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

Tim de Silva†
MIT Sloan

Click Here for Latest Version

October 6, 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 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 they are consistent with a Frisch labor supply elasticity of 0.11 and substantial frictions that limit labor supply adjustment. In this model, a constrained-optimal income-contingent loan generates welfare gains relative to a fixed repayment contract equivalent to a 1.3% increase in lifetime consumption, with the same fiscal cost. Adding forbearance to fixed repayment contracts generates smaller gains because it does not accelerate repayments from high-income borrowers. The labor supply responses to income-contingent repayment reduce the insurance it can provide at a given cost, but these responses are too small to justify fixed repayment contracts.

*Incomplete draft: Please do not circulate.** 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 and discussions. I also thank the ATO *ALife* and ABS DataLab teams for extensive data assistance, in particular Andrew Carter, Justin Holland, and Son Nguyen, Simone Melchionna for sharing his Fortran expertise, Andrew Norton for supplying data and responding to my never-ending stream of questions, and Jenn Mace for her unwavering support. Access to the data required for this project would not have been possible without the help 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'm 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. All remaining errors are my own.

†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).

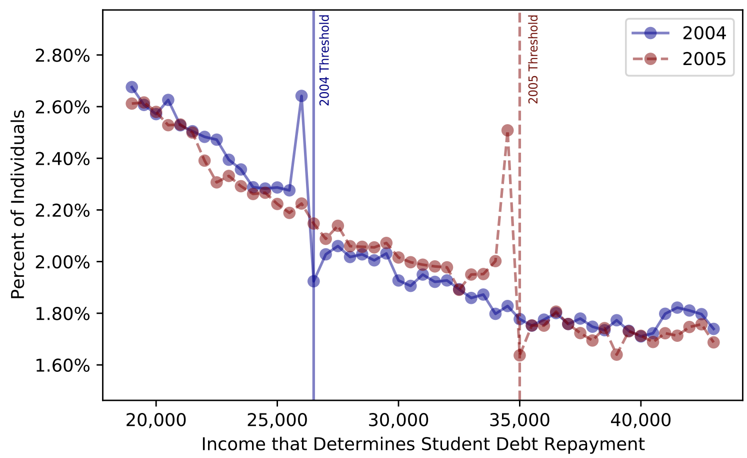
One potential policy to provide more insurance against income risk is to make student loans more equity-like by indexing payments to borrowers' incomes. This idea has been discussed extensively (Friedman 1955; Shiller 2004; Palacios 2004; Chapman 2006; Zingales 2012), and governments in the US, UK, Canada, and Australia have recently implemented it by providing income-contingent loans. In contrast to non-dischargeable 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 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 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, a constrained-optimal income-contingent loan provides gains relative to a 25-year fixed repayment contract equivalent to 1.3% of lifetime consumption, at the same fiscal cost. The moral hazard created by income-contingent repayment decreases the insurance 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 this moral hazard 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 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 individuals can only adjust their borrowing by changing their degree choices. This decision is likely less responsive than the other margins borrowers in the US can adjust, such as room and board or groceries.

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



Notes: This figure shows the distribution in Australian dollars of the income that determines individuals' repayments on their income-contingent loan 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 threshold below which individuals make no repayment and above which they repay 3% and 4% of their income in 2004 and 2005. The sample is the population of debtholders, subject to the sample selection criteria in Section 2.4. HELP Income is deflated to 2005 using the HELP indexation rate calculated from 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, and 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 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 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 located 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., wage reduction) or psychological (e.g., hassle costs).

I estimate the model by conducting 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, fixed adjustment cost of $\$400$ (i.e., 1% of mean earnings), and 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 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 of raising 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 0.2pp 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 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 repayments 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 of 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 is part of 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]Alternative options to providing insurance are to make student debt dischargeable, which has the cost of inducing strategic default (Yannelis 2020), universal loan forgiveness, which would be regressive (Catherine and Yannelis 2023), and 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 being the leading example (Chapman 2006) and other countries following (Barr et al. 2019). Theoretical work suggests 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 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 policies 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 policies 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 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 most of this literature, this model is dynamic because debt repayment involves intertemporal trade-offs, which turn out to be crucial for separate identification of the two optimization frictions.

[4] Other possible government policies towards 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 I attempt to estimate empirically through the lens of this expression.

Environment. Consider a government who 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 are 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. Assume all individuals are ex-ante identical so the government solves the following problem:

$$\max_{\theta} V(\theta) - \lambda' \left[D_0 - \sum_{t=0}^{T} \frac{E_0\left(d_t\right)}{\mathcal{R}_t} \right], \tag{1}$$

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. The following proposition characterizes the optimal financing contract via a perturbation, as in Saez (2002).

Proposition 1. *Define* $M_t = \frac{u_c(c_t,\ell_t)}{u_c(c_0,\ell_0)}$ *as individuals' time* t *to time 0 stochastic discount factor,* $\lambda = \lambda' \frac{\partial A_0}{\partial V}$ *as the marginal cost of public funds in dollars, and* θ^* *as a solution to (1) . Under appropriate* *regularity conditions, the following condition holds at $\theta = \theta^*$:*

$$\sum_{t=1}^{T} E_0\left[\underbrace{\left(\frac{\lambda}{\mathcal{R}_t} - M_t\right)}_{\substack{\text{amount of}\\ \text{risk-sharing}}}\frac{\partial d_t}{\partial \theta}\right] = \lambda\left[\underbrace{\frac{dD_0}{d\theta}}_{\substack{\text{borrowing}\\ \text{response}}} - \sum_{t=1}^{T}\frac{1}{\mathcal{R}_t}E_0\left(\underbrace{\frac{\partial d_t}{\partial y_t}\frac{dy_t}{d\theta}}_{\substack{\text{labor supply}\\ \text{response}}}\right)\right]. \tag{2}$$

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 the 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) 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 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 risk-averse individuals will borrow more ex-ante, $\frac{dD_0}{d\theta} > 0$, and 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 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 describes the two largest programs called HECS-HELP and FEE-HELP, which historically have made up over 90% of HELP borrowing.[6] HELP loans provided through these two programs can be used to finance tuition for undergraduate and graduate degree programs.[7] Tuition at public institutions is controlled by the government and varies by degree, while private universities generally charge higher tuition.[8] Most degrees at public institutions are classified as Commonwealth Supported Places (CSPs), in which the government provides a subsidy in the form of a contribution to the tuition owed by the student. The remaining tuition, after deducting the government's contribution, is paid by the student and 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 2012-2017 in which the system was "demand-driven" (D'Souza 2018; Norton 2019).

Australia 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 around $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 varies based on whether the degree belongs to one of three bands 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 annual compulsory repayment in year t is equal to

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

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, y_{it}, is the taxable income reported in a personal income tax return plus a few adjustments discussed in Section 2.5. The collection of HELP payments is integrated with the personal 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

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

[7] To finance non-tuition expenses, students on income support can use a Student Start-Up Loan, but these loans only supported less than 100,000 borrowers in 2020-21. All other students must self-finance these expenses, which is generally done using credit cards or taking jobs.

[8] Private institutions play a relatively small role in Australia, making up only 3 out of 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.

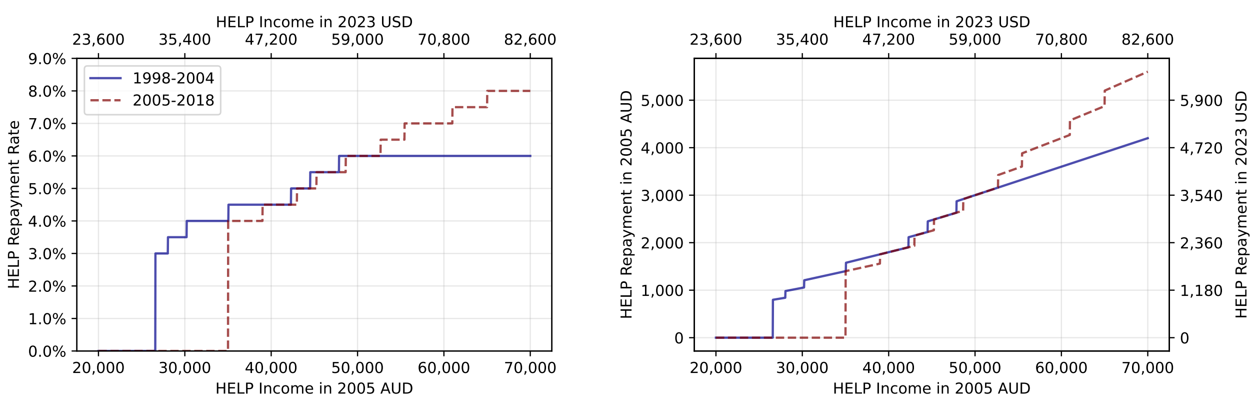
filing their tax returns. Individuals also have the option to make voluntary repayments at any time. Additional details on the timing and structure of repayments is presented in Appendix C.

Repayment of HELP debt continues until the remaining balance equals zero or the time of death. Partial repayment is common: as of 2004, around 25% of debt balances were forecasted to be written off due to death, and in 2019 that estimate was 36% (Martin 2004; Robinson 2019). This means HELP effectively forgives debt at the end of their 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.[9]

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 after the policy change in red. The most significant change was the location of the repayment threshold, which is the point at which individuals have to start making repayments, from around \$26,000 AUD to \$35,000 AUD. The median debtholder has a HELP Income between these two thresholds, so this policy change generated reductions in 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.

Figure 2. HELP Repayment Rates as a Function of Income: Before and After 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 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 using the AUD/USD exchange rate in June 2005 and the US CPI inflation rate between June 2005 and January 2023. Prior to 1998 and after 2018 there were other changes to the HELP repayment schedules that were smaller in magnitude.

The right panel of Figure 2 plots the required repayments, which illustrates that the repayment

[9] 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.

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., it 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 delivers less take-home pay and leisure.

However, the 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 that is deciding between locating below versus above the 2005 repayment threshold. Assume this borrower knows her income at $t = 1$ will be high enough such 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.[10] For an interest rate of around 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 the HELP repayment function, and the changes to it, was salient to debtholders. First, the repayment function is indexed to inflation, which means it updates every year. When it is published at the beginning of each tax year, the government makes that receives press coverage.[11] Second, the policy received media coverage at the time of the change (Marshall 2003). Finally, the fact that HELP Income determines repayment rates with a repayment threshold has not changed since the introduction of HECS in 1989, meaning debtholders are likely to understand the program's structure.

Government policy documents and media articles suggest the primary reason for this change was to reduce the burden placed on lower-income individuals, for whom 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 increase of student contributions by 25% (see Figure A2). These other changes, discussed in detail by Beer and Chapman (2004), were primarily aimed at those entering their

[10]Technically, r is the difference between the HELP interest rate, which is zero, and the borrower's private rate.
[11]For an example of an announcement, see https://www.legislation.gov.au/Details/C2022G00213.

degree programs rather than those repaying HELP debt. The simultaneous implementation of these other changes with the change in 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 the effects of changes in contract design reflect borrowers' actions rather than types (Karlan and Zinman 2009).[12] The same is not true in the US, where high-income borrowers choose fixed rather than income-driven repayment (Karamcheva et al. 2020), nor in countries with private providers of income-sharing agreements (Herbst et al. 2023). In principle, individuals in Australia could receive 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. The primary margin in which there is scope for adverse selection is on whether to pay upfront or borrow through HELP, but the zero interest rate on HELP 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 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 and tuition at public undergraduate institutions, which make up over 94% of the domestic enrollment share and 39/42 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 repayments. 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 by 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

[12] 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; DeFusco et al. 2022) and mortgages (Gupta and Hansman 2022).

contracts could pass through to tuition and thus initial debt balances (Kargar and Mann 2022).

One caveat of using HELP to identify labor supply responses to income-contingent repayment is that this program is heavily-subsidized. A less subsidized program would only draw in individuals that place higher values on education. If there is heterogeneity in the structural parameters governing labor supply that is correlated with the value of education, a program with a different subsidy would generate different labor supply responses. To mitigate this concern, my counterfactual analysis focuses on repayment contracts with a similar fiscal cost to HELP.

2.4 Data Sources

I use several sources of restricted-access de-identified administrative data. First, I use individual income tax returns from the Australian Taxation Office (ATO), which contain panel data on income components and basic demographic characteristics. Second, I use administrative data on HELP from the ATO that includes debt balances, repayments, and a flag for whether individuals acquired new debt balances in a given year. Two limitations of this data are that it does not allow me to identify any information on the source of borrowing, such as the degree choice, and it aggregates 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 that are (i) between ages 20 and 64, (ii) residents in Australia for tax purposes, (iii) not exempt from HELP repayment due to a Medicare exemption, and (iv) do not have any income from discretionary trusts.[13] I use this sample 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 has the same sample coverage as the population-level *ALife* data but a restricted set of variables. Due to data limitations, I use the first three filters from the *ALife* sample to construct a cross-sectional MADIP sample in 2016, the year in which the Census was administered.

I supplement these administrative datasets with the Household, Income and Labour Dynamics in Australia Survey (HILDA), which is 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

[13] 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.

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, which is the main sample in my analysis. The three columns separate the sample into individuals without HELP debt, individuals with 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 average HELP debt balances peak in real terms. Relative to non-debtholders, debtholders tend to be younger, less likely to be wage-earners, which is defined as having any self-employment income from partnerships, sole-traders, or personal-services, and have lower taxable income.

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; 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 D.

The most important variable introduced in Table 1 is HELP Income, which determines an individual's repayment rate on their 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 in 2004 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). Additional details on the construction of all variables are presented in Appendix D.

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 around \$10,800 in 2005 AUD (\$13,000 in 2020 USD), and around \$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 big impact for these individuals: the fraction below the threshold moved from 35% to 55% after the policy change.

Figure A3 shows how debt balances vary within-individual over time: most individuals' debt balances peak in real terms between ages 24 and 26, and are paid down in their mid-30s. However, around 15% of individuals who had 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 be 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 discontinuities in repayment rates and the policy change to these rates, illustrated 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, which covers around 40% of the entire population of debtholders.

These results show significant bunching below the repayment threshold from 2002 to 2007. In 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 the income distribution exhibits two important changes. First, the bunching at the 2004 repayment threshold disappears completely. Second, bunching appears immediately below the new repayment threshold. This provides clear evidence that borrowers adjust their income to avoid making income-contingent repayments.

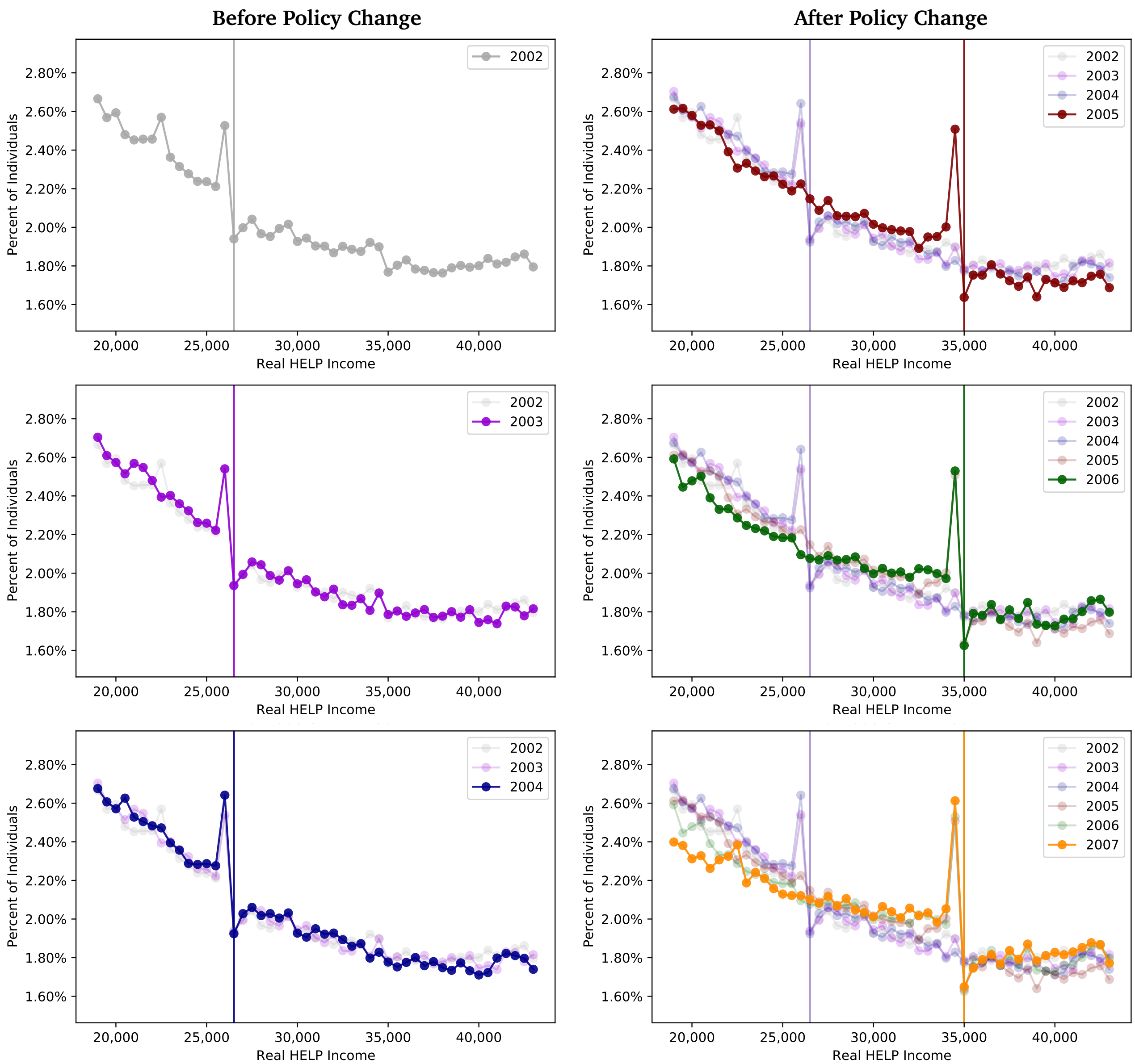
The fact that the bunching in Figure 3 responds quickly to the policy change shows it is not driven by mechanical features of Australia's tax system, such as the tendency to report incomes at round numbers. However, a possible threat to identification is the presence of other changes between 2002 and 2007 that affected individuals' incentives to report incomes of certain values. Although it is unlikely this could explain the evidence 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 A4. In contrast to the income distribution of debtholders, these results show no change in the income distribution of non-debtholders around the repayment threshold both before and after the policy change.[14]

HELP Income, defined in (3), consists of three components that individuals could adjust to locate below the repayment threshold. Figure A5 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.[15]

[14]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.

[15]The results in Figure A5 for HELP Income 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 around $90M higher than those implied by the observed distribution. This amounts to 42 bps of the total HELP compulsory repayments reported in the aggregated ATO HELP Data over this time period.

Figure 3. Income Distribution of HELP Debtholders around Repayment Threshold



Notes: This figure shows the distribution of real HELP Income in Australian dollars, which determines an individual's repayment rate on their 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 threshold. 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 have positive HELP debt balances in each year.

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, which is the finest level at which *ALife* reports occupation codes, using the standard deviation of annual (within-individual) changes in log hours worked. This measure is highest for occupations where it is relatively easy to adjust hours, such as for 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 A1 shows this measure for each occupation in my sample.

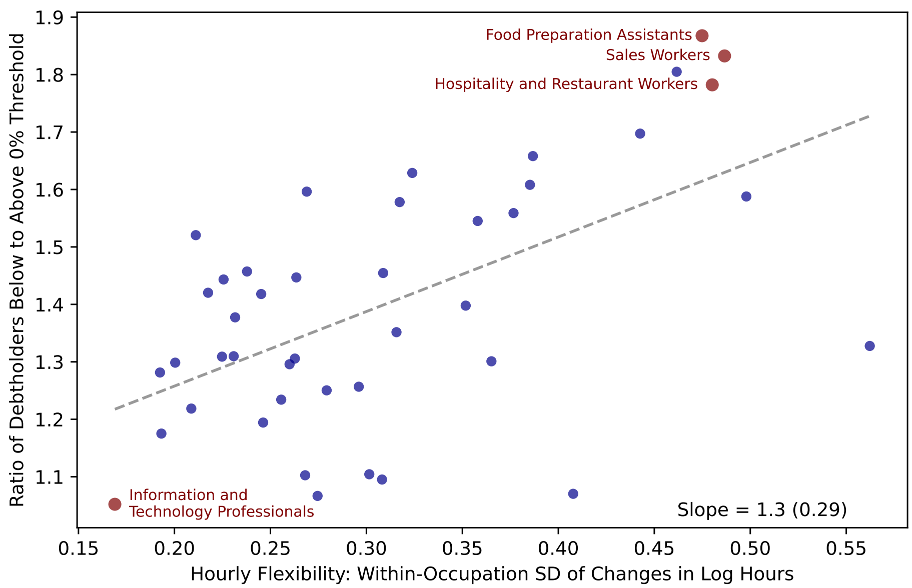
Figure 4 plots the amount of bunching between 2005 and 2018 among wage-earners below the new repayment threshold relative to this measure of hourly flexibility. I focus on the period after the policy change because this is when *ALife* has comprehensive coverage of occupation codes. Each point represents 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 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 relative to 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 relative to above the threshold. Quantitatively, Table A2 shows hourly flexibility explains 34% of the variation in bunching across occupations. Figure A6 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 the scope individuals have for tax evasion since its easier to misreport these sources of income relative to salary and wages, which are generally third-party reported (Paetzold and Winner 2016; Slemrod 2019). Figure A7 shows that this measure, unlike the measure of hourly flexibility in Figure 4, is exhibits little correlation with the amount of bunching below the repayment threshold.

3.3 Fact #3: Borrowers Below 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 from a question asked in the 2016 Census of Population and Housing

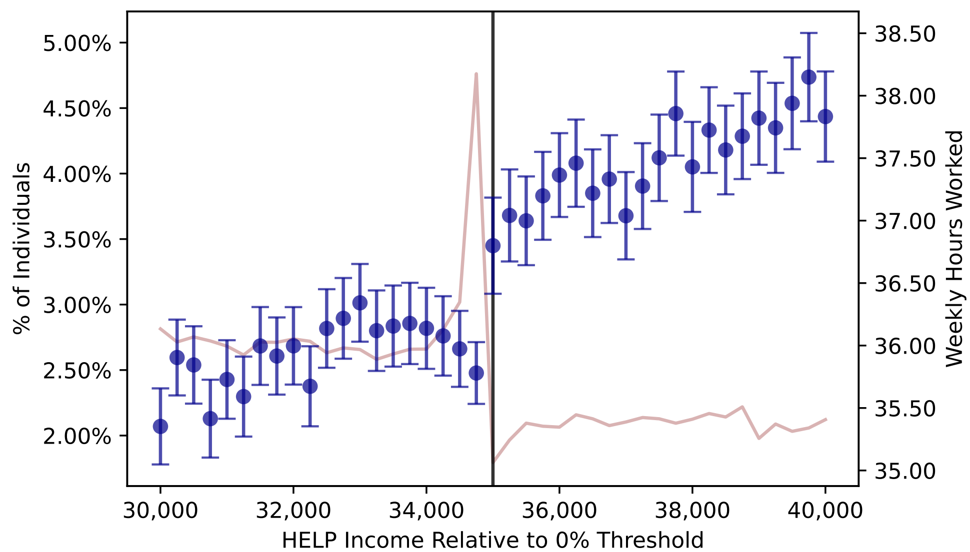
Figure 4. Variation in Bunching across Occupations based on Hourly Flexibility



Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and hourly flexibility by occupation. 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 over 2005 to 2018. Hourly flexibility is measured as the standard deviation of annual changes in log hours worked per week across all jobs reported among individuals in the 2002-2019 HILDA Survey Waves that satisfy the following conditions: (i) report being employed; (ii) earn a positive weekly wage; (iii) do not switch occupations between two subsequent years; (iv) are between ages 23 and 64. Prior to computing the standard deviation, annual changes in log hours are winsorized at 1%-99%. The standard deviation within each occupation is computed using longitudinal survey weights. The highlighted points correspond to several occupations of interest described in the text. The gray dashed line is regression line with the estimated slope coefficient 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 that are wage-earners and have positive HELP debt balances.

in which individuals report the number of hours worked in all jobs 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 the threshold. The standard work week in Australia is 38 hours, so this corresponds to a reduction of 2.6%.[16] This adjustment in hours worked occurs *within* an individuals' current occupation: Figure A9 finds little evidence that those below the repayment threshold are more likely to have switched occupations.

Figure 5. Self-Reported Hours Worked around 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 using 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 around the 2005 repayment threshold. The blue points present the average value of individuals' reported hours worked in all jobs during the week before the Census night 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.

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 of Census data available in MADIP. Second, as discussed in Section 2.4, the MADIP and *ALife* samples differ slightly. To mitigate concerns about sample selection, Figure A11 shows 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. As a result, I do not target this evidence directly when estimating my structural model.

[16]These results are not driven by a group of individuals outside the labor force earning only income from other sources: Figure A10 shows 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 come from exploring 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 beings and X is a constant intended to reach the upper bound at which the income distribution if 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:

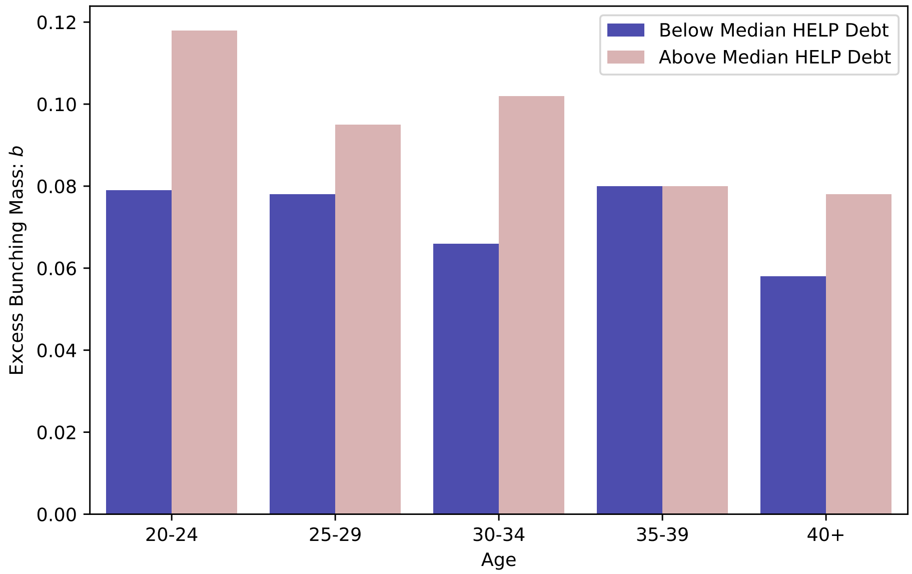
$$b = \frac{\text{observed density in } \mathcal{R}}{\text{counterfactual density in } \mathcal{R}} - 1. \tag{4}$$

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. Appendix E presents additional details on this procedure.

Figure 6 shows this estimated bunching statistic across groups of individuals with different ages and debt balances. I split debt balances at their median value within each year and then split ages into five year bins, which gives a similar number of observations within each bin. The results show two patterns. First, the amount of bunching increases in debt balances: at 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 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 A2 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 A8 and show that there are some occupations in which the average individual will almost certainly earn enough income to repay their debt, while there are others in which the average individual spends their entire life earning income below the repayment threshold. The results in Table A2 show that the amount bunching is larger in occupations with flatter income profiles and lower maximum incomes, both of which support the idea that 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 (above) median debt balances, where the median is calculated separately for each year. The calculation of b is detailed in Appendix E. Standard errors are omitted from this plot because the corresponding 95% confidence intervals are 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 have positive HELP debt balances.

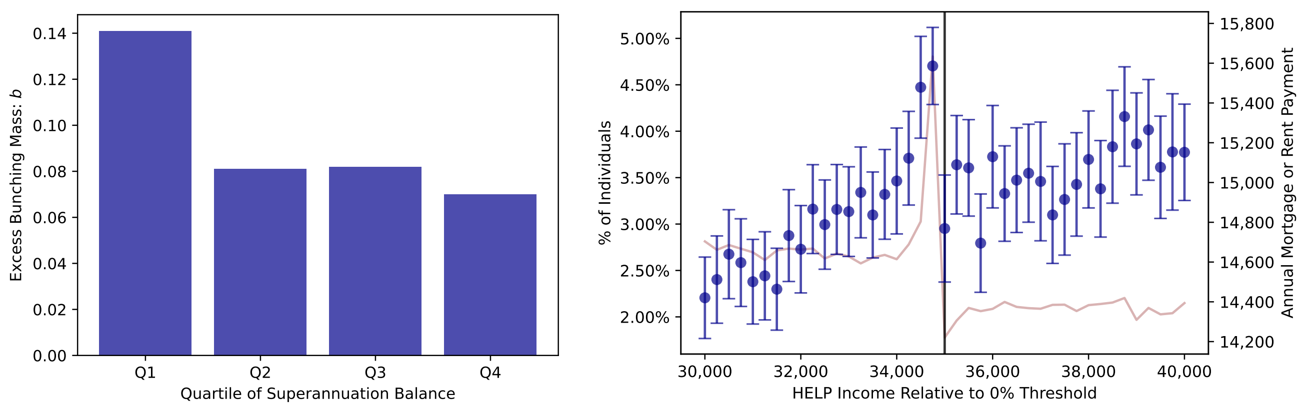
3.5 Fact #5: Bunching Decreases with Proxies for Liquidity

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 complementarity 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 a super account 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 that 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 the amount of bunching is highest for individuals in the bottom quartile, around twice as large as the top quartile. This evidence suggest liquidity constraints, which by revealed preference are tighter for individuals 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 their liquidity demands. 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 this pattern holds in the data: individuals immediately below the repayment threshold tend to have larger housing payments by around \$500-\$1000 (i.e., 3-6%).

Figure 7. Bunching, Retirement Wealth, and Housing Payments



Notes: X.

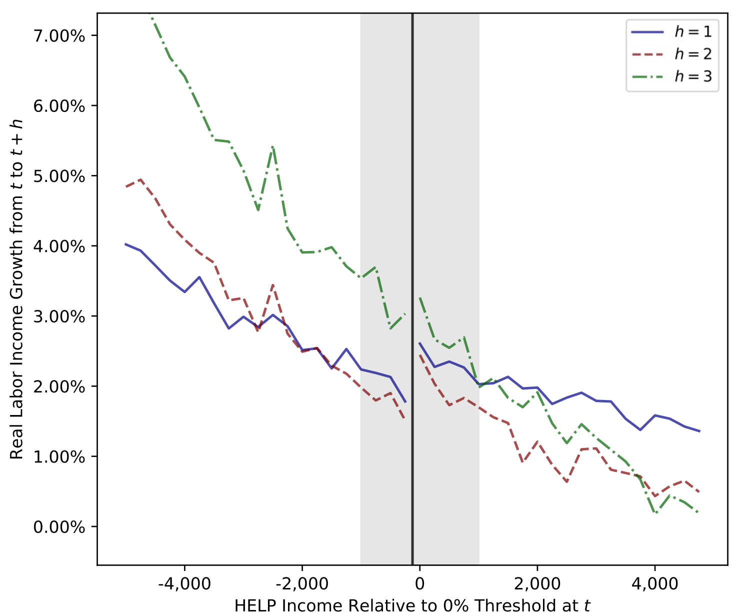
A final, more speculative finding that points to the importance of liquidity is presented in Figure A12, which plots the relationship between the amount of bunching and house prices from CoreLogic across geographic regions. Absent comprehensive data on wealth at the individual-level, house prices are a reasonable proxy for wealth because housing represents the largest form 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., 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.[17]

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 growth rate in Labor Income from year t to $t+h$ based on individuals' locations relative to the repayment threshold in year t. The results show individuals that bunch below the repayment threshold in year t experience lower income growth than those above the threshold in the subsequent year. However, this difference is small, only 1%, and disappears after three years. 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 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 no learning-by-doing is present: larger labor supply reductions could create sizeable longer-horizon costs. Instead, it suggests the size of the responses created by income-contingent repayment are not large enough to create costs over the horizons I observe.

Figure 8. Future Labor Income Growth around Repayment Threshold



Notes: X.

[17]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 it is likely a small driver of the lack of responses. First, the same of individuals around the repayment threshold are relatively low-income, while Kleven et al. (2023) find dynamic compensation plays an important role at the top of the income distribution. Second, Figure A9 shows no discontinuity in the probability of occupation switching around the repayment threshold.

3.7 Possible Other Mechanisms for Bunching Below 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 A7, suggest it cannot explain all of these responses. First, Figure A15 shows 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 the majority of individual tax evasion comes from self-employment income, with an estimated non-compliance rate for third-party reported items, such as salary and wages, of less than 1% (Slemrod 2019). Second, Figure A16 shows the amount of bunching only declines by 6% when restricting to the sample of Wage-Earners, who have substantially less flexibility in reporting their income. Third, Figure A14 shows the amount of bunching is almost identical between individuals who file their tax returns electronically and non-electronically. When filing electronically, pure evasion is much more difficult because sources of Labor Income are often pre-filled by the employer, and, if they are not, the ATO directly 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 I develop in Section 4 will overestimate how much labor supply responds to income-contingent repayment. There are two ways this could affect my normative results. First, if individuals equate the marginal benefits of evasion (i.e., reduced repayments) 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 where 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 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) provides evidence of such a response by firms to reduce income tax rates in Denmark, in which the vast majority of private-sector jobs are covered by collective bargaining agreements. Two findings suggest 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 A13 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, Figure A13 shows this distribution exhibits no bunching in my setting.

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 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).[18]

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), individuals receiving non-pecuniary benefits from work, or pro-social preferences in which individuals feel obligated to repay 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 hours constraints and adjustment costs play a role, and the limited evidence of future wage reductions associated with bunching.

4 Life Cycle Model with Endogenous 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 the moral hazard costs created by income-contingent repayment outweigh its insurance benefits? The section presents and estimates a structural model designed to answer these two questions. The key ingredients in the model are endogenous labor supply, which creates moral hazard 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

[18] One reason individuals may locate above the repayment threshold is that, unlike a tax, income-contingent loans have an additional effect: increasing labor supply today reduces the stock of debt tomorrow. If the value function is sufficiently decreasing in debt, it may be optimal not to locate below the threshold. In Appendix B, I show that for this to be the case, it must be the case that the value function is decreasing in debt more than it is increasing consumption. This is unlikely to be the case because HELP debt has a zero real interest rate, and individuals have the option to make voluntary repayments, but the majority do not.

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 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.[19] 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.[20] 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 calibrated values of n_a are hump-shaped.

[19](5) also 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. However, 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.

[20]Auclert and Rognlie (2017) point out that GHH preferences generate an additional source of amplification in response to shocks due to the complementarity of consumption and leisure. This amplification is not present in my model since wage rates are not determined in general equilibrium.

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 specification in (7) allows for idiosyncratic permanent and transitory shocks to wage rates, which is important because individuals can only self-insure against the latter in incomplete markets. The transitory component consists solely of ϵ_{ia}, which 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 for 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 "Non-Graduates". 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.[21]

4.1.5 Labor Supply Optimization Frictions

Individuals choose their labor supply at the same time 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 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.[22]

The first optimization friction is that choosing labor supply in the current period that is different from 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 individuals only adjust their labor supply 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).

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

[21] I do not allow for the possibility that the quadratic component of g_{ia} differs with $\mathcal{E}_i$. This is because *ALife* only covers 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 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.

[22] An alternative friction is optimization errors that could take two forms, both inconsistent with my empirical evidence. The first is anticipated errors, in which individuals know they cannot control labor supply perfectly. This, however, makes 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 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 predicts that the bunching will be diffuse around the repayment threshold, while the bunching in Figure 3 is sharp.

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.[23] Individuals that 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:

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

In this model, the interest rate and borrowing wedge are taken as exogenous. This is primarily done for tractability, but it is unlikely to affect the conclusions from my counterfactual analyses for two reasons. First, individuals with large student debt balances, who are most affected by the policy changes I consider, are young and hold a relatively small share of aggregate wealth. Second, simulation results show that the change in the aggregate stock of liquid assets in response to these policy changes is negligible, suggesting any change in the equilibrium interest rate would be small.

[23]This imperfect 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

The government earns revenue from progressive taxes on labor and asset income and student debt repayments. Total taxes on labor and asset income are denoted by $\tau_{ia} = \tau(y_{ia}, i_{ia}, t)$. 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 individuals' consumption exceeds their disutility from labor supply by $\underline{c}$ in the event they do not adjust the latter.[24] 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 wage rate, and ϵ_{ia} = transitory component of 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 the vector of these state

[24]The combination of GHH preferences and labor supply optimization frictions implies that there will be parts of the state space where individuals cannot ensure 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.

variables for individual i at age a as $\mathbf{s}_{ia}$ and $E_a(\cdot) = E(\cdot \mid \mathbf{s}_{ia+1})$ as the conditional expectation over the three shocks, ω_{ia+1}, ν_{ia+1}, and ϵ_{ia+1}. There are two controls: end-of-period liquid assets, A_{ia+1}, and labor supply, ℓ_{ia}, where consumption, c_{ia} is pinned down by the budget constraint.

Suppressing i subscripts, individuals at age $a < a_R$ that 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 $a < a_R$ that 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 standard numerical discrete-time dynamic programming techniques. The code to solve and simulate the model is compiled in Intel Fortran 2018 and executed in parallel using both MPI and OpenMP across 1,536 CPU threads. For additional details on the solution technique, see Appendix F.

4.2 Estimation Procedure

This section describes how I estimate the model. In a first step, I calibrate parameters that can be observed directly and others based on prior literature. In a second step, I estimate the remaining parameters using simulated minimum distance.

4.2.1 Calibrated Parameters

Table 2 shows the values of parameters that I can calibrate directly using either 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 G for additional details.

Demographics. Individuals are born at age 22, which corresponds to the typical age at which students graduate from university in Australia, retire at age 65, which is 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 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 using 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* that have positive debt balances, which is the year 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 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 to individuals above 22. The retirement pension is calculated following the Age Pension formula, the primary government-provided form of income-support to 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 I do not estimate due to a lack of identifying variation are relative risk aversion and the elasticity of intertemporal substitution. 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 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, which controls the elasticity of future wages to current labor supply. 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 using simulated minimum distance, which I denote by Θ:

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

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 of 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: the labor supply elasticity, ϕ, fixed adjustment cost, f, and Calvo adjustment probability, 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)

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	τ_b	14.6%
Borrowing limit	$\{\underline{A}_a\}$	HILDA Credit Card Limit
Probabilities of zero initial assets	$p_A(1)$, $p_A(0)$	0.197, 0.350
Means of $\log A_{ia_0}$	$\mu_A(1)$, $\mu_A(0)$	7.42, 6.79
Standard deviations of $\log A_{ia_0}$	$\sigma_A(1)$, $\sigma_A(0)$	1.72, 2.64
Student Debt		
Fraction of Graduates	p_E	0.308
Real interest rate on debt balances	r_d	0%
Mean of $\log D_{ia_0}$	μ_d	9.40
Standard deviation of $\log D_{ia_0}$	σ_d	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 value and/or sources of parameters in the model that are calibrated in a first-stage. Additional details on this calibration are presented in Appendix G.

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, which is a vector of moments, summary statistics, or auxiliary parameters, and a weighting matrix. Denote the empirical values of 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 I use are shown in Table A3 and discussed in the next section. Additional details on the calculation of each target in the data and within the model are presented in Appendix H. Because this optimization problem is high-dimensional and likely has several local optima, I perform the minimization using a modified version of the TikTak algorithm introduced by Arnoud et al. (2019).

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. Table A3 lists each estimation target and the parameter(s) that it primarily identifies. The discussion in this section is mostly qualitative; Table A4 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. I use bins of \$500 to minimize approximation error in my estimation of the model moments.

Fixed adjustment cost, f, and Calvo probability, λ. These two optimization frictions are jointly identified by the number of individuals above the repayment threshold: even with a very small labor supply elasticity, a model $f = 0$ and $\lambda = 1$ would predict no individuals 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 relative to the lowest 2005 0.5% threshold because the former has a discontinuity in 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 across debt balances because adjustment depends on whether individuals receive the adjustment 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 relative to 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 quartile 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 for 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 the education level dummy, in addition to the average level of income. If labor supply was exogenous, they could be estimated separately using 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 works similarly 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 future income growth: a larger variance of permanent shocks, σ_ν, delivers fatter tails in 5-year relative to 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 around 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 of income.

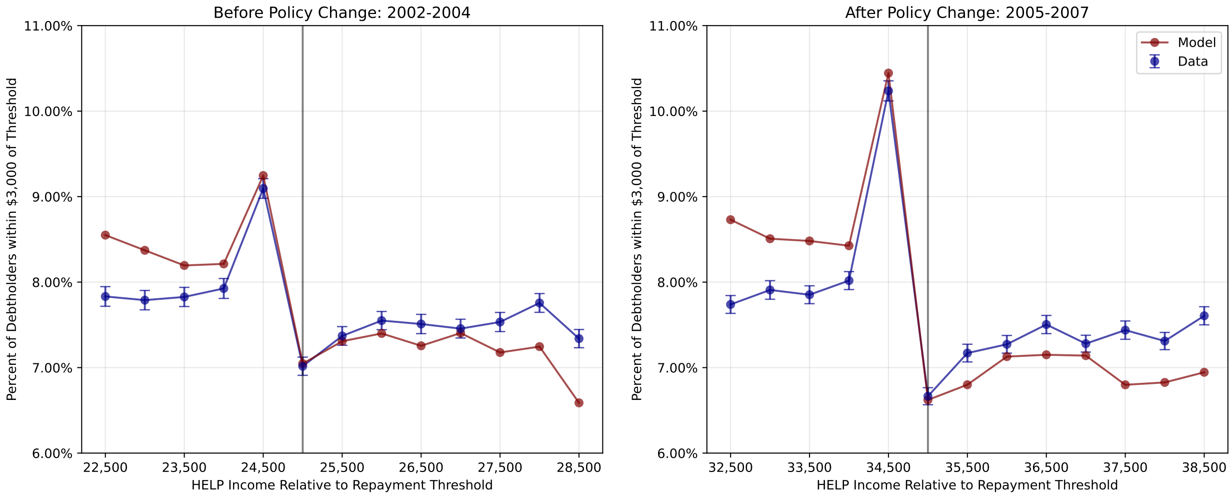
Figure 10 illustrates the model's fit of the amount of bunching at other repayment thresholds, in addition to among individuals with different debt balances. Consistent with Figure 9, the model replicates the bunching at the 2004 and 2005 repayment thresholds well. However, the model can also replicate 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 the amount of bunching at this threshold and the 0% threshold because the probability that individuals receive an adjustment shock is independent of 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

Table 3. Simulated Minimum Distance Estimation Results

Parameter		Estimation (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 Table A3. 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 but no Calvo adjustment; column (4) does the reverse; column (5) estimates the same model 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 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).

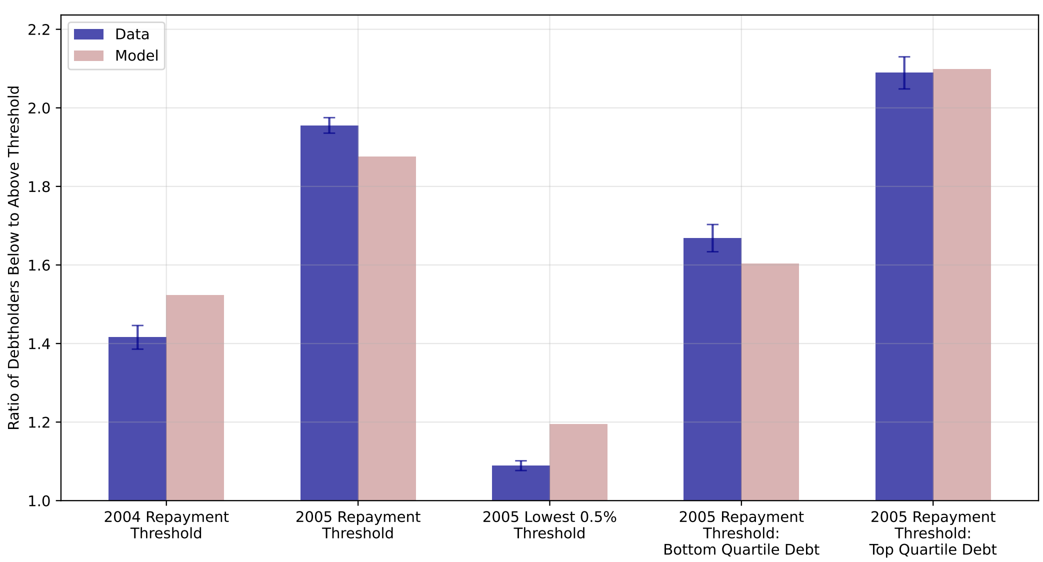
Figure 9. Baseline Model Fit: HELP Income Distribution around Policy Change



Notes: The left panel of this figure plots the HELP Income distribution within $3,000 of the repayment threshold in bins of $500 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 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. Additional details on the calculation of these estimation targets are presented in Appendix H.

underestimates.

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. plots the same quantities from the model with parameters set at the estimated values in column (1) of Table 3. Column (1) is 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 each individual-year observation into whether it falls within the bottom and top quartile of debt balances in 2005 AUD. Additional details on the calculation of these estimation targets are presented in Appendix H.

Table 4 shows the fit of the model on 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 depends on endogenous labor supply. To the extent the age profile of labor supply varies over the life cycle for reasons outside the model, it will be unable to match these age profiles.

Table 4 shows the cross-sectional variance of income is mostly increasing over the life cycle, a fact first documented by Deaton and Paxson (1994). 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 a limited form of 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 (Guvenen 2009a). Nevertheless, to address the concern that an upward bias in ρ would overstate the income risk and hence the insurance benefits from income-contingent loans, I consider alternative values of ρ when comparing different 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 in the baseline. This estimate is similar to 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 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).

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. Additional details on the calculation of these estimation targets are presented in Appendix H.

4.4 Identification of Labor Supply Elasticity and Optimization Frictions

The three most important parameters in my model are the labor supply elasticity, ϕ, Calvo adjustment probability, λ, and fixed adjustment cost f. 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 separate these different parameters that jointly determine individuals' 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 (1.6 million individuals over 68 years) and the fact that no choice variables are discretized in the solution (discussed in Appendix F) 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. In order 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 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. Section 4.4 shows that the two optimization frictions are crucial for matching the labor supply responses in the data and identifying the labor supply elasticity. 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 the baseline model, and that the fit of the model is mostly unchanged This suggests 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. Existing 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 most closely related. 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 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 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 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 median income. This suggests my estimated elasticity should be lower, given I do not study high-income individuals that 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 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 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 individuals face in my model, which I abstract from due to 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 0.77 in Guvenen et al. (2022). This primarily reflects that the cross-sectional standard deviation of income at age 22 in Australian data is around 20% lower than in US data. Additionally, I estimate a standard deviation of transitory shocks that is around 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 than in the US. Second, the fact that labor supply is endogenous implies that some transitory variation in income arises endogenously from labor supply adjustments rather than exogenous transitory wage shocks.[25] Lastly, my estimate of the standard deviation of permanent shocks is around 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 that I have heterogeneous income profiles across the two education groups (Guvenen 2009a), which requires a larger variance of permanent shocks to match the percentiles of 5-year income growth.

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

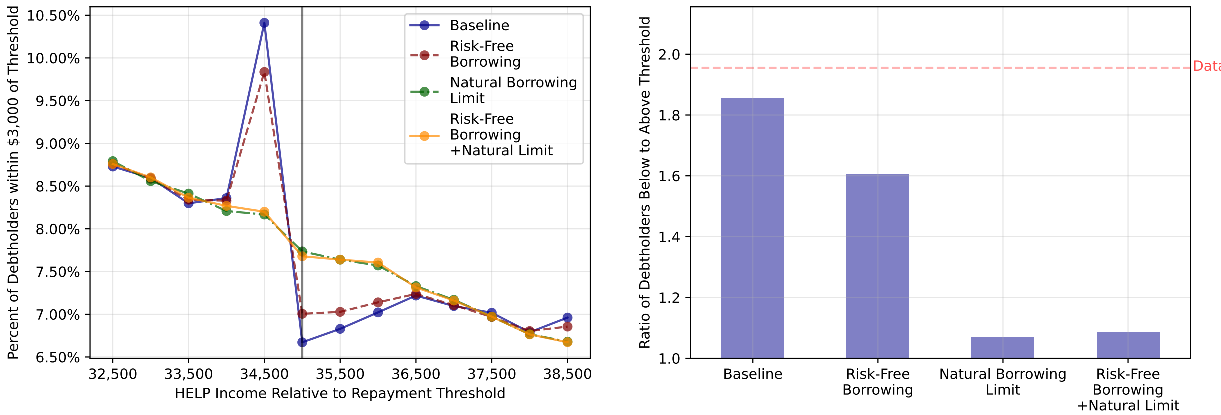
Figure 11 shows how the amount of bunching below the repayment threshold in the model varies depending on the tightness of liquidity constraints. The left and right panel plot the income distribution and the ratio of individuals below to above the 2005 repayment threshold, respectively, for the baseline 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, the amount of bunching decreases moderately: the amount of individuals below relative to 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.[26] 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 individuals with less wealth in the form of retirement savings are more likely to bunch below the repayment threshold. Figure A26 shows 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

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

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

Figure 11. The Effects of Liquidity Constraints 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, as in the right panel of Figure 9, 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.

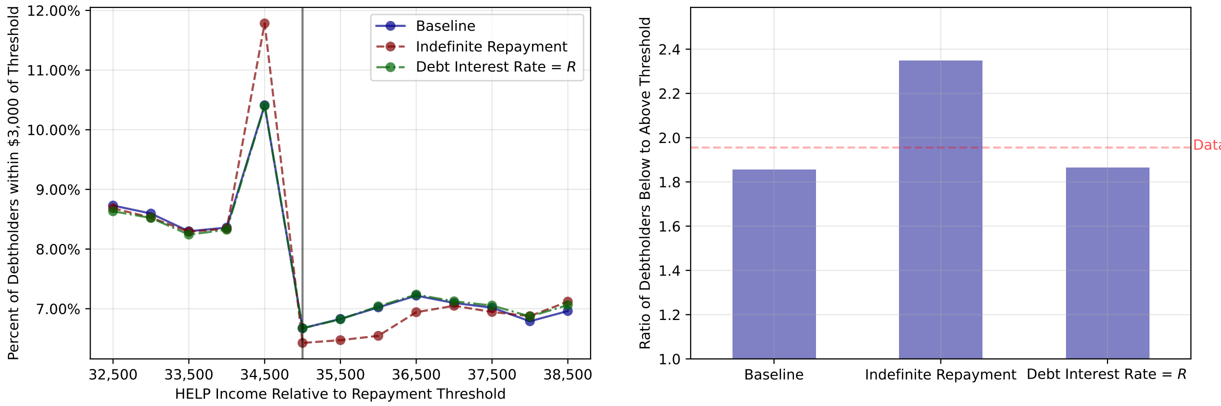
bankruptcy (Indarte 2023).

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 12 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 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 12 shows 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.

Figure 12. 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, as in the right panel of Figure 9, 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.

6 Normative Analysis of Repayment Contracts

This section uses my estimated structural model normatively to study the welfare and fiscal impact 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 all prices (e.g., wages and interest rates). This problem of choosing a single repayment contract is faced by governments that only offer 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 repayment contracts with a zero interest rate, as is the case in Australia.[27]

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 compute the welfare gains from constrained-optimal income-contingent contracts with the same fiscal cost as fixed repayment contracts.

6.1 Existing Income-Contingent Loans Improve Welfare, but Have Higher Fiscal Costs than Fixed Repayment

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. This fixed repayment contract corresponds to a standard debt contract in which individuals make constant repayments over the

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

25 years post-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 differs in that it is not income-contingent.

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 over individuals' lifetimes.[28] 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.[29] $\mathcal{R}_a$ 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 used during estimation. This specification is smooth and provides a close approximation to unconstrained optimal policies (Heathcote and Tsujiyama 2021), which is unlikely to be the case for the actual ATO Schedule. I also adopt a smoothed

[28] I ignore the retirement pension because I remove means-testing based on wealth in all counterfactuals for reasons discussed in Appendix G.

[29] 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 implies by the first-order condition of a hypothetical lender with discount rate, $\mathcal{R}_a$. Additionally, this definition is preferable when considering 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.

specification of the ATO unemployment benefit formula used in estimation; see Appendix G for additional details.

Results. The left panel of Figure 13 presents the welfare and fiscal impact of the income-contingent loans used in the US and Australia. For clarity, 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:[30] "*What value of a cash transfer at age a_0 would make an individual that attends college, prior to knowing her other initial states, indifferent between repaying under a new policy and repaying under 25-year fixed repayment?*"

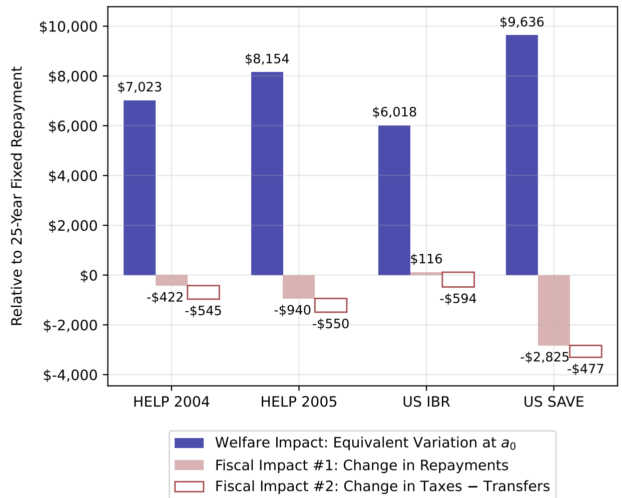
The first two columns show that both HELP repayment policies – before and after the policy change – provide gains equivalent to cash transfers of around \$7,500, which is 43% of the average initial debt balance in the model of \$17,500. These gains, however, come at a fiscal cost: in present value terms, the government collects around \$750 less in student loan repayments and \$550 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"), both in which individuals make repay a fixed rate of income earned above a certain threshold.[31] These two columns show that the two US IBR contracts deliver similar gains to HELP contracts but differ in fiscal cost. The current US IBR program has a fiscal cost that is around 60% lower than the HELP contracts, which is driven by the fact that 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 in this policy. Dividing the welfare gains by 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).

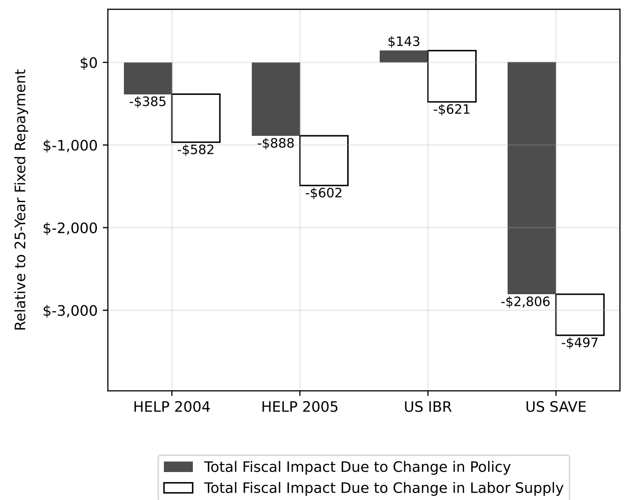
The right panel of Figure 13 decomposes the total fiscal cost associated with moving from 25-year fixed repayment to income-contingent loans, the sum of the two fiscal impacts shown in the left panel, into two components. The first component, shown in the top black component of each bar, is the change 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 around 50% of the total cost from switching to HELP 2004 and HELP 2005 and 130% for US IBR. For US Proposed IBR, it

[30] See Appendix J for details on the calculation of this welfare metric.

[31] I implement these contracts without loan forgiveness in order for them to be comparable to the HELP contracts and return to the effects of forgiveness later.

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





Notes: The left panel in this figure shows the welfare and fiscal impact of moving from 25-year fixed repayment to four different existing income-contingent repayment contracts: the HELP policies before and after the policy change, the existing US IBR program without forgiveness, and the new IBR program introduced by the Biden administration known as SAVE. The first dark blue bar in each column shows the equivalent variation at a_0 to an agent with $\mathcal{E} = 1$ that 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 individuals' labor supply remained at its value under 25-year fixed repayment. The second is the residual due to endogenous changes in labor supply.

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 13 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 A Constrained-Optimal Income-Contingent Loan Provides Welfare Gains at Same Fiscal Cost as Fixed Repayment

The evidence in Section 6.1 shows that the welfare gains of 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 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 constrained-planner's problem. I consider a social planner that maximizes borrower welfare by choosing one mandatory repayment contract. I assume 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 functional of the stochastic consumption and labor supply streams, which depends (implicitly) on the three policy parameters, to an individual who is "behind the veil of ignorance" with respect to her initial conditions.[32] The first constraint requires that the fiscal revenue from the chosen repayment contract is at least $\overline{\mathcal{G}}$, which I set equal to the revenue raised from a 25-year fixed repayment contract without any forbearance (i.e., payment pauses for low-income borrowers). I choose this contract because it creates a realistic fiscal cost and serves as a natural benchmark to an income-contingent loan given it has a similar repayment duration. I then consider the effect of adding forbearance in Section 6.4. 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, especially when considering higher-dimensional contracts, because it is a nonlinear constrained optimization problem in which the objective and constraints do not have closed-forms. I thus leverage a combination of barrier methods in numerical optimization (Nocedal and Wright 2006) and the TikTak global optimizer from Arnoud et al. (2019) detailed in Appendix K.

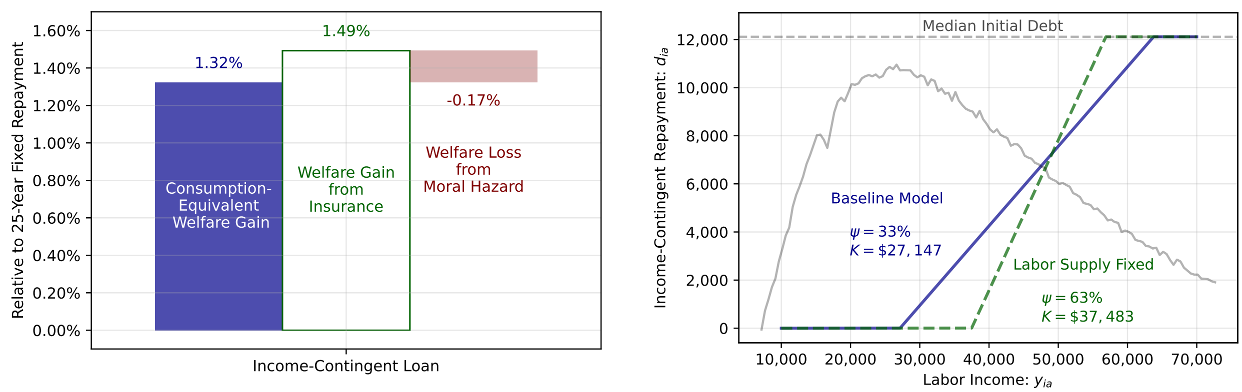
Solution to planner's problem. The red solid line in the right panel of Figure 14 plots repayments as a function of income on the constrained-optimal income-contingent loan that solves (17) for an individual with a median initial debt balance. This contract provides individuals with significant insurance 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 repayments begin in HELP 2004 system but lower than in HELP 2005. In US IBR con-

[32]As in Section 6.1, I focus only on the welfare of college-educated individuals with $\mathcal{E}_i = 1$.

tracts, 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.[33]

In order to collect sufficient revenue with a relatively high repayment threshold, the constrained-optimal contract has a repayment rate of ψ = 33%, around 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 repayments are capped by initial debt balances. 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. As a result, individuals below the threshold do not receive an increase in their cash on hand, eliminating the liquidity effect discussed in Section 5.1. The lack of bunching is consistent with Britton and Gruber (2020), who find limited bunching in the UK, where the repayment threshold changes the marginal repayment rate.

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



Notes: The left panel of this figure plots the consumption-equivalent welfare gain at a_0 of 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 initial debt balances 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 median initial debt balances, which places an upper bound on repayments from the income-contingent loans.

Effect of moral hazard. To isolate the impact of moral hazard on the design of income-contingent loans, the dashed green line in Figure 14 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.[34] The results show this alternative contract provides even more insurance than the contract

[33] As of 2023, the US federal poverty line for a single household is \$14,580 USD. Deflating this to 2005 USD using the CPI and then converting to 2005 AUD using 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.

[34] In this model, I exclude disutility from labor supply from welfare since individuals are not choosing it.

in my baseline model, with a 30pp 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 government revenue and affects the repayment contract the planner offers in equilibrium. Since the planner cannot raise a sufficient amount of revenue implementing the alternative 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 14 shows the welfare gain from the constrained-optimal income-contingent loan in Figure 14. To measure welfare gains, I use the metric from Benabou (2002): "*What value of g would make an individual that attends college, prior to knowing her initial states, indifferent between repaying under a new policy and repaying under 25-year fixed repayment contract with their consumption increased by $g\%$ in every state of their life?*" The leftmost blue bar in Figure 14 shows that the optimal income-contingent loan provides gains equivalent to a 1.32% increase in lifetime consumption relative to 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 14 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 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 of this wage-contingent loan and the constrained-optimal income-contingent loan. The results show that the cost of moral hazard is relatively small, accounting for 0.17pp or a 13% reduction in the total gain.

Welfare loss from lower repayment rate. As discussed above, the repayment rate on the constrained-optimal income-contingent loan is higher than those 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 0.20pp or 14%. Around half of this loss comes from a lower repayment rate requiring a lower repayment threshold to satisfy the government budget constraint, reducing the amount of insurance. The remaining half comes from the lower repayment threshold inducing labor supply responses by more individuals, which increases the loss from moral hazard.

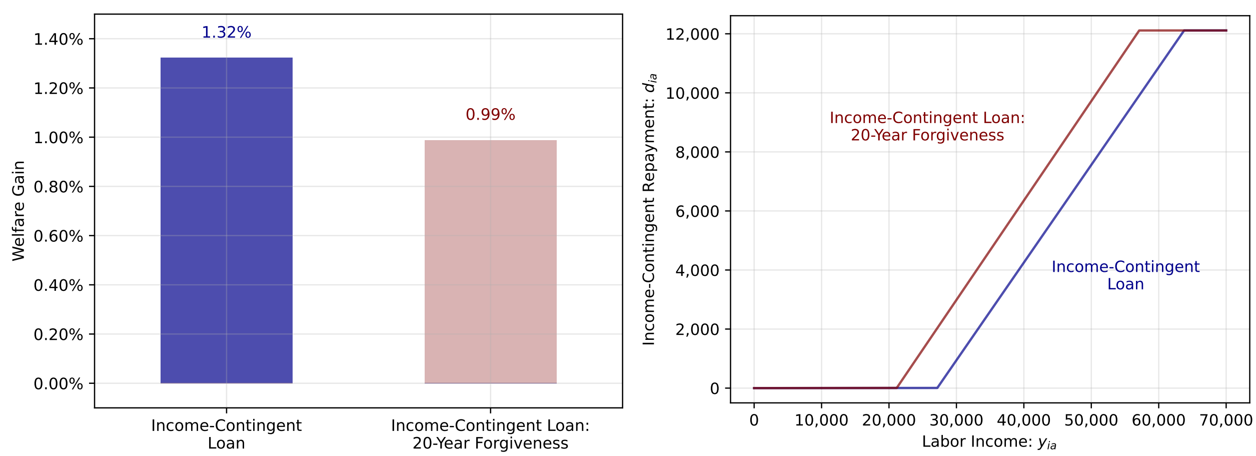
Comparison with existing contracts. Comparing the income-contingent loan in Figure 14 directly with existing contracts mixes differences that come from the former being constrained-optimal, but also that the latter raise different amounts of revenue. Figure A30 shows the results from resolving (17) with $\overline{\mathcal{G}}$ set equal to the revenue raised from the HELP 2004, HELP 2005, and US IBR contracts, separately. Consistent with the qualitative patterns in Figure 14, each constrained-optimal repayment contracts has a higher repayment threshold and rate that the corresponding benchmark contract.

6.3 Adding Forgiveness Reduces Welfare Gains of Income-Contingent Loans

I next consider the effects of adding forgiveness after a fixed horizon to income-contingent loans, as in the US and UK. The left panel of Figure 15 compares the gain from the income-contingent loan in Figure 14 with a constrained-optimal income-contingent loan with forgiveness at $a_0 + 20$, as in the currently available US IBR contracts. The latter contract generates a welfare gain of 0.99%, around 0.33pp lower than the contract without forgiveness repeated in the first column.[35]

The reduction in the gain from adding forgiveness reflects a combination of two forces. First, adding forgiveness at the same fiscal cost requires a lower repayment threshold of K=\$21,131, as shown in the right panel of Figure 15. The consequence of a lower repayment threshold is greater repayments from young borrowers in exchange for lowering repayments on older borrowers, for whom repayments are forgiven (Figure A31). This reduces the gain from insurance 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 that reduces the gain from forgiveness is that a finite forgiveness horizon increases the loss from moral hazard (Figure A29). With a finite forgiveness horizon, borrowers are more willing to reduce their labor supply to lower repayments because it is less likely they will have to make these repayments later in their life cycle.

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



Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from 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.

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

6.4 Income-Contingent Repayment Provides Larger Gains than Adding Forbearance

Relative to a fixed repayment contract, the income-contingent loan in Figure 14 has two key differences. First, the latter contract provides payment reductions for low-income borrowers, whose income is below the repayment threshold. Second, income-contingent loans collect more 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 16 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.[36] The left panel of Figure 16 shows 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.[37]

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 Figure 16, the income-contingent loan collects more 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.

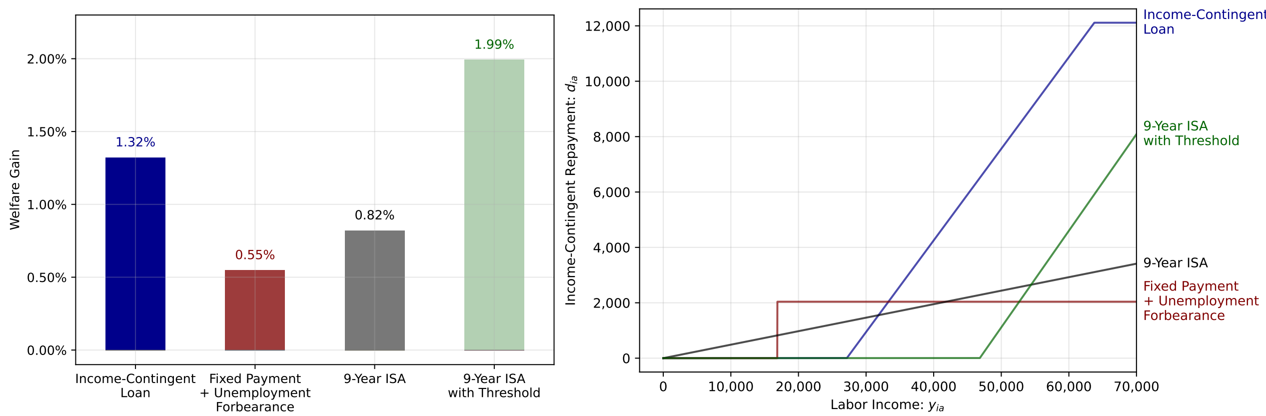
6.5 Equity Contracts Generate Larger, but More Dispersed, Welfare Gains

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). Setting aside these selection issues, 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

[36]An alternative contract would be a 25-year fixed repayment contract with the same unemployment forbearance, where the interest rate is adjusted to balance the government budget. I choose not to use this contract to ensure close comparability with income-contingent loans: the former makes payments conditional on debt balances, while income-contingent loans do not. Nevertheless, this alternative contract delivers a similar gain of 0.52%.

[37]A natural question is whether there are welfare gains to combining these two repayment contracts: Figure A33 shows that doing so optimally provides minimal welfare gains over the income-contingent loan in Figure 14.

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



Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from 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.

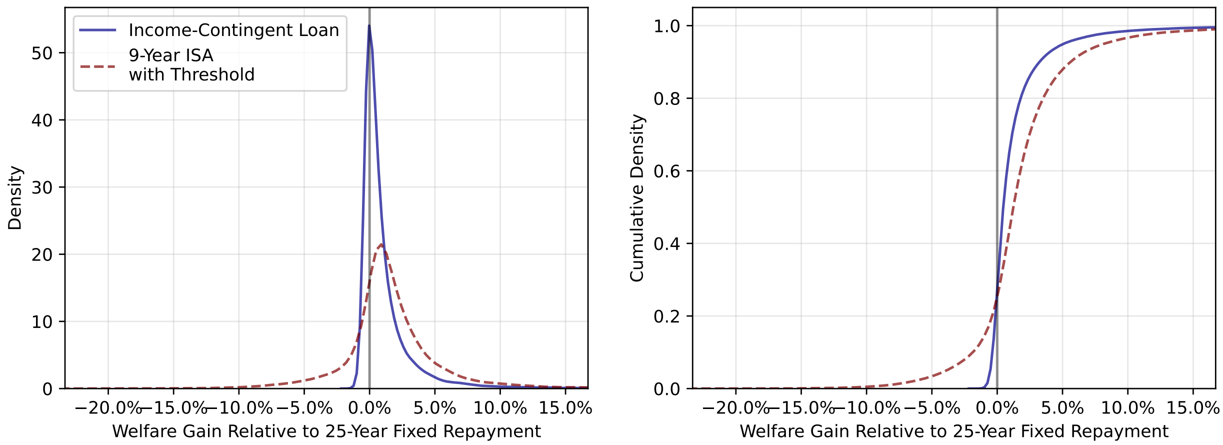
for nine years (Mumford 2022).

The third column in the left panel of Figure 16 shows the welfare gain from a nine-year ISA is 0.82%, where the parameter controlling the share of income repaid has been adjusted to balance the government budget. This gain is around 40% (or 0.5pp) 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 repayment reductions the most, in exchange for zero payments when they are older (i.e., after nine years).

The final column of Figure 16 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 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 low-income young 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 16 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 also more heterogeneous. Figure 17 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 gives gains for around 70% of individuals, while the remaining 30% experience small losses. These small losses are concentrated among high-income individuals, who are required to repay their loans faster under income-contingent relative to fixed repayment.

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



Notes: This figure plots the distribution of welfare gains at a_0 relative to 25-year fixed repayment from the constrained-optimal income-contingent loan in solid blue and 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. Due to computational constraints, the welfare gains in this plot are computed as the percent change in initial certainty-equivalent values, which corresponds to the value of g that would make an individual indifferent between the original contract and having their consumption net of the utility of labor supply increased by $g\%$ in every state of their life. This quantity is quantitatively very similar to the consumption-equivalent welfare gain used in other plots, but is easier to compute because it does not require solving a numerical fixed point for each initial state.

Figure 17 shows that the gains from the optimal equity contract are significantly more dispersed. Relative to 25-year fixed repayment, 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, which is sufficiently large to reverses the ranking of certainty-equivalents across terciles of initial debt (Figure A34).

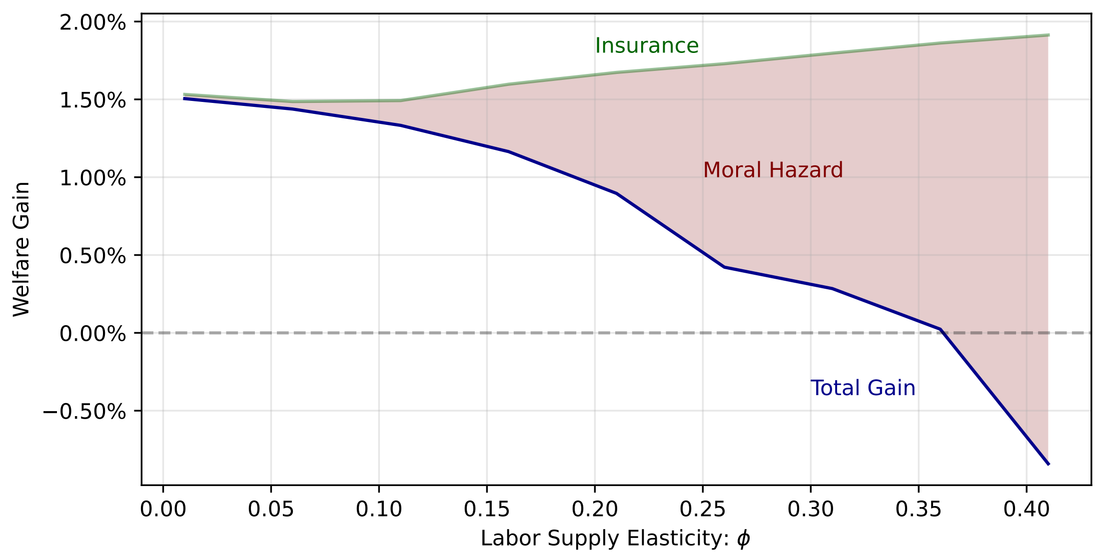
In sum, although properly-designed equity contracts give larger average welfare gains, they are also more likely to generate ex-ante responses not captured by my model because the distribution of gains across initial debt balances is significantly more dispersed. This suggests that income-contingent loans may be a more robust mechanism for implementing income-contingent repayment.

6.6 A Higher Labor Supply Elasticity Increases Welfare Loss from Moral Hazard, But These Losses Can Be Reduced with Alternative Contracts

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 gains from the resulting constrained-optimal contracts are plotted in Figure 18. 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 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 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 prior literature: its above the 75th percentile of the estimates reported in Figure A24.

Figure 18. Welfare Gains from Constrained-Optimal Income-Contingent Loan as a Function of ϕ



Notes: This 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, ϕ, 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 14. The point at which the dashed gray line intersects the solid blue line corresponds to $\phi = 0.37$, which is the labor supply elasticity above which the cost of moral hazard outweights the insurance benefits.

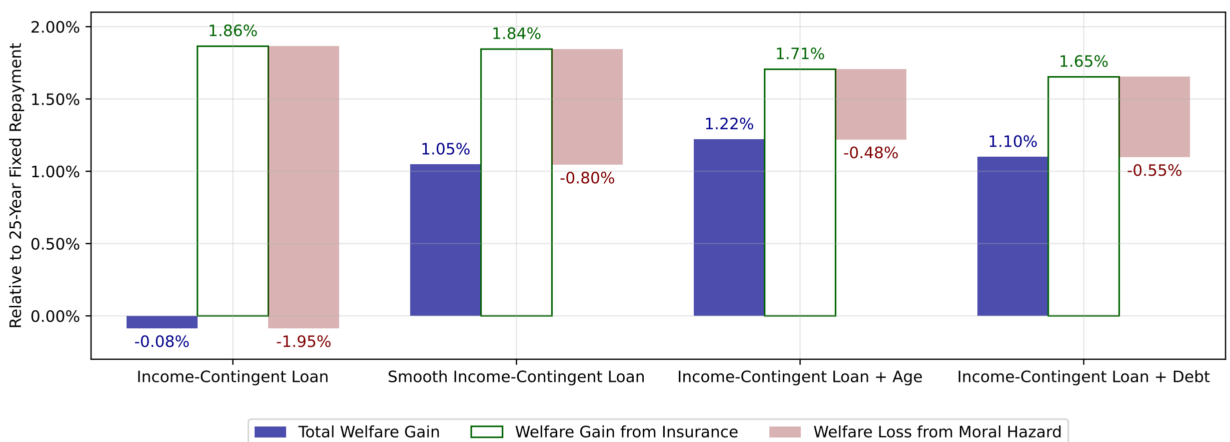
Motivated by Figure 18, I next consider whether the following alternative forms of income-contingent loans can reduce the welfare cost of moral hazard, even when $\phi = 0.37$:

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

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 repayments conditional on age and debt, respectively. For each of these alternative contracts, I solve (17) to find the constrained-optimal values of $\{\psi_i\}$.

Figure 19 shows the gains from these contracts in my baseline model with $\phi = 0.37$, in which the US IBR-style income-contingent loan delivers losses relative to 25-year fixed repayment.[38] The results show that all three of these contracts restore the gains of income-contingent repayment. These large gains come entirely from reducing the cost of moral hazard: the smooth income-contingent loan generates a 105pp reduction in this cost, while the age- and debt-contingent contracts generate additional 32pp and 25pp reductions, respectively. Figure A37 plots these constrained-optimal repayment contracts, which shows 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 that a contract that solves the unconstrained version of (17) must feature some insurance because the gains from insurance are first-order while the losses from moral hazard are second-order.

Figure 19. 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 14, for different constrained optimal repayment contracts described in the text. This analysis is performed with all parameters set at their estimated and calibrated values in the baseline model, except the labor supply elasticity ϕ is set equal to 0.37.

[38] Figure A36 shows the results in the baseline model. In this model, all three contracts deliver almost identical 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, as evident from the lack of bunching in Figure 14.

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 heterogeneity that is not in my baseline model. To assess the importance of this heterogeneity, I consider an extension with two group 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 the baseline model. Although this suggests 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 model with learning-by-doing estimated in column (5) of Table 3. This model generates similar but slightly larger gains than the baseline model. This is 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 repayments 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 relative to 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. There is disagreement in existing literature on the size of wealth effects on labor supply. For example, Cesarini et al. (2017) find relatively 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 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, row (4) also shows wealth effects have a minimal effect on the optimal contract.

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 US-style IBR contract that solves (17) and its corresponding consumption-equivalent welfare gain relative to 25-year fixed repayment in a series of alternative models described in the text. Each row presents the results from a different model that deviates from the baseline model in a specific way; the results from the baseline model, shown in Figure 14, are repeated at the bottom of the table. The welfare gain from insurance and welfare cost of moral hazard are not reported for the learning-by-doing model because in that model wage rates are endogenous, so a wage-contingent repayment contract also introduces some welfare costs of moral hazard. The last row in the table repeats the results for the baseline model. The second-to-last row shows the equally-weighted average of all values, excluding those from the baseline model.

Persistence of income risk. Because individuals can self-insure against transitory but not permanent shocks in incomplete markets, correctly estimating the persistent 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, raise the gains from income-contingent repayment, while a lower ρ does the opposite. These in row also affect the optimal financing contract, but this is mostly because chaning ρ in isolation has a meaningful effect on the distribution of income.

Non-normal income risk. Recent evidence from administrative data on highlights the importance of non-normal 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 independent two 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 baseline 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 of 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 debts, 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, which 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 similar gains, but the optimal contract provides more insurance to account for the US tax system being less progressive.

Higher level of initial debt. An important difference between the US and Australia is the level of initial debt 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 around $17,400 AUD in 2005 ($20,500 USD in 2023). 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 coefficient of relative risk aversion, γ, and the elasticity of intertemporal substitution, σ^{-1}. Starting from the baseline values, I first set $\gamma = 7.5$ as in Bansal and Yaron (2004), which increases both individuals' risk aversion but also introduces a demand for the early resolution of uncertainty (Epstein and Zin 1989). 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 Bansal and Yaron (2004). This reduces the welfare gain because some of the benefits of income-contingent repayment are from improving consumption-smoothing over time, which is less valuable with a higher EIS. Finally, 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 of 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 agents' consumption paths that affects welfare because of risk aversion and incomplete markets, and (iii) redistributive effects due to changes in consumption-equivalents across different initial conditions (Benabou 2002). Due to the non-homotheticity and non-convexities in my model, calculating these terms analytically is not possible. To assess the importance of each of these terms, I compare the gain in the baseline model with the gains 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 of the latter model should be due to level effects, while the difference between the two captures redistributive effects. The size of uncertainty effects can be estimated by comparing the baseline model to the model with no ex-post uncertainty. The results from these two models are shown in rows (16) and (17), which show that most of the gain comes from redistributive and uncertainty effects, with around half coming from each.

7 Conclusion

This paper studies the trade-off between providing insurance and disincentivizing labor supply in student loans with income-contingent repayment. I show borrowers adjust their labor supply to reduce 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 a fixed repayment contract with forbearance, they can provide more insurance by accelerating payments from high-income individuals. Relative to equity contracts, they are less likely to generate ex-ante responses because their 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). Alternatively, it may have an extensive margin effect through encouraging more borrowers to pursue higher education.

More broadly, the trade-off between insurance and incentives studied here applies when designing 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 they create. By carefully analyzing the insurance-incentive trade-off for student loans, this paper provides a model for approaching 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.

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

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*.

Auclert, Adrien and Matthew Rognlie (2017), "A note on multipliers in NK models with GHH preferences." *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."

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*.

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

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.

DeFusco, Anthony A., Tang Huan, and Constantine Yannelis (2022), "Measuing the Welfare Cost of Asymmetric Information in Consumer Credit Markets." *Working Paper*.

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.

Duffie, Darrell and Kenneth J. Singleton (1993), "Simulated Moments Estimation of Markov Models of Asset Prices." *Econometrica*, 61, 929–952.

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*.

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

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.

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.

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.

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

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.

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

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.

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

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.

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.

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

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

Saez, Emmanuel (2002), "Optimal Income Transfer Programs: Intensive versus Extensive Labor Supply Responses." *Quarterly Journal of Economics*, 1039–1074.

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

This appendix contains the following additional materials.

Appendix A. Model Parameters

Appendix B. Theoretical Appendix

B.1 Derivation of (2)

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

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

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

subject to:

$$\begin{aligned} &c + A' = AR + y - d(y, D), \quad y = w\ell, \\ &D' = D - d(y, D), \\ &d(y, D) = \min\{r(y) * y, D\}, \end{aligned}$$

where $d(y, D)$ denotes the required HELP repayment that is equal to the minimum of the HELP repayment in Figure 2 and the remaining debt balance. To simplify exposition, I assume throughout that utility is increasing in consumption, $u_c > 0$, decreasing in labor supply, $u_\ell < 0$, w is constant and IID across individuals, and the initial debt, D, is sufficiently high such that $D' > 0$ with probability one.

The first order condition for labor supply in this model is:

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

This equation shows income-contingent debt has two effects on labor supply. The first term captures the fact that income-contingent repayments discourage 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 want to choose to locate above the threshold if the marginal value of repaying their debt is sufficiently high. The following proposition shows how large the benefit of repaying must be to justify individuals locating above the repayment threshold.

Proposition B1. *To a first-approximation, individuals locate above a repayment threshold, T, if the following condition holds:*

$$-V_D d(T, D) > u_c d(T, D) - u_\ell \left(\ell^* - \frac{T}{w}\right),$$

where l^* is defined as the

Appendix C. Additional Institutional Details

C.1 Timing and Collection of HELP Repayments

Individuals can make compulsory HELP repayments, which are the repayments calculated according to the HELP repayment formula made at the time 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 using the March quarter CPI, which is referred to as the "indexation rate". The indexation rate is calculated by dividing the sum of the CPI index numbers 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.[39] 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 counted until the individual's tax return is filed.

ALife does not separately identify compulsory and voluntary repayments, so I need to make assumptions to estimate the latter. Since individuals generally file their tax returns after June 30th, I assume all compulsory repayments are made after indexation occurs on June 1st. For the typical individual with payments withheld by an employer, this assumption holds.[40] I also assume voluntary repayments are made prior to indexation occurring, since the ATO recommends making voluntary repayments prior to lodging tax returns.

Under these assumptions, an individual i's HELP debt evolves according to:

$$D_{it+1} = \left[D_{it} - r_{it} - v_{it+1}(1 + dct_{t+1}) + D^{new}_{it+1}\right] * (1 + \pi_{t+1}). \tag{18}$$

where D_{it} denotes debt balances measured as of June 30th in year t (prior to tax return filing), π_{t+1} denotes the indexation rate applied on June 1st of year $t+1$, r_{it} denotes compulsory repayments between July 1st and October 31st of year t, v_{it+1} denotes voluntary repayments made between July 1st of year t and May 31st of year $t+1$, dct_{t+1} denotes the discount provided for voluntary repayments between July 1st of year t and June 30th of year $t+1$[41], and D^{new}_{it+1} denotes new debt accumulated between July 1st of year t and June 30th of year $t+1$. In (18), there are two quantities that I cannot observe in *ALife*: v_{it} and D^{new}_{it}. *ALife* does, however, have a flag for when D^{new}_{it} is positive. Under the assumption that individuals do not make voluntary repayments when they accumulate new HELP debt, I can estimate voluntary repayments as:

$$v_{it} = \begin{cases} \frac{D_{it-1}*(1+\pi_t)-r_{it}-D_{it}}{1+dct_t} & \text{if } D^{new}_{it} = 0, \\ 0 & \text{else.} \end{cases} \tag{19}$$

To the extent that this second assumption is violated, I will under-estimate voluntary repayments.

[39] See here for additional details.

[40] If this assumption fails, it would have a quantitatively small impact on my results given inflation has been relatively stable in Australia around 2% annualized since 1990.

[41] This discount is only applied for voluntary repayments of more than $500.

C.2 Wage-Setting in Australia

There are three wage-setting methods in Australia. The first type is 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 this conditions is the Fair Work Commission, which operates at a national-level. The second type is Enterprise Agreements, which set a rate of pay and conditions for a group of employees through negotiation. This form of wage setting is analogous to labor unions in the US. Finally, Individual Arrangements set the wages and conditions for employees on an individual-basis. Individual Arrangements and Enterprise Agreements are the dominant forms of wage-setting, making up around 40% each of total wage-setting arrangements, while Award-Based Wages make up around 20%.[42]

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

Appendix D. Additional Details on Data and Variable Construction

D.1 Variable Definitions

This section provides additional details on variable definitions based on the underlying variables in *ALife*.[43] 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.

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 and 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 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 changes in the components added back to taxable income are not driving my main results.

Labor Income and Wage-Earner. Labor Income and the indicator for whether an individual is a wage-earner are constructed as:

```
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)
```

Capital Income. Capital Income is constructed as:

```
capitalvars = ['i_annuities_txd', 'i_annuities_untxd',
        'i_annuities_lsum_txd', 'i_annuities_lsum_untxd',
        'i_super_lsum_txd', 'i_super_lsum_untxd',
```

[43] For description of these underlying variables, see the following link: `https://alife-research.app/research/search/list`.

```
        '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. Net Deductions is constructed as:

```
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` in *ALife*, respectively.

Appendix E. Additional Details on Computing Bunching Statistic

Appendix F. Model Solution Details

Software and hardware. The code to solve and estimate the model is compiled in Intel Fortran 2018. Each solution and simulation is parallelized across 1536 threads on the MIT SuperCloud (Reuther et al. 2018).

Appendix G. First-Stage Calibration Details

This section provides a detailed description on the calibration of 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, which corresponds to the typical age at which students graduate university in Australia, retire at age 65, which is 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.[44] 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 so 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 are deflated to 2005 AUD using the indexation rates for HELP thresholds when they are compared with model moments.

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.[45] 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.[46] 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 total credit limit on all credit cards in the responding person's name, `crymbl`. Filtering to the sample of 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 weigh each year equally. Finally, I use

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

[45] 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

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

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 that are lone persons (`hhtype` = 24) between ages 18 and 22, I compute liquid assets as the sum of bank accounts 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 non-positive 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 weigh 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 I observe empirically. Additionally, because A_{ia} represents end-of-period savings, I scale A_{ia_0} by R^{-1} to so that the liquid assets at $a = a_0$ in the model matches the data.

Preference parameters. The preference parameters I do not estimate due to 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 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 repay 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* that have positive debt balances, which is the year 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 debt balances for all individual-years to 2005 AUD and then calculate the year in which each individual had their 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 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 $t \geq T^*$.[47] 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

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

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

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

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 I. 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 individuals pay increases in their income according to a schedule provided by the ATO.[48] 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 $t \geq T^*$:

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

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

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

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:

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

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 to individuals above 22 with low income due to unemployment. These benefits are means-tested based on income and assets. I use the formula

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

for payments in 2005 for a single individual with no children.[49] 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 also receive a net consumption floor. This floor is needed to ensure individuals consumption net of labor supply disutility, $c_{ia} - \kappa\frac{\ell_{ia}^{1+\phi^{-1}}}{1+\phi^{-1}}$, remains positive in the event 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 found my results are unchanged.

Retirement pension. Individuals in retirement receive a retirement pension from the government that is based on the Age Pension, which is the primary government-provided form of income-support to retirees in Australia. The age pension is available to individuals at age 65 and is means-tested based on assets and income. I use the formula for payments in 2005 for a single individual that is a homeowner based on assets, but 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 repayments on the government budget constraint through changes in asset accumulation.

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

Appendix H. Second-Stage Estimation Details

H.1 Model Simulation Procedure

Denote p_e as the fraction of individuals in the data at age 22 that have debt. I simulate N individuals, where q_e have debt at age 22 and $q_e > p_e$ so that I have a sufficient number of individuals to compute bunching moments. To ensure comparability with the data, I then only compute the moments that have observations on both individuals with $E = 1$ and $E = 2$ using all $(1 - q_e)N$ model observations for individuals with $E = 1$ but only x observations for individuals with $E = 2$, where x is given by:

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

H.2 Details on Construction of Estimation Targets

Due to 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.

When calculating all estimation targets targets in the data, I restrict to individuals who are age 22 between 1963 and 2019, consistent with the model.

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 $t \geq 1991$:
$$\log y_{ia} = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_0^E \mathcal{E}_i + \beta_1^E \mathcal{E}_i a$$
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 22 and 62, which is normalized to 1 in the data
8. Real distribution of HELP Income among debtholders in 2002-2004 within \$3000 of the 2004 repayment threshold in bins of \$500
9. Real distribution of HELP Income among debtholders in 2005-2007 within \$3000 of the 2005 repayment threshold in bins of \$500
10. Ratio of number of individuals with HELP Income within \$250 below to the number within \$250 above the 2004 repayment threshold in 1998-2004
11. Ratio of number of individuals with HELP Income within \$250 below to the number within \$250 above the 2005 repayment threshold in 2005-2018
12. Ratio of number of individuals with HELP Income within \$250 below to the number within \$250 above the 2005 repayment threshold in 2005-2018 among individuals in the bottom and top quartile of debt balances in each year

13. Ratio of number of individuals with HELP Income within $250 below to the number within $250 above the lowest 2005 0.5% threshold in 2005-2018

H.3 Choice of Weighting Matrix

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

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

This choice follows Guvenen et al. (2021) and is made because I have many estimation targets that differ greatly in scale.[50] 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 above repayment thresholds + average labor supply
3. Block #3: All remaining moments

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

H.4 Standard Errors

In order 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

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

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

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

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

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

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

[50] The choice of constant $\underline{w}$ is done to ensure 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.

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 using 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 all off-diagonal elements are zero[51] and compute G using two-sided finite-differentiation where with step sizes equal to 1% of the estimated parameter value following the recommendation of Judd (1998) (p. 281).[52] The standard errors for Θ^* are then $\sqrt{N^{-1}\text{diag}(\hat{V})}$.

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

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

Appendix I. Additional Details on Repayment Contracts

Fixed repayment. For an individual i at age a, the required repayment on 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 repayments start and a_E is the age at which repayments end. In the event that individuals cash on hand prior to debt payments falls below $d_{Fixed}(\cdot)$, I only make individuals repay their cash on hand. In this case, individuals will also receive the consumption floor since they have no resources for consumption. The following specifies the parameters on different fixed repayment contracts:

- 10-Year Fixed: $a_S = a_0$, $a_E = 10$
- 25-Year Fixed: $a_S = a_0$, $a_E = a_0 + 20$

Income-based repayment (IBR). For an individual i at age a, the required repayment on an IBR contract is:

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

The following specifies parameters on different IBR contracts:

- US IBR: $\psi = 10\%$, $K = 1.5 * pov$, $\overline{T} = a_R$
- US Proposed IBR: $\psi = 5\%$, $K = 2.25 * pov$, $\overline{T} = a_R$

where pov is 2023 US Poverty Line of $14,580 USD converted into AUD by adjusting for US CPI inflation from June 2005 to January 2023 the exchange rate in June 2005.[53] For simplicity, I do not implement the restriction in the US that IBR payments cannot exceed payments under a fixed repayment contract.[54]

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

$$d_{ISA}(a, D_{ia}, y_{ia}) = \begin{cases} 0, & \text{if } a > T_{ISA} \text{ or } y_{ia} < K_{ISA} \text{ or } D_{ia} < E(D_{ia_0} \mid \mathcal{E}_i = 1)(1 - cap_{ISA}), \\ \psi_{ISA} * y_{ia}, & \text{else.} \end{cases}$$

In this expression, T_{ISA} is the term of the ISA contract, K_{ISA} is the threshold above which payments are required, and cap_{ISA} is the maximum fraction of average initial debt balances an individual must repay. This structure of an ISA closely matches that of the ISAs provided by Purdue University in 2016-2017 (Mumford 2022). There is, however, one difference: the Purdue ISAs have the constraint $D_{ia} < D_{ia_0}(1 - cap_{ISA})$ instead of $D_{ia} < E(D_{ia_0} \mid \mathcal{E}_i = 1)(1 - cap_{ISA})$. I implement the latter constraint as an approximation, since the former would require an additional state variable.[55] Following the example ISA provided in Figure 1 of Mumford (2022), I set $T_{ISA} = 9$, $K_{ISA} = \$20,000$ USD in June 2017 deflated to June 2005 AUD, $cap_{ISA} = 2.5$, and $\psi_{ISA} = 4\%$.

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

[54]This has a qualitatively negligible effect on my results.

[55]To see the difference between the two constraints, recall the true constraint in an ISA at which payments cease is $\frac{\Sigma_{j=1}^{a} d_{ia}}{D_{ia_0}} > cap_{ISA}$, which implies $D_{ia_0} - D_{ia} > D_{ia_0} cap_{ISA}$ and thus $D_{ia} < D_{ia_0}(1 - cap_{ISA})$. Taking expectations of the right-hand side delivers the constraint I impose. In untabulated results, I find the welfare effects of different policies are quantitatively similar even if I set D_{ia_0} equal to the average initial debt balance among individuals with $\mathcal{E}_i = 1$. This suggests that the effects of my approximation to the repayment cap are unlikely to affect my results, since in this simulation my approximation to the contraint holds exactly.

Appendix J. Computation of Welfare Metrics

J.1 Equivalent Variation at $a = a_0$

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

The *equivalent variation* of policy p, π_p, relative to the 10-Year Fixed repayment contract is computed as the fixed point of the following equation in π:

$$\left[\int V_p(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}} = \left[\int V_{\text{10-Year Fixed}}(\mathbf{s}_0(\pi) \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}}.$$

This left-hand side of this equation corresponds to the Epstein-Zin certainty-equivalent functional of random consumption and labor supply streams under repayment policy p to an agent with education level $\mathcal{E}_i = 1$ who is "behind the veil of ignorance" with respect to $\mathbf{s}_0$. The right-hand side corresponds to the same quantity calculated under the 10-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.

J.2 Consumption-Equivalent Welfare Gain

Let $V_p(\mathbf{s}_0 \mid \mathcal{E}_i = E)$ and $F(\mathbf{s_0} \mid \mathcal{E}_i = E)$ denote the same quantities as above. Let $V_p^g(\mathbf{s}_0 \mid \mathcal{E}_i = E)$ denote $V_p(\mathbf{s}_0 \mid \mathcal{E}_i = E)$ evaluated in a model in which for all ages a individuals i get to consume $(1+g)c_{ia}$. The *consumption-equivalent gain* of policy p, g_p, relative to the 10-Year Fixed repayment contract is computed as the fixed point to the following equation in g:

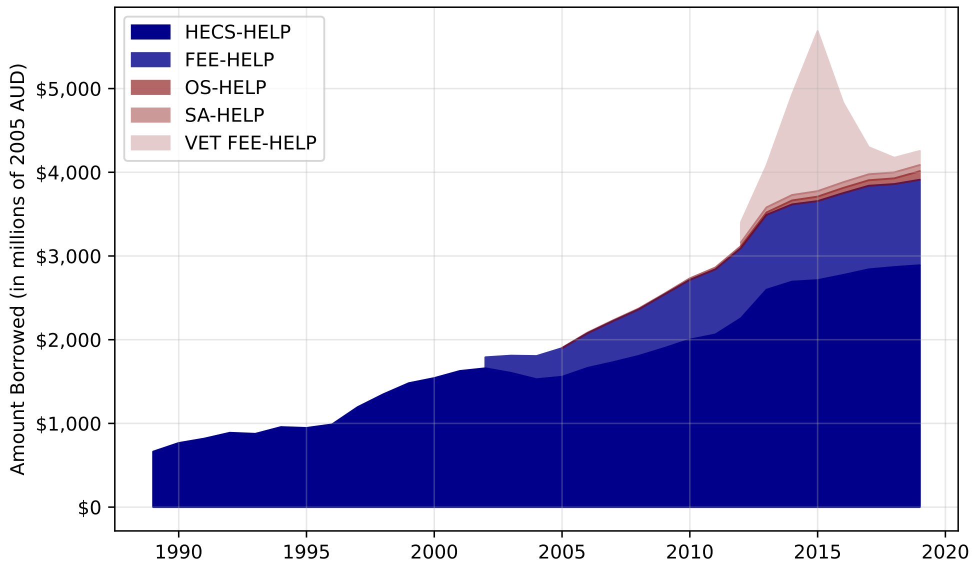
$$\left[\int V_p(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}} = \left[\int V^g_{\text{10-Year Fixed}}(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}}.$$

This metric corresponds to the value of g that would make individuals with $\mathcal{E}_i = 1$ indifferent between having to (i) repay their debt under repayment policy p and (ii) repay their debt under 10-Year Fixed *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.

Appendix K. Details on Constrained-Optimal Policies

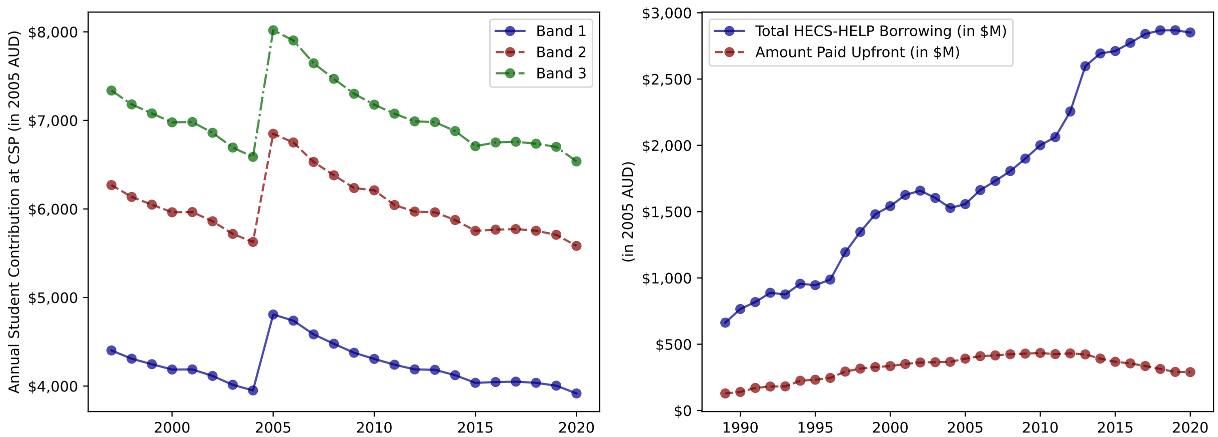
Appendix L. Additional Figures and Tables

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, which covers mostly undergraduate and postgraduate degrees at public institutions. FEE-HELP loans are used to cover the fees associated with degrees that are not Commonwealth Supported Places, such as undergraduate degrees at private institutions, and thus 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 that 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 provides (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). This data was obtained from Andrew Norton Higher Education Commentary.

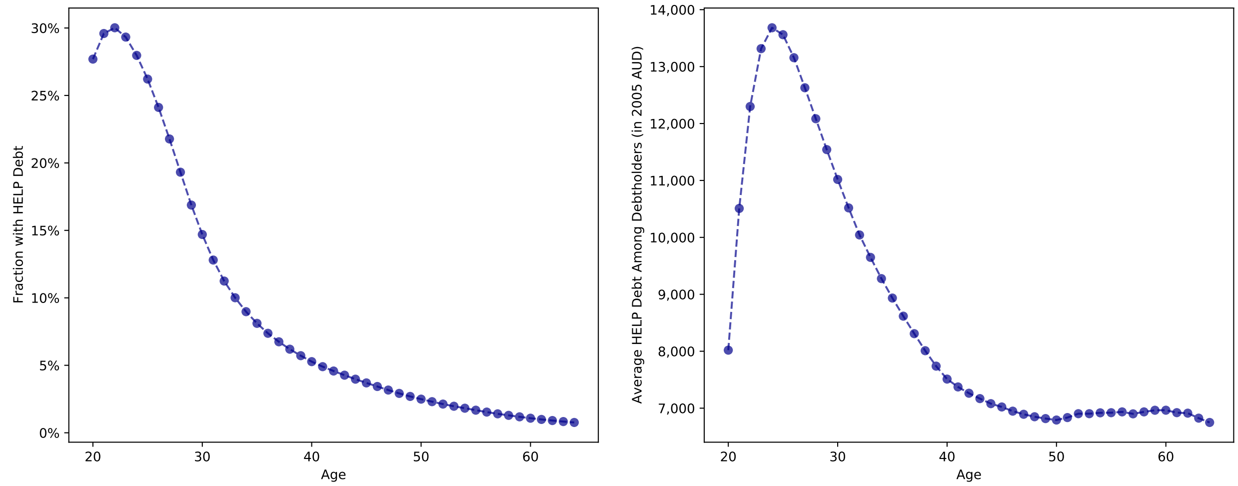
Figure A2. Student Contributions and Aggregate HELP Borrowing over Time



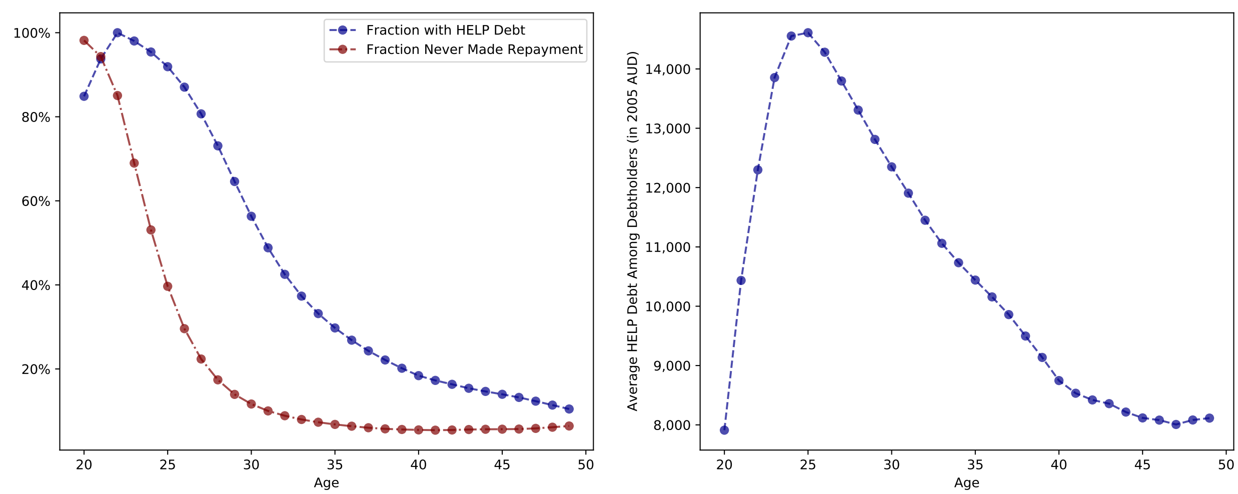
Notes: The left plot shows the time-series of student contributions in 2005 AUD for Commonwealth Supported Places (CSPs) based on the three separate bands of study classified by the Australian Government. These rates correspond to the cost of one year of coursework that must be covered with a HELP loan or by paying upfront. Prior to 2005, these rates were set by the government. After 2005, these rates were set by universities up to the maximum specified in this table, with most universities electing to charge the maximum. These three bands we're 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. The government also had separate tuition for nursing and education between 2005-2009 and mathematics, statistics, and science from 2009-2012, which were labeled as national priorities. The right plot shows the time-series of the aggregate amount of HECS-HELP borrowing and upfront payments in 2005 AUD. This data was obtained from Andrew Norton Higher Education Commentary.

Figure A3. Average Debt Balances by Age

Panel A: All Individuals

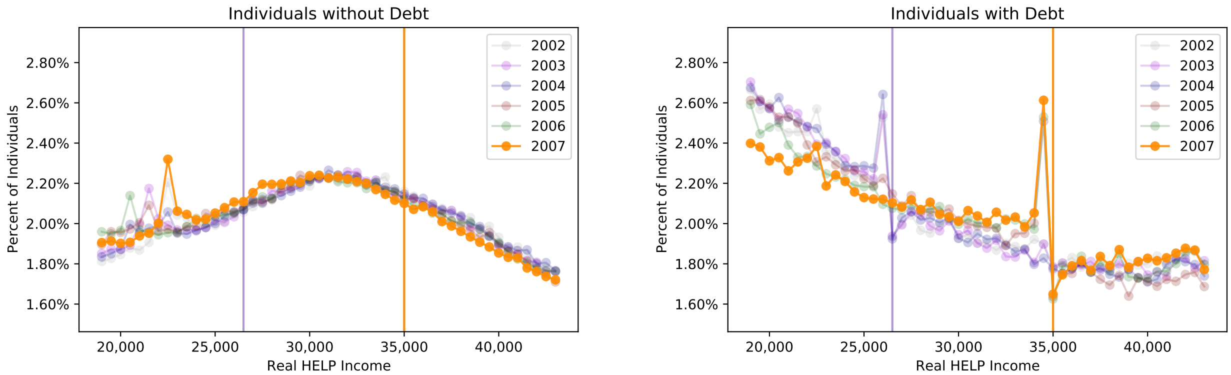


Panel B: Individuals with Positive Debt Balances at Age 22



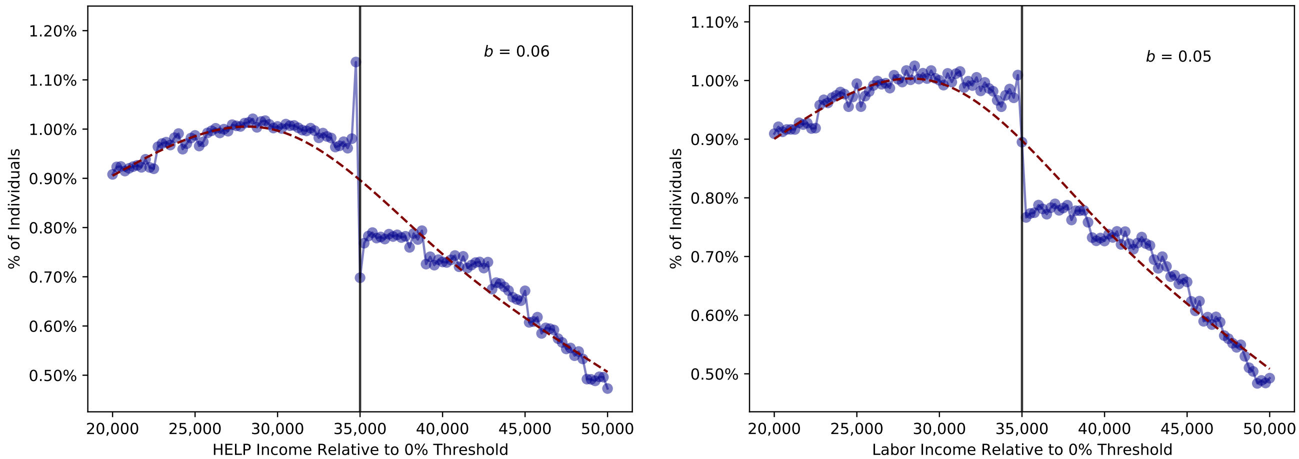
Notes: Panel A of this figure plots the fraction of individuals with HELP debt at each age in the left panel and the average HELP debt balance by age, in 2005 AUD, on the right. Panel B plots, in blue, the same quantities in Panel A among the subset of individuals who have positive debt balances at age 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 $2\% - 98\%$. The sample is the *ALife* sample defined in Section 2.4 from 1991-2019.

Figure A4. Real HELP Income Distribution of Debtholders and Non-Debtholders



Notes: The right panel of this figure replicates the bottom-right figure in Figure 3. The left panel replicates the exact same analysis among individuals that do not have debt in each year.

Figure A5. Distributions of HELP Income and Labor Income



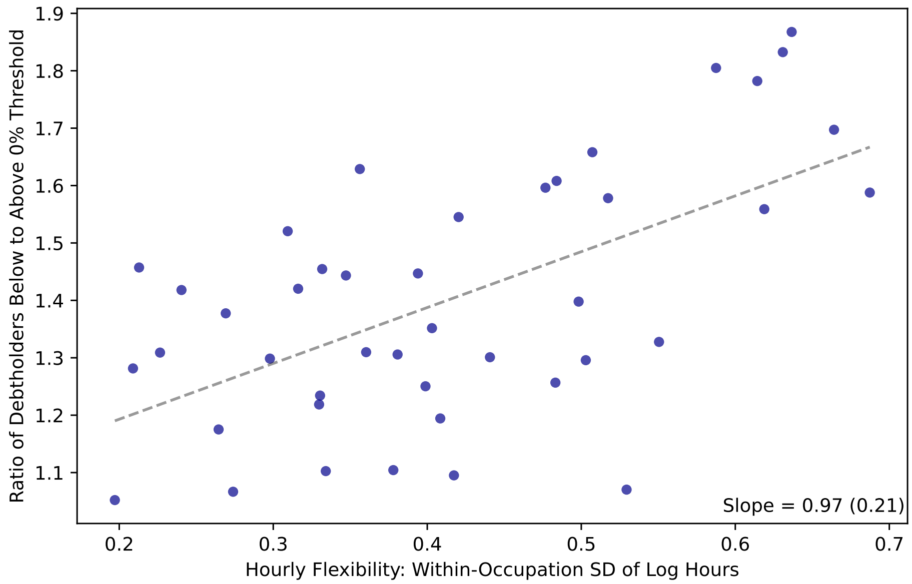
Notes: This figure plots the distribution of HELP and Labor Income in 2005 AUD relative to the repayment threshold after the policy change. This figure also plots the bunching statistic defined in (4) computed for the different distributions. Each bin corresponds to $250 AUD and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix E, 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 have positive HELP debt balances and that have less than 1% of HELP Income from sources other than Labor Income.

Table A1. 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

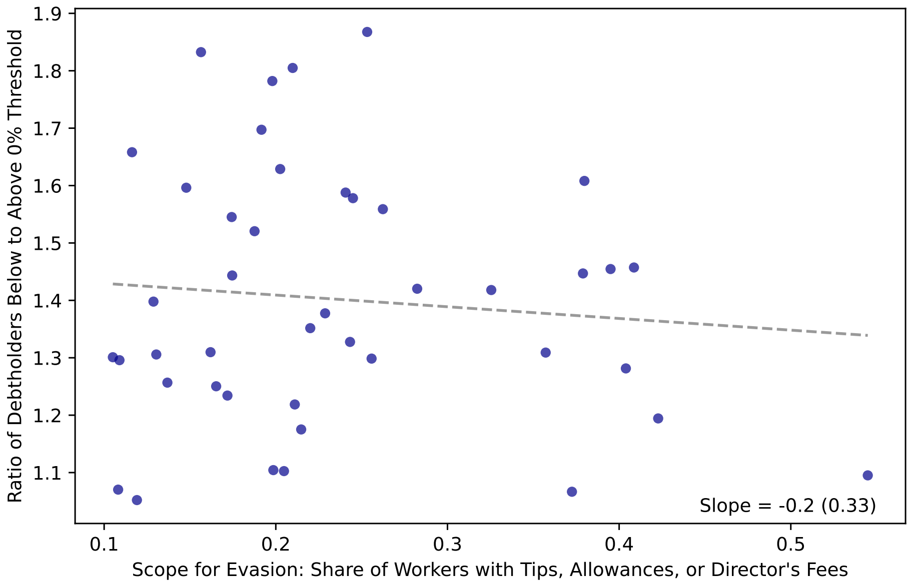
Notes: This table shows the measures of hourly flexibility at the 2-digit ANZSCO occupation-level used in Figure 4 and Figure A6. Hourly flexibility is measured as the standard deviation of annual changes, or the cross-sectional standard deviation, in log hours worked per week across all jobs reported among individuals in the 2002-2019 HILDA Survey Waves that satisfy the following conditions: (i) report being employed; (ii) earn a positive weekly wage; (iii) do not switch occupations between two subsequent years; (iv) are between ages 23 and 64. Prior to computing the standard deviation, annual changes in log hours are winsorized at 1%-99%. The standard deviation within each occupation is computed using longitudinal and cross-sectional survey weights when using annual changes and levels, respectively.

Figure A6. Variation in Bunching across Occupations based on Hourly Flexibility: Alternative Measure



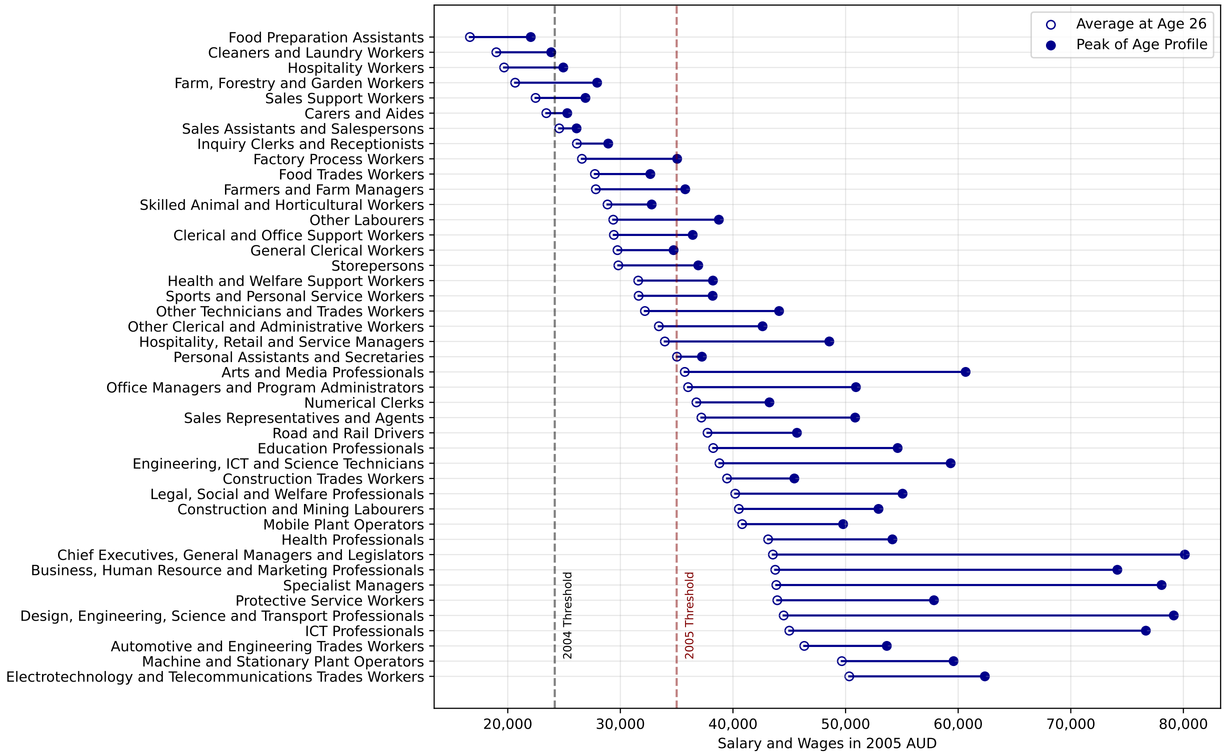
Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and an alternative measure of hourly flexibility by occupation. Each point represents a 2-digit ANZSCO occupation code reported in *ALife*. The amount of bunching is measured as the ratio of the number of individuals in that occupation within $2,500 below the repayment threshold to the number within $2,500 above the threshold over 2005 to 2018. Hourly flexibility is measured as the cross-sectional standard deviation of log hours worked per week across all jobs reported among individuals in the 2002-2019 HILDA Survey Waves that satisfy the following conditions: (i) report being employed; (ii) earn a positive weekly wage; (iii) do not switch occupations between two subsequent years; (iv) are between ages 23 and 64. Prior to computing the standard deviation, log hours are winsorized at 1%-99%. The standard deviation within each occupation is computed using cross-sectional survey weights. The highlighted points correspond to several occupations of interest described in the text. The gray dashed line is regression line with the estimated slope coefficient 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 that are wage-earners.

Figure A7. 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. See the notes in Table A2 for a detailed description of the measure of evasion.

Figure A8. Age Profiles of Wage Income across Occupations



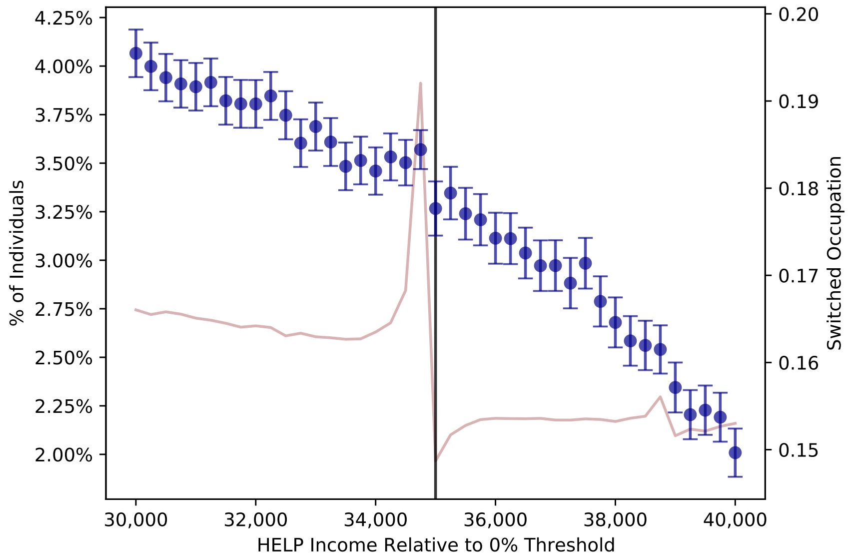
Notes: This figure plots characteristics of the age profile of salary and wages across 2-digit ANZSCO occupations. Occupation-specific age profiles are calculated by taking the average value of salary and wages across individuals in each occupation at a given age, after adjusting for inflation and removing 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, which satisfy the sample selection criteria in Section 2, are wage-earners, and have annual salary and wages that is greater than one-half the legal minimum wage times 13 full-time weeks (Guvenen et al. 2014).

Table A2. 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

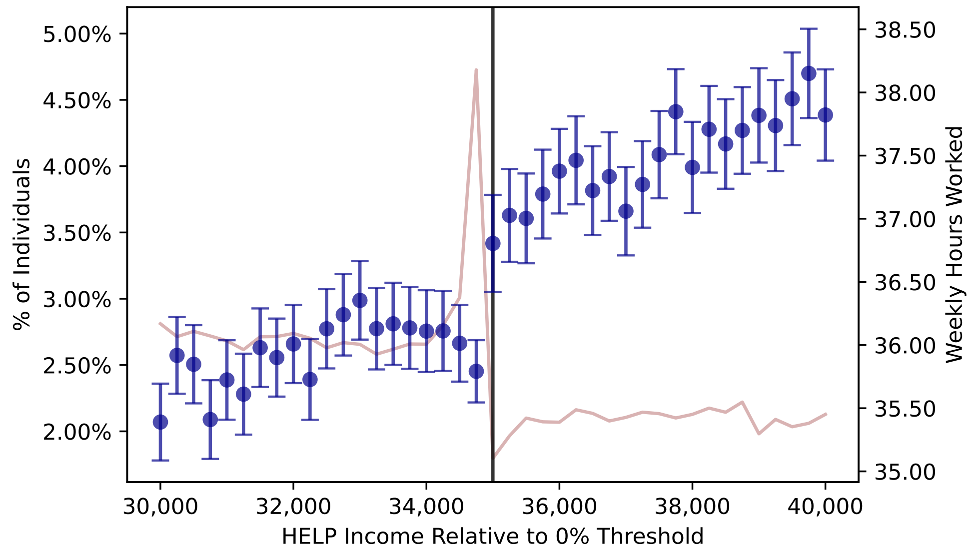
Notes: Each column of this table reports the results from an OLS regression run at the 2-digit ANZSCO occupation-level, with standard errors presented in paranthesis below coefficient estimates. The dependent variable in each column is the ratio of the number of debtholders within $2,500 below the repayment 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 that receive income from working in the form of allowances, tips, director's fees, consulting fees, or bonuses, which are reported jointly in the `i_allowances` variable in *ALife*. This variable is also used in Figure A7. Wage Slope corresponds to the occupation-specific average salary and wages at age 45, which is 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 prior to computing 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 A8. Standard errors are computed using a heteroscedasticity-robust estimator.

Figure A9. Probability of Switching Occupations around 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 using 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 around 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 positive HELP debt balances between 2005 and 2018.

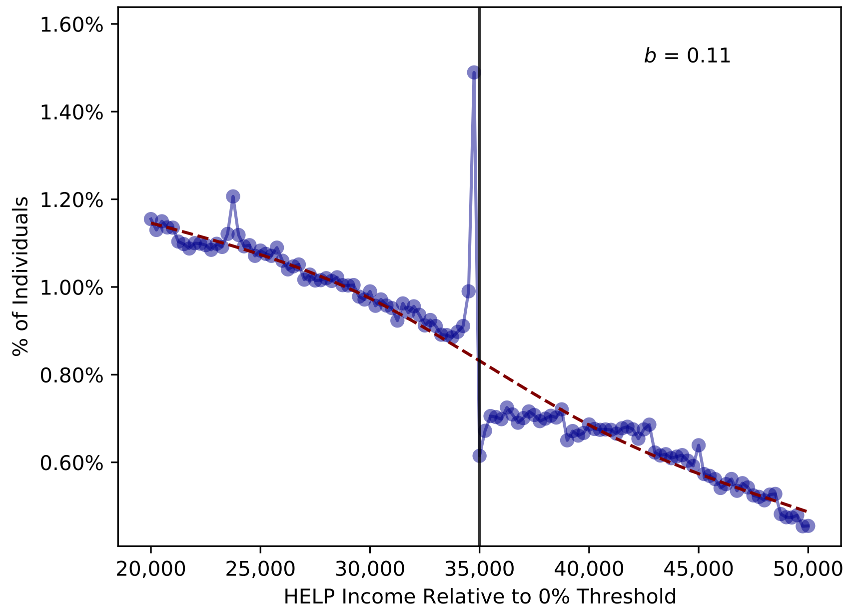
Figure A10. Self-Reported Hours Worked around Repayment Threshold: Positive Labor Income Individuals



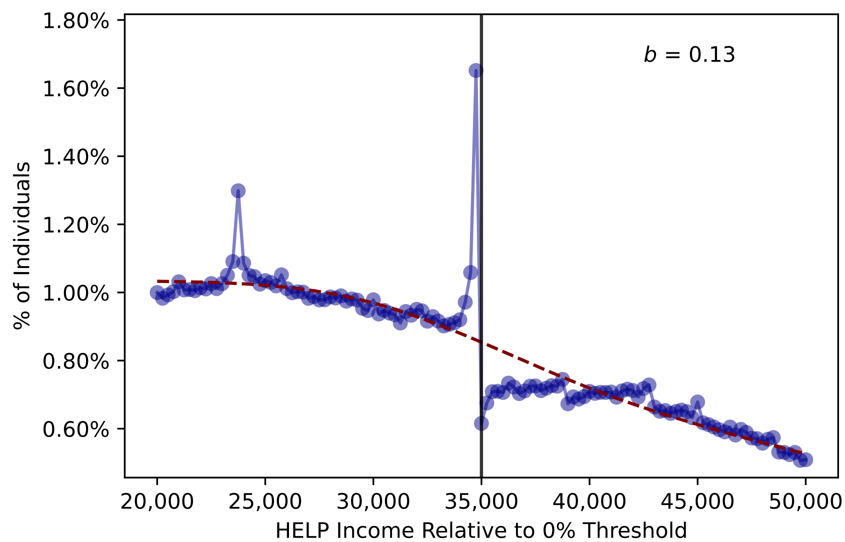
Notes: This figure replicates Figure 5 among the sample of individuals with positive Labor Income.

Figure A11. Distribution of HELP Income in *ALife* versus MADIP Sample

Panel A: ALife Sample in 2016

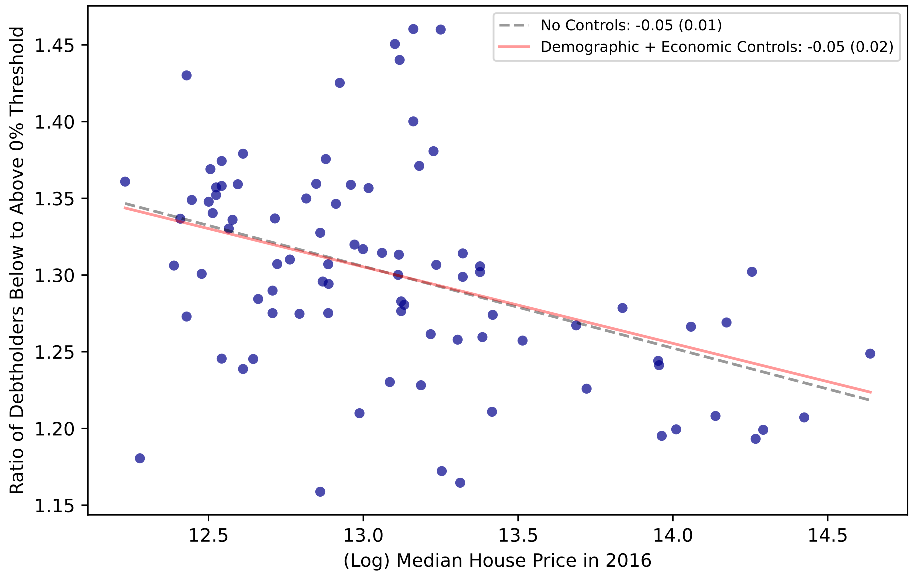


Panel B: MADIP Sample



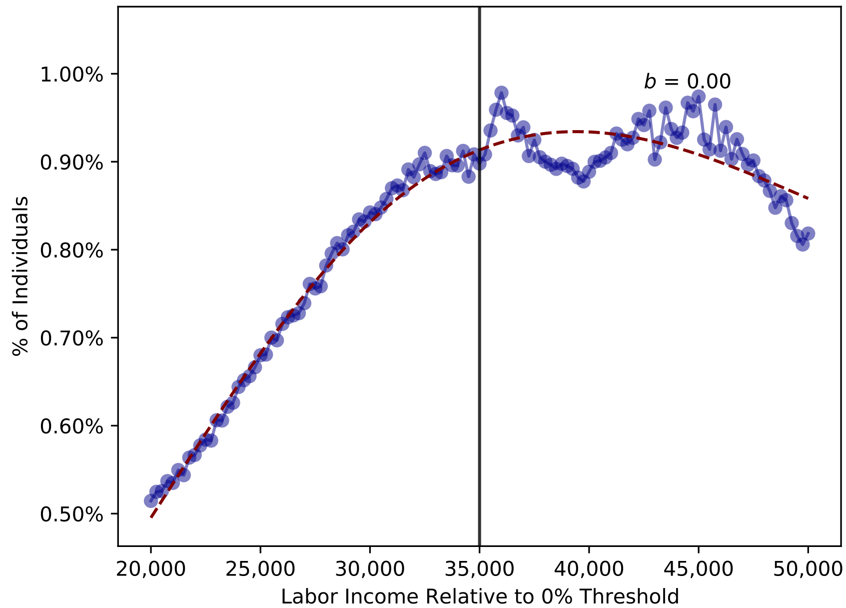
Notes: Panel A of this figure plots the distribution of HELP in 2005 AUD in 2016 relative to the repayment threshold and the bunching statistic defined in (4). Each bin corresponds to $250 AUD and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix E, 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 have 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 A12. Variation in Bunching across Geographic Regions based on Housing Wealth



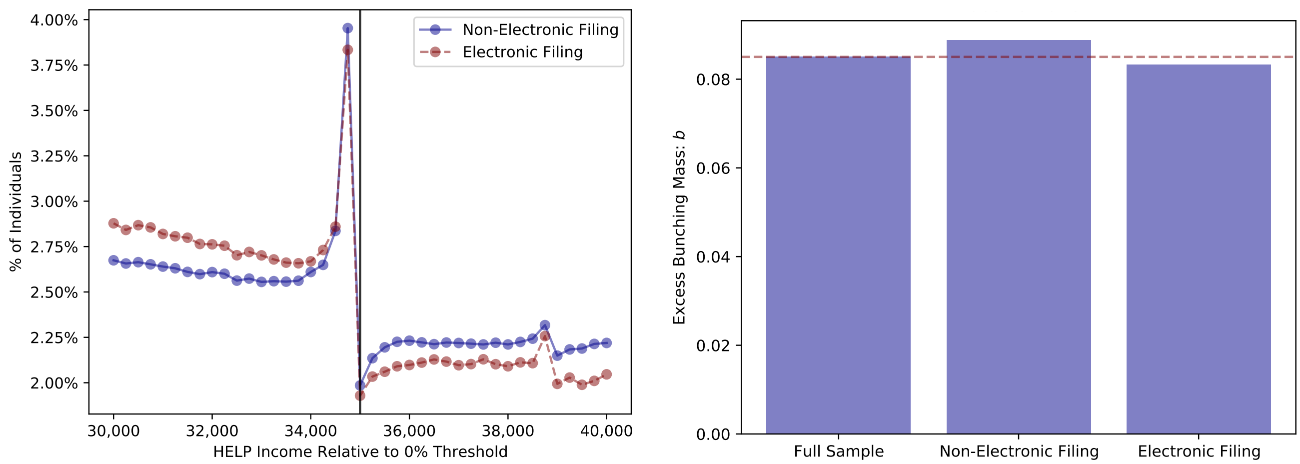
Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and house prices by geographic region. Each point represents a geographic SA4 region reported in *ALife*. For each individual-year, *ALife* contains the location of individuals' home addresses by SA4 region, which are non-overlapping 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 that 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, the 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 that are wage-earners and have positive HELP debt balances.

Figure A13. Distribution of Labor Income among Individuals with Deductions



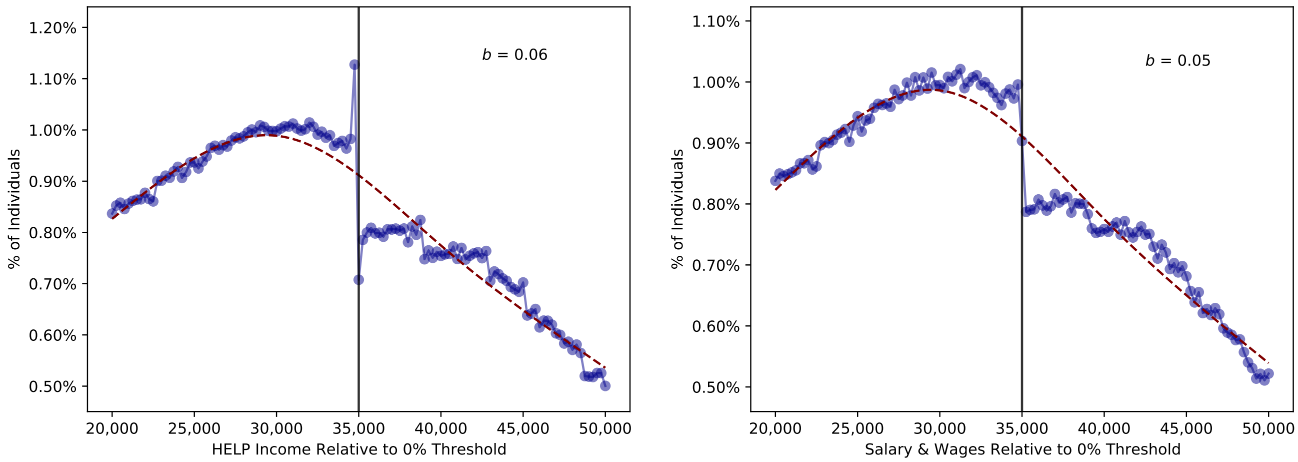
Notes: This figure plots the distribution of HELP Income in 2005 AUD relative to the repayment threshold after the policy change and the bunching statistic defined in (4). Each bin corresponds to \$250 AUD and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix E, 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 have positive HELP debt balances and that have at least \$1,000 in Net Deductions.

Figure A14. Distribution of HELP Income by Tax Filing Method



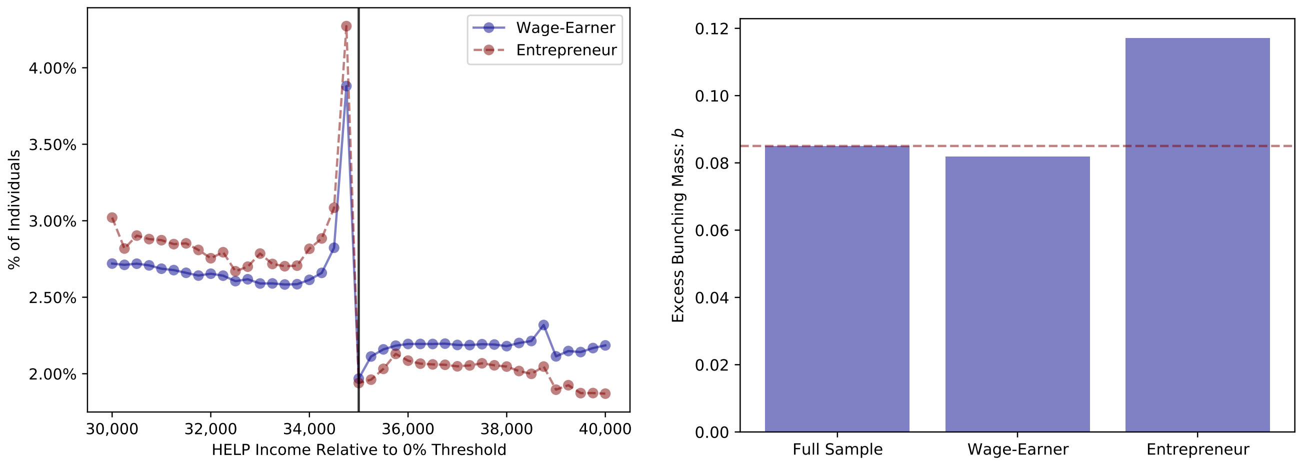
Notes: **X**.

Figure A15. Distributions of HELP Income and Salary and Wages



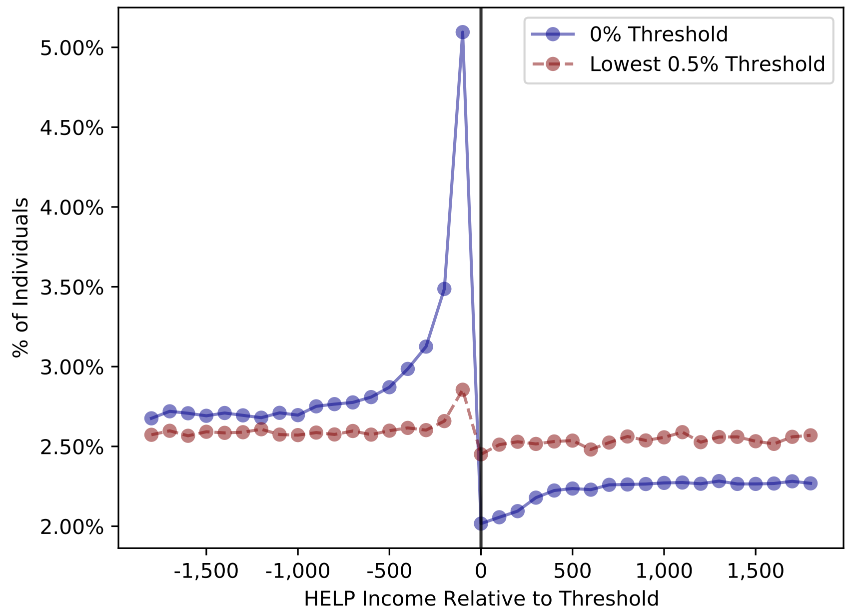
Notes: This figure replicates the analysis in Figure A5, replacing the right plot with Salary and Wages instead of Labor Income.

Figure A16. Distribution of HELP Income by Employment Type



Notes: X.

Figure A17. Distribution of HELP Income at Repayment Threshold versus Lowest 0.5% Threshold



Notes: This figure plots the distribution of HELP 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 have positive HELP debt balances.

Table A3. List of Estimation Targets in Simulated Minimum Distance Estimation

Estimation Target	Parameter(s) Most Sensitive to Target
Labor Supply Preference Parameters	
Real distribution of HELP Income among debtholders in 2002-2004 within $3000 of the 2004 repayment threshold in bins of $500	ϕ, f, λ
Real distribution of HELP Income among debtholders in 2005-2007 within $3000 of the 2005 repayment threshold in bins of $500	ϕ, f, λ
Ratio of number of individuals with HELP Income within $250 below to the number within $250 above the 2004 repayment threshold in 1998-2004	ϕ, f, λ
Ratio of number of individuals with HELP Income within $250 below to the number within $250 above the 2005 repayment threshold in 2005-2018	ϕ, f, λ
Ratio of number of individuals with HELP Income within $250 below to the number within $250 above the 2005 repayment threshold in 2005-2018 among individuals in the bottom and top quartile of debt balances in each year	f, λ
Ratio of number of individuals with HELP Income within $250 below to the number within $250 above the lowest 2005 0.5% threshold in 2005-2018	f, λ
Other Preference Parameters	
Average labor supply of employed individuals	κ
Average capital income between ages 40 and 44	β
Wage Profile Parameters	
Average salary & wages of employed individuals	δ_0
Regression coefficients of log salary & wages onto a and a^2	δ_1, δ_2
Regression coefficients of log salary & wages onto $\mathcal{E}_i$ and $\mathcal{E}_i a$ among $h \geq 1991$	δ_0^E, δ_1^E
Wage Risk Parameters	
Within-cohort cross-sectional variance of log salary & wages at age 22	σ_i
Within-cohort cross-sectional variance of log salary & wages at ages 32, 42, 52, and 62	ρ, σ_ν, σ_ϵ
10th and 90th percentiles of 1-year and 5-year salary & wages growth	σ_ν, σ_ϵ

Notes: This table lists the set of estimation targets used in my simulated minimum distance estimation, along with the parameter(s) that each target was chosen to identify. Additional details on the calculation of each estimation target are presented in Appendix H.

Table A4. Elasticity of Estimation Targets with Respect to Parameters

Panel A: Income Distribution Before 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 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

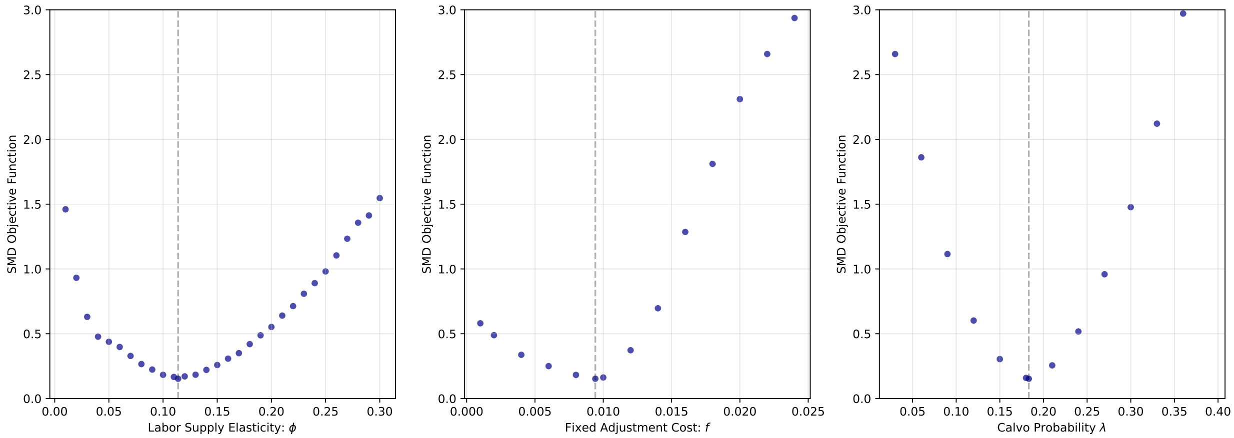
Table A4. Elasticity of Estimation Targets with Respect to Parameters (continued)

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 simulated estimation targets with respect to 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 rountine when estimating the model, which is the same width used when 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.

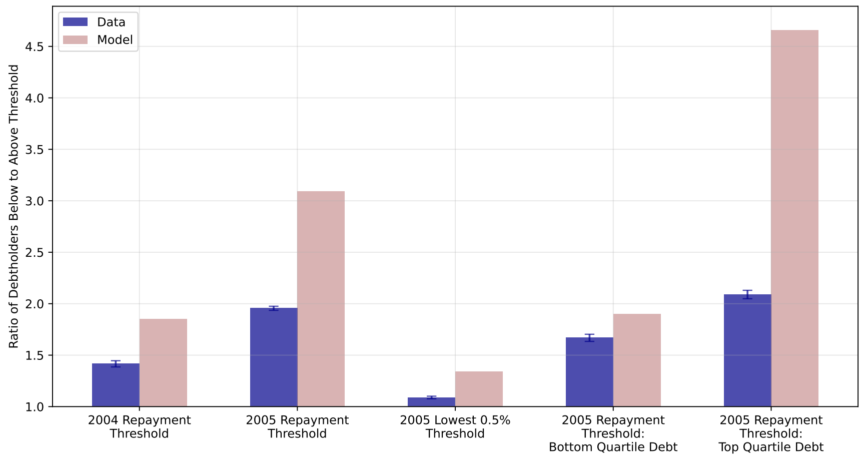
Figure A18. Local Identification of Labor Supply Parameters



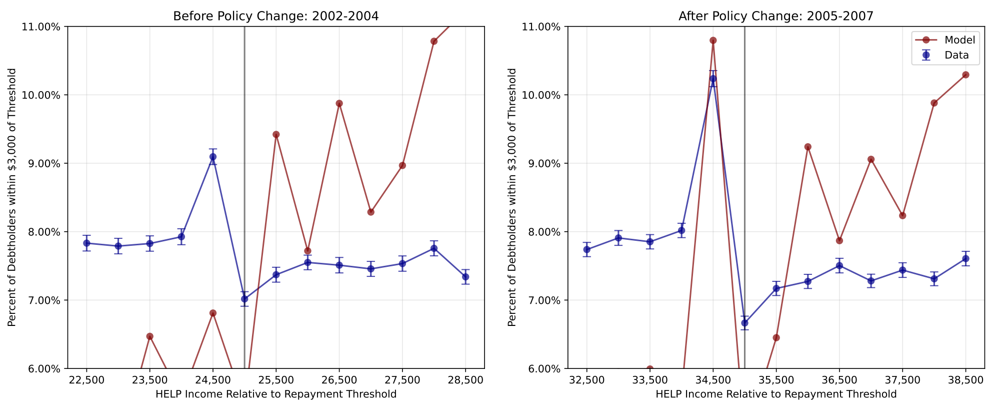
Notes: This figure plots the value of the simulated minimum distance objective function in the baseline estimation for different values of the three key parameters, ϕ, λ, and λ. Each point represent the objective function when solving the model at that parameter value, holding all other parameters fixed 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



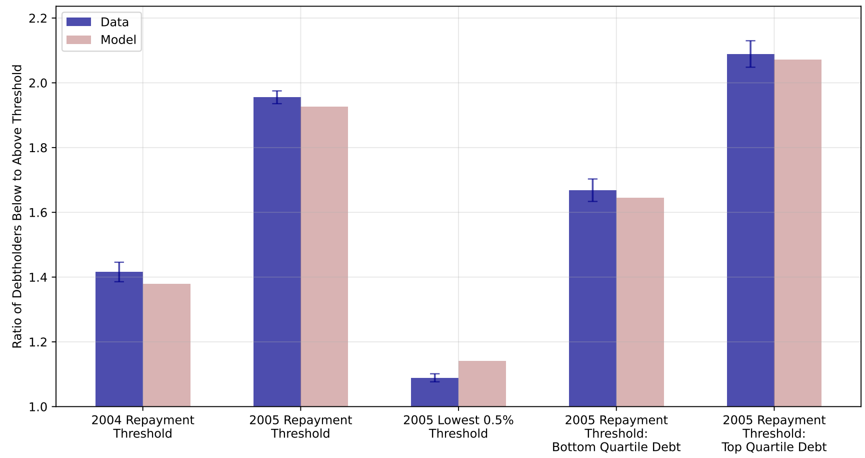
Panel C: Other Estimation Targets

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

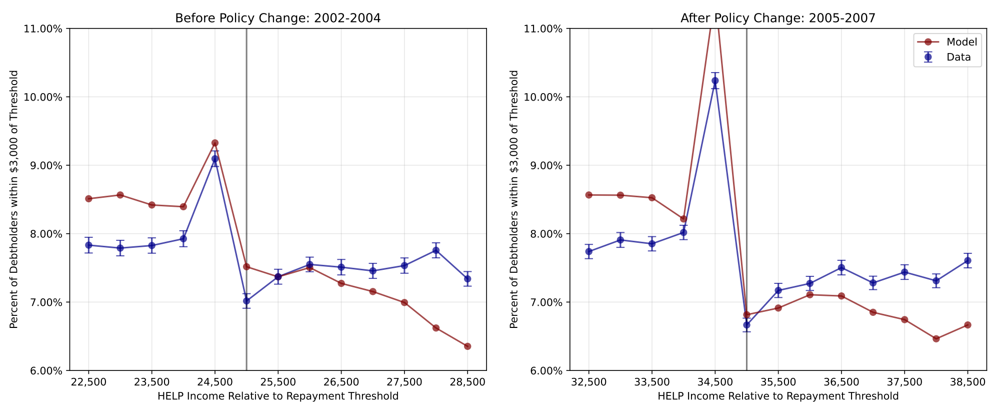
Notes: The results presented in this figure show the fit of the estimated model in column (2) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A20. Model Fit: No Calvo Adjustment

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



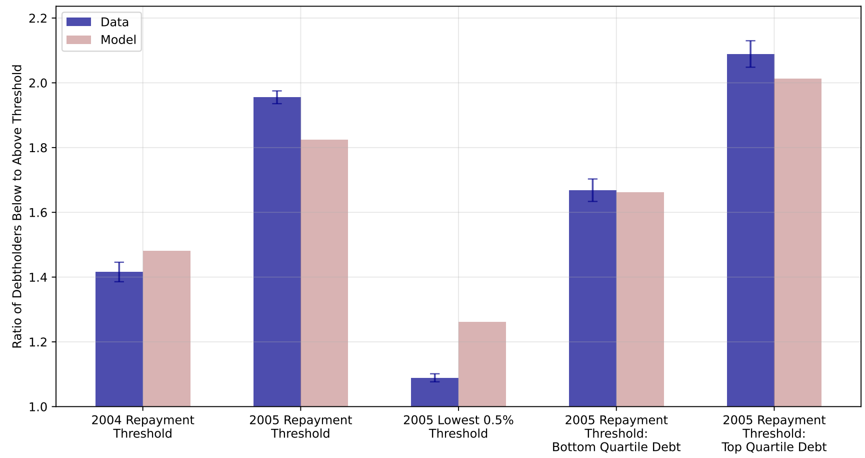
Panel C: Other Estimation Targets

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

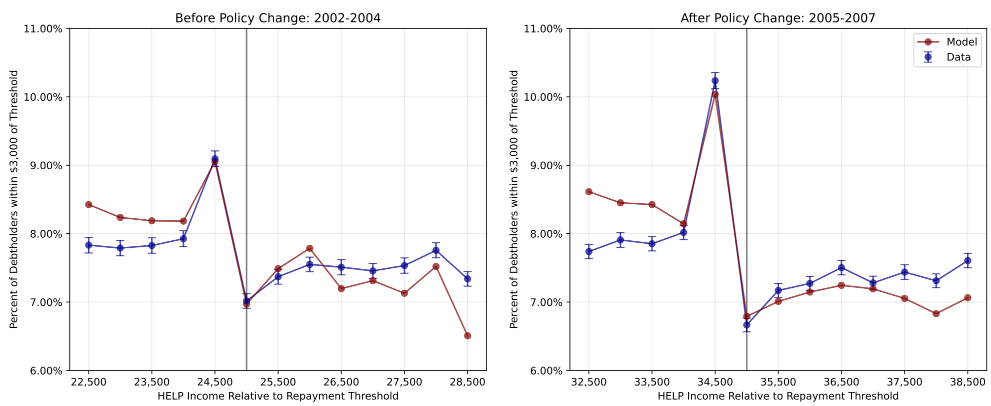
Notes: The results presented in this figure show the fit of the estimated model in column (3) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A21. Model Fit: No Fixed Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



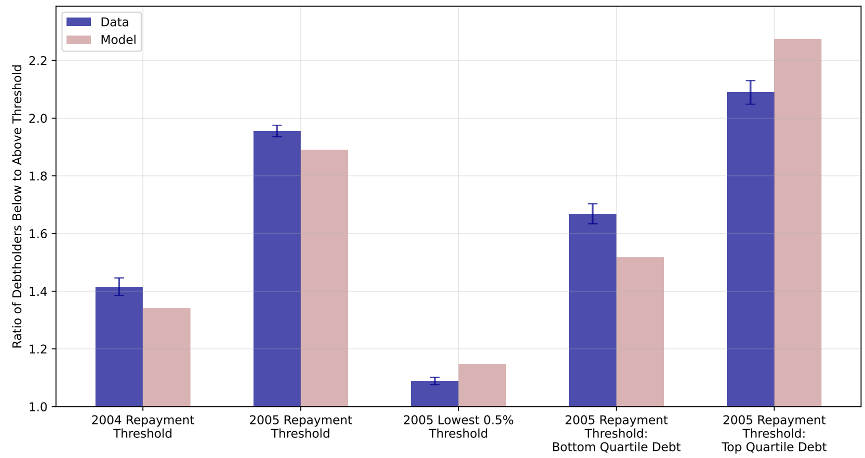
Panel C: Other Estimation Targets

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

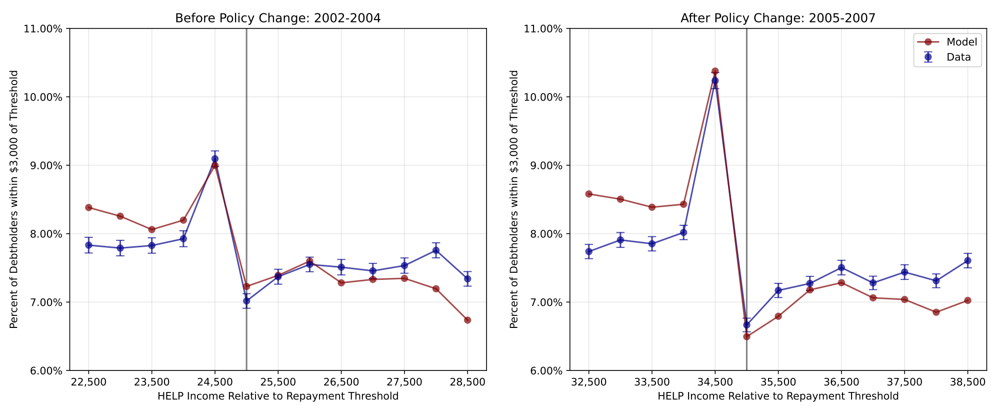
Notes: The results presented in this figure show the fit of the estimated model in column (4) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A22. Model Fit: Learning-by-Doing

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



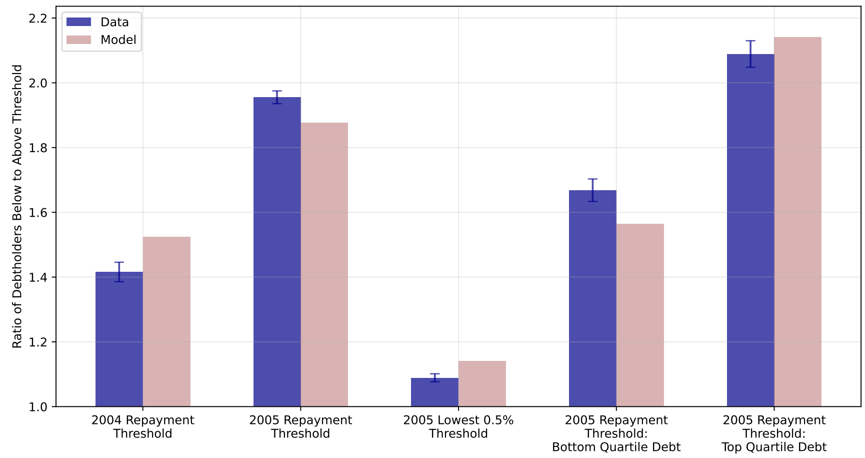
Panel C: Other Estimation Targets

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

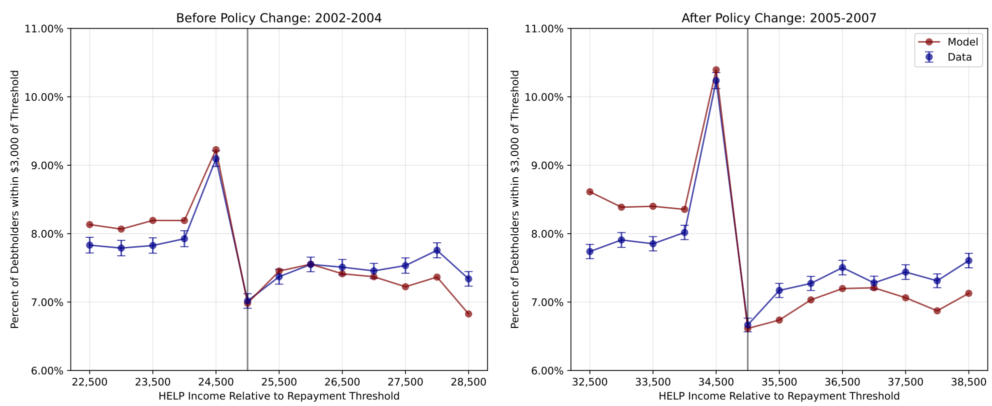
Notes: The results presented in this figure show the fit of the estimated model in column (5) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A23. Model Fit: Linear Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change

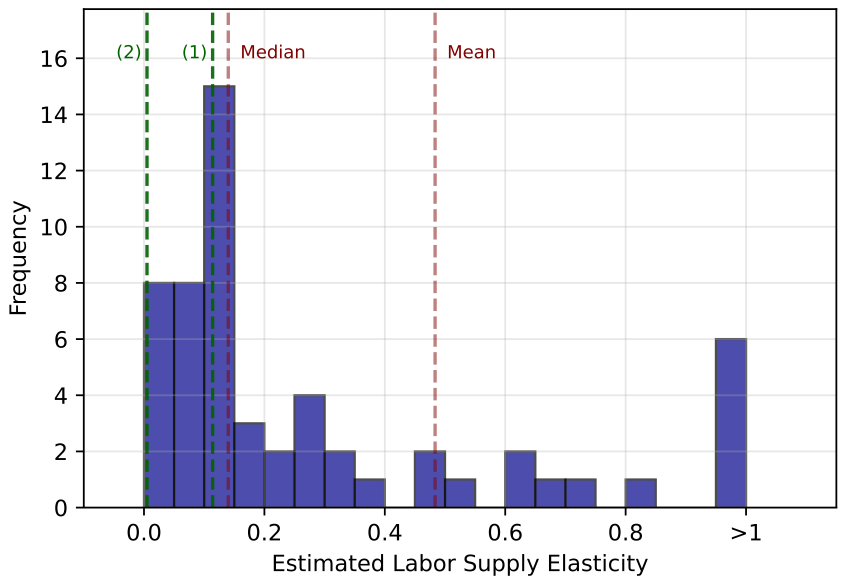


Panel C: Other Estimation Targets

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

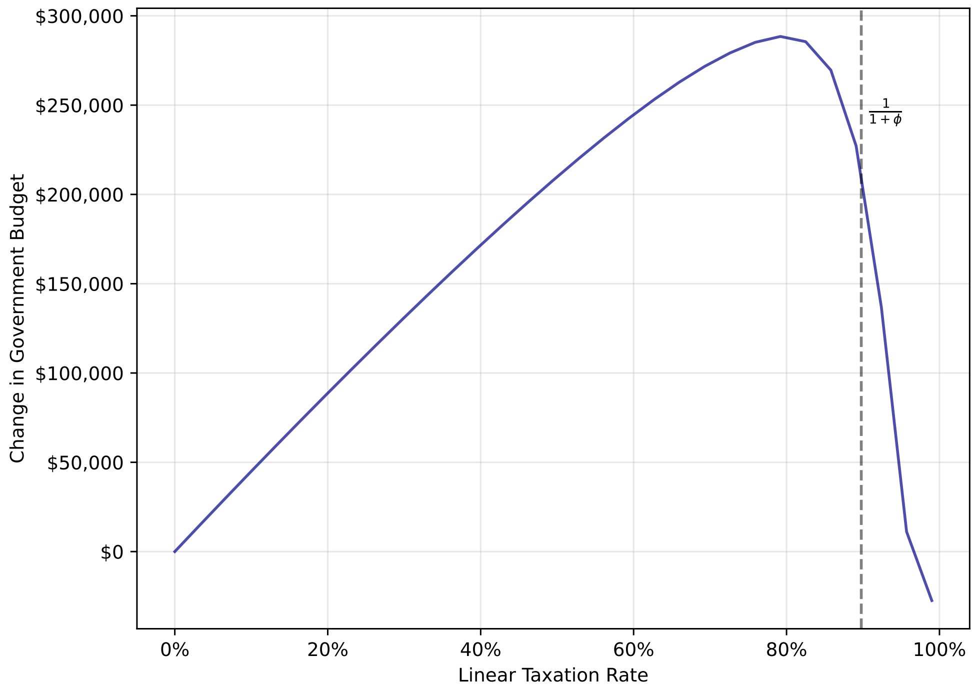
Notes: The results presented in this figure show the fit of the estimated model in column (6) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

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



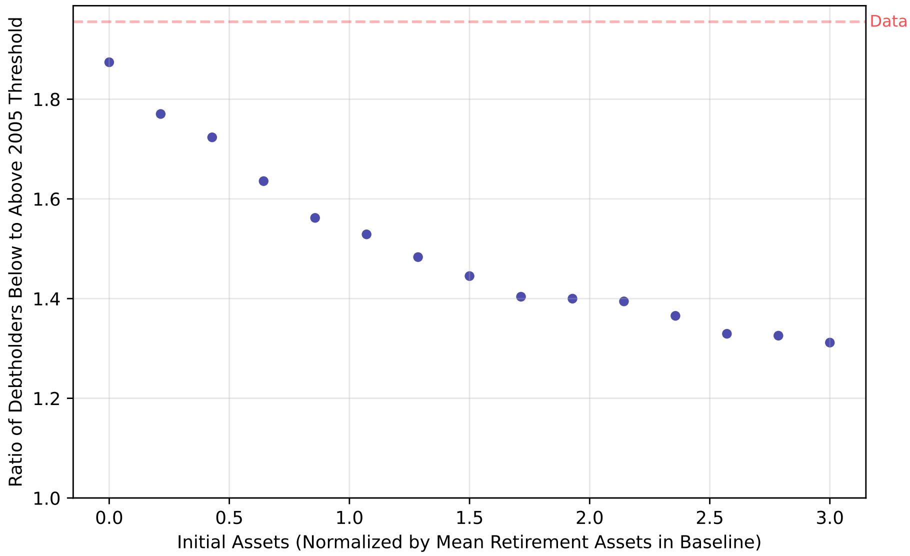
Notes: This figure plots a histogram of estimated intensive-margin labor supply elasticities in prior literature. I combine the estimates reported in Tables 6 and 7 of Keane (2011) and Table 1 of Chetty (2012). These estimates include intensive-margin Frisch (i.e., marginal utility-constant) and Hicksian (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 males or females. 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 trimming these observations. The two dashed green lines plot the estimates from columns (1) and (2) of Table 3, respectively.

Figure A25. Laffer Curve in Baseline Model



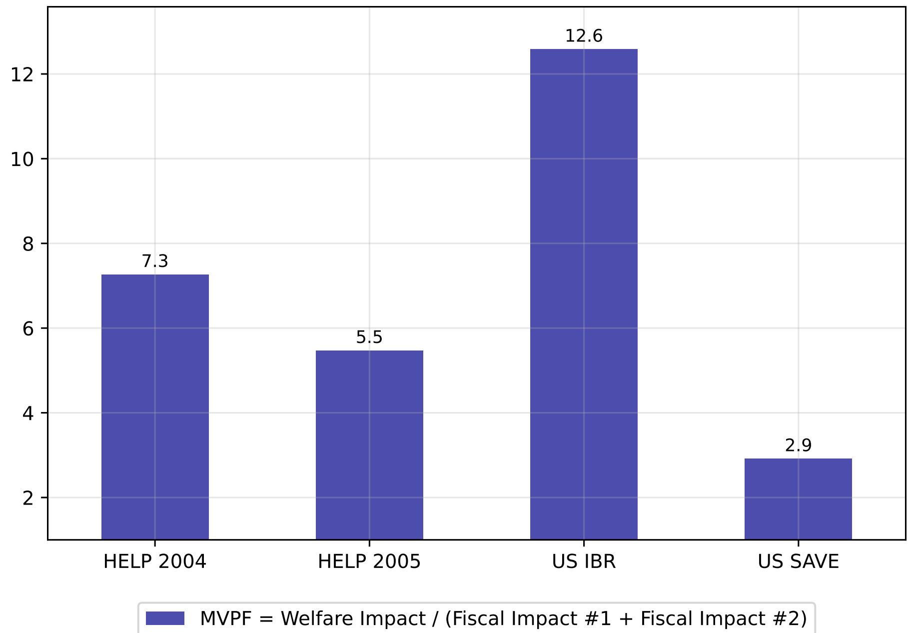
Notes: This figure plots the Laffer curve from a linear tax on income, τy_{ia}, in the baseline model. The horizontal axis corresponds to the value of the linear taxation rate, τ. The vertical axis shows that government revenue changes with respect to its value when $\tau = 0$. The vertical line corresponds 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 benefit conditional on wage rates so that the only effect on the government budget is coming through the linear taxation. Since the labor supply responses of educated individuals are what my model 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



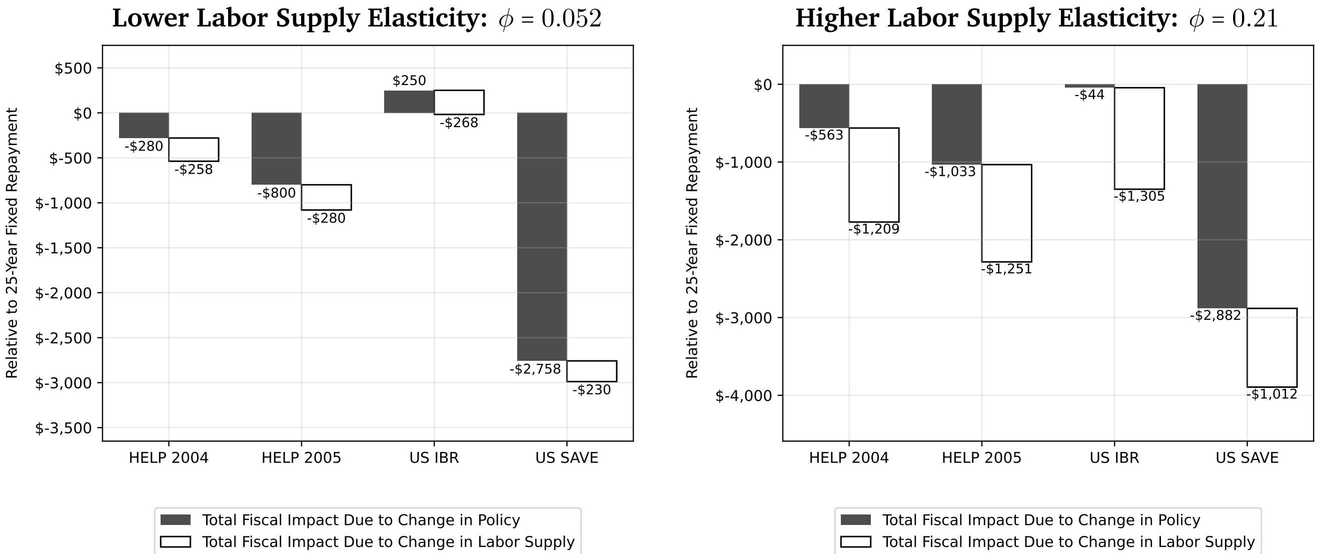
Notes: This figure plots the bunching below the 2005 repayment threshold between 2005 and 2018 as calculated in Figure 10 for different values of initial assets, A_0. The red dashed line in the plot corresponds to the value of this quantity in the data. For each value on the horizonal axis, I simulate from the model assuming 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



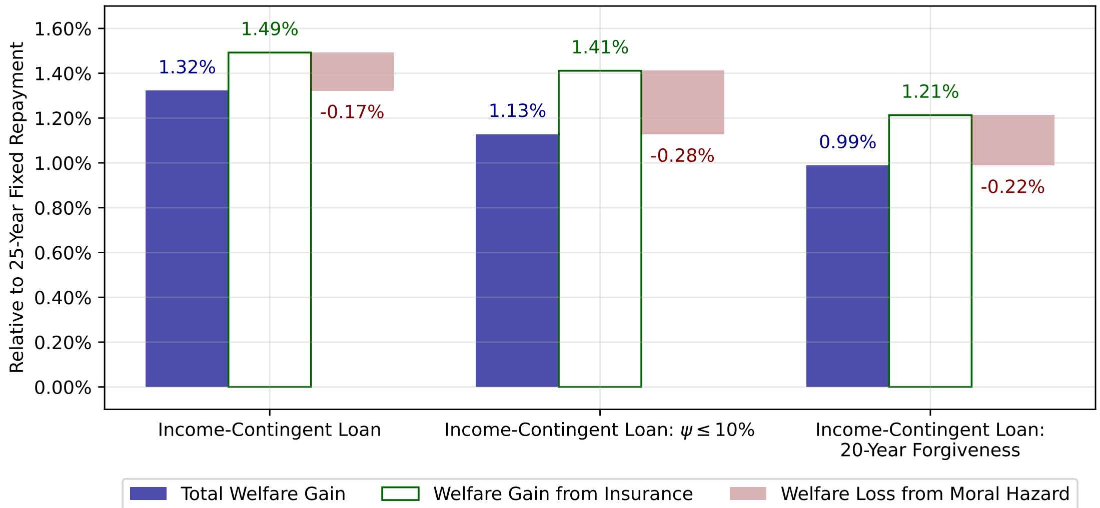
Notes: This figure plots the marginal value of public funds, defined by Hendren and Sprung-Keyser (2020), to moving from a 25-year fixed repayment contract to various existing income-contingent repayment contracts. This is computed by dividing the equivalent variation by the sum of the two fiscal impacts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

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



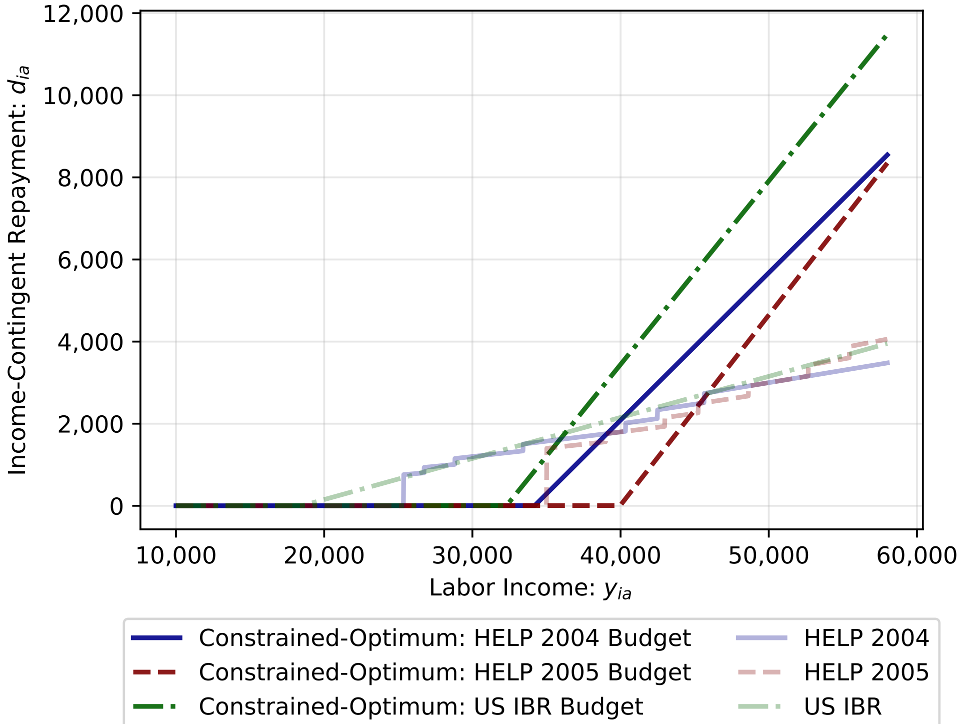
Notes: These two figures replicate the figure in the right panel of Figure 13 for two different values of the Frisch labor supply elasticity.

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 14, for different constrained optimal repayment contracts described in the text. This analysis is performed with all parameters set at their estimated and calibrated values in the baseline model.

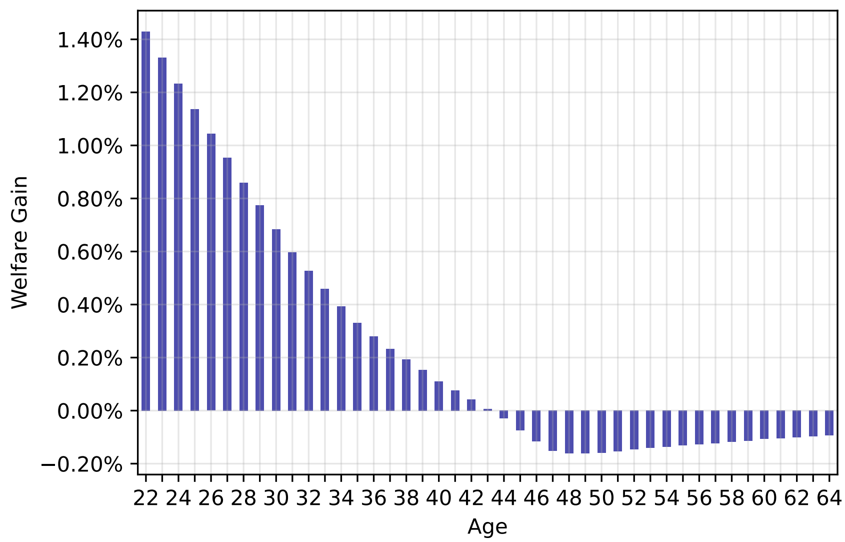
Figure A30. Comparison of Constrained-Optimal Income Contingent Loans with Existing Contracts



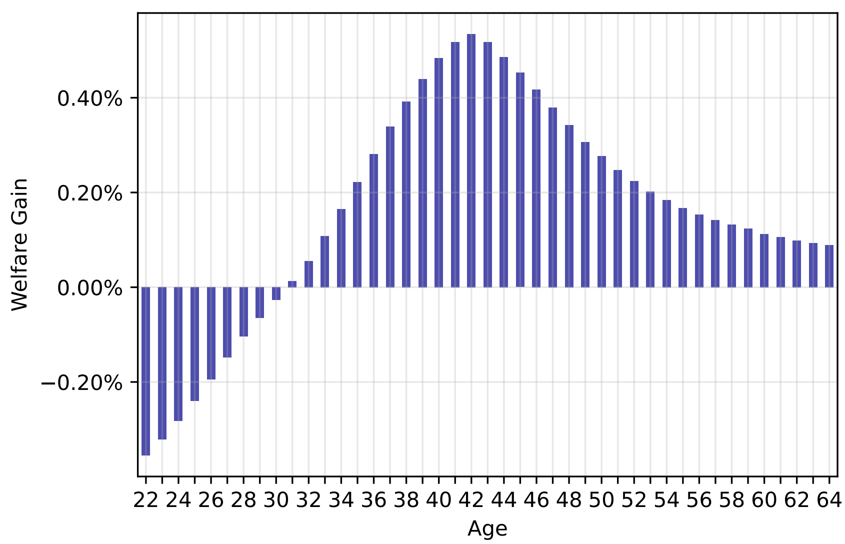
Notes: This figure shows the income-contigent repayments for several different repayment contracts. The light solid blue line is the 2004 HELP contract from Figure 2. The dark solid blue line corresponds to the constrained-optimal repayment contract in the baseline model that comes from solving (17)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

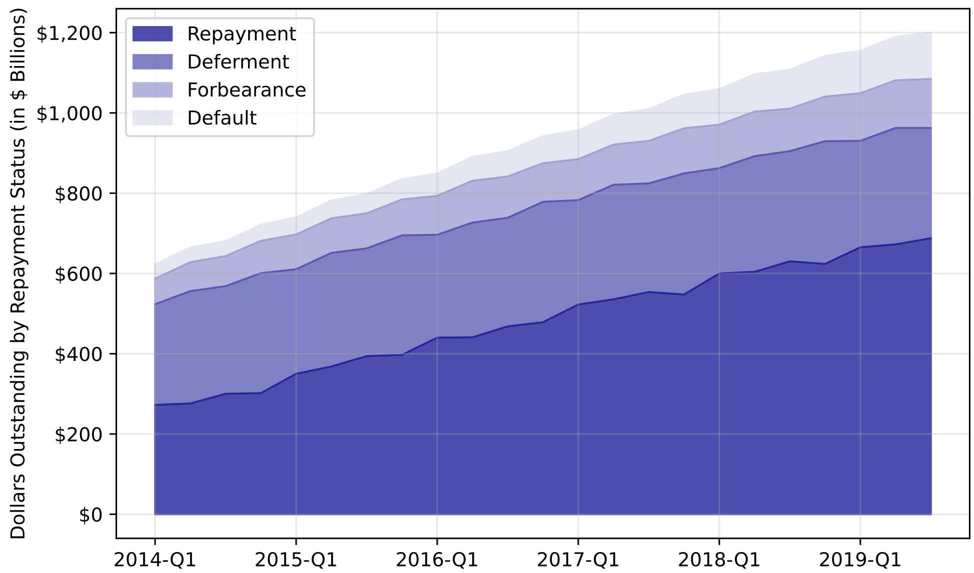


Panel B: Optimal Income-Contingent Loan with Forgiveness Relative to Optimal Income-Contingent Loan



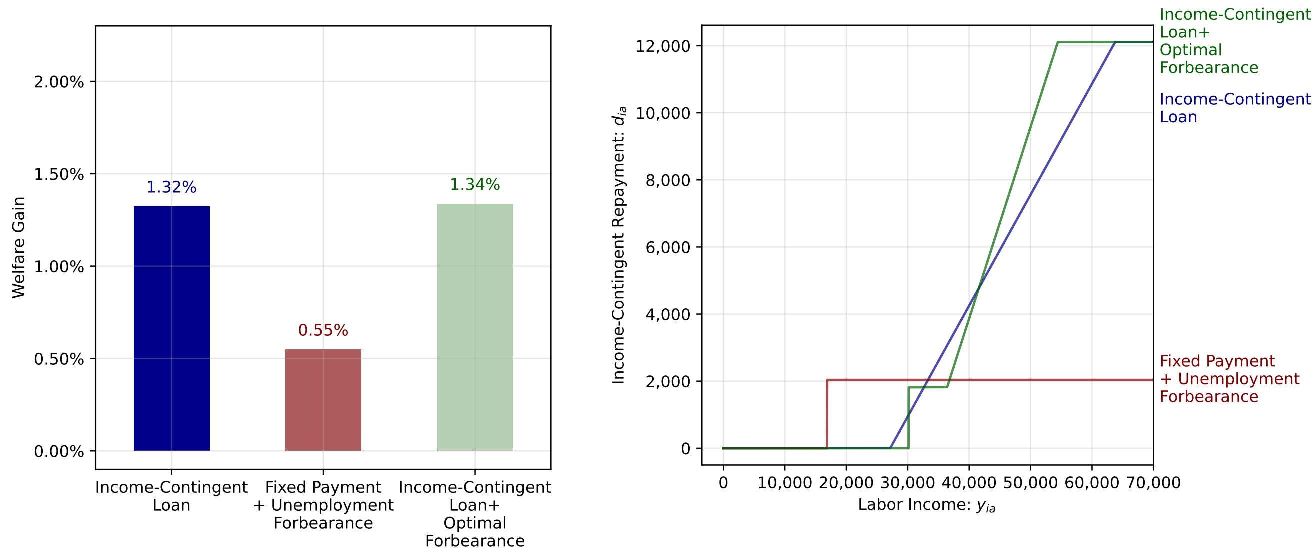
Notes: Panel A of this figure plots the average welfare gain at each age from the constrained-optimal income-contingent loan relative to 25-year fixed repayment. Panel B performs the same analysis for the welfare gain of the constrained-optimal income-contingent loan with forgiveness after 20 years relative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

Figure 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. This data was downloaded from the US Department of Education's Open Data Platform.

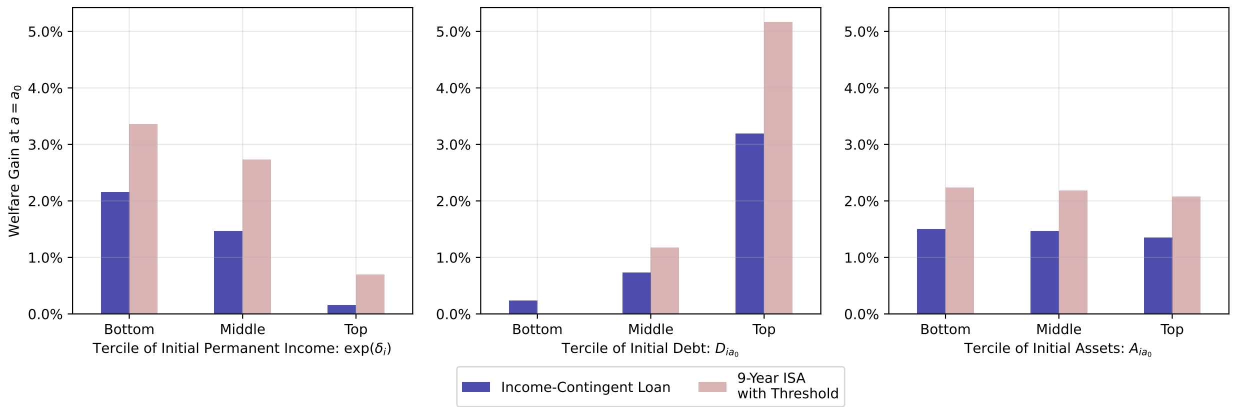
Figure A33. Welfare Gains from Adding Optimally-Chosen Forbearance to Income-Contingent Loan



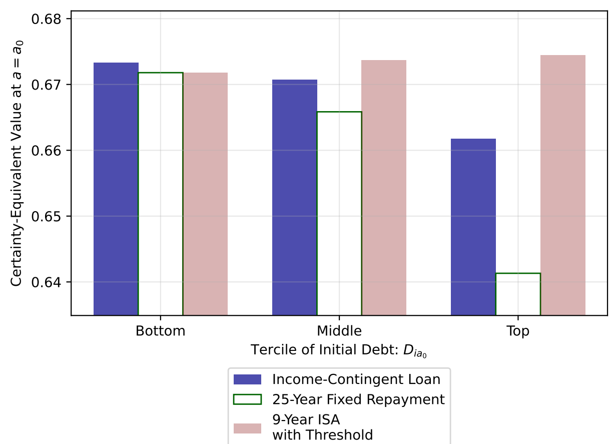
Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from different constrained-optimal repayment contracts described in the text and shown on the right. The repayments are shown for an individual with median initial debt.

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

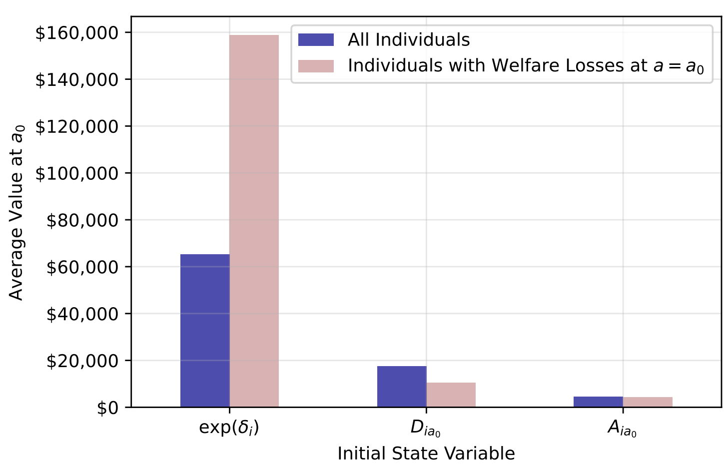
Panel A: Welfare Gains Across Initial States



Panel B: Variation in Certainty-Equivalents by Initial Debt



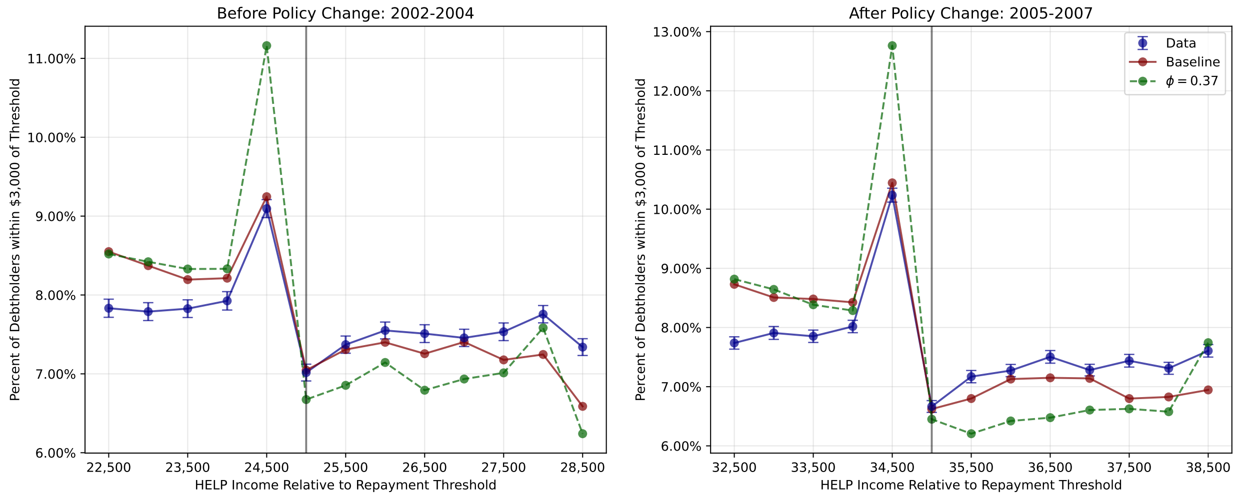
Panel C: Average Initial States by Welfare Gain from 9-Year ISA with Threshold



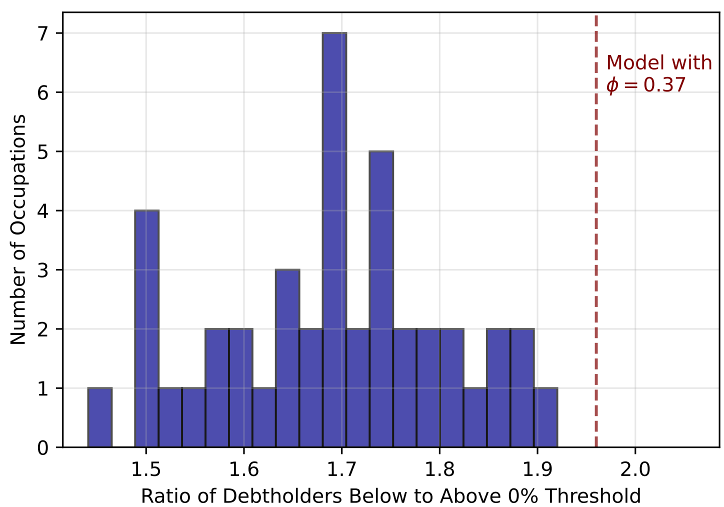
Notes: Panel A in this figure plots the welfare gains at a_0 computed in Figure 17 for different terciles of the three initial states that generate ex-ante heterogeneity in the model. Panel B plots the certainty-equivalent value at a_0 across terciles of initial debt. Panel C plots the average initial states of all 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 Baseline Model

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

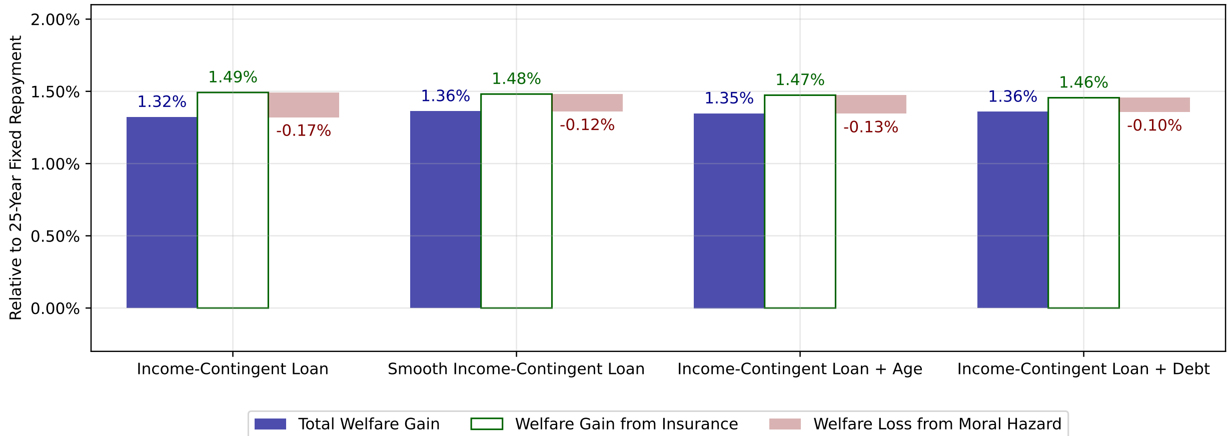


Panel B: Amount of Bunching Relative to Distribution Across Occupations



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 $a > a_0$.

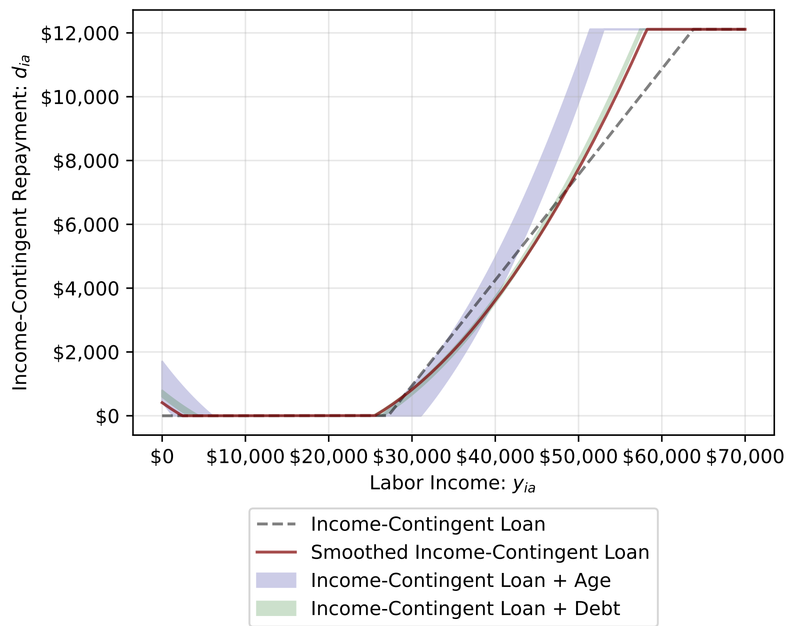
Figure A36. Welfare Gains from Alternative Forms of Income-Contingent Loans: Baseline Model



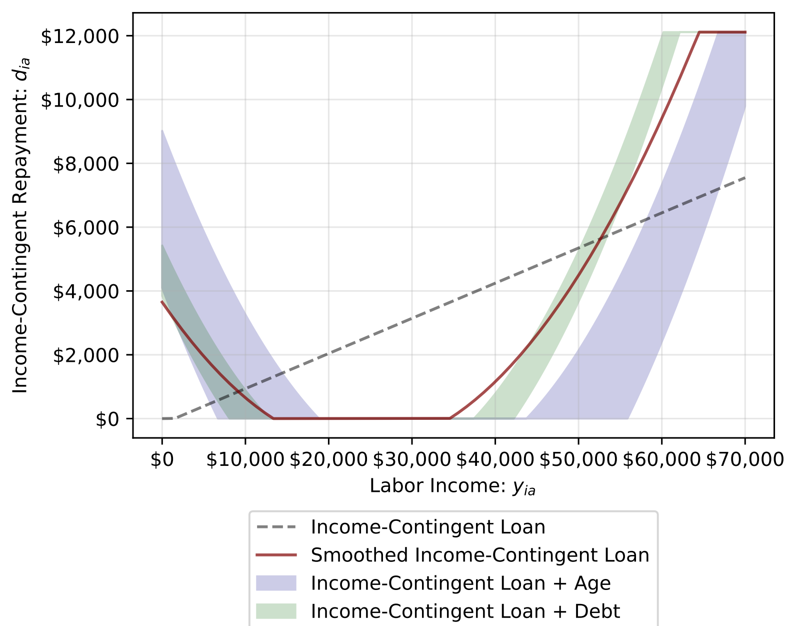
Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment, along with the decomposition performed in Figure 14, for different constrained optimal repayment contracts described in the text. This analysis is performed with all parameters set at their estimated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

Figure A37. Structure of Alternative Constrained-Optimal Income-Contingent Loans

Panel A: Baseline Model



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



Notes: This 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 an individual has initial debt balances 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 is 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 that 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 evaluating 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.