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Increasing Enrollment in Income-Driven Student Loan Repayment Plans: Evidence from the Navient Field Experiment

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ABSTRACT

We report evidence from a randomized field experiment conducted by a major student loan servicer, Navient, in which student loan borrowers received prepopulated applications for income-driven repayment (IDR) plans. Treatment increased IDR enrollment by 34 percentage points relative to the control group. Using the random treatment assignment as an instrument for IDR enrollment, we furthermore provide local average treatment effect (LATE) estimates of the effects of IDR enrollment on new delinquencies, monthly student loan payments, and consumer spending. Our study is the first field-experimental evaluation of a U.S. government program designed to address the soaring debt burdens of U.S. households.

UNDER THE STANDARD 10-YEAR REPAYMENT plan, student loan borrowers make fixed monthly payments over a 10-year period. To help borrowers avoid delinquency and default, the federal government provides various income-driven repayment (IDR) plans under which monthly payments depend on the borrower's discretionary income—the difference between her annual income

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and (typically) 150% of the Federal Poverty Guideline (FPG). Moreover, the repayment period is extended up to 25 years, at the end of which any loan balance outstanding is forgiven. According to the U.S. Government Accountability Office (2016), the implied subsidy provided by the federal government for federal student loans in IDR plans in fiscal year 2017 is estimated to be $74 billion. This corresponds to a 21% subsidy rate, or an average cost to the government of $21 for every $100 in student loans disbursed. Similarly, according to the Congressional Budget Office (2020), the implied subsidy cost of federal student loans issued between 2020 and 2029 in IDR plans is estimated to be $83 billion, corresponding to a 17% subsidy rate.[1]

Despite outreach efforts by the Education Department and student loan servicers, enrollment in IDR remains low. Estimates by the Treasury Department indicate that only about 20% of borrowers who are eligible for IDR are enrolled in the program (U.S. Government Accountability Office (2015)).[2] Take-up remains low even if borrowers are "prequalified" (that is, preapproved conditional on income verification) and hence aware of their program eligibility. According to Navient, a major student loan servicer, "only 27% of prequalified borrowers were returning their applications. We studied the process and secured customer feedback, and determined that the complexity and effort required to print, sign and return the IDR application was negatively impacting the application return rate" (Navient (2017, p. 8)).[3] This view is shared by the White House. In 2012, President Obama expressed frustration over the difficulties in applying for Income-Based Repayment (IBR)—a type of IDR plan introduced by his administration:[4]

[1] These are budget definitions of subsidy cost based on procedures required by the Federal Credit Reform Act of 1990 (FCRA). Under the FCRA approach, projected cash flows are discounted using interest rates on Treasury securities, which reflect the government's cost of funding the loans. This arguably differs from how most economists would compute the implied cost of a government subsidy, namely, by using counterfactual market prices. See Lucas and Moore (2010) and Eberly (2010) for a discussion in the context of student loans, and Lucas (2016) for a discussion of the benefits and costs of federal credit programs more generally. The closest counterpart to a market-based subsidy estimate is the Congressional Budget Office's "fair-value estimate," which accounts for "the higher interest rates that private lenders would charge if they were to offer loans with similar terms" (2020, p. 20). Under this estimate, the implied subsidy cost of federal student loans in IDR plans is significantly higher, at $212 billion, which corresponds to a subsidy rate of 43%.

[2] Estimating how many borrowers are eligible for IDR is difficult because monthly payments, which are an essential part of the means test to determine whether a borrower is eligible, depend on the borrower's (discretionary) income. However, only borrowers who actually apply for IDR are required to provide income information to the Education Department. In this one-time analysis, the Treasury Department matched administrative student loan data from the Education Department's National Student Loan Data System (NSLDS) to IRS tax return data for a random sample of student loan borrowers.

[3] A copy of the 2017 IDR application can be found in the Internet Appendix, which is available in the online version of this article on *The Journal of Finance* website.

[4] Improving Repayment Options for Federal Student Loan Borrowers, Presidential Memorandum, The White House, June 7, 2012.

> [T]oo many borrowers have had difficulties navigating and completing the IBR application process once they have started it [...] Although the Department of Education has recently removed some of the hurdles to completing the process, too many borrowers are still struggling to access this important repayment option due to difficulty in applying.

Student loan servicers such as Navient review the various IDR plan options with borrowers, inform them about their eligibility, and prequalify them for the program. However, to enroll in an IDR plan, borrowers must go to the Education Department's centralized application portal and either apply online or print out, sign, and return a completed paper application.[5] In an effort to simplify this process, Navient conducted a randomized field experiment between April and July 2017 whereby, after talking to a Navient call center agent on the phone, treatment borrowers received prepopulated IDR applications that could be signed and returned electronically, whereas borrowers in the control group had to apply in the (usual) way described above. Prefilling applications is a simple intervention that can potentially be applied in many social programs that was previously suggested by behavioral economists as a way to encourage program take-up (e.g., Bertrand, Mullainathan, and Shafir (2004) (2006))) as well as by Navient in various communications with federal agencies (e.g., Navient (2015b)).

In this article, we report findings from the Navient field experiment. The experiment involved over 7300 borrowers who, by virtue of Navient's automated Interactive Voice Response (IVR) system, were randomly assigned to call center agents ("repayment plan specialists"). Control and treatment borrowers are well-balanced with regard to both (pre-randomization) characteristics and outcome variables. Prior to the field experiment, both groups of borrowers exhibit parallel trends and IDR enrollment rates of about 24%. During the field experiment, however, their IDR enrollment rates diverge. While the IDR enrollment rate of control borrowers remains practically unchanged, that of treatment borrowers increases sharply. In August 2017, after the field experiment, the IDR enrollment rate of treatment borrowers is 60.5%, which is 2.5 times their enrollment rate in March 2017 and 2.3 times their counterfactual enrollment rate in August.

How significant is this increase in IDR enrollment, that is, what is the forgone benefit for borrowers who qualify for IDR but do not enroll? To address this question, we simulate loan repayment paths under IDR and under the standard 10-year plan for a range of borrowers with different incomes and monthly payments under the standard plan. We find that borrowers with low incomes and high monthly payments enjoy large instant payment reductions as well as substantial debt forgiveness when enrolling in IDR, and nearly all borrowers benefit from payment smoothing. For a typical borrower in our sample, who has been making payments under the standard plan for many years,

[5] About 40% of IDR applications are submitted fully online, half are submitted using paper only by printing out the application form, and the rest are submitted online but with hardcopy income documentation (Navient (2015b)).

the present value (PV) benefit from switching to IDR ranges from $3017 to $13,947. Although most borrowers benefit from enrolling in IDR, the question of whether society as a whole benefits is more complicated, as generous debt relief programs such as IDR may have "ex ante effects" by making student loan borrowing more attractive. As we argue in the paper, the answer to this question depends on whether one believes that the current volume of student loan borrowing is excessive or "not enough" (Avery and Turner (2012)).

In the final part of the paper, we use the random treatment assignment as an instrument for IDR enrollment to estimate the effects of IDR on monthly student loan payments, new delinquencies, and consumer spending (using credit card balances and new auto financing transactions). We find decreases in monthly payments of $355 and in new delinquencies of 7.05 percentage points, and increases in consumer spending that roughly equal the decreases in monthly payments. In some cases, the local average treatment effect (LATE) estimates are several times larger than the corresponding ordinary least squares (OLS) estimates. This difference between LATE and OLS estimates is potentially informative about marginal borrowers who respond to the treatment. Indeed, compliers in the field experiment are relatively less sophisticated borrowers who are struggling with applications and are therefore receptive to application assistance. Accordingly, the difference between the LATE and OLS estimates suggests that less sophisticated borrowers benefit significantly more from IDR enrollment than does the population average—in other words, IDR program benefits and borrower sophistication are negatively related.

Our study is the first field-experimental evaluation of a U.S. government program designed to address the soaring debt burdens of U.S. households. In September 2020, U.S. household debt stood at $14.35 trillion—$1.68 trillion higher than the previous peak in 2008. With $1.55 trillion in outstanding balances, student loan debt is the second-largest consumer debt category, behind mortgages ($9.86 trillion) and before auto loan debt ($1.36 trillion) and credit card debt ($0.81 trillion).[6] Various other studies provide quasi-experimental evidence on the effects of U.S. government programs designed to help households with their debt burdens. Many of these debt relief programs were introduced in the aftermath of the Great Recession. Perhaps most prominently, the Home Affordable Modification Program (HAMP) provides mortgage lenders and servicers with incentives to modify the mortgage terms of borrowers at risk of default (interest rate and principal reduction, forbearance, term extension). Mortgage payments are capped at a fraction of monthly income—similar to the income dependence of monthly student loan payments in IDR plans. Using a range of identification strategies, Agarwal et al. (2017) and Ganong and Noel (2020) study the effects of HAMP on mortgage payments, foreclosure,

[6] Quarterly Report on Household Debt and Credit, Federal Reserve Bank of New York (2020:Q3).

delinquency, default, and consumer spending.[7] Our paper studies the effects of IDR on student loan payments, delinquency, and consumer spending using the random treatment assignment as an instrument for IDR enrollment.

A large literature in behavioral household finance studies psychological frictions in financial decision-making. A prominent example is the failure of many U.S. households to (optimally) refinance their mortgages (e.g., Agarwal, Rosen, and Yao (2016), Keys, Pope, and Pope (2016)). Related, price dispersion in consumer credit markets has frequently been linked to a lack of consumer sophistication, although it can also arise in rational models with differential search costs (e.g., Agarwal et al. (2020)). In the context of student loans, Cadena and Keys (2013) find that many students who are offered interest-free student loans turn them down. While this could be due to a lack of understanding of how the subsidy works, the authors conclude that the evidence is most consistent with models of impulse control. By contrast, our paper focuses on the hassle costs associated with applications. As Bertrand, Mullainathan, and Shafir (2004) (2006)) point out, while many economists might view such hassle costs as too minor to be taken seriously, these are exactly the kinds of hassles that dissuade many people from taking up social programs. Agarwal, Chomsisengphet, and Lim (2017) provide a comprehensive review of the behavioral literature studying consumer financial decision-making.

Our paper is part of a growing literature in household finance that studies student loans. Looney and Yannelis (2015) highlight the importance of borrower composition and the institutions they attend for student loan defaults, while Mueller and Yannelis (2019) focus on house prices and labor market conditions. Amromin, Eberly, and Mondragon (2019) study whether households use home equity to finance educational spending and find that a dollar of home equity reduces student loan debt by up to 80 cents. Several recent studies focus on student loan repayment plans, including IDR. Amromin and Eberly (2016) discuss the macroeconomic and normative implications of federal student loan repayment plans. Abraham et al. (2020) use a survey experiment to investigate how the framing of IDR affects IDR take-up, and Cox, Kreisman, and Dynarski (2020) use an incentivized laboratory experiment to study the role of information complexity and the default plan option for IDR take-up. Mueller and Yannelis (2019) and Herbst (2019) both examine the association between IDR and borrower outcomes. Using administrative NSLDS data, Mueller and Yannelis study the implications for loan defaults by comparing IBR-eligible and non-IBR eligible borrowers before and after the introduction of the IBR program in 2009. Using data from a student loan servicer, Herbst studies the implications for various borrower outcomes, including loan delinquencies and defaults, by comparing borrowers who enroll in IDR with those that do not enroll after receiving a delinquency call from their loan servicer. Both empirical strategies are observational and do not employ an experiment.

[7] The Home Affordable Refinancing Program (HARP) is another debt relief program introduced in the aftermath of the Great Recession. Agarwal et al. (2015) examine the effects of HARP on mortgage payments, foreclosures, and consumer spending.

Finally, Di Maggio, Kalda, and Yao (2019) study the implications of debt discharge resulting from the dismissal of collection lawsuits filed by National Collegiate, the largest owner of private student debt, against borrowers who had previously defaulted.[8] Different from our setting, the debt relief does not affect short-term liquidity, as the defaulting student loan borrowers already failed to make payments prior to the lawsuits.

The rest of this paper is organized as follows. Section I provides an overview of IDR plans. Section II offers background on Navient, describes the field experiment, provides summary statistics, and discusses external validity. Section III lays out the empirical framework and discusses the validity of the experimental design. Section IV studies whether the treatment—prepopulated IDR applications—accomplished its objective of increasing IDR enrollment. Section V discusses the benefits (and costs) of IDR for both an individual borrower and society as a whole. Section VI studies the effects of IDR on borrower outcomes—monthly payments, new delinquencies, and consumer spending—using the random treatment assignment as an instrument for IDR enrollment. Finally, Section VII concludes.

I. Income-Driven Repayment Plans

Under the standard 10-year repayment plan, a student loan borrower who has trouble making her monthly payments may be eligible to temporarily reduce or suspend payments through deferment or forbearance. If she misses a payment, the loan becomes delinquent. If the loan is delinquent for 271 days, it goes into default. The consequences of student loan delinquency and default can be severe. After 90 days of delinquency, the loan servicer reports the delinquency to all major credit bureaus. A lower credit score may impair the borrower's access to credit, ability to rent or buy a home, or prospects of finding a job. When a federal student loan goes into default, the borrower may be charged collection fees, wages may be garnished, and tax refunds and federal benefit payments may be withheld. Unlike other types of loans, student loans are not dischargeable in bankruptcy.

The standard repayment plan is the default plan. To provide student loan borrowers with alternative repayment options, the government has introduced a series of IDR plans under which monthly payments depend on the borrower's discretionary income—the difference between annual income and (typically) 150% of the FPG, which depends in turn on family size. Under most IDR plans, monthly payments are capped at what they would have been under the standard plan. The repayment period is extended up to 25 years, depending on the plan, at the end of which any outstanding balance is forgiven. To enroll in IDR, borrowers must pass a means test, whereby monthly payments under IDR must be less than what they would have been under the standard plan. There are four main types of IDR plans: Income-Contingent Repayment

[8] Private student loan borrowers and borrowers in default are not eligible for IDR. About 92.1% of student loans are federally owned or guaranteed; the remainder are private.

(ICR) plans (introduced in 1994), IBR plans (2009), Pay As You Earn (PAYE) plans (2012), and Revised Pay As You Earn (REPAYE) plans (2015). Although the four plans differ in their generosity and in how monthly payments are calculated, the common objective is to help student loan borrowers avoid delinquency and default by making monthly payments affordable. Indeed, the Education Department advertises on its website that "[d]epending on your income and family size, you may have no monthly payment at all."[9] In the first quarter of 2017 (immediately prior to the field experiment), 27.4% of federal student loan borrowers are enrolled in one of the four IDR plans (Federal Student Aid Data Center) yet delinquency and default rates remain high, underscoring the need to enroll (even) more borrowers in IDR.

One reason more borrowers are not enrolled in IDR could be lack of awareness. Student loan servicers therefore make it a priority to educate borrowers about alternative repayment options such as IDR. However, even if the loan servicer makes direct contact with the borrower, enrollment remains low. In a survey of delinquent borrowers that discussed enrolling in IDR with a Navient call center agent and that were prequalified during the call, only about 27% took the necessary steps to enroll. The other 73% did not complete enrollment despite receiving follow-up calls and written reminders (Navient (2016)).

II. The Navient Field Experiment

A. Navient

Navient owns and services a portfolio of federally guaranteed loans originated under the Federal Family Education Loan (FFEL) Program, which ended following the passage of the Health Care and Education Reconciliation Act of 2010. In addition, Navient has a contract to service Direct Loans for the Education Department, and it services a smaller portfolio of private education loans that are not federally guaranteed. In 2017, the year of the field experiment, Navient serviced over $300 billion in student loans for approximately 12 million Direct Loan, FFEL, and private student loan customers. The field experiment pertained to (federally guaranteed) FFEL loans that were owned and serviced by Navient.

Besides handling billing and payments, the role of student loan servicers is to educate borrowers about alternative repayment options, such as IDR. In the past, Navient repeatedly called for the process of enrolling borrowers in IDR to be simplified. For instance, on January 23, 2017, a few months prior to the field experiment, Navient president and CEO Jack Remondi said in an interview with the *Washington Post*:

> In the IDR application process, once we review the program with the borrower and pre-qualify them for the program, we have to send them away from Navient to studentloans.gov where they have to complete a 12-page

[9] According to a survey of 12,500 student loan borrowers enrolled in IDR, 38% of all borrowers and 47% of new enrollees (first year in IDR) make zero monthly payments (Navient (2015a)).

> application. They do it on the government's website, either online or by printing it and filling it out. There are no edit checks in that process, so if a customer makes a mistake or selects the wrong program, it gets sent to us by the Department of Education. We then have to return it, tell the borrower they've made a mistake, fix it. All of those things are very time-consuming and complex. [...] We've asked the department to be able to co-browse with borrowers on the website to assist them in completing the application to make sure they complete it correctly. We've asked for the right to do verbal enrollment. We've argued extensively for simplification and received zero response or action.

B. Field Experiment

At Navient, calls are routed through an automated IVR system, as is typical for call centers, that interacts with the customer, gathers basic information, and then routes the customer to the appropriate call center agent. Customers are routed to a "repayment plan specialist" if they have questions about alternative repayment options or indicate having trouble making payments. Repayment plan specialists must follow a set routine when talking to customers. If a customer is delinquent or indicates having trouble making payments, the repayment plan specialist is instructed to present and model alternative repayment options, such as IDR. Indeed, Navient provides its repayment plan specialists with "suggested speaks" of how to ask questions about income and family size so as to model IDR even when the customer is actively requesting a forbearance.

Between April 12 and July 31, 2017, Navient conducted a field experiment in which FFEL borrowers were randomly assigned to two groups of repayment plan specialists. One group ("control agents") handled applications for IDR in the usual manner. That is, the repayment plan specialist modeled and reviewed repayment options with the borrower and, if she was eligible, prequalified her for the program. The borrower then completed the IDR application on her own, either by applying online through the Education Department's centralized application portal or by printing, signing, and returning a completed paper application. The other group ("treatment agents") also modeled and reviewed repayment options with the borrower and, if she was eligible, prequalified her for the program. However, after the phone call, the repayment plan specialist emailed the borrower a prepopulated IDR application that could be signed and returned electronically.[10]

During the field experiment, borrowers were randomly assigned to control and treatment agents. Navient's automated IVR system places borrowers in a holding queue until the call is answered by the next available agent. Call center agents, in turn, do not know the identity of the caller before answering the call. Accordingly, borrowers do not get to pick which repayment plan

[10] Borrowers who did not certify zero income also received the prepopulated IRS Form 4506-T allowing Navient to obtain income information directly from the IRS.

specialist they talk to, and vice versa. During the field experiment, 7319 unique FFEL borrowers were routed to a Navient repayment plan specialist.[11] Of those, 4163 borrowers were routed to a control agent ("control borrowers") and 3156 were routed to a treatment agent ("treatment borrowers").

C. Descriptive Statistics

We have monthly data at the individual borrower level for all 7319 FFEL borrowers who were part of the field experiment. For each borrower, we know the date of the call and whether she was routed to a control or treatment agent. For borrowers enrolled in IDR, we also have information on their income. All borrowers enrolled in IDR need to (re-)certify their income annually. Finally, for 7115 of the 7319 borrowers in our sample, we have information on monthly credit card balances and the number of individual auto financing lines for August 2016 and August 2017 based on TransUnion data.

Table I provides summary statistics. The table reports means and standard deviations for control borrowers. All statistics are from March 2017, except for credit card balances and auto financing lines, which are from August 2016. The typical student loan borrower in our sample is 42 years old. By comparison, the average age of student loan borrowers in repayment in administrative NSLDS data is 37 years (Mueller and Yannelis (2019)). Virtually all borrowers are U.S. citizens and they come from all four U.S. Census regions: 16.5% are from the West, 22.6% from the Midwest, 47.7% from the South, and 13.3% from the Northeast.

The average amount of student debt disbursed is $11,078. By comparison, the amount of student debt when entering into repayment for the 2008 repayment year cohort—the median repayment year cohort in our sample—in NSLDS data is $13,504 (Looney and Yannelis (2015)).[12] About 95.1% of borrowers in our sample have at least one subsidized loan.[13] About 7.9% are in deferment, 9.6% are in forbearance, and 23.6% are enrolled in IDR. By comparison, 26.2% of *all* of Navient's Direct Loan or Education Department-owned FFEL borrowers are enrolled in IDR in the first quarter of 2017.[14] The new delinquency rate—the fraction of borrowers who are 60 or more days

[11] If a borrower had multiple interactions with Navient during the field experiment, treatment status is assigned based on the first call made.

[12] This comparison is imperfect, as the amount of student debt when entering into repayment includes the amount disbursed plus accrued interest until the beginning of repayment, so it is naturally higher. For example, suppose $2769.5 ($2769.5 × 4 = $11,078) is disbursed in each of four years during college, and the interest rate on student loans is 6% annually. Then the amount of student debt when entering into repayment, including accrued interest, is $12,842, which is close to the $13,504 reported in NSLDS data.

[13] Subsidized loans are undergraduate loans requiring an income test to demonstrate financial needs. They do not accrue interest while the borrower is in college at least half-time or during deferment periods.

[14] In percentage of dollars, 41.4% of Navient's Direct Loan and Education Department-owned FFEL program loans are enrolled in IDR in the first quarter of 2017 (Federal Student Aid Data Center).

Table I

Descriptive Statistics

This table reports means and standard deviations for control borrowers. *West*, *Midwest*, *South*, and *Northeast* are indicators of the Census region in which the borrower lives. *Principal* is the original principal amount disbursed on the borrower's FFEL loans. *Subsidized* is an indicator of whether the borrower has at least one subsidized FFEL loan. *Deferment* and *Forbearance* are indicators of whether the borrower is in deferment and forbearance, respectively. *IDR* is an indicator of whether the borrower is enrolled in an IDR plan. *Monthly Payment* is the monthly payment made by the borrower on her FFEL loans. *New Delinquency* is an indicator of whether the borrower is 60 or more days past due for the first time. *Credit Card Balance* is the total balance on all of the borrower's credit cards. *Auto Financing Lines* is the number of individual auto financing lines associated with the borrower. All descriptive statistics are from March 2017 based on 4163 control borrowers, except for credit card balances and auto loans, which are from August 2016 based on 4064 control borrowers.

	Control Mean	*SD*
Age	42	10
Citizen	0.9918	0.0900
West	0.1645	0.3708
Midwest	0.2263	0.4185
South	0.4766	0.4995
Northeast	0.1326	0.3391
Principal	11,078	14,405
Subsidized	0.9508	0.2164
Deferment	0.0788	0.2694
Forbearance	0.0961	0.2947
IDR	0.2359	0.4246
Monthly payment	256	323
New delinquency	0.0190	0.1365
Credit card balance	1761	4441
Auto financing lines	1.52	1.62

delinquent for the first time—is 1.9%. Finally, the typical borrower in our sample makes monthly payments of $256 on her FFEL loans, has a credit card balance of $1761, and has 1.52 auto financing lines.

Many of our sample borrowers are likely having trouble making payments. First, a median repayment cohort of 2008 implies that, in March 2017, many of them have likely gone through multiple forbearances and deferments.[15] (This also explains why our sample borrowers are slightly older.) Second, while we do not have information on income for all of our sample borrowers, we do know that borrowers switching over to IDR during the field experiment have a mean income of $27,176, which is low compared to the average personal (not household) income of $48,986 in the United States in 2017. Third, many of our sample borrowers are negatively amortizing. In March 2017, the average balance outstanding is $17,494, which is 58% above the average disbursement amount of $11,078. Indeed, 30% of our sample borrowers exhibited increasing

[15] Under the standard 10-year repayment plan, a borrower who enters into repayment in 2007 or before would have paid off her student loan by 2017.

balances between January and March 2017. Finally, and perhaps most important, all of our sample borrowers called Navient to speak to a repayment plan specialist, suggesting that many, if not most, have been struggling to make their monthly payments.

Although our results may overstate the benefits of IDR for a randomly selected student loan borrower, they are informative about the group of student loan borrowers who the IDR program is trying to target: borrowers who are having trouble making payments because their income is low and/or their monthly payments are high. In fact, borrowers with sufficiently high incomes and/or low monthly standard payments are not eligible for IDR, as the means test requires that monthly payments under IDR be less than under the standard plan. Note that most field experiments pertaining to social programs do not use random population samples but rather targeted samples based on likely program eligibility. For instance, Finkelstein et al. (2012) focus on uninsured low-income adults who signed up on a waiting list for a spot in the Medicaid program, Bhargava and Manoli (2015) focus on tax filers who failed to claim their Earned Income Tax Credit (EITC) despite presumed eligibility and the receipt of a reminder notice, and Finkelstein and Notowidigo (2019) focus on elderly citizens who are on Medicaid and thus are likely also eligible for the Supplemental Nutrition Assistance Program (SNAP).

III. Empirical Framework

A. Intent-to-Treat Effect

We estimate the intent-to-treat (ITT) effect of assisting student loan borrowers with completing IDR applications. In the field experiment, treatment borrowers received prepopulated IDR applications after talking to a Navient repayment plan specialist on the phone. By contrast, control borrowers, after talking to the Navient repayment plan specialist, had to complete the IDR application on their own, either by applying online through the Education Department's centralized website or by printing, signing, and returning a completed paper application. We estimate the ITT effect of this intervention, that is, the difference in mean outcomes between control and treatment groups, by estimating the following equation using OLS:

$$y_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 X_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is an outcome variable for borrower i, $Treatment_i$ is an indicator variable for whether borrower i received a prepopulated IDR application, X_i is a set of pre-randomization covariates, and ε_{it} is the error term. Although the covariates are not strictly necessary for obtaining an unbiased estimate, they can potentially improve power by accounting for chance differences in borrower characteristics between treatment and control groups. The set of covariates includes the full set of pre-randomization borrower characteristics from Table I: borrower age, citizenship, indicators for the four Census regions (West, Midwest, South, Northeast), principal amount disbursed, and

Table II

Treatment-Control Balance

This table reports results from estimating equation (1) without controls using one of the variables from Table I as the dependent variable. All dependent variables are measured in March 2017, except for *Credit Card Balance* and *Auto Financing Lines*, which are measured in August 2016. *Treatment* is an indicator of whether the borrower is a treatment borrower. Standard errors are Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Panel A: Pre-Randomization Covariates

	Age	Citizen	West	Midwest	South
Treatment	–0.2330	0.0015	–0.0004	–0.0082	0.0008
	(0.2276)	(0.0020)	(0.0087)	(0.0098)	(0.0118)
Constant	41.94***	0.9918***	0.1645***	0.2263***	0.4766***
	(0.1496)	(0.0014)	(0.0057)	(0.0065)	(0.0008)
	Northeast	Principal	Subsidized	Deferment	Forbearance
Treatment	0.0078	–648.61*	–0.0056	0.0052	–0.0010
	(0.0081)	(339.21)	(0.0053)	(0.0065)	(0.0069)
Constant	0.1326***	11,077.55***	0.9508***	0.0788***	0.0961***
	(0.0053)	(223.27)	(0.0034)	(0.0042)	(0.0046)
N	7319	7319	7319	7319	7319

Panel B: Pre-Randomization Outcome Variables

	IDR	Monthly Payment	New Delinquency	Credit Card Balance	Auto Financing Lines
Treatment	0.0085	–2.66	–0.0044	38.52	0.0625
	(0.0100)	(7.54)	(0.0030)	(107.48)	(0.0401)
Constant	0.2359***	256.11***	0.0190***	1760.86***	1.52***
	(0.0066)	(5.00)	(0.0021)	(70.74)	(0.0265)
N	7319	7319	7319	7115	7115

indicators for whether the borrower is in deferment, is in forbearance, or has subsidized loans.

B. Validity of Experimental Design

Navient's automated IVR system ensures that the treatment was randomly assigned among borrowers. As explained above, borrowers are placed in a holding queue until the call is answered by the next available agent. Call center agents, in turn, do not know the identity of the caller before answering the call. Thus, borrowers do not get to pick which call center agent they talk to, and vice versa.

Table II examines the balance between treatment and control group based on pre-randomization variables. Panel A considers the full set of characteristics included in the set of covariates, X_i: age, citizenship, Census region, principal amount disbursed, and indicators for whether the borrower is in deferment, is in forbearance, or has subsidized loans. Panel B considers all of our main outcome variables: indicators for whether the borrower is enrolled in IDR and is newly delinquent, respectively, monthly student loan payments, monthly credit card balances, and number of individual auto financing lines. All pre-randomization variables are measured in March 2017, except for credit card balances and auto financing lines, which are measured in August 2016. In each case, we estimate equation (1) without controls using as the dependent variable the respective pre-randomization variable. We report both the regression constant, β_0, and the main coefficient of interest, β_1. Under the null of treatment-control balance, β_1 should be statistically insignificant, whereas β_0 should be equal to the control mean in Table I. As can be seen, the coefficient β_1 is marginally significant (at the 10% level) in only one out of 15 regressions, which is consistent with what one would expect by chance under random assignment. In all other cases, β_1 is insignificant.

C. *Local Average Treatment Effect*

While equation (1) provides an estimate of the total effect of assisting student loan borrowers with IDR applications, we are also interested in the effects of IDR enrollment on borrower outcomes. To this end, we model the relationship between borrower outcomes and IDR enrollment as follows:

$$y_{it} = \gamma_0 + \gamma_1 IDR_{it} + \gamma_2 X_i + \zeta_{it}, \tag{2}$$

where y_{it} is an outcome variable for borrower i, IDR_{it} indicates whether borrower i is enrolled in IDR, X_i is a set of pre-randomization covariates, and ζ_{it} is the error term. Our main outcome variables are monthly payments, new delinquencies, credit card balances, and number of individual auto financing lines. The set X_i of covariates is the same as in equation (1).

We estimate equation (2) using two-stage least squares. The first-stage equation is given by equation (1) with IDR_{it} as the dependent variable. For $Treatment_i$ to be a valid instrument, the exclusion restriction requires that assisting student loan borrowers with IDR applications affects borrower outcomes in equation (2) only through its effect on IDR enrollment. In other words, receiving prepopulated IDR applications has *no direct* effect on monthly payments, new delinquencies, or consumer spending, other than through its effect on IDR enrollment. Given this identifying assumption, we interpret the coefficient on IDR enrollment from instrumental variable estimation of equation (2) as a LATE. It provides an estimate of the effect of IDR enrollment on the set of compliers who enrolled because of the intervention and who would have not enrolled otherwise (Imbens and Angrist (1994)).

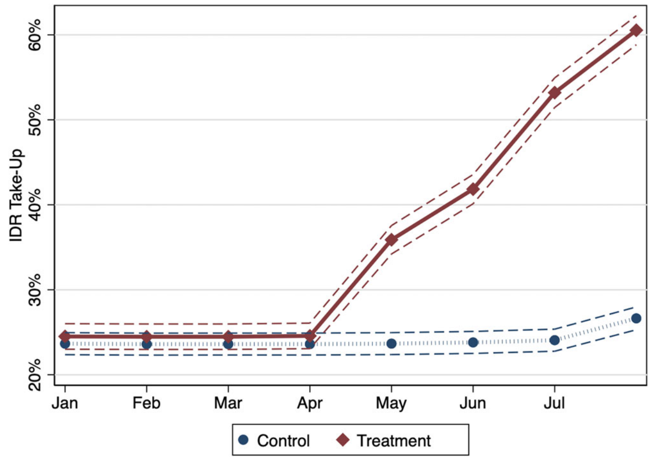

Figure 1. IDR take-up. This figure shows monthly cumulative enrollment rates in IDR for control and treatment borrowers. Dashed lines represent 95% confidence intervals. (Color figure can be viewed at wileyonlinelibrary.com)

IV. IDR Take-Up

In this section, we study whether the intervention—prepopulating IDR applications that could be signed and returned electronically—accomplished its objective of increasing IDR enrollment. In Section VI, we study the effects of IDR enrollment on borrower outcomes using the random treatment assignment as an instrument for IDR enrollment.

A. IDR Enrollment Rates

Figure 1 shows the cumulative percentage of control and treatment borrowers who are enrolled in IDR in a given month. As can be seen, both groups exhibit parallel trends prior to the field experiment—in fact, their IDR enrollment rates are statistically indistinguishable from one another. Enrollment rates in January, February, and March 2017 are about 24%, consistent with our pre-randomization estimates in Panel B of Table II. During the field experiment, the enrollment rate of control borrowers remains virtually unchanged. In August, after the field experiment, the enrollment rate stands at 26.6%. By contrast, the enrollment rate of treatment borrowers increases gradually. (The gradual increase reflects the fact that calls are spread out between April and July.) In August, 60.5% of treatment borrowers are enrolled in IDR—about 2.5 times their original enrollment rate in March and about 2.3 times their counterfactual enrollment rate in August.

Table III confirms this visual impression. We estimate equation (1) both with and without controls using IDR enrollment in August as the dependent variable. At the individual borrower level, IDR enrollment is an indicator of whether the borrower is enrolled in IDR in a given month. Accordingly, the

Table III
IDR Take-Up

This table reports results from estimating equation (1) using IDR enrollment in August 2017 as the dependent variable. *Treatment* is an indicator of whether the borrower is a treatment borrower. Column (1) is without controls. Column (2) includes the full set of pre-randomization covariates from Table II as controls. Standard errors are Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	(1)	(2)
Treatment	0.3391***	0.3407***
	(0.0111)	(0.0111)
Constant	0.2663***	0.2230***
	(0.0068)	(0.0767)
Controls	N	Y
N	7319	7319

coefficient β_1 on the *Treatment* dummy shows the difference in mean enrollment rates between control and treatment borrowers. In column (1), the regression constant is 0.2663, which corresponds to the August enrollment rate of control borrowers in Figure 1. Importantly, the coefficient on the *Treatment* dummy is 0.3391, implying an increase in IDR enrollment of 34 percentage points relative to the group of control borrowers. Adding up the two coefficients yields 0.6054, which corresponds to the August enrollment rate of treatment borrowers in Figure 1.

B. Alternative Interpretations

In the field experiment, borrowers who were randomly assigned to treatment agents received prepopulated IDR applications. Accordingly, we interpret the results in Figure 1 and Table III as reflecting the causal effect of receiving application assistance on IDR enrollment. A potential concern with this interpretation is that treatment agents may systematically differ from control agents in other ways unrelated to the prefilling of IDR applications, and these (other) differences may confound our results. Understanding the scope for potential confounds is especially important in view of the fact that the Consumer Financial Protection Bureau filed a lawsuit against Navient in January 2017 asserting that Navient did not do enough to enroll borrowers in IDR.[16] Navient, in contrast, had maintained for many years that the difficulty of enrolling borrowers in IDR lies in the complexity of the application process (e.g., Navient, 2015a, 2016; *Washington Post*, August 26, 2016). For instance, in 2016, about a year before the lawsuit, Navient asked the Education Department to run a field experiment on IDR enrollment, but the request was denied (*Washington Post*,

[16] See https://news.navient.com/legal-action-facts.

January 23, 2017). The current field experiment, in Spring 2017, was viewed as a "pilot program" to see whether it is possible to increase IDR enrollment.

Systematic differences between control and treatment agents may arise from behavioral responses (e.g., motivation, incentives) or selection. While it is impossible to completely rule out differences in behavior—for example, treatment agents expending more effort to enroll borrowers in IDR—to our knowledge there have been no differences in training, instructions, or incentives. Also, Navient's repayment plan specialists, like many call center agents, must follow a standardized script (including "suggested speaks") when talking to customers, which limits the scope for behavioral differences. As far as selection goes, the potential worry is that treatment agents may be positively selected, in the sense that they have a stronger "innate ability" to enroll borrowers in IDR. To examine this possibility, we match control and treatment agents from the field experiment to a *different* set of 1636 FFEL borrowers who dealt with these agents in the three months *prior to* the field experiment. During this (placebo) period, calls were also randomly assigned (by virtue of Navient's automated IVR system) but control and treatment agents did not (yet) differ in their authority to email prepopulated IDR applications. Figure IA.1 in the Internet Appendix shows the percentage of the 1636 borrowers enrolled in IDR in January, February, or March 2017 separately for borrowers who spoke with a treatment agent and borrowers who spoke with a control agent. As can be seen, control and treatment agents not only exhibit parallel trends, but their IDR enrollment rates during the placebo period are indistinguishable from each other.

Navient viewed the field experiment as a success and attributed the increase in IDR enrollment to the intervention—the prefilling of IDR applications that could be signed and returned electronically (Navient (2017)). It consequently began offering the treatment more broadly to all of its FFEL delinquent borrowers that it had previously spoken to and prequalified for the program. The broad rollout occurred in phases and began on August 28 and was completed on November 30, 2017.

C. Borrower Heterogeneity

As we show in Section V.B, borrowers with low incomes and high monthly payments benefit the most from IDR. Although it is not possible to identify individual compliers in the data, we can say something about their characteristics relative to the overall sample population. To this end, we follow Angrist and Pischke (2009, p. 171) and estimate our first-stage equation separately for different borrower subpopulations stratified by (pre-randomization) monthly payments. For a given subpopulation, the ratio of the subpopulation first-stage coefficient to the overall first-stage coefficient indicates the relative likelihood that compliers come from that particular subpopulation.

Table IV presents the results. We divide borrowers into quartiles based on their monthly payments in March 2017. For each quartile, we separately estimate equation (1) using IDR enrollment in August as the dependent

Table IV
Characterizing Compliers

This table presents variants of columns (1) and (2) of Table III in which equation (1) is estimated for subpopulations of borrowers stratified by pre-randomization monthly payments in March 2017. In columns (1) and (2), monthly payments are between \$0 and \$75; in columns (3) and (4), monthly payments are between \$76 and \$150; in columns (5) and (6), monthly payments are between \$151 and \$308; and in columns (7) and (8), monthly payments are above \$308. Odd-numbered columns are without controls. Even-numbered columns include the full set of pre-randomization covariates from Table II as controls. Standard errors are Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.1760***	0.2277***	0.3484***	0.3574***	0.3427***	0.3588***	0.3100***	0.3164***
	(0.0235)	(0.0225)	(0.0207)	(0.0205)	(0.0209)	(0.0206)	(0.0223)	(0.0219)
Constant	0.4002***	0.4359***	0.1448***	0.0046	0.1661***	0.3217**	0.2451***	0.1363
	(0.0150)	(0.1375)	(0.0109)	(0.1431)	(0.0118)	(0.1314)	(0.0132)	(0.1253)
Controls	N	Y	N	Y	N	Y	N	Y
N	1810	1810	1850	1850	1838	1838	1827	1827

variable.[17] As can be seen, compliers are less likely to come from the first quartile ($75 or less), while they are fairly evenly distributed across the other quartiles. Unfortunately, we cannot perform the same exercise using borrower income as only borrowers who are in IDR need to certify their income. That being said, we can see in our data that treatment borrowers who switch over to IDR during the field experiment—which includes the set of compliers—have a mean income of $27,176, which qualifies many (if not most) for zero monthly payments under IDR.[18]

V. Benefits (and Costs) of IDR Plans

Our results show that removing a seemingly small hassle—filling out an IDR application—increases IDR enrollment by 34 percentage points, or 127%. But how significant is this increase in IDR enrollment, that is, what is the forgone benefit for borrowers who qualify for IDR but do not enroll? To quantify this forgone benefit, and hence scale the implicit perceived cost of IDR enrollment, we compare simulated loan repayment paths under IDR and the standard 10-year plan for a range of borrowers with different incomes and monthly payments (and therefore loan amounts). We consider two income levels, $30,000 and $40,000, and three monthly payments, $100, $300, and $500. As a reference point, the average monthly payment in our sample is $256 (see Table I), and the average income of treatment borrowers who switch to IDR during the field experiment is $27,176 (see Section IV.C). To be conservative, we assume a family size of three and an income growth rate of 3% annually. If the family size is larger or the income growth rate is smaller (or income is lower or monthly payments are higher), the benefits of IDR enrollment are even greater.[19]

We separate the benefits of IDR enrollment into three categories: instant payment relief (Section V.A), debt forgiveness (Section V.B), and payment

[17] The number of observations is not exactly identical across bins due to multiple borrowers having the same monthly payment. More specifically, the first group includes 1809 borrowers (24.7%), the second group includes 1857 borrowers (25.4%), the third group includes 1827 borrowers (25.0%), and the fourth group includes 1826 borrowers (24.9%). It makes virtually no difference if we assign borrowers with the same monthly payment to the left or right of a given quartile cutoff.

[18] This lines up well with survey data. In a survey of 12,500 student loan borrowers enrolled in IDR, 18% of new enrollees (first year in IDR) report an annual household income of less than $15,000, while 57% report an annual household income of less than $35,000 (Navient (2015a)).

[19] We assume a loan interest rate of 6% and a discount rate of 4% annually—in line with assumptions made by the Congressional Budget Office (2020, p. 39). Given a family size of three, 150% of the FPG amounts to $32,580. Our FPG growth rate is 2.4% annually, which is the implicit FPG growth rate in the Education Department's *Loan Simulator*. We convert all annual growth rates into monthly growth rates to allow payments to vary at a monthly frequency. The IDR plan in our simulations is the original IBR plan, which is the relevant IDR plan available to FFEL borrowers in our sample. (The "new" IBR plan, which is only available to new borrowers on or after July 1, 2014, is even more generous.) Under the original IBR plan, any outstanding balance is forgiven after 25 years. Monthly payments are the lesser of 15% of discretionary income and what they would have been under the standard plan. Discretionary income is any income in excess of 150% of the FPG. Our simulated monthly IDR payments match those from the Education Department's *Loan Simulator*.

smoothing (Section V.D). Throughout we take the perspective of an individual borrower to gauge the implied cognitive costs of filling out and processing IDR applications. At the end of this section, we briefly discuss the role of government as well as broader implications for society.

A. Instant Payment Relief

Figure 2 shows that enrolling in IDR typically entails large, instant payment relief. With the exception of Panel D, monthly payments are much lower than under the standard plan for many years. Indeed, in Panels A to C, monthly payments under IDR are zero for almost 15 years. More generally, Figure 2 shows that there are two possible scenarios: income is either below (Panels A to C) or above (Panels D to F) 150% of the FPG. In the former case, monthly payments under IDR are zero; in the latter case, they are positive. In Panels A to C, monthly payments under IDR eventually become positive because income growth is higher than FPG growth, which implies that income eventually rises above 150% of the FPG. Finally, Panels D and E illustrate an important feature of (most) IDR plans, namely, monthly payments are capped at what they would have been under the standard plan.

Our simulations, like those by the Education Department's *Loan Simulator*, assume constant income growth. However, an important scenario for many borrowers is the possibility of a large negative income shock, as in the case of job loss. Although monthly payments under IDR drop along with the borrower's income in such a case (after income recertification), those under the standard plan remain fixed. And even though borrowers under the standard plan can apply for a temporary forbearance or deferment, such modifications are not automatically granted and must be approved by the loan servicer. Therefore, in addition to providing instant payment relief, IDR provides borrowers with valuable insurance against income shocks and thus ultimately against delinquency and default.[20]

B. Debt Forgiveness

Under IDR, any outstanding loan balance is forgiven at the end of the repayment period. Figure 2 illustrates the magnitude of this debt forgiveness. As can be seen, the *cumulative* payment amount—the sum of all monthly payments—is generally much lower under IDR, with the savings greatest when the

[20] How valuable is this insurance? Unlike other types of loans, student loans are not dischargeable in bankruptcy, and wages can be garnished for the rest of a borrower's working life. Wage garnishment in the United States is very effective. According to the Education Department, the cash recovery rate on defaulted student loans, after subtracting collection costs, is close to 100%, and the NPV recovery rate (which accounts for the timing of collected payments), again net of collection costs, is close to 90% (Department of Education, Student Loans Overview, Fiscal Year 2021 Budget Proposal). Hence, while student loan default entails many costs, including impaired credit access, it does not allow borrowers to get rid of their debt burdens. If anything, the value of insuring borrowers against default is therefore *higher* than for other types of consumer loans.

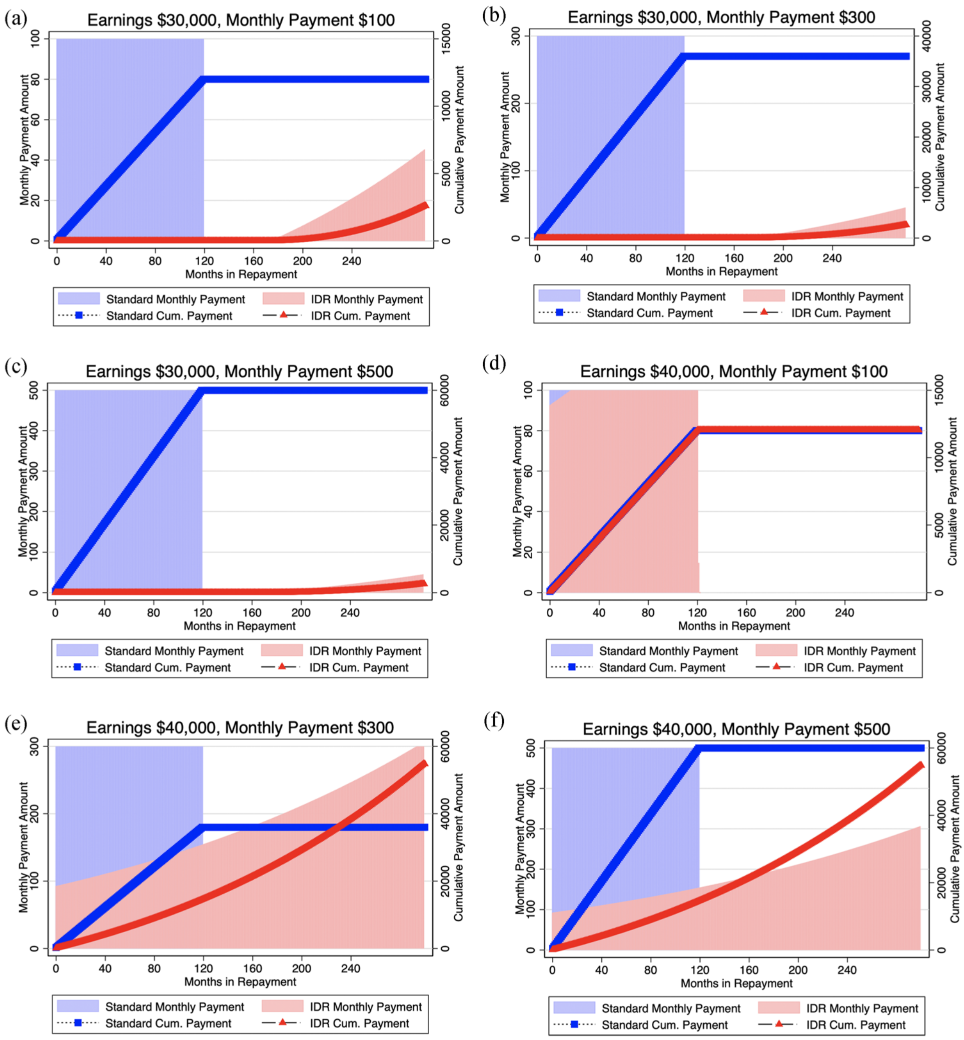

Figure 2. IDR payment simulations. This figure shows monthly and cumulative payments under the standard 10-year plan and under IDR for different levels of borrower earnings and monthly payments. The IDR plan is the (original) IBR plan described in Section V. (Color figure can be viewed at wileyonlinelibrary.com)

borrower's income is low and her monthly payments under the standard plan are high (as in Panel C). That being said, the cumulative payment amount does not always have to be lower under IDR. In Panel D, it is practically the same as under the standard plan, as the borrower pays off the loan in just a little over 10 years. And in Panel E, the cumulative payment amount under IDR is *higher* than under the standard plan. Although the loan is largely paid off at the end (there is relatively little debt forgiveness), interest has accrued throughout the

Table V

IDR Payment Simulations

This table provides additional statistics for the six scenarios in Figure 2. *Standard* refers to the 10-year standard plan. *Total Payments* is the sum of all monthly payments. *PV of Payments* is the PV of all monthly payments using a discount rate of 4% annually. *PV Amount Charged Off* is the PV of the outstanding (unpaid) balance under IDR, including accrued interest, at the end of the repayment period. *First Payment* is the first monthly payment under IDR; *Last Payment* is the last (nonzero) monthly payment under IDR

	30,000 Income		
Panels in Figure 2	Panel A	Panel B	Panel C
Standard Monthly Payment	100	300	500
(Disbursement amount)	(9007)	(27,022)	(45,037)
Standard total payments	12,000	36,000	60,000
Standard PV of payments	9910	29,730	49,550
	40,000 Income		
Panels in Figure 2	Panel D	Panel E	Panel F
IDR total payments	2611	2611	2611
IDR PV of payments	1106	1106	1106
PV difference in payments	8804	28,624	48,444
PV amount charged off	13,880	44,053	74,226
IDR first payment	0	0	0
IDR last payment	45	45	45
IDR total payments	12,050	54,808	54,830
IDR PV of payments	9923	31,496	31,504
PV difference in payments	–13	–1766	18,046
PV amount charged off	0	4211	34,376
IDR first payment	93	93	93
IDR last payment	100	300	306

entire repayment period. Ultimately, the amount of interest paid under IDR in Panel E is four times higher than under the standard plan ($36,260 vs. $8978).

Cumulative payment amounts do not take into account the time value of money. In Table V, we quantify the value of debt forgiveness in Figure 2 under IDR using two PV-based measures: the PV of the difference in monthly payments under the standard plan and IDR, and the PV of the amount charged off under IDR, defined as the outstanding (unpaid) loan balance at the end of the repayment period. Under IDR, this outstanding loan balance is forgiven. As can be seen, debt forgiveness under IDR can be substantial. For instance, in Panel B the PV of monthly payments under IDR is $28,624 lower than under the standard plan. In other words, the opportunity cost of (not) enrolling in IDR is $28,624. The PV of the amount charged off, $44,053, is even higher. Indeed, it is higher than the original loan balance of $27,022, which is possible as the outstanding loan balance at the end of the repayment period includes accrued interest.[21] In contrast, in Panel E the PV of monthly payments is $1766 higher under IDR. As discussed above, this is due to the fact that the amount of interest paid under IDR is four times higher than under the standard plan.

Naturally, if a borrower switches to IDR after several years of making payments under the standard plan, the loan balance, and therefore the possible debt forgiven, is smaller. To illustrate, consider again the income/monthly payment scenario from Panel B of Figure 2. If the borrower switches after five years, the PV (at the time of switching) of the difference in monthly payments is $16,028. If she switches after six, seven, or eight years, the savings are $13,118, $10,065, and $6865, respectively. Even if the borrower switches after nine years, with only one year left in the standard plan, the PV of the difference in monthly payments is still $3511.

What does this imply for the typical borrower in our sample? Given an average monthly payment of $256 and income of $27,176 (for treatment borrowers who switch to IDR), the opportunity cost of (not) enrolling in IDR, that is, the PV of the difference in monthly payments under the standard plan and IDR, is $25,370. However, this number is an upper bound. Since most borrowers in our sample have been making payments for many years, their opportunity cost of (not) enrolling in IDR is lower. For instance, a borrower who has been making payments for five years, still assuming a monthly payment of $256 and income of $27,176, would forgo "only" $13,947, while a borrower who has been making payments for six, seven, eight, or nine years would forgo $11,376, $8700, $5915, and $3017, respectively. Although the precise opportunity cost hinges on many factors, including the borrower's income, her monthly payments under the standard plan, and how many years she has been making payments, the range of numbers shown here suggests that the typical borrower in our sample would forgo substantial savings by not enrolling in IDR.

C. Comparison with Other Studies

Seemingly small hassle costs can have disproportionate effects on program take-up, especially when the program benefits are unclear or uncertain. In our context, borrowers may not fully understand, or trust, the amount of savings under IDR. Although student loan servicers inform borrowers about monthly savings under IDR, the overall PV benefits depend on many assumptions, including assumptions about the discount rate and future income growth.

[21] In Panel B, the loan is negatively amortizing throughout the repayment period despite positive payments in the last 10 years, as any unpaid interest is added to the balance. Negative amortization is typical for loans in IDR plans (Congressional Budget Office (2020, p. 15)).

For example, borrowers who overestimate their income growth will naturally underestimate the benefits of IDR. As we show below, our evidence suggests that the least sophisticated borrowers are the ones who stand to reap the greatest benefits from IDR.

With respect to application hassle, many studies find that the hassle involved with applications may prevent individuals from enrolling in social programs, often with significant negative consequences.[22] For example, in a field experiment in collaboration with the IRS, Bhargava and Manoli (2015) find that a simple "hassle intervention"—using a denser textual layout or including a few extra questions in the claims worksheet—reduces the take-up of EITC benefits by 17% to 27%. A typical nonclaimant is estimated to forgo \$1096 in EITC benefits, or about 12% of adjusted gross income. Note that unlike our PV estimates above, this opportunity cost pertains to a *single* year. Finkelstein and Notowidigo (2019) estimate the implied hassle costs of applying for SNAP (aka "food stamps"). Unlike our experiment, their field experiment studies application assistance together with an informational intervention ("Information Plus Assistance"). The intervention tripled SNAP enrollment. The cost of nonenrollment is estimated to be \$1500, or about 15% of household income. Again, this opportunity cost pertains to a single year. Finally, Bettinger et al. (2012) conduct a field experiment in which H&R Block tax professionals assisted individuals with completing the Free Application for Federal Student Aid (FAFSA). The intervention increased FAFSA filing rates by 40% to 165%, while college enrollment rates increased by 16% to 24%. Given an estimated NPV of a college education well above \$100,000 (Barrow and Malamud (2015)), this implies an opportunity cost of applications that is well above ours.

D. Payment Smoothing

Monthly payments under IDR vary with the borrower's income and are spread out over a long horizon of up to 25 years, depending on the plan. In contrast, monthly payments under the standard plan are fixed for 10 years and zero thereafter. Hence, we would expect monthly debt payments to be smoother under IDR.[23] Figure 3 plots the fraction of monthly income spent on making student loan payments under the standard plan and IDR for the six income/monthly payment scenarios from Figure 2. (The fraction is decreasing under the standard plan as income growth is positive while monthly payments

[22] As Bertrand, Mullainathan, and Shafir (2006, p. 16) note: "[w]hereas hassle costs may appear to a classical economist as too minor to be taken seriously, such hassles are likely to be especially detrimental in the context of program take-up." Currie (2006) provides a review of the early literature on program take-up. Explanations for the insufficient take-up of social programs are lack of information about eligibility, the stigma associated with program participation, and the hassle costs associated with enrollment. Bhargava and Manoli (2015, Section IV.A) provide a discussion of the hassle costs associated with program take-up.

[23] This argument only pertains to student debt payments. Whether overall debt payments are smoother depends on the nature of the other (e.g., mortgage, auto, credit card) debt payments.

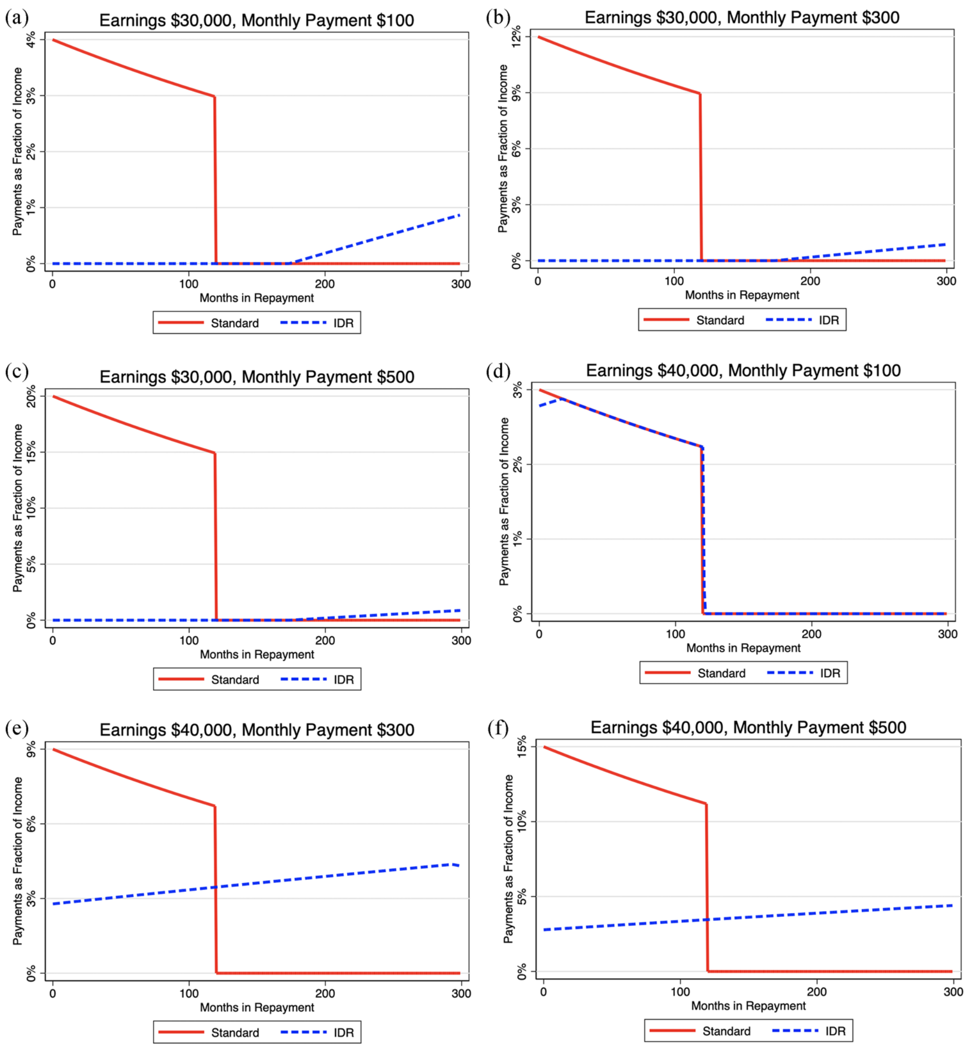

Figure 3. Payment smoothing. This figure shows the fraction of monthly income spent on student loan payments under IDR and under the standard plan for the six scenarios in Figure 2. (Color figure can be viewed at wileyonlinelibrary.com)

are fixed.) As can be seen, monthly payments as a fraction of income are generally much smoother under IDR. A notable exception is Panel D, where monthly payments are practically the same under both plans. In fact, even in Panel E, where the PV of monthly payments is higher under IDR (see Section V.B), monthly payments are significantly smoother under IDR. Hence, a third benefit of IDR, besides instant payment relief and debt forgiveness, is the smoothing of monthly payments.

E. Broader Implications

Many borrowers are likely to benefit from enrolling in IDR. A notable exception are borrowers with high incomes and low monthly payments (and hence low balances), who may end up paying more in interest, and therefore more in total, while not receiving much debt forgiveness (as in Panel E of Figure 2). However, these are not the typical borrowers who we see enrolling in IDR in our data.[24] Moreover, borrowers, and society at large, benefit from the reduction in delinquencies and defaults and from the (partial) insurance against labor income risk more generally. As previous studies show, "bad credit" and defaults may have significant adverse effects on future credit access, home ownership, family formation, and employment opportunities, among other things. On the other hand, tying student loan payments to income may potentially distort borrowers' choices during college as well as in the labor market.

A possible concern is that generous debt relief programs—such as IDR with its flexible repayment options and substantial debt forgiveness—may have "ex ante effects" by making student loan borrowing more attractive. Whether this is desirable is a matter of opinion. Although some observers, including media outlets and some politicians, frequently refer to the $1.6 trillion in outstanding student loan debt as a "student debt crisis," others caution that the economic rationale for the government provision of student loans is a market failure, namely, borrowers cannot pledge their future labor as collateral, which makes student loans fundamentally different from a car loan, mortgage, or business loan (e.g., Friedman (1962), Avery and Turner (2012), Dynarski (2014)).[25,26] Indeed, 92% of student loan debt in the United States is either issued or guaranteed by the federal government.[27] Hence, and different from other consumer credit markets, a unique feature of the student loan market is that the government is the primary (de facto monopolistic) lender, which provides generous subsidies not only through its student loan repayment program, but also—and perhaps especially—through its underlying student loan origination

[24] See Section IV.C. These are also not the typical borrowers who seem to enroll in IDR in administrative student loan data. Using data from the NSLDS, Karamcheva, Perry, and Yannelis (2020, p. 2) conclude that "Income-driven plans are adversely selected: Borrowers who are most likely to enroll are those with large balances and low post-graduation earnings."

[25] Examples of articles discussing the "student debt crisis" abound. For example: "What Is Driving the $1.5 Trillion Student Debt Crisis?" *Forbes*, September 1, 2020; "How Student Debt Became A $1.6 Trillion Crisis," *CNBC*, June 12, 2020; and "The Student Loan Debt Is $1.6 Trillion and People Are Struggling to Pay It Down," *CNN*, January 19, 2020.

[26] As Dynarski (2014, p. 2) notes, "there is no debt crisis: student debt levels are not large relative to the estimated payoff to a college education in the United States. Rather, there is a repayment crisis, with student loans paid when borrower's earnings are lowest and most variable."

[27] While 8% of student debt is private, those loans are different from federal student loans. As Dynarski (2016) points out, "there is a large, competitive, private market in a product misleadingly labeled 'student loans.' These private 'student loans' don't meet the standard definition of a student loan, because they typically require a creditworthy borrower or cosigner. This rules out most students: it's pretty unusual for a recent high school graduate to have a credit record that qualifies her as sole signatory on a private loan. These private 'student loans' are unsecured consumer credit with a soothing name [...]."

program.[28] Whether or not this government intervention is desirable from a societal perspective depends on whether one believes that student loan borrowing is excessive or perhaps not enough (see Avery and Turner (2012)).

VI. Borrower Outcomes

Using the random treatment assignment as an instrument for IDR enrollment, we study the effects of IDR on borrower outcomes: monthly payments, new delinquencies, and consumer spending (using credit card balances and new auto financing transactions). In each case, we present ITT effects from estimating equation (1), OLS estimates, and LATEs from instrumental variable estimation of equation (2). All borrower outcomes are measured in August 2017, one month after the field experiment. Prior to the field experiment, all outcomes are similar for control and treatment borrowers (see Section III.B).

A. Monthly Payments

In our simulations in Figure 2, IDR enrollment (almost always) leads to a large reduction in monthly payments—at least in the short run. Hence, the question is not so much whether monthly payments decline, but rather by how much, and whether the magnitudes can possibly tell us something about the marginal borrowers ("compliers") who respond to the treatment.

Figure 4 shows monthly payments for control and treatment borrowers in a given month. In the months before the field experiment, monthly payments trend slightly upward. Importantly, control and treatment borrowers exhibit parallel trends—in fact, their monthly payments are statistically indistinguishable from each another. Monthly payments of control borrowers continue on this upward trend during the field experiment, closing at \$273 in August. By contrast, monthly payments of treatment borrowers drop sharply during the field experiment, closing at \$152 in August, a decline of 40% relative to their March value and 44% relative to their counterfactual August value of \$273.[29]

Table VI confirms this visual impression. Columns (1) and (2) show ITT effects from estimating equation (1) using monthly payments in August 2017 as the dependent variable, with and without controls. In column (1), all estimates line up with the sample means from Figure 4: the regression constant is 272.70, which corresponds to the control mean in August, and the coefficient on the *Treatment* dummy is −120.52, which corresponds to the

[28] Federal student loans do not take the borrower's credit risk into account. As a result, their interest rate is generally lower than that of private student loans. However, federal student loans have borrowing limits—currently between \$5,500 and \$12,500 per year for undergraduate students. Private student loans are commonly used as a supplement when federal student loans do not cover a student's financial needs.

[29] Figure IA.2 in the Internet Appendix shows kernel density estimates of monthly payments in March and August separately for control and treatment borrowers. In March, the two distributions line up perfectly. By contrast, in August, the distribution associated with treatment borrowers exhibits a massive shift toward low and zero monthly payments.

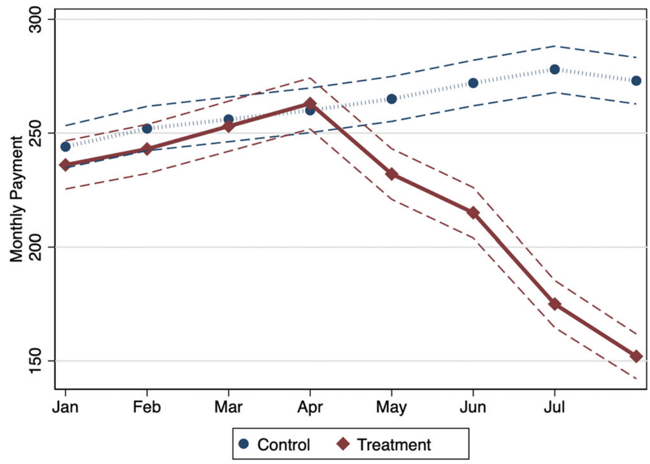

Figure 4. Monthly payments. This figure shows average monthly payments for control and treatment borrowers. Dashed lines represent 95% confidence intervals. (Color figure can be viewed at wileyonlinelibrary.com)

difference in means between control and treatment groups. Hence, the ITT effect of assisting borrowers with IDR applications is associated with a decrease in monthly payments of $120. Columns (3) to (6) examine the effect of IDR enrollment on monthly payments in August. Columns (3) and (4) present OLS estimates, while columns (5) and (6) present LATE estimates from instrumental variable estimation of equation (2). As can be seen, the LATE estimate in column (5) implies a reduction in monthly payments of $355, which is four times larger than the corresponding OLS estimate in column (3).[30] This difference between the LATE and OLS estimates is potentially informative about marginal borrowers who respond the treatment. In the field experiment, compliers are less sophisticated borrowers who are struggling with applications and are therefore receptive to application assistance. Thus, the difference between the LATE and OLS estimates suggests that less sophisticated borrowers benefit significantly more from IDR enrollment than does the population average, that is, borrower sophistication and program benefits are negatively correlated. For example, less sophisticated borrowers may have lower incomes, which would imply a larger decline in monthly payments upon enrolling in IDR.

B. New Delinquencies

Given the large decline in monthly payments, we would expect new delinquencies to decrease as well. Thus, like above, the question is not so much

[30] The decrease in monthly payments of $355 may not be permanent. As Figure 2 illustrates, monthly payments under IDR may remain low, or even zero, for a very long time, but they almost always increase at some point.

Table VI
Monthly Payments

This table reports results from estimating equations (1) and (2) using monthly payments in August 2017 as the dependent variable. *IDR* is an indicator of whether the borrower is enrolled in IDR in August 2017. *Treatment* is an indicator of whether the borrower is a treatment borrower. Columns (1) and (2) present ITT effects from estimating equation (1), columns (3) and (4) present OLS results from estimating equation (2), and columns (5) and (6) present LATEs from instrumental variable estimation of equation (2) using *Treatment* as an instrument for IDR enrollment. Odd-numbered columns are without controls. Even-numbered columns include the full set of pre-randomization covariates from Table II as controls. Standard errors are Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	ITT		OLS		LATE	
	(1)	(2)	(3)	(4)	(5)	(6)
IDR			–90.68***	–102.53***	–355.37***	–329.69***
			(7.82)	(6.30)	(23.82)	(19.80)
Treatment	–120.52***	–111.78***				
	(7.24)	(6.10)				
Constant	272.70***	–9.09	258.15***	–18.72	367.37***	78.72*
	(5.20)	(43.15)	(4.32)	(44.10)	(10.61)	(46.41)
Controls	N	Y	N	Y	N	Y
N	7319	7319	7319	7319	7319	7319

whether new delinquencies go down, but rather by how much, and whether the magnitudes can possibly tell us something about the compliers who respond to the treatment.

Figure 5 shows new delinquency rates—the fraction of borrowers who are 60 or more days past due for the first time—for control and treatment borrowers in a given month. Although the pattern is similar to that for monthly payments, new delinquency rates are much noisier. In any given month, only a few percent of borrowers are delinquent for the first time. Hence, relatively small changes in the number of newly delinquent borrowers can induce large swings in new delinquency rates. As can be seen, control and treatment borrowers are on similar trends prior to the field experiment. During the field experiment, however, new delinquency rates diverge. Specifically, while the new delinquency rate of control borrowers trends upward, consistent with the upward trend in monthly payments in Figure 4, the new delinquency rate of treatment borrowers declines. After the field experiment, in August, the new delinquency rate of treatment borrowers is 0.4%, whereas the new delinquency rate of control borrowers is 2.8%, with the difference between the two highly significant.

Table VII confirms this visual impression. The dependent variable is an indicator of whether the borrower is newly delinquent in August 2017. The ITT estimates in column (1) again line up perfectly with the sample means from Figure 5: the regression constant is 0.0283, which corresponds to the control mean in August, and the coefficient on the *Treatment* dummy is −0.0239, which

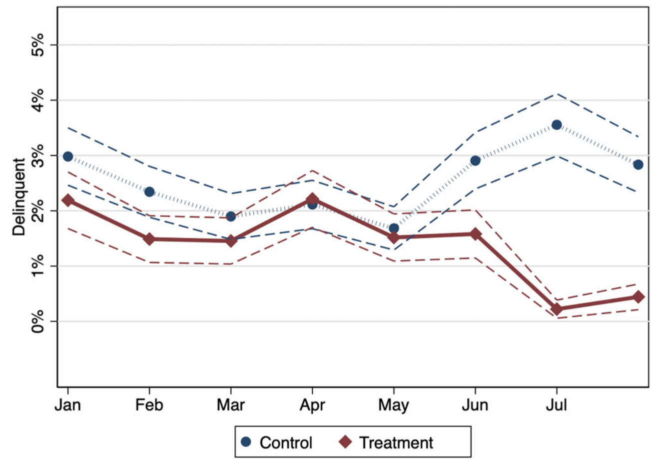

Figure 5. New delinquencies. This figure shows monthly new delinquency rates for control and treatment borrowers. Dashed lines represent 95% confidence intervals. (Color figure can be viewed at wileyonlinelibrary.com)

corresponds to the difference in means between control and treatment groups.[31] The LATE estimate in column (5) implies a decrease in new delinquencies of 7.05 percentage points, which is more than four times larger than the corresponding OLS estimate. As discussed above, this suggests that less sophisticated borrowers benefit relatively more from IDR enrollment than the population average.

C. Consumer Spending

Our estimates in Table VI show that borrowers who enroll in IDR experience large reductions in monthly payments of $355. In the final part of our analysis, we examine what borrowers do with the freed-up liquidity. We consider monthly credit card balances and—as a measure of durable consumer spending—new auto financing transactions.

Table VIII considers monthly credit card balances in August 2017. As column (5) shows, the LATE estimate implies that IDR enrollment is associated with an increase in monthly credit card balances of $343.[32] Although this result suggests that consumer spending goes up—credit card balances increase *because* money is spent on goods and services—changes in credit card balances are an imperfect measure of consumer spending. For this reason, many studies

[31] Figure IA.3 and Table IA.I in the Internet Appendix show that this result is not driven by borrowers with zero monthly payments. Although the magnitude is somewhat smaller when we exclude such borrowers—the treatment coefficient drops from −0.0239 to −0.0195—the effect remains large and highly significant.

[32] The first-stage regression for the sample of 7115 borrowers with available credit bureau data is virtually identical to that in Table III; the coefficient on the *Treatment* dummy is 0.3386 with standard error 0.0112, and the regression constant is 0.2659 with standard error 0.0070.

Table VII
New Delinquencies

This table reports results from estimating equations (1) and (2) using new delinquencies in August 2017 as the dependent variable. *New Delinquency* is an indicator of whether the borrower is 60 or more days past due for the first time. *IDR* is an indicator of whether the borrower is enrolled in IDR in August 2017. *Treatment* is an indicator of whether the borrower is a treatment borrower. Columns (1) and (2) present ITT effects from estimating equation (1), columns (3) and (4) present OLS results from estimating equation (2), and columns (5) and (6) present LATEs from instrumental variable estimation of equation (2) using *Treatment* as an instrument for IDR enrollment. Odd-numbered columns are without controls. Even-numbered columns include the full set of pre-randomization covariates from Table II as controls. Standard errors are Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	ITT		OLS		LATE	
	(1)	(2)	(3)	(4)	(5)	(6)
IDR			–0.0127***	–0.0127***	–0.0705***	–0.0710***
			(0.0030)	(0.0029)	(0.0095)	(0.0095)
Treatment	–0.0239***	–0.0241***				
	(0.0028)	(0.0029)				
Constant	0.0283***	0.0252**	0.0234***	0.0197*	0.0471***	0.0441**
	(0.0026)	(0.0111)	(0.0023)	(0.0110)	(0.0042)	(0.0222)
Controls	N	Y	N	Y	N	Y
N	7319	7319	7319	7319	7319	7319

Table VIII
Credit Card Balances

This table reports results from estimating equations (1) and (2) using credit card balances in August 2017 as the dependent variable. *Credit Card Balance* is the total balance on all of the borrower's credit cards. *IDR* is an indicator of whether the borrower is enrolled in IDR in August 2017. *Treatment* is an indicator of whether the borrower is a treatment borrower. Columns (1) and (2) present ITT effects from estimating equation (1), columns (3) and (4) present OLS results from estimating equation (2), and columns (5) and (6) present LATEs from instrumental variable estimation of equation (2) using *Treatment* as an instrument for IDR enrollment. Odd-numbered columns are without controls. Even-numbered columns include the full set of pre-randomization covariates from Table II as controls. The sample is restricted to 7115 borrowers with available credit bureau data. Standard errors are Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	ITT		OLS		LATE	
	(1)	(2)	(3)	(4)	(5)	(6)
IDR			233.94***	247.91***	343.16*	395.70**
			(61.86)	(63.25)	(180.91)	(183.41)
Treatment	116.20*	133.99**				
	(62.34)	(63.78)				
Constant	1810.33***	986.78***	1719.07***	925.90***	1718.07***	881.55***
	(38.06)	(354.42)	(39.25)	(358.19)	(80.48)	(392.79)
Controls	N	Y	N	Y	N	Y
N	7115	7115	7115	7115	7115	7115

Table IX

Auto Financing Lines

This table reports results from estimating equations (1) and (2) using auto financing lines in August 2017 as the dependent variable. *Auto Financing Lines* is the number of individual auto financing lines associated with the borrower. *IDR* is an indicator of whether the borrower is enrolled in IDR in August 2017. *Treatment* is an indicator of whether the borrower is a treatment borrower. Columns (1) and (2) present ITT effects from estimating equation (1), columns (3) and (4) present OLS results from estimating equation (2), and columns (5) and (6) present LATEs from instrumental variable estimation of equation (2) using *Treatment* as an instrument for IDR enrollment. Odd-numbered columns are without controls. Even-numbered columns include the full set of pre-randomization covariates from Table II as controls. The sample is restricted to 7115 borrowers with available credit bureau data. Standard errors are Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	ITT		OLS		LATE	
	(1)	(2)	(3)	(4)	(5)	(6)
IDR			–0.0129	–0.0147	0.2432*	0.2552**
			(0.0400)	(0.0408)	(0.1265)	(0.1287)
Treatment	0.0823**	0.0879**				
	(0.0389)	(0.0397)				
Constant	1.53***	1.47***	1.57***	1.52***	1.47***	1.41***
	(0.0255)	(0.0327)	(0.0233)	(0.0314)	(0.0503)	(0.0561)
Controls	N	Y	N	Y	N	Y
N	7115	7115	7115	7115	7115	7115

use auto purchases as an alternative measure of (durable) consumer spending (e.g., Mian, Rao and Sufi (2013), Agarwal et al. (2017)).[33] Although data on auto purchases are not available at the individual level—only at the ZIP-code level—one can proxy for auto purchases using new auto financing lines from credit bureau data (e.g., Agarwal et al. (2015), Di Maggio et al. (2017), Ganong and Noel (2020)). (Up to 90% of auto purchases in the United States are financed with debt.) Table IX considers new auto financing lines in August 2017. As column (5) shows, the LATE estimate implies that IDR enrollment is associated with 0.24 new auto financing transactions. To put this number into perspective, the median (25^{th} percentile) monthly auto loan payment in 2017 based on TransUnion data is \$378 (\$288), which implies an increase in monthly auto consumption of $0.24 \times \$378 = \$91$ ($0.24 \times \$288 = \$69$).[34]

[33] Di Maggio, Kermani, and Ramcharan (2015, Table 14) study auto purchases and credit card balances side by side and find that they respond similarly to monetary policy shocks.

[34] The field experiment runs from April to July 2017. We observe credit card balances and new auto financing lines before and after the field experiment, but not in between, in contrast to IDR enrollment, monthly payments, or new delinquencies. Thus, we cannot rule out the possibility that, theoretically, changes in credit card balances or new auto financing lines pre-date the treatment in some cases. However, for such pretreatment changes to explain our results, they would have to be spuriously correlated with the *Treatment* dummy, which is a random variable.

The large increase in consumer spending—which is similar in magnitude to the decrease in monthly payments—suggests that our sample borrowers are liquidity constrained. As mentioned before, their income is relatively low ($27,176 for treatment borrowers who switch to IDR), and many of them have likely been struggling to make repayments (see Section II.C).[35] That being said, an alternative explanation for the large consumption response is wealth effects. As discussed in Section V.B, enrolling in IDR may entail a significantly lower PV of payments, the anticipation of which may induce borrowers to increase consumption when they enroll. Although we cannot rule out such wealth effects in general, we believe they are small at best. While the literature documents large increases in consumer spending in response to liquidity shocks (e.g., Johnson, Parker, and Souleles (2006), Parker et al. (2013), Agarwal and Qian (2014), Baker (2018))—in fact, spending may increase by more than the liquidity shock itself[36]—marginal propensities to consume out of wealth have consistently been found to be small, typically between three and eight cents on the dollar (e.g., Zhou and Carroll (2012), Christelis, Georgarakos, and Jappelli (2015), Paiella and Pistaferri (2017), Aladangady (2017)). To illustrate, consider a typical sample borrower who has been making payments for five or more years. Suppose this borrower computes the PV of savings under IDR as we do in Section V.B and then spends the savings as a monthly consumption annuity over the following 30 years. The resulting increase in consumer spending is small: it ranges from $14 to $66 per month, which is only a fraction of the freed-up liquidity or, likewise, the increase in spending in Tables VIII and IX.[37]

D. Comparison with Other Studies

It is useful to relate our findings to those in other studies on debt relief. Using a randomized field experiment, Dobbie and Song (2020) find positive effects of long-term debt relief but not of short-term liquidity provision. While interest write-downs of $4302 in three to five years decrease the probability of filing for consumer bankruptcy by 3.1 percentage points, minimum payment reductions targeting short-run liquidity constraints *increase* the probability of filing for bankruptcy by 2.3 percentage points. In stark contrast, Ganong and Noel (2020), using quasi-experimental variation from HAMP, find that mortgage principal reductions that increase wealth without affecting liquidity have no impact on default or consumption, whereas maturity extensions that lower short-term mortgage payments (and improve liquidity) without

[35] The result in Table IV showing that IDR enrollment is higher among borrowers with large monthly payments further suggests that borrowers are liquidity constrained.

[36] Parker et al. (2013) find that low-income households spent 128% of their tax rebate from the Economic Stimulus Act of 2008 on consumption, consistent with the purchase of large durable goods.

[37] We assume monthly compounding of interest equivalent to 4% annually (the same discount rate as in Section V.B). For example, using a PV of $13,947, which corresponds to a typical borrower in our sample who has been making payments for five years, the monthly annuity payment is $66.01.

affecting long-term wealth have a positive impact: a 1% drop in monthly mortgage payments reduces mortgage default rates by 1.2%. The authors conclude that "liquidity, and not wealth, drives consumption and default decisions" (p. 3103), which is consistent with our discussion in Section VI.C. Similarly, exploiting variation in the timing of adjustable rate mortgage resets, Di Maggio et al. (2017) find that a 1% reduction in monthly mortgage payments reduces the likelihood of becoming delinquent by about 2%, while between 8.1% and 12.3% of the additional monthly liquidity is used for new car spending. By comparison, we find that a 1% reduction in monthly student loan payments reduces the likelihood of becoming newly delinquent by 1.9%, while between 12.9% and 16.9% of the freed-up monthly liquidity is used for new car spending.[38]

VII. Conclusion

Despite massive federal subsidies and outreach efforts by student loan servicers and the Education Department, take-up of IDR is low. Indeed, take-up remains low even if borrowers are prequalified and hence aware of their program eligibility. Survey evidence suggests that borrowers are overwhelmed by the complexity and effort required to fill out, sign, and return the IDR application. Between April and July 2017, Navient, a major student loan servicer, conducted a field experiment whereby, after talking to a Navient repayment plan specialist on the phone, treatment borrowers received prepopulated IDR applications that could be signed and returned electronically, whereas control borrowers had to go to the Education Department's centralized application portal and either apply online or print out, sign, and return a completed paper application.[39]

The evidence presented in this paper shows that a simple reduction in hassle cost, such as prefilling an application, can be highly effective: IDR enrollment among treatment borrowers increased by 34 percentage points relative to their counterfactual. Further evidence suggests that compliers—borrowers who enrolled in IDR because of the intervention—are borrowers with high monthly payments and low incomes. Indeed, such borrowers enjoy not only the largest instant decreases in payments upon enrolling in IDR, but also the largest debt forgiveness at the end of the extended repayment period.

Finally, using the random treatment assignment as an instrument for IDR enrollment, we study the effects of IDR on monthly student loan payments, new delinquencies, and consumer spending. Our LATE estimates are several

[38] Monthly student loan payments in the treatment group decrease by 44.2% relative to the control mean ($\$120.52/\$272.70 = 0.442$, see Table VI), while the new delinquency likelihood decreases by 84.5% ($0.0239/0.0283 = 0.845$, see Table VII), yielding an elasticity of $0.845/0.442 = 1.91$. New car spending increases between $(0.0823/1.53) \times \$288 = \$15.49$ and $(0.0823/1.53) \times \$378 = \$20.33$ relative to the control mean (see Table IX and Section VI.C), which implies that between $\$15.49/\$120.52 = 0.129$, or 12.9%, and $\$20.33/\$120.52 = 0.169$, or 16.9%, of the additional monthly liquidity is used for new car spending.

[39] Both groups of borrowers received help over the phone so as to prequalify for the program as well as an estimate of new lower monthly payments under the IDR plan.

times larger than the corresponding OLS estimates, suggesting that less sophisticated borrowers—who are struggling with applications and are therefore receptive to application assistance—benefit relatively more from enrolling in IDR than does the population average. In other words, program benefits and borrower sophistication are negatively related. More specifically, our LATE estimates show that monthly payments decrease by $355, new delinquencies decrease by 7.05 percentage points, and consumer spending increases by an amount similar to the decrease in monthly payments. The large magnitude of the consumption response suggests that our sample borrowers are likely to be liquidity constrained.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.