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Another Lesson on Caution in IDR Analysis: Using the 2019 Survey of Consumer Finances to Examine Income-Driven Repayment and Financial Outcomes

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We update Collier et al. (2021) by using the Survey of Consumer Finances (SCF) 2019 dataset to explore characteristics of enrollees in Income-Driven Repayment (IDR). SCF 2019 is more likely to include borrowers engaged in REPAYE. Findings support an ongoing need to encourage greater IDR participation for lowest-income borrowers and reinforced female borrowers were more likely than male borrowers to be enrolled. Again, model specification affects findings regarding IDR enrollment. REPAYE appears to have widened access to IDR by lowering the debt floor for entry. IDR enrollment was correlated with less money in a traditional checking account and a lower chance of engaging in retirement savings.

***Keywords*:** *Income-Driven Repayment, Student Loan Debt, Survey of Consumer Finances, Higher Education Policy*

Against the backdrop of the incoming Biden Administration and the pandemic-induced economic uncertainty, student loan debt again became a topic of intense national debate. Generally discussed are the merits of forgiveness and the function that Income-Driven Repayment (IDR) plays in the contemporary system (Catherine & Yannelis, 2020; Steinbaum, 2020). The conceptualization that student loan repayment should be tied to borrowers' income predates the current system (see Friedman, 1955); however, the *current* conceptualizations of national IDR policies arguably began in the 1990s with the development of the Income-Contingent Repayment plan (Shireman, 2017). Currently, four main plans that fall under the IDR umbrella: (1) Income-Contingent Repayment (ICR), (2) Income-Based Repayment (IBR), (3) Pay as you Earn Repayment Plan (PAYE), and (4) Revised Pay As You Earn Repayment Plan (REPAYE) – which was enacted in December 2015 (U.S. Congressional Budget Office, 2020). To date, research exploring the types of borrowers who take advantage of IDR and the financial effects on enrollees have been lacking (Collier, et al. 2021) - in part due to limited publicly available datasets that identify IDR enrollment and include information on debt loads and demographic characteristics (see Hillman & Bruecker, 2019). Recent attempts to identify who participates in IDR and relevant financial outcomes have also been flawed, by using convenience samples (Collier, 2020) or conducting analyses with datasets including a limited number of REPAYE enrollees (Collier et al., 2021). Generally, comprehensive data including REPAYE did not exist in public datasets, until the Survey of Consumer Finances (SCF) 2019 dataset was released late in 2020 (U.S. Federal Reserve Board, 2020). Therefore, this research *replicates* Collier and associates' (2021) models using the SCF 2019 dataset. The main questions are:

1. Does SCF 2019 data confirm Collier et al.'s findings of who participates in IDR?
2. Are there differences in outcomes between those in IDR and Traditional Repayment?

Prior Findings Using SCF 2016 Data

Collier et al. (2021) intended to bring clarity to the conversation surrounding who may be enrolled in IDR. However, their analyses revealed that outcomes were highly sensitive to model specification. Influenced by Collier's (2020) initial descriptive analysis, Collier and associates' (2021) first set of models suggested that female and minority borrowers were more likely than male and white borrowers to be enrolled in IDR. Overall, the amount of student loan debt (6 categories), level of educational attainment (6 categories), or wages (7 categories) were non-significant links to enrollment; except that those earning under $12,500 were 23-percentage points (pp) less likely to be enrolled than those earning between $40,000-54,999. The lack of findings between either loan debt or wages and participation in IDR was surprising.

Next, Collier et al. (2021) generated models guided by Looney & Yannelis (2018), who previously examined differences between those with "high" debt at or above $50,000 to borrowers with low debts. In these models, debt was denoted at "high" at $50,000+ and main effects were supplemented with a series of demographic, loan debt, and educational interaction terms. In two of the four models, female borrowers remained more likely to be enrolled in IDR, and in none were racial minority borrowers more or less likely than white borrowers to be enrolled. The analysis inspired by Looney & Yannelis highlighted that borrowers with "high" debt were between 10- and 30-pp more likely to be enrolled in IDR. Overall, Collier et al. (2021) found that whether student loan debt predicts participation in IDR depends on how the debt is measured, and whether race correlates with participation in IDR depends on covariates included within models.

Given how sensitive the findings were to model specification, the analyses did not greatly clarify the conversation. However, Collier et al. (2021) concluded that trying to identify trends *across* the models would be a prudent way to understand who enrolls in IDR and to understand conclusions that are not contingent on estimation parameters. They concluded that female and *possibly* minority borrowers were more likely to be enrolled, as were those with high debt loads. Furthermore, the lowest earners were less likely to be in IDR – which was problematic, given these individuals could 'most' use the financial safety that IDR intends to provide.

Collier et al. (2021) also tested for differences between those enrolled in IDR and those in traditional repayment plans for the outcomes of having savings, amount saved, the amount in a checking account, being a homeowner, payday loan usage, saving for retirement, and amount saved for retirement. Each model resulted in *null findings*, suggesting that those enrolled in IDR are statistically similar to those who were not. These findings are generally similar to Collier's (2020) prior study and suggest that IDR may be providing enough protection to keep financially-related outcomes statistically equalized despite the higher average debt load carried by those currently enrolled in IDR.

Analytic Plan Survey of Consumer Finances

Conducted every 3-years, the SCF is a national survey, where the sampling and adjustments make the panel survey nationally represented. In the past, SCF has been used in studies focused on inequality and wealth (Bricker et al., 2019), financial acumen and savings (Kim & Yuh, 2018), and of particular relevance, student loan debt (Blagg, 2018; Bricker et al., 2018; Charron-Chenier et al., 2020). The SCF is one of a few publicly available datasets that include an indicator of IDR enrollment. The SCF dataset is generated from a robust survey that captures demographic information and financially-related outcomes. The key difference driving this updated study is that SCF 2016 dataset is unlikely to have included many participants in the December-2015-passed REPAYE whereas the 2019 dataset is more likely to, especially given the uptake in REPAYE as time has progressed. As of 2017, of the total debt in IDR-related programs, almost 20% were in REPAYE. Much of the growth is due to recent borrowers (U.S. Congressional Budget Office, 2020). Given the generous terms of REPAYE, particularly that there are no income requirements to engage the plan (U.S. Department of Education, 2015), this update may help us identify more recent trends in IDR enrollment and associated outcomes. Note that the public SCF dataset does not identify individual IDR plans (the available variable is simply a binary indicator Y/N).

Like Collier et al. (2021), we downloaded and merged the main dataset with the replicate weight dataset. Next, we used the SCFCOMBO package for STATA (Nielsen, 2015; Pence, 2015) to apply survey weighting and account for the multiple imputation process, producing proper point estimates and standard errors for models. The details of variable manipulation provided by Collier et al. (2021) allowed us to exactly replicate their processes and generate models. Details related to the variable manipulation are found in Table 1. However, a few notes for readers: aligned with the prior study, we calculated a continuous variable summing all public and private student debt for both the respondent and their spouse/partner. Just as with Collier et al. (2021), wage data were tabulated from household wages and salary only. All models were linear regression; for binary outcomes (linear probability model), coefficients can be interpreted as the change in percentage point values of the dependent variable.

Table 1

Study_Variable Identification and Manipulations[1]

Variable	Description	SCF Codes
Student Loan Debt	Self or spousal reported total student loan debt – included federal and private.	Step 1 – Loan Debt Balances: X7805, X7828, X7851, X7928, X7951 Step 2 – Self or Spousal: X7978, X7883, X7888, X7893, X7898, X7993
IDR Enrollment	Binary indicator that individuals were enrolled in an Income-Based Repayment Plan, Pay as you Earn Plan, or Income- Contingent Repayment Plan."	X9306-X9311
Wages	Wages were generated from reported household wages and salary only	X5702

Savings	Total reported savings and a binary outcome on whether respondent had savings >0.	X3730, X3736, X3742, X3748, X3754, X3760
Checking Account	Initially, we identified the amounts participants reported in checking-related accounts. Next, we only counted checking amount when respondents recorded a "5" response for variables in Step 2. Binary outcome on whether respondent had checking account balance >0.	Step 1 – Checking Account Balance: X3506, X3510, X3514, X3518, X3522, X3526 Step 2 – Traditional Checking Account Balance: X3507, X3511, X3515, X3519, X3523, X3527
Retirement Savings	First, we classified the retirement accounts via identifying response "22 – Retirement/old age" to variables in Step 1. Next, we summarized account balances in the identified retirement savings accounts. Last, we generated a binary outcome determined by retirement>0.	Step 1 – Identifying Retirement Accounts: X3006, X3007, X7513, X7514, X7515, X6848 Step 2 – Summarizing Balances: X6551, X6559, X6552, X6560, X6553, X6561, X6554, X6562, X6756, X6757
Payday Loans	Binary indicator of whether anyone in the household had made use of a payday loan.	X7063
Homeownership	Binary outcome of owning a home, mobile home, mobile home and land, farm, or ranch.	X604, X614, X623, X716, X513, X526

1. We followed the exact approach Collier et al. (2021) highlighted.

Sample

Our analytic sample is the subset of participants in the 2019 SCF who indicated that they had student loan debt, which should be nationally representative of Americans with student loans. All sample descriptive statistics can be found in the online appendix.[1] Of borrowers with student loan debt, 35% were enrolled in IDR. Those in IDR show some observable differences from borrowers in traditional repayment – the group leaned female (30% v. 27%) and had a higher percentage of racial minority (43% v .39%) borrowers, had lower average wage income by $4,500, higher average student loan balance, were less likely to have privately-held debt, and more likely to come from middle-income categories (less likely to have incomes over $100,000 or under $12,500).

[1] Full sample descriptives table available at: https://drive.google.com/file/d/1f9tMqWKX3Mus8q5YQUmqbNPBSP43IKro/view?usp=sharing

Findings IDR Enrollment

Collier-Inspired Models

Although some characteristics showed the same relationship with IDR enrollment as in Collier et al.'s (2021) analysis of the 2016 data; our Collier (2020) inspired analyses generally show a very different overall pattern in which categories of debt and income relate to IDR participation. First, we showcase similar relationships - we again found female borrowers were more likely than male borrowers to be enrolled in IDR, by between 7- and 8-pp. We also confirmed when compared to those earning between $40,000-54,999, those earning <$12,500 were less likely to be enrolled by between -19- and -20-pp.

Next, we highlight differences between the Collier-inspired models using SCF 2016 and this analysis using the SCF 2019 data. We found that racial minority borrowers were not significantly correlated with IDR enrollment – opposing a previously consistent finding. Counter to null findings with the 2016 dataset for student loan debt load starting at $40,000 (10-pp) the chance of enrollment increased compared to households with $20,000 or less in debt. The highest chance of enrollment was for those with loan debts of $100,000+ (23-pp). Additionally, possessing private loans resulted in a -13- to -10-pp decreased chance of enrollment; 2-3 times the magnitude of the (insignificant) point estimate using the 2016 data.

Next, households with wages between $55,000-74,999 were 12-pp more likely to be enrolled in IDR than households with wages between $40,000-54,999. We suggest this outcome may result from REPAYE not requiring "low" income compared to loan balances (U.S. Department of Education, 2020); thus, expanding the entry point and may imply that borrowers in these higher earnings ranges feel that REPAYE offers a degree of financial safety that traditional repayment may not. Additionally, the highest earners, making $100,000+ were 11-pp less likely to be enrolled – a continuation of the breakdown to the "savvy" borrower narrative (see Delisle, 2013). As related to these models, more categorical variables flagged as significant and more closely mimicked trends found by Collier (2020) than with trends uncovered in Collier et al. (2021).

Table 2

Enrollment in IDR, Collier Inspired Models (Linear Probability Models)

	(1) IDR	(2) IDR	(3) IDR	(4) IDR	(5) IDR
Demographics					
Female	0.05	0.07^{+}	0.07*	0.08*	0.06
Age (centered)	0.00	0.00	0.00	-0.00	-0.00
Racial Minority	0.03	0.02	0.04	0.04	0.04^{+}
No children	0.03	0.02	0.02	0.05^{+}	0.02
Not married or cohabiting	-0.02	-0.02	-0.06	-0.10*	-0.05
Loan Characteristics					
SLD (centered)		0.00***	0.00***		
Has private debt	-0.10**	-0.10**	-0.13***	-0.13***	-0.13***
Loan Amount, reference is <$20K					
$20,000-39,999	-0.01				-0.00

$40,000-59,999	0.10*				0.13*
$60,000-74,999	0.11^{+}				0.11*
$75,000-99,999	0.21***				0.22***
$100,000+	0.23***				0.23***
Education, Reference is BA					
Less than HS Degree	0.01	0.01	0.01	-0.03	0.01
Some College	0.02	0.01	-0.02	-0.05	-0.00
Associates Degree	0.04	0.04	0.03	0.01	0.03
Masters	0.02	0.01	0.01	0.08	0.02
Professional Degree or PhD	-0.10	-0.15*	-0.11	-0.02	-0.06
Income					
Wage Income			0.00		0.00
Income Squared			-0.00^{+}		-0.00^{+}
Wage income, reference is $40,000-54,999					
<$12,500	-0.19***	-0.20***			
$12,500-24,999	-0.06	-0.07			
$25,000-39,999	-0.00	-0.00			
$55,000-74,999	0.12**	0.12*			
$75,000-99,999	0.06	0.05			
$100,000+	-0.11*	-0.11*			
Debt to Income Ratio				-0.00	
Adjusted r^2	.07	.08	.04	.01	.03
N	901	901	901	901	901

$^{+}$ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Looney & Yannelis Inspired Models

The Looney & Yannelis (2018) inspired SCF 2019 analyses uncovered one similar trend in that female borrowers were consistently more likely than male borrowers to be enrolled in IDR – at between 18- to 24-pp. Unlike the previous version of these models, this analysis suggests racial minority borrowers were 26-pp more likely than white borrowers to be enrolled. These point estimates are roughly double that in the Collier et al. (2021) study. Additionally, married borrowers are more likely to be enrolled (14-pp). While the "high" debt variable was a consistent, positive finding in Collier et al. (2021) study – here, we found no significant correlation. Given that REPAYE has made it easier to access IDR programs (U.S. Department of Education, 2015), we ran the same models with the "high" debt variable lowered to $40,000+, uncovering two significant findings (see Table 3, Model 4: 12-pp). To be noted, we lowered "high debt" to $40,000 based upon findings in Table 2. That high debt is still a predictor of IDR participation but starting at $40,000 instead of $50,000 in SLD suggests that REPAYE opened access to IDR programs by lowering the barrier to entrance determined by overall debt loads; implying, this policy shift was likely needed by many borrowers. Finally, compared to households with only government loans, those with private loan debt are about 12-percentage points less likely to be enrolled – consistent with the Collier-inspired models in Table 2.

Table 3

Enrollment in IDR, Looney & Yannelis Inspired Models (Linear Probability Models)

	(1) Alternative Debt and Education Coding	(2) Interactions with High Debt Status	(3) Most Promising Model	(4) Model With “High” Debt at $40K
Demographics				.
Female	0.24***	0.18**	0.24***	0.24***
Racial Minority	0.26***	0.26**	0.27***	0.26***
Married	0.14**	0.14*	0.14**	0.14**
Interaction Terms				.
Minority X Female	-0.34***	-0.29**	-0.34***	-0.34***
Married X Female	-0.17	-0.34	-0.18	-0.17
Minority X Married	-0.22**	-0.28**	-0.22**	-0.22**
F X Min. X Married	0.11	1.00**	0.11	0.10
Income and Debt Measures				.
Log Income	0.01*	0.01+	0.01*	0.01+
Debt to Income Ratio	0.00	-0.00	0.00	0.00
SLD <$30K	-0.09*	-0.09*	-0.09*	-0.03
SLD >$50K	0.08+	-0.07	0.07	
SLD >$40K				0.12**
Private SLD	-0.12***	-0.12***	-0.12***	-0.12***
Educational Attainment				.
No College	0.02	0.01	0.02	0.02
Some College	0.05	0.04	0.05	0.05

Advanced Degree	0.01	0.00	0.00	0.00
Interaction Terms				.
F High debt		0.29*	0.03	0.03
Min High debt		0.07		
Marr High debt		0.10		
F x Min High debt		-0.27		
F x Marr High debt		0.14		
Min x Marr High debt		0.09		
FRM High debt		-1.31**		
F Some College			-0.02	-0.02
Adjusted r^2	.04	.05	.04	.04
N	901	901	901	901

$^{+}$ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

IDR Enrollment and Financial Outcomes

Table 4 reveals that when compared to those in traditional repayment, borrowers in IDR were statistically similar regarding having a savings account, the amount saved, homeownership, payday loan usage, and retirement savings amount. Notably, the analysis using the 2016 data suggested enrollment in IDR was correlated to a decrease of $5,960 in retirement savings compared to those in Traditional Repayment; whereas our study correlated IDR enrollment to a decrease of $8,202 (-$2,242 difference) and is marginally significant at the p<.10 level.

Departing from Collier et al. (2021) who found only non-significant estimates, we found two significant outcomes: IDR enrollment was significantly correlated to having $1,004 less in a traditional checking account and to a 7-pp lower chance of saving for retirement. We are unable to observe whether this is a difference across the experience of all borrowers in IDR between the 2016 data and the 2019 data, a difference driven by new enrollees in IDR of all types, or a difference concentrated among those in REPAYE, who likely constitute the largest change in sample composition between the two analyses. Compared to the outcomes of the 2016 SCF analysis, those more recently in IDR seem somewhat worse off.

Table 4
Financial Outcomes: Savings, Homeownership, Retirement

	(1) Have Savings, (Y/N)	(2) Savings Amount	(3) Checking Amount	(4) Home Owner	(5) Payday Loan Use	(6) Saving for retirement (Y/N)	(7) Retirement Savings Amount
Student Loan Characteristics							
In IDR	0.01	102	-1,004*	-0.02	0.02	-0.07**	-8,202+
SLD (centered)	-0.00	-0.02	0.02***	0.00	0.00	-0.00	-0.16**
Has private debt	0.01	4,027+	1,227	-0.07*	-0.01	0.01	1,847
Demographics							
Female	0.07	-3,916*	-808+	-0.10**	0.04*	-0.02	-13,601*
Age (centered)	-0.01***	118	17	0.01***	0.00	0.01***	1,168**
Racial Minority	-0.06*	-86	-783	-0.11***	0.00	-0.17***	-5,873
Not married or cohabiting	-0.03	-3,783	-1,081+	-0.09*	0.01	-0.00	-133
No children	0.03	1,770	662	-0.14***	-0.02*	-0.01	6428
Education, Reference is BA							
Less than HS Degree	-0.05	-6,458***	119	-0.05	0.03*	-0.07+	-18,287**
Some College	-0.03	2,656	188	-0.08*	0.02	-0.05	-1,456
Associates Degree	-0.03	-3,102	776	-0.01	0.00	0.03	-12,584**
Masters	0.03	1,651	866	0.02	-0.01	0.01	16,440*
Professional Degree or PhD	0.06	13,359*	5,532	0.14**	-0.04*	0.11+	18,052
Wage Income Measures							
Wage Income	0.00***	0.00	0.01	0.00***	-0.00	0.00***	0.27+
Income Squared LogInc2	-0.00***	0.00*	0.00	-0.00***	0.00	-0.00***	0.00
Adjusted r^2	.03	.19	.21	.22	.01	.17	.12
N (unweighted)	901	483	901	901	901	901	343

$^{+}\ p \leq 0.10$, $^{*}\ p \leq 0.05$, $^{**}\ p \leq 0.01$, $^{***}\ p \leq 0.001$

Conclusion

Just as with Collier et al. (2021), we expected our *replication* to bring clarity. Instead, we have found that not only model specification but sample frame – even for a nationally representative sample – affect findings and that researchers must be careful when considering the development of these models and in interpreting outcomes. Given the variation based upon specification, we suggest following Collier and associates' advice, in that there is more power in the trends of established studies and across differing models. We are particularly confident in saying that households with the lowest earnings do not seem to be well represented in these programs – which is problematic given these are the households who may be most protected by IDR. Given the patterns we observe, we are comfortable in saying that female and minority borrowers are more likely than male and white borrowers to be enrolled in IDR. The relationship between race and participation in IDR remains complex, though: present solely in the Collier (2020)-based analyses in the 2016 SCF data and present solely in the Looney & Yannelis-based analyses in the 2019-data, and founded on the interaction terms, based almost entirely on high participation among men of color and married women of color. Strictly following the Looney & Yannelis (2018) delineation, we see no difference in enrollment patterns for those below and above a cut-point of $50,000 in SLD in the 2019 SCF data. However, several models found that those with "high" debt were more likely to be enrolled in IDR when we modified this variable to $40,000+. With this adjustment, perhaps as a function of REPAYE widening enrollment, the pattern remains present that IDR participation is greater among those with high levels of debt. Finally, IDR seems to be providing enough financial security for borrowers to engage many aspects of the American Dream, like homeownership. However, understanding why those in IDR seem to be doing less well across multiple financial health measures in 2019 compared to 2016 should be a priority for future research.

References

Blagg, K. (2018). *Who uses income-drive student loan repayment?* Urban Institute: Washington, DC. Retrieved from https://www.urban.org/urban-wire/who-usesincome-driven-studentloan-repayment

Bricker, J., Hansen, P., & Volz, A.H. (2019). Wealth concentration in the U.S. after augmenting the upper tail of the survey of consumer finances. *Economic Letters, 184*, 1-4. https://doi.org/10.1016/j.econlet.2019.108659

Catherine, S., & Yannelis, C. (2020). *The distributional effects of student loan forgiveness* (Working Paper No. 28175). National Bureau of Economic Research: Washington, DC. Retrieved from https://www.nber.org/system/files/working_papers/w28175/w28175.pdf

Charron-Chenier, R., Seamster, L., Shapiro, T., Sullivan, L. (2020). *Student debt forgiveness options: Implications for policy and racial equity* (Working Paper). Roosevelt Institute. Retrieved from https://rooseveltinstitute.org/publications/student-debt-forgivenessoptions-implications-for-policy-and-racial-equity/

Collier, D.A. (2020). Exploring IDR: A comparison of financial situations and behaviors between those in traditional student loan repayment and those in income-driven repayment. *Journal of Student Financial Aid, 49*(2), 1-24. https://ir.library.louisville.edu/jsfa/vol49/iss2/3

Collier, D.A., Fitzpatrick, D., & Marsicano, C. (2021). *Exploring the relationship of enrollment in income-driven repayment to borrower demographics and financial outcomes* (Working Paper). American Political Science Association. doi:10.33774/apsa-2019-nd8n2-v2

Delisle, J. (2013, Dec 4). *Beware savvy borrowers using income-based repayment.* New America: Washington, DC. Retrieved from https://www.newamerica.org/educationpolicy/edcentral/beware-savvy-borrowers-using-income-based-repayment/

Friedman, M. (1955). The role of government in education.

Hillman, N., & Bruecker, E. (2019, June 12). *Finding and using student loan data*. State Higher Education Executive Officers. Retrieved from https://postsecondarydata.sheeo.org/finding-and-using-student-loan-data/

Kim, K.T., & Yuh, Y. (2018). Financial knowledge and household saving: Evidence from the Survey of Consumer Finances. *Family and Consumer Sciences Research Journal, 47* (1), 5-24. doi:10.111/fcsr.12270

Lachenbruch, P.A. (2010). Stata tip 89: Estimating means and percentiles following multiple imputation. *The Stata Journal, 10*(3), 469-499.

Looney, A., & Yannelis, C. (2018). *Borrowers with large balances: Rising student debt and failing repayment rates*. Brookings Institute: Washington, DC. Retrieved from https://www.brookings.edu/wpcontent/uploads/2018/02/es_20180216_looneylargebalances.pdf

Nielsen, R. B. (2015). SCF complex sample specification for Stata. Technical note. Department of Financial Planning Housing and Consumer Economics, University of Georgia, Athens, GA. doi: 10.13140/RG.2.1.4126.8240

Pence, K. (2015). *SCFCOMBO: Stata module to estimate errors using the Survey of Consumer Finances*. Retrieved from https://econpapers.repec.org/software/bocbocode/s458017.htm

Shireman, R. (2017). Learn now, pay later: A history of income-contingent student loans in the United States. *The Annals of the American Academy, 671,* 184-201. doi:10.1177/0002716217701673

Steinbaum, M. (2020). *The student debt crisis of non-repayment.* Jain Family Institute: New York, NY. Retrieved from https://www.jainfamilyinstitute.org/assets/msd4-2020-studentdebt-crisis-is-a-crisis-of-non-repayment.pdf

U.S. Congressional Budget Office. (2020, Feb). *Income-driven repayment plans for student loans: Budgetary costs and policy options.* https://www.cbo.gov/system/files/202002/55968-CBO-IDRP.pdf

U.S. Department of Education. (2015). *Your federal student loans just got easier to REPAYE.* Retrieved from https://blog.ed.gov/2015/12/your-federal-student-loans-just-got-easier-torepaye/

U.S. Federal Reserve Board. (2020). *Survey of consumer finances* (SCF). Washington, DC. Retrieved from https://www.federalreserve.gov/econres/scfindex.htm