Insurance versus Moral Hazard in Income-Contingent Student Loan Repayment*

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January 17, 2024

Updated Regularly: Latest Version

Abstract

Student loans with income-contingent repayment insure borrowers against income risk but can reduce their incentives to earn more. Using a change in Australia's income-contingent repayment schedule, I show that borrowers reduce their labor supply to lower their repayments. These responses are larger among borrowers with more hourly flexibility, a lower probability of repayment, and tighter liquidity constraints. I use these responses to estimate a dynamic model of labor supply with frictions that generate imperfect adjustment. My estimates imply that the labor supply responses to income-contingent repayment decrease the optimal amount of insurance but are too small to justify fixed repayment contracts. Moving from a fixed repayment contract to a constrained-optimal income-contingent loan increases welfare by the equivalent of a 1.3% increase in lifetime consumption at no additional fiscal cost.

*I'm grateful to my dissertation committee, Taha Choukhmane, Jonathan A. Parker (co-chair), Lawrence D.W. Schmidt, Eric C. So, and David Thesmar (co-chair) for their continuous support. I thank Pat Adams, David Autor, Maxime Bonelli, Bruce Chapman, Hui Chen, Marc de la Barrera, Jan Eberly, Maryam Farboodi, Amy Finkelstein, Brice Green, Jonathan Gruber, Nathan Hendren, Sebastian Hillenbrand, Henrik Kleven, Tong Liu, Debbie Lucas, Pierfrancesco Mei, Simon Mongey, Lira Mota, Christopher Palmer, Jim Poterba, Charlie Rafkin, Antoinette Schoar, Andrei Shleifer, Kerry Siani, Adam Solomon, Yevhenii Usenko, Emil Verner, Adrien Verdelhan, Rodrigo Verdi, Gianluca Violante, Joe Weber, Toni Whited, Constantine Yannelis (discussant), and seminar participants at the 2023 FRA Conference, BlackRock Applied Research Award Panel, Olin Finance Conference Ph.D. Poster Session, Inter-Finance Ph.D. Seminar, Yale SOM, Princeton, Chicago Booth, MIT Sloan, and MIT Economics for helpful comments. I also thank the ATO *ALife* and ABS DataLab teams for data assistance, in particular Andrew Carter, Justin Holland, and Son Nguyen, Simone Melchionna for sharing his Fortran expertise, Andrew Norton for sharing data and for responding to my never-ending stream of questions, and Jenn Mace for her unwavering support. This project would not have been possible without the support of Anna Bedford, Nicholas Biddle, Andrew Norton, and Joe Weber. This research was supported by the Alfred P. Sloan Foundation through a Household Finance grant awarded to the National Bureau of Economic Research, MIT Sloan School of Management, Mark Kritzman and Elizabeth Gorman Research Fund, MIT Sloan Stone Fund, Thomas Anthony Pappas Endowed Scholarship, and the MIT Lincoln Laboratory Supercomputing Center. I am grateful to the ANU Centre for Social Research and Methods and University of Technology Sydney for hosting me as a visiting scholar. The results of these studies are based, in part, on tax data supplied by the Australian Taxation Office to the Australian Bureau of Statistics under the Taxation Administration Act 1953. The final page of this paper contains a full required disclaimer.

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In many countries, students finance higher education through government-provided student loans. These loans are the second-largest household liability in the US at $1.6 trillion and account for 10% of household debt in the US and UK. Traditionally, government-provided student loans have resembled debt contracts, where borrowers make fixed payments after graduation to repay their loan balances. Because student loans are generally not dischargeable in bankruptcy, these contracts force borrowers to bear most of the risk associated with the returns to higher education. Unfortunately, the risk of low income upon graduation materializes for many borrowers, with 25% of US borrowers defaulting within five years after graduation (Hanson 2022).

One potential policy to provide more insurance against income risk is to make student loans equity-like by linking repayments to borrowers' incomes. This idea has been discussed extensively (Friedman 1955; Shiller 2004; Palacios 2004; Chapman 2006; Zingales 2012), and governments in the US, UK, Canada, and Australia have recently implemented it by providing income-contingent loans. In contrast to nondischargeable debt contracts, income-contingent repayment provides insurance by reducing payments as a borrower's income declines. However, this insurance potentially comes at the cost of creating moral hazard: because repayments increase with income, borrowers have an incentive to reduce their labor supply to decrease repayments. Empirically, income-contingent repayment appears effective at providing insurance (Herbst 2023), but there is no consensus on the moral hazard effects that it creates (Yannelis and Tracey 2022).

The objective of this paper is to study two central questions. First, how does income-contingent repayment affect borrowers' labor supply? Second, what is the optimal form of income-contingent repayment that balances this moral hazard, if it exists, with providing insurance? To identify labor supply responses empirically, I leverage administrative data and policy variation from the Australian Higher Education Loan Programme (HELP), the first program to provide income-contingent loans nationwide. I then use these responses to estimate a dynamic model of labor supply and study the implications of various repayment contracts. In my normative analysis, I consider a government that maximizes borrower welfare, taking education and borrowing choices as given.

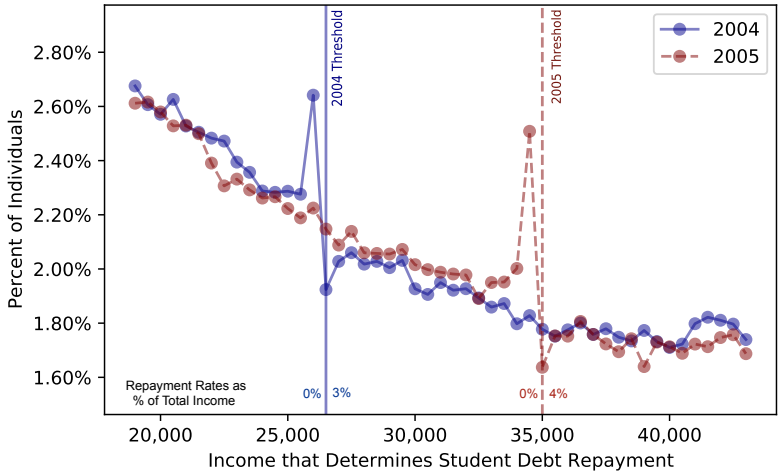
My main empirical finding is that borrowers reduce their labor supply to lower repayments on income-contingent loans. These responses are larger among borrowers with more hourly flexibility, a lower probability of repayment, and who are more liquidity-constrained. However, my structural estimation shows that these responses are consistent with a moderate (Frisch) labor supply elasticity and substantial frictions that limit labor supply adjustment. On the normative side, my estimates imply that moral hazard decreases the optimal amount of insurance but that there are still significant welfare gains from income-contingent repayment. Specifically, moving from a fixed repayment contract to a constrained-optimal income-contingent loan increases welfare by the equivalent of 1.3% of lifetime consumption at no additional fiscal cost. Adding forbearance to fixed repayment contracts is a poor substitute for income-contingent loans because it does not accelerate repayments from high-income borrowers. In sum, my results suggest that income-contingent repayment creates

moral hazard that affects contract design but that it is too small to justify fixed repayment contracts.

There are several benefits to studying how income-contingent repayment affects labor supply in Australia. First, there is limited scope for selection because the only available contract is a government-provided income-contingent loan. This is useful for identifying moral hazard (Karlan and Zinman 2009) and contrasts with the US, where borrowers select into repayment contracts based on expected earnings (Karamcheva et al. 2020). Second, Australia was the first country to introduce income-contingent loans in 1989, meaning borrowers are familiar with the availability and design of these contracts, unlike in the US (Abraham et al. 2020; Mueller and Yannelis 2022). Finally, these loans can only be used to cover (government-controlled) tuition, implying that borrowers can only adjust their initial debt by changing their degree choices. This decision is likely less responsive than the other margins that borrowers in the US can adjust, such as room and board.

In the first part of this paper, I document evidence of moral hazard from income-contingent repayment: borrowers reduce their labor supply to lower repayments on income-contingent loans. I identify this behavioral response by leveraging a 2005 policy change that increased the income threshold above which all borrowers begin loan repayment. Figure 1 summarizes the effects of this policy change by showing that the income distribution of student debtholders exhibits significant bunching below the repayment threshold, both before and after the reform. I present two pieces of evidence that suggest this bunching reflects labor supply responses rather than solely income-shifting or tax evasion. First, the bunching is larger in occupations with high hourly flexibility (e.g., bartenders) and almost nonexistent in those with low flexibility (e.g., software engineers). Second, using data from Australia's Census, I find that borrowers below the repayment threshold work 2–3% fewer hours (i.e., 1–2 fewer weeks per year) than those above the threshold.

Figure 1. Income Distribution for Debtholders around the Income-Contingent Loan Repayment Threshold



Notes: This figure shows the distribution of the income that determines repayments on income-contingent loans in 2004 and 2005, before and after the policy change. This income is called HELP income and equals taxable income (i.e., the sum of labor income, capital income, and deductions) plus investment losses, retirement contributions, foreign employment income, and fringe benefits. The vertical lines indicate the thresholds below which borrowers make no repayments and above which they repay 3% and 4% of their income. The sample is all debtholders subject to the criteria in Section 2.4. HELP income is deflated to 2005 AUD using the Consumer Price Index.

The second part of this paper develops a structural model of labor supply that quantitatively replicates the evidence in Figure 1. The purpose of the model is to translate this evidence into estimates of preference parameters and study the welfare implications of income-contingent repayment. In the model, borrowers choose consumption and labor supply over their life cycles. The two key ingredients are uninsurable income risk and endogenous labor supply, which create a trade-off between the insurance benefits and moral hazard costs of income-contingent repayment.

The evidence in Figure 1 is inconsistent with a frictionless formulation of this model. When borrowers' income crosses the repayment threshold, the fraction of *total* income that they repay increases from 0% to 3–4%. In a frictionless model, no borrowers would locate immediately above the threshold because locating below it delivers more leisure and cash on hand. Therefore, I introduce two optimization frictions (Chetty 2012) to explain borrowers locating above the repayment threshold. First, in each period, only a fraction of borrowers receive shocks that allow them to adjust labor supply à la Calvo (1983). These shocks could capture inattention or the arrival of job transitions at which hours can be adjusted. Second, adjusting labor supply requires paying a fixed cost, which could be monetary (e.g., a wage reduction) or psychological (e.g., hassle costs).

I estimate the model by simulating responses to the policy change in Figure 1 and find that they are consistent with a moderate labor supply elasticity and substantial optimization frictions. The key parameters that govern labor supply responses—the (Frisch) labor supply elasticity, fixed cost, and Calvo probability—are identified as follows. First, the labor supply elasticity is identified by the bunching below the repayment threshold: a larger elasticity implies more bunching. Second, the number of borrowers above the threshold jointly identifies the fixed cost and Calvo probability. Finally, these two frictions are separately identified based on how the bunching correlates with observable characteristics: a model with no fixed cost generates weak correlations because bunching primarily depends on the exogenous Calvo shock. The estimation results show that the evidence in Figure 1 is consistent with a labor supply elasticity of 0.11, a fixed cost of $\$400$ to adjust labor supply in each year (i.e., 1% of mean earnings), and a Calvo probability of 0.2. Although I study labor supply responses to student loans rather than income taxes or wages, the estimated labor supply elasticity is close to the median of 0.14 from the meta-analyses in Keane (2011) and Chetty (2012).

In the estimated model, two forces are quantitatively important for explaining the responses in Figure 1: uncertainty about debt repayment and a demand for liquidity. Unlike income taxes, the incentives created by income-contingent repayment depend on the probability of debt repayment: for borrowers anticipating repayment, bunching below the repayment threshold transfers repayments over time rather than permanently reducing them. In a counterfactual where borrowers anticipate fully repaying their debt, the model predicts that bunching in Figure 1 decreases by 60%. Empirically, this is consistent with the fact that the amount of bunching is larger among borrowers with more debt and in occupations with lower lifetime incomes, both of whom have a lower probability of repayment. The remaining 40% of the bunching in the model is driven by a demand for liquidity:

even when the present value of the change in repayments from locating below the repayment threshold is zero, borrowers may value the additional liquidity if they are liquidity-constrained. This importance of liquidity is supported empirically by the fact that borrowers below the repayment threshold have larger housing payments, which represent greater liquidity demands, and contribute less to a tax-advantaged but illiquid retirement savings account.

In the final part of the paper, I use the estimated model to study the welfare impact of different repayment contracts. My analysis considers a social planner that maximizes borrower welfare by choosing one contract, holding fixed borrowing behavior. This perspective isolates the trade-off between using income-contingent repayment to provide insurance and creating moral hazard.

My main normative result is that income-contingent loans generate meaningful welfare gains relative to fixed repayment contracts at the same fiscal cost. In my baseline analysis, I constrain the planner to income-contingent loans with two parameters, as in the US: an income threshold at which repayment begins and a repayment rate of income above this threshold. I then solve for the values of these parameters that maximize borrowers' lifetime utility subject to the constraint of raising the same revenue as a fixed repayment contract. The resulting constrained-optimal income-contingent loan increases welfare relative to a 25-year fixed repayment contract by the equivalent of a 1.3% increase in lifetime consumption. A first-best contract that provides insurance without creating moral hazard further increases welfare by only 0.2 pp of lifetime consumption. Nevertheless, labor supply responses are important for contract design: absent moral hazard, the optimal contract would provide more insurance to low-income borrowers with a 40% higher repayment threshold.

Income-contingent loans perform well relative to three other methods of providing insurance: loan forgiveness, adding forbearance to fixed repayment contracts, and equity contracts. First, adding forgiveness to income-contingent loans after a fixed horizon, as in the US and UK, lowers welfare relative to the constrained-optimal income-contingent loan. At a given fiscal cost, forgiveness transfers repayment burdens from old to young borrowers, which lowers welfare because young borrowers are more liquidity-constrained. Second, a fixed repayment contract with forbearance, a form of income-contingency that pauses repayments for low-income borrowers, also lowers welfare relative to the constrained-optimal income-contingent loan. This is because income-contingent loans accelerate repayment from high-income borrowers, enabling them to provide more insurance at a given cost. Finally, an equity contract in which borrowers make uncapped income-contingent repayments for a fixed horizon (Friedman 1955) yields welfare gains that are larger on average but significantly more dispersed than those from the constrained-optimal income-contingent loan. This dispersion suggests that equity contracts might cause ex-ante responses not captured by the model (e.g., additional borrowing) and, therefore, that income-contingent loans may be a more robust mechanism for implementing income-contingent repayment.

Related literature and contribution. This paper is most closely related to the literature on financing human capital, which spans household finance, public finance, and labor economics. Friedman (1955) popularized the idea that student loans should be equity-like and advocated using income-sharing agreements. Adverse selection prevents the private provision of these contracts (Herbst and Hendren 2021; Herbst et al. 2023), but a growing number of governments have attempted to correct this market failure by introducing income-contingent loans (Barr et al. 2019).[1] Theoretical work suggests that these loans provide a close approximation to Mirrlees (1974)–style optimal policies (Lochner and Monge-Naranjo 2016; Stantcheva 2017), which is supported by two empirical strands of literature on student loans (see Yannelis and Tracey 2022 for a review). The first documents debt overhang created by fixed repayment contracts, in which reductions in student debt decrease delinquencies and increase income and mobility (Di Maggio et al. 2021), increase homeownership (Mezza et al. 2020), and change education and occupation choices (Luo and Mongey 2019; Chakrabarti et al. 2020; Folch and Mazzone 2021; Hampole 2022; Murto 2022; Huang 2022; Abourezk-Pinkstone 2023).[2] The second studies income-contingent loans as a tool to mitigate these effects, finding reductions in delinquencies (Herbst 2023), mortgage defaults (Mueller and Yannelis 2019), and the passthrough of income variation to consumption (Gervais et al. 2022).[3]

This paper makes three contributions to this literature. First, it empirically characterizes the moral hazard created by income-contingent repayment, which has not been found in prior work (Chapman and Leigh 2009; Britton and Gruber 2020). Second, it provides a model of labor supply that replicates this evidence, finding an important role for optimization frictions, liquidity constraints, and dynamics. Finally, it quantifies the implications of this moral hazard for optimal contract design. Structural models in prior literature highlight the insurance benefits of income-contingent repayment but have not been disciplined to capture its moral hazard effects or been used to characterize optimal policy (Ji 2021; Folch and Mazzone 2021; Matsuda and Mazur 2022; Boutros et al. 2022).

There are several other literatures to which this paper is related. First, it is part of the literature in public finance that studies the insurance–moral hazard trade-off in social insurance (Chetty and Finkelstein 2013), such as unemployment insurance (Gruber 1997), health insurance (Einav et al. 2015), disability insurance (Bound et al. 2004), and consumer bankruptcy (Indarte 2023). My finding that borrowers reduce their labor supply to locate below the repayment threshold, which increases liquidity more than wealth, is consistent with liquidity driving responses to other forms of social insurance (Chetty 2008; Indarte 2023; Ganong and Noel 2023). Additionally, it complements the finding in Ganong and Noel (2020) that borrowers' decisions—in this case, labor supply instead of consumption—respond more to changes in short-term payments than long-term obligations.

[1] Other possible government policies toward human capital include subsidies for educational expenses (Benabou 2002; Bovenberg and Jacobs 2005; Stantcheva 2017) and grants (Abbott et al. 2019; Ebrahimian 2020).

[2] A related literature emphasizes the importance of credit constraints for college attendance (Carneiro and Heckman 2002; Lochner and Monge-Naranjo 2012), which student loans help relax (Amromin and Eberly 2016; Black et al. 2022).

[3] Alternatives to providing insurance are making student debt dischargeable, which has the cost of inducing strategic default (Yannelis 2020); implementing universal loan forgiveness, which would be regressive (Catherine and Yannelis 2023); and offering targeted loan forgiveness, which borrowers appear to value but fail to take up (Jacob et al. 2023).

Second, by studying state-contingent contracts, this paper is part of the literature in macro-finance on household security design.[4] Motivated by evidence of imperfect risk-sharing (Cochrane 1991) and the household balance sheet channel (Mian and Sufi 2014), this literature studies contracts that make liabilities more state-contingent, such as shared-appreciation mortgages (Caplin et al. 2007; Hartman-Glaser and Hébert 2020; Greenwald et al. 2021; Benetton et al. 2022) or adjustment-rate mortgages conditioned on aggregate shocks (Campbell et al. 2021). This paper contributes by studying one of the longest-running examples of such contracts and characterizing the welfare gains from alternative forms of state-contingent repayment. A distinguishing feature of my setting is limited strategic default, as student loans cannot be discharged in bankruptcy.

Third, this paper builds on the literature that uses bunching at discontinuities in tax rates to identify income elasticities (Saez 2010; Chetty et al. 2011). A central challenge in this literature is that patterns in bunching typically differ from the predictions of frictionless models, which has motivated various models with optimization frictions (Chetty 2012; Kleven and Waseem 2013; Anagol et al. 2022). This paper contributes by using quasi-experimental bunching evidence to estimate a structural model with two optimization frictions, fixed costs and Calvo adjustment, that have been used theoretically but not separately estimated (Werquin 2015). Unlike the models in most of this literature, this model is dynamic because debt repayment involves intertemporal trade-offs, which turns out to be crucial for the separate identification of the two frictions.

Finally, this paper contributes to the extensive literature on labor supply, which Appendix A reviews in detail. A closely related strand of this literature studies labor supply responses to income taxes. In contrast, this paper characterizes how labor supply responds to income-contingent loans, which create intertemporal trade-offs that taxes do not. Additionally, it estimates the first (to my knowledge) dynamic model of labor supply with both time- and state-dependent adjustment.

1 Motivating Framework

This section develops a simple framework to clarify the trade-off between insurance and moral hazard created by income-contingent repayment. The result is an expression that generalizes the Baily–Chetty formula (Baily 1978; Chetty 2006) for the optimal balance of insurance and moral hazard in unemployment insurance to my setting. I then discuss the behavioral responses that I attempt to estimate empirically through the lens of this expression.

Environment. Consider a government that provides a student loan, D_0, at $t = 0$ to an individual in exchange for mandatory repayments $d_t = d(D_t, y_t, \theta)$ at $t > 0$, where D_t denotes the outstanding debt balance, y_t denotes observable income, and θ is the parameters of a repayment contract. For example, an equity contract is captured by $d_t = y_t\theta$, while a debt contract would be a function of just

[4] Appendix A discusses how the contracting problem in this paper relates to the theoretical literature on security design.

D_t and θ. Individuals solve a standard life cycle problem by choosing labor supply, ℓ_t, consumption, c_t, and initial debt balances, D_0:

$$V(\theta) = \max_{\{c_t,\ell_t\}_{t=0}^{T}, D_0} \mathbf{E}_0 \sum_{t=0}^{T} u_t(c_t, \ell_t),$$

$$c_t + A_{t+1} = A_t R + y_t - d_t * \mathbf{1}_{t>0} + D_0 * \mathbf{1}_{t=0},$$

$$y_t = f(\ell_t, D_t, \omega_t), \quad d_t = d(y_t, \theta), \quad D_{t+1} = D_t(1 + r_d) - d_t.$$

Expectations are taken over the path of stochastic shocks, $\{\omega_t\}_{t=0}^{T}$, which present income risk to the individual and are not observable to the government (as in Mirrlees 1974). Individuals can only take the government-provided contract and have no other sources of external financing.

Planner's problem. The government chooses θ to maximize borrower welfare. Assuming that individuals are ex-ante identical, the government solves the following (second-best) problem:[5]

$$\max_{\theta} V(\theta) - \lambda' \left[D_0 - \sum_{t=1}^{T} \frac{\mathbf{E}_0 (d_t)}{\mathcal{R}_t} \right], \tag{1}$$

where λ' denotes the marginal cost of public funds or, equivalently, the multiplier on the government budget constraint and $\mathcal{R}_t$ denotes the government discount rate at horizon t. Additionally, let $M_t = \frac{u_c^t(c_t,\ell_t)}{u_c^0(c_0,\ell_0)}$ denote individuals' stochastic discount factor between $t = 0$ and $t = t$ and λ as the marginal cost of public funds in dollars. In Appendix B, I show that, under appropriate regularity conditions, the following is a necessary condition at a solution to (1):

$$\sum_{t=1}^{T} \mathbf{E}_0 \left[\underbrace{\left(\frac{\lambda}{\mathcal{R}_t} - M_t \right)}_{\substack{\text{amount of} \\ \text{risk-sharing}}} \frac{\partial d_t}{\partial \theta} \right] = \lambda \left[\underbrace{\frac{dD_0}{d\theta}}_{\substack{\text{borrowing} \\ \text{response}}} - \sum_{t=1}^{T} \frac{1}{\mathcal{R}_t} \mathbf{E}_0 \left(\underbrace{\frac{\partial d_t}{\partial y_t} \frac{dy_t}{d\theta}}_{\substack{\text{labor supply} \\ \text{response}}} \right) \right]. \tag{2}$$

The left-hand side of (2) is the *quantity of unshared risk*: it represents the difference between how the government values a perturbation to the repayment contract, $\frac{\partial d_t}{\partial \theta}$, and how the individual values it. If the government fully insures the individual, then individuals' stochastic discount factor does not vary across states (for a given t), and this quantity is small. The right-hand side of (2) is the sum of two behavioral responses. The first is *ex-ante moral hazard*, $\frac{dD_0}{d\theta}$: changing the repayment contract affects how much individuals borrow. The second behavioral response is *ex-post moral hazard*: changing the repayment contract affects individuals' incentives to earn income, which influences the amount that the government collects in repayments.

As an example, consider a policy change $d\theta$ that increases the amount of insurance by making low-income individuals pay less and high-income individuals pay more. In response, a natural

[5]This formulation of the government's problem abstracts from intergenerational redistribution, so λ' should be interpreted as the marginal cost of public funds for a given generation.

prediction is that risk-averse individuals will borrow more ex-ante, $\frac{dD_0}{d\theta} > 0$, low-income individuals will increase their labor supply, $\frac{dy_t}{d\theta} > 0$, and high-income individuals will reduce their labor supply, $\frac{dy_t}{d\theta} < 0$. The heart of the insurance–incentive trade-off is illustrated in (2): if these responses are small, the government can afford to bear most of the income risk. If they are large, individuals must bear the risk to limit borrowing and encourage labor supply.

The objective of this paper is to quantify the magnitude of *ex-post* moral hazard in income-contingent repayment, $\frac{dy_t}{d\theta}$, and study what it implies for optimal contract design. To do so, I leverage a setting with a change in the repayment contract, $d\theta$, that allows me to estimate $\frac{dy_t}{d\theta}$. One of the main benefits of this setting is that individuals have limited ability to adjust their initial debt balances, which reduces the scope for ex-ante moral hazard, $\frac{dD_0}{d\theta}$.

2 Institutional Background and Data

2.1 Overview of Australia's Higher Education Loan Programme (HELP)

In Australia, higher education is primarily financed using government-provided student loans through the Higher Education Loan Programme (HELP), which was introduced in 1989. There are five HELP programs that provide income-contingent loans to Australian citizens for different purposes. This section provides an overview of the two largest programs called HECS-HELP and FEE-HELP, which historically have accounted for over 90% of HELP borrowing; Appendix C.1 presents additional details.[6] HELP loans provided through these two programs can be used to finance tuition for undergraduate and graduate degree programs. Tuition at public institutions is controlled by the government and varies by degree, while private universities generally charge higher tuition. Most degrees at public institutions are classified as Commonwealth Supported Places (CSPs), in which the government provides a subsidy in the form of a contribution to the tuition owed by the student. The tuition remaining after the government's contribution is deducted is paid by the student and is called the student contribution. As of 2023, student contributions ranged from \$4,124 to \$15,142 AUD per year (\$2,700 to \$10,100 USD), with undergraduate degrees typically lasting 3–4 years. The number of CSPs in Australia has generally been capped by the government, except from 2012–2017, when the system was "demand-driven" (D'Souza 2018; Norton 2019).

Individuals who receive a CSP can either pay their student contribution upfront or borrow through the HECS-HELP program. Those who pursue degrees that are not CSPs are liable for full tuition and can either pay upfront or borrow through FEE-HELP. In both programs, most individuals choose to do the latter, with less than 10% of balances in 2022 being paid upfront (Department of Education and Training 2023). For borrowers who receive CSPs and access HECS-HELP, the largest program,

[6] Figure A2 plots the amount of borrowing over time and discusses the details of the different HELP programs.

their initial debt is equal to their student contribution. Given an average undergraduate student contribution of around $6,000 USD per year, tuition is comparable to that for US in-state public undergraduate degrees, which averages $9,000 USD per year (Hanson 2023). Figure A3 plots the time series of student contributions, aggregate HECS-HELP borrowing, and upfront payments.

HELP debt balances in subsequent years grow at the CPI inflation rate net of repayments, implying that HELP debt has a zero real interest rate. Individual i's compulsory repayment in year t is

$$\text{HELP Repayment}_{it} = \min\{r_t(y_{it}) * y_{it}, D_{it}\},$$

where y_{it} denotes HELP income, $r_t(\cdot)$ is the income-dependent repayment rate, and D_{it} denotes the beginning-of-year debt balance. HELP income is the taxable income reported in a personal income tax return plus a few adjustments discussed in Section 2.5. Collection of HELP payments is integrated with the income tax system, which is crucial for HELP's success relative to other income-contingent loan programs (Barr et al. 2019). All individuals file tax returns in Australia, so y_{it} refers to *individual* rather than household HELP income. For most borrowers, HELP repayments are withheld by their employer during the year and deducted from their debt after they file their tax returns. Individuals also have the option to make voluntary repayments at any time.

Repayment of HELP debt continues either until the remaining balance equals zero or until death. This means that HELP effectively forgives debt at the end of working life when borrowers stop generating sufficient income to make compulsory repayments, similar to the forgiveness embedded in US income-driven repayment plans. Partial repayment is common: as of 2004, approximately 25% of debt balances were forecast to be written off due to death (Martin 2004). As in the US, HELP debt cannot be discharged in bankruptcy.

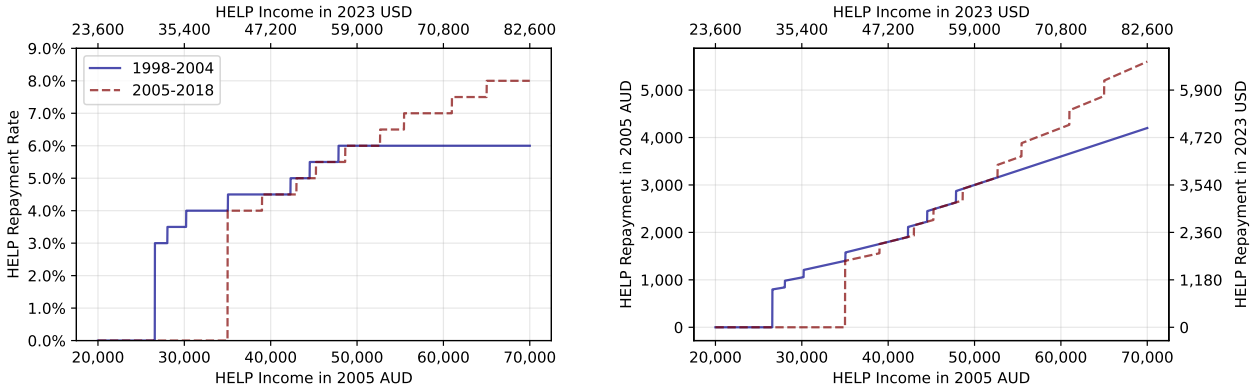
2.2 2004–2005 Policy Change to HELP Repayment Rates

The policy change that I exploit is a 2004–2005 change in the HELP repayment rate function, $r_t(\cdot)$. The left panel of Figure 2 plots repayment rates as a function of real HELP income before the policy change in blue and after the change in red.[7] The most significant change was the movement of the repayment threshold, the point at which borrowers start making repayments, from approximately $26,000 AUD to $35,000 AUD. The median debtholder has HELP income between these two thresholds, so this policy change generated reductions in repayments for many borrowers. It also generated an increase in repayment rates for borrowers with incomes above $50,000. Importantly, this policy change applied to all new and existing HELP debtholders.[8]

[7] Before 1998 and after 2018, there were other changes to the HELP repayment schedule, as discussed in Appendix C.1.

[8] This approach of identifying moral hazard by looking at the responses to changes in contract structure among individuals who have already taken up a contract has been applied in a variety of selection markets, such as consumer credit (Karlan and Zinman 2009) and mortgage markets (Gupta and Hansman 2022).

Figure 2. HELP Repayment Rates as a Function of Income: Before and After the Policy Change



Notes: The left panel of this figure shows HELP repayment rates as a percentage of HELP income, which are average rather than marginal repayment rates. The right panel shows the required HELP payments implied by the repayment rates on the left in 2005 Australian dollars on the left axis and 2023 US dollars on the right axis. The blue and red lines correspond to the rates before and after the policy change, respectively. The bottom axis in both panels is HELP income measured in 2005 Australian dollars and the repayment schedule, which is constant in real terms. The top axis measures HELP income in 2023 US dollars calculated with the AUD/USD exchange rate from June 2005 and the US CPI inflation rate between June 2005 and January 2023.

The right panel of Figure 2 plots required repayments in AUD, which illustrates that the repayment threshold creates a large incentive to reduce HELP income by generating a discontinuity in the *average* rather than marginal repayment rate. For example, consider a borrower with $35,000 of HELP income in 2005. For this borrower, earning an extra $1 of income results in a required HELP repayment of $35,001 × 4% ≈ $1,400 (i.e., the repayment threshold is a "notch" in the language of Kleven and Waseem 2013).

If borrowers chose their labor supply statically and treated repayments like an income tax, no borrowers would locate immediately above the repayment threshold because doing so would deliver less take-home pay and leisure. However, income-contingent repayment of debt differs from a tax in that it involves *dynamic*, in addition to static, trade-offs. For example, consider a borrower at $t = 0$ with a debt balance D_0 who is deciding between locating below versus above the 2005 repayment threshold. Locating below the threshold decreases her repayments at $t = 0$ by $1,400. However, under the assumption that this borrower's income at $t = 1$ will be high enough that the required payment is above D_0, this $1,400 repayment is simply transferred from $t = 0$ to $t = 1$. As a result, the present value of the reduction in repayments from locating below the repayment threshold is $\left(1 - \frac{p}{1+r}\right) \times \$1{,}400 = \frac{r+1-p}{1+r} \times \$1{,}400$, where r is the real interest rate and p is the probability of repayment at $t = 1$.[9] In other words, locating below the threshold has a large impact on current payments but a much smaller effect on the present value of payments as $p \to 1$. This makes the repayment threshold function similarly to the maturity extension program studied in Ganong and Noel (2020), which also increases borrowers' liquidity more than wealth.

There are several reasons to believe that the HELP repayment function and the changes to it

[9]Technically, r is the difference between the HELP interest rate, which is zero, and the borrower's private rate.

are salient to debtholders. First, the repayment function is indexed to inflation, which means that it updates every year. When it is published at the beginning of each tax year, the government ensures that the change receives press coverage.[10] Second, the policy change received media coverage at the time of its implementation (Marshall 2003). Finally, the fact that HELP income determines repayment rates and features a repayment threshold has not changed since the program's introduction in 1989, meaning that debtholders are likely to understand the program's structure.

Government policy documents and media articles suggest that the primary reason for the policy change was to provide relief for lower-income borrowers, whose payments were burdensome and contributed little to the total HELP budget (Nelson 2003). In addition to changing the repayment function, other changes were implemented in 2004–2005, such as the introduction of HELP loans for non-CSPs through FEE-HELP and a 25% increase in student contributions (see Figure A3). These other changes, discussed in detail by Beer and Chapman (2004), were primarily aimed at those entering their degree programs rather than those repaying HELP debt. The simultaneous implementation of these other changes with the change to the repayment threshold is not ideal for my analysis. However, it likely has a minimal effect, given that I focus on identifying moral hazard among individuals who have completed their degree programs.

2.3 Benefits of Studying Income-Contingent Repayment in Australia

In addition to the presence of high-quality administrative data and policy variation, there are several benefits to using HELP to identify labor supply responses to income-contingent repayment. First, there is limited selection on hidden information, such as unobservable types or expected moral hazard (Karlan and Zinman 2009), because HELP is the only government-provided student loan. The same is not true in the US (Karamcheva et al. 2020) or in countries with private providers of income-sharing agreements (Herbst et al. 2023). In principle, individuals in Australia could seek external financing from a bank or university. However, there is little economic incentive to do so because the interest rate would exceed the zero real rate on HELP loans. The primary margin along which there is scope for selection is whether to pay upfront or borrow through HELP, but the zero interest rate on HELP loans again implies little incentive to pay upfront.[11]

A second benefit of this setting is the likely limited *ex-ante* moral hazard, in which borrowers increase their HELP debt in anticipation of a lower probability of future repayment. HELP can only be used to cover tuition at public undergraduate institutions, which make up over 94% of the domestic enrollment share and have government-controlled tuition. As a result, borrowers can only adjust their debt by changing their choice of degree or institution. These are likely stickier decisions than the other margins that borrowers in the US can adjust, such as room and board or groceries.

[10] For an example of an announcement, see https://www.legislation.gov.au/Details/C2022G00213.

[11] In earlier years of HELP, upfront payments were subject to a discount, which created a small incentive to pay upfront. See Appendix C.1 for additional discussion.

The third benefit of studying HELP is that it is the longest-running government-provided income-contingent repayment program. The fact that this program has been around since 1989 suggests that borrowers understand the repayment incentives. The same is not true in the US, where borrowers are unaware of the existence and structure of income-driven repayment options (Abraham et al. 2020; Mueller and Yannelis 2022; JPMorgan Chase 2022). Finally, there are likely limited responses on the supply-side due to government tuition control. If this were not the case, changes in government-provided contracts could pass through to tuition and thus debt balances (Kargar and Mann 2023).

The institutional differences between Australia and the US make the former advantageous for identifying labor supply responses to income-contingent repayment. However, Appendix C.2 presents a detailed discussion of whether these and other differences could undermine the effectiveness of income-contingent repayment in the US.

2.4 Data Sources

I use restricted-access deidentified administrative data from several sources. First, I use individual income tax returns from the Australian Taxation Office (ATO), which contain panel data on income components and basic demographic characteristics. Second, I use administrative data on HELP from the ATO that include debt balances, repayments, and a flag for whether individuals acquired new debt balances in a given year. Two limitations of these data are that they do not allow me to identify any information on the source of borrowing, such as degree choice, and they aggregate debt across all HELP programs. Third, I leverage administrative data on superannuation balances and contributions from the ATO. These three datasets are linked for the universe of Australian taxpayers between 1991 and 2019 in the ATO Longitudinal Information Files, known as *ALife*. Starting from the population dataset in *ALife*, I restrict attention to individual–year observations for which the individuals (i) are between ages 20 and 64, (ii) are residents in Australia for tax purposes, (iii) are not exempt from HELP repayment due to a Medicare exemption, and (iv) do not have any income from discretionary trusts.[12] I use this sample, which covers all 4 million unique debtholders between 1991 and 2019, for my main analysis.

To obtain data on hours worked and housing payments, I use a linkage of these ATO data with the 2016 Census of Population and Housing. This linkage cannot be performed with *ALife* directly, so I instead perform the merge through the Australian Bureau of Statistics Multi-Agency Data Integration Project (MADIP). The ATO data in MADIP have the same sample coverage as the population-level *ALife* data but a restricted set of variables. Due to data limitations, I use the first three filters from the *ALife* sample to construct a cross-sectional MADIP sample in 2016, the year in which the census was administered.

[12] In Australia, there are unit trusts, in which trust beneficiaries have no discretion over entitlements, and discretionary trusts, in which beneficiaries have full discretion over entitlements. Discretionary trusts have been identified as potential sources of tax evasion (Australian Council of Social Service 2017), but *ALife* does not have information on the sources of trust income. I drop these observations to avoid attributing possible tax evasion to labor supply responses.

I supplement these administrative datasets with the Household, Income and Labour Dynamics in Australia Survey (HILDA), a household survey conducted by the Melbourne Institute that runs from 2002 to 2021. HILDA has a structure and questions similar to those the Survey of Consumer Finances in the US, except that it is a panel rather than a repeated cross-section.

2.5 Summary Statistics

Table 1 presents summary statistics on the *ALife* sample, the main sample in my analysis, for individuals with and without HELP debt. Relative to non-debtholders, debtholders tend to be younger, less likely to be wage-earners (defined as having any self-employment income from partnerships, sole-traders, or personal-services), and have lower taxable income. The most important variable is HELP income, which determines a borrower's HELP repayment rate. HELP income equals taxable income plus several other adjustments, such as adding back reportable superannuation contributions, investment losses, and fringe benefits. These adjustments are not relevant for most individuals: the difference between HELP and taxable income is less than $100 for over 93% of the observations in 2004. I decompose HELP Income into three terms:

$$\text{HELP Income} = \text{Labor Income} + \text{Capital Income} - \text{Net Deductions}. \tag{3}$$

Labor Income is defined as the sum of salary and wages, tips and allowances, and self-employment income. This represents the largest source of income for most individuals: 95% for debtholders and 91% for non-debtholders. Capital Income is defined as the sum of interest income, dividend income, capital gains, government superannuation and annuity income, rental income, and trust income. Net Deductions is defined as the residual in (3).

Table 1 shows that debtholders have lower HELP income, labor income, and capital income, in addition to fewer deductions, than non-debtholders. These differences are not surprising given the age differences between the two groups. The average debt balance among debtholders is $10,800 in 2005 AUD ($13,000 in 2020 USD) and $13,200 in 2005 AUD ($15,800 in 2020 USD) among 26-year-old debtholders, which is the age at which most individuals have finished university in Australia. Notably, the 2004–2005 policy change had a large impact on the number of debtholders below the repayment threshold: the fraction below the threshold moved from 51% to 67% after the change. Among 26-year-old debtholders, this fraction moved from 35% to 55%.

Figure A4 shows how debt balances vary within-individual over time: most borrowers' debt balances peak in real terms between ages 24 and 26 and are paid down in their mid-30s. However, around 15% of borrowers who have debt at age 22 in 1991 still have debt at age 50 in 2019. Given the increase in real tuition over time, this number is forecast to increase (Nelson 2003).

Table 1. Summary Statistics

	Non-Debtholders (1)	Debtholders (2)
Demographics		
Age	41.1	29.5
Female	0.46	0.60
Wage-Earner	0.85	0.91
Income Totals (in 2005 AUD)		
Taxable Income	37,695	27,796
HELP Income	38,756	28,586
Income Components (in 2005 AUD)		
Salary & Wages	32,415	26,068
Labor Income	35,480	27,136
Interest & Dividend Income	726	242
Capital Income	1,221	324
Net Deductions	-1,548	-1,099
HELP Variables		
HELP Debt (in 2005 AUD)	·	10,830
HELP Payment (in 2005 AUD)	·	991
HELP Debt at Age 26 (in 2005 AUD)	·	13,156
HELP Payment at Age 26 (in 2005 AUD)	·	1,305
HELP Income < 0% Threshold	0.50	0.65
HELP Income < 2004 0% Threshold	0.37	0.51
HELP Income < 2005 0% Threshold	0.52	0.67
Number of Unique Individuals	19,484,517	4,013,382
Number of Individual-Year Observations	247,118,713	27,316,037

Notes: This table presents summary statistics from the *ALife* sample from 1991 to 2019, subject to the sample selection criteria discussed in Section 2.4. Column (1) uses all individual–years with zero HELP debt; column (2) uses all individual–years with positive HELP debt. The values for all continuous variables represent means. All continuous variables are deflated to 2005 dollars based on the HELP threshold indexation rate. All continuous variables except HELP Debt and HELP Repayment are winsorized at 2%–98%. HELP Income < 0% Threshold corresponds to the mean of a dummy variable for whether HELP income in an individual–year was below the 0% HELP repayment threshold. HELP Income < 0% 2004 Threshold and HELP Income < 0% 2005 Threshold correspond to means between 1998–2004 and 2005—2018 for whether HELP income in an individual–year was below the HELP repayment threshold, respectively, after the thresholds are adjusted for inflation. Additional details on variable construction are presented in Appendix C.3.

3 Labor Supply Responses to Income-Contingent Repayment

This section uses the variation in HELP repayment rates from Figure 2 to document several facts about how labor supply responds to income-contingent repayment.

3.1 Fact #1: Bunching of HELP Income Below Repayment Threshold

The first fact is the presence of bunching in HELP income below the repayment threshold. Figure 3 plots the distribution of real HELP income for borrowers with HELP debt in the three years before and after the policy change. HELP income is deflated to 2005 Australian dollars using the HELP threshold indexation rate. The vertical line in each plot corresponds to the HELP repayment threshold in that

year, which is constant in real terms across the years in which there is no policy change. In these plots, I focus on borrowers with HELP income within $8,000 of the two repayment thresholds, who account for approximately 40% of the entire population of debtholders.

These results show significant bunching below the repayment threshold from 2002 to 2007. For the three years before the policy change, shown in the left panels of Figure 3, the amount of bunching and shape of the income distribution remain relatively constant. However, the right panels show two important changes to the income distribution after the change in 2005. First, the bunching at the 2004 repayment threshold disappears completely. Second, bunching appears immediately below the new repayment threshold, which provides clear evidence that borrowers adjust their income to avoid making income-contingent repayments. Figure A5 shows that the new bunching is primarily from older borrowers who fell between the old and new repayment thresholds in 2004.

The fact that the bunching in Figure 3 responds quickly to the policy change shows that it is not driven by mechanical features of Australia's tax system, such as the tendency to report incomes at round numbers. However, a possible threat to identification is the presence of other changes between 2002 and 2007 that affected individuals' incentives to report incomes of certain values. Although it is unlikely that this could explain the evidence in Figure 3, given that the bunching is sharp around the repayment threshold, I assess this possibility by examining the income distribution of non-debtholders in Figure A6. In contrast to the income distribution of debtholders, this distribution shows no changes around the repayment threshold either before or after the policy change.[13]

The bunching in Figure 3 is also present in the distribution of labor income, one of the three components of HELP income in (3). Figure A7 follows Chetty et al. (2011) and examines a sample of borrowers whose primary source of income is labor income and who thus require similar values of labor income to generate HELP income at the threshold. I then compute a measure of the bunching from Chetty et al. (2011) and find that it is 83% as large for labor income as for HELP income.[14]

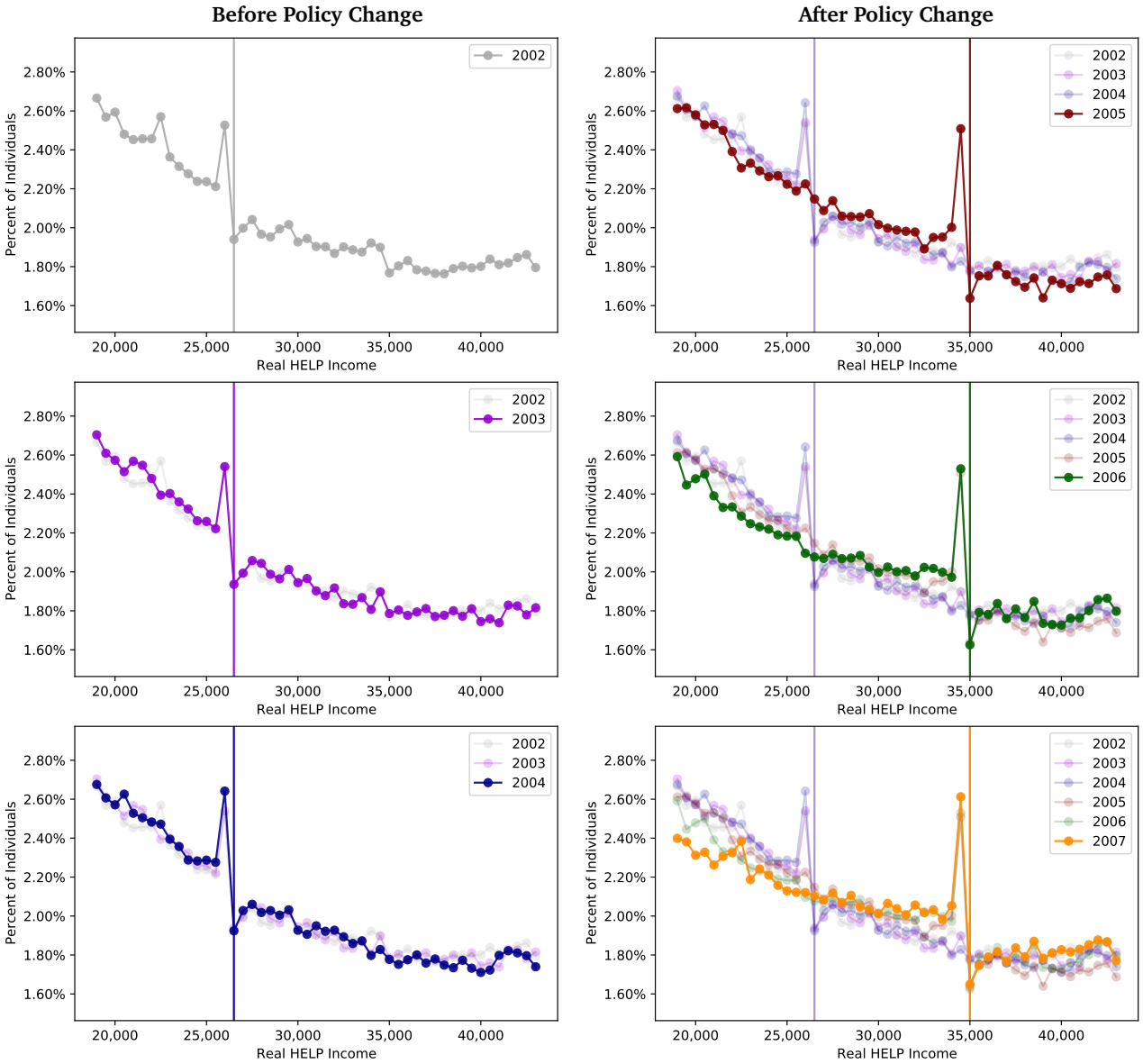
3.2 Fact #2: More Bunching in Occupations with Greater Hourly Flexibility

Next, I show that the bunching in Figure 3 is greater in occupations with more hourly flexibility. Using HILDA, I measure the amount of hourly flexibility in each 2-digit ANZSCO occupation, the finest level at which *ALife* reports occupation codes, as the standard deviation of annual changes in log hours worked. This measure is highest for workers in occupations where it is relatively easy to adjust hours, such as hospitality workers (e.g., bartenders) and food preparation assistants (e.g., fast-food workers), and lowest for those where it is more difficult, such as ICT professionals (e.g.,

[13] There are small changes in the income distribution of non-debtholders at lower values of income, which reflect changes in real terms of the second income tax bracket.

[14] Figure A7 can be used to estimate the dollar loss to the ATO from the bunching at the repayment threshold: the HELP repayments implied by the counterfactual distribution for HELP income estimated on the full sample from 2005 to 2018 are approximately $90M higher than those implied by the observed distribution. This amounts to 42 bps of the total HELP compulsory repayments reported in the aggregated ATO HELP Data over this time period.

Figure 3. Income Distribution of HELP Debtholders around the Repayment Threshold

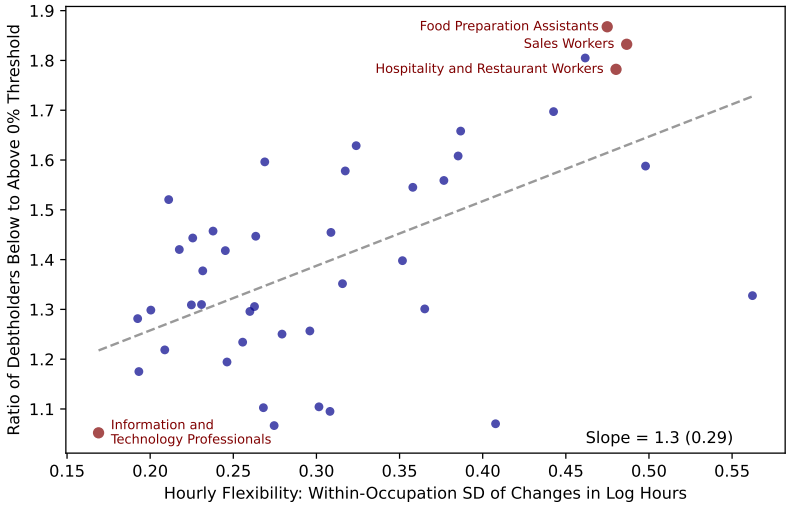


Notes: This figure shows the distribution of real HELP income in Australian dollars, which determines a borrower's repayment rate on her income-contingent loan, in the three years before and after the policy change to the repayment schedule between 2004 and 2005 that is illustrated in Figure 2. The vertical lines in the left (right) panel indicate the threshold above which borrowers begin making debt payments of 3% (4%) of their income before (after) the policy change. Each bin represents $500, and the plot focuses on borrowers within $8,000 of the two repayment thresholds. The bins are chosen so that they are centered around the 2005 repayment threshold. HELP income is deflated to 2005 Australian dollars using the HELP threshold indexation rate, which is based on the annual CPI. The sample is the *ALife* sample defined in Section 2.4, restricted to individuals with positive HELP debt balances in each year.

software engineers). Table A2 shows the value of this measure for each occupation in my sample.

Figure 4 plots the amount of bunching between 2005 and 2018 among wage-earners below the new repayment threshold relative to hourly flexibility. I focus on the period after the policy change because this is when *ALife* offers comprehensive coverage of occupation codes. Each point represents an occupation, and I measure the amount of bunching as the ratio of the number of borrowers in that

Figure 4. Variation in Bunching across Occupations Based on Hourly Flexibility



Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and hourly flexibility by occupation, where each point represents a 2-digit ANZSCO occupation. Bunching is measured as the ratio of the number of borrowers in that occupation within $2,500 below the repayment threshold to the number within $2,500 above the threshold over 2005 to 2018. Hourly flexibility is measured as the standard deviation of annual changes in log hours worked from HILDA; see Figure A8 for an alternative measure. The highlighted points correspond to occupations described in the text. The gray dashed line is the regression line, with the estimated slope and standard error reported at bottom right. The sample is the *ALife* sample defined in Section 2.4, restricted to the subset of individual–years for which the individuals are wage-earners and have positive HELP debt balances.

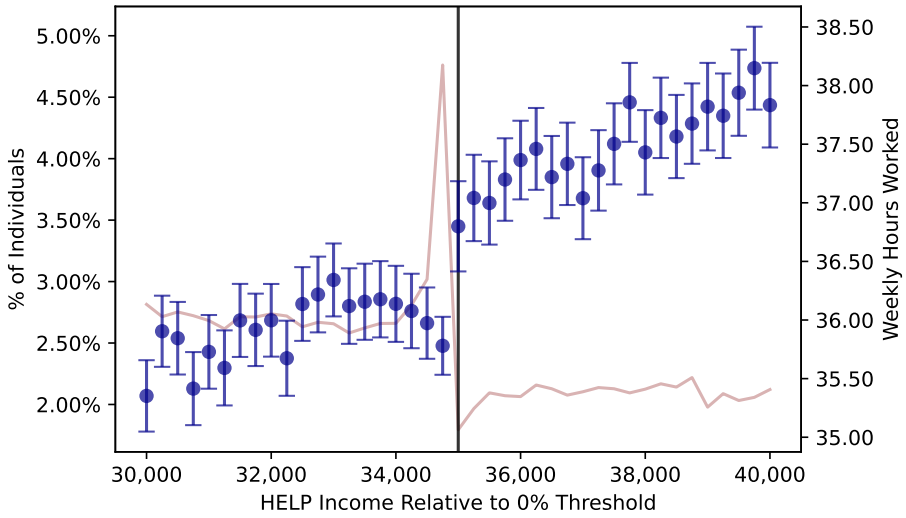
occupation within $2,500 below to the number above the threshold so that a ratio of one indicates no bunching (similar to Chetty et al. 2013). The results show that bunching is more common in occupations with greater hourly flexibility. For example, ICT Professionals have the lowest hourly flexibility with a standard deviation of annual changes in log hours of 0.17. In this occupation, there is only 5% more borrowers below than above the threshold. In contrast, hospitality workers have almost three times more hourly flexibility and exhibit significantly more bunching, with 80% more borrowers below than above the threshold. Quantitatively, Table A3 shows that hourly flexibility explains 34% of the variation in bunching across occupations.

One concern with the evidence in Figure 4 is that hourly flexibility might be correlated with tax evasion or income-shifting across occupations. To assess the importance of evasion, I calculate the share of workers in each occupation that receives labor income from allowances, tips, director's fees, consulting fees, or bonuses. This variable is a proxy for tax evasion because it is easier to misreport these other sources of income relative to salary and wages (Paetzold and Winner 2016; Slemrod 2019). Figure A9 shows that this measure, unlike hourly flexibility, exhibits little correlation with bunching below the repayment threshold.

3.3 Fact #3: Borrowers Below the Repayment Threshold Work Fewer Hours

A second piece of evidence that suggests that the bunching in Figure 3 reflects, at least in part, labor supply responses is that borrowers below the repayment threshold work fewer hours. I

Figure 5. Self-Reported Hours Worked around the Repayment Threshold



Notes: This figure plots the 2016 HELP income distribution in red and measured on the left axis. HELP income is deflated to 2005 with the HELP threshold indexation rate, which is based on the annual CPI. Each bin represents $250, and the bins are chosen so that they are centered around the 2005 repayment threshold. The blue points present the average value of individuals' reported hours worked from the 2016 Census of Population and Housing within each bin, along with 95% confidence intervals. The sample is the cross-sectional MADIP sample described in Section 2.4, restricted to individuals with positive HELP debt balances.

measure hours worked using a question in the 2016 Census of Population and Housing in which individuals report the number of hours worked during the week before the census night. Figure 5 plots the average hours worked in $250 bins of HELP income around the repayment threshold in the census year 2016, in addition to the distribution of HELP income in red.[15] The results show that borrowers locating immediately below the threshold work on average 1 hour less per week than those immediately above it, which is 2.6% of the standard 38 hour workweek in Australia.[16] This adjustment occurs within a borrower's current occupation: Figure A11 finds little evidence that those below the repayment threshold are more likely to have switched occupations.

The results in Figure 5 are subject to two caveats. First, as discussed in Section 2.4, the MADIP and *ALife* samples differ slightly. To mitigate concerns about sample selection, Figure A13 shows that the distribution of HELP income in 2016 across the two samples is quantitatively similar. Second, these data on hours worked are self-reported by employees, which introduces concerns about reporting issues. For this reason, I do not target this evidence directly when estimating the structural model.

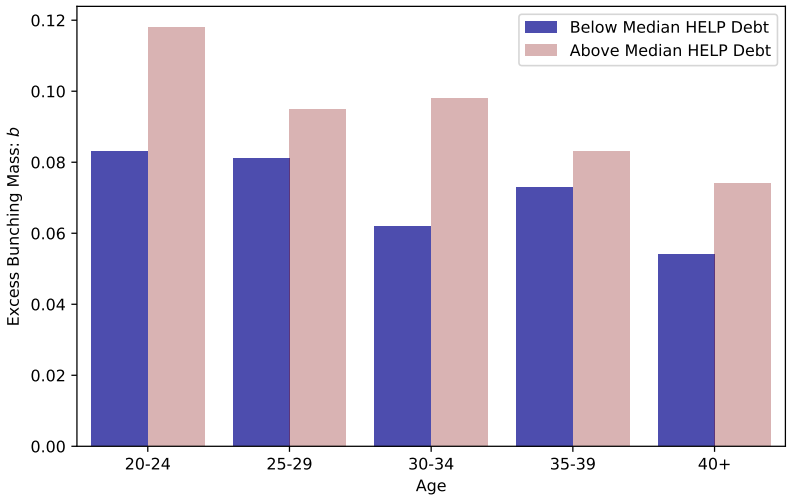
3.4 Fact #4: Bunching Decreases with Probability of Repayment and Age

Next, I show that the amount of bunching below the repayment threshold increases with debt balances and decreases with age. To measure the amount of bunching, I construct a bunching

[15] Figure 5 suggests that borrowers in the four bins below the threshold reduce their hours by around 0.75 per week. In partial equilibrium, this corresponds to a 0.007% reduction in aggregate hours worked by all employed individuals.

[16] These results are not driven by a group of borrowers outside the labor force earning only income from other sources: Figure A12 shows that the patterns are nearly identical in the sample of borrowers earning positive labor income.

Figure 6. Variation in Bunching by Debt Balances and Age



Notes: This figure plots the bunching statistic defined in (4) computed for different samples of debtholders based on age and debt balances. The age groups are listed on the horizontal axis. Within each age group, the blue (red) bars plot the estimated statistic for borrowers with below-median (above-median) debt balances, where the median is calculated separately for each year and age group. The calculation of b is detailed in Appendix C.4. Standard errors are omitted from this plot because the corresponding 95% confidence intervals overlap visually in the units of this plot. The sample is the *ALife* sample defined in Section 2.4 for the period between 2005 and 2018 after the policy change, restricted to individuals with positive HELP debt balances.

statistic following the literature that uses discontinuities in tax rates to estimate income elasticities (Chetty et al. 2011; Kleven and Waseem 2013). First, I fit a five-piece spline to each distribution, leaving out the region $\mathcal{R} = [\$32,500, \$35,000 + X]$. The choice of $\$32,500$ represents a conservative estimate of where the bunching begins, and X is a constant intended to reach the upper bound at which the income distribution is affected by the threshold. This spline corresponds to an estimate of the counterfactual distribution absent the threshold. Next, I iterate on X so that this counterfactual density integrates to 1. Finally, I compute the bunching statistic, b, as:

$$b = \frac{\text{observed density in } \mathcal{R}}{\text{counterfactual density in } \mathcal{R}} - 1. \tag{4}$$

This bunching statistic is an estimate of the excess number of borrowers below the threshold relative to a counterfactual distribution in which it did not exist.

Figure 6 shows the value of the bunching statistic across groups of borrowers with different ages and debt balances. I split ages into five-year bins, which gives a similar number of observations within each bin, and then split debt balances at their median value within each age and year. The results show two patterns. First, the amount of bunching increases in debt balances: for all age groups, the estimated value of b is higher among borrowers with above-median debt balances. This finding suggests that the probability of eventual repayment is an important determinant of labor supply responses. The second pattern is that the amount of bunching decreases with age: the estimated b is $22-33\%$ lower among borrowers above 40 than among those below 25. Given that borrowing constraints are tightest among young borrowers, this finding provides suggestive evidence

that liquidity constraints affect labor supply responses, which I test more directly in the next section.

The amount of bunching below the repayment threshold also varies based on the properties of occupation-specific wage profiles. These wage profiles are plotted in Figure A10, which shows that there are some occupations in which the average individual will almost certainly earn enough income to pay her debt while there are others in which the average individual spends her entire life below the repayment threshold. Table A3 shows that the amount of bunching is larger in occupations with flatter income profiles and lower maximum incomes, both of which support the idea that a lower probability of eventual repayment increases borrowers' willingness to reduce their labor supply.

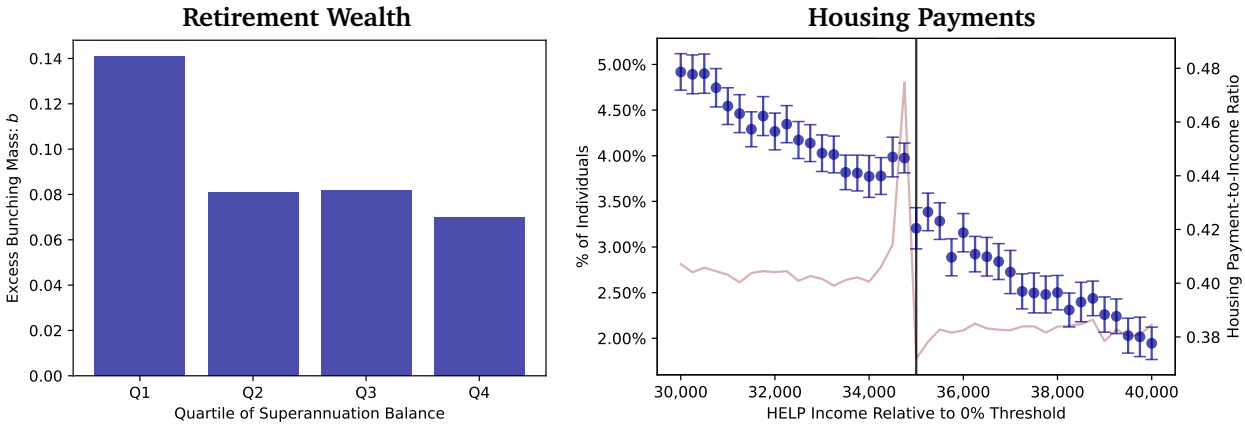
3.5 Fact #5: Bunching Decreases with Proxies for Liquidity

This section presents evidence that the responses in Figure 3 vary cross-sectionally with proxies for liquidity constraints. As discussed in Section 2.2, locating below the repayment threshold increases liquidity but has a smaller effect on wealth. Therefore, the evidence that borrowers reduce their labor supply to locate below the repayment threshold echoes the conclusion of Ganong and Noel (2020) that current budget constraints are important for understanding the behavior of indebted households. Absent direct measures of liquidity, I use several complementary measures to more directly assess its importance.

First, I find that the amount of bunching is larger among borrowers who reveal a preference for liquidity by holding less retirement wealth. The largest form of retirement savings in Australia is called superannuation ("super"), which is the second-largest source of household wealth (Australian Council of Social Service 2018). Contributions into super accounts primarily come from mandatory employer and voluntary employee contributions. Employee contributions, up to a limit, have generally been taxed at a rate lower than the personal income tax rate to incentivize saving. Therefore, super balances are a natural proxy for liquidity based on revealed preference: borrowers who have been unwilling to contribute to a tax-advantaged but illiquid account are implicitly revealing a high valuation of liquidity (similar to the rationale in Coyne et al. 2022). The left panel of Figure 7 plots the bunching statistic, b, based on quartiles of super balances from *ALife* that are defined within each year. The amount of bunching is highest for borrowers in the bottom quartile, approximately twice as large as the top quartile. This is also true within borrowers under age 30 (Figure A14).

Second, borrowers below the repayment threshold have larger housing payments. For most individuals, housing payments represent one of the largest sources of liquidity demand. Therefore, if liquidity influences labor supply responses, borrowers below the repayment threshold should have larger housing payments, or equivalently, borrowers with larger housing payments should be more likely to bunch below the repayment threshold. The right panel of Figure 7 shows that this prediction holds in the data: borrowers below the repayment threshold have larger housing

Figure 7. Bunching and Proxies for Liquidity Constraints



Notes: The left panel of this figure plots the bunching statistic defined in (4) computed for different samples of debtholders based on quartiles of superannuation balances computed within each year. The calculation of b is detailed in Appendix C.4. Standard errors are omitted because the corresponding 95% confidence intervals overlap visually in the units of this plot. The sample is the *ALife* sample defined in Section 2.4 between 2005 and 2018 after the policy change, restricted to individuals with positive HELP debt balances. The right panel replicates Figure 5 but plots the average housing payment–to–income ratios instead of hours worked within each bin. Error bars represent 95% confidence intervals.

payment–to–income ratios by approximately 2 percentage points, where housing payments are measured with combined mortgage and rent payments from the 2016 Census.

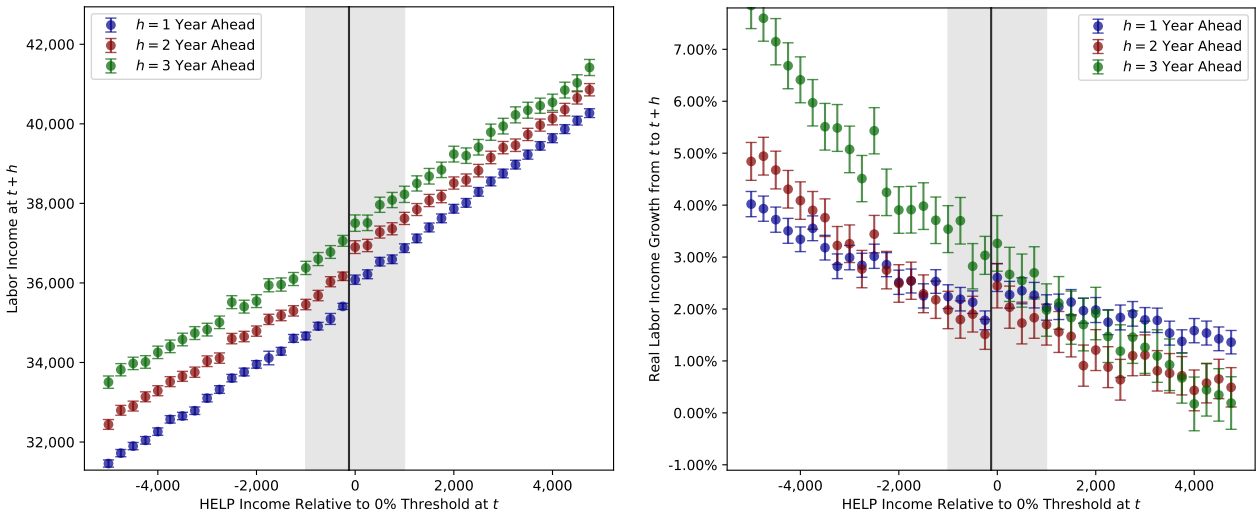
A final, more speculative finding that points to the importance of liquidity is that there is more bunching among borrowers in regions with less housing wealth. Figure A14 plots the relationship between the amount of bunching and house prices across geographic regions. Absent data on wealth at the individual-level, house prices serve as a reasonable proxy because housing represents the largest component of household wealth in Australia. The results show that the amount of bunching is lower in regions with higher house prices, which tend to be metropolitan areas (e.g., Sydney), and that this relationship is unaffected by controlling for demographic and economic characteristics, such as population size and the unemployment rate.

3.6 Fact #6: Limited Evidence of Future Wage Reductions from Bunching

The final empirical fact is that the distribution of future income is not meaningfully different for individuals who bunch below the repayment threshold. In models with learning-by-doing, also known as human capital accumulation or career effects (e.g., Keane and Rogerson 2015), current labor supply affects the stock of human capital and hence future wages. These models predict that the reduction in labor supply shown in Figure 5 comes at the cost of lower future wages.[17]

[17] A related model of dynamic compensation is presented in Kleven et al. (2023), where realized earnings only equal true latent earnings (hours × wages) at job transitions. I cannot test this mechanism because I do not observe job transitions, but two facts suggest that it is likely a weak determinant of the lack of responses. First, the sample of borrowers around the repayment threshold are low- to median-income, while Kleven et al. (2023) find that dynamic compensation plays an important role at the top of the income distribution. Second, Figure A11 shows no discontinuity in the probability of occupation switching around the repayment threshold.

Figure 8. Bunching Below the Repayment Threshold and Future Labor Income



Notes: The left panel of this figure plots average labor income in year $t + h$ within \$250 bins of the difference between borrowers' HELP income and the repayment threshold in year t. The bins are chosen to be centered around zero. The dark blue points correspond to h = one year; the red points are h = two years; the light green points are h = three years. The right panel replicates the left panel using labor income growth from t to $t + h$ computed as the change in log labor income between these two periods. Before computing income growth, values of labor income are trimmed from below at one-half the legal minimum wage times 13 full-time weeks and then trimmed at 5 times the interquartile range. Error bars represent 95% confidence intervals. The shaded region in both plots corresponds to within \$1000 of the threshold. HELP income and labor income are deflated to 2005 Australian dollars using the HELP threshold indexation rate. The sample is the *ALife* sample defined in Section 2.4, restricted to individuals with positive HELP debt balances in each year.

In the ideal experiment to identify the size of these future wage reductions, bunching would be randomly-assigned and, I could compare the future wages of bunchers and non-bunchers. Absent this ideal experiment, Figure 8 plots the average labor income and labor income growth from year t to $t + h$ based on borrowers' locations relative to the repayment threshold in year t. The results show that borrowers who bunch below the repayment threshold in year t experience slightly lower income growth than those above the threshold in the subsequent year. This difference is small, only 1%, and disappears after three years, the same horizon over which the bunching below the threshold persists (Figure A15). Additionally, there is little difference in the distribution of future labor income in terms of variance or skewness (Figure A16).

Nevertheless, this evidence should not be interpreted as suggesting that no learning-by-doing is present: larger labor supply reductions could create sizeable costs. Instead, it suggests that the size of the responses created by income-contingent repayment is not large enough to create costs over the horizons that I observe. Although this evidence is clearly subject to concerns about selection into bunching, a natural form of selection would be that borrowers with lower expected income growth would be more likely to bunch. In this case, the evidence in Figure 8, which suggests relatively small wage reductions from bunching, would serve as an upper bound.

3.7 Additional Results and Discussion

Evasion. An obvious explanation for the bunching in Figure 3 is evasion, in which borrowers misreport their incomes. Although this is illegal and difficult to identify empirically, several facts (in addition to the direct evidence of a labor supply response in Figure 5 and the lack of evidence for evasion in Figure A9) suggest that it cannot explain all of the responses. First, Figure A18 shows that the distribution of salary and wages exhibits substantial bunching around the repayment threshold, which is generally interpreted as evidence of hours-worked responses (see, e.g., Chetty et al. 2013). This is because the literature on tax evasion that uses random audits finds that the majority of individual tax evasion comes from self-employment income, with an estimated noncompliance rate of less than 1% for items with withholding and substantial reporting information, such as salary and wages (Slemrod 2019). Second, Table A4 shows that the amount of bunching declines by only 4% when I restrict to the sample of wage-earners, who have substantially less flexibility in reporting their income, and is almost identical between borrowers who file their tax returns electronically and nonelectronically. When taxes are filed electronically, pure evasion is more difficult because the sources of labor income are often prefilled by the employer and, if they are not, the ATO compares what the individual reports with the employer's payment summary. Finally, the sample of borrowers near the repayment threshold is around median income, unlike the evidence from prior literature that evasion is largest among high-income individuals, who have more avoidance opportunities (Slemrod and Yitzhaki 2002; Saez et al. 2012).

Nevertheless, it is likely that some of the responses in Figure 3 reflect evasion rather than solely labor supply. In this case, the model I develop in Section 4 will overestimate labor supply responses to income-contingent repayment. There are two ways in which this could affect my normative results. First, if the costs of evasion are entirely real resource costs, then whether the responses in HELP income reflect labor supply or evasion is irrelevant as long as the model can replicate them (Feldstein 1999). However, in the more likely case that some of the costs of evasion are transfers to other agents or the government (e.g., fines), my model will overstate the welfare costs of the moral hazard created by income-contingent repayment (Chetty 2009; Gorodnichenko et al. 2009), reinforcing the qualitative conclusions from my normative analysis.

Income-shifting across years. Another mechanism through which borrowers may locate below the repayment threshold is by transferring income to future years when they anticipate being above it, possibly by asking employers to delay their compensation. However, such intertemporal income shifting is inconsistent with Figure 8: borrowers below the threshold in a given year do not have higher income in future years.

Firm responses. An alternative mechanism to the labor supply response in Figure 5 would be a demand-side response, in which firms offer jobs with wages below the repayment threshold. Chetty et al. (2011) provide evidence of such a response by firms to reduce income taxes in Denmark,

where the vast majority of private-sector jobs are covered by collective bargaining agreements. Two findings suggest that this does not occur in my setting. First, the distribution of non-debtholders, who likely compete in overlapping labor markets, does not exhibit any bunching, as shown in Figure 3. Second, Figure A17 replicates Figure 9 from Chetty et al. (2011), plotting the distribution of labor income among borrowers with net deductions. In Chetty et al. (2011), this distribution still exhibits bunching around the threshold at which marginal tax rates change because firms offer jobs with salaries below the threshold, even though this threshold does not apply to these borrowers who claim deductions. In contrast, this distribution exhibits no bunching in my setting.

Other demographic heterogeneity. Table A4 examines heterogeneity in bunching based on the remaining demographic characteristics in the data. The results show almost no differences based on gender, 5% less bunching among borrowers with a spouse, and 12% less bunching among borrowers with dependent children. Although the first result contrasts with existing evidence that female labor supply is more elastic, an important caveat is that the responses that I estimate are local to the repayment threshold and thus do not capture extensive margin responses, which drive the larger responses among women (Saez et al. 2012).

3.8 Taking Stock of the Empirical Facts

Summary of empirical results. This section presents a series of empirical facts that can be summarized as follows. First, borrowers reduce their income in response to income-contingent repayment. These responses reflect, at least in part, labor supply responses rather than tax evasion or income-shifting, as borrowers below the repayment threshold work fewer hours and tend to be in occupations with more flexibility. Second, the size of these responses varies cross-sectionally based on two forces. The first is dynamics: borrowers with more debt and in occupations with lower income growth and maximum incomes, for whom the repayment reduction is more likely a permanent reduction rather than simply a transfer over time, exhibit greater responses. The second force is liquidity: borrowers who are likely liquidity-constrained, for whom the value of the repayment reduction is most valuable, are more willing to reduce their labor supply. Finally, there is limited evidence of a dynamic cost associated with the reductions in labor supply that income-contingent repayment creates.

Implications for structural model. In Section 4, I develop a structural model that is designed to explain this evidence. Consistent with the bunching below the repayment threshold and the importance of dynamics and liquidity, borrowers choose their labor supply dynamically by trading off the disutility of work with the benefits of higher income, and they choose their consumption subject to borrowing constraints. However, the evidence in Figure 3 provides a rejection of a model in which labor supply is determined *solely* by the disutility of work and the benefits of higher income. Since utility increases in consumption and leisure, such a model cannot generate any borrowers

immediately above the threshold because locating below it gives more consumption and leisure.[18]

The presence of borrowers above the repayment threshold thus raises the question of what mechanisms explain this lack of labor supply adjustment. Broadly, there are three possible explanations. First, borrowers may be unaware of the repayment threshold due to inattention (Chetty et al. 2013). Second, borrowers may be aware of the threshold but may be unable to adjust their labor supply due to costs associated with changing labor supply (Chetty 2012) or hours constraints (Chetty et al. 2011). Finally, borrowers may be able to adjust their labor supply but actively choose not to locate below the repayment threshold. This could be because of long-run costs associated with doing so (Keane and Rogerson 2015), the receipt of nonpecuniary benefits from work, or prosocial preferences leading borrowers to feel obligated to repay their debts. The model in Section 4 introduces optimization frictions, which capture the first two explanations but not the third. This choice is motivated by the fact that bunching increases with hourly flexibility, which suggests that hours constraints and adjustment costs play a role, and the limited evidence of future wage reductions.

4 Life Cycle Model with Labor Supply and Uninsurable Income Risk

The empirical analysis in Section 3 characterizes how labor supply responds to income-contingent repayment, but leaves open two important questions. First, how large are these responses quantitatively? Second, are these responses large enough to imply that the moral hazard created by income-contingent repayment outweighs the insurance benefits? The section presents and estimates a structural model designed to answer these two questions. The key ingredients in the model are endogenous labor supply, which creates moral hazard, uninsurable income risk, which creates a demand for insurance, and labor supply optimization frictions, which explain the presence of borrowers above the repayment threshold.

4.1 Model Description

4.1.1 Demographics

Time is discrete, and each period, t, corresponds to one calendar year. At $t = h \in \{\underline{h}, \underline{h}+1, ...\overline{h}\}$, a cohort h of individuals indexed by i are born at initial age a_0. The total number of individuals born in the economy is discrete and denoted by N, with a fraction μ_h born in cohort h. The initial age, a_0, should be interpreted as the age at which individuals exit college and enter the labor force. The age of an individual i in cohort h at time t is $a_{ht} = a_0 + t - h$. Before age a_T, individuals face age-dependent mortality risk, with the survival probability at age $a+1$ conditional on survival at age

[18] One reason borrowers may locate above the repayment threshold is that, unlike a tax, income-contingent loans have an additional effect: increasing labor supply reduces the stock of debt. If the value function is sufficiently decreasing in debt, it may be optimal not to locate below the threshold. In Appendix B, I show that this unlikely to be the case.

a denoted by m_a. Between ages a_0 and $a_R - 1$, individuals are in their working life and can supply labor to earn income. At age a_R, individuals exogenously transition to retirement and cannot supply labor; after age a_T, individuals die with probability one.

4.1.2 Preferences

In each period of working life, individuals choose consumption, c, and labor supply, ℓ. An individual i at age a has Epstein and Zin (1989)–Weil (1990) preferences over consumption and labor supply defined recursively by:

$$V_{ia} = \left[(1-\beta)\, n_a \left(\frac{c_{ia}}{n_a} - \kappa \frac{\ell_{ia}^{1+\phi^{-1}}}{1+\phi^{-1}} \right)^{1-\sigma} + \beta \left(m_a \mathbf{E}_a V_{ia+1}^{1-\gamma} \right)^{\frac{1-\sigma}{1-\gamma}} \right]^{\frac{1}{1-\sigma}}. \tag{5}$$

In (5), β is the discount factor, σ^{-1} is the intertemporal elasticity of substitution, γ is the cofficient of relative risk aversion, ϕ is the Frisch labor supply elasticity, κ is a scaling parameter, and n_a is an equivalence scale. This preference specification is a recursive generalization of Greenwood et al. (1988) (GHH) preferences and eliminates wealth effects on labor supply, meaning the marginal rate of substitution between c and l is independent of changes in c (as in Guvenen 2009b). This is consistent with empirical evidence that finds small labor supply responses to changes in wealth (Keane 2011; Cesarini et al. 2017). I use recursive rather than time-separable preferences so that I can independently assess the role of risk and time preferences independently in my normative analysis. The equivalence scale captures the evolution of household size over the life cycle, as in Lusardi et al. (2017). This generates a hump shape in consumption over the life cycle because the marginal utility of consumption increases with n_a and the calibrated values of n_a are hump shaped.

4.1.3 Labor Income Process

During working life, the labor income of individual i at age a, y_{ia}, is equal to the product of the individuals' wage rate, w_{ia}, and labor supply, l_{ia}, where the latter is chosen endogenously. An individuals' wage rate is modeled in partial equilibrium and consists of three components:

$$\log w_{ia} = g_{ia} + \theta_{ia} + \epsilon_{ia}. \tag{6}$$

The first component, g_{ia}, is a deterministic life cycle component whose specific form is discussed later. The other two components, θ_a and ϵ_a, capture the stochastic components of the wage process, which take the following forms:

$$\begin{aligned} \theta_{ia} &= \rho\theta_{ia-1} + \alpha \log(l_{ia-1}) + \nu_{ia}, \quad \theta_{ia_0} = \delta_i, \\ \delta_i \sim \mathcal{N}(0,\sigma_i^2), &\quad \nu_{ia} \sim \mathcal{N}(0,\sigma_\nu^2), \quad \epsilon_{ia} \sim \mathcal{N}(0,\sigma_\epsilon^2). \end{aligned} \tag{7}$$

The wage process in (7) allows for idiosyncratic permanent and transitory shocks, which is important because individuals can only self-insure against the latter in incomplete markets. The transitory component, ϵ_{ia}, is i.i.d. within and across individuals. The permanent component, θ_{ia}, depends on three factors: permanent shocks, ν_{ia}, which have persistence ρ; an individual fixed effect, δ_i, which captures ex-ante heterogeneity across individuals; and learning-by-doing following Keane and Rogerson (2015), in which past labor supply affect future wages with elasticity α. Although I find little evidence of learning-by-doing affecting bunching empirically, I estimate a version of the model with α set based on prior literature to assess its importance in my normative analysis.

Aside from the presence of learning-by-doing and the fact that θ_{ia} is not a random walk, this specification of the wage rate process is similar to the standard permanent-transitory income processes used in canonical life cycle models (Gourinchas and Parker 2002). A key difference, however, is that the *income* process is endogenous because individuals choose their labor supply.

4.1.4 Education Levels

In addition to having different initial permanent incomes through δ_i, individuals differ ex-ante based on their education levels. There are two education levels denoted by $\mathcal{E}_i \in \{0, 1\}$, where

$$\mathcal{E}_i \sim \text{Bernoulli}(p_E). \tag{8}$$

Individuals with $\mathcal{E}_i = 1$ are referred to as "borrowers", meaning they have a college degree that they borrowed to finance. Individuals' education level determines the deterministic component of their income process, g_{ia}, which takes the following form:

$$g_{ia} = \delta_0 + \delta_1 a + \delta_2 a^2 + \mathcal{E}_i \left(\delta_0^E + \delta_1^E a\right). \tag{9}$$

This specification captures that the returns to experience are quadratic (in logs), as in Mincer (1974), and that borrowers may have different wage levels and profiles.

4.1.5 Labor Supply Optimization Frictions

Individuals choose their labor supply at the same time that they choose consumption, which occurs at the end of each period after all shocks are realized. I introduce optimization frictions that prevent individuals from frictionlessly choosing their labor supply. As discussed in Section 3.8, these frictions are needed to generate borrowers above the repayment threshold. Because isolating the importance of every possible optimization friction is not possible given the available data and empirical variation, I instead follow Nakamura and Steinsson (2010) and Andersen et al. (2020) and consider a specification that nests the two canonical types of imperfect adjustment: state-dependent

and time-dependent adjustment.[19]

The first optimization friction is that choosing labor supply in the current period that is different from that in the past period, $\ell_{ia} \neq \ell_{ia-1}$, requires paying a fixed cost of f, except in individuals' first period of life. This fixed cost generates (S, s)–type behavior and makes labor supply adjustment state-dependent, meaning that individuals adjust their labor supply only when the benefits of adjustment are sufficiently high. This cost could capture real costs associated with changing labor supply, such as search costs associated with changing jobs when hours are constrained by firms, or psychological costs, such as the hassle costs of adjusting a work schedule. The fixed cost is modeled as a utility cost, as axiomatized by Masatlioglu and Ok (2005).

The second friction is that only a fraction λ of individuals in each period receive opportunities to their labor supply à la Calvo (1983). Formally, individuals with $\omega_{ia} = 1$ can adjust consumption and labor supply and those with $\omega_{ia} = 0$ can only adjust consumption, where:

$$\omega_{ia} \sim \begin{cases} 1, & \text{if } a = a_0, \\ \text{Bernoulli}(\lambda), & \text{else.} \end{cases} \tag{10}$$

The Calvo shock, ω_{ia}, generates time-dependent labor supply adjustment. Economically, it could capture frictions on the demand-side of the labor market that result in the slow arrival of opportunities to adjust labor supply or job transitions (as in Kleven et al. 2023). Alternatively, it could capture inattention, where $1 - \lambda$ is the fraction of inattentive individuals.[20] Individuals who receive the Calvo shock have to pay the fixed cost if they choose to adjust their labor supply.

4.1.6 Liquid Assets

At age a_0, individuals are endowed with a stock of liquid assets, A_{ia_0}, where

$$A_{ia_0} \sim \begin{cases} 0, & \text{with probability } p_A(\mathcal{E}_i), \\ \text{Log-normal}\left(\mu_A(\mathcal{E}_i), \sigma_A(\mathcal{E}_i)^2\right), & \text{with probability } 1 - p_A(\mathcal{E}_i). \end{cases} \tag{11}$$

The dependence of this distribution on $\mathcal{E}_i$ allows for the possibility that individuals with different education levels have different initial liquidity. In subsequent periods, liquid asset balances at the end of the period at age $a - 1$ are denoted by A_{ia}. Positive balances in the liquid asset pay a gross return of R. Individuals can also borrow using unsecured credit up to an age-dependent borrowing

[19] An alternative friction is optimization errors, which could take two forms, both inconsistent with the empirical evidence. The first is anticipated errors, in which individuals know that they cannot control labor supply perfectly. This, however, yields the prediction that there will be excess mass further to the left of the threshold as individuals reduce their labor supply even more to ensure that they do not end up above it, which is not the case in Figure 3. The second is unanticipated errors, where labor supply equals individuals' choice plus an error. This leads to the prediction that the bunching will be diffuse around the repayment threshold while the bunching in Figure 3 is sharp.

[20] This imperfectly captures inattention because agents are sophisticated about their inattention. Naive inattention introduces complications with individuals violating budget constraints that are beyond the scope of this paper.

limit, $\underline{A}_a$. The interest rate on borrowing is $R + \tau_b$, where τ_b captures the borrowing rate wedge. Asset income, i_{ia}, is received prior to consumption at age a and is equal to:

$$i_{ia} = r(A_{ia}) * A_{ia}, \quad r(A_{ia}) = R - 1 + \tau_b * \mathbf{1}_{A_{ia}<0}. \tag{12}$$

Interest and borrowing rates are taken as exogenous for tractability. This is unlikely to quantitatively affect the results because individuals with large student debt balances, who are most affected by the policy changes that I consider, are young and hold a small share of aggregate wealth.

4.1.7 Student Debt

At age a_0, individuals are also endowed with debt balances, D_{ia_0}, where

$$D_{ia_0} \sim \begin{cases} 0, & \text{if } \mathcal{E}_i = 0, \\ \text{Log-normal}\left(\mu_d, \sigma_d^2\right), & \text{if } \mathcal{E}_i = 1. \end{cases} \tag{13}$$

These initial debt balances are exogenous because I focus on the trade-off between insurance and ex-post moral hazard. In subsequent periods, debt balances evolve according to:

$$D_{ia+1} = (1 + r_d)D_{ia} - d_{ia}, \quad d_{ia} = d(y_{ia}, i_{ia}, D_{ia}, a, t), \tag{14}$$

where r_d is the (net) interest rate on student debt and d_{ia} is the required debt payment determined by the repayment function, $d(\cdot)$. This function depends on borrowers' income and debt balance; any outstanding debt is discharged once borrowers enter retirement at $a = a_R$ or upon death.

4.1.8 Government

A government earns revenue from progressive taxes on labor and asset income, denoted by $\tau_{ia} = \tau(y_{ia}, i_{ia}, t)$, and student debt repayments. Government expenditures include student loans to newborn individuals, means-tested unemployment benefits, $ui_{ia} = ui(y_{ia}, i_{ia}, A_{ia})$, and a means-tested retirement pension, $\overline{y}_R(A_{ia})$. The government also pays a net consumption floor, $\underline{c}_{ia}$, to ensure that consumption exceeds the disutility from labor supply by $\underline{c}$ in the event that individuals do not adjust the latter.[21] There is no deduction for interest paid on unsecured borrowing.

4.1.9 Recursive Formulation

Individuals solve a stochastic dynamic programming problem, which can be formulated recursively. There are five continuous state variables: A_{ia} = beginning-of-period liquid assets, ℓ_{ia-1} = past

[21] The combination of GHH preferences and optimization frictions implies that there are parts of the state space where individuals cannot ensure that consumption net of the disutility of labor supply is positive, which causes V_{ia} to be poorly-behaved. This consumption floor prevents that but is never received by any individuals in simulations.

labor supply, D_{ia} = student debt, θ_{ia} = persistence component of the wages, and ϵ_{ia} = transitory component of the wages. There are four discrete state variables: t = current year, a = age, $\mathcal{E}_i$ = level of education, and ω_{ia} = Calvo shock. Denote $\mathbf{s}_{ia}$ as the vector of these state variables for individual i at age a and $\mathbf{E}_a(\cdot) = E(\cdot \mid \mathbf{s}_{ia+1})$ as the conditional expectation over the three shocks, ω_{ia+1}, ν_{ia+1}, and ϵ_{ia+1}. There are two controls: end-of-period liquid assets, A_{ia+1}, and labor supply, ℓ_{ia}. Consumption, c_{ia}, is pinned down by the budget constraint.

Suppressing i subscripts, individuals at age $a < a_R$ who receive the Calvo shock and those at age $a = a_0$ solve the following problem:

$$V_a(\mathbf{s}_a) = \max_{A_{a+1},\ell_a} \left\{ (1-\beta)\, n_a \left[\frac{c_a}{n_a} - \kappa \frac{\ell_a^{1+\phi^{-1}}}{1+\phi^{-1}} - f * \mathbf{1}_{\ell_a \neq \ell_{a-1}} \right]^{1-\sigma} + \beta \left[m_a \mathbf{E}_a \left(V_{a+1}(\mathbf{s}_{a+1})^{1-\gamma} \right) \right]^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}}$$

subject to: (6), (7), (9), (10), (12), (14), and

$$c_a + A_{a+1} = y_a + A_a + i_a - d_a - \tau_a + ui_a$$

constraints: $A_{a+1} \geq \underline{A}_{a+1}$ and $\ell_a \geq 0$

boundary conditions: (7), (8), (11), (13), and $\ell_{a_0-1} = \ell_{a_0}$

Individuals at age $a < a_R$ who do not receive the Calvo shock solve the following problem:

$$V_a(\mathbf{s}_a) = \max_{A_{a+1}} \left\{ (1-\beta)\, n_a \left[\frac{c_a}{n_a} - \kappa \frac{\ell_{a-1}^{1+\phi^{-1}}}{1+\phi^{-1}} \right]^{1-\sigma} + \beta \left[m_a \mathbf{E}_a \left(V_{a+1}(\mathbf{s}_{a+1})^{1-\gamma} \right) \right]^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}}$$

subject to: (6), (7), (9), (10), (12), (14), and

$$c_a + A_{a+1} = y_a + A_a + i_a - d_a - \tau_a + ui_a + \underline{c}_a$$

constraint: $A_{a+1} \geq \underline{A}_{a+1}$

Retired individuals at age $a \geq a_R$ solve the following problem:

$$V_a(\mathbf{s}_a) = \max_{A_{a+1}} \left\{ (1-\beta)\, n_a \left(\frac{c_a}{n_a} \right)^{1-\sigma} + \beta \left[m_a \mathbf{E}_a \left(V_{a+1}(\mathbf{s}_{a+1})^{1-\gamma} \right) \right]^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}}$$

subject to: (12), (14), and $c_a + A_{a+1} = \overline{y}_R(A_{ia}) + A_a + i_a - \tau(0, i_a, t)$

constraint: $A_{a+1} \geq \underline{A}_{a+1}$

boundary condition: $V_{a_T}(\mathbf{s}) = (1-\beta)^{\frac{1}{1-\sigma}} c_{a_T} \ \forall \mathbf{s}$

The model is solved using numerical discrete-time dynamic programming. The code to solve and simulate the model is compiled in Intel Fortran 2023 and executed in parallel using both MPI and OpenMP across 1,536 CPU threads; see Appendix D.1 for additional details.

4.2 Estimation

4.2.1 Calibrated Parameters

Table 2 shows the values of parameters that I calibrate directly using observed data, formulas from the Australian tax and transfer system, or prior literature. I provide a brief description of this calibration; see Appendix D.2 for additional details.

Demographics. Individuals are born at age 22 (the typical age at which students graduate from university in Australia), retire at age 65 (the age at which the Australian retirement pension began to be paid in 2004), and die with certainty after age 89. Prior to age 89, mortality risk is calibrated using Australia's life tables. Cohort-specific birth rates are calibrated to match the fraction of 22-year-olds in each year in *ALife*. I use data on household sizes from HILDA to compute equivalence scales using the same procedure in Lusardi et al. (2017).

Interest rates and borrowing. There is no inflation in the model, and the numeraire is equal to $1 AUD in 2005. When compared with the model, all empirical values are deflated to 2005 AUD using the HELP threshold indexation rate. The real interest rate is set to 1.84%, the (geometric) average deposit rate between 1991 and 2019 in Australia. The unsecured borrowing rate is set based on average credit card borrowing rates and age-specific borrowing limits are set based on credit card limits in HILDA. The real interest rate on student debt is set to zero, as in HELP.

Initial conditions. The distribution of initial assets is calibrated to match the liquid wealth distribution of individuals between ages 18 and 22. The fraction of borrowers, p_E, is equal to the fraction of 22-year-old individuals in *ALife* with positive debt. The distribution of initial debt is set based on the distribution among borrowers younger than age 26 in *ALife*, the age by which most individuals have finished their undergraduate studies and debt balances peak in real terms.

Government taxes and transfers. Income and capital taxes are set to match the individual income tax schedules provided by the ATO in 2004 and 2005. Unemployment benefits are means-tested and calculated based on the Newstart Allowance, the primary form of government-provided income support in Australia for individuals above 22. The retirement pension is calculated following the Age Pension formula, the primary government-provided form of income-support for retirees in Australia. The age pension is available at age 65 and is means-tested based on assets and income.

Preference parameters. The preference parameters that I do not estimate due of a lack of identifying variation are relative risk aversion (RRA) and the elasticity of intertemporal substitution (EIS). I set $\gamma = \sigma = 2.23$ based on Choukhmane and de Silva (2023), which corresponds to time-separable preferences with a relative risk aversion of 2.23 and an EIS of $2.23^{-1} = 0.45$. In counterfactuals, I consider the effects of changing γ and σ independently, which introduces a preference for timing of the resolution of uncertainty.

Table 2. Values of Calibrated Model Parameters

Description	Parameter(s)	Values/Targets
Demographics		
Ages	$\{a_0, a_R, a_T\}$	$\{22, 65, 89\}$
Mortality rates	$\{m_a\}$	APA Life Tables
First and last cohorts	$\underline{h}$, $\overline{h}$	1963, 2019
Cohort birth probabilities	$\{\mu_h\}$	*ALife*
Equivalence scale	$\{n_a\}$	HILDA Household Size
Number of distinct individuals	N	1,600,000
Year of simulated policy change	T^*	2005
Assets		
Real interest rate	$R-1$	1.84%
Unsecured borrowing wedge and limit	τ_b, $\{\underline{A}_a\}$	14.6%, HILDA Credit Card Limit
Probabilities of zero initial assets	$p_A(1)$, $p_A(0)$	0.197, 0.350
Distribution for $\log A_{ia_0}$	$\mu_A(1)$, $\mu_A(0)$,	7.42, 6.79
	$\sigma_A(1)$, $\sigma_A(0)$	1.72, 2.64
Student Debt		
Fraction of borrowers	p_E	0.308
Real interest rate on debt balances	r_d	0%
Distribution for $\log D_{ia_0}$	μ_d, σ_d	9.40, 0.86
Debt repayment function	$d(\cdot)$	HELP 2004 at $t < T^*$, HELP 2005 at $t \geq T^*$
Government		
Income and capital taxes	$\tau(\cdot)$	ATO Income Tax Formulas
Unemployment benefits	$ui(\cdot)$	ATO Newstart Allowance
Retirement pension	$\overline{y}_R(\cdot)$	ATO Age Pension
Net consumption floor	$\underline{c}$	\$40
Preference Parameters		
Relative risk aversion	γ	2.23
Elasticity of intertemporal substitution	σ^{-1}	0.45
Learning-by-doing parameter	α	0, 0.24

Notes: This table shows the parameters that are calibrated in a first-stage. See Appendix D.2 for additional details.

Learning-by-doing. The data also do not provide sufficient variation to identify the learning-by-doing parameter, α. This is because learning-by-doing has a minimal effect on borrowers' incentives to bunch below the repayment threshold due to the envelope theorem. I thus consider two different values of $\alpha \in \{0, 0.24\}$, where the latter corresponds to the median value from the meta-analysis conducted by Best and Kleven (2012). I consider $\alpha = 0$ as the baseline model and compare the main results between these two models.

4.2.2 Simulated Minimum Distance Estimation

I estimate the remaining 14 parameters that cannot be calibrated directly, which I denote by Θ, using simulated minimum distance:

$$\Theta = \Bigg(\underbrace{\phi \quad f \quad \lambda \quad \kappa \quad \beta}_{\text{preference parameters}} \quad \underbrace{\delta_0 \quad \delta_1 \quad \delta_2 \quad \delta_0^E \quad \delta_1^E}_{\text{wage profile parameters}} \quad \underbrace{\rho \quad \sigma_\nu \quad \sigma_\epsilon \quad \sigma_i}_{\text{wage risk parameters}} \Bigg).$$

These parameters can be divided into three groups: preference parameters; parameters governing the age profile of wages, g_{ia}; parameters governing shocks to the wage process. In contrast to the standard approach in estimating life cycle models (e.g., Gourinchas and Parker 2002), I cannot estimate the latter two sets of parameters separately in a first stage because the income process is endogenous. I thus proceed by combining a standard set of estimation targets used to identify the latter two sets of parameters in models with exogenous income processes with the quasi-experimental variation from the policy change to the HELP repayment function.

Simulated policy change. I replicate the policy change shown in Figure 2 within the model by solving the model for two different specifications of the student debt repayment function, $d(\cdot)$: (i) the HELP 2004 repayment schedule and (ii) the HELP 2005 repayment schedule. Starting at $t = \underline{h} = 1963$, I simulate cohorts of individuals making choices under the 2004 schedule. At $t = T^* = 2005$, I then conduct a one-time unanticipated policy change in which all existing debtholders born at $t < T^*$ and subsequent debtholders start repaying under the 2005 schedule.

Estimator. I estimate Θ using simulated minimum distance, which consists of choosing a set of estimation targets and a weighting matrix. Denote the empirical values of the estimation targets as $\hat{m}$, the vector of the estimation targets estimated in the model via simulation as $m(\Theta)$, and the weighting matrix as $W(\Theta)$. The estimate of Θ is then defined as Θ^*, where

$$\Theta^* = \arg\min_{\Theta} \left(\hat{m} - m(\Theta)\right)' W(\Theta) \left(\hat{m} - m(\Theta)\right).$$

I choose $W(\Theta)$ so that this objective function equals the sum of squared arc-sin deviations between $\hat{m}$ and $m(\Theta)$. The 47 estimation targets are listed in Appendix D.3 and discussed below.

4.2.3 Choice of Estimation Targets and Parameter Identification

This section discusses the identification of parameters in the simulated minimum distance estimation. All parameters are jointly identified, but I choose the set of estimation targets so that each one is most sensitive to a subset of parameters. The discussion in this section is qualitative; Table A5 provides elasticities of estimation targets with respect to parameters as supporting evidence.

Labor supply elasticity, ϕ. The labor supply elasticity is identified by the extent of bunching in the HELP income distribution below the repayment thresholds both before and after the policy change: a larger elasticity implies greater mass below these thresholds. To characterize this bunching, I use the real distributions of HELP income among debtholders three years before and three years after the policy change. I focus on the distribution within $3,000 of the repayment thresholds so that these targets are primarily affected by the labor supply elasticity rather than wage profile parameters and use bins of $500 to minimize simulation error.

Fixed cost, f, and Calvo probability, λ. These optimization frictions are jointly identified by the mass above the repayment threshold: even with a very small labor supply elasticity, a model $f = 0$ and $\lambda = 1$ predicts that no borrowers locate immediately above the repayment threshold because locating below it increases cash on hand. To separately identify these two parameters, I exploit the fact that adjustment costs imply *state*-dependent labor supply responses. In particular, adjustment costs predict disproportionately more bunching at the 2005 repayment threshold than at the lowest 2005 0.5% threshold because the former has a discontinuity in the repayment rate of 4% rather than 0.5%. Additionally, adjustment costs generate larger bunching among borrowers with more debt, for whom the present discount value of reducing labor supply is larger. In contrast, a model with pure Calvo adjustment implies less heterogeneity in bunching with debt because adjustment primarily depends on whether borrowers receive the exogenous Calvo shock.

To target heterogeneity across thresholds with different repayment rates, I compute the ratio of borrowers below to above the 2004 threshold prior to the policy change, the 2005 threshold after the policy change, and the lowest 2005 0.5% threshold after the policy change (see Figure A19 for a comparison of the latter two). I then compute the same ratio at the 2005 threshold after the policy change among borrowers in the bottom and top quartiles of debt balances (within each year) to capture heterogeneity in bunching with debt balances.

Scaling parameter, κ. This parameter is identified by the average value of l_{ia}, which I normalize to one. A higher value increases the disutility of labor supply and thus lowers average values of l_{ia}.

Time discount factor, β. The time discount factor is identified by the average level of capital income. A higher value makes individuals more patient, increasing saving and hence capital income. I target capital income between ages 40 and 44, the midpoint of individuals' working lives.

Wage profile parameters, δ_0, δ_1, δ_2, δ_0^E, and δ_1^E. These parameters are primarily identified by the regressions of log income onto polynomials in age and an education-level indicator, in addition to average income. If labor supply were exogenous, they could be estimated separately with these estimation targets alone. However, with endogenous labor supply, these parameters control the *wage* rather than the income process and must be estimated jointly because the former is not observable.

Wage risk parameters, ρ, σ_ν, σ_ϵ, and σ_i. These parameters are identified by how the cross-

sectional variance of log income varies with age and the percentiles of income growth at one-year and five-year horizons. This set of moments is standard in the literature used to estimate exogenous income processes (e.g., Guvenen et al. 2022), and the identification is similar here even though the income process is endogenous. The cross-sectional variance at age 22 identifies σ_i, the variance of the initial permanent income. The extent to which the cross-sectional variance increases with age identifies the persistence of income shocks, ρ: more persistent shocks generate a greater increase in variance over the life cycle (Deaton and Paxson 1994). The sum of the variances of permanent and transitory income shocks, σ_ν and σ_ϵ, are identified by the level of this cross-sectional variance at later ages. These two variances are then separated using the percentiles of income growth: a larger variance of permanent shocks, σ_ν, delivers fatter tails in 5-year than in 1-year income growth.

4.3 Baseline Estimation Results and Model Fit

The results for the baseline model are reported in column (1) of Table 3. The estimate of the (Frisch) labor supply elasticity is 0.114. Appendix A shows this estimate is close to the median value of 0.14 for Frisch and Hicksian intensive margin elasticities reported in Keane (2011) and Chetty (2012), and discusses in detail how my results compares to the extensive existing literature on labor supply.[22] I estimate a fixed cost of \$377, approximately 1% of average income, and a Calvo probability of 0.183. This value of the Calvo probability implies that, in expectation, individuals receive an opportunity to adjust their labor supply every 5.4 years.

The baseline model provides a close fit to the bunching used to identify the key labor supply parameters. Figure 9 shows the model fits the distribution of HELP income before and after the policy change, especially the mass of borrowers immediately below and above the repayment threshold. There are slight differences at other points because the model cannot perfectly match the age profile of income. Figure 10 shows the fit on the bunching at other repayment thresholds, in addition to among borrowers with different debt balances. Consistent with Figure 9, the model replicates the bunching at the 2004 and 2005 repayment thresholds well. However, the model can also replicate the relatively small amount of bunching at the lowest 0.5% repayment threshold after the policy change. The presence of a fixed cost is crucial for this result: in a model with only Calvo adjustment, there is less of a difference in bunching at this threshold and the 0% threshold because the probability that borrowers receive the Calvo shock is independent of their level of income. Similarly, the presence of a fixed cost helps match the heterogeneity in bunching with debt balances. Quantitatively, the model misses on matching the bunching at the 0.5% threshold because doing so worsens the fit on other targets: increasing the fixed cost would improve the fit at the 0.5% threshold but would also decrease the amount of bunching among borrowers with low debt balances, which the model already underestimates.

[22] Because I identify ϕ using bunching in HELP income, it can also be interpreted as a reported income elasticity that aggregates both hours and non-hours responses (Feldstein 1999). Therefore, Appendix A compares my estimate of ϕ to existing estimates of both hours and taxable income elasticities.

Table 3. Simulated Minimum Distance Estimation Results

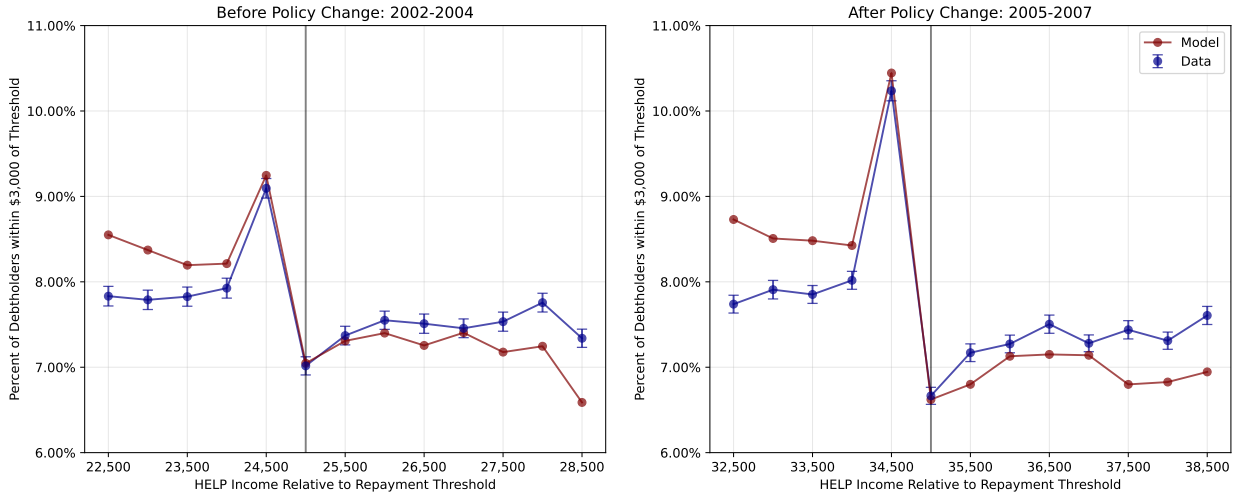
		Estimation						
Parameter		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Labor supply elasticity	ϕ	0.114	0.005	0.188	0.053	0.082	0.111	0.067
		(.004)	(.000)	(.003)	(.002)	(.002)	(.004)	(.002)
Adjustment cost	f	\$377	\$0	\$2278	\$0	\$762	\$513	\$848
		(\$13)	·	(\$21)	·	(\$10)	(\$19)	(\$11)
Calvo probability	λ	0.183	1	1	0.147	0.346	0.191	0.266
		(.003)	·	·	(.002)	(.009)	(.003)	(.005)
Scaling parameter	κ	0.560	0.030	0.059	0.510	1.242	0.593	0.448
		(.007)	(.003)	(.014)	(.012)	(.116)	(.001)	(.001)
Time discount factor	β	0.973	0.996	0.972	0.944	0.951	0.951	0.946
		(.001)	(.000)	(.001)	(.001)	(.001)	(.001)	(.001)
Wage profile parameters	δ_0	8.922	9.862	8.680	9.389	9.197	9.143	9.211
		(.009)	(.002)	(.006)	(.007)	(.007)	(.008)	(.008)
	δ_1	0.073	0.111	0.073	0.063	0.070	0.075	0.074
		(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
	δ_2	−0.001	−0.002	−0.001	−0.001	−0.001	−0.001	−0.001
		(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
	δ_0^E	−0.487	−0.294	−0.450	−0.530	−0.480	−0.478	−0.505
		(.002)	(.000)	(.001)	(.002)	(.002)	(.002)	(.002)
	δ_1^E	0.020	0.032	0.018	0.021	0.018	0.020	0.021
		(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Persistence of permanent shock	ρ	0.930	0.914	0.943	0.922	0.889	0.907	0.931
		(.000)	(.000)	(.000)	(.000)	(.000)	(.001)	(.001)
Standard deviation of permanent shock	σ_ν	0.236	0.076	0.196	0.268	0.288	0.275	0.246
		(.000)	(.000)	(.000)	(.000)	(.000)	(.001)	(.001)
Standard deviation of transitory shock	σ_ϵ	0.130	0.504	0.168	0.077	0.064	0.080	0.116
		(.000)	(.000)	(.000)	(.002)	(.002)	(.002)	(.001)
Standard deviation of individual FE	σ_i	0.599	0.101	0.541	0.654	0.625	0.612	0.632
		(.003)	(.001)	(.003)	(.003)	(.003)	(.003)	(.003)
Learning-by-doing parameter	α	0	0	0	0	0.24	0	0
Adjustment cost function		Fixed	Fixed	Fixed	Fixed	Fixed	Linear	Fixed
Misperception of debt payoff		No	No	No	No	No	No	Yes

Notes: This table shows the results from simulated minimum distance estimations. Each column corresponds to a separate estimation. Entries in the table are to parameter estimates with standard errors below in parentheses. All estimations use the same set of estimation targets described in Appendix D.3. Parameters that are fixed and not estimated are indicated with "·" in place of a standard error. Column (1) is the baseline estimation; column (2) estimates a model with no optimization frictions; column (3) estimates a model with only a fixed cost and no Calvo adjustment; column (4) does the reverse; column (5) estimates the same model as that in the column (1), except with the learning-by-doing parameter calibrated based on Best and Kleven (2012); column (6) estimates an alternative model to that in column (1) in which the adjustment cost function is $f * |\ell_a - \ell_{a-1}|$ (i.e., a linear cost) instead of $f * \mathbf{1}_{\ell_a \neq \ell_{a-1}}$ (i.e., a fixed cost); column (7) estimates an alternative model in which borrowers misperceive that their debt will never be paid off.

Table 4 shows the model provides a good fit to the remaining estimation targets, which are used to estimate the remaining parameters aside from the labor supply elasticity, fixed cost, and Calvo probability.[23] The model can replicate the average and the age profiles of labor income, which are most affected by the wage profile parameters. The fit is not perfect because income in the model is endogenous: if the age profile of labor supply varies over the life cycle for reasons outside the model, it will be unable to match these income profiles. The cross-sectional variance of income

[23] Appendix A discusses how my estimates of income risk parameters relate to existing literature that uses administrative data to estimate parametric models of income risk (Guvenen et al. 2021; Catherine 2022).

Figure 9. Baseline Model Fit: HELP Income Distribution around the Policy Change



Notes: The left panel of this figure plots the HELP income distribution within $3,000 of the repayment threshold in bins of $500 for the period before the policy change from 2002 to 2004 in the data in blue. Bars represent 95% confidence intervals based on bootstrapped standard errors with 1000 iterations. The red line plots the same quantities from the model with parameters set at the estimated values in column (1) of Table 3. The right panel replicates the left panel for the period after the policy change between 2005 and 2007. The vertical gray line in each plot indicates the repayment threshold, which is the point at which repayment begins.

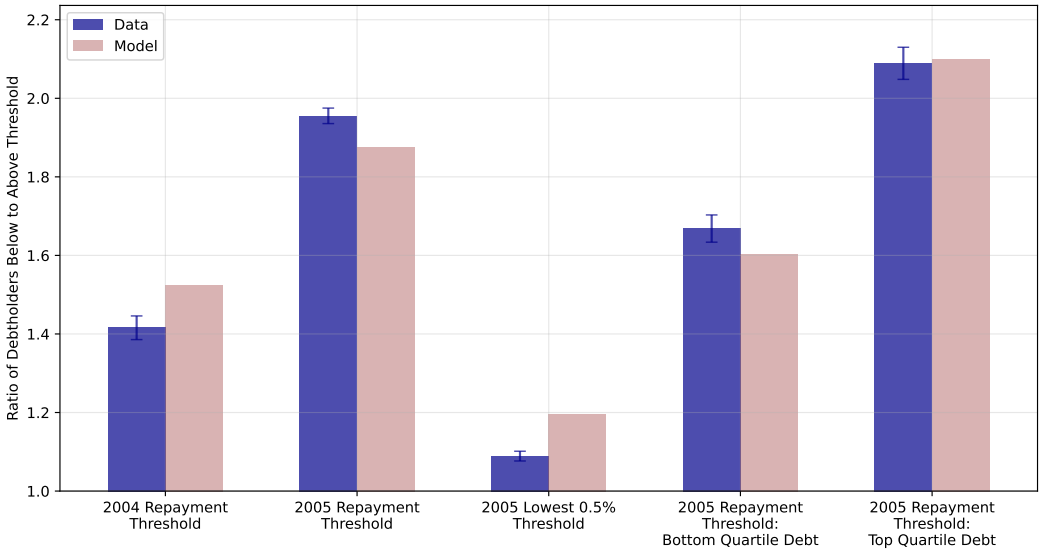
increases over the life cycle, and the model can replicate this pattern due to the high persistence of permanent shocks, $\rho = 0.93$. Guvenen (2009a) points out that such an estimate is upward-biased in models without heterogeneous income profiles. The model features profile heterogeneity across the two education groups, which brings the estimate of ρ down below typical unit root estimates in models with homogenous income profiles. Nevertheless, because an upward bias in ρ would overstate income risk and hence the insurance benefits from income-contingent loans, I consider alternative values of ρ in my normative analysis.

Finally, the model matches the level of capital income for middle-age individuals. This moment primarily identifies the annual discount factor, β, estimated at 0.973, similar to estimates in models that target consumption data (e.g., Gourinchas and Parker 2002). This estimate is also less than R^{-1}: individuals face a trade-off between wanting to consume at young ages due to impatience and accumulating precautionary savings, generating buffer-stock behavior (Carroll and Kimball 1996).

4.4 Identification of Labor Supply Elasticity and Optimization Frictions

The three most important parameters in the model—the labor supply elasticity, Calvo probability, and fixed cost—are well-identified by the estimation targets discussed in Section 4.2.3. Figure A20 plots the simulated minimum distance objective function across these parameters, which exhibits a clear (local) minimum. Additionally, this objective function is very smooth, lending confidence to the numerical solution technique. A large number of simulations and the fact that no choice variables are discretized in the solution are both critical for generating this smoothness.

Figure 10. Baseline Model Fit: Bunching around Thresholds



Notes: The blue bars in this figure show the ratio of the number of debtholders with \$250 below to \$250 above different thresholds, along with 95% confidence intervals based on bootstrapped standard errors with 1000 iterations. The red bars plot the same quantities from the model with parameters set at the estimated values in column (1) of Table 3. Column (1) is the 2004 repayment threshold between 1998 and 2004; column (2) is the 2005 repayment threshold between 2005 and 2018; column (3) is the lowest 2005 0.5% repayment threshold between 2005 and 2018; columns (4) and (5) plot the same quantity in column (2), splitting individual–year observations by whether they fall within the bottom or top quartile of debt balances in 2005 AUD.

To illustrate the importance of each optimization friction, I estimate three additional models. Column (2) of Table 3 and Figure A21 show the estimation results and fit of a model with no frictions (i.e., $f = 0$ and $\lambda = 1$). This estimation delivers an unreasonably low estimate of the labor supply elasticity, $\phi = 0.005$, and cannot fit most of the estimation targets in the data. Column (3) and Figure A22 show the results for a model with only a fixed cost (i.e., $\lambda = 1$). This delivers a more reasonable estimate of the labor supply elasticity, but the estimated model overpredicts the amount of bunching after the policy change. This is because the fixed cost that rationalizes the amount of bunching at other thresholds is too small to prevent more borrowers from bunching at the 2005 threshold, which has the largest change in repayment rate.

Finally, column (4) and Figure A23 show the results from a model with no fixed cost (i.e., $f = 0$). These estimation results are the closest of the three additional models to the baseline model in column (1), but the model struggles to match two key features of the data. First, the model generates too much bunching at the 0.5% threshold, which pushes the estimation to a lower value of ϕ. The intuition is that, without a fixed cost, labor supply adjustment depends on whether a borrower receives the Calvo shock, which is equally likely around all repayment thresholds. The fixed cost in column (1) helps reduce the amount of bunching at the 0.5% threshold because the cost outweighs the benefit for many borrowers, while being too small to affect the bunching at other thresholds where the benefit is larger. To compensate for the lower ϕ, which in turn predicts too little bunching at other thresholds, the estimation delivers a lower β to increase the amount of bunching. However,

Table 4. Baseline Model Fit: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	\$42,639	\$45,582
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.462
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.491
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.525
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.580
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.657
Linear Age Profile Term	0.077	0.080
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.554
Education Income Premium Slope	0.023	0.023
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.392
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.705
90th Percentile of 1-Year Labor Income Growth	0.415	0.393
90th Percentile of 5-Year Labor Income Growth	0.698	0.710
Average Labor Supply	1.000	0.963
Average Capital Income between Ages 40 and 44	\$1,338	\$1,332

Notes: This table shows the value of the remaining estimation targets not shown in Figure 9 and Figure 10 in the data and the model with parameters set at the estimated values in column (1) of Table 3.

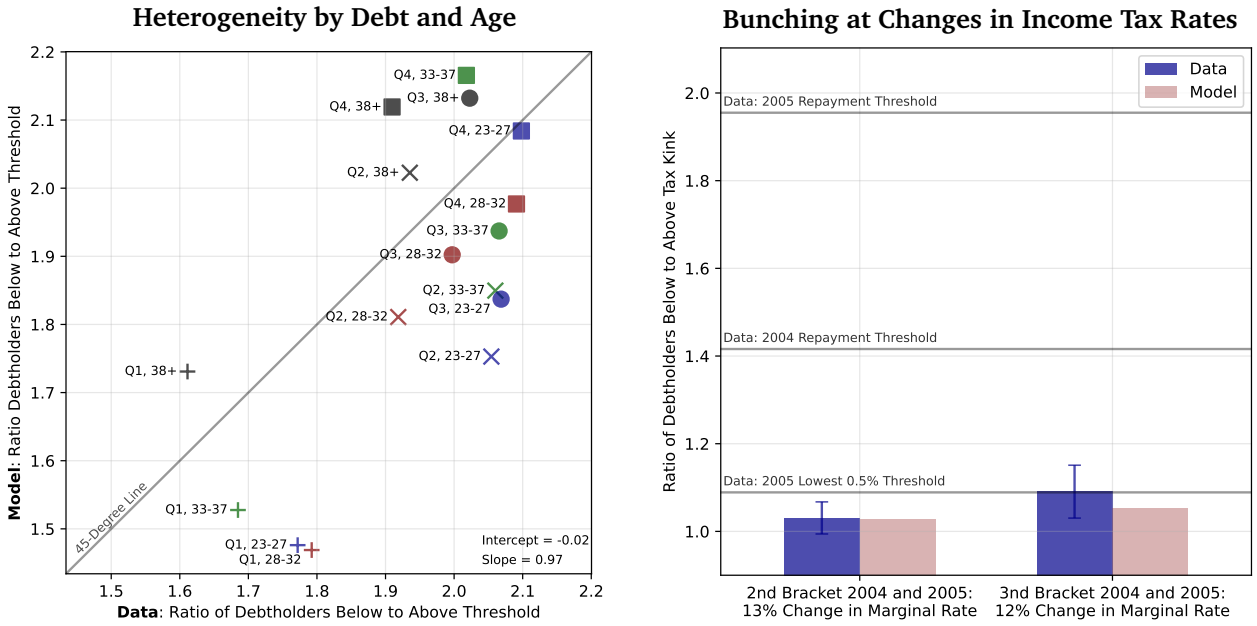
the lower discount factor causes the model to underestimate wealth accumulation.

4.5 Estimation Results from Alternative Models

Adding learning-by-doing. Column (5) of Table 3 and Figure A24 show the results from estimating a model with the learning-by-doing parameter, α, set equal to the median value from the meta-analysis in Best and Kleven (2012). This model fits the data worse than the baseline model, in particular on the heterogeneity in bunching by debt balances and the average levels of labor and capital income. The estimation of this model delivers a relatively similar labor supply elasticity but a higher estimate of the fixed cost and Calvo probability. This is because learning-by-doing makes bunching more costly for younger rather than older borrowers: the reduction in human capital is less important for older borrowers who have fewer periods to benefit from it. Since debt balances are negatively correlated with age, this model predicts too little heterogeneity in bunching with debt balances at the values of f and λ in column (1). Therefore, the estimation increases f and decreases λ to increase heterogeneity in bunching with debt balances.

Alternative adjustment cost specification. Column (6) of Table 3 and Figure A25 show the results from estimating a model with a linear adjustment cost, $f * |\ell_a - \ell_{a-1}|$, instead of a fixed cost, $f * \mathbf{1}_{\ell_a \neq \ell_{a-1}}$. The estimated labor supply elasticity is almost identical to that under the baseline model and that the fit of the model is mostly unchanged. This suggests that the parameter estimates are likely robust to misspecification of the exact type of optimization frictions.

Figure 11. Fit of Model on Nontargeted Bunching Statistics



Notes: The left panel of this figure shows a scatterplot of bunching below the 2005 repayment threshold for different samples in the data versus the model. Each point corresponds to a different sample based on quartiles of debt and age labeled in the plot. The quartiles of debt are calculated in the data after taking out year fixed effects and adjusting for inflation. These same quartiles are used in the model. Each age group is plotted in a different color, and each quartile of debt has a differently shaped marker on the plot. For each sample, bunching is measured as in Figure 10. The right panel shows the bunching statistics in Figure 10 computed around two points with changes in marginal income tax rates in 2004 and 2005 using taxable income instead of HELP income in the data (there is no difference in the model). Tax brackets are fixed in nominal terms, so when pooling 2004 and 2005, I adjust the thresholds and income using the HELP threshold indexation rate. Data values are presented in blue with 95% confidence intervals based on bootstrapped standard errors with 1000 iterations. Model values are presented in red. The sample is the *ALife* sample defined in Section 2.4 between 2005 and 2018, restricted to debtholders between 23 and 64. I impose the same sample filters in the model.

4.6 Model Validation on Nontargeted Bunching

Before using the estimated model to perform counterfactual analyses, I show that it can fit two sets of nontargeted bunching statistics. The first set is heterogeneity in bunching by debt balances and age around the 2005 repayment threshold. The left panel of Figure 11 shows a scatterplot of the bunching for different groups based on age and debt in the data versus the model. Many of the points lie close to the 45-degree line, and the estimate slope coefficient is 0.97, indicating that the model does a good job at replicating this heterogeneity. The largest discrepancy between the model and data is for young borrowers with low debt balances, for whom the model generates insufficient bunching. In contrast, Figure A27 shows the model with learning-by-doing fits much worse.

The estimated model can also replicate labor supply responses to income taxes. Figure 11 shows the bunching in the taxable income distribution around the two discontinuities in the marginal tax rates closest to the HELP repayment thresholds. The bunching around these tax "kinks" is much smaller than around the repayment thresholds but similar to the amount at the lowest 0.5% threshold. This is because these thresholds induce a change in marginal rather than average rates. The model replicates this relatively small amount of bunching at these thresholds well.

5 Three Determinants of Bunching Below the Repayment Threshold

As discussed in Section 2.2, the present value of bunching below the repayment threshold can be much different than the change in current repayments. To illustrate, assume that borrowers value repayments in two periods and discount cash flows in the second period with (net) interest rate r. Letting p denote the probability of repayment in the second period, the net present value (NPV) of locating below the repayment threshold after the policy change is

$$\underbrace{\$1400 \times \frac{r + (1-p)}{1+r}}_{\text{NPV gain from bunching}} \leq \underbrace{\$1400,}_{\text{liquidity gain from bunching}} \tag{15}$$

which is (weakly) smaller than the increase in liquidity.[24]

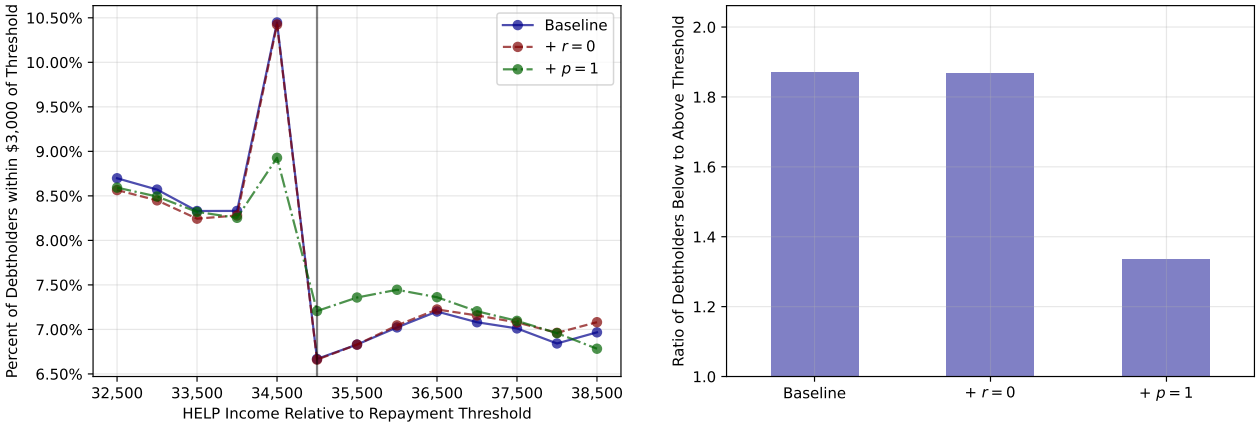
Motivated by (15), Figure 12 uses the estimated model to decompose the bunching below the 2005 repayment threshold into three distinct effects. The first effect is the bunching that arises from the difference between borrowers' discount rate and the debt interest rate (i.e., $r \neq 0$), which increases the NPV of bunching below the repayment threshold. Figure 12 shows that this has a negligible effect on the bunching below the repayment threshold. The second effect is that, even when $r = 0$, bunching below the repayment threshold has a positive NPV if borrowers do not anticipate repaying their debt (i.e., $p < 1$). The results in Figure 12 show that this channel accounts for the majority of the bunching: in a counterfactual where $p = 1$, bunching below the repayment threshold decreases by 61%. This model-based inference is consistent with the empirical evidence in Section 3 that the amount of bunching is larger among borrowers with a lower probability of repayment.

The remaining 39% of the bunching that remains even when $r = 0$ and $p = 1$ in Figure 12 reveals that a third effect is a quantitatively important driver of bunching below the repayment threshold: a demand for liquidity. When $r = 0$ and $p = 1$, the NPV of locating below the repayment threshold is zero. Nevertheless, locating below the repayment threshold still increases borrowers' current liquidity, which they may value if they are liquidity-constrained. This importance of liquidity is empirically supported by evidence in Section 3 that the amount of bunching increases with proxies for liquidity constraints. Additionally, it complements existing evidence that a demand for liquidity created by incomplete markets amplifies the moral hazard created by other forms of social insurance (Chetty 2008; Ganong and Noel 2023; Indarte 2023).

The large reduction in bunching from setting $p = 1$ illustrates an important way in which the incentives created by income-contingent repayment differ from those of an income tax. Because most borrowers anticipate repaying their debt with some probability, the labor supply response created by an income-contingent loan is larger than that of a tax for a given repayment function.

[24] Deriving this expression requires making two additional assumptions: (i) the probability of repayment in the second period, p, is independent of bunching in the first period; (ii) the interest rate on outstanding debt is zero.

Figure 12. Decomposition of Bunching Below the Repayment Threshold



Notes: The left panel of this figure plots the income distribution in bins of $500 around the 2005 repayment threshold between 2005 and 2018 in three different models, and the right panel plots the measure of bunching from Figure 10. The first model, Baseline, corresponds to the baseline model estimated in column (1) of Table 3 after the calibrated value of R in Table 2 is replaced with β^{-1}. The second model, $+r = 0$, corresponds to additionally setting $r_d = \beta^{-1} - 1$ in the first model. The third model, $+p = 1$, corresponds to taking the second model and setting $D_0 = 4\% * \$35000 = \$1400$ for all borrowers. Then, for each year in which borrowers have debt in the second model, borrowers' debt balances in the third model are unanticipatedly reset to $1400, regardless of whether they paid it off in the prior period. The purpose of this third model is to make borrowers anticipate repayment with probability one, while ensuring the set of borrowers who have positive debt balances in each year are the same as in the second model.

Another way of quantifying the importance of these dynamics is in column (7) of Table 3, which shows the estimation results from a model in which borrowers misperceive that their debt will never be paid off. Ignoring these dynamics leads to a 41% reduction in the estimated labor supply elasticity.

6 Welfare and Fiscal Impacts of Income-Contingent Loans

This section uses the estimated model to study the welfare and fiscal impacts of moving from fixed repayment contracts to income-contingent loans. In this analysis, I take the perspective of a social planner that seeks to maximize borrower welfare by choosing one mandatory repayment contract, taking borrowing choices and prices (i.e., wages and interest rates) as given. This problem of choosing a single contract is faced by governments that offer only one contract, as in Australia and the UK. In the baseline analysis, I focus on subsidized contracts with a zero interest rate, like those available in Australia.[25]

My analysis proceeds in two steps. First, I compare existing income-contingent loans with fixed repayment contracts, which is not a budget-neutral comparison. Second, I construct constrained-optimal income-contingent contracts that have the same fiscal cost as fixed repayment contracts.

[25]Under the new income-driven repayment plan in the US, known as SAVE, loan balances do not grow for borrowers who make their required monthly payments. Therefore, the interest rate is effectively zero for many borrowers.

6.1 Existing Income-Contingent Loans Improve Welfare at Higher Fiscal Cost

I begin by computing the welfare and fiscal impacts of moving to the income-contingent contracts used in Australia and the US from a 25-year fixed repayment contract without any forbearance (i.e., payment pauses for low-income borrowers). This fixed repayment contract is a debt contract in which borrowers make constant repayments for 25 years after graduation to repay their loan principal. I choose this as the benchmark because it is available in the US and has a similar duration to existing income-contingent contracts but is not income contingent. I implement it without forbearance to create a realistic fiscal cost and consider the effects of forbearance in Section 7.2.

Definition of government budget. I define the government budget, $\mathcal{G}$, as the expected discounted value of debt repayments and taxes net of transfers and debt issuance over borrowers' lifetimes,

$$\mathcal{G} \equiv \mathbf{E}_0 \left(\sum_{a=a_0}^{a_T} \underbrace{\frac{\tau_{ia} - ui_{ia} - \underline{c}_{ia}}{\mathcal{R}_a}}_{\text{taxes and transfers}} + \underbrace{\frac{d_{ia}}{\mathcal{R}_a} - D_{ia_0}}_{\text{debt repayments}} \right), \tag{16}$$

where $\mathbf{E}_0(\cdot)$ denotes an expectation taken over all states, including the initial state.[26] $\mathcal{R}_a$ denotes the government discount rate of payments made at age a relative to a_0, which is defined as

$$\mathcal{R}_a^{-1} = \beta^{a-a_0} \prod_{s=0}^{a-a_0} m_s. \tag{17}$$

I set $\mathcal{R}_a$ equal to individuals' time preference rate between a_0 and a, including discounting due to time preferences and mortality risk, for two reasons. First, a choice of $\mathcal{R}_a$ different from individuals' time preference rate allows the government to increase welfare simply by shifting deterministic payments over time (to take advantage of differences in discount rates). Because my analysis focuses on comparing repayment contracts, I want to abstract from this motive, which could be accomplished with other tools (e.g., taxation). Second, given $\beta < R^{-1}$, this discount rate is higher than the risk-free rate, consistent with the fact that student loan repayments likely have some correlation with aggregate shocks. In the baseline model, the average value of $\mathcal{R}_a$ for $a \in (a_0, a_R)$ is 1.03. In Section 8.4, I consider the effects of alternative discount rates.

The comparison of different repayment contracts is contingent on the tax and transfer system, which redistributes within and across individuals. For this normative analysis, I adopt the parametric

[26] I define the government budget in present-value terms rather than at the model's stationary distribution because the interpretation of the former is more intuitive, corresponding to the valuation implied by the first-order condition of a hypothetical lender with discount rate, $\mathcal{R}_a$. Additionally, this definition is preferable when I consider budget-neutral repayment policies in subsequent analyses because it ensures a reasonable path for budget deficits in the transition between two policies without the difficulties associated with fully characterizing transition dynamics. In particular, this definition ensures that, if the government were to immediately start giving loans to people graduating from college under two policies with equal values of $\mathcal{G}$, there would be no change in expected costs for this group of individuals.

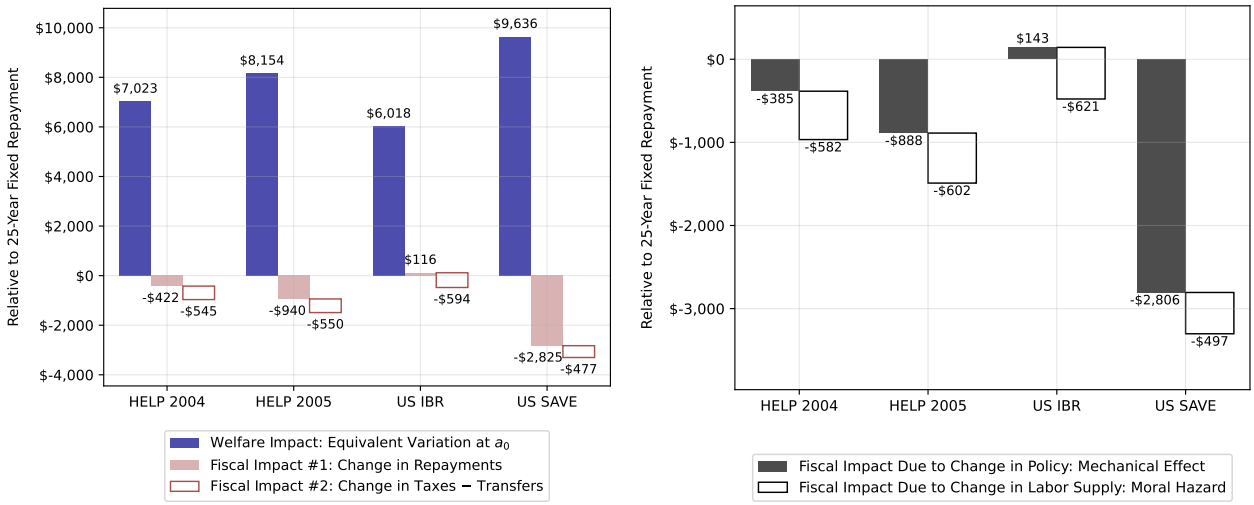
income tax specification from Heathcote et al. (2017) calibrated to match the ATO tax schedule and a smoothed specification of unemployment benefits; see Appendix D.2 for additional details.

Results. The left panel of Figure 13 shows the effects of moving from fixed repayment to various income-contingent loans. To measure the welfare impact in dollars, I compute the equivalent variation at $a = a_0$, which answers the following question: what value of a cash transfer at age a_0 would make a borrower, prior to knowing her initial states, indifferent between repaying under the given contract and 25-year fixed repayment? This panel also breaks the fiscal impact into the present value of the change in repayments and the change in other component $\mathcal{G}$, taxes net of transfers.

The first two columns show that both HELP contracts—those used before and those used after the policy change—improve welfare by the equivalent of an approximately $7,500 cash transfer, which is 43% of the average initial debt in the model. These gains, however, come at a fiscal cost: in present value terms, the government collects approximately $750 less in student loan repayments and $550 less in taxes net of transfers. The following two columns show the results for the income-based repayment (IBR) contract currently used in the US and the new IBR contract introduced by the Biden administration (known as SAVE), in both of which borrowers repay a fixed fraction of income above a certain threshold. These two US contracts deliver gains similar to those under HELP but differ in fiscal cost. The IBR program has a fiscal cost that is approximately 60% lower than that of HELP because repayments start at a lower value of income. In contrast, SAVE has a fiscal cost that is three times as large, reflecting its higher repayment threshold and lower repayment rate. Dividing the equivalent variation by the total fiscal cost delivers a marginal value of public funds (MVPF) for each policy relative to 25-year fixed repayment (Finkelstein and Hendren 2020). This MVPF (Figure A29) is highest for IBR and is high relative to typical estimates for policies targeting adults (Hendren and Sprung-Keyser 2020).

The moral hazard created by income-contingent repayment accounts for a significant fraction of the fiscal cost associated with moving from 25-year fixed repayment to income-contingent loans. The right panel of Figure 13 decomposes this total fiscal cost, the sum of the two fiscal impacts shown in the left panel, into two components. The first, shown in gray, is the mechanical effect: the change in $\mathcal{G}$ holding fixed borrowers' labor supply decisions at their values under 25-year fixed repayment. The second component, shown in white, is the incremental change in $\mathcal{G}$ due to the endogenous adjustment of labor supply, which measures the additional cost of moral hazard created by income-contingent loans that would be zero with exogenous labor supply. Moral hazard accounts for approximately 50% of the total cost from switching for HELP contracts and 130% for IBR. For SAVE, it accounts for only 15% of the fiscal cost because the smaller 5% repayment rate generates a smaller behavioral response than the 10% rate under IBR.

Figure 13. Effects of Moving from 25-Year Fixed Repayment to Existing Income-Contingent Loans



Notes: The left panel in this figure shows the welfare and fiscal impacts of moving from 25-year fixed repayment to different existing income-contingent contracts: the HELP policies before and after the policy change, the existing US IBR program without forgiveness, and the new IBR program known as SAVE. See Appendix D.4 for the exact implementation of each contract. The first dark blue bar in each column shows the equivalent variation at a_0 for an agent with $\mathcal{E}_i = 1$ who does not know her initial states. The second dark red bar shows the change in the government budget defined in (16) that comes from changes in debt repayments; the final white bar shows the change from taxes and transfers. The right panel in this figure decomposes the total fiscal cost, which is the sum of the latter two bars, into two effects. The first is the mechanical effect: the change in fiscal cost, assuming that borrowers' labor supply remained at its value under 25-year fixed repayment. The second is the residual attributable to endogenous changes in labor supply.

6.2 Welfare Gains from Constrained-Optimal Income-Contingent Loan

Section 6.1 shows that the welfare gains from existing income-contingent loans exceed their fiscal costs. In this section, I show that income-contingent loans can improve welfare relative to fixed repayment contracts, but at the same fiscal cost.

Definition of the constrained-planner's problem. I consider a social planner that maximizes borrower welfare by choosing one mandatory repayment contract. I begin assuming that this planner is constrained á la Ramsey (1927) to choosing income-contingent loans with the same structure as the income-contingent loans used in the US and UK. These contracts have two parameters that essentially make them call options on borrowers' incomes: the threshold at which repayment begins, K, and a repayment rate of income above the threshold, ψ. Aside from tractability, this restriction of the contract space is motivated by practical constraints that make implementing Mirrlees (1974)–style optimal policies difficult (Piketty and Saez 2013).

The planner's problem is thus:

$$\max_{\{\psi, K\}} \mathbf{E}_0 \left(V_{ia_0}^{1-\gamma} \right)^{\frac{1}{1-\gamma}}, \tag{18}$$

subject to:

$$\mathbf{E}_0\left(\sum_{a=a_0}^{a_T}\frac{\tau_{ia}-ui_{ia}-\underline{c}_{ia}}{\mathcal{R}_a}+\frac{d_{ia}}{\mathcal{R}_a}-D_{ia_0}\right)\geq\overline{\mathcal{G}},$$
$$d_{ia}=\min\left\{\psi*\max\left\{y_{ia}-K,0\right\},D_{ia}\right\}*\mathbf{1}_{a\leq a_R},$$
$$\psi\in[0,1],\quad K\geq 0.$$

The planner's objective function is the Epstein–Zin certainty-equivalent of the stochastic consumption and labor supply sequences to a borrower who is "behind the veil of ignorance" with respect to her initial conditions, which depends (implicitly) on the two policy parameters. The first constraint requires that the fiscal revenue be at least $\overline{\mathcal{G}}$, which I set equal to the revenue raised from 25-year fixed repayment without forbearance (see Section 6.1). The second and third constraints in (18) capture the informational and parametric restrictions imposed by a US IBR–style income-contingent loan. Solving (18) is numerically challenging; I leverage a combination of barrier methods and a global optimizer detailed in Appendix D.6.

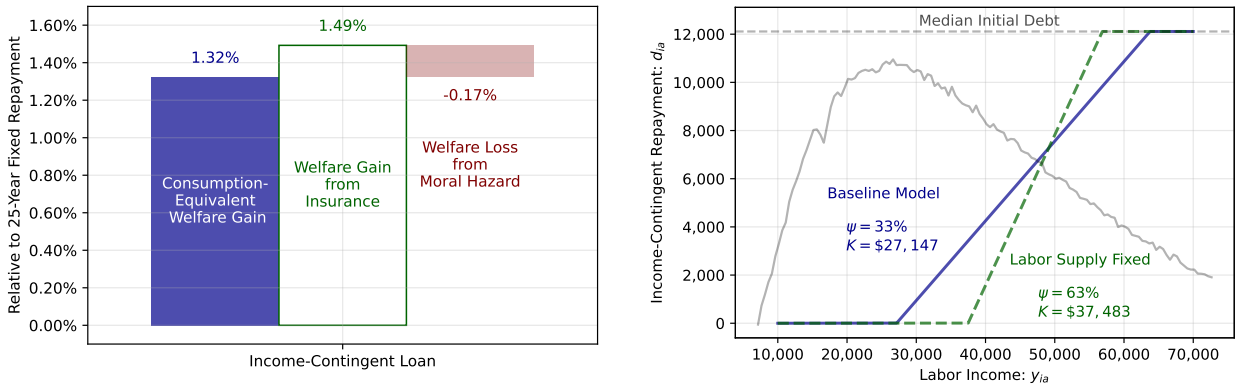
Solution to the planner's problem. The solid blue line in the right panel of Figure 14 plots repayments on the constrained-optimal income-contingent loan that solves (18) for a borrower with median initial debt. Relative to fixed repayment, this contract provides significant insurance: repayments do not start until the 26th percentile of the income distribution at K=\$27,147. In US IBR contracts, K is 1.5 times the US federal poverty line, which corresponds to 1.5∗\$12,320 = \$18,480 in 2005 AUD, or 68% of the optimal value of K.[27] To collect sufficient revenue with a relatively high threshold, the constrained-optimal contract has a repayment rate of $\psi = 33\%$, approximately three times the 10% repayment rate on IBR. In other words, it provides more insurance than IBR by reducing payments from low-income borrowers in exchange for payments from high-income borrowers. Although this repayment rate may appear high, it should not be compared to a tax rate: for high-income borrowers, the probability of repayment is almost one. Therefore, a high rate is not very distortionary because it simply transfers these repayments forward in time.

Effect of moral hazard. The constrained-optimal income-contingent loan is quite different without moral hazard. The dashed green line in Figure 14 plots the contract that solves (18) in a model where labor supply is fixed at its value under 25-year fixed repayment.[28] This contract provides even more insurance than the contract in the baseline model, with a 30 pp higher repayment rate and 40% higher threshold. This difference reflects a fiscal externality from a wedge between social and private incentives: borrowers do not internalize that locating below the threshold reduces government revenue and affects the contract that the planner offers in equilibrium. Since the planner cannot raise a sufficient amount of revenue by implementing this contract in the baseline model (because borrowers reduce their labor supply), the planner lowers the threshold to collect repayments from more borrowers and the repayment rate to induce a smaller behavioral response.

[27] As of 2023, the US federal poverty line for a single household is \$14,580 USD. Deflating this to 2005 USD with the CPI and then converting to 2005 AUD with the USD/AUD exchange rate as of June 2005 delivers \$12,320. This value of the poverty line is similar to the value reported by the Melbourne Institute in 2005 of \$11,511.

[28] In this analysis, I exclude disutility from labor supply from welfare because it is fixed.

Figure 14. Structure and Welfare Gains from Constrained-Optimal Income-Contingent Loans



Notes: The left panel of this figure plots the consumption-equivalent welfare gain at a_0 associated with moving from 25-year fixed repayment to the constrained-optimal US-style income-contingent loan shown in the solid blue line in the right graph. The left panel decomposes the total gain, shown in blue, into the welfare gain from insurance and the welfare loss from moral hazard. The welfare gain from insurance is computed by resolving (18) with payments conditional on wage rates instead of income and computing the welfare gain. The welfare loss from moral hazard is computed as a difference between the two. The right panel plots in solid blue the repayment contract that solves (18) in the baseline model and in dashed green the solution in a model in which labor supply remains fixed at its value under 25-year fixed repayment, assuming that a borrower has an initial debt balance equal to the median. The parameter values that solve (18) are shown next to each contract. The solid gray line plots the income distribution in bins of $500.

Welfare gains. The left panel of Figure 14 shows that the constrained-optimal income-contingent loan provides significant welfare gains. I measure welfare gains using the consumption-equivalent metric from Benabou (2002): what value of g would make a borrower, prior to knowing her initial states, indifferent between repaying under the given contract and under 25-year fixed repayment with her consumption increased by $g\%$ in every state? The leftmost blue bar in Figure 14 shows that moving from 25-year fixed repayment to the constrained-optimal income-contingent loan increases welfare by the equivalent of a 1.32% increase in lifetime consumption. This is also equivalent to a \$6,100 AUD (\$7,200 USD in 2023) cash transfer at a_0 or 47% of the gain from (non–budget-neutral) full forgiveness. In other words, improving contract design increases welfare relative to fixed repayment by almost half as much as full forgiveness, but has the same fiscal cost.

The effect of moral hazard on this welfare gain is relatively small. The second two bars in Figure 14 decompose the total gain into the gain from insurance and loss from moral hazard. To compute the former, I solve (18) again, instead assuming that debt repayments, d_{ia}, are contingent on *wage rates*, w_{ia}, instead of income, y_{ia}. This first-best contract is informationally infeasible, but its gains depend entirely on the insurance benefits and not on moral hazard.[29] Therefore, the welfare loss from moral hazard can be estimated as the difference between the gain under this first-best (wage-contingent) loan and that under the constrained-optimal income-contingent loan. The results show that the loss from moral hazard is relatively small, accounting for 0.17 pp or a 13% reduction in the total gain.

Welfare loss from a lower repayment rate. Using a lower repayment rate than the relatively high rate in the constrained-optimal contract reduces the welfare gain. Figure A30 shows that

[29] I use "first-best" loosely: this is not actually the first-best contract because I still constrain its functional form.

imposing the constraint that $\psi \leq 10\%$, the current repayment rate on US IBR contracts, reduces the total gain by 0.20 pp or 14%. Approximately half of this loss comes from the lower repayment rate requiring a lower repayment threshold to satisfy the government budget constraint, reducing the amount of insurance. The remaining half comes from the lower threshold inducing labor supply responses by more borrowers, which increases the loss from moral hazard.

Welfare loss from discontinuity in average repayment rate. The constrained-optimal contract induces almost no bunching at the repayment threshold, as shown in the right panel of Figure 14 in gray. This lack of bunching relative to Figure 3 reflects the fact that this threshold changes the *marginal* rather than *average* repayment rate, eliminating the liquidity effect in Section 5.[30] Nevertheless, Figure A31 shows that the welfare loss from using a contract with a change in the average rate is very small. Although a change in the average rate induces significantly more bunching at the threshold, optimization frictions imply that many borrowers do not reduce their labor supply. As a result, the planner can collect substantially more revenue from these borrowers than when the threshold changes the marginal rate, which in turn can be used to provide more insurance.

Comparison with existing contracts. A robust feature of the constrained-optimal contract is that it provides more insurance than existing contracts. Directly comparing the income-contingent loan in Figure 14 with existing contracts mixes differences that come from the former being constrained-optimal with differences that come from the latter raising different amounts of revenue. Figure A32 shows the results from resolving (18) with $\overline{\mathcal{G}}$ set equal to the revenue raised from the HELP 2004, HELP 2005, and US IBR contracts. In all cases, the constrained-optimal contract has a higher repayment threshold than the corresponding benchmark contract, regardless of whether the constrained-optimal contract changes the marginal or average repayment rate.

7 Income-Contingent Loans versus Other Forms of Insurance

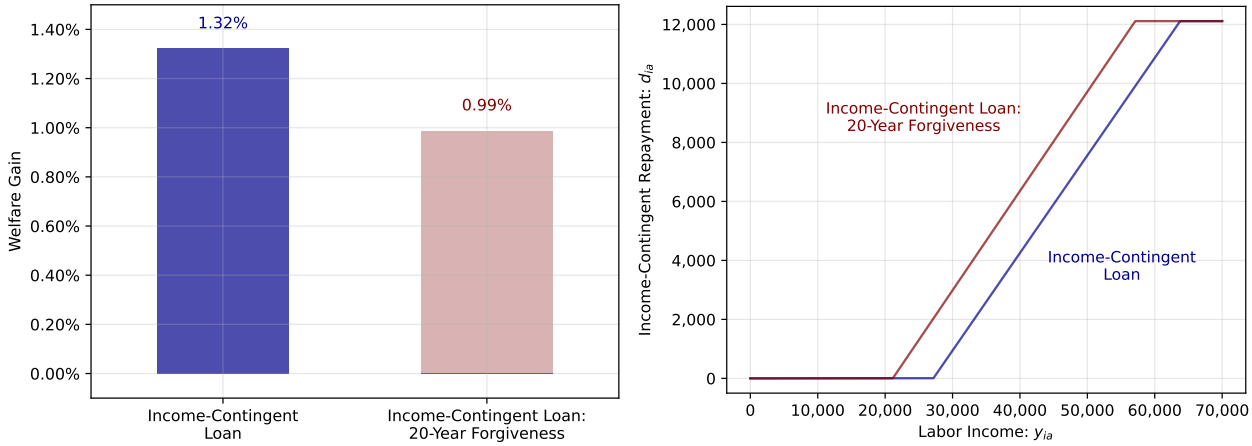
This section shows that the constrained-optimal income-contingent loan performs well relative to three other methods of providing insurance: loan forgiveness, adding forbearance to fixed repayment contracts, and equity contracts.

7.1 Adding Forgiveness Reduces the Welfare Gains from Income-Contingent Loans

I first consider the effects of adding forgiveness after a fixed horizon, a feature of the income-contingent loans in the US and UK. The left panel of Figure 15 compares the gain from the income-contingent loan in Figure 14 with a constrained-optimal income-contingent loan that has forgiveness at $a_0 + 20$, as in US IBR. The latter contract generates a welfare gain of 0.99%, 0.33 pp

[30] This is consistent with limited bunching at UK thresholds (Britton and Gruber 2020), which change marginal rates.

Figure 15. Effects of Adding Forgiveness to Constrained-Optimal Income-Contingent Loans



Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from the constrained-optimal contracts described in the text and shown on the right. Repayments are shown for a borrower with median initial debt.

lower than the contract without forgiveness repeated in the first column.[31]

The lower welfare gain from adding forgiveness reflects a combination of two forces. First, adding forgiveness at the same fiscal cost requires a lower threshold of $21,131, as shown in the right panel of Figure 15. The consequence of a lower repayment threshold is greater payments from young borrowers in exchange for lower payments from older borrowers, whose debt is forgiven (Figure A33). This reduces the insurance benefits of income-contingent loans because younger borrowers have a higher marginal value of wealth from tighter borrowing constraints and a stronger precautionary saving motive (Gourinchas and Parker 2002; Boutros et al. 2022). The second force is that a finite forgiveness horizon increases the loss from moral hazard (Figure A30): because of the dynamic effects in Section 5, borrowers are more willing to adjust their labor supply to reduce repayments because it is less likely that they will make these payments later in their life cycle.

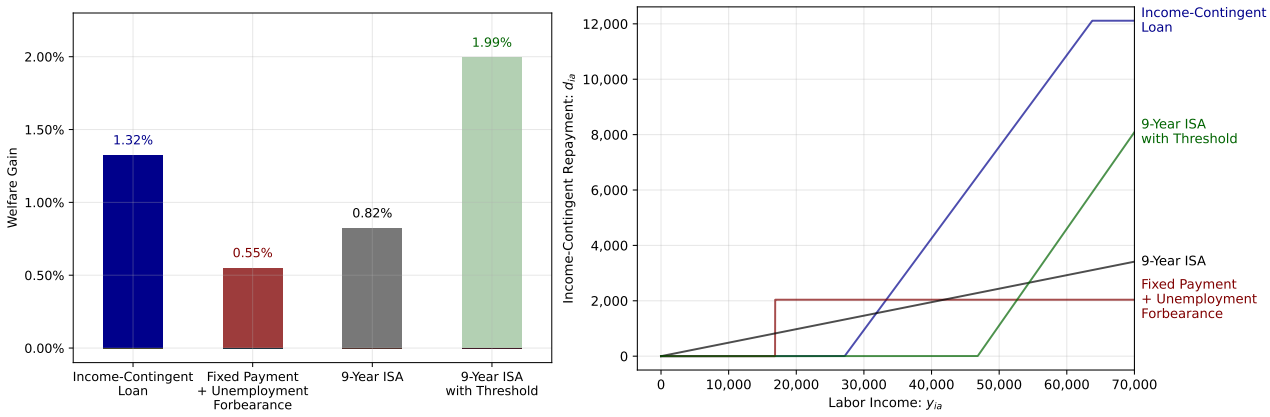
7.2 Income-Contingent Loans Provide Larger Gains than Adding Forbearance

The income-contingent loan in Figure 14 differs from a fixed repayment contract in two ways. First, it provides repayment reductions for low-income borrowers whose income is below the repayment threshold. Second, income-contingent loans collect more repayments from high-income borrowers, while repayments are independent of income under fixed repayment. In reality, the fixed repayment contracts in the US allow repayment to be delayed for low-income borrowers who receive deferment, forbearance, or default. As of 2019, 30% of outstanding debt in the US was in one of these three nonrepayment states (Figure A34).

Adding forbearance to fixed repayment contracts is a poor substitute for income-contingent loans.

[31] In untabulated results, I solve (18) optimizing over the forgiveness horizon and find that no forgiveness is optimal.

Figure 16. Welfare Gains from Alternative Contracts: Forbearance and Equity Contracts



Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from the constrained-optimal contracts described in the text and shown on the right. Repayments are shown for a borrower with median initial debt.

I consider a version of these contracts in which borrowers make payments that are independent of their income when it is above the point at which unemployment benefits stop being paid in Australia (43% above the poverty line) but they are allowed to access forbearance and avoid repayment when their income falls below this point. The constant payment made outside of forbearance is calculated by solving (18) to ensure that this contract has the same fiscal cost as other repayment contracts.[32] The left panel of Figure 16 shows that this contract delivers a welfare gain of only 0.55% relative to 25-year fixed repayment, less than half of the gain from the constrained-optimal income-contingent loan.[33]

The smaller gains from fixed repayment with forbearance reflect the benefits of the call option–like structure of fully income-contingent repayment. As shown in the right panel of Figure 16, the income-contingent loan collects more repayments from high-income borrowers. Although these borrowers are likely to pay off their debt, the acceleration of these repayments forward in time increases their expected discounted value. This, in turn, enables the social planner to set a higher repayment threshold, providing more insurance at a given cost (Figure A30).

7.3 Equity Contracts Generate Larger, but More Dispersed, Welfare Gains

The development of income-contingent loans was inspired by Friedman (1955), who advocated using equity contracts known as income-sharing agreements (ISAs). In an ISA, borrowers repay a share of their income for a fixed repayment period. Private provision of these contracts has been limited because of adverse selection (Herbst and Hendren 2021), but I can use the model to

[32] An alternative contract is 25-year fixed repayment with the same unemployment forbearance, where the interest rate is adjusted to balance the government budget. This contract delivers a similar gain of 0.52%. I focus on the contract described in the text because it is more directly comparable to the other contracts, which also have a zero interest rate.

[33] A natural question is whether there are welfare gains from combining these two repayment contracts: Figure A35 shows that doing so optimally provides minimal welfare gains over the income-contingent loan in Figure 14.

assess ISAs as a mandatory government-provided contract. I focus on ISAs that last nine years, the repayment period of the ISAs recently provided by Purdue University (Mumford 2022).[34]

A pure ISA, as proposed by Friedman (1955), performs worse than the constrained-optimal income-contingent loan. The third column in the left panel of Figure 16 shows that the welfare gain from a nine-year ISA is equivalent to 0.82% of lifetime consumption, where the parameter controlling the share of income repaid has been adjusted to balance the government budget. This is 40% lower than the gain from the constrained-optimal income-contingent loan, which reflects the same force that makes forgiveness perform worse: a pure ISA requires repayments from *all* borrowers in the first few years of their life, when they value payment reductions the most, in exchange for zero payments when they are older (i.e., after $a_0 + 9$).

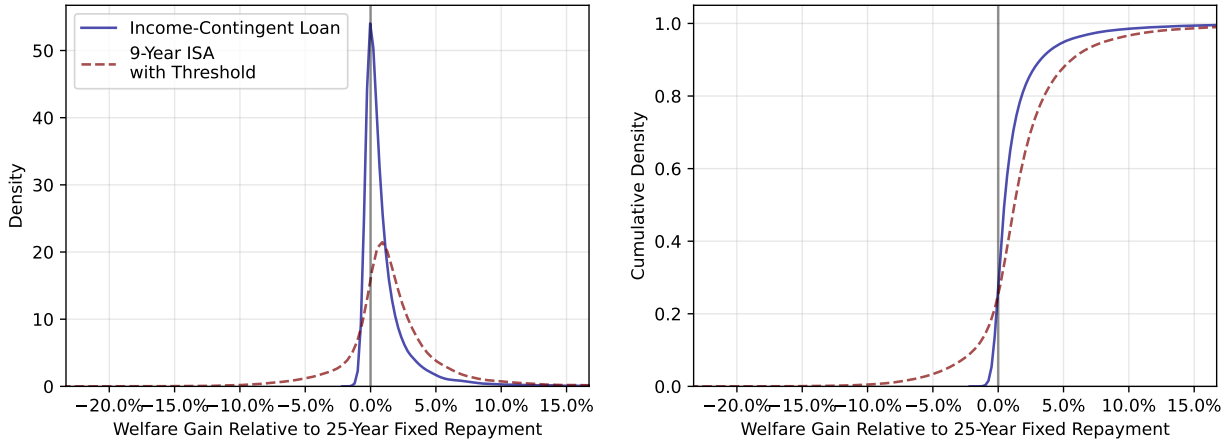
The final column of Figure 16 shows that an ISA with a repayment formula similar to that of an income-contingent loan does significantly better. In the 9-Year ISA with Threshold, borrowers only make payments when their income exceeds a certain threshold, which is chosen jointly with the income-share rate to solve (18). This contract performs better than a pure ISA because it avoids requiring payments from young low-income borrowers. Additionally, it outperforms the constrained-optimal income-contingent loan because it provides more insurance. With an income-contingent loan, repayments from high-income borrowers are capped by their initial debt. However, with an income-sharing agreement, these repayments are uncapped and can be used to finance lower repayments from low-income borrowers: the right panel shows that this manifests in a 70% higher threshold of K =\$46,821.[35] The reliance on repayments from high-income borrowers increases the loss from moral hazard, but this loss is small relative to the insurance benefits (Figure A30).

Although ISAs generate larger average gains, these gains are more heterogeneous. Figure 17 plots the distribution of welfare gains and losses at $a = a_0$ from the constrained-optimal income-contingent loan and ISA. Relative to 25-year fixed repayment, the income-contingent loan is welfare-improving for approximately 70% of borrowers, while the remaining 30% experience small losses. These small losses are concentrated among high-income borrowers with low debt balances, who make larger repayments than under fixed repayment. However, the gains from the ISA are significantly more dispersed: 18% of borrowers have losses greater than 0.5%, while only 1.2% of borrowers have losses this large under the income-contingent loan. This heterogeneity is primarily driven by losses from high-income borrowers, whose repayments are uncapped under an ISA. Additionally, because repayments are unaffected by debt, ISAs induce significant redistribution from low-debt to high-debt borrowers (Figure A36). Initial debt is exogenous, but with endogenous debt accumulation, this redistribution would likely generate borrowing responses that increase the fiscal cost of ISAs.

[34] When I optimize jointly over the ISA repayment period, I find that the maximum value of a_R is optimal because it reduces payments for young borrowers. I focus my analysis on nine-year contracts because they are closer to typical observed ISAs. However, the qualitative takeaways from the analysis are the same regardless of the repayment period.

[35] However, this also makes the welfare gains from equity contracts more likely to be overstated: ϕ is identified from median-income borrowers, while prior literature suggests elasticities increase with income (e.g., Gruber and Saez 2002).

Figure 17. Distribution of Gains from Constrained-Optimal Income-Contingent Loan and Equity Contract



Notes: This figure plots the distribution of welfare gains at a_0 relative to 25-year fixed repayment from the constrained-optimal income-contingent loan in solid blue and 9-Year ISA with Threshold in dashed red. The left panel plots the density of these gains and the right panel plots the cumulative density. These densities are estimated using with a Gaussian kernel and bandwidth that are chosen using Scott's rule. The welfare gains in this plot are computed as the percent change in initial certainty-equivalent values; see Appendix D.5.

In sum, although properly designed equity contracts improve welfare relative to income-contingent loans, they are more likely to generate ex-ante responses, such as additional borrowing, that may make income-contingent loans a more robust implementation of income-contingent repayment.

8 Robustness, Extensions, and Additional Discussion

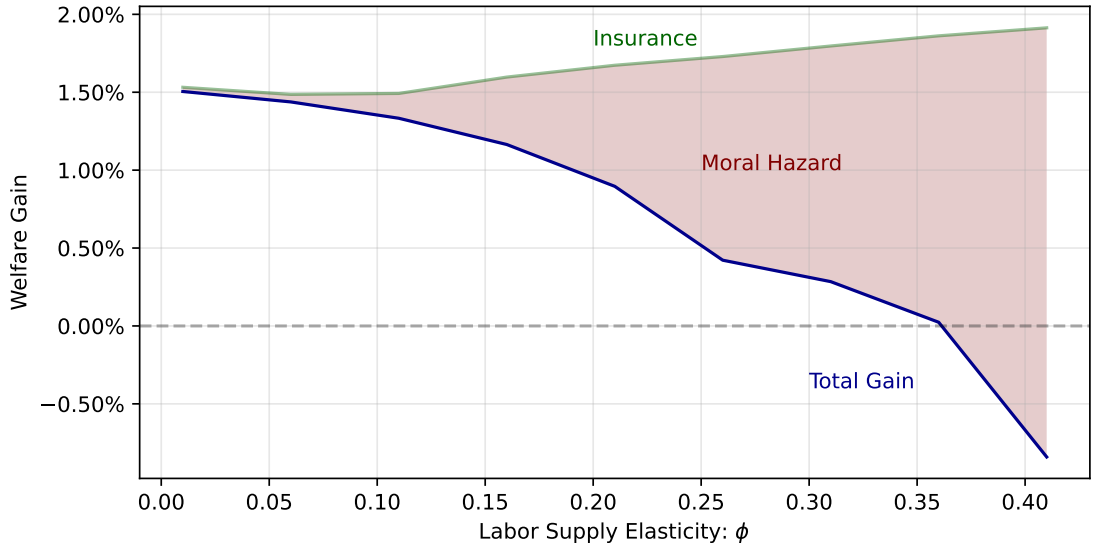
8.1 Effects of a Higher Labor Supply Elasticity

The welfare gains from income-contingent repayment decrease with the labor supply elasticity, ϕ. Figure 18 shows the consumption-equivalent gains from the income-contingent loan that solves (18) for different values of ϕ.[36] For income-contingent loans to deliver a welfare *loss* relative to fixed repayment, ϕ would have to be above 0.37. However, Figure A38 shows the bunching around the repayment thresholds, the most important estimation targets for identifying ϕ, in the baseline model when $\phi = 0.37$. There is significantly more bunching than in the data: the number of borrowers below relative to above the threshold is 70% larger and greater than the amount of bunching within any occupation. Additionally, an (intensive margin) labor supply elasticity of 0.37 is high relative to estimates in prior literature: it is above the 75th percentile of the estimates reported in Figure A1.

Alternative forms of income-contingent loans can reduce the welfare loss from moral hazard, even when $\phi = 0.37$. Figure 19 shows that an income-contingent loan with a smooth repayment function reduces this cost by 105 pp, while making this contract age- and debt-contingent gives additional

[36] Table A6 and Figure A42 show the effects of changing the fixed cost, Calvo probability, RRA and EIS.

Figure 18. Welfare Gains from Constrained-Optimal Income-Contingent Loan and Labor Supply Elasticity



Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment in blue from a constrained-optimal income-contingent loan that solves (18) in the baseline model. This planner's problem is solved for different values of ϕ with the resulting welfare gains shown in the plot and the resulting contracts shown in Figure A37. All other parameters are held fixed at their estimated and calibrated values. The light green and shaded regions show the contributions of insurance and moral hazard to this welfare gain, computed using the decomposition described in Figure 14. The dashed gray line corresponds to a welfare gain of zero.

reductions of around 30 pp.[37] Figure A40 plots these contracts: the smooth income-contingent loan takes a similar shape to the IBR-style loan, but the smoother structure reduces the loss from moral hazard. The latter two contracts increase payments with age and debt, both of which further reduce moral hazard by creating a future cost to reducing labor supply. These results are consistent with Shavell (1979), who shows that the unconstrained solution to (18) features some insurance: the gains from insurance are first-order while the losses from moral hazard are second-order.

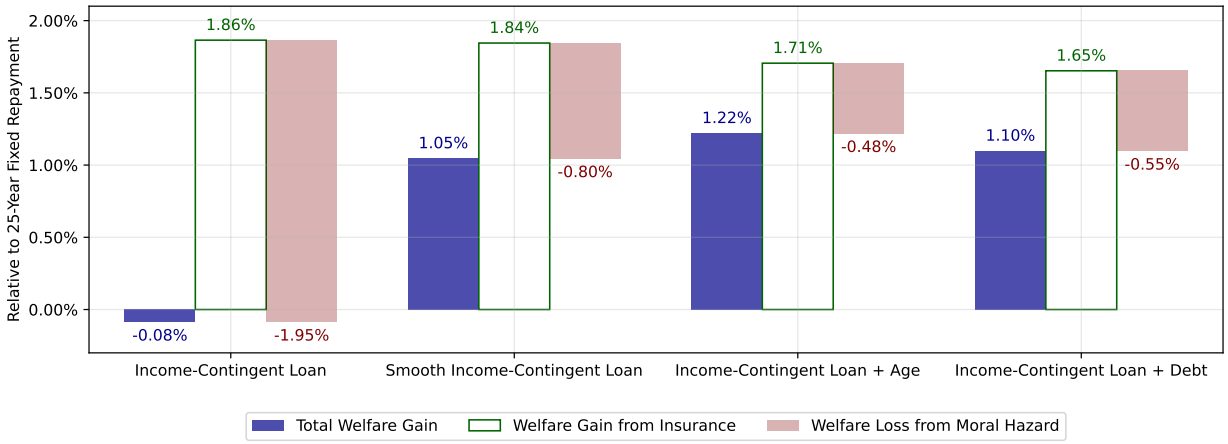
8.2 Endogenous Contract Selection

My analysis thus far has considered a single mandatory repayment contract. However, in the US, income-contingent loans are offered alongside fixed repayment, and borrowers with low expected earnings select the former (Karamcheva et al. 2020). In this section, I use the model to assess the quantitative importance of such endogenous contract selection by allowing borrowers to choose between 25-year fixed repayment and a constrained-optimal income-contingent contract. For simplicity, I give borrowers this choice at the beginning of their lifetimes *after* the realization of their initial states; the information to which borrowers have access when they select between contracts is an empirical question that I leave for future work.[38]

[37] Figure A39 shows the results in the baseline model. In this model, all three contracts deliver gains similar to those under the income-contingent loan considered in previous sections. This result reflects that the discontinuity in the marginal repayment rate at the repayment threshold is not very distortionary in the baseline model (Figure 14).

[38] There are two potential types of selection: classical adverse selection, in which borrowers select contracts based on their unobservable type, and selection on moral hazard, where borrowers select contracts based on expected hidden actions.

Figure 19. Welfare Gains from Alternative Contracts when Labor Supply Elasticity, $\phi = 0.37$



Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment, along with the decomposition performed in Figure 14, for different constrained-optimal repayment contracts. The first contract corresponds to a smoothed version of the US IBR–style income-contingent loans considered above, in which repayments are a quadratic function of income. The latter two contracts make repayments conditional on age and debt. See Appendix D.4 for additional details. This analysis is performed with all parameters set at their values in the baseline model except the labor supply elasticity, which is set equal to 0.37.

Endogenous contract selection is valuable to borrowers but creates additional fiscal costs. The top panel of Table 5 shows that 29% of borrowers select fixed repayment over the constrained-optimal income-contingent loan, primarily borrowers with high initial incomes and low initial debt, for whom payments are lower under fixed repayment. However, the equivalent variation and fiscal cost of this selection relative to mandating the income-contingent loan is small: only around $200 and $800, respectively. In contrast, Table 5 shows that these quantities are an order of magnitude larger for the constrained-optimal equity contract, 9-Year ISA with Threshold. This is because equity contracts rely more heavily on collecting repayments from high-income borrowers.

The welfare loss from this selection is small for income-contingent loans but much larger for equity contracts. To compute this welfare cost, I adjust income taxes to balance the government budget when individuals endogenously select between the two contracts. Then, I compute the consumption-equivalent gain in this economy relative to one in which 25-year fixed repayment is mandatory. For income-contingent loans, the bottom panel of Table 5 shows that this welfare gain is only 0.03 pp (or 3%) smaller than when income-contingent repayment is mandated. In contrast, this gain is 0.35 pp (or 18%) smaller for equity contracts. The fact that selection decreases welfare is a manifestation of the Hirshleifer (1971) effect: borrowers' private foreknowledge of their initial states reduces the scope for insurance against the realization of these states.

In sum, endogenous contract selection has a quantitatively important effect on the welfare gains from equity contracts because high-income borrowers, from whom the optimal contract collects most of the repayments, select fixed repayment and substantially reduce fiscal revenue. Selection

This section should be thought of as primarily considering the effects of the former because there is no heterogeneity in structural labor supply parameters; the effects of the latter are theoretically ambiguous (Karlan and Zinman 2009).

Table 5. Effects of Endogenous Contract Selection

	Constrained-Optimal Contract	
	Income-Contingent Loan	9-Year ISA with Threshold
% Choose 25-Year Fixed Repayment	29%	24%
Borrower Value of Selection	$180	$1,544
Fiscal Impact of Selection	-$757	-$6,841
Consumption-Equivalent Welfare Gains		
Contract Mandated	1.32%	1.99%
Selection + Taxes to Balance Budget	1.29%	1.64%
Welfare Impact of Selection	−0.03%	−0.35%

Notes: This table summarizes the effects of allowing borrowers to endogenously choose between 25-year fixed repayment and the constrained-optimal repayment contract shown in each column. Borrowers choose this contract at a_0 after they know their initial states, θ_{i0}, A_{i0}, and D_{i0}. The first three rows summarize the effects in terms of the fraction of borrowers who choose 25-year fixed repayment, the value of selection to borrowers measured as the equivalent variation at a_0 relative to the constrained-optimal repayment contract being mandated, and the fiscal impact of selection measured as the change in $\mathcal{G}$ defined in (16) (per individual). The final three rows quantify the welfare impact of selection in consumption-equivalents. The first of these three is the gains of mandated contracts from Figure 16; the second is the gain from allowing endogenous contract selection and the level of income taxes (a in Appendix D.2) on borrowers with $\mathcal{E}_i = 1$ to balance the government budget; the third is the difference between the previous two.

has less of an effect on the welfare gains from income-contingent loans because repayments are capped by initial debt. Given that this analysis abstracts from the fact that equity contracts are more likely to cause ex-ante borrowing responses, it reinforces the conclusion in Section 7.3 that income-contingent loans may be a more robust form of income-contingent repayment.

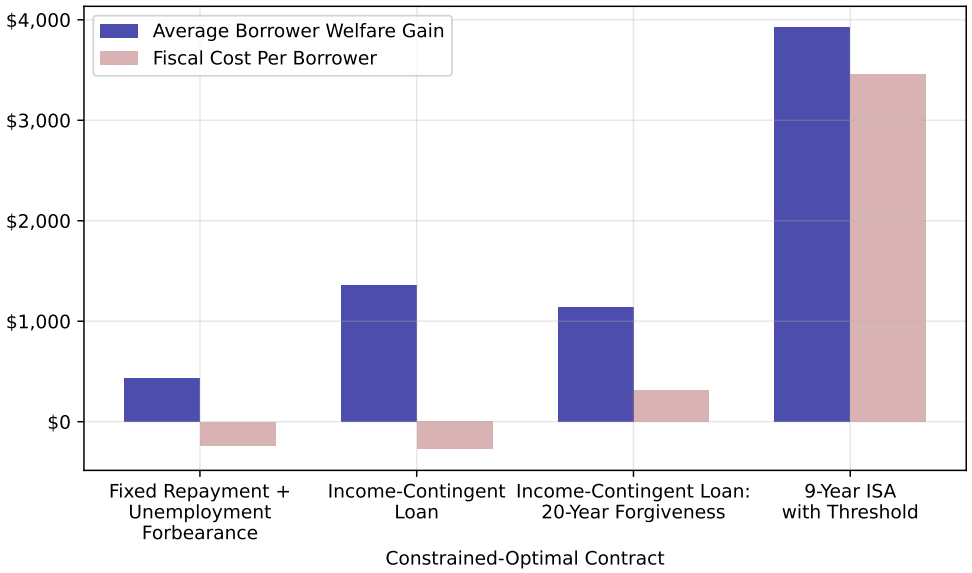
8.3 A Restructuring Experiment in which Ex-Ante Choices are Held Fixed

A limitation of the normative analysis in this paper is that it takes ex-ante borrowing and education choices as given. If these choices respond to the type of repayment contract independent of the total government subsidy, my results incorrectly characterize the optimal contract and its welfare gains. However, the direction of this bias is an empirical question.[39] On the one hand, income-contingent repayment may encourage borrowers to pursue riskier degrees, which may be welfare-improving if fixed repayment distorts these choices. Alternatively, income-contingent repayment may incentivize excess borrowing from individuals who anticipate never earning enough to repay their debt.

Figure 20 shows the effects of a hypothetical experiment in which outstanding student debt is restructured at the time of the 2004/05 policy change from 25-year fixed repayment to the various constrained-optimal contracts in Figure 16. Unlike previous analyses, the ex-ante borrowing and education choices of these existing borrowers are fixed. I measure the welfare impact as the average increase in utility (in dollars) across all borrowers with outstanding debt at the time of the change.

[39]This paper studies the effects of contracts that have identical total subsidies. Therefore, for omitting ex-ante education choices to affect my results, these choices would need to respond to changes in the utility value of repayments associated with different majors or degrees. Existing literature on major choice suggests the effects of such changes are likely small, given that non-pecuniary factors tend to be most important in driving these decisions (Patnaik et al. 2020).

Figure 20. Effects of Restructuring from 25-Year Fixed Repayment to Constrained-Optimal Contracts



Notes: This figure shows the results from an experiment in which all outstanding debt is restructured at the time of the 2004/05 policy change, $t = 2005$, from 25-year fixed repayment to the different constrained-optimal contracts in Figure 16. The dark blue bars plot the average welfare gain across borrowers in dollars. For each borrower, the dollar welfare gain is computed by scaling the increase in borrowers' utility at $t = 2005$ by the marginal value of wealth, computed numerically as the increase in utility from a $2,000 cash transfer absent restructuring. The light red bars plot the impact of restructuring on the government's budget per borrower, where positive (negative) values indicate an increase (decrease) in fiscal cost. The impact on the government budget per borrower is computed as the change in $\mathcal{G}$ between $t = 2005$ and the year of borrowers' death from restructuring, discounted at $\mathcal{R}_a$ with $a_0 = 2005$. This experiment is performed using the same simulation procedure used to estimate the model, with the exception of using the smoothed tax and transfer system and removing means-testing in retirement benefits (as in Section 6.1).

The fiscal impact is then computed as the present value per borrower of the change in government revenue (net of expenses) over the remainder of borrowers' lifetimes.

The results in Figure 20 show that restructuring from 25-year fixed repayment to the constrained-optimal income-contingent loan generates an average increase in borrowers' utility by around $1,500 ($15\%$ of the average debt balance) *and* a reduction in fiscal costs. This increase in utility is smaller than in Figure 14 because it reflects the average gain among outstanding debtholders, who have less to gain from restructuring because they have already realized their initial states and paid down some debt. Figure 20 also shows that income-contingent loans outperform other contracts in terms of their cost-effectiveness as a restructuring contract. Although all these contracts have the same expected cost over borrowers' lifetimes (by construction), loans with forgiveness and equity contracts are costly ways to restructure because they stop collecting repayments after the forgiveness and repayment horizons, respectively. In contrast, income-contingent loans without forgiveness do not stop collecting payments from higher-income borrowers beyond these horizons who have low marginal values of repayment reductions.

In sum, although my main analysis takes ex-ante decisions as given, restructuring outstanding debt to my constrained-optimal repayment contracts generates meaningful welfare gains among borrowers whose ex-ante choices are fixed by definition. Among the constrained-optimal contracts,

income-contingent loans appear the most effective, suggesting a (mandatory) restructuring of the $1.6 trillion of student debt in the US from fixed to income-contingent repayment may be beneficial.

8.4 Sensitivity to Model Misspecification

I conclude by evaluating the robustness of the income-contingent loan that solves (18) to model misspecification by considering several extensions and alternative parameterizations of the baseline model. The results are presented in Table 6 and referenced by row in the discussion below.

Occupation-level heterogeneity. The empirical analysis uncovered occupation-level heterogeneity that is not in the baseline model. To assess the importance of such heterogeneity, I consider an extension with two groups of borrowers (in equal proportions) who have different Calvo parameters, λ. I calibrate these two values of λ, holding all other parameters fixed at their baseline values, so that the amount of bunching in the two groups matches the lowest and highest across occupations (shown in Panel B of Figure A38), which results in values of 0.092 and 0.275. Row (1) shows that adding this heterogeneity delivers results that are quantitatively very similar to those of the baseline model. Although this suggests that occupation-level heterogeneity is not first order for my analysis, an important caveat is that, for tractability, I do not have heterogeneity in income profiles. Such heterogeneity could be important if it is correlated with hourly flexibility across occupations.

Learning-by-doing. Row (2) shows the results from the learning-by-doing model estimated in column (5) of Table 3. This model generates slightly larger gains than those under the baseline model because, with GHH preferences, borrowers have lower labor supply early in life under a fixed repayment contract when their consumption is low. With learning-by-doing, there is an added benefit of increasing labor supply early in life because it delivers higher wages and thus greater tax revenue later in life. This effect is larger than the second effect that learning-by-doing introduces, in which labor supply reductions to avoid repayment generate long-run wage and tax reductions.

Alternative optimization frictions. I assess the robustness of my results to the specific model of optimization frictions by considering the welfare gains in three alternative models. Rows (3) and (4) show the results from the models estimated in columns (3) and (4) of Table 3, in which the only friction is a fixed cost and Calvo adjustment, respectively. These results illustrate that the loss from moral hazard is larger when labor supply adjustment is state- rather than time-dependent. Row (6) shows the results from the model with linear adjustment costs in column (6) of Table 3. In this model, the optimal contract has a higher repayment threshold and rate, providing more insurance. This is because linear costs make large labor supply adjustments more costly than in a model with fixed costs. Large adjustments are most important for the fiscal externality of income-contingent repayment, so the smaller prevalence of these adjustments increases the amount of insurance that can be provided at a given cost.

Wealth effects on labor supply. Existing literature disagrees on the size of wealth effects on

Table 6. Welfare Gains from Constrained-Optimal Income-Contingent Loans in Alternative Models

	Difference from Baseline Model	Welfare Gain	= Insurance	+ Moral Hazard	ψ^*	K^*
(1)	Occupation Heterogeneity	1.32%	1.45%	−0.13%	41%	$28,694
(2)	Learning-by-Doing	1.68%	·	·	35%	$36,615
(3)	Fixed Adjustment Cost Only	1.00%	1.49%	−0.49%	21%	$22,711
(4)	Calvo Adjustment Only	2.02%	2.10%	−0.08%	64%	$46,452
(5)	Linear Adjustment Cost	1.74%	1.87%	−0.13%	53%	$43,560
(6)	Wealth Effects on Labor Supply	0.82%	1.05%	−0.23%	37%	$30,307
(7)	Less Persistent Shocks: $\rho = 0.8$	0.90%	1.14%	−0.23%	42%	$34,244
(8)	More Persistent Shocks: $\rho = 0.99$	1.35%	1.63%	−0.28%	35%	$18,949
(9)	Non-Normal Permanent Shocks	1.14%	1.43%	−0.30%	28%	$26,933
(10)	Debt Interest Rate = 2%	1.96%	2.14%	−0.18%	38%	$47,731
(11)	Planner Discount Rate = R	1.06%	1.41%	−0.35%	29%	$22,696
(12)	Planner Discount Rate = $R + 4\%$	1.60%	1.65%	−0.05%	46%	$34,441
(13)	US Tax System	1.18%	1.36%	−0.19%	38%	$28,838
(14)	Larger Initial Debt Balances	3.50%	4.72%	−1.22%	36%	$18,867
(15)	Risk-Free Borrowing: $\tau_b = 0\%$	1.23%	1.44%	−0.21%	37%	$27,824
(16)	No Ex-Post Uncertainty	0.58%	0.76%	−0.17%	27%	$18,098
(17)	No Uncertainty	−0.17%	0.15%	−0.32%	21%	$26,906
	Average	1.35%	1.61%	−0.29%	37%	$30,277
	Baseline Model	**1.32%**	**1.47%**	**-0.15%**	**33%**	**$27,147**

Notes: This table presents the optimal contract that solves (18) and its corresponding welfare gain relative to 25-year fixed repayment. Each row presents the results from a different model that deviates from the baseline model as described in the text; the results from the baseline model, shown in Figure 14, are repeated at the bottom of the table. The decomposition of the welfare gain is not reported for the learning-by-doing model because, in that model, wage rates are endogenous so a wage-contingent repayment contract still creates moral hazard. The second-to-last row shows the equally-weighted average of all values, excluding those from the baseline model.

labor supply: Cesarini et al. (2017) find small wealth effects from lottery winnings in Sweden, while Golosov et al. (2023) find larger effects from lottery winnings in the US. To assess the importance of wealth effects, I adjust the flow utility in (5) to be

$$\frac{1}{\eta}\left(\frac{c_{ia}}{n_a}\right)^{\eta} - \kappa\frac{\ell_{ia}^{1+\phi^{-1}}}{1+\phi^{-1}}.$$

I set $\eta = 0.5$ following the calibration in Keane (2011). Row (6) shows that the welfare gain is reduced slightly. With wealth effects, labor supply is less distorted early in life when consumption is low, which reduces the welfare gain from the improved smoothing of labor supply with income-contingent repayment. However, wealth effects have a minimal effect on the optimal contract.

Persistence of income risk. Because individuals can self-insure against transitory but not permanent shocks in incomplete markets, correctly estimating the persistence of income shocks is crucial for assessing the welfare impact of income-contingent repayment. Because estimates of this persistence vary between 0.8 and close to 1, depending on the degree of heterogeneity in income profiles (Guvenen 2009a), rows (7) and (8) consider the effect of these alternative values of ρ. A higher ρ, which increases the quantity of risk against which individuals would like to insure, raises the gains from income-contingent repayment, while a lower ρ does the opposite. The results also

show an effect on the optimal financing contract, but this is mostly because changing ρ in isolation has a meaningful effect on moments of the income distribution.

Non-normal income risk. Recent evidence from administrative data highlights the importance of non-normal income shocks (Guvenen et al. 2021). I introduce such shocks into the baseline model (without re-estimating it) by drawing ν_{ia} in (7) from a mixture of two independent normal distributions with different means and variances. I calibrate these parameters by estimating two models with exogenous income processes with and without the mixture of normals. I then multiply the values of the parameters in the former by the ratio of the estimates in Table 3 to the latter estimates. Row (9) shows that this has a small effect on the optimal contract and the gains from insurance but increases the loss from moral hazard.

Interest rate on debt. In my analysis, I set the real interest rate on debt to zero, as in HELP. However, in the US, debt balances have historically been subject to interest accumulation (although the new SAVE plan changes this). Row (10) shows the results when I instead use an interest rate of 2% above the real interest rate, similar to the markup on student loans above Treasury bill rates in the US (Ji 2021) and above the Bank of England base rate in the UK (Britton and Gruber 2020). This allows the planner to choose a higher repayment threshold that is financed by more interest payments from high income borrowers, increasing the gain from insurance.

Government discount rate. The model does not have aggregate risk, so the correct discount rate for debt repayments is the risk-free rate, which is lower than (17). Row (11) shows the effect of using this lower discount rate, which primarily increases the loss from moral hazard. In a model with aggregate shocks, student loan repayments would be discounted at a higher rate given that they are income-dependent and thus likely correlated with the business cycle. Row (12) shows that using a higher discount rate, the risk-free rate plus a 4% risk premium, increases the welfare gain slightly.

Alternative tax system. My analysis is contingent on the tax and transfer system, which is another means of redistributing within and across individuals. Row (13) shows results under an alternative tax system from Heathcote et al. (2017), which approximates the US system. The optimal contract is similar, but the gains from insurance are smaller because the US tax system is more progressive. In contrast, Appendix D.7 shows that when the progressivity of the tax system is optimized, there is no gain from using income-contingent loans relative to providing forbearance.

Higher level of initial debt. An important difference between the US and Australia is the level of initial debt that borrowers take on. In the 2019 Survey of Consumer Finances, the average initial debt among borrowers was $51,800 USD (Catherine and Yannelis 2023), while in the model, it is $17,400 in 2005 AUD ($20,500 in 2023 USD). Row (14) shows the effect of multiplying all initial debt balances by 2.51, the ratio of the previous two values. This increases the welfare gain from income-contingent repayment because higher debt balances make fixed repayment more

costly. However, higher debt balances also increase the amount of moral hazard by strengthening the dynamic effects in Section 5. This requires the optimal repayment contract to have a lower repayment threshold and increases the loss from moral hazard.

Risk-free borrowing. The borrowing rate in the model is calibrated to match rates on credit cards, which is higher than the rate of return on assets. Row (15) shows that eliminating this wedge between borrowing and lending rates reduces the welfare gains from income-contingent repayment, but quantitatively the results are very similar.

The role of level, uncertainty, and redistributive effects. The consumption-equivalent welfare gain from a policy reform comprises of three effects: (i) level effects due to changes in average consumption, (ii) uncertainty effects due to changes in the volatility of the consumption paths that affects welfare because of risk aversion and incomplete markets, and (iii) redistributive effects due to changes in consumption-equivalents across initial conditions (Benabou 2002). Because of the nonhomotheticity and nonconvexities in the model, calculating these terms analytically is not possible. Instead, I compare the results in the baseline model with those in two alternative models: a model with no ex-post uncertainty (aside from Calvo shocks) and a model with no ex-ante and no ex-post uncertainty. Intuitively, the gain in the latter model is due to level effects, while the difference between the two captures redistributive effects. Uncertainty effects can then be estimated by comparing the baseline model results to the results from the model with no ex-post uncertainty. These two sets of results are shown in Rows (16) and (17), which suggest that around half of the gain comes from redistributive and uncertainty effects, respectively.

Alternative risk and time preferences. Figure A42 shows the effect of moving the RRA, γ, and the EIS, σ^{-1}. Increasing γ leads to a higher welfare gain by increasing borrowers' valuation of insurance. Increasing σ^{-1} reduces the welfare gain because the benefits of income-contingent repayment come partly from improving consumption-smoothing over time, which is less valuable with a higher EIS. However, the welfare gains and optimal contract are more sensitive to γ than to σ^{-1}, suggesting that most of the benefits from income-contingent repayment come from smoothing repayments cross-sectionally rather than across time.

9 Conclusion

This paper studies the trade-off between insurance and moral hazard in student loans with income-contingent repayment. I show that borrowers reduce their labor supply to lower income-contingent repayments and that these responses are consistent with a moderate labor supply elasticity and substantial optimization frictions. My estimates suggest that income-contingent repayment provides significant welfare gains and that income-contingent loans are an effective and robust way of doing so. Relative to fixed repayment contracts with forbearance, income-contingent loans can provide

more insurance by accelerating payments from high-income borrowers. Relative to equity contracts, these loans are less adversely selected, less likely to generate ex-ante responses (e.g., additional borrowing), and more cost-efficient for restructuring outstanding debt.

The results in this paper speak to the ongoing "student debt crisis" in the US (Mitchell 2019). One possible solution to this "crisis" is to use income-contingent repayment contracts, such as those introduced by the Biden administration. This paper provides empirical evidence and a structural model that can be used to calibrate the effects of different contracts. Overall, my results suggest that ex-post moral hazard is likely too small to justify avoiding income-contingent repayment and that, among income-contingent contracts, income-contingent loans are relatively effective and robust. However, this analysis leaves open several questions, such as how education, occupation, and borrowing choices respond. Income-contingent repayment may affect choices on the intensive margin by encouraging borrowers to pursue degrees and occupations with riskier returns (Hampole 2022; Murto 2022; Abourezk-Pinkstone 2023) or on the extensive margin by encouraging more borrowers to pursue higher education. Quantifying these responses and their implications for optimal contract design is an important task for future research.

More broadly, the trade-off between insurance and moral hazard studied in this paper applies to the design of other state-contingent financing contracts. Two notable examples are shared-appreciation mortgages, which several governments and private firms have recently begun providing, and revenue-based financing for start-ups. As in the case of student loans, a key question is how to design these contracts to balance their insurance benefits with the behavioral distortions they create. By carefully analyzing the insurance–moral hazard trade-off for student loans, this paper provides a template for studying these issues in other contexts.

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Required Disclaimer for Use of MADIP Data

The results of these studies are based, in part, on Australian Business Registrar (ABR) data supplied by the Registrar to the ABS under A New Tax System (Australian Business Number) Act 1999 and tax data supplied by the ATO to the ABS under the Taxation Administration Act 1953. These require that such data is only used for the purpose of carrying out functions of the ABS. No individual information collected under the Census and Statistics Act 1905 is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes, and is not related to the ability of the data to support the ABR or ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of these data have been followed. Source data are de-identified and so data about specific individuals or firms has not been viewed in conducting this analysis. In accordance with the Census and Statistics Act 1905, results have been treated where necessary to ensure that they are not likely to enable identification of a particular person or organisation.

Internet Appendix for "Insurance versus Moral Hazard in Income-Contingent Student Loan Repayment"

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MIT Sloan

Latest Version of Full Draft

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Appendix A. Comparison with Existing Literature

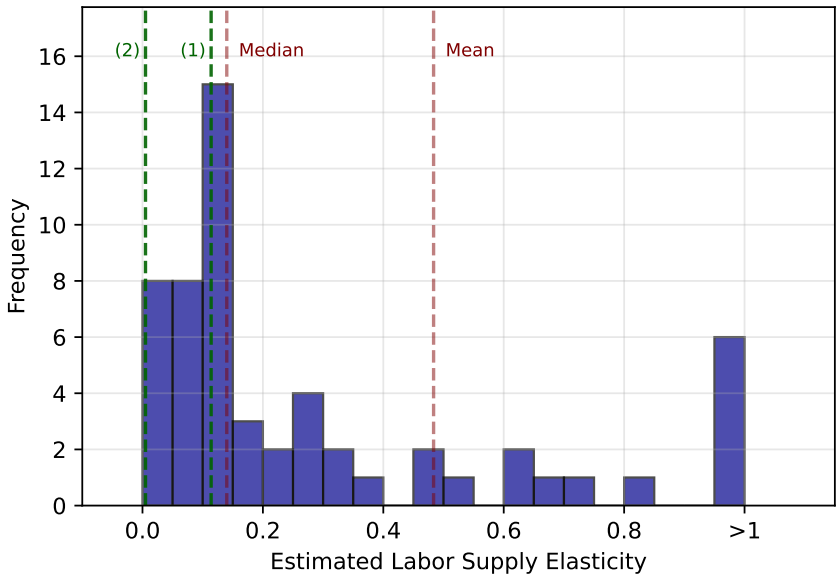
A.1 Literature on Labor Supply

The literature on labor supply is extremely vast (see Blundell and MaCurdy 1999 and Keane 2011 for reviews) and can be divided into four strands (Chetty 2012): the first uses data on hours worked to measure labor supply; the second uses income reported on tax returns to measure labor supply; the third also uses tax data, but focuses on top earners; and the fourth studies differences in hours worked in response to cross-sectional variation, such as variation in tax rates across countries. Because I identify ϕ using bunching in HELP income, it can also be interpreted as a reported income elasticity that aggregates both hours and non-hours responses (Feldstein 1999). Therefore, Figure A1 shows the distribution of labor supply elasticities estimated among studies in these first two strands of literature, which have the closest structural interpretation to ϕ. My baseline estimate of 0.11 is similar to the median of these estimates, 0.14. However, none of these studies explicitly account for optimization frictions, although some examine longer-run responses that might be less affected by such frictions. Assuming that these estimates do not account for frictions, the closer analog in my setting to these estimates would be my frictionless estimate of 0.005, which is smaller than most estimates.

There are several reasons why optimization frictions might be larger in my setting, making the frictionless elasticity smaller. First, my sample of individuals differs from the samples in most prior studies: they are college graduates early in their life cycles. These individuals are more likely to work in salaried jobs with less hourly flexibility and a less direct mapping between labor supply and income. Second, the variation that I exploit is the discontinuity in repayment rates at the threshold. As a result, the estimated elasticity applies to individuals with incomes near this threshold, which is around the median income. This suggests that my estimated elasticity should be smaller, given that I do not study high-income individuals, who typically have higher estimated elasticities (Gruber and Saez 2002). Finally, I cannot identify extensive margin responses, which are large in some populations such as married women (Saez et al. 2012). However, the individuals in my sample are likely to be less willing to make extensive margin adjustments, given that doing so would presumably have costs that would exceed the benefits of delayed debt repayment.

This paper builds on this extensive literature on labor supply in two ways. First, it empirically characterizes how labor supply responds to income-contingent repayment, which creates dynamic trade-offs that taxes do not. My finding that borrowers reduce their labor supply to locate below the repayment threshold, which, unlike a tax, increases liquidity more than wealth, connects this literature with evidence that consumption of indebted households responds to liquidity more than wealth (Ganong and Noel 2020). Second, I estimate the first (to my knowledge) model of labor supply with both time- and state-dependent adjustment. In this model, the choice of labor supply is *dynamic* for two reasons: these optimization frictions and income-contingent debt repayment. In this sense, my contribution is analogous to that of Einav et al. (2015), who show that a dynamic model of drug expenditure is necessary for replicating bunching at the Medicare Part D "donut hole." One way to compare the model with traditional models of labor supply is to compute the revenue-maximizing tax rate. In a static frictionless model of labor supply, this is $\frac{1}{1+\phi}$ or 90% given the estimate of $\phi = 0.11$, while in Figure A28, it is around 80% in the baseline model. This suggests that the model delivers reasonable estimates for the effects of income taxation despite being designed to capture the dynamic effects created by income-contingent repayment.

Figure A1. Distribution of Estimated Labor Supply Elasticities from Prior Studies



Notes: This figure plots a histogram of the intensive margin labor supply elasticities estimated in prior literature. I combine the estimates reported in Tables 6 and 7 of Keane (2011) and Table 1 of Chetty (2012). These estimates include intensive margin Frisch (i.e., marginal utility–constant) and Hicksian (i.e., wealth-constant) elasticities estimated among studies that measure labor supply using hours worked or taxable income, which have the closest structural interpretation to my estimates. This graph pools all studies, some using full populations, others using just men or women. See Keane (2011) and Chetty (2012) for a detailed discussion of the underlying studies. In the histogram, all studies that estimate a value above one are placed into the last bar, but the mean and median, shown in dashed red lines, are calculated before these observations are trimmed. The two dashed green lines plot the estimates from columns (1) and (2) of Table 3, respectively.

A.2 Literature on Labor Income Risk

A growing literature uses administrative data to estimate parametric models of labor income risk (see e.g., Guvenen et al. 2021; Catherine 2022). These income processes generally contain a richer set of stochastic shocks than those that individuals face in my model, which I omit because of computational constraints that arise with an endogenous income process. Nevertheless, it is instructive to compare my parameter estimates with those in the baseline specification from Guvenen et al. (2022), who estimate a similar model with exogenous income using US data.

My estimate of the standard deviation of the individual fixed effect is 0.60, lower than the 0.77 in Guvenen et al. (2022). This primarily reflects the cross-sectional standard deviation of income at age 22 being approximately 20% lower in Australia than in the US. Additionally, I estimate a standard deviation of transitory shocks that is approximately 30% smaller, which reflects the combination of two forces. First, the cross-sectional variance of income is lower, and the 10th/90th percentiles of income growth are less dispersed in Australia. Second, the fact that labor supply is endogenous implies that some transitory variation in income arises endogenously from labor supply adjustments rather than from transitory wage shocks.[2] Last, my estimate of the standard deviation of permanent shocks is approximately three times as large. In addition to differences in data, this primarily reflects that I estimate $\rho = 0.93$ rather than imposing $\rho = 1$. This lower ρ partly reflects the heterogeneity in income profiles across education groups, which requires a larger variance

[2]The fact that labor supply endogenously creates more volatility in income reflects the fact that GHH preferences have no wealth effects. In the baseline model, the ratio of the pooled variance of wage rates to income is 77%.

of permanent shocks to match the percentiles of 5-year income growth.

A.3 Literature on Security Design

An extensive theoretical literature in corporate finance, banking, and financial intermediation studies security design, attempting to rationalize the observed set of financing instruments with frictions such as moral hazard, adverse selection, and costly state verification (see e.g., Jensen and Meckling 1976; Townsend 1979; Diamond 1984; Innes 1990). Relative to the security design problems in this literature, the constrained-planner's problem in (18) has many differences that reflect differences in application. In particular, this paper considers repayment contracts between borrowers and the government, while this literature typically considers firms or financial intermediaries contracting with outside investors.

At a high level, there are three important differences between (18) and typical security design problems. First, in the case of the latter, security sellers (i.e., borrowers in my setting) typically exert no effort if the financing contract gives them no stake in the outcome (e.g., Hébert 2018). In contrast, in my setting, borrowers want to generate income that can be used for consumption regardless of the financing contract. In other words, borrowers always have a stake in the outcome, effectively weakening the moral hazard problem. The second difference is that incomplete markets create a wedge between the pricing kernels of security sellers (i.e., borrowers) and buyers (i.e., the government). This is not the case in standard security design problems, where both groups of agents are risk-neutral (e.g., Innes 1990; Hébert 2018). This difference creates scope for risk-sharing; the extent of risk-sharing in the optimal contract is an empirical question that depends on the size of the moral hazard problem.[3] The final difference is the specific type of moral hazard that I consider: a reduction in labor supply. This is most analogous to the moral hazard problem of incentivizing effort (Jensen and Meckling 1976; Innes 1990).[4] However, the literature on security design has studied various other forms of moral hazard that are not present in my model, such as risk-shifting and free disposal. I do not incorporate these in my model because I do not have any empirical evidence to discipline their exact forms or magnitudes.

Appendix B. Theoretical Appendix

B.1 Derivation of (2)

I assume the following regularity conditions hold: there exist values of $\{c_t, \ell_t\}_{t=0}^{T}$ and D_0 that maximize individuals' objective function; $u(\cdot)$, $f(\cdot)$, and $d(\cdot)$ are continuously differentiable; there exists a value of θ that maximizes (1). Under these assumptions, the envelope theorem implies that the first order condition to the planner's problem, (1), can be written as:

$$\sum_{t=1}^{T} \mathbf{E}_0 \left[u_c^t(c_t, \ell_t) \frac{\partial d_t}{\partial \theta} \right] = \lambda' \left[\sum_{t=1}^{T} \mathcal{R}_t^{-1} \mathbf{E}_0 \left(\frac{dd_t}{d\theta} \right) - \frac{dD_0}{d\theta} \right].$$

[3] Appendix D.7 shows that when the progressivity of the tax system is optimized, there is no gain from using income-contingent loans relative to debt contracts with forbearance. This is consistent with the optimality of debt for effort provision in the security design literature when there is no scope for risk-sharing. However, the fact that debt does not dominate might reflect that borrowers implicitly already have some skin in the game.

[4] Because my model is dynamic, there is some notion that borrowers shift other moments of the distribution of the net present value of repayments, but mostly it is from shifting the mean.

The left-hand side of this expression is the impact on borrower welfare from the change in repayments. The welfare impact of an infinitesimal change in the contract, $d\theta$, depends only on its direct effect on consumption. The impact of the change in repayment contract on individuals' decisions does not affect welfare because these effects are second-order: individuals are already making these choices to maximize $V(\theta)$. The right-hand side of this expression is the two fiscal externalities from the change in the repayment contract that individuals do not internalize. The first fiscal externality can be rewritten as:

$$\frac{dd_t}{d\theta} = \frac{\partial d_t}{\partial \theta} + \frac{\partial d_t}{\partial y_t}\frac{dy_t}{d\theta}.$$

This comprises two effects: a mechanical effect, which captures the change in the structure of the repayment contract on fiscal revenue, and a behavioral response. This behavioral response is ex-post moral hazard: individuals may adjust their labor supply in response to a change in the repayment contract. The second fiscal externality represents ex-ante moral hazard. Finally, note that the envelope theorem also implies that $u_c^0(c_0, \ell_0) = \frac{\partial V}{\partial A_0}$. Combining the previous three expressions with the definition of M_t and λ delivers the desired result.

B.2 Debt and Tax Effects of Income-Contingent Loans

Consider an individual with HELP debt, D, who chooses consumption, c, and labor supply, ℓ, to maximize the discounted sum of utility subject to a standard budget constraint and the HELP repayment contract. This problem can be formulated recursively as follows:

$$V(A, D) = \max_{c,\ell} u(c, \ell) + \beta \int V(A', D') dF_{w'|w}$$

subject to:

$$\begin{aligned} &c + A' = AR + y - d(y, D), \quad y = w\ell, \\ &D' = (1 + r_d)D - d(y, D), \quad w' = g(w, \omega), \quad \omega \sim F_\omega, \end{aligned}$$

where $d(y, D)$ denotes the required debt payment that depends on income and debt. I assume throughout that utility is increasing in consumption, $u_c > 0$, decreasing in labor supply, $u_\ell < 0$, d is differentiable in both arguments, and the initial debt, D, is sufficiently high such that $D' > 0$. The first order condition for labor supply is:

$$-\frac{u_\ell}{u_c w} = \underbrace{(1 - d_y)}_{\text{tax effect}} - \underbrace{\beta d_y \frac{\mathbf{E}V_{D'}}{u_c}}_{\text{debt effect}}.$$

This equation shows that income-contingent debt has two effects on labor supply. The first term captures that income-contingent repayments discourage labor supply by reducing the return on the marginal unit of labor supply, just like a tax. The second effect is specific to debt: increasing labor supply reduces the stock of future debt. If the value function decreases in debt, $V_{D'} < 0$, the debt effect implies that individuals may choose to locate above the threshold if the marginal value of repaying their debt is sufficiently high.

The first order condition for labor supply can be rewritten as:

$$-\frac{u_\ell}{w} = u_c + d_y \left(-\beta \mathbf{E}V_{D'} - u_c\right).$$

The previous expression shows that for the debt effect to dominate and make individuals locate above the repayment threshold, the (discounted) marginal value of reducing debt must be greater than the marginal utility of consumption. This is unlikely to be the case because HELP debt has a zero real rate, which means it is the lowest-cost source of borrowing that individuals can access. More formally, this can be shown as follows. Assume that debt repayment, d, is only a function of D when debt is repaid:

$$d(y, D) = \tilde{d}(y) * \mathbf{1}_{\tilde{d}(y)<(1+r_d)D} + D * \mathbf{1}_{\tilde{d}(y)\geq(1+r_d)D}.$$

This is the case for all income-contingent loans, and it implies that

$$d_D = \mathbf{1}_{\tilde{d}(y)\geq(1+r_d)D}.$$

Given that the envelope theorem implies that

$$V_D = -d_D u_c + \beta(1 + r_d)\mathbf{E}V_{D'},$$

combining the last two lines gives the following result:

$$\beta(1 + r_d) < 1 \implies -V_D \leq u_c.$$

In other words, if borrowers' private discount rate is below the (gross) interest rate on debt, consumption is more valuable than debt repayment, and individuals will not locate above the repayment threshold. The fact that individuals can make voluntary repayments but many do not supports this claim: if the marginal value of reducing debt was higher than consumption, more individuals should make voluntary payments.

Appendix C. Empirical Appendix

C.1 Additional Institutional Details

Timing and collection of HELP repayments. Individuals can make compulsory HELP repayments, which are the repayments calculated according to the HELP repayment schedule at the time the individual's tax returns are filed, or voluntary HELP repayments, which are additional repayments made at any point in time. If individuals are working, they are required to advise their employer if they have HELP debt. The employer will then withhold the corresponding compulsory repayment amounts from an individual's pay throughout the year if the individual's wage or salary is above the repayment threshold. These withheld amounts are used to cover any compulsory repayments due when the tax return is filed. The tax year in Australia runs from July 1st to June 30th (e.g., the 2023 income tax year runs from July 1st, 2022 to June 30th, 2023), and tax returns must be filed by October 31st. On June 1st, HELP debts are subject to indexation, which refers to increasing the outstanding debts based on the indexation rate. The indexation rate is the nominal interest rate on HELP debt, which is based on the year-on-year quarterly CPI calculated with the March quarter CPI. It is calculated by dividing the sum of the CPI for the four quarters ending in March of the current year by the sum of the index numbers for the four quarters ending in March for the preceding years.[5] For most individuals,

[5] See here for additional details.

indexation occurs prior to the deduction of compulsory repayments because these repayments are deducted at the time of tax filing, which generally occurs between July 1st and October 31st. This is true even if an employer withholds repayments, as these repayments are not applied until the individual's tax return is filed.

Other changes to HELP repayment schedule. Since HELP was introduced in 1989, there have been several changes to the repayment schedule detailed in Ey (2021). In the early years of the program, changes were more common: the schedule changed in 1991, 1994, 1996, and 1998. However, after 1998, there have been only two changes: the 2005 policy change that I study and a 2019 policy change that was phased in over two years. The fact that there have been several changes to the HELP repayment threshold is not ideal because it implies that the model will underestimate long-run labor supply responses: in the model, the policy change is unexpected and permanent, while empirically, individuals may expect other changes in the future that attenuate their responses. However, the size of this bias is likely small because news articles written at the time of the policy change suggest that the policy change was expected to last for several years. (e.g., Marshall 2003). In contrast, Figure A15 shows that the persistence of bunching below the repayment threshold is only around three years, likely shorter than when individuals expected a subsequent policy change. The same logic applies if the policy change was anticipated: because there is not a lot of persistence in individuals' responses, it is unlikely that they would not respond even if they expected a policy change in a few years.[6]

Discount for upfront and voluntary payments. In prior years, HELP provided discounts to individuals who paid their debt balances upfront and discounts for voluntary repayments. The upfront payment discount took the following values: 15% from 1989-1992, 25% from 1993-2004, 20% from 2005 to 2011, 10% from 2012 to 2016, and 0% after 2016. Unfortunately, *ALife* does not allow me to identify upfront payments, so I do not include this margin in the model. The fact that most upfront payments came from high-income individuals with family support (Norton 2018) suggests this is likely to bias my results in one of two ways. On the one hand, existing literature finds taxable income elasticities increase with income (e.g., Gruber and Saez 2002), which would suggest the model understates the moral hazard created by income-contingent repayment. On the other hand, the probability of repayment is higher for high-income individuals. Given labor supply responses decrease with the probability of repayment, this suggests the model overestimates the moral hazard income-contingent repayment creates, reinforcing my qualitative conclusions. Nevertheless, the fact that aggregate upfront payments have been low and stable despite the variation in discounts (Figure A3) suggests any bias from omitting this margin is likely to be small.

The discount for voluntary repayments took the following values: 0% from 1989-1994, 15% from 1995-2004, 10% from 2005-2011, 5% from 2012-2015, and 0% after 2015. Voluntary repayments cannot be precisely estimated in *ALife*. The fact that I do not model voluntary repayments likely leads to an upward bias in the estimate of the labor supply elasticity: the benefit of locating below the repayment threshold is even higher in a model with an option for voluntary repayments because doing so allows any payments individuals make to be classified as voluntary and thus subject to a discount. Nevertheless, this bias is likely small because voluntary repayments are uncommon for most borrowers (Norton and Cherastidtham 2016). In fact, personal finance websites suggest that young HELP debtors should avoid making voluntary repayments if they have credit card or personal debts and that if a debtor earns below the threshold, voluntarily paying off HELP debt is probably not the best use of money (MoneySmart 2016).

Wage-setting in Australia. There are three wage-setting methods in Australia. The first method is through

[6] Figure 3 shows little evidence of anticipation in the years leading up to the policy change.

award-based wages, in which centralized bodies set the minimum terms and conditions for employment, including a minimum wage. The primary body responsible for setting these conditions is the Fair Work Commission, which operates at national level. The second method is through enterprise agreements, which set a rate of pay and conditions for a group of employees through negotiation. This method of wage setting is analogous to that used by labor unions in the US. Finally, individual arrangements set wages and conditions for employees on an individual basis. Individual arrangements and enterprise agreements are the dominant forms of wage-setting, accounting for approximately 40% each of total wage-setting arrangements, while award-based wages make up approximately 20%.[7]

C.2 Comparison of Institutional Environments in Australia and US

This section describes similarities and differences between Australia and the US, summarized in Table A1. Although these countries are similar in many ways, some institutional differences are important when considering whether welfare gains from income-contingent repayment would generalize in the US.

The first notable difference is the cost of higher education: the student contribution at a public undergraduate institution for a Commonwealth Supported Place in Australia is around $6,400 USD after subtracting the government subsidy. This is comparable to the average undergraduate tuition at a 4-year in-state public institution in the US but much smaller than tuition for a 4-year (non-profit) private degree. Unlike in the US, where many students receive scholarships and grants that reduce tuition below the "sticker price", this is extremely rare in Australia. In addition to differences in tuition, the cost of room and board and books and supplies are slightly higher in the US. These higher costs contribute to the second difference between Australia and the US: the amount individuals borrow from government-provided student loans. In Australia, this is around $20,000 on average, while in the US, it's around $50,000 (Catherine and Yannelis 2023). The fact that debt balances are higher in the US means that the scope for welfare gains from optimizing contract design is even larger, as shown in Table 6. However, the higher loan balances also reflect that undergraduate degrees last a year longer in the US and, more importantly, that student loans in Australia can only be used to cover tuition.[8] Although the latter is useful for identification, as discussed in Section 2.3, it implies that borrowers in the US have more flexibility to adjust their borrowing using discretionary expenses, such as room and board. This introduces scope for ex-ante moral hazard, in which individuals who anticipate low incomes borrow more in anticipation of low repayment. Quantifying the strength of this force is an important task for future research because it could undermine the effectiveness of income-contingent repayment in the US. It is also especially relevant for the equity contracts studied in Section 7.3, which create large incentives to adjust initial debt balances.

Like in Australia, the US government is the only provider of income-contingent loans and these loans are not dischargeable in bankruptcy. However, in the US, the government offers non-income-contingent contracts, and an active private market provides financing to high-income borrowers at lower rates (Bachas 2019). Both of these features are useful for my empirical analysis, as discussed in Section 2.3, and the former is not an issue for my normative analysis since I focus on the design of a single government-provided financing contract. In contrast, the presence of a private market implies that the degree of insurance that can be provided by income-contingent repayment in the US is limited: trying to collect repayments quickly from high-income

[7] See, for example, https://www.rba.gov.au/publications/bulletin/2019/jun/pdf/wages-growth-by-pay-setting-method.pdf.

[8] To finance nontuition expenses, students on income support can use a Student Start-Up Loan, but these loans only supported fewer than 100,000 borrowers in 2020–21. All other students must self-finance these expenses, which they generally do by using credit cards or taking jobs.

Table A1. Comparison of Australia and US

Feature of Environment	Australia	US
Cost of Higher Education		
Public Undergraduate Tuition Cost	$2,700–$10,100 USD per year for CSPs	$9,500 USD per year for 4-Year In-State $39,000 USD per year for 4-Year Private Nonprofit
Prevalence of Scholarships	Rare	Common
Cost of Books and Supplies	$850 USD per year	$1,200 USD per year
Cost of Room and Board	$9,000 USD per year	$12,000 USD per year
Total Cost of Attendance	$15,850 USD per year	$22,700 USD per year
Bachelors Degree Length	3 Years	4 Years
Financing of Higher Education		
Initial Student Debt Borrowed	$8,100–$30,300 USD	$51,800 USD (Average)
Uses of Student Debt	Tuition only	Tuition, textbooks, fees, room and board
Provider of Income-Contingent Loans	Government	Government
Eligibility for Income-Contingent Loans	Australian and NZ citizens, permanent humanitarian resident	US citizens, permanent residents, eligible non-citizens
Interest Rate on Debt	CPI	~2% above T-Bill rate
Student Debt Dischargeable	No	No
Other Contracts Available	No	Yes
Private Financing Available	No	Yes
Government-Regulated Tuition	Yes	No
Enrollment Caps	Yes (for CSPs)	No
Student Population		
% of Population with Undergraduate Degree	38%	32%
% of Undergraduates at Private Universities	6%	26%
% of Undergraduates from Abroad	16%	5%
% of Current Students Employed	50%	40%
% Dropout within First Year	20%	33%
Income Distribution and Taxes/Transfers		
Median Personal Income	$33,500 USD	$40,500 USD
Poverty Line for Single Individual	$16,200 USD	$14,580 USD
Gini Coefficient for Income	0.32	0.38
Marginal Tax Rate at Average Income	41%	41%
Heathcote et al. (2017) Tax Progressivity	0.133	0.184
1-Month Individual UI Replacement Rate	23%	35%
Union Membership Rate	13.7%	10.3%

Notes: The sources for various statistics are shown as hyperlinks. All statistics are computed in the most recent year available.

borrowers to finance reduced payments from low-income borrowers may lead private lenders to cream-skim high-income borrowers with more favorable financing terms. Nevertheless, the analysis in Section 8.2 suggests that such selection is much more important for equity contracts than income-contingent loans.

An additional difference between Australia and the US is that HELP loans are significantly more subsidized

than student loans in the US because of the zero real interest rate. A less subsidized contract, such as those in the US, would only draw in individuals who place higher values on education. If the structural parameters governing labor supply are correlated with individuals' valuation of education, such a contract could generate different labor supply responses—this would be selection on moral hazard or an anticipated effort effect in the language of Karlan and Zinman (2009). Ex-ante, the sign of this correlation is unclear: individuals who place a higher value on education may be more motivated by non-pecuniary factors, which would lead to a negative correlation. Alternatively, these individuals may value education more because they have a higher labor supply elasticity and, thus, are more willing to work hard in response to higher wages, generating a positive correlation. Because of this concern, my counterfactual analysis focuses on repayment contracts with a similar fiscal cost to HELP. However, the caveat of this approach is that it limits the applicability of this analysis to the US, which provides a smaller subsidy.

The final important difference between the structure of higher education in Australia and the US is that the Australian government places caps on tuition at public universities[9] and has enrollment caps for Commonwealth Supported Places (the students who receive a government contribution to their tuition).[10] Because tuition is not government-regulated in the US, universities respond to changes in government subsidies by changing tuition, which is known as the "Bennett hypothesis" (Kargar and Mann 2023). In principle, universities could respond similarly to the adoption of government-provided income-contingent contracts, but, as my normative analysis shows, such contracts can be implemented even with the same subsidy level (i.e., fiscal cost) as fixed repayment contracts. Nevertheless, universities could still respond by changing tuition to select students with differential subsidies between the two types of repayment contracts. With no enrollment caps, universities could admit many borrowers with large subsidies, increasing the fiscal cost of income-contingent repayment to the government.

The bottom of Table A1 presents summary statistics on the income distribution and the social insurance system in Australia and the US. Median income and income inequality are lower in Australia: Australia has a Gini coefficient around halfway between France and the US. The personal income tax schedules are similar in terms of average level and progressivity, but Australia has a lower unemployment benefit replacement rate than the US, one of the lowest among OECD countries. Overall, Australia and the US are broadly similar in these aggregate statistics, suggesting differences in the institutional structure of higher education are more important when considering the applicability of my results to the US.

C.3 Data and Variable Construction

C.3.1 *ALife*

ALife provides access to a 10% random sample for approved projects. My code and analysis were tested on this sample and then were executed on the population sample by research professionals at *ALife*. The remainder of this section provides additional details on variable definitions based on the underlying variables that I construct. For description of these underlying variables, see the following link: `https://alife-research.app/research/search/list`. Variable definitions are presented in `Python 3.9`, where `df` refers to the

[9] Private institutions play a relatively small role in Australia, comprising only 3 out of the country's 42 universities and 6% of the domestic enrollment share as of 2021. These institutions are slightly more popular among international students, with 11.7% of the enrollment share. Private institutions are much more expensive than public ones, especially for domestic students, and primarily compete by offering more niche products.

[10] An exception is that during 2012–2017, these caps were not in place and the system was "demand-driven" (D'Souza 2018; Norton 2019).

underlying *ALife* dataset as a `Pandas DataFrame`. When variables are missing from *ALife* in a given year, they are replaced with zero unless otherwise mentioned in the text.

Demographic variables. Age is defined as `c_age_30_june`. Gender is defined based on `c_gender`. Additional demographic variables for whether an individual files a tax return electronically, has a child, or has a spouse are defined as follows:

```
df['electronic'] = df['c_lodgement_type'].isin(['MYTAX','ETAX']).astype(int)
df['has_child'] = (df['c_depend_child'].fillna(0) > 0).astype(int)
df['has_spouse'] = (df['sp_status_reported'] != '0_no_information').astype(int)
```

Salary & Wages. Defined as `i_salary_wage`. This item is technically reported by taxpayers, but it is third-party reported in the sense that the ATO receives pay-as-you-go payment summary data from employers that includes this item. This item is pre-filled if the taxpayer files electronically and the ATO cross-checks discrepancies between taxpayer- and employer-reported values.

Taxable Income. Defined as `ic_taxable_income_loss`.

HELP Income. The definition of HELP income has changed since the introduction of HECS in 1989. For the 1989 to 1996 Australian tax years, HELP income was equal to taxable income. Between 1996 and 1999, net rental losses were added back. Between 2000 and 2005, net rental losses and total reportable fringe benefits amounts were added back. Between 2006 and 2009, net rental losses, total reportable fringe benefits amounts, and exempt foreign employment income were added back. After 2010, net rental losses, total reportable fringe benefits amounts, exempt foreign employment income, net investment losses, and reportable superannuation contributions were added back. In *ALife*, I construct this variable as follows:

```
df['help_income'] = np.maximum(df['ic_taxable_income_loss'], 0)
adds = ['help_income']
if yr >= 2000:
  adds += ['it_rept_fringe_benefit']
if yr >= 2006:
  adds += ['isn_fsi_exempt_empl']
if yr >= 2010:
  adds += ['it_property_loss', 'it_invest_loss',
      'it_rept_empl_super_cont']
df[adds] = df[adds].fillna(0)
if yr >= 2000:
  df['it_rept_fringe_benefit'] *= ((df['it_rept_fringe_benefit'] >=
                    fringeb_tsh[yr]).astype(int))
df['help_income'] = df[adds].sum(axis = 1)
```

In this variable definition, `fringeb_tsh` refers to the reporting threshold for fringe benefits, which varies by year. This variable definition is not a perfect replication of HELP income due to a lack of data availability on certain items from the ATO. However, discussions with *ALife* suggest that any error in measurement is likely to be relatively small. Additionally, I find quantitatively similar results across years in which there is a change in the HELP repayment definition, suggesting that changes in the components added back to taxable income are not driving my main results.

Labor Income and Wage-Earner.

```
df['psi_b9'] = df['i_attributed_psi'].fillna(0)
df['psi_b14'] = df['is_psi_net'].fillna(0)
df['pship_b13'] = df[['pt_is_pship_dist_pp', 'pt_is_pship_dist_npp']].fillna(0).sum(axis = 1)
df['solet_b15'] = df[['is_bus_pp', 'is_bus_npp']].fillna(0).sum(axis = 1)
```

```
df['wage_earner'] = (np.abs(df[['psi_b9', 'pship_b13', 'solet_b15']]).max(axis = 1) == 0).astype(int)
laborvars = ['i_salary_wage', 'i_allowances', 'psi_b9', 'psi_b14',
        'pship_b13', 'solet_b15']
df['labor_income'] = df[laborvars].fillna(0).sum(axis = 1)
```

Interest & Dividend Income.

```
df['interest_dividend'] = df[['i_interest', 'i_div_frank', 'i_div_unfrank']].sum(axis = 1)
```

Capital Income.

```
capitalvars = ['i_annuities_txd', 'i_annuities_untxd',
        'i_annuities_lsum_txd', 'i_annuities_lsum_untxd',
        'i_super_lsum_txd', 'i_super_lsum_untxd',
        'i_interest', 'i_div_frank', 'i_div_unfrank',
        'pt_is_trust_dist_npp', 'pt_is_frank_dist_trust_npp',
        'is_cg_net', 'is_net_rent']
df['capital_income'] = df[capitalvars].fillna(0).sum(axis = 1)
```

Net Deductions.

```
df['net_deduc'] = -(df['help_income'] - df[['labor_income', 'capital_income']].sum(axis = 1))
```

HELP Debt and Repayment. HELP Debt and HELP Repayment correspond to the variables `help_debt_bal` and `hc_repayment`, respectively.

Superannuation balances. Defined as `sb_mem_bal`.

Occupation-level measure of evasion. The sample of individuals used to calculate this measure of evasion is the *ALife* 10% random sample of individuals in the population *ALife* dataset who satisfy the sample selection criteria in Section 2, are wage-earners, and have annual salary and wages greater than one-half the legal minimum wage times 13 full-time weeks (Guvenen et al. 2014). The evasion measure is then computed as the share of all workers in each occupation, `c_occupation`, who receive income from working in the form of allowances, tips, director's fees, consulting fees, or bonuses, which are reported jointly in `i_allowances`. This item is subject to the same reporting requirements as Salary & Wages.

Indicator variable for switching occupations. Equals one if the value of `c_occupation` changes from one year to the next for a given individual.

C.3.2 MADIP

MADIP provides access to population-level data on health, education, government payments, income and taxation, employment, and population demographics (including the census) over time for approved projects. I obtained access to the datasets from the ATO and the 2016 Census of Population and Housing, which I merge using a unique identifier known as the MADIP Spine. Based on the 2016 Census of Population and Housing, I construct the following variables.

HELP Income. Computed using same definition as in *ALife*.

Hours Worked. I measure hours worked using `HRSP`, which corresponds to individuals' reported hours worked in all jobs during the week before the census night.

Housing Payment–to–Income Ratio. This is calculated by annualizing monthly mortgage payments from the census files, `MRED`, and weekly rent payments, `RNTD`, by multiplying by 12 and 52, respectively. I adjust for inflation, converting these to 2005 AUD, using the HELP threshold indexation rate. I define total housing payments as the sum of the two. For the majority of individuals, only one is positive. I then divide by HELP Income to obtain the payment-to-income ratio.

C.3.3 HILDA

I construct the following variables from HILDA, which is publicly available.

Hourly Flexibility: panel measure. Hourly flexibility is measured as the standard deviation of annual changes in log hours worked per week across all jobs, `jbhruc`. Before computing this measure at the occupation-level, I restrict the sample to individuals in the 2002–2019 HILDA survey waves who satisfy the following conditions: (i) report being employed; (ii) earn a positive weekly wage; (iii) do not switch occupations between two subsequent years; and (iv) are between ages 23 and 64. Prior to computing the standard deviation, I winsorize annual changes in log hours at 1%–99%. The standard deviation within each occupation is computed with longitudinal survey weights.

Hourly Flexibility: cross-sectional measure. I construct an alternative measure of hourly flexibility as the cross-sectional standard deviation of log hours worked per week across all jobs, `jbhruc`. I impose the same sample filters as when I compute the panel-based measure. Prior to computing the standard deviation, I winsorize log hours at 1%–99%. The standard deviation within each occupation is computed with cross-sectional survey weights.

C.4 Computation of Excess Bunching Mass Statistic, b

The bunching statistic that I compute follows Chetty et al. (2011) and Kleven and Waseem (2013). First, I fit a five-piece spline to each distribution, leaving out the region $\mathcal{R} = [\$32,500, \$35,000 + X]$. When fitting this spline, I calculate the distribution in bins of $\$250$ and center the bins so that one bin is $(\$34,750, \$35,000]$. The choice of $\$32,500$ as a lower point of the bunching region represents a conservative estimate of where the bunching begins, and X is a constant intended to reach the upper bound at which the income distribution is affected by the threshold. This spline corresponds to an estimate of the counterfactual distribution absent the threshold. Formally, this counterfactual distribution is estimated by regressing the distribution onto the spline features along with separate indicator variables for each $\$250$ bin in $\mathcal{R}$.

Next, for each possible $X > 0$, I sum all the estimated coefficients on all the indicator variables and normalize by the sum of the estimated coefficients on the indicator variables below the threshold. Taking the absolute value of this delivers an estimate of the error in the estimate of the counterfactual density, since the sum of these coefficients should be zero under a proper counterfactual density. I then choose the value of X that minimizes this absolute error. Finally, I compute the bunching statistic, b, as:

$$b = \frac{\text{observed density in } \mathcal{R}}{\text{counterfactual density in } \mathcal{R}} - 1.$$

This bunching statistic is an estimate of the excess number of borrowers below the repayment threshold

relative to a counterfactual distribution in which the threshold did not exist.

Computing this bunching statistic requires specifying the area of the income distribution that is being approximated with the counterfactual density. In all figures that present the bunching statistic along with an income distribution, I approximate the counterfactual density on the same range as the plot. In all other figures, I approximate between $[\$30,000, \$40,000]$. This smaller window is chosen because in these other plots, in which I split the sample to explore heterogeneity, the income distribution is more noisy. Including points further away from this threshold causes the estimate of the counterfactual density to be poorly behaved.

Appendix D. Structural Model Appendix

D.1 Model Solution and Simulation

Discretization of state variables. I have five continuous state variables that I discretize. During retirement, liquid wealth, $A_a R$, is placed onto a grid with 101 points that varies with age. The lower point of the grid linearly decreases from the minimum allowed value based on the borrowing constraint $a = a_R$ to 0 at $a = a_T$. During working life, the grid has 31 points, and the lower point on the grid is set to the lowest value allowed by the borrowing constraint. At all ages, the upper point of the liquid wealth grid is 100 times the numeraire, which is \$40,000 AUD in 2005, and the points are on a power grid with curvature parameter 0.2.[11] Debt, D_a, is placed onto a power grid that varies with age with 11 grid points, curvature parameter 0.35, a lower value of 0, and an upper value that starts at 3.67 at $a = a_0$ and is multiplied by $1 + r_d$ in each subsequent period. Past labor supply, l_a, is placed on a grid with 25 grid points. The grid is centered at 1 and ranges from 0 to 2. The upper and lower halves of the grid are split into 2 and are power grids with curvature parameter 0.5. The grid for θ_i depends on the parameter values and has 21 points. The grid is centered at zero with upper and lower bounds equal to $\pm 4\sqrt{\sigma_i^2 + \sigma_\nu^2}$. Each half of the grid is a power-spaced grid with curvature parameter 0.7. The grid for ϵ_a is computed as the nodes from a Gauss–Hermite quadrature with 7 nodes. The remaining states are age, which is discretized on a grid that is evenly spaced from a_0 to a_T with increments of one; time, which takes two values $t \in \{2004, 2005\}$ to index before and after the policy change; the Calvo shock, which takes a value of zero or one; and $\mathcal{E}_i \in \{0, 1\}$.

Solution algorithm. The model has a finite horizon and a terminal condition and hence can be solved by means of backward induction in age starting with the terminal condition in the final year of life. There are two notable aspects of the solution algorithm that are crucial for getting the simulated minimum distance objective function to be smooth in the set of parameters in Figure A20. First, no choice variables are discretized, meaning I use continuous optimization routines rather than grid searches to find optimal policies. Second, I use Gauss–Hermite quadratures to integrate all continuous shocks, which means that continuous shocks are drawn from continuous rather than discretized distributions when I simulate from the model.

For the period during retirement, I keep track of one value function that is a function of two states: wealth and age. The terminal condition for the model is that $E_{a_T-1} V_{a_T}^{1-\gamma} = 0$, which embeds the assumption that $u_d^{1-\gamma} = 0$, where u_d is the utility upon death. This assumption is standard in life cycle models with recursive

[11] A power grid for an array of values x is a grid that is evenly spaced on the unit interval for the function $x^{k^{-1}}$, where k is the curvature parameter. The grid is the adjusted from the unit interval based on the specified lower and upper grid points.

preferences.[12] Starting with this condition, I then solve the model in prior periods by finding the optimal consumption-savings choice using a golden-section search with boundaries set based on the borrowing constraint and positive consumption. I continue this backward induction until $a = a_R - 1$.

During working life, I keep track of two value functions that are solved separately for each $\mathcal{E}_i \in \{0, 1\}$. I describe how I solve for one of these, since the approach is the same, with the only difference that a different value of $\mathcal{E}_i$ changes the state transition equations. This backward induction during working life begins with the value function at retirement, $a = a_R$, as the terminal condition. At each age, for each of the grid points in the seven-dimensional state space that excludes the Calvo shock, I solve for optimal choices of savings and labor supply. I do this twice: once in the case when $\omega_a = 0$, in which case I solve for savings using a golden-section search and labor supply is held fixed, and once for the case in which $\omega_a = 1$, where I solve for savings *and* labor supply using a Nelder–Mead algorithm. The bounds for the Nelder–Mead algorithm are set based on the budget constraint for assets and between 0 and 10 for labor supply. The starting point is set equal to β times cash-on-hand for assets and 1 for labor supply. I perform the Nelder–Mead up to three times, varying the starting point for labor supply, until the result passes a convergence check. When solving for these optimal policy functions at a, I have to integrate V_{a+1} over θ_{a+1}, which depends on the stochastic shock, ν_{a+1}, and have to interpolate the value function in the continuous states. I perform the integration using a Gauss–Hermite quadrature with 9 nodes and use linear interpolation (and extrapolation, if necessary).[13] Linear interpolation is extremely accurate, which allows me to use few grid points as long as choice variables are not discretized, because the Epstein–Zin value function is approximately linear in wealth. Having solved for optimal choices and hence the value function in the seven-dimensional state space at each age, I then integrate out ω_a and ϵ_a to obtain a value function that depends on five states for each age: past labor supply, debt, permanent income, liquid savings, and t.[14] I continue this backward induction until $a = a_0$ and perform it twice for each $\mathcal{E}_i \in \{0, 1\}$.

Simulation procedure. I simulate N individuals, where q_e have debt at age 22 and $q_e = 0.9 > p_e$ so that I oversample individuals with $\mathcal{E}_i = 1$ to obtain a smaller approximation error among most of the estimation targets, which are computed among this group. To ensure comparability with the data, I then compute only the estimation targets that have observations on both individuals with $\mathcal{E}_i = 0$ and those with $\mathcal{E}_i = 1$ using all $(1 - q_e)N$ model observations for individuals with $\mathcal{E}_i = 0$ but only x observations for individuals with $\mathcal{E}_i = 1$, where x is given by:

$$\frac{x}{N(1-q_e)+x} = p_e \Rightarrow x = N(1-q_e)\frac{p_e}{1-p_e}.$$

Software and hardware. The code to solve and estimate the model was compiled with the `mpiifort` compiler from the January 2023 version of Intel oneAPI. Each solution and simulation was parallelized across 768 CPUs using MPI and then double-threaded across the two threads on each CPU using OpenMP, using a total of 1536 threads on the MIT SuperCloud (Reuther et al. 2018). For a given set of parameters, each iteration of solving the model, simulating from it, and calculating the simulated minimum distance objective function took approximately 30 seconds in total when parallelized across all these threads. The number of simulations, N, was chosen to be as large as possible while still being able to fit the necessary outputs in double precision in RAM of each CPU, which is 4GB.

[12] With $\gamma > 1$, it implies that $u_d = \infty$. Bommier et al. (2020) point out some undesirable implications of this assumption in models where mortality is endogenous, which is not the case in my model.

[13] When solving the model with learning-by-doing, I add a constant of 0.001 to l_{ia-1} in (7) when integrating over θ_{a+1} to prevent numerical instability.

[14] At all places where I integrate, I compute certainty-equivalents rather than expectations since I am using Epstein–Zin preferences.

D.2 First-Stage Calibration

This section provides a detailed description on the calibration of the parameters discussed in Section 4.2.1. Whenever possible, I calibrate parameters to match their observed values during the *ALife* sample period.

Demographics. Individuals are born at age 22 (the typical age at which students graduate university in Australia), retire at age 65 (the age at which the Australian retirement pension began to be paid in 2004), and die with certainty after age 89. Survival probabilities prior to age 89 are taken from the APA life tables.[15] I calculate the cohort-specific birth rates, $\{\mu_h\}$, by constructing a dataset of individuals from *ALife* at $a = a_0$ and then calculating the fraction of individuals who are age a_0 in each year between $\underline{h}$ and $\overline{h}$. I set the number of distinct individuals to 1.6 million, which is the largest value that allows me to store simulated results from the model in double precision and stay within memory constraints.

To compute equivalence scales, I use data from the HILDA Household-Level File on the number of the adults in each household, `hhadult`, the number of children, defined as the sum of `hh0_4`, `hh5_9`, and `hh10_14`, and the age of the head of the household, `hgage1`. Following Lusardi et al. (2017), I compute the average number of adults and children for each age of the head of the household, denoted by adults_a and children_a. I then compute the equivalence scale at each age using the formula in Lusardi et al. (2017):

$$\tilde{n}_a = \left(\text{adults}_a + 0.7 * \text{children}_a\right)^{0.75}.$$

Finally, I normalize equivalence scales such that the average value is one, so that a household in the model corresponds to the size of the average household in the data:

$$n_a = \frac{\tilde{n}_a}{\sum_a \tilde{n}_a} * a_T.$$

Numeraire. The numeraire in the model is equal to \$1 AUD in 2005. There is no inflation in the model, so all empirical estimation targets, when they are compared with model values, are deflated to 2005 AUD with the indexation rates for HELP thresholds.

Interest rates. To calculate the real interest rate, I compute the average (gross) deposit interest rate in Australia in each year between 1991 and 2019, which is the time period of my *ALife* sample. I then divide these deposit rates in each year in each year by the (gross) inflation rate based on the CPI.[16] I take the geometric average of the resulting time series of real deposit rates between 1991 and 2019, which delivers $R = 1.0184$. To calculate the borrowing rate, I use the average standard credit card rate reported by the Reserve Bank of Australia between 2000 and 2019.[17] After deflating by the same CPI series and computing the geometric average, I obtain an average real credit card rate of 15.4%. Over 2000–2019, the geometric average of the real deposit rate was 0.8%, so I set $\tau_b = 15.4\% - 0.8\% = 14.6\%$.

Borrowing limit. I calculate the age-specific borrowing limit, $\{\underline{A}_a\}_{a=a_0}^{a_T}$, using data on credit card borrowing limits from HILDA. I start from the combined household level files from the 2002, 2006, 2010, 2014, and 2018 waves, which have Wealth modules that contain the total credit limit on all credit cards in the responding

[15] See https://aga.gov.au/publications/life-tables/australian-life-tables-2005-07.

[16] See https://data.worldbank.org/indicator/FR.INR.DPST?locations=AU and https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?locations=AU for these two data series.

[17] See https://www.finder.com.au/credit-cards/credit-card-statistics#interest-rates.

person's name, `crymbl`. Filtering the sample to individuals between 22 and 90, I deflate this variable to 2005 AUD and winsorize at 1%–99%. I then estimate a linear regression of this variable onto a constant and a fourth-order polynomial in age using weighted least squares, where the weights are the cross-sectional survey weights normalized to weight each year equally. Finally, I use the predicted value from this regression for each age as $\underline{A}_a$. The resulting values are:

$$\underline{A}_a = 1.402 \times 10^4 - 1401.63 * a + 33.14 * a^2 - 0.3682 * a^3 + 0.0017 * a^4.$$

Initial assets. I calculate the parameters that govern the initial asset distribution using data on asset holdings from HILDA. I start from the combined household-level files from the 2002, 2006, 2010, 2014, and 2018 waves, which have Wealth modules that contain household-level information on asset holdings. Among individuals who are lone persons (`hhtype` = 24) between ages 18 and 22, I compute liquid assets as the sum of bank account balances (`hwtbani`), cash, money market and debt investments (`hwcaini`), and equity investments (`hweqini`) minus credit card debt (`hwccdti`) and other personal debt (`hwothdi`), deflate the resulting estimates to 2005 AUD, and winsorize at 1%–99%. I split the sample into individuals with HELP debt, who correspond to $\mathcal{E}_i = 1$ in the model, and those wihout HELP debt, who correspond to $\mathcal{E}_i = 0$. I then estimate the fraction of individuals with nonpositive asset balances, $p_A(\mathcal{E}_i)$. Among the individuals in each group with posiitve asset balances, I estimate $\mu_A(\mathcal{E}_i)$ and $\sigma_A(\mathcal{E}_i)$ by fitting a normal distribution to the distribution of positive asset balances among individuals in each group, adjusting for the cross-sectional survey weights that are normalized to weight each year equally. The resulting estimates are shown in Table 2. When simulating from this distribution, I impose an upper bound equal to the largest value that I observe empirically. Additionally, because A_{ia} represents end-of-period savings, I scale A_{ia_0} by R^{-1} so that the liquid assets at $a = a_0$ in the model match the data.

Preference parameters. The preference parameters that I do not estimate because of a lack of identifying variation are relative risk aversion and the elasticity of intertemporal substition. I set $\gamma = \sigma = 2.23$ based on the results in Choukhmane and de Silva (2023), so preferences are time-separable in the baseline. In counterfactuals, I consider the effect of moving risk and time preferences independently.

Interest rate on student debt. I set the (net) interest rate on student debt, r_d, equal to zero, which is the case for HELP debt. In all counterfactuals that I consider, I leave this interest rate set to zero. This is done because the model does not include endogenous early repayment of debt balances. With a zero interest rate, this abstraction is without loss of generality since borrowers have no incentive to pay their debt early.

Distribution of education levels. I set the fraction of individuals with that are borrowers, p_E, equal to the fraction of 22-year-old individuals in *ALife* who have positive debt balances (22 is the age by which most individuals have started their undergraduate degrees in Australia).

Initial student debt balances. I calculate the parameters that govern the initial debt distribution using data on HELP debt balances from *ALife*. First, I deflate the debt balances for all individual–years to 2005 AUD and then calculate the year in which each individual had her maximum real debt balance. From these debt balances, I drop observations in which (i) individuals are not classified by *ALife* as having acquired new debt balances, (ii) the maximum occurs in the year 2019, which is the final year of data, and (iii) individuals are older than 26 years old, which is the age by which most individuals have finished undergraduate studies in Australia and debt balances reach their maximum in real terms. Finally, I estimate μ_d and σ_d by fitting a

normal distribution to the logarithm of these debt balances. When simulating from this distribution, I impose an upper bound equal to the largest value that I observe empirically.

Student debt repayment function. When estimating the model, I use the HELP 2004 repayment function at $t < T^*$ and the HELP 2005 repayment function at $t \geq T^*$.[18] Formally, I set $d(y,i,D,a,t) = \mathbf{1}_{a<a_R} * \min\{HELP_t(y+\max\{i,0\}) * (y+\max\{i,0\}), (1+r_d)D\}$, where

$$HELP_t(x) = \mathbf{1}_{t<T^*} HELP_{04}(x/\pi_{05}) + \mathbf{1}_{t\geq T^*} HELP_{05}(x),$$

$$HELP_{04}(x) = \begin{cases} 0 & \text{if } x \leq 25347, \\ 0.03 & \text{else if } x \leq 26371, \\ 0.035 & \text{else if } x \leq 28805, \\ 0.04 & \text{else if } x \leq 33414, \\ 0.045 & \text{else if } x \leq 40328, \\ 0.05 & \text{else if } x \leq 42447, \\ 0.055 & \text{else if } x \leq 45628, \\ 0.06 & \text{else,} \end{cases} \quad HELP_{05}(x) = \begin{cases} 0 & \text{if } x \leq 35000, \\ 0.04 & \text{else if } x \leq 38987, \\ 0.045 & \text{else if } x \leq 42972, \\ 0.05 & \text{else if } x \leq 45232, \\ 0.055 & \text{else if } x \leq 48621, \\ 0.06 & \text{else if } x \leq 52657, \\ 0.065 & \text{else if } x \leq 55429, \\ 0.07 & \text{else if } x \leq 60971, \\ 0.075 & \text{else if } x \leq 64999, \\ 0.08 & \text{else,} \end{cases}$$

where π_{05} is the inflation rate used for the HELP indexation thresholds between 2004 and 2005. In counterfactuals, I consider alternative repayment contracts described in Appendix D.4. In these counterfactuals, I consider repayments that are contingent only on wage income, y_{ia}, and not capital income, i_{ia}.

Income and capital taxation. In Australia, income taxes are paid on taxable income, which aggregates both wage income and capital income. The marginal tax rate that individuals pay increases in their income according to a schedule provided by the ATO.[19] When I estimate the model, I set $\tau(y,i,t) = T_t(y+\max\{i,0\})$, where T_t is equal to the ATO 2003/04 Income Tax Formula at $t < T^*$ and the ATO 2004/05 Formula at $t \geq T^*$:

$$T_t(x) = \mathbf{1}_{t<T^*} T_{04}(x/\pi_{05}) + \mathbf{1}_{t\geq T^*} T_{05}(x),$$

$$T_{04}(x) = \begin{cases} 0 & \text{if } x \leq 6000, \\ 0.17 * (x - 6000) & \text{else if } x \leq 21600, \\ 2652 + 0.3 * (x - 21600) & \text{else if } x \leq 52000, \\ 11952 + 0.42 * (x - 52000) & \text{else if } x \leq 62500, \\ 16362 + 0.47 * (x - 62500) & \text{else,} \end{cases}$$

$$T_{05}(x) = \begin{cases} 0 & \text{if } x \leq 6000, \\ 0.17 * (x - 6000) & \text{else if } x \leq 21600, \\ 2652 + 0.3 * (x - 21600) & \text{else if } x \leq 58000, \\ 13752 + 0.42 * (x - 58000) & \text{else if } x \leq 70000, \\ 18792 + 0.47 * (x - 70000) & \text{else,} \end{cases}$$

[18] See https://atotaxrates.info/individual-tax-rates-resident/hecs-repayment/.

[19] See https://www.ato.gov.au/Rates/Individual-income-tax-for-prior-years/.

where π_{05} is the inflation rate used for the HELP indexation thresholds between 2004 and 2005. For individuals in retirement with $a \geq a_R$, I do not change the income tax schedule to avoid keeping track of an additional state variable. When comparing across student debt repayment policies, I eliminate taxes on capital income and adopt the following parametric income tax schedule, which Heathcote and Tsujiyama (2021) show provides a close approximation to constrained-efficient Mirrlees solutions, which is unlikely to be the case for the actual ATO schedule:

$$\tau(y,i,t) = y - ay^b.$$

I estimate a and b using the methodology from Heathcote et al. (2017) applied on the 2005 ATO tax schedule, which delivers $a = 1.1296$ and $b = 0.8678$.

Unemployment benefits and net consumption floor. Unemployment benefits are set equal to the payments provided by the Newstart allowance, which is the primary form of government-provided income support for individuals above 22 with low income due to unemployment. These benefits are means-tested based on income and assets. I use the formula for payments in 2005 for a single individual with no children.[20] This formula is:

$$\frac{ui(y,i,A)}{26} = \begin{cases} 0 & \text{if } A \geq 153000 \text{ or } (y+\max\{i,0\})/26 > 648.57, \\ 394.6 & \text{else if } (y+\max\{i,0\})/26 \leq 62, \\ 394.6 - 0.5 * (y+\max\{i,0\} - 62) & \text{else if } (y+\max\{i,0\})/26 \leq 142, \\ 354.6 - 0.7 * (y+\max\{i,0\} - 142) & \text{else.} \end{cases}$$

When comparing across student debt repayment policies, I adopt the following smoothed specification of this formula and eliminate dependence on capital income and assets to remove the impact of changes in student debt repayments on the government budget constraint through changes in asset accumulation:

$$ui(y,i,A) = 26 * \max\left\{394.60 - y * \frac{394.60}{16863}, 0\right\}.$$

In addition to unemployment benefits, individuals receive a net consumption floor payment. This floor is needed to ensure that individuals' consumption net of labor supply disutility, $c_{ia} - \kappa \frac{\ell_{ia}^{1+\phi^{-1}}}{1+\phi^{-1}}$, remains positive in the event that they do not adjust their labor supply. The consumption floor is set equal to:

$$\underline{c}_a = \max\left\{\underline{c} + \kappa \frac{\ell_{a-1}^{1+\phi^{-1}}}{1+\phi^{-1}} - M_a, 0\right\},$$

where

$$M_a = y_a + A_a + i_a - d_a - \tau(y_a, i_a, t) + ui(y_a, i_a, A_a)$$

and $\underline{c}$ is the minimum value of net consumption. I set $\underline{c} = \$40$ but have experimented with higher values up to $\$400$ and have found that the results remain unchanged.

Retirement pension. Individuals in retirement receive a retirement pension from the government that is based on the age pension, which is the primary form of government-provided income support for retirees in Australia. The age pension is available to individuals at age 65 and is means-tested based on assets and

[20] See https://melbourneinstitute.unimelb.edu.au/__data/assets/pdf_file/0006/2378733/co029_0501en.pdf.

income. I use the formula for payments in 2005 for a single individual who is a homeowner based on assets, but I exclude means-testing on income since individuals earn no labor income in retirement. This formula is:

$$\overline{y}(A) = \begin{cases} 12402 & \text{if } A \leq 153000, \\ 12402 - 3 * 26 * \left\lfloor \frac{A-153000}{1000} \right\rfloor & \text{else if } A \leq 312000, \\ 0 & \text{else.} \end{cases}$$

When comparing across student debt repayment policies, I remove means-testing and give everyone the full pension of $\$12402$ to remove the impact of changes in student debt payments on the government budget constraint through changes in asset accumulation.

D.3 Second-Stage Simulated Minimum Distance Estimation

Construction of estimation targets. The set of estimation targets that I use is:

1. Average y_{ia} of employed individuals between 22 and 64
2. OLS estimates of β_1 and β_2 from estimating the following equation among employed individuals between ages 22 and 64:
$$\log y_{ia} = \beta_0 + \beta_1 a + \beta_2 a^2$$
3. OLS estimates β_0^E and β_1^E from estimating the following equation among individuals that reach age 22 at $t \geq 1991$:[21]
$$\log y_{ia} = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_0^E \mathcal{E}_i + \beta_1^E \mathcal{E}_i a$$
4. Within-cohort cross-sectional variance of $\log y_{ia}$ at age 22, 32, 42, 52, and 62
5. 10th and 90th percentiles of $y_{ia+1} - y_{ia}$ and $y_{ia+5} - y_{ia}$
6. Average i_{ia} among individuals between ages 40 and 44
7. Average l_{ia} among employed individuals between ages 23 and 64, which is normalized to 1 in the data
8. Real distribution of HELP income among debtholders aged 23 to 64 in 2002–2004 within $3000 of the 2004 repayment threshold in bins of $500
9. Real distribution of HELP income among debtholders aged 23 to 64 in 2005–2007 within $3000 of the 2005 repayment threshold in bins of $500
10. Ratio of number of debtholders aged 23 to 64 with HELP income within $250 below to the number within $250 above the 2004 repayment threshold in 1998–2004
11. Ratio of number of debtholders aged 23 to 64 with HELP income within $250 below to the number within $250 above the 2005 repayment threshold in 2005–2018
12. Ratio of number of debtholders aged 23 to 64 with HELP income within $250 below to the number within $250 above the 2005 repayment threshold in 2005–2018 in the bottom and top quartiles of debt balances in each year

[21] I do not allow for the possibility that the quadratic component of g_{ia} differs with $\mathcal{E}_i$. This is because *ALife* covers only 1991–2019 and does not have direct measures of education. Since I instead infer education level based on the presence of HELP debt, the oldest individual whom I observe in the sample with $\mathcal{E}_i = 1$ is around age 50–55. Without the final 5–10 years of working life, it is difficult to identify this additional parameter.

13. Ratio of number of debtholders aged 23 to 64 with HELP income within \$250 below to the number within \$250 above the lowest 2005 0.5% threshold in 2005–2018

In these definitions, y_{ia} refers to the value of Salary and Wages in *ALife*, and i_{ia} refers to Capital Income defined in Appendix C.3. Because of data access restrictions, I construct the first six set of estimation targets using a 10% random sample of *ALife* data. This likely has little effect on the results because these estimation targets are very precisely estimated and are not the primary targets responsible for identifying the structural parameters of interest. For these estimation targets, I restrict to wage-earners between 22, the first age in the model, and 64, the age at which individuals retire in the model, and winsorize both y_{ia} and i_{ia} from above at 99.999% following Guvenen et al. (2014). When computing the estimation targets based on y_{ia}, I restrict to individuals who have annual salary and wages greater than one-half the legal minimum wage times 13 full-time weeks following Guvenen et al. (2014). When calculating all estimation targets in the data, I also restrict to individuals who were age 22 between 1963 and 2019 to match the cohorts simulated in the model.

Weighting matrix. I choose the weighting matrix, $W(\Theta)$, such that the simulated minimum distance objective function corresponds to the sum of squared arc-sin deviations between $\hat{m}$ and $m(\Theta)$. Specifically, I set $W(\Theta) = \text{diag}\,(w(\Theta))$, where

$$w(\Theta) = \left(0.5 \times \max\left\{\underline{w}, |\hat{m}| + |m(\Theta)|\right\}\right)^{-2}.$$

This choice follows Guvenen et al. (2021) and is made because I have many estimation targets that differ greatly in scale.[22] I do not use the optimal weighting matrix because some of these targets are estimated from population-level data and thus have very small asymptotic variances that make the objective function unstable. I also follow Guvenen et al. (2021) and adjust $w(\Theta)$ so that the following blocks of estimation targets receive equal weight.

1. Block #1: All income distribution estimation targets in 2002–2004 and 2005–2007
2. Block #2: All estimation targets that are ratios of individuals below to individuals above repayment thresholds + average labor supply
3. Block #3: All remaining estimation targets

This is done to ensure that blocks of estimation targets receive equal importance because they primarily identify different structural parameters.

Global optimization algorithm. I compute the value of Θ that minimizes the simulated minimum distance objective function using a variant of the TikTak algorithm from Arnoud et al. (2019). I start by evaluating the objective function at $4,000$ pseudorandom Halton points that cover the parameter space. I then take the top 10 candidate points and perform a Nelder–Mead optimization at each of these 10 points. Finally, I use the Nelder–Mead solutions at each of these 10 points to perform a second round of 10 additional Nelder–Mead optimizations. Specifically, I rank the 10 solutions from the first set of optimizations and start the first optimization of the second round at the best point. Then, to start each of the remaining $i = 2, ..., 10$ optimizations, I use as a starting point the weighted average of the current candidate optimum and the ith

[22] The choice of constant $\underline{w}$ is made to ensure that the objective function remains well-behaved even as the targets become small and possibly differ in sign between the model and data. I set $\underline{w} = 0.01$ based on experimentation, but at the global optimum, this lower bound does not bind and thus does not meaningfully affect the results.

ranked point, with the weighting function and parameters chosen exactly as in Arnoud et al. (2019). In each of these Nelder-Meads, the convergence criteria are a relative objective tolerance of 0.01 or 400 iterations. In a final polishing phase, I perform a Nelder-Mead with a tolerance of 0.001 and a maximum of 1000 iterations.

Calculation of standard errors. To apply standard asymptotic theory to calculate standard errors, I rewrite the simulated minimum distance objective function as

$$\Theta^* = \arg\min_{\Theta} g(\Theta)' g(\Theta),$$

where

$$g(\Theta) = \text{diag}\left(\sqrt{w(\Theta)}\right)(m(\Theta) - \hat{m}).$$

Denote the true value of the parameters, Θ, as Θ_0. Under standard regularity conditions (e.g., McFadden 1989; Duffie and Singleton 1993),

$$\sqrt{N}(\Theta^* - \Theta_0) \xrightarrow{d} N(0, V),$$

where $\xrightarrow{d}$ denotes convergence in distribution as the number of sample observations, N, tends to infinity for a ratio of the number of model simulations to data observations, S. The asymptotic variance, V, is given by

$$V = \left(1 + \frac{1}{S}\right)[GG']^{-1} G\Omega G' [GG']^{-1},$$

where $G = \frac{\partial}{\partial \Theta} g(\Theta)$,

$$\Omega = \Omega_0 \Lambda, \quad \sqrt{N}\hat{m} \xrightarrow{d} N(m_0, \Omega_0),$$

$$\Lambda = \text{diag}\left(4 * c_0 * \left[\mathbf{1}_{\underline{w} \leq |\hat{m}| + |m(\Theta)|} * \frac{|m(\Theta)||\hat{m}| + m(\Theta)\hat{m}}{|\hat{m}|\left(|m(\Theta)| + |\hat{m}|\right)^2} + \mathbf{1}_{\underline{w} > |\hat{m}| + |m(\Theta)|} * \underline{w}^{-1}\right]^2\right),$$

all multiplication and division in the definition of Λ is performed element-wise, all quantities are evaluated at Θ_0, and c_0 is a vector that accounts for the reweighting of the different blocks of estimation targets discussed above. The previous two equations define the asymptotic variance of $g(\Theta)$, denoted by Ω, which is derived by means of the delta method and the asymptotic distribution of $\hat{m}$.

By the continuous mapping theorem, each component of V can be estimated by replacing population quantities with sample analogs evaulated at the simulated minimum distance estimate of Θ. I estimate Ω_0 via bootstrap assuming that all off-diagonal elements are zero[23] and compute G using two-sided finite differentiation with step sizes equal to 1% of the estimated parameter value following the recommendation of Judd (1998) (p. 281).[24] The standard errors for Θ^* are then $\sqrt{N^{-1}\text{diag}(\hat{V})}$.

D.4 Description of Repayment Contracts

Fixed repayment. For a borrower i at age a, the required payment on a fixed repayment contract is:

$$d_{Fixed}(a, D_{ia}) = \begin{cases} 0, & \text{if } a < a_S \\ D_{ia} * \frac{r_d}{1-(1+r_d)^{-(a_E-(a-a_0+1)+1)}}, & \text{else,} \end{cases}$$

[23] I cannot compute off-diagonal elements because the estimation targets are calculated from different samples, which do not all fit in the RAM of the virtual machine used to access the data.

[24] I compute the standard error of average labor supply using the hours worked reported in HILDA, after normalizing it to have a mean of one.

where a_S is the first age at which payments start and a_E is the age at which payments end. In the event that borrowers' cash-on-hand prior to making debt payments falls below $d_{Fixed}(\cdot)$, I make borrowers pay only their cash-on-hand. In this case, borrowers will also receive the consumption floor payment since they have no resources for consumption. A 25-year fixed repayment contract corresponds to $a_S = a_0$, $a_E = a_0 + 20$, and $r_d = 0\%$.

US-style income-contingent loans. For a borrower i at age a, the required repayment on a US-style income-contingent loan is:

$$d_{IBR}(D_{ia}, y_{ia}) = \min\{\psi * \max\{y_a - K, 0\}, (1 + r_d)D_{ia}\} * \mathbf{1}_{a \leq \overline{T}}.$$

The following specifies the parameters for the different IBR contracts that I implement in the text:

- IBR: $\psi = 10\%$, $K = 1.5 * pov$, $\overline{T} = a_R$, $r_d = 0\%$
- SAVE: $\psi = 5\%$, $K = 2.25 * pov$, $\overline{T} = a_R$, $r_d = 0\%$
- Constrained-Optimal Income-Contingent Loan: ψ and K chosen to solve (18), $\overline{T} = a_R$, $r_d = 0\%$
- Constrained-Optimal Income-Contingent Loan with 20-Year Forgiveness: ψ and K chosen to solve (18), $\overline{T} = a_0 + 20$, $r_d = 0\%$

where pov is the 2023 US poverty line of $14,580 USD converted into AUD by adjusting for US CPI inflation from June 2005 to January 2023 by the exchange rate in June 2005.[25] For simplicity, I do not implement the restriction in the US that IBR payments cannot exceed payments under a fixed repayment contract. In practice, these repayment contracts also have forgiveness after a fixed period of time. I do not implement this to make them more comparable to HELP contracts but return to the effect of adding forgiveness separately.

Fixed payment + unemployment forbearance. For a borrower i at age a, the required payment is:

$$d_{Fixed+UI} = \min\{\psi, (1 + r_d)D_{ia}\} * \mathbf{1}_{a<a_R} * \mathbf{1}_{y_{ia} \geq \$16,863},$$

where ψ is chosen to solve (18) with this alternative repayment contract. The value of $\$16,863$ corresponds to the phase-out point of unemployment benefits described in Appendix D.2.

Income-sharing agreements. For a borrower i at age a, the required payment under an income-sharing agreement is equal to:

$$d_{ISA}(a, D_{ia}, y_{ia}) = \begin{cases} 0, & \text{if } a > T \text{ or } y_{ia} < K, \\ \psi * y_{ia}, & \text{else.} \end{cases}$$

In this expression, T_{ISA} is the term of the ISA contract and K is the threshold above which payments are required. The parameters on the different income-sharing agreements that I implement in the text are:

- 9-Year ISA: $T = 9$, ψ chosen to solve (18), $K = 0$
- 9-Year ISA + Threshold: $T = 9$, ψ and K chosen to solve (18)

[25] This equals $12,320, which is almost identical to the $11,511 poverty line reported by the Melbourne Institute.

This structure of these 9-year ISAs closely matches that of the ISAs provided by Purdue University in 2016–2017 (Mumford 2022) with one difference: the Purdue ISAs have the constraint $D_{ia} < D_{ia_0}(1 - cap_{ISA})$, where cap_{ISA} corresponds to the maximum multiple of the initial debt balance that a borrower can pay.

Alternative income-contingent loans. Figure 19 uses the following forms of income-contingent loans:

$$\begin{aligned}
\text{Smooth Income-Contingent Loan}: &\quad d_{ia} = \min\left\{\max\left\{\psi_0 + \psi_1 y_{ia} + \psi_2 y_{ia}^2, 0\right\}, D_{ia}\right\}, \\
\text{Income-Contingent Loan + Age}: &\quad d_{ia} = \min\left\{\max\left\{\psi_0 + \psi_1 y_{ia} + \psi_2 y_{ia}^2 + \psi_3 a, 0\right\}, D_{ia}\right\}, \\
\text{Income-Contingent Loan + Debt}: &\quad d_{ia} = \min\left\{\max\left\{\psi_0 + \psi_1 y_{ia} + \psi_2 y_{ia}^2 + \psi_3 D_{ia}, 0\right\}, D_{ia}\right\}.
\end{aligned}$$

The first contract corresponds to a smoothed version of the US IBR–style income-contingent loans considered above, in which repayments are a quadratic function of income. The latter two contracts make payments conditional on age and debt, respectively. For each of these alternative contracts, I solve (18) to find the constrained-optimal values of $\{\psi_i\}$.

D.5 Computation of Welfare Metrics

Equivalent variation. Let $\mathbf{s}_0$ be the vector of four stochastic initial conditions in the model: education-level $\mathcal{E}_i$, permanent income δ_i, assets, A_{ia_0}, and debt balances D_{ia_0}. Let $\mathbf{s}_0(\pi)$ be the same vector with initial assets $A_{ia_0} + \pi$ instead of A_{ia_0}. Denote the value function at $a = a_0$ and initial states $\mathbf{s}_0$ with education level $\mathcal{E}_i = E$ under repayment policy p as $V_p(\mathbf{s}_0 \mid \mathcal{E}_i = E)$, and denote the joint conditional distribution of the four stochastic initial conditions as $F(\mathbf{s_0} \mid \mathcal{E}_i = E)$.

The *equivalent variation* of policy p, π_p, relative to the 25-year fixed repayment contract is computed as the fixed point of the following equation in π:

$$\left[\int V_p(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}} = \left[\int V_{\text{25-Year Fixed}}(\mathbf{s}_0(\pi) \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}}.$$

This left-hand side of this equation corresponds to the Epstein–Zin certainty-equivalent functional of random consumption and labor supply streams under repayment policy p to an agent with education level $\mathcal{E}_i = 1$ who is "behind the veil of ignorance" with respect to $\mathbf{s}_0$. The right-hand side corresponds to the same quantity calculated under the 25-year fixed repayment contract when borrowers receive a deterministic cash transfer of π at $a = a_0$. I compute this fixed point using a standard bisection root-finding algorithm.

Consumption-equivalent welfare gain. Let $V_p(\mathbf{s}_0 \mid \mathcal{E}_i = E)$ and $F(\mathbf{s_0} \mid \mathcal{E}_i = E)$ denote the same quantities as above. Let $V_p^g(\mathbf{s}_0 \mid \mathcal{E}_i = E)$ denote $V_p(\mathbf{s}_0 \mid \mathcal{E}_i = E)$ evaluated in a model in which, for all ages a, borrowers i get to consume $(1 + g)c_{ia}$. The *consumption-equivalent gain* of policy p, g_p, relative to the 25-year fixed repayment contract is computed as the fixed point to the following equation in g:

$$\left[\int V_p(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}} = \left[\int V^g_{\text{25-Year Fixed}}(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}}.$$

This metric corresponds to the value of g that would make borrowers with $\mathcal{E}_i = 1$ indifferent between having to (i) pay their debt under repayment policy p and (ii) pay their debt under 25-year fixed repayment *and* having their consumption increased by $g\%$ in every state during their lifetime. I compute this fixed point

using a standard bisection root-finding algorithm.

Net consumption-equivalent welfare gain. Due to computational constraints, some results (e.g., Figure 17) present *net* consumption-equivalent welfare gains instead of consumption-equivalent welfare gains. These two are quantitatively very similar, but the former are easier to compute because doing so does not require solving a numerical fixed point for each possible state. This alternative welfare metric corresponds to the value of g that would make a borrower indifferent between the original contract and having her consumption net of the disutility of labor supply increased by $g\%$ in every state of her life. For a given set of exogenous states and two policies, it is computed as the percent change in certainty-equivalent values.

D.6 Computation of Constrained-Optimal Repayment Contracts

Solving (18) is numerically challenging, especially when higher-dimensional contracts are considered, because it is a nonlinear constrained optimization problem in which the objective and constraints do not have closed forms. I use a combination of a standard barrier method in numerical optimization (Nocedal and Wright 2006) and a global optimizer. Specifically, I set the objective function in (18) to an extremely large value in the event that the first constraint, which corresponds to the government budget constraint, is violated by more than a tolerance of \$1. I then perform the minimization of this objective function using the TikTak optimizer from Arnoud et al. (2019). Due to memory and computational constraints, I set $N = 50{,}000$ when solving for constrained-optimal policies and only simulate individuals with $\mathcal{E}_i = 1$ (individuals with $\mathcal{E}_i = 0$ do not affect the planner's problem).

D.7 Welfare Gains with Optimal Tax and Transfer System

This section examines how an optimally-set tax and transfer system affects the welfare gains from constrained-optimal repayment contracts. I consider the parametric tax and transfer schedule, $\tau(y, i, t) = y - ay^b$, and the smoothed unemployment benefit formula that are described in Appendix D.2. I begin by eliminating all debt repayments and then solving for the values of a and b that maximize the objective function in (18) within the baseline model, subject to the constraint that $\mathcal{G} = 0$. Given these values of a and b, I then solve (18) using the different classes of repayment contracts considered in the main text.

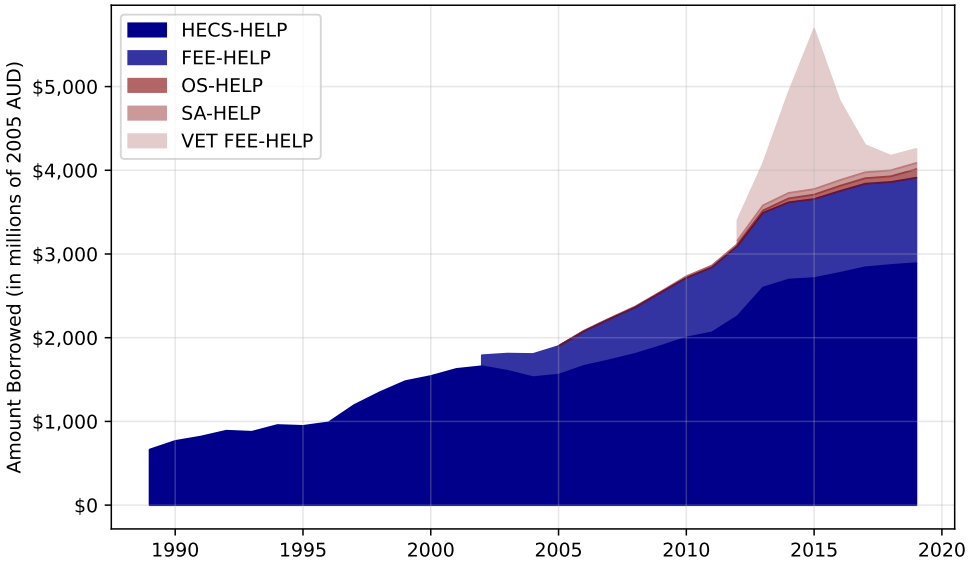
The right panel of Figure A41 shows that the design of the constrained-optimal repayment contract is much different once the tax system has been optimized. The gain from a fixed repayment contract with forbearance is identical to that of the constrained-optimal income-contingent loan, suggesting the call option-like structure of income-contingent loans is less important. The design of the third contract considered in Figure A41 verifies this: the optimal income-contingent loan with forbearance has very little income-contingency outside the forbearance region. This is because the tax system has been optimized to provide insurance in the absence of student debt. However, the repayment of debt using fixed repayment contracts places a disproportionate burden on low-income individuals, who are close to their borrowing constraints and now have to repay a large fraction of their incomes. Reducing payments for these individuals by adding forbearance is thus still valuable. In contrast, there is little to be gained by collecting payments more quickly from higher-income individuals. With an optimal tax system, the demand for insurance is sufficiently low that it can be provided with forbearance alone.

The welfare gains from providing insurance with income-contingent repayment are also smaller under the optimized tax system. The right panel of Figure A41 shows that the welfare gain from moving from 25-year fixed repayment to the constrained-optimal income-contingent loan is equivalent to a 0.13% increase in lifetime consumption, around ten times smaller than in the baseline model. The smaller gain is driven by a reduction in the welfare gain from insurance: the gain from insurance is only 0.24% vs. 1.49% in the baseline model, while the loss from moral hazard is -0.11% (vs. -0.15% in the baseline model). This is to be expected: with a tax and transfer system that is designed to reduce the welfare losses from incomplete markets, there is less scope for providing insurance by optimizing student loan contract design. However, the welfare gain is still positive because income-contingent repayment helps insure low-income individuals, as described above.

In sum, optimizing the tax and transfer system reduces borrowers' demands for insurance, which leads to an optimal contract with less insurance and smaller gains from income-contingent repayment. In reality, the design of these two systems should be considered jointly, as in Stantcheva (2017). However, my model is not well-suited for this purpose because it does not capture the larger income elasticities among top earners (Gruber and Saez 2002), which are most important for designing the tax system, and does not feature endogenous human capital acquisition.

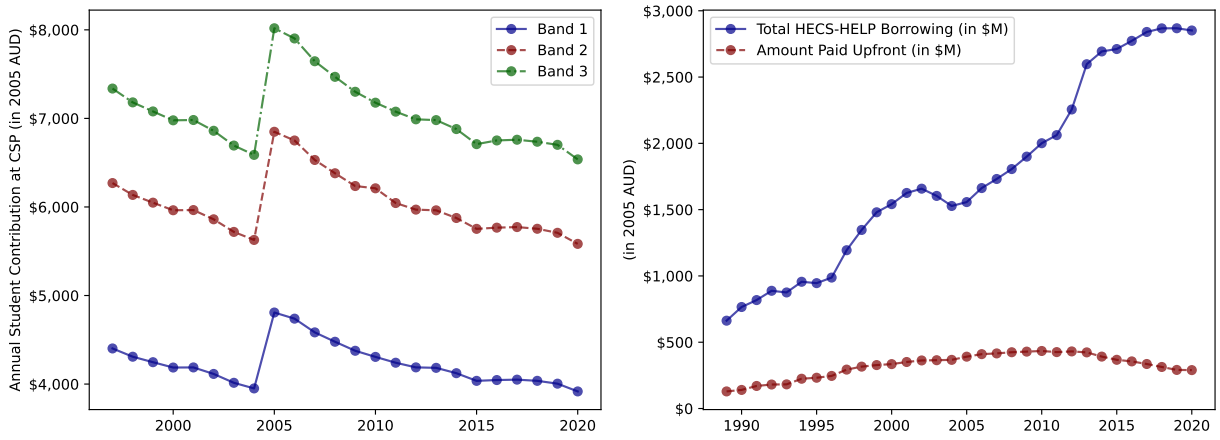
Appendix E. Additional Figures and Tables

Figure A2. Student Contributions and Aggregate HELP Borrowing over Time



Notes: This figure plots the time series of the total amount borrowed each year among the five different HELP programs in millions of 2005 AUD. HECS-HELP refers to the primary HELP program that provides loans to cover student contribution amounts for Commonwealth Supported Places (CSPs), which cover mostly undergraduate and postgraduate degrees at public institutions. FEE-HELP loans are used to cover the fees associated with non-CSP degrees, such as undergraduate degrees at private institutions, which must be covered in full. FEE-HELP was introduced in 2005 and between 2002 and 2004 was formally called PELS. OS-HELP loans are used to cover expenses for students enrolled in a CSP degree who want to study overseas. SA-HELP loans are used to pay student services and amenities fees. VET FEE-HELP covers tuition fees for vocational education and training courses. VET FEE-HELP was closed on December 31st, 2016, and formally replaced by a different program called VET Student Loans on January 1st, 2017. The rapid increase in debt balances and subsequent closing of VET FEE-HELP was driven by fraud and corrupt behavior among vocational education providers (Australian National Audit Office 2016). A significant fraction of this debt has been written off in recent years (HELP Receivable Report 2021, DESE Annual Report 2022). Along with FEE-HELP and OS-HELP, borrowing through VET FEE-HELP has historically required incurring a loan fee that is around 20% of the amount borrowed. These data were obtained from Andrew Norton Higher Education Commentary.

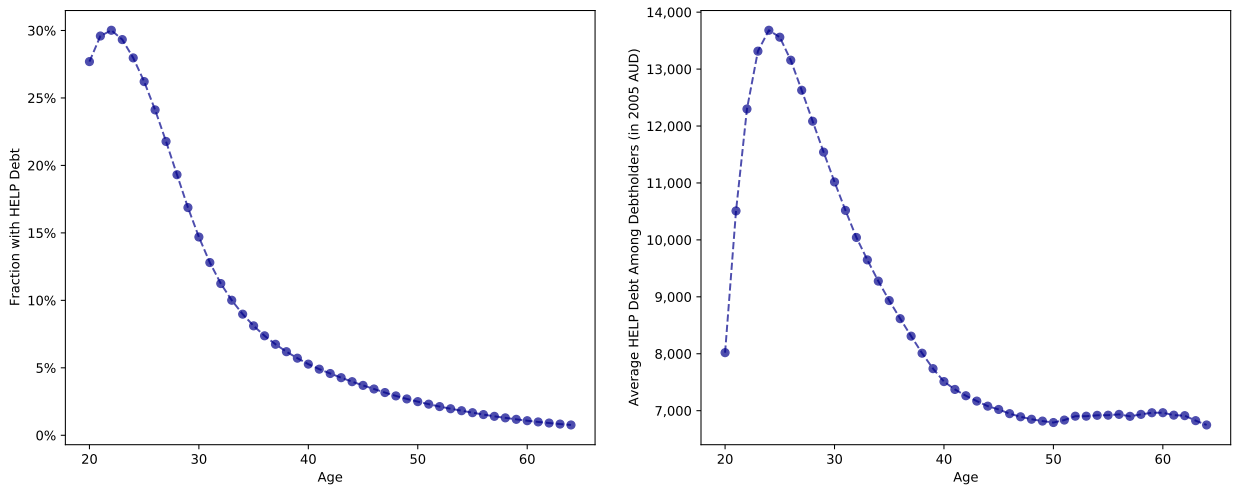
Figure A3. Student Contributions and Aggregate HELP Borrowing over Time



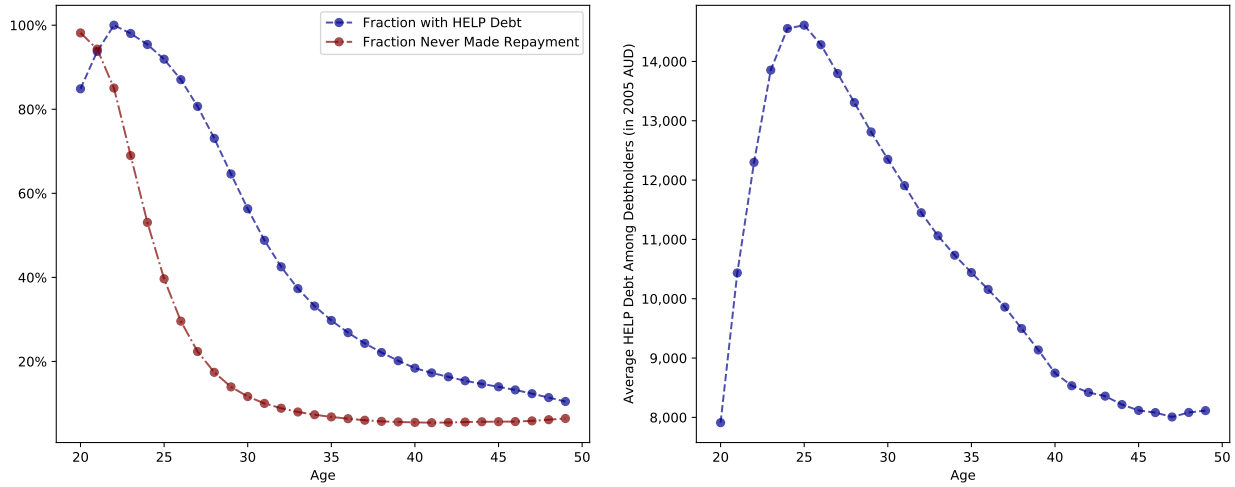
Notes: The left plot shows the time series of student contributions in 2005 AUD for Commonwealth Supported Places (CSPs) based on the three separate bands of study classified by the Australian government. These rates correspond to the cost of one year of coursework that must be covered with a HELP loan or by paying upfront. Prior to 2005, these rates were set by the government. After 2005, the rates were set by universities up to the maximum specified in this table, with most universities electing to charge the maximum. These three bands were introduced in 1997 and phased out in 2021 with the introduction of the Job Ready Graduates Package. Band 1 covers humanities, behavioral science, social studies, education, clinical psychology, foreign languages, visual and performing arts, education, and nursing. Band 2 covers computing, built environment, other health, allied health, engineering, surveying, agriculture, science, and maths. Band 3 covers law, dentistry, medicine, veterinary science, accounting, administration, economics, and commerce. Business and economics were Band 2 prior to 2008. Between 2005 and 2009, the government also had separate tuition for nursing and education and, from 2009 to 2012, for mathematics, statistics, and science, which were labeled national priorities. The right plot shows the time series of the aggregate amount of HECS-HELP borrowing and upfront payments in 2005 AUD. These data were obtained from Andrew Norton Higher Education Commentary.

Figure A4. Average Debt Balances by Age

Panel A: All Individuals



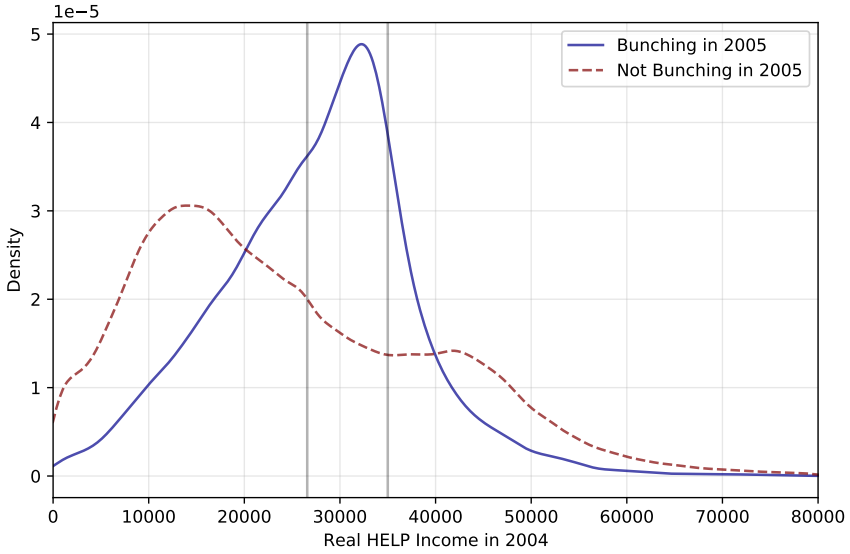
Panel B: Individuals with Positive Debt Balances at Age 22



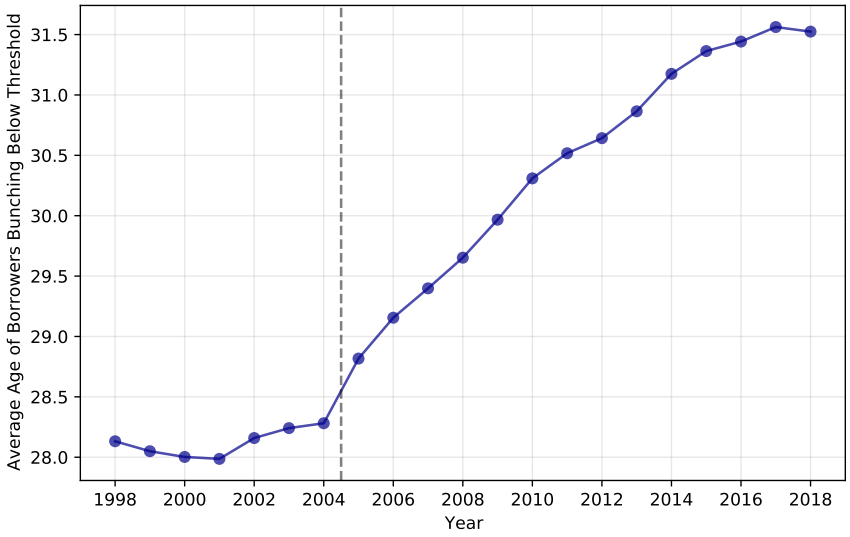
Notes: Panel A of this figure plots the fraction of individuals with HELP debt at each age in the left panel and the average HELP debt balances in 2005 AUD by age on the right. Panel B plots, in blue, the same quantity in Panel A among the subset of individuals who have positive debt balances at age 22 at some point during 1991–2019. The fraction of borrowers who have never made a HELP payment is also shown in the left panel in red. Debt balances are winsorized at 2% and 98%. The sample is the *ALife* sample defined in Section 2.4 from 1991 to 2019.

Figure A5. Characteristics of Borrowers Below Repayment Thresholds

Panel A: Prior Location of Borrowers Below New Repayment Threshold



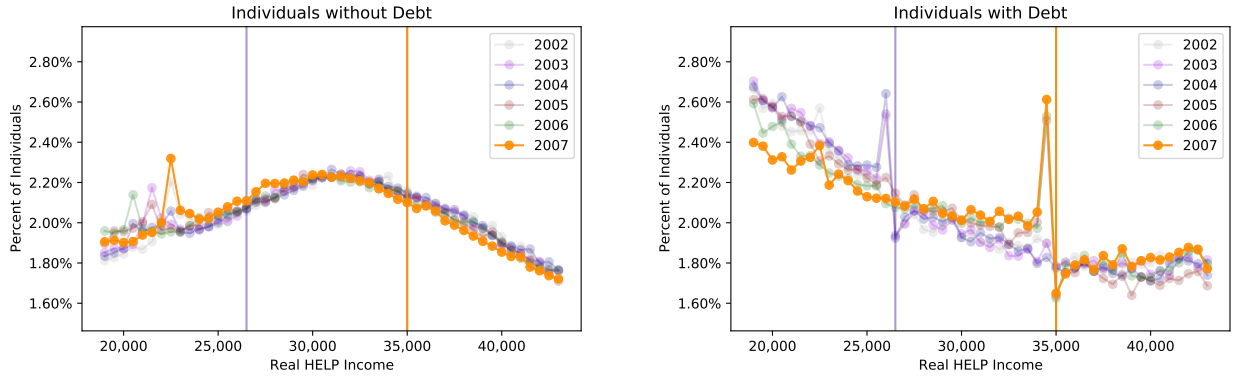
Panel B: Age of Borrowers Below Repayment Threshold



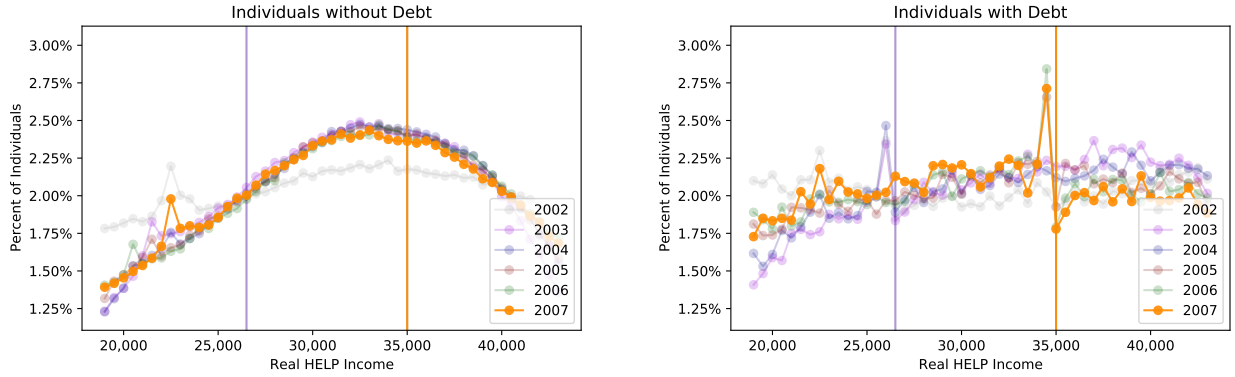
Notes: Panel A of this figure plots the HELP income distribution in 2004 of borrowers based on their HELP income in 2005. The solid blue line corresponds to the distribution for borrowers who have HELP income (in 2005 AUD) within $2500 of the repayment threshold in 2005. The dashed red line corresponds to all other borrowers. These densities are estimated using with a Gaussian kernel and bandwidth that are chosen using Scott's rule. Panel B of this figure plots the average age of borrowers who have HELP income in 2005 AUD within $2500 of the repayment threshold. The dashed gray line corresponds to the period between the policy change. HELP income is deflated to 2005 Australian dollars using the HELP threshold indexation rate, which is based on the annual CPI. The sample is the *ALife* sample defined in Section 2.4, restricted to individuals with positive HELP debt balances in each year.

Figure A6. Comparison of HELP Income Distribution for Debtholders and Non-Debtholders

Panel A: Full Sample

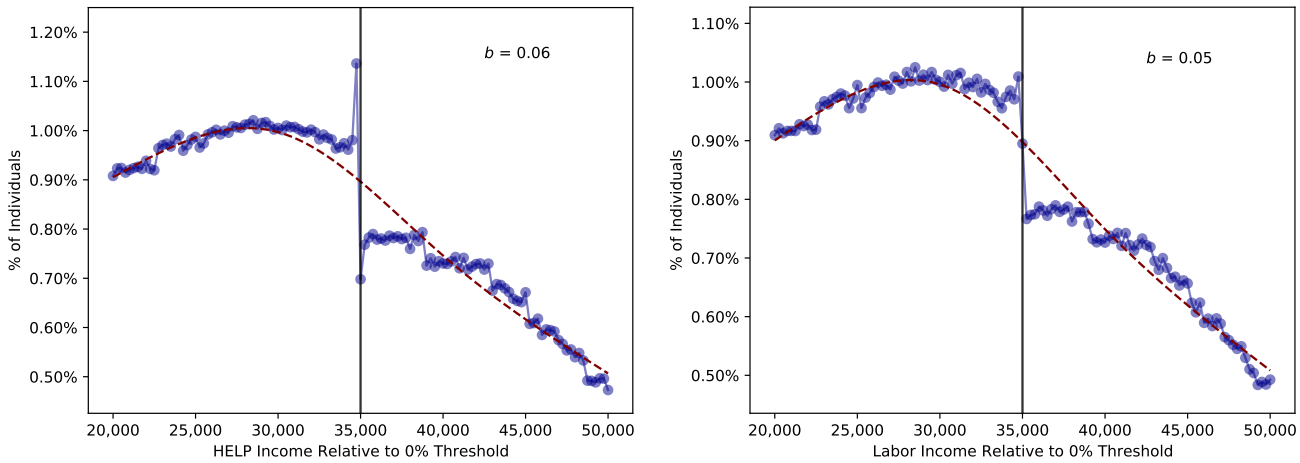


Panel B: Sample of Borrowers Held Fixed from 2002



Notes: The right panel in Panel A of this figure replicates the bottom-right figure in Figure 3. The left panel in Panel A replicates the same analysis among individuals who do not have debt in each year. Panel B replicates the analysis in Panel A holding the sample of borrowers fixed to those who were present in the sample with HELP income (in 2005 AUD) between $20,000 and $50,000 in 2002.

Figure A7. Distributions of HELP Income and Labor Income



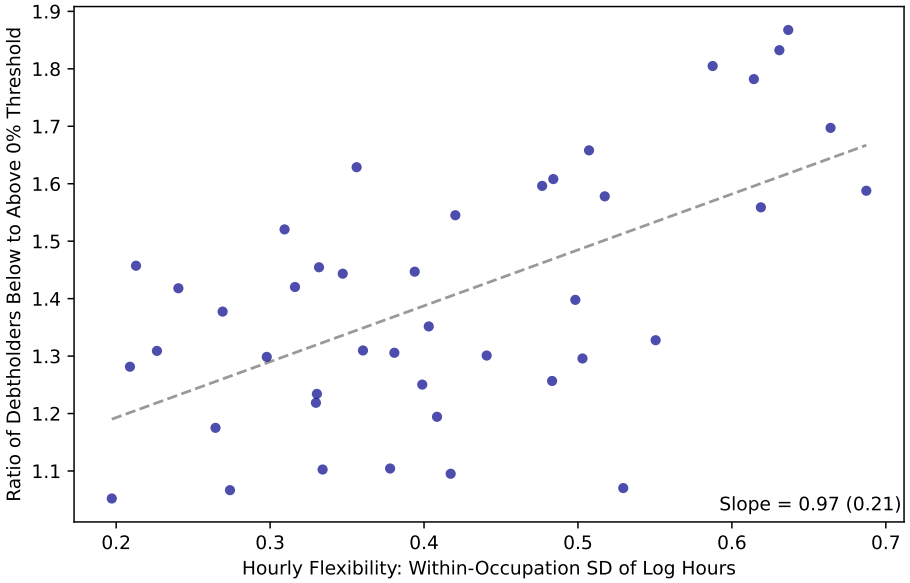
Notes: This figure plots the distributions of HELP and labor income (in 2005 AUD) relative to the repayment threshold after the policy change. This figure also plots the bunching statistic defined in (4) computed for the different distributions. Each bin corresponds to $250 AUD, and bins are chosen so that they center on the 2005 repayment threshold. The calculation of b is detailed in Appendix C.4, and the counterfactual density estimated in this procedure is plotted in the dashed red line. The sample is the *ALife* sample defined in Section 2.4 for the period between 2005 and 2018 after the policy change, restricted to individuals with positive HELP debt balances and less than 1% of HELP income from sources other than labor income.

Table A2. Hourly Flexibility Measures by 2-Digit ANZSCO Occupation

Occupation Title	SD Change in Log Hours	SD Log Hours
ICT Professionals	0.169	0.197
Electrotechnology and Telecommunications Trades Workers	0.192	0.209
Specialist Managers	0.193	0.265
Chief Executives, General Managers and Legislators	0.2	0.298
Engineering, ICT and Science Technicians	0.209	0.33
Factory Process Workers	0.211	0.309
Sales Representatives and Agents	0.218	0.316
Automotive and Engineering Trades Workers	0.225	0.226
Hospitality, Retail and Service Managers	0.226	0.347
Other Clerical and Administrative Workers	0.231	0.36
Machine and Stationary Plant Operators	0.232	0.269
Construction Trades Workers	0.238	0.213
Mobile Plant Operators	0.245	0.24
Health and Welfare Support Workers	0.246	0.408
Business, Human Resource and Marketing Professionals	0.256	0.33
Personal Assistants and Secretaries	0.26	0.503
Office Managers and Program Administrators	0.263	0.381
Road and Rail Drivers	0.263	0.394
Design, Engineering, Science and Transport Professionals	0.268	0.334
Inquiry Clerks and Receptionists	0.269	0.477
Protective Service Workers	0.275	0.274
Clerical and Office Support Workers	0.279	0.399
Numerical Clerks	0.296	0.483
Legal, Social and Welfare Professionals	0.302	0.378
Health Professionals	0.308	0.417
Construction and Mining Labourers	0.309	0.332
Other Technicians and Trades Workers	0.316	0.403
Skilled Animal and Horticultural Workers	0.317	0.517
Storepersons	0.324	0.356
General Clerical Workers	0.352	0.498
Food Trades Workers	0.358	0.42
Farmers and Farm Managers	0.365	0.441
Other Labourers	0.377	0.619
Carers and Aides	0.385	0.484
Farm, Forestry and Garden Workers	0.387	0.507
Education Professionals	0.408	0.529
Sales Support Workers	0.443	0.664
Cleaners and Laundry Workers	0.462	0.588
Food Preparation Assistants	0.475	0.637
Hospitality Workers	0.48	0.614
Sales Assistants and Salespersons	0.487	0.631
Sports and Personal Service Workers	0.498	0.687
Arts and Media Professionals	0.562	0.55

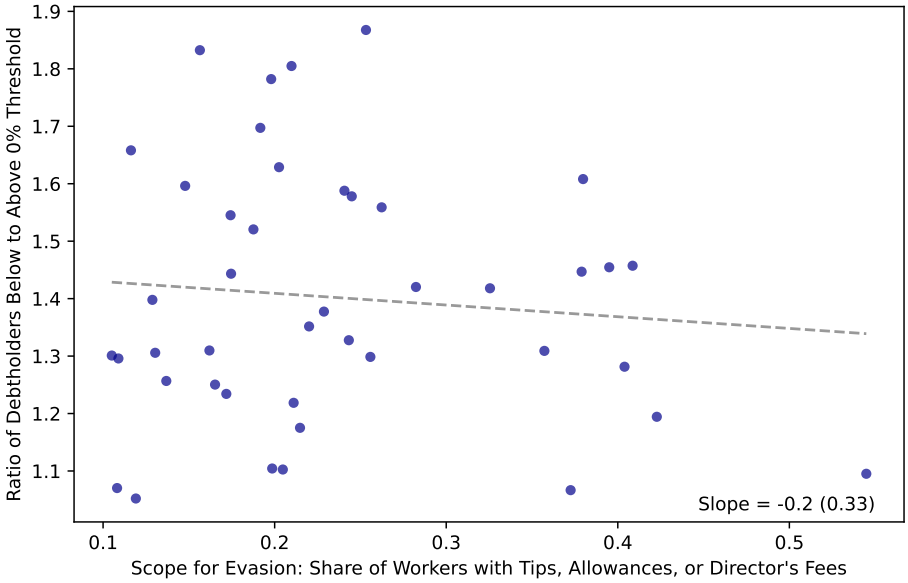
Notes: This table shows the measures of hourly flexibility at the 2-digit ANZSCO occupation-level used in Figure 4 and Figure A8. Hourly flexibility is measured as the standard deviation of annual changes, or the cross-sectional standard deviation, in log hours worked per week from HILDA.

Figure A8. Variation in Bunching across Occupations Based on Hourly Flexibility: Alternative Measure



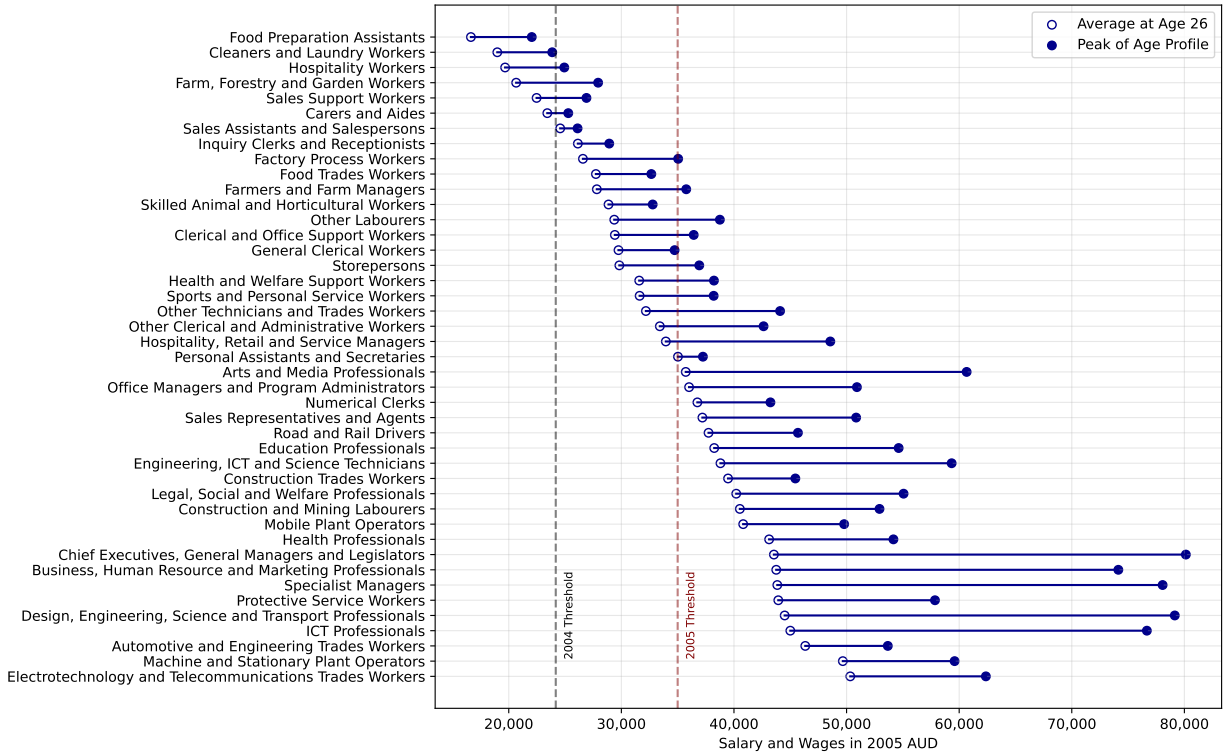
Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and an alternative measure of hourly flexibility by occupation. Each point represents a 2-digit ANZSCO occupation code reported in *ALife*. The amount of bunching is measured as the ratio of the number of borrowers in that occupation within $2,500 below the repayment threshold to the number within $2,500 above the threshold for the period over 2005 to 2018. Hourly flexibility is measured as the cross-sectional standard deviation of log hours worked per week. The gray dashed line is the regression line with the estimated slope coefficient and standard error reported at bottom right. The sample is the *ALife* sample defined in Section 2.4, restricted to the subset of individual–years for which the borrowers are wage-earners.

Figure A9. Variation in Bunching across Occupations Based on Scope for Evasion



Notes: This figure replicates Figure 4 with a measure of evasion at the occupation level instead of hourly flexibility on the horizontal axis. The measure of evasion is the fraction of individuals within each occupation who receive income from tips, allowances, or director's fees; see Appendix C.3 for additional details. This evasion measure is computed for the sample of individuals described in Figure A10.

Figure A10. Age Profiles of Wage Income across Occupations



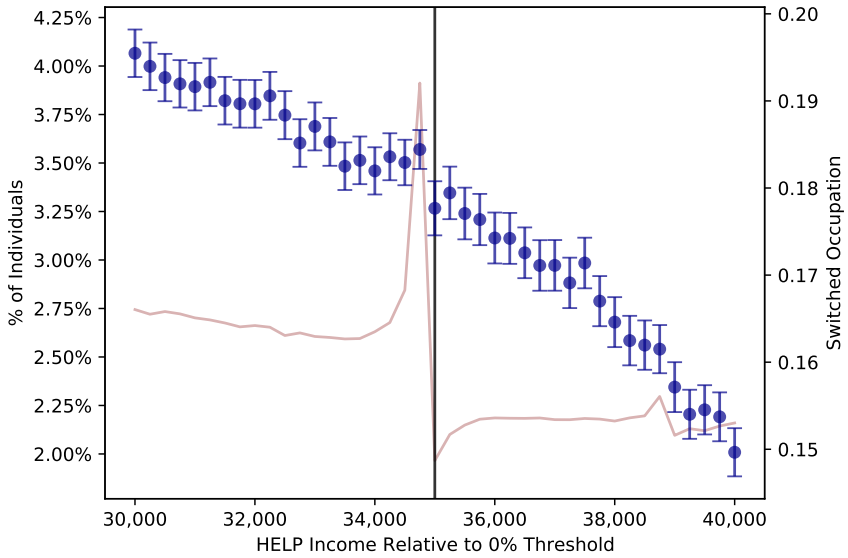
Notes: This figure plots characteristics of the age profile of salary and wages across 2-digit ANZSCO occupations. Occupation-specific age profiles are calculated by taking the average value of salary and wages across individuals in each occupation at a given age, after adjusting for inflation and removing year fixed effects. The figure then plots the value of each occupation profile at age 26 in white and the maximum value in the occupation profile in blue, with a blue line connecting the two. The sample of individuals used to calculate these age profiles is the *ALife* 10% random sample of individuals in the population *ALife* dataset who satisfy the sample selection criteria in Section 2, are wage-earners, and have annual salary and wages greater than one-half the legal minimum wage times 13 full-time weeks (Guvenen et al. 2014).

Table A3. Correlates of Bunching across Occupations

	Ratio of Debtholders Below to Above Threshold						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hourly Flexibility: SD of Changes in Log Hours	1.30	·	·	·	1.30	1.05	0.50
	(0.35)	·	·	·	(0.35)	(0.28)	(0.23)
Evasion: Share with Non-Wage Income	·	−0.20	·	·	−0.02	−0.17	0.05
	·	(0.30)	·	·	(0.30)	(0.30)	(0.25)
Income Slope: Mean Wage at 45 / Mean Wage at 26	·	·	−0.53	·	·	−0.40	·
	·	·	(0.10)	·	·	(0.12)	·
Income Peak: Maximum Wage in Occupation Profile	·	·	·	−0.48	·	·	−0.40
	·	·	·	(0.06)	·	·	(0.07)
R^2	0.34	0.01	0.23	0.58	0.34	0.46	0.62
Number of Occupations	43	43	43	43	43	43	43

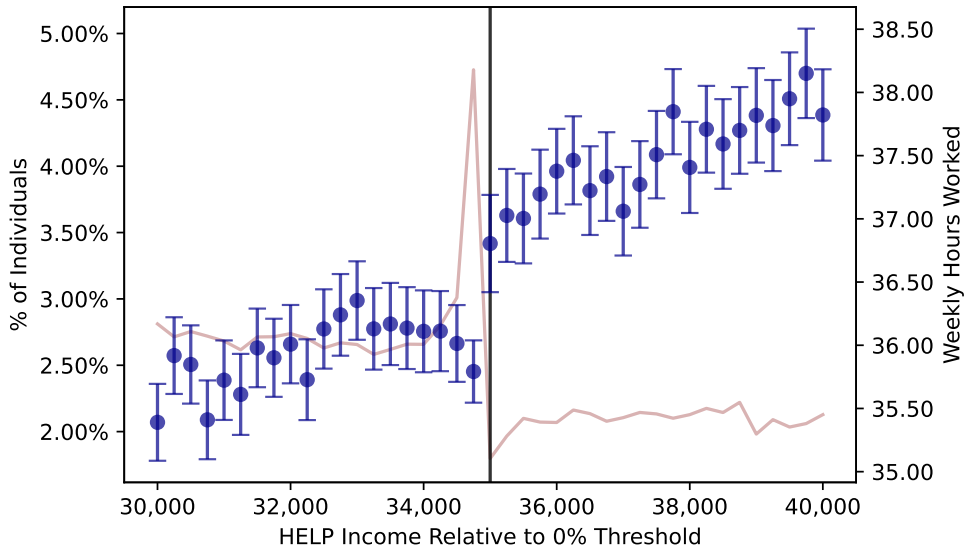
Notes: Each column of this table reports the results from an OLS regression run at the 2-digit ANZSCO occupation-level, with standard errors presented in parentheses below the coefficient estimates. The dependent variable in each column is the ratio of the number of debtholders within $2,500 below the repayment threshold to the number within $2,500 above the repayment threshold, as shown in Figure 4. Hourly Flexibility corresponds to the same measure used in Figure 4. Evasion corresponds to the share of all workers in each occupation who receive income from working in the form of allowances, tips, director's fees, consulting fees, or bonuses. Wage Slope corresponds to the occupation-specific average salary and wages at age 45, the age at which the pooled average of salary and wages reaches its maximum, divided by the average at 26 minus 1. Wage Peak corresponds to the maximum income in an occupation-specific age profile, normalized by the average value across all occupations. Salary and wages are adjusted for inflation, and year fixed effects are removed before computation of the occupation-specific age profiles used in the prior two measures. The Evasion, Wage Slope, and Wage Peak variables are calculated on the same sample of individuals used in Figure A10. Standard errors are computed with a heteroskedasticity-robust estimator.

Figure A11. Probability of Switching Occupations around the Repayment Threshold in 2005–2018



Notes: This figure plots the real HELP income distribution between 2005 and 2018 in red and measured on the left axis. HELP income is deflated to 2005 with the HELP threshold indexation rate, which is based on the annual CPI. Each bin represents $250, and the plot focuses on borrowers within $5,000 of the repayment threshold. The bins are chosen so that they are centered on the 2005 repayment threshold. The blue points present the fraction of individual–years in each bin in which borrowers' 2-digit ANZSCO occupation code differs from that of the previous year, along with 95% confidence intervals. The sample is the *ALife* sample defined in Section 2.4, restricted to the subset of individual–years with positive HELP debt balances between 2005 and 2018.

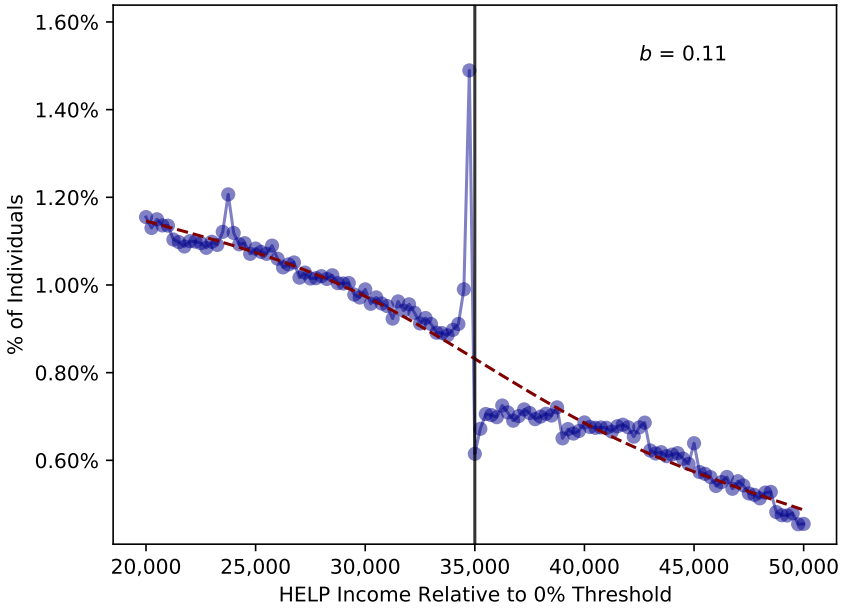
Figure A12. Self-Reported Hours Worked around the Repayment Threshold: Borrowers with Positive Labor Income



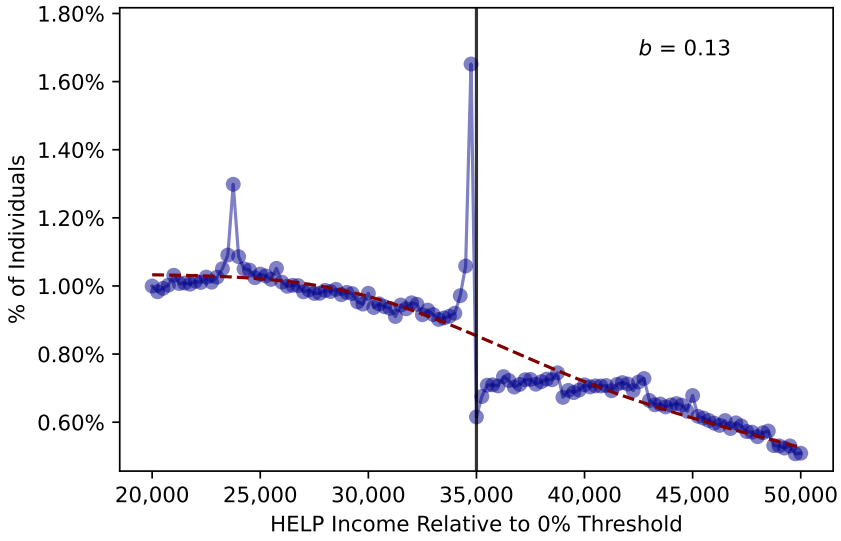
Notes: This figure replicates Figure 5 for the sample of borrowers with positive labor income.

Figure A13. Distribution of HELP Income in *ALife* versus MADIP Sample

Panel A: ALife Sample in 2016



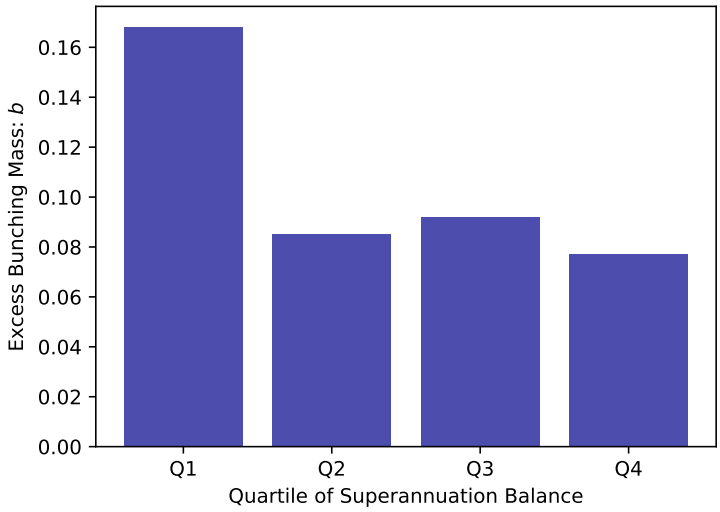
Panel B: MADIP Sample



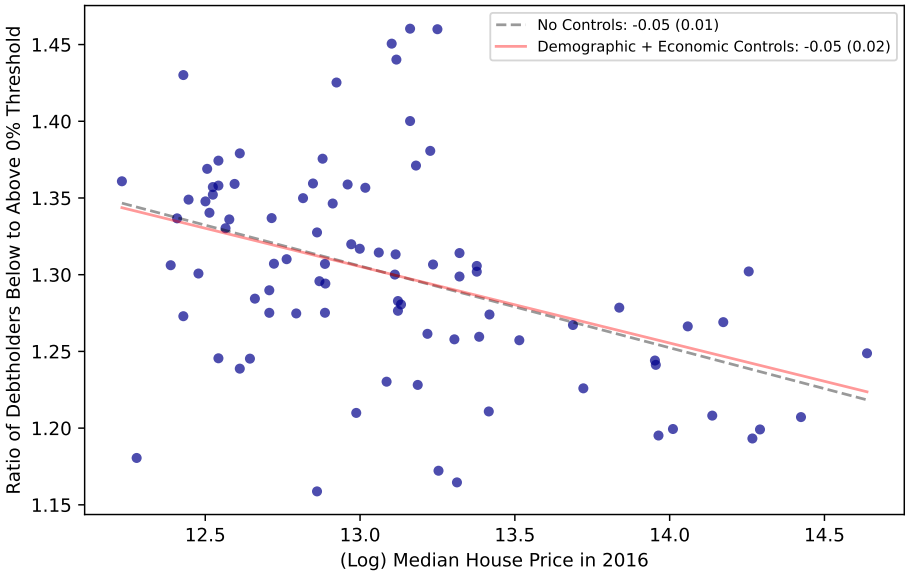
Notes: Panel A of this figure plots the distribution of HELP income (in 2005 AUD) in 2016 relative to the repayment threshold and the bunching statistic defined in (4). Each bin corresponds to $250 AUD, and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix C.4, and the counterfactual density estimated in this procedure is plotted in the dashed red line. The sample in this panel is the *ALife* sample defined in Section 2.4 in 2016, restricted to individuals with positive HELP debt balances. Panel B performs the same analysis in the cross-sectional MADIP sample, restricting to individuals with positive HELP debt balances.

Figure A14. Additional Tests of Link Between Bunching and Liquidity Constraints

Panel A: Bunching Heterogeneity by Superannuation Balances: Ages 20–29

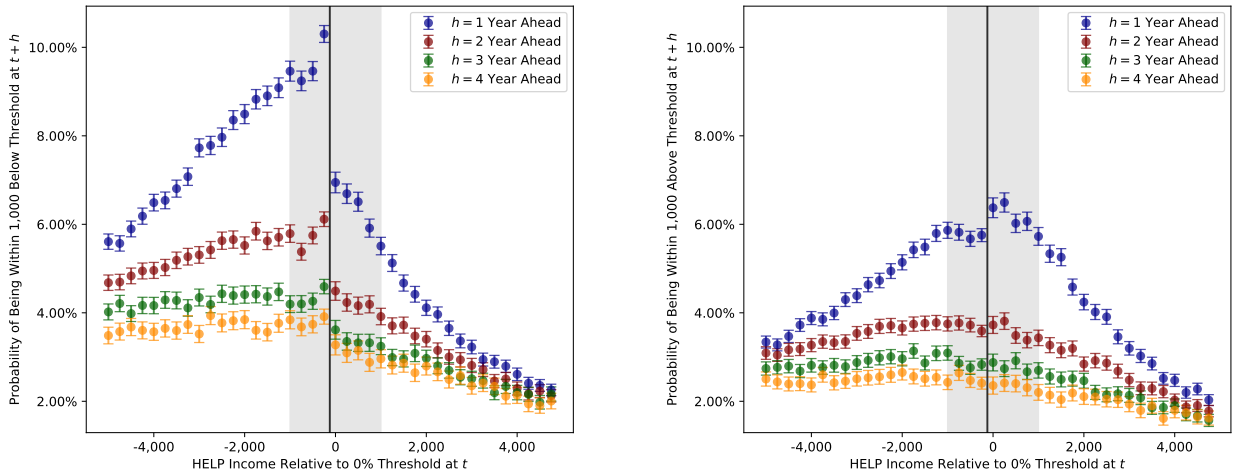


Panel B: Variation in Bunching across Geographic Regions Based on Housing Wealth



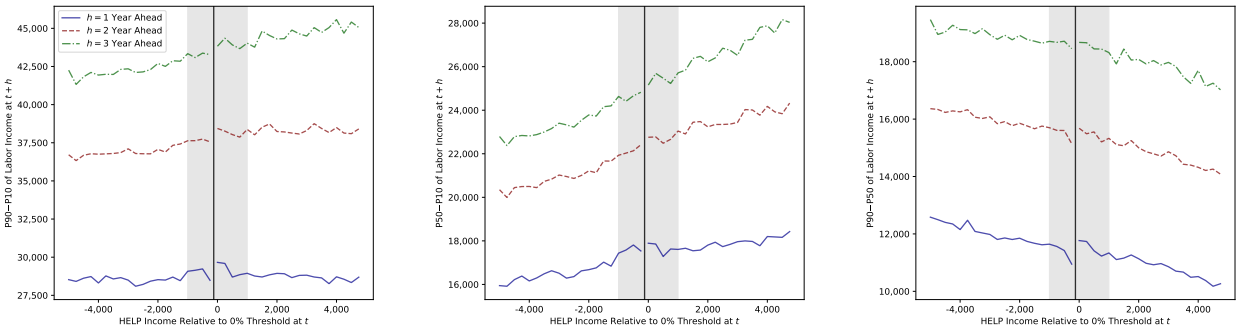
Notes: Panel A of this figure replicates the analysis in the left panel of Figure 7 among borrowers who are ages 20–29. Panel B of this figure plots the relationship between the amount of bunching below the repayment threshold and house prices by geographic region. Each point represents a geographic statistical area level-4 (SA4) region reported in *ALife*. For each individual–year, *ALife* contains the location of individuals' home addresses by SA4 region. SA4s are nonoverlapping geographical regions designed by the Australian Bureau of Statistics to reflect one or more labor markets aggregated based on economic, social and geographic characteristics. There are 106 SA4s covering Australia, and they generally have a population of between 100,000 to 300,000 people in regional areas and between 300,000 to 500,000 people in metropolitan areas. The amount of bunching is measured as the ratio of the number of borrowers in that occupation within $2,500 below the repayment threshold to the number within $2,500 above the threshold over 2005 to 2018. The horizontal axis corresponds to the log median transacted residential established house price in 2016 calculated by CoreLogic and reported by the ABS in the Data by Region Release. The gray dashed line corresponds to the line from a regression with no controls, while the red solid line corresponds to a regression controlling for log population size, median age, unemployment rate, and labor force participation rate. The slope coefficient estimates from both regressions are reported in the legend. The sample is the *ALife* sample defined in Section 2.4, restricted to the subset of individual–years for which the individuals are wage-earners and have positive HELP debt balances.

Figure A15. Persistence of Bunching Below Repayment Threshold



Notes: The left panel of this figure plots the fraction of borrowers with HELP income at $t + h$ that is within \$1,000 of the repayment threshold within \$250 bins of the difference between borrowers' HELP income and the repayment threshold in year t. The bins are chosen so that they are centered around zero. The dark blue line corresponds to h = one year; the dashed red line is h = two years; the dotted green line is h = three years; the solid orange line is h = four years. The right panel replicates the left plot with the fraction of borrowers within \$1,000 above the repayment threshold. Error bars represent 95% confidence intervals. The shaded gray region in both plots corresponds to the area within \$1,000 of the repayment threshold. The sample is the *ALife* sample defined in Section 2.4, restricted to individuals with positive HELP debt balances in each year.

Figure A16. Bunching Below Repayment Threshold and Distribution of Future Labor Income



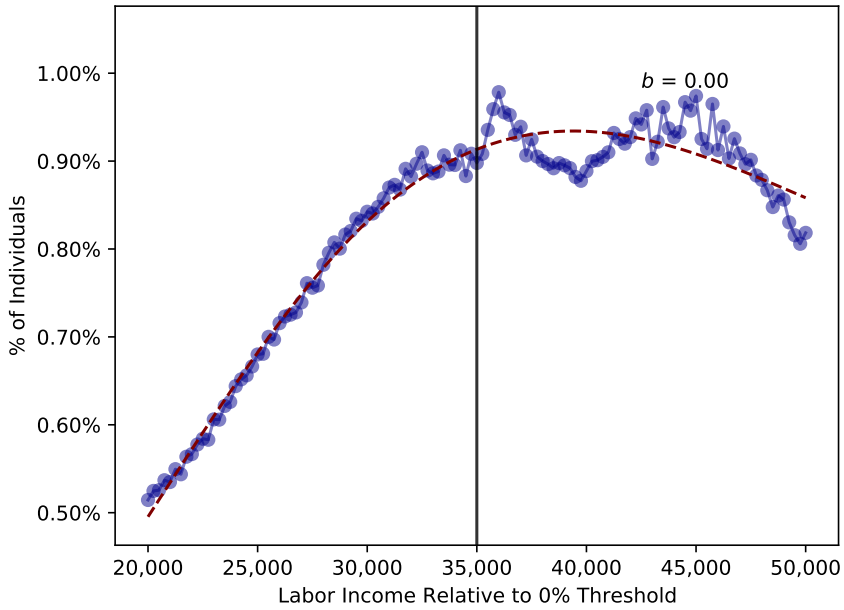
Notes: Each panel in this figure replicates the left panel of Figure 8 using different summary statistics within each $250 bin of HELP income instead of averages. The left panel plots the 90th minus 10th percentiles of labor income at h. The middle panel plots the 50th minus 10th percentiles of labor income at h. The right panel plots the 90th minus 50th percentiles of labor income at h.

Table A4. Additional Sources of Heterogeneity in Bunching

Sample	Estimated Bunching Statistic: b
Non-Electronic Filers	0.086
Electronic Filers	0.082
Wage-Earners	0.081
Entrepreneurs (Not Wage-Earners)	0.117
Females	0.081
Males	0.083
No Dependent Children	0.086
Has Dependent Children	0.077
No Spouse	0.085
Has Spouse	0.081
Full Sample	**0.084**

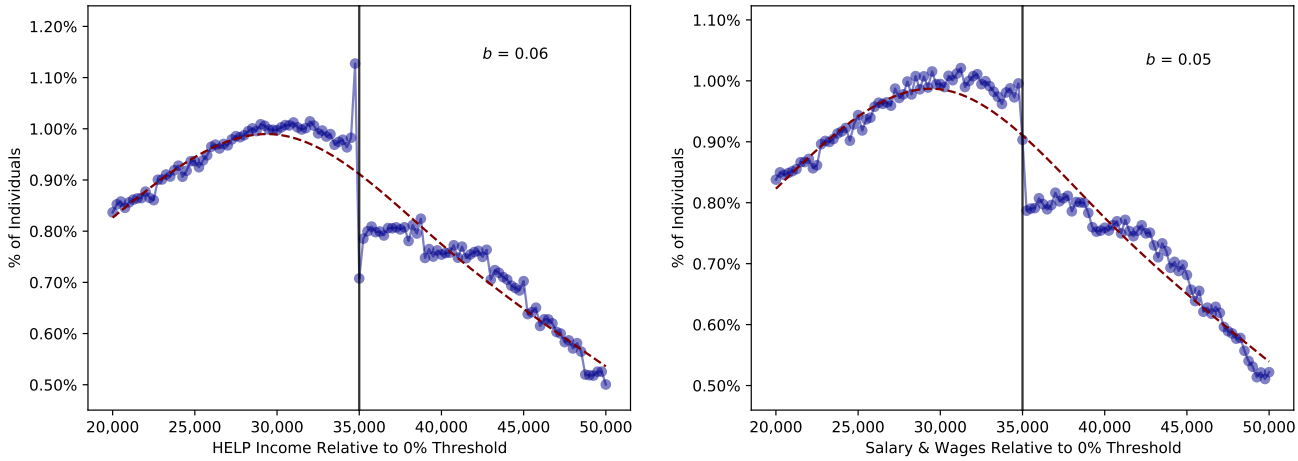
Notes: This table shows the bunching statistic defined in (4) computed for different samples of debtholders. The calculation of b is detailed in Appendix C.4. The sample in each row is the *ALife* sample defined in Section 2.4 for the period between 2005 and 2018 after the policy change, restricted to borrowers with positive HELP debt balances for whom the sample restrictions specified in each row are satisfied. The first two rows split borrowers based on whether they file their tax returns electronically; the third and fourth split the sample into wage-earners and non–wage-earners; the fifth and sixth split the sample based on gender; the seventh and eighth split the sample based on whether a borrower reports having a dependent child; and the ninth and tenth split the sample based on whether a borrower reports having a spouse.

Figure A17. Distribution of Labor Income among Borrowers with Deductions



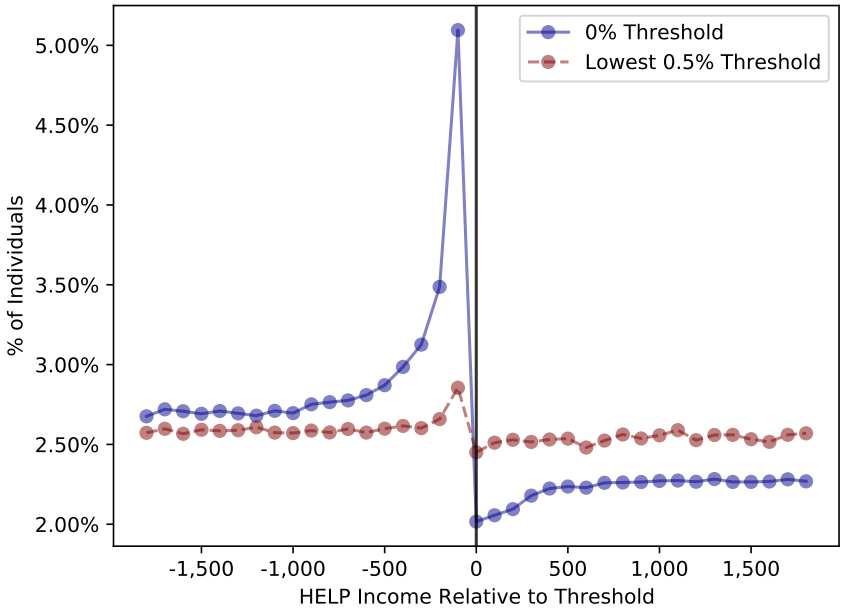
Notes: This figure plots the distribution of HELP income in 2005 AUD relative to the repayment threshold after the policy change and the bunching statistic defined in (4). Each bin corresponds to $250 AUD, and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix C.4, and the counterfactual density estimated in this procedure is plotted in the dashed red line. The sample is the *ALife* sample defined in Section 2.4 between 2005 and 2018 after the policy change, restricted to individuals with positive HELP debt balances and who have at least $1,000 in net deductions.

Figure A18. Distributions of HELP Income and Salary and Wages



Notes: This figure replicates the analysis in Figure A7, replacing the right plot with salary and wages instead of labor income.

Figure A19. Distribution of HELP Income at Repayment Threshold versus Lowest 0.5% Threshold



Notes: This figure plots the distribution of HELP income (in 2005 AUD) relative to the repayment threshold in solid blue and the lowest 0.5% threshold at $38,987 in dashed red. Each bin corresponds to $100 AUD, and bins are chosen so that they are centered around each threshold. The sample in this panel is the *ALife* sample defined in Section 2.4, restricted to individuals with positive HELP debt balances.

Table A5. Elasticity of Estimation Targets with Respect to Parameters

Panel A: Income Distribution Before the Policy Change

	y=22500	y=23000	y=23500	y=24000	y=24500	y=25000	y=25500	y=26000	y=26500	y=27000	y=27500	y=28000	y=28500
ϕ	0.01	0.00	0.02	0.01	0.08	-0.03	-0.04	-0.02	-0.03	-0.02	-0.00	0.02	-0.03
f	0.01	0.01	0.00	0.01	-0.16	0.09	0.06	-0.01	0.05	-0.02	-0.01	-0.05	0.03
λ	-0.01	-0.01	-0.02	-0.01	0.21	-0.13	-0.08	-0.00	-0.02	-0.00	-0.00	0.04	-0.02
β	0.39	0.33	-0.29	0.33	-2.80	0.61	1.51	0.29	0.79	-0.41	0.15	-1.27	1.06
κ	0.00	-0.00	0.01	0.02	-0.00	0.02	-0.01	-0.02	0.01	0.00	0.00	-0.03	-0.01
δ_0	-1.38	-1.37	-2.31	-0.37	-0.44	-0.56	0.23	0.42	1.00	0.65	1.71	1.22	2.39
δ_1	-0.45	-0.37	-0.44	-0.29	-0.13	0.03	0.03	0.20	0.24	0.30	0.34	0.46	0.38
δ_2	-0.16	-0.17	-0.10	-0.06	-0.02	-0.07	-0.05	0.06	0.07	0.10	0.06	0.22	0.24
δ_0^E	-0.04	-0.03	0.05	-0.15	-0.05	-0.16	0.22	-0.06	-0.16	-0.16	0.23	0.27	0.08
δ_1^E	-0.12	-0.13	-0.10	-0.00	-0.04	-0.04	-0.06	0.06	0.03	0.13	0.11	0.13	0.12
ρ	0.35	1.47	0.74	0.13	0.04	-0.59	0.03	-1.04	0.06	-0.23	0.40	-0.80	-1.01
σ_ν	0.14	0.10	0.03	0.04	0.10	-0.05	-0.05	-0.04	-0.06	-0.01	-0.13	-0.05	-0.11
σ_ϵ	0.00	0.02	-0.02	0.00	0.01	0.00	-0.01	-0.01	0.02	-0.02	-0.01	0.00	0.00
σ_i	0.03	0.06	-0.01	0.04	-0.02	0.01	-0.07	-0.05	0.03	0.05	-0.05	-0.01	-0.03

Panel B: Income Distribution After the Policy Change

	y=32500	y=33000	y=33500	y=34000	y=34500	y=35000	y=35500	y=36000	y=36500	y=37000	y=37500	y=38000	y=38500
ϕ	-0.01	-0.03	0.01	0.03	0.12	-0.04	-0.06	-0.07	-0.07	-0.03	0.02	-0.01	0.08
f	0.03	-0.00	0.02	0.03	-0.16	0.09	0.07	0.05	-0.01	-0.01	-0.01	-0.01	-0.03
λ	-0.03	0.02	-0.03	0.02	0.28	-0.19	-0.12	-0.12	-0.04	0.01	0.00	0.01	0.04
β	0.12	0.79	-0.10	-0.00	-1.87	0.88	0.38	0.61	0.34	0.59	-0.58	-0.49	0.04
κ	0.01	0.00	0.02	-0.01	-0.01	0.02	0.01	0.02	-0.02	-0.02	-0.01	0.00	-0.02
δ_0	-1.54	-0.39	-0.40	-0.93	-0.81	0.35	0.07	0.67	0.07	1.60	0.53	0.86	1.06
δ_1	-0.41	-0.27	-0.12	-0.22	-0.20	0.07	0.18	0.16	0.17	0.32	0.11	0.22	0.34
δ_2	-0.13	-0.17	-0.07	-0.03	-0.08	-0.01	-0.03	0.07	0.06	0.17	0.16	0.13	0.07
δ_0^E	0.12	-0.35	-0.09	0.17	-0.16	0.05	-0.11	-0.05	0.25	0.22	0.02	0.10	-0.06
δ_1^E	-0.06	-0.12	-0.15	-0.05	0.01	-0.03	-0.01	0.04	0.17	0.11	0.10	0.05	0.02
ρ	0.27	0.97	-0.65	-0.15	0.73	0.65	0.49	-1.03	0.03	-0.76	-3.37	1.04	1.37
σ_ν	-0.01	0.01	0.01	0.03	0.07	-0.03	-0.04	-0.07	0.00	-0.01	-0.02	0.01	-0.01
σ_ϵ	-0.00	0.01	-0.02	-0.05	0.01	0.00	0.04	0.03	-0.01	-0.02	0.01	-0.01	0.01
σ_i	-0.02	-0.08	-0.03	0.07	0.05	-0.03	0.01	-0.03	0.01	0.01	0.04	-0.06	0.04

Panel C: Ratios Below to Above Repayment Thresholds

	Ratio 2004 0%	Ratio 2005 0%	Ratio 2005 0.5%	Ratio 2005 0%, Q1 Debt	Ratio 2005 0%, Q4 Debt
ϕ	0.20	0.22	0.13	0.22	0.20
f	-0.40	-0.34	-0.12	-0.34	-0.33
λ	0.52	0.64	0.16	0.37	0.82
β	-4.48	-4.93	-1.26	-4.91	-3.14
κ	-0.00	-0.02	-0.03	-0.05	0.01
δ_0	0.57	-1.28	-1.17	-1.99	0.04
δ_1	0.00	-0.26	-0.23	-0.23	-0.43
δ_2	0.05	-0.17	-0.07	-0.30	-0.10
δ_0^E	0.24	-0.27	-0.05	-0.17	-0.50
δ_1^E	-0.02	0.01	-0.07	-0.01	0.01
ρ	-0.35	0.44	0.82	1.04	1.20
σ_ν	0.15	0.19	0.13	0.26	0.08
σ_ϵ	0.02	0.01	-0.01	-0.01	0.05
σ_i	-0.03	0.10	-0.03	0.17	0.20

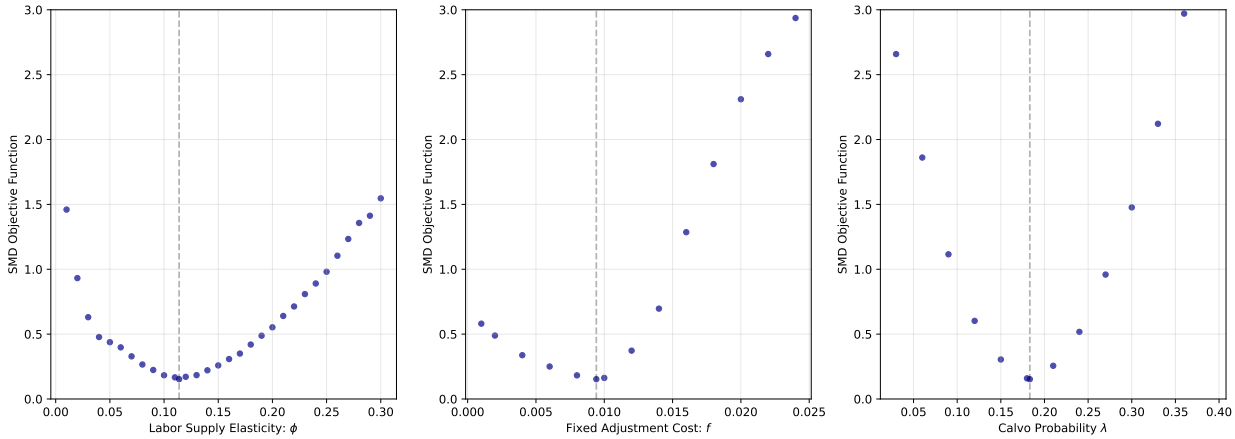
Table A5. Elasticity of Estimation Targets with Respect to Parameters (continued)

Panel D: Remaining Estimation Targets

	Mean y	SD at 22	SD at 32	SD at 42	SD at 52	SD at 62	β_1	β_2	P10 1-Yr	P10 5-Yr	P90 1-Yr	P90 5-Yr	β_0^E	β_1^E	Mean i at 40	Mean l
ϕ	0.00	0.19	0.16	0.16	0.16	0.18	0.00	0.01	-0.01	-0.04	0.02	0.04	-0.09	0.09	0.00	-0.01
f	-0.00	-0.01	-0.01	-0.02	-0.03	-0.03	-0.00	0.01	0.00	0.01	-0.01	-0.01	0.02	-0.01	0.02	-0.04
λ	0.02	0.07	0.08	0.07	0.07	0.06	0.02	-0.02	-0.01	-0.04	0.02	0.04	-0.04	0.03	0.01	0.09
β	0.06	-0.12	-0.22	-0.63	-0.96	-0.60	0.00	0.10	0.09	0.20	-0.11	-0.27	0.04	-0.03	20.11	0.27
κ	-0.06	0.00	0.01	0.01	0.01	0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	-0.07	-0.30
δ_0	9.93	-0.27	-0.59	-0.68	-0.75	-0.69	-0.08	0.08	0.06	0.15	-0.07	-0.18	0.16	-0.25	12.48	4.48
δ_1	3.30	-0.10	-0.15	-0.20	-0.24	-0.16	0.98	0.05	0.02	0.05	-0.02	-0.05	0.08	-0.10	2.01	1.33
δ_2	1.64	-0.04	-0.06	-0.10	-0.14	-0.10	-0.02	1.15	0.01	0.03	-0.01	-0.02	0.04	-0.05	-0.02	0.60
δ_0^E	0.21	-0.03	0.07	0.16	0.24	0.29	0.00	-0.00	0.00	0.00	-0.00	-0.00	1.00	-0.01	0.16	0.24
δ_1^E	0.37	-0.03	0.09	0.28	0.51	0.73	0.08	0.00	-0.00	-0.01	-0.00	0.00	0.05	0.95	0.09	0.37
ρ	2.41	0.55	9.45	11.52	11.25	9.81	-0.21	0.22	0.14	-0.54	-0.12	0.57	-0.06	0.06	4.94	-0.43
σ_ν	0.36	-0.01	1.39	1.68	1.60	1.38	-0.04	0.05	-0.62	-0.84	0.62	0.83	-0.03	0.01	1.40	-0.14
σ_ϵ	0.02	0.06	0.06	0.06	0.05	0.04	-0.00	0.00	-0.33	-0.10	0.33	0.10	-0.00	-0.00	0.04	-0.01
σ_i	0.08	1.76	0.44	0.10	0.02	0.00	-0.03	0.03	-0.00	-0.03	0.00	0.03	-0.00	-0.00	0.40	0.04

Notes: This table reports the elasticity of the simulated estimation targets with respect to the estimated structural parameters. The four panels present the results for different sets of estimation targets. In each panel, the entry in row i and column j is an estimate of the derivative of the log of the estimation target in column j with respect to the log of the structural parameter in row i. I approximate this derivative locally around the estimated set of structural parameters in column (1) of Table 3 by central differencing. Since some estimation targets and parameters are negative, I take the absolute value before taking logarithms and then multiply the result by -1 if the parameter or estimation target is negative. The width between the lower and upper points in central differencing is set equal to half of the step size used in the Nelder–Mead optimization routine in estimating the model, which is the same width used in computing the Jacobian matrix used to calculate standard errors. Panels A and B provide the results for the estimation targets shown in Figure 9. Panel C provides the results for the targets in Figure 10. Panel D provides the results for the remaining set of estimation targets shown in Table 4.

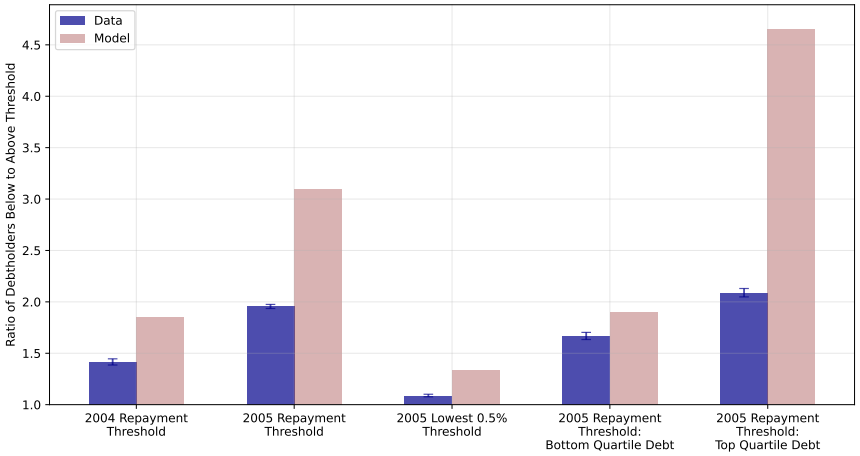
Figure A20. Local Identification of Labor Supply Parameters



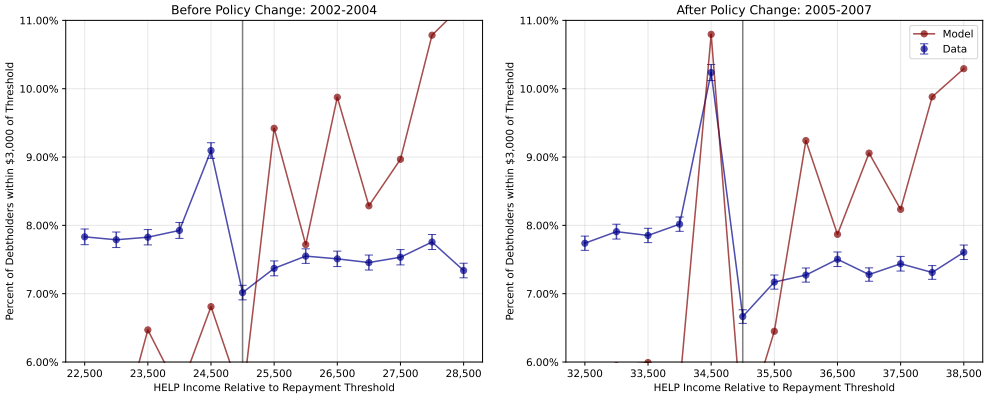
Notes: This figure plots the value of the simulated minimum distance objective function in the baseline estimation for different values of the three key parameters, ϕ, λ, and λ. Each point represents the objective function when the model is solved at that parameter value, with all other parameters held fixed at their estimated values from column (1) of Table 3. The vertical gray dashed line indicates the estimated value of each parameter.

Figure A21. Model Fit: No Optimization Frictions

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



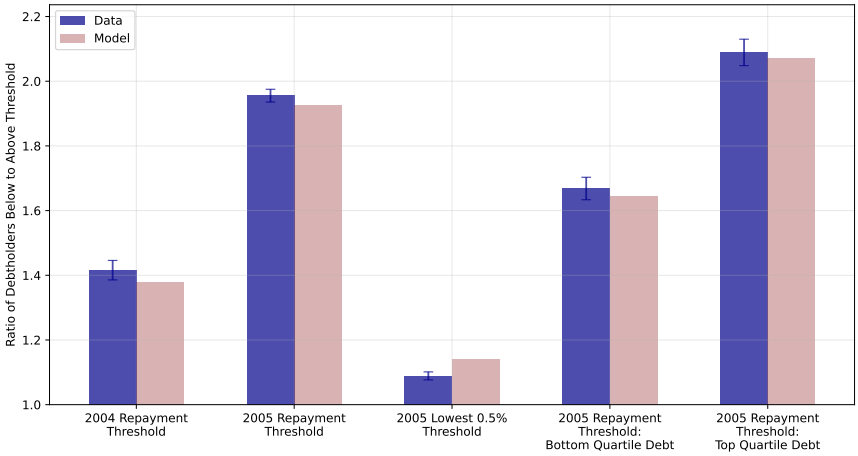
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	$42639	$62169
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.304
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.403
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.533
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.661
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.319
Linear Age Profile Term	0.077	0.058
Quadratic Age Profile Term	−0.001	−0.002
Education Income Premium Constant	−0.574	−0.299
Education Income Premium Slope	0.023	0.033
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.913
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.945
90th Percentile of 1-Year Labor Income Growth	0.415	0.911
90th Percentile of 5-Year Labor Income Growth	0.698	0.928
Average Labor Supply	1.000	1.245
Average Capital Income between Ages 40 and 44	$1338	$8646

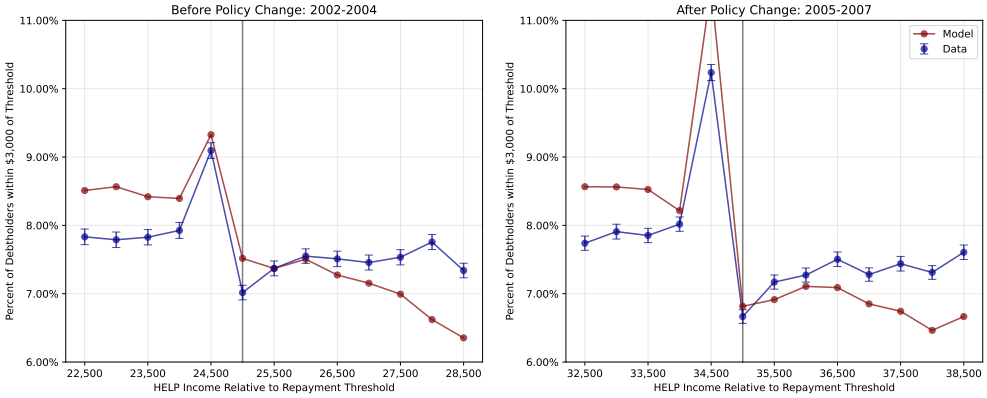
Notes: The results presented in this figure show the fit of the estimated model in column (2) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A22. Model Fit: No Calvo Adjustment

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



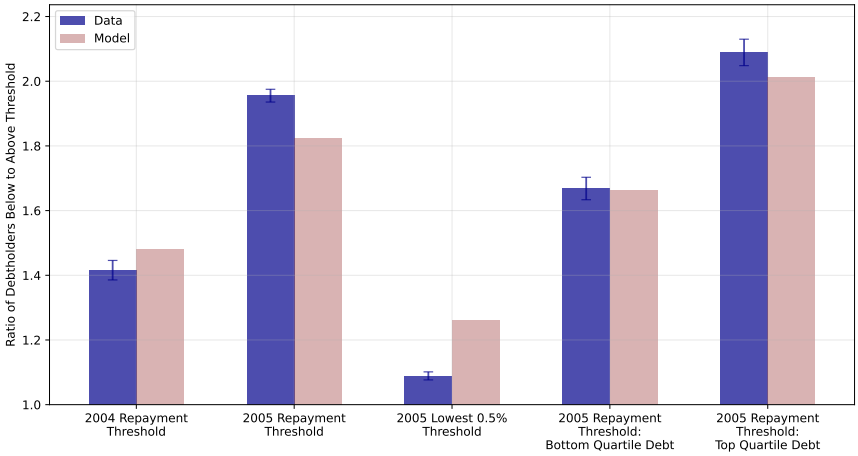
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	$42639	$45691
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.483
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.493
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.523
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.584
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.648
Linear Age Profile Term	0.077	0.082
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.543
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.407
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.661
90th Percentile of 1-Year Labor Income Growth	0.415	0.411
90th Percentile of 5-Year Labor Income Growth	0.698	0.676
Average Labor Supply	1.000	1.247
Average Capital Income between Ages 40 and 44	$1338	$1295

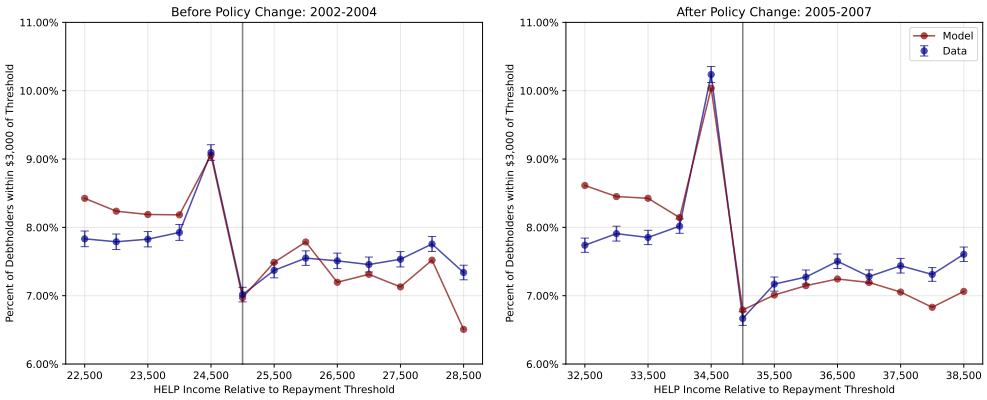
Notes: The results presented in this figure show the fit of the estimated model in column (3) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A23. Model Fit: No Fixed Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



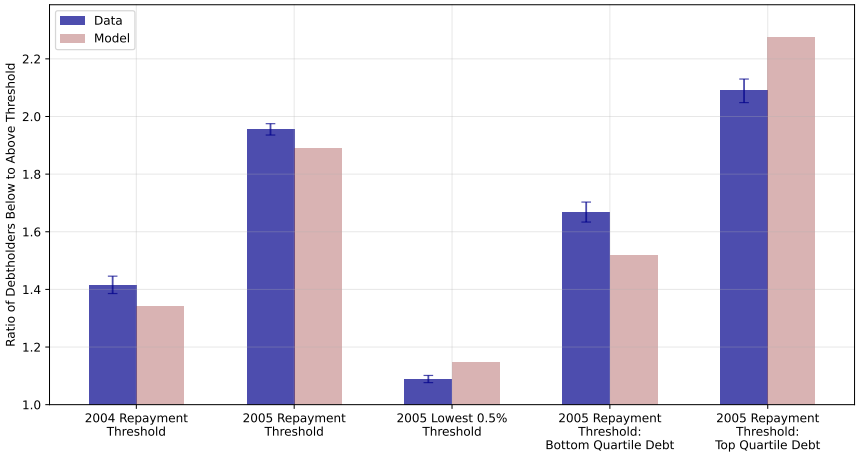
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	$42639	$46896
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.474
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.507
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.537
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.585
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.641
Linear Age Profile Term	0.077	0.070
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.572
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.378
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.746
90th Percentile of 1-Year Labor Income Growth	0.415	0.379
90th Percentile of 5-Year Labor Income Growth	0.698	0.749
Average Labor Supply	1.000	0.991
Average Capital Income between Ages 40 and 44	$1338	$1301

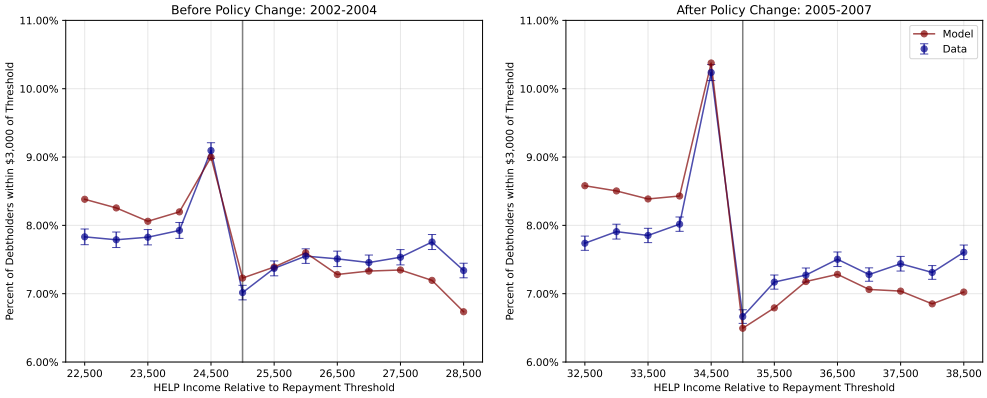
Notes: The results presented in this figure show the fit of the estimated model in column (4) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A24. Model Fit: Learning-by-Doing

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



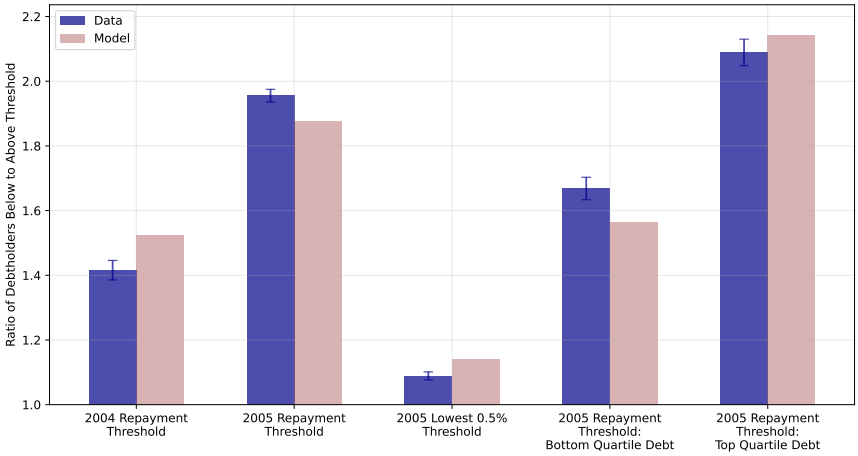
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	$42639	$48506
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.452
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.501
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.526
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.580
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.674
Linear Age Profile Term	0.077	0.075
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.581
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.401
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.787
90th Percentile of 1-Year Labor Income Growth	0.415	0.401
90th Percentile of 5-Year Labor Income Growth	0.698	0.790
Average Labor Supply	1.000	1.012
Average Capital Income between Ages 40 and 44	$1338	$1295

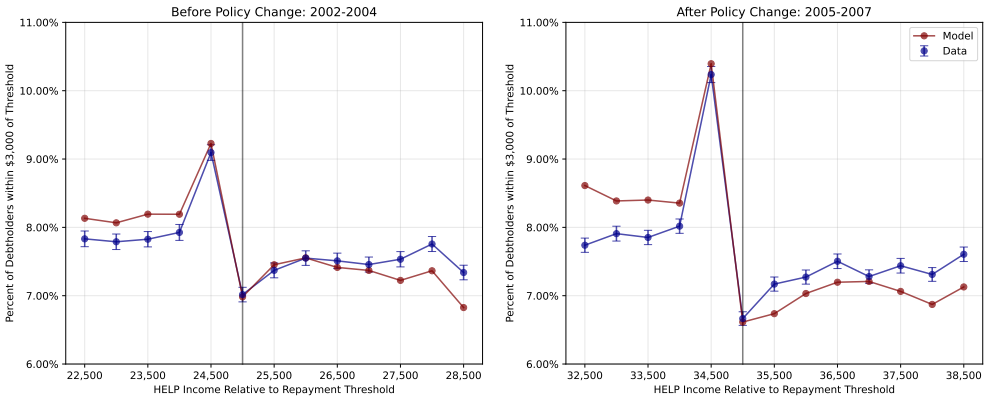
Notes: The results presented in this figure show the fit of the estimated model in column (5) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A25. Model Fit: Linear Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



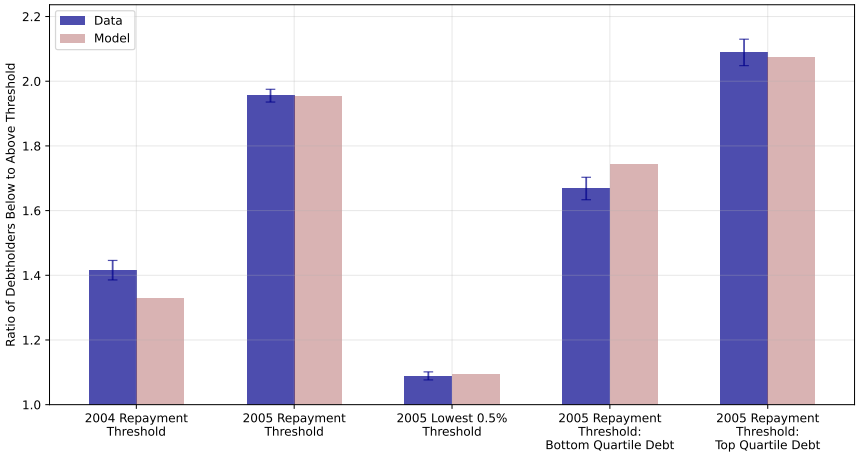
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	$42639	$49640
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.461
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.492
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.525
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.582
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.662
Linear Age Profile Term	0.077	0.081
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.544
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.395
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.774
90th Percentile of 1-Year Labor Income Growth	0.415	0.395
90th Percentile of 5-Year Labor Income Growth	0.698	0.778
Average Labor Supply	1.000	0.960
Average Capital Income between Ages 40 and 44	$1338	$1375

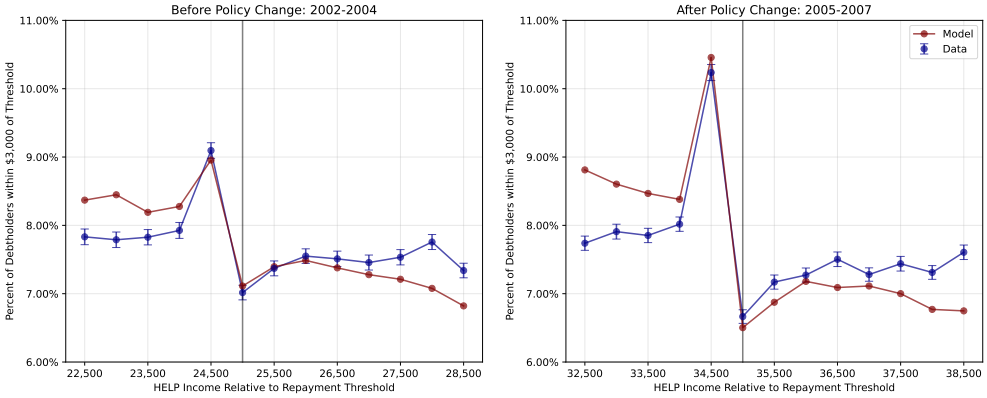
Notes: The results presented in this figure show the fit of the estimated model in column (6) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A26. Model Fit: Misperception of Debt Payoff

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change

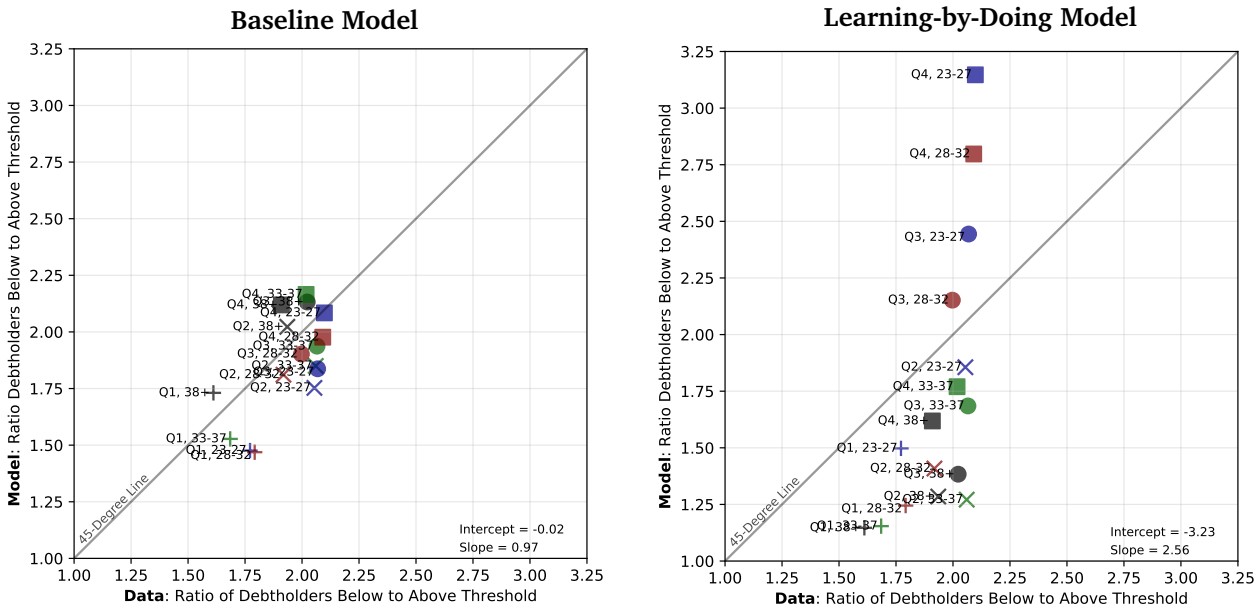


Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	$42639	$44875
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.467
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.504
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.538
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.590
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.642
Linear Age Profile Term	0.077	0.080
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.564
Education Income Premium Slope	0.023	0.023
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.386
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.716
90th Percentile of 1-Year Labor Income Growth	0.415	0.386
90th Percentile of 5-Year Labor Income Growth	0.698	0.717
Average Labor Supply	1.000	1.004
Average Capital Income between Ages 40 and 44	$1338	$1326

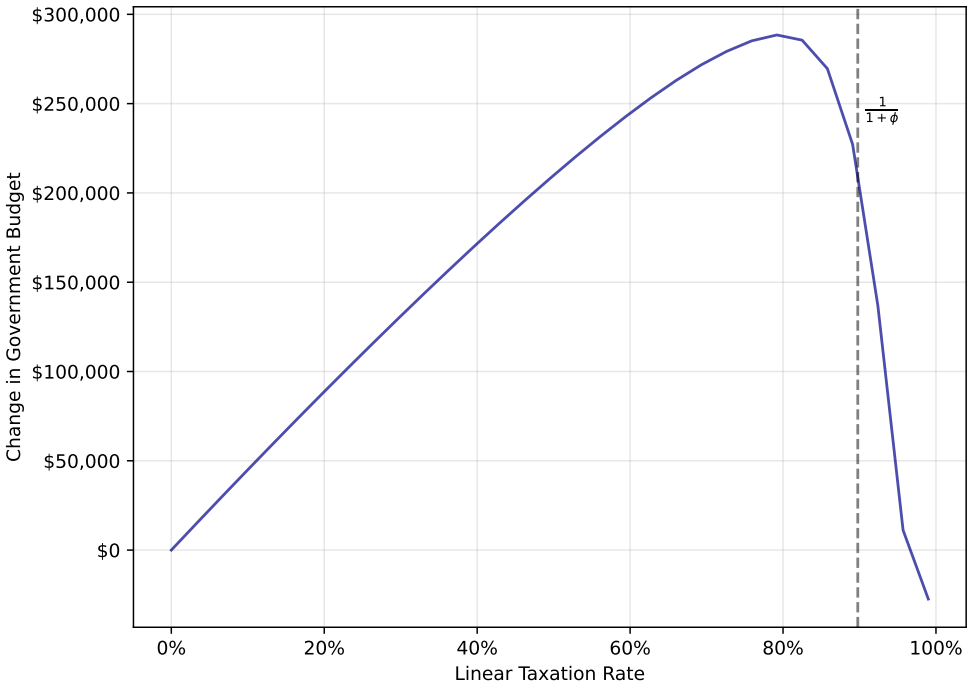
Notes: The results presented in this figure show the fit of the estimated model in column (7) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A27. Fit on Nontargeted Bunching Heterogeneity: Baseline vs. Learning-by-Doing Models



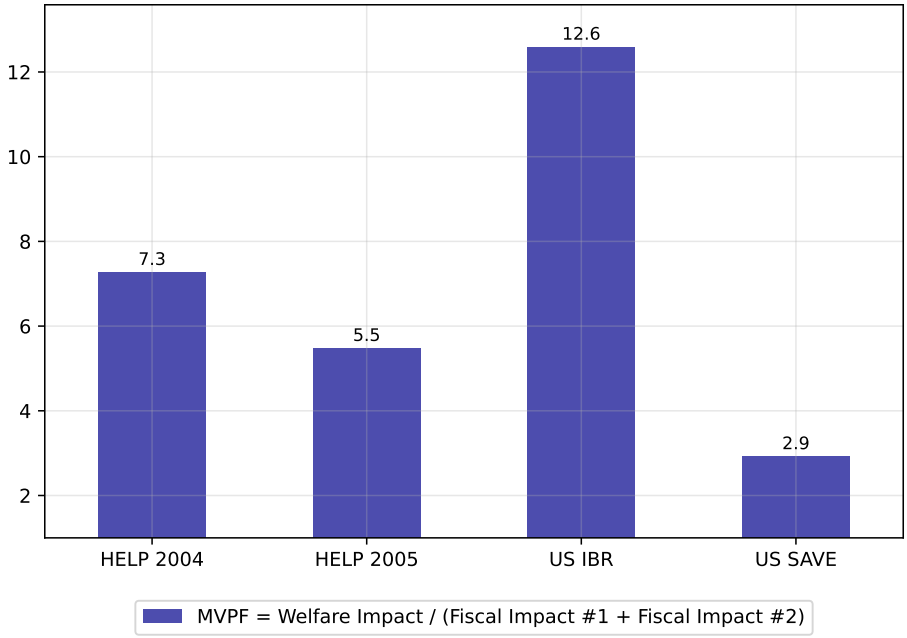
Notes: The left panel of this figure reproduces the results in the left panel in Figure 11 using different axes to match the right panel of this figure, which replicates the left panel for the model with learning-by-doing estimated in column (5) of Table 3. See the notes in Figure 11 for additional details on how these figures are constructed.

Figure A28. Laffer Curve in Baseline Model



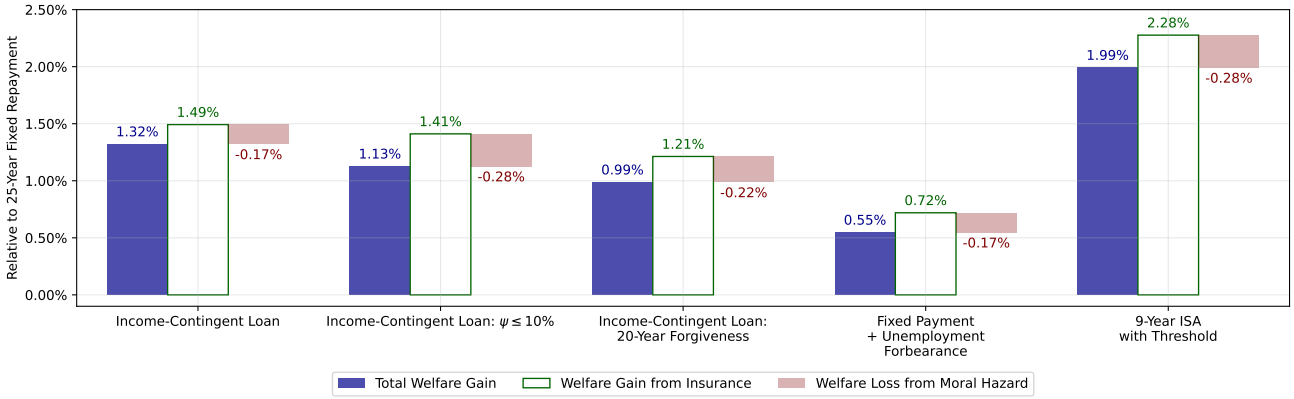
Notes: This figure plots the Laffer curve from a linear tax on income, τy_{ia}, in the baseline model. The horizontal axis corresponds to the value of the linear taxation rate, τ. The vertical axis shows that government revenue changes with respect to its value when $\tau = 0$. The vertical line corresponds to the revenue-maximizing tax rate in the canonical static frictionless model of labor supply (Saez 2001) evaluated at the estimate of ϕ in column (1) of Table 3. When computing this Laffer curve, I turn off other forms of income taxation, eliminate debt repayment, and make unemployment benefits conditional on wage rates so that the only effect on the government budget comes through the linear taxation. Since the labor supply responses of borrowers are what the model is designed to capture, I apply the tax only to individuals with $\mathcal{E}_i = 1$.

Figure A29. Marginal Value of Public Funds of Replacing 25-Year Fixed Repayment with Existing Contracts



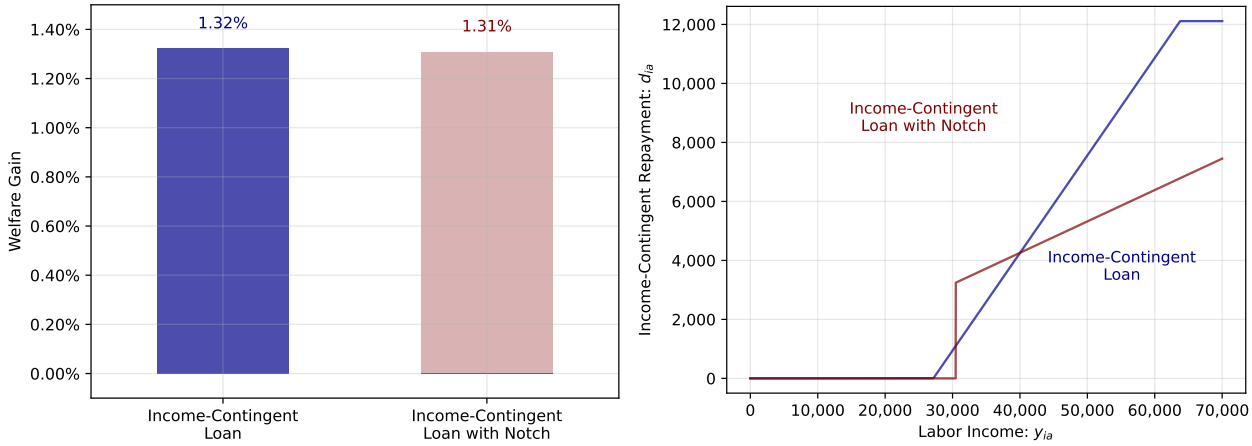
Notes: This figure plots the marginal value of public funds, defined by Hendren and Sprung-Keyser (2020), to moving from a 25-year fixed repayment contract to various existing income-contingent repayment contracts. This is computed by dividing the equivalent variation by the sum of the two fiscal impacts presented in Figure 13.

Figure A30. Welfare Gains from Alternative Constrained-Optimal Income-Contingent Loans



Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment, along with the decomposition performed in Figure 14, for different constrained-optimal repayment contracts described in the text. This analysis is performed with all parameters set at their estimated and calibrated values in the baseline model.

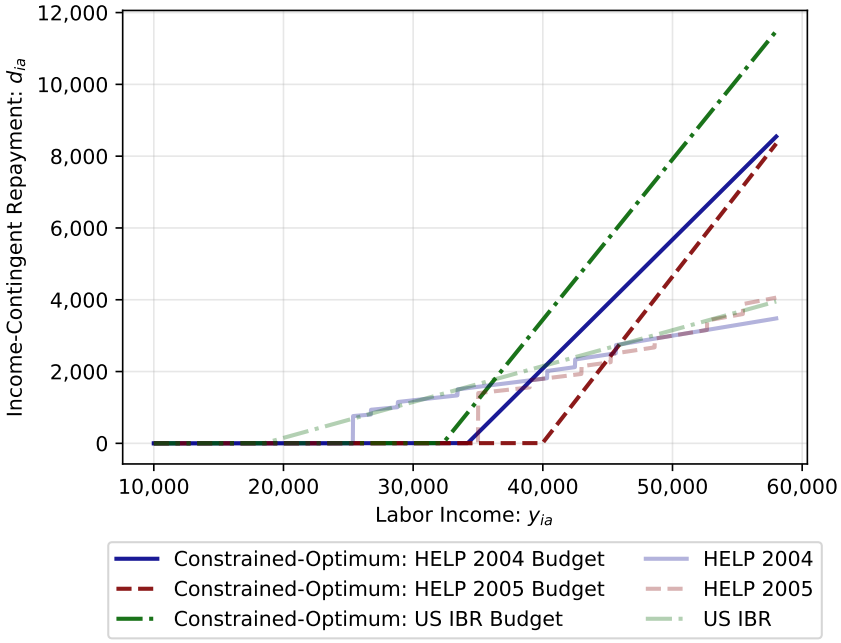
Figure A31. Effects of Discontinuity in Average Rather than Marginal Repayment Rate



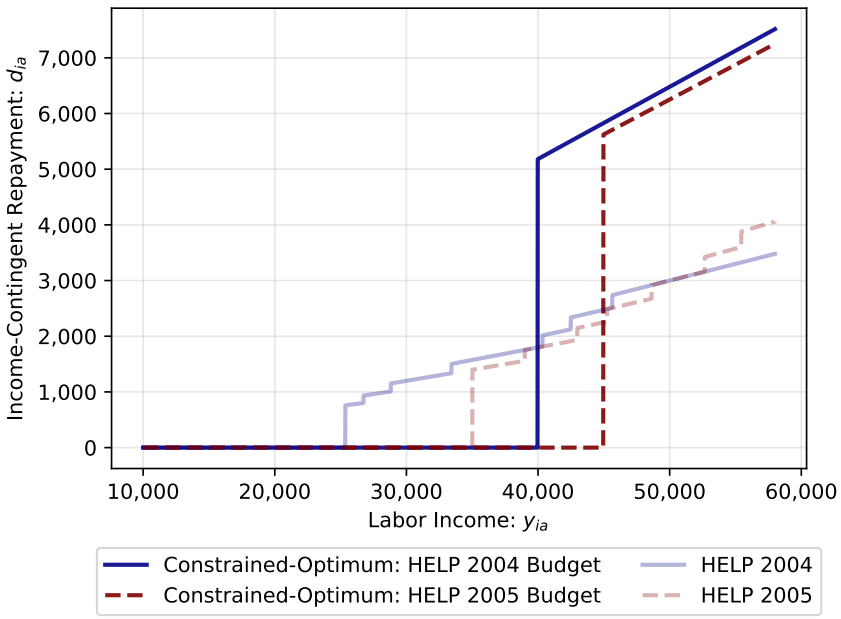
Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from different constrained-optimal repayment contracts shown on the right. The repayments are shown for a borrower with median initial debt. The first contract is the constrained-optimal income-contingent loan that solves (18). The second contract is a constrained-optimal contract with a notch, where the repayment threshold changes average rather than marginal repayment rates, as in Australia.

Figure A32. Comparison of Constrained-Optimal Contracts with Existing Contracts

Panel A: Constrained-Optimal Income-Contingent Loans



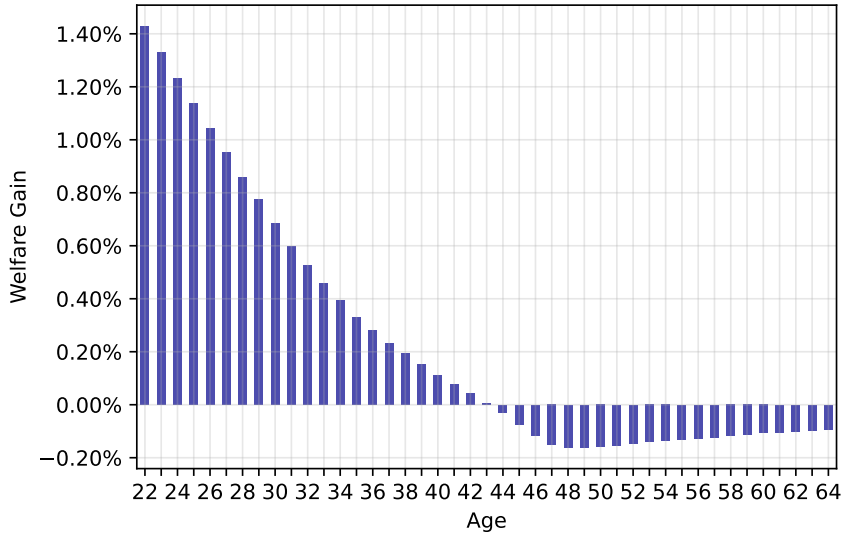
Panel B: Constrained-Optimal Income-Contingent Loans with a Notch



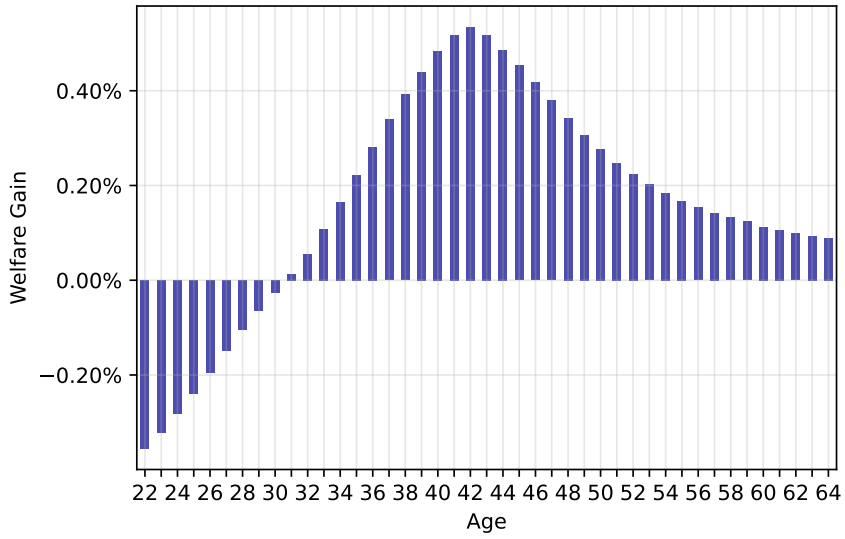
Notes: This figure shows income-contingent repayments for different repayment contracts. Panel A compares constrained-optimal income-contingent loans with existing contracts. Panel B compares constrained-optimal income-contingent loans with a change in *average* rather than marginal repayment rates with HELP contracts, which also have a discontinuity in the average repayment rate. The light solid blue line is the 2004 HELP contract from Figure 2. The dark solid blue line corresponds to the constrained-optimal repayment contract in the baseline model that comes from solving (18) with $\overline{\mathcal{G}}$ set equal to the revenue raised by this contract. The solid and light-dashed red and green lines show the same analysis with the 2005 HELP and the US IBR contracts.

Figure A33. Heterogeneity in Welfare Gains by Age

Panel A: Optimal Income-Contingent Loan Relative to 25-Year Fixed Repayment

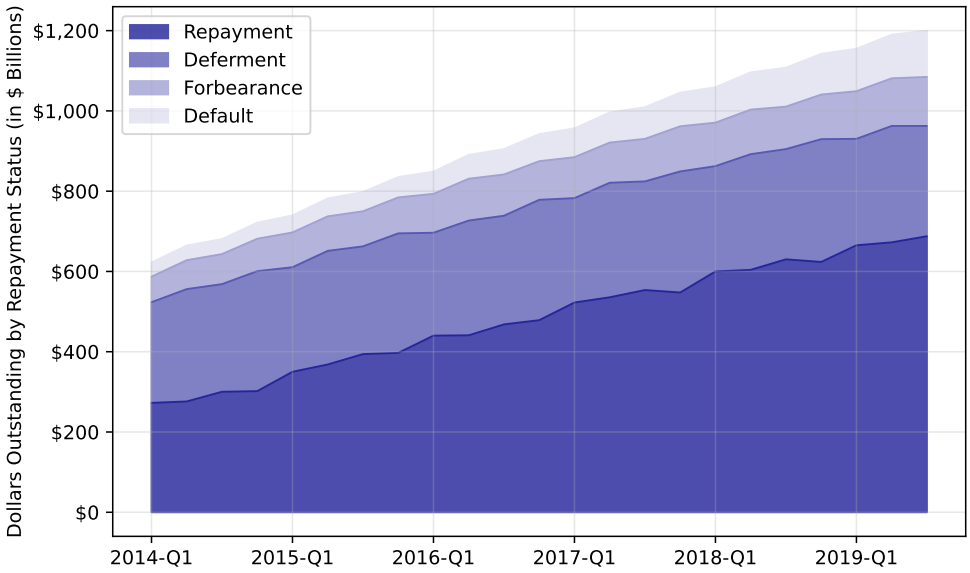


Panel B: Optimal Income-Contingent Loan with Forgiveness Relative to Optimal Income-Contingent Loan



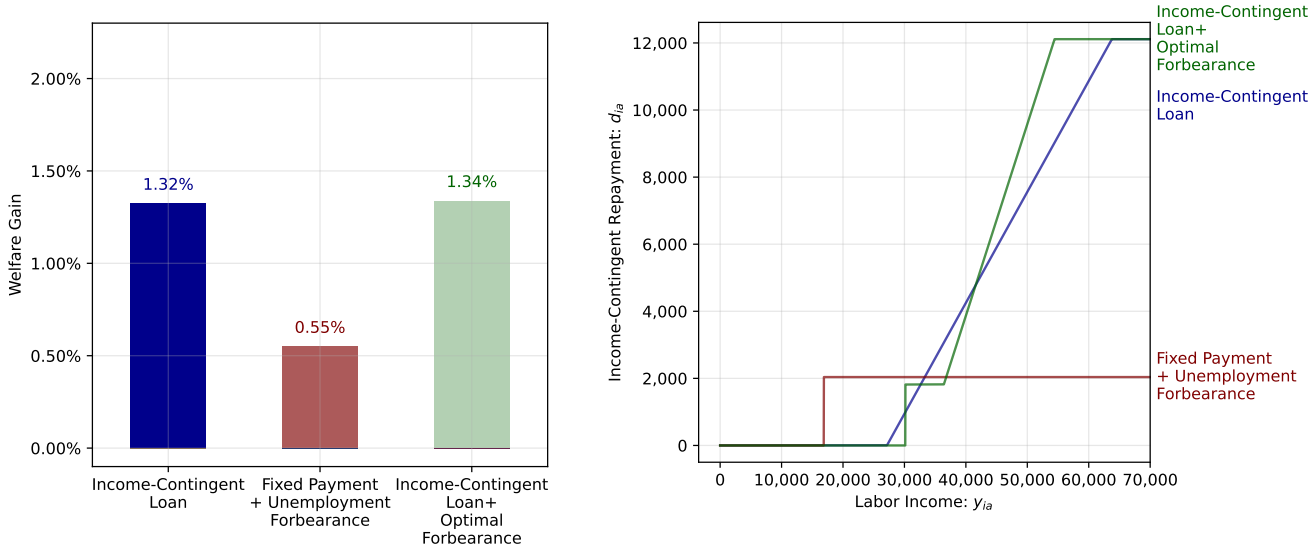
Notes: Panel A of this figure plots the average welfare gain at each age from the constrained-optimal income-contingent loan relative to 25-year fixed repayment. Panel B performs the same analysis for the welfare gain of the constrained-optimal income-contingent loan with forgiveness after 20 years relative to the constrained-optimal income-contingent loans. The welfare gains in this plotted are computed as the percent change in certainty-equivalents at each age; see the notes to Figure 17 for additional details.

Figure A34. Repayment Status of Government-Provided Student Loans in the US



Notes: This figure plots the fraction of total outstanding student debt balances in the US Federal Government Direct Loan Portfolio that are in one of four repayment states: current repayment, deferment, forbearance, and default. These data were downloaded from the US Department of Education's Open Data Platform.

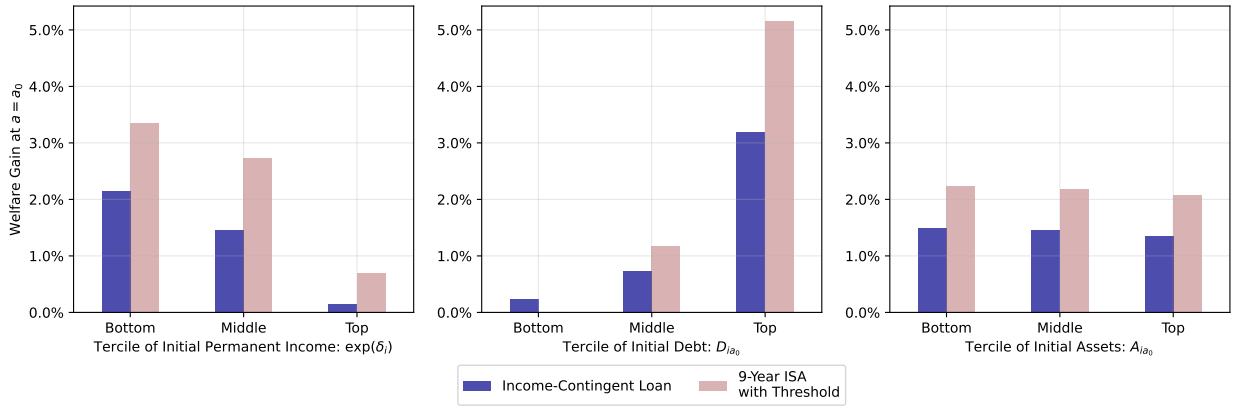
Figure A35. Welfare Gains from Addition of Optimally Chosen Forbearance to Income-Contingent Loan



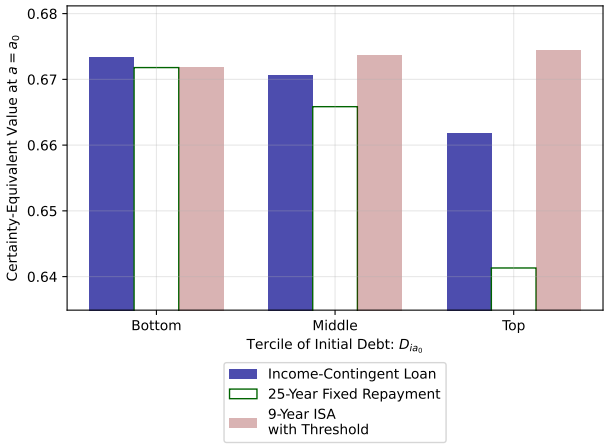
Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from constrained-optimal contracts described in the text and shown on the right. Repayments are shown for a borrower with median initial debt.

Figure A36. Heterogeneity in Welfare Gains from Constrained-Optimal 9-Year ISA with Threshold

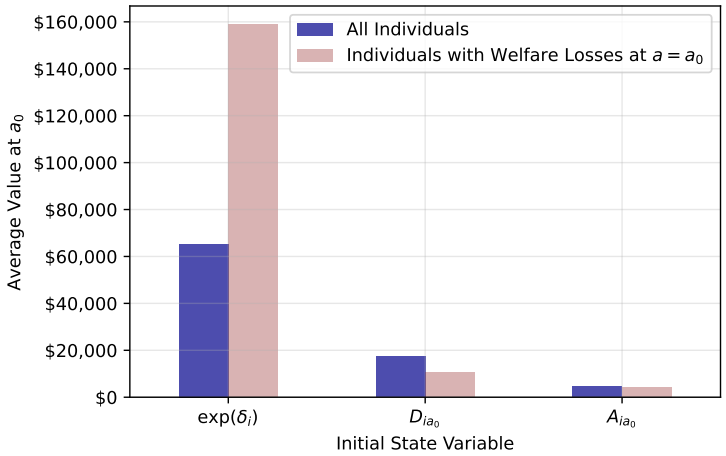
Panel A: Welfare Gains across Initial States



Panel B: Variation in Certainty-Equivalents by Initial Debt

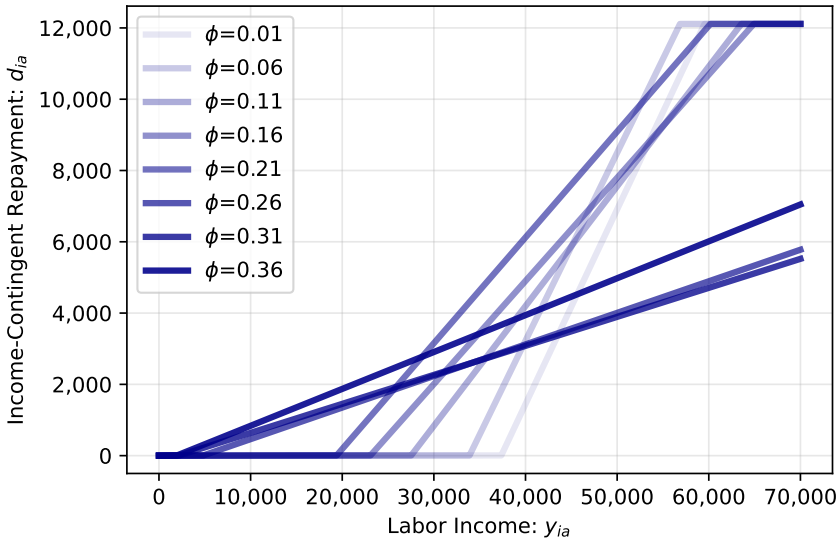


Panel C: Average Initial States by Welfare Gain from 9-Year ISA with Threshold



Notes: Panel A in this figure plots the welfare gains at a_0 computed in Figure 17 for different terciles of the three initial states that generate ex-ante heterogeneity in the model. Panel B plots the certainty-equivalent value at a_0 across terciles of initial debt. Panel C plots the average initial states of all borrowers versus those that experience welfare losses from the constrained-optimal 9-Year ISA with Threshold relative to 25-year fixed repayment.

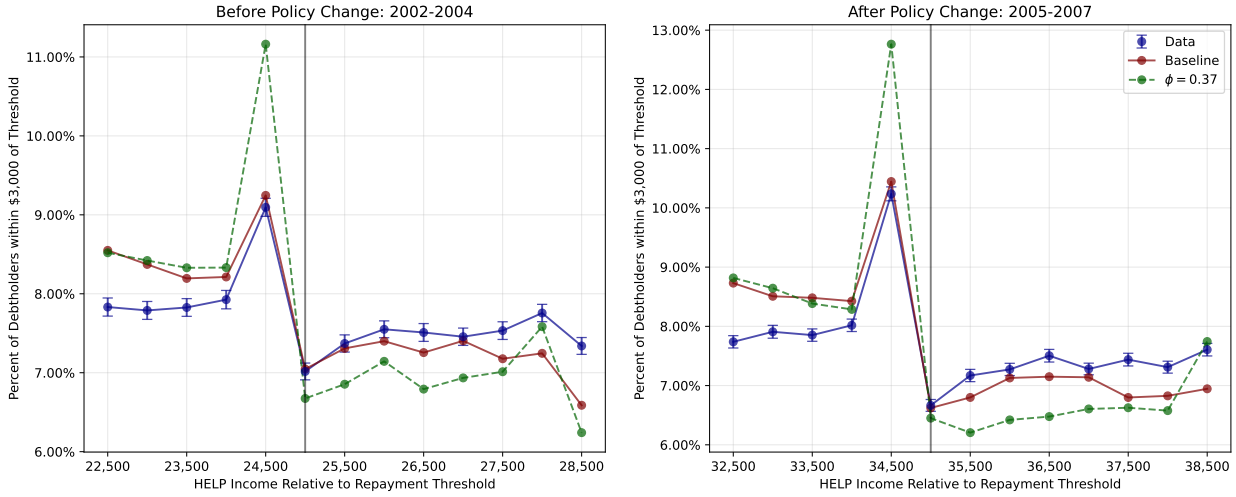
Figure A37. Constrained-Optimal Income-Contingent Loans as a Function of ϕ



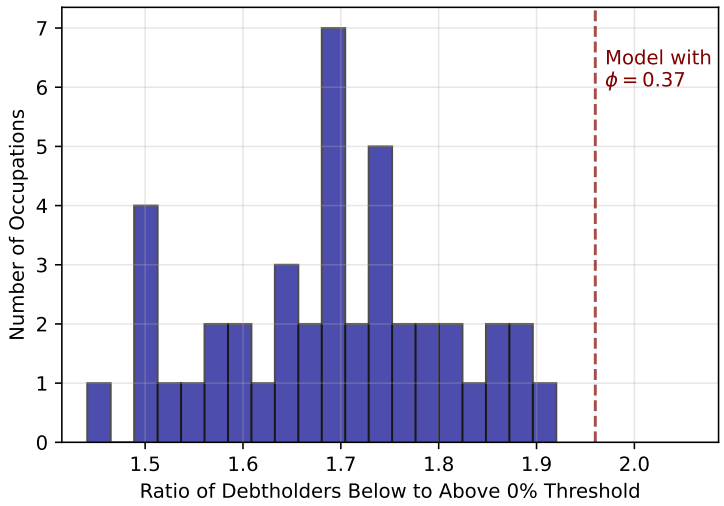
Notes: This figure shows the constrained-optimal income-contingent loans that solve (18) in the baseline model for different values of ϕ. The resulting welfare gains are shown in Figure 18.

Figure A38. Implications of Setting $\phi = 0.37$ in the Baseline Model

Panel A: Fit of Model on Bunching Used in Estimation

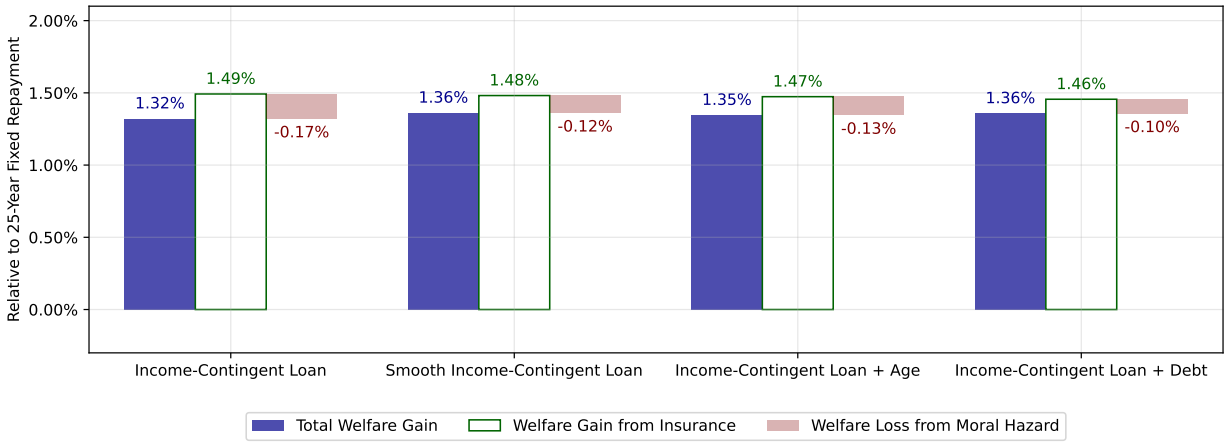


Panel B: Amount of Bunching Relative to Distribution across Occupations



Notes: This figure presents results for the baseline model estimated in column (1) of Table 3 with all parameters set at their estimated and calibrated values, except for $\phi = 0.37$. Panel A shows the fit of this model relative to the data and baseline model on the estimation targets in Figure 9. Panel B plots the distribution across occupations of the ratio of the number of debtholders within $500 below the 2005 repayment threshold to the number within $500 above it between 2005 in 2018 in blue bars. The vertical dashed red line corresponds to the same statistic computed within the model among borrowers with positive debt balances and $a > a_0$.

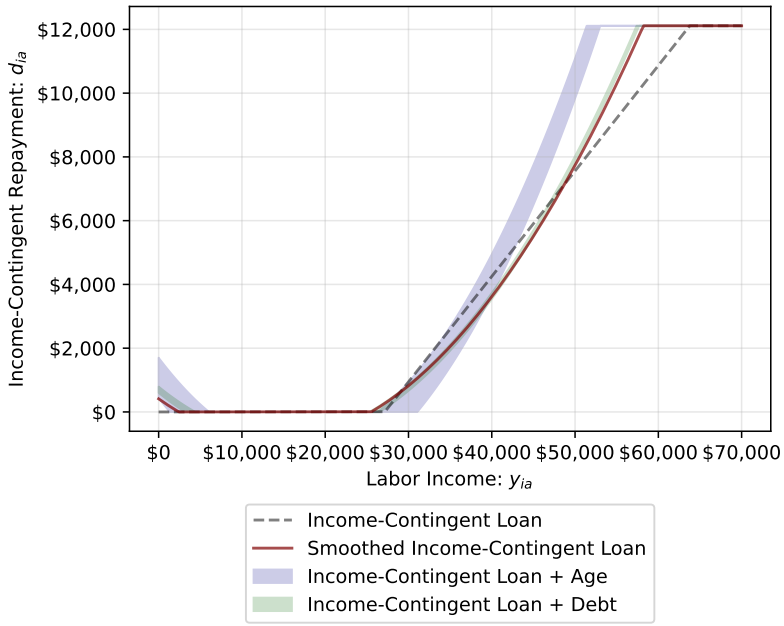
Figure A39. Welfare Gains from Alternative Forms of Income-Contingent Loans: Baseline Model



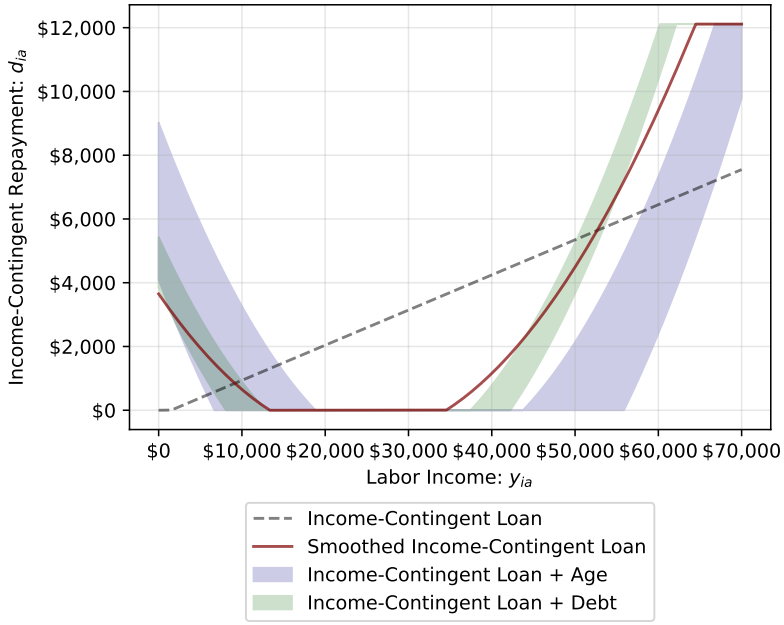
Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment, along with the decomposition performed in Figure 14, for different constrained-optimal repayment contracts described in the text. This analysis is performed with all parameters set at their estimated and calibrated values in the baseline model.

Figure A40. Structure of Alternative Constrained-Optimal Income-Contingent Loans

Panel A: Baseline Model



Panel B: Baseline Model with $\phi = 0.37$



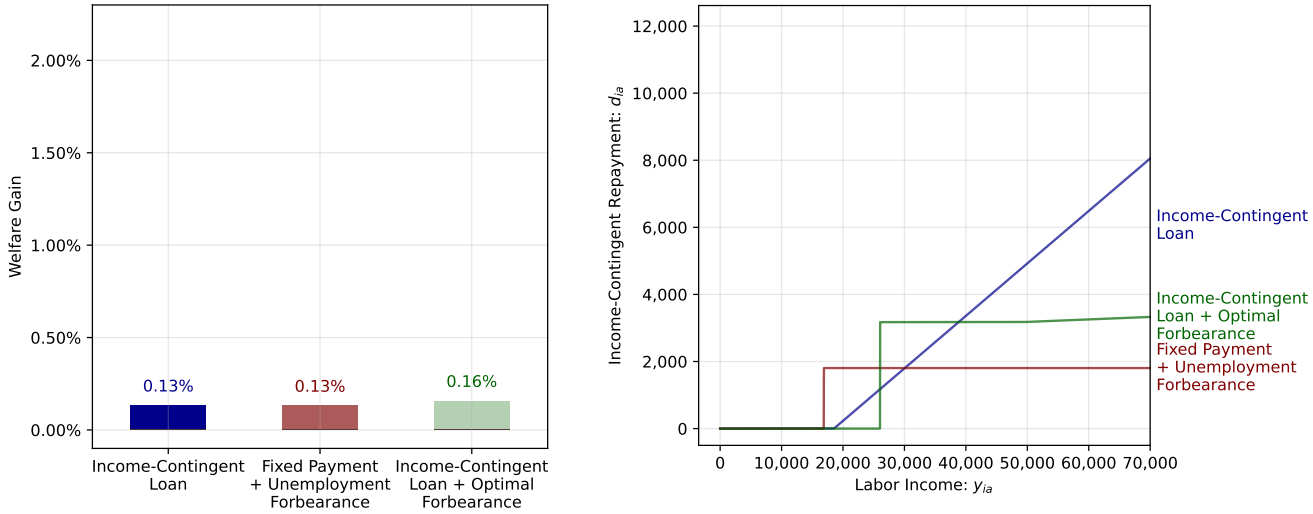
Notes: These figures plot the repayments as a function of income for the values of parameters for different classes of constrained-optimal repayment contracts described in the text that solve (18), assuming that a borrower has an initial debt balance equal to the median. Panel A shows the results for the baseline model; Panel B shows the results for the baseline model with $\phi = 0.37$. The dashed gray line plots a US-style income-contingent loan. The solid red line is the Smoothed Income-Contingent Loan. The shaded blue region plots the range of payments on the Income-Contingent Loan + Age, where the boundaries of the region correspond to evaluating at $a = a_0$ and the 90th percentile of a among borrowers who payoff their debt (or die) in the next period, respectively. The shaded green region plots the range of payments on the Income-Contingent Loan + Debt, where the boundaries of the region correspond to the evaluation at $D_{ia} = 0$ and the 90th percentile of D_{ia_0}, respectively. In the latter two plots, payments are increasing in age and debt, so the upper bounds of the shaded region correspond to the upper two evaluation points.

Table A6. Welfare Gains from Constrained-Optimal Income-Contingent Loans: Varying f and λ

	Difference from Baseline Model	Welfare Gain	= Insurance	+ Moral Hazard	ψ^*	K^*
(1)	f = 0	1.31%	1.61%	−0.3%	46%	$29,618
(2)	f = $2278	1.49%	1.65%	−0.16%	64%	$33,915
(3)	λ = 1	1.27%	1.34%	−0.07%	38%	$28,191
(4)	λ = 0.147	1.32%	1.47%	−0.15%	40%	$28,492
	Baseline Model	**1.32%**	**1.47%**	**-0.15%**	**33%**	**$27,147**

Notes: This table presents the optimal contract that solves (18) and its corresponding welfare gain relative to 25-year fixed repayment. Each row presents the results from a different model that deviates from the baseline model by setting one parameter as specified in the row. The results from the baseline model, shown in Figure 14, are repeated at the bottom of the table.

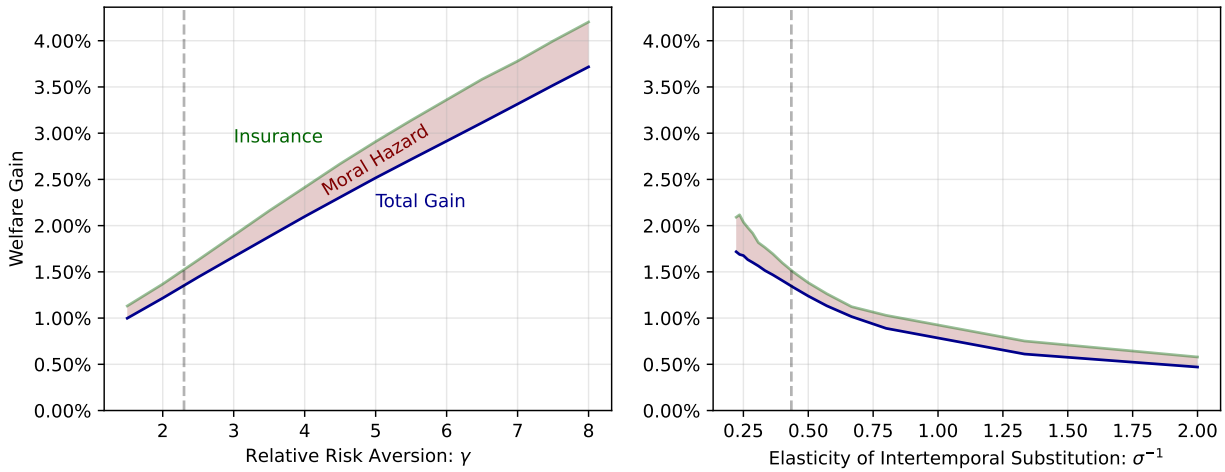
Figure A41. Welfare Gains from Constrained-Optimal Contracts under Optimal Tax and Transfer System



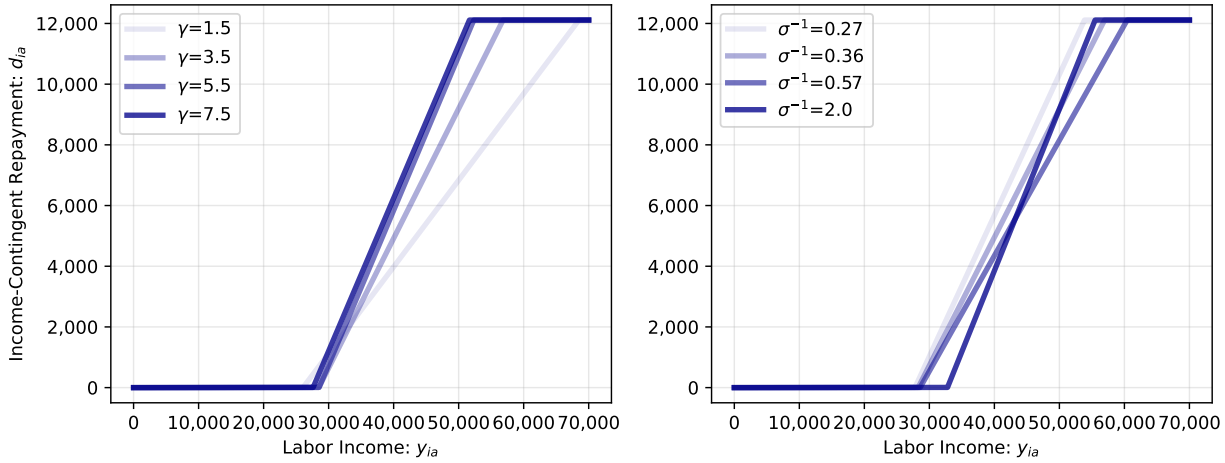
Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from constrained-optimal contracts described in the text and shown on the right. Repayments are shown for a borrower with median initial debt. This analysis is conducted within the baseline model after the tax and transfer system has been optimized; see Appendix D.7 for additional details.

Figure A42. Effects of Changing Relative Risk Aversion and Elasticity of Intertemporal Substitution

Panel A: Consumption-Equivalent Welfare Gains



Panel B: Constrained-Optimal Income-Contingent Loans



Notes: Panel A of this figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment in blue from a constrained-optimal income-contingent loan that solves (18) in the baseline model. This planner's problem is solved for different values of γ and σ with the resulting welfare gains shown in the plot and the resulting contracts shown in Panel B, for a subset of values. All other parameters are held fixed at their estimated and calibrated values. The light green and shaded regions show the contributions of insurance and moral hazard to this welfare gain, computed using the decomposition described in Figure 14. The dashed gray line corresponds to the value of the parameters in the baseline model.

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