Financial Consequences of Student Loan Delinquency, Default, and Servicer Quality

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Abstract

Student loans are now the third largest form of household debt, and nearly 6 million federal student loan borrowers are in default. Student loans cannot be discharged in bankruptcy, and the federal government has unique levers for collecting on defaulted debt, leading to potentially severe financial consequences for borrowers. Using consumer credit panel data, I examine the credit market consequences of student loan delinquency and default and the role that student loan servicers play in contributing to borrower outcomes. I exploit random assignment of student loan borrowers to student loan servicers to study the direct effect of servicers on borrowers' credit outcomes and to isolate variation in the likelihood of default that is not correlated with borrower characteristics. I find that being assigned to a higher-default servicer increases a borrower's likelihood of default by approximately 6%. However, there is a precisely estimated null effect of servicer assignment on measures of borrowers' likelihood of financial distress, credit access, and zip-code characteristics. These findings suggest that averting a servicer-induced default does not yield considerable benefits for marginal borrowers' credit outcomes, but that servicers are meaningful drivers of student loan repayment outcomes.

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1 Introduction

Student loan debt currently is the third largest form of household debt after mortgages and auto loans (Federal Reserve Bank of New York, 2024). While many student loan borrowers are able to successfully make payments on their loans, the Department of Education (ED) estimates that about 8.5 percent of borrowers were delinquent and 20 percent were in default at the beginning of 2020 (U.S. Department of Education, Federal Student Aid Data Center, 2024). Borrowers in delinquency or default tend to be from groups historically marginalized in higher education, which is likely to deepen pre-existing inequality (Houle and Addo, 2019; Scott-Clayton and Li, 2016). In contrast to other forms of household debt, student loans cannot be discharged in bankruptcy and are not subject to a statute of limitations on debt collection.[1] As a result, struggling borrowers are left with limited options to address long-term repayment issues and severe delinquencies and defaults are common.

Delinquency and default are costly for borrowers and the federal government. They can damage an individual's credit record and limit their ability to access other forms of credit to buy a home or car, rent an apartment, or get a job.[2] Borrowers in default also may face withholding of their wages, Social Security payments, or tax refunds. In some cases, states can revoke borrowers' occupational licenses if they are in default on their student loans. At the same time, newly released data from the Department of Education show that the median amount collected from defaulted borrowers in the last five years is $0 for borrowers who have been in default for more than seven years.[3] Despite the scale of federal student loan

[1]This is largely motivated by concerns that due to the inability to collateralize human capital investments, strategic default incentives may be particularly large in the student loan market. Yannelis (2020) finds that removing bankruptcy protection and increasing wage garnishment reduce student loan nonrepayment rates (eg. evidence of strategic behavior) but concludes that these magnitudes are not substantially different than in other consumer credit markets, which function with bankruptcy protection. Bankruptcy protection has been shown to have a positive effect on individuals'employment, earnings, and financial health (Dobbie and Song, 2015; Dobbie et al., 2017). This largely is driven by a deterioration in outcomes for those who do not get approved, which Dobbie et al. (2017) show is in part due to wage garnishment.

[2]Research shows that the removal of a derogatory mark on an individuals'credit report increases credit scores and credit usage (Dobbie et al., 2020; Musto, 2004). The research on employment effects is mixed, with some studies finding an economically small effect on employment and some finding increases employment, particularly for some subgroups (Bos et al., 2018; Friedberg et al., 2021).

[3]Median amounts collected range from $34 to $384 for borrowers who were in default for between 3 to 6

lending and the federal government's broad authority to force collection, little is known about how delinquency and default affect student loan borrowers' short- and long-term financial outcomes.

In recent years, policymakers and advocates have focused on the ways that student loan servicers contribute to borrower outcomes. Student loan servicers are federal government contractors that handle many of the most critical functions of student loan repayment. They play an important, yet largely understudied role in the student loan system. While all servicers face the same contract requirements, each servicer has discretion over the policies and procedures used to engage with borrowers, with minimal guidance from the Department of Education on best practices. As a result, borrowers have variable experiences when it comes to repaying their student loans, which has resulted in numerous investigations and enforcement actions taken by government agencies in recent years.[4] Servicers' actions also have led to a series of ongoing reforms focused on increasing standardization of services and accountability for borrower outcomes.

In this paper, I investigate the relationship between student loan delinquency and default, student loan servicers, and borrowers' credit outcomes. To do so, I use a novel dataset, the University of California Consumer Credit Panel (UCCCP), which has two important features for my analysis. First, I use granular information on borrowers repayment trajectories to implement an event study design. Second, I take advantage of an anonymized servicer identifier in the data to implement an instrumental variables design exploiting random assignment of student loan borrowers to student loan servicers.

To begin, I present novel evidence on the relationship between student loan delinquency

years (U.S. Department of Education, Negotiated Rulemaking for Higher Education, 2023).

[4]For example, the Consumer Financial Protection Bureau first sued Navient in 2017 for providing borrowers with inaccurate information or incorrectly processing payments. Recently, they filed a court order to ban Navient from servicing federal Direct Loans. Several state attorneys general (including Massachusetts, New York, and Pennsylvania) also have sued Navient and another federal loan servicer, PHEAA, for mishandling borrower accounts. See: https://www.consumerfinance.gov/about-us/newsroom/cfpb-sues-nations-largest-student-loan-company-navient-failing-borrowers-every-stage-repayment/ and https://www.insidehighered.com/news/2021/02/11/pennsylvania-higher-education-assistance-agency-settles-suit-brought-massachusetts.

and default and credit outcomes using an event study approach. I examine how delinquent and defaulted borrowers' credit outcomes evolve around their first 90 day delinquency. While these event studies require strong assumptions to interpret the estimates as causal, I document trends that are important for understanding the factors that are correlated with default and post-default outcomes.

Event study estimates suggest that delinquent and defaulted borrowers are facing financial distress more broadly when they first become delinquent on a student loan. The likelihood of having a delinquency or collections on non-student loan forms of credit is increasing in the two years prior to a student loan delinquency. These borrowers have low average credit scores prior to delinquency and experience a large initial decline of about 60 points (approximately 66% of a standard deviation in credit scores) when they first become delinquent. This is relatively short-lived, though, and after 12 quarters both groups of borrowers have credit scores about 10 points lower than their pre-delinquency level. On measures of credit access, delinquent borrowers recover after six quarters, while defaulted borrowers continue to experience declining outcomes.

The causal effect of student loan delinquency and default on credit outcomes depends in part on borrowers' other circumstances. If student loan default is unique in setting people on a bad financial trajectory and they are not able to recover, then we might expect the causal effect of default to be large. Conversely, the causal effect could be minimal if student loan delinquency is bundled with other bad credit outcomes simultaneously. Borrowers' delinquencies and defaults on other forms of credit that happen simultaneously to a student loan default also will impact their credit scores, and thus future credit access.

The event study analysis suggests the presence of time-varying unobserved factors that are correlated with both default and post-default outcomes. For this reason, I turn to an instrumental variables approach in the second part of the paper. This approach allows me to examine the direct effect of student loan servicers in driving student loan default and associated outcomes. I exploit the random assignment of new student loan borrowers to student loan servicers. Specifically, I create a measure of servicer quality that represents the average likelihood of default among borrowers assigned to the same servicer. I then examine the effect of being assigned to a lower or higher quality servicer on borrowers' student loan repayment and non-student loan credit outcomes. This research design can be nested within the examiner fixed effects framework, which uses random assignment of individuals to judges or examiners with different propensities to assign some treatment to estimate the causal effect of that treatment.[5]

I find that being assigned to a relatively lower quality student loan servicer increases the likelihood of both delinquency and default. Being assigned to a servicer with a one standard deviation higher default rate increases the likelihood of default by 2 percentage points (a 6% increase). While this effect is strong, it does not have spillovers onto borrowers' other credit outcomes. Six years after a borrower's student loan origination, being initially assigned to a lower quality servicer has no impact on credit scores or access to other forms of credit.

Using this measure of servicer quality as an instrument, I estimate the effect of default. Similarly, I find a null effect of default on measures of borrowers' financial distress, access to credit, borrowing, and zip-code characteristics.

Taken together, these results suggest that while student loan servicers do impact borrowers' likelihood of student loan delinquency and default, the broader effect of these adverse credit events is minimal for the marginal defaulter. As the event studies show, borrowers on average are exhibiting signs of financial distress in the lead-up to student loan delinquency. This could be driven by correlated shocks, which will affect their ability to repay across multiple forms of credit and will negatively affect their credit ratings prior to delinquency. Additionally, the event studies show that declines in credit scores for this group of borrowers are relatively short-lived, although average credit scores are low. In the context of other delinquencies and collections debt, a servicer-induced student loan default does not seem to

[5]This approach using as-if random assignment of cases to decision makers was pioneered by Kling (2006) to study the effect of incarceration length on labor market earnings. The strategy has since been adapted to many other settings. See Table A.1 of Chyn et al. (2024) for a list of examples.

worsen borrowers' credit outcomes in any meaningful way.

This paper makes two central contributions to our understanding of the determinants and incidence of student loan delinquency and default. First, I document a previously unexamined mechanism for student loan delinquency and default — student loan servicers. Using newly available data that links loans with an anonymized servicer identifier, I show a causal relationship between student loan servicer assignment and borrower repayment outcomes. Second, I combine an event study approach and instrumental variables design to study the relationship between default and borrowers credit outcomes. In the event studies, I provide new descriptive evidence that documents trajectories of borrower outcomes around the timing of student loan delinquency and default. I then show how servicer-induced default affects credit outcomes to provide insight into the long run impacts of servicer assignment and of student loan default. Together, these analyses help to disentangle the role of correlated shocks and causation in measuring the effect of student loan default.

Much of the prior research examining the causes of student loan default focuses on borrower or institution characteristics. This body of work has found that delinquencies and defaults are driven by individuals with low levels of debt (Mezza and Sommer, 2016) and those who attend for-profit institutions (Looney and Yannelis, 2015; Armona et al., 2022). More recent work has established a causal relationship between specific student loan policies and delinquency. For example, Black et al. (2023) show that access to additional loans through increased loan limits decreases delinquency. Additionally, income-driven repayment decreases delinquency, at least in the short-term (Herbst, 2023). I contribute to this body of work by documenting the role of student loan servicers in driving default. This feature of the student loan system is distinct from borrower or institution characteristics yet has implications for borrowers' ability to repay their student loans.

Academic research on student loan servicers is scarce. Darolia and Sullivan (2020) examine the incentives servicers face and document variation across servicers in publicly available performance measures. Herbst (2023) estimates the effect of income-driven repayment on borrower outcomes utilizing variation in the servicer call center agents' ability to enroll borrowers. No prior research examines how servicers affect loan outcomes. This paper is the first to exploit the random variation derived from how borrowers get assigned to servicers in the federal student loan system.

Related work examines the role of servicers and the incentives they face in the mortgage market. These papers document variation in mortgage servicers' propensity to offer mortgage modifications to delinquent borrowers that cannot be explained by borrower characteristics (Agarwal et al., 2017; Kruger, 2018; Aiello, 2022). In recent work, Kermani and Wong (2021) study the effect of mortgage modifications on racial disparities in housing returns. They implement an instrumental variables design using variation in servicers' propensities to modify mortgages as an instrument. Similarly, Kim et al. (2022) find that servicers of federally-backed mortgages differed in their propensity to enroll delinquent borrowers in the CARES Act mortgage forbearance program, despite universal eligibility. They then implement a difference-in-differences design using this servicer-level variation to estimate the causal effect of forbearance on borrower outcomes. While these papers show the importance of servicers in other loan markets, the structure of student loans and role of servicers in this setting are unique.

While many papers attempt to examine the causes of default, there is little evidence on the incidence of default. Reports using data from nationally representative surveys and focus groups document that many borrowers struggle to exit or stay out of default and that the penalties of default caused additional financial hardship (Delisle et al., 2018; Sattelmeyer, 2022). The work most closely related to this paper is Blagg (2018). Using annual-level snapshots from credit data, she shows that in the years leading up to a default, borrowers' credit scores decline and then show a small increase right after default. In the event study analysis, I extend and improve upon this through the use of more granular data that allows me to plot borrower trajectories at the quarterly level. I also document that servicer-induced default does not significantly affect borrowers' credit scores.

This paper also is related to the literature that studies the effect of home foreclosure on individuals' later credit and financial outcomes. In a study using a randomized judge design, Diamond et al. (2020) find that foreclosure causes housing instability, reduced homeownership, and increased financial distress, including increased delinquencies on other debts. Despite these patterns, they find that foreclosure does not have much of an effect on credit scores. They argue this is due to the fact that most of the effect on credit scores comes from the prior delinquencies and the bank's decision to file foreclosure, rather than on the foreclosure outcome itself. Consistent with this result, I find that servicer-induced student loan default does not have spillovers onto borrowers' other credit outcomes.

This research speaks to two important and ongoing policy debates around the federal student loan system: improving student loan servicing and helping borrowers in default. First, I show that student loan servicers have a causal effect on borrowers' student loan repayment outcomes and that borrowers most likely to be induced to default by their servicer are more likely to be disadvantaged borrowers. This fact can inform decisions about how to improve the student loan servicing system, particularly for struggling borrowers. Second, I show that servicer-induced default at the 270 day threshold does not impact borrowers' credit outcomes. These findings suggest that there may be other dimensions of student loan delinquency and default where interventions may have a more meaningful benefit for borrowers.

The remainder of the article is organized as follows. Section 2 provides institutional details relevant for understanding student loan delinquency, default, and the role of servicers. Section 3 describes the data and sample selection process. Section 4 provides new descriptive evidence on the evolution of outcomes among delinquent and defaulted borrowers. Section 5 describes the servicer instrumental variables design and discusses the key underlying assumptions. Section 6 presents the main results of my analysis. Section 7 concludes.

2 Background: Student Loan Delinquency, Default, and Servicers

The majority of student loans are either guaranteed or directly owned by the federal government. These loans are not secured by any collateral and generally are not contingent on credit scores. Federal student loans have subsidized interest rates, which are set by Congress, and undergraduate student loan borrowers face yearly and lifetime loan limits. There are now approximately 42 million individuals with outstanding federal student loans. Thirty-two percent of federal student loan borrowers have outstanding balances less than \$10,000, and an additional 43 percent have balances between \$10,000 and \$40,000 (Ma and Pender, 2023). When borrowers enter repayment six months after leaving school, they face a complex set of options, including a standard 10-year repayment plan and several different income-driven repayment plan options.

2.1 Student Loan Servicers

Student loan servicers play a critical and under-appreciated role in federal student loan programs. They are the primary point of contact for borrowers once they leave school. Servicer responsibilities include account management, payment processing, and providing borrowers with information on payment plans. Importantly, if a borrower has missed scheduled payments, their servicer should assist them in getting back on track. Servicers must comply with some minimal guidance from the Department of Education about how to interact with borrowers, but they have a lot of discretion over policies and practices they use to engage with borrowers. This includes the frequency and type of communication with borrowers, call center staffing and training, as well as computer systems and technology. This discretion is intended to improve borrower outcomes by encouraging competition among servicers. At the same time, it leads to a set of unregulated policies that could have large impacts on borrowers that currently are not well understood.

2.1.1 Contracts and Incentives

During the 2008 financial crisis, the federal government acquired loans from private lenders and began originating a larger volume of loans under the Direct Loan program.[6] To manage this larger loan volume, the Department of Education brought on a group of for-profit companies, not-for-profit companies, and state-based entities as federal contractors.[7] Prior to this policy shift, loans made through the Direct Loan program were serviced by a sole contractor. Due to performance issues with this servicer, policymakers sought to infuse competition into the design of this new servicing system.

These early servicing contracts have two features that incentivize servicers to keep loans current. First, servicers are paid a monthly fee for each loan that varies with the loan status. Monthly fees ranged from $0.45 for loans that are severely delinquent to $2.85 for loans that are current in repayment. The full schedule of fees is shown in Table 1. Second, servicers compete for allocations of newly-originated student loans based on their past performance. The Department of Education collects and reports a set of performance metrics that determine the share of new loans each servicer will receive every quarter. These metrics include the percent of the servicer's portfolio that is current, that is between 91-270 days delinquent, and that is between 271 and 360 days delinquent. They also include school, borrower, and federal employee satisfaction surveys. Servicers are ranked from best to worst on each metric and assigned points based on this relative ranking. Final allocation percentages are determined by the share of total points that each servicer receives. Performance metrics are calculated every quarter, and allocation shares are updated every six months (two quarters).

[6] Prior to 2008, there were two separate federal student loan programs: the Federal Family Education Loan program (FFEL) and the Direct loan program. The FFEL program allowed private lenders to make student loans that were guaranteed by the federal government. In the Direct Loan program, loans are directly owned by the federal government. Starting in 2010, all newly originated loans are made through the Direct Loan program.

[7] The first contracts were signed in June 2009. This initial set of servicers were a mix of for-profit and state-based entities referred to as the Title IV Additional Servicers (TIVAS). In 2011, additional contracts were signed with several smaller companies and state-affiliated agencies known as the not-for-profit servicers (NFPs).

2.1.2 Assignment process

The Department of Education randomly assigns new loans to servicers to ensure that servicers are competing over portfolios of similar borrowers. Borrowers do not have discretion over which servicer handles their loans, except in a few special circumstances, all of which require borrower-initiated switching after the initial assignment.[8] When new loans are disbursed they are assigned to a servicer. If a borrower has an existing student loan, their new loan will be assigned to the same servicer as the existing loan. If they do not have an existing loan, the loan will be assigned according to the process described below.

There are two features that dictate how many and which individual loans get assigned to a servicer: (1) the allocation shares that determine the share of new loans each servicer will receive described in section 2.1.1, and (2) the order in which loans are assigned, which rotates on a daily basis and is not related to servicer performance. Figure 1 depicts a stylized example of the servicer assignment process for new loans. In this example, there are three servicers. On the first day, there are 100 new borrowers to be assigned. On the second day, there are 75 new borrowers to be assigned. Servicer allocation shares, which remain constant within a given quarter, are in parentheses next to the name. First, individuals are sorted according to a person identifier given to them by the Department of Education. Borrowers are then assigned to each servicer according to the pre-determined servicer order for that day. The number of new loans assigned to each servicer s on day d is indicated by n_{sd}. While some servicers receive more loans than others, this process ensures that, on average, borrowers will look similar on observables and unobservables across servicers.

[8] Borrowers who enter a specific loan forgiveness or discharge plan also may switch servicers since these plans are typically administered by one servicer. For example, PHEAA is the loan servicer that administers the Public Service Loan Forgiveness (PSLF) program and Nelnet services the Total and Permanent Disability Discharge program (TPDD).

2.1.3 Performance issues

Published metrics suggest that servicers vary in their quality in terms of keeping borrowers in good standing with their student loan payments, particularly for the most at-risk borrowers. Figure 2 shows delinquency rates for the second quarter of 2019. For borrowers who graduated, delinquency rates at both 91-270 days and more than 270 days are relatively low and are similar across servicers. In contrast, delinquency rates are much higher on average for borrowers who did not graduate. In addition, there are substantial differences across servicers — some have delinquency rates that are two to three times as high as others.

Analyses of student loan borrower complaints, investigations by government agencies, and enforcement actions taken by ED and several State Attorneys General document issues related to the quality and accuracy of information provided to borrowers, outreach and engagement strategies, proper record-keeping, as well as compliance with federal guidelines. In focus groups with student loan borrowers, researchers found that borrowers' repayment experiences are varied and dependent on their student loan servicer. Some borrowers reported that their servicers "gave them the information they needed, and that working with the servicer resulted in favorable outcomes." Others, mainly borrowers who were behind on payments, said their servicer added to their confusion and that they received inconsistent information (Pew Charitable Trusts, 2020).

Table 2 shows results of call monitoring audits performed by the Office of Federal Student Aid (FSA) in April and May 2017 (Office of Inspector General, 2019). FSA failed 3.3% of a random sample of monitored calls for not being in compliance with standards. Call-fail rates for some servicers were substantially higher than this average (9.8% and 5% for PHEAA and Missouri, respectively). Additionally, the share of failed calls that were due to the servicer not providing the borrower with sufficient information ranged from a low of 8.3% to 86% of failed calls. These findings support the idea that there is considerable variation in quality across servicers that could affect student loan outcomes like delinquency and default.

2.2 Student Loan Delinquency and Default

Figure 3 shows a timeline of student loan delinquency and default. If a scheduled monthly payment is missed, a loan is considered delinquent. While borrowers, their servicer, and the Department of Education observe delinquencies of less than 90 days, these delinquencies are not reported to credit bureaus. Delinquencies are reported to credit bureaus only after 90 days of missed payments.[9] After 270 days of missed payments, a loan is technically in default. Between days 270 to 360 of missed payments, borrowers remain assigned to their student loan servicer and can bring their loans out of default by making payments or using deferments or forbearances. During this period, the monthly fee paid to servicers' drops from $1.23 per loan to $0.45. After 360 days of missed payments, the borrower is transferred from their assigned servicer, thus entering the debt collection process. Servicers no longer receive payment for the borrower, but the defaulted borrower is also no longer included in the calculation of their performance metrics for the period. At this point, borrowers lose access to income- driven repayment plans, deferments, and forbearances. Finally, after 425 days of missed payments the loan is transferred to a private collections agency and the entire unpaid balance plus any accrued interest becomes due. Processes for withholding of tax refunds, Social Security payments, and wage garnishment also begin at this stage.[10] During this period, interest on the loan continues to accrue, in contrast to other forms of consumer credit.

Borrowers typically have few options to exit default, including full loan payoff, rehabilitation, or consolidation. Full loan payoff requires paying the full outstanding principal, interest, and collection fees of the defaulted loan. In this case, a record of the default will remain on the borrowers' credit report for up to seven years. Borrowers can rehabilitate their

[9] This is in contrast to most other forms of consumer credit, where delinquencies are typically reported on a monthly basis. In 2022, the major credit bureaus made substantial changes to how medical debt is reported on credit records, including removing medical debt in collections in the calculation of VantageScores.

[10] Using data from ADP, DeFusco et al. (2024) show that 0.4 percent of workers were having wages garnished for at least one defaulted student loan by the end of 2019. The average length of garnishment spells is 7.6 months compared with 4.8 months for other debt.

loans by making nine on-time payments within a 10-month period. The default is resolved on a borrower's credit report, although the preceding delinquencies remain. This option is not available to borrowers who have defaulted more than once. Borrowers also can exit default by consolidating existing loans into a new loan and making three on-time payments. In this case, the default is not removed from the individual's credit report, and this option is only available to those who have not previously consolidated their loans. Remaining in long-term default or exiting through one of these pathways has an unknown effect on borrowers' credit scores and access to credit.

3 Data

I rely primarily on data from the University of California Consumer Credit Panel (UCCCP). This is a longitudinal dataset following roughly 60 million consumers with credit reports on a quarterly basis since 2004. The underlying credit records are sourced from one of the three nationwide credit bureaus. I use the UCCCP nationally representative 2 percent sample.

The UCCCP contains loan-level information on student loans, auto loans, credit cards, mortgages, and other forms of credit. For each credit item, the data include the account opening date, account type, account condition (open, closed, in deferment, in repayment, etc.), principal amount, borrowing limits (for credit cards), and latest balance. It also includes a payment status code at the monthly level. Importantly, each credit item is linked to an anonymized identifier that indicates the loan originator or servicer. At the individual level the UCCCP contains demographic information on gender, month and year of birth, and 5-digit zip codes. Credit scores also are included at the quarterly level.

3.1 Sample Selection

From the loan level data, I build an individual level dataset for student loan borrowers with an eligible federal student loan. Federal student loans are not identified differently than private student loans in credit panel data.[11] Therefore, I define eligible student loans as individual loans (e.g. not cosigned) that were originated after June 30, 2010 with a principal amount less than the independent student borrowing limit ($12,500). This first student loan is treated as the focal student loan and the individual-level panel is constructed around this date.

I remove borrowers who cannot be matched to an age or gender or zip code. I restrict on borrowers who are observed with a credit record at least one quarter prior to the focal student loan origination. A little less than half of student loan borrowers did not have a credit record prior to their student loan origination. To ensure that I am examining outcomes for students who borrowed for their own undergraduate education, rather than parent's borrowing for a child's education or adults borrowing for graduate education, I also implement two additional sample criteria: I restrict to borrowers who are younger than 35 prior to student loan origination and who do not have a mortgage at the time of student loan origination. Borrowers in this sample thus are between the ages of 17 to 35 when originating a first student loan.

I incorporate all credit records associated with these borrowers. For each quarter relative to the origination date of the focal student loan, I aggregate loan status and balances for non-student loan credit items. This includes credit scores, auto loans and leases, credit cards, mortgages, and collections debts. I examine outcomes across three domains: financial distress, credit access, and borrowing. Within the financial distress category, I focus on the likelihood of having any non-student loan delinquency or collections item and the balances on those accounts. To measure credit access, I examine credit scores, the likelihood of having any open revolving account, and credit card limits. For borrowing, I examine the likelihood of having an auto loan or lease, which has been used as a proxy for durable goods consumption in prior literature. I also examine characteristics of borrowers' zip-code: the log median household income and an indicator for whether or not borrowers' live in a lower-income

[11] Federal student loans account for approximately 93% of all outstanding student loan debt.

zip-code than prior to student loan origination.

3.2 Measuring Delinquency and Default

In each quarterly update, the loan level data contain monthly payment status codes for the previous 24 months. This allows me to measure the exact month that borrowers enter delinquency or technical default (at 270 days delinquent), rather than relying on status updates at the end of each quarter. This is important because if a borrower falls delinquent in the middle of a quarter but gets current by the end of the quarter, that delinquency will be missed in a quarterly update.

Additionally, this monthly payment status allows me to measure defaults more precisely. The monthly payment status codes only indicate delinquencies up to 180 days past due. So, if a borrower remains delinquent the status code will report as 180 days delinquent for repeated months. These codes are retrospective and indicate whether or not a given loan was current or delinquent in a given month. The delinquency codes include separate indicators for 30 days, 60 days, 90 days, or 180 days delinquent. I convert repeated observations of the 180 day delinquencies into technical defaults at the 270 day delinquency threshold.

I combine the month and year of a borrower's first 90 day delinquency and first technical default with the individual-level panel. To calculate the time to a borrower's first delinquency or default, I subtract the delinquency and default month and year from the origination date of the focal student loan. This defines the treatment used in the servicer analysis.

3.3 Selecting servicers

The UCCCP contains anonymized identifiers for loan originators or servicers, but I do not observe directly the name for each servicer. Because my empirical strategy relies on variation stemming from the assignment process of federal student loans to servicers, I need to ensure the loans and servicer identifiers I am including in my analysis sample are indeed the relevant federal student loans. I select a group of servicer identifiers as the federal student loan servicers by examining the shares of new loans awarded to this group.

For each year in my study period, I identify the number of federal student loan servicers with contracts with the federal government. I then create a servicer identifier by quarter panel using only student loans that are individual accounts and have principal amounts less than the federal dependent student loan limit (i.e. more restrictive than my analysis sample). In each quarter, I rank the servicer identifiers by the share of newly originated student loans they have. I then assign the top identifiers as the federal servicers based on the number of servicers with contracts in a given year. For example, if there are five servicers in that year, then I will take the top five ranked identifiers. This approach accounts for over 90% of new loans in each period, comparable to the overall share of new student loans that are originated by the federal government.

3.4 Descriptive Statistics

Table 3 shows summary statistics for the resulting analysis sample. Statistics are calculated at the borrower level for the quarter in which they originated the focal student loan. The sample is majority female and has an average age of 24. The origination amount of the focal student loan is $2,870 on average, slightly below the federal dependent student borrowing limit. About 51% of borrowers in this sample are ever 90 days delinquent, 32% are ever 180 days delinquent, and about 30.5% ever default. The average credit score at the time of student loan origination is 609 points. Almost half of borrowers have at least one credit card, and about 17% of borrowers have an auto loan or lease.

4 Event Studies

This section provides new descriptive facts about the credit outcomes of student loan borrowers who experience delinquency or default. I implement an event study design to characterize the relationship between student loan delinquency and default and borrowers' credit outcomes. In these event studies, I focus on a sample of student loan borrowers who ever experienced a 90 day delinquency. I examine how outcomes evolve for two groups: 1) borrowers who experience a 90-day delinquency but do not default and 2) borrowers who experience a 90 day delinquency and ultimately default.

For each individual i, I denote $t = 0$ as the quarter-year in which the individual first experiences a 90 day delinquency. All other periods in the data are then indexed relative to that period. I estimate event studies of the following form:

$$Y_{it} = \gamma_t + \alpha * D_i + \sum_{t,t\neq -4} \beta_t + \sum_{t,t\neq -4} \delta_t * D_i + \epsilon_{it}, \tag{1}$$

where Y_{it} is the outcome of interest for individual i in quarter t and D_i is an indicator for whether individual i defaults. β_t are coefficients on indicators from time relative to the 90 day delinquency, and δ_t are coefficients on indicators for relative time interacted with the default outcome. The only controls included are calendar year dummies, γ_t. The omitted period is four quarters prior to the 90 day delinquency, and standard errors are clustered at the individual level.

Figures 4 through 6 plot regression estimates of β_t for the delinquent group and $\alpha + \delta_t + \beta_t$ for the defaulted group. The mean outcome of the delinquent group in the omitted period is added to both sets of coefficients to simplify the interpretation of the magnitudes.

Figure 4 displays event study results for outcomes related to financial distress. Panel A shows that both groups experience an increased likelihood of having a delinquency or collections prior to the student loan delinquency. In the quarter of student loan delinquency, 37% of delinquent borrowers and 41% of defaulted borrowers have another delinquency or collections. These rates slowly begin to decline for the delinquent group but remain relatively high and stable for the default group. Total balances (Panel B) on these delinquent or collections accounts follow similar patterns for both groups of borrowers. Average balances increase in the lead-up to delinquency and then begin to decline.

In Figure 5, I show outcomes related to measures of credit access and borrowing. Panel

A shows that credit scores decline slightly for both groups prior to their first student loan delinquency, although this decline is steeper for the defaulted group. Eight quarters before borrowers experience their first student loan delinquency, they have average credit scores between 540 and 560 points, which are classified as subprime credit scores. Both groups experience sharp drops in their credit score in the quarter of their student loan delinquency. Credit scores begin to recover for both groups after about 2 quarters. After 12 quarters, the delinquent group has credit scores about 10 points lower than in the period before delinquency, and the default group has a larger reduction of 20 points.

Turning to other outcomes, in Panels B through D we see outcomes diverge more starkly for these two groups of borrowers. In Panel B, the likelihood of having any open revolving account declines for both groups after a student loan delinquency. After about six quarters, this begins to recover for the delinquent group but remains low for the defaulted group. In Panel C, both groups of borrowers have declines in credit card limits immediately after a 90 day delinquency. Again, credit card limits begin to improve for delinquent borrowers after about six quarters. Delinquent borrowers experience small declines in the likelihood of having an auto loan or lease (Panel D), while defaulted borrowers see a larger decline that remains through the following 12 quarters.

In Figure 6, I show how borrowers zip-code characteristics change around delinquency. In Panel A, I show the zip-code log median household income. This fluctuates for delinquent borrowers but remains relatively flat over time. In contrast, defaulted borrowers experience a steady decline in zip-code income in the two years prior to delinquency. This trend then remains flat through the following 12 quarters. In Panel B, I show the likelihood of living in a lower-income zip-code than at student loan origination changes around delinquency. Both groups of borrowers exhibit increases in this indicator over time.

Together, these trends show that both delinquent and defaulted borrowers experience increased rates of financial distress prior to experiencing a student loan delinquency. Delinquent borrowers recover more quickly and do not appear to have limited access to credit after their delinquency. While credit scores for the defaulted group begin to recover after an initial stark decline, delinquency rates on other forms of credit remain high. Rates of access to other forms of credit remain low for defaulted borrowers even 12 quarters after default.

The event study analysis highlights the dynamics of student loan delinquency and default. However, this analysis also reveals patterns that are consistent with changes to credit outcomes being correlated with both the delinquency and eventual default. Defaulted borrowers have lower credit scores, less access to credit, and higher rates of other delinquencies and collections prior to student loan delinquency. They also experience sharper changes in some of these outcomes, particularly credit scores and zip-code income, in the immediate lead up to delinquency. These patterns motivate the use of the instrumental variables research design described in the next section.

5 Servicer Design

Consider a basic model that relates financial outcomes, such as credit scores, to an indicator for whether an individual was ever delinquent or in default on a student loan:

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 \mathbf{X}_i + \epsilon_i, \tag{2}$$

where Y_i is the outcome of interest for individual i, D_i is an indicator for student loan delinquency or default, $\mathbf{X}_i$ is a set of loan- and individual-level control variables, and ϵ_i is an error term.

The key problem for estimating a causal effect of default on financial outcomes is that OLS estimates of (2) are likely to be biased by the correlation between defaulting and unobserved borrower characteristics that also are related to financial outcomes. Event study estimates presented in Section 4 suggest that whether a borrower defaults may depend on unobserved shocks that affect both default and subsequent outcomes.

The ideal experiment to estimate the impact of default on borrower's credit outcomes would be to randomly vary default across borrowers. While such an experiment is infeasible in practice, I approach this ideal by isolating plausibly exogenous variation in the likelihood of default. I do so by exploiting a feature of the student loan repayment system: the fact that student loan borrowers are randomly assigned to student loan servicers upon taking out an initial student loan. This approach is similar in spirit to an examiner tendency design. I discuss the similarities and differences in more detail in Section 5.2. Borrowers are assigned to a servicer when they take out their first student loan, and these servicers vary in terms of their likelihood of helping borrowers avoid default. All future loans are assigned to the same servicer. These assignments are done randomly to ensure that all servicers have similar-looking portfolios of borrowers. I describe the assignment process in more detail in Section 2.

5.1 Instrumental Variables

5.1.1 The Servicer Quality Instrument

I start by creating a measure of servicer quality, which I call the "servicer score." The score is constructed at the servicer-by-quarter level and measures the average likelihood of default of all borrowers assigned to the same servicer in the same quarter. I focus on quarters because the allocation shares that determine servicers new loan awards are constant within a quarter.

Using the simple average of the binary outcome of a student loan default is problematic because not all servicers entered the system at the same time. This means that a set of the oldest servicers could face higher rates of default simply because more of the borrowers in their portfolio have held their loans for longer. To account for this potential confounder, I residualize the binary measure of default with respect to the quarter-year of the borrower's first student loan. I define the residualized measure of default as D_i^*:

$$D_i^* = D_i - \hat{\gamma}_o, \tag{3}$$

where $\hat{\gamma}_o$ are the estimated fixed effects for the student loan origination quarter-year.

I then use this residualized default rate to construct the servicer-by-quarter instrument, $Z_{i(sp)}$. Following the literature, I recompute this as a leave-one-out mean to purge the score assigned to borrower i from their own default outcome.

For each individual with an initial assignment to servicer s in allocation quarter p, I calculate the share of individuals assigned to servicer s in allocation quarter p that defaulted, excluding the outcome for borrower i. Formally,

$$Z_{i(sp)} = \left(\frac{1}{n_{sp} - 1}\right)\left(\sum_{k \neq i} D^{*}_{k(sp)}\right), \tag{4}$$

where n_{sp} is the number of borrowers assigned to servicer s in allocation quarter p. Finally, I scale $Z_{i(sp)}$ so that one unit corresponds to one standard deviation in the residualized default rate measure. Figure 7 documents the distribution of the residualized servicer score measure, showing substantial variation.

5.1.2 Instrumental Variables Assumptions

There are several assumptions that must be met in order for the servicer score to be a valid instrument for default. If these assumptions are satisfied, the IV estimand will be interpretable as a positive weighted average of local treatment effects on compliers, where compliers are defined as borrowers who would not have defaulted had they been assigned to a different servicer (Imbens and Angrist 1994). This section discusses each assumption, providing institutional details and empirical evidence in support of these assumptions.

i. Relevance

I begin by showing the first-stage relationship between the servicer score and whether an individual borrower defaults. This relationship is visually represented in Figure 7. Figure 7 shows the results of a local linear regression of the residualized default rate on the servicer score, suggesting that being assigned to a servicer with a higher score is associated with a higher likelihood of default.

In addition, I estimate the likelihood of defaulting as a function of the servicer score instrument using a linear probability model. Table 4 reports results from the following regression:

$$D_i = \phi Z_{i(sp)} + X_i'\alpha + \epsilon_i, \tag{5}$$

where $Z_{i(sp)}$ are leave-out measures of servicer quality that are allowed to vary across allocation quarters. The vector $\mathbf{X}_i'$ includes fixed effects for the quarter-year of student loan origination and controls for gender, zip code median household income, age at first student loan origination, and first student loan origination amount.

In column 1 of Table 4, I show the outcome of the regression of the likelihood of default on the servicer score. In column 2, I add into the regression additional individual characteristics at the time of student loan origination. In both columns, there is a statistically significant relationship between the servicer score and the dependent variable of default, with a magnitude that remains similar at about 2 percentage points. This supports the identification approach as the strength of the first stage relationship does not change when including controls. This means that a one standard deviation increase in the servicer score (e.g. a servicer with a higher default rate), is associated with a 2 percentage point increase in the likelihood of default, relative to a dependent variable mean of 27 percent. The servicer score has a large and statistically significant effect on the likelihood of default, with a partial F-statistic for the servicer score in the range of 70 to 76. This relieves concerns about a potential weak instrument.

ii. Independence

For the instrument to be valid, the servicer score must be independent of borrower characteristics. For example, if borrowers with a higher risk of default are assigned to "worse" servicers, we will not be able to distinguish between selection and the actual servicer effect. To address this concern, I conduct balance tests to confirm that borrowers do not vary systematically by servicer score. I find that the servicer score is balanced with respect to borrower characteristics at baseline.

Column 1 of Table 5 reports linear probability estimates of the correlation between borrower characteristics and the likelihood of default, after controlling for origination quarter-year fixed effects. As shown, default is highly correlated with borrower and loan characteristics.

Column 2 reports estimates from an identical regression except the dependent variable is the standardized servicer score. The servicer score is not correlated with most of these observed characteristics, consistent with borrowers being randomly assigned to servicers. The coefficient on the first student loan origination amount is statistically significant, but the magnitude is economically small. This says that a $1000 increase in first student loan origination amount decreases the servicer score by .002 standard deviation units. Zip-code median income is also marginally statistically significant, but this estimated coefficient has the opposite sign as the corresponding coefficient from column (1). This suggests that an increase in zip-code level household income is associated with being assigned to a higher-default servicer.

Finally, in column 3, I construct a measure of predicted default using the borrower characteristics from the regression in column (1) and show that this measure of predicted default is not correlated with the service score. These results show that servicers with ranging default propensities handle observationally similar borrowers. Crucially, the independence assumption is enough to support a causal interpretation of the reduced form. I discuss this claim in more detail below.

iii. Exclusion

To interpret the results of the IV as the causal effect of default, the servicer score must affect credit outcomes only through student loan default. There are two main concerns related to the exclusion restriction: (1) student loan servicers could have a direct effect on non-student loan credit outcomes and (2) the servicer score based on default may capture other dimensions of servicer quality that affect borrower outcomes.

While I cannot directly test for the first possible violation of the exclusion restriction, it is unlikely that servicers would affect outcomes beyond student loan repayment. For example, one possible way this assumption could be violated is if being assigned to a better quality servicer improves your financial literacy in all areas and not just through the performance on your student loans. While possible, this is unlikely since servicers have a very narrow scope of practice. Additionally, if this sort of mechanism were at play, this would bias my estimate toward a larger negative effect. Ultimately, I find a null effect of servicer quality on borrowers' non-student loan credit outcomes. Unless being assigned to a worse servicer improves your non-student loan credit outcomes, this form of bias is unlikely to be present.

As discussed in Section 2, servicers are borrowers' main point of contact during the repayment process and as such may influence other aspects of the borrowers' repayment record beyond default. In particular, if and how a servicer impacts whether or not borrowers' are ever 90 days delinquent also could affect credit outcomes. Since all borrowers who end up in default will have experienced a 90 day delinquency, this presents a potential problem.[12] The multidimensionality of servicer quality could make it challenging to isolate the impact of default (Mueller-Smith 2015; Bhuller et al 2020). Delinquency is a mechanism through which serivcers could impact a borrowers' likelihood of default, but the event study analysis suggests that delinquency may have effects on credit separate from default. It is possible that higher quality servicers are more likely to have both lower delinquency rates and lower default rates. If this is the case, baseline estimates will capture a linear combination of the effect of being delinquent and the effect of defaulting. This would over-estimate the effect of default on credit outcomes because it would also capture the effect of delinquency. Ultimately, I estimate null effects so concerns about over-estimating the treatment effect of default due to delinquency are less relevant.

iv. Monotonicity

In order to interpret the estimates as a positively weighted average of local average treatment effects, the impact of servicer assignment on the probability of default must be

[12]This is similar to papers that study incarceration and conviction, where in order to be incarcerated defendants must have been convicted.

monotonic across borrowers. In this setting, the monotonicity assumption implies that if a borrower defaults when assigned to a higher quality servicer, they should also default when assigned to a lower quality one. The strictest version of this assumption - pairwise monotonicity - essentially requires that all servicers have the same ranking of borrowers in terms of their default propensity. This condition could fail if servicers are relatively high quality for some borrowers and relatively low quality for others.

I cannot test this assumption directly, but one testable implication of the monotonicity assumption is that first-stage estimates should be nonnegative for any subsample of borrowers. As is common in the literature, I conduct this test and present results in Table 6. Consistent with the monotonicity assumption, I find that the relationship between the residualized servicer score and default is positive and significant in all subsamples.

5.2 Comparison to other examiner designs

This approach is similar to a long line of literature that uses random assignment of cases to decision makers. It has been applied in studies across a range of settings and topics, including pre-trial detention, bankruptcy protection, and SNAP receipt.[13] The key ingredient in these studies is that examiners with different tendencies will expose comparable individuals to different treatments or interventions. These tendencies thus are used to instrument for treatment exposure.

This setting differs from the typical setting in that the "examiner" in this case is not an individual decision-maker, but rather a company. Despite this difference, the same conceptual model underlying most examiner tendency designs applies. The examiner decision is modeled as a cost-benefit problem, where the solution is a threshold crossing value that compares the probability that the treatment has net benefit to some cutoff value. This cutoff value may vary across examiners because of differences in preferences, information, or behavior. Servicers also face a cost-benefit problem when determining how to allocate

[13] Table A.1 in Chyn et al. (2024) describes over 71 studies that feature various types of decision-makers.

resources to borrowers in their portfolios. Servicers have discretion over many of the policies and practices they employ. Interventions to assist struggling borrowers can be costly and those costs may vary across the different servicers. Costs could vary depending on size of the servicer, technology employed, or skill level of staff.

While many papers that use this approach rely on individual decision-making of a judge or case examiner as the mechanism that generates variation, the examiner tendency framework also has been applied to other settings. In particular, two papers that are most similar to my setting are Herbst (2023) and Kermani and Wong (2021). Herbst (2023) uses random assignment to call center agents at a student loan servicer to instrument for enrollment in income-driven repayment. The call-center agent does not get to decide who is eligible for income-driven repayment. Rather, the instrument is essentially measuring how effective a given call center agent is at getting a borrower to enroll. This is similar in spirit to the mechanism driving variation in default here, where the instrument measures how well servicers do at preventing borrowers from defaulting. Kermani and Wong (2021) study the effect of mortgage modifications on racial disparities in housing returns using variation across servicers in their propensity to modify mortgages as an instrument. Prior research suggests that this variation across servicers is linked to the incentives that servicers face (Agarwal et al., 2011; Kruger, 2018; Agarwal et al., 2017). In my setting, servicers have incentives to keep loans current, but these incentives are weakened when a borrower crosses the 270 day delinquency threshold.

5.3 Estimation and implementation

5.3.1 2SLS

I estimate the following two-stage least squares model:

$$D_i = \phi Z_{i(sp)} + X_i'\alpha + \epsilon_i \tag{6}$$

$$Y_i^t = \beta D_i + X_i'\delta + \upsilon_i, \tag{7}$$

where the least squares regression is estimated separately by quarter from origination. Here, D_i is an indicator for whether borrower i ever defaults, Y_i^t is the observed outcome t quarters after origination, and X_i is a set of controls for individual and loan characteristics. Controls include origination year-quarter fixed effects, gender, zip-code median household income in the quarter before student loan origination, age at student loan origination, and first student loan origination amount. If the IV assumptions are satisfied, we can interpret β as the causal effect of default. If the servicer score impacts financial outcomes through any other channels, then the resulting estimates also will capture the effect associated with servicer assignment that is not directly attributable to default.

5.3.2 Reduced form

Due to the difficulty of disentangling the causal effects of delinquency and default discussed above, I also estimate reduced form effects for all outcomes of interest. These can be interpreted as the causal effect of being assigned to a higher or lower quality servicer. The causal interpretation of the reduced form effects only requires the first two assumptions be satisfied: relevance and independence. Critically, it does not require the assumption that the only reason servicers impact outcomes is through their effect on default. The causal effect of servicers on borrower outcomes is an important question on its own, since these are important actors within the student loan system about whom little is currently known.

Controlling for observable borrower characteristics, I regress each outcome of interest on the servicer score instrument described above. To show how outcomes evolve over time, I again estimate this model separately by quarter from student loan origination. The formal estimating equation is:

$$Y_i^t = \theta Z_{i(sp)} + X_i'\lambda + \mu_i, \tag{8}$$

where Y_i^t is the observed outcome t quarters after origination, $Z_{i(sp)}$ is the servicer score instrument for borrower i assigned to servicer s in allocation quarter p, and X_i is a set of controls for individual and loan characteristics. Controls include year-quarter fixed effects, gender, zip code median household income, age at student loan origination, and first student loan origination amount. These estimates measure the effect of being assigned to a one standard deviation lower quality servicer (ie. with a higher average default rate) on student loan and non-student loan credit outcomes.

6 Results

6.1 Reduced Form: Effect of Servicer Quality

This section presents results based on the specification in equation (8). These estimates reflect the direct effect of servicer assignment on borrowers' student loan and non-student loan credit outcomes in the first six years (24 quarters) from their first student loan origination. Coefficients and 95% confidence intervals are plotted in Figures 8 through 11. Coefficient estimates and standard errors are displayed in Table 7.

I first consider how servicer assignment affects delinquency and default on student loans with results shown in Figure 8. These are similar to the first stage results shown in Table 4, but with effects estimated separately by quarter from student loan origination. Figure 8 reveals that being assigned to a servicer with higher default rates significantly increases the probability of experiencing a 90-day delinquency (Panel A) or a default (Panel B). At 24 quarters post-origination, the likelihood of a 90-day delinquency rises by 1 percentage point, while the probability of default increases by 2 percentage points.

Next, I examine measures of financial distress. This includes: having any non-student loan account delinquency or collections account and the total balances on these accounts. Figure 9 and Panel A of Table 7 show that being assigned to a higher-default servicer has an economically small effect on both outcomes, which is not statistically different from zero even at the 10% level. The estimates for the likelihood of having a delinquency or collections account range from -0.2 percentage points to 0.03 percentage points, with estimated 95 percent confidence intervals that exclude effects larger than 0.6 percentage points. Estimates of the effect of being assigned to a higher-default servicer on total balances in delinquency or collections range from a decrease of $36 to an increase of $12. Across the first 20 quarters, I can rule out changes in total balances greater than $100 in either direction. Standard errors get larger toward the end of the panel, but estimates remain statistically indistinguishable from zero.

I then focus on credit access and borrowing indicators, including credit scores, the probability of having an open revolving account, credit card limits, and the probability of having an auto loan or lease. Overall, these findings suggest that being assigned to a higher-default servicer has a minimal impact across all three measures of credit access and borrowing. Panel A of Figure 10 and Panel B of Table 7 show estimates of the servicer effect on credit scores, which range from -0.7 points to 0.8 points. The estimated 95% confidence intervals can rule out effects larger than about a 2 point change in either direction. This is less than 2% of a standard deviation of the credit score pre-origination. Similarly, I find null effects on both alternative measures of credit access: the probability of having an open revolving account (Panel B) and credit card limits (Panel C). Estimates on any open revolving account range from -0.2 to 0.2 percentage points. I can rule out effects larger than a 0.8 percentage point change in either direction from the 95% confidence interval. The estimates on credit card limits range from a decline of $27 to an increase of $16. In most quarters, the 95% confidence intervals exclude changes larger than about $100 in either direction. Being assigned to a higher-default servicer has no effect on the probability of having an auto loan or lease (Panel D of Figure 10 and Panel C of Table 7). The estimates are economically small and are not statistically significant. They range from -0.1 to 0.02 percentage points. The estimated 95% confidence intervals rule out an effect larger than 0.5 percentage points in either direction.

Finally, in Figure 11 and Panel D of Table 7 I show results for outcomes related to borrowers' zip-code median income. In Panel A, I plot coefficients estimating the effect of being assigned to a higher-default servicer on the log median income in a borrower's zip-code. Panel B shows the probability of living in a zip code with a lower median income than at the time of student loan origination. For log median income, estimates range from -0.2 to -0.08 percent across quarters. The estimated 95% confidence intervals exclude effects larger than a decline of 0.5% or an increase of 0.2%. The change in the probability of living in a lower income zip-code from being assigned to a worse quality servicer ranges from -0.2 percentage points to 0.2 percentage points. The estimated 95% confidence intervals rule out effects larger than a 0.7 percentage point change in either direction.

6.2 OLS and IV: Effect of Default

In this section, I present OLS and IV estimates of the effects of default on measures of borrowers' financial distress, credit access, borrowing, and zip-code characteristics. Results from the specification in equation (2) are presented in Table 8. Results from the 2SLS specification in equations (6) and (7) are shown in Table 9. OLS estimates in these specifications differ from the event studies by being relative to origination rather than delinquency. Overall, OLS estimates present a similar story to the event study analysis: borrowers experience large, negative effects of default. In contrast, IV estimates are close to zero and are not statistically significant.

When examining measures of financial distress, the IV estimates tend to be closer to zero relative to the OLS estimates, providing evidence of potential selection bias in the OLS results. OLS estimates are presented in Panel A of Table 8 and IV estimates are presented in Panel A of Table 9. OLS estimates show a positive effect of default on the likelihood of having a non-student loan delinquency or collections account. Estimates range from 16 to 25 percentage points and are increasing in quarters from student loan origination. In contrast, the IV estimates are closer to zero and occasionally have the opposite sign, although all estimates lack precision. By 21-24 quarters from origination, the IV estimate suggests an 8.5 percentage point decrease in the likelihood of having a non-student loan delinquency or collections account. The estimated 95% confidence interval spans from -31 to 14 percentage points. For balances on delinquency or collections accounts, a similar pattern emerges. OLS estimates are generally large and positive, although they do not follow a clear time trend. The IV estimates are mixed, with some being positive and others negative, but the imprecision of the estimates makes it difficult to draw firm conclusions.

Panel B of Tables 8 and 9 present OLS and IV estimates for measures of credit access. When considering credit scores, OLS estimates show declines ranging from -67 to -114 points. The most severe decline occurs between quarters 9 and 12 after origination, followed by a gradual recovery. This mimics the recovery seen in the event study analysis examining credit scores. In contrast, IV estimates of the effect of default on credit scores are negative during the first 12 quarters but turn positive thereafter. Notably, the IV estimates are much smaller in magnitude than the OLS estimates. For instance, when the OLS estimate shows the largest decline in credit scores of 114 points, the IV estimate is only -8 points, with a 95% confidence interval ranging from -58 to 42 points. In all periods, the OLS estimates fall outside the lower bound of the IV confidence interval.

The effect of default on the probability of having an open revolving account shows a similar pattern. OLS estimates are consistently negative in all quarters, ranging from a -32 percentage points to -46 percentage points. IV estimates, however, are more attenuated and sometimes even have the opposite sign as the OLS estimates. For example, the OLS estimate for quarters 21-24 is -44 percentage points, while the IV estimate is -13.8 percentage points, with a 95% confidence interval that ranges from -38 to 10 percentage points.

For credit card limits, OLS estimates of the effect of default show a steady decline over time, with defaulters experiencing an average credit limit reduction of $6,700 by the 24th quarter. IV estimates are closer to zero. In quarters 21-24 from origination, the IV estimate shows a reduction in credit limits of $847, but the confidence interval is wide, ranging from

-\$6,500 to \$4,900.

In Panel C of Tables 8 and 9, I show results for outcomes related to borrowing. When examining the likelihood of having an auto loan, OLS estimates again show deteriorating outcomes over time. Estimates range from -8 percentage points to -22 percentage points by quarters 21-24 from origination. In contrast, the IV estimate in the last period is just -0.4 percentage points, although it is imprecise.

Finally, the effect of default on zip-code median income ranges from -3% to -6% according to OLS estimates (Panel D of Table 8). In contrast to other outcomes, here the IV estimates are slightly larger than the OLS estimates. IV estimates range from -4% to -14% across quarters (Panel D of Table 9). In quarters 21-24, the IV estimate of the effect of default on zip-code median income is -7%, though this estimate is still not statistically significant. The estimated 95% confidence interval rules out effects larger than a 22 percent decline or a 9 percent increase. A similar pattern emerges when looking at the indicator for living in a lower-income zip code than at the time of student loan origination. OLS estimates are positive and around 6-7 percentage points in all quarters. In some but not all quarters, IV estimates are larger than OLS estimates, although they continue to be imprecise. For example, in quarters 21-24 the IV estimate of the effect of default is 11.5 percentage point increase in the likelihood of living in a lower-income zip-code, with a 95% confidence interval ranging from -11 percentage points to 34 percentage points.

6.3 Discussion

OLS estimates of equation (2) and the event studies in Section 4 show large negative effects of default on borrower outcomes, but these are not reflected in the servicer instrumental variables design. Reduced form results of the effect of servicer assignment show a statistically significant effect on student loan repayment outcomes but precisely estimated null effects on borrowers' non-student loan related credit outcomes. The 2SLS estimates of the effect of default using the servicer score instrument are larger in magnitude, but no estimate is statistically significantly different from zero for any outcome.

While this result may be surprising, there is evidence from other contexts that credit scores might not change that much as a result of a culminating negative credit event (eg. default, foreclosure) that comes after a series of preceding negative credit marks. For example, Kluender et al. (2024) show that forgiving medical collections debt has a small average effect on credit scores, which is concentrated among those for whom forgiveness restores a clean credit report. Similarly, in a study on the effects of foreclosure, Diamond et al. (2020) find that the final foreclosure decision has a small effect on credit scores due to the preceding delinquencies that occur for both the treated and control group in their setting.

Additionally, these results are consistent with other papers that study the effect of student loan policies on delinquency, default, and credit scores. These papers find a decline in student loan delinquency as a result of some student loan policy, but either no change or a very small change in credit scores. Black et al. (2023) find declines in 90 day and 270 day delinquency of 1.3 percentage points and 1.8 percentage points, respectively, as a result of loan limit increases. There is no effect on credit scores as a result of these loan limit increases, however. Similarly, Herbst (2023) finds an 8 percentage point decline in 90 day delinquency and only a 5 point increase in credit scores as a result of enrollment in income-driven repayment. This change in delinquency rates is about four times larger than the effect I estimate, suggesting it may be difficult to pick up any kind of change in credit scores as a result of delinquency or default. In contrast to these papers, I estimate the effect of student loan servicer quality on borrower outcomes, as well as the effect of default specifically.

While the event studies do show a stark decline in credit scores when borrowers first show a 90 day delinquency on a student loan, they also show a relatively quick recovery. It is important to note that both groups of borrowers shown in the event studies (those who are delinquent but do not default and those who default) have relatively low average credit scores to begin with. Credit scores begin to recover for both groups after about three quarters. Twelve quarters after the first 90 day delinquency, both groups have average credit scores about 10 points lower than in the quarter before delinquency. Both the larger immediate decline in credit scores of 20 to 25 points and the smaller, longer-term decline are within the 95% confidence interval of the IV estimate on credit scores.

The IV estimates and event studies also may differ due to the nature of the IV estimand. The IV estimates represent the local average treatment effect for those induced to default by their servicer, not the average treatment effect. In Tables 10 and 11, I characterize the share of compliers and their characteristics following the approach developed by Abadie (2003) and Dahl et al. (2014), and applied by Dobbie et al. (2018), Bhuller et al. (2020), and Agan et al. (2023). I estimate that about 14% of the sample are compliers. The compliers are more likely to be older and male than the overall sample. In addition, they are more likely to reside in a lower-income zip-code when first taking out a student loan and to have subprime credit scores prior to origination. These factors may alter the treatment effect of default for this particular group of student loan borrowers compared with the average defaulter.

Finally, due to the differing structure of the event study analysis and the IV analysis, the IV estimates may mask some of the dynamics that are visible in the event studies. In the IV analysis, a borrower is treated if they ever default within the panel (24 quarters since originating a student loan). This definition of treatment is constant within a borrower, even though default is a dynamic outcome. Among borrowers who default, there is variation in when they default. In Figure 12, I plot the share of defaulters who have ever had a 90 day delinquency, ever defaulted, have a current delinquency, or a current student loan collections by quarter from origination. The share of defaulters that have a 90 day delinquency begins to increase around quarter four. But around quarter six, the lines for ever delinquent and current delinquency begin to diverge. The share of defaulters with a current delinquency reaches a peak in quarter seven and then begins to decline. These begin to decline as borrowers enter default and then continue to decline as borrowers either exit default by getting their loans current or by entering collections. The downward trend in the share of defaulters with a current delinquency reflects people moving into default (and, therefore, out of delinquency), but also borrowers newly entering delinquency. Thus, the share of defaulters who have defaulted by quarter of origination steadily increases over time. This implies that in each IV coefficient, the effect of default is measured using a combination of outcomes for three groups of treated borrowers: (1) borrowers who have already defaulted and are either still in default or have exited; (2) borrowers who have newly entered default in that quarter; and (3) borrows who eventually will be treated but have not yet experienced default. Given the relatively short-lived effect of default on credit scores documented in the event studies, this approach will attenuate any larger effect if it only occurs in the period right after default. Ultimately, even if this approach does not pick up adverse short-run effects of default, long-run effects appear to be small.

There are many plausible explanations for the null effect I find across outcomes. These two empirical approaches highlight different dimensions of student loan delinquency and default, both of which bring new insights into the forefront. The event study approach highlights the dynamics of student loan delinquency and default. These show borrowers are facing financial distress along many dimensions prior to student loan delinquency and that defaulters fare worse along many dimensions. They also show that credit score declines are relatively short-lived, although these borrowers have subprime credit scores before and after experiencing delinquency. The IV design isolates variation in the likelihood of default that is not driven by borrower characteristics and shows that the marginal complier does not have worse overall credit outcomes as a result of servicer-induced default.

7 Conclusion

Student loan default is a widespread phenomenon in the federal student loan system, with around 6 million federal student loan borrowers in default. These borrowers tend to be from backgrounds historically disadvantaged in higher education. In recent years, growing awareness of the scale and potential consequences of student loan default has led to increasing attention from advocates and policymakers. Concern over this has been a main driver of recent Biden Administration policies aimed at helping distressed student loan borrowers, such as the FreshStart program to assist borrowers in resolving defaults and a proposed plan for loan forgiveness aimed at those experiencing financial hardship. Despite this interest, the effects of default remain poorly understood.

At the same time, student loan servicers have come to the forefront of policy discussions about the student loan system. Many of the issues raised touch on ways that servicer practices have disadvantaged borrowers, including misleading borrowers about repayment options, failing to keep proper records of payments, and variable outreach and engagement strategies. While servicers are seen as an important part of the student loan repayment system, evidence of their impact on borrower outcomes is limited.

Using consumer credit panel data, I explore how student loan delinquency, default, and student loan servicers affect borrowers' credit outcomes. I employ both an event study design and an instrumental variables design that enables me to isolate exogenous variation in the likelihood of default. I document signs of increasing financial distress in the lead-up to borrowers' first student loan delinquency across a broad range of credit outcomes. These suggest that delinquency often is preceded by adverse events. I also show that while both delinquent and defaulted borrowers experience sharp declines in their credit scores in the same quarter as their student loan delinquency, both groups experience a recovery in credit scores in the following quarters. Despite this finding, measures of credit access remain low for defaulted borrowers in the three years following their first delinquency.

Exploiting random assignment of student loan borrowers to servicers, I estimate causal effects of being assigned to a lower quality servicer on student loan and non-student loan credit outcomes. I demonstrate that being assigned to a lower quality servicer increases borrowers' likelihood of falling delinquent or defaulting by 2 percentage points (approximately 6 percent). While servicers have a strong causal link with borrowers' student loan outcomes, this effect does not spill over onto borrowers' broader credit outcomes.

I then implement an instrumental variables design, using servicer quality as an instrument for the likelihood of default. I estimate the effect of default on marginal student loan borrowers who are induced to default by their servicer. On average, these borrowers are older, have lower initial credit scores, and are more likely to reside in lower-income zip-codes. IV estimates similarly show a null effect of default on measures of borrowers' financial distress, access to credit, borrowing, and zip-code characteristics.

My results suggest that averting a default does not yield considerable benefits for borrowers along the dimensions studied. In many cases, borrowers are already showing signs of financial distress that will negatively affect their credit ratings prior to experiencing a student loan delinquency or default. The addition of a default does not worsen their situation in any meaningful way. This might seem contrary to conventional wisdom, but it is consistent with existing descriptive evidence that presents a more complicated picture of default. This research shows that about half of borrowers successfully exit default within three years (Delisle et al., 2018) and that, on average, borrowers who default have lower credit scores in the year prior to default than in the year of default (Blagg, 2018).

Default can be thought of as a bundle of different policies that phase-in at different times and interact with one another in complicated ways. There may be additional dimensions of default that are important to explore. For example, not all borrowers who default according to the 270 day delinquency threshold will experience forced payment mechanisms, like wage garnishments, but this could have a different effect on borrowers. Additionally, there are several pathways to exit default and each option has different implications for what is visible on their credit reports. Finally, other outcomes beyond those observable in credit panel data may be more impacted by default, particularly for this group of borrowers who have limited access to credit to begin with due to their low credit scores.

This research speaks to an ongoing and active policy debate on how to handle student loan delinquency, default, and the role that student loan servicers play in the system. My results suggest that efforts to prevent earlier delinquencies, rather than default, might provide borrowers with more meaningful benefits on their credit records. Additionally, more research should be done to understand which servicer practices have a positive impact on the repayment outcomes of borrowers. Borrowers, particularly those who struggle with repayment, may benefit from increased standardization of practices and procedures across servicers.

Tables and Figures

Table 1: Servicer Monthly Fees

Number of Days Delinquent	Monthly Fee
0-5 Days	\$2.85
6-30 Days	\$2.11
31-90 Days	\$1.46
91-150 Days	\$1.35
151-270 Days	\$1.23
Greater than 270 Days	\$0.45

Notes: This table presents the monthly fees paid to servicers by the number of days delinquent of the loan.

Table 2: Calls that FSA Monitored and Failed, April and May 2017

Servicer	Number of Calls Evaluated	Number of Calls that Failed	Percentage of Calls that Failed	Number Failed Due to Servicer Not Providing Sufficient Information	Percentage of Failed Calls Due to Servicer Not Providing Sufficient Information
Oklahoma	920	12	1.30%	1	8.3%
Utah	893	25	2.80%	3	12.0%
PHEAA	1850	181	9.78%	33	18.2%
EdFinancial Services	973	19	1.95%	4	21.1%
Navient	1946	9	0.46%	2	22.2%
Missouri	1267	63	4.97%	18	28.6%
New Hampshire	749	8	1.07%	3	37.5%
Nelnet	1337	13	0.97%	6	46.2%
Great Lakes	575	14	2.43%	12	85.7%
Total	10510	344	3.27%	80	23.3%

Source: Office of the Inspector General, U.S. Department of Education; calculations by the author.

Table 3: Summary Statistics

	(1) Mean	(2) SD
Age	24.447	4.609
First SL Origination Amount ($100s)	28.709	18.633
Zip-Code Log Median HH Income	10.966	0.379
Female	0.573	0.495
Ever 90 Days Delinquent	0.512	0.500
Ever 180 Days Delinquent	0.320	0.467
Ever Default	0.306	0.461
Any Non-SL Delinquency or Collections	0.157	0.363
Total Balance: Non-SL Delinquency or Collections	3.154	19.159
Credit Score	609.1	90.2
Subprime Credit Score	0.558	0.497
Any Open Revolving Account	0.492	0.500
Credit Card Limit	26.092	65.850
Any Auto Loan or Lease	0.169	0.375
Observations	24910	

Notes: This table reports summary statistics at the borrower level in the quarter prior to first student loan origination. The sample is a balanced sample of borrowers who are observed for 6 years post first student loan origination. First student loan origination amount is the principal amount of the borrowers first observed student loan. Zip-code median income is the 2010 income for the borrower's recorded 5-digit zip code. Any non-student loan delinquency or collections is an indicator for whether or not the borrower has a non-student loan account delinquent or in collections. Total balance: non-student loan delinquency or collections is the balance on these accounts. Subprime credit score is an indicator if the borrower's credit score is below 619 points. Any open revolving account is an indicator if the borrower has an open credit card or other revolving credit account.

Table 4: First Stage: Servicer Score and Default

	(1) Default	(2) Default
Servicer Score	0.022***	0.021***
	(0.003)	(0.002)
Age at SL Origination		0.002***
		(0.001)
First SL Orig Amount ($1000s)		-0.001***
		(0.000)
Log Zip Median HH Income		-0.065***
		(0.007)
Female		-0.056***
		(0.005)
Credit Score		-0.002***
		(0.000)
F-stat	70.375	76.496
P-value	0.000	0.000
Dep. Mean	0.306	0.306
N	24910	24910

Notes: This table reports results from the first-stage regression of default on servicer score. Columns 1 and 2 report estimated coefficients from an OLS regression of default against the variables listed in addition to origination quarter-year fixed effects. Regressions are estimated on a balanced sample of borrowers who are observed for 6 years post first student loan origination. Robust standard errors are reported in parentheses. The p-value reported at the bottom of the column is for an F-test of the significance of the servicer score.

Table 5: Balance Test

	(1) Default Ever	(2) Servicer Score	(3) Predicted Default
Age at SL Origination	0.002***	0.000	
	(0.001)	(0.002)	
First SL Orig Amount ($1000s)	-0.001***	-0.002***	
	(0.000)	(0.000)	
Log Zip Median HH Income	-0.064***	0.032*	
	(0.007)	(0.019)	
Female	-0.055***	0.020	
	(0.005)	(0.014)	
Credit Score	-0.002***	-0.000	
	(0.000)	(0.000)	
Servicer Score			0.001
			(0.001)
F-stat	1252.265	5.426	1.113
P-value	0.000	0.000	0.291
Dep. Mean	0.306	0.028	0.306
N	24910	24910	24910

Notes: This table reports balance test results. Column 1 reports the estimated coefficients from an OLS regression of an indicator for default against the variables listed, as well as origination quarter-year fixed effects. Column 2 reports estimates from an identical regression, except with the dependent variable equal to the standardized servicer score. Column 3 presents results from a regression of predicted default on the servicer score. Predicted default is constructed using the results of the regression in Column 1. Regressions are estimated on a balanced sample of borrowers who are observed for 6 years post first student loan origination. Robust standard errors are reported in parentheses. The p-value reported at the bottom of the column is for an F-test of the joint significance of the variables listed on the left.

Table 6: First Stage by Subgroup

	Age		**Gender**		**Zip-Code Income**		**Credit Score**		**First SL Orig Amount**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Subsample	> 22	≤ 22	Male	Female	$>$ Median	$\leq$ Median	≥ 619	< 619	$>$ \$3,500	$\leq$ \$3,500
Servicer Score	0.024***	0.016***	0.026***	0.018***	0.018***	0.023***	0.014***	0.028***	0.025***	0.019***
(Standard Error)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.003)
Dep. Mean	0.343	0.245	0.322	0.294	0.235	0.377	0.121	0.487	0.247	0.324
F-stat	57.583	15.833	44.414	29.660	30.959	39.613	22.928	49.702	22.704	46.292
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	15482	9428	10648	14262	12459	12451	12338	12572	5865	19045

Notes: This table reports results from the first-stage regression of default on servicer score by subgroup. The regressions are estimated on subsamples of the analysis sample described in the notes to Table **??**. Regressions include the same control variables used in Table **??** and origination quarter-year fixed effects. Regressions are estimated on a balanced sample of borrowers who are observed for 6 years post first student loan origination. Robust standard errors are reported in parentheses. The p-value reported at the bottom of the column is for an F-test of the significance of the servicer score.

Table 7: Estimates of the Effect of Servicer Score on Credit Outcomes (Reduced Form)

	(1)	(2)	(3)	(4)	(5)	(6)
Quarters from Origination	1-4	5-8	9-12	13-16	17-20	21-24
Panel A. Financial Distress						
Any Non-SL Delinquency or Collections	-0.001	-0.001	0.000	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Mean	0.226	0.271	0.276	0.298	0.322	0.346
Total Balance: Non-SL Delinquencies or Collections	0.028	0.007	-0.062	0.121	-0.182	-0.367
	(0.201)	(0.197)	(0.227)	(0.300)	(0.321)	(0.536)
Dep. Mean	5.202	6.178	7.184	9.178	11.439	13.775
Panel B. Credit Access						
Credit Score	-0.362	-0.738	-0.170	0.202	0.773	0.384
	(0.431)	(0.521)	(0.540)	(0.542)	(0.549)	(0.553)
Dep. Mean	585.447	581.236	587.396	597.371	606.626	613.985
Any Open Revolving Account	-0.001	0.001	0.001	0.001	0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Dep. Mean	0.499	0.519	0.545	0.572	0.598	0.615
Credit Card Limit	-0.273	-0.179	0.133	0.162	0.033	-0.175
	(0.349)	(0.386)	(0.418)	(0.467)	(0.522)	(0.608)
Dep. Mean	29.049	33.905	40.324	47.814	56.578	65.928
Panel C. Borrowing						
Any Auto Loan or Lease	-0.000	0.000	-0.000	0.000	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Dep. Mean	0.187	0.221	0.264	0.309	0.349	0.380
Panel D. Zip-Code Characteristics						
Log Zip Median Income	-0.003**	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Dep. Mean	10.966	10.961	10.962	10.965	10.968	10.971
Lower Income Zip	0.003	0.001	-0.000	-0.001	-0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Mean	0.151	0.215	0.250	0.272	0.293	0.310
N	99640	99640	99640	99640	99640	99640

Notes: This table reports reduced form estimates of the effect of the servicer score on pooled quarterly credit outcomes. The dependent variable is listed on the left of each row. Each column reports estimates from separate OLS regressions on outcomes in the indicated quarters following student loan origination. All regressions include quarter-year fixed effects, as well as controls for gender, age at student loan origination, and log zip median household income. Robust standard errors are clustered at the borrower level and are reported in parentheses.

Table 8: OLS Estimates of the Effect of Default on Credit Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Quarters from Origination	1-4	5-8	9-12	13-16	17-20	21-24
Panel A. Financial Distress						
Any Non-SL Delinquency or Collections	0.168***	0.226***	0.235***	0.245***	0.247***	0.255***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Dep. Mean	0.226	0.271	0.276	0.298	0.322	0.346
Total Balance: Non-SL Delinquencies or Collections	3.066***	4.095***	4.119***	3.686***	2.023**	0.513
	(0.631)	(0.552)	(0.673)	(0.749)	(0.825)	(1.053)
Dep. Mean	5.202	6.178	7.184	9.178	11.439	13.775
Panel B. Credit Access						
Credit Score	-67.980***	-106.572***	-114.701***	-107.713***	-98.157***	-88.931***
	(0.902)	(1.068)	(1.019)	(1.005)	(1.032)	(1.063)
Dep. Mean	585.447	581.236	587.396	597.371	606.626	613.985
Any Open Revolving Account	-0.326***	-0.368***	-0.413***	-0.453***	-0.464***	-0.442***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Dep. Mean	0.499	0.519	0.545	0.572	0.598	0.615
Credit Card Limit	-25.034***	-30.613***	-38.746***	-48.160***	-58.002***	-66.883***
	(0.638)	(0.670)	(0.704)	(0.764)	(0.867)	(0.999)
Dep. Mean	29.049	33.905	40.324	47.814	56.578	65.928
Panel C. Borrowing						
Any Auto Loan or Lease	-0.090***	-0.108***	-0.142***	-0.172***	-0.201***	-0.219***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Dep. Mean	0.187	0.221	0.264	0.309	0.349	0.380
Panel D. Zip-Code Characteristics						
Log Zip Median Income	-0.026***	-0.037***	-0.045***	-0.052***	-0.055***	-0.060***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dep. Mean	10.966	10.961	10.962	10.965	10.968	10.971
Lower Income Zip	0.065***	0.079***	0.074***	0.072***	0.065***	0.063***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Dep. Mean	0.151	0.215	0.250	0.272	0.293	0.310
N	99640	99640	99640	99640	99640	99640

Notes: This table reports OLS estimates of the effect of default on pooled quarterly credit outcomes. The dependent variable is listed on the left of each row. Each column reports estimates from separate OLS regressions on outcomes in the indicated quarters following student loan origination. All regressions include quarter-year fixed effects, as well as controls for gender, age at student loan origination, and log zip median household income. Robust standard errors are clustered at the borrower level and are reported in parentheses.

Table 9: 2SLS Estimates of the Effect of Default on Credit Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Quarters from Origination	1-4	5-8	9-12	13-16	17-20	21-24
Panel A. Financial Distress						
Any Non-SL Delinquency or Collections	-0.034	-0.024	0.016	-0.038	-0.069	-0.086
	(0.092)	(0.098)	(0.095)	(0.105)	(0.112)	(0.116)
Dep. Mean	0.226	0.271	0.276	0.298	0.322	0.346
Total Balance: Non-SL Delinquencies or Collections	1.377	0.324	-3.002	5.869	-8.836	-17.818
	(9.767)	(9.564)	(11.045)	(14.579)	(15.624)	(26.078)
Dep. Mean	5.202	6.178	7.184	9.178	11.439	13.775
Panel B. Credit Access						
Credit Score	-17.423	-35.777	-8.246	9.785	37.680	18.459
	(20.025)	(23.320)	(25.651)	(26.833)	(29.016)	(27.482)
Dep. Mean	585.447	581.236	587.396	597.371	606.626	613.985
Any Open Revolving Account	-0.061	0.025	0.038	0.029	0.073	-0.138
	(0.125)	(0.129)	(0.131)	(0.130)	(0.133)	(0.122)
Dep. Mean	0.499	0.519	0.545	0.572	0.598	0.615
Credit Card Limit	-13.258	-8.711	6.434	7.888	1.620	-8.478
	(16.753)	(18.531)	(20.492)	(22.931)	(25.407)	(29.270)
Dep. Mean	29.049	33.905	40.324	47.814	56.578	65.928
Panel C. Borrowing						
Any Auto Loan or Lease	-0.010	0.010	-0.003	0.011	-0.050	-0.005
	(0.104)	(0.112)	(0.119)	(0.125)	(0.126)	(0.130)
Dep. Mean	0.187	0.221	0.264	0.309	0.349	0.380
Panel D. Zip-Code Characteristics						
Log Zip Median Income	-0.141**	-0.076	-0.087	-0.069	-0.041	-0.069
	(0.059)	(0.066)	(0.071)	(0.075)	(0.078)	(0.080)
Dep. Mean	10.966	10.961	10.962	10.965	10.968	10.971
Lower Income Zip	0.124	0.027	-0.006	-0.034	-0.089	0.115
	(0.092)	(0.104)	(0.110)	(0.115)	(0.117)	(0.116)
Dep. Mean	0.151	0.215	0.250	0.272	0.293	0.310
N	99640	99640	99640	99640	99640	99640

Notes: This table reports two-stage least squares estimates of the effect of default on pooled quarterly credit outcomes. The dependent variable is listed on the left of each row. Each column reports estimates from a separate 2SLS regression on outcomes in the indicated quarters following student loan origination. All regressions include quarter-year fixed effects, as well as controls for gender, age at student loan origination, and log zip median household income. Robust standard errors are clustered at the borrower level and are reported in parentheses.

Table 10: Sample Share by Compliance Type

	(1)	(2)
	1%	2%
Compliers	0.141	0.113
Always Takers	0.236	0.252
Never Takers	0.623	0.635

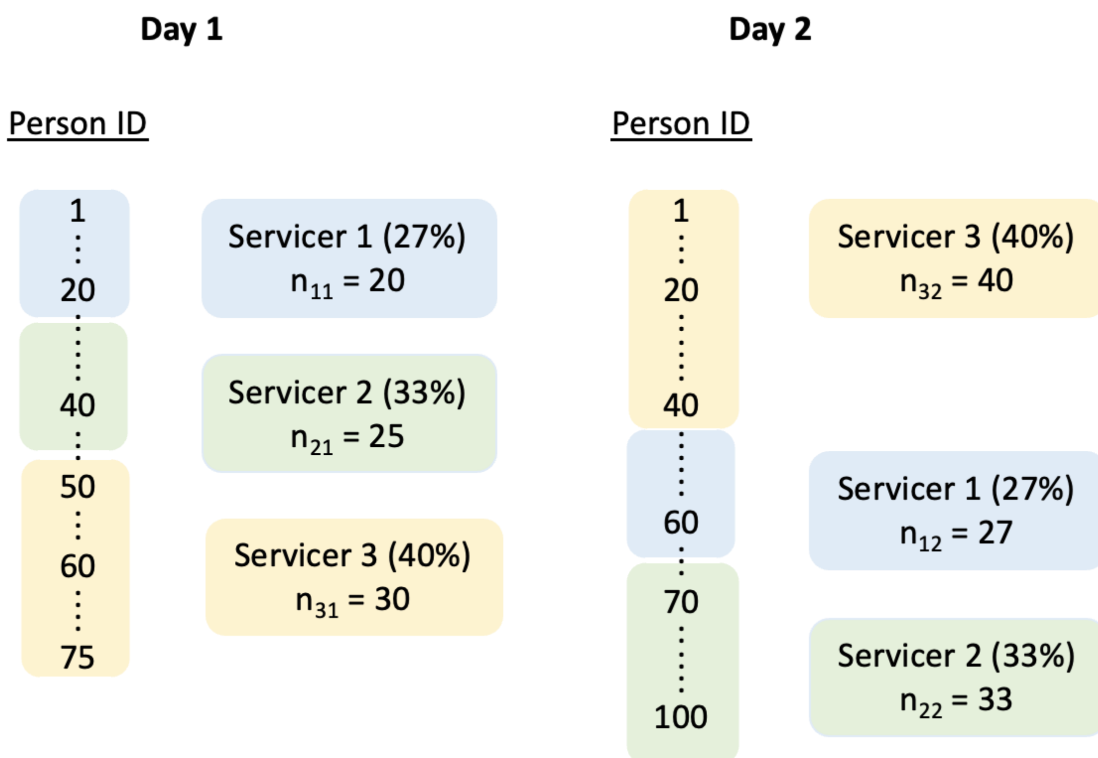
Notes: This tables shows estimates of the shares of the sample that are compliers, always-takers, and never-takers. The fraction of always-takers, π_a, is estimated by the share of borrowers who default when assigned to the lowest-default servicer. The fraction of never-takers, π_n, is estimated by the share of do not default when assigned to the highest-default servicer. The fraction of compliers is $1 - \pi_a - \pi_n$. Lowest-default servicers are defined by being at the 1st or 2nd percentile of the residualized servicer score distribution, and highest-default servicers are defined as being at the 99th or 98th percentile.

Table 11: Characteristics of Marginal Defaulters

	(1) Pr[X = x]	(2) Pr[X = x|Complier]	(3) Ratio
Age $<$ 22	0.622	0.668	1.076
Age $\geq$ 22	0.378	0.323	0.855
Zip-Code Income $<$ Median	0.500	0.441	0.882
Zip-Code Income $\geq$ Median	0.500	0.560	1.120
Credit Score $\geq$ 619	0.446	0.247	0.553
Credit Score $<$ 619	0.554	0.672	1.212
First SL Orig Amount $>$ \$3500	0.235	0.190	0.808
First SL Orig Amount $\leq$ \$3500	0.765	0.726	0.950
Male	0.427	0.524	1.226
Female	0.573	0.484	0.845
Never 90 Days Delinquent	0.488	0.001	0.002
Ever 90 Days Delinquent	0.512	0.584	1.141

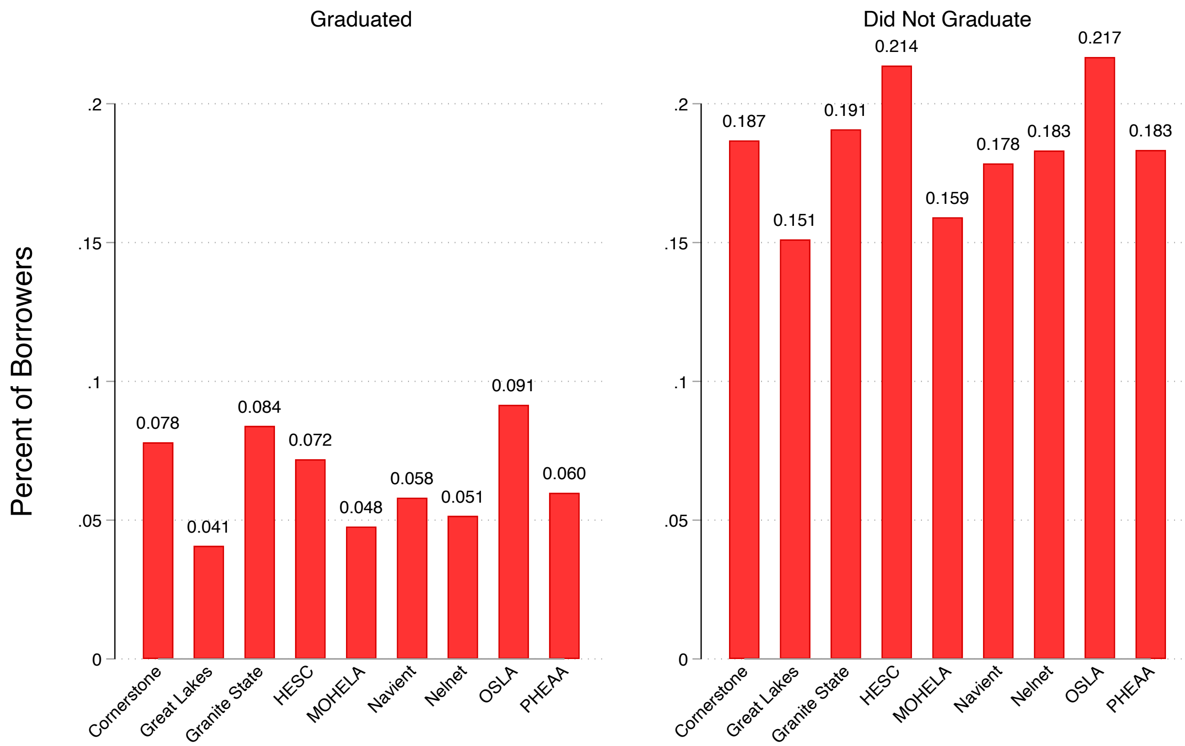
Notes: This table describes the observable characteristics of the complier sample, relative to the full sample. Column (1) shows the probability that an individual in the analysis sample has a given characteristic. Column (2) shows the probability that someone in the complier group has that characteristic. Column (3) shows the ratio of the two. The estimates in Column (2) are constructed by calculating the shares of compliers within these various subsamples. The complier share calculations rely on a linear first-stage estimation and a 1 percentile cutoff to define the lowest-default servicer score.

Figure 1: Servicer Assignment Process



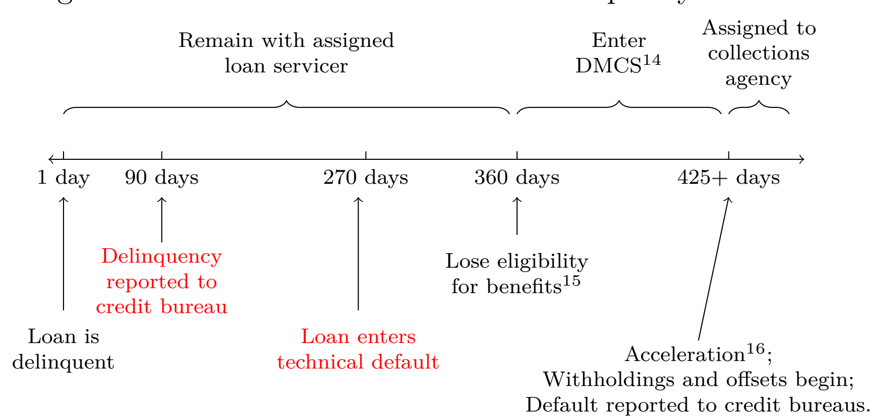
Notes: This figure depicts a stylized example of the servicer assignment process for new loans. Individuals are sorted according to a person identifier given to them by the Department of Education. This process is conducted daily and changes slightly from day to day. In this example, there are 75 new borrowers on day 1 and 100 new borrowers on day 2. Servicer allocation shares are in parentheses next to the name and indicate the share of new loans each servicer gets allocated. These are determined by the servicers' relative ranking on the set of performance metrics described in Section **??**. n_{sd} indicates the number of new loans assigned to servicer s on day d. The order is determined by the servicer priority number which rotates on a daily basis.

Figure 2: Share of Federal Student Loan Portfolio 91-270 Days Delinquent by Servicer, Q2 2019



Notes: Bars represent the percent of borrowers in each servicers' repayment portfolio that are delinquent by 91-270 days. These include borrowers with no consolidation or Parent PLUS loans, with separation dates 1,095 days or greater from the last day of the current quarter, disaggregated by graduation status. // Source: Quarterly Performance Results, Federal Student Aid, U.S. Department of Education; calculations by the author.

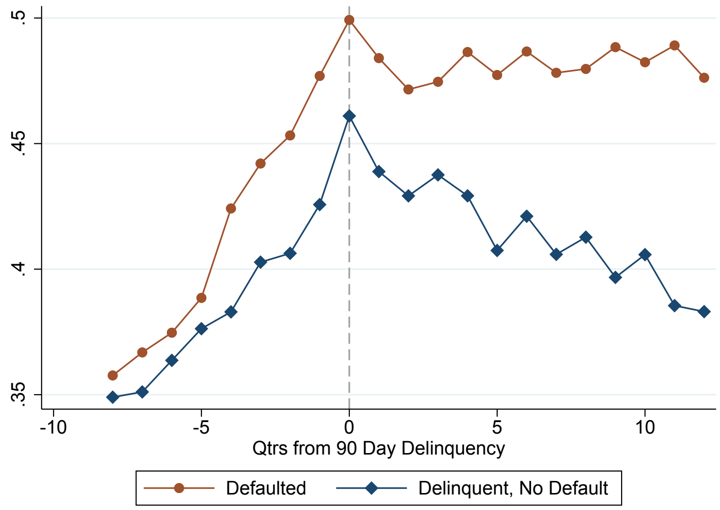
Figure 3: Timeline of Student Loan Delinquency and Default



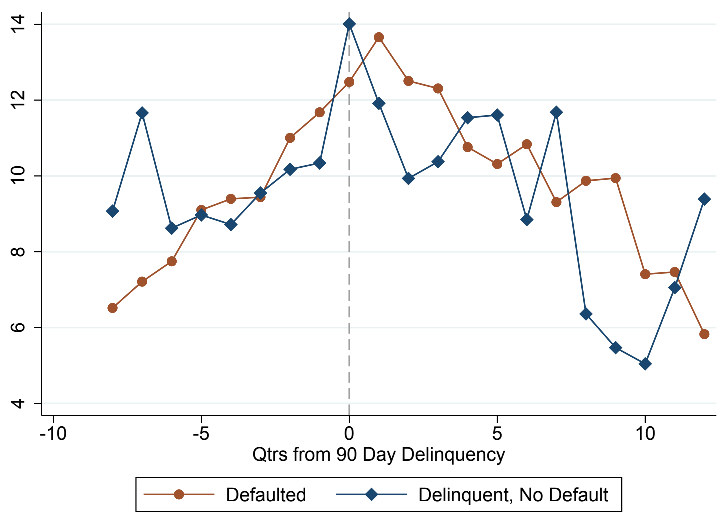
Notes: This figure shows a timeline of a borrower's journey through delinquency and default and the associated consequences at key junctures.

Figure 4: Financial Distress Outcomes Relative to the Time of 90 Day Delinquency

Panel A. Any Non-Student Loan Delinquency or Collections Account

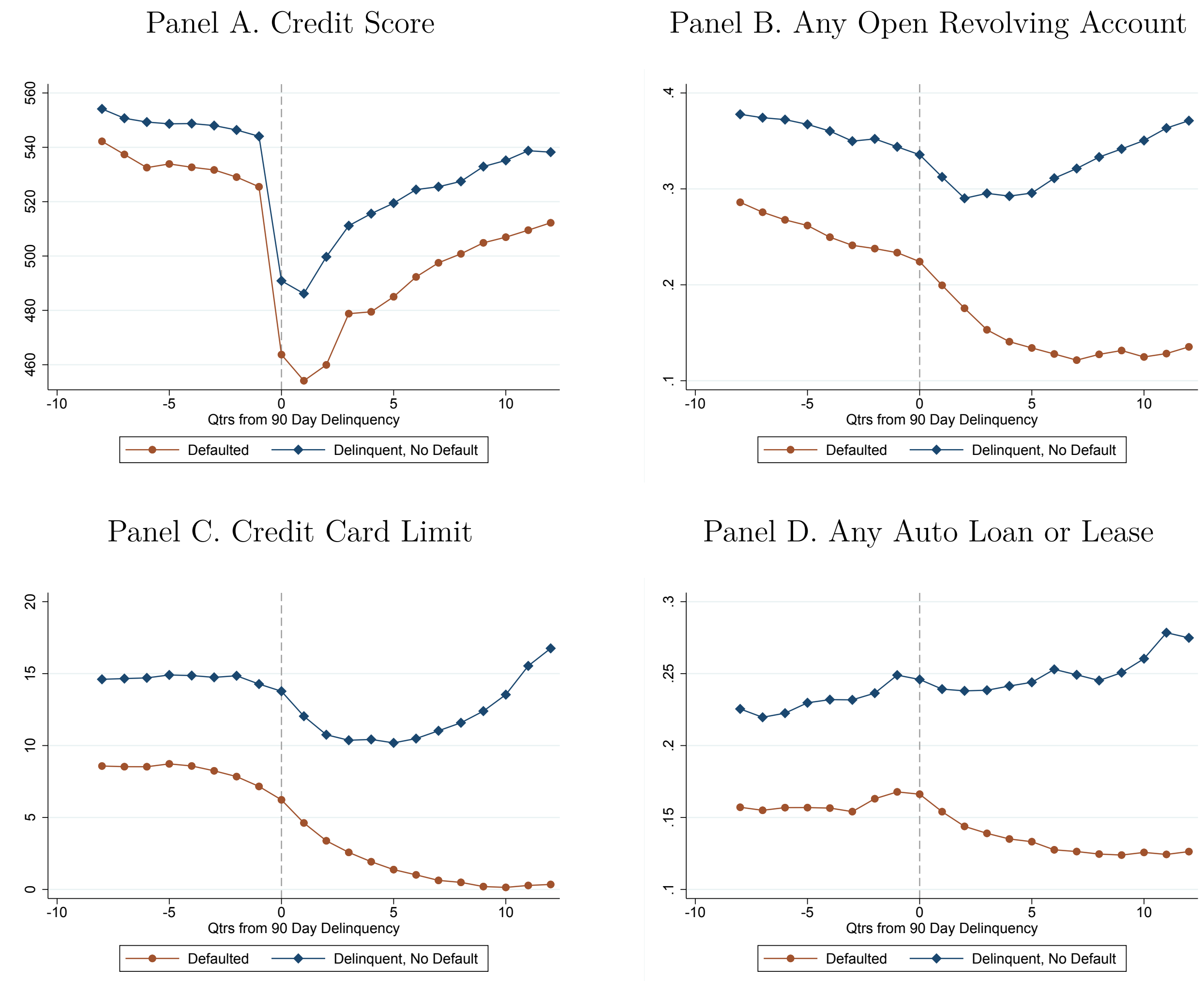


Panel B. Total Balance: Non-Student Loan Delinquencies or Collections Account



Notes: This figure shows trends in credit outcomes relative to 90 day delinquency on a student loan separately for delinquent borrowers and defaulted borrowers. I estimate equation **??** and plot the coefficient for the delinquent and defaulted groups in each time period. The only controls are calendar year dummies. For both sets of coefficients, I add in the delinquent group mean in the omitted period so that the magnitudes are easy to interpret. All outcomes are measured at the quarterly frequency.

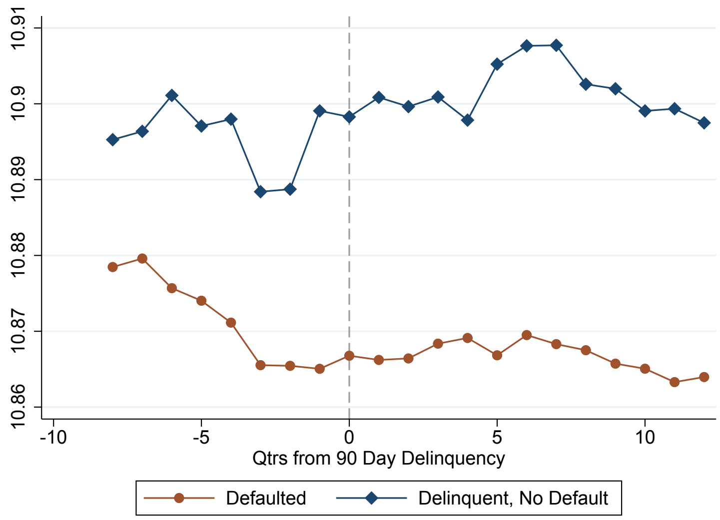
Figure 5: Credit Access and Borrowing Outcomes Relative to the Time of 90 Day Delinquency



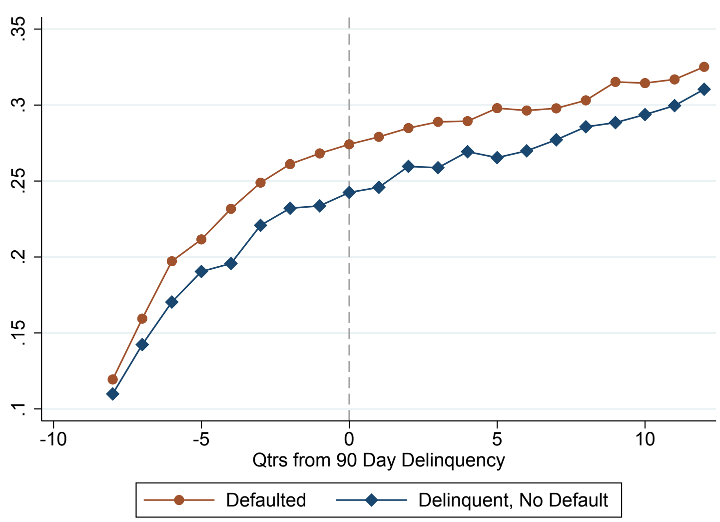
Notes: This figure shows trends in credit outcomes relative to 90 day delinquency on a student loan separately for delinquent borrowers and defaulted borrowers. I estimate equation **??** and plot the coefficient for the delinquent and defaulted groups in each time period. The only controls are calendar year dummies. For both sets of coefficients, I add in the delinquent group mean in the omitted period so that the magnitudes are easy to interpret. All outcomes are measured at the quarterly frequency.

Figure 6: Zip-Code Characteristics Relative to the Time of 90 Day Delinquency

Panel A. Zip-Code Log Median Income

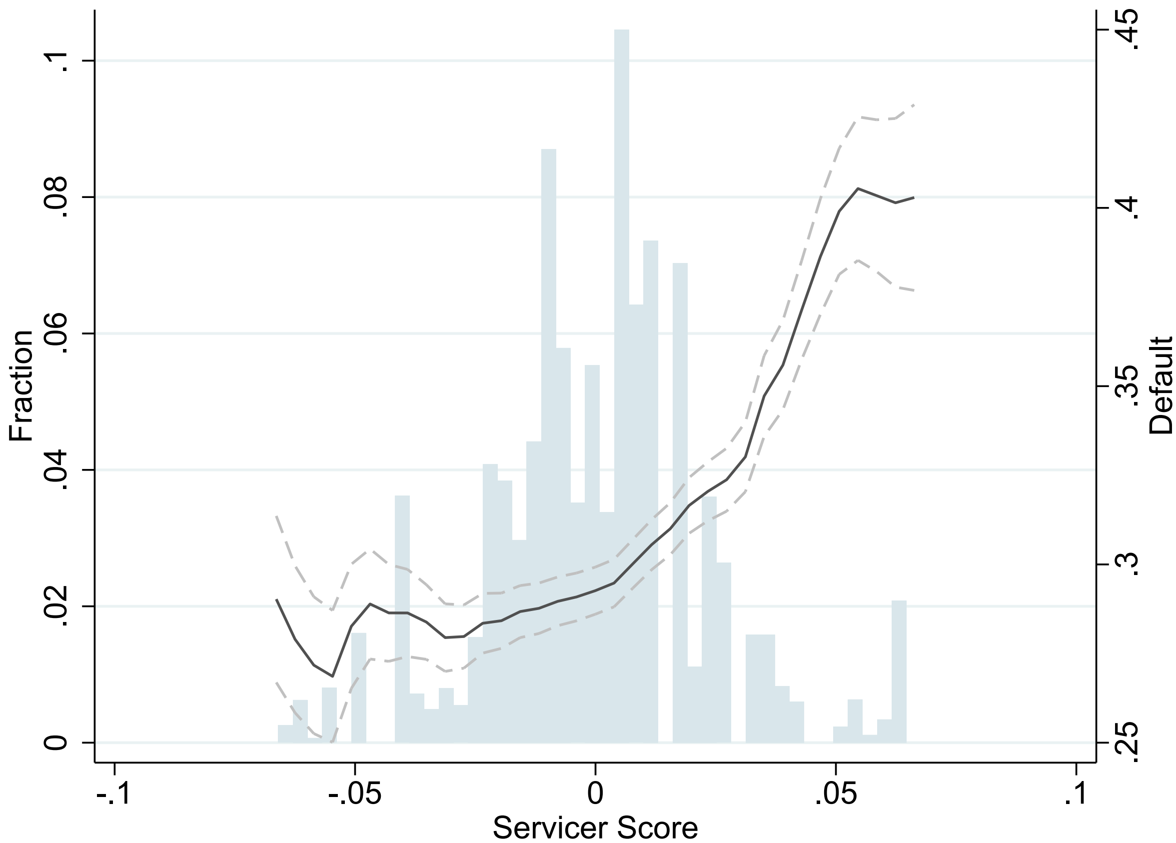


Panel B. Lower Income Zip-Code



Notes: This figure shows trends in credit outcomes relative to 90 day delinquency on a student loan separately for delinquent borrowers and defaulted borrowers. I estimate equation **??** and plot the coefficient for the delinquent and defaulted groups in each time period. The only controls are calendar year dummies. For both sets of coefficients, I add in the delinquent group mean in the omitted period so that the magnitudes are easy to interpret. All outcomes are measured at the quarterly frequency.

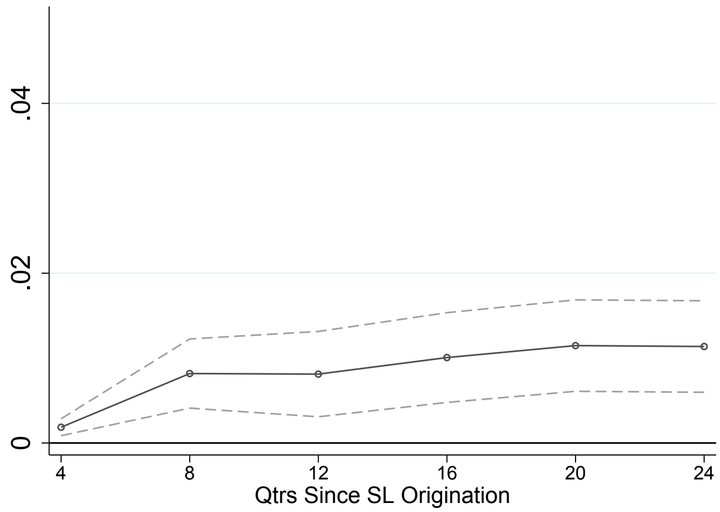
Figure 7: Servicer Score and Default



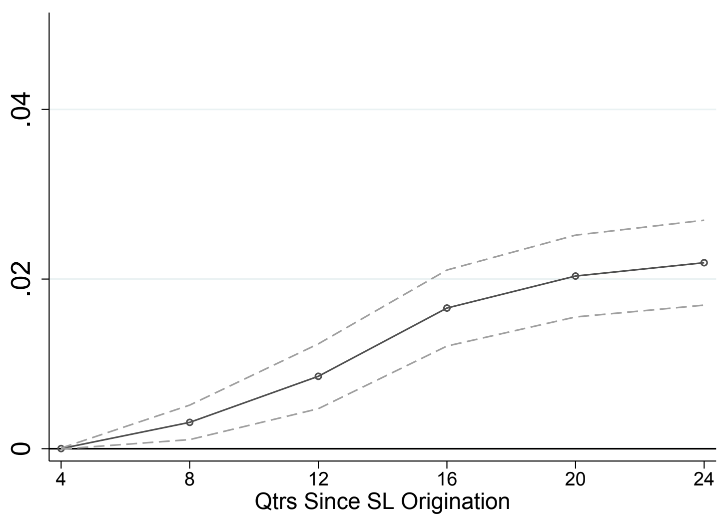
Notes: This figure shows a histogram of the servicer score, residualized by origination quarter-year, with the fraction of borrowers indicated along the left vertical axis. The solid and dashed lines, plotted against the right axis, represent predicted means with 95 percent confidence intervals from a local linear regression of residualized default on the servicer score.

Figure 8: Effect of Servicer Score on Student Loan 90 Day Delinquency and Default

Panel A. Ever 90-Days Delinquent on Student Loan



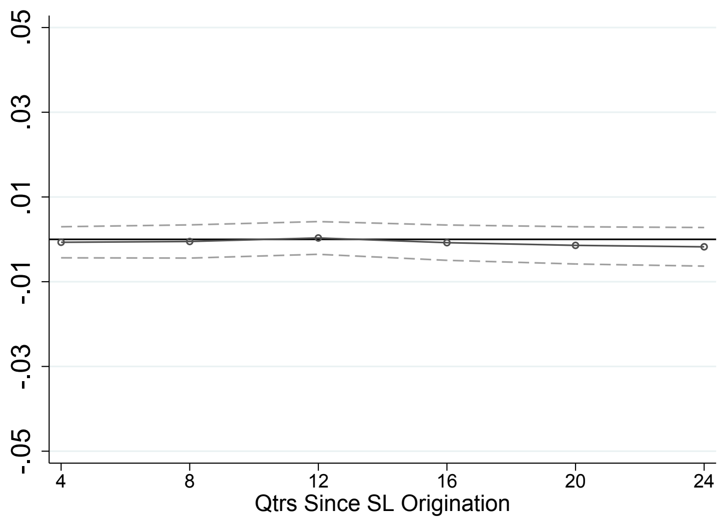
Panel B. Ever Default on Student Loan



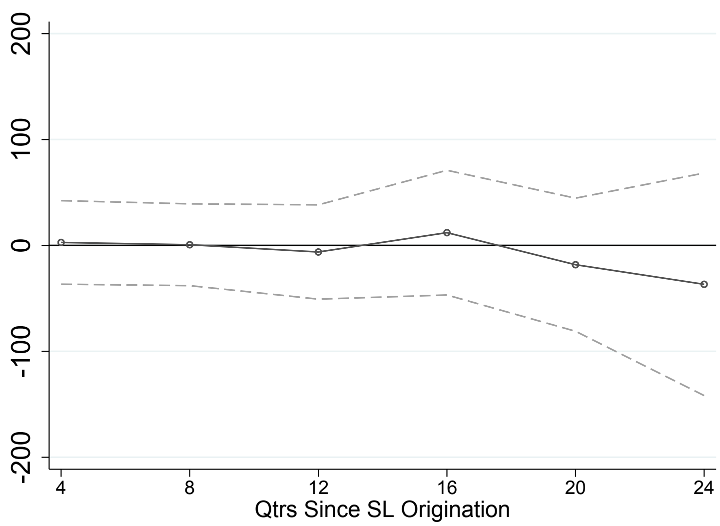
Notes: This figure reports reduced form estimates of the effect of the servicer score on pooled quarterly credit outcomes. Each point represents the estimated effect of being assigned to a higher-default servicer on the outcomes listed. Quarters from first student loan origination are plotted along the x-axis. Dashed lines represent 95 percent confidence intervals. All regressions include quarter-year fixed effects, as well as controls for gender, age at student loan origination, and log zip median household income. Robust standard errors are clustered at the borrower level.

Figure 9: Effect of Servicer Score on Financial Distress Outcomes

Panel A. Any Non-Student Loan Delinquency or Collections Account

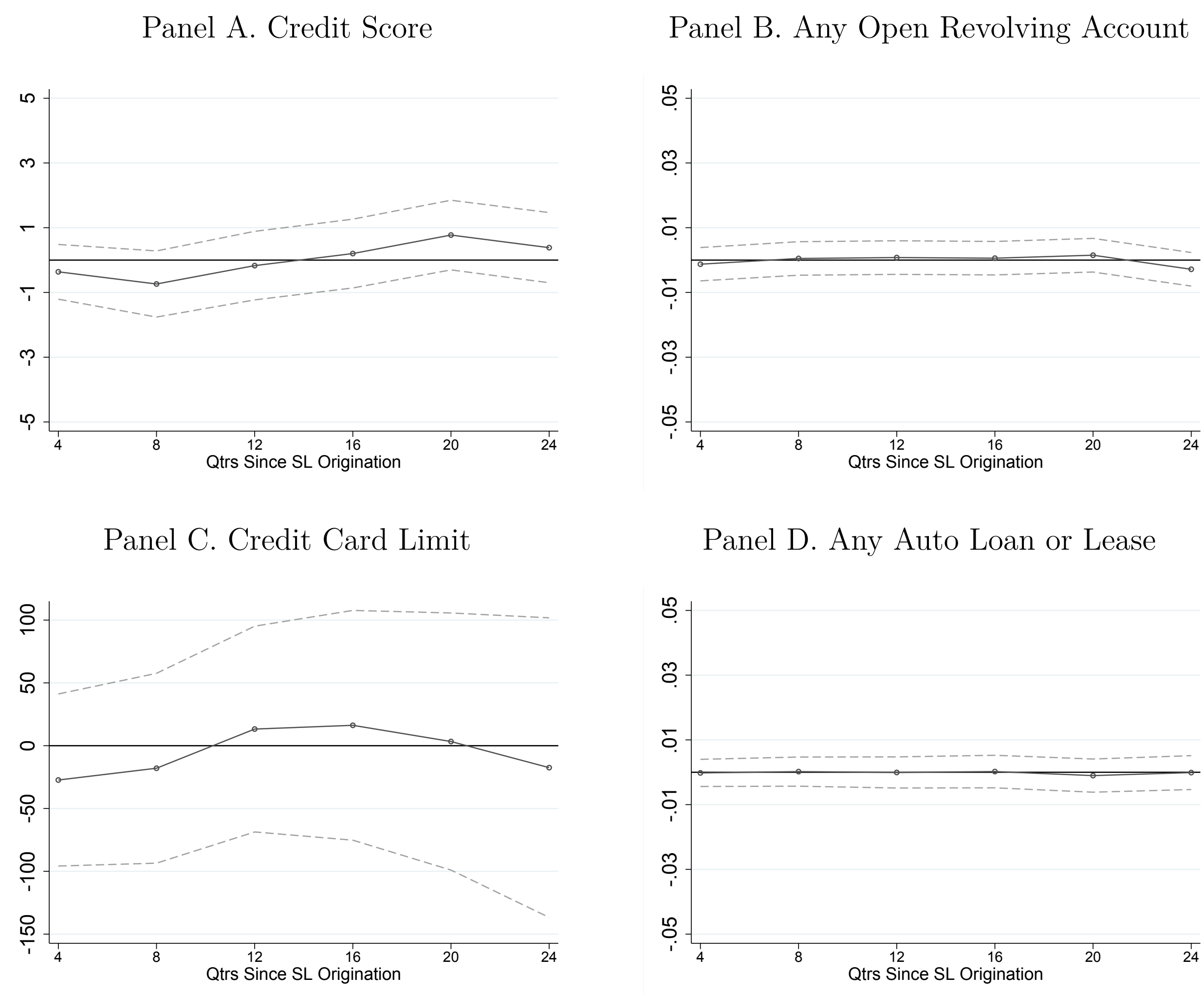


Panel B. Total Balance: Non-Student Loan Delinquencies or Collections Account



Notes: This figure reports reduced form estimates of the effect of the servicer score on pooled quarterly credit outcomes. Each point represents the estimated effect of being assigned to a higher-default servicer on the outcomes listed. Quarters from first student loan origination are plotted along the x-axis. Dashed lines represent 95 percent confidence intervals. All regressions include quarter-year fixed effects, as well as controls for gender, age at student loan origination, and log zip median household income. Robust standard errors are clustered at the borrower level.

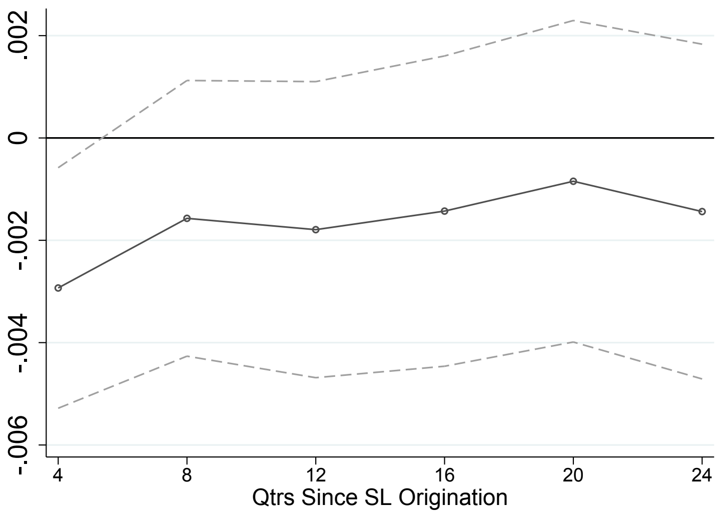
Figure 10: Effect of Servicer Score on Credit Access and Borrowing Outcomes



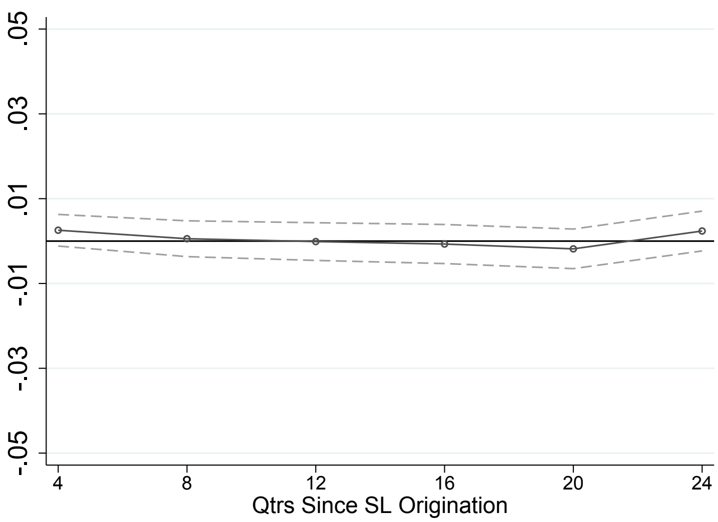
Notes: This figure reports reduced form estimates of the effect of the servicer score on pooled quarterly credit outcomes. Each point represents the estimated effect of being assigned to a higher-default servicer on the outcomes listed. Quarters from first student loan origination are plotted along the x-axis. Dashed lines represent 95 percent confidence intervals. All regressions include quarter-year fixed effects, as well as controls for gender, age at student loan origination, and log zip median household income. Robust standard errors are clustered at the borrower level.

Figure 11: Effect of Servicer Score on Zip-Code Characteristic Outcomes

Panel A. Zip-Code Log Median Income

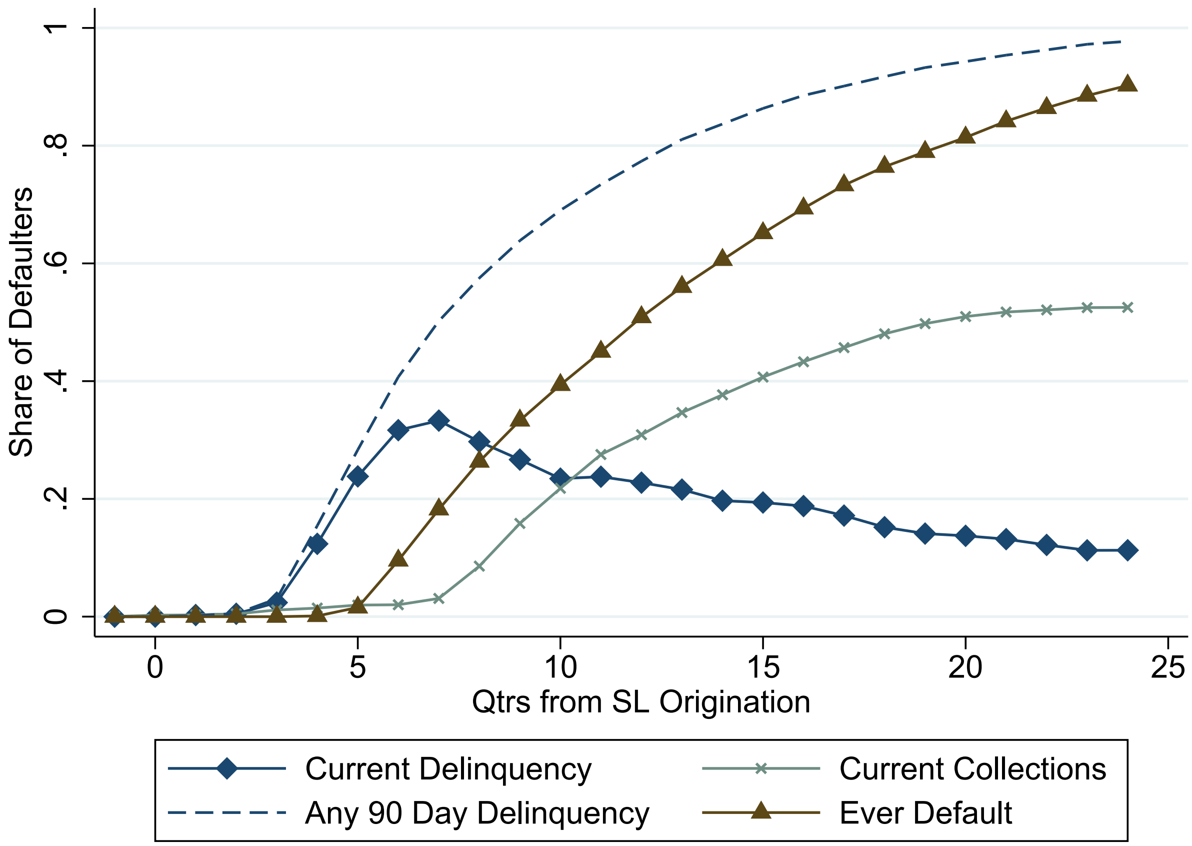


Panel B. Lower Income Zip-Code



Notes: This figure reports reduced form estimates of the effect of the servicer score on pooled quarterly credit outcomes. Each point represents the estimated effect of being assigned to a higher-default servicer on the outcomes listed. Quarters from first student loan origination are plotted along the x-axis. Dashed lines represent 95 percent confidence intervals. All regressions include quarter-year fixed effects, as well as controls for gender, age at student loan origination, and log zip median household income. Robust standard errors are clustered at the borrower level.

Figure 12: Share of Defaulters Treated by Quarter Since SL Origination



Notes: This figure plots the share of defaulters with a current delinquency, a current collections, any 90 day delinquency, or any default by quarter from student loan origination.

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