Saving and Consumption Responses to Student Loan Forbearance

Justin Katz *

This version: June 2026

Abstract

To study the impacts of debt relief versus cash transfers, I compare saving and consumption responses to student loan forbearance and stimulus checks in the 2020 CARES Act. Borrowers non-optimally use much of the liquidity received from forbearance to voluntarily prepay 0%-interest student debt instead of high-interest obligations, despite prioritizing high-interest debts when receiving stimulus checks. Consistent with this flypaper effect, the marginal propensity to spend (MPX) out of forbearance liquidity is less than half that of stimulus checks. A calibration exercise estimates that the flypaper effect makes forbearance less effective and more costly as a countercyclical fiscal tool.

Keywords: student loan forbearance, stimulus, household finance, consumer credit

JEL classification: G50, G51, D14, D91, I22, H3, H81, E21

* Boston College Carroll School of Management. Email: justin.katz@bc.edu I am greatly indebted to Emily Williams and Marco Di Maggio for making this project possible, and I'm especially grateful to my advisers John Campbell, Ed Glaeser, David Laibson, and Adi Sunderam. For valuable comments and discussions, I thank John Beshears, Sage Belz, James Choi, Lindsey Currier, Gabe Chodorow-Reich, Helene Hall, Ruru Hoong, Ray Kluender, Sheisha Kulkarni, Sean Lee, Ethan Matlin, Dominic Russel, Suproteem Sarkar, Jesse Shapiro, Jeremy Stein, Winnie van Dijk, Constantine Yannelis, and participants at the 2023 IIPF Conference, the 2024 CFPB Research Conference, the 2025 WFA Student Loan session, and the Harvard workshops in financial economics, public finance and labor, and macroeconomics. I gratefully acknowledge support from The Institute of Consumer Money Management (ICMM) Pre-doctoral Fellowship on Consumer Financial Management, awarded through the NBER. The Harvard University-Area Committee on the Use of Human Subjects approved the survey instrument in this paper under expedited review as Protocol IRB23-0003 – contact kate_schaffenberger@harvard.edu for details. Survey analysis was preregistered with the Wharton Credibility Lab as AsPredicted #124145, and the American Economic Association Registry for Randomized Controlled Trials as #AEARCTR-0011040. The AsPredicted analysis plan is available at https://aspredicted.org/ej67r.pdf. The AEA RCT pre-analysis plan is available at https://doi.org/10.1257/rct.11040-1.0. All errors are mine.

Household liquidity constraints are pervasive and central to counter-cyclical policy design.[1] Liquidity constraints are especially important in determining the efficacy of debt relief and direct cash transfers in supporting aggregate demand during downturns. Existing work often implicitly treats liquidity from such policies as fungible, in that effects on behavior do not depend on its source. For example, previous studies argue that if consumption falls during recessions due to liquidity constraints, allowing borrowers to temporarily defer debt repayments can support consumption at a lower fiscal cost than direct transfers such as stimulus checks (Eberly and Krishnamurthy 2014, Cherry et al. 2021).

This paper directly compares the impact of liquidity from debt relief versus direct cash transfers. I do so using quasi-experimental policy variation from two programs implemented in the 2020 CARES Act at the start of the Covid-19 recession. The first placed all federally-owned student loans in administrative forbearance, automatically pausing payments and setting interest rates on outstanding balances to 0% for 81% of the $1.6 trillion student loan market (Fed 2020). The second authorized direct stimulus check payments to most US households.

To study these policies, I build a new dataset connecting student loan repayment, stimulus check receipt, and consumption outcomes. I identify federal student loan and stimulus check payments within a large high-frequency administrative transactions panel, and trace out person-level spending across linked bank, debit card, and credit card accounts.

I document a strong liquidity flypaper effect: borrowers' saving and consumption responses to liquidity depend on its source. Borrowers use liquidity from the student loan payment pause to non-optimally make large student loan prepayments, rather than repay higher interest obligations. By contrast, the same borrowers do not use stimulus checks to pay down student loans, instead increasing consumption or repaying high-interest debt. Due to this flypaper effect, forbearance liquidity increases consumption by far less than stimulus checks. I survey borrowers and find that low financial sophistication and debt repayment heuristics drive this behavior. Using a partial equilibrium model calibrated with sufficient statistics from transactions data, I find that the flypaper effect reduces the aggregate demand response to forbearance, both in total and per dollar of fiscal cost. This implies that to achieve a given increase in aggregate demand, the government must rely more on stimulus checks at a higher overall fiscal cost.

The first part of the paper studies how debt relief versus cash transfers impacts household saving and consumption. Such comparisons are empirically difficult because the policies often target different populations: debt relief usually targets distressed, high-leverage households (Noel and Wachter 2021), while stimulus checks are distributed more broadly. The CARES

[1] Kaplan and Violante (2022) review evidence attributing high marginal propensities to consume to low liquid asset holdings, with implications for fiscal and monetary policy. Piskorski and Seru (2018) summarize the applied theory literature advocating for temporary mortgage payment relief during recessions to allow liquidity constrained households to smooth consumption.

Act policy context overcomes this challenge because debt relief applied universally and automatically alongside stimulus checks. This makes it possible to compare forbearance and cash transfers for the same borrowers, in a similar economic environment, without concerns about selection based on take-up.

To benchmark behavior with no flypaper effect, I derive three predictions from a dynamic incomplete-markets model in which consumers respect the fungibility of financial resources. First, because consumers minimize interest costs conditional on consumption, they will not prepay 0% interest debt if they have other interest-bearing debt or saving opportunities. Second, if consumers *do* prepay, then they should increase prepayments when receiving unexpected cash windfalls like stimulus checks. Third, the difference in marginal propensity to consume (MPC) out of forbearance liquidity and stimulus checks is, to a first order, bounded by the MPC out of wealth multiplied by the difference in wealth transfers from the policies. This bound is close to zero, given previous literature showing a negligible MPC out of wealth (e.g. Paiella and Pistaferri 2017, Ganong and Noel 2020); the model thus predicts MPCs to be similar.

Borrower behavior in the transactions panel rejects these predictions. Many borrowers keep making payments on 0% federal student loans after forbearance begins, contrary to the first model prediction and policy default. In an interrupted time-series design examining changes in loan repayment when forbearance starts, borrowers use 44% of forbearance liquidity to prepay federal student debt during the program's first four weeks. Prepayment persists at similar levels many months thereafter. Program implementation details and repayment patterns indicate this behavior was intentional, not due to inattention or inertia. I replicate this finding using the Survey of Consumer Finances and administrative Department of Education data. Continued payments are especially surprising because the policy extended repayment timelines, meaning borrowers would not have to make catch-up payments. For borrowers with a long outstanding loan term, prepayments mean actively turning down a multi-year, interest-free loan.

Contrary to the second prediction, the same borrowers use almost none of their stimulus checks to pay off federal student loans. Prepayments therefore cannot be explained by a lack of higher-yielding saving vehicles, a desire to delever, or student debt aversion. Adapting Baker et al. (2020), I estimate the impact of stimulus checks on federal student loan repayments using within-person changes in repayment before and after checks arrive, where variation in arrival timing allows estimation of calendar time trends. Borrowers spend under 1% of their stimulus checks on federal student loans over four weeks. Borrowers thus do not treat forbearance liquidity as fungible with other cash windfalls.

Because of this non-fungibility, borrowers deviate from the cost-minimizing debt repayment strategy. Borrowers with high-interest credit card and private student loan debt use 40% and 33%, respectively, of their forbearance liquidity to prepay student loans in forbearance. This

is a clear financial mistake. The same borrowers use stimulus checks to prioritize high-interest debt first. For example, borrowers with credit card debt, who use all of their forbearance liquidity to prepay federal student loans, use only 1% of their stimulus checks to do so, and *instead* use 9.3% of their stimulus checks to repay credit card debt over a month.

The gap between how borrowers spend forbearance and stimulus check windfalls suggests a flypaper effect: forbearance liquidity "sticks" to student loan repayment. This predicts a lower marginal propensity to spend (MPX) out of forbearance liquidity compared to cash transfers.

As predicted by the flypaper effect, and violating the third prediction, borrowers spend less of their forbearance liquidity than their stimulus checks. I estimate the forbearance consumption MPX using a difference-in-difference design: I compare borrowers with similar pre-forbearance repayment paths who happen to complete scheduled loan repayments at different times. I use borrowers who finished debt repayments just before March 2020, and so did not receive liquidity from forbearance, to trace out counterfactual spending for similar borrowers with outstanding balances when forbearance began.[2] The four-week stimulus check MPX is 17.1% for total spending and 9.3% for nondurable spending. For forbearance, by contrast, 95% confidence intervals reject an MPX larger than one-fourth of the stimulus check MPX for total spending, and one-third for nondurable spending.

The lower forbearance MPX reflects two forces. First, forbearance raises cash-on-hand by less, because many borrowers keep repaying. Second, borrowers spend less of the increased cash-on-hand – even those who stop repaying. This second force matters: if borrowers instead spent extra cash-on-hand from stopped payments at the same rate as their stimulus checks, the forbearance MPX would be 60-65% as large as the stimulus check MPX, much higher than the difference-in-differences estimates.

To understand what drives these results, I survey borrowers about how they used stimulus checks and forbearance liquidity. Borrowers who make debt repayment mistakes, or who treat the windfalls differently, explain that they use debt repayment heuristics or are reluctant to adjust an ad-hoc budget. Many borrowers misunderstand financial incentives that the 0% student debt interest rate creates. Borrowers often justify forbearance prepayments as "financially smart" due to the 0% interest rate, and 50% fail to minimize costs in a debt repayment prioritization hypothetical. A pre-registered experiment suggests that the flypaper effect emerges from heuristic debt repayment targets combined with low financial sophistication. Framing a hypothetical cash transfer as targeting "borrowers with student debt" rather than "all households" affects heuristics without conveying economic information, and increases student loan payments by 45% for low-financial sophistication respondents.

[2] An appendix shows similar results from another difference-in-differences design comparing borrowers with a low vs. high federal loan share but a fixed amount of total debt, where the former get less forbearance liquidity.

Next, I propose a way to rationalize this behavior within a consumption-saving model. I model debt repayment heuristics and ad-hoc budgeting as total saving and debt repayment targets that generate flow utility costs if missed. Such "target deviation costs" imply continued student loan payments during forbearance and a cash transfer MPX that exceeds the forbearance MPX. The model also predicts a high MPC out of cash windfalls for unconstrained, high-income consumers, matching findings in other contexts by, for example, Kueng (2018).

The last part of the paper studies fiscal policy implications. I present a partial-equilibrium framework where a government uses a rescue package with forbearance and stimulus checks to boost the consumption of heterogeneous consumers. The framework is not meant to imply that student loan forbearance and stimulus checks are direct substitutes, or the only policies the government might use to increase spending, but rather aims to contextualize spending effects and fiscal costs of student loan forbearance. The transfers differ in "resource targeting," depending on which consumers receive liquidity; "behavioral targeting," depending on which consumers endogenously "take-up" forbearance by stopping payments; and a "flypaper" effect attributed to target deviation costs.

Two sufficient statistics quantify the flypaper effect. First, the MPX on student loans out of forbearance liquidity measures "take-up" – that is, how much forbearance increases cash-on-hand. Second, the consumption MPX out of forbearance liquidity relative to stimulus checks captures how much of the increased cash-on-hand borrowers spend, given take-up. A simple expression links these forces to forbearance's fiscal cost efficiency, defined as the change in consumption from shifting a dollar in fiscal cost from stimulus checks to forbearance. Both forces reduce forbearance's aggregate spending effect, but only the second impacts its fiscal cost efficiency: the government bears no fiscal cost when borrowers keep paying their loans.

I calibrate parameters using the transactions data, and find that the flypaper effect lowers forbearance's fiscal efficiency as implemented in the CARES Act. Without the flypaper effect, student loan forbearance increases consumption at a low fiscal cost compared to stimulus checks, because it transfers less wealth, despite not targeting higher MPX borrowers. But the flypaper effect significantly reduces forbearance's spending effect and cost efficiency: matching the no-flypaper consumption response requires raising stimulus check payments by 18% and fiscal outlays by 12%. The flypaper effect also raises the cost of a more generous forbearance policy that defers catch-up payments for longer. It shortens the longest deferral period over which forbearance remains as cost-efficient as stimulus checks from 9.1 to 3.8 years.

This paper connects with several literatures. First, I contribute to an expanding literature on the importance of liquidity constraints for consumption and counter-cyclical fiscal policy. Previous papers find large consumption responses to stimulus checks concentrated among low-liquidity households (e.g. Parker et al. 2013, Baker et al. 2020). A parallel literature focuses

on the real impact of debt relief, with emphasis on mortgage modification schemes providing monthly payment or principal balance relief during the 2008 financial crisis.[3] Both literatures typically find that current liquidity drives default and consumption. Eberly and Krishnamurthy (2014) argue that the importance of liquidity favors forbearance rather than write-downs to prevent mortgage delinquency, because the former has a lower fiscal cost. These findings seem to suggest that governments can use forbearance to stimulate consumption at a lower cost than direct transfers like stimulus checks (Cherry et al. 2021, Lee and Maghzian 2023).

This logic hinges on the relative effects of liquidity from each type of windfall. My contribution is to provide theory and evidence to explicitly compare the consumption and debt repayment effects of debt relief and cash transfers. I show that borrowers do not treat all liquidity as the same, and by focusing on a fixed group of recipients, rule out borrower heterogeneity as the primary driver. This means that policy must account for the manner in which liquidity is delivered in recessions. I formalize the impact of this behavioral constraint in a tractable framework that takes micro-MPX estimates as sufficient statistics to evaluate relative fiscal efficiency. My findings connect with contemporaneous work by Dinerstein, Yannelis, and Chen (2024) and Chava, Tookes, and Zhang (2023), who use credit bureau data and different empirical designs to document that forbearance increases payments and balances for non-student loan debt. My results complement this work by providing direct evidence on spending and an explicit comparison between forbearance and stimulus payments.

I also contribute to a smaller literature documenting flypaper effects in other settings. Previous work identifies non-fungibility in household consumption (Milkman and Beshears 2009, Hastings and Shapiro 2013, Hastings and Shapiro 2018) that impacts borrowing (Di Maggio, Katz, and Williams 2022), as well as flypaper effects in financial markets due to quantitative easing targeting certain assets (Di Maggio, Kermani, and Palmer 2020). I focus on flypaper effects in salient and high-stakes household debt repayment decisions, where I show that borrowers treat liquidity from windfalls as non-fungible. I connect this non-fungibility to meaningful debt repayment prioritization mistakes, and identify its main psychological drivers as a combination of ad-hoc budgeting, reliance on heuristics, and low financial knowledge. This helps explain debt prioritization errors identified in other contexts (e.g. Gathergood et al. 2019).

Finally, I advance the study of student debt relief in particular. The growth in student debt into the second-largest consumer debt category after mortgages has prompted proposals to forgive student debt, which would simultaneously reduce outstanding balances and monthly

[3]For example, see Ganong and Noel (2020), Agarwal et al. (2017), Fuster and Willen (2017), Tracy and Wright (2016). Di Maggio et al. (2017) estimates the consumption impacts of changes in monthly mortgage payments due to ARM resets during the recession. Ganong and Noel (2020) also study consumption, but do not report consumption results for their payment modification natural experiment. Examples outside the mortgage context include Aydin (2023) (personal loans) and Di Maggio, Kalda, and Yao (2019) (student loans).

payments (Yannelis and Tracey 2022, Sylvain and Constantine 2020). Since I study a universal policy that did not target distressed borrowers, my estimates reflect the likely effects of increased liquidity due to widespread debt relief. The low forbearance consumption MPX suggests that monthly payments do not constrain consumption for many borrowers who are current and in repayment. The low MPX also implies a high short-run saving rate out of liquidity from relief, meaning lower monthly payments could facilitate wealth formation.

Sections 1-7 respectively describe the US student loan market and CARES Act; present predictions from an incomplete-markets lifecycle model; describe the data; present empirical results; propose a model to rationalize results; quantify fiscal policy implications; and conclude.

1 Institutional background

The US student loan market Student loans are the second-largest consumer debt category after residential mortgages, with $1.58 trillion in outstanding balances as of 2021Q3 across roughly 43 million borrowers (NY Fed, 2021, Hanson 2023). The average borrower owes about $35,000, and median balances are around $23,000.

Before 2010, the federal government supported student borrowing with two main programs: the Federal Family Education Loan (FFEL) program, and the Federal Direct Loan (DL) program.[4] Under the FFEL program, students received loans funded, originated, and serviced by private lenders. The government guaranteed these loans in the case of default. Under the Direct Loan program, students received loans funded with government capital and owned by the Department of Education.

Under federally-sponsored lending programs, students may be eligible for preferential terms like reduced interest during school based on family income, but federal loans are available to all students. Loans are structured as fully amortizing fixed rate term loans with a prepayment option. The standard term is 10 years with a fixed monthly minimum. If borrowers make payments exceeding the monthly minimum, they can subsequently pay less than their monthly payment without becoming delinquent. Borrowers may also be eligible for income-driven payment plans, which cap monthly payments at a fraction of discretionary income and forgive outstanding debt after a fixed number of years.[5]

Loans issued under federally-sponsored programs may not fully cover higher education

[4]Before 2017, the government also subsidized Perkins loans for students with exceptional financial need. In 2019 Q4 Perkins balances were 0.4% of total DL, FFEL, and Perkins balances (Department of Education 2026).

[5]Borrowers may elect a plan with increasing minimum payments over the loan term, and borrowers with large balances can extend their term to 25 years. In 2019Q4, about 55% of borrowers in repayment were enrolled in repayment plans with 10-year terms, 8% had terms exceeding 10 years, 31% were enrolled in income-driven repayment plans, and 6% are enrolled in "alternative" repayment plans (Department of Education 2023).

costs due to per-borrower limits, and so students may also pay for school using private loans. Private loans are generally less attractive to borrowers. They carry higher interest rates and lack the generous options for income-driven repayment and forbearance that federal loans do. Lending under federal programs accounted for about 92% of outstanding balances (Measure-One 2019).

Due to policy choices around 2010, the federal government directly owns the vast majority of outstanding loans issued through government programs. In 2010, the FFEL program was discontinued, so since 2010, loans to finance post-secondary education are DL loans owned by the Department of Education. During the financial crisis, the federal government also purchased FFEL loans from private lenders to support the student loan market, and by 2019 Q4 owned 34% of FFEL program balances for 49% of FFEL program borrowers. By 2019 Q4, the federal government owned 88% of outstanding DL and FFEL balances, with the remaining 12% held by private lenders (Department of Education 2026). This implies the overall federal government ownership share, including all private lending, was 81% in 2019 Q4 (Fed 2020).

Federally-owned debt – regardless of whether originally issued under the DL or the FFEL program – is serviced by a limited set of companies contracted by the federal government. Many of these companies are monolines set up for the sole purpose of servicing federally-owned student debt, meaning they do *not* service private student loans or privately-held FFEL loans. I use this institutional feature to distinguish between federally-owned and private student debt, and identify loans that are eligible for automatic forbearance.

Hereafter, I interchangeably refer to federally-owned loans as "federal debt" or "federal loans", encompassing both Direct Loans and FFEL loans owned by the Department of Education.

CARES Act and automatic student loan forbearance The Trump administration announced that it would suspend interest payments on student loans on March 13, 2020, as part of its national emergency declaration in response to the ongoing spread of Covid-19 in the US. By March 20, the administration announced that it would also suspend payments. At this point, it was not clear what loans were eligible for the interest and payment suspensions, how long they would last, or whether catch-up payments would be required.

The 2020 Coronavirus Aid, Relief, and Economic Security (CARES) Act, passed on March 27, 2020, formalized the federal government's student loan forbearance policy. The policy automatically placed *all* federally-owned loans – both Federal Direct Loans and FFEL loans owned by the federal government – into administrative forbearance on an opt-out basis.[6] The

[6]The 2020 CARES Act "suspend[ed] all payments due for loans made under part D [Direct Loans] and part B [FFEL] (that are held by the Department of Education) of title IV of the Higher Education Act of 1965" (U.S. Congress 2020 §3513(a)).

interest rate on all outstanding debt was set to zero percent.[7] If borrowers had autopay set up through their loan servicer, the Education Department required that servicers automatically disable it.[8] The law also prevented missed payments from negatively impacting borrower credit scores.[9] Borrowers on income-driven repayment plans or working towards the federal Public Service Loan Forgiveness plan received credit for missed payments in forbearance as if they had made them.[10] The law also required that the Department of Education notify borrowers of the payment pause within 15 days of the Act's passage (U.S. Congress 2020 §3513(e)): see Appendix Figure F.13 for an example of key information communicated to borrowers. I take the passage of the CARES Act on March 27 as the start of the forbearance program, though I also look for evidence of anticipatory behavior in advance of the change.

The policy was originally set to end on September 30, 2020. However, the Trump and Biden administrations repeatedly extended the policy. The Department of Education estimates that the program cost $25 billion over the first six months, with a total cost of $123 billion through September 30, 2022 after several extensions.[11] The program ended August 2023.

CARES Act and direct stimulus payments The CARES Act also included provisions for direct "Economic Impact Payments" (EIP) to be paid to independent US adults. Each household would receive a payment of at most $1,200 per adult and $500 per dependent child, with payments reduced for high-income households. The IRS determined eligibility based on 2019 tax returns if available, and 2018 tax returns otherwise.

The IRS planned to deliver checks to adults with direct deposit information on file between April 9 and April 17. After that, the IRS planned to start mailing paper checks, targeting individuals with lower taxable income first. Payments largely concluded by the end of May.[12] In my sample, about 85% of student loan borrowers received their EIP from April 14-15.

[7] "...interest shall not accrue [...] for the period of suspension"(U.S. Congress 2020 §3513(b)).

[8] As of April 2, 2020, the Department of Education's Covid-19 Q&A page posted "Q: What will happen to my regular auto-debit payments if I do nothing? A: Auto-debit payments are suspended during the administrative forbearance" (Department of Education 2020).

[9] "...the Secretary [of Education] shall ensure that, for the purpose of reporting information about the loan to a consumer reporting agency, any payment that has been suspended is treated as if were a regularly scheduled payment made by a borrower" (U.S. Congress 2020 §3513(d)).

[10] "...the Secretary shall deem each month for which a loan payment was suspended [...] as if the borrower [...] had made a payment for the purpose of any loan forgiveness program or loan rehabilitation program" (U.S. Congress 2020 §3513(c)), including income-driven repayment and Public Service Loan Forgiveness plans starting on March 27, 2020 (Hegji 2024).

[11] See Appendix C.1 for calculation from Ed Department publications.

[12] For more details about the disbursement timeline, see Appendix Table A.1 in Baker et al. (2020).

2 Predictions from a consumption-saving model

This section uses a dynamic incomplete-markets model to benchmark responses to unanticipated student loan forbearance and stimulus checks when borrowers respect the fungibility of liquid resources. Appendix A provides proofs.

Setup A borrower lives for $T \in \mathbb{N} \cup \infty$ periods. In period $t = 0$, the borrower has J amortizing debt accounts indexed by j with balances B_{j0} to repay. Accounts have gross interest rate R_{jt} and time-varying borrowing limit L_{jt}, which generate an effective minimum payment schedule, where $B_{jt} \leq L_{jt}\ \forall t$. Accounts allow for prepayment. The borrower has a liquid checking account with balance X_t that permits saving and borrowing up to limit L_0 at gross interest rate R_0. I refer to X_t as "cash-on-hand." Collect debt repayment parameters into $\theta := \{R_{jt}, L_{jt}\}_{j,t}$. Borrowers treat these parameters as known in advance.

Each period, the borrower first receives income $y_t \overset{\text{iid}}{\sim} G$.Borrowers then sequentially choose total saving x_t and debt repayments $\{p_{jt}\}$, with student loan payments p_{st} chosen last. Borrowers do not expect the environment to change within a period. If the environment doesn't change, their sequential choices coincide with the solution if they were to optimize jointly. The value function given state variables X_t and $\{B_{jt}\}_{j \in J}$ satisfies the following Bellman equation, where $P := \sum_j p_j$ and the expectation is taken over y_{t+1}:

$$V_t(X_t, \{B_{jt}\}_j; \theta) = \max_{x, \{p_j\}_j} U(X_t - x) + \delta E V_{t+1}\left(R_0[x - P] + y_{t+1}, \left\{R_{j,t+1}(B_{jt} - p_j)\right\}; \theta\right) \quad (1)$$

$$\text{s.t. } X_t - x + \sum_j p_j \in [0, X_t + L_0],\ p_j \in \left[B_{jt} - L_{j,t+1}, B_{jt}\right],\ X_t - x \geq 0 \quad (2)$$

where flow utility U is increasing and concave. The solution implies total saving, consumption, and debt repayment policies $x_t\left(X_t, \{B_{jt}\}_j; \theta\right)$, $c_t\left(X_t, \{B_{jt}\}_j; \theta\right)$, and $p_{jt}\left(X_t, \{B_{jt}\}_j; \theta\right)$ that hold when the environment is unchanged within-period.[13]

Effects of stimulus payments and forbearance Stimulus checks delivered in period t unexpectedly increase liquid account balances by ΔX between periods $t-1$ and t, so that $X_t = R_0(X_{t-1} - P_{t-1}) + y_t + \Delta X$. The change is unexpected because $y_t + \Delta X$ does not follow the income process G. To study effects on behavior, I compare policies evaluated at $(X_t, \{B_{jt}\}_j; \theta)$ to policies at $(X_t + \Delta X, \{B_{jt}\}_j; \theta)$. I refer to ΔX as liquidity from stimulus checks.

Federal student loan forbearance starting period t is announced at the end of period $t-1$, after all choices except federal student loan payments have been made. Forbearance lasting for F periods is represented by a change from θ to θ'. During forbearance, net interest falls to

[13] See Appendix A for conditions guaranteeing that policy functions exist, are unique, and are continuous.

zero, so $R'_{sl} = 1$ for $l \in [t, t+F]$. The repayment schedule is frozen until forbearance ends, so $L'_{sl} = L_{s,t-1}$ for $l \in [t, t+F]$ and $L'_{sl} = L_{s,l-F}$ for $l > t+F$. Period $t-1$ student loan payments when forbearance is announced in t are, where $P_{-s,t-1}(\cdot;\theta) := \sum_{j\neq s} p_{j,t-1}(\cdot;\theta)$:

$$\begin{aligned} p^f_{s,t-1}(X_{t-1}, \{B_{j,t-1}\}_j; \theta, \theta') := \arg\max_{p_s}\ & U(X_{t-1} - x_{t-1}(\cdot;\theta)) \\ & + \delta EV_t\left(R_0\left(x_{t-1}(\cdot;\theta) - P_{-s,t-1}(\cdot;\theta) - p_s\right) + y_t, R_{st}(B_{s,t-1} - p_s), \{B_{jt}\}_{j\neq s}; \theta'\right) \\ & \text{s.t. } (2) \end{aligned} \tag{3}$$

To study effects on behavior, I compare policies evaluated at $(X_t, \{B_{jt}\}_j; \theta)$ to those evaluated at $(X'_t, B'_{st}, \{B_{jt}\}_{j\neq s}; \theta')$, where X'_t, B'_{st} may differ from X_t, B_{st} because $p_{s,t-1}(\cdot;\theta) \neq p^f_{s,t-1}(\cdot;\theta,\theta')$.

Claim 1 (Optimal debt repayment) *Payment p_{jt} exceeds the minimum payment required to ensure $B_{jt} \leq L_{jt}$ only if: (i) all accounts with strictly higher interest are fully repaid; and (ii) the interest rate on B_{jt} weakly exceeds the checking account interest rate, i.e. $R_{jt} \geq R_0$.*

Call p_{jt} a marginal payment if it is strictly between the minimum payment and the full balance, and call account j a marginal account. Then:

1. *For any two $j, k \in \{1, \ldots, J\}$, payments p_{jt} and p_{kt} are marginal payments only if $R_{jt} = R_{kt}$.*
2. *Increased saving from a stimulus check received in t will increase p_{jt} if j is the unique marginal account before and after the check arrives. If j is not marginal, p_{jt} will not change.*
3. *If forbearance starting in t is announced when $t-1$ ends, then $p^f_{s,t-1}(\cdot;\theta,\theta') = 0$ if $R_0 \geq 1$.*

Applied to forbearance, part (2) explains that stimulus checks will increase student loan payments during forbearance if student loans are the marginal saving vehicle. Part (3) says student loan payments should drop to zero so long as the yield on liquid saving is non-negative.[14]

Define $\Delta p_{st} := p_{s,t-1}(\cdot;\theta) \geq 0$. This represents the increase in liquid resources in period t due to forbearance, equal to the $t-1$ payments had forbearance not occurred (θ), because optimal $t-1$ payments under forbearance (θ') are zero.

Claim 2 (Stimulus checks vs. forbearance) *Define Δc^w_t and Δp^w_{jt} as consumption and debt payment impacts of a stimulus check of size ΔX in period t, and define Δc^f_t and $\Delta p^f_{jt}, j \neq s$ as consumption and debt payment impacts of forbearance shifting θ to θ'. Suppose $R_0 = 1$.*

If consumption and non-student loan debt repayment are weakly decreasing in student loan balances B_{st} and student loan interest and limits $R_{s,t+l}, L_{s,t+l}, l \in [t, t+F]$, then to a first order:

$$\frac{\Delta c^w_t}{\Delta X} - \frac{\Delta c^f_t}{\Delta p_{st}} \leq \left|\frac{\partial c_t(\cdot)}{\partial B_{st}} R_{st}\right|; \quad \frac{\Delta p^w_{jt}}{\Delta X} - \frac{\Delta p^f_{jt}}{\Delta p_{st}} \leq \left|\frac{\partial p_{jt}(\cdot)}{\partial B_{st}} R_{st}\right|,\ j \neq s \tag{4}$$

[14] The borrower strictly prefers saving in a zero-interest checking account for precautionary reasons.

Define $\frac{\Delta c_t^w}{\Delta X}$ as the MPC out of stimulus checks, and $\frac{\Delta c_t^f}{\Delta p_{st}}$ the MPC out of forbearance liquidity. Claim 2 says the difference between these MPCs is bounded by the consumption impact of higher student loan balances $\frac{\partial c_t}{\partial B_{st}}$ owing to lower period $t-1$ student loan payments.

To understand this result, consider policies where $\Delta X = \Delta p_{st}$. Stimulus checks increase consumption by increasing checking account balances by ΔX. Forbearance increases checking account balances by the same amount due to timing assumptions and the endogenous decrease in student loan payments. But consumption changes through three other channels as well. First, decreased student loan payments increase student loan balances; second, the interest rate pause reduces debt service expenses; and third, the modified repayment timeline gives borrowers more flexibility (akin to a credit line extension). By assumption, the first effect decreases, and the latter two increase, consumption. The first "MPC out of wealth" channel is therefore an upper bound on the MPC difference.

When combined with estimates of MPCs out of unexpected wealth changes in the literature, Claim 2 shows that the model predicts very similar MPCs out of stimulus checks and forbearance liquidity. First, the upper bound in equation (4) is likely quite small. Ganong and Noel (2020) estimate a precise annual MPC out of changes in US housing wealth of 0.003, while Paiella and Pistaferri (2017) estimate annual MPCs out of unexpected wealth shocks of around 0.01 to 0.03 using Italian survey data (where housing wealth drives most of the effect). In my context, the upper bound is probably even smaller than 1-3%. Changes in housing wealth may relax liquidity constraints by boosting collateral (as in Ortalo-Magné and Rady 2006 and Campbell and Cocco 2007) whereas changes in student loan balances do not. Moreover, I estimate MPCs over a four-week horizon, where MPCs are likely lower than these annual estimates.[15] Second, the upper bound binds if forbearance does not increase borrower net worth. This is unlikely, as forbearance lowered the present-value of interest payments by $25 billion.

3 Data and sample selection

3.1 Transactions data

Data overview. I obtain de-identified, individual-level consumer transaction data from a large US data provider. The provider cleans and categorizes raw transaction data from major banks and FinTech firms, and offers the resulting dataset as a product to investors. The provider obtains data primarily through direct agreements with financial institutions, rather than consumers, although all data are user-permissioned (e.g. through terms of service).

[15] For example, Parker et al. (2013) estimate a six-month stimulus payment MPC that is 60% higher than the three-month MPC.

The data contain information on credit card, debit card, and bank account transactions, with links across accounts owned by the same consumer, for about 60 million individuals from January 2010 to May 2021. I observe transaction amount, date, and description for all credits and debits made to each account, along with some merchant information and metadata. The data also include demographic data on income and county of residence.

The data provider groups transactions into approximately 40 categories using merchant and transaction descriptions. I use these categories to construct expenditure and income variables. For expenditure, I distinguish between durables and broad non-durables, and further separate non-durable expenditure into food, household spending, and a residual "other non-durable" category. Net savings includes direct transactions into saving, investment, or retirement accounts and payments on credit cards, mortgages, autos and insurance, and tax. I calculate income by summing regular salary and income from investments and other irregular sources.

For the borrowers with linked credit card accounts, I also compute a lower bound on interest-bearing credit card balances. Specifically, I calculate cumulative charges and repayments on linked cards and estimate the daily lower bound on interest-bearing credit card debt as the difference between cumulative repayments and charges as of 52 days prior.[16]

Identifying student loan borrowers. I identify student loan borrowers using student loan repayments. I measure student loan repayment through transactions to known student loan servicers, identified using merchant name extracted by the data provider and manual text searches of transaction descriptions. Specifically, I tracked payments to the 10 companies that contracted with the Department of Education to service the federal student debt portfolio, as well as 30 companies that service private student loans originated by major lenders. I use payments to the private-exclusive servicers to identify private student debt. Appendix B lists these servicers.

Identifying federally-owned student loans eligible for federal student loan forbearance. Student loans owned by the federal government – and therefore automatically eligible for forbearance – are serviced by a small number of servicers on annual government contracts. These servicers are made public each year. Some of them *exclusively* service student loans owned by the federal government – for example, until their federal contract expired in December 2021, FedLoan Servicing was a separate company set up by the Pennsylvania Higher Education Assistance Agency for the sole purpose of servicing student loans owned by the Department of

[16] I accumulate charges and repayments starting on Jan 1, 2019. I choose 52 days to align with the at most 31 days between the purchase and statement closing date, plus a 21-day grace period (the industry standard). This is a lower bound because the method (i) only calculates debt incurred after Jan 1, 2019; (ii) ignores debt held on unconnected accounts; and (iii) does not account for shortened grace periods for accounts revolving debt.

Education.[17] Payments to these servicers must therefore be for government-owned loans – either Direct Loans, or government-owned FFEL loans – which are all eligible for federal student loan forbearance. Some servicers, such as EdFinancial, contract with both the federal government and private and *commercial* FFEL lenders. Payments to these servicers may or may not be for government-owned loans, and therefore may or may not be eligible for forbearance. I only treat a loan as eligible for forbearance if the servicer *exclusively* services federally-owned debt; I conservatively do not treat loans paid to servicers that service *both* federally-owned and private debt as eligible for forbearance. I use public information to determine which servicers are federal-exclusive; see Appendix B for details.

This method only allows me to identify student loan repayments, not balances. I cannot identify borrowers with outstanding balances in default, with outstanding balances in forbearance, or who are sufficiently paid ahead that no monthly payments are required.[18]

Sample selection and summary statistics. I construct a panel restricted to active users with federal student debt in repayment observed between January 2019 and January 2021. To exclude people who exit the sample or for whom I do not observe primary accounts, I define active users as those who (i) have more than five transactions in each month; and (ii) have annual spending exceeding the income of a half-time minimum wage worker.

I identify borrowers in repayment as those who make regular payments between January 2019 and February 2020. Among users with any federal student loan payments during the sample period, I require users both: (i) make payments in at least two out of every three months; and (ii) have average repayment amounts above $20 per month. The first restriction gives some allowance for borrowers who pay ahead and subsequently skip payments; the second restriction excludes borrowers with minimal balances.

These restrictions produce a balanced panel of around 312,000 borrowers. Table 1 presents summary statistics for 2019 characteristics of the main panel of federal student loan borrowers, split by quartile of 2019 total student loan repayments. Total monthly student loan payments are about $340 on average, ranging from $66 per month in the bottom quartile to $856 per month in the top quartile. The bulk of these payments go towards repaying federal loans, although about 9% of borrowers hold private loans as well. The average annual income is around

[17] In a 2022 email exchange with the author, Keith New, PHEAA's director of media and public relations, said FedLoan Servicing "was set up specifically to service federally owned loans so that type of loan comprised the portfolio." Another example is Great Lakes, set up by Nelnet to service the federally-owned portfolio; in a 2022 email exchange, Philip Morgan, executive director at Nelnet, confirmed that "all servicing volume on Great Lakes' servicing platform was federally owned debt." In my study period, FedLoan Servicing and Great Lakes were the largest federal servicers.

[18] Figure 2 in Cherry et al. (2021) shows that around 50% of borrowers were already in forbearance before automatic forbearance began. These borrowers are unlikely to be in my sample. However, they also receive no liquidity from forbearance in the sense defined in Section 2, meaning they should be excluded from the analysis.

$85,000, with higher incomes for borrowers with higher monthly student loan payments.

Table 1: Sample summary statistics for transactions panel

	Student loan payment quartile				
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Average
Total student loan pmt	65.8	158	284	856	341
Federal student loan pmt	65.1	155	274	818	328
Has private student loans	.0255	.045	.0781	.204	.0882
Private student loan pmt | has private pmt	25.9	58.5	110	402	266
Total income	64,314	74,376	83,043	118,118	84,963
Has mortgage	.299	.337	.349	.388	.343
Mortgage pmt | has mortgage pmt	1,091	1,207	1,323	1,602	1,323
Has savings pmts	.308	.316	.326	.367	.329
Savings pmts | has savings pmts	232	298	342	550	363
Has linked credit card	.353	.374	.368	.382	.369
Has revolving debt | has linked card	.377	.366	.335	.282	.339
Revolving debt lower bound | has linked card + debt	1,487	5,804	1,797	2,143	2,884
Total expenditure	3,405	3,601	3,663	4,370	3,760
Food expenditure	713	724	709	735	720
Household expenditure	719	744	755	864	770
Other nondurable expenditure	1,297	1,355	1,388	1,732	1,443
Durable expenditure	655	644	625	681	651
N	78,328	78,329	78,327	78,328	313,312

Source: Transactions panel. The table displays summary statistics for the main panel in 2019, split by quartile of 2019 total student loan payments. For continuous variables, entries are mean monthly values in USD; for discrete variables, entries are the fraction with positive values during the year. Conditional means condition on having a positive value, except for revolving credit card debt, where means condition on having a positive value in a given month.

3.2 Public data sources

I validate the transaction data's representativeness using the nationally-representative Survey of Consumer Finances (SCF). The SCF collects detailed information on household assets, liabilities, and income, and I use it to evaluate the transactions data measurement of student loan payments. I also use the SCF to replicate key findings from the transactions data on voluntary student loan prepayment during forbearance. The Department of Education releases quarterly data on outstanding balances on loans issued through federally-sponsored lending programs. I use the Department of Education data as additional validation for my finding of continued voluntary prepayment of federal student loans in forbearance. Appendix Section C.2 describes these additional sources and my data processing steps.

3.3 Student borrower survey

I survey borrowers with student debt to understand financial literacy, program knowledge, and motivations for non-standard debt repayment behavior during forbearance. In March 2023, I recruited 798 US adults who had student debt at some point since 2019 using Prolific, an online survey platform with high attention and high comprehension participants (Eyal et al. 2021).

The survey's first part identifies borrowers exhibiting non-fungibility and debt repayment mistakes by violating Claims 1 and 2 in their response to forbearance and stimulus checks.

The second part assesses borrower knowledge about the student loan forbearance program and financial sophistication. To assess program knowledge, I first ask broadly about program familiarity, key program features, and beliefs about own eligibility. I assess financial sophistication by testing whether borrowers understand incentives created by interest rate variation. I ask borrowers how they would use $100 to repay two credit cards, one with balance $200 and APR 25%, and the other with balance $300 and APR 20%. I classify borrowers who use any of their budget to pay down the low-APR card as making a financial mistake.

In the third part, I directly ask respondents with student loan repayment inconsistencies or mistakes to explain their actions. I asked respondents to write an explanation in a text box to encourage reasoning about actual motivations, and then presented a separate screen where participants could select multiple pre-specified options. I chose pre-specified justifications based on frequent free responses in piloting and to test specific theories.

Finally, I run a framing experiment asking how borrowers would spend a $300 windfall over a year in a scenario with significant credit card and student debt. I randomly describe the payment as made to (i) "all US households" because "US households are struggling financially," or (ii) "borrowers with student debt" because "households with student debt are struggling financially." If borrowers violate fungibility because they target non-optimal debt repayment levels, then alternative framings may impact behavior by appealing to different ad-hoc budgeting rules or heuristics. I also cross-randomize the student loan interest rate to be 0% or 7% to test for interactions with borrowers not knowing how to respond to interest rate differences.

See Appendix D for details about sample recruitment, survey structure, and pre-registration.

4 Empirical strategy and results

This section uses transactions data to provide quasi-experimental evidence of the liquidity flypaper effect, then identifies its drivers with survey evidence.

4.1 Non-fungibility and debt repayment mistakes

Claim 1 shows that once forbearance begins, borrowers respecting the fungibility of financial resources – especially those with other interest-bearing debt – should stop repaying federal student loans. If repayment remains optimal, borrowers should use stimulus checks to repay student loans.

This section rejects these predictions. Borrowers make significant post-forbearance repayments, despite not using stimulus checks to repay federal student loans. This non-fungibility generates debt repayment mistakes: borrowers with significant interest-bearing debts also make federal student loan payments in forbearance, despite repaying high-interest debt first when using liquidity from stimulus checks.

4.1.1 Empirical strategy: MPX out of forbearance and stimulus check liquidity

I aim to estimate $MPX^f_{p_s} := E\left[\frac{p^o_{is}}{\Delta p_{is}}\right]$ and $MPX^w_m := E\left[\frac{\Delta m^w_i}{\Delta X}\right]$ over the first four weeks following each transfer. $MPX^f_{p_s}$ gives the fraction of forbearance liquidity used to prepay federal student loans, where Δp_{is} is liquidity from forbearance, given by the change in optimal student loan payments when forbearance is announced, and p^o_{is} represents *observed* payments during forbearance. This represents spending out of forbearance liquidity because cost-minimizing payments during forbearance are $p_{is}(\cdot;\theta') = 0$. MPX^w_m gives the fraction of stimulus check liquidity used on outcome m (e.g. federal student loan payments), and depends on Δm^w_{it}, the change in m due to stimulus checks, and ΔX, stimulus check size.

To examine whether borrowers use liquid resources consistently, I measure the correlation between $MPX^f_{p_s}$ and $MPX^w_{p_j}$ for payments on other debts p_j. This estimates how borrowers who spend forbearance liquidity on federal student loans use their stimulus check liquidity.

Forbearance MPX on federal student loans I estimate $MPX^f_{p_s}$ using an interrupted time series design, exploiting high-frequency changes in repayment around program onset. I first estimate the following, where t indexes weeks and i indexes borrowers:

$$p_{s,it} = \beta_0 + \beta_1 Week_t + \beta_2 Post_t \times Week_t + \alpha Post_t + \varepsilon_{it} \tag{5}$$

where $Week_t$ indicates weeks relative to the start of forbearance and $Post_t$ is an indicator equal to one after forbearance begins. I restrict to observations in the four weeks before and after forbearance began, omitting observations from the week of program onset due to implementation lags.[19] Appendix C.6 presents results from estimates with common time trends before and after forbearance begins ($\beta_1 = \beta_2$). I next estimate the four-week MPX on student loans as $\widehat{MPX}^f_{p_s} := \left(\sum_{t=0}^{3}\hat{\beta}_0 + \left(\hat{\beta}_1 + \hat{\beta}_2\right)\cdot t + \hat{\alpha}\right) \Big/ \left(\sum_{t=0}^{3}\hat{\beta}_0 + \hat{\beta}_1 \cdot t\right)$. The numerator calculates fitted values for payments in the four weeks post-forbearance. The denominator predicts student loan payments had forbearance not occurred by extrapolating the linear pre-forbearance repayment trend. The identifying assumption is that absent forbearance, repayments would have

[19] The CARES Act passed on a Friday, and I see some payments initiated on Friday that processed over the weekend. Servicers seem to have ironed out implementation by April 1, 2020.

evolved on a linear trend relative to repayments in the prior four weeks.

A concern with this assumption is that many borrowers would have defaulted absent forbearance due to the deteriorating economic environment. However, the linear trend should capture non-repayment due to economic hardship before the CARES Act passed. Moreover, this concern implies I may *overestimate* counterfactual payments. If anything, $\widehat{MPX}^{f}_{p_s}$ is a lower bound, and I may *underestimate* the difference between the forbearance and stimulus check MPX on student loans.

Stimulus payment MPX on federal student loans I estimate the stimulus payment MPX on federal student loans by adapting the design from Baker et al. (2020). Intuitively, I compare within-person student loan payments before and after EIP receipt, and use variation in EIP timing across borrowers with similar characteristics to estimate counterfactual time trends in the post-receipt period. I estimate the following specification, where t indexes days:

$$p_{s,it} = \gamma_i + \delta_{yt} + \sum_k \mu_k \mathbb{1}(t \in T_k)_i \cdot EIP_i + \varepsilon_{it} \tag{6}$$

where EIP_i is borrower i's stimulus payment and $\mathbb{1}(t \in T_k)_i$ is an indicator equal to one if date t is in the set of T_k periods after the date that borrower i receives the stimulus payment.

My main specification sets $T_k \in \{T_{Pre}, T_{MPX}, T_{Post}\}$, where $T_{Pre} = [t_{min}, -7)$, $T_{MPX} = [0, 28]$, and $T_{Post} = (28, t_{max}]$. The coefficient of interest is $\mu_{MPX} = MPX^{w}_{p_s}$, the four-week MPX on federal student loans out of stimulus checks. Borrower fixed effects γ_i control for unobserved time-invariant factors that impact payments, such as minimum payments or latent desires to repay debt sooner. Income-by-time fixed effects δ_{yt} control for unobserved time trends that vary by permanent income, proxied using 2019 total income. Allowing income-specific time trends is important because Chetty et al. (2020) finds that spending declined more for high income workers when the pandemic began. The identifying assumption is that unobserved, borrower-specific student loan payment time trends within income class are uncorrelated with stimulus receipt timing.[20]

I evaluate the identifying assumption by estimating a version of (6) with $T_k \in \{t : t \in [-7, 28]\}$, where coefficients μ_k represent the daily MPX. The assumption is more plausible if $\mu_k \approx 0$ for $k < 0$ before stimulus check receipt, and increase sharply when $k = 0$.[21]

In Appendix C.7, I estimate a version of equation (6) using the estimator described in Borusyak, Jaravel, and Spiess (2024) to address concerns about non-constant weights on heterogeneous treatment effects in staggered difference-in-differences designs. Results are similar.

[20] The regression also uses cross-sectional variation in the EIP payment size to estimate μ_k.

[21] Observing $\mu_k > 0$ for $k < 0$ does not necessarily imply the identifying assumptions are violated because borrowers might increase spending in anticipation of stimulus check receipt if they are not liquidity constrained.

I also use specification (6) to estimate the stimulus check MPX on other outcomes m.

Correlation between forbearance and stimulus check MPX I also estimate equation (6) with event time coefficients interacted with borrowers' student loan MPX out of forbearance:

$$p_{j,it} = \gamma_i + \delta_{yt} + \sum_{k \in \{Pre, MPX, Post\}} \left[\mu_k + \phi_k \cdot MPX^f_{p_s,i} \right] \mathbb{1}\left(t \in T_k\right)_i \cdot EIP_i + \varepsilon_{it} \tag{7}$$

I estimate $MPX^f_{p_s,i}$ by dividing a borrower's total realized student loan payments in April and May by average monthly payments before February 2020. This specification gives the MPX on payments p_j out of stimulus payments as a function of the fraction of forbearance liquidity used to repay federal student debt: $\widehat{MPX}^w_{p_j,i} = \hat{\mu}_{MPX} + \hat{\phi}_{MPX} \cdot \widehat{MPX}^f_{p_s,i}$.

4.1.2 Implementation and results

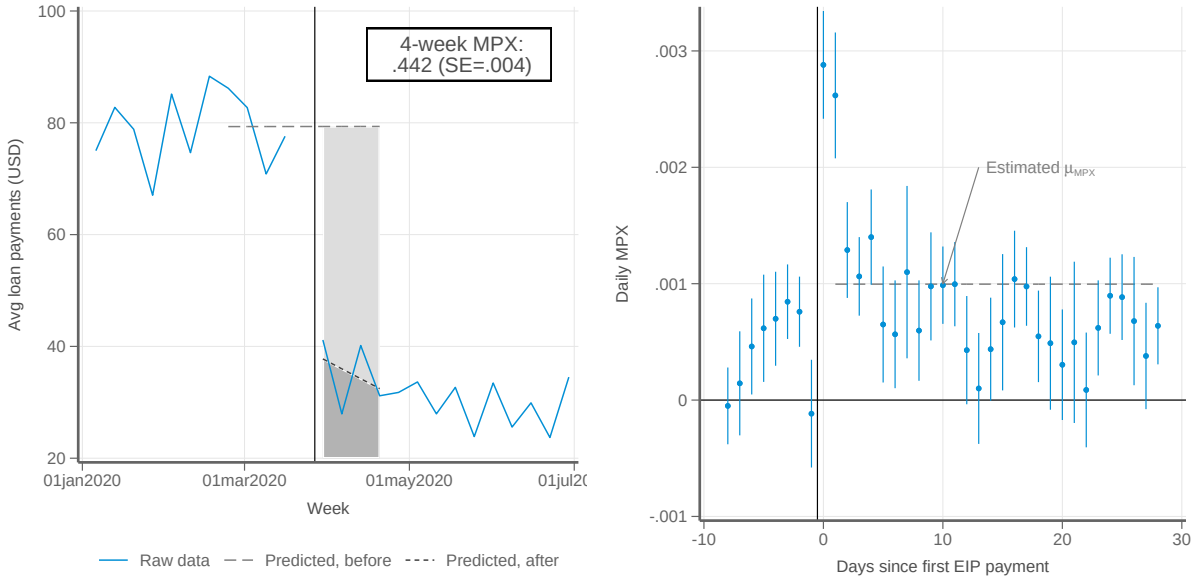
This section shows five results. Results 1-3 establish that borrowers treat liquidity from forbearance as non-fungible with liquidity from cash transfers. This causes a flypaper effect, where forbearance liquidity "sticks" to student loan repayment. Results 4 and 5 indicate this flypaper effect generates costly debt repayment mistakes. Where possible, Appendix Section C.3 quantitatively replicates these results using the Survey of Consumer Finances, meaning they are not an artifact of transactions data.

1. Borrowers use a significant fraction of forbearance liquidity to prepay federal student loans. Figure 1a plots average borrower payments on federal student loans by calendar week to illustrate the variation used to estimate $\widehat{MPX}^f_{p_s}$. Before forbearance, borrowers paid an average of around \$80 per week, consistent with the average of \$328 a month in Table 1. At the onset of forbearance, payments drop to around \$40 per week, but are persistently positive.

I also plot predicted values from specification (5) to compare actual payments to counterfactual payments predicted using pre-forbearance time trends. The estimate $\widehat{MPX}^f_{p_s}$ integrates predicted values from the actual and counterfactual payment trends in the four weeks after forbearance begins and takes the ratio. The first column in Table 2, Panel A reports the result: on average, borrowers used about 44% (SE = 0.4%) of the liquidity from forbearance to prepay federal debt over the first four weeks of the program. Repayments persist for months after April 2020, showing that delayed borrower reactions do not drive results. Appendix C.6 shows results are unchanged if I impose common time trends ($\beta_1 = \beta_2$) when estimating (5).

There are two reasons to support the identifying assumption that pre-forbearance trends generate reasonable predictions of counterfactual payments. First, repayment trends are flat in the four weeks before forbearance, despite March economic hardship. Borrowers in my sample

Figure 1: MPX on federal student loans, by liquidity source



(a) MPX out of forbearance liquidity

(b) MPX out of stimulus checks

Source: Transactions panel. The vertical line indicates the onset of forbearance. Panel (a): The "raw data" series plots average weekly payments on federal student loans for the full sample. The "predicted–before" and "predicted–after" series plot predicted values from coefficient estimates of specification (5), pre- and post-forbearance. The estimate of the MPX on student loans out of forbearance liquidity is the ratio between the post-forbearance predicted values integrated over four weeks of the post-forbearance period and the pre-forbearance predicted values extrapolated over the same four weeks of the post-forbearance period. Panel (b): The figure plots event time coefficient estimates from (6) with $T_k \in \{t : t \in [-7, 28]\}$, where $\hat{\mu}_k$ represent daily MPX on federal student loans out of stimulus checks. Horizontal line plots $\hat{\mu}_{MPX}$ estimated from (6) relative to the pre-EIP average. Spikes plot 95% confidence intervals calculated from borrower-clustered robust standard errors.

– who have some college education – may have escaped negative shocks leading to missed payments, as initial Covid-related job losses were concentrated among low-wage workers (Chetty et al. 2020). This supports predicting counterfactual payments using a linear trend estimated on pre-forbearance payments.

Second, a placebo test, where I apply my methodology to *private* loan payments for borrowers with both federal and private loans, shows no large post-forbearance drop in payments. If the pre-forbearance linear trend predicts post-forbearance private loan repayments, I should estimate an MPX on these loans of about one. The second column in Table 2, Panel A shows a point estimate of 0.93 (95% CI: [0.89,0.97]). The pre-forbearance trend slightly over-estimates post-forbearance repayments, although this could partly reflect private forbearance. Hence, estimates may face a small downward bias.[22]

These averages obscure heterogeneous borrower responses to forbearance liquidity. Appendix Figure F.10 shows that the fraction of borrowers making payments on federal student

[22]Appendix C.6 presents results from another placebo test with borrowers who only have private debt. This group has no forbearance treatment, but is likely much less representative, because borrowers have no federal debt only in very unusual circumstances. This placebo test implies a slightly larger downwards bias.

loans declines by an amount proportional to the average payment drop in Figure 1a. Therefore, borrowers spend either all or none of their forbearance liquidity on student loan prepayments. This echoes Coibion, Gorodnichenko, and Weber (2020), who find in surveys that the individual-level MPX on debt repayments out of stimulus checks clusters at zero and one.

In the Appendix, I replicate the result that many borrowers make large payments on federal student loans subject to the payment pause during forbearance, using SCF data (Appendix Table C.1, Panel A), aggregated Department of Education data (Appendix Section C.5), and internal Department of Education data (Appendix Figure C.2).[23] My transaction data estimates also align with results from analysis of credit bureau data in Goss, Mangrum, and Scally (2023), who find that among borrowers with declining balances pre-forbearance, about 34% continued to reduce their balances, almost identical to estimates from Figure F.11. This validates the result that borrowers use much of their forbearance liquidity to prepay federal student loans.

2. Borrowers with higher student loan payments prepay more during forbearance. Higher economic stakes due to higher payment levels do not induce borrowers to spend less forbearance liquidity repaying federal debt. The last four rows of the first column in Table 2, Panel A estimate $\widehat{MPX}^{f}_{p_s}$ for borrowers imputed to have different levels of federal student debt, split by total 2019 federal student loan payments normalized by 2019 income (a debt-to-income ratio). $\widehat{MPX}^{f}_{p_s}$ is about 17% *higher* in the top debt-to-income quartile than the lower quartiles. Appendix Table C.1, Panel B replicates this pattern using the SCF.

3. Borrowers do not use stimulus checks to prepay federal student loans. Prepaying 0% interest student debt might be consistent with fully-informed, rational behavior if alternatives offered equal (or even negative) yields. In this case, borrowers would also use saving from windfalls such as stimulus check payments to repay student loans, as formalized in Claim 1.

Figure 1b investigates this by plotting estimates from specification (6) with $T_k \in \{t : t \in [-7, 28]\}$ where coefficients represent the daily MPX on federal student loan repayments out of stimulus payments.[24] Federal student loan repayments increase sharply on stimulus check receipt. But magnitudes are minuscule, at most around 25-30 basis points. The first column in Table 2, Panel B uses $\hat{\mu}_{MPX}$ from the main version of specification (6) to estimate the four-week MPX on federal student loans out of stimulus checks. The MPX is 0.93%, a statistically significant 43 percentage points lower than $\widehat{MPX}^{f}_{p_s}$ (SE of the difference = 0.4pp). This violates

[23] As shown in Appendix Figure C.3, the forbearance program shifted student loans from "in repayment" status to "in forbearance" status. But in the federal data reporting scheme, loan status is an administrative category, not a description of repayment behavior; borrowers in administrative forbearance who make voluntary payments remain in the "forbearance" reporting category.

[24] I include the full sample of borrowers, regardless of whether they received stimulus checks. Borrowers who do not receive stimulus payments improve estimation of income decile by calendar time trends.

models where agents respect fungibility of financial resources, and suggests that borrowers viewed the two transfers as non-fungible.

4. Borrowers prepay 0% interest federal student loans instead of higher-yielding consumer debt. I examine federal student loan prepayment during forbearance for borrowers with credit card or private student debt. Neither debt category carries prepayment penalties, and the economic stakes of mis-prioritizing payments on these debts are high due to high interest rates.[25] Furthermore, if prepayment in forbearance relates to borrower views on education debt, then borrowers may treat private student debt similarly.

I first study the 37% of my sample with a linked credit card for whom I can impute a lower bound on balances. Table 1 shows that at least 34% of these accounts revolve debt in 2019.

Many federal student loan prepayers simultaneously hold substantial interest-bearing credit card debt. In Figure 2, I condition on borrowers with outstanding credit card debt from March through June 2020 (the "credit card mistakes" sample, for whom prepayment is an unambiguous mistake[26]), and track federal debt repayment from the start of forbearance in April through May. Points left of the vertical dashed line show values for the full linked credit-card sample.

About 25% prioritize student loan repayments while revolving debt, a slightly lower proportion than in the full sample. The left panel plots the fraction of borrowers who make any payments on federal student loans by credit card debt quintile. Highly indebted borrowers are less likely to make the mistake, but even 23% of borrowers with over $10,000 in credit card debt prepay their student loans.[27]

This mistake is costly. The right panel conditions on borrowers making prepayments between April and June, and plots prepayment amounts by credit card debt level. The mean borrower with at least $10,000 in credit card debt paid around $930 towards their 0% interest student loan between April and May. The annualized cost of this mistake is around $\$930 \times 17\% \approx \$158$. If borrowers continue making this mistake, over a year they would pay around $6 \times \$158 = \$948$ in excess interest.

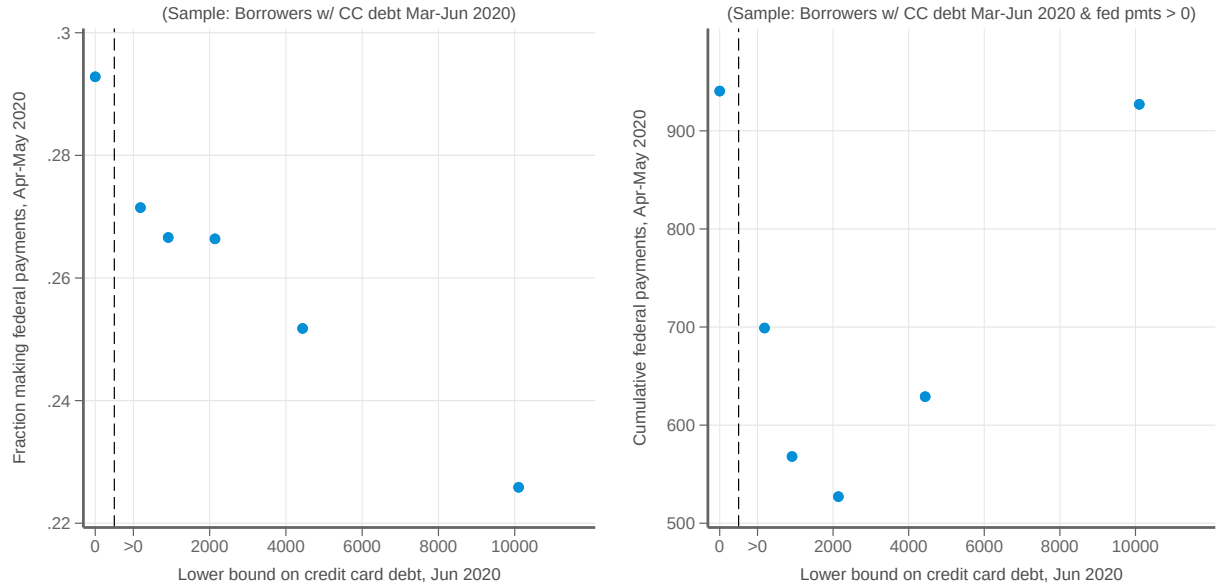
The third column in Table 2, Panel A quantifies this mistake in MPX terms. Borrowers with credit card debt use 40% of their forbearance liquidity to prepay their 0% interest federal student loans during the first four weeks of forbearance. Even borrowers in the highest credit card debt quartile, with median debt levels around $8,600, or 12% of 2019 income, spend over

[25] In March 2020, the average APR paid on credit card debt was 17% (McCann 2022, Federal Reserve Board 2023), and the average 10-year private student loan fixed rate was around 6% (Carter 2022).

[26] Appendix Figure F.11 plots the fraction of borrowers making federal debt payments each month, split by credit card debt during the last week before forbearance began. Such borrowers might not be making a mistake, since they could have repaid their credit card debt before forbearance started.

[27] Since credit card debt levels are a lower bound, estimated slopes have attenuation bias. If the true slope between credit card debt and student loan payments is negative, the slope estimate will be biased towards zero.

Figure 2: Debt repayment mistakes versus credit card debt levels



Source: Transactions panel. The figure plots debt repayment mistakes for the sample of borrowers who have a linked credit card account and a positive revolving balance from March through June 2020. The left panel plots the fraction of borrowers who make any payments on federal debt between April and May 2020, and the right panel plots average cumulative payments on federal debt between April and May 2020. Each panel plots the mean value on each axis within each credit card debt quintile. The lower bound on credit card debt as of June 2020 is winsorized at the 95% level.

30% of the liquidity received from forbearance on prepaying federal student debt.

I find similar results for the 8.8% of borrowers with private student loans. I impute a lower bound on balances by summing private student loan payments between June 1, 2020 and January 1, 2021. The fourth column in Table 2, Panel A shows that such borrowers spend 33% of the liquidity received from forbearance on federal debt, slightly lower than the full sample or credit card borrowers. Appendix C.8 presents additional results for private borrowers.

Appendix Table C.1, Panel C replicates these patterns using the 2022 SCF, showing 35% of federal borrowers with revolving credit card debt and 50% of borrowers with private student loan debt prepay federal student loans during forbearance. The SCF also has direct information on the interest rates on the other debts that households are prioritizing below their 0% interest federal student loans. For example, among credit card borrowers with positive federal student loan payments, the balance-weighted average interest rate on revolving balances is 18.0%. The table shows a similar failure to prioritize high-interest debt for borrowers with positive mortgage and auto debt with interest rates of 3.6% and 5.1%, respectively.

5. Borrowers appropriately prioritize repaying high-yield debt out of stimulus checks. Repayment mistakes might reflect that borrowers struggle to appropriately prioritize debt repayments in response to liquidity windfalls in general. To test this, Table 2, Panel B uses specifications (6) and (7) to estimate the MPX out of stimulus checks on credit card debt repayment

Table 2: Four-week MPX out of forbearance and stimulus checks

A. MPX on student loans out of forbearance liquidity

Outcome	Full sample	Private SL debt > 0	CC debt > 0, Apr-June 2020	Private SL debt > 0, June 2020
Federal SL pmts	0.442***	0.366***	0.397***	0.332***
	(0.004)	(0.01)	(0.017)	(0.011)
Private SL pmts		0.931***		
		(0.022)		
p-val of diff vs. fed SL pmts		0.000		
Federal SL pmts split by:	2019 fed pmt / income		June 2020 CC debt / 2019 income	Apr-June 2020 private SL pmts / 2019 income
Q1	0.413***		0.471***	0.273***
	(0.013)		(0.04)	(0.017)
Q2	0.39***		0.396***	0.314***
	(0.009)		(0.041)	(0.314)
Q3	0.417***		0.368***	0.352***
	(0.007)		(0.018)	(0.021)
Q4	0.482***		0.328***	0.396***
	(0.007)		(0.019)	(0.029)
N in sample	313,312	27,536	22,580	17,336

B. MPX out of stimulus checks

Outcome	Full sample	CC debt > 0, March 2020 (Above-median debt)	CC debt > 0, Apr-June 2020 (Above-median debt)	Private SL debt > 0, June 2020 (Above-median debt)
Federal SL pmts	0.009***	0.012	0.006	0.006
	(0.002)	(0.007)	(0.004)	(0.011)
p-val of diff vs. forbearance MPX	0.000	0.000	0.000	0.000
Total spending	0.174***	0.134***	0.129**	0.142*
	(0.01)	(0.04)	(0.044)	(0.061)
Broad nondurable	0.09***	0.059*	0.069*	0.042
	(0.006)	(0.028)	(0.031)	(0.054)
Credit card pmts		0.15***	0.075***	
		(0.029)	(0.014)	
p-val of diff vs. fed SL pmts		0.000	0.000	
Private SL pmts				0.04**
				(0.013)
p-val of diff vs. fed SL pmts				0.058
Credit card pmts			0.072***	
(SL MPX = 0)			(0.015)	
Credit card pmts			0.093***	
(SL MPX = 1)			(0.015)	
Private SL pmts				0.036*
(SL MPX = 0)				(0.016)
Private SL pmts				0.044*
(SL MPX = 1)				(0.022)
N in sample	313,312	14,947	11,290	8,668

Source: Transactions panel. * p=0.05, ** p=0.01, *** p=0.001. Each entry gives estimated four-week MPX on the variable listed in the "outcome" column out of liquidity from forbearance (Panel A) or stimulus checks (Panel B). Robust standard errors clustered at the borrower level are reported in parentheses. Panel A: Column 1 reports estimates on the full sample and splits by quartiles of 2019 federal student loan payments-to-income ratios. Column 2 restricts to borrowers with both federal and private student loan debt as a placebo test. Column 3 restricts to borrowers with interest-bearing credit-card debt each month from April-June 2020, with sample splits by quartiles of June 2020 credit card debt to 2019 income ratios. Column 4 restricts to borrowers with outstanding private student debt as of June 2020, with sample splits by quartiles of payments on private student debt between April-June 2020 to income ratios. Panel B: The first five rows report $\hat{\mu}_{MPX} \times 30$ from separate regressions from specification (6). The row "p-val diff vs. forbearance MPX" reports the p-value of a test of equality of the MPX out of stimulus checks and forbearance liquidity on federal student loans, calculated by taking the difference in 1,000 bootstraps and inverting the largest $1-\alpha/2$-level confidence interval not containing 0. Remaining rows report $\hat{\mu}_{MPX} \times 30$ and $\left(\hat{\mu}_{MPX} + \hat{\phi}_{MPX}\right) \times 30$ for the MPX on credit card and private student loan payments for borrowers with a forbearance MPX on student loans of zero and one, respectively, estimated using specification (7). Column 1 reports estimates for the full sample; Column 2 for borrowers with an above-median lower bound on credit card debt for the week of March 16, 2020; Column 3 for such borrowers with above-median average debt as of June 2020; and Column 4 for borrowers with above-median cumulative private student loan payments between June 1, 2020 and January 1, 2021.

for indebted borrowers. Rather than make the same debt prioritization mistakes, the same set of borrowers use their stimulus checks to pay off credit card debt but not federal student loans.

The second column examines borrowers with above-median credit card debt when forbearance began. Such borrowers spend about 15% of their stimulus checks on repaying credit card debt over the first month – an economically-significant amount, given its similar magnitude to the estimated MPX on consumption expenditures. The third column shows that borrowers with above-median debt in the "credit card mistakes" sample use 7.5% of their stimulus checks to repay credit card debt in the first month. Across subsamples, borrowers use precisely none of their stimulus checks to repay federal student debt (p-value of the diff = 0.000).

The last two rows of Table 2, column 3 report estimates from specification (7). The fifth row estimates the MPX for borrowers who stopped payments ($30 \times \hat{\mu}_{MPX}$), and the sixth row estimates the MPX for borrowers who used all of their forbearance liquidity to repay federal loans ($30 \times (\hat{\mu}_{MPX} + \hat{\phi}_{MPX})$). Borrowers who mistakenly prepaid federal student loans rather than credit card debt used *more* of their stimulus checks to pay down that debt.

The fourth column in Table 2, Panel B similarly shows that borrowers with private student debt use their stimulus checks to prioritize private over federal student loan repayment. Borrowers with above-median debt spend 4% of their stimulus checks paying down private student debt, but use essentially nothing to repay federal loans (p-value of the diff = 0.058). Estimates from specification (7) confirm this inconsistency.

Alternative explanations These results appear consistent with mechanical inattention. If borrowers did not know about the program or its details, they would both repay student loans at pre-forbearance levels and not use their stimulus checks to increase repayment.

There are six reasons to reject this alternative explanation. First, the program included many "nudges" to induce take-up among inattentive or uninformed borrowers. The payment pause was automatic and opt-out, so borrowers stopped receiving monthly bills notifying of payments due. Loan servicers were required to stop payments for borrowers with autopay.[28] If borrowers took no action, payments stopped. Borrower inattention would therefore bias results *against* finding a high forbearance MPX on federal loans.

Second, borrowers were *ex-ante* likely to know about the program. Federal student loans are prominent on borrower balance sheets, and the pandemic response dominated the news and public discourse in March and April 2020. The CARES Act required borrower notification

[28]Borrowers could in principle have "push" autopay through their bank that would not automatically shut off when forbearance begins. However, "push" autopay is uncommon, since federal law requires a 0.25% interest rate discount for borrowers who set up autopay through their servicer. Appendix Table G.15 shows that only 24% of prepayers use push autopay and are not more likely to do so than non-prepayers, and Appendix C.9 shows repayment patterns are inconsistent with widespread autopay usage.

about the program by April 11, 2020. The Department of Education student loan information webpage and the websites of all federal student loan servicers prominently displayed notices with information about the payment pause (see Appendix Figure F.13).

Third, mistakes do not consistently shrink with economic stakes, as rational inattention theories would predict. Table 2, Panel A shows that if anything, borrowers with the highest debt-to-income ratios have a *higher* forbearance MPX on student loans.

Fourth, as shown in Appendix C.9, payment amounts became more variable and clustered at round numbers, evidence that borrowers made active post-forbearance repayment choices.

Fifth, the borrower characteristics that predict prepayment during forbearance are inconsistent with borrower inattention. In Appendix Section C.4, I regress an indicator for federal student loan prepayment during forbearance on demographics, student loan characteristics, and borrower financial attitudes using the 2022 SCF. Appendix Table C.2, column 4 shows that prepayers have higher income and are more likely to be on income-driven repayment plans, meaning they likely closely monitor changing repayment requirements. By contrast, borrowers using autopay are not more likely to continue making payments. Additionally, prepayment is more likely for borrowers who report higher willingness to take risk, cutting against prepayment as risk averse behavior in face of policy uncertainty.

Sixth, borrowers who continue student loan payments are not "habit" consumers, and instead rapidly adjust behavior in response to government policy. Table G.14 shows estimates of the four-week consumption expenditure MPX out of stimulus checks for potential "passive" borrowers who made student loan payments after forbearance began but before stimulus checks arrived (and potentially changed borrower behavior). These borrowers have a total spending MPX of 16%, and a broad nondurable MPX of 7.9%.

There are other reasons to prepay student debt during forbearance. Borrowers may have wanted to lower debt-to-income ratios before applying for a mortgage, recognized that student loans are not dischargeable in bankruptcy, or found student loan debt aversive. However, such arguments predict similar student loan repayment out of stimulus checks, which the data reject.

4.2 Expenditure responses

This section shows that the flypaper effect documented in Section 4.1 reduces consumption expenditure out of forbearance liquidity relative to stimulus checks.

4.2.1 Empirical strategy and implementation details

Claim 2 predicts that forbearance impacts consumption and debt repayment for two reasons. First, borrower cash on hand increases because it is optimal to stop student loan payments.

Second, consumption or non-student loan debt repayment increases due to higher cash on hand. On a per-dollar basis, the stimulus check response should approximate this second effect.

Because borrowers overpay their student loans, cash on hand increases by less than the amount of forbearance liquidity received. Additionally, behavioral responses to forbearance appear inconsistent with responses to stimulus checks. Hence, an extra dollar in cash-on-hand from forbearance and stimulus checks may have different consumption impacts.

I use a difference-in-differences design to estimate consumption responses to forbearance and use problem (1)'s structure to interpret results. Implied expenditure out of forbearance cash on hand is much lower than expenditure out of stimulus checks. However, even if the implied expenditure rate were identical, the MPX out of *total* liquidity would be much lower for forbearance than stimulus checks.

Difference-in-difference design. Recently paid-off borrowers. I would ideally compare the change in spending for *ex-ante* identical borrowers receiving different amounts of liquidity from forbearance. To approximate this, I use the fact that otherwise similar borrowers may have slightly different repayment dates on their federal student loans. Since federal loans have a common loan term by default, two borrowers experiencing common income and other economic shocks may finish repaying their loans at different times.

Consider two groups of federal borrowers with similar pre-forbearance repayment trajectories, where one group pays off their loans slightly before the government announced forbearance. The group who recently repaid their loans receives no liquidity from forbearance. I use these borrowers as a control group to trace out counterfactual spending patterns for the "continuous payment" group with outstanding balances, who *do* receive liquidity from forbearance.

Appendix Figure F.14 visualizes the treatment variation. I plot monthly federal student loan payments for borrowers who recently paid off their loans and borrowers with debt outstanding when forbearance began. I group borrowers by pre-forbearance (or pre-repayment, for the paid-off sample) loan payment quartile (deciles in estimation). Intuitively, I first compare the change in spending between borrowers in the recently paid-off group to borrowers who still have debt, before and after forbearance, holding fixed pre-forbearance payment levels. I then correlate the difference in pre-versus-post forbearance spending between the two groups with differences in forbearance liquidity each group obtains.

I translate this intuition into the following regression, where t indexes month:

$$c_{it} = \gamma_i + \delta_{yt} + \omega_{p_s,t} + \sum_{k=-7}^{8} \sigma_k \mathbb{1}(t = k)_i \cdot \Delta p_{is} + \varepsilon_{it} \tag{8}$$

where c_{it} is an expenditure variable, γ_i are borrower fixed effects, δ_{yt} are time-by-permanent

income decile fixed effects, $\omega_{p_s,t}$ are time-by-pre-forbearance payment decile fixed effects, and Δp_{is} is liquidity received from forbearance, given by pre-forbearance payments. The coefficients of interest are σ_k, which estimate how liquidity from forbearance in the treatment group impacted spending relative to the control group. The identifying assumption is that absent forbearance, spending would have evolved in parallel for borrowers still in repayment and recently paid-off borrowers with similar initial debt and income levels.

Under the parallel trends assumption, the coefficients σ_k are the causal impact of an extra dollar of monthly forbearance liquidity on spending in the k^{th} month after forbearance starts. I report two ways of transforming this into an MPX out of forbearance liquidity. First, I report $\hat{\sigma}_0$. This is the first-month MPX assuming that borrowers adjust their expenditure starting from program announcement, but only take into account the additional liquidity they will receive over the first month. The second approach recognizes that households with liquidity constraints may only adjust expenditures when liquidity actually *arrives*. Forbearance liquidity arrives on typical payment due dates. These are distributed throughout the month, motivating an estimate that averages over the program's first two months: $0.5 \times (\hat{\sigma}_0 + \hat{\sigma}_1)$.[29]

Since I do not observe loan balances, I must impute when a borrower has repaid her loans, and screen out possible refinancing activity. I describe the full procedure in Appendix C.10. To summarize, I start with a sample of borrowers who stop making payments in 2019Q2-Q3. I check a number of conditions to verify that borrowers stopped making payments because they finished paying off their loans, rather than other reasons, and apply symmetric conditions to the treatment group of borrowers who *continue* making loan payments.

Robustness. Heterogeneous federal-private debt mix. Appendix C.11 presents quantitatively similar results from an alternative design that compares borrowers with a different mix of federal and private loans. This approach compares borrowers with only federal debt and borrowers with a similar amount of *total* debt, split between federal and private loans.

Interpreting estimates. The difference-in-differences designs estimate $MPX_c^f := E\left[\frac{\Delta c_i^f}{\Delta p_{is}}\right]$. Applying a first-order approximation to the consumption policy function from Section 2, and assuming the upper bound in equation (4) binds at zero, the change in consumption is $\Delta c_i^f \approx \frac{\partial c_i(\cdot)}{\partial X} \Delta p_{is}^o$. In this expression, Δp_{is}^o is the observed decrease in student loan payments, $\Delta p_{is}^o :=$

[29] This assumes a uniform distribution of payment dates, which the data approximately support. Both measures may overstate the forbearance MPX. The first ignores that forward-looking, unconstrained borrowers may adjust their expenditure not just in response to the anticipated extra liquidity over the first month, but also future months. The second measure faces a similar issue, since the event time coefficients σ_1 mix the one-month MPX for borrowers with due dates late in the month with the second-month MPX out of the event month 0 transfers and the one-month MPX out of the event month 1 transfers. Therefore, the natural experiment estimates likely *overestimate* the MPX out of forbearance, making comparisons with the semi-structural MPX directionally robust.

$p^o_{is}(\cdot;\theta) - p^o_{is}(\cdot;\theta')$. This implies that $MPX^f_c \approx E\left[\frac{\partial c_i(\cdot)}{\partial X} \cdot \left(1 - MPX^f_{p_s,i}\right)\right]$.

I use this decomposition in two ways. First, I estimate implied expenditure out of forbearance cash-on-hand as $\widehat{MPX}^f_c / \left(1 - \widehat{MPX}^f_{p_s}\right)$, with $\widehat{MPX}^f_{p_s}$ estimated as in Section 4.1.1. A lower value than the MPX out of stimulus checks indicates that borrowers spend less out of cash-on-hand originally earmarked for debt repayment, and implies $\frac{\partial c_i}{\partial X}$ differs for forbearance and stimulus checks due to different sources of ∂X.

Second, I estimate the counterfactual "semi-structural" MPX out of *total* forbearance liquidity if $\frac{\partial c_i}{\partial X}$ were the same for forbearance and stimulus checks: $\widehat{MPX}^{f,semi}_c = N^{-1}\sum_i \widehat{\frac{\partial c_i}{\partial X}} \cdot \left(1 - \widehat{MPX}^f_{p_s,i}\right)$. This indicates how much of the difference between MPX^f_c and the MPX out of stimulus checks reflects student loan prepayment versus differences in expenditure out of cash-on-hand, conditional on prepayment.[30]

To estimate the "semi-structural" MPX, I parameterize $\frac{\partial c_i}{\partial X} = \mu_{MPX} + \phi_{MPX} \cdot MPX^f_{p_s,i}$ and estimate μ_{MPX}, ϕ_{MPX}, and $MPX^f_{p_s,i}$ as in specification (7). Appendix C.12 shows results are unchanged if I: (i) parameterize $\frac{\partial c_i}{\partial X}$ non-linearly to allow more flexible correlations with $MPX^f_{p_s,i}$; and (ii) estimate μ, ϕ with the imputation estimator in Borusyak, Jaravel, and Spiess (2024).

4.2.2 Results

I first evaluate the identifying assumption for the difference-in-differences design: parallel trends between treatment and control groups after forbearance begins. If parallel trends hold prior to forbearance, they more plausibly hold afterwards. Figure 3 plots $\hat{\sigma}_k$ from specification (8).[31] The figure shows no pre-trends. I therefore interpret $\hat{\sigma}_k$ as the causal impact of an extra dollar of monthly forbearance liquidity on spending in the k^{th} month after forbearance starts.

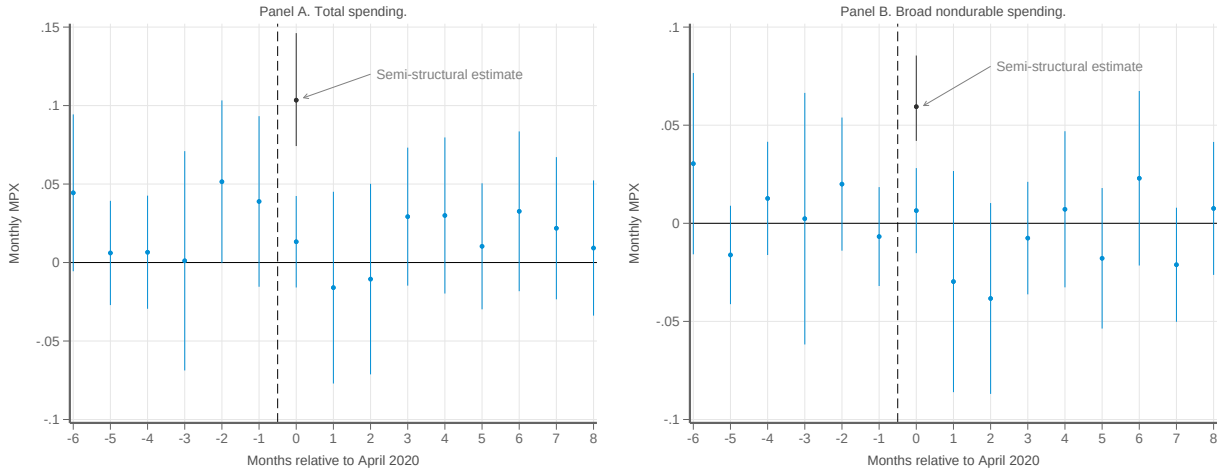
Table 3 presents estimates. Panel A focuses on the sample used in the paid-off borrowers difference-in-differences design, and reports results for total and broad nondurable spending. Borrowers spend about 17.1% of their stimulus checks in the first four weeks, with 9.3% spent on nondurables. The MPX out of forbearance liquidity is much lower. Point estimates range from -1.1% to 1.3%, and are insignificant at the 5% level. 95% confidence intervals rule out a forbearance MPX exceeding 4.24% for total spending (one-fourth of the MPX out of stimulus checks) and 2.8% for nondurable spending (30% of the MPX out of stimulus checks).

These results reject Claim 2. Claim 2, combined with estimates from the literature, predicts that the *annual* stimulus check MPC should exceed the forbearance MPC by less than 3pp. However, the smallest stimulus check MPX that I cannot reject is 9.7pp larger than the largest

[30] Appendix C.10 describes the exact treatment effect the recently paid-off borrower identification strategy delivers and how I apply the semi-structural approach to estimate a comparable average.

[31] Omitting one coefficient is required to avoid multicollinearity. To see this, divide specifications (8) by Δp_{is}. It is then clear that estimation is not possible with the full set of event time effects σ_k.

Figure 3: Effect of forbearance on monthly spending – recently paid off borrowers



Source: Transactions panel. The figure plots event time coefficients $\hat{\sigma}_k$ estimated from specification (8), where the outcome variable is either total (Panel A) or nondurable (Panel B) spending. Spikes plot robust 95% confidence intervals clustered at the borrower level.

Table 3: Four-week spending MPX, stimulus checks vs. forbearance

	A. Paid off borrowers		B. Full sample	
Spending	Total	Broad nondurable	Total	Broad nondurable
Liquidity source and measurement				
Stimulus checks	0.171***	0.093***	0.174***	0.09***
	(0.016)	(0.01)	(0.01)	(0.006)
Forbearance: Paid off borrowers (Month 1)	0.013	0.006		
	(0.015)	(0.011)		
Implied expenditure out of forbearance cash-on-hand	0.022	0.011		
	[-0.017,0.052]	[-0.002,0.039]		
Forbearance: Paid off borrowers (Month 2)	-0.001	-0.012		
	(0.018)	(0.017)		
Implied expenditure out of forbearance cash-on-hand	-0.002	-0.02		
	[-0.034,0.053]	[-0.058,0.024]		
Forbearance: Semi-structural	0.119**	0.099***	0.103***	0.059***
	[0.061,0.179]	[0.071,0.13]	[0.074,0.146]	[0.042,0.086]
N	130,144	130,144	313,312	313,312

Source: Transactions panel. * p=0.05, ** p=0.01, *** p=0.001. Each entry reports a four-week MPX out of stimulus checks or forbearance, with robust standard errors clustered at the borrower level in parentheses below. Columns indicate the estimation sample, and rows indicate both the liquidity source (stimulus checks or forbearance) and estimation strategy. The outcome is either total (Panel A) or broad non-durable (Panel B) spending. Semi-structural standard errors and hypothesis tests are computed via bootstrap; I report the standard deviation of the estimate from 150 bootstraps, and calculate p-values by inverting the largest $1-\alpha/2$-level confidence interval that does not contain zero.

total spending forbearance MPX that I cannot reject.

Why is the MPX out of forbearance liquidity so low relative to stimulus checks? Expenditure out of forbearance cash-on-hand is very low: 95% confidence intervals rule out effects greater than 5.3% (total) and 3.9% (nondurables). However, semi-structural estimates show that significant loan prepayment out of forbearance liquidity also matters. Indeed, Panel B reports

that even if the full sample expenditure out of forbearance cash-on-hand equaled the stimulus check MPX, the forbearance MPX would be 35-40% lower than that of stimulus checks.

4.3 Survey results: Motivations for student loan payment in forbearance

The transaction data results show that borrowers do not treat financial resources as fungible when repaying debt. Non-fungibility appears to result from a flypaper effect, where liquidity "sticks" to the student loan repayment context in which it is provided. Forbearance liquidity also retains a "shadow of savings," evidenced by low implied expenditure out of forbearance cash-on-hand that does not "stick" to student loan repayments.

Appendix D.4 replicates these results in the survey. For example, 37% of borrowers prepaid between the start of forbearance and the survey date.[32]

The survey asks questions to identify features of a model to describe this behavior. I present three findings. First, low program knowledge does not explain most prepayment during forbearance. Second, limited financial sophistication alone cannot explain forbearance prepayment or the inconsistent use of forbearance and stimulus check liquidity. Third, no single dominant factor explains cost minimization failures and the flypaper effect. However, borrowers appear to have: (i) a student loan payment target that may depart from the cost-minimizing allocation; and (ii) real or perceived costs to adjusting payments relative to the target.

Policy knowledge. Most student borrowers are familiar with program terms. In Table 4a, about 80% of respondents report familiarity with the program, and only about 10-15% answer questions about key program terms incorrectly. Borrowers making payments during forbearance do know somewhat less, but even in this group, over 80% correctly answered questions about key program terms. Only 18.4% of prepayers said they continued payments because they did not know about the payment pause or thought they were ineligible (Table 4b), and only 7-10% of respondents cite program unawareness when explaining debt repayment mistakes or inconsistent use of forbearance and stimulus check liquidity (Tables 4c and 4d).

Financial sophistication. Borrowers may continue student loan payments if they did not understand incentives created by a 0% interest rate. In piloting, borrowers frequently wrote in free-response sections that repayment was a good financial move given the 0% interest rate on student debt. Does this financial mistake explain prepayment in forbearance?

Many borrowers making payments in forbearance do not prioritize debt payments to minimize interest costs. In a credit card repayment hypothetical, Table 4a indicates that 51%

[32]To make the survey and transactions sample comparable, I exclude borrowers who were in school, grace, deferment, or forbearance in February 2020 who would not have made payments before forbearance.

of prepayers partly repay the low-interest card. When directly asked, 41% of prepayers said repaying early was financially smart due to the 0% interest rate (Table 4b).

However, misunderstanding cost-minimizing responses to interest rates cannot jointly explain forbearance prepayment and inconsistent use of forbearance and stimulus liquidity. Table 4a shows that non-prepayers had the same error rate on the financial sophistication screen. Furthermore, 0% rates do not seem to induce prepayment out of other windfalls. Appendix Table D.10 reports that 78% of borrowers who justify prepaying because of the 0% interest do *not* use their stimulus checks to repay their federal loan.

Flypaper effect Survey answers indicate that borrowers have debt repayment targets that deviate from cost-minimizing payment levels, and perceive deviating from targets as costly.

Debt repayment targets. Debt repayment targets could arise from multiple sources. First, many borrowers cite debt repayment heuristics when explaining their debt repayment mistakes. In Table 4b, 54% of prepayers explain they "always try to repay debt as quickly as possible." In Table 4c, a plurality of prepayers with interest-bearing debt continued payments "to make progress on all debts to keep things balanced" or because progress on repaying student debt is an "important financial goal." In Table 4d, a 35% plurality of prepayers did not use stimulus checks to pay off student debt to spread their windfall across different uses.

Second, debt repayment targets may keep student loan payments aligned with a pre-specified ad-hoc budget (as in Antonides, De Groot, and Van Raaij (2011) and Hastings and Shapiro (2013)). Across the repayment mistakes and inconsistencies in Table 4, 20-30% of respondents explain their behavior by saying they did not want to deviate from their budget.

Third, borrowers might not select cost-minimizing repayment targets because they myopically ignore interdependencies across debt repayment choices. In Table 4c, 11-13% of prepayers with costly debt say they think about repaying debts independently. In Table 4d, 15% think about debt repayment separately from other financial choices, and 18% do not see the connection between use of stimulus checks and forbearance liquidity at all.

Fourth, borrowers might set targets based on expected optimal behavior if they perceive costs to cost-minimizing each period, discussed next.

Perceived deviation costs. Several costs of deviating from targets appear to constrain behavior. Given that limited financial sophistication appears widespread, borrowers may bear substantial information processing or time costs to cost minimize. Moreover, for consumers using ad-hoc financial budgeting rules, it likely takes time and effort to redo budgets if payments change. In Table 4b, 14.4% of prepayers say they kept paying because "it was too much hassle to stop payments, keep track of when repayments resume, and restart them."

Appendix D.5 considers costs due to "soft commitments" by sophisticated time-inconsistent

	No	Yes	Diff	p-value	Total
Familiar with program	.851	.718	.133	.000453	.802
Incorrect: SL pause in effect April 2020	.098	.184	-.0859	.00736	.13
Incorrect: SL pause in effect now	.0507	.178	-.127	5.94e-06	.0979
Incorrect: Interest rate 0%	.0439	.149	-.106	.0000563	.083
Incorrect: Balloon pmts required	.0541	.23	-.176	8.04e-09	.119
Incorrect: Negative credit score effects	.139	.201	-.0626	.0752	.162
Incorrect: Demonstrated hardship required	.0743	.184	-.11	.000303	.115
Sophistication: CC paydown mistake	.493	.511	-.0183	.703	.5
Sophistication: % devoted to low-interest card	24	28.1	-4.09	.163	25.5
Count	296	174	.	.	470

(a) Program knowledge and financial sophistication by loan payment in forbearance.

	Mean
I didn't know about / think I was eligible for the payment pause.	.184
I always try to repay debt as quickly as possible.	.54
Repaying early was financially smart b/c interest was 0%.	.414
I budgeted for student loan payments and didn't want to make adjustments.	.213
It was too much hassle to stop / restart payments.	.144
I did not trust myself to put enough money aside for when payments resumed.	.115
It wasn't worth paying attention to changing student debt policies.	.0862
None of these apply.	.0517
Count	174

(b) Justifications for loan payments in forbearance.

	Stimulus check action | debt	
	Don't pay with stim check	Pay with stim check
I try to make some progress on all debts to keep things balanced.	.483	.605
I always make payments b/c paying off student debt an important financial goal.	.402	.
Repaying student debt was financially smart due to the 0% interest rate.	.299	.263
I budgeted for student debt payments and didn't want to make adjustments.	.23	.342
Didn't occur to me to adjust b/c I think about debt pmts separately.	.115	.132
None of these apply.	.0805	.105
I didn't know about / didn't think I was eligible for the payment pause.	.069	.105
Count	87	38

(c) Justifications for non-optimal debt prioritization.

	Mean
Needed stim. check for other things / already made some student loan payments.	.349
Needed stim. check for other things / didn't want to adjust budget.	.317
These decisions don't seem connected.	.183
Needed stim. check for other things / didn't occur to me.	.151
Think about SL pmts separately / didn't occur to me.	.151
I didn't know about / didn't think I was eligible for the payment pause.	.103
None of these apply.	.0714
Count	126

(d) Justifications for inconsistent use of stimulus.

Table 4: Survey responses

Source: Student borrower survey. Panel 4a: The "No" and "Yes" columns give means for borrowers who do and do not stop making payments after forbearance begins, "Difference" gives the difference, "p-value" reports the p-value of a t-test of equivalent means, and the "Total" column gives pooled full sample means. Participants are coded as familiar with program if they say they are moderately, very, or extremely familiar. Participants answer program knowledge questions incorrectly if they answer "probably no (yes)" or "definitely no (yes)" to questions with answer yes (no). Participants make a CC paydown mistake if they put anything towards the low APR card in the debt repayment hypothetical. Panel 4b gives answers to: "Why did you continue to make payments on your federal student loans after March 2020?" Panel 4c: The table conditions on borrowers with: (i) federal debt in March 2020; (ii) interest-bearing non-federal debt in March 2020; (iii) made payments on federal student debt after March 2020; (iv) did not prioritize repaying non-federal student debt; and (v) were not still in school, a grace period, deferment or forbearance as of February 2020. The first column restricts to those not using their stimulus checks to repay any of their non-federal student debt, while the second column restricts to those using their stimulus checks to repay non-federal student debt. Entries list the fraction of respondents selecting each justification when asked why they continued to make payments on their federal student debt, despite having interest-bearing debt (in column 1) or despite not using stimulus checks to repay student debt (in column 2). Panel 4d: The table requires (i), (iii), (v), and (vi) borrowers do not use their stimulus checks to repay their federal student loans. Entries report the fraction selecting each justification when explaining why they kept making federal student loan payments in forbearance despite not using their stimulus checks to do so.

borrowers or limited attention, but finds these alternatives appear less relevant.

Framing experiment Borrowers who fail to cost-minimize and use forbearance liquidity and stimulus checks inconsistently could fall into two groups. First, borrowers lacking financial sophistication might use ad-hoc budgets or heuristics to guide payments. Second, borrowers might *know* how to minimize costs, but find doing so costly and so set forward-looking targets. The framing experiment helps separate these groups. Framing confers no economic information and so should not impact the second group's target. However, framing a cash transfer as helping student borrowers may impact the first group's targets by changing how a transfer is *perceived*, by, for example, expanding their student loan payment budget or increasing the amount they feel they should pay to keep up with their obligations.

Experimental results in Appendix Table G.16 support these predictions. Column 3 shows that among those who make a mistake in the debt prioritization hypothetical, framing a $300 windfall as directed to households with student debt increases student debt repayment by 5pp of the windfall on a base of 11%, or 45%. Framing effects are statistically zero and 5.5pp lower among more financially sophisticated borrowers (SE of difference = 2.99%, p-value 0.066).

5 Modeling the liquidity flypaper effect

This section presents a consumption-saving model where consumers have goals over total savings and debt repayment flows to represent the flypaper effect identified in the transactions data and survey responses. The model aims to flexibly capture the many heuristics and intuitions expressed in the survey, while remaining parsimonious enough to yield a sufficient statistics representation for policy evaluation.

Setup and solution The setup and notation are as in Section 2. Flow utility now includes additively-separable costs for adjusting control variables relative to a goal g_j. I denote these "target deviation costs" with $\gamma_j(p_j, g_{jt})$ and $\gamma_x(x, g_{xt})$ for account j and total saving, which increase in $\left|p_j - g_{jt}\right|$ and $|x - g_{xt}|$, respectively. Goals may vary over time due to, for example, a time-varying upper-level optimization. Define $\boldsymbol{\Gamma}(x, \{p_j\}_j, g_x, \{g_j\}_j) := (\gamma_x(x, g_x), \{\gamma_j(p_j, g_j)\}_j)'$.

Each period, the consumer solves, subject to constraints and state transitions as in (1):

$$\max_{x, p_{j_j}} \underbrace{U(X_t - x) + \delta E V_{t+1}\left[X_{t+1}, \left\{B_{j,t+1}\right\}_j\right]}_{\text{standard, } := v_t\left(x, \{p_j\}_j; \cdot\right)} - \underbrace{\mathbf{1}'\boldsymbol{\Gamma}\left(x, \{p_j\}_j, g_{xt}, \{g_{jt}\}_j\right)}_{\text{sum of target deviation costs}} \text{ s.t. (2)} \tag{9}$$

where $\mathbf{1}$ is a vector of ones. The continuation value function $V_{t+1}(\cdot)$ is the perceived value of

entering period $t+1$ with liquid balances X_{t+1} and debt $\{B_{j,t+1}\}_j$.[33]

Inter-temporally, total saving target deviation costs make consumption more sensitive to income by tying x_t to g_t. Intra-temporally, debt repayment target deviation costs push p_j towards g_j and away from cost-minimizing by repaying high-interest debt first. Moreover, transferring resources away from a debt repayment goal and towards consumption is especially costly, since it requires bearing both debt repayment and total saving target deviation costs.

I parameterize γ with fixed target deviation costs invariant to the size of the deviation, with $\gamma_j(p_j, g_{jt}) := b_j \cdot \mathbb{1}\{p_j \neq g_{jt}\}$ and $\gamma_x(x, g_{xt}) := b_x \cdot \mathbb{1}\{x \neq g_{xt}\}$. Two facts motivate this parameterization. First, costs in the survey, such as hassle costs to adjustment, are mostly fixed. Second, Appendix Figure F.10 shows a large drop in the fraction of borrowers making *any* payments in forbearance, suggesting that if borrowers stop payments, they stop them entirely.

To solve problem (9), consumers choose which of $(x_t, \{p_j\}_j)$ to set equal to their goals, and choose the rest using FOCs that maximize $v_t(x, \{p_j\}_j; \cdot)$. Consumers select the set to fix to goals to maximize $v_t(x, \{p_j\}_j; \cdot) - \mathbb{1}'\Gamma(x, \{p_j\}_j)$. Appendix A.2 describes this procedure formally.

The solution reduces dimensionality and may significantly simplify a consumer's problem. Part (1) of Claim 3 in Appendix A.2 shows that consumers solving this problem use an intuitive cutoff rule, fixing $p_j = g_j$ if b_{ij} is sufficiently high, and choosing it using the FOC otherwise. Furthermore, consumers often only have a few options to compare – only four in a context with a checking account and student debt.

Problem (9) shares similarities with the category budgeting model in Hastings and Shapiro (2013), where consumers incur a quadratic flow utility cost for gasoline expenditures that deviate from mean transaction amounts. I extend this model to include goals over multiple controls in a dynamic context. Additionally, parameterizing γ as a fixed cost better matches my debt repayment context, as a model with quadratic adjustment costs would counterfactually predict small nonzero student loan payments for borrowers during forbearance.

Predictions Claim 3 describes the debt repayment strategy and Claim 4 compares consumption responses to forbearance versus stimulus checks for a consumer solving problem (9) with fixed target deviation costs. I state and interpret the claims formally in Appendix A.2.

The claims make several predictions that align with findings from the transaction data. First, some consumers with $g_s > 0$ will continue making payments in forbearance, even if they have other interest-bearing debt, to avoid bearing target deviation costs. Borrowers adjusting payments may stop them entirely (subject to some conditions on V described in Claim 3).[34]

[33] Defining the continuation value recursively, as in (1), would (i) preclude forces such as time inconsistency; and (ii) require a stance on how g_{jt} is expected to evolve. See the discussion following Claim 3 in Appendix A.2.

[34] The conditions hold when V is defined recursively through a Bellman equation, but fail when consumers have unconventional beliefs about incentives created by interest rate differentials. For example, pop finance guru

Second, if a consumer continues to pay their student loans during forbearance, they are unlikely to increase their student loan payments when they get a stimulus check. Continued payments during forbearance indicate the consumer finds deviating from their target costly. Such a consumer is *also* less likely to deviate from target by *overpaying* relative to their goal.

Third, borrowers will save more out of liquidity from forbearance than stimulus checks. Some borrowers who stop paying student debt after forbearance will continue meeting total saving goals, leaving consumption unchanged. This matches the Section 4.2.2 finding that the implied expenditure out of forbearance cash-on-hand is lower than the stimulus check MPX.

Finally, some consumers will have a high MPX out of windfalls, even absent liquidity constraints. Consumers who stick to total saving targets will have an MPC of one. This explains the high MPX out of stimulus checks for borrowers who overpay student loans in forbearance (indicating no liquidity constraints). This also provides a new explanation for high MPCs out of windfalls for unconstrained households (Kueng 2018, Kaplan and Violante 2022).

Sufficient statistics The response to student loan forbearance highlights two empirical objects that quantify the relevance of target deviation costs. Consider the setup in Claim 4, where a consumer has only student debt and a checking account, with target deviation costs $\boldsymbol{b}_i \in \{0, b_s\} \times \{0, b_x\}$ where $b_{is} > 0 \implies p_{is} = g_s$ and $b_{ix} > 0 \implies x_i = g_x$.

The post-forbearance change in student loan payments relative to pre-forbearance levels quantifies the prevalence of high student loan payment target deviation costs. Student loan payments drop by p_{st}, the optimal payment absent forbearance, if $b_{is} = 0$. Payments are unchanged if $b_{is} > 0$. The MPX on student loans out of forbearance liquidity, $MPX^f_{p_s,i} := p^o_{is}/\Delta p_{is}$, summarizes this information.

Moreover, the gap between the consumption response to stimulus checks and forbearance, conditional on endogenous changes in student loan payments Δp_{is}, quantifies the prevalence of total saving target deviation costs. If $b_{ix} = 0$, then $\Delta c_i \approx \frac{\partial c_i}{\partial X} \Delta p^o_{is}$, where $\frac{\partial c_i}{\partial X}$ equals (to a first order) the stimulus check MPC, and Δp^o_{is} is the endogenous (i.e. observed) first-period change in payments. If $b_{ix} > 0$, then $\Delta c_i = 0$. To summarize this gap, define an indicator χ_i that equals one when a consumer chooses x_t according to the FOC, not their saving goal. The average total spending MPX out of student loan forbearance is therefore, to a first order:

$$\underbrace{E\left[\frac{\Delta c^f_{it}}{\Delta p_{ist}}\right]}_{\text{empirical average forbearance MPX}} \approx \tilde{\gamma} \cdot \underbrace{E\left[\left(1 - MPX^f_{p_s,i}\right) \cdot \left(\frac{\Delta c^w_{it}}{\Delta X}\right)\right]}_{\text{semi-structural MPX, } \widehat{MPX}^{f,semi}_c} - E\left[\mathbb{1}\{b_{is} = 0\}\varepsilon_{it}\right] \tag{10}$$

Dave Ramsey's recommendation that borrowers use the "snowball method" of prioritizing small balances first, regardless of the interest rate, implies V that breaks the condition.

where $\tilde{\gamma} := (E[\chi_i] + \text{Cov}(\chi_i, \xi_i)/E[\xi_i])$ for $\xi_i := \left(1 - MPX^f_{p_s,i}\right) \cdot \left(\frac{\Delta c^w_{it}}{\Delta X}\right)$. The left-hand side equals the total consumption MPX out of forbearance liquidity. Claim 4 shows that $\varepsilon_{it} \leq \left|\frac{\partial c_{it}}{\partial B_{st}} R_{st}\right|$ (as in Claim 2). In Section 4.2.2, the semi-structural MPX exceeds natural experiment estimates by too much for $E[\mathbb{1}\{b_{is} = 0\}\varepsilon_{it}]$ to explain. Therefore, $\tilde{\gamma} < 1 \implies \Pr(\chi_i = 0) > 0$. This implies the presence of total saving target deviation costs.

6 Implications for counter-cyclical fiscal policy

In dynamic incomplete-markets saving-consumption models, consumers have a high MPX out of stimulus payments when they face near-binding liquidity constraints. Because forbearance also targets liquidity, such models predict it should generate a similar aggregate demand response at a potentially lower fiscal cost.

However, I find that student borrowers spend and save forbearance liquidity differently than stimulus checks. I present a partial-equilibrium framework to calibrate how this difference shapes student loan forbearance's spending effects and fiscal cost, both of which depend on the sufficient statistics described above and estimated in the transactions data.

To benchmark these effects, I consider an economic rescue package that includes both student loan forbearance and stimulus checks. This is not to imply the two are substitutes – they may have different goals and impact different populations – nor to treat the CARES Act student loan payment pause as representative of forbearance generally, which, as detailed below, can have different effects depending on whom it targets. Instead, the goal is to contextualize the flypaper effect's impact on student loan forbearance, using stimulus checks as a point of reference as another way to stimulate aggregate demand by increasing liquidity.

Setup The economy has a unit mass of heterogeneous consumers with one-month MPCs out of unanticipated cash-on-hand of $L_i \in [0, 1]$. This behavior approximates various microfoundations. Borrowers with $L_i \approx 1$ could represent consumers with near-binding liquidity constraints, as in Zeldes (1989), low discount factors, as in Campbell and Mankiw (1991), or illiquid savings and adjustment costs, as in Kaplan and Violante (2014). Borrowers with $L_i \approx 0$ could represent infinitely-lived, forward-looking Ricardian consumers who face no liquidity constraints and anticipate no present-value wealth transfer from stimulus checks.

Consumers make monthly student debt payments p_i. The gross risk-free rate is R, and the interest rate on student debt is $R + \Delta R$. Borrowers have T_s months before their student debt is repaid. I assume that ΔR reflects administration costs, so loans have no markups.

Consumers face an uninsurable negative income shock. The government wants to raise aggregate consumption within a student borrower population by a target amount using student

loan forbearance and stimulus checks.

Forbearance and stimulus checks I adopt the institutional details of the CARES Act student loan payment pause. Forbearance pauses required student loan payments and sets $\Delta R = 0$ for six months, with no balloon or catch-up payments. Borrower i receives p_i in liquidity in the first month of forbearance. Forbearance causes student loan payments to decrease by $(1-\eta_i)\cdot p_i$, where η_i is the MPX on student loans out of forbearance liquidity. Consumption increases by $\chi_i \cdot (1-\eta_i)\cdot p_i \cdot L_i$, where $\chi_i \leq 1$ is the wedge between the MPC out of forbearance cash-on-hand and cash windfalls.

The fiscal cost of forbearance is the present value cost of advancing six consecutive one-month zero-spread loans of balance $(1-\eta_i)\cdot p_i$ for a term of T_s. The total cost is therefore $G_f := \tilde{R}(T_s)\Delta R E[(1-\eta_i)p_i]$, where $\tilde{R}(T_s)$ is a constant defined in Appendix E.1.

The government can also send out targeted stimulus checks with value W_i. Borrowers spend $W_i L_i$, and the present-value fiscal cost is G_w.

Define $\rho_i := \frac{p_i}{E[p_i]}$ and $w_i := \frac{W_i}{G_w}$, the fraction of each transfer allocated to borrower i. Appendix E.1 derives expressions for ΔC_f and ΔC_w, the aggregate consumption impacts of forbearance and stimulus checks over the first month, respectively.

Forbearance fiscal cost efficiency Forbearance has a fiscal cost advantage over stimulus checks if it increases one-month consumption by more per dollar of present-value fiscal cost. I define the forbearance fiscal cost efficiency $E_f := (\Delta C_f - \Delta C_w)/G_f$ as the increase in one-month aggregate consumption from the government using forbearance rather than spending an equivalent amount on stimulus checks. Appendix E.1 shows that:

$$\frac{E_f}{E[w_i L_i]} = \underbrace{\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)}_{\text{average cost}} \underbrace{\left(\frac{E[\rho_i L_i]}{E[w_i L_i]}\right)}_{\text{resource targeting}} \underbrace{\left(1 + \frac{\text{Cov}(\chi_i(1-\eta_i), \rho_i L_i)}{E[\chi_i(1-\eta_i)]E[\rho_i L_i]}\right)}_{\text{behavioral targeting}} \underbrace{\left(\frac{E[\chi_i(1-\eta_i)]}{E[\rho_i(1-\eta_i)]}\right)}_{\text{flypaper effect}} - 1 \quad (11)$$

When this expression is positive, the transfer increases consumption by more when delivered through forbearance rather than stimulus checks.

Three forces impact E_f. First, forbearance might have a lower cost due to an "average cost effect": forbearance can increase spending by L_i today at the cost of the present-value of forgone interest on a dollar in loan payments, which might be less than the dollar required to raise spending by L_i using stimulus checks. This effect depends on $\tilde{R}(T_s)\Delta R$, the present value of forgone interest on each dollar in missed payments. Second, forbearance could better target relief to a constrained population. This depends on whether borrowers with high loan payments have higher L_i than people receiving large stimulus checks, captured in the "resource targeting" term. Targeting also depends on "behavioral targeting", where liquidity delivered

to more constrained borrowers ($\rho_i L_i$) is more likely to be consumed ($\chi_i(1-\eta_i)$) rather than saved or used to prepay loans. The covariance between $\rho_i L_i$ and $\chi_i(1-\eta_i)$ reflects this force. Behavioral targeting could reduce government spending if borrowers with low MPCs continue paying their debts, as no resources are transferred to such borrowers.

Third, borrowers might use forbearance liquidity to prepay their student loans rather than consume, the "flypaper effect." If $\chi_i = 1$ and $\rho_i \perp \eta_i$, then the flypaper effect does not impact E_f because lower fiscal costs exactly offset lower consumption. Lower $E[\chi_i]$ will lower E_f, as some people who stop paying their loans do not use extra resources for consumption. A negative correlation between ρ_i and η_i will increase E_f, because people with high payments, for whom forbearance is expensive, reject forbearance by continuing payments.

Models such as problem (1) would have $\eta_i \approx 0$ and $\chi_i \approx 1$. Empirically, I find that $E[\eta_i] > 0$ and $\chi_i \neq 1$, possibly reflecting student debt repayment and total saving target deviation costs. What does this imply about economic rescue package design?

Quantifying E_f I assume $\chi_i(1-\eta_i) \perp L_i, \rho_i$ to write equation (11) in terms of observables:

$$E_f = \Bigg[\underbrace{\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)}_{\text{average cost effect}} \cdot \underbrace{\left(\frac{E[L_i] + \text{Cov}(\rho_i, L_i)}{E[L_i] + \text{Cov}(w_i, L_i)}\right)}_{:=\kappa\text{, resource targeting}} \cdot \underbrace{\left(\frac{\gamma}{1-\eta}\right)}_{\text{flypaper effect}} - 1 \Bigg] \cdot \underbrace{E[w_i L_i]}_{\text{stimulus check aggregate MPX}} \tag{12}$$

where $\eta := E[\eta_i]$ and $\gamma := \frac{MPX_c^f}{MPX_c^w} = \frac{E[\chi_i(1-\eta_i)L_i]}{E[L_i]}$. This ratio of the forbearance and stimulus check consumption MPX is observable, and through the lens of the Section 5 model, depends on the level of and correlation between total saving and student loan payment target deviation costs.

The assumption that $\rho_i \perp \eta_i$ is supported by the first column in Table 2, Panel A. However, the assumption that $\eta_i \perp \rho_i, L_i$ rules out behavioral targeting and "advantageous take-up." Appendix E.5 shows that relaxing this assumption and allowing for "advantageous take-up" does not impact results, indicating it is not quantitatively important in this context.

Table 5, Panel A presents parameter values to calibrate terms in equation (12). I choose low interest rates, spreads, and months remaining on loans to conservatively boost forbearance's efficiency relative to stimulus checks. I calibrate the transfer size using amounts in the transactions data. I take the stimulus check aggregate MPX as $E[w_i L_i] = 0.174$, because under minimal assumptions it equals the stimulus check total spending MPX.[35] Finally, I use estimates from Section 4 to calibrate sufficient statistics $\eta = 0.44$ and $\gamma = 0.25$.[36] Appendix E.2 describes

[35] The stimulus check design estimates the average MPX for those who receive stimulus (ATE on the treated). Assuming no correlation between check size conditional on receipt and MPC, the micro and aggregate MPX align.

[36] From Section 4.2.2, the full sample stimulus check consumption MPX is 17.4%. The upper-bound forbearance

the sensitivity of terms in (12) to parameter choice.

The "average cost" term depends on the student loan interest rate spread ΔR, the market rate R, and forbearance length T_s, which determines how long the government must wait before it is repaid for lost interest. The calibrated average cost term is $2.6 > 1$, so forbearance has a large cost advantage under equal resource targeting ($\kappa = 1$) and no flypaper effect ($\frac{\gamma}{1-\eta} = 1$).

The "resource targeting" term moderates the forbearance fiscal cost advantage, depending on whether forbearance better targets resources towards high MPC borrowers. Appendix E.4 uses variation from the stimulus check natural experiment to estimate $\hat{\kappa} = 0.92 < 1$.[37] Forbearance therefore did not target high MPX borrowers as well as stimulus checks did, perhaps because high human capital households with high student loan payments could better self-insure against shocks relative to lower-income households targeted with stimulus checks.

The first column in Table 5, Panel B shows that with no flypaper effect, E_f is 0.25, meaning per dollar of spending, forbearance delivers 25 cents more in aggregate spending. But given estimates of γ and η, the flypaper effect makes forbearance less cost efficient, and E_f falls to 0.01. The flypaper effect has a much greater effect on fiscal cost than, for example, resource targeting. I next use two calibration exercises to illustrate policy implications. Appendix E.1 provides derivations.

Calibration exercises. How does the flypaper effect impact the design of a package with student loan forbearance and stimulus checks similar to the CARES Act? I first quantify how much the government would have to increase stimulus checks to make up for lower spending from forbearance. Table 5, Panel B shows that with no flypaper effect, consumption increases by $291. However, accounting for the flypaper effect, increased consumption from forbearance is 75% lower. To keep the total consumption increase from the rescue package fixed, the government would have to increase stimulus checks by about 18%, increasing the total package cost by 12.3%.

The second exercise shows how the flypaper effect limits forbearance's generosity by requiring earlier catch-up payments for forbearance to retain its fiscal cost advantage. Earlier catch-up payments are equivalent to lowering T_s. Define the "break-even forbearance length" as the maximum term T^{BE} where $E_f \geq 0$ – the longest the government can allow borrowers to defer catch-up payments before forbearance loses its fiscal cost advantage. Table 5, Panel B shows that the flypaper effect significantly reduces T^{BE}, shrinking the set of forbearance poli-

consumption MPX from natural experiments is 4.3%.

[37] I cannot estimate $\rho_i L_i$ for borrowers who receive forbearance but not stimulus checks. I overcome this by parameterizing L_i as a function of observables and extrapolating. For robustness, I also estimate non-parametric bounds, which under minimal assumptions implies $\kappa \in [0.45, 1.63]$. Appendix Table E.12 shows alternative admissible κ do not qualitatively change results. See Appendix E.4 for details.

Table 5: Fiscal policy implications: Calibrated values and calibration results

Panel A. Calibrated parameters

Description	Variable	Value
Net riskfree rate (%)	$R-1$	2.2%
Student loan spread (%)	ΔR	1.9%
Months remaining (months)	T_s	42
Avg. stimulus check ($)	$E[W_i]$	1,350
Avg. student loan pmt ($)	$E[p_i]$	350
Stimulus check MPC	$E[w_i L_i]$	0.174
Forbear. student loan MPX	η	0.44
Forbear. vs. stim. check MPC	γ	0.25
Avg. cost effect	$(\tilde{R}(T_s)\Delta R)^{-1}$	2.63
Resource targeting effect	κ	0.92
Flypaper effect	$\frac{\gamma}{1-\eta}$	0.45

Panel B. Calibration results

Description	No flypaper ($\frac{\gamma}{1-\eta}=1$)	Flypaper ($\frac{\gamma}{1-\eta}=0.45$)	%Δ
Forbear. fiscal cost effcy. E_f	0.25	0.014	-94.4%
Calibration 1.			
1-month consumption increase ($)	290.9	290.9	
From forbearance ($)	56.0	14.0	-75.0%
From stimulus checks ($)	234.9	276.9	17.9%
Stimulus check size ($)	1350.0	1591.5	17.9%
Rescue package cost ($)	1483.1	1666.0	12.3%
Calibration 2.			
Break-even term (months)	109.3	45.5	-58.3%

cies that have a cost advantage over direct transfers. With $\gamma = 1, \eta = 0$, $T^{BE} = 109$ months, which falls 58% to 46 months with the estimated flypaper effect.

7 Conclusion

This paper uses the US government's large-scale student debt relief and cash transfers implemented in the CARES Act to study how households adjust debt repayment and consumption in response to liquidity from debt relief. I document a liquidity flypaper effect: borrowers use a large fraction of liquidity received from relief to prepay 0% interest federal student debt, even if they have high-interest credit card or private student debt. The same borrowers behave inconsistently when faced with other windfalls, with almost none of the funds from stimulus checks used to repay federal student debt. This flypaper effect, which rejects fungibility of liquidity from forbearance and cash transfers, predicts that borrowers would have a higher short-term consumption response to cash transfers relative to forbearance liquidity. Using quasi-experimental variation, I find support for that prediction.

Survey evidence implies that this flypaper effect occurs because borrowers (i) have limited financial sophistication and (ii) adhere to debt repayment targets resulting from budgeting and heuristics that do not minimize interest costs. I incorporate these results with an adjustment costs modification to a saving-consumption model.

My findings matter for designing economic rescue programs that aim to increase aggregate consumption. The liquidity flypaper effect implies that policymakers must rely more on stimulus checks to reach aggregate consumption targets; because stimulus checks typically have a higher fiscal cost than forbearance, this requires incurring a higher total fiscal cost. Governments also have less room to defer catch-up payments before forbearance becomes costlier than stimulus checks.

This paper gives evidence against models where consumers treat financial resources as fungible when making debt repayment decisions, and suggests non-fungibility as a potential driver of debt repayment mistakes. My results show that developing micro-founded theories of debt repayment is crucial to compare effects of different countercyclical fiscal policy tools.

References

Agarwal, Sumit et al. (2017). "Policy intervention in debt renegotiation: Evidence from the home affordable modification program". In: *Journal of Political Economy* 125.3, pp. 654–712. ISSN: 1537534X. DOI: 10.1086/691701.

Antonides, Gerrit, I Manon De Groot, and W Fred Van Raaij (2011). "Mental budgeting and the management of household finance". In: *Journal of Economic Psychology* 32.4, pp. 546–555.

Aydin, Deniz (2023). "Forbearance vs. Interest Rates: Experimental Tests of Liquidity and Strategic Default Triggers". In.

Baker, Scott R et al. (May 2020). *Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments*. Working Paper 27097. National Bureau of Economic Research. DOI: 10.3386/w27097. URL: http://www.nber.org/papers/w27097.

Borusyak, Kiril, Xavier Jaravel, and Jann Spiess (2024). "Revisiting event study designs: Robust and efficient estimation". In: *Review of Economic Studies*.

Campbell, John Y and Joao F Cocco (2007). "How do house prices affect consumption? Evidence from micro data". In: *Journal of Monetary Economics* 54.3, pp. 591–621.

Campbell, John Y and Mankiw (1991). "The response of consumption to income: a cross-country investigation". In: *European economic review* 35.4, pp. 723–756.

Carter, Matt (Dec. 2022). "Current private student loan interest rates". In: *Credible*. URL: www.credible.com/blog/student-loans/student-loan-interest-rates/.

Chava, Sudheer, Heather Tookes, and Yafei Zhang (2023). "Leaving Them Hanging: Student Loan Forbearance, Distressed Borrowers, and Their Lenders". In: *SSRN*.

Cherry, Susan F et al. (2021). *Government and private household debt relief during covid-19*. Tech. rep. National Bureau of Economic Research.

Chetty, Raj et al. (June 2020). *The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data*. Working Paper 27431. National Bureau of Economic Research. DOI: 10.3386/w27431. URL: http://www.nber.org/papers/w27431.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber (Aug. 2020). *How Did U.S. Consumers Use Their Stimulus Payments?* Working Paper 27693. National Bureau of Economic Research. DOI: 10.3386/w27693. URL: http://www.nber.org/papers/w27693.

Department of Education (2020). *Coronavirus and Forbearance Info for Students, Borrowers, and Parents*. https://studentaid.gov/announcements-events/coronavirus. Archived April 2, 2020 via the Internet Archive Wayback Machine. Available at https://web.archive.org/web/20200402222203/https://studentaid.gov/announcements-events/coronavirus. (Visited on 07/09/2026).

— (2026). *Federal Student Loan Portfolio*. https://studentaid.gov/data-center/student/portfolio. Accessed: 2026-07-09.

Department of Education, The (2023). *Federal Student Loan Portfolio*. URL: studentaid.gov/data-center/student/portfolio.

Di Maggio, Marco, Ankit Kalda, and Vincent Yao (May 2019). *Second Chance: Life without Student Debt*. NBER Working Paper 25810. DOI: 10.3386/w25810.

Di Maggio, Marco, Justin Katz, and Emily Williams (Sept. 2022). *Buy Now, Pay Later Credit: User Characteristics and Effects on Spending Patterns*. Working Paper 30508. National Bureau of Economic Research. DOI: 10.3386/w30508. URL: http://www.nber.org/papers/w30508.

Di Maggio, Marco, Amir Kermani, and Christopher J Palmer (2020). "How quantitative easing works: Evidence on the refinancing channel". In: *The Review of Economic Studies* 87.3, pp. 1498–1528.

Di Maggio, Marco et al. (2017). "Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging". In: *American Economic Review* 107.11, pp. 3350–3588. ISSN: 00028282. DOI: 10.1257/aer.20141313.

Dinerstein, Michael, Constantine Yannelis, and Ching-Tse Chen (2024). "Debt moratoria: Evidence from student loan forbearance". In: *American Economic Review: Insights* 6.2, pp. 196–213.

Eberly, Janice and Arvind Krishnamurthy (2014). "Efficient credit policies in a housing debt crisis". In: *Brookings Papers on Economic Activity* FALL 2014, pp. 73–118. ISSN: 15334465. DOI: 10.1353/eca.2014.0013.

Eyal, Peer et al. (2021). "Data quality of platforms and panels for online behavioral research". In: *Behavior Research Methods*, pp. 1–20.

Fed (2020). *Consumer Credit – G.19: Memo Items (Levels), Historical Data*. https://www.federalreserve.gov/releases/g19/hist/cc_hist_memo_levels.html. Accessed: 2026-07-09.

Federal Reserve Board, The (2023). *Consumer Credit - G.19*. URL: www.federalreserve.gov/releases/g19/current/.

Fuster, Andreas and Paul S Willen (2017). "Payment Size, Negative Equity, and Mortgage Default". In: 9.4, pp. 167–191.

Ganong, Peter and Pascal Noel (Oct. 2020). "Liquidity versus Wealth in Household Debt Obligations: Evidence from Housing Policy in the Great Recession". In: *American Economic Review* 110.10, pp. 3100–3138. DOI: 10.1257/aer.20181243.

Gathergood, John et al. (Mar. 2019). "How Do Individuals Repay Their Debt? The Balance-Matching Heuristic". In: *American Economic Review* 109.3, pp. 844–75. DOI: 10.1257/aer.20180288. URL: www.aeaweb.org/articles?id=10.1257/aer.20180288.

Goss, Jacob, Daniel Mangrum, and Joelle Scally (Jan. 2023). *Student loan repayment during the pandemic forbearance*. URL: libertystreeteconomics.newyorkfed.org/2022/03/student-loan-repayment-during-the-pandemic-forbearance/.

Hanson, Melanie (Jan. 2023). *Student loan debt statistics [2023]: Average + total debt*. URL: educationdata.org/student-loan-debt-statistics.

Hastings and Shapiro (June 2013). "Fungibility and Consumer Choice: Evidence from Commodity Price Shocks*". In: *The Quarterly Journal of Economics* 128.4, pp. 1449–1498. ISSN: 0033-5533. DOI: 10.1093/qje/qjt018.

— (Dec. 2018). "How Are SNAP Benefits Spent? Evidence from a Retail Panel". In: *American Economic Review* 108.12, pp. 3493–3540. DOI: 10.1257/aer.20170866.

Hegji, Alexandra (Aug. 2024). *Student Loans: A Timeline of Actions Taken in Light of the COVID-19 Pandemic*. CRS In Focus Report IF12136. Updated August 27, 2024. Congressional Research Service. URL: https://www.congress.gov/crs-product/IF12136.

Kaplan, Greg and Giovanni L Violante (2014). "A model of the consumption response to fiscal stimulus payments". In: *Econometrica* 82.4, pp. 1199–1239.

— (2022). "The marginal propensity to consume in heterogeneous agent models". In: *Annual Review of Economics* 14, pp. 747–775.

Kueng, Lorenz (2018). "Excess sensitivity of high-income consumers". In: *The Quarterly Journal of Economics* 133.4, pp. 1693–1751.

Lee, Sean Chanwook and Omeed Maghzian (2023). "Household Liquidity and Macroeconomic Stabilization: Evidence from Mortgage Forbearance". In.

McCann, Adam (Nov. 2022). "Historical credit card interest rates". In: *WalletHub*. URL: wallethub.com/edu/cc/historical-credit-card-interest-rates/25577.

MeasureOne (2019). *The MeasureOne Private Student Loan Report*. Q3 2019 Report. Archived via the Internet Archive Wayback Machine; accessed 2026-07-09. MeasureOne. URL: https://web.archive.org/web/20200608122828/https://cdn2.hubspot.net/hubfs/6171800/assets/downloads/MeasureOne%20Private%20Student%20Loan%20Report%20Q3%202019.pdf.

Milkman, Katherine L and John Beshears (2009). "Mental accounting and small windfalls: Evidence from an online grocer". In: *Journal of Economic Behavior & Organization* 71.2, pp. 384–394.

Noel, Pascal and Susan Wachter (2021). "Comments and Discussion on Government and Private Household Debt Relief during COVID-19". In: *Brookings Papers on Economic Activity*, pp. 200–222.

NY Fed, (Nov. 2021). *Quarterly Report on Household Debt and Credit*.

Ortalo-Magné, François and Sven Rady (Apr. 2006). "Housing Market Dynamics: On the Contribution of Income Shocks and Credit Constraints*". In: *The Review of Economic Studies* 73.2, pp. 459–485. ISSN: 0034-6527. DOI: 10.1111/j.1467-937X.2006.383_1.x.

Paiella, Monica and Luigi Pistaferri (Oct. 2017). "Decomposing the Wealth Effect on Consumption". In: *The Review of Economics and Statistics* 99.4, pp. 710–721. ISSN: 0034-6535.

Parker, Jonathan A. et al. (Oct. 2013). "Consumer Spending and the Economic Stimulus Payments of 2008". In: *American Economic Review* 103.6, pp. 2530–53.

Piskorski, Tomasz and Amit Seru (2018). "Mortgage market design: Lessons from the Great Recession". In: *Brookings Papers on Economic Activity* 2018.1, pp. 429–513.

Sylvain, Catherine and Yannelis Constantine (2020). "The Distributional Effects of Student Loan Forgiveness". In: *Becker Friedman Institute for Economics Working Paper* 2020-169.

Tracy, Joseph and Joshua Wright (2016). "Payment changes and default risk: The impact of refinancing on expected credit losses". In: *Journal of Urban Economics* 93, pp. 60–70. ISSN: 00941190. DOI: 10.1016/j.jue.2016.03.007.

U.S. Congress (Mar. 2020). *Coronavirus Aid, Relief, and Economic Security Act (CARES Act)*. Public Law 116-136, 134 Stat. 281. H.R. 748, 116th Congress, enacted March 27, 2020. URL: https://www.congress.gov/116/bills/hr748/BILLS-116hr748enr.xml.

Yannelis, Constantine and Greg Tracey (2022). "Student loans and borrower outcomes". In: *Annual Review of Financial Economics* 14, pp. 167–186.

Zeldes, Stephen P (1989). “Consumption and liquidity constraints: an empirical investigation”. In: *Journal of political economy* 97.2, pp. 305–346.

Online appendix to: "Saving and Consumption Responses to Student Loan Forbearance"

Justin Katz

June 2026

Table of Contents

A Proofs and derivations 1
A.1 Saving-consumption model in Section 2 . . . 1
A.2 Model with target deviation costs . . . 7

B Transactions data appendix 16
B.1 Identifying student loan borrowers . . . 16
B.2 Identifying private student loan servicers . . . 16
B.3 Identifying Sallie Mae payments . . . 17

C Additional empirical analysis 19
C.1 Accounting cost of student loan forbearance . . . 19
C.2 Additional public data sources . . . 19
C.3 Replication of main results using Survey of Consumer Finances . . . 24
C.4 Drivers of prepayment during forbearance in the Survey of Consumer Finances. . . . 26
C.5 Replication of voluntary prepayment in Department of Education data . . . 28
C.6 Robustness: MPX on federal student loans out of forbearance liquidity . . . 32
C.7 Robustness: Alternative estimates of MPX out of stimulus check liquidity 33
C.8 Additional analysis of borrowers with private student debt. . . . 34
C.9 Evidence against alternative explanations for prepayment during forbearance 35
C.10 Consumption impact of forbearance: Recently paid-off borrowers implementation details . . . 36
C.11 Consumption impact of forbearance robustness: Federal / private debt mix 38
C.12 Robustness: Alternative estimates for MPX out of forbearance liquidity . . . 42

D Survey appendix 44

D.1 Recruitment details . . . 44
D.2 Survey instrument details . . . 45
D.3 Pre-registration . . . 45
D.4 Summary statistics and replicating transaction data results . . . 45
D.5 Time-inconsistent preferences and limited attention as alternative explanations. . . . 47

E Fiscal policy calibration appendix 49
E.1 Calibration exercise derivations . . . 49
E.2 Sensitivity of E_f to calibrated values . . . 50
E.3 Additional details on computations for Calibration 1 . . . 52
E.4 Forbearance targeting estimates . . . 53
E.5 Forbearance targeting: Alternative correlation assumptions . . . 57

F Additional figures 61

G Additional tables 66

A Proofs and derivations

A.1 Saving-consumption model in Section 2

Conditions guaranteeing existence, uniqueness, and continuity of policy functions If $T = \infty$, then if problem (1) satisfies the conditions in Stokey and Lucas (1989) Theorem 9.8, the policy functions $x_t(\cdot)$, $c_t(\cdot)$, and $p_{jt}(\cdot)$ exist, are unique, and are continuous. These conditions are met if: (i) $(x_t, \{p_j\}_j)$ take values on a convex Borel set; (ii) y_t is a Markov process that takes values in a compact Borel set and its transition function Q has the Feller property; (iii) the budget set is non-empty, compact, and convex; (iv) $U(\cdot)$ is bounded, continuous, and concave; and (v) $\delta \in (0,1)$. If $U(\cdot)$ is continuously differentiable, Theorem 9.10 ensures that $V(\cdot)$ is as well. Section 9.7 in Stokey and Lucas (1989) discusses additional conditions to ensure policy functions are also differentiable to arbitrary order.

If $T = N$, then the Bellman equations can be recursively substituted to obtain the original sequence problem. The sequence problem implies unique and continuous policy function solutions $x_t(\cdot), c_t(\cdot)$, and $p_{jt}(\cdot)$ if y_t is a Markov process with transition function Q that has the Feller property, $U(\cdot)$ is continuous and strictly concave, $\delta \in (0,1)$, and the budget set is non-empty, compact, convex, and continuous (Stokey and Lucas, 1989, Theorem 3.6 and Lemma 3.7, where Q having the Feller property ensures the expectation over y_t is bounded and continuous with respect to the controls).

In what follows, I assume conditions necessary so that $V(\cdot)$ and policy functions are continuous and differentiable. The value function $V_t(\cdot)$ has a time index because the agent might have a finite horizon ($T = N$).

Proof of Claim 1. Start by writing out the definition of the Bellman equation with more detail on constraints:

$$V_t\left(X_t, \{B_{jt}\}_j; \theta\right) = \max_{x, \{p_j\}_j} \left\{ U(X_t - x) + \delta E V_{t+1}\left(R_0 \left[x - \sum_j p_j \right] + y_{t+1}, \left\{ R_{j,t+1}(B_{jt} - p_j) \right\}; \theta \right) \right\} \tag{A.1}$$

$$\text{s.t. } X_t - x + \sum_j p_j \geq 0 \quad [\alpha_t] \tag{A.2}$$

$$X_t + L_0 \geq X_t - x + \sum_j p_j \quad [\beta_t] \tag{A.3}$$

$$p_j \geq B_{jt} - L_{j,t+1} \; \forall j \quad [\lambda_{jt}] \tag{A.4}$$

$$B_{jt} \geq p_j \; \forall j \quad [\mu_{jt}] \tag{A.5}$$

$$X_t - x \geq 0 \quad [\sigma_t] \tag{A.6}$$

where brackets indicate the (positive) Lagrange multipliers on each constraint. The solution implies total saving, consumption, and debt repayment policy functions:

$$x_t\left(X_t,\{B_{jt}\}_j;\theta\right);\quad c_t\left(X_t,\{B_{jt}\}_j;\theta\right):=X_t-x_t\left(X_t,\{B_{jt}\}_j;\theta\right);\quad p_{jt}\left(X_t,\{B_{jt}\}_j;\theta\right) \tag{A.7}$$

I first derive the optimal paydown strategy for allocating payments across accounts B_j. The FOC for p_j is:

$$0=-\delta R_0\frac{\partial EV_{t+1}}{\partial x_{t+1}}-\delta R_{j,t+1}\frac{\partial EV_{t+1}}{\partial B_{j,t+1}}+\alpha_t-\beta_t+\lambda_{jt}-\mu_{jt} \tag{A.8}$$

Therefore, for any two $j,k\in\{1,\dots,J\}$:

$$-\delta R_{j,t+1}\frac{\partial EV_{t+1}}{\partial B_{j,t+1}}+\lambda_{jt}-\mu_{jt}=-\delta R_{k,t+1}\frac{\partial EV_{t+1}}{\partial B_{k,t+1}}+\lambda_{kt}-\mu_{kt} \tag{A.9}$$

Iterating equation (A.1) forward one period, differentiating with respect to $B_{j,t+1}$, and applying the envelope theorem yields:

$$\frac{\partial V_{t+1}}{\partial B_{j,t+1}}=\delta R_{j,t+2}\frac{\partial EV_{t+2}}{\partial B_{j,t+2}}+\mu_{j,t+1}-\lambda_{j,t+1} \tag{A.10}$$

Applying equation (A.8) iterated one period forward implies:

$$\delta R_{j,t+2}\frac{\partial EV_{t+2}}{\partial B_{j,t+2}}=-\delta R_0\frac{\partial EV_{t+2}}{\partial X_{t+2}}+\lambda_{j,t+1}-\mu_{j,t+1}-\beta_{t+1}+\alpha_{t+1}$$

Therefore, for all j:

$$\frac{\partial V_{t+1}}{\partial B_{j,t+1}}=-\delta R_0\frac{\partial EV_{t+2}}{\partial X_{t+2}}+\alpha_{t+1}-\beta_{t+1}:=DV_{t+1}<0$$

so $\frac{\partial EV_{t+1}}{\partial B_{j,t+1}}$ is constant across j. Substituting into (A.9):

$$-\delta EDV_{t+1}\left(R_{j,t+1}-R_{k,t+1}\right)=(\lambda_{kt}-\lambda_{jt})-(\mu_{kt}-\mu_{jt}) \tag{A.11}$$

If $R_{j,t+1}>R_{k,t+1}$, then $(\lambda_{kt}-\lambda_{jt})-(\mu_{kt}-\mu_{jt})>0$. Therefore, at least one of the constraints on p_j or p_k must bind.

Note that if $\lambda_{kt}>0$ then $\mu_{kt}=0$ and vice versa, and similar for j. It is possible for both $\lambda_{kt}>0$ and $\lambda_{jt}>0$ – in that case, the agent makes minimum payments on both accounts. Similarly, it is possible for both $\mu_{kt}>0$ and $\mu_{jt}>0$ – in that case, the agent fully pays off both accounts.

Suppose the agent pays more than the minimum amount on account k, so that $\lambda_{kt}=0$

and $\mu_{kt} \geq 0$. Then: (i) it must hold that $\lambda_{jt} = 0$, so the minimum payment does not bind for j; and (ii) $\mu_{jt} > 0$, so all the balances on account j are repaid. This completes the proof for $j, k \in \{1, \ldots, J\}$, i.e. part (i) of the only if statement in Claim 1.

All that remains is to show that p_j binds at the minimum payment for $j \in \{1, \ldots, J\}$ if $R_{jt} < R_0$. From the envelope theorem, we know that:

$$\frac{\partial V_{t+1}}{\partial X_{t+1}} = U'(\cdot) + \delta R_0 \frac{\partial E_{t+1} V_{t+2}}{\partial X_{t+2}} + \alpha_{t+1} + \sigma_{t+1} \tag{A.12}$$

$$\frac{\partial V_{t+1}}{\partial B_{j,t+1}} = \delta R_{j,t+2} \frac{\partial E_{t+1} V_{t+2}}{\partial B_{j,t+2}} + \mu_{j,t+1} - \lambda_{j,t+1} \tag{A.13}$$

Iterating equation (A.8) forward one period:

$$0 = -\delta R_0 \frac{\partial E_{t+1} V_{t+2}}{\partial X_{t+2}} - \delta R_{j,t+2} \frac{\partial E_{t+1} V_{t+2}}{\partial B_{j,t+2}} + \alpha_{t+1} - \beta_{t+1} + \lambda_{j,t+1} - \mu_{j,t+1} \tag{A.14}$$

Combining with equation (A.13):

$$\frac{\partial V_{t+1}}{\partial B_{j,t+1}} = -\delta R_0 \frac{\partial E_{t+1} V_{t+2}}{\partial X_{t+2}} + \alpha_{t+1} - \beta_{t+1} \tag{A.15}$$

Substituting equations (A.15) and (A.12) into the original FOC for p_j in period t (equation (A.8)):

$$\begin{aligned} \delta R_0 E_t U'(\cdot) = \delta R_0 \frac{\partial E_t V_{t+2}}{\partial X_{t+2}} \delta \left(R_{j,t+1} - R_0 \right) + \delta R_{j,t+1} E_t \beta_{t+1} \\ - \delta \left[R_0 E_t (\alpha_{t+1} + \sigma_{t+1}) + R_{j,t+1} E_t (\alpha_{t+1}) \right] + \alpha_t - \beta_t + \lambda_{jt} - \mu_{jt} \end{aligned} \tag{A.16}$$

Finally, take the FOC with respect to x in period $t+1$:

$$0 = -U'(\cdot) + \delta R_0 \frac{\partial E_{t+1} V_{t+2}}{\partial X_{t+2}} - (\alpha_{t+1} + \sigma_{t+1}) + \beta_{t+1} \implies \tag{A.17}$$

$$E_t \beta_{t+1} = E_t U'(\cdot) - \delta R_0 \frac{\partial E_t V_{t+2}}{\partial X_{t+2}} + E_t (\alpha_{t+1} + \sigma_{t+1}) \tag{A.18}$$

Substituting into equation (A.16):

$$\begin{aligned} \delta (R_0 - R_{j,t+1}) E_t U'(\cdot) = \delta R_0 \frac{\partial E_t V_{t+2}}{\partial X_{t+2}} \left[\delta \left(R_{j,t+1} - R_0 \right) - R_{j,t+1} \right] \\ - \delta \left[(R_0 - R_{j,t+1}) E_t (\alpha_{t+1} + \sigma_{t+1}) + R_{j,t+1} E_t (\alpha_{t+1} - \beta_{t+1}) \right] + \alpha_t - \beta_t + \lambda_{jt} - \mu_{jt} \end{aligned} \tag{A.19}$$

Suppose that $R_0 \geq R_{j,t+1}$. Then: (i) the left-hand side of equation (A.19) is weakly positive because $U' \geq 0$; (ii) the first term on the right-hand side is negative, since $\frac{\partial E_t V_{t+2}}{\partial X_{t+2}} > 0$ and

$\delta(R_{j,t+1}-R_0)-R_{j,t+1}<0$; and (iii) the second term on the right-hand side is weakly negative, since $R_0-R_{j,t+1}\geq 0$, $E_t\alpha_{t+1}\geq 0$, and $E_t\sigma_{t+1}\geq 0$.

Therefore:

$$R_0 \geq R_{j,t+1} \implies \alpha_t-\beta_t+\lambda_{jt}-\mu_{jt}>0 \tag{A.20}$$

where the inequality is strict so long as V_{t+2} is strictly concave in X_{t+2}. Satisfying this expression requires $\alpha_t>0$ and / or $\lambda_{jt}>0$. If $\lambda_{jt}>0$, then payments on j are at the minimum. If $\alpha_t>0$, then $X_t-x+\sum_k p_k=0$, which – since $X_t-x\geq 0$, and $p_j\geq 0$ implicitly so long as $B_{jt}-L_{j,t+1}\geq 0$ – implies that $p_j=0$ for all j. In this case, p_j must be at the minimum as well. This proves part (ii) of the only if statement.

I now show the claims about the marginal payments and marginal accounts. To see part (1) of Claim 1, note that if j and k are both marginal, then $\lambda_{kt}=\lambda_{jt}=\mu_{kt}=\mu_{jt}=0$, which implies from equation (A.11) that $R_{j,t+1}=R_{k,t+1}$.

Part (2) of Claim 1 is an immediate application of the paydown strategy in light of new liquidity ΔX. By definition, the only payment that can change when saving increases as a result of the stimulus check is the unique marginal account.

The proof of part (3) is very similar to the proof of part (ii) of the only if statement above. Take the FOC of problem (3), with multipliers defined as in equations (A.2) - (A.5):

$$0=-\delta R_0\frac{\partial E_{t-1}V_t(\cdot;\theta')}{\partial X_t}-\delta R_{st}\frac{\partial E_{t-1}V_t(\cdot;\theta')}{\partial B_{st}}+\alpha_{t-1}-\beta_{t-1}+\lambda_{s,t-1}-\mu_{s,t-1} \tag{A.21}$$

The multipliers are implicitly conditional on θ'. From the envelope theorem:

$$\frac{\partial V_t(\cdot;\theta')}{\partial X_t}=U'(\cdot)+\delta R_0\frac{\partial E_tV_{t+1}(\cdot;\theta')}{\partial X_{t+1}}+\alpha_t+\sigma_t \tag{A.22}$$

$$\frac{\partial V_t(\cdot;\theta')}{\partial B_{st}}=\delta R_{s,t+1}\frac{\partial E_tV_{t+1}(\cdot;\theta')}{\partial B_{s,t+1}}+\mu_{st}-\lambda_{st} \tag{A.23}$$

The coefficient β_t does not appear in equation (A.22) because X_t appears on both sides of constraint (A.3). Furthermore, the FOC for p_s in period t (when there is no unexpected change in the environment) is:

$$0=-\delta R_0\frac{\partial E_tV_{t+1}(\cdot;\theta')}{\partial X_{t+1}}-\delta R_{s,t+1}\frac{\partial E_tV_{t+1}(\cdot;\theta')}{\partial B_{s,t+1}}+\alpha_t-\beta_t+\lambda_{st}-\mu_{st} \tag{A.24}$$

Combining equations (A.24) and (A.23):

$$\frac{\partial V_t(\cdot;\theta')}{\partial B_{st}}=-\delta R_0\frac{\partial E_tV_{t+1}(\cdot;\theta')}{\partial X_{t+1}}+\alpha_t-\beta_t \tag{A.25}$$

Substituting (A.22) and (A.25) into equation (A.21):

$$\delta R_0 E_{t-1} U'(\cdot) = \frac{\partial E_{t-1} V_{t+1}(\cdot;\theta')}{\partial X_{t+1}} \delta^2 R_0 (R_{st} - R_0) + \delta R_{st} E_{t-1} \beta_t$$
$$- \delta E_{t-1} (R_0(\alpha_t + \sigma_t) + R_{st}\alpha_t) + (\alpha_{t-1} - \beta_{t-1}) + \left(\lambda_{s,t-1} - \mu_{s,t-1}\right) \tag{A.26}$$

Finishing the proof requires quantifying $E_{t-1}\beta_t$. Taking the FOC with respect to x_t in period t:

$$0 = -U'(\cdot) + \delta R_0 \frac{\partial E_t V_{t+1}(\cdot;\theta')}{\partial X_{t+1}} - (\alpha_t + \sigma_t) + \beta_t \implies \tag{A.27}$$

$$E_{t-1}\beta_t = E_{t-1}U'(\cdot) - \delta R_0 \frac{\partial E_{t-1} V_{t+1}(\cdot;\theta')}{\partial X_{t+1}} + E_{t-1}(\alpha_t + \sigma_t) \tag{A.28}$$

Substituting into equation (A.26):

$$\delta (R_0 - R_{st}) E_{t-1} U'(\cdot) = \delta R_0 \frac{\partial E_{t-1} V_{t+1}(\cdot;\theta')}{\partial X_{t+1}} (\delta(R_{st} - R_0) - R_{st})$$
$$+ \delta(R_{st} - R_0) E_{t-1}(\alpha_t + \sigma_t) - \delta E_{t-1} R_{st} \alpha_t + (\alpha_{t-1} - \beta_{t-1}) + (\lambda_{s,t-1} - \mu_{s,t-1}) \tag{A.29}$$

The left-hand side is weakly positive, because U is increasing, and $R_{st} = 1 \implies \delta(R_0 - R_{st}) \geq 0$. On the right-hand side, the first term is negative, since $\frac{\partial E_{t-1} V_{t+1}(\cdot;\theta')}{\partial X_{t+1}} > 0$ and $R_{st} \leq R_0$ implies that $\delta(R_{st} - R_0) - R_{st} < 0$. The second and third terms are both weakly negative, since $R_{st} - R_0 \leq 0$ and both $E_{t-1}\alpha_t, E_{t-1}\sigma_t \geq 0$. Putting everything together:

$$R_{st} \leq R_0 \implies (\alpha_{t-1} - \beta_{t-1}) + \left(\lambda_{s,t-1} - \mu_{s,t-1}\right) > 0 \tag{A.30}$$

This can only hold if either α_{t-1} or $\lambda_{s,t-1}$ are positive. If $\lambda_{s,t-1} > 0$, then $p_{s,t-1}$ binds at its minimum payment, i.e. $p_{s,t-1} = 0$. If $\alpha_{t-1} > 0$, then $X_t - x_{t-1}(\cdot;\theta) + \sum_{j \neq s} p_{j,t-1}(\cdot;\theta) + p^f_{s,t-1}(\cdot;\theta') = 0$, which (since all $p_{jt}, j \neq s$ are positive and $X_{t-1} - x_{t-1} \geq 0$) requires that $p_{s,t-1} = 0$. This completes the proof. □

Proof of Claim 2. For the first bound in equation (4), apply a first-order Taylor expansion around $(X_t, \{B_{jt}\}; \theta)$ to the consumption and debt repayment policy functions in (A.7). We have:

$$c_t(X_t + \Delta X, \{B_{jt}\}; \theta) - c_t(X_t, \{B_{jt}\}; \theta) \approx \frac{\partial c_t(X_t, \{B_{jt}\}; \theta)}{\partial X_t} \Delta X \tag{A.31}$$

$$p_{jt}(X_t + \Delta X, \{B_{jt}\}; \theta) - p_{jt}(X_t, \{B_{jt}\}; \theta) \approx \frac{\partial p_{jt}(X_t, \{B_{jt}\}; \theta)}{\partial X_t} \Delta X \tag{A.32}$$

For the second bound in equation (4), use the timing assumptions to write the consumption and debt repayment policy functions in (A.7) as:

$$c_t^f\left(R_0\left[X_{t-1}-c_{t-1}-\sum_j p_{j,t-1}\right]+y_t,\left\{R_{jt}\left(B_{j,t-1}-p_{j,t-1}\right)\right\};\theta\right) \tag{A.33}$$

$$p_{jt}^f\left(R_0\left[X_{t-1}-c_{t-1}-\sum_j p_{j,t-1}\right]+y_t,\left\{R_{jt}\left(B_{j,t-1}-p_{j,t-1}\right)\right\};\theta\right) \tag{A.34}$$

Given timing assumptions, forbearance only impacts: (i) period $t-1$ student loan repayments $p_{s,t-1}$; and (ii) student loan interest rates and minimum balances $R_{s,t+l}, L_{s,t+l}$ for $l\in[0,F]$. The change in period-t interest rates impacts balances in period t.

Applying a first-order Taylor expansion around $(X_t,\{B_{jt}\};\theta)$ gives:

$$\begin{aligned}
&c_t(X_t,\{B_{jt}\};\theta)-c_t\left(X_t+R_0p_{s,t-1}(\theta),B_{st}-(R_{st}-1)B_{s,t-1}+R_{st}p_{s,t-1},\{B_{jt}\}_{j\neq s};\theta'\right)\\
&\quad\approx\frac{\partial c_t(X_t,\{B_{jt}\};\theta)}{\partial X_t}R_0p_{s,t-1}(\theta)+\frac{\partial c_t(X_t,\{B_{jt}\};\theta)}{\partial B_{st}}\left(R_{st}p_{s,t-1}(\theta)-(R_{st}-1)B_{s,t-1}\right)\\
&\qquad+\sum_{l=1}^{F}\left(\frac{\partial c_t(X_t,\{B_{jt}\};\theta)}{\partial R_{s,t+l}}\Delta R_{s,t+l}+\frac{\partial c_t(X_t,\{B_{jt}\};\theta)}{\partial L_{s,t+l}}\Delta L_{s,t+l}\right)
\end{aligned} \tag{A.35}$$

$$\begin{aligned}
&p_{jt}(X_t,\{B_{jt}\};\theta)-p_{jt}\left(X_t+R_0p_{s,t-1}(\theta),B_{st}-(R_{st}-1)B_{s,t-1}+R_{st}p_{s,t-1},\{B_{jt}\}_{j\neq s};\theta'\right)\\
&\quad\approx\frac{\partial p_{jt}(X_t,\{B_{jt}\};\theta)}{\partial X_t}R_0p_{s,t-1}(\theta)+\frac{\partial p_{jt}(X_t,\{B_{jt}\};\theta)}{\partial B_{st}}\left(R_{st}p_{s,t-1}-(R_{st}-1)B_{s,t-1}\right)\\
&\qquad+\sum_{l=1}^{F}\left(\frac{\partial p_{jt}(X_t,\{B_{jt}\};\theta)}{\partial R_{s,t+l}}\Delta R_{s,t+l}+\frac{\partial p_{jt}(X_t,\{B_{jt}\};\theta)}{\partial L_{s,t+l}}\Delta L_{s,t+l}\right)
\end{aligned} \tag{A.36}$$

Combining equations (A.31) and (A.32) with equations (A.35) and (A.36), and applying $R_0=1$ and $\Delta p_{st}=p_{s,t-1}(\theta)$:

$$\begin{aligned}
\frac{\Delta c_t^w(X_t,\{B_{jt}\};\theta)}{\Delta X}-\frac{\Delta c_t^f(X_t,\{B_{jt}\};\theta)}{\Delta p_{st}}&\approx-\left(\frac{\partial c_t(\cdot)}{\partial B_{st}}R_{st}\right)+\\
&\underbrace{\left(\frac{\partial c_t(\cdot)}{\partial B_{st}}\frac{[R_{st}-1]B_{s,t-1}}{\Delta p_{st}}-\left[\sum_{l=1}^{F}\frac{\partial c_t(\cdot)}{\partial R_{s,t+l}}\frac{\Delta R_{s,t+l}}{\Delta p_{st}}+\frac{\partial c_t}{\partial L_{s,t+l}}\frac{\Delta L_{s,t+l}}{\Delta p_{st}}\right]\right)}_{\leq 0}\\
&\leq\left|\frac{\partial c_t(\cdot)}{\partial B_{st}}R_{st}\right|
\end{aligned} \tag{A.37}$$

The inequality in the final line follows because by assumption, $\frac{\partial c}{\partial B_{st}}\leq 0$, $\frac{\partial c_t}{\partial R_{s,t+l}}\leq 0$, and $\frac{\partial c_t}{\partial L_{s,t+l}}\leq$

0, and forbearance means $\Delta R_{s,t+l}, \Delta L_{s,t+l} \leq 0$. Similarly, for Δp_{jt}:

$$\frac{\Delta p^w_{jt}(X_t, \{B_{jt}\}; \theta)}{\Delta X} - \frac{\Delta p^f_{jt}(X_t, \{B_{jt}\}; \theta)}{\Delta p_{st}} \approx -\left(\frac{\partial p_{jt}(\cdot)}{\partial B_{st}} R_{st}\right) + \underbrace{\left(\frac{\partial p_{jt}(\cdot)}{\partial B_{st}} \frac{[R_{st} - 1]B_{s,t-1}}{\Delta p_{st}} - \left[\sum_{l=1}^{F} \frac{\partial p_{jt}(\cdot)}{\partial R_{s,t+l}} \frac{\Delta R_{s,t+l}}{\Delta p_{st}} + \frac{\partial p_{jt}}{\partial L_{s,t+l}} \frac{\Delta L_{s,t+l}}{\Delta p_{st}}\right]\right)}_{\leq 0}$$

$$\leq \left|\frac{\partial p_{jt}(\cdot)}{\partial B_{st}} R_{st}\right| \tag{A.38}$$

□

A.2 Model with target deviation costs

A.2.1 Notation details for solution to lifecycle model with fixed target deviation costs

This subsection formally describes the definition of p^m_j and x^m where $m = o$ from Section 5. Recalling notation, if $m_j = g$, then $p^m_j = g_j$ (or $x^m = g_x$ for the $J+1$th element), and if $m_j = o$, then the jth element is chosen according to the FOCs in the following problem:

$$\max_{\{p^m_j : m_j \neq g\} \cup \{x^m : m_{j+1} \neq g\}} v_t\left(x^m, \{p^m_j\}_j; \cdot\right) \tag{A.39}$$

$$\text{s.t.} \quad X_t - x^m + \sum_j p^m_j \in [0, X_t + L_0], \quad p^m_j \in \left[B_{jt} - L_{j,t+1}, B_{jt}\right], \quad X_t - x^m \geq 0 \tag{A.40}$$

This takes as given the total saving and debt repayment levels chosen to align with debt repayment goals as specified by the vector m, and maximizes over the remaining controls. The consumer then chooses the vector m^* that maximizes utility, inclusive of adjustment costs:[38]

$$m^* := \arg\max_m v_t\left(x^m, \left\{p^m_j\right\}_j; \cdot\right) - \left(b_x \cdot \mathbb{1}\{x^m \neq g_{xt}\} + \sum_j b_j \cdot \mathbb{1}\left\{p^m_j \neq g_{jt}\right\}\right) \tag{A.41}$$

A.2.2 Updating Claims 1 and 2

Preliminaries Before stating Claims 3 and 4, a few preliminaries.

First, define consumption and payment functions as solutions to the full optimization prob-

[38] The problem does not include constraints, which are implicitly in the definition of x^m, p^m_j from equation (A.39). Also, note that nothing prevents $p^m_j = g_{jt}$ where $m_j = o$ – for instance, if goals are set in a forward-looking way based on expected future conditions and realizations align with expectations.

lem:

$$\left(x_t^m(X_t,\{B_{jt}\}_j;\theta),\left\{p_{jt}^m(X_t,\{B_{jt}\}_j;\theta)\right\}_j\right):=$$

$$\arg\max_{x,\{p_j\}_j}\ U(X_t-x)+\delta EV_{t+1}\left(R_0\left(x-\sum_j p_j\right)+y_{t+1},\left\{R_{j,t+1}(B_{jt}-p_j)\right\}_j;\theta\right)$$

$$-\left(\gamma_x(x,g_{xt})+\sum_j\gamma_j(p_j,g_{jt})\right) \tag{A.42}$$

$$\text{s.t. } X_t-x+\sum_j p_j\geq 0\quad[\alpha_t] \tag{A.43}$$

$$X_t+L_0\geq X_t-x+\sum_j p_j\quad[\beta_t] \tag{A.44}$$

$$p_j\geq B_{jt}-L_{j,t+1}\quad[\lambda_{jt}] \tag{A.45}$$

$$B_{jt}\geq p_j\quad[\mu_{jt}] \tag{A.46}$$

$$X_t-x\geq 0\quad[\sigma_t] \tag{A.47}$$

Define $c_t^m(X_t,\{B_{jt}\}_j;\theta):=X_t-x_t^m(X_t,\{B_{jt}\}_j;\theta)$.

Second, adopt the timing assumptions for forbearance as in section 2: specifically, that forbearance starting in period t is announced at the end of period $t-1$, after all payments besides student loans have been chosen.

Next, define $\Delta c_t^{w,m}$ and $\Delta c_t^{f,m}$, the consumption effect of a stimulus check ΔX and forbearance, analogously to Section 2:

$$\Delta c_t^{w,m}:=c_t^m(X_t+\Delta X,B_{st};\theta)-c_t^m(X_t,B_{st};\theta) \tag{A.48}$$

$$\Delta c_t^{f,m}:=c_t^m(X_t',B_{st}';\theta')-c_t^m(X_t,B_{st};\theta) \tag{A.49}$$

$$\Delta p_{st}^m:=p_{s,t-1}^m(X_{t-1},B_{s,t-1};\theta)-p_{s,t-1}^m(X_{t-1}',B_{s,t-1};\theta') \tag{A.50}$$

where X_t',B_{st}' differ from X_t,B_{st} due to endogenous changes in period $t-1$ student loan payments, relevant because of the timing assumption from Section 2.

Finally, define the choice of student loan payments in period $t-1$ when forbearance is announced as:

$$p_{s,t-1}^{f,m}(X_{t-1},\{B_{j,t-1}\}_j;\theta,\theta'):=\arg\max_{p_s}\ v_{t-1}\left(x_{t-1}(\cdot;\theta),\{p_{j,t-1}(\cdot;\theta)\}_{j\neq s},p_s;X_{t-1},\{B_{j,t-1}\}_j,\theta'\right)$$

$$-\mathbf{1}'\Gamma\left(x_{t-1}(\cdot;\theta),\{p_{j,t-1}(\cdot;\theta)\}_{j\neq s},p_s;X_{t-1},\{B_{j,t-1}\}_j\right) \tag{A.51}$$

$$\text{s.t. } (A.43)-(A.47)$$

Liquidity from forbearance is therefore:

$$\Delta p^{m}_{st} = p_{s,t-1}(\cdot;\theta) - p^{f,m}_{s,t-1}(\cdot;\theta') \tag{A.52}$$

Claim 3 (Debt repayment with target deviation costs)

1. *Each debt account j has a level of target deviation costs $\underline{b}_j$ where p_j is chosen from the FOC ($m^*_j = o$) for $b_j < \underline{b}_j$, and p_j is chosen to align with debt repayment goals ($m^*_j = g$) for $b_j \geq \underline{b}_j$, holding fixed $b_k, k \neq j$. A similar result holds for total saving x.*

2. *Hold fixed total saving x_t. Suppose that $m^*_j = o$, and $m^*_k = o$ for at least one $k \neq j$. Then p_j is a marginal payment as defined in Claim 1 only if $R_{jt} = R_{kt}$, provided that $\frac{\partial EV_{t+1}}{\partial B_j} = \frac{\partial EV_{t+1}}{\partial B_k}$.*

3. *Suppose that a consumer has checking account balance X_t and student loan balances B_{st}. Suppose that $R_0 > R_{st}$ and both total saving and student debt repayment are chosen from FOCs ($m^*_s = m^*_x = o$). Then student loan payments binding at the minimum is equivalent to $-\frac{\partial EV_{t+1}}{\partial B_{s,t+1}} \leq \frac{\partial EV_{t+1}}{\partial X_{t+1}}$ at the optimum.*

4. *If forbearance starting in t is announced when $t-1$ ends, then if student loan payments are chosen according to FOCs in period $t-1$, $p^f_{s,t-1}(\cdot;\theta,\theta') = 0$ when $R_0 > R_{st}$ is equivalent to $-\frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial B_{st}} \leq \frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial X_t}$ at the optimum.*

Interpreting Claim 3 Part (1) of Claim 3 shows that for a given level of target adjustment costs $\boldsymbol{b}$ and account balances, a consumer has a threshold where they will choose payments on account j optimally so long as b_j is sufficiently low.

Parts (2) and (3) of Claim 3 give conditions on V_{t+1} so that the consumer appropriately prioritizes saving and debt repayment when chosen according to FOCs. Both conditions hold when V is defined recursively through the Bellman equation. By leaving EV unconstrained, the model accommodates a broader set of behaviors that might lead to debt repayment mistakes. For example, Dave Ramsey's "snowball" method could be modeled as $-\frac{\partial EV_{t+1}}{\partial B_j} > -\frac{\partial EV_{t+1}}{\partial B_k}$ if $B_j > B_k$.

The condition on EV_{t+1} in part (2) says that for two payment levels p_j and p_k chosen according to FOCs, the consumer will correctly prioritize the high-interest account if they perceive that marginally reducing the dollar amount of balances in accounts j and k will increase their continuation value by the same amount. This may not hold if consumers have unconventional beliefs about the economic incentives created by different interest rates.

Part (3) of Claim 3 means that when interest rates on student loans go to zero, borrowers will stop payments if the condition on EV_{t+1} holds. The condition means that a consumer will stop making student debt payments when they expect that next-period liquid savings will be "too low" relative to student debt balances compared with their choice if V were defined

recursively as equal to (9).[39] The condition will hold if the consumer expects to excessively pay down student loans in the future. If the consumer expects to repay loans too slowly (due to, for example, low saving goals or sophisticated present bias), the condition might not hold.

Proof of Claim 3 To prove part (1), fix j and introduce some notation. First, $\boldsymbol{b}$ is the vector of target adjustment costs. Second, $m^*(\boldsymbol{b})$ gives the value of m that solves problem (A.41). Third, let:

$$V^m := v_t\left(x^m, \left\{p_j^m\right\}_j; \cdot\right) \tag{A.53}$$

$$B^m(\boldsymbol{b}) := \left(b_x \cdot \mathbb{1}\left\{x^m \neq g_{xt}\right\} + \sum_{k \neq j} b_k \cdot \mathbb{1}\left\{p_k^m \neq g_{kt}\right\}\right) \tag{A.54}$$

Notice that V^m does not depend on $\boldsymbol{b}$ conditional on m, and $B^m(\cdot)$ does not include target adjustment costs for p_j. Now fix $b_k, k \neq j$. Suppose that $b_j = 0$, and define $m^0 := m^*\left(\{b_k\}_{k\neq j}, 0\right)$. Since $b_j = 0$, the consumer faces no cost to choosing p_j according to the FOC. Therefore, by definition, $m_j^0 = o$.

Define the cutoff $\underline{b}_j$ as follows:

$$\underline{b}_j := \inf\left\{b_j : \max_m V^m(b_j,\cdot) - B^m(b_j,\cdot) - b_j > \max_{m:m_j=o} V^m(b_j,\cdot) - B^m(b_j,\cdot)\right\} \tag{A.55}$$

In words, $\underline{b}_j$ is the smallest target adjustment cost that causes the consumer to switch from choosing p_j according to the FOC to fixing $p_j = g_{jt}$. Call $\underline{m} := m^*(\underline{b}_j, \{b_k\}_{k\neq j})$. Note that $\underline{b}_j$ only exists if $p_j^{o,\cdot} \neq g_{jt}$.

Fix some $b_j' > \underline{b}_j$. Let $m' := m^*(b_j', \{b_k\}_{k\neq j})$, and assume towards a contradiction that $m_j' = o$. By definition (and suppressing $\boldsymbol{b}$ arguments):

$$V^{\underline{m}} - B^{\underline{m}} < V^{m'} - B^{m'} - b_j \tag{A.56}$$

But also by definition, $V^{\underline{m}} - B^{\underline{m}} > V^{m^0} - B^{m^0} - \underline{b}_j$. Therefore:

$$V^{m^0} - B^{m^0} - \underline{b}_j < V^{\underline{m}} - B^{\underline{m}} < V^{m'} - B^{m'} - b_j' \implies \tag{A.57}$$

$$0 < b_j' - \underline{b}_j < \left(V^{m'} - B^{m'}\right) - \left(V^{m^0} - B^{m^0}\right) \tag{A.58}$$

Note that none of the objects on the right-hand side depend on b_j. Therefore, the expression on the right-hand side contradicts the definition of m^0, which says that $V^{m^0} - B^{m^0} \geq V^m - B^m$ for all m. Therefore, $b_j < \underline{b}_j \implies m_j^*(b_j,\cdot) = o$ by definition, and $b_j > \underline{b}_j \implies m_j^*(b_j,\cdot) = g$

[39] Savings are "too low" because the condition would hold with equality if V were defined recursively, and the solution to the resulting Bellman equation also solves the sequence problem that maximizes lifetime value.

because the converse is a contradiction. This establishes the single-crossing property described in part (1) of Claim 3. A similar argument holds for total saving, though the notation is slightly different.

To prove part (2), take the FOC for p_j in problem (A.42):

$$-\delta R_0 \frac{\partial EV_{t+1}}{\partial X} - \delta R_{j,t+1} \frac{\partial EV_{t+1}}{\partial B_j} + \alpha_t - \beta_t + \lambda_{jt} - \mu_{jt} = 0 \tag{A.59}$$

Therefore:

$$\lambda_{jt} - \mu_{jt} - \delta R_{j,t+1} \frac{\partial EV_{t+1}}{\partial B_j} = \lambda_{kt} - \mu_{kt} - \delta R_{k,t+1} \frac{\partial EV_{t+1}}{\partial B_k} \tag{A.60}$$

If $\frac{\partial EV_{t+1}}{\partial B_j} = \frac{\partial EV_{t+1}}{\partial B_k}$, then:

$$-\frac{\partial EV_{t+1}}{\partial B_j}\left(R_{j,t+1} - R_{k,t+1}\right) = \left(\lambda_{kt} - \lambda_{jt}\right) - \left(\mu_{kt} - \mu_{jt}\right) \tag{A.61}$$

This is the same as condition (A.11), which we can interpret as saying that at least one of the constraints on either p_j or p_k must bind if $R_j \neq R_k$.

To prove part (3), rearrange equation (A.59) into:

$$\delta \frac{\partial EV_{t+1}}{\partial X}\left(-\frac{\frac{\partial EV_{t+1}}{\partial B_j}}{\frac{\partial EV_{t+1}}{\partial X}} R_{j,t+1} - R_0\right) + (\alpha_t - \beta_t) = \mu_{jt} - \lambda_{jt} \tag{A.62}$$

Assume first that the total non-negativity constraint in α_t does not bind, and the liquidity constraint β_t does not bind. Then:

$$\left(R_{s,t+1} < R_0 \implies \mu_{st} < \lambda_{st}\right) \iff -\frac{\partial EV_{t+1}}{\partial B_s} \leq \frac{\partial EV_{t+1}}{\partial X} \tag{A.63}$$

In words, forbearance ($R_{st} < R_0$) implies that a consumer will stop making payments ($\mu_{st} < \lambda_{st}$) when they expect that next-period liquid savings will be weakly too low relative to the unconstrained maximum ($-\frac{\partial EV_{t+1}}{\partial B_s} \leq \frac{\partial EV_{t+1}}{\partial X}$).

To complete the argument, assume $\alpha_t > 0$ and / or $\beta_t > 0$. We have:

$$\left(R_{s,t+1} < R_0 \implies \mu_{st} < \lambda_{st} + (\alpha_t - \beta_t)\right) \iff -\frac{\partial EV_{t+1}}{\partial B_s} \leq \frac{\partial EV_{t+1}}{\partial X} \tag{A.64}$$

Now, forbearance requires that $\mu_{st} < \lambda_{st} + (\alpha_t - \beta_t)$. This implies that $\lambda_{st} > 0$, i.e. borrowers stop making student loan payments. Suppose otherwise. Then $\alpha_t > 0$ implies $X_t - x - \sum_k p_k = 0$. But since $X_t - x \geq 0$ and $p_k \geq 0$ implicitly, it must be the case that $p_s = 0$, meaning $\lambda_{st} > 0$ – a contradiction. See text for a discussion of the economic content of the assumption on the

value function.

To prove part (4), take the FOC for p_s in problem (A.51):

$$-\delta R_0 \frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial X_t} - \delta R_{st} \frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial B_{st}} + \alpha_{t-1} - \beta_{t-1} + \lambda_{s,t-1} - \mu_{s,t-1} = 0 \tag{A.65}$$

Rearrange this into:

$$\delta \frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial X_t} \left(-\frac{\frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial B_{st}}}{\frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial X_t}} R_{st} - R_0 \right) + \alpha_{t-1} - \beta_{t-1} = \mu_{s,t-1} - \lambda_{s,t-1} \tag{A.66}$$

Therefore:

$$\left(R_{st} < R_0 \implies \mu_{s,t-1} < \lambda_{s,t-1} + \alpha_{t-1} - \beta_{t-1} \right) \iff -\frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial B_{st}} \leq \frac{\partial E_{t-1} V_t(\cdot;\theta')}{\partial X_t} \tag{A.67}$$

As explained above, if $R_{st} < R_0$, then $\lambda_{s,t-1} > 0$, which implies $p_{s,t-1}$ binds at the minimum, as required.

□

Claim 4 (Consumption impact comparison with target deviation costs) *Suppose a consumer has only student debt B_{st} and a checking account X_t, and that the condition on EV in Claim 3, part (3) holds in period $t-1$. Let $\boldsymbol{b}_i \in \{0, b_s\} \times \{0, b_x\}$ where b_s and b_x are high enough so that if $b_{is} > 0$ then $m^*_{is} = g$ and if $b_{ix} > 0$ then $m^*_{ix} = g$.*

Assume that $R_0 = 1$, and that consumption is weakly decreasing in student loan balances B_{st} and student loan interest and limits $R_{s,t+l}, L_{s,t+l}, l \in [t, t+F]$.

Consider a stimulus policy that involves a payment of ΔX in period t, and a forbearance policy that shifts θ to θ' (as defined in Section 2). Then:

1. *The change in consumption due to stimulus payments is $\Delta c_t^{w,m_i} \approx \frac{\partial c_t^{m_i}(\cdot)}{\partial X_t} \Delta X$ if $b_{ix} = 0$, and $\Delta c_t^{w,m_i} = \Delta X$ otherwise.*

2. *The change in consumption due to forbearance is:*

$$\Delta c_t^{f,m_i} \begin{cases} \approx \left(\frac{\partial c_t^{m_i}(\cdot)}{\partial X_t} - \varepsilon_t^{m_i} \right) \Delta p_{st}^{m_i} & \text{if } b_{ix} = 0 \\ = 0 & \text{otherwise.} \end{cases} \quad \text{where} \quad \Delta p_{st}^{m_i} = \begin{cases} p_{s,t-1}^{m_i} & \text{if } b_{is} = 0 \\ 0 & \text{otherwise.} \end{cases} \tag{A.68}$$

where $\varepsilon_t^{m_i}$ is defined in equation (A.75) and is bounded by:

$$\varepsilon_t^{m_i} \leq \left| \frac{\partial c_t^{m_i}}{\partial B_{st}} R_{st} \right| \tag{A.69}$$

Proof of Claim 4 Consider cases where $b_{ix} > 0$ and / or $b_{is} > 0$. By definition:

$$\Delta c_t^{w,m_i} = 0 \text{ if } b_{ix} > 0 \tag{A.70}$$

$$\Delta c_t^{f,m_i} = 0 \text{ if } b_{ix} > 0 \tag{A.71}$$

$$\Delta p_{st}^{f,m_i} = 0 \text{ if } b_{is} > 0 \tag{A.72}$$

Now consider cases where $b_{ix} = 0$. In this case, consumption is chosen according to FOCs of problem (A.42). A first-order Taylor expansion gives:

$$\Delta c_t^{w,m_i} = \frac{\partial c_t^{m_i}}{\partial X_t} \Delta X \tag{A.73}$$

Equations (A.70) and (A.73) together deliver part (1) of the claim.

For part (2), note first that $X_t' = R_0\left(x_{t-1}(\cdot) - p_{s,t-1}^{m_i}(\cdot)\right)$ and $B_{st}' = R_{st}(B_{s,t-1} - p_{s,t-1}^{m_i}(\cdot))$. A first-order Taylor expansion therefore gives:

$$\begin{aligned}\Delta c_t^{f,m_i} = \frac{\partial c_t^{m_i}}{\partial X_t} R_0 \Delta p_{st}^{f,m_i} - \frac{\partial c_t^{m_i}}{\partial B_{st}}\left((R_{st}-1)B_{s,t-1} - R_{st}p_{s,t-1}^{m_i}\right) \\ + \sum_{l=1}^{F}\left(\frac{\partial c_t^{m_i}}{\partial R_{s,t+l}}\Delta R_{s,t+l} + \frac{\partial c_t}{\partial L_{s,t+l}}\Delta L_{s,t+l}\right)\end{aligned} \tag{A.74}$$

Applying the assumption $R_0 = 1$:

$$\begin{aligned}\Delta c_t^{f,m_i} = \frac{\partial c_t^{m_i}}{\partial X_t}\Delta p_{st}^{f,m_i} \\ \underbrace{-\left(\frac{\partial c_t^{m_i}}{\partial B_{st}}\left((R_{st}-1)B_{s,t-1} - R_{st}p_{s,t-1}^{m_i}\right) - \sum_{l=1}^{F}\left(\frac{\partial c_t^{m_i}}{\partial R_{s,t+l}}\Delta R_{s,t+l} + \frac{\partial c_t}{\partial L_{s,t+l}}\Delta L_{s,t+l}\right)\right)}_{:=\varepsilon_t^{m_i}\Delta p_{st}^{f,m_i}}\end{aligned} \tag{A.75}$$

The assumed comparative statics on $c_t^{m_i}(\cdot)$ imply that all terms in $\varepsilon_t^{m_i}\Delta p_{st}^{f,m_i}$ besides $\frac{\partial c_t^{m_i}}{\partial B_{st}} R_{st} p_{s,t-1}^{m_i}$ are negative. Therefore:

$$\varepsilon_t^{m_i} \leq \left|\frac{\partial c_t^{m_i}}{\partial B_{st}} R_{st}\right| \tag{A.76}$$

Together, equations (A.71), (A.75), and (A.76) deliver part (2) of the claim. □

A.2.3 Derivation of equation (10)

From Claim 4, to a first-order:

$$\frac{\Delta c_t^{w,m_i}}{\Delta X} \approx \chi_i \cdot \frac{\partial c_t^{m_i}(\cdot)}{\partial X_t} \tag{A.77}$$

$$\frac{\Delta c_t^{f,m_i}}{p_{s,t-1}^{m_i}(\cdot;\theta)} \approx \chi_i \cdot \left(\frac{\partial c_t^{m_i}(\cdot)}{\partial X_t} - \varepsilon_t^{m_i} \right) \frac{\Delta p_{st}^{m_i}}{p_{s,t-1}^{m_i}(\cdot;\theta)} \tag{A.78}$$

where $\Delta p_{st}^{m_i} = p_{s,t-1}^{m_i}(\cdot;\theta) - p_{s,t-1}^{m_i}(\cdot;\theta')$. By definition:

$$MPX_{i,p_s}^{f} = \frac{p_{s,t-1}^{m_i}(\cdot;\theta')}{p_{s,t-1}^{m_i}(\cdot;\theta)} \tag{A.79}$$

Therefore:

$$1 - MPX_{i,p_s}^{f} = \frac{\Delta p_{st}^{m_i}}{p_{s,t-1}^{m_i}(\cdot;\theta)} \tag{A.80}$$

Moreover:

$$\frac{\Delta p_{st}^{m_i}}{p_{s,t-1}^{m_i}} = \begin{cases} 0 & \text{if } b_{is} > 0 \\ 1 & \text{if } b_{is} = 0 \end{cases} \tag{A.81}$$

Hence:

$$\frac{\Delta c_t^{f,m_i}}{p_{s,t-1}^{m_i}(\cdot;\theta)} \approx \chi_i \cdot \left(1 - MPX_{i,p_s}^{f}\right) \cdot \left(\frac{\Delta c_t^{w,m_i}}{\Delta X} \right) - \mathbb{1}_{b_{is}=0} \cdot \varepsilon_t^{m_i} \tag{A.82}$$

Take expectations across i of equation (A.82):

$$E\left[\frac{\Delta c_t^{f,m_i}}{p_{s,t-1}^{m_i}(\cdot;\theta)} \right] \approx E\left[\chi_i \cdot \left(1 - MPX_{i,p_s}^{f}\right) \cdot \left(\frac{\Delta c_t^{w,m_i}}{\Delta X} \right) \right] - E\left[\mathbb{1}_{b_{is}=0} \varepsilon_t^{m_i} \right] \tag{A.83}$$

$$\begin{aligned} &= E[\chi_i] E\left[\left(1 - MPX_{i,p_s}^{f}\right) \cdot \left(\frac{\Delta c_t^{w,m_i}}{\Delta X} \right) \right] \\ &\quad + \mathrm{Cov}\left(\chi_i, \left(1 - MPX_{i,p_s}^{f}\right) \cdot \left(\frac{\Delta c_t^{w,m_i}}{\Delta X} \right) \right) - E\left[\mathbb{1}_{b_{is}=0} \varepsilon_t^{m_i} \right] \end{aligned} \tag{A.84}$$

$$= \tilde{\gamma} \cdot E\left[\left(1 - MPX_{i,p_s}^{f}\right) \cdot \left(\frac{\Delta c_t^{w,m_i}}{\Delta X} \right) \right] - E\left[\mathbb{1}_{b_{is}=0} \varepsilon_t^{m_i} \right] \tag{A.85}$$

To convert this to the expression in the text, substitute in the following definitions:

$$\Delta p_{ist} := p^{m_i}_{s,t-1}(\cdot;\theta) - p^{m_i}_{s,t-1}(\cdot;\theta-) \tag{A.86}$$

$$p_{is,t-1} := p^{m_i}_{s,t-1}(\cdot;\theta) \tag{A.87}$$

$$\Delta c^{f}_{it} := \Delta c^{f,m_i}_{t} \tag{A.88}$$

$$\Delta c^{w}_{it} := \Delta c^{w,m_i}_{t} \tag{A.89}$$

$$\frac{\partial c_{it}}{\partial B_{st}} := \frac{\partial c^{m_i}_{t}}{\partial B_{st}} \tag{A.90}$$

$$\varepsilon_{it} := \varepsilon^{m_i}_{t} \tag{A.91}$$

B Transactions data appendix

B.1 Identifying student loan borrowers

I identify student loan repayments using debit transactions made to private and federal student loan servicing companies. To identify federal borrowers, I specifically search for FedLoan / PHEAA, Great Lakes, HESC / EdFinancial, OHELA, Navient, Nelnet, OSLA, ESCI, GSMR, and Cornerstone, which had contracts to service federal loans at some point during my study period. During this period, FedLoan, Great Lakes, and Cornerstone were federal-exclusive servicers, meaning I can guarantee that payments to these servicers are payments on federal student debt.

The government renews contracts every year and sometimes changes servicers. I use Internet archives and Department of Education releases to verify that transactions classified as federal loan repayments are made to a servicer with a federal contract in the year of payment.

For loans over 360 days delinquent, the government transfers loan servicing to a separate collections company. I exclude payments to this servicer; while defaulted loans enjoyed some CARES Act relief, repayments are often irregular and negotiated directly between borrowers and the collections agency, and so likely exhibit different dynamics relative to non-defaulted borrowers.

B.2 Identifying private student loan servicers

There are no public sources that provide a comprehensive list of all private student loan servicing companies. To ensure that I identify servicers who handle most outstanding private student loan debt, I start from market share estimates reported in the Student Borrower Protection Center (SBPC) 2020 report on private student lending (SBPC, 2020, Figure 9). The SBPC market share estimates compile information from the Fed's G.19 consumer credit series; the MeasureOne Private Student Loan Consortium, an industry group; financial filings from large publicly-traded lenders; and other public sources. I divide the market into three categories of originators:

1. Large publicly-traded student loan originators (60% market share): Consists of Sallie Mae, Navient, Wells Fargo, Citizens, Discover, and PNC;
2. State-backed student loan companies (6% market share);
3. Other small or private firms and credit unions (34% market share)

For category (1), I use public documents to identify the servicers used by each originator. For categories (2) and (3), I first use public sources to generate comprehensive lists of major originators within the category, and then manually identify servicers for each originator. In particular:

- *State-backed student loan companies.* I identify originators based on publications from the Education Finance Council (EFC), the national trade association representing nonprofit and state-based higher education finance organizations. I use the 2019 Non-profit and State-based Education Loan Handbook, which lists 25 member institutions originating loans (EFC, 2019).

- *Smaller private originators.* The SBPC characterizes this category as consisting of fintechs and other non-depository institutions specializing in student lending; credit unions; and small or private regional banks that extend student loans. It would be infeasible to comprehensively search for all such originators, so I identify major players by studying lenders reviewed by Nerdwallet, a popular online personal finance website. I pulled recommended lenders for both private loan origination (link) and refinancing (link) as of January 2022. According to Nerdwallet's methodology (link for origination and link for refinancing), the editorial staff surveys banks, credit unions, online lenders, and specialty lenders, including the top 10 lenders by online search volume. This search adds another 15 unique originating institutions, given considerable overlap with the first two lists.

Some originators service loans themselves, and others contract with either standalone servicing companies or the servicing divisions of large student loan issuers. In total, the large publicly-traded student loan originators use 11 servicers. State-backed student loan companies add another 15 unique servicers, and smaller private originators add another 4. Together, I search for payments made to a total of 30 student loan servicers.

B.3 Identifying Sallie Mae payments

Recall that I partly identify payments to student loan servicers using transaction description text. As a privacy protection measure, my data provider runs a machine-learning algorithm on raw data to remove personally identifiable information from transaction descriptions, including names. The algorithm sometimes censors "Sallie Mae" due to semantic similarity to a woman's name. I identify such instances using the following procedure:

- First, I restrict to users who have at least one transaction with "Sallie Mae" in the description;

- Second, I search for payments in other months where: (i) the dollar amount of the payment is within $20; (ii) the payment occurs in the same week of the month; (iii) the transaction description has the text " XXXXXX XXX " (a censored version of "Sallie Mae"); and (iv) the data provider classified the payment as a loan.

C Additional empirical analysis

C.1 Accounting cost of student loan forbearance

The Ed Department estimates costs as the present value of the change in interest spread less savings due to forgone servicing and overhead charges, with the discount rate based on Treasury yields. The Ed Department fiscal year starts on Oct 1. The program cost $25.0 billion over the first six months (Department of Education, 2020, p. 59), $49.5 billion from Oct 1, 2020 through Sep 30, 2021 (Department of Education, 2021, p. 64), and $48.6 billion from Oct 1, 2021 through Sep 30, 2022 (Department of Education, 2022, p. 69).

C.2 Additional public data sources

This section describes the Survey of Consumer Finances (SCF), the Consumer Expenditure Survey (CEX), and the Department of Education Federal Student Loan Portfolio data, which I use for supplementary analysis.

C.2.1 Survey of Consumer Finances.

Overview. The SCF is a cross-sectional survey conducted by the Federal Reserve every three years. The survey asks a representative sample of US households detailed questions about household assets, liabilities, and income. The survey also includes questions intended to gauge financial attitudes, knowledge, and sophistication.

I use public-use microdata from the 2019 and 2022 surveys, drawing from both Summary Extract files, which provide aggregate income, assets, and liabilities concepts, and full public datasets. The 2019 survey interviewed 5,783 families between May and December 2019, before student loan forbearance.[40] The 2022 survey interviewed 4,602 families between May and December 2022, after forbearance began. The unit of analysis in the SCF is a "primary economic unit" (PEU), which consists of the primary income-earning individual or couple in a household, along with any financial dependents. I will interchangeably refer to PEUs as "households" when discussing the SCF. The SCF uses multiple imputation to impute missing values, which yields five replicates for each household case.

Unless otherwise noted, estimates use sampling weights to adjust for nonresponse bias (variable `wgt0` from the Summary Extract File). I construct standard errors that account for

[40] While the SCF aims to conduct interviews from May-December, a small share of interviews happen in the first four months of the subsequent year. In the 2019 survey, 9% of interviews took place from January to April 2020 (Bhutta et al., 2020).

both imputation and sampling uncertainty. To estimate the standard error attributable to imputation, I use variability across the SCF's multiple imputation replicates. To estimate the standard error attributable to sampling, I use replicate weights and multiplicity factors released as part of the full public dataset. I calculate standard errors for sample means and regression coefficients using the Stata program `scfcombo` (Pence 2015).

Sample selection and identifying borrowers eligible for federal student loan forbearance. For each household, the SCF asks about up to 7 student loans. For each loan, respondents report key loan details, including outstanding balances, loan interest rates, whether the loan is a federal student loan, and whether they are on an income-driven repayment scheme. Borrowers describe repayment behavior: whether they are currently making payments, typical monthly repayment amounts, and whether they are not required to make payments because they are still enrolled or in a post-graduation grace period. They also answer questions about how the loan was used, including whose education the loan financed; in what year and at what age students last attended the program the loan financed; and whether students completed the program the loan financed.

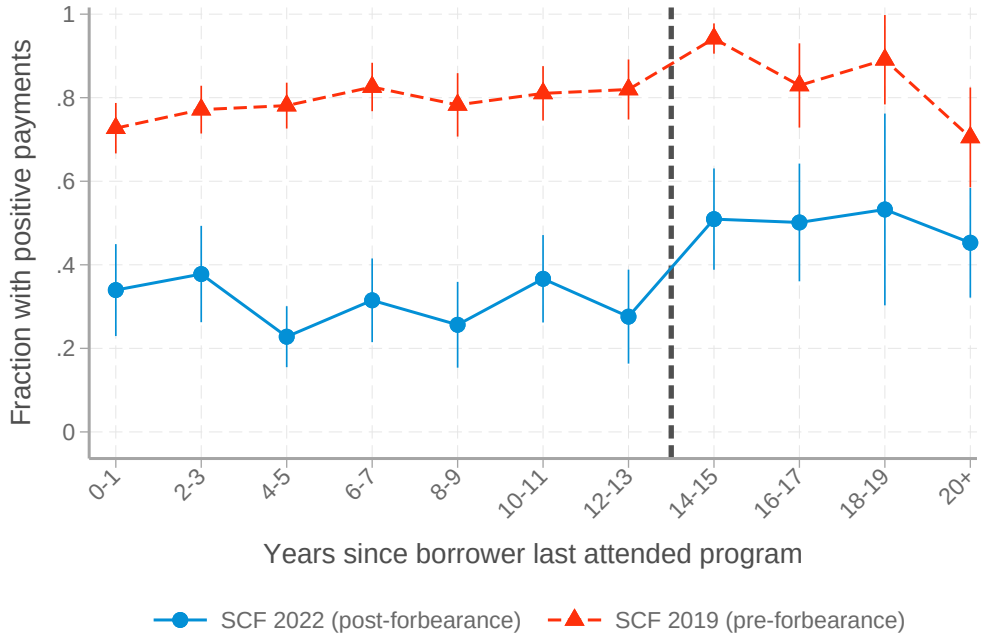
My sample consists of households with at least one federal student loan where the borrower is neither still enrolled nor in a post-graduation grace period where repayments are not expected. Because these households have federal student loans, they are eligible for the universal payment pause. I primarily identify these loans using a question asking whether each student loan is federal. However, borrowers might answer this question incorrectly for private student loans issued under the now-defunct Federal Family Education Loan (FFEL) program.

I therefore also show results using two other definitions that restrict to loans that borrowers report as federal that were issued after the government terminated the FFEL program in July 2010. The first definition requires that a loan financed a program last attended less than 13 years ago (for 2022) or 10 years ago (for 2019). The second definition requires that a loan financed the education of someone aged under 29 (in the 2022 survey) or under 26 (in the 2019 survey), meaning they were 18 in 2010 and hence extremely unlikely to get an FFEL loan. If the loan financed the education of the respondent or their spouse / partner, I can observe age directly. If the loan financed the education of the respondent's cohabitating child, I can infer age based on questions about the age of cohabitating children. If the loan financed the education of someone else (e.g. grandchild), I conservatively assume the student is above age 29.

Some borrowers appear to incorrectly report FFEL loans as federal, but conditioning on loans that financed programs last attended after 2010 appears to address this issue. Figure C.1 plots the fraction of borrowers with at least one loan reported as federal making payments

against the number of years since the student last attended the program the loan financed. Only some FFEL loans owned by the federal government were eligible for CARES Act forbearance, meaning repayment rates on FFEL loans should be higher. Indeed, in the 2022 SCF, taken after the federal payment pause, repayment rates are 23.4pp lower for loans 12-13 years old – and therefore originated after the FFEL program was canceled in 2010 – compared with loans 14-15 years old (p-value of diff=0.009). This difference is not due to a generic relationship between loan age and repayment rates, which are roughly flat at around 80% in the 2019 SCF, taken before the payment pause. In the 2022 SCF, repayment does not vary with years since program was attended for loans under 13 years old. Together, this indicates that conditioning on borrowers last attending the program less than 13 years ago in the 2022 SCF excludes any private FFEL loans where borrowers are not eligible for federal student loan forbearance.

Figure C.1: SCF: Loan repayment vs. loan age



Source: SCF, author's calculations. The figure plots the fraction of households who report making payments on federal student loans against the number of years since the program the loan financed was last attended. The sample restricts to borrowers who report positive balances on federal loans and are not still enrolled or in post-graduation grace periods. Blue circles show the 2022 SCF, and red triangles show the 2019 SCF. Years since program last attended are binned into two-year increments. Shares are calculated using sampling weights; spikes plot 95% confidence intervals constructed from standard errors that account for both sampling and imputation uncertainty.

Constructing other balance sheet variables and income. Besides information on federal student loans, my analysis requires information on private student loan balances, revolving credit card balances, mortgage balances and payments, 529/educational savings account balances, total net worth, pre-tax income, and after-tax income.

I estimate private student loan balances by summing balances for student loans that households indicate are private. To estimate revolving credit card balances, I use the SCF question

asking households about remaining balances still owed after the last payment. While the SCF asks about 529/educational savings directly, the public use dataset lumps these balances in with HSA balances. I use these combined balances as a proxy for 529 balances. Following S. C. Lee and Maxted (2026), I focus on high-interest balances – that is, credit card balances where households report an interest rate above 5% – to screen out 0% interest promotional periods. To align measurement with the transaction data, I restrict to balances on general purpose credit cards rather than store cards only accepted at certain merchants.

I use summary variables in the SCF summary extract file to measure non-HELOC mortgage balances, mortgage payments, total net worth, and pre-tax family income. I impute income tax liability, using NBER TAXSIM v35 to compute federal taxes, and assuming a 5% state tax liability. To apply TAXSIM to the SCF, I adapt Kevin Moore's SAS code to Stata. Unlike Kevin Moore's code, I (i) split business income proportionally across married-filing-separately households, rather than assuming a 50-50 split; and (ii) assume that taxpayers only bear the statutory burden of FICA taxes, rather than the full burden.[41]

Imputing required student loan payments. The SCF asks about the amount that households *actually* pay on their student loans. For some analysis, I am interested in the *required* monthly payment on each loan – that is, the minimum payment required to remain in good standing.

I therefore impute the required monthly payment using the following approach. For loans on standard repayment plans (not income-driven repayment), I impute the fixed payment that fully amortizes the remaining loan balance. Specifically, I estimate $P_S := B \cdot \frac{r \cdot (1+r)^m}{(1+r)^m - 1}$, where P_S is the monthly payment, B the remaining balance, r the monthly interest rate, and m the remaining term in months. B and r are reported directly in the SCF, and I impute m based on the year that borrowers expect each loan to be repaid. This calculation estimates monthly payments for each individual loan and then re-aggregates to get total monthly loan payments at the household level.

For loans on income-driven repayment schemes, I impute payments under the scheme that minimizes borrowers' monthly payment. In 2019 and 2022, there were three key income-driven repayment schemes: (i) income-based repayment (IBR), where borrowers pay 10% of discretionary income if the first loan was originated after July 1, 2014, and 15% otherwise; (ii) pay-as-you-earn (PAYE), where borrowers pay 10% of discretionary income if their first loan was disbursed after Oct 1, 2007 and the most recent loan was disbursed after Oct 1, 2011; and (iii) income-contingent repayment (ICR), where borrowers pay the minimum of 20% of discretionary income and the cost of fully amortizing the remaining balance over a 12-year

[41] This means that conceptually, I do not have to inflate pre-tax income by the imputed employer component of FICA taxes.

horizon. Parents borrowing for their children's education are *only* eligible for ICR; almost all federally-owned loans that finance the borrower's education are eligible for all three plans, so long as loans meet origination date requirements.

First, I determine the set of income-driven schemes for which each borrower is eligible. Eligibility is determined at the tax unit, not household or loan, level – I therefore sort each loan into tax units using each loan's ownership and the survey respondent's reported tax filing status (single, married filing jointly, married filing separately). I then impute the last year of loan origination as the last year of program attendance, and impute the first year of loan origination as the imputed last year minus the borrower's years of education. Finally, I impute eligibility based on whether the borrower is a parent or a student and the imputed first and last years of loan origination.

Second, I impute required payments under all eligible schemes. Each defines discretionary income as tax unit adjusted gross income (AGI) minus 150% of the federal poverty line, which depends on the number of dependents in each tax unit. I use imputations from TAXSIM calculations to determine tax unit AGI and the number of dependents, and use the poverty line for the 48 contiguous US states.

Finally, I calculate P_I as the minimum between P_S and the IDR schemes for which each tax unit is eligible. I then re-aggregate up to the household level by summing across P_I for each tax unit in a household.

C.2.2 Department of Education Federal Student Loan Portfolio.

The Department of Education releases quarterly data on outstanding student loans originated under federally-sponsored lending programs. The releases aggregate loan-level data from the National Student Loan Data System (NSLDS), a centralized database that the Department of Education uses to track all DL, Perkins, and FFEL loans (both commercial and federally owned). The NSLDS tracks detailed information on loan status (e.g., in grace period, in repayment, in forbearance, in default), loan terms (e.g. on standard repayment, graduated repayment, income-driven repayment), and loan ownership.

I download the table "Portfolio by Loan Status," available at this web link. This table shows total loan balances by loan status for three types of loans: (i) Direct Loans held by the federal government, (ii) FFEL loans owned by the federal government, and (iii) FFEL loans held by private lenders. (i) and (ii) are all subject to the automatic payment pause, while none of (iii) are.

C.3 Replication of main results using Survey of Consumer Finances

Table C.1 replicates facts 1, 2, and 4 from Section 4.1.2 using the Survey of Consumer Finances. The first column reproduces results from the transactions data. The next three columns show results for borrowers eligible for student loan forbearance in the 2022 SCF, using three different approaches to determine eligibility. The "full" column assumes that borrowers accurately self-report whether they have a federal student loan that is forbearance-eligible. The next two columns apply additional filters to strip out mis-reported FFEL loans that were not eligible for forbearance by excluding loans originated before the FFEL program was canceled in 2010. The "loan $<$ 13yrs" column requires that loans financed a program most recently attended in or after 2011, after the FFEL program ended. The "age $\leq$ 29" column requires that borrowers are aged 29 and under in 2022, meaning they were under 18 in 2010 and hence very unlikely to attend school the last time FFEL loans were available. See Section C.2.1 for data processing details, including additional evidence that these approaches appropriately identify forbearance eligibility. Stars indicate the p-value of a two sample t-test of difference in means between the transaction data and the SCF sample in each column.

Panel A of Table C.1 shows Fact 1: federal student borrowers continued to make substantial voluntary student loan payments during forbearance. In both transactions data and the SCF, average payments on federal loans fell around 66% to between \$106and \$153per month. This reflects around one-third of borrowers paying around \$300 per month. Estimated repayment rates and levels conditional on repayment are strikingly similar between the transactions data and self-reported SCF. This is especially true for the "loan $<$ 13yrs" and "age $\leq$ 29" columns, which correct for potentially mis-reported forbearance eligibility and give results that are statistically identical to the transactions data. For example, in the transactions data, 34.0% of federal borrowers make voluntary payments on loans during forbearance, almost identical to the 34.5% of federal borrowers with loans under 13 years old (p-value of diff=0.837), and 35.5% of federal borrowers under age 29 (p-value of diff=0.691).

Panel B of Table C.1 shows Fact 2: borrowers with higher student loan payments prepay more during forbearance. I show the fraction of households making positive federal student loan payments, split by quartiles of the ratio of 2019 payments to 2019 income (as in the main text) or imputed 2019 payments. In transactions data, prepayment rises for households with higher 2019 payments and payments relative to income. Because the SCF is not a panel, 2019 payments are not observed for households in 2022. I therefore impute 2019 payments in the 2022 dataset. I estimate the relationship between 2019 payments and 2019 imputed monthly required payments, 2019 income, loan characteristics, and household characteristics; use estimated coefficients to predict 2019 payments for observations in the 2022 SCF; and use

predicted 2019 payments to form debt-to-income and 2019 payment quartiles.

Specifically, I first estimate the following reverse regression in SCF 2019 (with imputed payments on LHS to avoid attenuation bias):

$$\ln P_{i,req} = \alpha_1 \ln P_{i,obs} + \alpha_2 I(IDR)_i + \alpha_3 I(Partner)_i + \alpha_4 \ln P_{i,obs} \times I(IDR)_i + \alpha_5 I(Partner)_i \times I(IDR)_i + \gamma_{g(i)} + \varepsilon_i \quad \text{(C.1)}$$

with $P_{i,req}$ imputed required minimum student loan payments, $P_{i,obs}$ observed actual student loan payments, $I(IDR)_i$ and $I(Partner)$ indicators for being on an income-driven repayment plan and having a partner, respectively, and $\gamma_{g(i)}$ fixed effects for 2019 after-tax income ventiles, 2019 age deciles, and their interactions with $I(IDR)_i$. Specification C.1 has a reasonable fit, with an adjusted R-squared of 0.501. I then predict 2019 actual student loan payments using 2022 data as $\hat{P}_{i,obs} = \exp\left(\frac{\ln P_{i,req} - \hat{\alpha}_2 I(IDR)_i - \hat{\alpha}_3 I(Partner)_i - \hat{\alpha}_5 I(IDR)_i \times I(Partner)_i - \hat{\gamma}_{g(i)}}{\hat{\alpha}_1 + \hat{\alpha}_4}\right)$. In principle, this prediction requires knowing the 2019 values of each covariate in 2022. In practice, I assume that imputed payments, IDR status, and partnership status are all unchanged between 2019-2022; deflate 2022 income to 2019 income using BLS growth in average weekly wages from 2019-2022; and reduce 2022 age by three. For consistency with transactions data, I drop observations with predicted 2019 payments under $25.

As in the transaction data, the SCF share making positive federal student loan payments is generally rising in the predicted 2019 debt-to-income ratio and predicted 2019 federal payments.

Panel C of Table C.1 shows Fact 4: borrowers prepay federal student loans during forbearance while holding higher-yielding consumer debt. In both transactions data and in the SCF, a substantial share of borrowers voluntarily prepay 0%-interest federal student debt while either revolving high-interest credit card debt (recall I restrict to credit card borrowing at a 5% rate or higher) or borrowing with private student loans. If anything, the transaction data understates the scale of borrowers' failure to cost-minimize during forbearance. This makes sense because the transaction data gives a lower bound for both revolving card debt and private student debt and so likely undercounts both.

In Panel C, I also use the SCF to extend results from the transactions data in several ways. First, I examine voluntary prepayment for households with mortgage and auto debt. Many federal borrowers with mortgage and auto debt also fail to cost-minimize by prepaying loans in forbearance. Second, for each consumer debt category, I calculate the interest rate on the debts that prepayers are prioritizing below their 0%-interest federal student debt. In each category, there is a large gap between the interest rate prepayers face on consumer debt and the 0% interest rate on federal student loans, meaning voluntary prepayments represent an

Table C.1: Replicating main results in SCF

	Transactions data	SCF 2022 (post-forbearance)		
	(i) post-forbearance	(ii) full	(iii) loan < 13yrs	(iv) age ≤ 29
A. Voluntary student loan payments during forbearance				
Avg. federal pmt ($/mo)	111	153*	145	106
% change vs. 2019	-66.1%	-55.9%	-59.9%	-66.6%
Avg. federal pmt | positive federal pmt ($/mo)	327	396	421	299
Positive federal student loan pmts (share)	0.340	0.385**	0.345	0.355
% change vs. 2019	-66.0%	-61.5%**	-65.5%	-64.5%
B. Federal student loan payments by debt level				
Positive federal student loan pmts by amount				
Debt-to-income Q1	0.275	0.401**	0.297	0.210
Debt-to-income Q2	0.316	0.391	0.341	0.255
Debt-to-income Q3	0.355	0.257*	0.252	0.588*
Debt-to-income Q4	0.415	0.441	0.384	0.236**
Pmt 2019 Q1	0.268	0.315	0.264	0.167
Pmt 2019 Q2	0.322	0.334	0.270	0.431
Pmt 2019 Q3	0.376	0.376	0.332	0.302
Pmt 2019 Q4	0.394	0.466	0.409	0.401
C. Federal student loan payments by other borrowing				
Positive federal pmt | revolving card debt (share)	0.299	0.427***	0.386**	0.346
Avg. interest-bearing card rate		16.8%	17.0%	18.0%
Positive federal pmt | has private student debt (share)	0.286	0.552***	0.495*	0.494
Avg. private student loan rate		5.5%	5.1%	4.5%
Positive federal pmt | has mortgage (share)		0.529	0.461	0.524
Avg. mortgage rate		3.7%	3.7%	3.6%
Positive federal pmt | has auto debt (share)		0.459	0.419	0.475
Avg. auto loan rate		5.3%	5.8%	5.1%
N	313,312	615	468	129

Source: SCF, transactions panel. * p<0.05, ** p<0.01, *** p<0.001, based on t-tests of difference in means comparing each SCF column to the transactions data column, calculated using both sampling and replicate weights. The first column uses the main transactions panel from the main text (federal student loan payments in 2019 with monthly payments > $25). The next three columns use the 2022 SCF. The column labeled "full" restricts to households with positive student loan balances reported as federal. The column labeled "loan < 13yrs" restricts to households with positive student loan balances reported as federal that financed a program last attended under 13 years ago, i.e. after 2010 when the FFEL program was canceled. The column labeled "age ≤ 29" restricts to households with positive student loan balances that financed the education of a student under age 29, i.e. under 18 in 2010, when FFEL program loans were last available. See Section C.2.1 for additional details. Panel A shows average payments on federal student loans, defined using the "federal loan" definition of each column. For consistency with the transactions data column, % changes vs. 2019 in SCF columns are calculated from 2019 SCF observations where households make positive federal student loan payments. Panel B shows the share making positive federal student loan payments by 2019 loan repayment level. The first four rows split by quartiles of actual (transactions data) or predicted (SCF) 2019 debt-to-income ratios, calculated as total 2019 federal student loan payments divided by observed (transactions data) or after-tax (SCF) income. The next four rows split by quartiles of predicted 2019 federal student loan payments. Panel C shows the share of households with other types of interest-bearing consumer debt who make federal student loan payments during forbearance. In SCF columns, revolving card debt restricts to high-interest debt on general purpose credit cards, and throughout interest rates are balance-weighted across all reported debts within each category.

economically-significant failure to cost minimize.

C.4 Drivers of prepayment during forbearance in the Survey of Consumer Finances.

Table C.2 uses rich data on household demographics, assets, income, and financial attitudes to understand the correlates of voluntary prepayment during forbearance. I use the primary SCF federal student borrower sample, described in Section C.2.1.

Columns (i)-(iii) show raw differences between payers and non-payers in demographics, student loan characteristics, and financial attitudes and knowledge. Payers have higher income and wealth, have larger families, and are slightly more educated. They are more likely to have completed the program their loan financed, less likely to think they will never repay their loan, and much more likely to be on an income-driven repayment program. While a similar share of payers and non-payers have tax-advantaged education savings accounts, payers have higher balances. Payers and non-payers display high levels of financial sophistication, largely answering questions about compound interest and inflation correctly. Interestingly, *payers* are more likely to correctly answer that a diversified stock portfolio is lower risk than a portfolio with just one stock. This question is often used to test financial sophistication, but could also reflect a more general preference for mixing across investments and accounts when making financial decisions. This could encourage borrowers to spread repayments across debt accounts, and make them reluctant to drop student loan payments to zero. Payers are slightly more likely to use autopay.

Column (iv) regression-adjusts these differences in means by regressing an indicator for making payments on federal loans in forbearance on all demographics, loan characteristics, and financial attitudes and knowledge indicators. Income remains a robust predictor of pre-payment, as does enrollment in an income-driven repayment plan and repayment expectations.

Table C.2: Drivers of prepayment during forbearance in SCF.

	Raw differences			Regression-adjusted	
	(i) Payers	(ii) Non-payers	(iii) Difference	(iv) Payer = 1	
Demographics					
Pre-tax income (col. iv = ln points)	$173,180	$89,295	$83,884***	0.081***	(0.021)
Net worth > 0 (share)	0.892	0.669	0.223***	−0.016	(0.169)
Net worth | >0 (col. iv = ln points)	$595,472	$300,852	$294,619***	0.016	(0.015)
Respondent age (yrs)	41.5	40.6	1.0	−0.004**	(0.001)
Household size (count)	2.94	2.58	0.36**	0.018	(0.012)
Education (yrs)	15.6	15.1	0.6**	0.011	(0.007)
Loan characteristics					
Loan for own/spouse educ (share)	0.921	0.935	−0.014	−0.046	(0.056)
Completed program (share)	0.799	0.694	0.105**	0.052	(0.035)
On IDR plan (share)	0.494	0.057	0.437***	0.582***	(0.032)
Never expects to repay (share)	0.019	0.047	−0.028*	−0.154*	(0.074)
Has educ. savings acct (share)	0.077	0.052	0.026	−0.497	(0.304)
Educ savings bal | has acct (col. iv = ln points)	$35,378	$8,127	$27,251*	0.054	(0.035)
Financial attitudes and knowledge					
Compound interest correct (share)	0.826	0.807	0.019	−0.022	(0.035)
Inflation correct (share)	0.833	0.797	0.036	−0.053	(0.040)
Diversification correct (share)	0.746	0.617	0.129**	0.054	(0.035)
Expects econ better, 5yr (share)	0.311	0.287	0.024	0.029	(0.031)
Expects econ better, 1yr (share)	0.118	0.133	−0.015	−0.002	(0.048)
Uses autopay (share)	0.903	0.835	0.068*	−0.025	(0.044)
Risk-taking willingness (0–10)	5.10	4.13	0.98***	0.021**	(0.007)
N (households)	234	381		614	
Adjusted R^2				0.388	

Source: SCF. * p<0.05, ** p<0.01, *** p<0.001, based on hypothesis tests of difference from zero calculated using both sampling and replicate weights. The sample is households in the 2022 SCF with positive student loan balances reported as federal. The first three columns report raw means and difference in means between households with and without positive payments on federal student loans. The fourth column reports coefficients from a multiple regression that uses rows as RHS variables. Pre-tax income, net worth, and education savings balances are calculated in levels for columns (i)-(iii) but in logs for column (iv); note column (iv) drops one household that reports zero income. "Compound interest correct" refers to the share correctly answering a question that qualitatively asks households to calculate compound interest. "Inflation correct" refers to the share correctly answering a question that qualitatively asks households to reason about real income growth in the context of inflation. "Diversification correct" refers to the share correctly answering that a diversified stock portfolio is less risky than a single-stock portfolio. "Uses autopay" refers to the share using autopay to pay *any* bill.

C.5 Replication of voluntary prepayment in Department of Education data

This section uses administrative data from the Department of Education to replicate Fact 1: borrowers make substantial voluntary prepayments on their federal loans during forbearance.

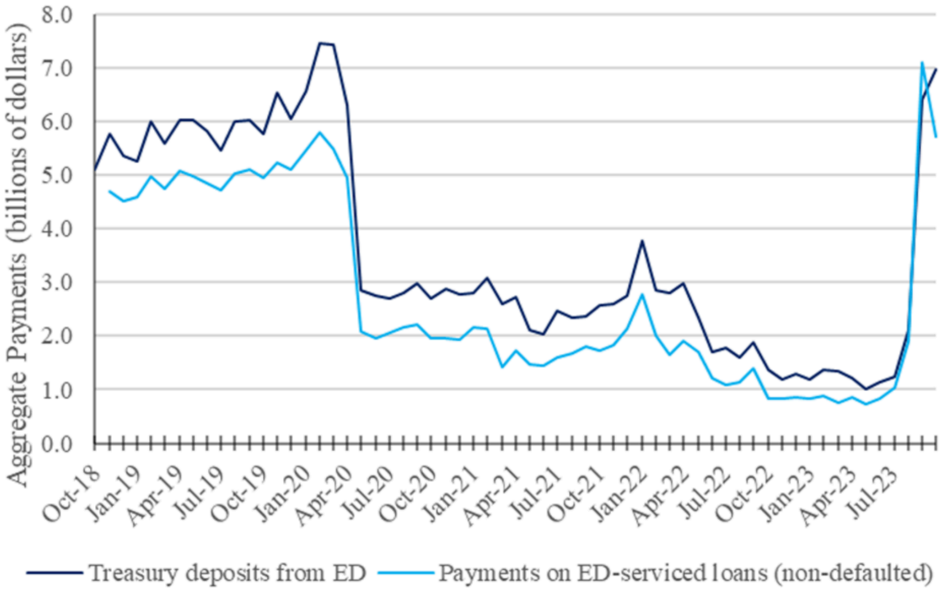
C.5.1 Internal Department of Education data.

I first reproduce the results from a Department of Education report on repayment of federally-owned loans (Matsudaira, Pollard, and Lee 2023). The report used internal Department of Education data from the National Student Loan Data System (see Appendix Section C.2.2).

Figure C.2 plots aggregate monthly payments on student loans eligible for automatic forbearance, summing payments on direct loans and federally-owned FFEL loans. The light blue bottom line shows internal data from the NSLDS, while the dark blue top line shows deposits

into the Department of Education's account at the US Treasury.[42] Neither data source includes payments on commercially-held FFEL or Perkins loans, meaning all payments are on loans that are eligible for the payment pause. In the NSLDS series, monthly payments fall from around $5 billion per month in March 2020 to $2 billion per month once forbearance begins. Post-forbearance repayment is roughly 40% of pre-forbearance repayment – very close to the findings in Fact 1 using transaction data.

Figure C.2: Department of Education: Payments on federally-owned loans during forbearance.



Source: Matsudaira, Pollard, and Lee (2023) (US Department of Education Office of the Chief Economist), using internal data from the National Student Loan Data System and US Department of the Treasury. The figure plots aggregate monthly payments on federally-owned student loans (Direct Loans, federally-owned FFEL and Perkins), which are all eligible for the CARES Act payment pause. The light blue line shows results from the internal National Student Loan Data System, which include payments on federally-owned loans that are not in default. The dark blue line shows daily deposits to the Department of Education's account at the US Treasury from the public Daily Treasury Statement, which includes payments on federally-owned loans, regardless of default status, and other Department of Education deposits that do not involve student loans.

C.5.2 Publicly-available Department of Education data.

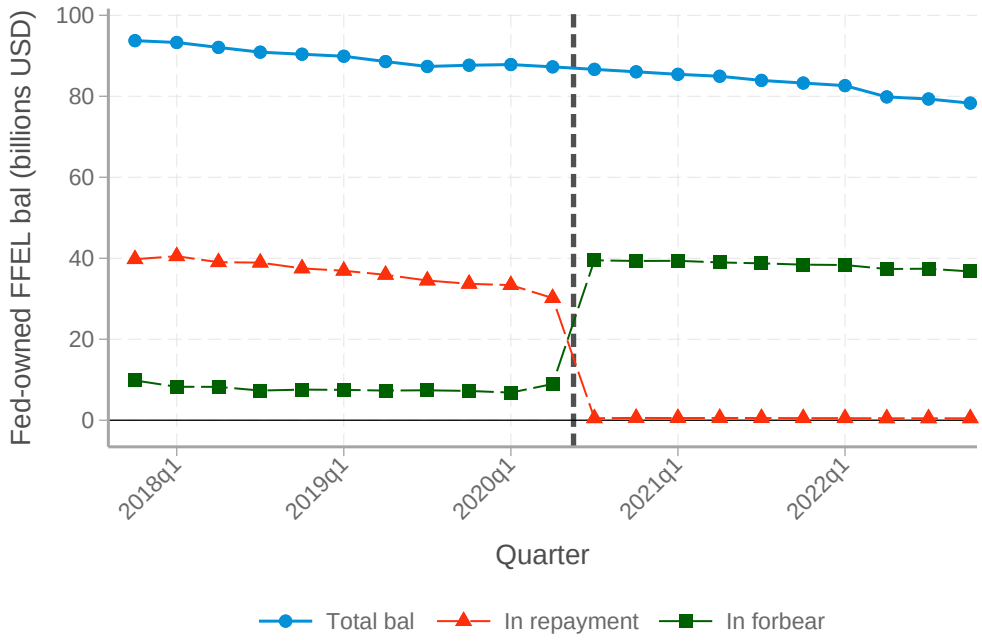
I next replicate these results with publically-available aggregate data from the Department of Education Federal Student Loan Portfolio reports. Specifically, I estimate prepayment rates for federal borrowers in automatic forbearance who have FFEL loans owned by the federal government. I focus on federal-owned FFEL loans because this is the only loan category automatically eligible for the federal payment pause for which I can use Department of Education data to measure repayment. The Department of Education reports aggregate quarterly balances by loan type, status, and ownership. For Direct Loans, quarterly balance changes reflect

[42]Deposits at the Treasury are higher because they include collections and wage garnishment on defaulted student loans as well as deposits unrelated to student loans.

a combination of repayment and new borrowing, since the program is still active. For FFEL loans, quarterly balance changes *only* reflect repayment, since the program was discontinued in 2010.[43]

Figure C.3 plots total outstanding balances for federally-owned FFEL loans: blue circles plot total balances, red triangles balances in repayment, and green squares balances in forbearance. The figure illustrates that these federally-owned loans are universally-eligible for forbearance: by 2020Q3, all loans with status "in repayment" have transitioned to status "in forbearance". Between 2020Q3 and the end of 2022, the balances of borrowers with loan status "in forbearance" clearly fall, indicating that borrowers have continued to repay their loans.[44]

Figure C.3: Department of Education: Federally-owned FFEL balances by loan status.



Source: Department of Education. The figure plots total outstanding balances in USD billions for FFEL loans owned by the US federal government. Blue circles plot total balances. Red triangles plot balances in repayment. Green squares plot balances in forbearance.

I use the decrease in balances from these data to impute repayments before and after forbearance. Define B_t as quarter-t balances, p_t as student loan payments, and R as the gross quarterly interest rate. Substituting the transition $B_{t+1} = R(B_t - p_t)$, the proportional decrease

[43] Since I'm looking at *federally-owned* FFEL loans, balances could change due to new government purchases of FFEL portfolios from private lenders. This is not possible because Congressional authorization for new FFEL purchases ended in 2010 (Congressional Research Service 2025).

[44] This highlights that a loan status of "in forbearance" vs. "in repayment" is just an administrative classification, not a description of borrower repayment behavior.

in balances is:

$$\frac{B_t - B_{t+1}}{B_t} = 1 - R + R \cdot \frac{p}{B} \tag{C.2}$$

Because I observe the left-hand side, $(B_t - B_{t+1})/B_t$, with an assumption on R I can back out the repayment rate p/B. After forbearance, I know that loans in forbearance have $R = 1$ (0% net interest). Before forbearance, I estimate implied repayment under three assumptions: interest rates equal (i) the minimum for any FFEL loan over the pre-forbearance period; (ii) the balance-weighted average interest rate among loans imputed as FFEL in the 2019 SCF; and (iii) the maximum for any FFEL loan over the pre-forbearance period. Rates (i) and (iii) can be easily observed; the government publishes the interest rate for all types of FFEL loans each year.[45] The results therefore cover the potential range of possible outcomes.

I impute pre-forbearance repayments by taking the average of $(B_t - B_{t+1})/(RB_t) + (R-1)/R = p/B$, where B is total balances, calculated each quarter from 2018Q4 to 2019Q4, assuming that R takes either its minimum, imputed average, or maximum value as described above. I impute repayment of loans in forbearance by taking the average of $(B_t - B_{t+1})/B_t$, where B is the balances of loans in forbearance, from 2020Q4 to 2021Q4, using the fact that $R = 1$ during forbearance.

Table C.3 shows results, where each column shows calculations for each of the interest rate assumptions for the pre-forbearance period.

Before forbearance, from 2018Q4 to 2019Q4, total balances decreased by an average of 0.57% per quarter. This implies a repayment rate of between 1.2% and 2.5% per quarter. Under the average interest rate assumption of 5.23%, the repayment rate is about 1.8% per quarter, or 7.1% per year. At this rate, borrowers repay within an average of 14 years, consistent with a 10-15 year repayment horizon on typical student loans.

After forbearance, from 2020Q4 to 2021Q4, balances of loans in forbearance decreased by an average of 0.5% per quarter. Since interest rates were zero on loans in forbearance, this implies a repayment rate around 0.5%.

This implies that the repayment rate for loans in forbearance was about 29% of their pre-forbearance level under the average interest rate assumption, with a range between 21% and 43%. The central estimate of 29% is similar to the proportional repayment rate estimated in Fact 1.

There are a few caveats. Some of the pre-forbearance change in balances could reflect the federal government writing off loans in deep default, or borrowers consolidating their

[45] FFEL loans originated after 2006 have a fixed interest rate. FFEL loans originated before 2006 are variable-rate, and the Department of Education publishes their variable rates each year.

federally-owned FFEL loans into direct consolidated loans (possible if borrowers can attest that they could not obtain acceptable terms from FFEL consolidation lenders). But both forces push FFEL balances to decrease faster *before* than *after* forbearance: once a loan is in forbearance, it can no longer enter default, and borrowers in forbearance have less of an incentive to consolidate to improve terms when they already don't have to make payments. Both likely lead my method to understate post-forbearance repayment, making my estimates a lower bound.

Table C.3: Department of Education: Imputed repayment rates for federal loans during forbearance.

	Pre-forbearance interest rate (annual %)		
	2.65%	5.23%	8.50%
Pre-forbearance Δ balances (%/qtr)	0.57	0.57	0.57
Implied repayment (% of bal/qtr)	1.20	1.78	2.48
Post-forbearance Δ balances (%/qtr)	0.51	0.51	0.51
Implied repayment (% of bal/qtr)	0.51	0.51	0.51
Post-forbearance repayment (% of pre-forbearance repayment)	**42.8**	**28.8**	**20.7**

Source: Department of Education. The first row shows the average quarterly decrease in total balances in the pre-forbearance period, from 2018Q4-2019Q4. The second row shows implied quarterly repayment rates, using quarterly interest rates inferred from the annual interest rate in the column header and using equation (C.2). The third row shows the average quarterly decrease in balances for loans in forbearance during the post-forbearance period, from 2020Q4-2021Q4. The fourth shows implied repayment rates, under the 0% net interest rate during forbearance. The final row shows the repayment rate of loans in forbearance as a percentage of the pre-forbearance total repayment rate. The first column uses the lowest interest rate for any FFEL loan observed during the pre-forbearance period. The second column uses the balance-weighted average of interest rates on loans imputed as FFEL in the 2019 SCF. The third column uses the highest interest rate for any FFEL loan observed during the pre-forbearance period.

C.6 Robustness: MPX on federal student loans out of forbearance liquidity

This subsection presents robustness analysis for Section 4.1. Results are in Table C.4.

Panel A gives the four-week MPX on federal student loans out of forbearance liquidity on average and split by quartiles of both 2019 average loan payments and the ratio of 2019 average loan payments to 2019 income, restricting the time trend in equation (5) to have common slopes before and after the onset of forbearance ($\beta_1 = \beta_2$).

Panel B presents results from the placebo test from the main text, again restricting to common slopes before and after forbearance begins.

Panel C presents results from another placebo test restricting to borrowers who are only observed to have payments on private student loans, both with and without the common slopes restriction.[46] The point estimate indicates that payments on private student loans declined by about 13% over the four weeks following the start of forbearance. This may not be a good representation of counterfactual payments on federal student loans absent forbearance. A

[46]The estimates look identical with and without the restriction, but that is only because the common slopes assumption matters so little for the estimates.

unique set of circumstances leads borrowers to have payments only on private student loans – only 5% of my sample is in this category. First, they could be in deferment, default, or grace on federal but not private student debt. Such borrowers may be especially financially precarious and hence more likely to stop private loan payments during Covid-related distress. Second, they could have refinanced federal debt. Such "active refinancers" may have refinanced *again* as interest rates fell around the start of Covid. I do not have a complete set of servicers of private student debt, and so I may lose track of some such refinancers. A final possibility is that some may have stopped paying because they thought their private debt was federal, and subject to forbearance. This may be more likely among those without private debt; people with both private and federal debt would only receive notice on *some* of their accounts, possibly emphasizing that private debt is not eligible.

Table C.4: Four-week MPX on federal student loans out of forbearance liquidity – Robustness

	Outcome / sample split	Common slopes?	All	Quartile 1	Quartile 2	Quartile 3	Quartile 4
A. Full sample	Fed loans, all	Yes	0.453				
			(0.003)				
	Fed loans, by 2019 pmt	Yes		0.467	0.437	0.441	0.460
				(0.012)	(0.008)	(0.006)	(0.46)
	Fed loans, by 2019	Yes		0.425	0.402	0.431	0.489
	(pmt / income)			(0.011)	(0.007)	(0.006)	(0.489)
B. Placebo. Borrowers with private loans	Private loans, all	Yes	0.931				
			(0.022)				
C. Placebo. Borrowers with only private loans	Private loans, all	No	0.869				
			(0.02)				
	Private loans, all	Yes	0.869				
			(0.02)				

Source: Author's calculations. Each entry gives estimated four-week MPX on federal student loans out of forbearance liquidity using the methodology described in Section 4.1, with robust standard errors clustered at the borrower level reported in parentheses. The "common slopes" column indicates whether I restrict $\beta_1 = \beta_2$ when estimating equation (5). Panel A gives estimates for the full population and subsamples split by quartiles of total payments on federal student loans in 2019. Panel B restricts to borrowers with both federal and private student loan debt in repayment, and compares the estimate of four-week MPX on federal student loans out of forbearance liquidity with a placebo test applying the same methodology to private student loans which were not subject to forbearance. Panel C is the same as Panel B, except the sample is borrowers with no federal (i.e. only private) student loans.

C.7 Robustness: Alternative estimates of MPX out of stimulus check liquidity

This subsection describes results from estimating specifications (6) and (7) using the imputation estimator described in Borusyak, Jaravel, and Spiess (2024). I report an equal-weighted average of treatment effects over the 30 days after stimulus checks arrive. For standard error calculation, I assume treatment effect homogeneity across borrowers conditional on event time. As discussed in Borusyak, Jaravel, and Spiess (2024), Section 4.3, the resulting standard errors are conservative under misspecification of this auxiliary treatment effect homogeneity assumption.

Table C.5 replicates Panel B of Table 2. In most cases, point estimates are quite similar or almost identical. In all but one case (discussed below), 95% confidence intervals of the point estimates overlap.

There are two points worth mentioning. First, estimates of the MPX on federal student loan payments on the full sample and private student borrower sample are slightly higher in Table C.5 than in Table 2. In the full sample, the FE estimate is about 1%, compared with 2% using the imputation estimator. In the private student borrower sample, the estimate is 2.7% vs. 0.6%. Both are much smaller than the estimated MPX on federal student loans out of forbearance liquidity.

Second, while the estimated MPX on credit card and private student loan payments out of stimulus check liquidity remain higher then the estimated MPX on federal student loan payments, the effect is statistically weaker than in FE estimates. This is especially the case for private student debt.

Table C.5: Four-week MPX out of stimulus checks – Robustness

Outcome	Full sample	CC debt > 0, March 2020	CC debt > 0, Apr-June 2020	Private SL debt > 0, June 2020
		(Above-median debt)	(Above-median debt)	(Above-median debt)
Federal SL pmts	0.023***	0.012	0.013	0.027*
	(0.003)	(0.011)	(0.013)	(0.013)
Total spending	0.17***	0.141**	0.116*	0.248**
	(0.011)	(0.049)	(0.05)	(0.078)
Broad nondurable	0.072***	0.086**	0.07*	0.106*
	(0.007)	(0.032)	(0.032)	(0.053)
Credit card pmts		0.093**	0.042**	
		(0.034)	(0.016)	
Private SL pmts				0.016
				(0.015)
Credit card pmts			0.048	
(SL MPX = 0)			(0.031)	
Credit card pmts			0.048**	
(SL MPX = 1)			(0.015)	
Private SL pmts				0.006
(SL MPX = 0)				(0.027)
Private SL pmts				0.033*
(SL MPX = 1)				(0.017)
N in sample	313,312	14,947	11,290	8,668

Source: Author's calculations. * p=0.05, ** p=0.01, *** p=0.001. This table replicates Panel B of Table 2, except estimates of the four-week MPX out of stimulus checks use the estimator described by Borusyak, Jaravel, and Spiess (2024). See Appendix Section C.7 for methodological details, and section 3.1 for descriptions of expenditure category construction.

C.8 Additional analysis of borrowers with private student debt.

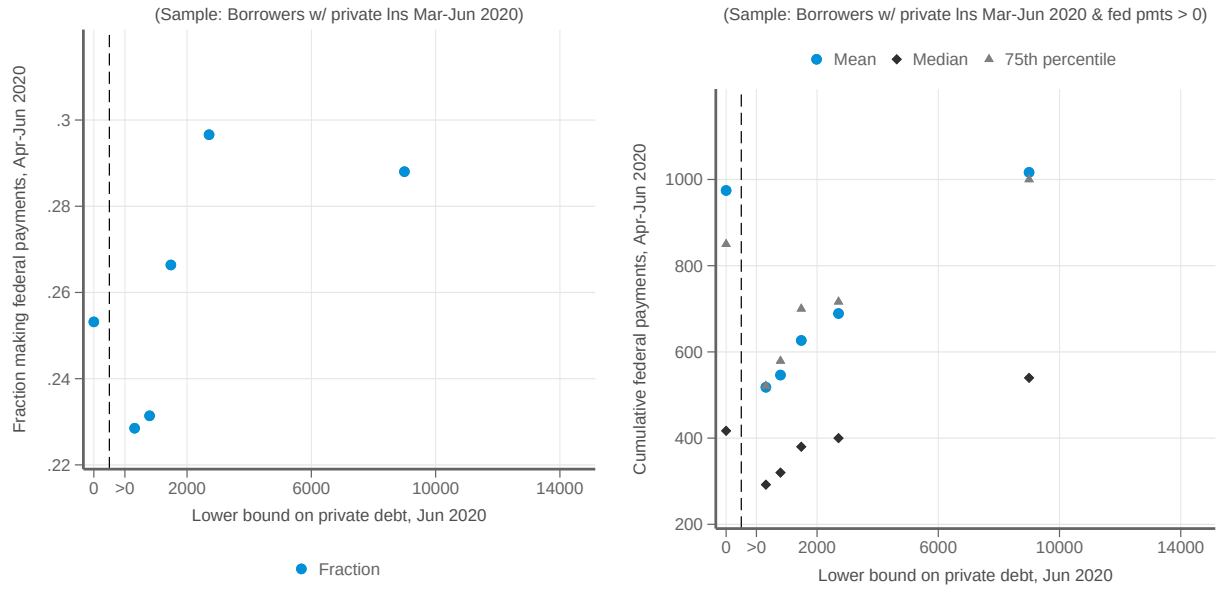
This subsection provides additional analysis for borrowers with private student loans (fact 4 in Section 4.1).

First, a comment on heterogeneity analysis based on imputed private student loan balances. Because my approach imputes higher balances for people in a comfortable financial position

who possibly pay ahead of schedule, I approach heterogeneity based on imputed balances with caution. I report them in the main text for completeness, but do not view the estimates as particularly reliable.

Second, I examine some basic summary statistics for borrowers imputed to have private student loans when forbearance began, similar to those presented in Figure 2. Appendix Figure C.4 shows that about 26% of borrowers with private student loan balances make the mistake of prepaying federal student debt in April and May, and the 75th percentile borrower with at least $9,000 in private student debt paid around $1,000 towards their 0%-interest federal student loan over that period.

Figure C.4: Debt repayment mistakes by cumulative private student loan payments



Source: Author's calculations. The figure plots debt repayment mistakes for the sample of borrowers who made positive payments on private student loans after June 1, 2020. The left panel plots the fraction of borrowers who make any payments on federal debt between April and June 2020, and the right panel plots the mean, median, and 75th percentile of cumulative payments on federal debt between April and June 2020. Each panel plots the mean value on each axis within each decile of cumulative private loan payments from June 1, 2020 through January 1, 2021. X-axis values are winsorized at the 95% level.

C.9 Evidence against alternative explanations for prepayment during forbearance

This subsection fleshes out arguments made in Section 4.1.2.

First, recall the argument that "push" autopay cannot explain results. Repayment patterns suggest that "pull" autopay is also unlikely to drive results. Autopay usage predicts that borrowers (i) pay the same amount each month post-forbearance; and (ii) pay the same amount before and after forbearance began. Contrary to (i), among borrowers making at least one federal student loan payment from April 2020 to January 2021, only 6.4% pay the same amount

each month; contrary to (ii), only 30.0% pay equal amounts in January, February, and April 2020 (allowing for ± $20 differences).

Next, recall the argument that repayment patterns provide affirmative evidence that borrowers make an active choice to repay their loans. At the onset of forbearance, repayment amounts (i) become more variable; and (ii) start clustering at whole, round numbers.

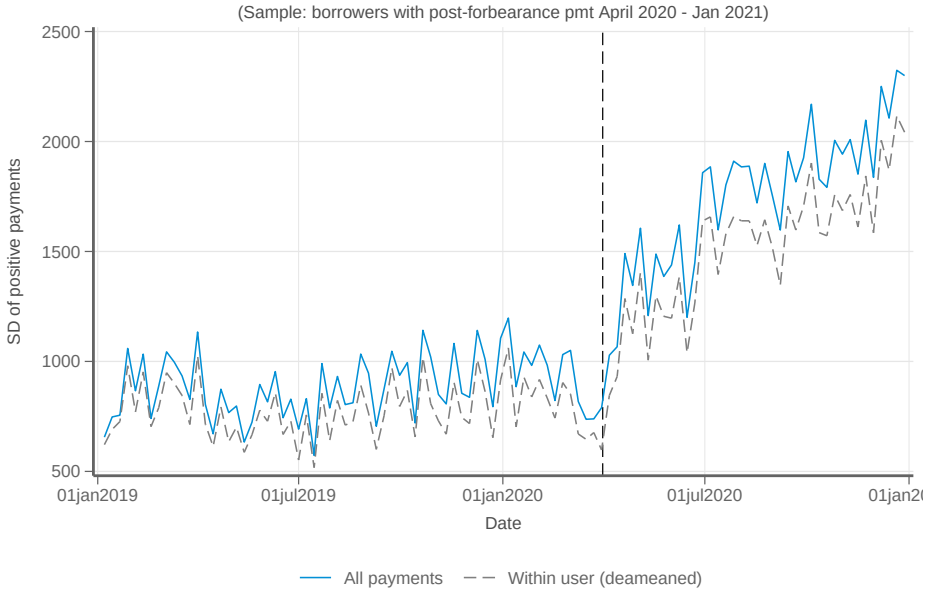
Appendix Figure C.5 shows evidence for (i). I restrict to borrowers making at least one post-forbearance loan payment, and in the solid series plot the sample standard deviation of nonzero payments in each week. Payment dispersion sharply and immediately rises when forbearance begins, with the standard deviation increasing by about 50% by the end of April. To see that changes in borrower-level repayment amounts, not changing patterns in repayment timing, drive the change, I also demean observations at the borrower level and in the dashed series report the standard deviation of the demeaned panel. For evidence on (ii), in Appendix Figure C.6 I plot the fraction of nonzero payments that are exact multiples of $5, $25, or $100 in each week, again among the fixed sample of borrowers who make a post-forbearance federal loan repayment. The fraction paying an exact multiple of $100 almost doubles from around 18% in March to around 37% by mid-April. Voluntary or manual payments are more likely to bunch at round numbers than "pull" autopayments or minimum payments. Thus, the increase in the proportion of payments that bunch at round numbers indicates more voluntary – and hence intentional – repayment. Collectively, these patterns suggest that many borrowers continued making payments because they perceived that doing so was the optimal response to forbearance, rather than following pre-forbearance habits.

C.10 Consumption impact of forbearance: Recently paid-off borrowers implementation details

Since I do not see federal student loan balances, I must impute when a borrower has repaid her loans. I start with a sample of borrowers who stop making payments as of a particular calendar date. I then check a number of conditions to verify that borrowers stopped making payments because they finished paying off their loans, rather than other reasons. Finally, I apply symmetric conditions to borrowers who *continue* making loan payments as the treatment group.

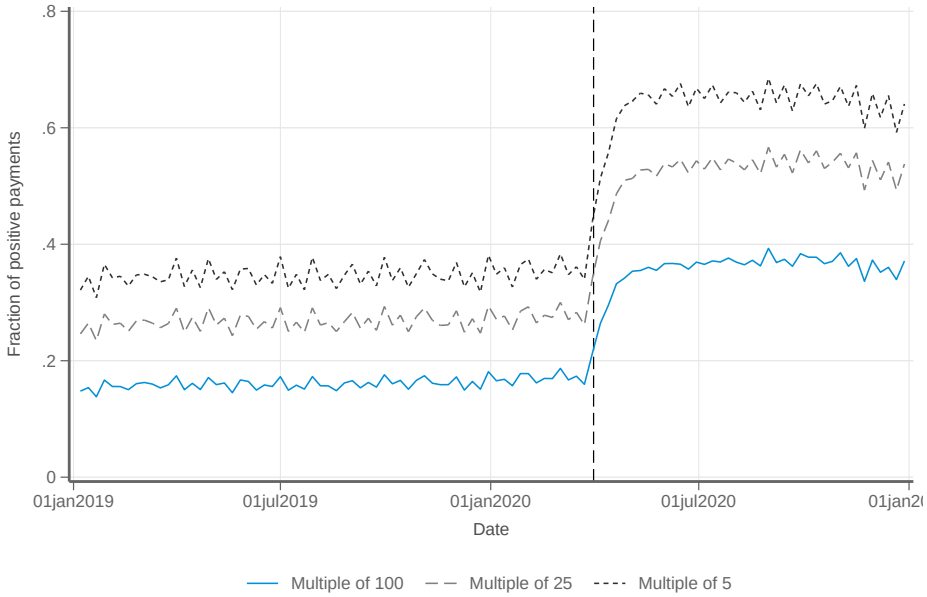
I consider borrowers who permanently stop making payments in the second and third quarters of 2019. I choose this date range for two reasons. First, it is possible that such borrowers either (i) defaulted on their loans or (ii) merely took a few months to stop paying after paying ahead before planning to resume. To account for these possibilities, I require that payments never resume after initially stopping, and that borrowers made consistent payments

Figure C.5: Standard deviation on federal student loan repayments by week



Source: Author's calculations. The sample restricts to borrowers who make at least one post-forbearance payment on federal student loans between April 2020 and January 2021. The solid series plots the sample standard deviation of nonzero payments each week. The dashed series demeans observations at the borrower level before computing the standard deviation to show "within-user" variance trends.

Figure C.6: Fraction of federal student loan payments at round numbers



Source: Author's calculations. The sample restricts to borrowers who make at least one post-forbearance payment on federal student loans between April 2020 and January 2021. Each series plots the fraction of nonzero loan payments each week that are exact multiples of 100 (solid, blue), 25 (dash, light gray), or 5 (dots, dark gray).

each month before stopping. Choosing the second and third quarters of 2019 gives me several months both before and after payments stop to make sure that both of these conditions are met. As previously indicated, and to ensure that my treatment group has similar repay-

ment patterns to the control group, I apply this continuous payment requirement to borrowers who have not repaid their debt before forbearance begins as well. Second, the end of loan repayment and ensuing liquidity may itself have an independent short-run treatment effect on spending. I therefore choose a date sufficiently far from the onset of forbearance that such treatment effects are unlikely to bias the estimated impact of forbearance.

Finally, it is also possible that federal payments cease because a borrower has decided to refinance her loan with a private lender. Borrowers who choose to refinance are likely different in unobservable ways compared with those who do not, since (i) riskier borrowers have less of an incentive to refinance, and (ii) refinancing might correlate with financial sophistication, which itself could correlate with spending patterns at the onset of the pandemic. To avoid this possibility, I drop borrowers with only private debt.

Given these restrictions and the experimental design, the coefficients σ_k in specification (8) estimate an average treatment effect on borrowers with only federal debt who meet the continuous payment requirement but have not repaid their debt before forbearance begins. I therefore apply the estimator $\widehat{MPX}_c^{f,semi}$ to this subpopulation when forming semi-structural estimates for this sample.

C.11 Consumption impact of forbearance robustness: Federal / private debt mix

This subsection describes a second natural experiment used to estimate the forbearance consumption MPX. Results are quantitatively similar to those from the payment-end natural experiment considered in Section 4.2.

C.11.1 Empirical approach

This approach uses the intuition that cumulative human capital investment influences spending outcomes, and exploits heterogeneity in the ways that borrowers happened to finance a common level of human capital investment. Specifically, the student loan forbearance program only applied to federally-owned debt, meaning that borrowers with private debt did not receive relief from the program.

I therefore compare spending outcomes before and after forbearance for borrowers who only have federal debt, and borrowers who have a similar amount of *total* debt, financed using a mix of federal and private loans. Since these groups have similar levels of education debt, I argue that they have made similar levels of human capital investments – regardless of the original circumstances that caused them to choose different financing schemes. [47]

[47] Students typically borrow as much as they can using federal programs before turning to the private student

Figure C.7 visualizes the treatment variation I use to estimate expenditure responses. The solid blue line indicates average total (federal) student loan payments each month for borrowers with only federal debt, while the gray long-dashed and short-dashed series plot average student loan payments each month for borrowers with both federal and private debt. The long-dashed series gives total student loan payments, and the short-dashed series gives student loan payments on federal loans. For quartiles 3 and 4, federal student loan payments constitute slightly more than half of total student loan payments for borrowers with both federal and private debt before forbearance begins. I group borrowers based on the quartile of pre-forbearance total debt repayment. Comparing the blue solid series to the gray long-dashed series shows that total debt repayment trajectories before forbearance are similar across the two groups. However, since borrowers with both federal and private debt have a lower federal share of total payments, they receive less liquidity when forbearance begins. Indeed, total payments drop by more in the federal-only group relative to the group with both federal and private debt. Intuitively, the identification strategy holds fixed pre-forbearance debt payments, compares the spending change before and after forbearance for borrowers with only federal debt to the change for borrowers with both federal and private debt, and correlates the difference with the difference in amount of forbearance liquidity received by the two groups. While Figure C.7 groups by quartile, I use more granular pre-forbearance payment deciles for estimation.

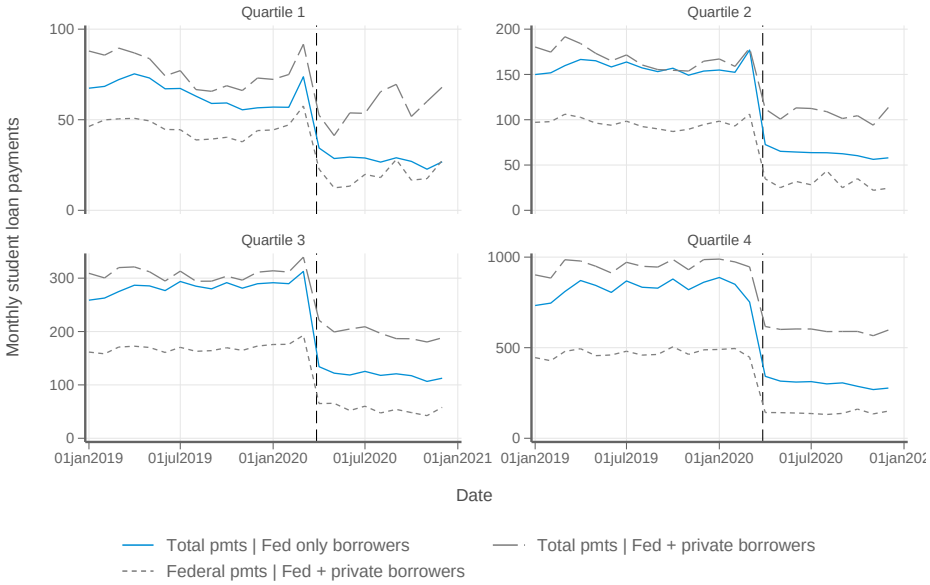
I translate this into regression form using the following specification, where t indexes month:

$$c_{it} = \gamma_i + \delta_{yt} + \chi_{ft} + \omega_{p_s,t} + \tilde{\omega}_{p_s,t} \times Total_Pmt_i + \sum_{k=-7}^{8} \sigma_k^2 \mathbb{1}(t=k)_i \cdot Fed_Pmt_i + \varepsilon_{it} \quad \text{(C.3)}$$

where coefficients have the same definition as in specification (8) with three exceptions. First, the coefficients $\tilde{\omega}_{p_s,t} \times Total_Pmt_i$ represent time-by-pre-forbearance payment decile indicators interacted with a variable giving total pre-forbearance student loan payment levels for all borrowers – both private and federal borrowing. Second, the variable Fed_Pmt_i gives the amount of liquidity received by borrowers with only federal debt, and equals zero for borrowers who have any private debt. Third, the coefficients χ_{ft} interact time indicators with an indicator variable that equals one when a borrower has any private debt. This set of fixed effects means that σ_k^2 is measured using intensive margin variation in the amount of liquidity received from forbearance for borrowers with only federal debt versus a mix of federal and private debt. It is meant to reduce concerns about time-varying spending differences driven by

loan market, where interest rates tend to be higher and repayment terms less forgiving. Limits on federal borrowing depend mostly on family background.

Figure C.7: Monthly student loan payments by loan payment quartile, federal-only borrowers vs. federal and private borrowers



Source: Author's calculations. The figure illustrates the treatment variation used in the federal-private payment mix natural experiment. Each series plots average monthly student loan payments for borrowers in the sample. The blue solid series gives values for borrowers with only federal student loans. The gray dashed series plot values for borrowers with both federal and private debt. The long-dashed series plots total student loan payments (summing federal and private), while the short-dashed series plots federal student loan repayments. Panels group borrowers by quartile of total pre-forbearance student loan payments.

selection into obtaining *any* private debt.[48]

The coefficients of interest are σ_k^2, which intuitively deliver the expenditure effect of an additional dollar in federal debt, holding fixed total debt, in event time period k. The identifying assumption to interpret these coefficients as a causal effect is that absent forbearance, spending trends would have evolved in parallel for borrowers with the same overall payment levels but a different composition of debt payments between federal and private borrowing, controlling for income-by-time trends.

C.11.2 Implementation details

Borrowers get to choose whether they take out private or federal debt. This raises the threat to identification that borrower debt mix correlates with time trends near the start of the Covid pandemic. I previously argued that conditional on the level of borrowing, borrower consumption patterns should evolve similarly, even if the initial debt mix at first correlated with a borrower's socioeconomic status. However, this argument does not apply if borrowers can adjust their debt mix after obtaining their education.

More specifically, refinancing activity that alters the borrower debt mix may threaten identi-

[48] Results are similar without this set of fixed effects, indicating that this concern has limited impacts on results.

fication for reasons previously mentioned. I therefore make sample selection choices to exclude borrowers who appear to refinance. To do so, I require that borrowers with both federal and private payments continue to make payments on federal debt for more than 31 days after the first recorded private debt payment. This ensures that private payments do not emerge as a replacement to federal student loan payments.

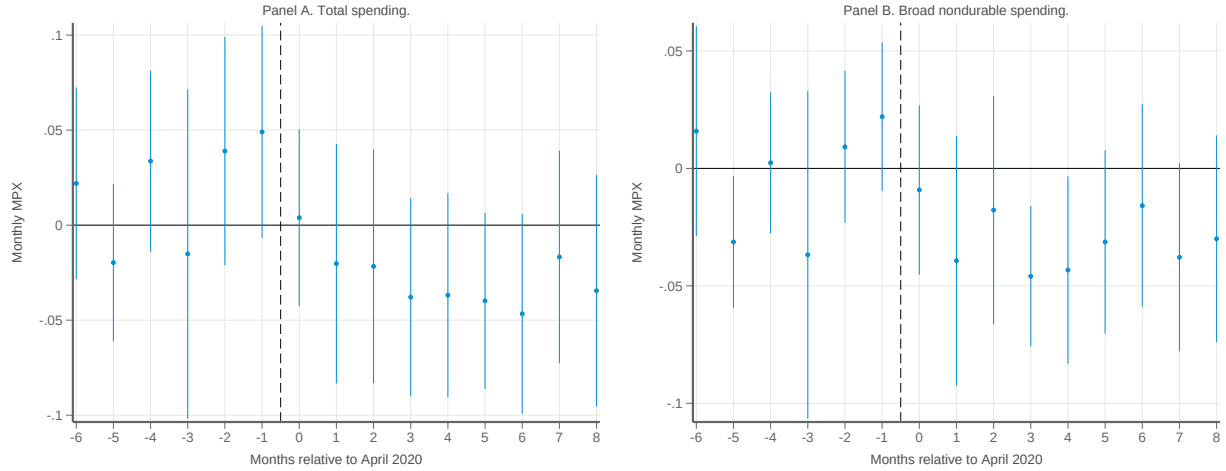
Given these restrictions and the experimental design, the coefficients σ_k^2 in specification (C.3) estimate an average treatment effect on borrowers with only federal debt. I therefore apply the estimator $\widehat{MPX}_c^{f,semi}$ to this restricted population when forming semi-structural estimates for this sample.

C.11.3 Results

To evaluate the identifying assumption behind the natural experiment, Figure C.8 plots $\hat{\sigma}_k^2$ from specification (C.3). I omit the coefficient that interacts the event time coefficient representing more than six months before forbearance begins with payment amount.

The figure broadly shows no pre-trends, supporting the interpretation that σ_k^2 represents the causal impact of an additional dollar of monthly forbearance liquidity on spending in the k^{th} month following the start of forbearance.

Figure C.8: Effect of forbearance on monthly spending – heterogeneous federal-private debt mix



Source: Author's calculations. The figure plots event time coefficients $\hat{\sigma}_k^2$ estimated from specification (C.3). Spikes plot robust 95% confidence intervals clustered at the borrower level. The left panel shows estimates where the outcome variable is total spending. The right panel shows estimates where the outcome variable is broad nondurable spending.

Table C.6 presents full results. Stimulus payment MPX and semi-structural forbearance MPX estimates are similar to previous columns. This second natural experiment again suggests a lower forbearance MPX than either the stimulus payment or semi-structural MPX. Specifically,

the estimated forbearance MPX has a statistically-insignificant point estimate of -0.8 to 0.4%, with 95% confidence intervals ruling out estimates greater than 5.1%.

Panel B reports estimates for the broad nondurable spending MPX out of stimulus payment and forbearance liquidity. Borrowers spend about 9% of their stimulus checks on nondurables within the first four weeks. Estimates from the heterogeneous federal-private debt mix natural experiment give statistically insignificant point estimates of -2.4 to -0.9%, with 95% confidence intervals ruling out estimates exceeding 2.6%.

Table C.6: Four-week spending MPX, stimulus vs. student loan forbearance, Federal-private mix natural experiment

	C. Federal-private mix	
Spending	Total	Broad nondurable
Liquidity source and measurement		
Stimulus checks	0.177***	0.052
	(0.01)	(0.03)
Forbearance: Paid off borrowers (Month 1)	0.004	-0.009
	(0.024)	(0.018)
Implied expenditure out of forbearance cash-on-hand	0.022***	0.011
	[0.002,0.117]	[-0.023,0.04]
Forbearance: Paid off borrowers (Month 2)	-0.008	-0.024
	(0.021)	(0.017)
Implied expenditure out of forbearance cash-on-hand	-0.002	-0.02
	[-0.046,0.074]	[-0.071,-0.001]
Forbearance: Semi-structural	0.113***	0.08***
	[0.083,0.155]	[0.065,0.104]
N	285,663	285,663

Source: Author's calculations. * p=0.05, ** p=0.01, *** p=0.001. Each entry reports a four-week MPX out of either the first round of stimulus payments or student loan forbearance, with robust standard errors clustered at the borrower level in parentheses below. Rows indicate both the liquidity source (stimulus payments or student loan forbearance) and the estimation strategy (semi-structural and the federal-private mix natural experiment). Panel A gives the four-week total spending MPX, and Panel B gives the four-week broad nondurable spending MPX. Semi-structural standard errors and hypothesis tests are computed via bootstrap; I report the standard deviation of the estimate from 150 bootstraps, and calculate p-values by inverting the largest $1-\alpha/2$-level confidence interval that does not contain zero. Note that the row labeled "N" refers to the number of borrowers included in the estimated average treatment effect, which may be smaller than the number of borrowers in the regressions used for natural experiment exercises. See section C.11 for details on estimation, and see section 3.1 for detailed descriptions of expenditure category construction.

C.12 Robustness: Alternative estimates for MPX out of forbearance liquidity

This subsection describes robustness exercises for the analysis summarized in Table 3 and described in Section 4.2. I report results for the sample included in the paid-off borrowers difference-in-differences, the full sample, and the federal-vs-private borrowers difference-in-differences described in Appendix Section C.11.

The results are in Table C.7. The second row reports an alternative estimate of the semi-structural MPX given by $\widehat{MPX}_c^{f,semi}$ in the main text. Specifically, rather than parameterizing $\frac{\partial c_i}{\partial X}$ as a linear function of $MPX^f_{p_s,i}$, I instead allow a more flexible functional form:

$$\frac{\partial c_i}{\partial X} = \phi_0 + \sum_k \mu_k \mathbb{1}(MPX^f_{p_s,i} \in T_k) \cdot MPX^f_{p_s,i} \tag{C.4}$$

where T_k are bins of $MPX^f_{p_s,i}$. I choose 5 bins: one bin for $MPX^f_{p_s,i} = 0$, and four equal-sized bins split by quartiles of positive $MPX^f_{p_s,i}$.

The third row reports an alternative estimate of the semi-structural MPX, where instead of estimating the parameters of the linear relationship between $\frac{\partial c_i}{\partial X}$ and $MPX^f_{p_s,i}$ using the fixed effects estimator as in the main text, I instead use the imputation estimator from Borusyak, Jaravel, and Spiess (2024).

Table C.7: Four-week spending MPX, stimulus vs. student loan forbearance, miscellaneous robustness

	A. Paid off borrowers		B. Full sample		C. Federal-private mix	
Spending	Total	Broad nondurable	Total	Broad nondurable	Total	Broad nondurable
Analysis						
Stimulus check MPX: imputation estimator	0.15*** (0.017)	0.069*** (0.011)	0.17*** (0.011)	0.072*** (0.007)	0.168*** (0.012)	0.069*** (0.008)
Semi-structural MPX: Nonlinear OLS estimates	0.126*** [0.105, 0.146]	0.071*** [0.059, 0.083]	0.109*** [0.096, 0.121]	0.057*** [0.05, 0.066]	0.11*** [0.096, 0.124]	0.058*** [0.05, 0.066]
Semi-structural MPX: imputation estimator	0.106*** [0.069, 0.139]	0.049*** [0.028, 0.073]	0.091*** [0.069, 0.113]	0.038*** [0.024, 0.052]	0.082*** [0.06, 0.104]	0.038*** [0.024, 0.052]
N	130,144	130,144	313,312	313,312	285,663	285,663

Source: Author's calculations. * p=0.05, ** p=0.01, *** p=0.001. Each entry reports a four-week MPX out of either the first round of stimulus payments or student loan forbearance, with robust standard errors clustered at the borrower level in parentheses, and bootstrapped 95% confidence intervals from 1,000 draws in brackets, as relevant. Rows indicate liquidity source (stimulus checks or forbearance) and details about estimation strategy. Columns indicate sample and spending outcome variables. Rows titled with "imputation estimator" refer to the estimator described in Borusyak, Jaravel, and Spiess (2024). See section C.12 for details on estimation, and see section 3.1 for detailed descriptions of expenditure category construction.

D Survey appendix

D.1 Recruitment details

I recruited survey participants using Prolific, an online survey platform. Recruitment ran from March 4, 2023 to March 7, 2023, and the main survey ran from March 9, 2023 to March 13, 2023.

My target population was US adults who had outstanding student debt when forbearance began in March 2020. To recruit an appropriate population, I first ran a short screening survey with a question that asked respondents whether they had outstanding student debt anytime from 2019 to the present. I sent the screening survey to a balanced sample of men and women who had completed at least a high school education.[49] I described the screening survey as a one-minute "academic study" conducted by researchers at Harvard without specifying that the screening survey attempted to identify borrowers with outstanding student debt. I added dummy questions about exercise habits, cohabitation with family members, and car ownership to ensure honest answers to the student debt screen. I paid 2,800 participants $0.20 to complete the survey. With a median answer time of 37 seconds, the effective hourly compensation was about $20 / hr.

I then sent the full survey, hosted on Qualtrics, to the 1,025 respondents who reported in the screening survey that they had outstanding student debt at some point between 2019 and the present. I described the follow-up survey as a "student debt study" designed to understand borrower experiences with student debt. The survey was advertised to take about 10 minutes (despite taking a median of around 7 minutes in piloting), and respondents were paid $2 for their time. The median respondent completed the survey in 7.5 minutes, for an effective hourly compensation of about $16.1 / hr.

In accordance with my pre-registration plan, I instructed Prolific to recruit until I received 800 responses. This number was motivated by power calculations I conducted for the experimental hypothetical question described in the text. Due to Prolific not closing off responses quickly enough, I ended up with 801 responses on Qualtrics. Out of the 801 responses I received, two respondents decided not to participate when asked to complete the Qualtrics informed consent form. One respondent failed a pre-registered sample selection screen – namely, spending at least nine seconds before answering a complicated hypothetical question. Therefore, the final survey had 798 valid responses.

[49] I included people who completed technical or community college.

D.2 Survey instrument details

I asked the modules described in the main text in the following order. I first asked questions to identify student loan debt repayment mistakes. Then I ran the experiment. I then assessed policy knowledge, asked borrowers why they made student loan debt repayment mistakes if relevant, and closed with the financial sophistication screen.

The full set of survey questions is available here:
https://jdikatz.github.io/assets/files/forbearance_survey_questions_20230308.pdf.

D.3 Pre-registration

I preregistered experimental survey components using the Wharton Credibility Lab's AsPredicted platform and the AEA RCT Registry. The analysis plan registered with the AEA details the power calculations that I used to arrive at a targeted sample size of 800 borrowers.

- The AEA RCT Registry analysis plan is available here:
  https://doi.org/10.1257/rct.11040-1.1.
- The AsPredicted analysis plan is available here:
  https://aspredicted.org/ej67r.pdf.

The full set of pre-registered survey splits are in Appendix Table D.8.

D.4 Summary statistics and replicating transaction data results

Table D.9 presents summary statistics for the full sample of survey respondents. The average respondent is aged 36, has 2.6 people in their household, and has modal annual income between $50,000-100,000. Around 90% of respondents report having federally-owned student debt as of March 2020.[50]

Table D.9 also replicates core empirical results from the transactions data in the survey sample. First, a large fraction of borrowers continue to make payments on federal student debt, even after forbearance begins. Among those with any student debt in March 2020, 32% have made payments between the start of forbearance and the present. Excluding borrowers who were in school, their grace period, deferment, or forbearance in February 2020, the fraction rises to 37%. I use this more restrictive version of continued payments when conditioning on

[50]The remaining 10% likely ended up in the sample because they were college students or recent graduates who did not have debt in March 2020, but took out debt between March 2020 and the present.

Table D.8: Survey: Framing x interest rate experimental results (all)

VARIABLES	(1) SL repay	(2) SL repay	(3) SL repay	(4) SL repay	(5) SL repay	(6) SL repay	(7) SL repay	(8) SL repay	(9) SL repay	(10) SL repay	(11) SL repay	(12) SL repay	(13) SL repay	(14) SL repay
Cue category = 1, Student borrowers	0.0242				0.0490**				0.0192	0.0171				
	(0.0153)				(0.0205)				(0.0281)	(0.0294)				
Age	-0.000554	-0.000585		-0.000531	-0.000397	-0.000591		-0.000372		-0.00392		-0.00383		-0.00387
	(0.000874)	(0.000875)		(0.000873)	(0.00138)	(0.00139)		(0.00138)		(0.00688)		(0.00687)		(0.00689)
Age squared	5.85e-07	6.10e-07		5.67e-07	3.99e-07	5.82e-07		3.81e-07		6.21e-05		6.14e-05		6.17e-05
	(9.15e-07)	(9.15e-07)		(9.13e-07)	(1.44e-06)	(1.45e-06)		(1.44e-06)		(9.83e-05)		(9.80e-05)		(9.84e-05)
Age missing = o,	-	-		-	-	-		-		-		-		-
Income<50k	0.0197	0.0188		0.0199	0.0105	0.00604		0.0109		0.0604*		0.0630*		0.0655*
	(0.0184)	(0.0184)		(0.0184)	(0.0250)	(0.0252)		(0.0250)		(0.0348)		(0.0352)		(0.0355)
Income 50-100k	0.0224	0.0223		0.0229	0.0275	0.0261		0.0283		0.0580*		0.0627*		0.0634*
	(0.0191)	(0.0190)		(0.0191)	(0.0285)	(0.0286)		(0.0286)		(0.0344)		(0.0346)		(0.0350)
Has CC debt	0.00309	0.00180		0.00322	0.0350	0.0340		0.0363		0.00674		0.00632		0.00744
	(0.0234)	(0.0233)		(0.0233)	(0.0293)	(0.0286)		(0.0292)		(0.0394)		(0.0392)		(0.0389)
Has SL debt	-0.0413	-0.0385		-0.0418	-0.0193	-0.0104		-0.0195		-0.0187		-0.0194		-0.0217
	(0.0437)	(0.0436)		(0.0438)	(0.0675)	(0.0678)		(0.0677)		(0.0483)		(0.0468)		(0.0487)
Has other non-mtg debt	-0.0425	-0.0442		-0.0438	-0.0740	-0.0801		-0.0777		-0.0141		-0.0194		-0.0191
	(0.0349)	(0.0346)		(0.0347)	(0.0505)	(0.0501)		(0.0509)		(0.0596)		(0.0591)		(0.0593)
Has mtg debt	0.0241	0.0249		0.0242	0.0234	0.0253		0.0238		-0.0511		-0.0492		-0.0474
	(0.0154)	(0.0154)		(0.0154)	(0.0230)	(0.0232)		(0.0230)		(0.0330)		(0.0329)		(0.0329)
SL interest rate = 1, 7%		-0.00868				-0.0132					-0.0327	-0.0374		
		(0.0150)				(0.0212)					(0.0280)	(0.0287)		
Treatment arm = 2, SL cue, 7% interest			0.00650	0.00893			0.00828	0.0134					0.0398	0.0480
			(0.0231)	(0.0229)			(0.0338)	(0.0340)					(0.0390)	(0.0403)
Treatment arm = 3, US cue, 0% interest			-0.0235	-0.0238			-0.0499*	-0.0485					-0.00960	-0.00456
			(0.0210)	(0.0213)			(0.0292)	(0.0295)					(0.0353)	(0.0369)
Treatment arm = 4, US cue, 7% interest			-0.0188	-0.0155			-0.0421	-0.0360					0.0140	0.0208
			(0.0205)	(0.0206)			(0.0293)	(0.0300)					(0.0380)	(0.0390)
Constant	0.138***	0.156***	0.0968***	0.159***	0.126*	0.161**	0.131***	0.169**	0.110***	0.186	0.136***	0.213*	0.108***	0.178
	(0.0494)	(0.0527)	(0.0156)	(0.0528)	(0.0662)	(0.0700)	(0.0235)	(0.0737)	(0.0199)	(0.120)	(0.0218)	(0.120)	(0.0232)	(0.121)
Observations	798	798	798	798	439	439	439	439	304	304	304	304	304	304
R-squared	0.012	0.010	0.003	0.013	0.023	0.012	0.013	0.024	0.002	0.032	0.004	0.037	0.006	0.039
Sample	Full	Full	Full	Full	Mistake	Mistake	Mistake	Mistake	Repay	Repay	Repay	Repay	Repay	Repay

Source: Supplemental student borrower survey / author's calculations. This table presents regression results from a framing survey. Borrowers were asked how they would spend a $300 stimulus check over the course of a year, given large outstanding student loan and credit card balances. Participants were sorted into one of four experimental conditions. In two conditions, stimulus was framed as a transfer to all US households; in two conditions, stimulus was framed as a transfer to student borrowers. In another two conditions, the interest rate on student debt was quoted at 0%, while in the remaining conditions, the interest rate on student debt was quoted at 7%. The table reports the effect of the student borrower framing (first row) and the 7% interest rate (second row) treatment conditions on student loan repayment as a fraction of the total transfer. The first three columns show results for the full sample. The second three columns show results for the sample of borrowers who make a credit card repayment mistake in a separate financial sophistication screen. The third three columns show results for the sample of borrowers who continue to make payments on their federal student debt after forbearance begins. All regressions were pre-registered as part of the experimental pre-analysis plan.

borrowers who continue to make payments for the remaining table rows, since it better aligns with my transaction data sample selection criteria.[51]

Second, borrowers use liquidity from stimulus payments inconsistently with liquidity from forbearance. While 37% of borrowers required to make payments as of February 2020 continue to make payments after forbearance begins, around 80% of those same borrowers do *not* use their stimulus checks to make payments on their federal loans. Third, borrowers with other interest-bearing debt also prepay. Among those who prepay federal student loans after forbearance begins, 47.7% have interest-bearing credit card debt and 70.5% have interest-bearing credit card, auto, medical, or mortgage debt in March 2020. Among borrowers with credit card debt in March 2020 who prepaid federal student loan debt post-forbearance, 35% used their stimulus checks to pay down credit card debt.

Table D.9: Survey: Debt repayment mistakes, non-fungibility, and demographics.

	Mean	SE of mean
Has federal student debt, March 2020	.904	.0105
Continued federal pmts | has federal debt March 2020	.315	.0173
Continued pmts | pmts required in Feb 2020	.37	.0223
Used stimulus for fed loans | continued pmts + got check	.208	.0323
CC debt in March 2020 | continued pmts	.477	.038
Interest-bearing debt March 2020 | continued pmts	.705	.0348
Used stimulus to repay non-federal debt | continued pmts	.302	.0365
Used stimulus to repay non-federal debt | continued pmts + has debt + got check	.333	.0412
Used stimulus to repay CC debt | continued pmts + has cc debt + got check	.348	.0508
Age	36.4	1.18
Income<50k	.323	.0166
Income 50-100k	.372	.0171
Income>100k	.305	.0163
Household size	2.61	.0517
Count	798	

Source: Supplemental student borrower survey / author's calculations. The table presents survey summary statistics. The second row conditions on borrowers who say they have outstanding federal debt in March 2020. The third row conditions on borrowers who say they have outstanding federal debt in March 2020, excluding borrowers who report that they were still in school, were in a grace period, were in deferment or forbearance, or did not have student loans as of February 2020. The remaining "continued pmts" conditions condition on this second form of continuing payments.

D.5 Time-inconsistent preferences and limited attention as alternative explanations.

This subsection considers alternative types of costs that might generate debt repayment mistakes or inconsistent use of liquidity from forbearance and stimulus.

Sophisticated time-inconsistent borrowers may continue payments as a "soft commitment" (Bryan, Karlan, and Nelson, 2010): from the perspective of long-run preferences, stopping

[51] Recall that the transaction sample selects borrowers who made payments on federal debt during 2019. Borrowers who were in school, grace, deferment, or forbearance as of February 2020 likely did not make any payments during 2019, and hence would not meet my transactions data sample selection criteria.

payments could facilitate over-consumption by increasing liquid resources available to present-focused selves. However, in Table 4b, only 12% of prepayers did so because they "did not trust [themselves] to put enough money aside" for when payments resumed. Among this group, only 20% implemented this strategy by repaying federal student loans using stimulus check funds (Appendix Table D.10). Moreover, if attention is limited or costly, then borrowers may continue making payments because they optimally choose to ignore higher-frequency changes in government student loan policy (Caplin, 2016, Gabaix, 2019). However, in Table 4b, only 8.6% of prepayers "continued making payments" because "it wasn't worth paying attention to changing student debt policies."

Table D.10: Survey: Justifications for student loan payments in forbearance, detail

	Mean
Used stimulus to prepay federal loan | 0% interest justification	.222
Used stimulus to prepay federal loan | self control justification	.2
Used stimulus to prepay federal loan | always repay debt justification	.213
Used stimulus to repay debt | always repay debt justification	.394
Autopay with servicer | hassle justification	.4
Count	174

Source: Student borrower survey. Rows 1 and 2 report the fraction of respondents who justified their repayment behavior for 0% interest or self control reasons who also used their stimulus checks to repay student debt. Row 3 reports the fraction of respondents who justified their repayment behavior due to the hassle of stopping and restarting who said they made payments via autopay with their student loan servicer.

E Fiscal policy calibration appendix

E.1 Calibration exercise derivations

E.1.1 Consumption impact of forbearance versus stimulus checks

In a model where high MPCs are due to liquidity constraints and borrowers cost-minimize in response to forbearance, a spender would increase consumption by $p_i \cdot L_i$. However, target deviation costs reduce the consumption MPX out of forbearance liquidity relative to the cash windfall consumption MPX (Claim 4). Define $\gamma := \frac{MPX_c^f}{MPX_c^w} = \frac{E[\chi_i(1-\eta_i)L_i]}{E[L_i]}$ as in the text, where χ_i equals one if borrower i chooses saving optimally and zero otherwise. The term $\chi_i(1-\eta_i)$ represents how a dollar of cash windfall MPC translates into a forbearance MPC. The second equality comes from Equation (10).

The parameter γ depends on (i) total saving target deviation costs and (ii) the correlation between target deviation costs for total saving and student loan repayment.

The fiscal cost of forbearance is the present value cost of advancing six consecutive one-month, zero spread loans of balance $(1-\eta_i)p_i$ for term T_s. The per-period cost is $\Delta RE[(1-\eta_i)p_i]$. The present-value cost is:

$$G_f = \sum_{q=0}^{5}\left(\sum_{t=q}^{T_s+q}\frac{\Delta RE[(1-\eta_i)p_i]}{R^t}\right) \tag{E.1}$$

$$= \Delta RE[(1-\eta_i)p_i]\cdot\left(\sum_{t=0}^{T_s}R^{-t}\right)\left(\sum_{q=0}^{5}R^{-q}\right) \tag{E.2}$$

$$= \tilde{R}(T_s)\Delta RE[(1-\eta_i)p_i] \tag{E.3}$$

where $\tilde{R}(T_s) := \frac{(R^{T_s+1}-1)(R^6-1)}{R^{T_s+5}(R-1)^2}$.

The total consumption impact of forbearance depends on whether relief is targeted towards borrowers with high consumption MPC L_i. The one-month consumption impact of forbearance is $\Delta C_f := E[p_i]\cdot E[\chi_i(1-\eta_i)\rho_i L_i]$, which can be rewritten as:

$$\Delta C_f = E[p_i]\cdot E[\chi_i(1-\eta_i)]\cdot\left(E[L_i] + \underbrace{\mathrm{Cov}(\rho_i, L_i)}_{\text{resource targeting}} + \underbrace{\frac{\mathrm{Cov}\left(\chi_i(1-\eta_i), \rho_i L_i\right)}{E[\chi_i(1-\eta_i)]}}_{\text{behavioral targeting}}\right) \tag{E.4}$$

This depends on: (i) total liquidity delivered by the transfer, ($E[p_i]$); (ii) average consumer MPCs ($E[L_i]$); (iii) the average effect of marginal forbearance liquidity on cash-on-hand ($E[\chi_i(1-\eta_i)]$), and (iv) two types of targeting. The "resource targeting" term reflects program targeting towards constrained borrowers with high L_i. The "behavioral targeting" term reflects program

targeting towards constrained borrowers who actually spend the liquidity from forbearance – or have low target deviation costs. This captures whether unconstrained borrowers with low L_i are less likely to "take up" forbearance and instead continue repaying their debt.

Now consider a direct cash transfer policy where the government sends a total of G_w to borrowers as stimulus checks. Borrower i gets $w_i G_w$, where w_i is the share of total spending targeted towards i. Borrowers spend $w_i L_i G_w$. The present-value fiscal cost is G_w, and the consumption impact is:

$$\Delta C_w := G_w \cdot E[w_i L_i] = G_w \left(\mathrm{Cov}(w_i, L_i) + E[L_i]\right) \tag{E.5}$$

As in (E.4), the total consumption impact depends on the size of the transfer, average constraints, and targeting toward constrained borrowers.

Applying the definition of E_f, setting $G_w = G_f$, and using equations (E.4) and (E.5):

$$\begin{aligned}
E_f &:= \frac{\Delta C_f - \Delta C_w}{G_f} \\
&= \frac{E[p_i] \cdot E\left[\chi_i(1-\eta_i)\rho_i L_i\right] - G_w \cdot E[w_i L_i]}{\tilde{R}(T_s)\Delta R E[(1-\eta_i)\rho_i] \cdot E[p_i]} \\
&= \frac{E\left[\chi_i(1-\eta_i)\rho_i L_i\right]}{\tilde{R}(T_s)\Delta R E[(1-\eta_i)\rho_i]} - E[w_i L_i] \\
&= \left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)\left(\frac{E[\rho_i L_i]E[\chi_i(1-\eta_i)] + \mathrm{Cov}(\chi_i(1-\eta_i), \rho_i L_i)}{E[(1-\eta_i)\rho_i]}\right) - E[w_i L_i] \\
&= \left[\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)\left(\frac{E[\rho_i L_i]}{E[w_i L_i]}\right)\left(1 + \frac{\mathrm{Cov}(\chi_i(1-\eta_i), \rho_i L_i)}{E[\chi_i(1-\eta_i)]E[\rho_i L_i]}\right)\left(\frac{E[\chi_i(1-\eta_i)]}{E[\rho_i(1-\eta_i)]}\right) - 1\right] E[w_i L_i]
\end{aligned} \tag{E.6}$$

Rearranging equation (E.6) yields expression (11) in the main text.

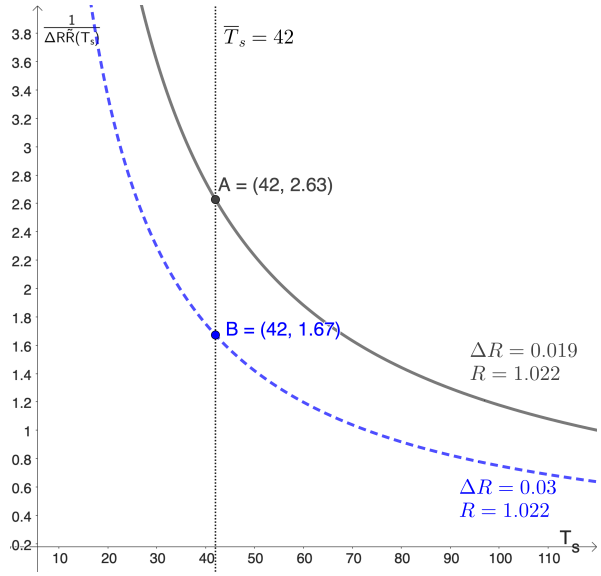
E.2 Sensitivity of E_f to calibrated values

This section gives additional details for how E_f varies with calibrated parameters.

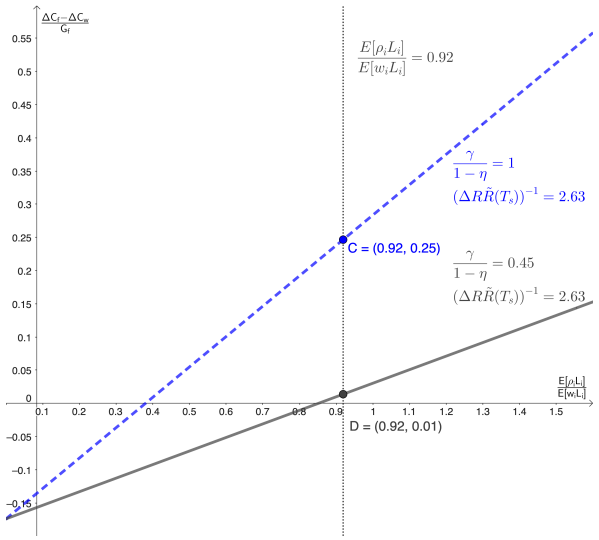
Figure E.9, Panel E.9a shows how the average cost effect depends on forbearance length T_s and the interest rate spread on student loans ΔR. The grey solid line shows the relationship for $\Delta R = 1.9\%$, and the dashed blue line shows the relationship for $\Delta R = 3\%$. More generous forbearance due to a longer remaining term on outstanding loans or a higher interest rate spread erodes the forbearance fiscal cost advantage relative to stimulus checks. Since there are no catch-up payments, the outstanding term impacts how long the government must wait before it is repaid for forgone interest, the amount of which is controlled by ΔR.

The grey dotted line shows my choice of $T_s = 42$ months. This intersects with the grey

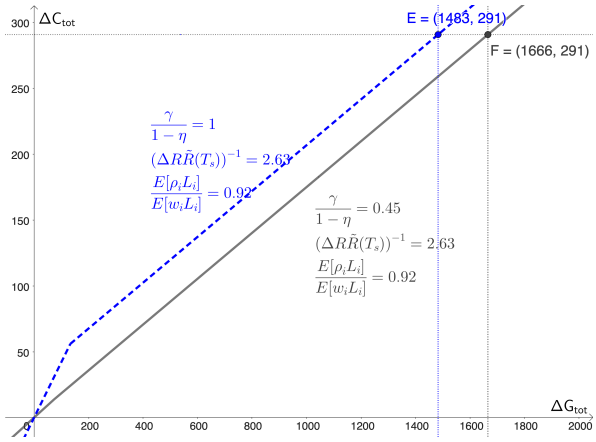
Figure E.9: Impact of flypaper effect on countercyclical fiscal policy design: Sensitivity to calibrated values



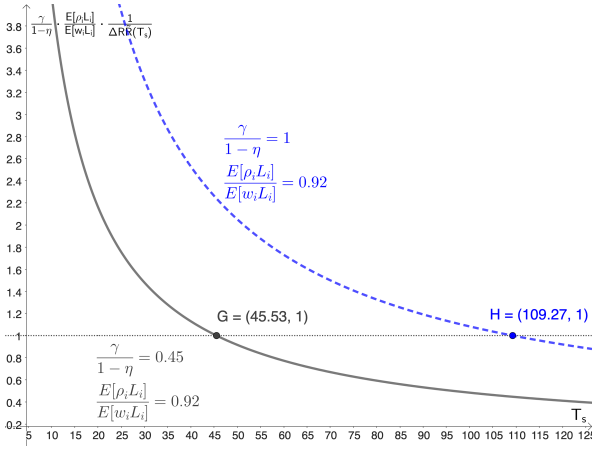
(a) Average cost effect vs. remaining loan repayment term.



(b) Forbearance fiscal cost efficiency vs. targeting effect.



(c) Calibration 1. Stimulus check size.



(d) Calibration 2. Break-even repayment term.

The gray solid line plots estimates with $\gamma = 0.25, \eta = 0.44$, and the blue dashed line reports estimates under $\gamma = 1, \eta = 0$ Panel (a) shows how the reciprocal of the present value of the fiscal cost per dollar of forbearance liquidity (vertical axis) varies by the number of months left until borrowers repay their loan (horizontal axis). The text refers to the quantity on the vertical axis as the "average cost" effect. Point A gives baseline estimates for the average cost effect assuming $T_s = 42$ months remaining on student loans; point B shows how the average cost effect changes when the student loan spread increases from 1.9% to 3%. Panel (b) shows how forbearance fiscal cost efficiency relative to stimulus checks (vertical axis) varies based on how well forbearance liquidity is targeted towards high MPX households relative to stimulus checks (horizontal axis, denoted the "targeting effect"). The blue dashed line shows the relationship assuming no flypaper effect ($\gamma = 1, \eta = 0$). The grey solid line shows the relationship given the flypaper effect estimated in the transactions data ($\gamma = 0.25, \eta = 0.44$). The vertical dotted line denotes the baseline estimated targeting effect from Appendix E.4. Comparing points C and D indicates that the flypaper effect reduces the forbearance fiscal cost efficiency from $E_f = 0.25$ to $E_f = 0.01$. Panel (c) plots total spending on forbearance and stimulus checks against one-month total consumption changes. The vertical line intersection E plots expected government spending if $\gamma = 1, \eta = 0$. Panel (d) plots repayment term T_s on the horizontal axis against the first term in brackets in equation (12) on the vertical axis. The break-even repayment term is where this line intersects one.
See Section 6 for details.

solid line at point A to show the estimate of the average cost effect in the baseline calibration of 2.63.

Figure E.9, Panel E.9b fixes the forbearance average cost effect at point A in Panel E.9a, and shows how variation in the targeting effect κ and flypaper effect $\frac{\gamma}{1-\eta}$ impact E_f. This plot fixes $E[w_i L_i]$ at its baseline value of 0.17. The blue dashed line ignores the flypaper effect, and shows the relationship between the targeting effect and the forbearance fiscal cost efficiency. Given its average cost advantage, forbearance remains more efficient even if it is much more poorly targeted than stimulus checks. The gray solid line shows how the flypaper effect changes this assessment. Since the estimated flypaper effect counteracts the average cost effect, it: (i) blunts forbearance's fiscal cost advantage; and (ii) requires better-targeted forbearance for forbearance to retain a fiscal cost advantage.

My estimate of $\hat{\kappa} = 0.92$ is plotted as a vertical line in Figure E.9, Panel E.9b. This shows how E_f drops from 0.25 (Point C) to 0.01 (Point D) once accounting for the estimated flypaper effect.

Figure E.9, Panel E.9c plots the present value of total government spending against the total one-month increase in consumption ΔC_{tot}. The dashed blue line assumes no flypaper effect, while the solid gray line uses estimated γ and η. The vertical line intersecting point E plots the expected cost of the rescue package, which I estimate to be \$1,483 given average student loan payment and stimulus check size in the transactions data.

The package was originally expected to increase consumption by \$291 (point E). The flypaper effect implies that forbearance only increases consumption by \$14, rather than the expected \$56. Stimulus checks would have to total \$1,591 (18% higher) to make up the difference, bringing the total fiscal cost to \$1,666 (point F, 12% higher).

Figure E.9, Panel E.9d plots break-even forbearance length T^{BE} against T_s. When $\gamma = 1$ and $\eta = 0$, $T^{BE} = 110$ (point H). The flypaper effect implies that $T^{BE} = 46$ (point G), 58% lower.

E.3 Additional details on computations for Calibration 1

To calculate the expected cost of the rescue package, note that:

$$G_{tot} = G_w + G_f \tag{E.7}$$

Using the formulas in the text and applying $\eta = 0, \chi = 1$, $G_f = \tilde{R}(T_s)\Delta RE[(1-\eta_i)p_i]$. Moreover, $G_w = E[w_i G_w]$, the average stimulus check size. Since $E[p_i] \approx 350$ in the transactions

data, we have:

$$G_{tot} = 350 \times 2.63^{-1} + 1,350 = 1,483 \tag{E.8}$$

as cited in the text.

Total consumption would be expected to increase by:

$$0.174 \times \kappa \times E[p_i] + 0.174 \times E[w_i G_w] = 291 \tag{E.9}$$

as in the text.

How would the estimated flypaper effect impact the package, holding fixed the increase in one-month aggregate consumption? Total consumption from forbearance becomes:

$$0.174 \times \kappa \times \gamma \times E[p_i] = 14 \tag{E.10}$$

Therefore, stimulus checks must increase consumption by $291 - 14 = 277$. This requires stimulus checks of size $277/0.174 = 1,591$.

E.4 Forbearance targeting estimates

This section describes the procedure for estimating κ in equation (12), which impacts how the different targeting properties of student loan forbearance and stimulus checks impact the forbearance fiscal cost efficiency. Recall that:

$$\kappa = \frac{E[\rho_i L_i]}{E[w_i L_i]} \tag{E.11}$$

and from Section 4.2.2, $\widehat{E[w_i L_i]} = 0.174$. Therefore, estimating κ requires an estimate of $E[\rho_i L_i]$.

It would be conceptually straightforward to combine (i) information on pre-forbearance student loan payments and (ii) individual-level stimulus check MPX estimates to estimate $E[\rho_i L_i | w_i > 0]$. However, about one-third of borrowers receiving liquidity from forbearance do not receive a stimulus check. I use the method outlined in Section E.4.1 in the main text, where I parameterize L_i as a function of observables and use these observables to predict L_i for $w_i = 0$. In Section E.4.2, I calculate bounds on $E[\rho_i L_i]$ making very minimal assumptions on $E[L_i | w_i = 0]$, and discuss implications for the quantitative exercise in Section 6.

E.4.1 Parametric approach

Assume that:

$$L_i = \mu(x_i) + \varepsilon_i \approx \sum_k \mu_k \cdot \mathbb{1}\{x_i \in k\} + \varepsilon_i \tag{E.12}$$

where $\mu(\cdot)$ is a flexible function of liquid assets when stimulus checks arrive approximated by the constants μ_k, where μ_k is the estimated stimulus check MPX for people in liquid asset quintile k. Assume the residual $\varepsilon_i \perp \rho_i$. Then we can estimate:

$$\widehat{E[\rho_i L_i]} = \sum_k \Pr(x_i \in k) \cdot \hat{\mu}_k \cdot \widehat{E[\rho_i | x_i \in k]} \tag{E.13}$$

I do not observe liquid assets directly, so I proxy for it using savings in March 2020 as a fraction of 2019 income. People with large dis-savings during that period are likely experiencing financial distress, and hence likely have a higher short-run MPX.[52] I estimate μ_k by estimating equation (6) separately for quintiles in proxied liquid assets. Appendix Table E.11 reports estimates for each quintile, along with $E[p_i]$, $E[\rho_i]$, $\hat{\mu}_k$, implied estimates for $\Pr(x_i \in k) \cdot \mu_k \cdot E[\rho_i]$, and the resulting estimate for $E[\rho_i L_i]$ using equation (E.13). Borrowers with lower proxied liquidity broadly have a higher estimated one-month MPX out of stimulus checks – the MPX declines from 22.1% in the bottom liquidity quintile to 12.0% in the top liquidity quintile. There is a loose positive correlation between monthly student loan payments and proxied liquidity.

Overall, Table E.11 shows that $\widehat{E[\rho_i L_i]} = 0.16$. This is slightly less than $\widehat{E[w_i L_i]}$, suggesting that forbearance liquidity is slightly less well-targeted than liquidity from stimulus checks, assuming universal take-up. These estimates imply that $\hat{\kappa} = 0.92$.

E.4.2 Non-parametric approach

This section shows how to estimate nonparametric bounds on $E[\rho_i L_i]$ while making fewer assumptions than in section E.4.1.

[52] In a buffer-stock incomplete-markets lifecycle model, households with low total assets when stimulus checks arrive would have the highest MPX, all else equal. In my transactions data, I observe inflows and outflows, but not liquid balances. I could estimate a lower bound on balances using net inflows anchored to a particular date. While this would produce a valid lower bound, the lower bound does not necessarily preserve rank because the gap between the bound and true balances is correlated with true balances. For example, consider person A with $5,000 in January 2019 who net dis-saves $5,000 between January 2019 and March 2020, and person B with $10,000 in January 2019 who net dis-saves $6,000 between January 2019 and March 2020. I would correctly estimate a lower bound of -$5,000 for person A and -$6,000 for person B, but incorrectly infer that person A has more liquid assets as of March 2020.

Table E.11: Calibration: Estimating $E[\rho_i L_i]$

	Estimated $E[p_i]$	Estimated $\Pr(x_i \in k) \cdot E[\rho_i \mid x_i \in k]$	Estimated μ_k	Estimated $\Pr(x_i \in k) \cdot \mu_k \cdot E[\rho_i \mid x_i \in k]$
Proxied liquidity quintile				
1	311.376	0.186	0.221***	0.041
			(0.024)	
2	275.897	0.165	0.139***	0.023
			(0.02)	
3	314.551	0.188	0.176***	0.033
			(0.019)	
4	368.441	0.221	0.155***	0.034
			(0.023)	
5	399.714	0.239	0.12***	0.029
			(0.027)	
$\widehat{E[\rho_i L_i]}$				0.16

Source: Author's calculations. This table presents calculations used to estimate $E[\rho_i L_i]$ in Appendix Section E.4.1. Rows indicate proxied liquidity quintile, where proxied liquidity is the ratio between net savings in March 2020 and total 2019 income. The first column reports the average student loan payments used to calculate liquidity from forbearance within each liquidity quintile. The second column normalizes liquidity from forbearance by total transfers assuming a unit mass of borrowers. The third column reports the estimated one-month MPX out of stimulus check liquidity for each liquidity quintile, along with robust standard errors clustered at the person level in parentheses. The final column takes the product of the second and third columns, with results summed in the final row.

Assumptions. Assume that stimulus checks are on average weakly targeted towards high MPC people, and that the MPC out of a windfall is bounded below zero and one:

$$E[L_i \mid w_i > 0] \geq E[L_i \mid w_i = 0] \tag{E.14}$$

$$L_i \in [0, 1] \tag{E.15}$$

Derivation. By definition:

$$E[\rho_i L_i] = \Pr(w_i > 0) E[\rho_i L_i \mid w_i > 0] + \Pr(w_i = 0) E[\rho_i L_i \mid w_i = 0] \tag{E.16}$$

It is straightforward to estimate $E[\rho_i L_i \mid w_i > 0]$ using the stimulus check natural experiment. The probabilities $\Pr(w_i > 0)$ and $\Pr(w_i = 0)$ are also easy to estimate.

Let $G(\cdot \mid w_i = 0)$ denote the conditional CDF for ρ_i. Then the term $E[\rho_i L_i \mid w_i = 0]$ has the following bounds:

$$E[\rho_i L_i \mid w_i = 0] \in [0, (E[L_i \mid w_i > 0]) \cdot E[\rho_i \mid 1 - G(\rho_i \mid w_i = 0) \leq E[L_i \mid w_i > 0]]] \tag{E.17}$$

The lower bound follows because assumption (E.15) implies that $E[L_i \mid w_i = 0] \geq 0$.

The upper bound comes from maximizing the correlation between ρ_i and L_i assuming maximum possible variance in L_i, subject to the constraints in (E.14) and (E.15). That involves matching the highest ρ_i to the highest L_i, the second-highest ρ_i to the second-highest L_i, and so on. The variance-maximizing distribution of L_i such that $E[L_i \mid w_i = 0] \leq E[L_i \mid w_i > 0]$ assumes that a fraction $E[L_i \mid w_i > 0]$ of the sample has $L_i = 1$, and everyone else has $L_i = 0$. Therefore, for all i where $L_i > 0$ and $w_i = 0$, $\rho_i L_i = \rho_i$.

This implies the upper bound becomes:

$$E[\rho_i L_i | w_i = 0] = \Pr(L_i > 0) \cdot E[\rho_i L_i | L_i > 0] = \Pr(L_i > 0) \cdot E[\rho_i | L_i > 0] \tag{E.18}$$

All that remains is to determine ρ_i for i where $L_i > 0$ for the upper bound. Since $E[L_i|w_i = 0] \leq E[L_i|w_i > 0]$, the maximum fraction of i with $L_i = 1$ is $E[L_i|w_i > 0]$. Hence in equation (E.18):

$$\begin{aligned} \Pr(L_i > 0) &= E[L_i|w_i > 0] \\ E[\rho_i|L_i > 0] &= E[\rho_i|1 - G(\rho_i|w_i = 0) \leq E[L_i|w_i > 0]] \end{aligned}$$

Putting everything together delivers the upper bound in equation (E.17). The corresponding bounds for $E[\rho_i L_i]$ are then:

$$\begin{aligned} E[\rho_i L_i] \in [&\Pr(w_i > 0) E[\rho_i L_i | w_i > 0], \\ &\Pr(w_i > 0) E[\rho_i L_i | w_i > 0] \\ &+ \Pr(w_i = 0) \cdot (E[L_i|w_i > 0]) \cdot E[\rho_i | 1 - G(\rho_i|w_i = 0) \leq E[L_i|w_i > 0]]] \end{aligned} \tag{E.19}$$

Implementation. First, I use my full-sample estimate of the stimulus check MPX to estimate $E[L_i|w_i > 0]$:

$$\widehat{E[L_i|w_i > 0]} = 0.174 \tag{E.20}$$

This is a valid estimate because the difference-in-differences design in the stimulus check natural experiment estimates an average treatment effect on the treated.

Second, I estimate $E[\rho_i|1 - G(\rho_i|w_i = 0) \leq E[L_i|w_i > 0]]$ as the average ρ_i for borrowers with ρ_i at or above the $(1 - 0.174) \times 100 = 82.6^{\text{th}}$ percentile of the student loan payment distribution.

Third, I must estimate $E[\rho_i L_i|w_i > 0]$. To do so, I parameterize $L_i = L_0 + L_1 \cdot \rho_i$, so that:

$$E[\rho_i L_i | w_i > 0] = E[\rho_i \cdot (L_0 + L_1 \rho_i)] = L_0 E[\rho_i | w_i > 0] + L_1 \cdot E[\rho_i^2 | w_i > 0] \tag{E.21}$$

To estimate L_0 and L_1, I estimate a version of equation (6) where I interact individual event time coefficients with the normalized liquidity from forbearance, ρ_i:

$$\begin{aligned} c_{j,it} = &\gamma_i + \delta_{yt} + \mu_{pre} \mathbb{1}(t < -7) \cdot EIP_i + \mu_{MPX} \mathbb{1}(t \in [0, 28]) \cdot EIP_i + \mu_{post} \mathbb{1}(t > 28) \cdot EIP_i \\ &+ \eta_{pre} \mathbb{1}(t < -7) \cdot EIP_i \times \rho_i + \eta_{MPX} \mathbb{1}(t \in [0, 28]) \cdot EIP_i \times \rho_i \\ &+ \eta_{post} \mathbb{1}(t > 28) \cdot EIP_i \times \rho_i + \varepsilon_{it} \end{aligned} \tag{E.22}$$

Then $\hat{L_0} = \hat{\mu}_{MPX}$ and $\hat{L_1} = \hat{\eta}_{MPX}$, and it is straightforward to estimate $E[\rho_i|w_i > 0]$ and $E[\rho_i^2|w_i > 0]$ from sample averages.

Results. Appendix Table E.12, Panel A shows results of the bounds estimates. The results show that κ is bounded between 0.45 and 1.63. Panel B shows how results from calibration exercises change in the upper and lower bound case. Accounting for the flypaper effect is quantitatively relevant in all cases. It is quantitatively *more* important in scenarios where forbearance does a comparatively better job targeting high MPC borrowers. In scenarios where forbearance is not well targeted, and κ is close to the bottom of its bounds, then failing to account for the flypaper effect would cause policymakers to inappropriately conclude that forbearance has a fiscal cost advantage relative to direct stimulus checks.

Table E.12: Calibration: Nonparametric bounds for $E[\rho_i L_i]$

Panel A.	
Variable	Estimate
$Pr(w_i > 0)$	0.662
$E[L_i\|w_i > 0]$	0.174
$E[\rho_i\|1 - G(\rho_i\|w_i = 0) \leq E[L_i\|w_i > 0]]$	3.507
$E[\rho_i L_i\|w_i > 0]$	0.118
$E[\rho_i L_i]$ lower bound	0.078
$E[\rho_i L_i]$ upper bound	0.284
κ lower bound	0.448
κ upper bound	1.633
κ point estimate	0.921

Panel B.			
κ	0.448	0.921	1.633
E_f, assuming $\frac{\gamma}{1-\eta} = 1$	0.03	0.25	0.57
E_f, assuming $\frac{\gamma}{1-\eta} = 0.45$	-0.08	0.01	0.16
Pct increase in stimulus package cost	4.0%	12.3%	24.9%
Pct increase in stimulus checks	11.7%	20.7%	31.9%
Number of months change in break-even term	-28.8	-63.7	-128.6
Pct change in break-even term	-57.6%	-58.3%	-60.3%

Source: Author's calculations. This table presents calculations used to estimate $E[\rho_i L_i]$ in Appendix Section E.4.2. Panel A presents quantities used to estimate the upper and lower bound for $\kappa = \frac{E[\rho_i L_i]}{E[w_i L_i]}$ using equation (E.19), along with the estimated upper and lower bound. Panel B shows how the range of admissible κ impact the quantities cited in the two calibration exercises from Section 6.

E.5 Forbearance targeting: Alternative correlation assumptions

This section relaxes the assumption in Section 6 that assume away scope for behavioral targeting and advantageous take-up.

Assume now that $\chi_i \perp \eta_i, L_i, \rho_i$, but that η_i, L_i, and ρ_i might be correlated. Equation (11)

becomes:

$$E_f = \left[\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)\cdot\left(\frac{E[\rho_i L_i]}{E[w_i L_i]}\right)\cdot\left(1+\frac{\text{Cov}(1-\eta_i,\rho_i L_i)}{E[1-\eta_i]E[\rho_i L_i]}\right)\cdot\left(E[\chi_i]\frac{E[1-\eta_i]}{E[\rho_i(1-\eta_i)]}\right)-1\right]\cdot E[w_i L_i] \tag{E.23}$$

$$= \left[\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)\cdot\left(\frac{E[(1-\eta_i)\rho_i L_i]}{E[w_i L_i]}\right)\cdot\left(\frac{E[\chi_i]}{E[\rho_i(1-\eta_i)]}\right)-1\right]\cdot E[w_i L_i] \tag{E.24}$$

This leaves three new terms to estimate.

First, I estimate $E[(1-\eta_i)\rho_i L_i]$ using a method similar to the "parametric approach" in Section E.4.1. However, I parameterize L_i in a different way to accommodate possible correlation between η_i and L_i. I divide the sample into 25 bins based on x_i and η_i quintiles.[53] I then estimate μ_k separately for each bin using the regression:

$$L_i = \sum_k \mu_k \cdot \mathbb{1}\{(x_i,\eta_i)\in k\} + \varepsilon_i \tag{E.25}$$

I then estimate:

$$\widehat{E[(1-\eta_i)\rho_i L_i]} = \sum_k \Pr(x_i\in k)\cdot\hat{\mu}_k\cdot\widehat{E[(1-\eta_i)\rho_i|(x_i,\eta_i)\in k]} \tag{E.26}$$

where I use individual-level estimates of η_i, the MPX on student loans out of forbearance liquidity, from Section 4.2.2.

Second, I estimate $E[\rho_i(1-\eta_i)]$ directly using individual-level estimates of ρ_i and η_i described above.

Finally, I need to estimate $E[\chi_i]$. Note that given my assumptions:

$$\gamma = \frac{E[\chi_i(1-\eta_i)L_i]}{E[L_i]} = E[\chi_i]\frac{E[(1-\eta_i)L_i]}{E[L_i]} \implies E[\chi_i] = \frac{\gamma}{E[(1-\eta_i)L_i]/E[L_i]} \tag{E.27}$$

Note that the denominator is the ratio between the semi-structural consumption MPX out of forbearance liquidity, and the denominator is the consumption MPX out of stimulus checks. I can calibrate all terms on the RHS using results from the transactions data, which gives a value for $E[\chi_i]$. Looking at Table 3, semi-structural estimates of the total spending forbearance MPX in the sample of paid-off borrowers implies that $E[(1-\eta_i)L_i]\approx 0.09$. Along with the stimulus check total spending MPX of ≈ 0.17 for this sample, this implies that $E[\chi_i]\approx 0.47$. The structural interpretation is that roughly half of borrowers face saving target deviation costs sufficiently large to prevent saving less than their goal in response to forbearance liquidity.

[53] Bins for x_i are true quintiles. I place all $\eta_i = 0$ in one bin, and then create 4 other bins as the quartiles conditional on $\eta_i > 0$.

Table E.13 collects estimates of all these objects and reports the implied E_f, along with results from the main text calibration exercises. The estimated forbearance fiscal cost efficiency, after taking into account $\eta_i > 0$ and $\chi_i \neq 1$, is almost identical to estimates in the main text, with $E_f = 0.014$. It is therefore unsurprising that the estimates for the change in total stimulus package cost, change in stimulus check size, and change in break-even term are also very similar to those in the main text.

Table E.13: Calibration: Allowing correlation between η_i and ρ_i, L_i

Variable	Value
$E[\chi]$	0.47
$E[(1-\eta_i)\rho_i L_i]$	0.107
$E[(1-\eta_i)\rho_i]$	0.706
E_f	0.014
Pct increase in stimulus package cost	0.123
Pct increase in stimulus check size	0.164
Number of months change in break-even term	-64.5
Pct change in break-even term	-0.586

Source: Author's calculations. This table presents results from Appendix Section E.5. The top half of the table reports key objects estimated or calibrated in that section. The bottom half reports implications for total stimulus package costs, the size of stimulus checks, and the impact on the break-even forbearance term.

Appendix Bibliography

Bhutta, Neil et al. (Sept. 2020). "Changes in U.S. Family Finances from 2016 to 2019: Evidence from the Survey of Consumer Finances". In: *Federal Reserve Bulletin* 106.5. URL: https://www.federalreserve.gov/publications/files/scf20.pdf.

Borusyak, Kiril, Xavier Jaravel, and Jann Spiess (2024). "Revisiting event study designs: Robust and efficient estimation". In: *Review of Economic Studies*.

Bryan, Gharad, Dean Karlan, and Scott Nelson (2010). "Commitment devices". In: *Annu. Rev. Econ.* 2.1, pp. 671–698.

Caplin, Andrew (2016). "Measuring and modeling attention". In: *Annual Review of Economics* 8, pp. 379–403.

Congressional Research Service (Dec. 2025). *The Office of Federal Student Aid as a Performance-Based Organization*. CRS Report R46143. Updated December 4, 2025. Congressional Research Service. URL: https://www.everycrsreport.com/reports/R46143.html.

Department of Education, The (Nov. 2020). *FY 2020 Agency Financial Report*.

— (Nov. 2021). *FY 2021 Agency Financial Report*.

— (Nov. 2022). *FY 2022 Agency Financial Report*.

EFC (2019). *2019-2020 Non-profit and state-based education loan handbook*. URL: cdn.ymaws.com/www.efc.org/resource/resmgr/efc_members/2019-2020_nfp_loan_handbook.pdf.

Gabaix, Xavier (2019). "Behavioral inattention". In: *Handbook of behavioral economics: Applications and foundations 1*. Vol. 2. Elsevier, pp. 261–343.

Lee, Sean Chanwook and Peter Maxted (Feb. 2026). "Credit Card Borrowing in Heterogeneous-Agent Models: Reconciling Theory and Data". Working paper. URL: https://static1.squarespace.com/static/6186b3b155561c2ab5fe4957/t/6986a6888214d37399f6c8a8/1770432136272/CreditCardBorrowing_Feb2026.pdf.

Matsudaira, Jordan, Daniel Pollard, and Victoria Lee (Oct. 2023). *Trends in Federal Student Loan Borrower Payments Through the End of the Payment Pause: A Comparison of Different Federal Data Sources*. U.S. Department of Education, Office of the Under Secretary, Office of the Chief Economist Blog. Removed from ed.gov; archived at https://web.archive.org/web/20231106194258/https://sites.ed.gov/ous/2023/10/trends-in-federal-student-loan-borrower-payments-through-the-end-of-the-payment-pause-a-comparison-of-different-federal-data-sources/ (capture of November 6, 2023; accessed July 13, 2026). URL: https://sites.ed.gov/ous/2023/10/trends-in-federal-student-loan-borrower-payments-through-the-end-of-the-payment-pause-a-comparison-of-different-federal-data-sources/.

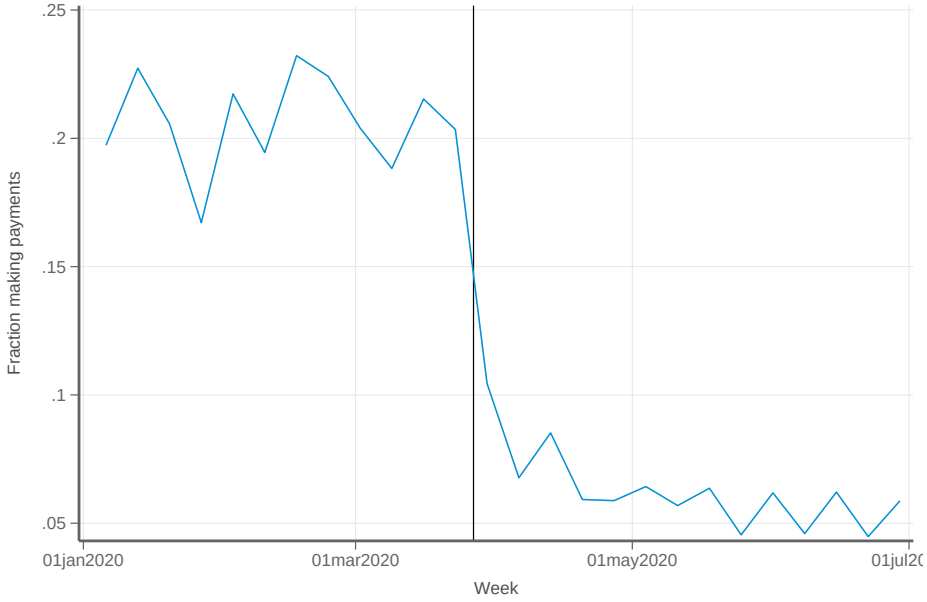
Pence, Karen (2015). "SCFCOMBO: Stata module to estimate errors using the Survey of Consumer Finances". In.

SBPC (Apr. 2020). *Private Student Lending*. URL: protectborrowers.org/wp-content/uploads/2020/04/PSL-Report_042020.pdf.

Stokey, Nancy L. and Robert E. Lucas (1989). *Recursive Methods in Economic Dynamics*. Harvard University Press. ISBN: 9780674750968. URL: http://www.jstor.org/stable/j.ctvjnrt76 (visited on 12/19/2023).

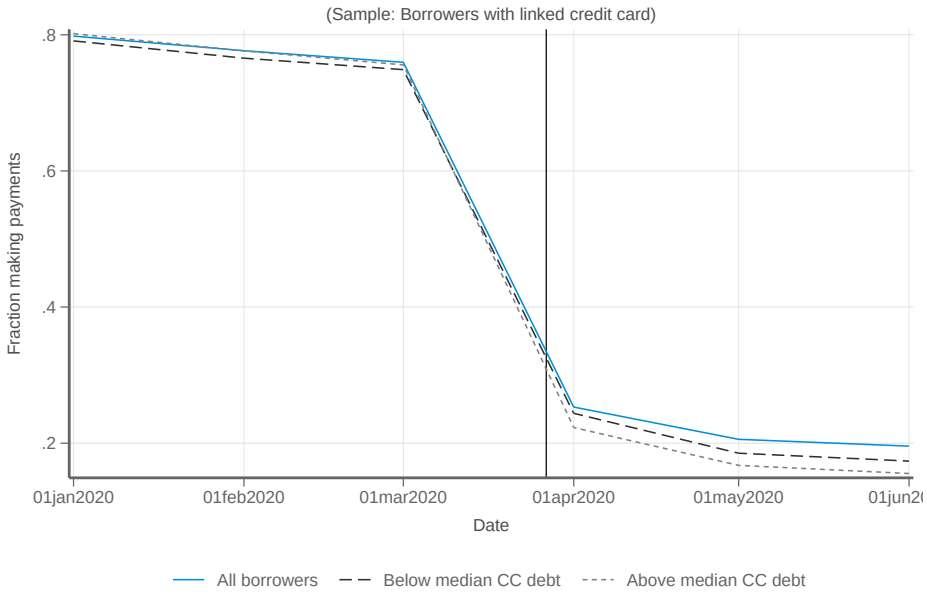
F Additional figures

Figure F.10: Fraction making payments on federal student loans by week



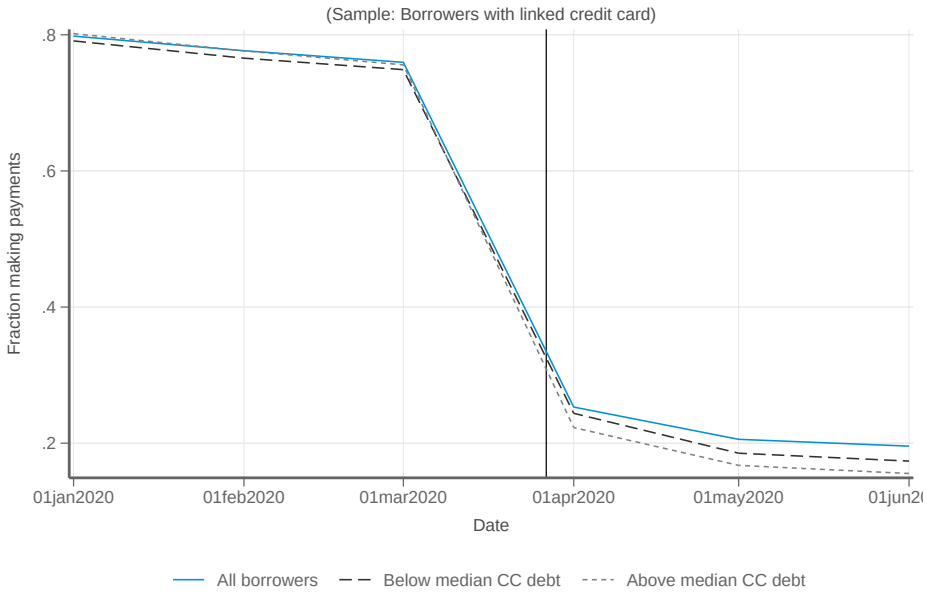
Source: Author's calculations. The figure plots the fraction of borrowers in the full sample who make payments on federal student loans in each week. The vertical line indicates the onset of automatic forbearance.

Figure F.11: Fraction making payments on federal student loans by month and credit card debt level

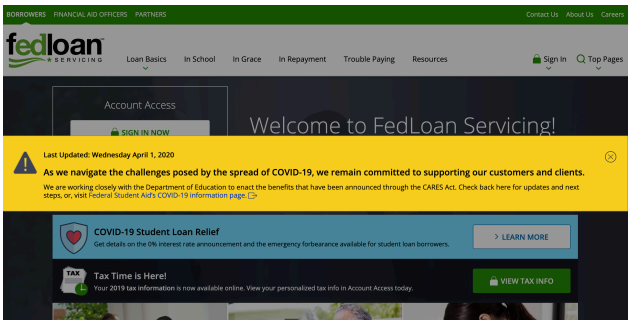


Source: Author's calculations. The figure restricts to federal student loan borrowers with a linked credit card account, and plots the fraction who make a payment on federal debt in each month. The solid blue line shows the average for the full sample. The black dashed and gray dotted lines restrict to borrowers with a positive lower bound on credit card debt the week of March 16, 2020. The black dashed line plots the fraction of borrowers making repayments for such borrowers with a credit card debt lower bound below the median, and the gray dotted line plots the fraction for borrowers with a credit card debt lower bound above the median. The vertical line indicates the onset of automatic forbearance.

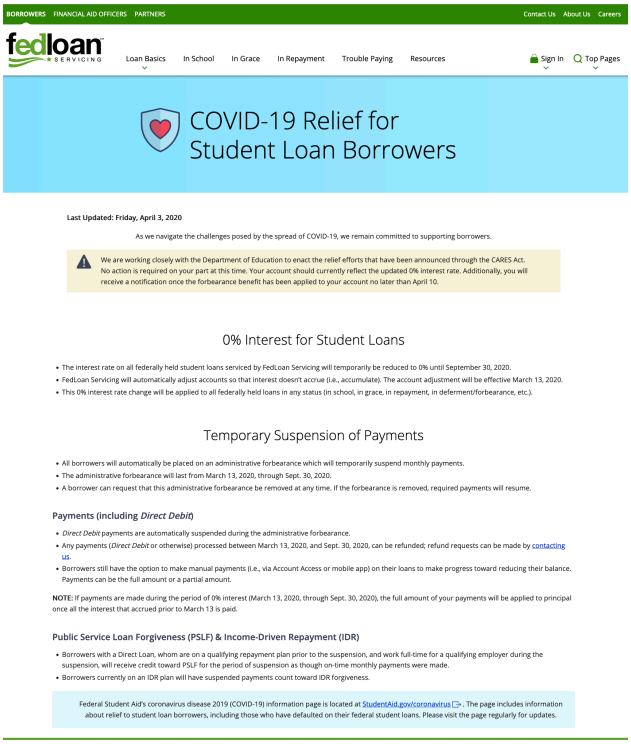
Figure F.12: Fraction making payments on federal student loans by month and credit card debt level, credit card debt sample



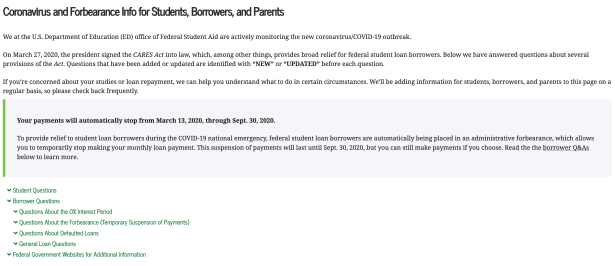
Source: Author's calculations. The figure restricts to federal student loan borrowers with a linked credit card account, and plots the fraction who make a payment on federal debt in each month. The solid blue line shows the average for the full sample. The black dashed and gray dotted lines restrict to borrowers with a positive lower bound on credit card debt from March through June 2020. The black dashed line plots the fraction of borrowers making repayments for such borrowers with a credit card debt lower bound below the median, and the gray dotted line plots the fraction for borrowers with a credit card debt lower bound above the median. The vertical line indicates the onset of automatic forbearance.



(a) FedLoan Servicing home page, April 2, 2020



(b) FedLoan Servicing Covid information for borrowers, April 3, 2020

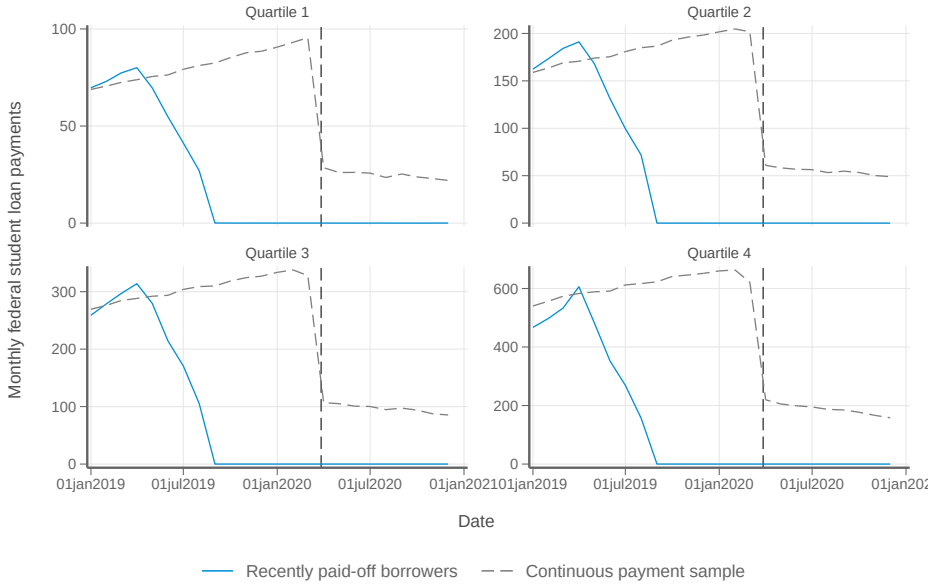


(c) Ed Department Covid info page, April 2, 2020

Figure F.13: Communications with borrowers around start of forbearance

Source: Internet Archive Wayback Machine. Panel F.13a displays a screenshot from the Fedloan Servicing homepage on April 2, 2020 (link). Note the popup with a link to the Ed Department covid information page (Panel F.13c), and the notice about relief below the popup with a link to learn more. Panel F.13b contains a screenshot of the Fedloan Servicing Covid info linked on the homepage, with the snapshot from April 3, 2020. Panel F.13c shows the federal government communication homepage, with links to extensive info about the program.

Figure F.14: Federal student loan pmts, recently paid-off vs. continuous pmt sample



Source: Transactions panel. The figure plots average monthly federal student loan payments for borrowers with only federal student debt. The blue solid series gives values for borrowers completing student loan repayments in Q2 or Q3 2019. The gray dashed series plots values for borrowers who haven't completed debt repayment before forbearance begins, but meet "continuous payment" sample restrictions applied to recently paid-off sample. Each panel plots values for borrowers within each quartile of pre-forbearance (and pre-repaid) federal student loan payments. These figures winsorize student loan repayments at the 5% and 95% level.

G Additional tables

Table G.14: Four-week MPX out of first round stimulus payments, prepayers before stimulus checks arrive

	Sample: Pre-April 15 pay
Total spending	0.16***
	(0.023)
Broad nondurable	0.079***
	(0.013)
N	62,267

Source: Author's calculations. * p=0.05, ** p=0.01, *** p=0.001. This table reports estimated four-week MPX on April 2020 stimulus checks using the methodology described in Section 4.1. The sample is restricted to borrowers who make a payment on federal student loans before stimulus checks are received on April 15. Each entry reports $\hat{\mu}_{MPX} \times 30$ from a separate regression of the form in specification (6), with rows indicating outcome variables and columns indicating estimation sample. Robust standard errors clustered at the borrower level are reported in parentheses. See section 3.1 for detailed descriptions of expenditure category construction.

Table G.15: Survey: Student loan payment method by student loan payment in forbearance.

	No	Yes	Difference	p-value	Total
Pay manually online | ever made pmts	.496	.506	-.00978	.844	.5
Pay via autopay with servicer | ever made pmts	.298	.282	.0168	.71	.291
Pay via autopay with bank | ever made pmts	.185	.241	-.0559	.165	.209
Pay via mail by check | ever made pmts	.0161	.0345	-.0184	.223	.0237
Pay via other method | ever made pmts	.0242	.0115	.0127	.348	.019
N	296	174	.	.	470

Source: Student borrower survey. The table presents survey responses to program familiarity and financial sophistication questions. The "No" and "Yes" columns gives means for borrowers who stop and do not stop making payments after forbearance begins, the "Difference" column gives the difference in means, the "p-value" column reports the p-value of a t-test of equivalent means, and the "Total" column gives pooled full sample means. The table displays the fraction of borrowers who use each method to pay their student loans. The table conditions on borrowers who do *not* answer to this question that they never make regular payments.

Table G.16: Survey: Framing x interest rate experimental results (main)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	SL repay	SL repay	SL repay	SL repay	SL repay	SL repay
Cue category = 1, Student borrowers	0.0244		0.0502**		-0.00487	
	(0.0150)		(0.0209)		(0.0213)	
SL interest rate = 1, 7%		-0.00573		-0.00839		-0.00174
		(0.0151)		(0.0209)		(0.0213)
Constant	0.0756***	0.0907***	0.0845***	0.113***	0.0643***	0.0627***
	(0.00966)	(0.0108)	(0.0123)	(0.0150)	(0.0153)	(0.0152)
Observations	798	798	439	439	359	359
R-squared	0.003	0.000	0.013	0.000	0.000	0.000
Sample	Full	Full	Mistake	Mistake	No mistake	No mistake

Source: Student borrower survey. This table presents regression results from a framing experiment. Borrowers were asked how they would spend a $300 stimulus check over the course of a year, given large outstanding student loan and credit card balances. Stimulus was framed as a transfer to either all US households or student borrowers, and the interest rate on student debt was quoted at either 0% or 7%. Participants were cross-randomized across these four experimental conditions. The table reports the effect of the student borrower framing (first row) and the 7% interest rate (second row) treatment conditions on student loan repayment as a fraction of the total transfer. The first two columns show results for the full sample. The second two columns show results for the sample of borrowers who make a credit card repayment mistake in a separate financial sophistication screen. The third two columns show results for the sample of borrowers who continue to make payments on their federal student debt after forbearance begins. All regressions were pre-registered.