Saving and Consumption Responses to Student Loan Forbearance

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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

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When falling incomes cause distressed households to cut consumption during recessions, policymakers can use a combination of debt relief and direct cash transfers to stimulate aggregate demand. Previous work argues that if households cut spending mostly due to temporary liquidity constraints, debt relief allowing leveraged borrowers to defer payments can support consumption at a low fiscal cost (Eberly and Krishnamurthy 2014, Cherry et al. 2021). The efficient policy mix in downturns hinges on how households adjust saving, debt payments, and consumption in response to each form of relief.

This paper studies the impact of debt relief versus cash transfers on household saving and consumption. I compare responses to the US government's student loan forbearance program and stimulus check payments enacted as part of the 2020 CARES Act when the Covid-19 recession began. The forbearance program put all federally-owned student loans into administrative forbearance, impacting 92% of the $1.5 trillion student loan market (Fed 2020). The program automatically paused all monthly payments and set interest on outstanding debt to 0%. The CARES Act also authorized direct cash payments to most US households.

Comparing consumer responses to debt relief and stimulus payments is empirically challenging because the policies often target populations facing different financial circumstances. Debt relief often targets households facing acute distress due to high leverage (Noel and Wachter 2021), while governments distribute stimulus checks more broadly. Two features of the CARES Act policy context help overcome this challenge. First, debt relief applied universally and automatically, not just to distressed households. This enables measurement of average effects across all households and reduces concerns about selection based on take-up. Second, since the CARES Act also included stimulus checks, it is possible to compare responses to forbearance and cash transfers for the same borrowers in a similar economic environment.

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

The paper measures the effects of each policy on debt repayment and consumption expenditure, comparing estimates to predictions from workhorse consumption-saving models. Borrowers respond to the payment pause non-optimally by making voluntary student loan prepayments, resulting in lower consumption effects relative to stimulus checks. I survey borrowers to identify drivers of this behavior, and present a consumption-saving model with non-standard flow utility to rationalize results. Finally, I provide a framework to quantify the impact of this behavior on forbearance's effectiveness as a counter-cyclical fiscal tool.

The first part of the paper examines whether borrower behavior aligns with predictions from a dynamic incomplete-markets model of the sort often used to represent saving and consumption choices. Because liquid resources are fungible, the model predicts that consumers only make voluntary debt prepayments if they lack higher-yielding alternatives, such as other debt. If consumers prepay, then they should *increase* prepayments in response to unanticipated cash windfalls such as stimulus checks. The model also implies that the difference between the marginal propensity to consume (MPC) out of liquidity from forbearance and stimulus checks is, to a first order, bounded by the consumption impact of the difference in wealth transfers from the policies. Previous literature (Paiella and Pistaferri 2017, Ganong and Noel 2020) shows this consumption impact to be negligible, meaning the model 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 optimal debt repayment strategy and the policy default. In an interrupted time-series design examining changes in loan repayment when forbearance begins, borrowers use about 45% of forbearance liquidity to prepay federal student debt over 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. Continued payments are surprising. Besides waiving required payments and interest, the policy extended repayment timelines to prevent catch-up payments. For borrowers with a long outstanding loan term, prepayments meant actively rejecting a multi-year, interest-free loan.

The same borrowers use a much smaller fraction of their stimulus checks to pay off federal student loans. This shows that prepayment during forbearance is unlikely to reflect a lack of higher-yielding saving alternatives, demand for deleveraging, or student debt aversion. Adapting Baker et al. (2020), I estimate the impact of stimulus checks on federal student loan repayments using high-frequency within-person changes in repayment before and after checks arrive, where arrival timing variation allows estimating calendar time trends. Borrowers spend under 1% of their stimulus checks on federal student loans over four weeks, implying they do not treat liquidity from forbearance as fungible with other cash windfalls.

This non-fungibility creates costly violations of the optimal debt pay-down policy. Borrowers with high-interest credit card and private student loan debt use 40% and 33%, respectively, of their forbearance liquidity to prioritize federal student debt prepayment. This is a clear financial mistake. These same borrowers better prioritize debt repayment out of stimulus checks. For example, borrowers with credit card debt using all of their forbearance liquidity on federal student loans spend 9.3% of their stimulus checks on credit card payments over a month, but only 1% on federal student debt.

Excess student loan payments and inconsistent use of stimulus check liquidity together suggest a flypaper effect in which forbearance "sticks" to student loan repayment. This predicts a lower marginal propensity to spend (MPX) on consumption goods out of forbearance liquidity versus cash transfers.

As predicted by such a flypaper effect, borrowers spend a much lower fraction of the liquidity received from forbearance than from stimulus checks. I estimate the forbearance consumption MPX using a difference-in-difference design comparing borrowers with similar repayment trajectories who happen to complete scheduled loan repayments at different times. I use borrowers who finished repaying their debt just before March 2020, and hence did not receive liquidity from forbearance, to trace out counterfactual spending for similar borrowers with outstanding balances when forbearance began.[1] While the four-week stimulus check MPX is about 17% for total expenditure and 9% for nondurable expenditure, 95% confidence intervals reject a forbearance MPX more than one-quarter and one-third as large, respectively. The low forbearance MPX largely reflects low expenditure out of forbearance cash-on-hand for those who stop repayments. If borrowers spent the same out of extra cash-on-hand from foregone payments and stimulus checks, the overall forbearance MPX would be statistically indistinguishable from (although lower than) the stimulus check MPX.

I investigate drivers of these results using a survey asking borrowers to explain their use of stimulus check and forbearance liquidity. Borrowers who make debt repayment mistakes or inconsistently use liquidity from these sources mention debt repayment heuristics or reluctance 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 heuristic debt repayment targets, combined with low financial sophistication, lead to the flypaper effect. 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.

Next, I offer 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).

Lastly, I study implications of my findings for fiscal policy design. I consider a partial-equilibrium framework where a government uses forbearance and stimulus checks to boost aggregate consumption among heterogeneous consumers. The transfers differ in "resource tar-

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

geting," determined by which consumers receive liquidity; "behavioral targeting," depending on which consumers endogenous "take-up" forbearance by stopping payments; and a "flypaper" effect attributed to target deviation costs. Two sufficient statistics quantify the flypaper effect: the MPX on student loans out of forbearance liquidity, which reduces take-up, and the consumption MPX out of forbearance liquidity relative to cash windfalls. A simple expression links these forces to forbearance's fiscal cost efficiency, defined as the change in consumption from reallocating a dollar in fiscal expenditure from stimulus checks to forbearance.

Using the transactions data, I calibrate the flypaper effect's impact on forbearance's fiscal cost efficiency as implemented in the CARES Act. Student loan forbearance does not target high-MPX borrowers, but absent target deviation costs, it is more cost-efficient because it can increase liquidity while transferring less wealth than stimulus checks. However, the flypaper effect mostly eliminates this cost advantage. Because the consumption MPX out of forbearance liquidity is lower than out of stimulus checks, the program requires 21% larger stimulus checks and a 12% higher fiscal outlay to increase consumption by as much as without the flypaper effect. Forbearance's lower consumption MPX also limits how generous it can be before losing its cost edge. With target deviation costs, forbearance is less efficient if catch-up payments are deferred beyond 3.8 years, versus 9.2 years without target deviation costs.

This paper connects with several literatures. First, previous work documents non-fungibility in consumption (Milkman and Beshears 2009, Hastings and Shapiro 2013, Hastings and Shapiro 2018), potentially impacting borrowing (Di Maggio, Katz, and Williams 2022). I show that households also treat liquidity as non-fungible when making debt repayment decisions in a salient and high-stakes context. I connect this perceived 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)).

Second, my findings advance the literature on the real impacts of debt relief. Much existing work focuses on mortgage principal or monthly payment relief during the 2008 financial crisis (Ganong and Noel 2020, Agarwal et al. 2017, Di Maggio et al. 2017, Fuster and Willen 2017, Tracy and Wright 2016). Since student debt is the second-largest consumer debt category after mortgages, a growing number of papers study student debt relief in particular (Yannelis and Tracey 2022, Mueller and Yannelis 2019, Di Maggio, Kalda, and Yao 2019).

I make several contributions to this literature. Since I study a universal policy that did not target distressed borrowers, estimates reflect likely effects of more widespread debt relief. This is especially valuable in the student loan context given recent policy debates around student debt forgiveness, which would both reduce outstanding balances and monthly payments (Yannelis and Tracey 2022, Sylvain and Constantine 2020). The low forbearance consumption

MPX suggests that monthly payments do not create consumption constraints 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.

Moreover, I provide estimates of debt repayment and consumption responses to relief that mostly provides additional liquidity, in contrast to much previous work that analyzes policies simultaneously changing liquidity and net worth. Exceptions include Ganong and Noel (2020) and Aydn (2023), who find that for constrained borrowers, delinquency and default respond more to payment modifications that increase short-term liquidity, such as forbearance, than to debt write-downs. These papers argue that liquidity constraints drive default behavior, but do not estimate consumption effects of increased liquidity from lower payments.

Finally, I provide theory and evidence to directly compare the consumption and debt repayment effects of debt relief and cash transfers. Eberly and Krishnamurthy (2014) argue that the importance of liquidity constraints favors forbearance rather than write-downs to prevent delinquency, because the former incurs a lower fiscal cost. A parallel literature finds large consumption responses to stimulus checks, also attributed to liquidity constraints (Parker et al. 2013, Baker et al. 2020). Put together, these findings seem to suggest that governments can use forbearance to stimulate consumption at a lower cost than other transfers like stimulus checks (Cherry et al. 2021, Lee and Maghzian 2023).

This logic hinges on the relative effects of liquidity from each windfall, a comparison I evaluate explicitly. I provide novel evidence that borrowers use liquidity from each windfall quite differently, and by focusing on a fixed group of recipients, rule out borrower heterogeneity as the primary driver. I formalize the impact of this inconsistency on policy design in a tractable calibration framework that takes micro-MPX estimates as sufficient statistics to evaluate relative fiscal efficiency. By comparing responses to forbearance and stimulus checks, I advance contemporaneous work by Dinerstein, Yannelis, and Chen (2023) and Chava, Tookes, and Zhang (2023), which use credit bureau data and a different empirical design to show that CARES Act student loan forbearance increases private debt payments and levels.

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 (Fed 2021, Hanson 2023). The average borrower owes about $35,000, and median balances are around $23,000.

Since 2010, the federal government has offered loans to finance postsecondary education through the Federal Direct Loan program. Direct Loans are owned by the US Department of Education. Students may be eligible for preferential terms like reduced interest during school based on family income, but federal loans are available to all students. Federal loans may not fully cover higher education costs due to per-borrower limits.

Federal 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.[2]

Borrowers can also pay for school using private student 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. Federal lending accounts for about 92% of outstanding balances (Elan, Christopher, and Teslow 2021).

The federal government contracts with a limited set of companies to service the student debt that it owns. Many of these companies are monolines set up for the sole purpose of servicing federally-owned student debt. I use this institutional feature to distinguish between federal and private student debt, and identify loans that are eligible for automatic forbearance.

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 into administrative forbearance on an opt-out basis.[3] The interest rate on all outstanding debt was set to zero percent. If borrowers had

[2] 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).

[3] Prior to 2010, the Federal Family Education Loan (FFEL) program provided government guarantees to commercially-issued loans. The program ended in 2010, but some FFEL loans remain outstanding. FFEL loans

autopay set up through their loan servicer, the law required that servicers automatically disable it. The law also prevented missed payments from negatively impacting borrower credit scores. 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. 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.[4] 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 lower AGI individuals first. Payments largely concluded by the end of May.[5] In my sample, about 85% of student loan borrowers received their EIP on either April 14 or April 15.

2 Predictions from a consumption-saving model

This section studies how consumers in an incomplete-markets lifecycle model respond to student loan forbearance compared to unanticipated stimulus checks. Appendix A provides proofs.

Setup A consumer lives for $T \in \mathbb{N} \cup \infty$ periods. In period $t = 0$, the consumer has J amortizing debt accounts 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 consumer 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 $\theta \equiv \{R_{jt}, L_{jt}\}_{j,t}$. Borrowers treat these parameters as known in advance.

owned by commercial banks were not eligible for forbearance. But the federal government purchased some FFEL loans in 2010-2011, and such loans *were* eligible for forbearance.

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

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

Each period, the consumer first receives income $y_t \overset{\text{iid}}{\sim} G$.[6] Borrowers then sequentially choose total saving x_t and debt repayments $\{p_{jt}\}$, with student loan payments p_{st} chosen last by convention. Borrowers do not expect the environment to change within a period. If the environment doesn't change, they make choices as if are optimizing jointly, not sequentially. The value function given state variables X_t and $\{B_{jt}\}_j$ satisfies the following Bellman equation, where the expectation is taken over y_{t+1} and $P \equiv \sum_j p_j$:

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

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

where 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.[7]

Effects of stimulus payments and forbearance Stimulus checks delivered in period t generate an unexpected change in liquid account balances of ΔX between period $t-1$ and period t, so that $X_t = R_0(X_{t-1} - P_{t-1}) + y_{t+1} + \Delta X$. The change is unexpected because $y_{t+1} + \Delta X$ 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 total saving and debt repayment 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 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 $l > t+F$.

Given timing assumptions, student loan payments in period $t-1$ are given by:

$$p^f_{s,t-1}(X_{t-1}, \{B_{j,t-1}\}_j; \theta, \theta') \equiv \arg\max_{p_s} U(X_{t-1} - x_{t-1}(\cdot; \theta))$$
$$+ \delta E V_t\left(R_0\left(x_{t-1}(\cdot; \theta) - P_{-j,t-1}(\cdot; \theta) - p_s\right) + y_t, R_{st}(B_{j,t-t} - p_s), \{B_{jt}\}_{j \neq s}; \theta'\right) \text{ s.t. } (2) \quad (3)$$

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 only if: (i) all accounts with strictly higher interest are fully repaid; and (ii) the interest rate on B_j exceeds the*

[6] Extending to a persistent income process is simple, and only requires adding a state variable.

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

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* $R_0 \geq 1$.

Part (2) explains that stimulus checks will increase student loan payments during forbearance if student loans are the marginal saving vehicle, and part (3) says student loan payments should drop to zero if a borrower has any prepayable interest-bearing debt.[8]

Define $\Delta p_{st} \equiv p_{s,t-1}(\cdot;\theta) \geq 0$. This represents the increase in liquid resources in period t due to forbearance, because optimal $t-1$ payments under forbearance 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:*

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

Define $\frac{\Delta c^w_t}{\Delta X}$ as the MPC out of stimulus checks, and $\frac{\Delta c^f_t}{\Delta p_{st}}$ 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 – a direct wealth transfer. 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.

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

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 J. Y. 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.[9] 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 aggregator obtains data primarily through direct agreements with financial institutions, rather than consumers, although all data are user-permissioned (e.g. through terms of service).

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.

[9] For example, Parker et al. (2013) find that the six-month MPC out of 2008 stimulus payments is 60% higher than the three-month MPC.

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.[10]

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. Since the federal government contracts with a small set of servicers, the servicer determines forbearance eligibility. While some servicers contract exclusively with the federal government, others also have private clients; I classify federal student loan repayments as transactions with federal-exclusive servicers.[11] 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.[12]

I also track payments to 30 companies that service private student loans originated by major lenders, but were not eligible for automatic forbearance under the CARES Act. This allows me to identify borrowers with private debt. Appendix B has details on identifying private loans.

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

[10] 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 date and the statement closing date, plus a 21-day grace period (the federally-mandated minimum and industry standard). This is a lower bound because: (i) the method only calculates debt incurred after January 1, 2019; (ii) the method ignores debt held on unconnected accounts; and (iii) credit card companies cancel grace periods for users with interest-bearing debt.

[11] Publicly-available information indicates which servicers are federal-exclusive. I reached out to all federal exclusive providers to confirm that all loans in the company portfolio were eligible for automatic forbearance under the CARES Act. I received responses from the two largest servicers, who both confirmed. I have run basic results in Section 4.1 separately using payments to these servicers, which confirm that among this subset, post-forbearance loan repayment rates are similar to the full sample.

[12] 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.

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

Table 1: Sample summary statistics for transactions panel

	Avg student loan pmt quartile				
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Total
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 at positive values over the year. Conditional means are conditional on having a positive value over the year, except for revolving credit card debt, where means are conditional on having a positive value in a given month. A lower bound on revolving debt is calculated by summing credits and debits for users with linked credit card accounts.

3.2 Survey data

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 with student debt at some point since 2019 using Prolific, an online survey platform with high attention and 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 empirically test Claims 1 and 2 before turning to survey results to identify relevant features of a model describing observed behavior.

4.1 Non-fungibility and debt repayment mistakes

Claim 1 shows that after the onset of forbearance, borrowers – 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 payments in forbearance, despite repaying high-interest debt first when using liquidity from stimulus checks. Divergent debt repayment responses to forbearance and stimulus checks also challenges Claim 2.

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

I aim to estimate $MPX^{f}_{p_s} \equiv \frac{p^o_s - p_s(\cdot;\theta')}{p_s(\cdot;\theta) - p_s(\cdot;\theta')} = \frac{p^o_s}{p_s(\cdot;\theta)}$ and $MPX^{w}_{m} \equiv \frac{\Delta m^w}{\Delta X}$. $MPX^{f}_{p_s}$ gives the fraction of forbearance liquidity used to prepay federal student loans. The numerator is the difference in observed student loan payments relative to the optimal payments under forbearance, $p_s(\cdot;\theta') = 0$. The denominator is the amount of forbearance liquidity received, equal to optimal payments absent forbearance. MPX^{w}_{m} gives the fraction of stimulus check liquidity used on outcome m – for example, federal student loan payments – and depends on Δm^w, the change in m due to stimulus checks, and ΔX, stimulus check size.

To examine whether borrowers use liquid resources consistently, I estimate how use of stimulus checks to repay other debts varies with the amount of forbearance liquidity a borrower uses to prepay federal student loans. To do so, I estimate the correlation between $MPX^{f}_{p_s}$ and $MPX^{w}_{p_j}$ for payments on other debts p_j.

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 exclude observations from the week of program onset due to implementation lags,[13] and observations four weeks before and after forbearance began. Appendix C.2 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 $\widehat{MPX}^{f}_{p_s} \equiv \left(\sum_{t=0}^{3} \hat{\beta}_0 + \left(\hat{\beta}_1 + \hat{\beta}_2\right) \cdot t + \hat{\alpha}\right) \Big/ \left(\sum_{t=0}^{3} \hat{\beta}_0 + \hat{\beta}_1 \cdot t\right)$. The numerator gives 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 evolved on a linear trend relative to repayments in the previous four weeks. A concern with this assumption is that the deteriorating economic environment would have caused many borrowers to default absent forbearance. First, the linear trend should capture non-repayment due to economic hardship before the CARES Act passed. Second, this concern implies the linear trend *overestimates* counterfactual payments, so $\widehat{MPX}^{f}_{p_s}$ is a lower bound. If anything, I may therefore *underestimate* the difference between the forbearance and stimulus check MPX on student loans.

[13]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.

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:

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

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 μ_{MPX}, 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 sharply for higher 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.[14]

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 $k = 0$.[15]

In Appendix C.3, 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.

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

Correlation between forbearance and stimulus check MPX To examine how people spending forbearance liquidity on federal student loans use their stimulus checks to repay other debts, I estimate equation (6) with event time coefficients interacted with borrowers' estimated stu-

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

[15] 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.

dent loan MPX out of forbearance:

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

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: $\widehat{MPX}^w_{p_j,i} = \hat{\mu}_{MPX} + \hat{\phi}_{MPX} \cdot \widehat{MPX}^f_{p_s,i}$, where $\hat{\phi}_{MPX}$ estimates the covariance between $\widehat{MPX}^w_{p_j,i}$ and $\widehat{MPX}^f_{p_s,i}$.

4.1.2 Implementation and results

The first three results establish that borrowers treat liquidity from forbearance as non-fungible with liquidity from cash transfers.

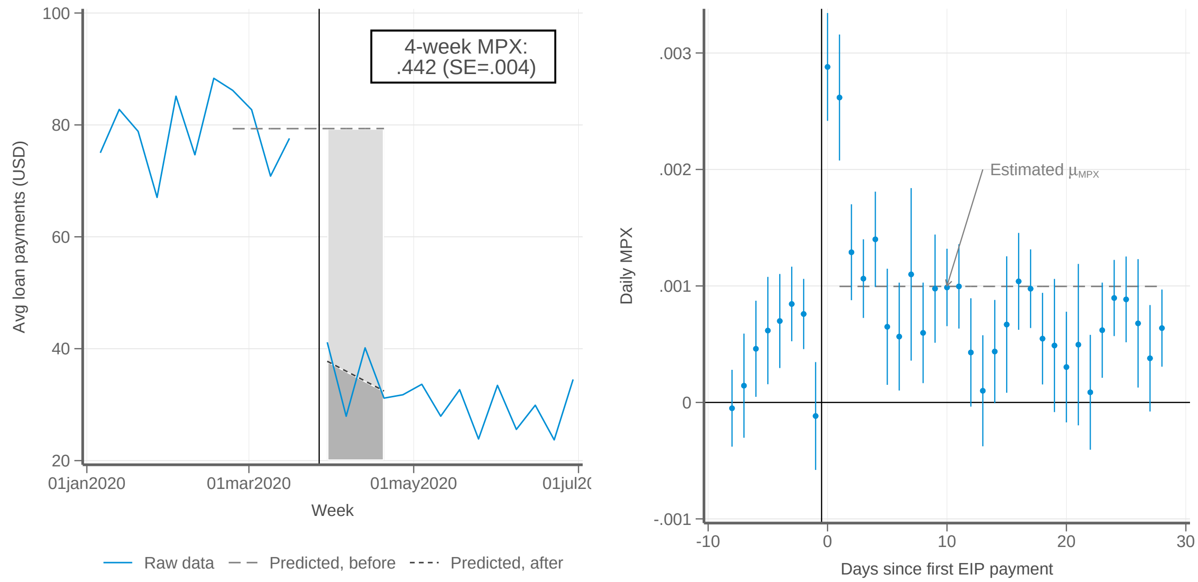
1. Borrowers use a significant fraction of forbearance liquidity to prepay federal student loans. Figure 1a plots average borrower payments on federal student loans by calendar week to illustrate the variation used to estimate $\widehat{MPX}^f_{p_s}$. Before forbearance, borrowers paid an average of 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 persist above zero. Therefore, borrowers use much of the liquidity from forbearance to repay their student debt.

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 taking 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.[16] Repayments persist for months after April 2020, showing that delayed borrower reactions do not drive results. Appendix C.2 shows results are unchanged if I impose common time trends ($\beta_1 = \beta_2$) when estimating (5).

There are two reasons to support interpreting this estimate as a four-week MPX. First, repayment trends are flat in the four weeks before forbearance, despite March economic hardship. Borrowers in my sample – who have some college education – may have escaped negative

[16] These results align with estimates from representative credit bureau samples. Goss, Mangrum, and Scally (2023) finds that among borrowers with declining balances pre-forbearance, about 34% continued to reduce their balances, almost identical to estimates from Figure F.2. In Cherry et al. (2021), before the pandemic, 50% of student loans were in forbearance (Figure 2), with likely zero payments. Around 80% of borrowers missed payments from March 2020-May 2021 (Figure A7, Panel (d)) . Therefore, around 40% of borrowers who were not in forbearance prior to forbearance continued making payments after forbearance.

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 pre-forbearance predicted values integrated over four weeks of the post-forbearance period and the post-forbearance predicted values integrated over 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.

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 using payments on *private* loans, which were not subject to forbearance, builds confidence that pre-forbearance trends generate reasonable predictions of counterfactual payments. I apply my methodology to private loan payments for borrowers with private and federal student loans. I should estimate an MPX on private student loans of around one if a pre-forbearance linear trend well-approximates post-forbearance repayment. The second column in Table 2, Panel A shows a point estimate of 0.93 (95% confidence interval: [0.89,0.97]). The pre-forbearance trend slightly over-estimates post-forbearance repayments, although this could partly reflect private forbearance. Hence, my estimates may face a small downward bias.[17]

To give insight into borrower-level heterogeneity, Appendix Figure F.1 plots the fraction of borrowers who make payments on federal student loans each week. The post-forbearance

[17]Appendix C.2 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.

decline is roughly proportional to average payments drop shown in Figure 1a. Therefore, borrowers chose to either spend either all or none of their forbearance liquidity on prepayments. This echoes Coibion, Gorodnichenko, and Weber (2020), who use surveys to find that the individual-level MPX on debt repayments out of stimulus checks clusters at zero and one.

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.

3. Borrowers do not use stimulus checks to prepay federal student loans. Student loan prepayments after forbearance need not be inconsistent with fully-informed, rational behavior. Prepaying 0% interest student debt might be attractive if alternatives offered equivalent (or even negative) yields. In this case, borrowers would also use saving from other windfalls – in particular, stimulus check payments – to repay student loans, intuition formalized in Claim 1.

Figure 1b investigates this by plotting estimates from specification (6) with $T_s \in \{t : t \in [-7, 28]\}$ where coefficients represent the daily MPX on federal student loan repayments out of stimulus payments.[18] Federal student loan repayments increase sharply on stimulus check receipt. But magnitudes are miniscule, 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 forbearance liquidity. I plot the estimate in Figure 1b for comparison with daily estimates. The MPX is 0.93%, a statistically significant 43 percentage points lower than $\widehat{MPX}^f_{p_s}$ (SE of the difference = 0.4%). This behavior violates predictions of savings models where agents respect fungibility of financial resources, and suggests that borrowers viewed the two transfers as non-fungible.

The next two results indicate this non-fungibility generates costly debt repayment mistakes.

4. Borrowers prepay 0% 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.[19] Furthermore, if prepayment in forbearance relates to borrower views on education debt, then

[18] 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.

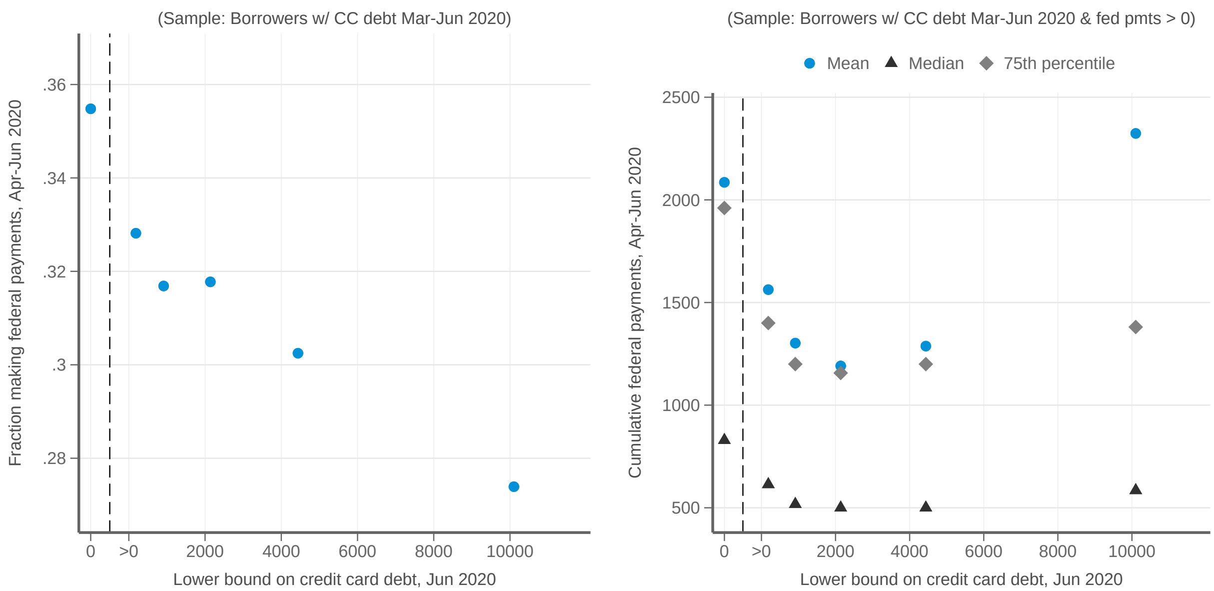
[19] In March 2020, the average APR paid on credit card debt were 17% (McCann 2022, Federal Reserve Board 2023), and the average 10-year private student loan fixed rate was around 6% (Carter 2022).

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[20]), and track federal debt repayment from the start of forbearance in April through June. Points left of the vertical line show values for the full linked credit-card sample.

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 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 credit card debt decile. The lower bound on credit card debt as of June 2020 is winsorized at the 95% level.

About 30% make this mistake, 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 27% of borrowers with over $10,000 in credit card debt prepay their student loans.[21]

How costly is this mistake? The right panel conditions on borrowers making prepayments between April and June, and plots prepayment amounts by credit card debt level. A borrower

[20] Appendix Figure F.2 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.

[21] 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.

with at least \$10,000 in credit card debt paid around \$1,400 towards their 0%-interest student loan from April to June at the 75th repayment percentile. The annualized cost of this mistake is around $\$1,400 \times 17\% \approx \$238$. If borrowers continue making this mistake, over a year they would pay around $6 \times \$238 = \$1,428$ 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 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.4 presents additional results for private borrowers.

5. Borrowers appropriately prioritize repaying high-yield debt out of cash windfalls. 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 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

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 $\mu_{\hat{MPX}} \times 30$ 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 borrowers with above-median cumulative private student loan payments between June 1, 2020 to January 1, 2021.

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. 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 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.8).

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, borrowers may make payments using "push" autopay through their bank rather than "pull" autopay with their servicer. This is uncommon, since federal law requires a 0.25% interest rate discount for borrowers with "pull" autopay. Appendix Table G.7 shows that only 24% of prepayers use push autopay and are not more likely to do so than non-prepayers, and Appendix C.5 shows repayment patterns are inconsistent with widespread autopay usage.

Fifth, as shown in Appendix C.5, payment amounts became more variable and clustered at round numbers, evidence that borrowers made active post-forbearance repayment choices.

Sixth, borrowers who continue student loan payments are not "habit" consumers, and instead rapidly adjust behavior in response to government policy. Table G.3 shows estimates of the four-week consumption expenditure MPX out of stimulus checks for hypothetical "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 apply 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

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 MPX 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.9 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:

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

where c_{it} is an expenditure variable, γ_i are borrower fixed effects, γ_{yt} are time-by-permanent income decile fixed effects, $\omega_{p_s,t}$ are time-by-pre-forbearance payment decile fixed effects, and Pmt_i is pre-forbearance payment levels for borrowers with outstanding student debt when forbearance began. Since Pmt_i is the liquidity received by borrowers with outstanding debt relative to the control group who just repaid their loans, the coefficients of interest are σ_k^1. 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 levels, controlling for income-by-time trends.

Under the parallel trends assumption, the coefficients σ_k^1 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 $\hat{\sigma}_0^1$. 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: $0.5 \times \left(\hat{\sigma}_0^1 + \hat{\sigma}_1^1\right)$.[22]

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.6. 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.

[22] 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_1^1 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.

Robustness. Heterogeneous federal-private debt mix. Appendix C.7 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 approach estimates $MPX_c^f \equiv E\left[\frac{\Delta c_i^f}{\Delta p_{si}}\right]$, where Δc_i^f and Δp_{si} are borrower i's change in consumption and optimal student loan payments, respectively, due to forbearance. Applying a first-order approximation to the consumption policy function from Section 2, the change in consumption is $\Delta c_i^f \approx \frac{\partial c_i(\cdot)}{\partial X}\Delta p_{si}^o$, where $\Delta p_{si}^o \equiv p_{si}^o(\cdot;\theta) - p_{si}^o(\cdot;\theta')$ represents the *observed* decrease in student loan payments following forbearance. This expression implicitly assumes that the lower bound in equation (4) binds at zero. This implies that $MPX_c^f \approx E\left[\frac{\partial c_i(\cdot)}{\partial X}\cdot\left(1-MPX_{p_s}^f\right)\right]$.

I use this decomposition in two ways. First, I estimate implied expenditure out of forbearance cash-on-hand as $\widehat{MPX}_c^f / \left(1-\widehat{MPX}_{p_s}^f\right)$, with $\widehat{MPX}_{p_s}^f$ estimated as in Section 4.1.1. A lower value than the MPX out of stimulus checks indicates lower spending out of cash-on-hand originally earmarked for debt repayment.

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. This is a plug-in estimate of MPX_c^f, given by: $\widehat{MPX}_c^{f,semi} = N^{-1}\sum_i \widehat{\frac{\partial c_i}{\partial X}}\cdot\left(1-\widehat{MPX}_{p_s,i}^f\right)$. This indicates how much of the difference between MPX_c^f and the MPX out of stimulus checks reflects student loan prepayment versus differences in expenditure out of cash-on-hand, conditional on prepayment.[23]

In the main specification, I parameterize $\frac{\partial c_i}{\partial X} = \mu_{MPX} + \phi_{MPX}\cdot MPX_{p_s,i}^f$ and estimate μ_{MPX}, ϕ_{MPX}, and $MPX_{p_s,i}^f$ as in specification (7). Appendix C.8 shows that results are unchanged if I: (i) parameterize $\frac{\partial c_i}{\partial X}$ nonlinearly to allow more flexible correlations with $MPX_{p_s,i}^f$; and (ii) estimate μ, ϕ with the imputation estimator in Borusyak, Jaravel, and Spiess (2024).

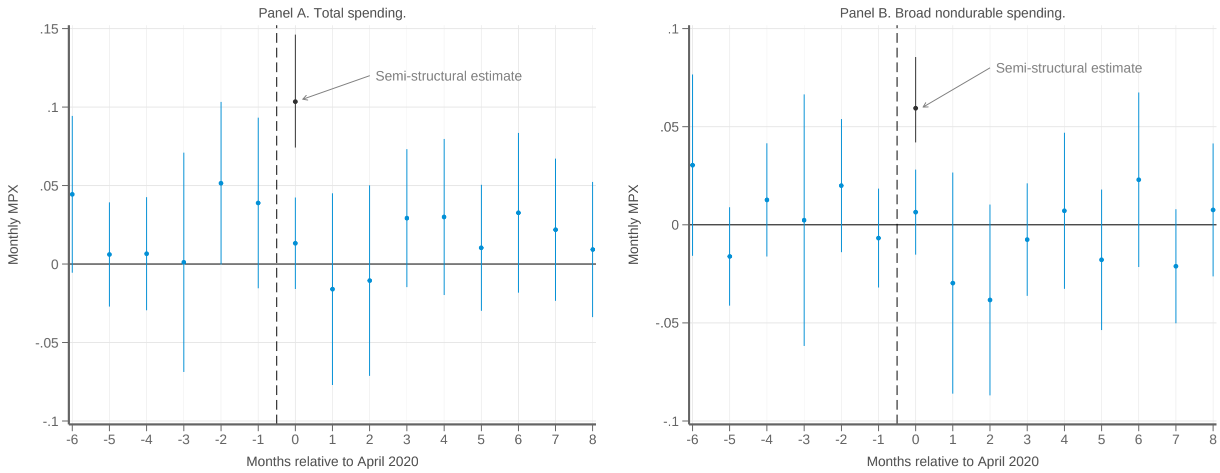
4.2.2 Results

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 $\hat{\sigma}_k^1$ from specification (8).[24] The figure shows no pre-trends. I therefore interpret $\hat{\sigma}_k^1$ as the causal impact of an extra dollar of monthly forbearance liquidity on spending in the k^{th} month after forbearance starts.

[23] Appendix C.6 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.

[24] Omitting one coefficient is required to avoid multicollinearity. To see this, divide specifications (8) by Pmt_i. 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 $\hat{\sigma}_k^1$ 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 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 -1.1-1.3%, 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 and literature estimates bound the difference between *annual* stimulus check and forbearance MPCs by less than 3pp. I can reject a total spending forbearance MPX that is 9.7pp less than the smallest stimulus check MPX that I cannot reject.

What drives the low MPX out of forbearance liquidity relative to stimulus checks? First, the implied 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). Based on semi-structural estimates, significant loan prepayment out of forbearance liquidity is also relevant.

Panel B reports full-sample stimulus check MPX and semi-structural estimates. Estimates imply that even if expenditure out of forbearance cash-on-hand were the same as the MPX out of stimulus checks, the forbearance MPX would be 30% lower than that of stimulus checks.

4.3 Survey results: Motivations for student loan payment in forbearance

The transaction data results shows 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

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 either the first round of stimulus checks or student loan 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.

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.[25]

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 less, but even in this group, over 80% correctly answered questions about key

[25] 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.

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% 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 G.8 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, between 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 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.9 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 debt repayment mistakes

This section rationalizes transactions data and survey results with a consumption-saving model where consumers have goals over total savings and debt repayment flows. 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 is 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

Table 4: Survey responses

	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.

Source: Student borrower survey. Panel 4a: The "No" and "Yes" columns gives means for borrowers who 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 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.

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 $\boldsymbol{\Gamma}(x, \{p_j\}_j, g_x, \{g_j\}_j) \equiv (\gamma_x(x, g_x), \{\gamma_j(p_j, g_j)\}_j)'$.

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

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

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 $\left\{B_{j,t+1}\right\}_j$.[26]

Inter-temporally, total saving target deviation costs makes 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 so that target deviation costs do not scale with the size of the deviation:

$$\gamma_j(p_j, g_{jt}) \equiv b_j \cdot \mathbb{1}\{p_j \neq g_{jt}\}, \quad \gamma_x(x, g_{xt}) \equiv b_x \cdot \mathbb{1}\{x \neq g_{xt}\}, \tag{10}$$

where $(\{b_j\}, b_x)$ could vary across individuals. Two data features motivate this parameterization. First, target deviation costs in the survey, such as hassle costs to adjustment, are mostly fixed. Second, Appendix Figure F.1 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 consider choosing each set of control variables $(x_t, \{p_j\}_j)$ to fix to goals g_x, g_j, with the remainder chosen according to FOCs that maximize $v_t(x, \{p_j\}_j; \cdot)$. Consumers select the set to fix to goals to maximize the sum of $v_t(x, \{p_j\}_j; \cdot)$ less the sum of realized target deviation costs. 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

[26] 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.

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 target deviation costs as in (10). 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).[27]

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 indicates 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 expendure 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. Condisider 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 $b_s > 0 \implies p_s = g_s$ and $b_x > 0 \implies x = g_x$.

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, $MPX^f_{i,p_s} \equiv \Delta p_{ist}/p_{is,t-1} > 0$, summarizes this information.

Moreover, the gap between the consumption response to stimulus checks and forbearance,

[27] 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 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.

conditional on endogenous changes in student loan payments Δp_s, quantifies the prevalence of total saving target deviation costs. If $b_{ix} = 0$, then $\Delta c \approx \frac{\partial c}{\partial X}\Delta p_s$, where $\frac{\partial c}{\partial X}$ equals (to a first order) the stimulus check MPC, and Δp_s is the endogenous first-period change in payments. If $b_{ix} > 0$, then $\Delta c = 0$. 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, to a first order:

$$\underbrace{E\left[\frac{\Delta c^f_{it}}{p_{st}}\right]}_{\text{empirical average forbearance MPX}} \approx \tilde{\gamma}\cdot \underbrace{E\left[\left(1-MPX^f_{ip_s}\right)\cdot\left(\frac{\Delta c^w_{it}}{\Delta X}\right)\right]}_{\text{semi-structural MPX, }\widehat{MPX}^{f,semi}_{p_s}} + E\left[\mathbb{1}_{b_{is}=0}\varepsilon_{it}\right] \tag{11}$$

where $\tilde{\gamma} \equiv (E[\chi_i] + \mathrm{Cov}(\chi_i,\xi_i)/E[\xi_i])$ for $\xi_i \equiv \left(1-MPX^f_{ip_s}\right)\cdot\left(\frac{\Delta c^w_{it}}{\Delta X}\right)$. The left-hand side equals the total consumption MPX out of forbearance liquidity. Claim 4 shows that $-\varepsilon_{it} \le \left|\frac{\partial c_{it}}{\partial B_{st}}R_{st}\right|$ (as in Claim 2). In Section 4.2.2, the semi-structural MPX exceeds natural experiment estimates by too much for $E\left[\mathbb{1}_{b_{is}=0}\varepsilon_{it}\right]$ 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 incomplete-markets lifecycle models, consumers exhibit a high MPX out of direct stimulus payments when they face near-binding liquidity constraints. Such models predict that forbearance, which targets liquidity, should produce a similar aggregate demand response as forbearance at a potentially lower fiscal cost. This makes forbearance seem inexpensive for policymakers choosing fiscal tools to raise aggregate consumption in downturns.

However, my results show that student borrowers spend and save differently out of liquidity from forbearance and stimulus checks. I present a partial-equilibrium framework to calibrate how this behavior impacts stimulus check size relative to forbearance in an economic rescue package and forbearance's fiscal cost advantage relative to stimulus checks. Both depend on sufficient statistics described above and estimated in the transactions data.

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 constant 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 by a fixed amount using forbearance and stimulus checks.

Forbearance and stimulus checks The government implements forbearance b pausing required student loan payments and setting $\Delta R = 0$ for six months, with no balloon or catch-up payments. Borrower i receives p_i in liquidity. 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 $G_f \equiv \tilde{R}(T_s)\Delta R_s E[(1-\eta_i)p_i]$, where $\tilde{R}(T_s) \equiv \frac{\left(R^{T_s+1}-1\right)\left(R^6-1\right)}{R^{T_s+5}(R-1)^2}$.

To implement a sitmuls check policy, the government sends borrower i a stimulus check with value W_i. Borrowers spend $W_i L_i$. The present-value fiscal cost is G_w.

Define $\rho_i \equiv \frac{p_i}{E[p_i]}$ and $w_i \equiv \frac{W_i}{G_w}$, the fraction of each transfer allocated to borrower i. Appendix E.1 derives expressions for C_f and C_w, the aggregate consumption impacts of forbearance and stimulus checks, respectively.

Forbearance fiscal cost efficiency Forbearance has a fiscal cost advantage over stimulus checks if it generates a greater one-month consumption response for a fixed present-value fiscal cost. I define the forbearance fiscal cost efficiency $E_f \equiv (\Delta C_f - \Delta C_w)/G_f$ as the incremental increase in one-month aggregate consumption generated by using government funds for forbearance rather than stimulus checks. Appendix E.1 shows that:

$$\frac{E_f}{E[w_i L_i]} = \underbrace{\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)}_{\text{average cost}} \underbrace{\left(\frac{E[\rho_i L_i]}{E[w_i L_i]}\right)}_{\text{resource targeting}} \underbrace{\left(1 + \frac{\mathrm{Cov}(\chi_i(1-\eta_i), \rho_i L_i)}{E[\chi_i(1-\eta_i)]E[\rho_i L_i]}\right)}_{\text{behavioral targeting}} \underbrace{\left(\frac{E[\chi_i(1-\eta_i)]}{E[\rho_i(1-\eta_i)]}\right)}_{\text{flypaper effect}} - 1 \quad (12)$$

When this expression is positive, the consumption impact of the transfer is greater when delivered through forbearance rather than stimulus payments.

Three forces impact E_f. First, forbearance might have a lower fiscal cost because the cost to get a constrained borrower to increase spending by L_i today equals the present value of forgone interest on a dollar in loan payments, which may be less than a dollar. This "average cost 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 payments have higher L_i than people receiving large stimulus checks, reflected in the "resource targeting" term, and whether forbearance has advantageous "take-up," with liquidity delivered to more constrained borrowers ($\rho_i L_i$) more likely to be consumed, not used to prepay loans in forbearance or increase cash-on-hand ($\chi_i(1-\eta_i)$). The covariance between $\rho_i L_i$ and $\chi_i(1-\eta_i)$ in the "behavioral targeting" term reflects this force. Behavioral targeting could save the government money if borrowers with low MPCs continue paying their debts (implying no government expenditure).

Third, borrowers might, on average, use forbearance liquidity to prepay their student loans rather than consume, the "flypaper effect." This effect is lower if payment size ρ_i is negatively correlated with η_i, meaning people with high payments keep making them during forbearance.

Lifecycle 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 that $\chi_i(1-\eta_i) \perp L_i, \rho_i$. The first column in Table 2, Panel A supports the assumption that $\rho_i \perp \eta_i$. With this assumption, equation (12) becomes:

$$E_f = \left[\underbrace{\left(\frac{1}{\tilde{R}(T_s)\Delta R} \right)}_{\text{average cost effect}} \cdot \underbrace{\left(\frac{E[L_i] + \mathrm{Cov}(\rho_i, L_i)}{E[L_i] + \mathrm{Cov}(w_i, L_i)} \right)}_{\equiv \kappa,\ \text{resource targeting}} \cdot \underbrace{\left(\frac{\gamma}{1-\eta} \right)}_{\text{flypaper effect}} - 1 \right] \cdot \underbrace{E[w_i L_i]}_{\text{stimulus check aggregate MPX}} \tag{13}$$

where $\eta \equiv E[\eta_i]$ and $\gamma \equiv \frac{MPX_c^f}{MPX_c^w} = \frac{E[\chi_i(1-\eta_i)L_i]}{E[L_i]}$. 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.

Equation (13) allows for resource targeting but rules out behavioral targeting and "advantageous take-up." Appendix E.5 shows that allowing for "advantageous take-up" does not impact results, indicating it is not quantitatively important in this context.

I next calibrate the terms in equation (13). The top of Table 5, Panel A presents parameter values. 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 full sample stimulus check total MPX.[28] Finally, I use estimates from Section 4 to calibrate sufficient statistics $\eta = 0.44$ and $\gamma = 0.25$.[29]

[28]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.

[29]From Section 4.2.2, the stimulus check consumption MPX is around 17.4%. The upper-bound forbearance consumption MPX from natural experiments is around 4.3%.

Appendix E.2 describes the sensitivity of terms in (13) 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 $\hat{\kappa} = 0.92 < 1$.[30] Forbearance therefore did not target high MPX borrowers as well as stimulus checks did, perhaps reflecting that 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 absent a flypaper effect, E_f is 0.25, meaning per dollar of spending, forbearance delivers 25 cents more in aggregate consumption. But given estimates of γ and η, the flypaper effect almost neutralizes the forbearance cost advantage, as E_f falls to 0.01. Note the flypaper effect has a much greater effect on the relative fiscal cost of the two transfers than, for example, resource targeting. I turn to two calibration exercises to illustrate implications for policy design. Appendix E.1 provides more details on calculations.

Calibration exercises. How does the flypaper effect impact the design of a package similar to the CARES Act? I first quanify how the mix of student loan forbearance and stimulus checks would change. Assume that policymakers aim to increase one-month aggregate consumption among student borrowers, and planned that $\gamma = 1$ and $\eta = 0$. Table 5, Panel B shows that given transfer sizes, policymakers expected 1-month consumption to increase 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 policies that have a cost advantage over direct transfers. With $\gamma = 1, \eta = 0$, $T^{BE} = 109$ months,

[30] 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 G.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%

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. 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. These results suggest that borrowers view transfers as non-fungible, and in particular points to a flypaper effect where liquidity from forbearance "sticks" to federal student loan payments. Such a flypaper effect that rejects fungibility of liquidity from forbearance and cash transfers predicts that borrowers would have a higher short-term consumption response to a dollar in cash transfers relative to a dollar in liquidity from forbearance. Using a range of identification strategies, I find evidence supporting that prediction.

In a survey to identify drivers of this behavior, I find that (i) borrowers adhere to debt repayment targets due primarily to budgeting and heuristics; and (ii) limited financial sophistication causes adherence to targets above incentives generated by interest rates. I rationalize these results with an adjustment costs modification to an incomplete-markets lifecycle model.

Finally, my findings matter for designing economic rescue programs that aim to increase aggregate consumption. My estimates imply that policymakers must rely more on stimulus checks to reach aggregate consumption targets at a higher total fiscal cost; and 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 suggest perceived non-fungibility as a potential driver of debt repayment mistakes. My results show that developing microfounded theories of is crucial to evaluate the relative effects of different countercyclical fiscal policy tools and ongoing debates about the aggregate effects of additional student debt relief.

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

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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:

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

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 $j,k\in\{1,\ldots,J\}$:

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

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:

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

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 $R_0 - R_{j,t+1} > 0$, $E_t\alpha_{t+1} \geq 0$, 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:

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

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

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:

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

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

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

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

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

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

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

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

Substituting into equation (A.26):

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

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:

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

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 part (1), 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:

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

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

For part (2), 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:

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

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

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:[31]

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

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-

[31]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:

$$\Big(x_t^m(X_t,\{B_{jt}\}_j;\theta),\Big\{p_{jt}^m(X_t,\{B_{jt}\}_j)\Big\}_j;\theta\Big)\equiv$$

$$\arg\max_{x,\{p_j\}_j} U(X_t-x)+\delta EV_{t+1}\left(R_0\left(x-\sum_j p_j\right)+y_{t+1},\left\{R_{j,t+1}(B_{jt}-p_j)\right\}_j;\theta\right)$$
$$-\left(\gamma_x(x,g_{xt})+\sum_j \gamma_j(p_j,g_{jt})\right) \tag{A.42}$$
$$\text{s.t. } X_t-x+\sum_j p_j\geq 0 \quad [\alpha_t] \tag{A.43}$$
$$X_t+L_x\geq X_t-x+p_s \quad [\beta_t] \tag{A.44}$$
$$p_j\geq B_{jt}-L_{j,t+1} \quad [\lambda_{jt}] \tag{A.45}$$
$$B_{jt}\geq p_j \quad [\mu_{jt}] \tag{A.46}$$
$$X_t-x\geq 0 \quad [\sigma_t] \tag{A.47}$$

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

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:

$$\Delta c_t^{w,m}\equiv c_t^m(X_t+\Delta X,B_{st};\theta)-c_t^m(X_t,B_{st};\theta) \tag{A.48}$$
$$\Delta c_t^{f,m}\equiv c_t^m(X_t',B_{st}';\theta')-c_t^m(X_t,B_{st};\theta) \tag{A.49}$$
$$\Delta p_{st}^m\equiv p_{s,t-1}^m(X_{t-1},B_{s,t-1};\theta)-p_{s,t-1}^m(X_{t-1}',B_{s,t-1};\theta') \tag{A.50}$$

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:

$$p_{s,t-1}^{f,m}(X_{t-1},\{B_{j,t-1}\}_j;\theta,\theta')\equiv \arg\max_{p_s} v_{t-1}\left(x_{t-1}(\cdot;\theta),\{p_{j,t-1}(\cdot;\theta)\}_{j\neq s},p_s;X_{t-1},\{B_{j,t-1}\}_j,\theta'\right)$$
$$-\mathbf{1}'\Gamma\left(x_{t-1}(\cdot;\theta),\{p_{j,t-1}(\cdot;\theta)\}_{j\neq s},p_s;X_{t-1},\{B_{j,t-1}\}_j\right) \tag{A.51}$$
$$\text{s.t. } (A.43)-(A.47)$$

Liquidity from forbearance is therefore:

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

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 $R_{jt} = R_{kt}$ if $\frac{\partial EV_{t+1}}{\partial B_j} = \frac{\partial EV_{t+1}}{\partial B_k}$.*

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).[32] 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:

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

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

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 $m^0 \equiv m^*\left(\{b_k\}_{k \neq j}, 0\right)$. 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:

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

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 $\underline{m} \equiv m^*(\underline{b}_j, \{b_k\}_{k \neq j})$. Note that $\underline{b}_j$ only exists if $p_j^{o,\cdot} \neq g_{jt}$.

Fix some $b_j' > \underline{b}_j$. Let $m' \equiv m^*(b_j', \{b_k\}_{k \neq j})$, 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 $b_j > \underline{b}_j \implies m_j^*(b_j, \cdot) = g$

[32] 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 ($-\frac{\partial EV_{t+1}}{\partial B_s} \leq \frac{\partial EV_{t+1}}{\partial B_x}$).

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 $\alpha_t = 0$, i.e. $X_t - x - \sum_k p_k = 0$. 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):

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

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 Appendix 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 $B_{st}' = R_{st}(B_{s,t-1} - p_{s,t-1}(\cdot))$. A first-order Taylor expansion therefore gives:

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

Applying the assumption $R_0 = 1$:

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

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 positive. 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 (11)

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):

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

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

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

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

$$\Delta p_{ist} \equiv p^{m_i}_{s,t-1}(\cdot, \theta') - p^{m_i}_{s,t-1}(\cdot; \theta) \tag{A.86}$$

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

$$\Delta c^f_{it} \equiv \Delta c^{f,m_i}_t \tag{A.88}$$

$$\Delta c^w_{it} \equiv \Delta c^{w,m_i}_t \tag{A.89}$$

$$\frac{\partial c_{it}}{\partial B_{st}} \equiv \frac{\partial c^{m_i}_t}{\partial B_{st}} \tag{A.90}$$

$$\varepsilon_{it} \equiv \varepsilon^{m_i}_t \tag{A.91}$$

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, FedLoans, 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 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 the program

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 Robustness: MPX on federal student loans out of forbearance liquidity

This subsection presents robustness analysis for Section 4.1. Results are in Table G.1.

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.[33] 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 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

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

with both private and federal debt would only receive notice on *some* of their accounts, possibly emphasizing that private debt is not eligible.

C.3 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 G.2 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 G.2 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.

C.4 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 F.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 75^{th} 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.

C.5 Evidence against alternative explanations for prepayment during forbearance

This subsection fleshes out arguments made in Section 4.1.2.

First, recall the fourth argument, that "pull" autopay cannot explain results. Repayment patterns suggest that "pull" autopay is 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 $\pm$ \$20 differences).

Next, recall the fifth 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 F.5 shows evidence for (i). I restrict to borrowers making 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, rather than 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 F.7 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.6 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 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 repayment 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^1 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.7 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.7.1 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. [34]

Figure F.10 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 through 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

[34] Students typically borrow as much as they can using federal programs before turning to the private student loan market, where interest rates tend to be higher and repayment terms less forgiving. Limits on federal borrowing depend mostly on family background.

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 F.10 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:

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

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 selection into obtaining *any* private debt.[35]

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.7.2 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.

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

More specifically, refinancing activity that alters the borrower debt mix may threaten identification 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.1) 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.7.3 Results

To evaluate the identifying assumption behind the natural experiment, Figure F.11 plots $\hat{\sigma}_k^2$ from specification (C.1) to evaluate the second natural experiment. 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.

Table G.4 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%.

C.8 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-difference design, the full sample, and the federal-vs-private borrowers difference-in-difference design described in Appendix Section 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:

$$\frac{\partial c_i}{\partial X} = \phi_0 + \sum_k \mu_k \mathbb{1}(MPX^f_{p_s,i} \in T_k) \cdot MPX^f_{p_s,i} \tag{C.2}$$

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).

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 and the present. I sent the screening survey to a balanced sample of men and women who had completed at least a high school education.[36]. 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 \$0.2 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.

[36] 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 G.10.

D.4 Summary statistics and replicating transaction data results

Table G.6 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.[37]

Table G.6 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

[37]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.

borrowers who continue to make payments for the remaining table rows, since it better aligns with my transaction data sample selection criteria.[38]

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 prepayed federal student loan debt post-forbearance, 35% used their stimulus checks to pay down credit card debt.

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 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 G.8). 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."

[38]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.

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 $\gamma \equiv \frac{MPX_c^f}{MPX_c^w} = \frac{E[\chi_i(1-\eta_i)L_i]}{E[L_i]}$ 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 (11).

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 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 $\Delta C_f \equiv E[p_i] \cdot E[\chi_i(1-\eta_i)\rho_i L_i]$, which can be rewritten as:

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

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:

$$\Delta C_w \equiv G_w \cdot E[w_i L_i] = G_w \left(\mathrm{Cov}(w_i, L_i) + E[L_i]\right) \tag{E.2}$$

As in (E.1), 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.1) and (E.2):

$$\begin{aligned}
E_f &\equiv \frac{\Delta C_f - \Delta C_w}{G_f} \\
&= \frac{E[p_i]\cdot E[\chi_i(1-\eta_i)\rho_i L_i] - G_w \cdot E[w_i L_i]}{\tilde{R}(T_s)\Delta R_s E[(1-\eta_i)\rho_i]\cdot E[p_i]} \\
&= \frac{E[\chi_i(1-\eta_i)\rho_i L_i]}{\tilde{R}(T_s)\Delta R_s E[(1-\eta_i)\rho_i]} - E[w_i L_i] \\
&= \left(\frac{1}{\tilde{R}(T_s)\Delta R_s}\right)\left(\frac{E[\rho_i L_i]E[\chi_i(1-\eta_i)] + \mathrm{Cov}(\chi_i(1-\eta_i), \rho_i L_i)}{E[(1-\eta_i)\rho_i]}\right) - E[w_i L_i] \\
&= \left[\left(\frac{1}{\tilde{R}(T_s)\Delta R_s}\right)\left(\frac{E[\rho_i L_i]}{E[w_i L_i]}\right)\left(1 + \frac{\mathrm{Cov}(\chi_i(1-\eta_i), \rho_i L_i)}{E[\chi_i(1-\eta_i)]E[\rho_i L_i]}\right)\left(\frac{E[\chi_i(1-\eta_i)]}{E[\rho_i(1-\eta_i)]}\right) - 1\right]E[w_i L_i]
\end{aligned} \tag{E.3}$$

Rearranging equation (E.3) yields expression (12) 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 F.12, Panel F.12a 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 solid line at point A to show the estimate of the average cost effect in the baseline calibration of 2.63.

Figure F.12, Panel F.12b fixes the forbearance average cost effect at point A in Panel F.12a, 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 F.12, Panel F.12b. This shows how E_f drops from 0.25 (Point C) to 0.01 (Point D) once accounting for the estimated flypaper effect.

Figure F.12, Panel F.12c 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 F.12, Panel F.12d 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:

$$G_{tot} = G_w + G_f \tag{E.4}$$

Using the formulas in the text and applying $\eta = 0, \chi = 1$, $G_f = \tilde{R}(T_s)\Delta R_s E[(1-\eta_i)p_i]$. 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:

$$G_{tot} = 350 \times 2.63^{-1} + 1,350 = 1,483 \tag{E.5}$$

as cited in the text.

Total consumption would be expected to increase by:

$$0.174 \times \kappa \times E[p_i] + 0.174 \times E[w_i G_w] = 291 \tag{E.6}$$

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:

$$0.174 \times \kappa \times \gamma \times E[p_i] = 14 \tag{E.7}$$

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 (13), which impacts how the different targeting properties of student loan forbearance and stimulus checks impact the forbearance fiscal cost efficiency. Recall that:

$$\kappa=\frac{E[\rho_i L_i]}{E[w_i L_i]} \tag{E.8}$$

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:

$$L_i=\mu(x_i)+\varepsilon_i\approx\sum_k \mu_k\cdot\mathbb{1}\{x_i\in k\}+\varepsilon_i \tag{E.9}$$

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:

$$\widehat{E[\rho_i L_i]}=\sum_k \Pr(x_i\in k)\cdot\hat{\mu}_k\cdot E[\widehat{\rho_i|x_i\in} k] \tag{E.10}$$

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 dissavings during that period are likely experiencing financial distress, and hence likely have a higher short-run MPX.[39] I estimate μ_k by estimating

[39] 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

equation (6) separately for quintiles in proxied liquid assets. Appendix Table G.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.10). 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 G.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.

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:

$$E[L_i | w_i > 0] \geq E[L_i | w_i = 0] \tag{E.11}$$

$$L_i \in [0, 1] \tag{E.12}$$

Derivation. By definition:

$$E[\rho_i L_i] = \Pr(w_i > 0) E[\rho_i L_i | w_i > 0] + \Pr(w_i = 0) E[\rho_i L_i | w_i = 0] \tag{E.13}$$

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

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

$$E[\rho_i L_i | w_i = 0] \in [0, (E[L_i | w_i > 0]) \cdot E[\rho_i | 1 - G(\rho_i | w_i = 0) \leq E[L_i | w_i > 0]]] \tag{E.14}$$

The lower bound follows because assumption (E.12) implies that $E[L_i | w_i = 0] \geq 0$.

The upper bound comes from maximizing the correlation between ρ_i and L_i assuming

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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 dissaves \$5,000 between January 2019 and March 2020, and person B with \$10,000 in January 2019 who net dissaves \$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.

maximum possible variance in L_i, subject to the constraints in (E.11) and (E.12). 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 $E[L_i|w_i = 0] \leq E[L_i|w_i > 0]$ assumes that a fraction $E[L_i|w_i > 0]$ 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:

$$E[\rho_i L_i|w_i = 0] = \Pr(L_i > 0) \cdot E[\rho_i L_i|L_i > 0] = \Pr(L_i > 0) \cdot E[\rho_i|L_i > 0] \tag{E.15}$$

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.15):

$$\begin{aligned} \Pr(L_i > 0) &= E[L_i|w_i > 0] \\ E[\rho_i|L_i > 0] &= E[\rho_i|1 - G(\rho_i|w_i = 0) \leq E[L_i|w_i > 0]] \end{aligned}$$

Putting everything together delivers the upper bound in equation (E.14). The corresponding bounds for $E[\rho_i L_i]$ are then:

$$\begin{aligned} E[\rho_i L_i] \in [&\Pr(w_i > 0)E[\rho_i L_i|w_i > 0], \\ &\Pr(w_i > 0)E[\rho_i L_i|w_i > 0] + \Pr(w_i = 0) \cdot (E[L_i|w_i > 0]) \cdot E[\rho_i|1 - G(\rho_i|w_i = 0) \leq E[L_i|w_i > 0]]] \end{aligned} \tag{E.16}$$

Implementation. First, I use my full-sample estimate of the stimulus check MPX to estimate $E[L_i|w_i > 0]$:

$$E[\widehat{L_i|w_i > 0}] = 0.174 \tag{E.17}$$

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:

$$E[\rho_i L_i|w_i > 0] = E[\rho_i \cdot (L_0 + L_1\rho_i)] = L_0 E[\rho_i|w_i > 0] + L_1 \cdot E[\rho_i^2|w_i > 0] \tag{E.18}$$

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:

$$\begin{aligned} c_{j,it} &= \gamma_i + \delta_{yt} + \mu_{pre}\mathbb{1}(t<-7)\cdot EIP_i + \mu_{MPX}\mathbb{1}(t\in[0,28])\cdot EIP_i + \mu_{post}\mathbb{1}(t>28)\cdot EIP_i \\ &\quad + \eta_{pre}\mathbb{1}(t<-7)\cdot EIP_i\times\rho_i + \eta_{MPX}\mathbb{1}(t\in[0,28])\cdot EIP_i\times\rho_i \\ &\quad + \eta_{post}\mathbb{1}(t>28)\cdot EIP_i\times\rho_i + \varepsilon_{it} \end{aligned} \tag{E.19}$$

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 G.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.

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 (12) becomes:

$$E_f = \left[\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)\cdot\left(\frac{E[\rho_i L_i]}{E[w_i L_i]}\right)\cdot\left(1+\frac{\text{Cov}(1-\eta_i,\rho_i L_i)}{E[1-\eta_i]E[\rho_i L_i]}\right)\cdot\left(E[\chi_i]\frac{E[1-\eta_i]}{E[\rho_i(1-\eta_i)]}\right)-1\right]\cdot E[w_i L_i] \tag{E.20}$$

$$= \left[\left(\frac{1}{\tilde{R}(T_s)\Delta R}\right)\cdot\left(\frac{E[(1-\eta_i)\rho_i L_i]}{E[w_i L_i]}\right)\cdot\left(\frac{E[\chi_i]}{E[\rho_i(1-\eta_i)]}\right)-1\right]\cdot E[w_i L_i] \tag{E.21}$$

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.[40] I then

[40] 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 $\eta_i > 0$.

estimate μ_k separately for each bin using the regression:

$$L_i = \sum_k \mu_k \cdot \mathbb{1}\{(x_i, \eta_i) \in k\} + \varepsilon_i \tag{E.22}$$

I then estimate:

$$E[\widehat{(1-\eta_i)\rho_i} L_i] = \sum_k \Pr(x_i \in k) \cdot \hat{\mu}_k \cdot E[\widehat{(1-\eta_i)\rho_i | (x_i}, \eta_i) \in k] \tag{E.23}$$

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:

$$\gamma = \frac{E[\chi_i(1-\eta_i)L_i]}{E[L_i]} = E[\chi_i]\frac{E[(1-\eta_i)L_i]}{E[L_i]} \implies E[\chi_i] = \frac{\gamma}{E[(1-\eta_i)L_i]/E[L_i]} \tag{E.24}$$

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.

Table G.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.

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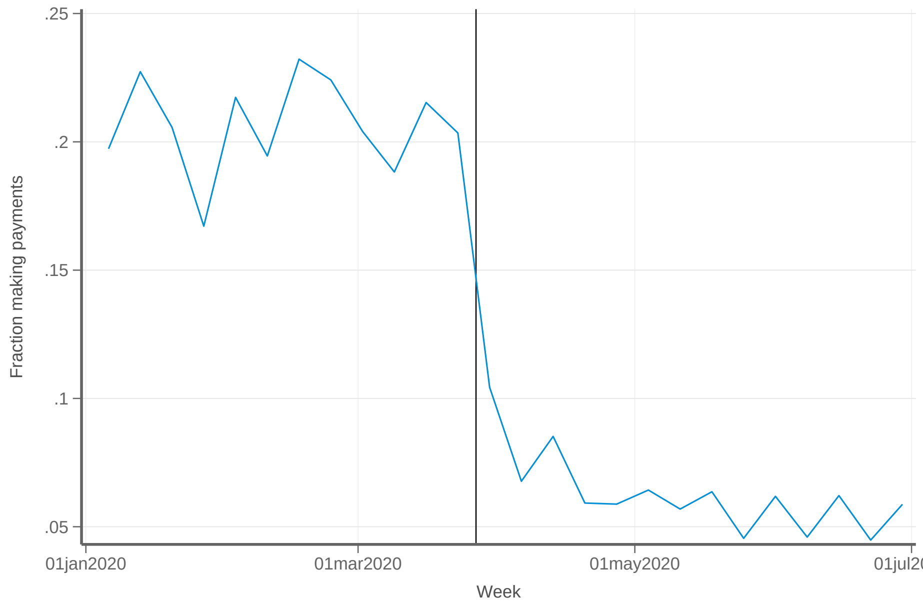
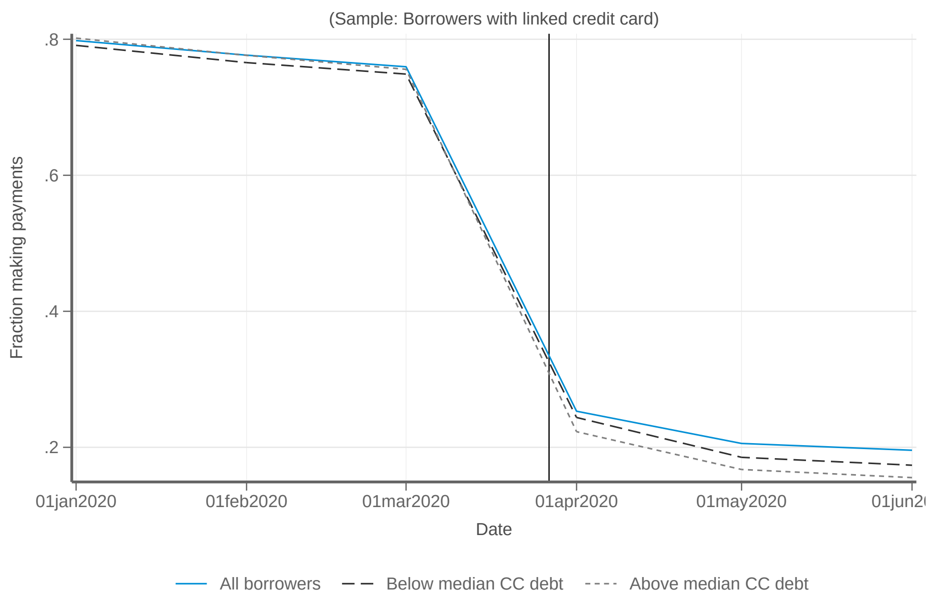
F Additional figures

Figure F.1: Fraction making payments on federal student loans by week



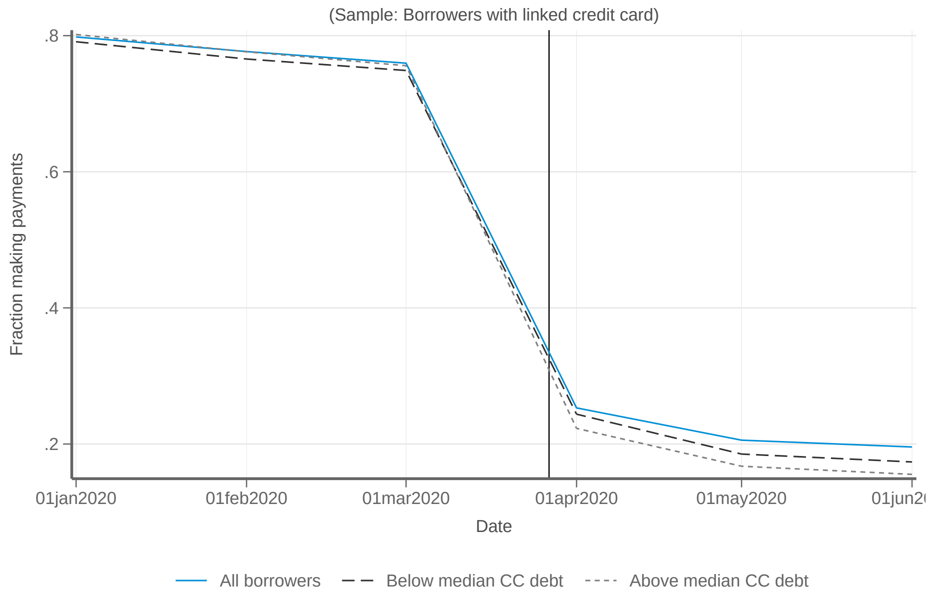
Source: Author's calculations. The figure plots the fraction of borrowers in the full sample who make payments on federal student loans in each week. The vertical line indicates the onset of automatic forbearance.

Figure F.2: Fraction making payments on federal student loans by month and credit card debt level



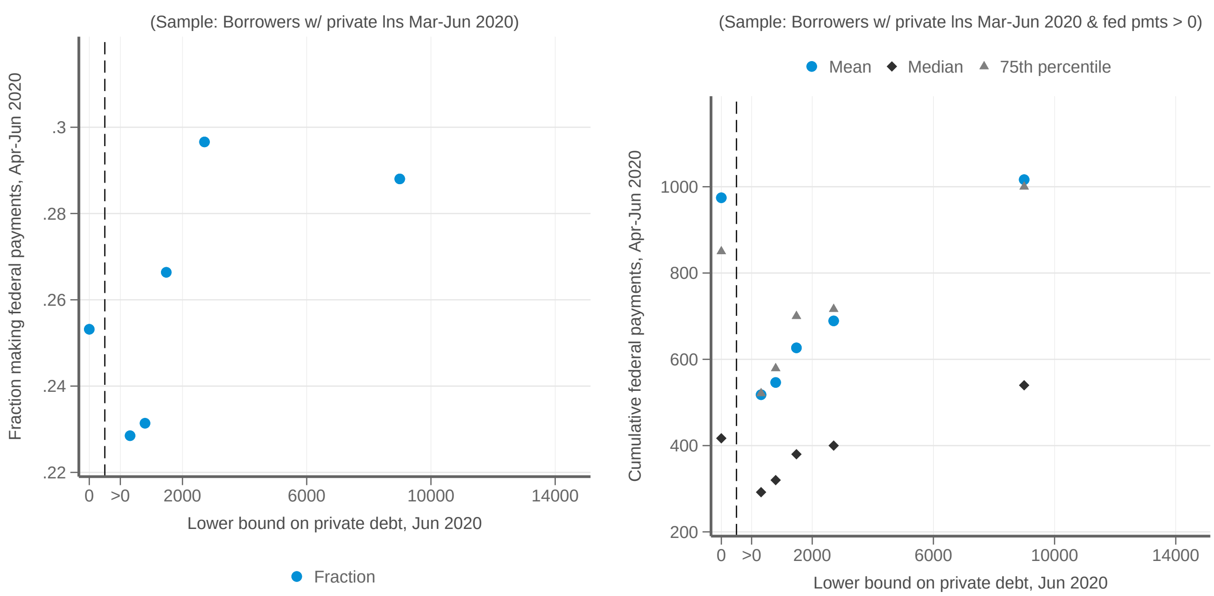
Source: Author's calculations. The figure restricts to federal student loan borrowers with a linked credit card account, and plots the fraction who make a payment on federal debt in each month. The solid blue line shows the average for the full sample. The black dashed and gray dotted lines restrict 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.3: Fraction making payments on federal student loans by month and credit card debt level, credit card debt sample



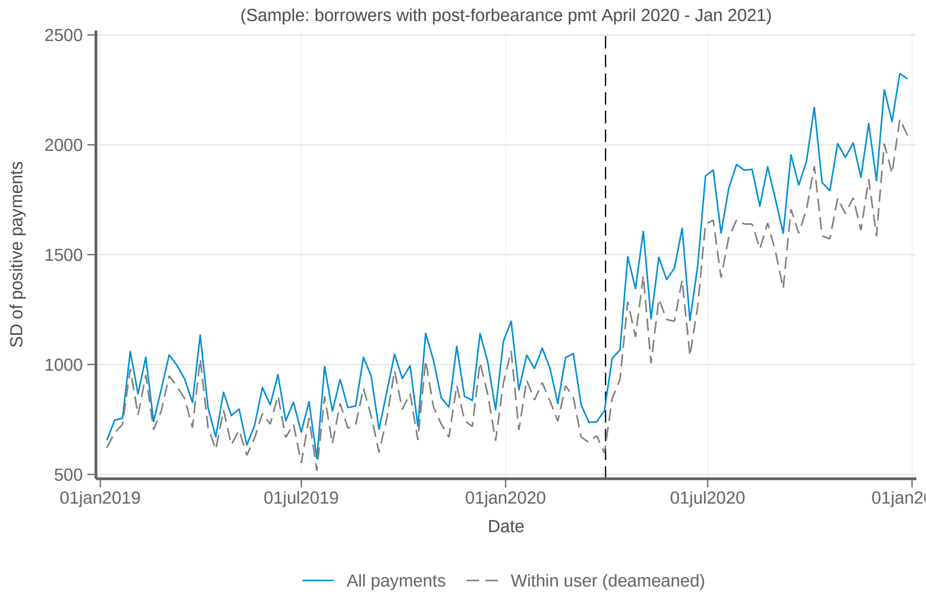
Source: Author's calculations. The figure restricts to federal student loan borrowers with a linked credit card account, and plots the fraction who make a payment on federal debt in each month. The solid blue line shows the average for the full sample. The black dashed and gray dotted lines restrict 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.

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



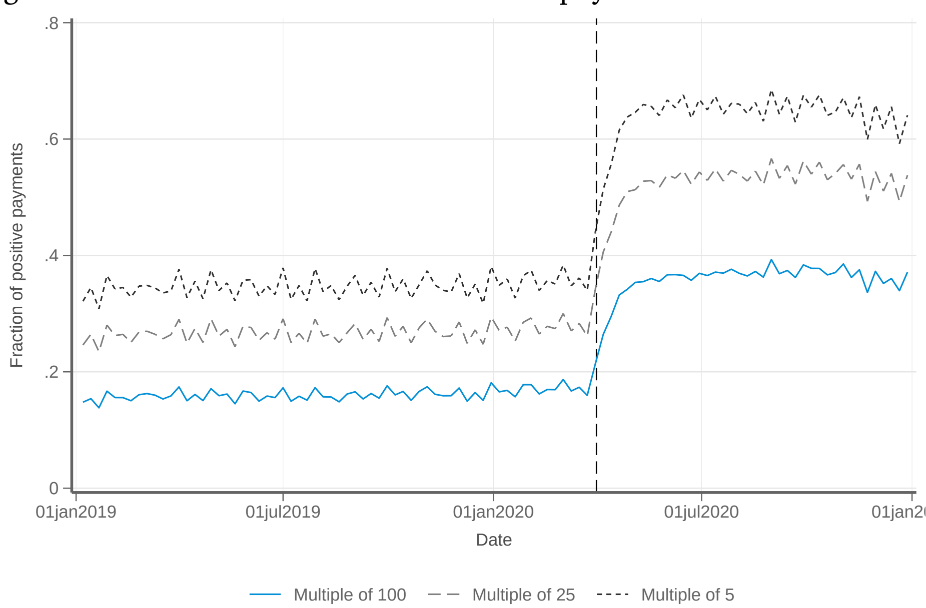
Source: Author's calculations. The figure plots debt repayment mistakes for the sample of borrowers who made positive payments on private student loans after June 1, 2020. The left panel plots the fraction of borrowers who make any payments on federal debt between April and June 2020, and the right panel 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.

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



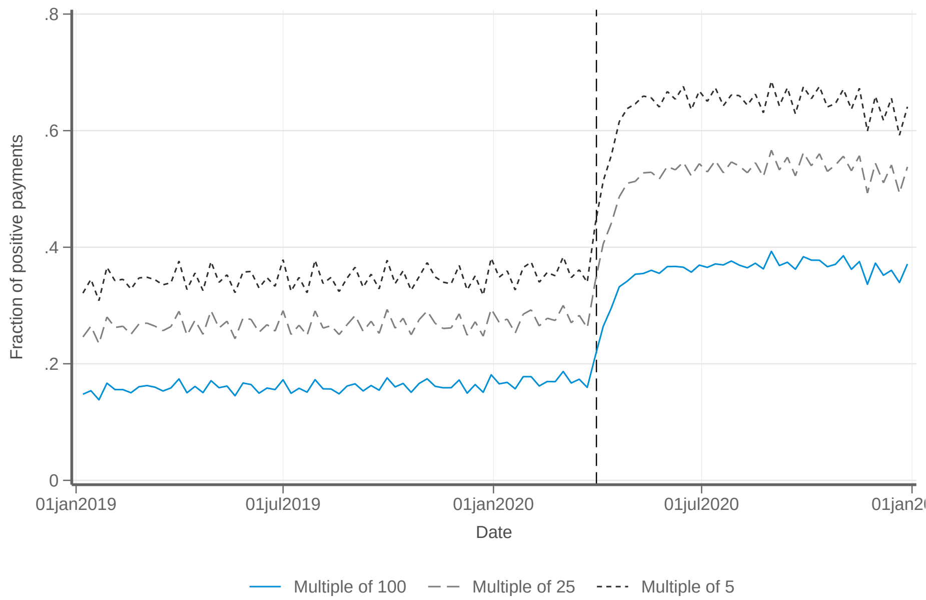
Source: Author's calculations. The sample restricts to borrowers who make at least one post-forbearance payment on federal student loans between April 2020 and January 2021. The solid series plots the sample standard deviation of nonzero payments each week. The dashed series demeans observations at the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

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

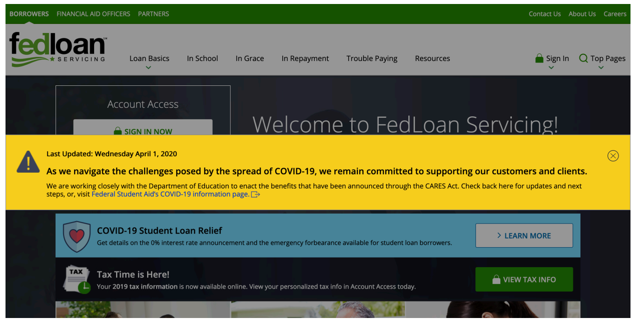


Source: Author's calculations. The sample restricts to borrowers who make at least one post-forbearance payment on federal student loans between April 2020 and January 2021. Each series plots the fraction of nonzero loan payments each week that are exact multiples of 100 (solid, blue), 25 (dash, light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

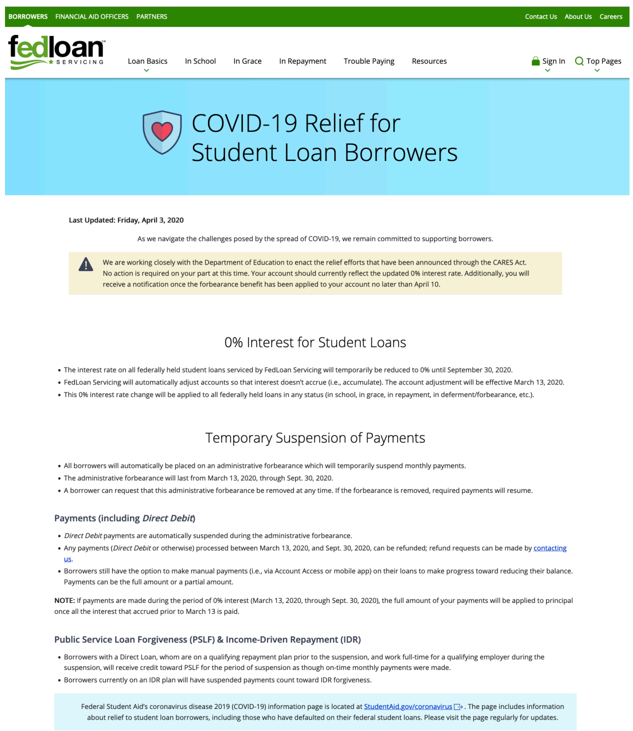
Figure F.7: Fraction of federal student loan payments at round numbers



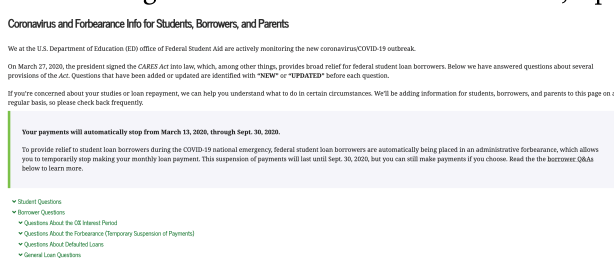
Source: Author's calculations. The sample restricts to borrowers who make at least one post-forbearance payment on federal student loans between April 2020 and January 2021. Each series plots the fraction of nonzero loan payments each week that are exact multiples of 100 (solid, blue), 25 (dash, light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



(a) FedLoan Servicing home page, April 2, 2020



(b) FedLoan Servicing Covid information for borrowers, April 3, 2020

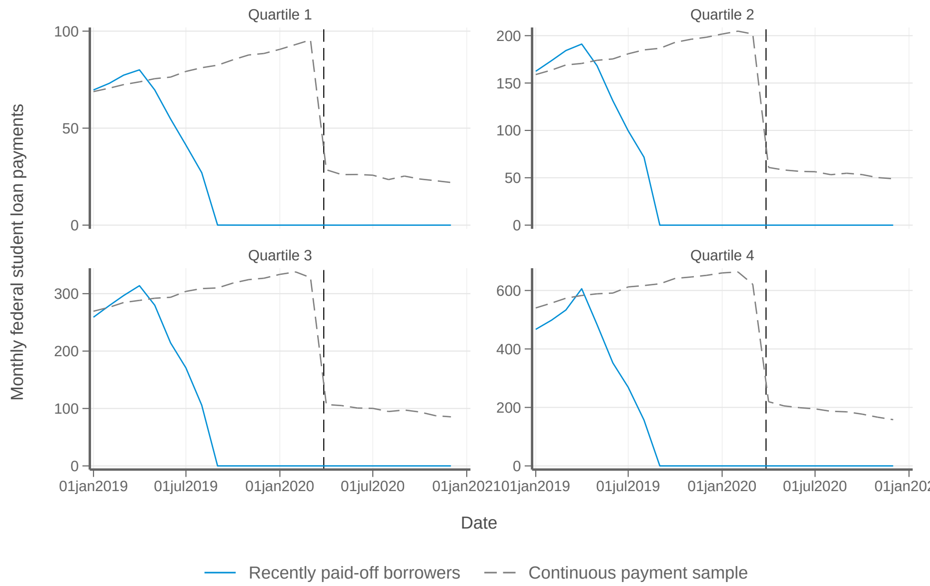


(c) Ed Department Covid info page, April 2, 2020

Figure F.8: Communications with borrowers around start of forbearance

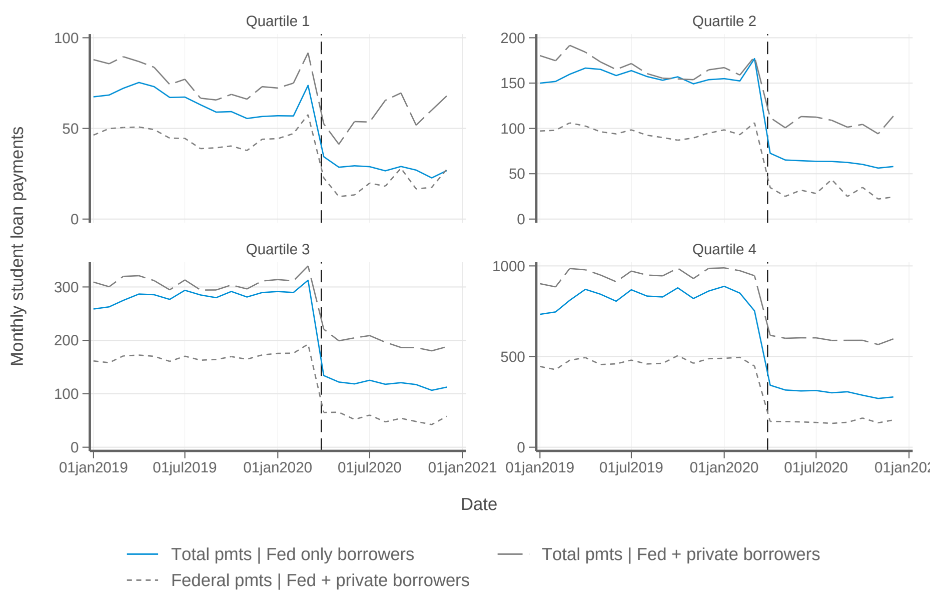
Source: Internet Archive Wayback Machine. Panel F.8a displays a screenshot from the Fedloan Servicing homepage on April 2, 2020 (link). Note the popup with a link to the Ed Department covid information page (Panel F.8c), and the notice about relief below the popup with a link to learn more. Panel F.8b contains a screenshot of the Fedloan Servicing Covid info linked on the homepage, with the snapshot from April 3, 2020. Panel F.8c shows the federal government communication homepage, with links to extensive info about the program.

Figure F.9: Federal student loan pmts, recently paid-off vs. continuous pmt sample



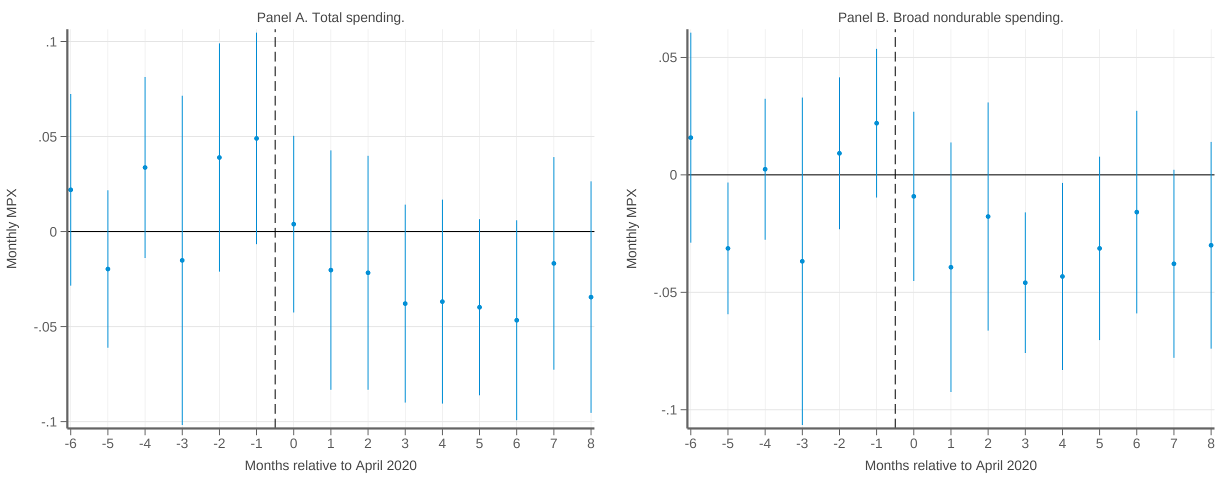
Source: Transactions panel. The figure plots average monthly federal student loan payments for borrowers with only federal student debt. The blue solid series gives values for borrowers completing student loan repayments in Q2 or Q3 2019. The gray dashed series plots values for borrowers who haven't 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.

Figure F.10: Monthly student loan payments by loan payment quartile, federal-only borrowers vs. federal and private borrowers



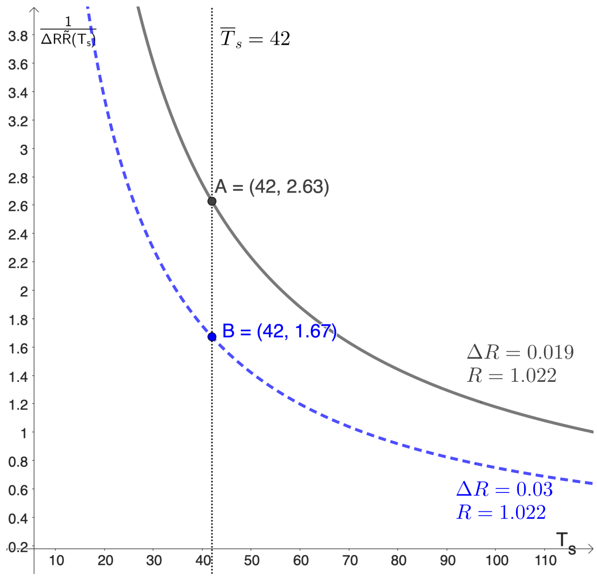
Source: Author's calculations. The figure illustrates the treatment variation used in the federal-private payment mix natural experiment. Each series plots average monthly student loan payments for borrowers in the sample. The blue solid series gives values for borrowers with only federal student loans. 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.

Figure F.11: Effect of forbearance on monthly spending – heterogeneous federal-private debt mix

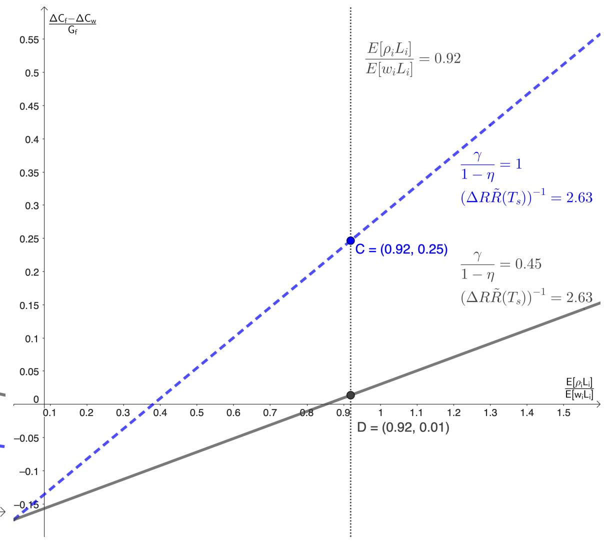


Source: Author's calculations. The figure plots event time coefficients $\hat{\sigma}_k^2$ estimated from specification (C.1). Spikes plot robust 95% confidence intervals clustered at the borrower level. The left panel shows estimates where the outcome variable is total spending. The right panel shows estimates where the outcome variable is broad nondurable spending.

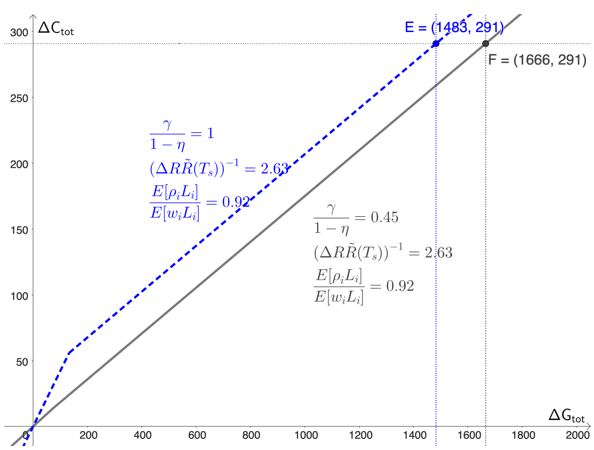
Figure F.12: Impact of flypaper effect on countercyclical fiscal policy design: Sensitivity to calibrated values



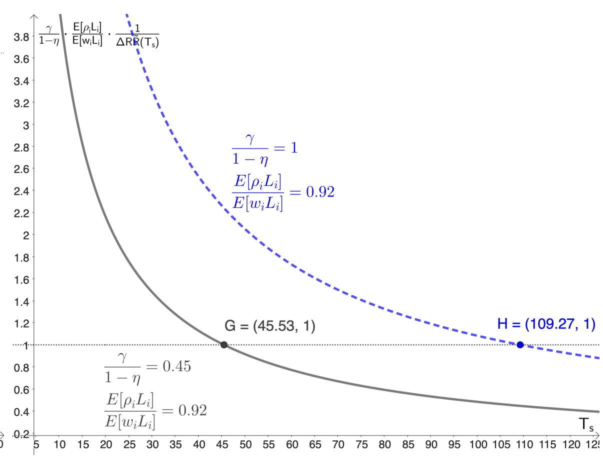
(a) Average cost effect vs. remaining loan repayment term.



(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 (13) on the vertical axis. The break-even repayment term is where this line intersects one.
See Section 6 for details.

G Additional tables

Table G.1: 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 (pmt / income)	Yes		0.425	0.402	0.431	0.489
				(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.

Table G.2: 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 (SL MPX = 0)			0.048	
			(0.031)	
Credit card pmts (SL MPX = 1)			0.048**	
			(0.015)	
Private SL pmts (SL MPX = 0)				0.006
				(0.027)
Private SL pmts (SL MPX = 1)				0.033*
				(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.3 for methodological details, and section 3.1 for descriptions of expenditure category construction.

Table G.3: 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.4: 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.7 for details on estimation, and see section 3.1 for detailed descriptions of expenditure category construction.

Table G.5: 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.8 for details on estimation, and see section 3.1 for detailed descriptions of expenditure category construction.

Table G.6: 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.

Table G.7: 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.8: 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.

Table G.9: 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.

Table G.10: 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.

Table G.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.

Table G.12: Calibration: Nonparametric bounds for $E[\rho_i L_i]$

Panel A.

Variable	Estimate
$Pr(w_i > 0)$	0.662
$E[L_i \mid w_i > 0]$	0.174
$E[\rho_i \mid 1 - G(\rho_i \mid w_i = 0) \leq E[L_i \mid w_i > 0]]$	3.507
$E[\rho_i L_i \mid w_i > 0]$	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.16), 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.

Table G.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.