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

Tim de Silva†
MIT Sloan

Updated Regularly: Latest Version

October 13, 2023

Abstract

This paper studies the trade-off between providing insurance and disincentivizing labor supply in student loans with income-contingent repayment. Using discontinuities in income-contingent repayment rates from Australia, I show that borrowers adjust their labor supply to reduce repayments. These responses are larger in occupations with more hourly flexibility, among younger borrowers with more debt, and among liquidity-constrained borrowers with less wealth and larger housing payments. I use these responses to estimate a structural model and find that they are consistent with a Frisch labor supply elasticity of 0.11 and substantial frictions that limit labor supply adjustment. In this model, relative to a fixed repayment contract, a constrained-optimal income-contingent loan generates welfare gains equivalent to a 1.3% increase in lifetime consumption, at the same fiscal cost. Adding forbearance to fixed repayment contracts generates smaller gains because it does not accelerate repayment from high-income borrowers. The labor supply responses to income-contingent repayment reduce the insurance that it can provide at a given cost, but these responses are too small to justify fixed repayment contracts.

*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, Tong Liu, Debbie Lucas, Pierfrancesco Mei, Lira Mota, Christopher Palmer, Jim Poterba, Charlie Rafkin, Antoinette Schoar, Andrei Shleifer, Kerry Siani, Adam Solomon, Yevhenii Usenko, Emil Verner, Adrien Verdelhan, Rodrigo Verdi, Joe Weber, Toni Whited, Constantine Yannelis, and seminar participants at the Inter-Finance PhD Seminar, 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 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, Stone Finance Ph.D Fund, Thomas Anthony Pappas Endowed Scholarship, MIT SuperCloud, and the 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.

†Contact information: www.timdesilva.me, tdesilva@mit.edu.

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 individuals 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).

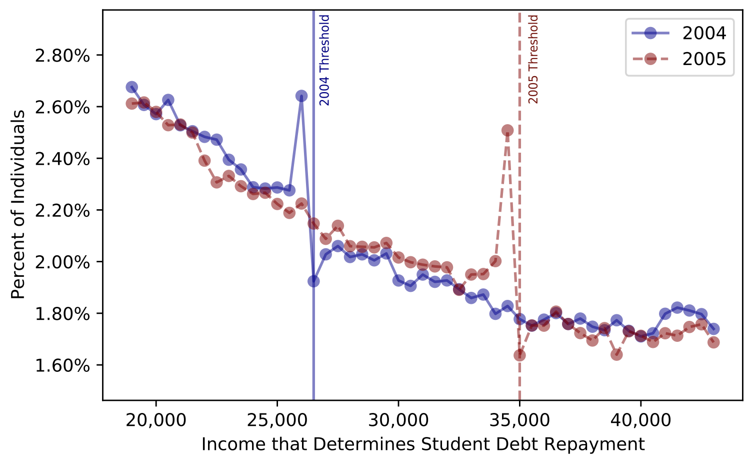
One potential policy to provide more insurance against income risk is to make student loans more equity-like by indexing payments to borrowers' incomes. This idea has been discussed extensively (Friedman 1955; Shiller 2004; Palacios 2004; Chapman 2006; Zingales 2012), and governments in the US, UK, Canada, 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 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 and through what mechanisms does income-contingent repayment affect borrowers' labor supply? Second, what form of income-contingent repayment in a government-provided financing contract optimally balances the cost of moral hazard with the benefits of 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 structural life cycle model and study the implications of various forms of income-contingent repayment. In my normative analysis, I consider a social planner 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 in occupations with more hourly flexibility, among young borrowers with more debt, and among liquidity-constrained borrowers. However, my structural estimation shows that these responses are quantitatively small: replicating this evidence requires a relatively low (Frisch) labor supply elasticity of 0.11 and substantial frictions that limit labor supply adjustment. On the normative side, these responses imply significant welfare gains from income-contingent repayment. Specifically, relative to a 25-year fixed repayment contract, a constrained-optimal income-contingent loan provides gains equivalent to 1.3% of lifetime consumption, at the same fiscal cost. The moral hazard created by income-contingent repayment decreases the insurance that this contract can provide at a given cost. However, adding forbearance to fixed repayment contracts generates smaller gains 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, 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 2021). Second, there is limited scope for adverse selection due to a lack of alternative financing options. This is useful for identification because it implies that responses to the policy change reflect moral hazard rather than selection (Karlan and Zinman 2009), in contrast with the US, where lower-income borrowers select into income-contingent repayment (Karamcheva et al. 2020). Third, these loans can only cover tuition, which is mostly government-controlled, implying that individuals can only adjust their borrowing 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 or groceries.

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



Notes: This figure shows the distribution of the income (in Australian dollars) that determines individuals' repayments on their income-contingent loans in 2004 and 2005 (before and after the policy change). This income is called HELP income and is equal to 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 in 2004 and 2005 below which individuals make no repayments and above which they repay 3% and 4% of their income. The sample is the population of debtholders, subject to the sample selection criteria in Section 2.4. HELP income is deflated to 2005 dollars using the Consumer Price Index.

I begin by documenting evidence of moral hazard from income-contingent repayment: individuals reduce their labor supply to minimize repayments on income-contingent loans. Figure 1 summarizes this behavioral response by plotting the income distribution of student debtholders in the two years surrounding the policy change. The vertical lines indicate the income-contingent threshold at which loan repayment begins, which was increased after the policy change. The income distribution exhibits significant bunching below the threshold both before and after the policy change, which I show is also present in the distribution of labor income. I present two pieces of evidence that suggest the bunching in Figure 1 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 non-existent in those with low flexibility (e.g., software engineers). Second, using data from Australia's Census, I find that individuals below the repayment threshold work 2–3% fewer hours (i.e., 1–2 fewer weeks per year) than those above the threshold.

Next, I develop a structural model of labor supply that quantitatively replicates the evidence in Figure 1. The purpose of developing this model is to translate this evidence into estimates of preference parameters and study the normative implications of income-contingent repayment. In the model, overlapping generations of individuals choose consumption and labor supply over their life cycles. During working life, individuals repay their government-provided loans; their labor income equals the product of endogenous labor supply and exogenous wage rates, where the latter is subject to uninsurable idiosyncratic risk. The two key ingredients in this model 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 in which labor supply is chosen to equate the marginal cost of working with the marginal benefits of higher income. When individuals' income crosses the repayment threshold, the fraction of *total* annual income that they repay increases from 0% to 3–4%, or $1,400 AUD in 2005 ($1,800 USD in 2023). Under the standard assumption that utility is increasing in consumption and leisure, this model predicts that no individuals would locate immediately above the threshold because locating below it delivers more leisure and $1,400 more cash on hand.

Motivated by the evidence that labor supply responses increase with hourly flexibility, I add optimization frictions (Chetty 2012) to the model to explain individuals locating above the repayment threshold. Because isolating the importance of every possible optimization friction is not feasible, I introduce two frictions that jointly characterize how several could affect labor supply adjustment in reduced form. First, in each period, only a fraction of individuals 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 implementing the policy change from Figure 1 in the model and find that, although the responses in Figure 1 may appear large, rationalizing them requires labor supply to be relatively inelastic. The model's key parameters for determining labor supply responses are the (Frisch) labor supply elasticity, fixed adjustment cost, and Calvo probability. The labor supply elasticity is identified by the extent of bunching below the repayment threshold: a larger elasticity implies more bunching. The number of individuals above the repayment threshold then identifies the adjustment cost and Calvo probability: without these frictions, no individuals would be above the threshold. The estimation results show that replicating the evidence in Figure 1 requires a labor supply elasticity of 0.11, a fixed adjustment cost of $\$400$ (i.e., 1% of mean earnings), and a Calvo probability of 0.2. This estimate of the labor supply elasticity is similar to the mean elasticity of 0.15 from the meta-analysis in Chetty (2012). However, this meta-analysis is among studies without optimization frictions, while the frictions that I estimate are quantitatively large: in a (misspecified) model without both frictions, the estimated elasticity is 0.005.

The estimated model highlights two important drivers of labor supply that also receive empirical support: liquidity constraints and dynamics. Liquidity constraints increase the value of the additional cash on hand from locating below the repayment threshold. In a counterfactual where individuals can freely borrow at the riskless rate, the model predicts the bunching in Figure 1 disappears almost entirely. Empirically, this importance of liquidity is supported by the fact that individuals 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. The second driver of labor supply responses is that, unlike a tax, the incentives created by income-contingent repayment are dynamic and depend on the probability of repayment. In the model, these dynamics are quantitatively important: the bunching in Figure 1 is twice as large in a counterfactual where repayments continue indefinitely, in which case bunching reduces total repayments rather than transferring them over time. This result is consistent with the fact that the amount of bunching is larger among individuals with more debt and in occupations with lower lifetime incomes.

In the final part of the paper, I use my structural model to study contract design and find that contracts with income-contingent repayment provide welfare gains relative to standard debt (i.e., fixed repayment) contracts, even after considering the moral hazard they create. My analysis considers a social planner that maximizes borrowers' lifetime utility by choosing one mandatory repayment contract, holding fixed borrowing behavior. This perspective isolates the central trade-off in income-contingent repayment between providing insurance and disincentivizing labor supply.

My main normative result is that income-contingent loans can simultaneously generate meaningful welfare gains and identical fiscal costs to fixed repayment contracts. I consider 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 borrower welfare subject to the constraint that the contract the same revenue as a fixed repayment contract. The resulting constrained-optimal income-contingent loan provides gains equivalent to 1.3% of lifetime consumption relative to a 25-year fixed repayment contract, which is currently offered in the US and has a similar repayment duration without income-contingent payments. The cost of the moral hazard from income-contingent repayment is small: the consumption-equivalent gain from an alternative (infeasible) contract with wage-contingent repayments, which provides insurance without distorting labor supply, is only 0.2 pp higher at 1.5%. Despite this small cost, labor supply responses quantitatively affect contract design: if labor supply did not respond to income-contingent repayment, the optimal contract would provide more insurance to low-income borrowers with a 40% higher repayment threshold.

I conclude by studying the welfare impact of three alternative income-contingent repayment contracts: income-contingent loans with forgiveness, fixed repayment contracts with forbearance, and income-sharing agreements. First, adding forgiveness to income-contingent loans after a fixed horizon, as is done in the US and UK, generates losses relative to the constrained-optimal income-contingent loan. For a given fiscal cost, forgiveness increases repayments for young relative to old borrowers, which leads to losses because young individuals have a higher marginal value of wealth. Second, a fixed repayment contract with forbearance, a form of income-contingency that pauses repayments for low-income borrowers, generates losses 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, equity contracts known as income-sharing agreements, which were originated by Friedman (1955) and recently implemented by Purdue University, yield gains that are larger on average but significantly more dispersed than those from income-contingent loans. This finding suggests that equity contracts cause ex-ante responses not captured by the model, implying that income-contingent loans may be a more robust mechanism for implementing income-contingent repayment.

Related literature and contribution. This paper sits at the intersection of household finance, public finance, and macro-finance. In its focus on the trade-off between insurance and moral hazard, this paper falls within the literature on various forms of social insurance (Chetty and Finkelstein 2013), such as unemployment insurance (Gruber 1997; Ganong and Noel 2019), bankruptcy protection (Dobbie and Song 2015; Auclert et al. 2019), and health insurance (Einav et al. 2017). Two strands of this literature that focus on student debt are directly related (see Amromin and Eberly 2016 for a review). The first documents forms of debt overhang, in which reductions in student debt decrease delinquencies (Di Maggio et al. 2021), increase homeownership (Mezza et al. 2020), and change choices of education and occupations (Luo and Mongey 2019; Chakrabarti et al. 2020; Folch and Mazzone 2021; Hampole 2022; Murto 2022; Huang 2022).[1] The second strand studies income-contingent loans as a tool to mitigate these effects, finding reductions in unsecured delinquencies (Herbst 2023), mortgage defaults (Mueller and Yannelis 2019), and the passthrough of income variation to consumption (Gervais et al. 2022).[2]

This paper makes three contributions to these literatures. First, it empirically identifies labor supply responses to income-contingent repayment, which have not been found in other settings (Britton and Gruber 2020).[3] Second, it provides a dynamic model of labor supply that rationalizes these responses, finding an important role for optimization frictions and liquidity constraints. The latter complements existing evidence that liquidity drives responses to other social insurance pro-

[1]A related literature emphasizes the importance in credit constraints for college attendance (Carneiro and Heckman 2002), which student loans can help relax (Black et al. 2022).

[2]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).

[3]This paper builds on Chapman and Leigh (2009), who study the Australian student loan system using survey data.

grams (Chetty 2008; Ganong and Noel 2023; Indarte 2023). Finally, it quantifies the implications of these responses for optimal contract design. Prior literature highlights the insurance benefits of income-contingent loans but has not had evidence to discipline their moral hazard effects or characterized optimal policy (Ji 2021; Matsuda and Mazur 2022; Boutros et al. 2022).

This paper is also related to the literature on human capital financing. The idea that student loans should be equity-like was popularized by Friedman (1955), who advocated the use of income-sharing agreements. Adverse selection prevents the private provision of such contracts (Herbst and Hendren 2021; Herbst et al. 2023), so a growing number of governments have attempted to correct this market failure by introducing income-contingent loans, with Australia leading (Chapman 2006) and other countries later following suit (Barr et al. 2019). Theoretical work suggests that these loans provide a close approximation to optimal policies (Lochner and Monge-Naranjo 2016; Stantcheva 2017).[4] This paper contributes by quantifying how the moral hazard that these loans create affects optimal contract design.

By studying state-contingent contracts, this paper is part of the literature on household security design. 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.

Finally, this paper builds on literature that uses bunching at tax kinks and notches to identify income elasticities (Saez 2010; Chetty et al. 2011).[5] 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 estimating a model with two optimization frictions, adjustment 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 separate identification of the two optimization frictions.

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

[5] Section 4.6 discusses in more detail how this paper relates to the extensive existing literature on labor supply.

1 Motivating Framework

This section develops a simple framework to clarify the trade-off between insurance and incentives 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 incentives 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 $d_t = d(D_t, y_t, \theta)$ for $t > 0$, 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 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:

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

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

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

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 (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 individuals are ex-ante identical, the government solves the following problem:

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

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 $M_t = \frac{u_c(c_t, \ell_t)}{u_c(c_0, \ell_0)}$ denote individuals' stochastic discount factor between $t = 0$ and $t = t$ and λ as the marginal cost of public funds in dollars. In Appendix A, 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. In contrast, if the individual is not fully-insured, then the difference between these valuations is large. The right-hand side of (2) is the sum of two behavioral responses. The first is an *ex-ante* moral hazard effect, $\frac{dD_0}{d\theta}$: changing the repayment contract affects how much individuals borrow. The second behavioral response represents *ex-post* moral hazard: changing the repayment contract affects individuals' incentives to adjust their income, which affects 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 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 most of 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 (discussed in Section 2) 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 different HELP programs that provide identical income-contingent loans 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, and Appendix B.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

[6] Figure A1 plots the amount of borrowing over time and discusses the details of the different HELP programs.

the government provides a subsidy in the form of a contribution to the tuition owed by the student. The remaining tuition, 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), and undergraduate degrees typically last 3–4 years. The number of CSPs in Australia has generally been capped by the government, except during 2012–2017, when the system was "demand-driven" (D'Souza 2018; Norton 2019).

Australian citizens who receive a CSP can either pay their student contribution upfront or borrow through the HECS-HELP program. Individuals who pursue degrees that are not CSPs are liable for full tuition and can either pay upfront or borrow through the FEE-HELP program. In both cases, 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 that receive CSPs and access HECS-HELP, the largest program, their initial debt is equal to their student contribution. Given an average undergraduate student contribution of approximately $6,000 USD per year, these debt burdens are comparable to tuition for US in-state public undergraduate programs, which averages around $9,000 (Hanson 2023). Figure A2 plots the time series of student contributions for different CSPs, which vary based on which of three bands the degree belongs to and the aggregate amount of HECS-HELP borrowing and upfront payments.

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

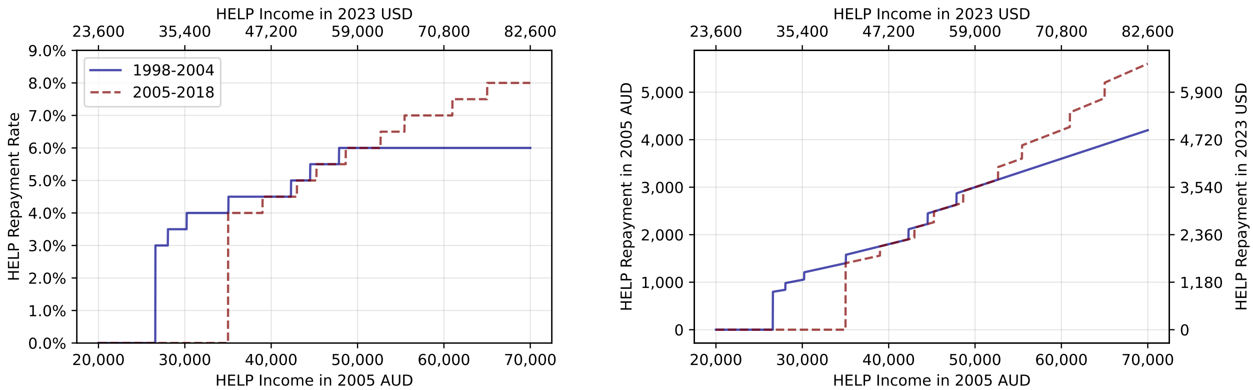
$$\text{HELP Repayment}_{it} = \min\{r_t(y_{it}) * y_{it}, D_{it}\},$$

where y_{it} denotes HELP income, $r_t(\cdot)$ is the income-dependent repayment rate, and D_{it} denotes the current debt balance. HELP income is the taxable income reported in a personal income tax return plus a few adjustments that are discussed in Section 2.5. Collection of HELP payments is integrated with the income tax system, and all individuals file tax returns in Australia, so y_{it} refers to *individual* rather than household HELP income. For most individuals, HELP repayments are withheld by their employer throughout the year and deducted from their debt balances after they file their tax returns. Individuals also have the option to make voluntary repayments at any time.

Repayment of HELP debt continues until the remaining balance equals zero or death. Partial repayment is common: as of 2004, approximately 25% of debt balances were forecast to be written off due to death, and in 2019, that estimate was 36% (Martin 2004; Robinson 2019). 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. As in the US, HELP debt cannot be discharged in bankruptcy.[7]

[7]Aside from death, the only case in which HELP debt is canceled is if an individual withdraws from the corresponding units of study before the census date in a given year.

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. There were other changes prior to 1998 and after 2018 to the HELP repayment schedules that were smaller in magnitude.

2.2 2004–2005 Policy Change to HELP Repayment Rates

The policy change 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 prior to the policy change in blue and that after the policy change in red. The most significant change was the movement of the repayment threshold, which is the point at which individuals have to 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 the required repayments for many individuals. It also generated an increase in repayment rates for high-earners with incomes above \$50,000. This policy change applied to all new and existing HELP debtholders.

The right panel of Figure 2 plots the required repayments, 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 an individual with \$35,000 of HELP income in 2005. For this individual, 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 individuals chose their labor supply statically and treated repayments like an income tax, no individuals 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 debt balance D_0 who is deciding between locating below versus above the 2005 repayment threshold. Assume this borrower knows that her income at $t = 1$ will be high enough that the required HELP payment is above D_0. For this borrower, locating below the repayment threshold decreases her repayments at $t = 0$ by \$1,400. However, because the borrower will have a high enough income at $t = 1$ to repay her debt, this \$1,400 repayment is simply transferred from $t = 0$ to $t = 1$. As a result, the net present value of the reduction in repayments from locating below the repayment threshold is $\left(1 - \frac{1}{1+r}\right) \times$ \$1,400 = $r \times$ \$1,400, where r is the real interest rate.[8] For an interest rate 1%, this corresponds to only \$140, which illustrates that locating below the repayment threshold has a large impact on current payments but a much smaller effect on the present discounted value of payments (for those who anticipate debt repayment). This setting is similar to the maturity extension program studied in Ganong and Noel (2020), which also increases borrowers' liquidity with minimal effects on wealth.

There are several reasons to believe that the HELP repayment function and the changes to it were 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 makes sure that it receives press coverage.[9] 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 introduction of HECS 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 individuals, whose payments were burdensome and contributed little to the total HELP budget (Nelson 2003; Marshall 2003). In addition to changing the HELP repayment function, other policy changes were implemented in 2004–2005, such as the introduction of HELP loans for private undergraduate and graduate degrees through FEE-HELP and a 25% increase in student contributions (see Figure A2). 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. However, it likely has a minimal effect on my analysis, which focuses on identifying moral hazard among individuals who have already completed their degree programs.

2.3 Benefits of Studying Income-Contingent Repayment in Australia

In addition to 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 room for adverse selection of high-income individuals into non–income-based repayment contracts because HELP is the only government-provided student loan, which implies that the ef-

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

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

fects of changes in contract design reflect borrowers' actions rather than their types (Karlan and Zinman 2009).[10] The same is not true in the US, where high-income borrowers choose fixed rather than income-driven repayment (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 this because the interest rate would exceed the zero real interest rate on HELP loans. The primary margin along which there is scope for adverse selection is on whether to pay upfront or borrow through HELP, but the zero interest rate on HELP loans again implies little incentive to pay upfront. In practice, the amount of upfront borrowing has been low and stable, with most payments coming from individuals with family support (Norton 2018).

A second benefit of this setting is the likely limited *ex-ante* moral hazard, in which individuals increase (decrease) their initial HELP debt in anticipation of a lower (higher) probability of future repayment. As described above, HELP can only be used to cover tuition at public undergraduate institutions, which make up over 94% of the domestic enrollment share and 39 of the 42 universities, is controlled by the government. As a result, individuals can only adjust their initial HELP debt by changing their choice of degree or institution, which are likely stickier decisions than the other margins borrowers in the US can adjust, such as room and board or groceries.

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 structure of income-contingent repayment. 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 2021; JPMorgan Chase 2022). A final benefit is that there are limited responses on the supply-side of higher education due to government tuition control at public universities. If this were not the case, changes in government-provided financing contracts could pass through to tuition and thus initial debt balances (Kargar and Mann 2022).

The institutional differences between Australia and the US make the former advantageous for identifying labor supply responses to income-contingent repayment. Appendix B.1 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

[10] This approach of identifying moral hazard by looking at the responses to changes in contract structure among individuals who have already taken up the contract has been applied in a variety of selection markets, such as consumer credit (Einav et al. 2012) and mortgage markets (Gupta and Hansman 2022).

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 the 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.[11] I use this sample, which covers over 4 million unique debtholders between 1991 and 2019, for my main analysis that only requires tax and HELP data.

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 the *ALife* data 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 from 2016, the year in which the census was administered.

I supplement these administrative datasets with 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 similar structure and questions to 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. The three columns separate the sample into individuals with and without HELP debt and 26-year-old HELP debtholders, which is the age at which most individuals have finished university in Australia and begun work and HELP debt balances peak in real terms. 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 introduced in Table 1 is HELP income, which determines an individid-

[11] 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.

Table 1. Summary Statistics

	Sample of Individuals		
	Non-Debtholders (1)	Debtholders (2)	26-Year-Old Debtholders (3)
Demographics			
Age	41.1	29.5	26
Female	0.46	0.60	0.57
Wage-Earner	0.85	0.91	0.93
Income Totals			
Taxable Income	37,695	27,796	32,929
HELP Income	38,756	28,586	33,721
Income Components			
Salary & Wages	32,415	26,068	32,091
Labor Income	35,480	27,136	32,999
Interest & Dividend Income	726	242	224
Capital Income	1,221	324	184
Net Deductions	-1,548	-1,099	-554
HELP Variables			
HELP Debt	·	10,830	13,156
HELP Payment	·	991	1,305
HELP Income < 0% Threshold	0.50	0.65	0.51
HELP Income < 2004 0% Threshold	0.37	0.51	0.35
HELP Income < 2005 0% Threshold	0.52	0.67	0.55
Number of Observations	247,118,713	27,316,037	1,701,464

Notes: This table presents summary statistics from the *ALife* sample from 1991-2019, subject to the sample selection criteria discussed in Section 2.4. Each column represents a different sample of individuals: column (1) uses all individual–years with zero HELP debt; column (2) uses all individual–years with positive HELP debt; and column (3) uses all individual–years in which the individual is age 26. 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 adjusting the thresholds for inflation. Additional details on variable construction are presented in Appendix B.2.

ual's repayment rate on her HELP debt according to Figure 2. HELP income equals taxable income plus several other adjustments, such as adding back reportable superannuation contributions and investment losses. These adjustments are not relevant for most individuals: the difference between HELP and taxable income is less than $100 for over 93% of 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. Importantly, Capital Income does not capture flow income from owner-occupied housing, which cannot be inferred from income tax returns because Australia does not have a mortgage interest deduction. Net Deductions is defined as the residual in (3).

Table 1 shows 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 approximately \$10,800 in 2005 AUD (\$13,000 in 2020 USD), and approximately \$13,200 in 2005 AUD (\$15,800 in 2020 USD) among 26-year-old debtholders. Notably, most debtholders (65%) in each year are below the HELP repayment threshold, especially after the 2004-2005 policy change. Focusing on 26-year-old debtholders who have likely finished college and entered the workforce, around half are below the threshold. The 2004–2005 policy change had a larger impact for these individuals: the fraction below the threshold moved from 35% to 55% after the change.

Figure A3 shows how debt balances vary within-individual over time: most individuals' debt balances peak in real terms when they are between ages 24 and 26 and are paid down in their mid-30s. However, around 15% of individuals 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 forecasted to become much higher with around 36% of outstanding debt expected to be not paid off (Robinson 2019).

3 Labor Supply Responses to Income-Contingent Repayment

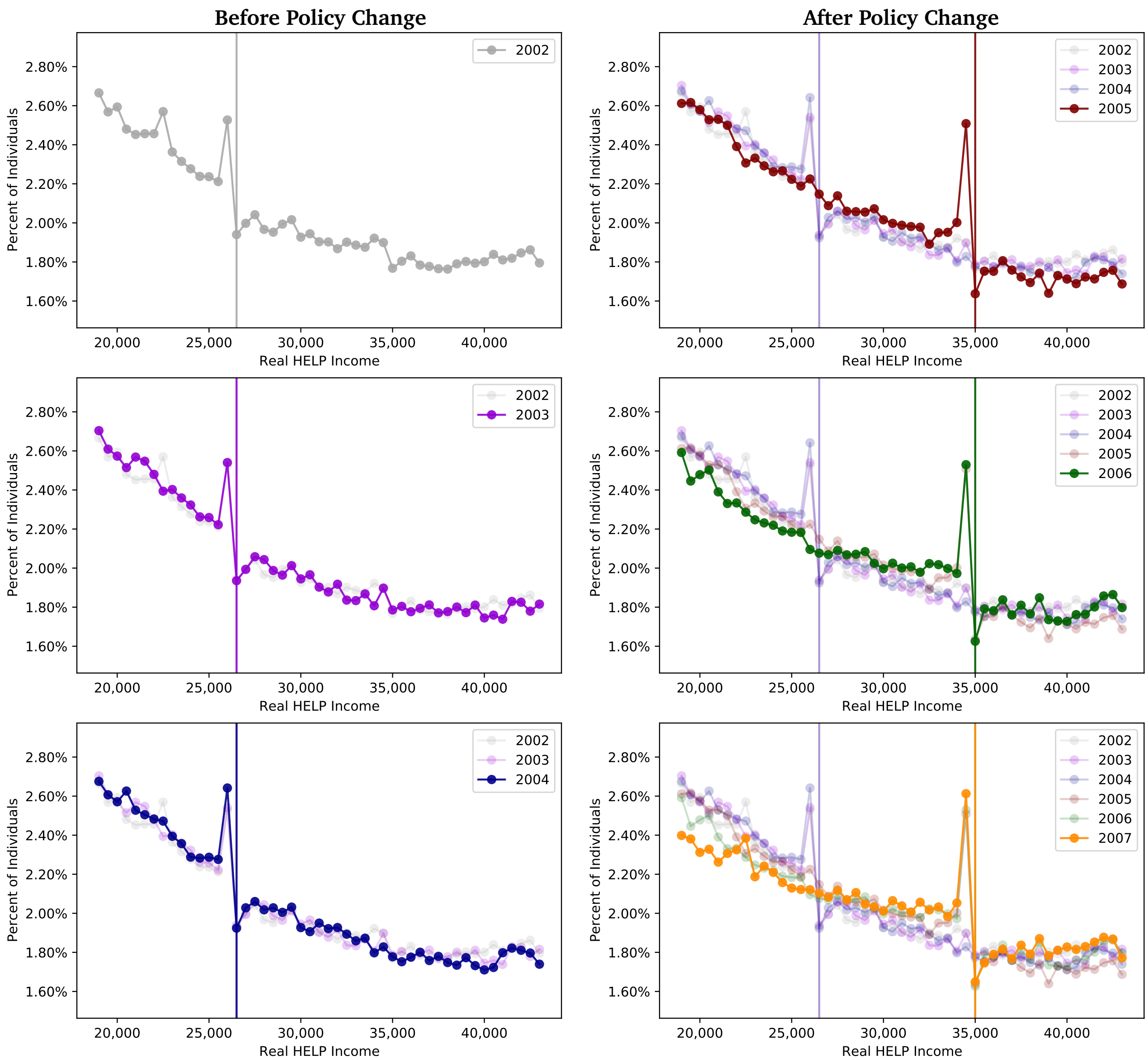
This section uses the variation in repayment rates shown in Figure 2 to document several facts about how labor supply responds to income-contingent repayment.

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

Figure 3 plots the distribution of real HELP income for individuals 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 three panels, the amount of bunching and shape of the income distribution remain relatively constant. However, after the policy change in 2005, the right three panels of Figure 3 show two important changes to the income distribution.

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 an individual'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 individuals begin making debt payments of 3% (4%) of their income before (after) the policy change. Each bin represents $500, and the plot focuses on individuals 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.

First, the bunching at the 2004 repayment threshold disappears completely. Second, bunching appears immediately below the new repayment threshold, which Figure A4 shows primarily comes from individuals who fell between the old and new repayment thresholds in 2004 and who are older than the individuals below the old threshold. This provides clear evidence that borrowers adjust their income to avoid making income-contingent repayments.

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 the bunching is sharp around the repayment threshold, I assess this possibility by examining the income distribution of non-debtholders in Figure A5. In contrast to the income distribution of debtholders, these results show no change in the income distribution of non-debtholders around the repayment threshold either before or after the policy change.[12]

HELP income, defined in (3), consists of three components that individuals could adjust to locate below the repayment threshold. Figure A6 provides evidence that the responses in Figure 3 comes from adjustments in labor income. In particular, I follow Chetty et al. (2011) and examine a sample of individuals whose primary source of income is labor income. This ensures that all individuals require similar values of labor income to generate HELP income at the repayment threshold. I then compute a measure of bunching from Chetty et al. (2011) (described in Section 3.4) for the distributions of HELP and labor income. The results show the amount of bunching in labor income is 83% as large as that of HELP income.[13]

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

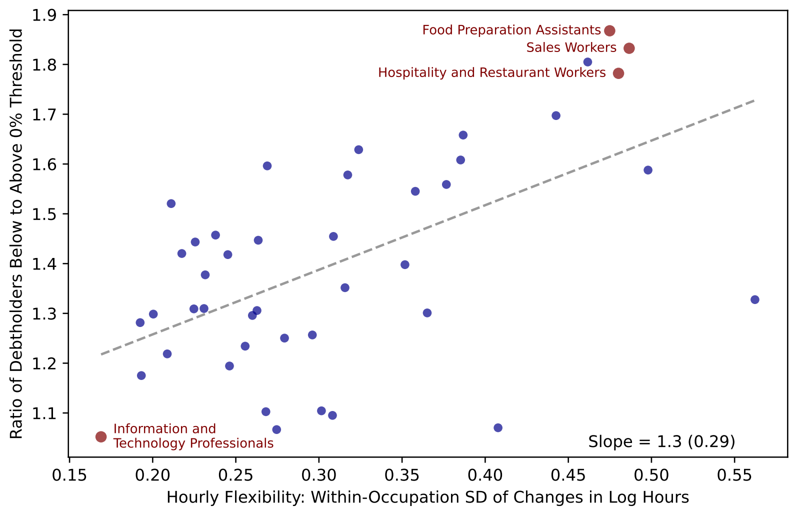
Next, I explore variation in the bunching in Figure 3 across different occupations. Using HILDA, I measure the amount of hourly flexibility in each 2-digit ANZSCO occupation, the finest level at which *ALife* reports occupation codes, using the standard deviation of annual changes in log hours worked. 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., software engineers). Table A2 shows 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 this measure of 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 a 2-digit occupation, and I measure the amount of bunching as the ratio of the number of individuals in that occupation within \$2,500 below to the number above the threshold, similar to Chetty et al. (2013), so that a ratio of one indicates no bunching. The results

[12] 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.

[13] Figure A6 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 2005–2018 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 4. Variation in Bunching across Occupations Based on Hourly Flexibility

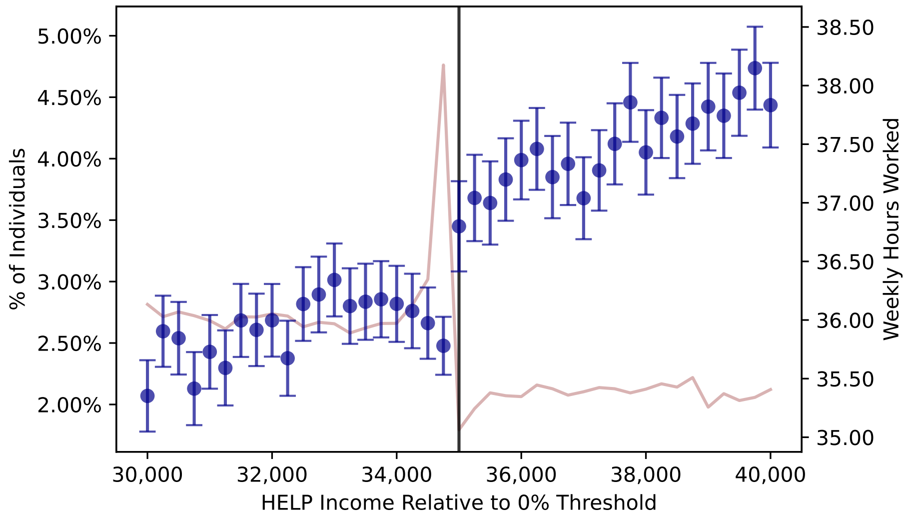


Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and hourly flexibility by occupation, where each point represents a 2-digit ANZSCO occupation. The amount of bunching is measured as the ratio of the number of individuals in that occupation within \$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. 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 in the 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.

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 change in log hours of 0.17. In this occupation, there is only 5% more individuals below than above the threshold. In contrast, hospitality workers have almost three times more hourly flexibility with a standard deviation of annual change in log hours of 0.48 and exhibit significantly more bunching, with 80% more individuals below than above the threshold. Quantitatively, Table A3 shows that hourly flexibility explains 34% of the variation in bunching across occupations. Figure A7 shows a similar pattern using an alternative measure of hourly flexibility.

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 more directly, I calculate the share of all workers in each occupation that receives income from working in the form of allowances, tips, director's fees, consulting fees, or bonuses. This variable is a proxy for tax evasion because it is easier to misreport these sources of income relative to salary and wages (Paetzold and Winner 2016; Slemrod 2019). Figure A8 shows that this measure, unlike the measure of hourly flexibility, exhibits little correlation with bunching below the repayment threshold.

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.

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

To provide further evidence that the bunching in Figure 3 reflects, at least in part, labor supply responses, I next use responses to a question asked 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 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. The results show that individuals locating immediately below the threshold work on average around 1 hour less per week than those immediately above it. The standard workweek in Australia is 38 hours, so this corresponds to a reduction of 2.6%.[14] This adjustment in hours worked occurs *within* an individual's current occupation: Figure A10 finds little evidence that those below the repayment threshold are more likely to have switched occupations.

The results in Figure 5 are subject to a few caveats. First, this test can only be performed in 2016 because this is the only year for which Census data are available in MADIP. Second, as discussed in Section 2.4, the MADIP and *ALife* samples differ slightly. To mitigate concerns about sample selection, Figure A12 shows that the distribution of HELP income in 2016 across the two samples is quantitatively similar. Finally, 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 my structural model.

[14] These results are not driven by a group of individuals outside the labor force earning only income from other sources: Figure A11 shows that the patterns are nearly identical in the sample of individuals earning positive labor income.

3.4 Fact #4: Bunching Increases with Debt and Decreases with Age

The next two facts relative to heterogeneity in the bunching from Figure 3 with observable characteristics. To measure the amount of bunching systematically, I construct a bunching statistic following the literature that uses discontinuities in tax rates to estimate taxable 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:

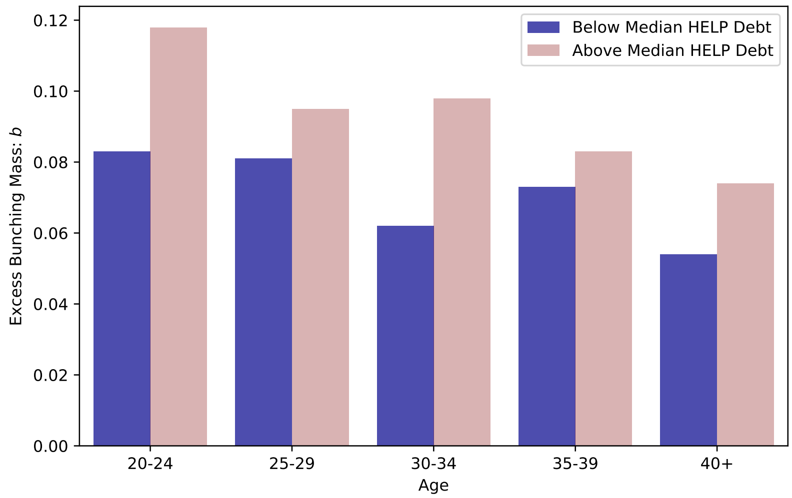
$$b = \frac{\text{observed density in } \mathcal{R}}{\text{counterfactual density in } \mathcal{R}} - 1. \tag{4}$$

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

Figure 6 shows this estimated bunching statistic across groups of individuals with different ages and debt balances. I split individuals by age 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 except 35–39, the estimated value of b is higher among individuals with above-median debt balances. The fact that bunching increases with debt suggests that the probability of eventual repayment is an important driver of labor supply responses. The second pattern is that the amount of bunching decreases with age: the estimated b is $22-33\%$ lower among individuals above 40 than among those below 25. Given that borrowing constraints are tightest among young individuals, this finding provides suggestive evidence that liquidity affects labor supply responses, which I test more rigorously in the next section.

Table A3 further explores the role of dynamics, which the variation in responses with debt balances suggests is important, by leveraging variation in occupation-specific wage profiles. These wage profiles are plotted in Figure A9 and show 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 earning income below the repayment threshold. The results in Table A3 show 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 individuals' willingness to reduce their labor supply.

Figure 6. Variation in Bunching by Debt Balances and Age



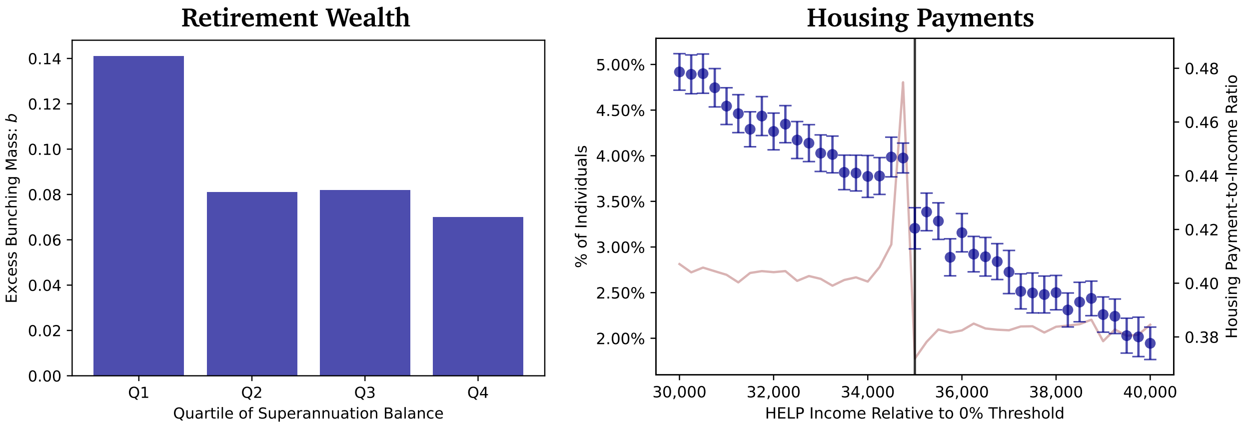
Notes: This figure plots the bunching statistic defined in (4) computed for different samples of debtholders based on age and debt balances. The age groups are listed on the horizontal axis. Within each age group, the blue (red) bars plot the estimated statistic for individuals with below-median (above-median) debt balances, where the median is calculated separately for each year and age group. The calculation of b is detailed in Appendix B.3. 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.

3.5 Fact #5: Bunching Decreases with Proxies for Liquidity

As discussed in Section 2.2, locating below the repayment threshold increases liquidity but has a minimal effect on wealth for most borrowers. Therefore, the evidence that individuals 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. In this section, I study the importance of liquidity by examining how the responses in Figure 3 vary cross-sectionally with proxies for liquidity constraints. Absent direct measures of liquidity, I use several complementary measures to assess its importance.

First, I use data on superannuation balances from *ALife*. Superannuation ("super") represents the largest form of retirement savings in Australia and 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 super 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: individuals who are unwilling to contribute to a tax-advantaged but illiquid account are implicitly revealing a high valuation of liquidity (similar to Coyne et al. 2022). The left panel of Figure 7 plots the estimated statistic, b, based on quartiles of super balances defined within each year. The results show that the amount of bunching is highest for individuals in the bottom quartile, approximately twice as large as the top quartile, which also holds within individuals under 30 (Figure A13). This evidence suggest that liquidity constraints, which by revealed preference are tighter for individuals

Figure 7. Bunching and Proxies for Liquidity Constraints



Notes: This left panel of this figure plots the bunching statistic defined in (4) computed for different samples of debtholders based on quatiles of superannuation balances computed within each year. The calculation of b is detailed in Appendix B.3. 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 plotting average housing payment–to–income ratios instead of hours worked within each bin.

with lower balances, are an important driver of the labor supply responses in Figure 3.

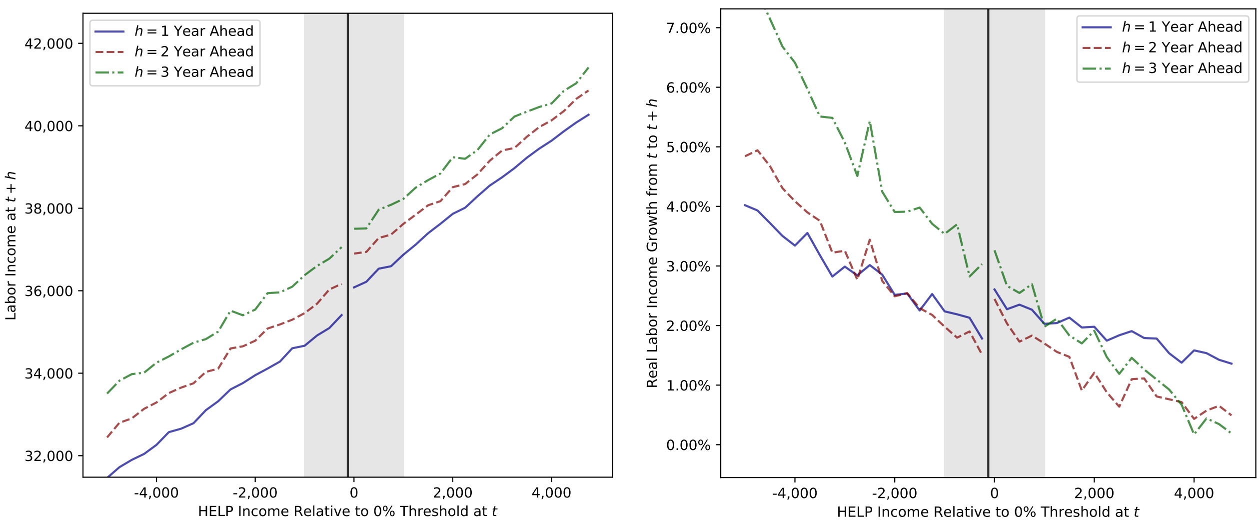
My second piece of evidence leverages data on annual combined mortgage and rent payments from the 2016 census using the MADIP sample. For most individuals, housing payments represent one of the largest sources of liquidity demand. Therefore, if liquidity influences labor supply responses, individuals below the repayment threshold should have larger housing payments, or equivalently, individuals with larger housing payments should be more likely to bunch below the repayment threshold. The right panel of Figure 7 shows that this pattern holds in the data: individuals immediately below the repayment threshold tend to have larger housing payment–to–income ratios by approximately 2 percentage points.

A final, more speculative finding that points to the importance of liquidity is presented in Figure A13, which plots the relationship between the amount of bunching and house prices from CoreLogic across geographic regions. Absent comprehensive data on wealth at the individual-level, house prices are a reasonable proxy for wealth 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

My final empirical fact comes from exploring the dynamic effects of the bunching in Figure 3. In models with learning-by-doing, also known as human capital accumulation or career effects (e.g.,

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



Notes: The left panel of this figure plots the average labor income in year $t + h$ within \$250 bins of the difference between individuals' 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 right panel replicates the left plot 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. Income growth is trimmed at 5 times the interquartile range. The shaded gray region in both plots corresponds to within \$500 of the repayment 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.

Keane and Rogerson 2015), the choice of current labor supply affects the stock of human capital and hence future wages. As a result, these models predict that the reduction in labor supply shown in Figure 5 comes at the cost of lower future wages.[15]

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 individuals' locations relative to the repayment threshold in year t. The results show that individuals 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, as is evident from the lack of a discontinuity in average labor income. Additionally, Figure A14 shows that there is little difference in the distribution of future labor income in terms of variance or skewness.

Although this evidence is clearly subject to concerns about selection into bunching, a natural form of selection would be that individuals with lower expected income growth would be more likely to

[15]A related model of dynamic compensation is presented in Kleven et al. (2023), where individuals' realized earnings only equals their true latent earnings (hours × wages) at job transitions. I cannot test this hypothesis in my setting because I do not observe job transitions, but two facts suggest that it is likely a small driver of the lack of responses. First, the sample of individuals around the repayment threshold are relatively low-income, while Kleven et al. (2023) find that dynamic compensation plays an important role at the top of the income distribution. Second, Figure A10 shows no discontinuity in the probability of occupation switching around the repayment threshold.

bunch. In this case, the evidence in Figure 8, which suggests relatively small wage reductions from bunching, would serve as an upper bound. Nevertheless, this evidence should not be interpreted as suggesting that no learning-by-doing is present: larger labor supply reductions could create sizeable longer-horizon 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.

3.7 Other Possible Mechanisms for Bunching Below the Repayment Threshold

This section discusses the possibility of other mechanisms through which individuals could reduce their income to locate below the repayment threshold.

Evasion. An obvious explanation for the bunching in Figure 3 is evasion, in which individuals 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 A8, suggest that it cannot explain all of these responses. First, Figure A16 shows that the distribution of salary and wages exhibits substantial bunching around the repayment threshold. Bunching in the distribution of salary and wages is generally interpreted as evidence of hours-worked responses (see, e.g., Chetty et al. 2013) 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 non-compliance rate for items with withholding and substantial reporting information, such as salary and wages, of less than 1% (Slemrod 2019). Second, Table A4 shows that the amount of bunching declines by only 4% when restricting to the sample of wage-earners, who have substantially less flexibility in reporting their income. Third, Table A4 shows that the amount of bunching is almost identical between individuals who file their tax returns electronically and non-electronically. When taxes are filed electonically, pure evasion is much more difficult because the sources of labor income are often pre-filled 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 individuals near the repayment threshold is around median income. This contrasts with 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 at least some of the responses in Figure 3 reflect evasion rather than labor supply. If this is the case, the model that I develop in Section 4 will overestimate how much labor supply responds to income-contingent repayment. There are two ways in which this could affect my normative results. First, if individuals equate the marginal benefits of evasion (i.e., reduced payments) with the marginal *social* cost of evasion, then whether the responses in HELP income reflect labor supply or evasion is irrelevant as long as my model can replicate them (Feldstein 1999). In the more likely case that the private and social costs of evasion are not equal, my results would overstate the welfare costs of moral hazard created by income-contingent repayment

(Chetty 2009), reinforcing the qualitative conclusions from my normative analysis.

Income-shifting across years. The repayment threshold incentivizes individuals to transfer income to the future if they anticipate being above the threshold later on. In practice, this could take the form of employees asking employers to delay some of their compensation. Figure 8 shows that this does not happen empirically: individuals below the repayment 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 tax rates 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 compete in the same labor market, does not exhibit any bunching, as shown in Figure 3. Second, Figure A15 replicates Figure 9 from Chetty et al. (2011), which plots the distribution of labor income among individuals 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 individuals 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 my data. The results show almost no differences based on gender, 5% less bunching among individuals with a spouse, and 12% less bunching among individuals 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 here are local to the repayment threshold and thus do not capture extensive-margin responses, which tend to be larger among women (Saez et al. 2012).

3.8 Summary of Empirical Results and Implications for Structural Model

Summary of results. This section has presented empirical facts about how labor supply responds to income-contingent repayment 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 entirely tax evasion or income-sharing, as borrowers below the repayment threshold work fewer hours and tend to be in occupations with more flexibility. Second, the size of the labor supply responses to income-contingent repayment vary cross-sectionally based on two forces. The first force is dynamics: borrowers with more debt and in occupations with wage profiles that peak closer to the threshold, 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 to be 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 model. In Section 4, I develop a structural model motivated by this empirical evidence. Consistent with the bunching below the repayment threshold and the importance of dynamics and liquidity, the model is dynamic, and individuals choose their labor supply by trading off the disutility of work with the benefits of higher income and choose consumption subject to borrowing constraints. However, the evidence in Figure 3 also provides a rejection of a model in which labor supply is determined *solely* by trading-off the disutility of work with the benefits of higher income because locating immediately below the threshold increases take-home pay. If utility increases in consumption and leisure, such a model cannot generate any individuals immediately above the threshold because locating below it strictly dominates: it delivers more consumption with less labor supply (Kleven and Waseem 2013).[16]

The presence of individuals above the repayment threshold thus raises the question of what mechanism should be added to the model to explain this lack of labor supply adjustment. Broadly speaking, there are three possible explanations. First, individuals may be unaware of the repayment threshold due to inattention (Chetty et al. 2013). Second, individuals 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, individuals 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 individuals to feel obligated to pay their debts. The model in Section 4 introduces optimization frictions to explain the presence of individuals above the repayment threshold, which capture the first two explanations but not the third. This choice is motivated by my finding that the amount of bunching increases with hourly flexibility, which suggests that hours constraints and adjustment costs play a role, and the limited evidence of future wage reductions associated with the bunching.

4 Life Cycle Model with Labor Supply and Uninsurable Income Risk

The empirical analysis in Section 3 documents labor supply responses to income-contingent repayment. However, this analysis leaves open two important questions. First, how large are these responses quantitatively? Second, are these responses large enough to imply that the moral hazard costs created by income-contingent repayment outweigh its insurance benefits? The section

[16]One reason individuals 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 A, I show that this force is likely small.

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 in response to income-contingent repayment, and uninsurable income risk, which creates a demand for insurance that income-contingent repayment can provide.

4.1 Model Description

4.1.1 Demographics

Time is discrete, and each period, t, corresponds to one calendar year. At time $t = h \in \{\underline{h}, \underline{h} + 1, ...\overline{h}\}$, a cohort h of individuals indexed by i are born at an initial age a_0 and live at most a_T periods. The total number of distinct individuals born in the economy is discrete and denoted by N, where a fraction μ_h of individuals are 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, where the survival probability at age $a+1$ conditional on survival age a is 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.

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:

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

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 elasticity of labor supply, κ is a scaling parameter, and n_a is an equivalence scale. This preference specification follows Guvenen (2009b) and represents a recursive generalization of Greenwood et al. (1988) (GHH) preferences. These preferences eliminate wealth effects on labor supply, meaning the marginal rate of substitution between c and l is independent of changes in c. This assumption is consistent with empirical evidence that finds relatively limited 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 in my normative analyses. 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 stochastic components of an individuals' wage process, which take the following forms:

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

This 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 is captured by θ_{ia}, which depends on three factors. First, it depends on permanent shocks ν_{ia}, which have persistence captured by ρ. Second, it depends on an individual fixed effect, δ_i, which captures ex-ante heterogeneity across individuals. Finally, it exhibits learning-by-doing following Keane and Rogerson (2015), in which past values of labor supply affect future wage rates 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 policy counterfactuals.

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 income 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 "graduates", meaning they have a college degree, while those with $\mathcal{E}_i = 0$ are referred to as "nongraduates". 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 graduates 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 individuals locating 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.[17]

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 working hours schedule. The fixed cost is modeled as a utility cost, as axiomatized by Masatlioglu and Ok (2005).

[17]An alternative friction is optimization errors, which could take two forms, both inconsistent with my 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.

The second optimization 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 choose consumption and labor supply and those with $\omega_{ia} = 0$ can only adjust consumption, where:

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

This adjustment shock, ω_{ia}, generates time-dependent labor supply adjustment. Economically, this shock 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, this could capture simple inattention, where $1 - \lambda$ captures the fraction of inattentive individuals.[18] Individuals who receive the Calvo shock have to pay the fixed cost to adjust their labor supply.

4.1.6 Liquid Assets

At age a_0, individuals are endowed with an initial 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 also have different initial liquidity. In subsequent periods, individuals' liquid asset balances after consumption 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 limit, $\underline{A}_a$. The interest rate on borrowing is $R + \tau_b$, where τ_b captures the borrowing rate wedge. Individuals' asset income, i_{ia}, is received prior to consumption at age a and is equal to:

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

The interest rate and borrowing wedge are taken as exogenous. This is primarily done for tractability but is unlikely to quantitatively affect my counterfactual analyses 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.

[18] 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.

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 in my model because I focus on the trade-off between insurance and moral hazard ex-post. 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 student debt repayment that is determined by the repayment function, $d(\cdot)$. This repayment function depends on individuals' income, debt balance, and age. I assume any outstanding debt is discharged once individuals enter retirement at $a = a_R$ or upon death. When I estimate the model, this repayment function is set equal to the HELP repayment function in Figure 2.

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 at $a = a_0$, 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 individuals' consumption exceeds their disutility from labor supply by $\underline{c}$ in the event that they do not adjust the latter.[19] For all government taxes and transfers, including debt repayments, 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 labor supply, D_{ia} = student debt balance, θ_{ia} = persistence component of the wage rate, and ϵ_{ia} = transitory component of the wage rate. There are four discrete state variables: t = current year, a = age, $\mathcal{E}_i$ = level of education, and ω_{ia} = Calvo adjustment shock. Denote as $\mathbf{s}_{ia}$ the vector of these state variables for individual i at age a and as $E_a(\cdot) = E(\cdot \mid \mathbf{s}_{ia+1})$ the conditional expectation

[19]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.

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}, where consumption, c_{ia}, is pinned down by the budget constraint.

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

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

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 adjustment shock solve the following problem:

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

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:

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

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 techniques. The code to solve and simulate the model was compiled in Intel Fortran 2018 and executed in parallel with both MPI and OpenMP across 1,536 CPU threads. See Appendix C.1 for additional details.

4.2 Estimation Procedure

4.2.1 Calibrated Parameters

Table 2 shows the values of parameters that I can calibrate directly using observed data, formulas from the Australian tax and transfer system, or prior literature. In what follows, I provide a brief description of this calibration; see Appendix C.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, individuals' mortality risk is calibrated to match that in 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 model moments, all empirical moments are deflated to 2005 AUD with the indexation rates for HELP thresholds. The real interest rate is set to 1.84%, the (geometric) average real interest rate paid on deposits between 1991 and 2019 in Australia. The unsecured borrowing rate is set based on average credit card borrowing rates. Age-specific borrowing limits are set based on credit card limits reported in HILDA. The real interest rate on student debt is set to zero since HELP debt has a nominal interest rate equal to inflation.

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 individuals with college degrees, p_E, is 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. The distribution of initial debt balances is set based on the distribution of debt balances among individuals younger than age 26 in *ALife*, the age by which most individuals have finished their undergraduate studies in Australia and debt balances reach their maximum 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 because 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 increasing γ and decreasing σ to the calibration used in

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 graduates	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 C.2 for additional details.

Bansal and Yaron (2004), which introduces a preference for early resolution of uncertainty.

Learning-by-doing. My 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 individuals' 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 my baseline model and compare my 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:

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

These parameters can be divided into three groups: preference parameters; parameters governing the age profile of wages, g_{ia}, and finally, 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 my income process is endogenous. I thus proceed by combining a standard set of moments 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. As detailed in the Section 4.2.3, individuals' responses to this policy change are what allow me to separately identify the three most important parameters: ϕ, f, and λ.

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 formula and (ii) the HELP 2005 repayment formula. Starting at $t = \underline{h} = 1963$, I simulate cohorts of individuals making choices under the 2004 formula. 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 formula.

Estimator. I estimate the vector of parameters, Θ, using simulated minimum distance. This procedure 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 at parameters Θ as $m(\Theta)$, and the weighting matrix as $W(\Theta)$. My 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 C.3 and discussed in the next section.

4.2.3 Selection of Estimation Targets and Parameter Identification

I next discuss how each parameter is identified by the estimation targets in my 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 mostly qualitative; Table A5 provides the elasticities of each estimation target with respect to each structural parameter 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 adjustment 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 no individuals locating 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 individuals 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 individuals receive the Calvo shock.

To characterize bunching at different thresholds and among individuals with different debt balances using a manageable number of estimation targets, I compute the ratio of individuals within $250 below to within $250 above each threshold in each sample. This ratio captures the extent of bunching: more bunching implies more individuals below than above the threshold and thus a higher ratio. To target heterogeneity across thresholds with different repayment rates, I compute this ratio at the 2004 threshold prior to the policy change, at the 2005 threshold after the policy change, and at the lowest 2005 0.5% threshold after the policy change (see Figure A17 for a comparison of the latter two). I then compute it at the 2005 threshold after the policy change among individuals in the bottom and top quartiles of debt balances (within each year) to target heterogeneity in responses across debt balances.

Labor supply scaling parameter, κ. This parameter is simply a scaling parameter that determines the scale of l_{ia}. It 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 moments 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 my baseline simulated minimum distance estimation are reported in column (1) of Table 3. My baseline estimate of the (Frisch) labor supply elasticity is 0.114. This estimate is close to the mean value of 0.15 reported for Hicksian intensive-margin labor supply elasticities, which corresponds to ϕ in my model given the absence of wealth effects, from a meta-analysis of hours and taxable income responses in Chetty (2012). The baseline estimation also delivers a fixed adjustment cost of \$377, which corresponds to approximately 1% of average income in the model, and Calvo adjustment probability of 0.183. This value of the Calvo parameter implies that, in expectation, individuals receive an opportunity to adjust their labor supply every 5.4 years.

Figure 9 shows how the baseline model fits the distribution of HELP income before and after the policy change. The model provides a close approximation of both distributions, especially the mass of individuals immediately below and above the two repayment thresholds. There are slight differences at other points that reflect the fact that the model cannot perfectly match the age profile

Table 3. Simulated Minimum Distance Estimation Results

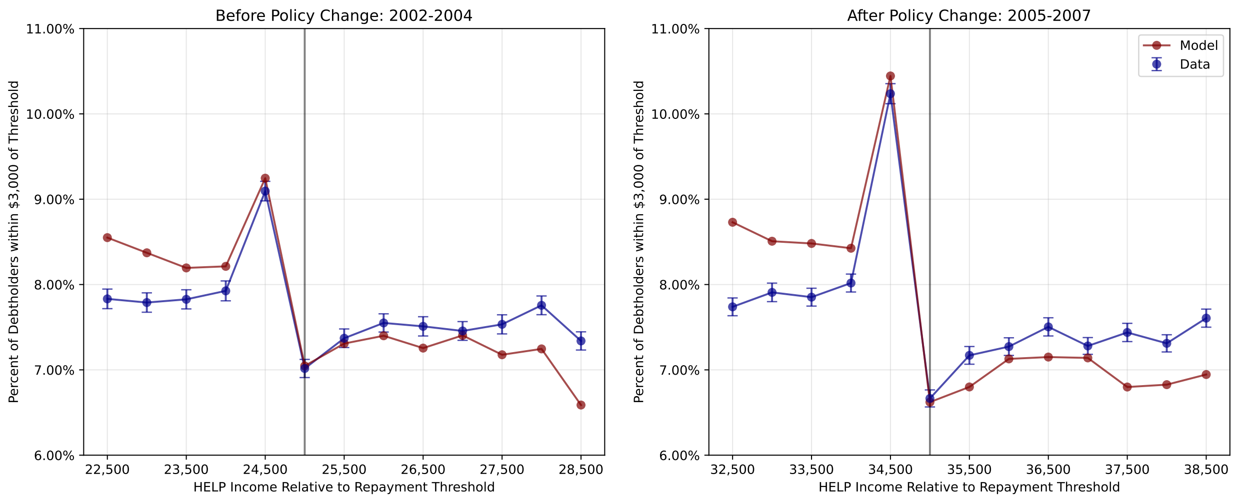
		Estimation					
Parameter		(1)	(2)	(3)	(4)	(5)	(6)
Labor supply elasticity	ϕ	0.114	0.005	0.188	0.053	0.082	0.111
		(.004)	(.000)	(.003)	(.002)	(.002)	(.004)
Adjustment cost parameter	f	$377	$0	$2278	$0	$762	$513
		($13)	·	($21)	·	($10)	($19)
Calvo parameter	λ	0.183	1	1	0.147	0.346	0.191
		(.003)	·	·	(.002)	(.009)	(.003)
Labor supply scaling parameter	κ	0.560	0.030	0.059	0.510	1.242	0.593
		(.007)	(.003)	(.014)	(.012)	(.116)	(.001)
Time discount factor	β	0.973	0.996	0.972	0.944	0.951	0.951
		(.001)	(.000)	(.001)	(.001)	(.001)	(.001)
Wage profile parameters	δ_0	8.922	9.862	8.680	9.389	9.197	9.143
		(.009)	(.002)	(.006)	(.007)	(.007)	(.008)
	δ_1	0.073	0.111	0.073	0.063	0.070	0.075
		(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
	δ_2	−0.001	−0.002	−0.001	−0.001	−0.001	−0.001
		(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
	δ_0^E	−0.487	−0.294	−0.450	−0.530	−0.480	−0.478
		(.002)	(.000)	(.001)	(.002)	(.002)	(.002)
	δ_1^E	0.020	0.032	0.018	0.021	0.018	0.020
		(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Persistence of permanent shock	ρ	0.930	0.914	0.943	0.922	0.889	0.907
		(.000)	(.000)	(.000)	(.000)	(.000)	(.001)
Standard deviation of permanent shock	σ_ν	0.236	0.076	0.196	0.268	0.288	0.275
		(.000)	(.000)	(.000)	(.000)	(.000)	(.001)
Standard deviation of transitory shock	σ_ϵ	0.130	0.504	0.168	0.077	0.064	0.080
		(.000)	(.000)	(.000)	(.002)	(.002)	(.002)
Standard deviation of individual FE	σ_i	0.599	0.101	0.541	0.654	0.625	0.612
		(.003)	(.001)	(.003)	(.003)	(.003)	(.003)
Learning-by-doing parameter	α	0	0	0	0	0.24	0
Adjustment cost function		Fixed	Fixed	Fixed	Fixed	Fixed	Linear

Notes: This table shows the results from simulated minimum distance estimations. Each column corresponds to a separate estimation. Entries in the table correspond to parameter estimations with standard errors presented below in parentheses. All estimations use the same set of estimation targets in Appendix C.3. Parameters that are fixed at their respective values and not estimated are indicated with "·" in place of a standard error. Column (1) corresponds to the baseline estimation; column (2) estimates a model with no optimization frictions; column (3) estimates a model with only a fixed adjustment 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 adjustment cost) instead of $f * \mathbf{1}_{\ell_a \neq \ell_{a-1}}$ (i.e., a fixed adjustment cost).

of income.

Figure 10 illustrates the model's fit of the amount of bunching at other repayment thresholds, in addition to among individuals 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 adjustment 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 individuals receive an adjustment shock is independent of

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



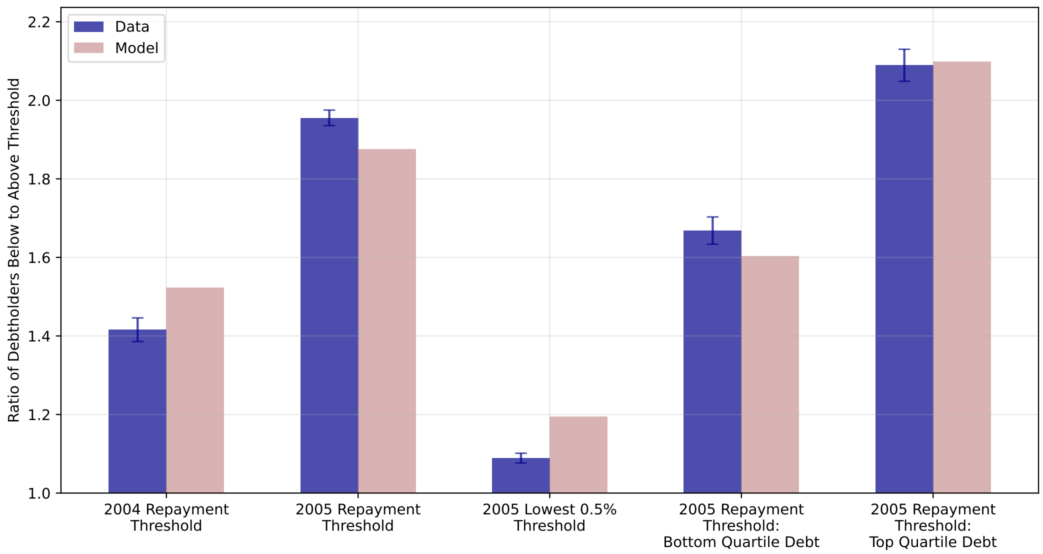
Notes: The left panel of this figure plots the HELP income distribution within $3,000 of the repayment threshold in bins of $500 for the period before the policy change from 2002 to 2004 in the data in blue. Bars represent 95% confidence intervals based on bootstrapped standard errors with 1000 iterations. 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 black line in each plot indicates the repayment threshold, which is the point at which repayment begins.

their level of income. Similarly, the presence of an adjustment cost helps match the difference in bunching between individuals with low and high debt balances. Quantitatively, the model misses slightly on matching the right amount of bunching at the 0.5% threshold. This is because matching this moment better would require performing worse on the others: increasing the adjustment cost would improve the fit at the lower 0.5% threshold but would also further decrease the amount of bunching among individuals with low debt balances, which the model already underestimates.

Table 4 shows the fit of the model to the remaining target moments, which are primarily used to estimate the remaining parameters outside of the labor supply elasticity, fixed adjustment cost, and Calvo parameter. The model provides a relatively good fit to average labor income and the age profiles of income, which are most affected by the wage profile parameters in Table 3. 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 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. My model features profile heterogeneity across the two education groups, which brings my 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 when comparing repayment policies.

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. This estimate is similar to

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.

Table 4. Baseline Model Fit: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	45581.953
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	1338.846	1332.459

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.

typical estimates in life cycle models that target consumption data explicitly (e.g., Gourinchas and Parker 2002) and is less than R^{-1}. The latter finding implies that individuals face a trade-off between wanting to consume at young ages due to impatience and accumulating precautionary savings, which generates buffer-stock behavior (Carroll and Kimball 1996).

4.4 Identification of Labor Supply Elasticity and Optimization Frictions

The three most important parameters in my model are the labor supply elasticity, Calvo probability, and fixed adjustment cost. Figure A18 plots the simulated minimum distance objective function across these three parameters, which exhibits a clear (local) minimum. This illustrates that my estimated targets discussed in Section 4.2.3 provide enough variation to separately identify these parameters that jointly determine labor supply responses. Additionally, Figure A18 shows that the objective function is very smooth, which lends confidence to my numerical solution technique. A large number of simulations and the fact that no choice variables are discretized in the solution (discussed in Appendix C.1) are both important for generating this smoothness.

To illustrate the importance of each optimization friction, I estimate three additional models. Column (2) of Table 3 and Figure A19 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 moments in the data. Column (3) and Figure A20 show the results for a model with only a fixed adjustment cost (i.e., $\lambda = 1$). This model delivers a more reasonable estimate of the labor supply elasticity but overpredicts the amount of bunching after the policy change. This is because the fixed adjustment cost that rationalizes the amount of bunching at other thresholds is too small to prevent more individuals from bunching at the 2005 repayment threshold, which has the largest change in repayment rate.

Finally, column (4) and Figure A21 show the results from a model with no fixed adjustment cost (i.e., $f = 0$). These estimation results are the closest of the three additional models to the baseline model in column (1), but this 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 for this is straightforward: without a fixed adjustment cost, labor supply adjustment depends on whether an individual receives the Calvo shock, which is equally likely around all repayment thresholds. The small fixed adjustment cost in column (1) helps reduce the amount of bunching at the 0.5% threshold because the cost outweighs the benefit for many individuals while still 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, this lower estimate of the discount factor then causes the model to miss on a second key moment: it underestimates the amount of wealth accumulation.

4.5 Estimation Results from Alternative Models

Adding learning-by-doing. Column (5) of Table 3 and Figure A22 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). The results show that 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 adjustment cost and Calvo parameter. This is because learning-by-doing makes bunching significantly costly for younger rather than older people: the reduction in human capital is less important for older borrowers who have fewer periods to benefit from it. As a result, this model predicts that the amount of bunching increases with age, in contrast to the data (and baseline model). Additionally, 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 λ to make adjustment more state-dependent, increasing heterogeneity in bunching with debt balances.

Alternative adjustment cost specification. Column (6) of Table 3 and Figure A23 show the results from estimating an alternative model with a different adjustment cost: a linear adjustment cost, $f * |\ell_a - \ell_{a-1}|$, instead of a fixed adjustment cost, $f * \mathbf{1}_{\ell_a \neq \ell_{a-1}}$. The results show that 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 my parameter estimates are likely robust to misspecification of the exact type of optimization frictions.

4.6 Connection of Estimation Results with Existing Literatures

Literature on labor supply. The literature on labor supply is extremely vast 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; the fourth studies differences in hours worked in response to cross-sectional variation, such as variation in tax rates across countries. Figure A24 shows the distribution of labor supply elasticities estimated among studies in these first two strands of literature, which are the most closely related to this paper. My baseline estimate 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.

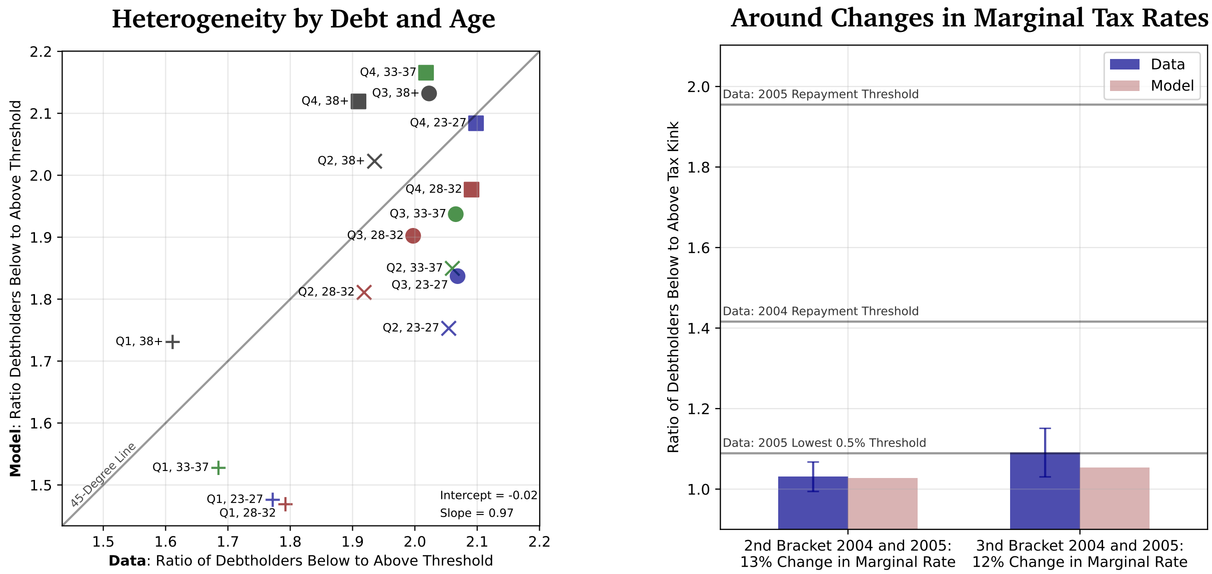
There are several reasons why optimization frictions might be larger in my setting, making the frictionless elasticity smaller. First, my sample of individuals differs from the samples in most prior studies: they are college graduates early in their life cycles. These individuals are more likely to work 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 lower, 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). 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 with minimal changes in 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) dynamic model of labor supply with both time- and state-dependent adjustment. One way to compare my 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 my estimate of $\phi = 0.11$, while in Figure A25, it is around 80% in my baseline model. This suggests that my model delivers reasonable estimates for the effects of income taxation, despite being designed to capture the dynamic effects created by income-contingent repayment.

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, which is lower than the 0.77 in Guvenen et al. (2022). This primarily reflects that the cross-sectional standard deviation of income at age 22 is approximately 20% lower in the Australian than in the US data. 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 transitory wage shocks.[20] 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 heterogeneous income profiles across education groups, which requires a larger variance of permanent shocks to match the percentiles of 5-year income growth.

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

Figure 11. Fit of Model on Nontargeted Bunching Statistics



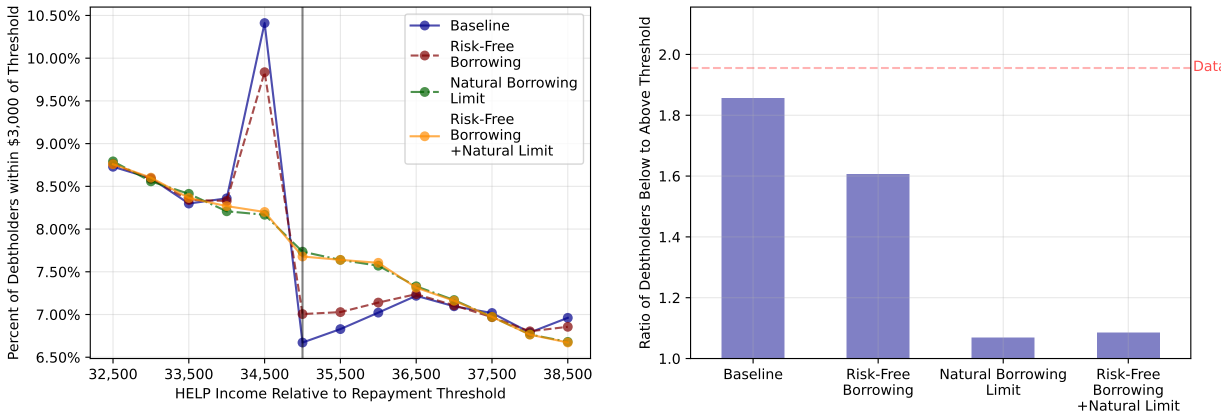
Notes: The left panel of this figure shows a scatterplot of bunching below the 2005 repayment threshold for different samples in the data versus the model. Each point corresponds to a different sample based on quartiles of debt and age labeled in the plot. The quartiles of debt are calculated in the 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.

4.7 Model Validation on Nontargeted Bunching

Before using the estimated model to perform counterfactual analyses, I assess whether 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 the data is for young individuals with low debt balances, for whom the model generates insufficient bunching.

The second set of non-targeted bunching statistics is shown in the right panel of Figure 11, which are the bunching in taxable income around the two discontinuities in the marginal tax rates closest to the HELP repayment thresholds. The bunching around these "kinks" is much smalller than around the repayment thresholds, while it is 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 results show the model replicates this relatively small amount of bunching at these thresholds well.

Figure 12. The Effects of Liquidity Constraints on Bunching in the Estimated Model



Notes: The left panel of this figure plots the income distribution in bins of $500 around the 2005 repayment threshold between 2005 and 2018 for different models described in the text. The right panel plots the bunching below the 2005 repayment threshold between 2005 and 2018 as calculated in Figure 10. The red dashed line in the plot corresponds to the value of this quantity in the data.

5 Two Drivers of Responses to Income-Contingent Repayment

Section 3 shows that the labor supply responses to income-contingent repayment vary based on two forces: liquidity constraints and dynamics. This section uses my estimated model to quantify the strength of these forces.

5.1 Liquidity Constraints Amplify Labor Supply Responses

Figure 12 shows how the amount of bunching below the repayment threshold in the model varies depending on the tightness of liquidity constraints. The left and right panels plot the income distribution and the ratio of individuals below to individuals above the 2005 repayment threshold, respectively, for the baseline model, and three counterfactuals. The first counterfactual, Risk-Free Borrowing, eliminates the extra interest paid on borrowing by setting $\tau_b = 0$. Comparing this result with the baseline, we observe that the amount of bunching decreases moderately: the number of individuals below relative to that of individuals above the threshold decreases from 1.85 to 1.6, where 1 corresponds to no bunching. The second counterfactual, Natural Borrowing Limit, relaxes individuals' borrowing constraints, $\{\underline{A}_a\}$, to the natural borrowing limit.[21] In this counterfactual, the amount of bunching is reduced almost entirely. The third counterfactual, Risk-Free Borrowing + Natural Limit, shows that additionally setting $\tau_b = 0$ at the natural borrowing limit delivers similar results.

Empirically, Figure 7 shows that individuals with less wealth in the form of retirement savings

[21]The natural borrowing limit cannot be computed analytically in my model. I approximate it numerically and find that it corresponds to relaxing the baseline borrowing constraint by approximately a factor of four.

are more likely to bunch below the repayment threshold. Figure A26 shows that a similar pattern holds in my estimated model: the amount of bunching decreases monotonically in individuals' initial assets. In the model, this is because additional wealth diminishes the importance of liquidity constraints by providing resources to smooth income shocks and reducing precautionary saving. In sum, these results show how a demand for liquidity created by incomplete markets amplifies labor supply responses, which is consistent with evidence from other social insurance programs such as unemployment insurance (Chetty 2008), mortgage default (Ganong and Noel 2023), and consumer bankruptcy (Indarte 2023).

5.2 Dynamics Attenuate Labor Supply Responses

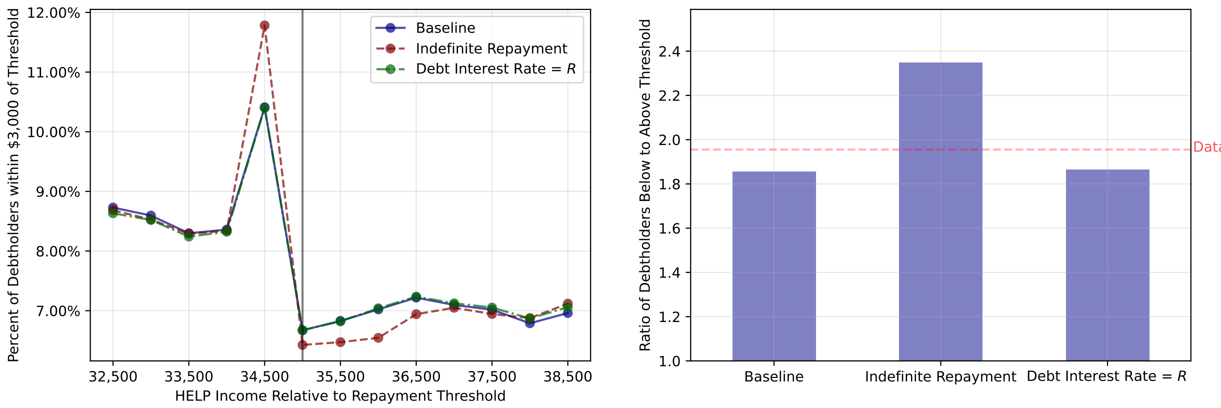
The second force that Section 3 showed was an important driver of labor supply responses was dynamics: borrowers with a lower probability of eventual repayment exhibit greater responses. To assess the importance of these dynamics, Figure 13 shows the results from a counterfactual in which the constraint that repayments are set to zero after an individuals' debt balance is paid off is eliminated. This effectively makes income-contingent loan repayments an income tax or equity contract, where payments continue indefinitely. The results show that this has a large effect on labor supply responses, generating almost twice as bunching below the repayment threshold.

An extensive literature studies labor supply responses to taxes (Saez et al. 2012). In addition to the dynamic incentives, another difference between an income-contingent loan and an income tax is that the former has an interest rate. When this interest rate is lower than the interest rate on borrowing, income-contingent loans provide an additional incentive to reduce labor supply because doing so lowers the effective borrowing rate. The second counterfactual in Figure 13 shows that this turns out to be much less important than the dynamic incentives: eliminating the interest rate differential by setting $1 + r_d = R$ has a minimal effect on the amount of bunching.

6 Normative Analysis of Repayment Contracts

This section uses my estimated structural model normatively to study the welfare and fiscal impacts of alternative repayment contracts. In this analysis, I take the perspective of a social planner who maximizes borrowers' expected lifetime utility by choosing one mandatory repayment contract, holding fixed borrowing choices and prices (e.g., wages and interest rates). This problem of choosing a single repayment contract is faced by governments that offer only one contract, such as Australia and the UK. Additionally, this choice reflects the fact that my model does not capture endogenous contract selection across borrowers. In my baseline analysis, I focus on subsidized

Figure 13. The Effects of Debt Repayment on Bunching in Estimated Model



Notes: The left panel in this figure plots the income distribution in bins of $500 around the 2005 repayment threshold between 2005 and 2018 for different models described in the text. The right panel plots the bunching below the 2005 repayment threshold between 2005 and 2018 as calculated in Figure 10. The red dashed line in the plot corresponds to the value of this quantity in the data.

repayment contracts with a zero interest rate, like those available in Australia.[22]

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

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

I begin by computing the welfare and fiscal impacts of various repayment contracts used in Australia and the US relative to a 25-year fixed repayment contract without any forbearance (i.e., payment pauses for low-income borrowers). This fixed repayment contract is a standard debt contract in which individuals make constant repayments for 25 years after graduation to repay their loan principal. I choose this contract as the benchmark because it is available in the US and has a similar duration to income-contingent contracts but is not income-contingent. I implement the contract without forbearance to create a realistic fiscal cost and then consider the effect of adding forbearance in Section 6.4.

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

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

over individuals' lifetimes. Formally,

$$\mathcal{G} \equiv \mathbf{E}_0 \left(\sum_{a=a_0}^{a_T} \underbrace{\frac{\tau_{ia} - ui_{ia} - \underline{c}_{ia}}{\mathcal{R}_a}}_{\text{taxes and transfers}} + \underbrace{\frac{d_{ia}}{\mathcal{R}_a} - D_{ia_0}}_{\text{debt repayments}} \right), \tag{15}$$

where $\mathbf{E}_0(\cdot)$ denotes an expectation taken over all states, including the initial state.[23] $\mathcal{R}_a$ denotes the government discount rate of payments made at age a relative to a_0, which I set equal to:

$$\mathcal{R}_a = \beta^{-(a-a_0)} \prod_{s=0}^{a-a_0} m_s. \tag{16}$$

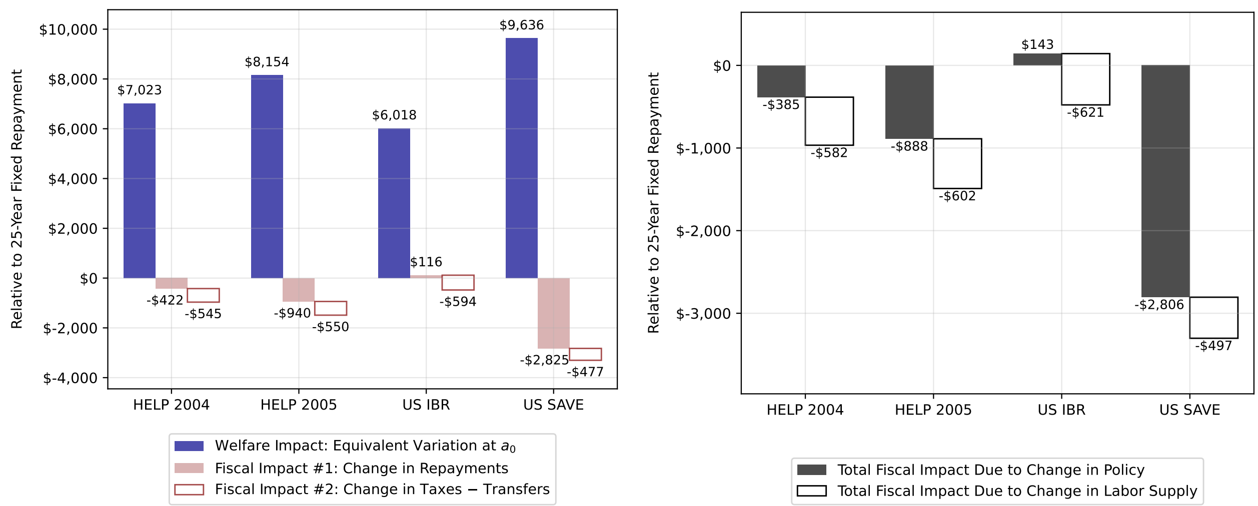
I set $\mathcal{R}_a$ equal to individuals' discount rates between a_0 and a, including discounting due to time preferences and mortality risk, for two reasons. First, a choice of $\mathcal{R}_a$ different from individuals' time preferences allows the government to increase welfare simply by shifting around deterministic payments over time to take advantage of differences in discount rates. Because my analysis focuses on comparing alternative 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 choice of 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 my baseline model, the average value of $\mathcal{R}_a$ for $a \in (a_0, a_R)$ is 1.03. In Section 6.7, I consider the effect of using alternative discount rates.

The comparison of different repayment contracts in my model is contingent on the tax and transfer system, which is an alternative way to redistribute within and across individuals. For my normative analysis, I adopt the parametric specification of the tax system studied in Heathcote et al. (2017) calibrated to match the ATO tax schedule and a smoothed specification of the ATO unemployment benefit formula; see Appendix C.2 for additional details.

Results. The left panel of Figure 14 presents the welfare and fiscal impacts of the income-contingent loans used in the US and Australia. This panel breaks the fiscal impact into the present value of the change in repayments and the change in other components $\mathcal{G}$, which are taxes net of transfers. To measure the dollar welfare impact of an alternative repayment contract, 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 an individual who attends college, prior to knowing her other initial states, indifferent between repaying under a new policy and repaying under 25-year fixed repayment?

[23] I define the government budget in present-value terms rather than at the model's stationary distribution because the former has a more intuitive interpretation: it corresponds 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 to this group of individuals.

Figure 14. 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 C.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 $\mathcal{E} = 1$ who does not know her initial states. The second dark red bar shows the change in the government budget defined in (15) 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 change in the total fiscal cost for each policy, assuming that individuals' labor supply remained at its value under 25-year fixed repayment. The second is the residual attributable to endogenous changes in labor supply.

The first two columns show that both HELP repayment policies—those corresponding to the periods before and after the policy change—provide gains equivalent to cash transfers of approximately $7,500, which is 43% of the average initial debt balance in the model of $17,500. 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 individuals pay a fixed rate of income earned above a certain threshold. These two columns show that the two US IBR contracts deliver gains similar to those under HELP contracts but differ in fiscal cost. The current US IBR program has a fiscal cost that is approximately 60% lower than that of the HELP contracts because repayments start at a lower value of income. In contrast, the proposed IBR program has a fiscal cost that is three times as large, reflecting the higher repayment threshold and lower repayment rate under this policy. Dividing the welfare gains 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 (reported in Figure A27) is highest for US IBR and is high relative to typical estimates for policies targeting adults (Hendren and Sprung-Keyser 2020).

The right panel of Figure 14 decomposes the total fiscal cost associated with moving from 25-year fixed repayment to income-contingent loans, the sum of the two fiscal impacts shown in the left panel, into two components. The first component, shown in the top black component of each bar, is the change in $\mathcal{G}$ holding fixed individuals' labor supply decisions at their values under 25-year fixed repayment. The second component, shown below in blue, is the incremental change in $\mathcal{G}$ due to the endogenous adjustment of labor supply. In other words, this second component measures the additional cost of the moral hazard created by income-contingent loans and would be zero in a model with exogenous labor supply. This moral hazard accounts for approximately 50% of the total cost from switching to HELP 2004 and HELP 2005 and 130% for US IBR. For the newly proposed US IBR, it accounts for only 15% of the fiscal cost, reflecting that the smaller 5% repayment rate generates a smaller behavioral response than the 10% rate under US IBR.

Effects of changing labor supply elasticity. Figure A28 reproduces the right panel of Figure 14 for different values of the elasticity of labor supply, ϕ. Increasing ϕ to twice its estimated value leads to a doubling of the cost of moral hazard, while reducing it by half leads to a cost reduction of over 60%. These results highlight the importance of correctly identifying the labor supply elasticity for quantifying the fiscal impact of income-contingent loans.

6.2 Welfare Gains from Constrained-Optimal Income-Contingent Loan

The evidence in Section 6.1 shows that the welfare gains from existing income-contingent loans are large relative to their fiscal costs. In this section, I construct income-contingent loans with the same fiscal costs as those under fixed repayment contracts to assess whether these contracts can still provide gains and study the optimal form of income-contingent loans at a given cost.

Definition of the constrained-planner's problem. I consider a social planner who maximizes borrower welfare by choosing one mandatory repayment contract. I assume that this planner is constrained á la Ramsey (1927) to choosing income-contingent loans with the same structure as US IBR contracts and the income-contingent loans used in the UK. These contracts have two parameters that make them essentially call options on individuals' 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 social planner's problem is thus:

$$\max_{\{\psi, K\}} \mathbf{E}_0 \left(V_{ia_0}^{1-\gamma} \right)^{\frac{1}{1-\gamma}}, \tag{17}$$

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 objective function in this problem corresponds to the Epstein–Zin certainty-equivalent of the stochastic consumption and labor supply sequences, which depends (implicitly) on the three policy parameters, to an individual who is "behind the veil of ignorance" with respect to her initial conditions. The first constraint requires that the fiscal revenue be at least $\overline{\mathcal{G}}$, which I set equal to the revenue raised from the 25-year fixed repayment contract without forbearance in Section 6.1. The second and third constraints in (17) capture the informational and parametric restrictions imposed by a US IBR–style income-contingent loan. Solving (17) is numerically challenging; I leverage a combination of barrier methods and a global optimizer detailed in Appendix C.6.

Solution to the planner's problem. The red solid line in the right panel of Figure 15 plots payments as a function of income on the constrained-optimal income-contingent loan that solves (17) for an individual with a median initial debt balance. This contract provides individuals with significant insurance relative to a fixed repayment contract, as payments do not start until the 26th percentile of the income distribution at K=\$27,147. This value of K is similar to the threshold at which repayment began under the HELP 2004 system but lower than that under HELP 2005. In US IBR contracts, K is set equal to 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.[24]

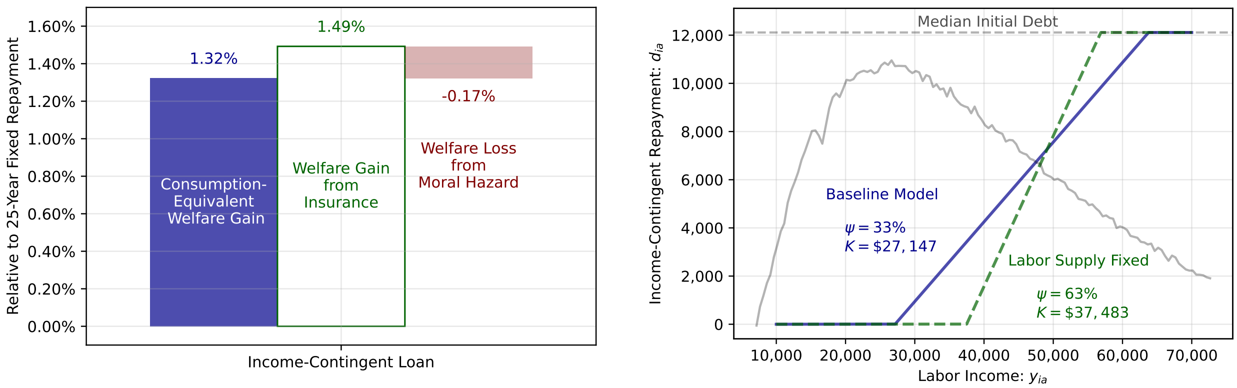
To collect sufficient revenue with a relatively high repayment threshold, the constrained-optimal contract has a repayment rate of ψ = 33%, approximately three times the 10% repayment rate on current US IBR contracts. In other words, the optimal contract provides more insurance than current US IBR contracts by reducing payments from low-income borrowers in exchange for payments from high-income borrowers, with payments capped by initial debt balance. Although this repayment rate is relatively high, it induces almost no bunching at the repayment threshold, as shown in the income distribution in gray. This lack of bunching relative to the evidence in Figure 3 reflects the fact that this threshold changes the *marginal* rather than *average* repayment rate: locating below the threshold does not increase cash on hand, eliminating the liquidity effect discussed in Section 5.1. The lack of bunching is consistent with limited bunching at UK repayment thresholds (Britton and Gruber 2020), which change marginal rather than average repayment rates.

Effect of moral hazard. To isolate the impact of moral hazard on the design of income-contingent loans, the dashed green line in Figure 15 plots the contract that solves (17) in a model where individuals' labor supply is fixed at its value under the baseline 25-year fixed repayment contract.[25] The results show that this alternative contract provides even more insurance than the contract in my baseline model, with a 30 pp higher repayment rate and 40% higher threshold. This reflects that labor supply responses create a fiscal externality from a wedge between social and private incentives: individuals do not internalize that locating below the threshold reduces gov-

[24]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.

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

Figure 15. 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 (17) 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 the repayment contract that solves (17) in the baseline model in solid blue and the solution in a model in which labor supply remains fixed at its value under 25-year fixed repayment in dashed green, assuming an individual has an initial debt balance equal to the median. The parameter values that solve (17) are shown next to each contract. The solid gray line plots the income distribution in bins of \$500. The dashed gray line plots the median initial debt balance, which places an upper bound on payments on income-contingent loans.

ernment 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 individuals reduce their labor supply, the planner lowers the repayment threshold to collect revenue from more individuals and the repayment rate to induce a smaller behavioral response.

Welfare gains. The left panel of Figure 15 shows the welfare gain from the constrained-optimal income-contingent loan in the right panel of the figure. To measure welfare gains, I use the metric from Benabou (2002): What value of g would make an individual who attends college, prior to knowing her initial states, indifferent between repaying under a new policy and repaying under 25-year fixed repayment contract with her consumption increased by $g\%$ in every state of her life? The leftmost blue bar in Figure 15 shows that the optimal income-contingent loan provides gains equivalent to a 1.32% increase in lifetime consumption relative to that under 25-year fixed repayment. This corresponds to 47% of the gain from forgiving debt balances entirely, which is not budget-neutral.

The second two bars in Figure 15 decompose the total gain shown in the first bar into the gain from providing insurance and loss from moral hazard. To compute the former, I solve (17) again, instead assuming that debt repayments, d_{ia}, can be made contingent on *wage rates*, w_{ia}, instead of income, y_{ia}. This contract is informationally infeasible, but its gains depend entirely on the insurance benefits and not on labor supply responses. Therefore, the welfare cost of moral hazard corresponds to the difference between the gain under this wage-contingent loan and that under the constrained-optimal income-contingent loan. The results show that the cost of 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. As discussed above, the repayment rate on the constrained-optimal income-contingent loan is higher than the rates in the US. Figure A29 shows that 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 and thus reducing the amount of insurance. The remaining half comes from the lower repayment threshold inducing labor supply responses by more individuals, which increases the loss from moral hazard.

Comparison with existing contracts. Comparing the income-contingent loan in Figure 15 directly 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 A30 shows separately the results from resolving (17) with $\overline{\mathcal{G}}$ set equal to the revenue raised from the HELP 2004, HELP 2005, and US IBR contracts. Consistent with Figure 15, each constrained-optimal contract has a higher repayment threshold and rate than the corresponding benchmark contract.

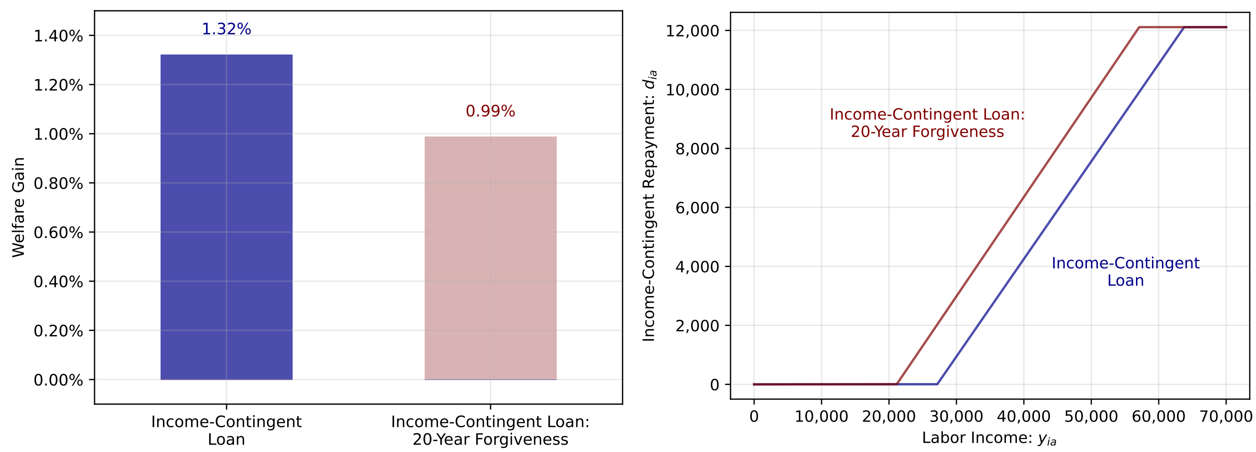
6.3 Adding Forgiveness Reduces the Welfare Gains from Income-Contingent Loans

I next consider the effects of adding forgiveness after a fixed horizon, a feature of income-contingent loans in the US and UK. The left panel of Figure 16 compares the gain from the income-contingent loan in Figure 15 with a constrained-optimal income-contingent loan with forgiveness at $a_0 + 20$, as in the currently available US IBR contracts. The latter contract generates a welfare gain of 0.99%, 0.33 pp lower than the contract without forgiveness repeated in the first column.[26]

The lower gain from adding forgiveness reflects a combination of two forces. First, adding forgiveness at the same fiscal cost requires a lower repayment threshold of \$21,131, as shown in the right panel of Figure 16. The consequence of a lower repayment threshold is greater payments from young borrowers in exchange for lower payments on older borrowers, for whom repayment is forgiven (Figure A31). This reduces the insurance benefits because younger borrowers have a higher marginal value of wealth from tighter borrowing constraints and stronger precautionary saving motives (Gourinchas and Parker 2002; Boutros et al. 2022). The second force is that a finite forgiveness horizon increases the loss from moral hazard (Figure A29). With a finite forgiveness horizon, borrowers are more willing to adjust their labor supply to reduce payments because it is less likely that they will make these payments later in their life cycle.

[26] In untabulated results, I solve (17) optimizing over the forgiveness horizon and find that no forgiveness is optimal.

Figure 16. 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 different constrained-optimal repayment contracts described in the text and shown on the right. The repayments are shown for an individual with median initial debt.

6.4 Income-Contingent Loans Provide Larger Gains than Adding Forbearance

Relative to a fixed repayment contract, the income-contingent loan in Figure 15 differs in two ways. First, the latter contract provides payment reductions for low-income borrowers, whose income is below the repayment threshold. Second, income-contingent loans collect higher payments from high-income borrowers, while repayments are independent of income under a fixed repayment contract. In reality, the fixed repayment contracts implemented in the US allow payments to be delayed if borrowers receive deferment, forbearance, or default. For example, Figure A32 shows that 30% of outstanding debt in the US, as of 2019, was in one of these three non-repayment states.

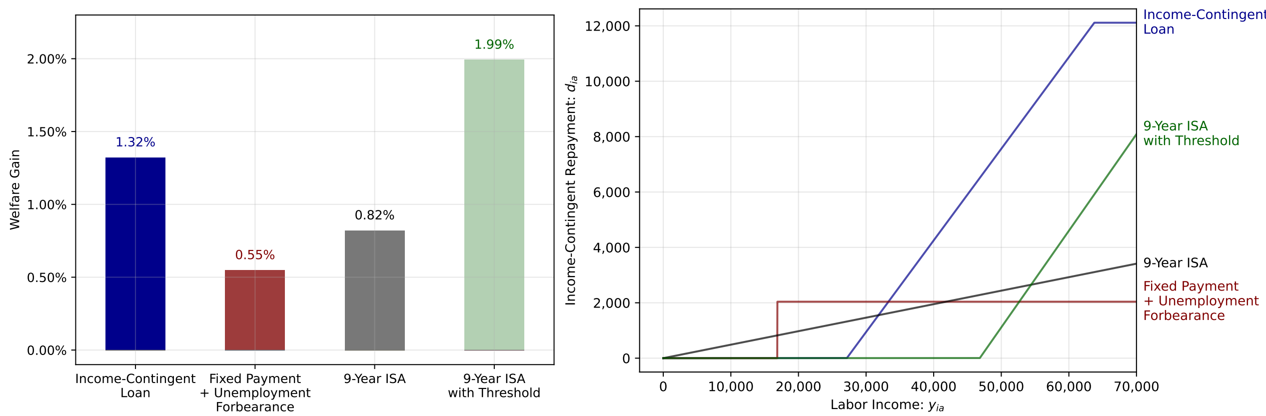
Figure 17 shows the welfare gain from a fixed repayment contract with forbearance, in which borrowers make constant payments that are independent of their income when their income is above $16,384, the point at which unemployment benefits stop being paid in Australia (43% above the poverty line), but are allowed to access unlimited forbearance and make zero payments when their income falls below this point. The constant payment made outside of forbearance is calculated by solving (17) to ensure this contract has the same fiscal cost as other repayment contracts.[27] The left panel of Figure 17 shows that this contract delivers a gain of only 0.55% relative to 25-year fixed repayment, less than half of the gain from the constrained-optimal income-contingent loan.[28]

The smaller gains from a fixed repayment contract with forbearance reflects the benefits of the call option-like structure of fully income-contingent repayment. As shown in the right panel of

[27]An alternative contract is a 25-year fixed repayment contract 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%.

[28]A natural question is whether there are welfare gains from combining these two repayment contracts: Figure A33 shows that doing so optimally provides minimal welfare gains over the income-contingent loan in Figure 15.

Figure 17. 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 different constrained-optimal repayment contracts described in the text and shown on the right. The repayments are shown for an individual with median initial debt.

Figure 17, the income-contingent loan collects higher payments from high-income individuals. Although these individuals are likely to pay off their debt, the acceleration of these payments increases their expected discounted value. This in turn enables the social planner to have a higher repayment threshold, increasing insurance at a given cost.

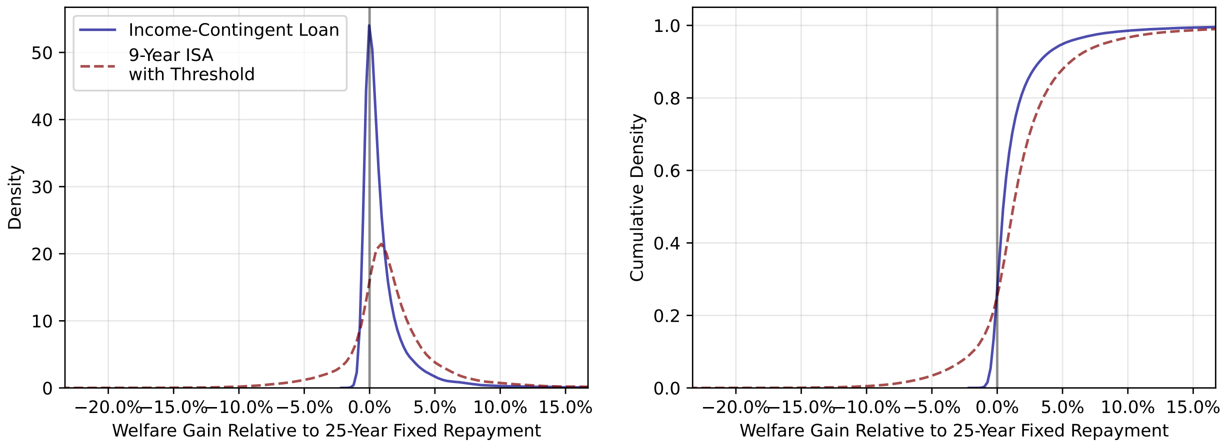
6.5 Equity Contracts Generate Larger, but More Dispersed, Welfare Gains

The development of income-contingent loans was motivated by Friedman (1955), who advocated using equity contracts known as income-sharing agreements (ISAs) in which individuals repay a percentage of their income for a fixed repayment period. Successful implementation of these contracts has been relatively limited due to adverse selection (Herbst and Hendren 2021), so I next use my model to assess the desirability of income-sharing agreements as a mandatory government-provided financing contract. I model ISAs after those provided by Purdue University in 2016–2017, in which individuals repay a constant fraction of their income for nine years (Mumford 2022).

The third column in the left panel of Figure 17 shows that the welfare gain from a nine-year ISA is 0.82%, where the parameter controlling the share of income paid has been adjusted to balance the government budget. This gain is approximately 40% (or 0.5 pp) lower than the gain from the constrained-optimal income-contingent loan. The lower gain reflects the same force that generates smaller gains from forgiveness: a pure ISA requires payments from all borrowers in the first few years of their life, which is when they value payment reductions the most, in exchange for zero payments when they are older (i.e., after nine years).

The final column of Figure 17 shows that a modified ISA offered by Purdue University does significantly better. In the 9-Year ISA with Threshold, borrowers only make payments when their income

Figure 18. Distribution of Gains from Constrained-Optimal Income-Contingent Loan and Equity Contract



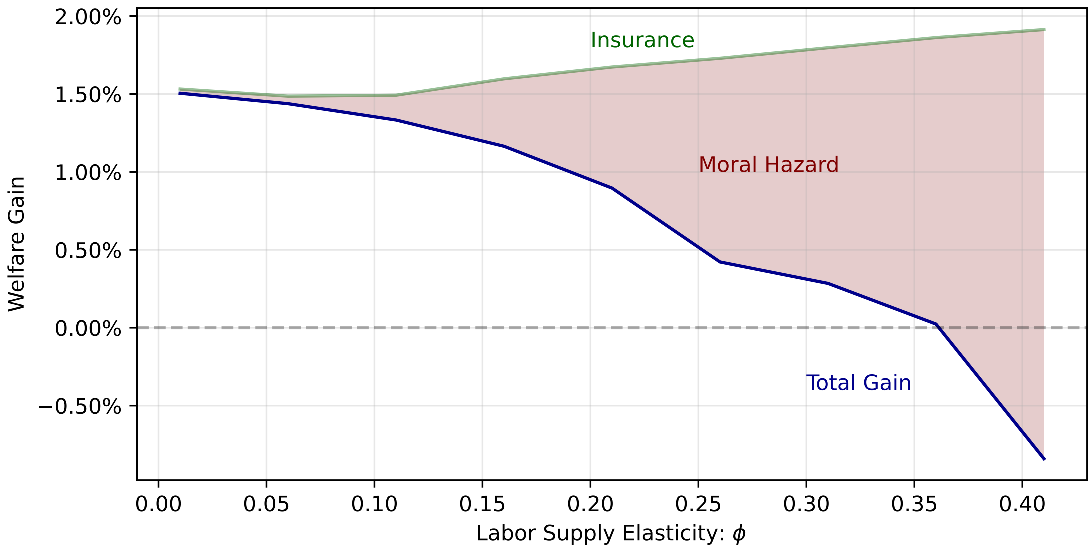
Notes: This figure plots the distribution of welfare gains at a_0 relative to 25-year fixed repayment from the constrained-optimal income-contingent loan in solid blue and the 9-Year ISA with Threshold, described in the text, in dashed red. The left panel plots the density of these gains and the right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

exceeds a certain threshold, which is chosen jointly with the income-share rate to solve (17). 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 greater insurance. With an income-contingent loan, repayments from high-income individuals are capped by their initial debt balances. However, with an income-sharing agreement, these payments are uncapped and thus can be used to finance even lower repayments from low-income individuals. The right panel of Figure 17 shows how this manifests in a 70% higher repayment threshold of K =$46,821.

Although equity contracts generate larger gains on average, these gains are more heterogeneous. Figure 18 plots the distribution of welfare gains and losses at $a = a_0$ from the constrained-optimal income-contingent loan and 9-year ISA with threshold. Relative to 25-year fixed repayment, the income-contingent loan yields gains for approximately 70% of individuals, while the remaining 30% experience small losses. These small losses are concentrated among high-income individuals, who are required to pay their loans faster under income-contingent than under fixed repayment. Relative to these gains, the gains from the optimal equity contract 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 individuals whose repayments are uncapped under an equity contract. Additionally, income-sharing agreements induce significant redistribution from individuals with low to individuals with high debt balances that is large enough to reverse the ranking of certainty-equivalents across terciles of initial debt (Figure A34).

In sum, although properly designed equity contracts yield larger average welfare gains, they are

Figure 19. Welfare Gains from Constrained-Optimal Income-Contingent Loan as a Function of ϕ



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 (17) in the baseline model. This planner's problem is then solved for different values of the Frisch elasticity with the results shown in the plot. 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 15. The point at which the dashed gray line intersects the solid blue line corresponds to $\phi = 0.37$.

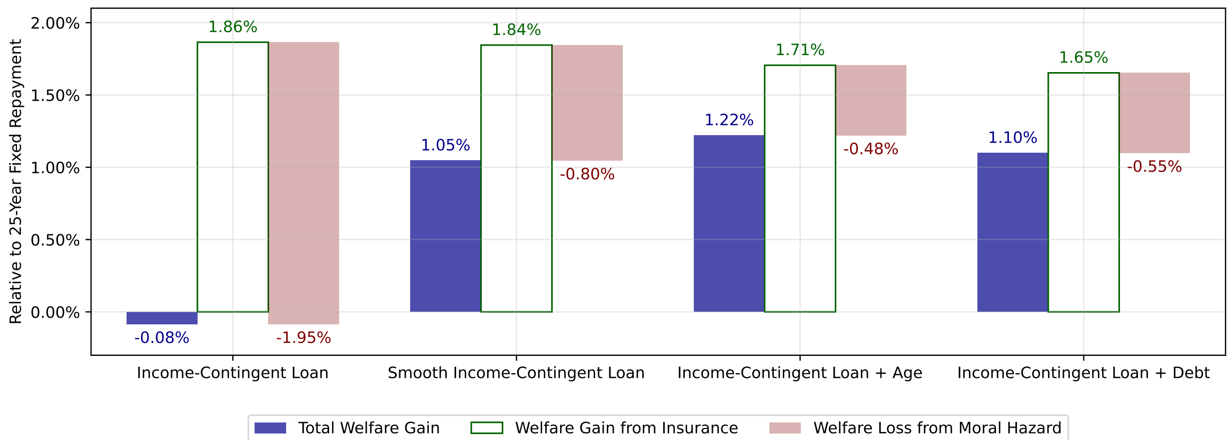
also more likely to generate ex-ante responses not captured by my model because the distribution of gains is significantly more dispersed. This suggests that income-contingent loans may be a more robust mechanism for implementing income-contingent repayment.

6.6 The Effects of a Higher Labor Supply Elasticity

To assess the robustness of the welfare gains from income-contingent repayment, I re-compute the income-contingent loan that solves (17) for different values of the labor supply elasticity, ϕ. The resulting welfare gains are plotted in Figure 19. The results show that for income-contingent loans to deliver a welfare *loss* relative to fixed repayment contracts, ϕ would have to be above 0.37. This higher value of ϕ increases the moral hazard cost of income-contingent repayment while having minimal effect on its insurance benefits. At this value of ϕ, the loss from moral hazard is 10 times as large as in the baseline model and outweighs the insurance benefits.

Figure A35 plots the fit of this alternative model in which fixed repayment is optimal on the most important set of moments for identifying the labor supply elasticity in structural estimation: bunching around the repayment thresholds. These results show that this model generates significantly more bunching than the baseline model and the data. Quantitatively, the number of individuals below relative to the number above the threshold is around 70% larger, more than within any occupation. Additionally, the value of $\phi = 0.37$ in this model is high relative to estimates from prior

Figure 20. Welfare Gains from Alternative Forms of Income-Contingent Loans when $\phi = 0.37$



Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment, along with the decomposition performed in Figure 15, 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 C.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.

literature: its above the 75th percentile of the estimates reported in Figure A24.

Figure 20 shows that alternative forms of income-contingent loans can reduce the welfare cost of moral hazard, even when $\phi = 0.37$.[29] The smooth income-contingent loan generates a 105 pp reduction in this cost, while the age- and debt-contingent contracts generate additional 32 pp and 25 pp reductions, respectively. Figure A37 plots these constrained-optimal repayment contracts, which shows that the smooth income-contingent loan takes a similar shape to the IBR-style loan. However, the smoother repayment structure helps minimize labor supply responses, reducing the cost of moral hazard. The age- and debt-contingent contracts increase payments with age and debt balances, both of which further reduce the moral hazard from income-contingent repayment by increasing the future cost associated with reducing current labor supply. These results are consistent with Shavell (1979), who shows the unconstrained solution to (17) features some insurance because the gains from insurance are first-order while the losses from moral hazard are second-order.

6.7 Sensitivity of Welfare Gains to Model Mispecification

This section evaluates the robustness of the constrained-optimal income-contingent loan that solve (17) to model mispecification by considering several extensions and alternative parameter values to the baseline model. The results are presented by row in Table 5 and discussed below.

Occupation-level heterogeneity. My empirical analysis presented evidence of occupation-level

[29] Figure A36 shows the results in the baseline model. In this model, all three contracts deliver similar gains to 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 15).

Table 5. 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)	Linear Adjustment Costs	1.74%	1.87%	−0.13%	53%	\$43,560
(4)	Wealth Effects on Labor Supply	0.82%	1.05%	−0.23%	37%	\$30,307
(5)	Less Persistent Shocks: $\rho = 0.8$	0.90%	1.14%	−0.23%	42%	\$34,244
(6)	More Persistent Shocks: $\rho = 0.99$	1.35%	1.63%	−0.28%	35%	\$18,949
(7)	Non-Normal Permanent Shocks	1.14%	1.43%	−0.30%	28%	\$26,933
(8)	Debt Interest Rate = 2%	1.96%	2.14%	−0.18%	38%	\$47,731
(9)	Planner Discount Rate = R	1.06%	1.41%	−0.35%	29%	\$22,696
(10)	Planner Discount Rate = $R + 4\%$	1.60%	1.65%	−0.05%	46%	\$34,441
(11)	US Tax System	1.18%	1.36%	−0.19%	38%	\$28,838
(12)	Larger Initial Debt Balances	3.50%	4.72%	−1.22%	36%	\$18,867
(13)	High RRA: $\gamma = 7.5$	3.52%	4.00%	−0.48%	50%	\$27,607
(14)	High EIS: $\sigma^{-1} = 1.5$	0.57%	0.70%	−0.13%	42%	\$30,905
(15)	High RRA + High EIS	1.87%	2.29%	−0.43%	49%	\$28,641
(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	1.41%	1.62%	−0.24%	36%	\$28,492
	Baseline Model	**1.32%**	**1.47%**	**-0.15%**	**33%**	**\$27,147**

Notes: This table presents the optimal contract that solves (17) 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 15, 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.

heterogeneity that is not in my baseline model. To assess the importance of this heterogeneity, I consider an extension with two groups of individuals (in equal proportions) that have different values of the Calvo parameter, 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 A35), 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, in principle, be important if it was 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, individuals 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 reductions.

Alternative adjustment costs. Row (3) shows the results from the model with linear adjustment costs, which is estimated in column (6) of Table 3. In this model, the optimal repayment contract has a higher repayment threshold and repayment rate, effectively providing more insurance. This is because linear adjustment costs makes large labor supply adjustments more costly than they are in a model with fixed adjustment 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 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

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

and set $\eta = 0.5$ following the calibration in Keane (2011). Row (4) 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 various policies. 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 (5) and (6) consider the effect of these alternative values of ρ. The results show that 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 the distribution of income.

Nonnormal income risk. Recent evidence from administrative data highlights the importance of nonnormal income shocks (Guvenen et al. 2021). I introduce such shocks into my baseline model, without re-estimating the model, by drawing ν_{ia} in (7) from a mixture of two independent normal distributions with different means and variances. I calibrate these additional 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 my estimates in Table 3 to the latter estimates. Row (7) shows that this has a small effect on the optimal contract and the gains from insurance but increases the cost of moral hazard.

Interest rate on debt. In my analysis, I set the real interest rate on debt balances to zero, as in the HELP program. However, in the US, debt balances have historically been subject to interest accumulation, although the new SAVE plan changes this. Row (8) shows the results when I instead use an interest rate of 2% above the real interest rate, which is 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 increases the welfare gain from insurance because there is more room to provide insurance when interest payments can be collected from higher-income borrowers who would have paid off their debt, which is reflected in the higher repayment threshold.

Discount rates for the government budget. My model does not have aggregate risk, so the correct discount rate for debt repayments is the risk-free rate, which is lower than (16). Row (9) 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 (10) 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 current tax and transfer system in the model because student debt policies may be trying to undo suboptimalities in tax system. To assess the robustness of the results, I recompute my gains using the tax and transfer system from Heathcote et al. (2017) that approximates the US system. The results in Row (11) show the optimal contract is relatively similar, but the gains from insurance are smaller because the US tax system is already more progressive.

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 my model, it is $17,400 in 2005 AUD ($20,500 in 2023 USD). Row (12) 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 increasing the present-discounted value of reducing labor supply. This requires the optimal repayment contract to have a lower repayment threshold and increases the loss from moral hazard.

Alternative risk and time preferences. Rows (13)–(15) show the effect of moving the RRA, γ, and the EIS, σ^{-1}. Starting from the baseline values, I first set $\gamma = 7.5$ as in Bansal and Yaron (2004) (BY), which increases risk aversion but also introduces a demand for the early resolution of uncertainty. This increases the gain from income-contingent repayment, as individuals value insurance more, which results in the optimal contract providing more insurance. Next, I set $\sigma^{-1} = 1.5$ as in BY. This reduces the welfare gain because the benefits of income-contingent repayment are partly from improving consumption-smoothing over time, which is less valuable with a higher EIS. Moving both the EIS and RRA at the same time delivers a welfare gain between these two.

The role of level, uncertainty, and redistributive effects. The consumption-equivalent welfare gain from a policy reform is comprised 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 my model, calculating these terms analytically is not possible. Therefore, I instead compare the results in the baseline model with those in two alternative models: a model without any ex-post uncertainty (aside from Calvo shocks) and a model without any ex-ante and ex-post uncertainty. Intuitively, the gain in the latter model should be due to level effects, while the difference between the two captures redistributive effects. Uncertainty effects can 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.

7 Conclusion

This paper studies the trade-off between providing insurance and disincentivizing labor supply in student loans with income-contingent repayment. I show that borrowers adjust their labor supply to reduce their income-contingent repayments, but these responses are small from the perspective of a structural model. This evidence implies that income-contingent repayment can provide significant welfare gains, and my analysis suggests that income-contingent loans are an effective and robust way of doing so. Relative to fixed repayment contracts with forbearance, such loans can provide more insurance by accelerating payments from high-income individuals. Relative to equity contracts, these loans are less likely to generate ex-ante responses because the associated welfare gains are much less dispersed.

The results in this paper have direct relevance for the ongoing "student debt crisis" in the US. My evidence suggests that the ex-post moral hazard created by income-contingent repayment is likely too small to justify avoiding using these contracts. Additionally, this paper's empirical evidence and structural model can be used to calibrate the effects of different income-contingent repayment contracts, such as the SAVE plan introduced by the Biden administration. However, the analysis in this paper leaves open several questions, most importantly, how education and borrowing choices respond to income-contingent repayment. Income-contingent repayment may affect education choices on the intensive margin by encouraging borrowers to study degrees with riskier returns (Hampole 2022; Murto 2022) or on the extensive margin by encouraging more borrowers to pursue higher education. Additionally, in the US, student loans can finance discretionary items, such as room and board or groceries. This implies that income-contingent repayment may change borrowing independently of education choices.

More broadly, the trade-off between insurance and incentives studied here 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. Like student loans, a key question is how to design these contracts to balance their insurance benefits with the behavioral distortions that they create. By carefully analyzing the insurance–incentive trade-off for student loans, this paper provides a template for studying these issues in other contexts.

References

Abbott, Brant, Giovanni Gallipoli, Costas Meghir, and Giovanni L. Violante (2019), "Education policy and intergenerational transfers in equilibrium." *Journal of Political Economy*, 127, 2569–2624.

Abraham, Katharine G., Emel Filiz-Ozbay, Erkut Y. Ozbay, and Lesley J. Turner (2020), "Framing effects, earnings expectations, and the design of student loan repayment schemes." *Journal of Public Economics*, 183.

Amromin, Gene and Janice Eberly (2016), "Education Financing and Student Lending." *Annual Review of Financial Economics*, 8, 289–315.

Anagol, Santosh, Benjamin B Lockwood, Allan Davids, and Tarun Ramadorai (2022), "Diffuse Bunching with Lumpy Incomes: Theory and Estimation." *Working Paper*, 66.

Andersen, Steffen, John Y. Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai (2020), "Sources of inaction in household finance: Evidence from the danish mortgage market." *American Economic Review*, 110, 3184–3230.

Auclert, Adrien, Will S Dobbie, and Paul S. Goldsmith-Pinkham (2019), "Macroeconomic Effects of Debt Relief: Consumer Bankruptcy Protections in the Great Recession." *Working Paper*.

Australian Council of Social Service (2017), "Ending tax avoidance, evasion and money laundering through private trusts." ACOSS Policy Briefing.

Australian Council of Social Service (2018), "Components of Australia's wealth."

Bachas, Natalie (2019), "The Impact of Risk-Based Pricing in the Student Loan Market: Evidence from Borrower Repayment Decisions." *Working Paper*.

Baily, Neil (1978), "Some Aspects of Optimal Unemployment Insurance." *Journal of Public Economics*, 10, 379–402.

Bansal, Ravi and Amir Yaron (2004), "Risks for the long run: A potential resolution of asset pricing puzzles." *Journal of Finance*, 59, 1481–1509.

Barr, Nicholas, Bruce Chapman, Lorraine Dearden, and Susan Dynarski (2019), "The US college loans system: Lessons from Australia and England." *Economics of Education Review*, 71, 32–48.

Beer, Gillian and Bruce Chapman (2004), "HECS System Changes: Impact on Students." *Agenda - A Journal of Policy Analysis and Reform*, 11.

Benabou, Roland (2002), "Tax and Education Policy in a Heterogeneous-Agent Economy: What Levels of Redistribution Maximize Growth and Efficiency?" *Econometrica*, 70, 481–517.

Benetton, Matteo, Philippe Bracke, João F. Cocco, and Nicola Garbarino (2022), "Housing Consumption and Investment: Evidence from Shared Equity Mortgages." *Review of Financial Studies*.

Best, Michael and Henrik Kleven (2012), "Optimal Income Taxation with Career Effects of Work Effort." *Working Paper*.

Black, Sandra E., Jeffrey T. Denning, Lisa J. Dettling, Sarena Goodman, and Lesley J. Turner (2022), "Taking It to the Limit: Effects of Increased Student Loan Availability on Attainment, Earnings, and Financial Well-Being." *Working Paper*.

Boutros, Michael, Nuno Clara, and Francisco Gomes (2022), "Borrow Now, Pay Even Later: A Quantitative Analysis of Student Debt Payment Plans." *SSRN Electronic Journal*.

Bovenberg, A. Lans and Bas Jacobs (2005), "Redistribution and education subsidies are Siamese twins." *Journal of Public Economics*, 89, 2005–2035.

Britton, Jack and Jonathan Gruber (2020), “Do income contingent student loans reduce labor supply?” *Economics of Education Review*, 79, 102061.

Calvo, Guillermo A. (1983), “Staggered prices in a utility-maximizing framework.” *Journal of Monetary Economics*, 12, 383–398.

Campbell, John Y., Nuno Clara, and João F. Cocco (2021), “Structuring Mortgages for Macroeconomic Stability.” *The Journal of Finance*, 76, 2525–2576.

Caplin, Andrew, James H. Carr, Fredrick Pollock, and Zhong Yi Tong (2007), “Shared-Equity Mortgages, Housing Affordability, and Homeownership.” *Working Paper*.

Carneiro, Pedro and James J. Heckman (2002), “The Evidence on Credit Constraints in Post-Secondary Schooling.” *The Economic Journal*, 112, 705–734.

Carroll, Christopher D. and Miles S. Kimball (1996), “On the Concavity of the Consumption Function.” *Econometrica*, 64, 981–992.

Catherine, Sylvain (2022), “Countercyclical Income Risk and Portfolio Choices over the Life-Cycle.” *Review of Financial Studies*, 35, 4054.

Catherine, Sylvain and Constantine Yannelis (2023), “The Distributional Effects of Student Loan Forgiveness.” *Journal of Financial Economics*.

Cesarini, David, Erik Lindqvist, Matthew J. Notowidigdo, and Robert Ostling (2017), “The Effect of Wealth on Individual and Household Labor Supply: Evidence from Swedish Lotteries.” *American Economic Review*, 107, 34.

Chakrabarti, Rajashri, Vyacheslav Fos, Andres Liberman, and Constantine Yannelis (2020), “Tuition, Debt, and Human Capital.” *Working Paper*.

Chapman, Bruce (2006), “Chapter 25 Income Contingent Loans for Higher Education: International Reforms.” In *Handbook of the Economics of Education*, volume 2, 1435–1503, Elsevier.

Chapman, Bruce and Andrew Leigh (2009), “Do Very High Tax Rates Induce Bunching? Implications for the Design of Income Contingent Loan Schemes.” *Economic Record*, 85, 276–289.

Chetty, R., J. N. Friedman, T. Olsen, and L. Pistaferri (2011), “Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records.” *The Quarterly Journal of Economics*, 126, 749–804.

Chetty, Raj (2006), “A general formula for the optimal level of social insurance.” *Journal of Public Economics*, 90, 1879–1901.

Chetty, Raj (2008), “Moral hazard versus liquidity and optimal unemployment insurance.” *Journal of Political Economy*, 116, 173–234.

Chetty, Raj (2009), “Is the Taxable Income Elasticity Sufficient to Calculate Deadweight Loss? The Implications of Evasion and Avoidance.” *American Economic Journal: Economic Policy*, 1, 31–52.

Chetty, Raj (2012), “Bounds on Elasticities With Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply.” *Econometrica*, 80, 969–1018.

Chetty, Raj and Amy Finkelstein (2013), “Social Insurance: Connecting Theory to Data.” In *Handbook of Public Economics*, volume 5, Elsevier B.V.

Chetty, Raj, John N Friedman, and Emmanuel Saez (2013), “Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings.” *American Economic Review*, 103, 2683–2721.

Choukhmane, Taha and Tim de Silva (2023), “What Drives Investors’ Portfolio Choices? Separating Risk Preferences from Frictions.” *Working Paper*.

Cochrane, John H. (1991), "A simple test of consumption insurance." *Journal of Political Economy*, 93, 957–978.

Coyne, David, Itzik Fadlon, and Tommaso Porzio (2022), "Measuring Valuation of Liquidity with Penalized Withdrawals." *Working Paper*.

Deaton, Angus and Christina H Paxson (1994), "Intertemporal Choice and Inequality." *Journal of Political Economy*, 102, 437–468.

Department of Education and Training (2023), "HECS-HELP Determinations." Technical report, Australian Government.

Di Maggio, Marco, Ankit Kalda, and Vincent W. Yao (2021), "Second Chance: Life without Student Debt." *Journal of Finance*.

Dobbie, Will and Jae Song (2015), "Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection." *American Economic Review*, 105, 1272–1311.

D'Souza, Gabriela (2018), "A higher education bubble?" *Working Paper*.

Ebrahimian, Mehran (2020), "Student Loans and Social Mobility." *SSRN Electronic Journal*.

Einav, Liran, Amy Finkelstein, and Paul Schrimpf (2017), "Bunching at the kink: Implications for spending responses to health insurance contracts." *Journal of Public Economics*, 146, 27–40.

Einav, Liran, Mark Jenkins, and Jonathan Levin (2012), "Contract Pricing in Consumer Credit Markets." *Econometrica*, 80, 1387–1432.

Epstein, Larry G. and Stanley E. Zin (1989), "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework." *Econometrica*, 57, 937.

Feldstein, Martin (1999), "Tax Avoidance and the Deadweight Loss of the Income Tax." *Review of Economics and Statistics*, 81, 674–680.

Finkelstein, Amy and Nathaniel Hendren (2020), "Welfare analysis meets causal inference." *Journal of Economic Perspectives*, 34, 146–167.

Folch, Marc and Luca Mazzone (2021), "Go Big or Buy a Home: Student Debt, Career Choices and Wealth Accumulation." *SSRN Electronic Journal*.

Friedman, Milton (1955), "The Role of Government in Education." In *Economics and the Public Interest* (Robert A. Solow, ed.), Rutgers University Press, New Brunswick, New Jersey.

Ganong, Peter and Pascal Noel (2019), "Consumer spending during unemployment: Positive and normative implications." *American Economic Review*, 109, 2383–2424.

Ganong, Peter and Pascal Noel (2020), "Liquidity versus wealth in household debt obligations: Evidence from housing policy in the great recession." *American Economic Review*, 110, 3100–3138.

Ganong, Peter and Pascal Noel (2023), "Why Do Borrowers Default on Mortgages?" *The Quarterly Journal of Economics*.

Gervais, Martin, Qian Liu, and Lance Lochner (2022), "The Insurance Implications of Government Student Loan Repayment Schemes." *Working Paper*.

Golosov, Mikhail, Michael Graber, Magne Mogstad, and David Novgorodsky (2023), "How Americans Respond to Idiosyncratic and Exogenous Changes in Household Wealth and Unearned Income." *Working Paper*.

Gourinchas, Pierre-Olivier and Jonathan A. Parker (2002), "Consumption over the life cycle." *Econometrica*, 70, 47–89.

Greenwald, Daniel L., Tim Landvoigt, and Stijn Van Nieuwerburgh (2021), "Financial Fragility with SAM?" *Journal of Finance*, 76, 651–706.

Greenwood, Jeremy, Zvi Hercowitz, and Gregory W Huffman (1988), "Investment, Capacity Utilization, and the Real Business Cycle." *American Economic Review*, 78, 402–417.

Gruber, Jon and Emmanuel Saez (2002), "The elasticity of taxable income: Evidence and implications." *Journal of Public Economics*, 32.

Gruber, Jonathan (1997), "The Consumption Smoothing Benefits of Unemployment Insurance." *American Economic Review*, 87, 192–205.

Gupta, Arpit and Christopher Hansman (2022), "Selection, Leverage, and Default in the Mortgage Market." *The Review of Financial Studies*, 35, 720–770.

Guvenen, Fatih (2009a), "An empirical investigation of labor income processes." *Review of Economic Dynamics*, 12, 58–79.

Guvenen, Fatih (2009b), "A Parsimonious Macroeconomic Model for Asset Pricing." *Econometrica*, 77, 1711–1750.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song (2021), "What Do Data on Millions of U.S. Workers Reveal About Lifecycle Earnings Dynamics?" *Econometrica*, 89, 2303–2339.

Guvenen, Fatih, Alisdair McKay, and Conor Ryan (2022), "A Tractable Income Process for Business Cycle Analysis." *Working Paper*.

Hampole, Menaka V (2022), "Financial Frictions and Human Capital Investments." *Working Paper*.

Hanson, Melanie (2022), "Student Loan Default Rate." Technical report, Education Data Initiative.

Hanson, Melanie (2023), "Average Cost of College & Tuition." Technical report, Education Data Initiative.

Hartman-Glaser, Barney and Benjamin Hébert (2020), "The Insurance Is the Lemon: Failing to Index Contracts." *Journal of Finance*, 75, 463–506.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante (2017), "Optimal Tax Progressivity: An Analytical Framework." *The Quarterly Journal of Economics*, 132, 1693–1754.

Hendren, Nathaniel and Ben Sprung-Keyser (2020), "A Unified Welfare Analysis of Government Policies." *The Quarterly Journal of Economics*, 135, 1209–1318.

Herbst, Daniel (2023), "Liquidity and Insurance in Student-Loan Contracts: The Effects of Income-Driven Repayment on Borrower Outcomes." *American Economic Journal: Applied Economics*, 15, 1–25.

Herbst, Daniel and Nathaniel Hendren (2021), "Opportunity Unraveled: Private Information and the Missing Markets for Financing Human Capital." *Working Paper*.

Herbst, Daniel, Miguel Palacios, and Constantine Yannelis (2023), "Equity and Incentives in Household Finance." *Working Paper*.

Huang, Yueling (2022), "Rethinking College Financing: Wealth, College Majors, and Macroeconomic Consequences." *Working Paper*.

Indarte, Sasha (2023), "Moral Hazard versus Liquidity in Household Bankruptcy." *Journal of Finance*, 78, 2421–2464.

Jacob, Brian A, Damon Jones, and Benjamin J Keys (2023), "The Value of Student Debt Relief and the Role of Administrative Barriers: Evidence from the Teacher Loan Forgiveness Program." *Working Paper*.

Ji, Yan (2021), "Job Search under Debt: Aggregate Implications of Student Loans." *Journal of Monetary Economics*, 117, 741–759.

JPMorgan Chase (2022), "Income Driven Repayment: Who needs student loan payment relief?" Technical report.

Karamcheva, Nadia, Jeffrey Perry, and Constantine Yannelis (2020), "Income-Driven Repayment Plans for Student Loans." *Working Paper*.

Kargar, Mahyar and William Mann (2022), "The Incidence of Student Loan Subsidies: Evidence from the PLUS Program." *The Review of Financial Studies*, hhac031.

Karlan, Dean and Jonathan Zinman (2009), "Observing Unobservables: Identifying Information Asymmetries With a Consumer Credit Field Experiment." *Econometrica*, 77, 1993–2008.

Keane, Michael and Richard Rogerson (2015), "Reconciling Micro and Macro Labor Supply Elasticities: A Structural Perspective." *Annual Review of Economics*, 7, 89–117.

Keane, Michael P (2011), "Labor Supply and Taxes: A Survey." *Journal of Economic Literature*, 49, 961–1075.

Kleven, Henrik, Claus Kreiner, Kristian Larsen, and Jakob Søgaard (2023), "Micro vs Macro Labor Supply Elasticities: The Role of Dynamic Returns to Effort." *Working Paper*.

Kleven, Henrik J. and Mazhar Waseem (2013), "Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan*." *The Quarterly Journal of Economics*, 128, 669–723.

Lochner, Lance and A. Monge-Naranjo (2016), *Student Loans and Repayment: Theory, Evidence, and Policy*, volume 5. Elsevier B.V.

Luo, Mi and Simon Mongey (2019), "Assets and Job Choice: Student Debt, Wages, and Amenities." *Working Paper*.

Lusardi, Annamaria, Pierre Carl Michaud, and Olivia S. Mitchell (2017), "Optimal financial knowledge and wealth inequality." *Journal of Political Economy*, 125, 431–477.

Marshall, Kate (2003), "Ease HECS burden on students, say universities." *Australian Financial Review*.

Martin, Chelsey (2004), "For one in four, HECS now a lifelong debt." *Australian Financial Review*.

Masatlioglu, Yusufcan and Efe A. Ok (2005), "Rational choice with status quo bias." *Journal of Economic Theory*, 121, 1–29.

Matsuda, Kazushige and Karol Mazur (2022), "College education and income contingent loans in equilibrium." *Journal of Monetary Economics*, 132, 100–117.

Mezza, Alvaro, Daniel Ringo, Shane Sherlund, and Kamila Sommer (2020), "Student loans and homeownership." *Journal of Labor Economics*, 38, 215–260.

Mian, Atif and Amir Sufi (2014), *House of Debt: How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again*. University of Chicago Press, Chicago, IL.

Mincer, Jacob (1974), *Schooling, Experience, and Earnings*. National Bureau of Economic Research.

Mirrlees, J. (1974), "Notes on Welfare Economics, Information and Uncertainty." In *Essays on Economic Behavior under Uncertainty*, Amsterdam: North Holland.

Mueller, Holger M. and Constantine Yannelis (2019), "The rise in student loan defaults." *Journal of Financial Economics*, 131, 1–19.

Mueller, Holger M. and Constantine Yannelis (2021), "Reducing Barriers to Enrollment in Federal Student Loan Repayment Plans: Evidence from the Navient Field Experiment." *Journal of Finance*.

Mumford, Kevin J. (2022), "Student Selection into an Income Share Agreement." *Working Paper*.

Murto, Michael J (2022), "Student Loans and Human Capital Investments." *Working Paper*.

Nakamura, Emi and Jon Steinsson (2010), "Monetary Non-Neutrality in a Multi-Sector Menu Cost Model." *Quarterly Journal of Economics*.

Nelson, Brendan (2003), "Our universities: Backing Australia's future." Technical report, Commonwealth of Australia, Canberra, ACT.

Norton, Andrew (2018), "Has abolishing the discount for upfront payment of student contributions made a difference to upfront payment rates?" Technical report.

Norton, Andrew (2019), "Demand-driven funding for universities is frozen. What does this mean and should the policy be restored?" *The Conversation*.

Paetzold, Jörg and Hannes Winner (2016), "Taking the high road? Compliance with commuter tax allowances and the role of evasion spillovers." *Journal of Public Economics*, 143, 1–14.

Palacios, Miguel (2004), *Investing in Human Capital, A Capital Markets Approach to Student Funding*. Cambridge University Press.

Piketty, Thomas and Emmanuel Saez (2013), "Optimal Labor Income Taxation." In *Handbook of Public Economics*, volume 5, 391–474, Elsevier.

Ramsey, F. P. (1927), "A Contribution to the Theory of Taxation." *The Economic Journal*, 145, 47–61.

Robinson, Natasha (2019), "Documents reveal the Government looked at recovering HELP loans from deceased estates." *ABC News*.

Saez, Emmanuel (2010), "Do Taxpayers Bunch at Kink Points?" *American Economic Journal: Economic Policy*, 2, 180–212.

Saez, Emmanuel, Joel Slemrod, and Seth H Giertz (2012), "The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review." *Journal of Economic Literature*, 50, 3–50.

Shavell, Steven (1979), "On Moral Hazard and Insurance." *The Quarterly Journal of Economics*, 93, 541–562.

Shiller, Robert J. (2004), *The New Financial Order: Risks in the 21st Century*. Princeton University Press, Princeton, NJ.

Slemrod, Joel (2019), "Tax Compliance and Enforcement." *Journal of Economic Literature*, 57, 904–954.

Slemrod, Joel and Shlomo Yitzhaki (2002), "Tax Avoidance, Evasion, and Administration." *Handbook of Public Economics*, 3, 1425–1465.

Stantcheva, Stefanie (2017), "Optimal taxation and human capital policies over the life cycle." *Journal of Political Economy*, 125, 1931–1990.

Weil, Philippe (1990), "Nonexpected Utility in Macroeconomics." *Quarterly Journal of Economics*, 105, 29–42.

Werquin, Nicolas (2015), "Income Taxation with Frictional Labor Supply." *Working Paper*.

Yannelis, Constantine (2020), "Strategic Default on Student Loans." *Working Paper*.

Yannelis, Constantine and Greg Tracey (2022), "Student Loans and Borrower Outcomes." *Annual Review of Financial Economics*.

Zingales, Luigi (2012), "The College Graduate as Collateral." *The New York Times*.

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"

Tim de Silva[1]
MIT Sloan

Full Draft

Contents

[1]Contact information: www.timdesilva.me, tdesilva@mit.edu.

Appendix A. Theoretical Appendix

A.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; $V(\theta)$ is 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:

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

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:

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

This comprises two effects: a mechanical revenue 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 $u_c(c_0, \ell_0) = \frac{\partial V}{\partial A_0}$. Combining the previous three expressions with the definition of M_t and λ delivers the desired result.

A.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 formulated recursively as follows:

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

subject to:

$$c + A' = AR + y - d(y, D), \quad y = w\ell,$$
$$D' = D - d(y, D), \quad w' = g(w, \omega), \quad \omega \sim F_\omega,$$

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:

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

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 an effect that is specific to debt: increasing labor supply today reduces the stock of debt tomorrow. Assuming the value function is decreasing 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:

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

The previous expression shows that for the debt effect to dominate and make individuals locate above the repayment threshold, the marginal value of reducing debt must be greater than the marginal utility of consumption. This is unlikely to be the case empirically because HELP debt has a zero real interest rate, which means it is the lowest-cost source of borrowing that individuals can access. The fact that individuals can make voluntary debt repayments, but many do not supports this claim: if the marginal value of reducing debt was higher than consumption, then more individuals should be making voluntary payments.

Appendix B. Empirical Appendix

B.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 formula at the time the individual's tax returns are filed, or voluntary HELP repayments, which are additional repayments made at any point in time, to repay their HELP debt. If individuals are working, they are required to advise their employer if they have HELP debt. The employer will then withhold the corresponding 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 then used to cover any compulsory repayments due when the tax return is filed. The income 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 of each year, HELP debts are subject to indexation, which refers to increasing the outstanding debt balance based on the indexation rate. The nominal interest rate on HELP debt is based on the year-on-year quarterly CPI calculated with the March quarter CPI, which is referred to as the indexation rate. The indexation rate 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.[2] For most individuals, 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.

[2] See here for additional details.

Wage-setting in Australia. There are three wage-setting methods in Australia. The first method is through 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%.[3]

Comparison of higher education environment between Australia and US. This section describes differences in the higher education environments 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 the welfare gains from income-contingent repayment that I estimate 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 5. 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.[4] 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.

Like in Australia, the US government is the only provider of income-contingent loans. 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 borrowers to finance reduced payments from low-income borrowers may lead private lenders to cream-skim high-income borrowers with more favorable

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

[4] 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.

financing terms.

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. 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 and has enrollment caps for Commonwealth Supported Places (the students who receive a government contribution to their tuition).[5] Because tuition is not government-regulated in the US, universities respond to changes in government subsidies by changing tuition, known as the "Bennett hypothesis" (Kargar and Mann 2022). 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.

B.2 Data and Variable Construction

B.2.1 *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

[5] Private institutions play a relatively small role in Australia, comprising only 3 out of the country's 43 universities and 5.8% 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.

Table A1. Comparison of Aggregate Statistics in Australia versus 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
Interest Rate on Debt	CPI	~2% above T-Bill rate
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%
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%

Notes: The sources for various statistics are shown as hyperlinks. All statistics are computed in the most recent year available, which is always after 2019.

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 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)
```

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.

B.2.2 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.

B.2.3 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.

B.3 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 individuals 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 much noiser. Including points further away from this threshold causes the estimate of the counterfactual density to be poorly behaved.

Appendix C. Structural Model Appendix

C.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.[6] 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 with 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 A18. 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 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 preferences.[7] 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 $a = a_R - 1$.

[6] 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.

[7] 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.

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).[8] Linear interpolation is extremely accurate in my setting, 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.[9] 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 moments 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.

[8] 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.
[9] At all places where I integrate, I compute certainty-equivalents rather than expectations since I am using Epstein–Zin preferences.

C.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.[10] 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):

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

Finally, I normalize equivalence scales such that the average value is one, so that a household in my 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 moments, 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.[11] 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.[12] 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 respond-

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

[11] 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.

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

ing 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 my model does not include endogenous early repayment of debt balances. With a zero interest rate, this abstraction is without loss of generality since individuals have no incentive to pay their debt early.

Distribution of education levels. I set the fraction of individuals with college degrees, 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 $t \geq T^*$.[13] 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

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

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

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 C.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.[14] 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 $t \geq T^*$:

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

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

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

[13] See https://atotaxrates.info/individual-tax-rates-resident/hecs-repayment/.
[14] 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.[15] 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 my 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

[15] 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.

C.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 $t \geq 1991$:footnoteI 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.
$$\log y_{ia} = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_0^E \mathcal{E}_i + \beta_1^E \mathcal{E}_i a$$
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

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 B.2. 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 affect on my results because these moments are very precisely estimated and are not the primary moments responsible for identifying my structural parameters of interest. For these moments, I restrict to wage-earners between 22, the first age in my 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 moments 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 $W(\Theta) = \text{diag}\left(w(\Theta)\right)$, 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.[16] 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 moments in 2002–2004 and 2005–2007
2. Block #2: All moments that are ratios of individuals below to individuals above repayment thresholds + average labor supply
3. Block #3: All remaining moments

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.

[16] 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 my results.

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 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),

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

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

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

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 moments 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[17] 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).[18] The standard errors for Θ^* are then $\sqrt{N^{-1}\text{diag}(\hat{V})}$.

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

[18] 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.

C.4 Description of Repayment Contracts

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

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

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 individuals' cash-on-hand prior to making debt payments falls below $d_{Fixed}(\cdot)$, I make individuals pay only their cash-on-hand. In this case, individuals 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 an individual i at age a, the required repayment on an 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:

- US IBR: $\psi = 10\%$, $K = 1.5 * pov$, $\overline{T} = a_R$, $r_d = 0\%$
- US 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 (17), $\overline{T} = a_R$, $r_d = 0\%$
- Constrained-Optimal Income-Contingent Loan with 20-Year Forgiveness: ψ and K chosen to solve (17), $\overline{T} = a_0 + 20$, $r_d = 0\%$

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.[19] 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 an individual 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 (17) with this alternative repayment contract. The value of $\$16,863$ corresponds to the phase-out point of unemployment benefits described in Appendix C.2.

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

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

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

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

- 9-Year ISA: $T = 9$, ψ chosen to solve (17), $K = 0$
- 9-Year ISA + Threshold: $T = 9$, ψ and K chosen to solve (17)

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 an individual can pay.

Alternative income-contingent loans. Figure 20 uses the following alternative 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 (17) to find the constrained-optimal values of $\{\psi_i\}$.

C.5 Computation of Welfare Metrics

Equivalent variation. Let 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 $\mathrm{s}_0(\pi)$ 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 s_0 with education level $\mathcal{E}_i = E$ under repayment policy p as $V_p(\mathrm{s}_0 \mid \mathcal{E}_i = E)$, 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:

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

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 s_0. The right-hand side corresponds to the same quantity calculated under the 25-year fixed repayment contract when individuals 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 $V_p(\mathrm{s}_0 \mid \mathcal{E}_i = E)$ and $F(\mathbf{s_0} \mid \mathcal{E}_i = E)$ denote the same quantities as above. Let $V_p^g(\mathrm{s}_0 \mid \mathcal{E}_i = E)$ denote $V_p(\mathrm{s}_0 \mid \mathcal{E}_i = E)$ evaluated in a model in which, for all ages a, individuals

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 individuals 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.

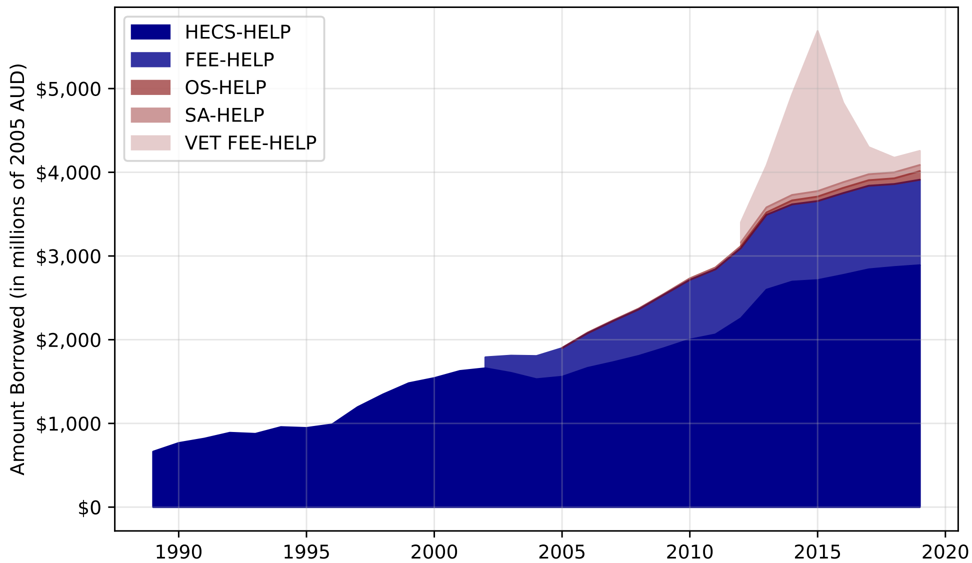
Net consumption-equivalent welfare gain. Due to computational constraints, some results (e.g., Figure 18) present *net* consumption-equivalent welfare gains instead of consumption-equivalent welfare gains. These two are quantitatively very similar, but the former are significantly easier to compute because 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 an individual 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.

C.6 Computation of Constrained-Optimal Repayment Contracts

Solving (17) 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 (17) 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).

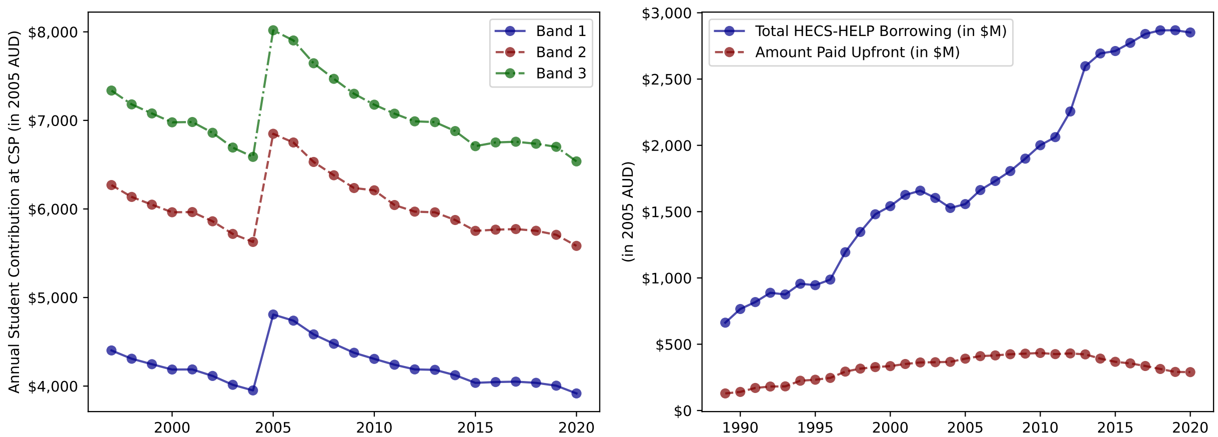
Appendix D. Additional Figures and Tables

Figure A1. 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. SA-HELP loans are used to pay student services and amenities fees. OS-HELP loans are used to cover expenses for students enrolled in a CSP degree who want to study overseas. 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 Receiveable Report 2021, DESE Annual Report 2022). These data were obtained from Andrew Norton Higher Education Commentary.

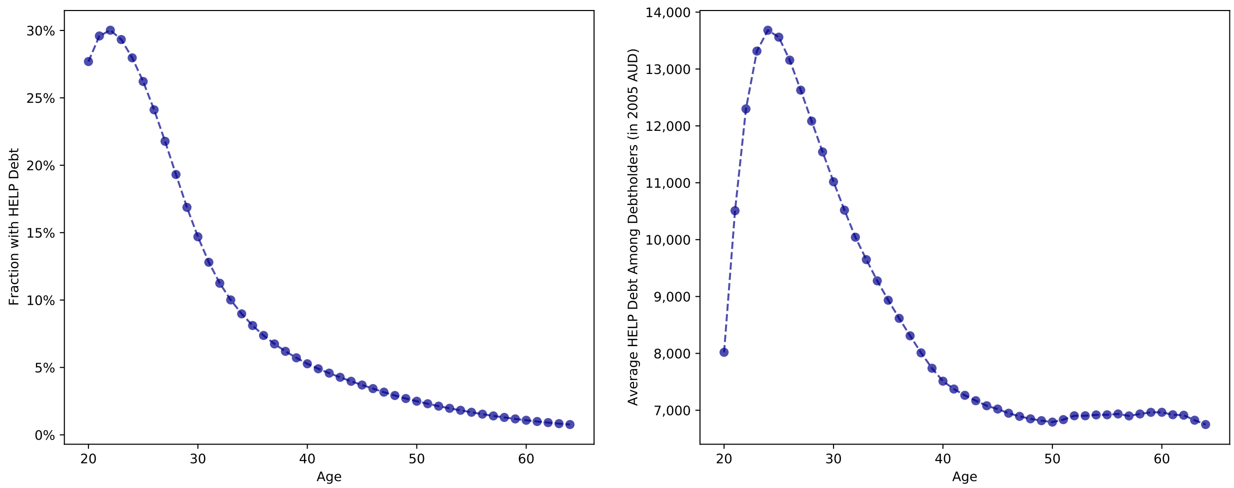
Figure A2. Student Contributions and Aggregate HELP Borrowing over Time



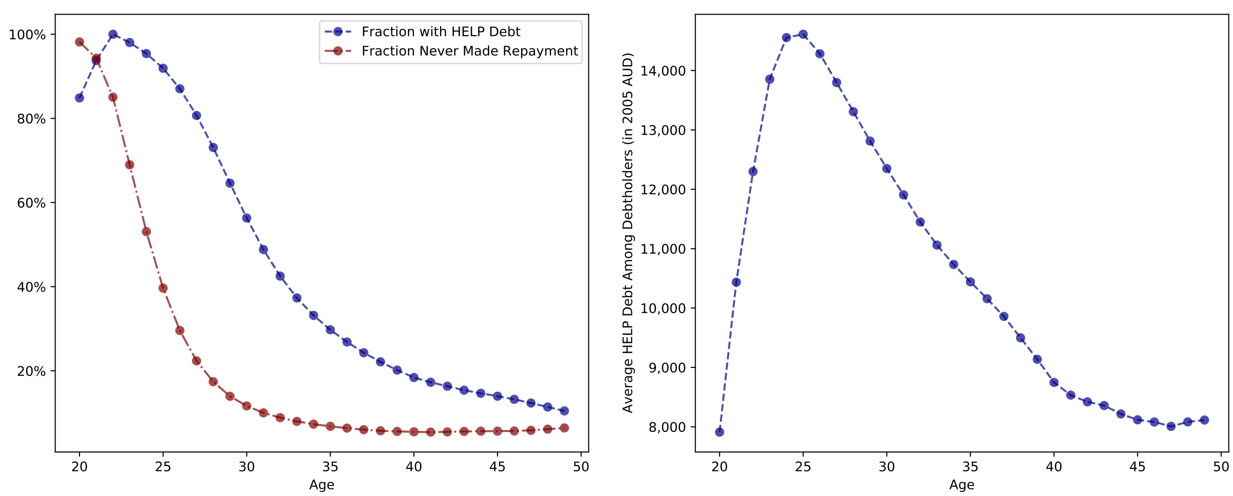
Notes: The left plot shows the time series of student contributions in 2005 AUD for Commonwealth Supported Places (CSPs) based on the three separate bands of study classified by the Australian government. These rates correspond to the cost of one year of coursework that must be covered with a HELP loan 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, behavioural 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 A3. Average Debt Balances by Age

Panel A: All Individuals



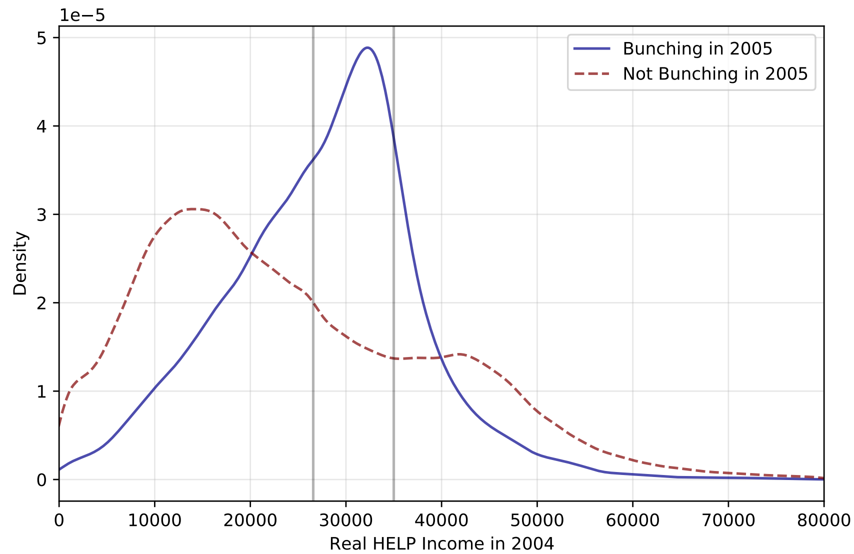
Panel B: Individuals with Positive Debt Balances at Age 22



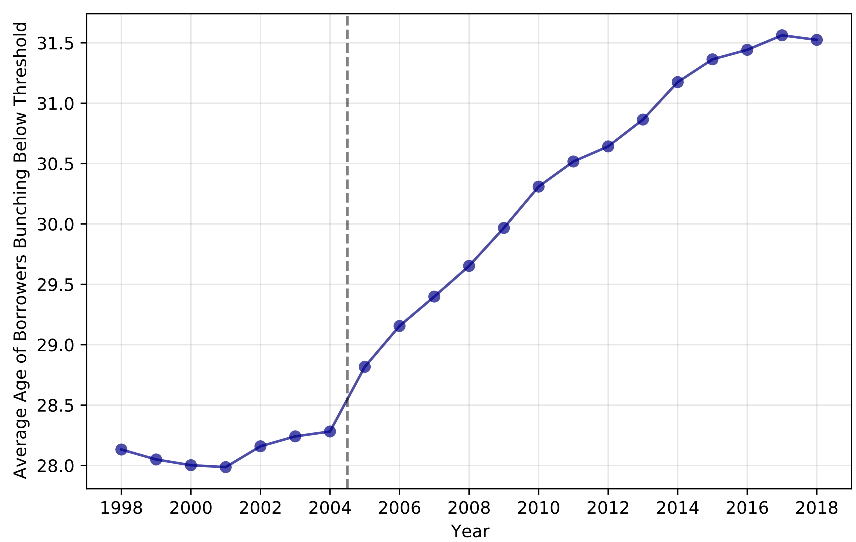
Notes: Panel A of this figure plots the fraction of individuals with HELP debt at each age in the left panel and the average HELP debt balances in 2005 AUD by age on the right. Panel B plots, in blue, the same quantity in Panel A among the subset of individuals who have positive debt balances at age 22 at some point during 1991–2019. The fraction of individuals 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 A4. Characteristics of Individuals Below Repayment Thresholds

Panel A: Prior Location of Individuals Below New Repayment Threshold



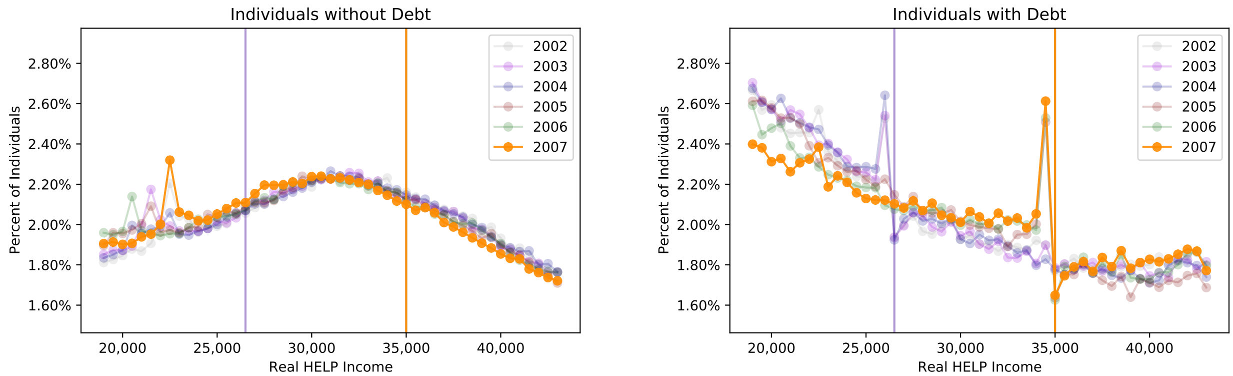
Panel B: Age of Individuals Below Repayment Threshold



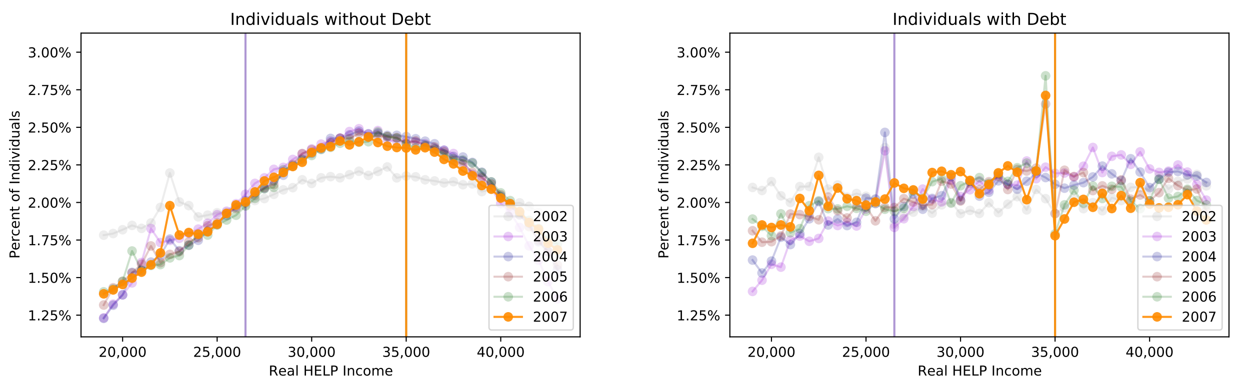
Notes: Panel A of this figure plots the HELP income distribution in 2004 of individuals based on their HELP income in 2005. The solid blue line corresponds to the distribution for individuals who have HELP income in 2005 AUD within $2500 of the repayment threshold in 2005. The dashed red line corresponds to all other individuals. These densities are estimated using a kernel density estimation with a Gaussian kernel and bandwidth chosen using Scott's rule. Panel B of this figure plots the average age of individuals 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 A5. Comparison of HELP Income Distribution for Debtholders and Non-Debtholders

Panel A: Full Sample

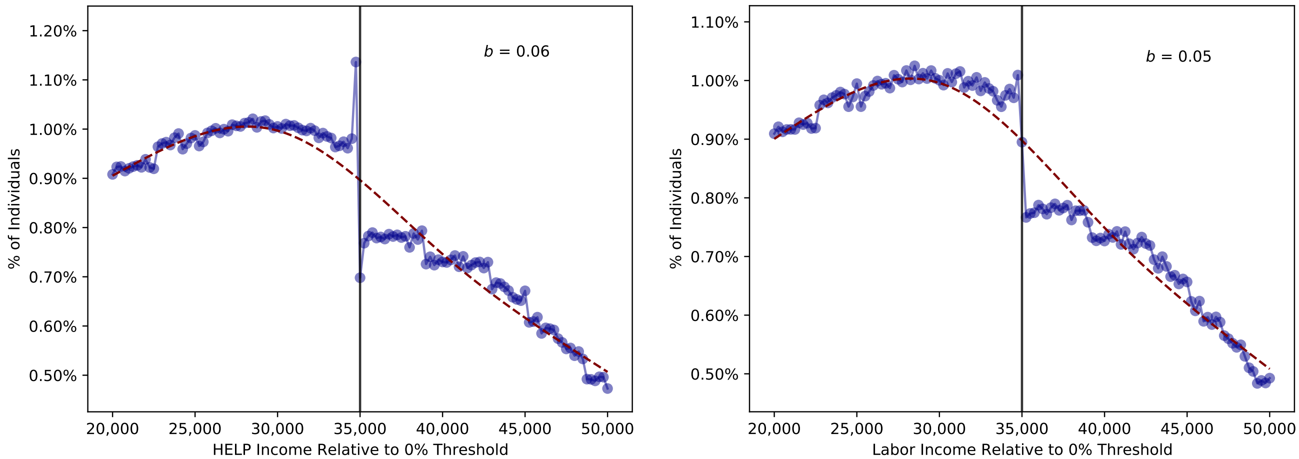


Panel B: Sample of Individuals Held Fixed from 2002



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 exact same analysis among individuals who do not have debt in each year. Panel B replicates the analysis in Panel A holding the sample of individuals fixed to those who were present in the sample with HELP income (in 2005 AUD) between $20,000 and $50,000 in 2002.

Figure A6. Distributions of HELP Income and Labor Income



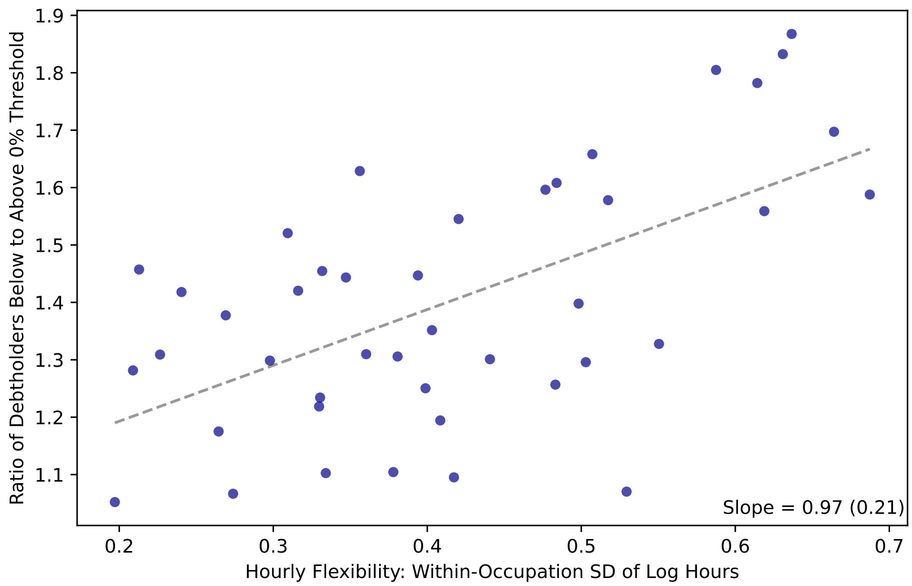
Notes: This figure plots the distributions of HELP and labor income in 2005 AUD relative to the repayment threshold after the policy change. This figure also plots the bunching statistic defined in (4) computed for the different distributions. Each bin corresponds to $250 AUD, and bins are chosen so that they center on the 2005 repayment threshold. The calculation of b is detailed in Appendix B.3, 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

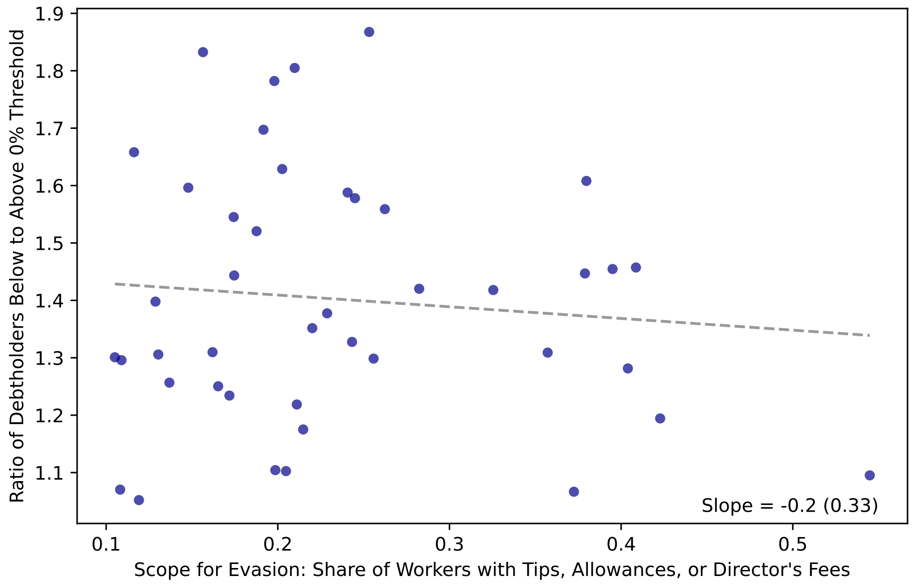
Notes: This table shows the measures of hourly flexibility at the 2-digit ANZSCO occupation-level used in Figure 4 and Figure A7. Hourly flexibility is measured as the standard deviation of annual changes, or the cross-sectional standard deviation, in log hours worked per week from HILDA.

Figure A7. Variation in Bunching across Occupations Based on Hourly Flexibility: Alternative Measure



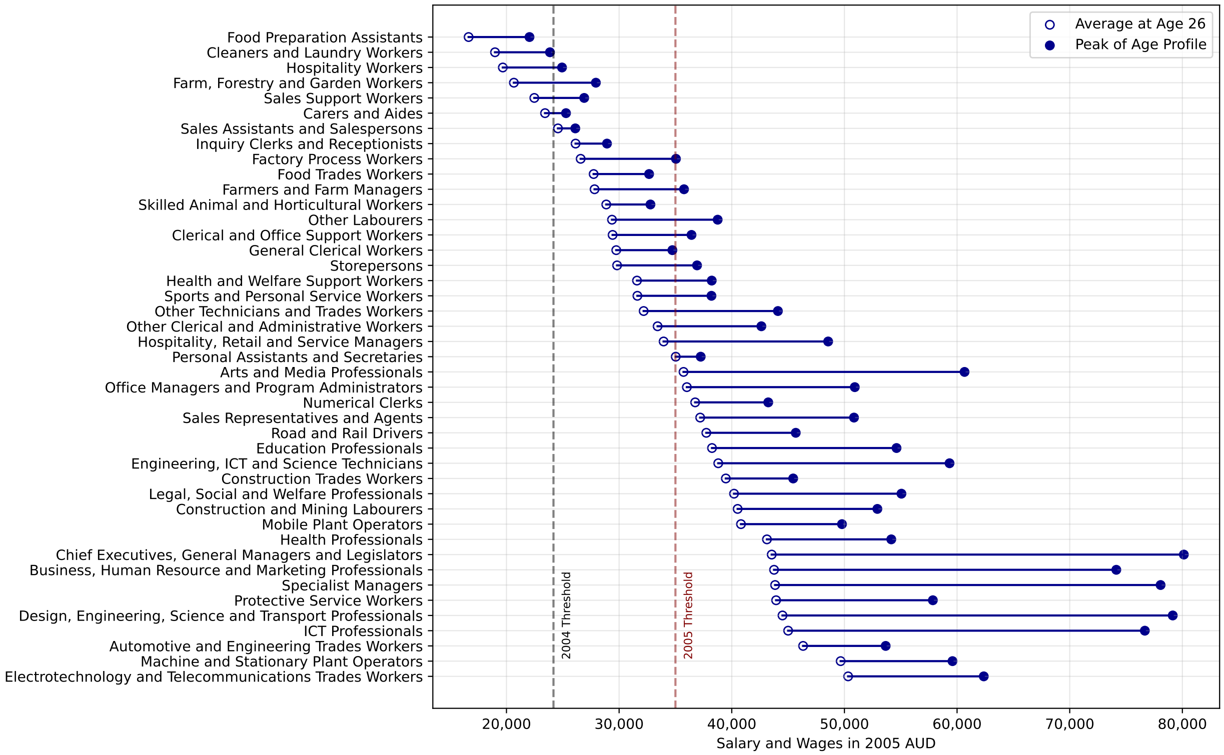
Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and an alternative measure of hourly flexibility by occupation. Each point represents a 2-digit ANZSCO occupation code reported in *ALife*. The amount of bunching is measured as the ratio of the number of individuals 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 individuals are wage-earners.

Figure A8. 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 B.2 for additional details. This evasion measure is computed for the sample of individuals described in Figure A9.

Figure A9. Age Profiles of Wage Income across Occupations



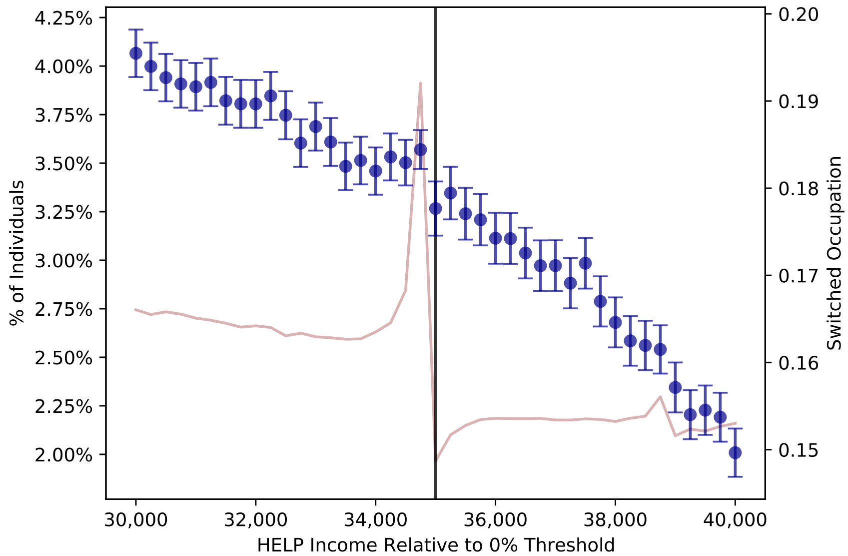
Notes: This figure plots characteristics of the age profile of salary and wages across 2-digit ANZSCO occupations. Occupation-specific age profiles are calculated by taking the average value of salary and wages across individuals in each occupation at a given age, after adjusting for inflation and removing 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

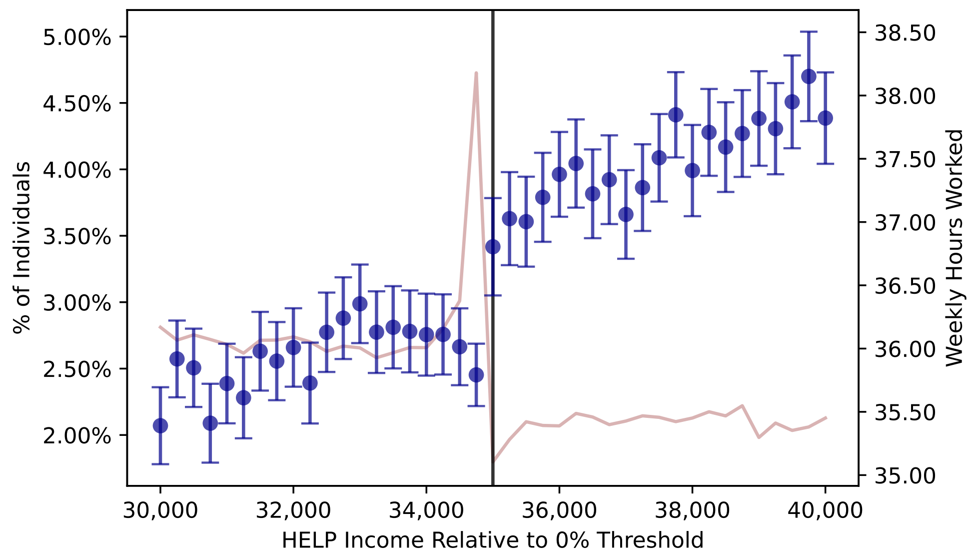
Notes: Each column of this table reports the results from an OLS regression run at the 2-digit ANZSCO occupation-level, with standard errors presented in parantheses below the coefficient estimates. The dependent variable in each column is the ratio of the number of debtholders within $2,500 below the 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 A9. Standard errors are computed with a heteroscedasticity-robust estimator.

Figure A10. 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 individuals 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 the individuals' 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.

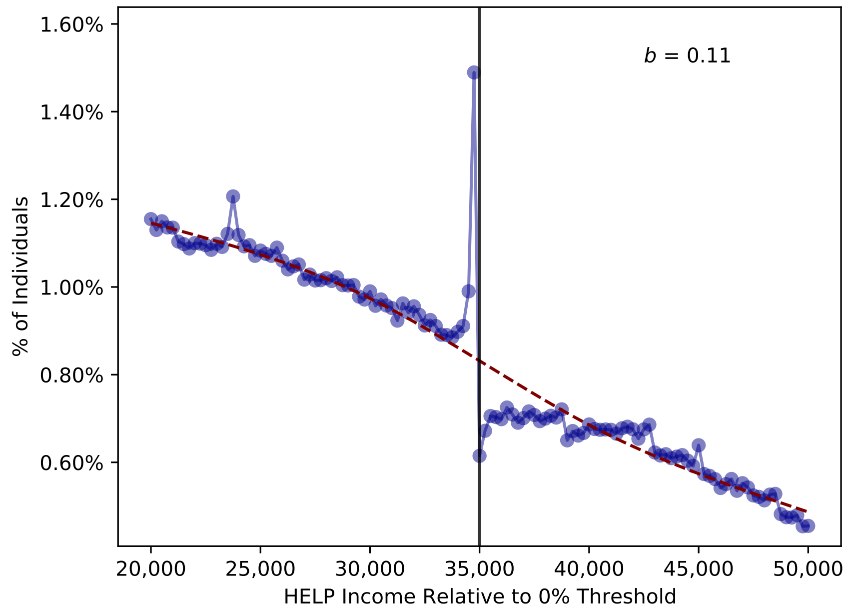
Figure A11. Self-Reported Hours Worked around the Repayment Threshold: Individuals with Positive Labor Income



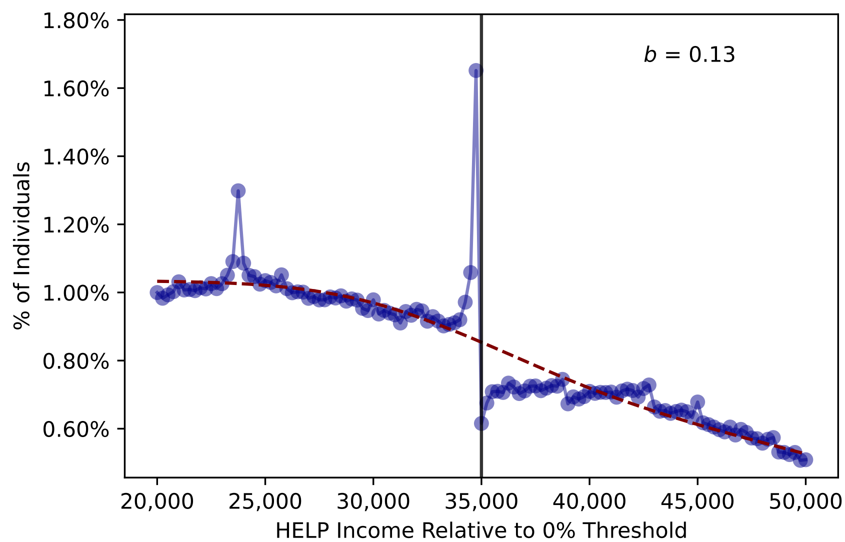
Notes: This figure replicates Figure 5 for the sample of individuals with positive labor income.

Figure A12. Distribution of HELP Income in *ALife* versus MADIP Sample

Panel A: ALife Sample in 2016



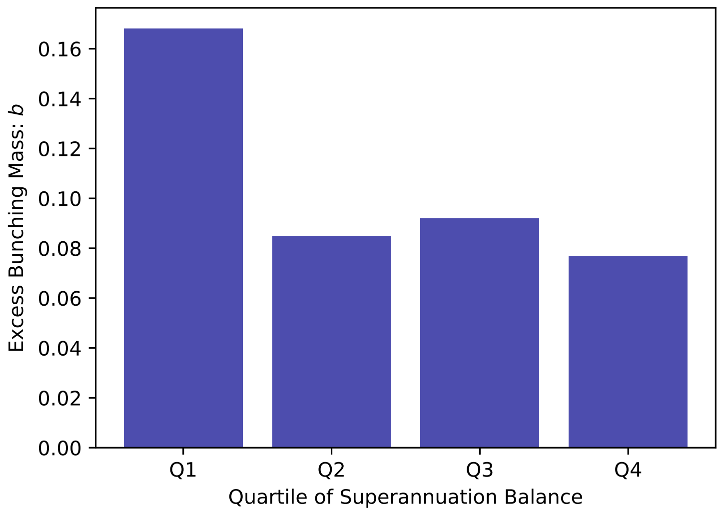
Panel B: MADIP Sample



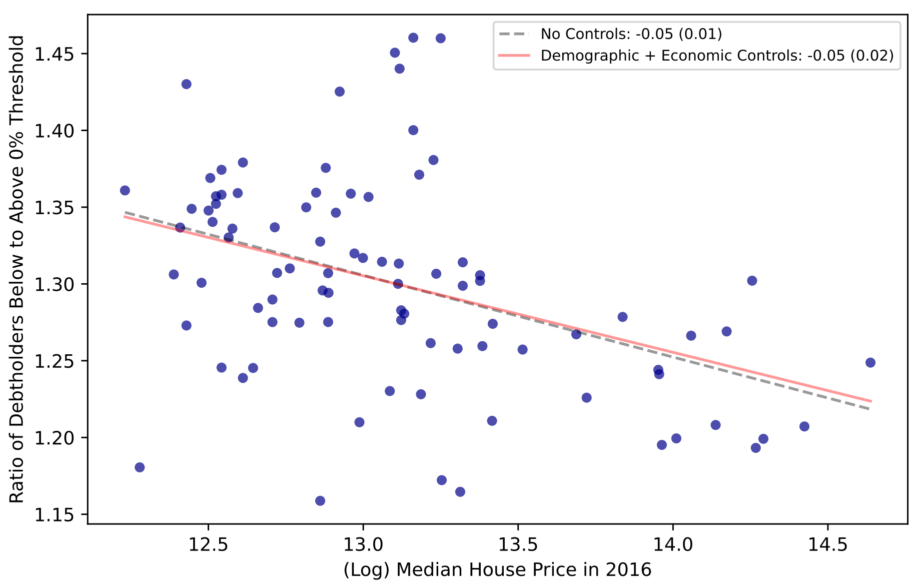
Notes: Panel A of this figure plots the distribution of HELP income (in 2005 AUD) in 2016 relative to the repayment threshold and the bunching statistic defined in (4). Each bin corresponds to $250 AUD, and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix B.3, 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 A13. Additional Tests of Link Between Bunching and Liquidity Constraints

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

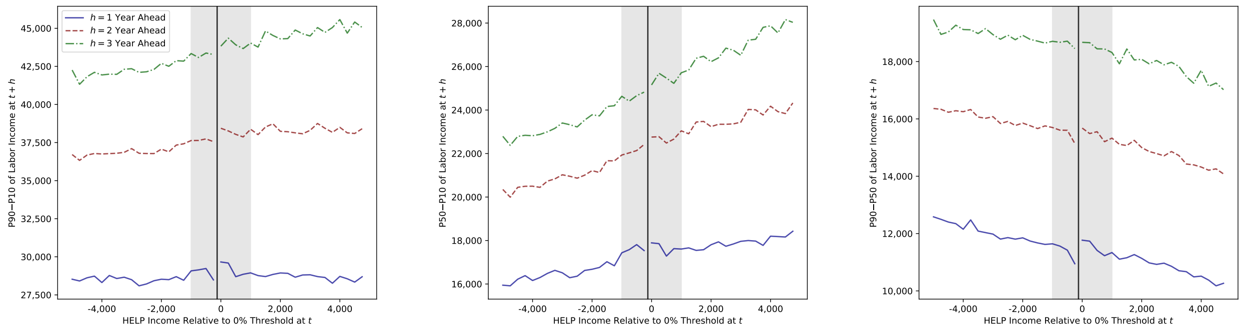


Panel B: Variation in Bunching across Geographic Regions based on Housing Wealth



Notes: Panel A of this figure replicates the analysis in the left panel of Figure 7 among individuals 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 SA4 region reported in *ALife*. For each individual–year, *ALife* contains the location of individuals' home addresses by SA4 region, which are nonoverlapping geographic regions that cover Australia. Statistical areas level 4 (SA4s) are 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 populations of between 300,000 to 500,000 people in metropolitan areas. The amount of bunching is measured as the ratio of the number of individuals 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 A14. Bunching Below Repayment Threshold and Distribution of Future Labor Income



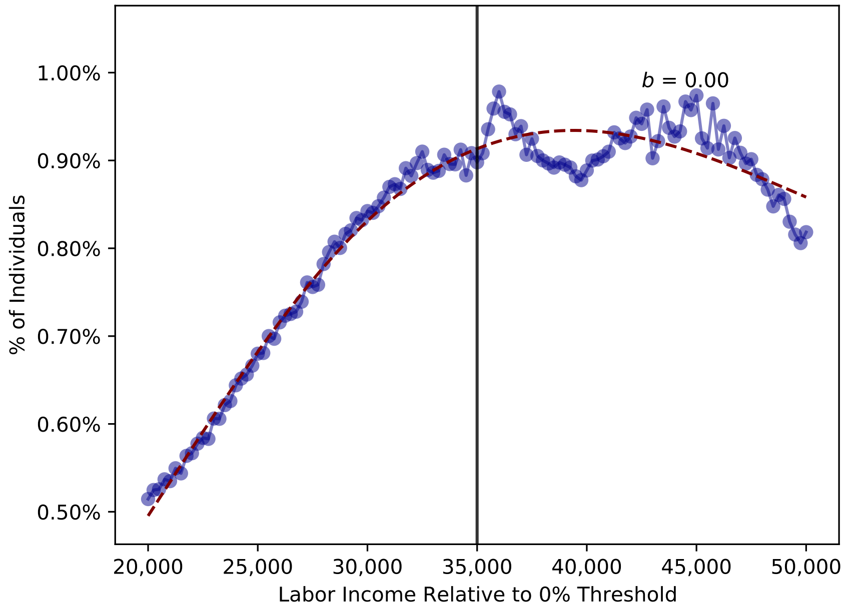
Notes: Each panel in this figure replicates the left panel of Figure 8 using different summary statistics within each $250 bin of HELP income instead of averages. The left panel plots the 90th minus 10th percentiles of labor income at h. The middle panel plots the 50th minus 10th percentiles of labor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

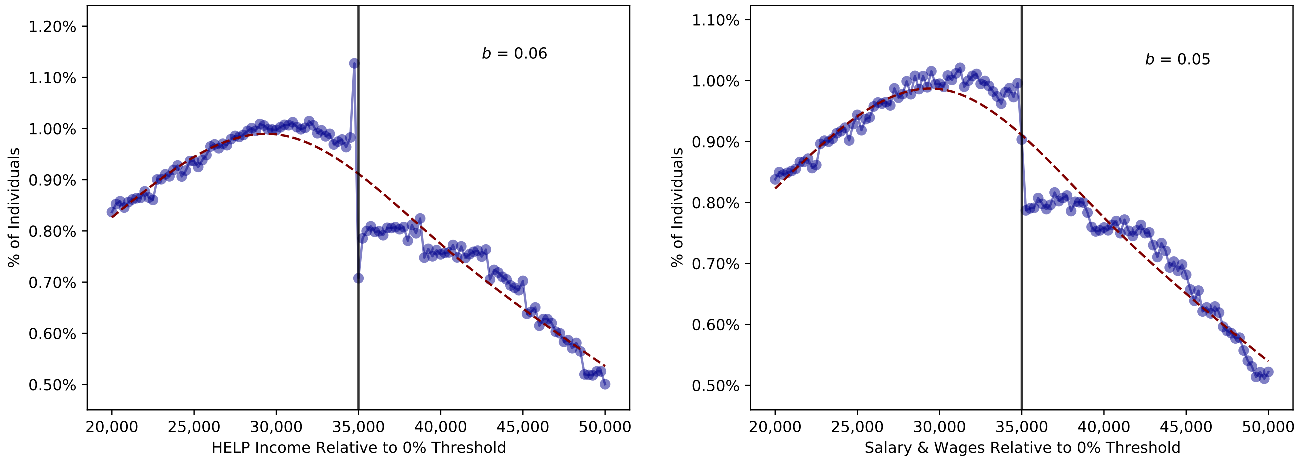
Notes: This table shows the bunching statistic defined in (4) computed for different samples of debtholders. The calculation of b is detailed in Appendix B.3. The sample in each row is the *ALife* sample defined in Section 2.4 for the period between 2005 and 2018 after the policy change, restricted to individuals with positive HELP debt balances for whom the sample restrictions specified int each row are satisfied. The first two rows split individuals 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 an individual reports having a dependent child; and the ninth and tenth split the sample based on whether an individual reports having a spouse.

Figure A15. Distribution of Labor Income among Individuals with Deductions



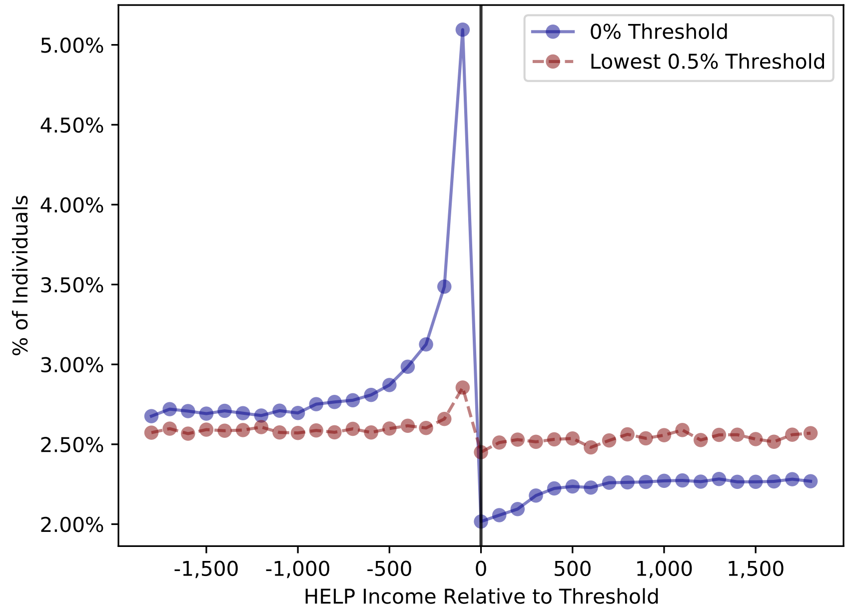
Notes: This figure plots the distribution of HELP income in 2005 AUD relative to the repayment threshold after the policy change and the bunching statistic defined in (4). Each bin corresponds to \$250 AUD and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix B.3, 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 A16. Distributions of HELP Income and Salary and Wages



Notes: This figure replicates the analysis in Figure A6, replacing the right plot with salary and wages instead of labor income.

Figure A17. 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

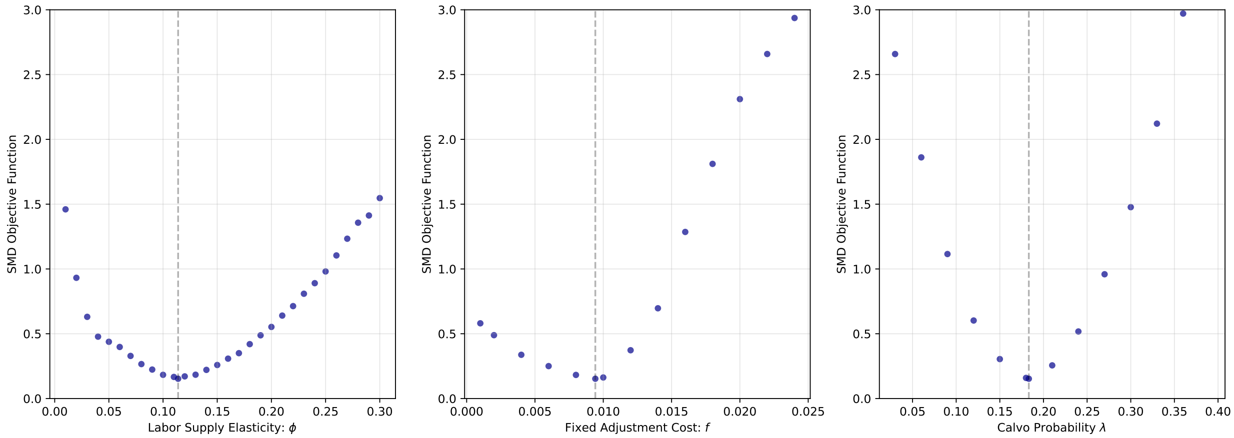
Table A5. Elasticity of Estimation Targets with Respect to Parameters (continued)

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 moment 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.

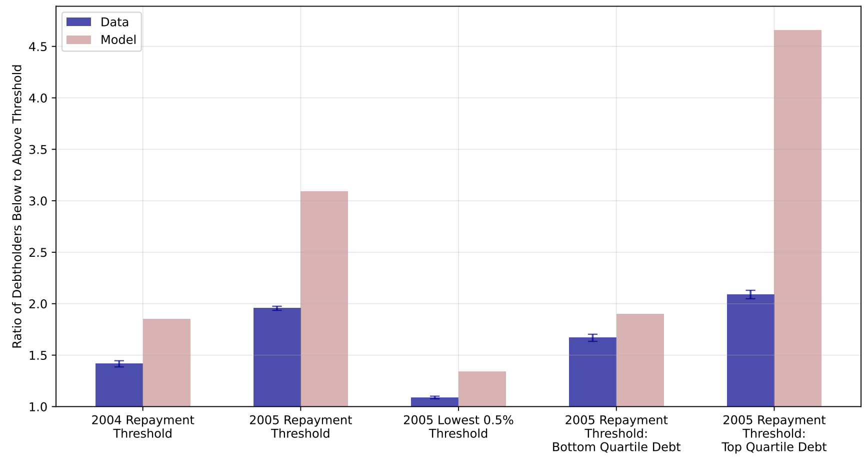
Figure A18. Local Identification of Labor Supply Parameters



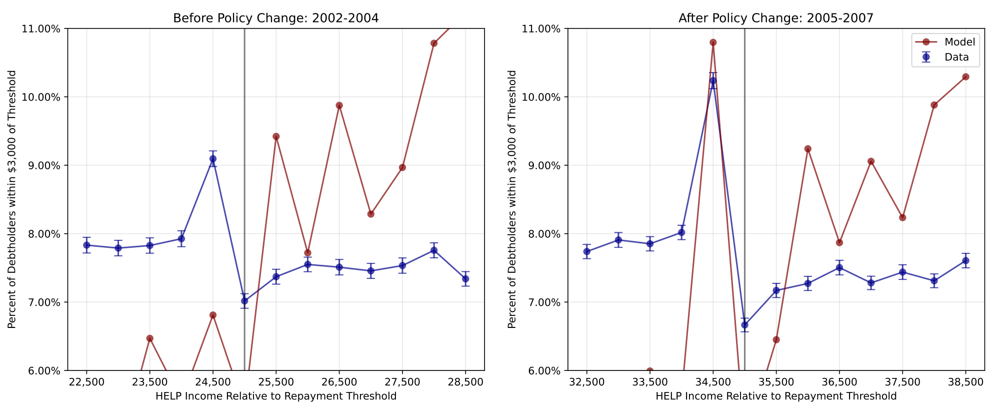
Notes: This figure plots the value of the simulated minimum distance objective function in the baseline estimation for different values of the three key parameters, ϕ, λ, and λ. Each point represents the objective function when the model is solved at that parameter value, with all other parameters held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

Figure A19. Model Fit: No Optimization Frictions

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



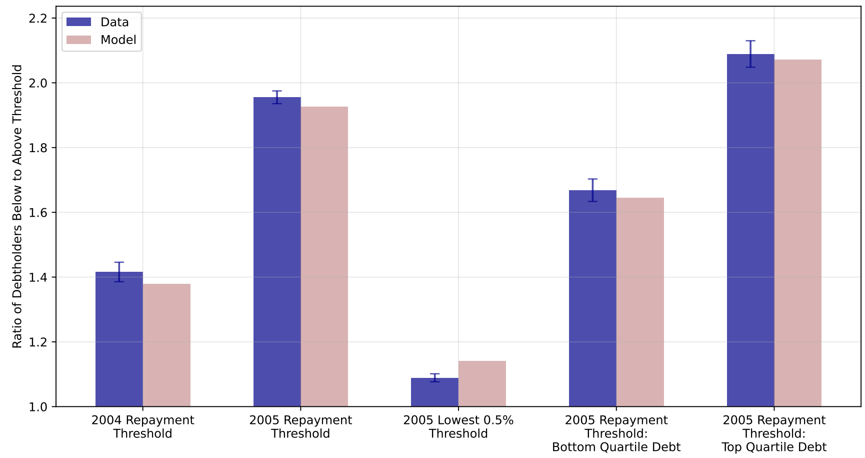
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	62169.068
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	1338.846	8646.369

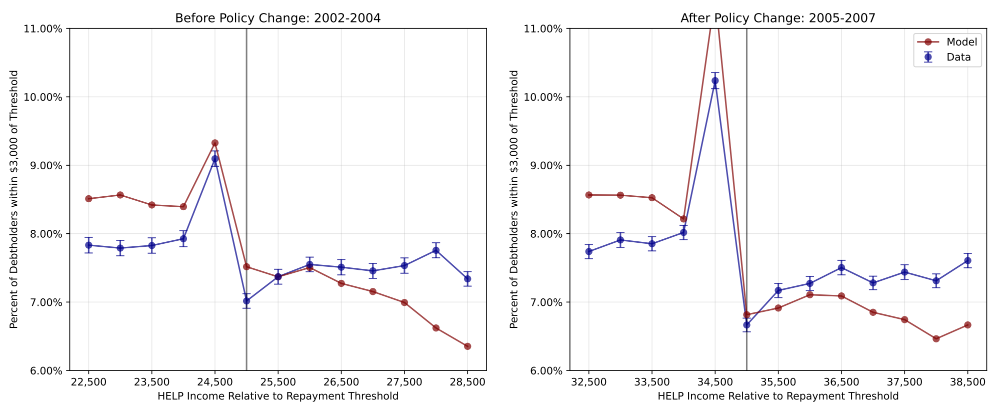
Notes: The results presented in this figure show the fit of the estimated model in column (2) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A20. Model Fit: No Calvo Adjustment

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



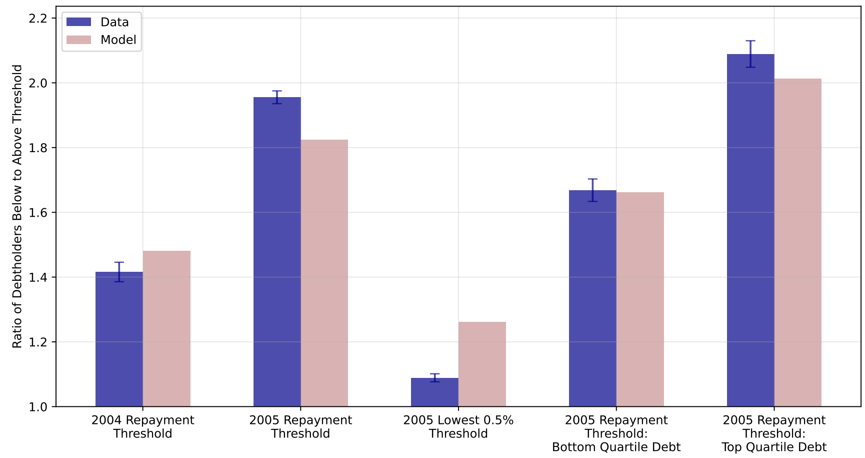
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	45691.108
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	1338.846	1295.642

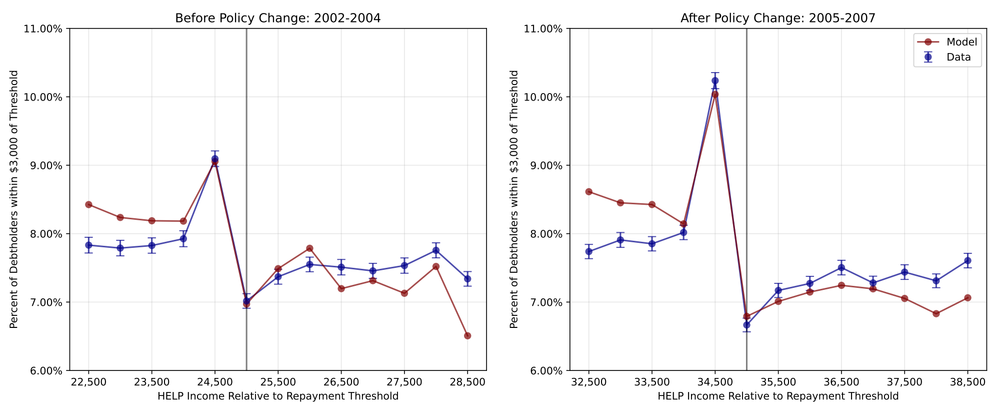
Notes: The results presented in this figure show the fit of the estimated model in column (3) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A21. Model Fit: No Fixed Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



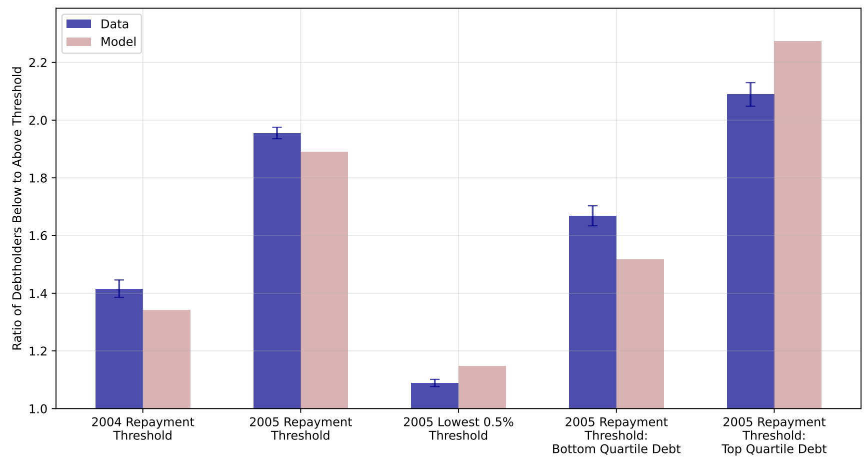
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	46896.491
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	1338.846	1301.442

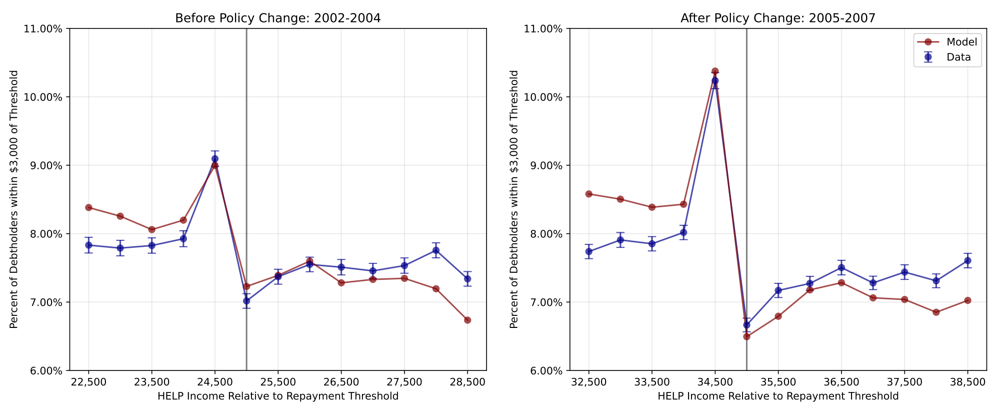
Notes: The results presented in this figure show the fit of the estimated model in column (4) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A22. Model Fit: Learning-by-Doing

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



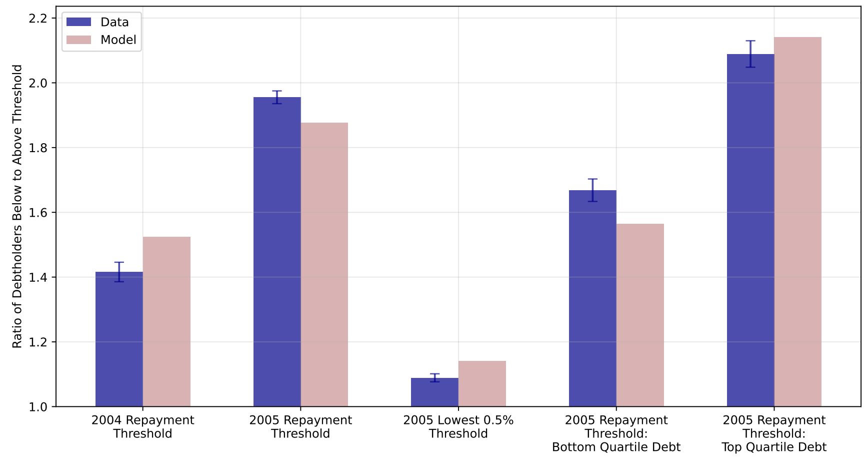
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	48506.656
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	1338.846	1295.803

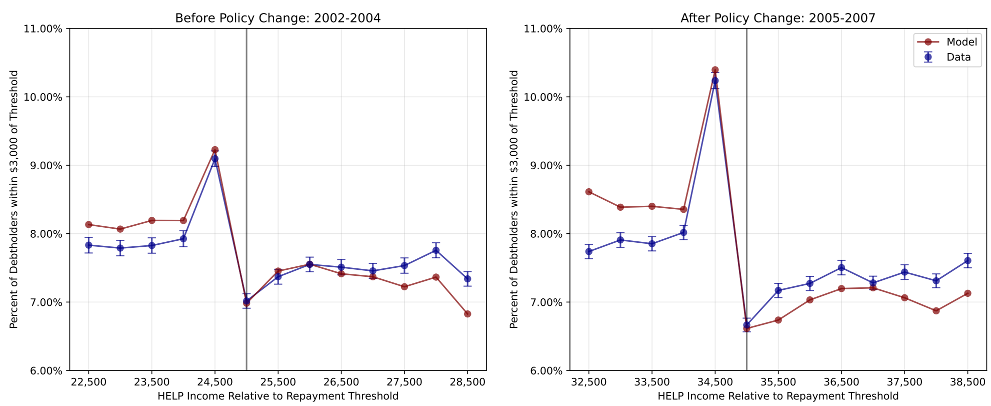
Notes: The results presented in this figure show the fit of the estimated model in column (5) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A23. Model Fit: Linear Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change

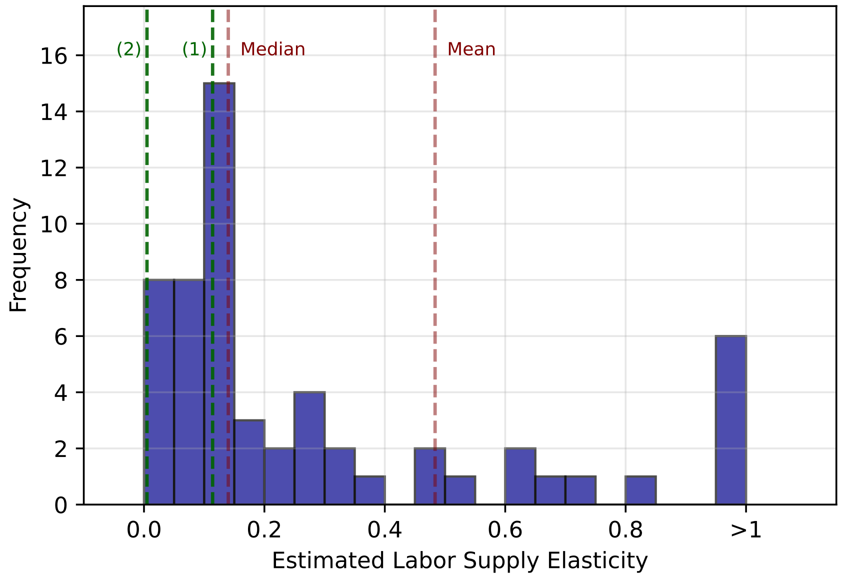


Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	49640.064
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	1338.846	1375.534

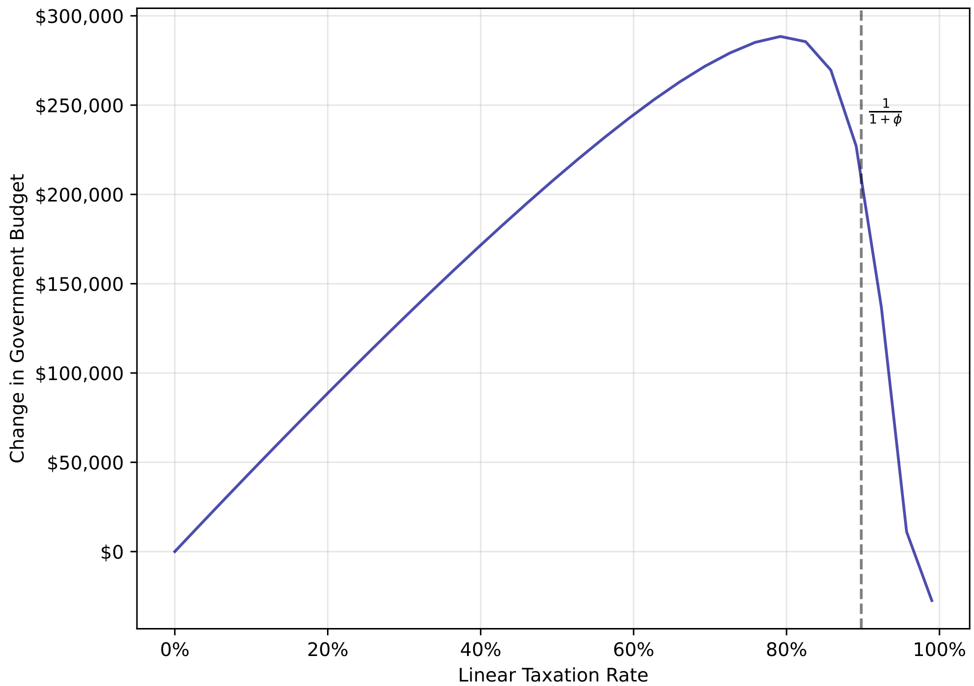
Notes: The results presented in this figure show the fit of the estimated model in column (6) of Table 3 to the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A24. Distribution of Estimated Labor Supply Elasticities from Prior Studies



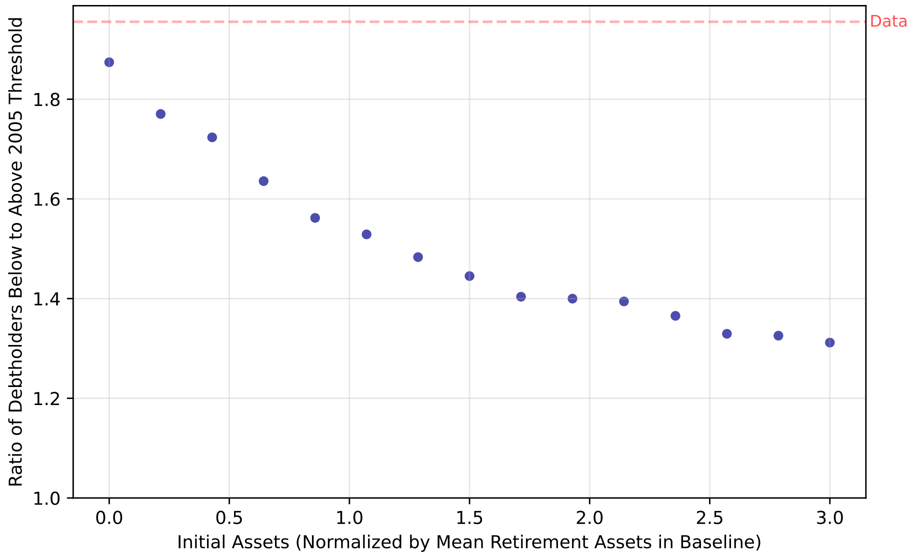
Notes: This figure plots a histogram of estimated intensive-margin labor supply elasticities in prior literature. I combine the estimates reported in Tables 6 and 7 of Keane (2011) and Table 1 of Chetty (2012). These estimates include intensive-margin Frisch (i.e., marginal utility–constant) and Hicksian (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.

Figure A25. Laffer Curve in Baseline Model



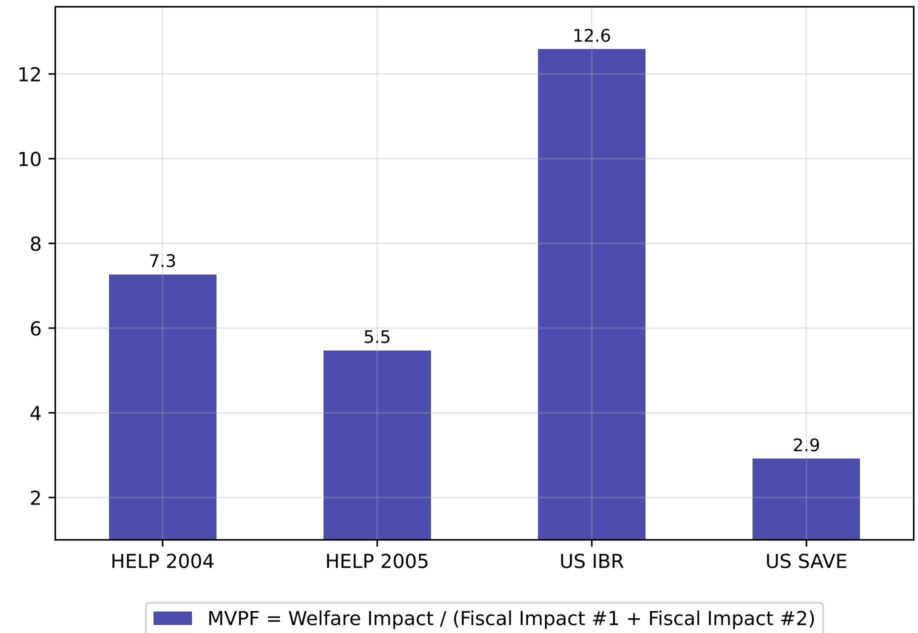
Notes: This figure plots the Laffer curve from a linear tax on income, τy_{ia}, in the baseline model. The horizontal axis corresponds to the value of the linear taxation rate, τ. The vertical axis shows that government revenue changes with respect to its value when $\tau = 0$. The vertical line corresponds to the revenue-maximizing tax rate in the canonical static frictionless model of labor supply (Saez 2001) evaluated at my 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 educated individuals are what my model is designed to capture, I apply the tax only to individuals with $\mathcal{E}_i = 1$.

Figure A26. Relationship Between Bunching Below Repayment Threshold and Liquidity in Model



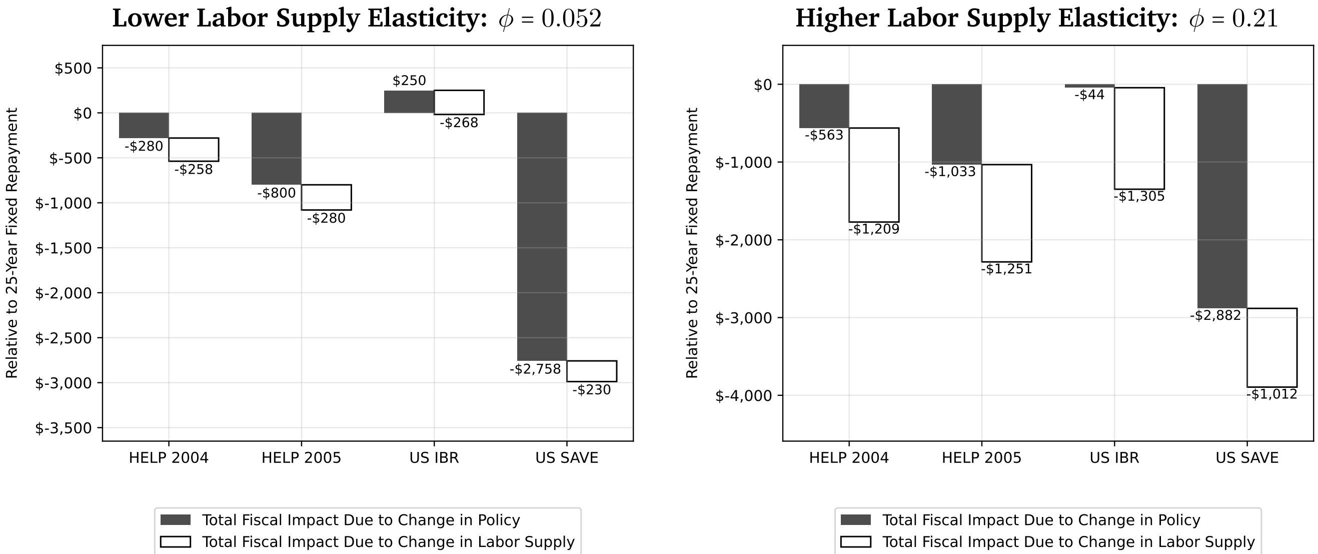
Notes: This figure plots the bunching below the 2005 repayment threshold between 2005 and 2018 as calculated in Figure 10 for different values of initial assets, A_0. The red dashed line in the plot corresponds to the value of this quantity in the data. For each value on the horizonal axis, I simulate from the model assuming that all individuals have that level of initial assets. The horizontal axis is scaled by the average value of A_{ia} at retirement, $a = a_R$, in the baseline model.

Figure A27. Marginal Value of Public Funds of Replacing 25-Year Fixed Repayment with Existing Contracts



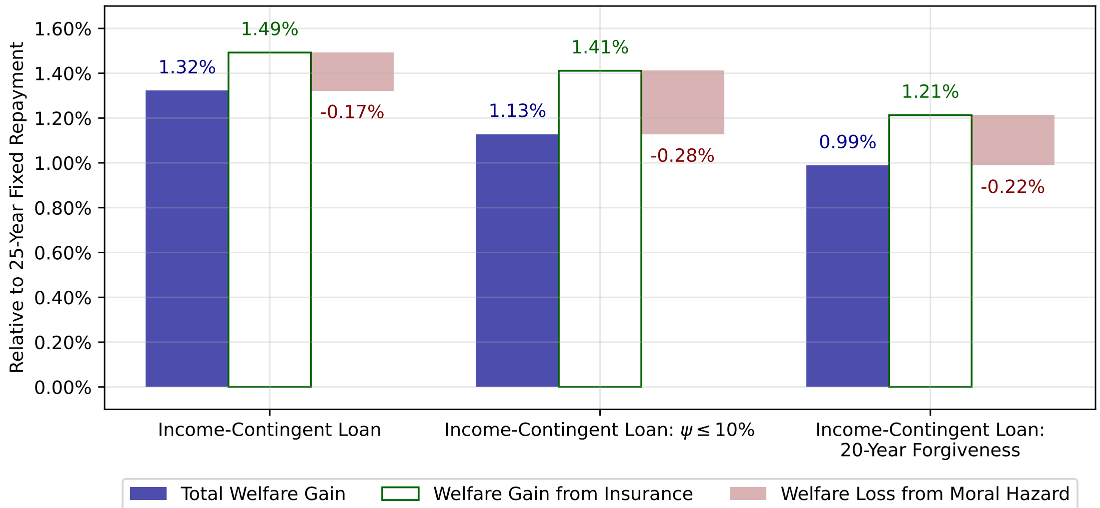
Notes: This figure plots the marginal value of public funds, defined by Hendren and Sprung-Keyser (2020), to moving from a 25-year fixed repayment contract to various existing income-contingent repayment contracts. This is computed by dividing the equivalent variation by the sum of the two fiscal impacts presented in Figure 14.

Figure A28. Decompositions of Fiscal Impact of Existing Income-Contingent Loans: Alternative ϕ



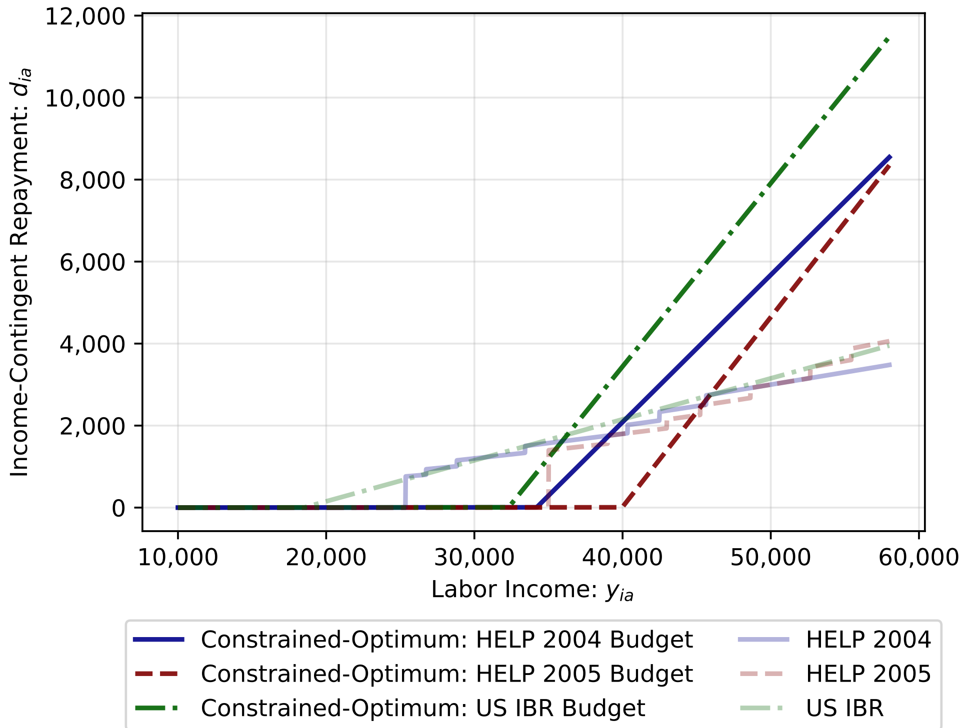
Notes: These two figures replicate the figure in the right panel of Figure 14 for two different values of the Frisch labor supply elasticity.

Figure A29. 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 15, 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.

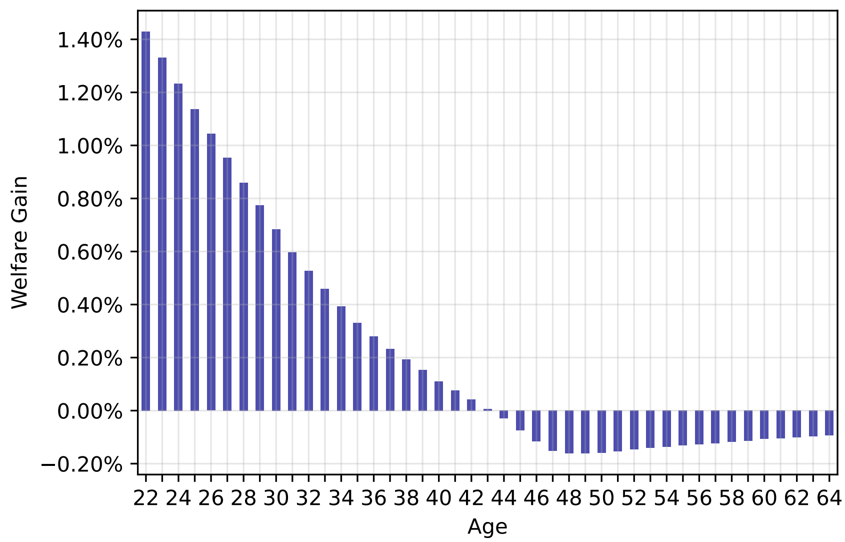
Figure A30. Comparison of Constrained-Optimal Income-Contingent Loans with Existing Contracts



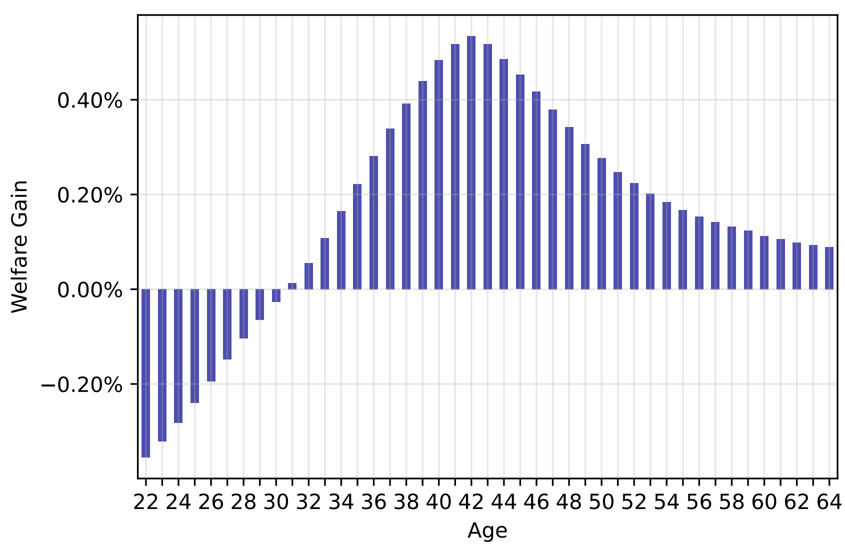
Notes: This figure shows the income-contigent repayments for several different repayment contracts. The light solid blue line is the 2004 HELP contract from Figure 2. The dark solid blue line corresponds to the constrained-optimal repayment contract in the baseline model that comes from solving (17) with $\overline{\mathcal{G}}$ set equal to the revenue raised by this contract. The solid and light-dashed red and green lines perform the same analysis with the 2005 HELP and the US IBR contracts.

Figure A31. Heterogeneity in Welfare Gains by Age

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

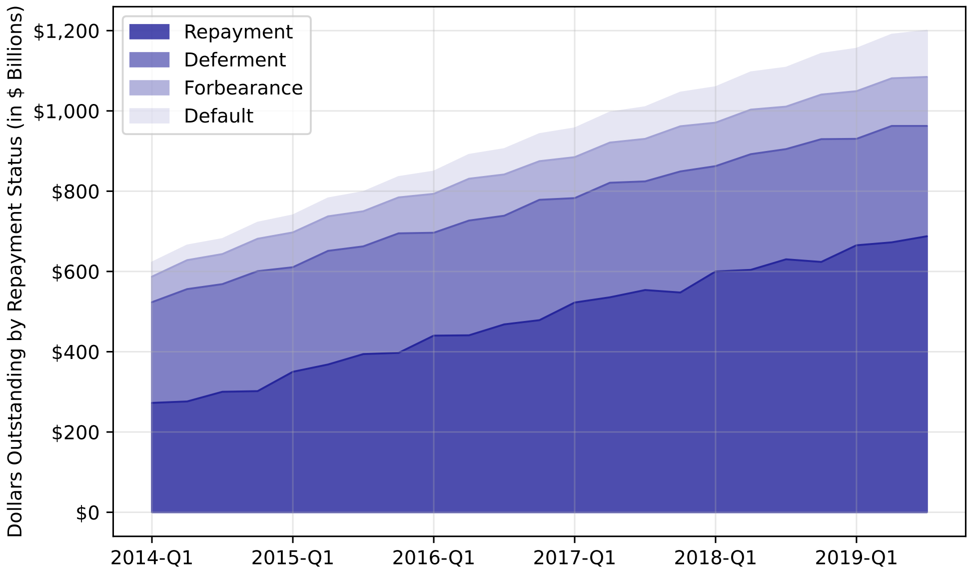


Panel B: Optimal Income-Contingent Loan with Forgiveness Relative to Optimal Income-Contingent Loan



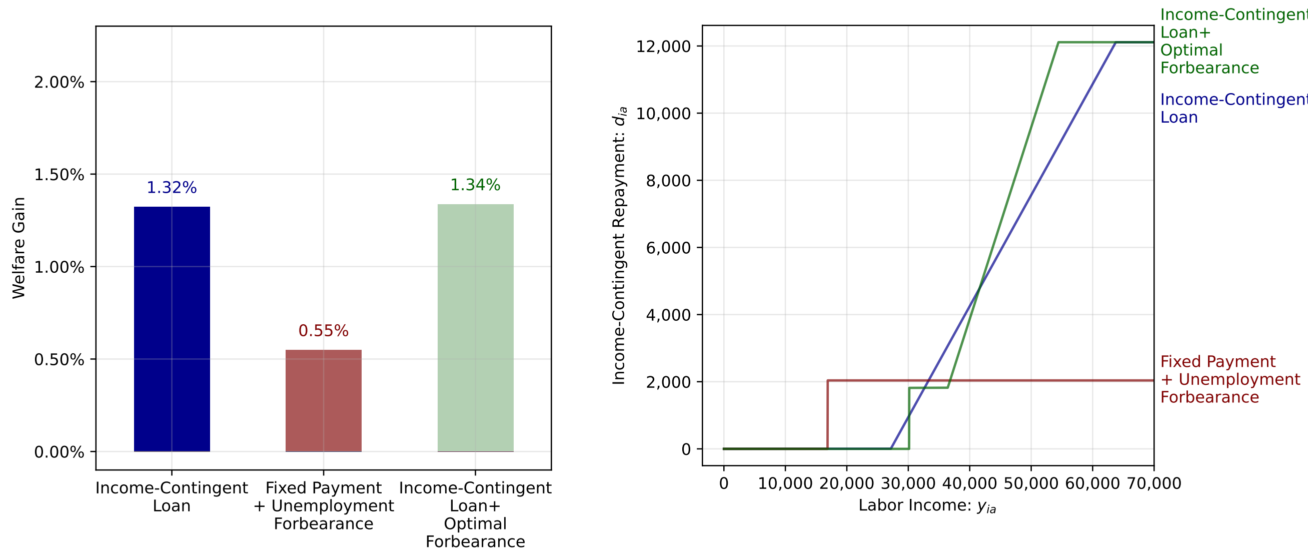
Notes: Panel A of this figure plots the average welfare gain at each age from the constrained-optimal income-contingent loan relative to 25-year fixed repayment. Panel B performs the same analysis for the welfare gain of the constrained-optimal income-contingent loan with forgiveness after 20 years relative 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 18 for additional details.

Figure A32. Repayment Status of Government-Provided Student Loans in the US



Notes: This figure plots the fraction of total outstanding student debt in the US Federal Government Direct Loan Portfolio that is 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.

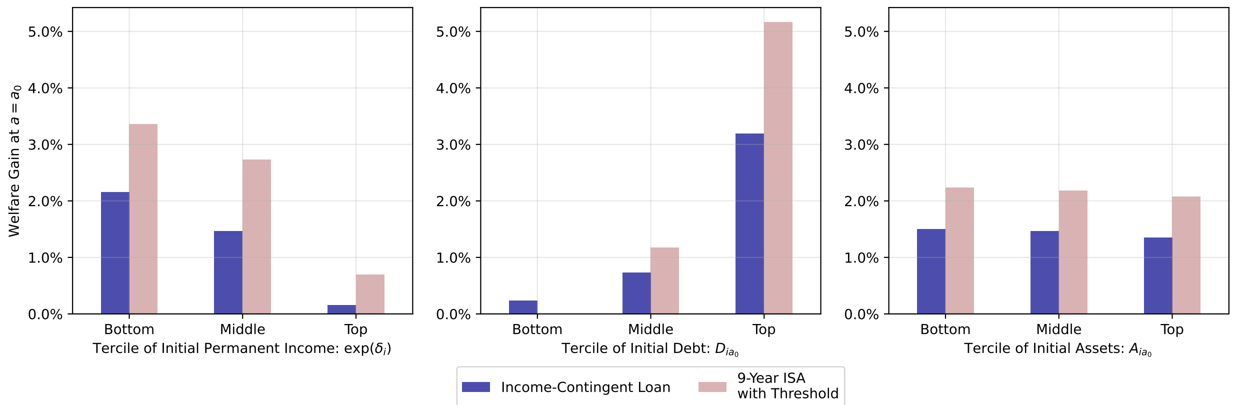
Figure A33. Welfare Gains from Addition of Optimally Chosen Forbearance to Income-Contingent Loan



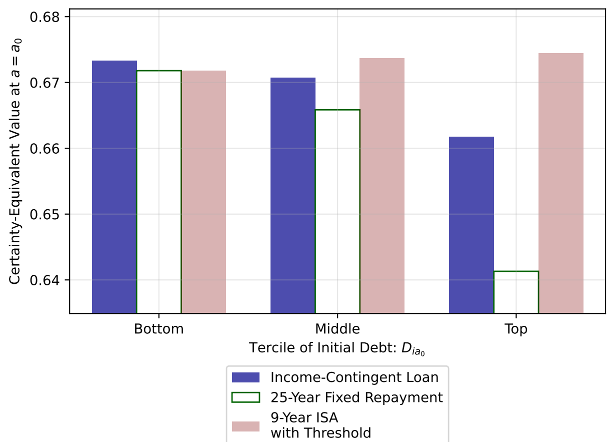
Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from different constrained-optimal repayment contracts described in the text and shown on the right. The repayments are shown for an individual with median initial debt.

Figure A34. Heterogeneity in Welfare Gains from Constrained-Optimal 9-Year ISA with Threshold

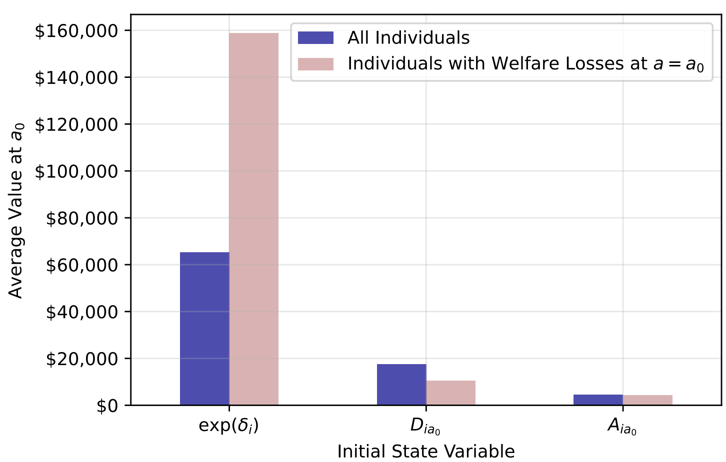
Panel A: Welfare Gains Across Initial States



Panel B: Variation in Certainty-Equivalents by Initial Debt



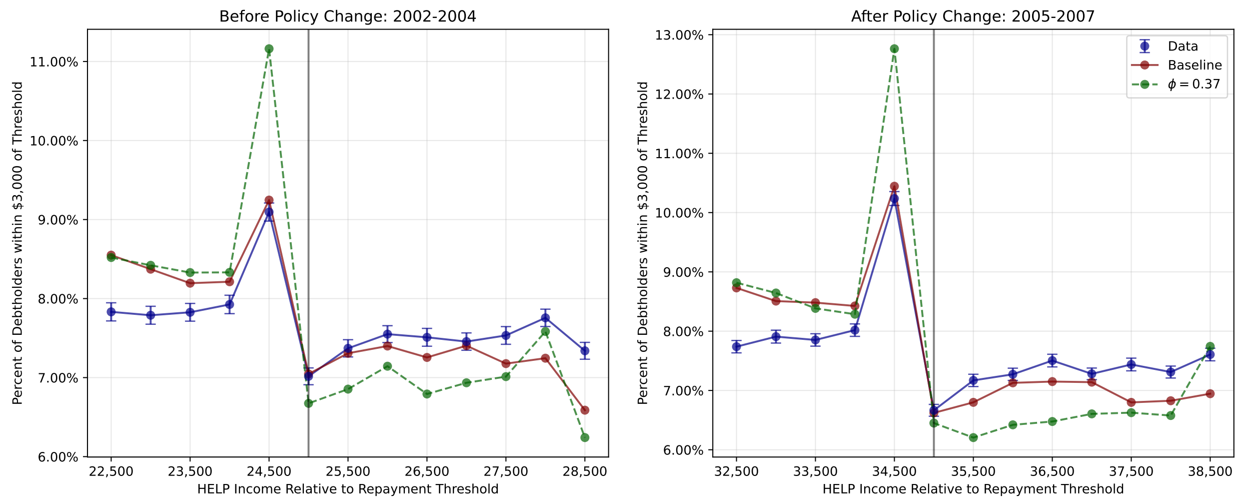
Panel C: Average Initial States by Welfare Gain from 9-Year ISA with Threshold



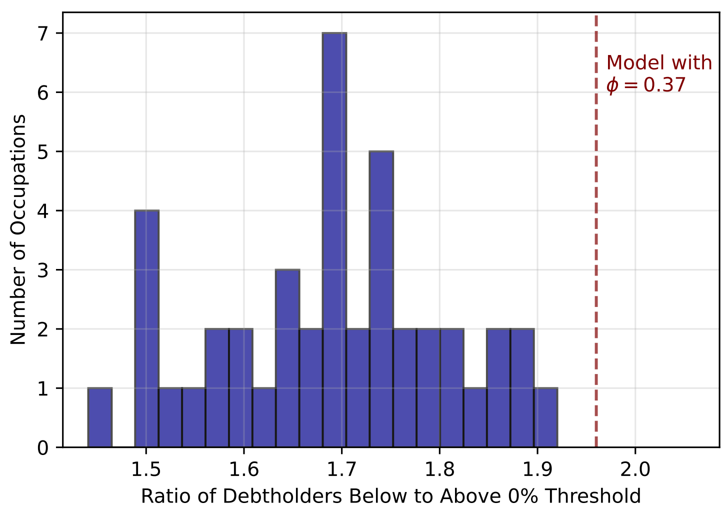
Notes: Panel A in this figure plots the welfare gains at a_0 computed in Figure 18 for different terciles of the three initial states that generate ex-ante heterogeneity in the model. Panel B plots the certainty-equivalent value at a_0 across terciles of initial debt. Panel C plots the average initial states of all individuals versus those that experience welfare losses from the constrained-optimal 9-Year ISA with Threshold relative to 25-year fixed repayment.

Figure A35. Implications of Setting $\phi = 0.37$ in the Baseline Model

Panel A: Fit of Model on Bunching Moments Used in Estimation

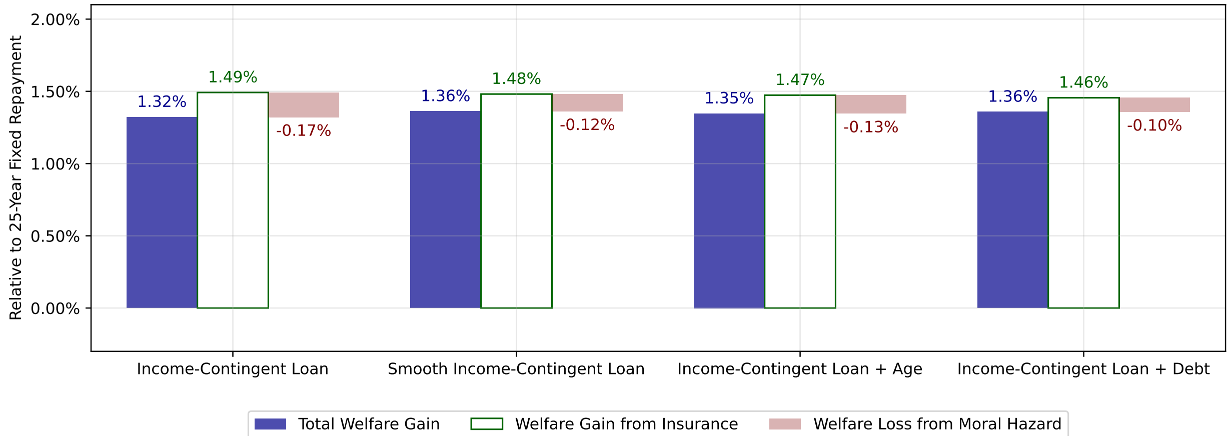


Panel B: Amount of Bunching Relative to Distribution Across Occupations



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 moments 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 individuals with positive debt balances and $a > a_0$.

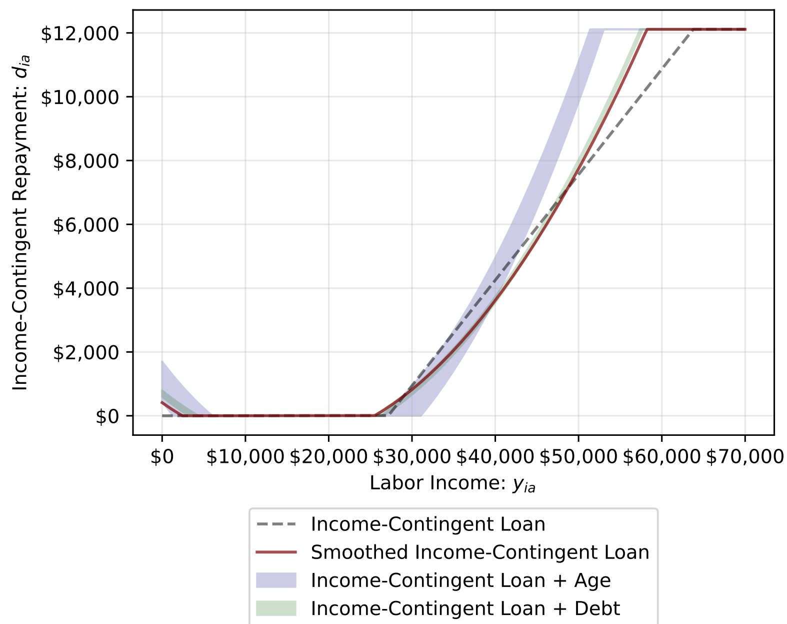
Figure A36. Welfare Gains from Alternative Forms of Income-Contingent Loans: Baseline Model



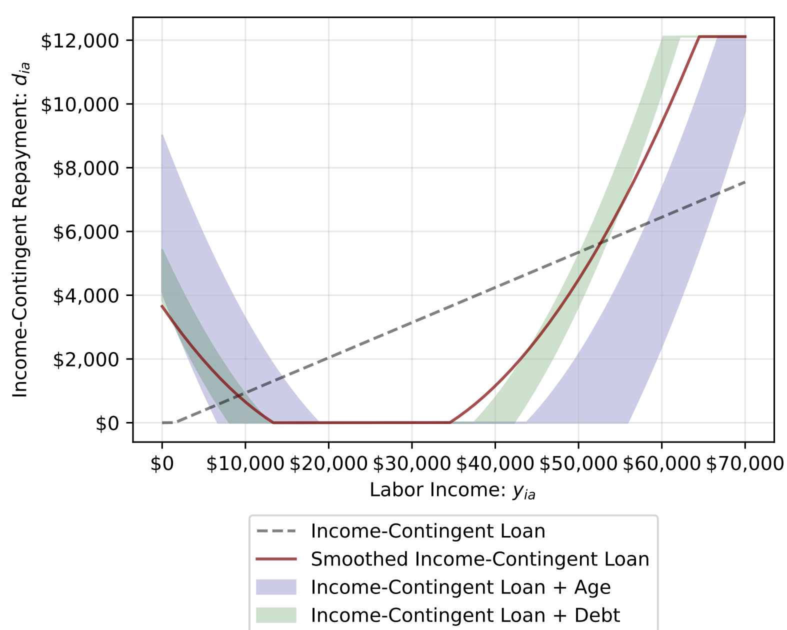
Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment, along with the decomposition performed in Figure 15, for different constrained-optimal repayment contracts described in the text. This analysis is performed with all parameters set at their estimated and calibrated values in the baseline model.

Figure A37. 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 (17), assuming that an individual 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 individuals 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.

References

Arnoud, Antoine, Fatih Guvenen, and Tatjana Kleineberg (2019), "Benchmarking Global Optimizers." *Working Paper*.

Bommier, Antoine, Daniel Harenberg, François Le Grand, and Cormac O'Dea (2020), "Recursive Preferences, the Value of Life, and Household Finance." *SSRN Electronic Journal*.

Chetty, R., J. N. Friedman, T. Olsen, and L. Pistaferri (2011), "Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records." *The Quarterly Journal of Economics*, 126, 749–804.

Chetty, Raj (2012), "Bounds on Elasticities With Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply." *Econometrica*, 80, 969–1018.

Choukhmane, Taha and Tim de Silva (2023), "What Drives Investors' Portfolio Choices? Separating Risk Preferences from Frictions." *Working Paper*.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song (2021), "What Do Data on Millions of U.S. Workers Reveal About Lifecycle Earnings Dynamics?" *Econometrica*, 89, 2303–2339.

Guvenen, Fatih, Serdar Ozkan, and Jae Song (2014), "The nature of countercyclical income risk." *Journal of Political Economy*, 122, 621–660.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante (2017), "Optimal Tax Progressivity: An Analytical Framework." *The Quarterly Journal of Economics*, 132, 1693–1754.

Heathcote, Jonathan and Hitoshi Tsujiyama (2021), "Optimal Income Taxation: Mirrlees Meets Ramsey." *Journal of Political Economy*, 129, 3141–3184.

Hendren, Nathaniel and Ben Sprung-Keyser (2020), "A Unified Welfare Analysis of Government Policies." *The Quarterly Journal of Economics*, 135, 1209–1318.

Judd, Kenneth L. (1998), *Numerical Methods in Economics*. MIT Press, Cambridge, MA.

Keane, Michael P (2011), "Labor Supply and Taxes: A Survey." *Journal of Economic Literature*, 49, 961–1075.

Kleven, Henrik J. and Mazhar Waseem (2013), "Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan*." *The Quarterly Journal of Economics*, 128, 669–723.

Lusardi, Annamaria, Pierre Carl Michaud, and Olivia S. Mitchell (2017), "Optimal financial knowledge and wealth inequality." *Journal of Political Economy*, 125, 431–477.

McFadden, Daniel (1989), "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration." *Econometrica*, 57, 995–1026.

Mumford, Kevin J. (2022), "Student Selection into an Income Share Agreement." *Working Paper*.

Nocedal, Jorge and Stephen J. Wright (2006), *Numerical Optimization*, 2nd ed edition. Springer Series in Operations Research, Springer, New York.

Reuther, Albert, Jeremy Kepner, Chansup Byun, Siddharth Samsi, William Arcand, David Bestor, Bill Bergeron, Vijay Gadepally, Michael Houle, Matthew Hubbell, Michael Jones, Anna Klein, Lauren Milechin, Julia Mullen, Andrew Prout, Antonio Rosa, Charles Yee, and Peter Michaeleas (2018), "Interactive supercomputing on 40,000 cores for machine learning and data analysis." In *2018 IEEE High Performance Extreme Computing Conference (HPEC)*, 1–6.

Saez, Emmanuel (2001), "Using Elasticities to Derive Optimal Income Tax Rates." *Review of Economic Studies*, 68, 205–229.