on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR*	1914.227***	2048.347***	546.971*	99.047	-81.802	-627.055*	-1300.036***	-1758.215***	-2005.981***	-2602.141***	-3222.694***	-3645.293***	-3622.579***	-3401.158***	-2215.408**	-1933.641*	-2766.707**
	(172.246)	(191.281)	(212.608)	(228.024)	(249.791)	(275.015)	(309.592)	(342.547)	(379.337)	(424.705)	(479.687)	(541.270)	(593.424)	(663.418)	(694.173)	(786.123)	(966.593)
N	121639	121795	123682	125312	125980	124549	124479	124732	123158	122231	121467	120744	119913	113297	101497	93857	88596

Note:* $p < 0.05$,** $p < 0.01$,*** $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 14: Potential Treatment Dates

Plan	Date Enacted	Time horizon	Payment Amount	Financial Need
ICR	1995	25 years	20%	NO
PAYE	7/2013	20 years	10%	YES
REPAYE	7/2016	20-25 years	10%	NO
IBR-Borrowers before 2014	2007	25 years	15%	YES
IBR-Borrowers after 2014	2010	20 years	10%	YES

Table 15: Heterogeneity by Payment Plan

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR*	0.021**	0.029***	0.034***	0.037***	0.037***	0.039***	0.038***	0.045***	0.041**	0.053***	0.047**	0.050**	0.050**	0.056**	0.071**	0.073**	0.066*
	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)	(0.011)	(0.011)	(0.012)	(0.013)	(0.014)	(0.015)	(0.016)	(0.017)	(0.019)	(0.022)	(0.025)	(0.030)
IDR* x Indicator for PAYE Eligible	0.009	0.003	0.003	0.003	0.007	0.000	0.011	0.009	0.012	0.005	0.014	0.010	-0.004	-0.002	0.007	-0.020	-0.029
	(0.009)	(0.010)	(0.011)	(0.012)	(0.013)	(0.014)	(0.014)	(0.016)	(0.017)	(0.018)	(0.019)	(0.021)	(0.023)	(0.025)	(0.028)	(0.032)	(0.038)
Indicator for Paye Eligible	-0.008***	-0.009***	-0.009***	-0.009***	-0.010***	-0.010***	-0.012***	-0.012***	-0.013***	-0.013***	-0.015***	-0.015***	-0.013***	-0.013***	-0.014***	-0.012**	-0.010*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
N	121639	121795	123682	125312	125980	124549	124479	124732	123158	122231	121467	120744	119913	113297	101497	93857	88596

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 16: Heterogeneity by Initial Amount Borrowed Bin

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR	0.053***	0.056***	0.068***	0.061***	0.069***	0.076***	0.083***	0.087***	0.098***	0.110***	0.106***	0.103***	0.093**	0.083*	0.122**	0.147***	0.118*
	(0.013)	(0.014)	(0.014)	(0.015)	(0.016)	(0.017)	(0.019)	(0.021)	(0.023)	(0.025)	(0.026)	(0.027)	(0.031)	(0.034)	(0.038)	(0.042)	(0.050)
Instrument IDR x 2nd Quartile Borrowing	-0.036*	-0.036*	-0.048**	-0.037*	-0.041*	-0.046*	-0.055*	-0.054*	-0.070*	-0.080**	-0.069*	-0.064	-0.074	-0.056	-0.080	-0.108*	-0.104
	(0.015)	(0.016)	(0.017)	(0.019)	(0.020)	(0.021)	(0.023)	(0.026)	(0.028)	(0.031)	(0.032)	(0.035)	(0.039)	(0.043)	(0.048)	(0.052)	(0.062)
Instrument IDR x 3rd Quartile Borrowing	-0.034*	-0.030	-0.034*	-0.027	-0.032	-0.043*	-0.034	-0.037	-0.054*	-0.057*	-0.051	-0.048	-0.029	-0.014	-0.038	-0.056	-0.034
	(0.014)	(0.016)	(0.017)	(0.018)	(0.019)	(0.020)	(0.022)	(0.024)	(0.026)	(0.029)	(0.030)	(0.032)	(0.036)	(0.040)	(0.044)	(0.049)	(0.058)
Instrument IDR x 4th Quartile Borrowing	-0.024	-0.022	-0.029	-0.014	-0.026	-0.035	-0.040	-0.035	-0.034	-0.043	-0.051	-0.044	-0.054	-0.014	-0.055	-0.203***	-0.168*
	(0.015)	(0.017)	(0.017)	(0.019)	(0.020)	(0.021)	(0.024)	(0.026)	(0.028)	(0.031)	(0.032)	(0.035)	(0.039)	(0.044)	(0.050)	(0.057)	(0.071)
2nd quartile borrowing	0.016***	0.019***	0.022***	0.021***	0.022***	0.025***	0.026***	0.026***	0.027***	0.030***	0.028***	0.027***	0.028***	0.028***	0.030***	0.031***	0.031***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
3rd quartile borrowing	0.023***	0.026***	0.028***	0.028***	0.030***	0.034***	0.032***	0.033***	0.036***	0.037***	0.037***	0.037***	0.036***	0.036***	0.039***	0.042***	0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
4th quartile borrowing	0.026***	0.031***	0.034***	0.034***	0.039***	0.043***	0.044***	0.045***	0.046***	0.049***	0.053***	0.054***	0.061***	0.056***	0.060***	0.082***	0.082***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
N	121639	121795	123682	125312	125980	124549	124479	124732	123158	122231	121467	120744	119913	113297	101497	93857	88596

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 17: 2SLS: Likelihood Past Due on Student Loans on IDR

	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
IDR*	-0.208***	-0.229***	-0.241***	-0.260***	-0.284***	-0.304***	-0.340***	-0.341***	-0.353***	-0.355***	-0.326***	-0.323***	-0.301***	-0.266***	-0.216***	-0.183***	-0.182***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)	(0.017)	(0.018)	(0.019)	(0.019)	(0.020)	(0.022)	(0.025)	(0.029)	(0.033)
N	138767	138659	140523	142048	142549	140794	140701	140905	139056	138057	137170	136258	135288	127563	114113	105510	99433

Note:$*$ $p < 0.05$,$**$ $p < 0.01$,$***$ $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 18: 2SLS: Credit Score on IDR

	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
IDR*	48.346***	49.826***	49.966***	52.366***	54.176***	56.268***	55.932***	57.102***	58.637***	59.579***	59.695***	61.739***	62.017***	61.783***	58.920***	57.838***	56.792***
	(2.663)	(2.714)	(2.784)	(2.905)	(3.022)	(3.139)	(3.303)	(3.463)	(3.642)	(3.830)	(4.017)	(4.245)	(4.493)	(4.881)	(5.623)	(6.491)	(7.489)
N	138767	138659	140523	142048	142549	140794	140701	140905	139056	138057	137170	136258	135288	127563	114113	105510	99433

Note:$*$ $p < 0.05$,$**$ $p < 0.01$,$***$ $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 19: OLS: Works in teacher or health care occupation

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR	0.000	0.001	0.001	0.000	-0.000	0.001	-0.001	-0.000	0.001	-0.001	-0.002	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
N	138769	138660	140524	142049	142550	140795	140702	140907	139058	138059	137171	136259	135289	127564	114113	105510	99433

Note: $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 20: 2SLS: Works in teacher or health care occupation

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR*	0.002	0.002	-0.001	0.006	0.007	0.006	0.006	0.006	0.010	0.015**	0.009	0.014*	0.015*	0.012	0.022*	0.019	0.027*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)	(0.012)
N	138767	138659	140523	142048	142549	140794	140701	140905	139056	138057	137170	136258	135288	127563	114113	105510	99433

Note: $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 21: OLS: Has mortgage on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR	0.033***	0.034***	0.032***	0.034***	0.032***	0.030***	0.028***	0.027***	0.029***	0.027***	0.027***	0.022***	0.019***	0.015***	0.012***	0.006	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
N	121645	121799	123685	125315	125983	124552	124482	124736	123162	122235	121471	120749	119918	113302	101501	93858	88598

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 22: 2SLS: Has mortgage on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR*	0.088***	0.098***	0.087***	0.091***	0.094***	0.090***	0.097***	0.115***	0.127***	0.134***	0.134***	0.140***	0.162***	0.176***	0.148***	0.156***	0.144***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)	(0.013)	(0.014)	(0.015)	(0.016)	(0.018)	(0.019)	(0.021)	(0.023)	(0.027)	(0.031)
N	121639	121795	123682	125312	125980	124549	124479	124732	123158	122231	121467	120744	119913	113297	101497	93857	88596

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 23: OLS: Has small personally guaranteed business loan on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR	0.015***	0.014***	0.012***	0.012***	0.011***	0.010***	0.009***	0.009***	0.011***	0.010***	0.008***	0.008***	0.008***	0.007***	0.006**	0.007**	0.005*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	121645	121799	123685	125315	125983	124552	124482	124736	123162	122235	121471	120749	119918	113302	101501	93858	88598

Note: $* \ p < 0.05, ** \ p < 0.01, *** \ p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 24: 2SLS: Has small personally guaranteed business loan on IDR

	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR*	0.021**	0.019**	0.016*	0.014*	0.016*	0.018*	0.018*	0.019*	0.017	0.023*	0.021*	0.015	0.010	0.011	-0.006	-0.014	-0.013
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.013)	(0.014)	(0.017)
N	121639	121795	123682	125312	125980	124549	124479	124732	123158	122231	121467	120744	119913	113297	101497	93857	88596

Note:$*$ $p < 0.05$,$**$ $p < 0.01$,$***$ $p < 0.001$ Standard errors in parentheses. This table shows by quarter since end of first deferment spell after leaving college.

Table 25: IDR Choice Set by Treatment Group

Borrower with Direct Loans	ICR	REPAYE	IBR and potential payment	PAYE
Originating from 2007-10/2011	YES	YES	YES–15% of Disposable Income	NO
Originating from 2011-7/2014	YES	YES	YES–15% of Disposable Income	YES
Originating only after 7/2014	YES	YES	YES–10% of Disposable Income	YES

Table 26: DID-IV groups

Treatment	Control Borrowers	Treated Borrowers	Date of Treatment
PAYE roll-out	Loans 1/2010-9/2011	Loans 10/2011-7/2013	7/2013
IBR for New Borrowers	Last loan before 2014	Last loan after 2014	End of in-school deferment spell
REPAYE roll-out	All borrowers pre-2016	All borrowers post-2016	7/2016

Table 27: Exclusion Restriction Test

Quarter	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
IDR	0.031***	0.034***	0.036***	0.038***	0.041***	0.038***	0.043***	0.049***	0.048***	0.058***	0.058***	0.054***	0.049***	0.062***	0.066***	0.047**	0.032
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.012)	(0.013)	(0.015)	(0.017)	(0.019)
default	-0.001	0.014	-0.003	-0.021	-0.029**	-0.034**	-0.033**	-0.026*	-0.037**	-0.039**	-0.044**	-0.040*	-0.040	-0.027	-0.116	-0.223*	-0.311
	(0.015)	(0.017)	(0.012)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(0.015)	(0.017)	(0.024)	(0.054)	(0.078)	(0.112)	(0.172)
N	97017	93080	90261	89837	93503	93405	92338	91420	89301	87696	86042	84404	82773	77035	67979	61598	56793

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

References

J. D. Angrist and G. W. Imbens. Identification and estimation of local average treatment effects. *Econometrica*, 62:467–476, 1994.

H. Beyer, J. Hastings, C. Neilson, and S. Zimmerman. Connecting student loans to labor market outcomes: Policy lessons from chile. *American Economic Review*, 105(5):508–13, 2015.

S. E. Black, J. T. Denning, L. J. Dettling, S. Goodman, and L. J. Turner. Taking it to the limit: Effects of increased student loan availability on attainment, earnings, and financial well-being. *American Economic Review*, 113(12):3357–3400, 2023.

M. Boutros, N. Clara, and F. Gomes. Borrow now, pay even later: A quantitative analysis of student debt payment plans. *Journal of Financial Economics*, 159:103898, 2024.

J. Britton and J. Gruber. Do income contingent student loans reduce labor supply? *Economics of Education Review*, 79:102061, 2020. ISSN 0272-7757. doi: https://doi.org/10.1016/j.econedurev.2020.102061. URL https://www.sciencedirect.com/science/article/pii/S0272775720305471.

C. F. P. Bureau. Cfpb sues nation's largest student loan company navient for failing borrowers at every stage of repayment. *Consumer Financial Protection Bureau Press Release*, 2017.

B. Chapman and A. Doris. Modelling higher education financing reform for ireland. *Economics of education review*, 71:109–119, 2019.

B. Chapman and A. Leigh. Do very high tax rates induce bunching? implications for the design of income contingent loan schemes. *Economic Record*, 85(270):276–289, 2009.

M. Dinerstein, D. Koustas, C. Yannelis, and S. Earnest. Student loan forgiveness. *Available at SSRN 4899176*, 2024.

B. Frandsen, L. Lefgren, and E. Leslie. Judging judge fixed effects. *American Economic Review*, 113(1):253–277, 2023.

D. Herbst. The impact of income-driven repayment on student borrower outcomes. *American Economic Journal: Applied Economics*, 15(1):1–25, 2023.

J. R. Kling. Incarceration length, employment, and earnings. *American Economic Review*, 96(3):863–876, 2006.

D. S. Lee, J. McCrary, M. J. Moreira, J. R. Porter, and L. Yap. What to do when you can't use'1.96'confidence intervals for iv. Technical report, National Bureau of Economic Research, 2023.

M. Luo and S. Mongey. Assets and job choice: Student debt, wages and amenities. Technical report, National Bureau of Economic Research, 2019.

H. M. Mueller and C. Yannelis. Reducing barriers to enrollment in federal student loan repayment plans: Evidence from the navient field experiment. 2019.

J. Rothstein and C. E. Rouse. Constrained after college: Student loans and early-career occupational choices. *Journal of Public Economics*, 95(1-2):149–163, 2011.

J. Weidner. Does student debt reduce earnings? *Princeton University, Unpublished*, 2016.

M. Welch. Financial consequences of student loan delinquency, default, and servicer quality. *Working Paper*, 2024.

M. Wiswall and B. Zafar. How do college students respond to public information about earnings? *Journal of Human Capital*, 9(2):117–169, 2015.

C. Yannelis and G. Tracey. Student loans and borrower outcomes. *Annual Review of Financial Economics*, 14:167–186, 2022.

A Identifying Loans in Data

This appendix contains information regarding data dives on the data quality along with decisions we have made regarding our project. Our goal through this project is to identify individuals on income driven repayment plans. To do so, we need to separate federal loans form private loans; we also need to examine the agreed payment plans. It is important to note that any figures and numbers reported in this section use a 1% of the 2% national sample. Future iterations of this project will update these figures and numbers to be in line with the rest of the paper. THis has been done to ease computational time.

A.1 Identifying Federal Loans:

We identify federal direct loans with the following restrictions:

- Account condition code A1 for an open loan
- Ownership of the loan is identified as the borrowers (ECOA CD of 0,1,2,7,A,B,G,H)
- Open year is 2010 or later (institutional detail)
- Broad kind of business is either education-related or government (see section below)

A.2 What is broad kind of business?

In the UC-CCP, each line of credit has a kind of business code which corresponds to the kind of business executed by the lender. The first character identifies a broad category such as automotive (A), banks (B), etc. The second character is more detailed. We note this code is not unique within lender and may change depending on which line of credit we examine.

A.3 Why do we use broad kind of business?

Using the broad kind of business is a choice we are making that is distinct from other identification strategies. While federal direct loans were subject to the pause, private loans were not. When we looked at scheduled payments over the payment pause, we noticed different trends based on the kind of business of the lender servicing the student loan.

A.4 Identifying undergraduate loans and graduate/PP loans:

Similar to Black, Denning, Dettling, Goodman, and Turner (2023), we use undergraduate loan limits to restrict our data. We create an indicator for whether the student loan is below the undergraduate loan limit. One small difference that we make is the student loan must be below the undergraduate maximum loan limit the quarter before the first deferment period ends. Unsubsidized loans would not have interest capitalization until the period after; this definition also controls for multiple disbursements which may send the loan above the undergraduate maximum. In the figure below we document the number of student loan borrowers with loans within undergraduate loan limits, graduate loan limits, and above graduate loan limits. We note that the majority of student loan borrowers have loans below the undergraduate maximum, although we see a steady increase in the number of borrowers between the graduate and undergraduate maximum. This corresponds to potentially increasing tuition costs and graduate attendance. We also see increases in loans above the maximum, especially in 2022. These increases likely correspond to consolidation.

A.5 Identifying Repayment using Scheduled Payments

We use scheduled payments and payment status to identify the current repayment plan of a loan. When we examined the pre-2020 data, we saw the majority of scheduled payments are positive or the loan is in deferment or forbearance. After 2020, the majority of loans have a scheduled payment value of 0. We do note some issues in the data with payments coded as zero and conflicting payment information. Pre-2012 did have a percentage of zero scheduled payments; however, this issue appears to disappear after 2011. Approximately 2% of our selected sample of student loans has conflicting changes in balances, scheduled payments, and loan status. We cannot find a reasonable explanation as to why the balances are increasing or stagnant when the loan is in repayment, not deferment or forbearance, and loan payments are not being reported but the loan remains current. Either the account is misreported as current and the borrower is not making payments as scheduled or the scheduled payment amount is incorrect and should be lower than the interest rate. We do see some of these loans have a dash in their current payment status in the future which would suggest there was a reporting issue but we do not currently quantify how often this occurs. We intend to either impute values or drop these individuals from the sample in the future. We need to verify that these are random missing across servicers, not non-random missing. If not, this is a potential threat to identification. Additionally, this finding provides an avenue of further data exploration in terms of how payments are marked with relation to the loan status.

A.6 Identifying Repayment Plans

We identify loans in IDR by process of elimination. We cannot draw conclusions about repayment plans if the loan is still in deferment from school; therefore, we exclude these loans from our sample. For non-deferred loans, we calculate how much the scheduled payment should be if the loan was in a standard based repayment plan. If the loan matches the calculated standard repayment plan, then it is in the standard repayment plan. If the scheduled repayment does not match and the loan status is current, then the loan is in IDR. Example Loan Repayment Classification We provide an example to illustrate our repayment classification strategy. We will take a loan with a final disbursement amount of 5,500 in September 2014. We suppose the scheduled payment is 40 dollars. Our current identification strategy is as follows:

1. Is the loan deferred?
   - If yes, then deferred. If no, continue to 2.
     - We assume this loan is not deferred for the nature of the exercise.
2. Does the scheduled payment match what the standard repayment should be given the year the loan was originally disbursed?
   - If yes, then it is in standard repayment. If no, continue to 3.
     - The origination date is between 7/1/14-6/30/15. Therefore the interest rate is 4.66% and the effective monthly interest rate is 0.388%. We use the formula below to calculate the scheduled payment. We use one dollar on either side of the calculated payment to account for rounding. In our example, the calculated scheduled payment is 57.43 dollars. Therefore, scheduled payments between 56 dollars and 58 dollars would be considered a standard repayment payment.
     - A scheduled payment of 40 dollars is not standard repayment.

$$57.43 = 5500\frac{0.38 * ((1 + 0.38)^{120})}{((1 + 0.38)^{120}) - 1}$$

3. If not, does it match the standard repayment if the borrower receives a 25 basis point reduction from automatic payments?
   - If yes, then standard repayment. If no, continue to 4.
     - We repeat the calculation but use 4.41% (4.65%-.25) to calculate the scheduled payment. A 40 dollar scheduled payment is still below the calculated amount.
     - Therefore, we conclude this is not an undergraduate student loan in standard repayment.

4. If not, does the specified payment match the graduate rate or parent plus?
   - If yes, then standard repayment. If no, continue to 5.
     - We use the posted interest rate for graduate and parent plus loans. The interest rate for graduate loans disbursed in this time period was 6.21%. A 40 dollar scheduled payment is below the calculated standard graduate payment.
     - Therefore, we conclude this is not a graduate student loan in standard repayment.
5. Does the scheduled payment match the Perkins rate?
   - If yes, then standard repayment. If no, continue to 6.
     - The Perkins rate was 5% in 2014. A 40 dollar scheduled payment is still below the calculated payment.
     - Therefore, we conclude this is not a Perkins student loan in standard repayment.
6. To do: Does the scheduled payment meet a graduated repayment plan?
   - To meet a graduated plan, we need see whether monthly payments increase every 2 years but not more than 3X the amount. We also know IDR repayments are not required to cover interest but graduate repayment plans are.
   - If yes, then graduated. If no, continue onto 7.
7. If the payment does not match the scheduled repayment amount, is the loan current?
   - If no, then in collections. If yes, continue to 8.
     - This loan is current so we continue to 8.
8. Is the file date within the payment pause dates?
   - If yes, then it is paused. If no, then in IDR.
   - This loan with a 40 dollar repayment is in IDR since the file date is in 2015.

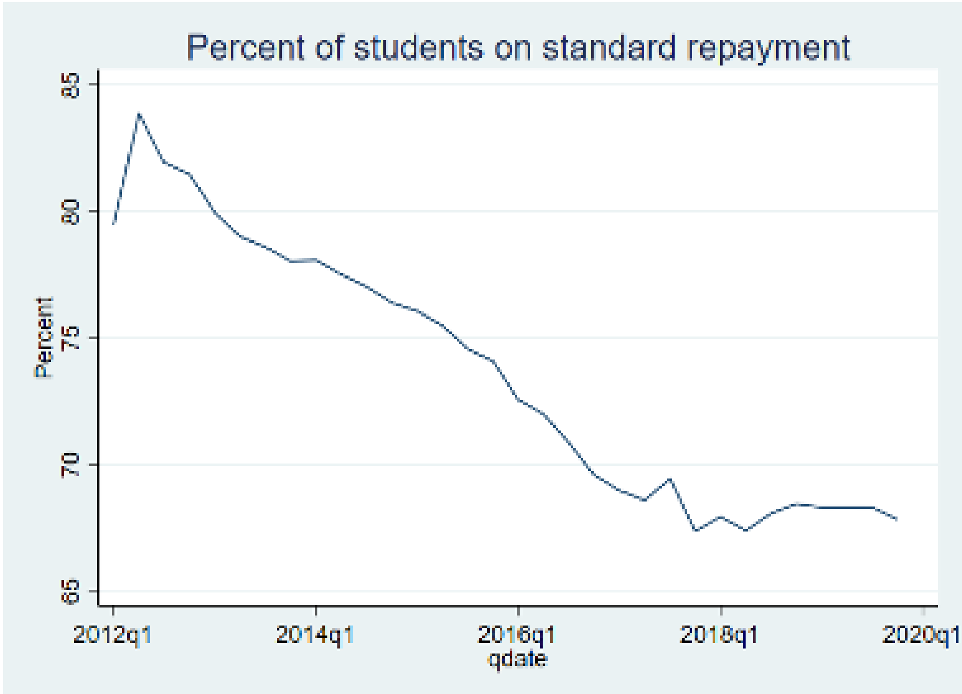
B Descriptive Graphs of IDR vs Standard Payments

We present three sets of figures to picture how repayment plans are coded in the data. First, we present an aggregated time series of percentage of borrowers in non-standard repayment plans. Figure 3 should mirror Figure 2-1 CBO publication 56277. Next, we present a set of graphs depicting the total amount of student loan dollars in each status code in a given year by what year the loan was disbursed. Our second set of figures depicts how student loan balances change for selected individuals and how our payment plans map to these changes in balances. These individuals were selected as individuals who have at least one student loan that is coded as in standard, IBR, or deferment in 2018. We choose 2018 since it is pre-pause.

In Figure 3, we present the percentage of our sample which is classified as being on the standard based repayment plan. All loans are restricted to those which pass the undergraduate maximum, educational loan, and date issuance restrictions. We select individuals who have a loan repayment plan prescribed. We do not exclude individuals who are currently in deferment or forbearance if they also have a repayment amount specified. Our goal is to recreate Figure 2-1 CBO publication 56277 using the steps we described above. We do exclude pre-2012 data since we know there are potential quality issues and the patterns and the computed values do not match the CBO figure. Additionally, there are some borrowers coded on multiple plans. This affects about 10% of the sample. We currently code those borrowers on standard repayment if more than 99% of the balances are on standard repayment and IDR if 99% are on IDR. If the borrower is in between, we do half and half. We do see some borrowers have multiple lenders with one lender on IDR and one lender on standard and unless we were certain, we did not want to mix those.

While Figure 3 does not exactly match the CBO figure, it does generally match the trend. In the CBO figure, approximately 90% of students are on a standard repayment plan in 2012. There is an accelerated decline starting in 2014 and the levels flatten to around 80% in 2017. Our current figure overestimates about 10% of individuals on standard repayment. This is likely due to us not currently including graduated repayment options in our current calculations.

Figure 3: Percent of Students on Standard Repayment



B.1 Descriptive Statistics for IDR Plans

In Figures 4, 5, and 6, we show the distribution of actual payments for individuals in IDR and standard repayment plans. Quarterly payments for each individual are aggregated across all tradelines that satisfy our four main criteria: educational loan after July 2010 that is below the undergraduate maximum and is open. Bins for IDR are shown in red and bins for standard based repayment are shown in blue. These graphs represent the entire sample from 2010-2020; therefore, individuals may appear more than once in the graph. On average, individuals classified as being on IDR are paying slightly less than the monthly payments from the payments from individuals on the standard based repayment plans. There is a fairly long tail for both IDR and the standard based repayment plan which may represent a few extreme outliers.

Figure 4: Scheduled Repayment Amounts by Plan Type

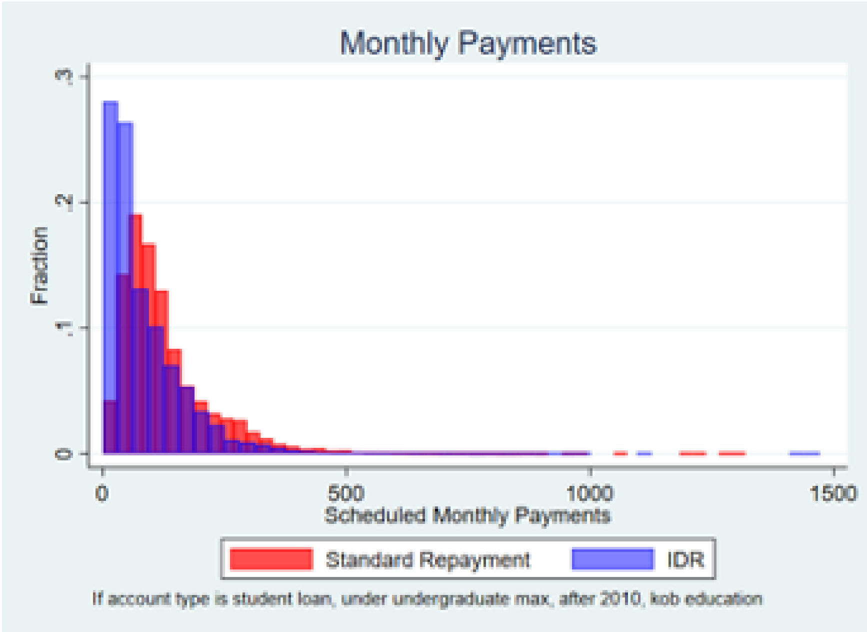


Figure 5: Actual Repayment Amounts by Plan Type

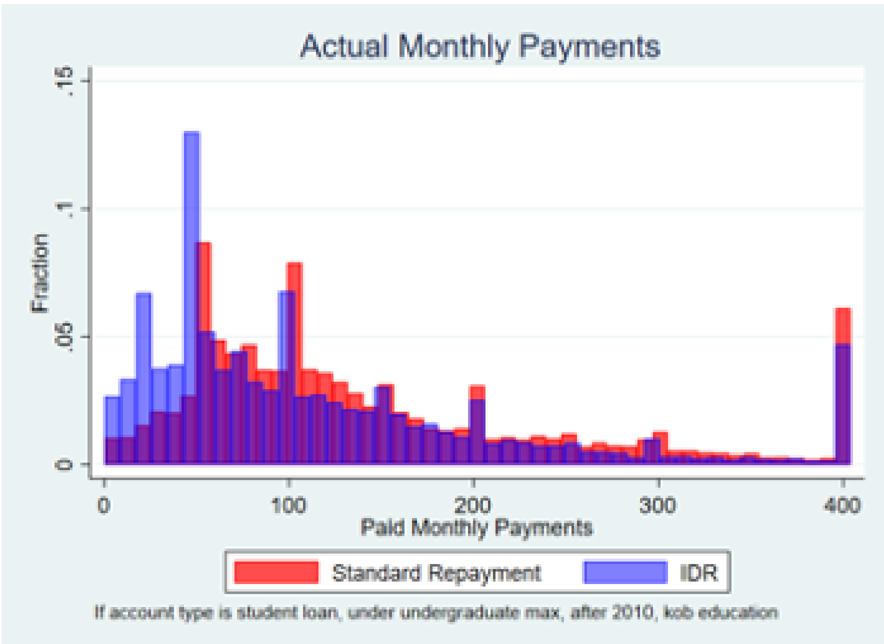
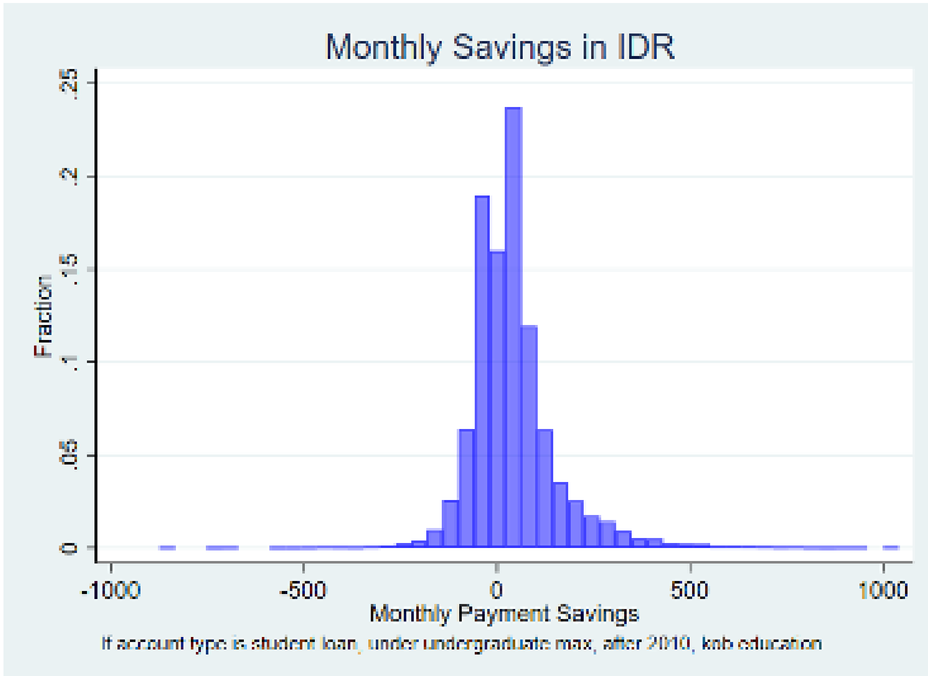


Figure 6: Monthly Savings in IDR (Scheduled Repayment-Hypothetical Standard Payment)



In Figures 7 and 8, we present numbers on how balances change with regards to the repayment plan for the 2014 cohort. We take the date of the last undergraduate loan and assign that to individuals as a graduation date. We then track how the balances change over each quarter and assign the loans to either growing, shrinking or staying the same. The black line represents those with shrinking balances. The blue line represents those with growing balances and the grey line represents those with unchanged balances from quarter to quarter. Each graph should have minimal loans prior to the graduation date by the nature of the data. We should then see an increase in the loans reported once the repayment period starts. As we would expect, we see a greater amount of dispersion in the IDR group. We see that while most standard payments are associated with a declining balance, not all IDR payments are. We also can see that even though IDR plans were available for the majority of the repayment period, not all borrowers are on IDR. This is consistent with our previous graphs which show about 70% of the undergraduate student loan population on a standard based repayment plan.

Figure 7: Growing, Shrinking, or Stagnant Balances for IDR Borrowers from 2014 Cohort

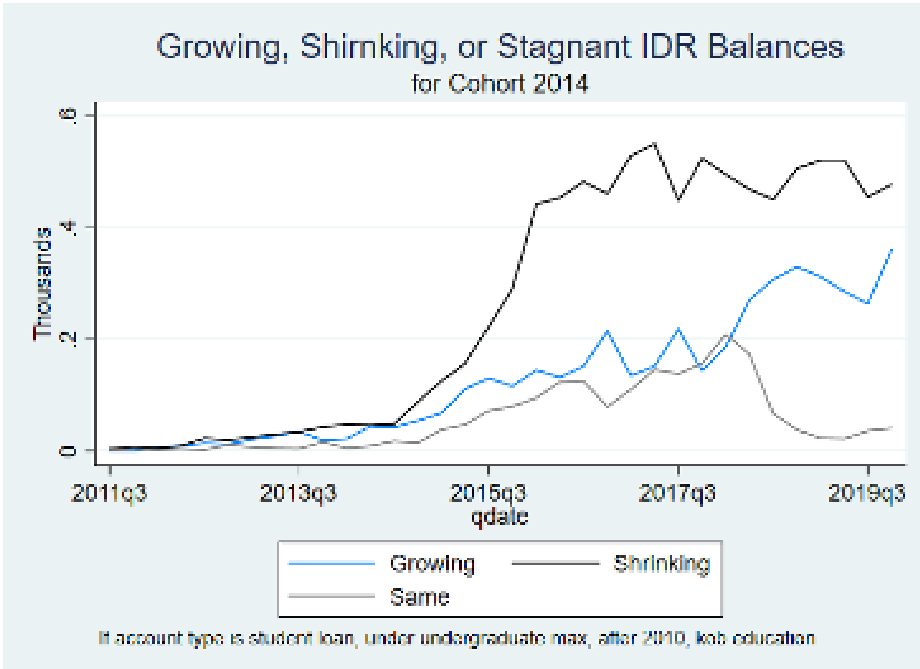
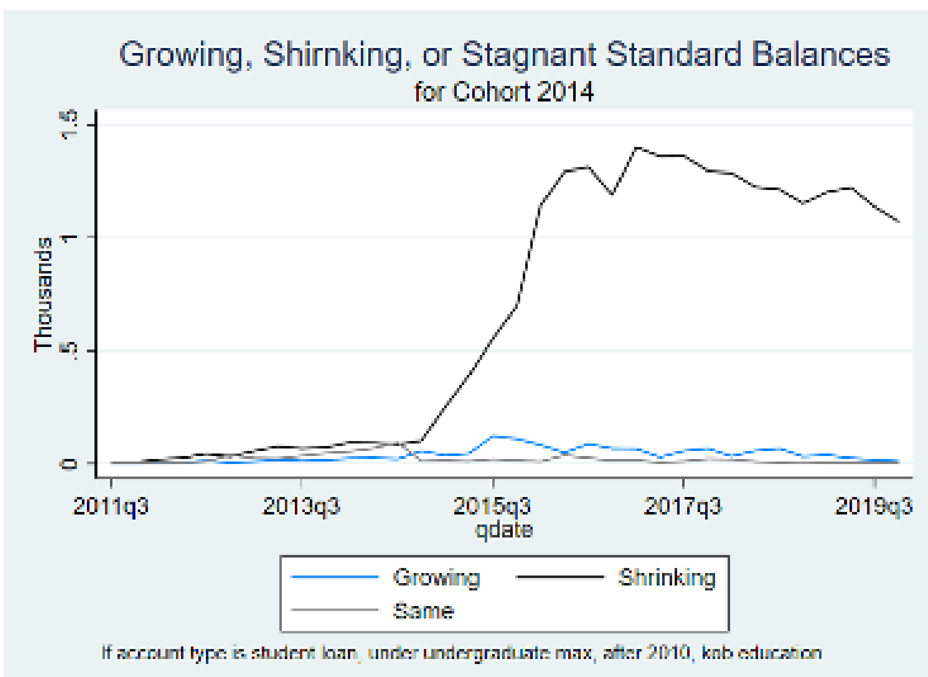


Figure 8: Growing, Shrinking, or Stagnant Balances for Standard Borrowers from 2014 Cohort



C Robustness to Other Servicer Services

To ensure validity of our exclusion restriction, we incorporate the instrument proposed by Welch (2024) into our main specification. As robustness to our specification, we adapt a more flexible approach by including the likelihood of the servicer being in default in our main specification, which Welch (2024) is her measure of servicer quality. We argue both could be a valid argument, but we do not think the quality of the servicer can be measured soley by the likelihood of their loans in default. Including both gives us the following model to estiamte,

$$Y_{it} = \beta_{0t} + \beta_{1t} IDR_{it} + \beta_{2t} D_{it} + \Gamma X_{it} + \epsilon_{it}. \tag{8}$$

This equation extends Equation (1), with the additional of D_{it}, which denotes the likelihood of the student loan being in default. As discussed in the main text, we argue the necessity of an instrument for *IDR* and construct it following the methodology outlined in Equation (5). For similar reasons highlighted by Welch (2024), an instrument for servicer quality—measured as the likelihood of being in default—is also required. We construct our instrument for default, following the approach described in Welch (2024). Just like being on IDR, default likelihood cannot be directly included in the regression, which means we use the following instrument, to instrument for the likelihood of D_{it}. The following equation shows how we estimate the residualized default, D_{it} values for individual i at time t,

$$D^*_{it} = D_{it} - \Gamma X_{it} = V_{st} + \nu_{it} \tag{9}$$

We note that the correlation between our two instruments is rather low, suggesting that they capture distinct dimensions of variation and are unlikely to suffer from issues of multicollinearity and thus can both be included in our model as outlined in Equation (8).

We show results in Table 27 and our findings reveal no significant changes in our estimates when including the default likelihood variable. Our estimates of the likelihood an individual takes out an additional student loan on IDR is largely unchanged. Consistent with the results reported in Welch (2024), we observe no substantial effect of the likelihood of default on other credit outcomes at the beginning of the time period. We do find that default leads to a lower likelihood of an individual taking out an additional student loan, which is consistent with individuals being ineligible for additional student loans while in default. This additional check also suggests that our additional student loan indicator is robust to student loan consolidation due to defaults.