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

Tim de Silva†
MIT Sloan

Click Here for Latest Version

September 14, 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 repayment rates from the Australian student loan system, I show borrowers adjust their labor supply to reduce repayments on income-contingent loans. These responses are larger in occupations with more hourly flexibility, among young borrowers with high debt balances, 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 a welfare gain relative to a fixed repayment contract equivalent to 1.3% of lifetime consumption, with the same fiscal cost. Equity contracts generate welfare gains that are larger on average but significantly more dispersed. The labor supply responses created by income-contingent repayment reduce the insurance these contracts can provide at a given cost, but they are too small to justify fixed repayment contracts.

*__Incomplete draft: Please do not circulate without permission.__ I'm grateful to my dissertation committee, Jonathan A. Parker (co-chair), David Thesmar (co-chair), Taha Choukhmane, Lawrence D.W. Schmidt, and Eric C. So for their continuous support. I thank Pat Adams, David Autor, Maxime Bonelli, Bruce Chapman, Marc de la Barrera, Maryam Farboodi, Amy Finkelstein, Brice Green, Jonathan Gruber, Sebastian Hillenbrand, Debbie Lucas, Pierfrancesco Mei, Christopher Palmer, Jim Poterba, Charlie Rafkin, Antoinette Schoar, Andrei Shleifer, Kerry Siani, Adam Solomon, Yevhenii Usenko, Emil Verner, Adrien Verdelhan, Rodrigo Verdi, 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 (Federal Reserve Board 2023; Student Loans Company 2023). 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).

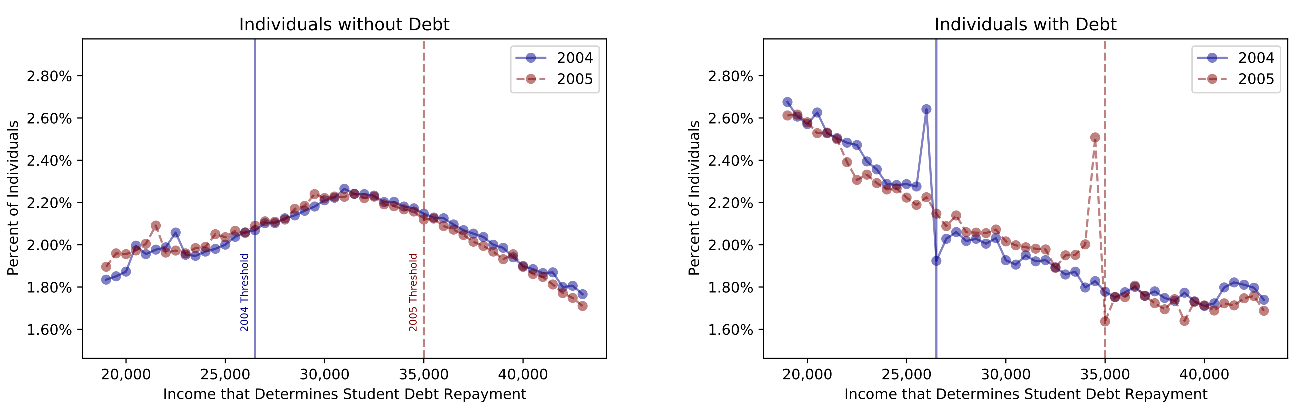
One potential policy to provide borrowers with more insurance against income risk is to make student loans more equity-like by indexing payments to borrowers' incomes. This idea has been discussed extensively (Friedman 1955; Shiller 2004; Palacios 2004; Chapman 2006; Zingales 2012), and governments in 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 their income and hence repayments. Empirically, income-contingent repayment appears effective at providing insurance (Mueller and Yannelis 2019; 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 against income risk? 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 welfare implications 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 high debt balances, and among liquidity-constrained borrowers. My structural estimation shows this evidence is consistent with a (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 contracts with income-contingent repayment. Specifically, a constrained-optimal income-contingent loan provides a welfare gain relative to a 25-year fixed repayment contract equivalent to 1.3% of lifetime consumption while incurring the same fiscal cost. Equity contracts (i.e., income-sharing agreements) generate welfare gains that are larger on average but significantly more dispersed. Additionally, the moral hazard created by income-contingent repayment decreases the insurance these contracts can provide at a given cost. 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 using the Australian setting to identify labor supply responses to income-contingent repayment. First, Australia was the first country to introduce income-contingent loans over 30 years ago in 1989, meaning borrowers are familiar with the availability and design of these contracts, unlike in the US (Abraham, Filiz-Ozbay, Ozbay, and Turner 2020; Mueller and Yannelis 2021). Second, the policy environment provides identifying variation with both discontinuities in income-contingent repayment rates and a significant policy change to these rates in 2005. Third, there is limited scope for adverse selection due to a lack of alternative financing options. This is useful for identification because it implies individuals' responses to the policy change reflect moral hazard rather than selection (Karlan and Zinman 2009), in contrast to US, where lower-income borrowers select into income-contingent repayment (Karamcheva, Perry, and Yannelis 2020). Finally, I use administrative data linking personal income tax returns, student loan balances, and Census responses for the population of debtholders, which is not available in other settings.

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



Notes: This figure shows the income distribution in Australian dollars that determines an individual's repayment rate on their income-contingent loan in 2004 and 2005 before and after the policy change, respectively. This income is called HELP Income and is equal to an individual's taxable income (i.e., the sum of labor income, capital income, and deductions), plus investment and rental losses, retirement contributions, foreign employment income, and fringe benefits. The vertical lines indicate the threshold above which individuals begin making debt payments of 3% and 4% of their income in 2004 and 2005, respectively. The sample is the entire population of individuals in Australia that file tax returns each year, subject to the sample selection criteria discussed in Section 2.4. HELP Income is deflated to 2005 Australian dollars using the HELP Threshold indexation rate based on annual CPI inflation. The left (right) graph restricts to individuals with zero (positive) HELP debt balances in each year.

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 and non-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 as part of the policy change. The distribution for debtholders exhibits significant bunching below the threshold, while the distribution for non-debtholders is smooth. In principle, this bunching could reflect labor supply responses that reduce labor income, the dominant source of income for most individuals, adjustments to other sources of income, such as saving less to reduce capital income, or tax evasion. I present three pieces of evidence that suggest the bunching in Figure 1 reflects labor supply responses. First, it is also present in the distribution of labor income, which is generally reported directly by employers and difficult to manipulate without labor supply adjustments. Second, the bunching is twice as large for occupations with high hourly flexibility (e.g., bartenders) relative to those with low flexibility (e.g., software engineers). Finally, I use data on hours worked from Australia's Census and show that individuals below the repayment threshold work 2-3% fewer hours (i.e., 1-2 fewer weeks per year) than those above the threshold.

In the second part of the paper, I develop a structural model of labor supply that quantitatively replicates the behavioral responses in Figure 1. The purpose of developing this model is to translate these labor supply responses into estimates of structural parameters and study the normative implications of income-contingent repayment. In the model, overlapping generations of individuals make consumption-saving and labor supply decisions over their life cycles. In each period, an individual's labor income is equal to the product of endogenous labor supply and an exogenous wage rate, where the latter is subject to uninsurable idiosyncratic risk. During working life, individuals repay their government-provided loans according to the contract specified by the government.

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 additional work effort 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%. In 2005, this corresponds to around $1,400 AUD ($1,800 USD in 2023). Assuming utility is increasing in consumption and leisure, no individuals would locate immediately above the threshold because locating below it delivers more leisure and $1,400 more cash on hand. Therefore, I explore whether optimization frictions (Chetty 2012) and learning-by-doing (Keane and Rogerson 2015), which increase the short- and long-run costs of reducing labor supply, can explain the presence of individuals above the threshold.

I find that optimization frictions best explain the lack of labor supply adjustment by individuals above the repayment threshold. These frictions could take various forms, such as inattention to repayment rates or costs associated with changing hours worked. Because isolating the importance of every possible friction is not feasible, I introduce two frictions to my model that jointly characterize how several frictions could limit labor supply adjustment in reduced-form. The first is that, in each period, only a fraction of individuals receive shocks that allow them to adjust their labor supply à la Calvo (1983). These shocks could capture pure inattention or the arrival of job transitions. The second optimization friction is that adjusting labor supply requires paying a fixed cost, which could be monetary (e.g., a wage reduction) or psychological (e.g., hassle costs).

The most important parameters for determining labor supply responses in my model are the (Frisch) labor supply elasticity, fixed adjustment cost, and Calvo probability. These parameters are identified by the following empirical patterns. The labor supply elasticity determines the extent of bunching below the repayment threshold illustrated in Figure 1: a larger elasticity implies more bunching. The number of individuals above the repayment threshold then jointly identifies the adjustment cost and Calvo probability: without these frictions, no individuals would be above the threshold. To separate these adjustment frictions, I exploit the fact that adjustment costs predict disproportionately more bunching at thresholds with greater changes in repayment rates and among individuals with more debt, in which case the incentives to reduce labor supply are larger.

I estimate the model by conducting the policy change from Figure 1 in the model and find that quantitatively replicating the behavioral responses to this policy change, in addition to properties of income over the life cycle, requires a labor supply elasticity of 0.11, fixed adjustment cost of $\$400$, and Calvo probability of 0.2. This estimate of the labor supply elasticity is slightly lower than the mean elasticity of 0.15 from the meta-analysis in Chetty (2012). My estimate of the fixed cost implies individuals pay around 1% of average earnings to adjust their labor supply, while the Calvo probability implies individuals receive an opportunity to adjust their labor supply every five years on average. These optimization frictions are crucial for identifying the labor supply elasticity: in a misspecified model without both frictions, the estimated elasticity is 0.005.

My model highlights two factors as quantitatively important in driving individuals' labor supply responses that also receive empirical support: borrowing constraints and the expectation of future debt repayment. Borrowing constraints increase the incentive to reduce labor supply by raising 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, my model predicts the amount of bunching decreases almost entirely. This importance of liquidity is supported empirically by the fact that individuals below the repayment threshold have larger mortgage and rent payments, which represent greater liquidity demands, have less wealth in the form of retirement savings, and are located in regions with lower house prices. The second important driver of labor supply responses is that debt repayment ceases after initial balances are repaid: the amount of bunching is almost twice as large in a counterfactual where debt repayments continue indefinitely. This finding is consistent with the greater bunching among individuals with higher debt balances, for whom eventual repayment is less likely, and highlights an important way in which the effects of income-contingent loans on labor supply differ from those of income taxes.

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. This constrained-optimal income-contingent loan provides a welfare gain 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 in this income-contingent loan is small: the consumption-equivalent welfare gain from an alternative (infeasible) contract with wage-contingent repayments, which provides insurance without causing distortions in labor supply, is only 0.2pp higher at 1.5%. Despite this relatively small cost, labor supply responses quantitatively affect contract design: if labor supply did not respond to income-contingent repayment, the optimal contract provides more insurance to low-income borrowers with a 40% higher repayment threshold.

I conclude by studying the welfare impact of two alternative income-contingent repayment contracts: income-contingent loans with forgiveness and income-sharing agreements. First, I find that adding forgiveness to income-contingent loans after a fixed horizon, as done in the US and UK, generates welfare losses relative to the constrained-optimal income-contingent loan. For a given fiscal cost, forgiveness increases repayments for young relative to old borrowers, which generates welfare losses because young individuals have a higher marginal value of wealth due to tighter borrowing constraints and greater precautionary-saving motives. Second, I show that income-sharing agreements, which were advocated for by Friedman (1955) and recently implemented by Purdue University, generate welfare gains that are larger on average but significantly more dispersed than those of income-contingent loans. This finding suggests that income-sharing agreements are more likely to generate ex-ante responses not captured by my model, implying that income-contingent loans may be a more robust mechanism for implementing income-contingent repayment.

Related literature and contributions. This paper sits at the intersection of literatures in household finance, public finance, and macro-finance. In its focus on the trade-off between insurance and incentives, this paper is part of a large literature on various forms of social insurance (Chetty and Finkelstein 2013), such as unemployment insurance (Baily 1978; Gruber 1997; Ganong and Noel 2019), mortgage debt relief (Ganong and Noel 2020), bankruptcy protection (Dobbie and Song 2015; Auclert, Dobbie, and Goldsmith-Pinkham 2019; Indarte 2023), and health insurance (Einav, Finkelstein, and Schrimpf 2017; Bornstein and Indarte 2022). Two strands of this literature that focus on student debt are directly related.[1] The first strand documents various forms

[1] See Amromin and Eberly (2016), Lochner and Monge-Naranjo (2016), and Yannelis and Tracey (2022) for reviews.

of debt overhang, in which reductions in student debt balances causes borrowers to enter default and deliquency less often (Mueller and Yannelis 2019; Di Maggio, Kalda, and Yao 2021), increase homeownership (Mezza, Ringo, Sherlund, and Sommer 2020), and change their choice of major, degree, or occupation (Chakrabarti, Fos, Liberman, and Yannelis 2020; Folch and Mazzone 2021; Hampole 2022; Murto 2022; Huang 2022; Luo and Mongey 2019; Ji 2021).[2] The second strand studies the effectiveness of income-contingent loans in mitigating these effects, finding reductions in unsecured credit delinquencies (Herbst 2023), mortgage defaults (Mueller and Yannelis 2019), and the passthrough of income variation to consumption (Gervais, Liu, and Lochner 2022).[3] Taken together, this evidence provides empirical support to arguments in favor of using equity-like financing for human capital (Friedman 1955; Shiller 2004; Palacios 2004; Mian and Sufi 2014).[4]

This paper makes three contributions to these literatures. First, I empirically document evidence of ex-post moral hazard (i.e., labor supply responses) created by income-contingent repayment, which has not been found in other settings (Britton and Gruber 2020; Herbst, Palacios, and Yannelis 2023).[5] Second, this paper provides a structural model of labor supply that rationalizes these responses, finding an important role for liquidity constraints and labor supply adjustment frictions. Finally, I quantify how these responses affect the welfare gains of constrained-optimal repayment contracts. Prior literature has highlighted the insurance benefits of income-contingent loans, without having empirical evidence to discipline the moral hazard effects or characterizing optimal policy (Ji 2021; Matsuda and Mazur 2022; Boutros, Clara, and Gomes 2022; Catherine and Yannelis 2023).

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, Chapman, Dearden, and Dynarski 2019). Theoretical work suggests these loans provide a close approximation to Mirrlees (1974)-style optimal policies (Lochner and Monge-Naranjo 2016; Stantcheva 2017).[6] This paper contributes by quantifying how the moral hazard these loans create affects optimal contract design.

[2]A related literature in labor economics emphasizes the importance in credit constraints for college attendance (Carneiro and Heckman 2002; Belley and Lochner 2007). Compared to a counterfactual with no loans, student loans can help relax credit constraints and increase degree completion (Black, Denning, Dettling, Goodman, and Turner 2022).

[3]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, Jones, and Keys 2023).

[4]Recent empirical work on the higher-order moments of income risk (Guvenen, Karahan, Ozkan, and Song 2021; Braxton, Herkenhoff, Rothbaum, and Schmidt 2021) provides an additional motive for increasing insurance.

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

[6]Other parts of this literature study other government policies towards human capital, such as subsidies for educational expenses (Benabou 2002; Bovenberg and Jacobs 2005), expanding access to grants (Abbott, Gallipoli, Meghir, and Violante 2019; Ebrahimian 2020), and relaxing parental credit constraints (Caucutt and Lochner 2020).

However, an important limitation of this paper is that it takes education and borrowing choices as given. Identifying whether and how these choices respond to income-contingent repayment is an important avenue for future research.

By studying state-contingent financing contracts, this paper connects to a broader literature on household security design. This literature is motivated by empirical evidence of imperfect risk-sharing (Cochrane 1991; Blundell, Pistaferri, and Preston 2008) and the household balance sheet channel, in which household leverage makes consumption more responsive to shocks (Mian, Rao, and Sufi 2013; Baker 2018; Verner and Gyöngyösi 2020). This evidence suggests policies that make household liabilities more state-contingent are desirable, such as shared-appreciation mortgages (Caplin, Carr, Pollock, and Tong 2007; Mian and Sufi 2014; Greenwald, Landvoigt, and Van Nieuwerburgh 2021), adjustment-rate mortgages conditioned on aggregate shocks (Campbell, Clara, and Cocco 2021), or more generous debt relief (Ganong and Noel 2020). I contribute to this literature by empirically studying one of the longest-running examples of such policies and quantitatively characterizing the welfare gains from alternative forms of state-contingent repayment. An important difference in my setting is the limited scope for strategic default, as student loans cannot be discharged in bankruptcy.

Finally, the variation this paper uses to identify labor supply responses builds on the literature that exploits non-linearities in tax schedules to estimate labor supply elasticities (Saez 2010; Chetty, Friedman, Olsen, and Pistaferri 2011; Kleven and Waseem 2013; Fagereng and Ring 2021). Consistent with this literature, this paper highlights the importance of frictions that limit labor supply adjustment, but it also makes two contributions. First, I separate the role of fixed costs and Calvo adjustment, which have both been used to model adjustment frictions but have not been separately estimated (Werquin 2015). I do this by leveraging novel variation in the present-discounted value of incentives is not present with taxes and a dynamic model of labor supply with both ingredients, which is similar to the "Calvo-Plus" model of price-setting in Nakamura and Steinsson (2010) and the model of mortgage refinancing in Andersen, Campbell, Nielsen, and Ramadorai (2020). Second, I show liquidity constraints can play a significant role in labor supply responses, which is consistent with the importance of liquidity in driving responses to other social insurance programs, such as unemployment insurance (Chetty 2008), mortgage default (Ganong and Noel 2022), and consumer bankruptcy (Indarte 2023). This result cautions against estimating structural models of labor supply without frictions in credit or insurance markets.

1 Motivating Framework

This section develops a simple framework to clarify the trade-off between insurance and incentives in the context of income-contingent loans. 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 (and do not 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 an debt contract would be a function of just D_t and θ. Individuals solve a standard life cycle problem choosing labor supply, ℓ_t, consumption, c_t, and initial debt balances, D_0:

$$V(\theta) = \max_{\{c_t,\ell_t\}_{t=0}^{T}, D_0} E_0 \sum_{t=0}^{T} u^t(c_t, \ell_t),$$

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

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

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, as in my setting.

Planner's problem. The government chooses θ to maximize individual welfare. Assume all individuals are ex-ante identical so the government solves the following problem:[7]

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

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 pertubation, as in Saez (2002).

Proposition 1. *Define* $M_t = \frac{u_c^t(c_t,\ell_t)}{u_c^0 t(c_0,\ell_0)}$ *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 pertubation to the repayment contract, $\frac{\partial d_t}{\partial \theta}$, and how the individual values

[7]The result in (2) can be easily generalized to the case of heterogeneous agents and non-utilitarian welfare weights.

it. If the government fully insures the individual, then the individuals' stochastic discount factor is equal to R^{-1} 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.[8]

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, then 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 and sources of *ex-post* moral hazard in income-contingent loans, $\frac{dy_t}{d\theta}$, and study what it implies for optimal contract design. To do so, I leverage a setting in which there is a change in the repayment contract $d\theta$, which allows me to estimate $\frac{dy_t}{d\theta}$. This setting, however, does not allow me to identify ex-ante moral hazard, $\frac{dD_0}{d\theta}$, because the policy variation applies to all incoming students, which makes it difficult to identify this effect separately from time- and cohort-specific shocks. Although I would ideally study this margin as well, I am comfortable abstracting from it due to institutional details in Australia discussed in Section 2.3 that make it difficult for individuals to adjust initial debt balances.

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). HELP was introduced in 1989 and prior to 2005 was called the Higher Education Contribution Scheme (HECS). HELP loans can be used to finance tuition[9] for all undergraduate and graduate degree programs at public institutions.[10]

[8] (2) can be rewritten as the marginal value of public funds defined by Hendren and Sprung-Keyser (2020), letting τ_t denote the tax and transfer function: $\sum_{t=1}^{T} E\left(M_t \frac{\partial d_t}{\partial \theta}\right)\left[\sum_{t=1}^{T} \frac{1}{R^t} E\left[\frac{dy_t}{d\theta}\left(\frac{\partial d_t}{\partial y_t} + \frac{\partial \tau_t}{\partial y_t}\right)\right] - \frac{dD_0}{d\theta}\right]^{-1}$.

[9] 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.

[10] 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

Tuition at public institutions is controlled by the government and varies by disciplines. For undergraduate courses at these institutions, which are called Commonwealth Supported Places (CSPs), the government provides a subsidy in the form of 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, with the exception of 2012-2017 in which the system was "demand-driven" (D'Souza 2018; Norton 2019).

Australian citizens have the option to either pay their student contribution upfront or borrow through HELP. Most individuals choose to do the latter, with less than 10% of new debt in 2022 being paid upfront (Department of Education and Training 2023). If individuals borrow through HELP, their initial debt is equal to their student contribution.[11] 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 A1 plots the student contribution over time, in addition to the aggregate amount of HELP borrowing and upfront payments.

HELP debt balances in subsequent years grow at inflation net of repayments, meaning HELP debt as a zero real interest rate. Individual i's annual compulsory repayment in a given year 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 defined as the taxable income reported an individual's personal income tax return plus a few adjustments discussed in Section 2.5. For most individuals, HELP repayments are witheld by their employer throughout the year and deducted from their debt balances after 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).[12] This means HELP effectively forgives debt for borrowers at the end of their working-life when they stop generating sufficient income to make compulsory repayments, simliar to the forgiveness

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.

[11] Universities receive the student contribution regardless of whether individuals borrow through HELP because in the latter case it is paid by the Australian Government.

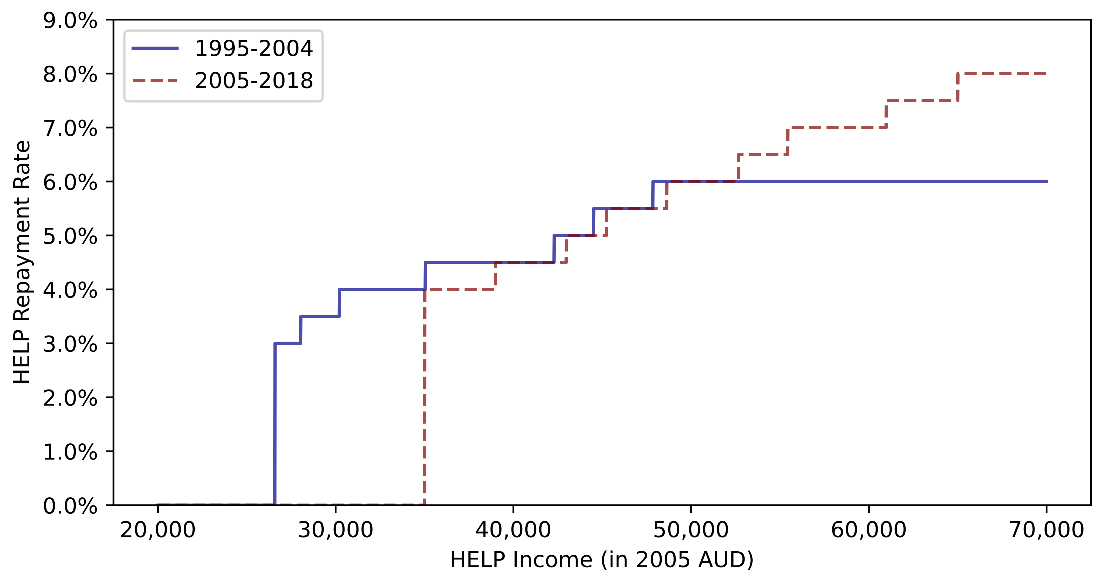
[12] I reached a similar estimate of 40% by forecasting individuals income using occupation-age-gender-specific average growth rates.

embedded in US income-driven repayment plans. As in the US, HELP debt cannot be discharged in bankruptcy.[13]

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, $r_t(\cdot)$. 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 average HELP Income among debtholders is around $30,000, 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. Importantly, this policy change applied to all new and existing HELP debtholders, which implies that behavioral responses are driven by moral hazard rather than adverse selection (Karlan and Zinman 2009).[14]

Figure 2. HELP Repayment Rates as a Function of Income: Before and After 2004-05 Policy Change



Notes: This figure shows HELP repayment rates as a percentage of HELP Income for different levels of HELP Income. The blue line shows repayment rates in 2004 prior to the policy change and the red line shows repayment rates in 2005 after the policy change. See Figure A2 for a plot of how marginal HELP repayment rates vary with income.

The repayment threshold creates a large incentive to reduce HELP Income because it generates

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

[14] 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, Jenkins, and Levin 2012; DeFusco, Huan, and Yannelis 2022), mortgages (Gupta and Hansman 2022), and health insurance (Einav and Finkelstein 2011).

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 $\$35{,}001 * 4\% \approx \$1{,}400$. In a frictionless static model of labor supply, no individuals would choose to locate immediately above the repayment threshold because doing so delivers less take-home pay and leisure relative to locating below it.[15] The repayment functions feature several other discontinuities in average repayment rates shown in Figure 2. These are much smaller: 0.5% versus 3% and 4% at the repayment threshold in 2004 and 2005, respectively.

There are several reasons to believe this change to the HELP repayment function were salient to debtholders. First, the policy received media coverage at the time of the change (Marshall 2003). Second, 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 (Medhora 2018).[16] 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 structure of the program.

Government policy documents and media articles suggest the primary reason for this policy 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 the 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 A1). These other changes were primarily aimed at those entering their degree programs rather than those repaying HELP debt.[17] The simultaneous implementation of these other changes with the change in repayment threshold is not ideal. However, it likely has a miminal effect on my analysis, which focuses on identifying moral hazard among individuals that already completed their degree programs.

2.3 Benefits of Studying Income-Contingent Repayment in Australia

In addition to the presence of high-quality administrative data and policy variation, there are several benefits to using HELP as a setting 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). The same is not true in the US, where high-income borrowers choose

[15] In the literature on labor supply responses to taxes, this threshold corresponds a notch rather than a kink (Kleven and Waseem 2013).

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

[17] See Chapman and Salvage (2001) and Beer and Chapman (2004) for a detailed discussion of these changes.

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 recieve external financing from a bank or university, but 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 the choice of 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, the only way individuals can adjust their initial HELP debt is by changing their choice of degree or insitution, 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 loan program. The fact that this program has been around since 1989 suggests borrowers understand the structure of the 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). An final benefit is that there are no responses by the supply-side of higher education due to government tuition control. If this were not the case, changes in government-provided financing contracts could pass through to tuition and thus initial debt balances (Kargar and Mann 2022).

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 the components of individual income and basic demographics 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. 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.[18] 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, which is the year in which the Census was administered.

I supplement these administrative datasets with survey data on household balance sheets from 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 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.

The most important variable introduced in Table 1 is HELP Income, which determines an individuals' repayment rate on their HELP debt according to Figure 2. HELP Income is equal to 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.

[18]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. These two make up around 48% and 52% of trusts respectively. There are two main sources of trust income: (i) investment income from listed and unlisted securities, including money market funds, equities, and rental properties (e.g. Vanguard managed trust funds), and (ii) capital or labor income from business held in trust structure. These make up around 65% and 35% of total trust income respectively. 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. Therefore, I choose to drop these observations from my analysis to order to avoid attributing possible tax evasion to labor supply responses. This represents less than 2.5% of debtholders at the time of the policy change in 2004. In results available upon request, I show my main findings are quantitatively similar when keeping these observations.

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. 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.

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.[19] 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, the majority of 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 A4 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 (see Figure A3), 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 Loans

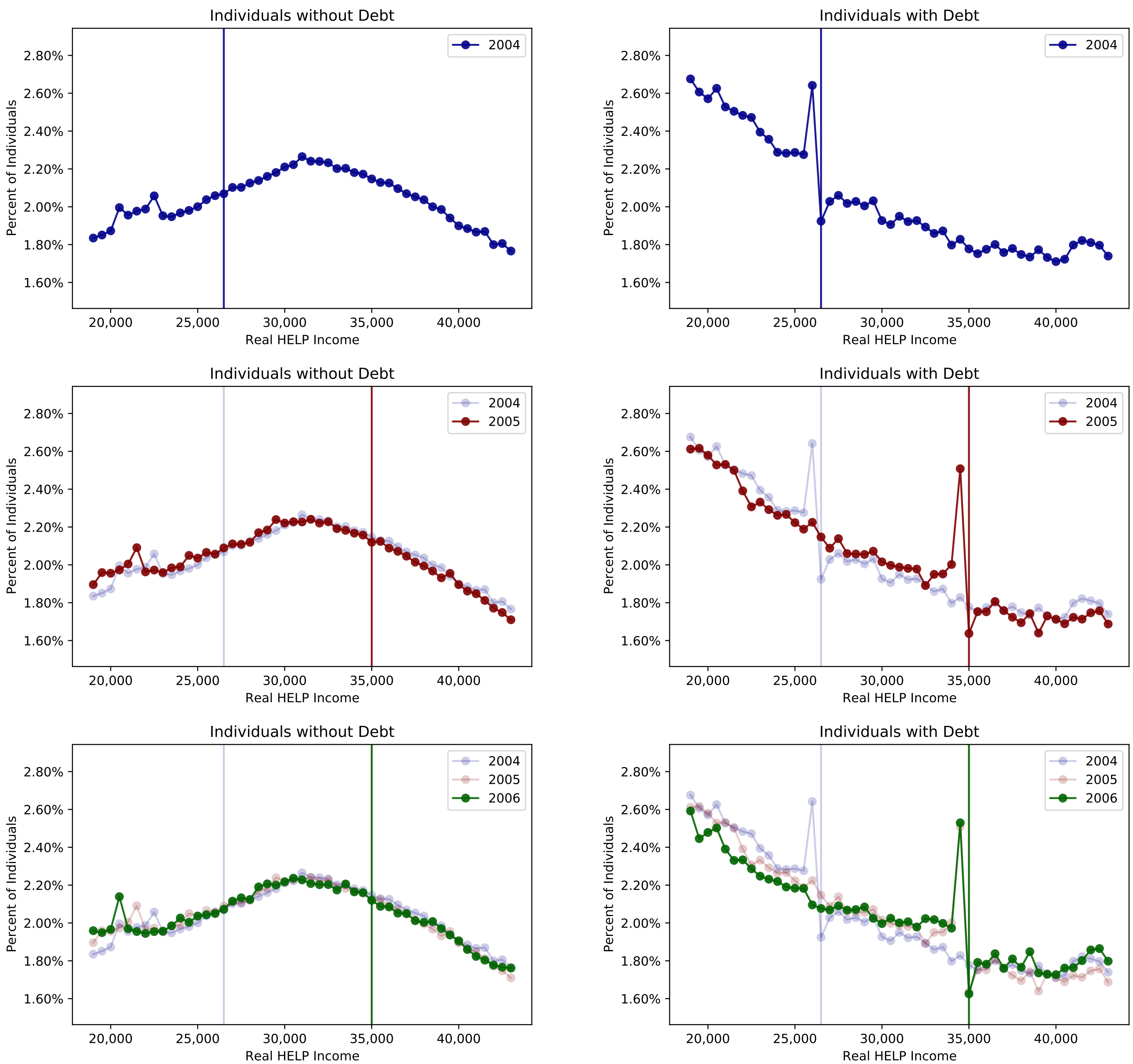
3.1 Bunching Below the HELP Repayment Threshold

Figure 3 plots the distribution of real HELP Income before and after the policy change for non-debtholders and debtholders in the left and right panels, respectively. HELP Income is deflated to 2005 Australian dollars using the HELP Threshold indexation rate. The vertical line in each plot

[19] Trust income is a relatively common form of income in Australia because many individuals hold assets in the form of managed investment trusts, which effectively are counterparts to mutual funds in the US. These funds are also provided by large investment managers (e.g. Vanguard) and generate passive income from the asset class of choice, but have a different governance structure.

corresponds to the HELP repayment threshold in that year, which is constant in real terms before the policy change. The results show the income distribution of non-debtholders exhibits no bunching around the HELP repayment threshold. In contrast, the income distribution of debtholders exhibits substantial bunching around the threshold, with minimial bunching at other locations.

Figure 3. Real HELP Income Distribution in 2004-2006



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 2004 prior to the policy change and in 2005 and 2006 after the policy change. The vertical lines indicate the threshold above which individuals begin making debt payments of 3% and 4% of their income before and after the policy change, respectively. The sample is the entire population of individuals in Australia that file tax returns in each year, subject to the sample selection criteria discussed in Section 2.4. HELP Income is deflated to 2005 Australian dollars using the HELP Threshold indexation rate, which is based on the annual CPI. The left (right) graph restricts to individuals with zero (positive) HELP debt balances. For the same plots in years further from the policy change, see Figure A5.

The middle panel of Figure 3 shows two important changes in the income distribution of debtholders after the policy change in 2005. First, the bunching at the 2004 repayment threshold disappears completely. Second, bunching appears immediately below the new repayment threshold. In contrast, no changes are present in the income distribution of non-debtholders. The bottom panel of Figure 3 and Figure A5 show very similar patterns of bunching below the repayment threshold is present in the subsequent years.[20]

The two main facts from Figure 3 are the presence of significant bunching below the repayment threshold, but also the lack of adjustment by many individuals right above the repayment threshold. In the next two sections, I discuss explanations for each of these facts in turn.

3.2 Is Bunching is Driven by Labor Supply Adjustment?

Figure 3 provides clear evidence of individuals adjusting their HELP Income to avoid making debt repayments. The fact that the income distribution responds quickly to the policy change for debtholders but is unaffected for non-debtholders suggests the bunching is driven by a desire to reduce loan repayments and is not driven by mechanical features of Australia's tax system, such as the tendency to report incomes at round numbers.

There are three margins through which individuals could adjust their HELP Income to locate below the repayment threshold. The first is to make changes in labor supply that reduce Labor Income, such as reducing hours worked. The second is through is to make real adjustments that reduce the other two components of HELP Income in (3), such as saving less to reduce capital income or claiming additional deductions. The final margin is tax evasion. Such tax evasion could be legal, in which individuals shift income to forms of compensation that are not counted in HELP Income from those that are not, or illegal, such as misreporting HELP Income. The remainder of this section presents three findings that suggest an important margin of adjustment is the first one: changes in labor supply.

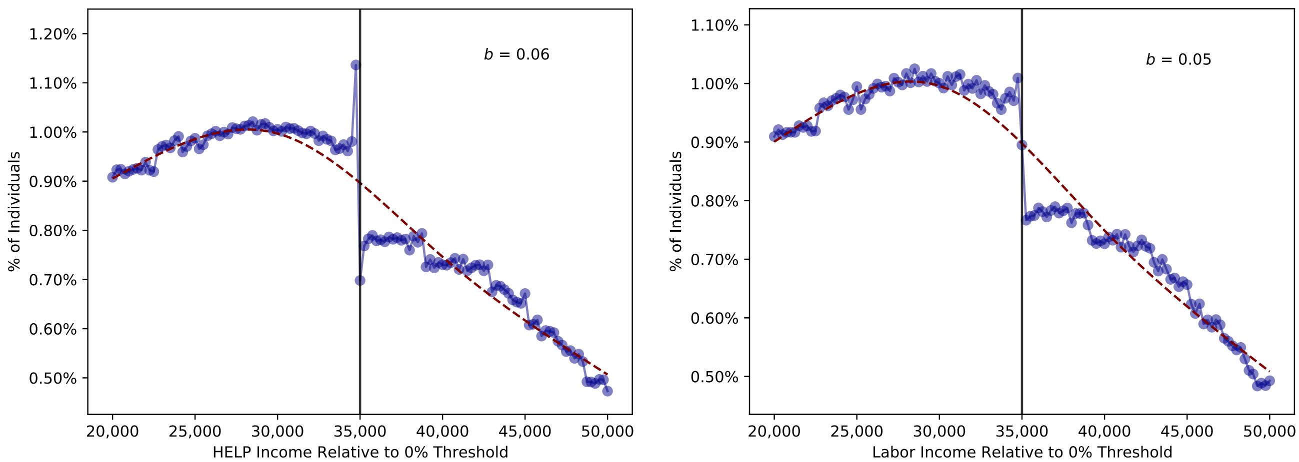
3.2.1 Finding #1: Bunching is Present in the Distribution of Labor Income

Figure 4 plots the distribution of real HELP and Labor Income relative to the new repayment threshold after the policy change. Following Chetty et al. (2011), I focus on the sample of individuals whose primary source of income is Labor Income and earn less than 1% of income from other sources. This ensures all individuals require similar values of Labor Income to generate HELP Income at the repayment threshold. The left panel shows significant bunching in the distribution

[20] In 2004-2008, there are also movements in the personal income tax brackets that affect the income distribution for non-debtholders. These tax brackets are not indexed to inflation, so in 2002 and 2003 they move in real terms, which generates small changes in the real HELP Income distribution for non-debtholders.

of HELP Income, consistent with the results Figure 3. However, the right panel shows the amount of bunching in the distribution of Labor Income is almost as large.

Figure 4. Distributions of Real HELP Income and Labor Income in 2005-2018



To quantitatively compare the amount of bunching in the distribution of HELP and Labor Income, I construct a bunching statistic following the literature that estimates 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.

The estimated value of b for both the distribution of HELP Income and Labor Income are shown in the top right of Figure 4 with the counterfactual distributions plotted in the dashed lines. Comparing the bunching statistics shows the amount of bunching in Labor Income is 83% as large as that of HELP Income. These results show the primary margin of adjustment is Labor Income, which is not entirely surprising given it makes up the majority of borrowers' income (Table 1).[21]

[21]These results can also 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 over this time period reported in the aggregated ATO HELP Data.

3.2.2 Finding #2: More Bunching in Occupations with Greater Hours Flexibility

Having established bunching in the distribution of Labor Income, I now examine whether this bunching reflects labor supply adjustments or tax evasion, in which individuals shift labor income compensation to sources that are not counted in HELP Income. The next two sections present evidence of real labor supply adjustments, after which I discuss the possibility of other mechanisms.

Using survey data from HILDA, I compute two measures of hours flexibility across all individuals within each 2-digit ANZSCO occupation, which is the finest level at which *ALife* reports occupation codes: (i) cross-sectional standard deviation of log hours, and (ii) standard deviation of annual changes in log hours. These measures are highest for occupations where it is relatively easy to adjust hours, such as for Hospitality Workers and Sales Assistants, and lowest for those where it is more difficult, such as ICT Professionals and Engineers. Table A1 shows these measures for each occupation code in my sample.

Figure 5 plots the amount of bunching among wage-earners below the new repayment threshold relative to the two measures of hours flexibility in the left and right panels, respectively. 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 that are within $2,500 below to the number that are above the threshold, similar to Chetty, Friedman, and Saez (2013).[22] A ratio of one indicates no bunching.

The results show that bunching is more common in occupations with greater hours flexibility. For example, ICT Professionals have the lowest hours flexibility with a standard deviation of annual change in log hours of 0.17. In this occupation, there is only 30% more individuals below relative to above the threshold. In contrast, Hospitality Workers have almost three times more hours flexibility with a standard deviation of annual change in log hours of 0.48 and exhibit over twice as much bunching, with 70% more individuals below relative to above the threshold.

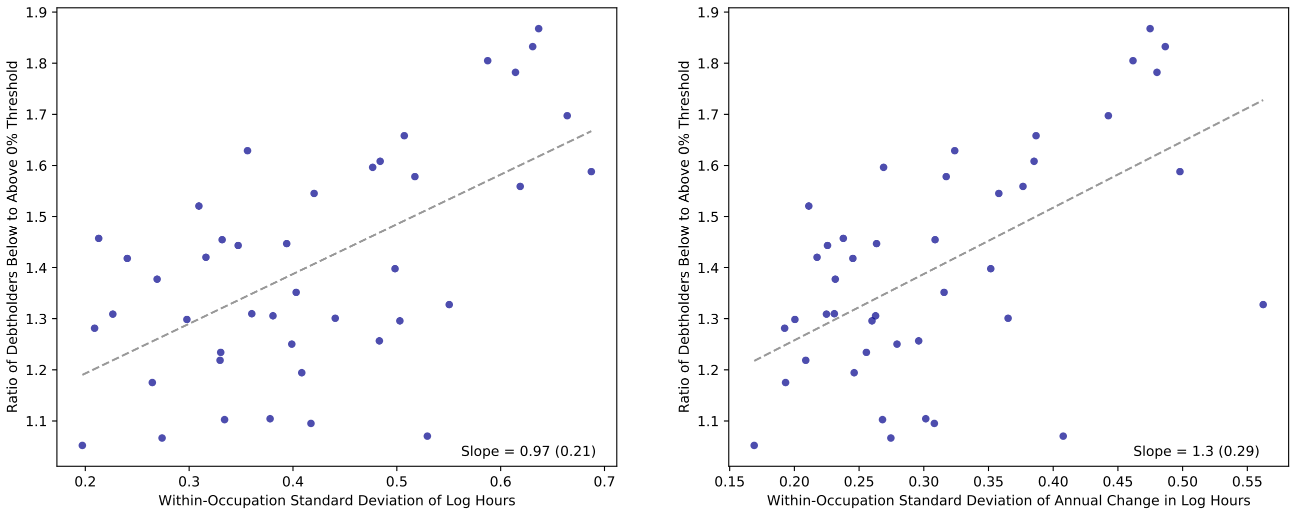
3.2.3 Finding #3: Individuals Bunching Below Repayment Threshold Work Fewer Hours

The final piece of evidence that suggests the bunching in Figure 3 is driven by labor supply adjustments is the fact that borrowers locating below the repayment threshold work fewer hours. To measure hours worked, I use a question from the Census of Population and Housing in which individuals report the number of hours worked in all jobs during the week prior to Census night. I construct this measure MADIP sample that provides a linkage between ATO data and the Census responses in 2016.

Figure 6 plots average hours worked in $250 bins of HELP Income around the repayment thresh-

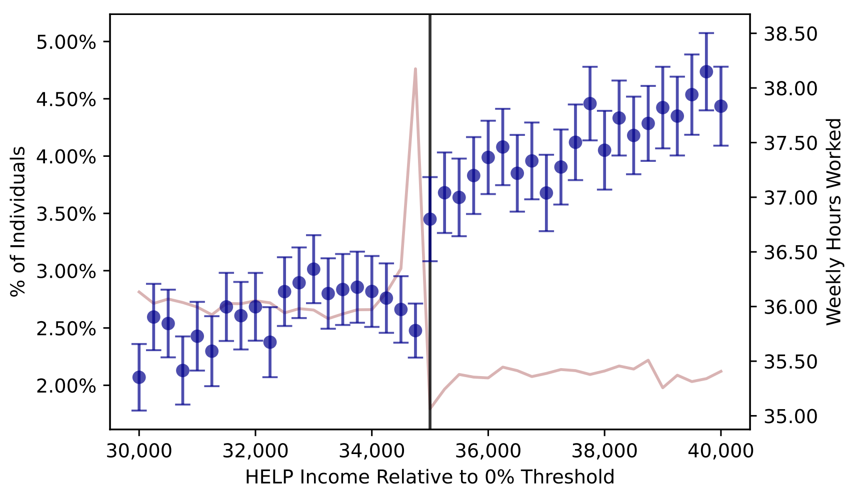
[22] I cannot compute b due to a lack of sufficient observations within each occupation.

Figure 5. Bunching across Occupations based on Hours Flexibility: 2005-2018



old, in addition to the distribution of HELP Income in red.[23] The results show 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%.[24] This adjustment in hours worked occurs *within* an individuals' current occupation: Figure A9 finds little evidence that those below the repayment threshold being more likely to have switched occupations.

Figure 6. Average Hours Worked around Repayment Threshold in 2016



The results in Figure 6 are subject to a few caveats. First, this test can only be performed

[23] I choose $250 bins because it is the smallest bin that satisfies the DataLab disclosure requirements, which require a sufficient number of observations in each bin.

[24] These results are not driven by a group of individuals outside the labor force earning only income from other sources: Figure A6 shows the patterns are nearly identical in the sample of individuals earning positive Labor Income.

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 A7 shows the distribution of HELP Income in 2016 across the two samples is very similar. Finally, these data on hours worked are self-reported by employees rather than employers, which introduces concerns about reporting issues. As a result, I do not target this evidence directly when estimating my structural model, but instead view it as providing qualitative support for the mechanisms included in the model.

3.2.4 Non-Labor Supply Mechanisms to Reduce Labor Income

Outside reducing labor supply, individuals could reduce their Labor Income in several other ways. I now discuss the evidence for each of these additional margins in turn.

Pure evasion. An obvious explanation for the bunching in Figure 3 is pure evasion, in which individuals misreport their Labor Income. Although this is illegal and difficult to identify empirically, several facts, in addition to the direct evidence of a labor supply response in Figure 6, suggest it does not play a large role. First, Figure A11 replicates the analysis Figure 4 replacing Labor Income with salary and wages and shows this distribution also 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).[25] Second, Figure A10 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 are around median income. This contrasts with the high income sample of individuals for which prior literature has documented such shifting responses are prevalent (Slemrod and Yitzhaki 2002).

Income-shifting across years. The repayment threshold provides individuals with the incentive 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 7, discussed in Section 3.3, shows this does not happen empirically: individuals who locate below the repayment threshold in a given year do not have higher income in future years.

Income-shifting within years. An alternative to shifting compensation over time would be to

[25] An alternative test is to compare the bunching among wage-earners and entrepreneurs in the full sample, which Figure A12 shows are relatively similar.

shift compensation to forms that are not included in HELP Income. This cannot be observed directly, but it is likely limited for the typical employee in this setting because HELP Income already includes many forms of non-wage compensation, such as retirement contributions, foreign employment income, and employer fringe benefits (see Appendix D).

Firm responses. An alternative mechanism to the labor supply response in Figure 6 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 coverged by collective bargaining agreements.[26] Two findings suggests 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 A8 replicates Figure 9 from Chetty et al. (2011), which plots the distribution of Labor Income among individuals with positive 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 A8 shows this distribution exhibits no bunching in my setting.

3.3 What Prevents Adjustment by Borrowers Above Repayment Threshold?

In addition to significant bunching below the repayment threshold, Figure 3 shows a significant fraction of debtholders do *not* adjust their labor supply and choose to locate above the threshold. This evidence provides a rejection of static frictionless models of labor supply used to study responses to taxes (e.g., Saez 2010). To see this, recall that locating immediately below the threshold delivers a 3% and 4% increase in take-home pay before and after the policy change, respectively (Figure 2). However, in frictionless labor supply models, individuals' utility increases in consumption and decreases in labor supply. Therefore, locating immediately below the threshold strictly dominates locating above it because it delivers more consumption with less labor supply (Kleven and Waseem 2013). In the remainder of this section, I explore possible extensions that could explain the presence of individuals above the repayment threshold.

The first extension to consider is the fact that the presence of income-contingent debt makes labor supply a dynamic decision. Like a tax, an income-contingent loan decreases the return on the marginal unit of labor supply. However, income-contingent loans have an additional debt effect: increasing labor supply today reduces the stock of debt tomorrow. If an individual's value function is sufficiently decreasing in debt, this effect encourages individuals to not reduce their labor supply and locate below the threshold. In Appendix B, I use a simple dynamic model to show that in order for the debt effect to explain individuals locating above the threshold, it must be the case

[26] Appendix C contains additional details on the wage-setting process in Australia.

that individuals' value function is decreasing in debt more than it is increasing consumption. This is unlikely to be the case for two reasons. First, HELP debt has a zero real interest rate, so there is little incentive to repay the debt early. Second, individuals have the option to make voluntary repayments but, as discussed in Appendix C, very few do. If the marginal value of reducing debt was this high, more individuals should be making voluntary repayments.

Prior literature on labor supply highlights two alternative forces that can reconcile small short-run labor supply responses with larger macro elasticities: learning-by-doing, also known as human capital accumulation or career effects, and optimization frictions. Because both of these explanations introduce a cost to reducing labor supply, they can in principle explain the lack of adjustment by individuals above the repayment threshold. I now discuss these two explanations in turn.

3.3.1 Learning-by-Doing

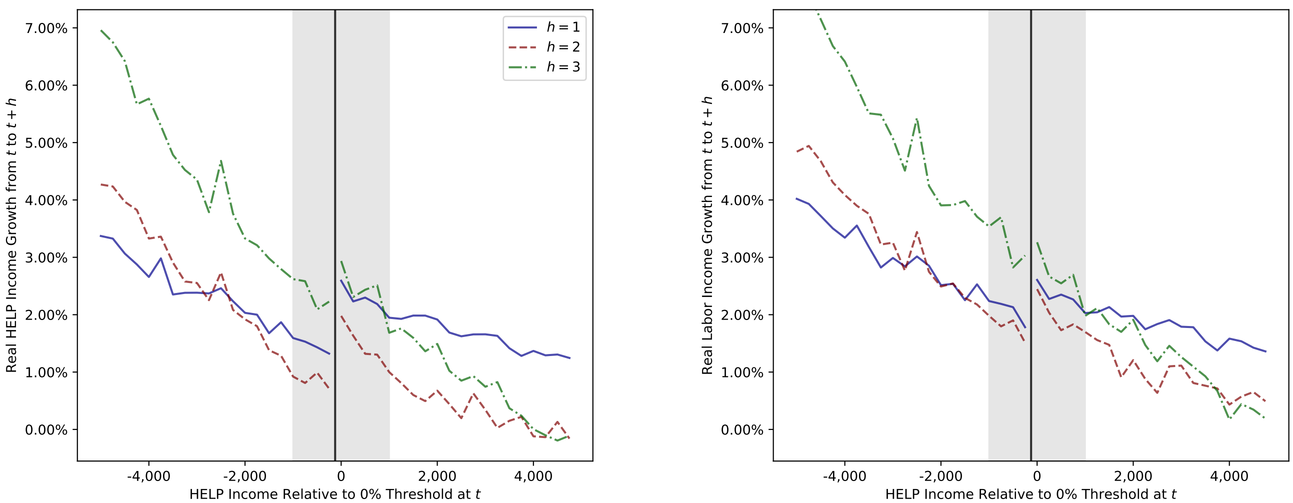
Learning-by-doing refers to the idea that the choice of labor supply today affects the stock of human capital and hence future wages (Keane and Wolpin 1997; Imai and Keane 2004; Best and Kleven 2012; Keane and Rogerson 2015; Makris and Pavan 2021). As a result, learning-by-doing generates a cost to reducing labor supply to bunch below the repayment threshold: reducing labor supply today will decrease future wages.[27]

In the ideal experiment, bunching would be randomly-assigned and I could compare the future wages of bunchers and non-bunchers to identify learning-by-doing. Absent this ideal experiment, Figure 7 plots the average growth rate in HELP Income and 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 slightly lower income growth than those above the threshold by 1% in the subsequent year, but this difference disappears after three years. This evidence provides limited support for the presence of learning-by-doing, but is subject to concerns about selection into bunching. Nevertheless, this evidence is useful because it is natural to expect that individuals with lower expected income growth would be more likely to bunch, in which case Figure 7 would overstate the presence of learning-by-doing.

An additional prediction of models with learning-by-doing is that labor supply responses should be larger among older individuals (Keane 2016). The intuition is that the cost of lower human capital is relatively small for old individuals, who have fewer working years remaining. Figure 8 tests this prediction by computing the bunching statistic, b, defined in (4) by age group and finds

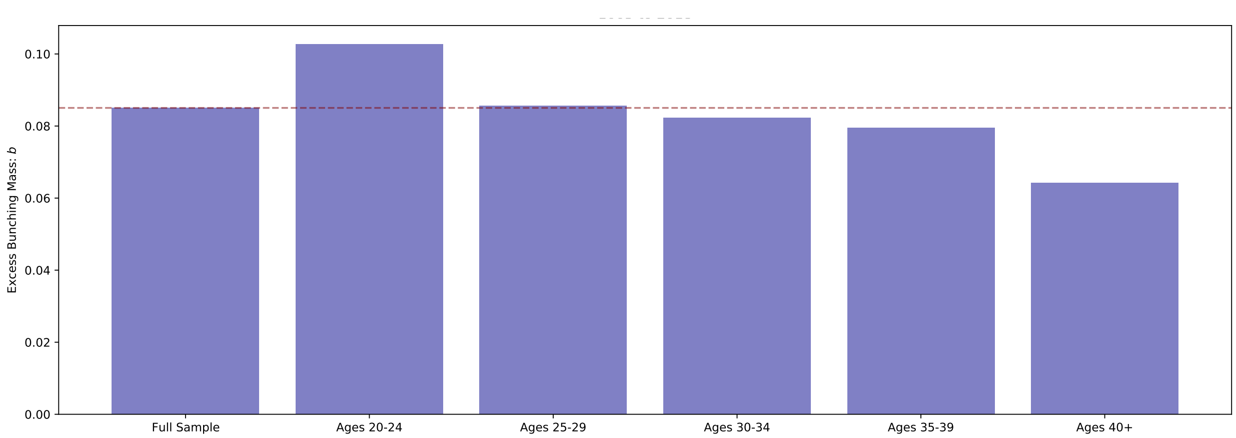
[27] A related model of dynamic compensation is presented in Kleven, Kreiner, Larsen, and Søgaard (2023), where individuals' realized earnings only equals their true latent earnings (hours × wages) at job transitions. I cannot test this hypothesis in my setting because I do not observe job transitions, 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.

Figure 7. Future Income Growth around Repayment Threshold



it decreases monotonically with age.[28] These differences are quantitatively large: the estimated b is around 50% larger for individuals in their early 20s relative to those older than 40. This finding provides further evidence against learning-by-doing and also suggests a role for liquidity constraints, which are more binding for younger individuals with less liquid wealth and credit history.

Figure 8. Bunching Statistic by Age in 2005-2018



3.3.2 Optimization Frictions

There are several forms of optimization frictions that could limit labor supply adjustment, such as inattention (Chetty, Looney, and Kroft 2009; Chetty et al. 2013), real or psychological costs to

[28]The underlying income distributions are plotted in Figure A13.

changing labor supply (Chetty 2012; Kleven and Waseem 2013), or the inability to find a job with the desired hours (Chetty et al. 2011). Since isolating the importance of each possible friction is not possible given the available data and empirical variation, I instead follow Nakamura and Steinsson (2010) and Andersen et al. (2020) and attempt to quantify the importance of two different classes of models with adjustment frictions: state-dependent and time-dependent models of adjustment.[29] The canonical formulation of state-dependent models is the (S, s) model in which adjustment requires paying a fixed cost (Caplin and Leahy 2010).[30] An example of a friction in my setting that could be modeled with a state-dependent model of adjustment would be hassle costs of changing hours worked. In time-dependent models of adjustment, such as Calvo (1983), unobserved shocks move the probability of adjustment that are independent of the benefits from adjustment. In the context of labor supply adjustment, these shocks could pure inattention or the arrival of opportunities to adjust hours worked.[31]

I now discuss two pieces of empirical evidence that I leverage in my structural estimation to separately identify the role of state- and time-dependent adjustment. The main prediction of a state-dependent adjustment model, such as a (S, s) model in which adjustment requires paying a fixed cost, is that adjustment should be more common when the benefits of adjusting are larger. In my setting, there are two sources of variation in the incentives provided by income-contingent loans to reduce labor supply. The first is variation in the static incentives depending on an individuals' current income shown in Figure 2: individuals right above the repayment threshold after the policy change receive a 4% increase in cash on hand ($1,400 AUD) from reducing their labor supply, while individuals right above the second discontinuity in the repayment schedule at $38,987 experience receive only a 0.5% increase in cash on hand ($195 AUD).

The left panel of Figure 9 plots the income distribution of debtholders around the repayment threshold in addition to the second 0.5% discontinuity. In a time-dependent adjustment model, individuals above both discontinuities that receive adjustment shocks would locate below them to increase cash on hand. However, in a state-dependent model, individuals would be more likely to locate above the second discontinuity because gains from adjusting are much smaller. As evident from Figure 9, there is almost no bunching below the second discontinuity.

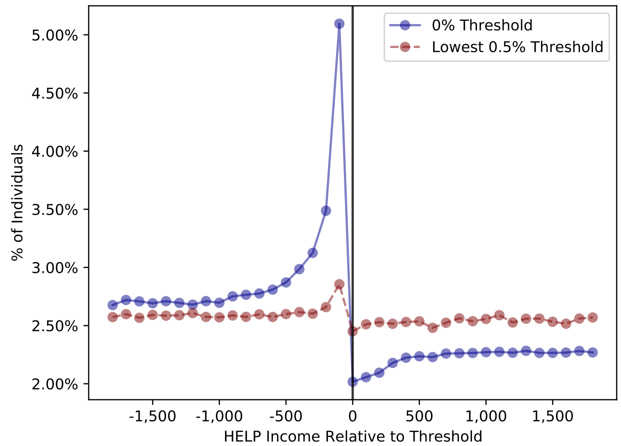
The second source of variation in the incentives to reduce labor supply is in the present dis-

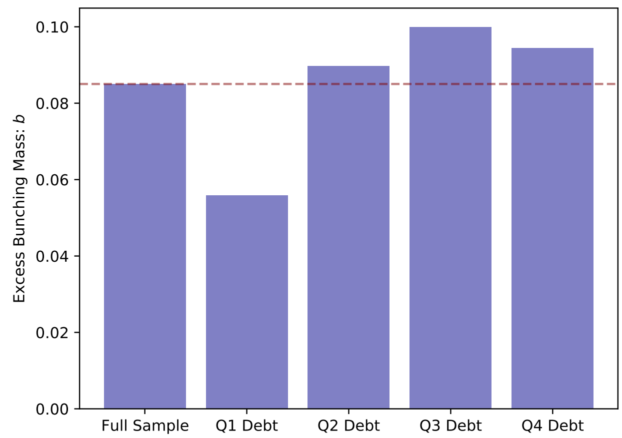
[29] An alternative optimization friction is optimization errors (or noise) that could take two forms, both of which are inconsistent with my evidence. The first is anticipated errors, in which individuals know they cannot control labor supply perfectly. This, however, makes the prediction there will 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 optimization errors, where labor supply equals individuals' choice plus an error. This makes the prediction that the bunching will be diffuse around the repayment threshold (as in Chetty et al. 2013), while the bunching in Figure 3 is sharp.

[30] The (S, s) model has been used to model several decisions in household finance, such as portfolio choice (Abel, Eberly, and Panageas 2013) and saving decisions (Choukhmane 2021), but also in many other settings, such as price-setting (Caplin and Spulber 1987) and capital investment (Caballero and Engel 1999).

[31] Time-dependent models of adjustment provide a good fit to mortgage refinancing and retail investor portfolio rebalancing behavior (Andersen et al. 2020; Giglio, Maggiori, Stroebel, and Utkus 2021).

Figure 9. Evidence of State-Dependent Labor Supply Adjustment





counted value of future incentives, which depends on an individuals' debt balance. This variation is not present with a tax, in which there is no corresponding stock of taxes. With a small debt balance that will be paid off with high probability, the benefit to locating below the repayment threshold is minimal because it simply transfers debt repayments from a couple periods in the future to today, which represents a small gain in present value terms. In contrast, with a large debt balance that is unlikely to be paid off, the benefit is large because the payment avoided will likely never be paid. In the presence of labor supply adjustment costs, as in a state-dependent model, individuals with high debt balances will therefore be much more likely to locate below the repayment threshold. If the lack of adjustment is instead driven by inattention, as in a time-dependent model, then the amount of bunching simply depends on whether individuals receive adjustment shocks and is independent of debt balances. The right panel of Figure 9 plots the bunching statistic, b, estimated separately on quartiles of debt balances within each year.[32] The results show a large difference: individuals in the bottom-quartile of debt balances exhibit around 40-50% less bunching than those in the top two quartiles. Table A2 shows this pattern in Figure 9 holds within age groups.

In sum, the evidence in Figure 9 motivates a model of labor supply adjustment that is state-dependent. Section 4 uses this evidence to estimate a structural model of labor supply that features both time- and state-dependent adjustment.

4 The Model

This section presents and estimates a structural life cycle model that I use positively to understand the key forces that shape the bunching below and lack of bunching above the repayment

[32]The underlying income distributions are plotted in Figure A14.

threshold in Section 5, and normatively to study the optimal design of government-provided financing contracts in Section 6. The key ingredients of this model are endogenous labor supply, which creates moral hazard in response to income-contingent debt repayment, and uninsurable income risk, which creates a demand for insurance by individuals.

4.1 Model Description

4.1.1 Demographics

Time is discrete and each period, t, corresponds to one calendar year. At time $t = h \in \{\underline{h}, \underline{h}+1, \ldots \overline{h}\}$, 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 $a_{ht} = a_0 + t - h$. Prior to 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 the labor supply scaling parameter, and n_a is an equivalence scale.[33] This preference specification follows Guvenen (2009b) and represents a recursive generalization of Greenwood, Hercowitz, and Huffman (1988) (GHH) preferences. These preferences eliminate wealth effects on labor supply, meaning the marginal rate

[33] (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, Harenberg, Le Grand, and O'Dea (2020) point out some undesirable implications of this assumption in models where mortality is endogeneous, which is not the case in my model.

of substitution between c and l is independent of changes in c.[34] This assumption is consistent with empirical evidence that finds relatively limited labor supply responses to changes in wealth (Keane 2011; Cesarini, Lindqvist, Notowidigdo, and Ostling 2017). I use recursive rather than time-separable preferences so that I can assess the role of risk and time preferences independently in my normative analyses. The equivalence scale captures the evolution of household size over the life cycle, as in Lusardi, Michaud, and Mitchell (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.

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 is made up 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:[35]

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

This specification in (7) allows for permanent and transitory shocks to wage rates, which is important because individuals can only self-insure against the latter in incomplete markets (Blundell et al. 2008). 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 (2016), 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 spec-

[34] 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.

[35] To avoid numerical instability, I add a constant of 0.001 to l_{ia-1} in (7).

ification of the wage rate process is similar to the standard permanent-transitory income processes used in canonical life cycle models of consumption and portfolio choice (Zeldes 1989; Gourinchas and Parker 2002; Cocco, Gomes, and Maenhout 2005). A key difference, however, is that the *income* process is endogeneous because individuals choose their labor supply.

4.1.4 Education Levels

In addition to having different initial permanent income through δ_i, individuals also 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 the fact that the returns to experience are quadratic (in logs), as in Mincer (1974), and that Graduates may have different wage levels and profiles.[36]

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. Motivated by the evidence in Section 3.3.2, I introduce two optimization frictions that prevent individuals from frictionlessly choosing their labor supply to target any level of labor income.

The first adjustment 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).

[36] 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.

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

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

This adjustment shock, ω_{ia}, generates time-dependent labor supply adjustment. Economically, this shock could capture frictions on the demand-side of the labor market that generate 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.[37]

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.

[37] This is an imperfect way of modeling inattention because agents are sophisticated about their lack of inattention. However, modeling naive inattention introduces complications with individuals violating their 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 $a = a_R$[38] or upon death. When I estimate the model, this repayment function is set equal to the HELP repayment function in Figure 2. In counterfactuals, I consider alternative repayment functions, such as those in the US and income-sharing agreements.

4.1.8 Government

The government earns revenue from progressive taxes on labor and asset income, in addition to from 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.[39] 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} =

[38] I do this because individuals' only source of income in retirement is capital income and the counterfactual repayment contracts I consider are contingent solely on wage income.

[39] The combination of GHH preferences and labor supply adjustment frictions implies that there will be parts of the state space where individuals cannot ensure consumption net of the disulity of labor supply is positive, which causes V_{ia} to be poorly-behaved. This consumption floor prevents that and directly affects less than X% of individuals in simulations.

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 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 key parameters in the model, which are the labor supply preference parameters, discount factor, and parameters controlling the wage process, using simulated minimum distance.

4.2.1 Calibrated Parameters

Table 2 shows the values of parameters that I can calibrate directly using either observed Australian data or formulas from the Australian tax and transfer system. 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 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 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. All empirical moments are deflated to 2005 AUD using the indexation rates for HELP thresholds when compared with model moments. The real interest rate is set to 1.84%, which is 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, 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*, which is 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, which is the primary form of government-provided income support in Australia to individuals above 22. The retirement pension is calculated following the Age Pension formula, 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.

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 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 captures 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.[40] I thus consider two different values of $\alpha \in \{0, 0.24\}$, where 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 only discuss results from the latter where they differ significantly from the former.

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 of consumption and portfolio choice (e.g., Gourinchas and Parker 2002; Cocco et al. 2005), I cannot estimate the latter two sets of parameters separately in a first-stage because my income process is endogeneous. 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

[40] Formally, when $\alpha > 0$ there is a long-run cost associated with reducing labor supply to locate below the repayment threshold. For an individual who is considering locating below the threshold, this cost is second-order because the learning-by-doing function is differentiable. In contrast, the benefit from the increase in cash-on-hand from locating below the threshold is first-order. See Kleven and Waseem (2013) for additional discussion.

Table 2. Calibrated Parameters

Description	Parameter(s)	Values/Targets
Demographics		
Age in first year of life	a_0	22
Age in first year of retirement	a_R	65
Age in final year of life	a_T	89
Mortaility 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		
Numeraire	$\cdot$	\$1 AUD in 2005
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
Preference Parameters		
Relative risk aversion	γ	2.23
Elasticity of intertemporal substitution	σ^{-1}	0.45
Learning-by-doing parameter	α	0, 0.24
Student Debt		
Fraction of Graduates	p_E	0.308
Real interest rate on debt balances	r_d	0%
Means of $\log D_{ia_0}$	μ_d	9.40
Standard deviations 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

Notes: Additional details are presented in Appendix G.

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) 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.[41]

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 set of 47 estimation targets I use are shown in Table 3 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, Guvenen, and Kleineberg (2019) detailed in Appendix H.

4.2.3 Selection of Estimation Targets and Parameter Identification

I now discuss how each parameter is identified by the estimation targets in my simulated minimum distance estimation. All parameters are of course jointly identified, but I choose the set of estimation targets so that each one is most sensitive to a subset of parameters. Table 3 lists each estimation target and the parameter(s) that it primarily identifies. The discussion in this section is mostly qualitative; Table A3 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 in the 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

[41] As discussed in Appendix G, I also change $\tau(\cdot)$ which was modified slightly in 2005.

than wage profile parameters and choose 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 adjustment 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 simply 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. 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.[42] 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 endogeneous labor supply, these parameters control the *wage* rather than income process and must be estimated jointly because the former is not

[42]I compute the standard error of this moment using the hours worked reported HILDA, after normalizing it to have a mean of one.

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, McKay, and Ryan 2022) and the identification works similarly here, even though the income process is endogeneous. 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 peristence of income shocks, ρ: more persistent shocks generate a greater an 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, generates fatter tails in 5-year relative to 1-year income growth.

Table 3. 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: Additional details are presented in Appendix H.

4.3 Baseline Estimation Results and Model Fit

The results for my baseline simulated minimum distance estimation are reported in column (1) of Table 4. 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.

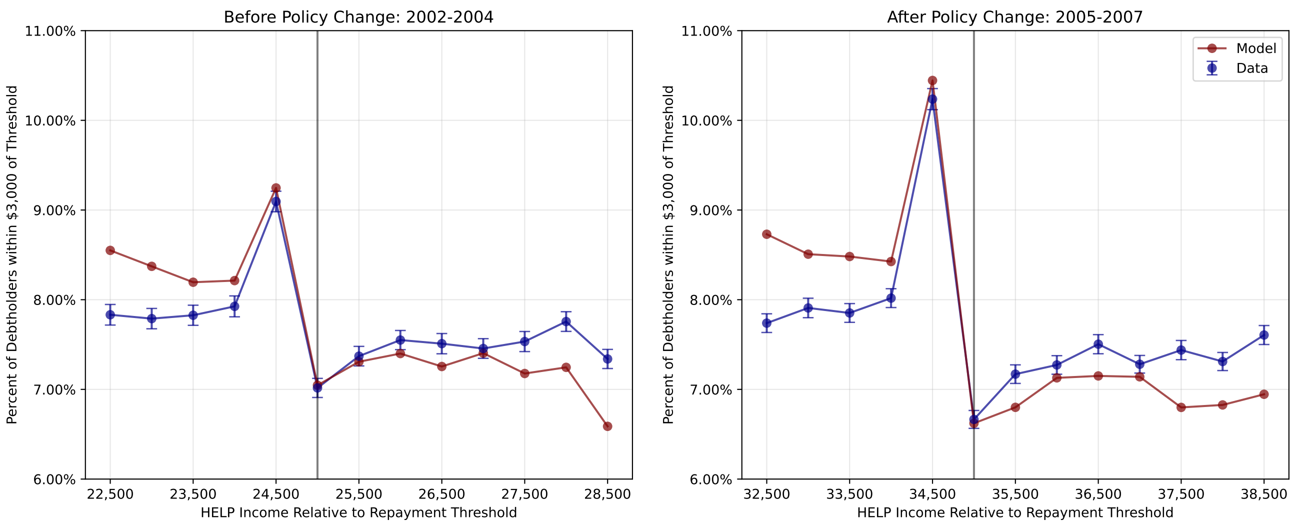
Table 4. Simulated Minimum Distance Estimation Results

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

Notes: This table shows the results from simulated minimum distance estimations, where 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 3. Parameters that are fixed at their respective values and not estimated are indicated with "·" in place of a standard error.

Figure 10 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. Baseline Model Fit: HELP Income Distribution around Policy Change

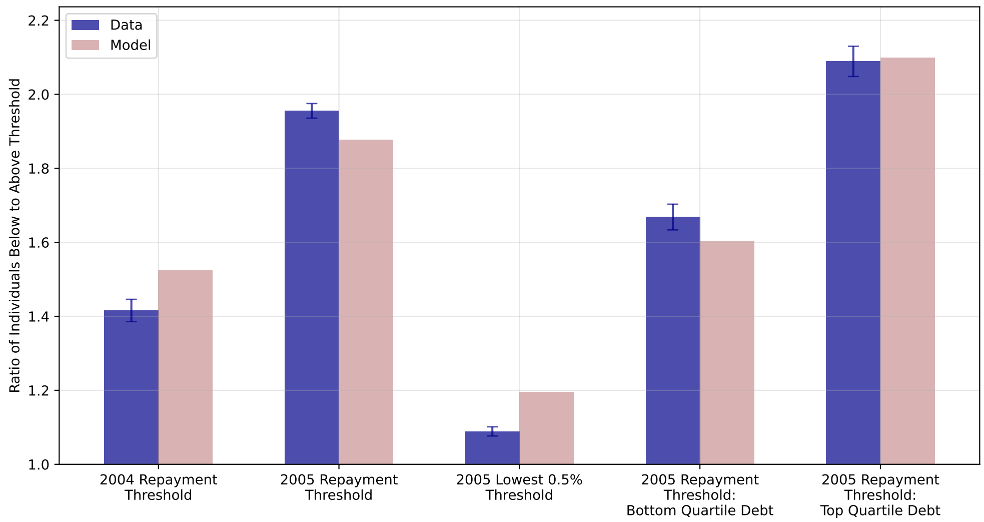


Notes: Bars represent 95% confidence intervals based on bootstrapped standard errors with 1000 iterations.

Figure 11 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 10, the model replicates the bunching at the 2004 and 2005 repayment thresholds well. However, the model is also able to 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% thresholds. This is because matching this moment better would require performing worse on the others: increasing the adjustment cost would improve the fit at the lower 0.5% threshold, but would also further decrease the amount of bunching among individuals with low debt balances, which the model already underestimates.

Table 5 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 4. The fit is not perfect because income in the model depends on endogenous labor supply. To the extent the age

Figure 11. Baseline Model Fit: Bunching around Thresholds



Notes: Bars represent 95% confidence intervals based on bootstrapped standard errors with 1000 iterations.

profile of labor supply varies over the life cycle for reasons outside the model, it will be unable to match these age profiles.

Table 5 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 is able to replicate this pattern due to the high persistence of permanent shocks, $\rho = 0.93$. Guvenen (2009a) points out 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 over-state the amount of 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 generates a similar level of capital income for individuals in middle age to the data. This moment is what primarily identifies the annual discount factor, β, which is 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; Carroll 1997).

Table 5. 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

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 A15 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 A15 shows 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 4 and Figure A16 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 A17 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 A18 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 outweights 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 Additional Discussion of Estimation Results

Model-implied Laffer curve. One way to compare my model with traditional models of labor supply is to compute the Laffer curve. In a static frictionless model of labor supply, the revenue-maximizing linear tax rate is $\frac{1}{1+\phi}$ (Saez 2001), which is 90% given my estimate of $\phi = 0.11$. Figure A20 plots the Laffer curve in my model and shows the revenue-maximizing tax rate is around 80%. This suggests that my model delivers reasonable estimates for the effects of income taxation, despite the fact that it was estimated to match the effects of income-contingent loans.

Wage risk parameters. A growing literature uses administrative data to estimate parametric models of labor income risk (see e.g., Guvenen, Ozkan, and Song 2014; Guvenen et al. 2021; Braxton et al. 2021; Guvenen et al. 2022; 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 exogenous income model 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 the fact that the cross-sectional standard deviation of income at age 22 in my 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 some transitory variation in income arises endogenously from labor supply adjustments rather than exogenous transitory wage shocks.[43] Lastly, my estimate of the standard deviation of permanent shocks is around three times as large.[44] In addition to differ-

[43] 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%.

[44] My estimate of the variance of permanent shocks is similar to Catherine (2022), who estimates a richer model using

ences in data, this primarily reflects the fact that I estimate $\rho = 0.93$ rather than imposing $\rho = 1$. This lower value of ρ partly reflects the fact 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.

Learning-by-doing. X

4.6 Model Validation on Untargeted Moments

Bunching at tax thresholds. X

Lack of bunching at UK repayment thresholds. X

5 Positive Analysis of Labor Supply Responses

5.1 Bunching Below Repayment Threshold Reveals a Demand for Liquidity

A demand for liquidity created by incomplete markets has been identified as an important driver of individuals' responses to various social insurance programs, such unemployment insurance (Chetty 2008), mortgage default (Ganong and Noel 2022), and consumer bankruptcy (Indarte 2023). In this section, I explore the extent to which the labor supply responses I observe empirically are driven by the same mechanism in two steps. First, I use my structural model to quantify the fraction of the bunching that is driven by borrowing constraints, and, second, I provide empirical support for the importance of liquidity in the data.

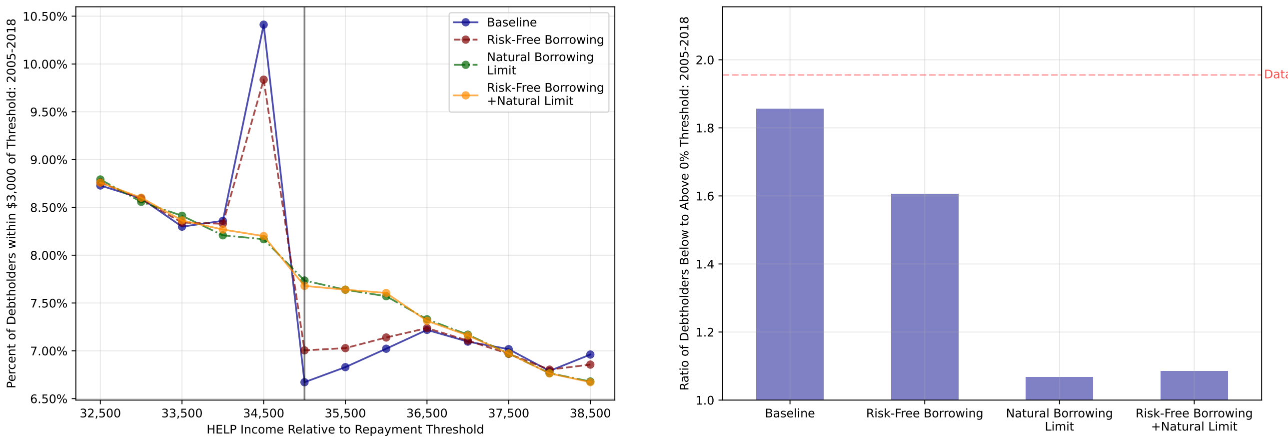
5.1.1 Evidence from Model

Figure 12 shows how the amount of bunching below the repayment threshold in the model varies depending on the degree of market incompleteness individuals face. 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, corresponds to eliminating 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'

a similar set of moments to Guvenen et al. (2022).

borrowing constraints, $\{\underline{A}_a\}$, to the natural borrowing limit.[45] 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.

Figure 12. Borrowing Constraints and Labor Supply Responses in Model



Notes: The right panel plots the number of debtholders within \$250 below divided by the fraction of debtholders within \$250 above the repayment threshold over years 2005-2018.

The prediction in Figure 12 cannot be tested directly empirically because the tightness of borrowing constraints is not directly observable. However, a testable implication of the importance of borrowing constraints is shown in Figure A21: the amount of bunching decreases monotonically in the amount of liquidity individuals have. Quantitatively, endowing individuals at $a = 0$ with the average wealth at retirement in the baseline model reduces the amount of bunching by around 40%. Higher values of A_0 diminish the importance of borrowing constraints by providing resources to smooth income shocks and reducing precautionary saving.

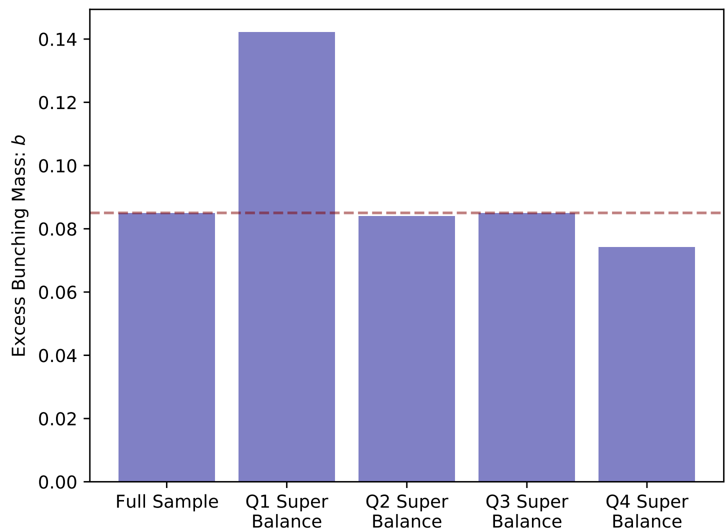
5.1.2 Evidence from Data

I now provide several complementary pieces of evidence that jointly support the qualitative prediction that labor supply responses are driven by a demand for liquidity. My first piece of evidence uses 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 two sources: 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.

[45]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 13 plots the estimated statistic, b, based on quartiles of superannuation balances in each year. The results show the amount of bunching is highest for individuals in the bottom quartile of superannuation balances, around 65% higher than in than in the full-sample.[46] This evidence is consistent with these individuals being more liquidity constrained and thus unwilling to use liquidity for tax-advantaged retirement saving, providing empirical support for the prediction that increasing individuals' liquidity leads to smaller labor supply responses.

Figure 13. Bunching Statistic by Quartiles of Retirement Wealth in 2005-2018



Notes: The panel uses the *ALife* sample, covering 2005-2018. For the underlying income distributions, see Figure A22.

Absent comprehensive data on wealth at the individual-level, my second piece of evidence that suggests individuals labor supply responses reveal a demand for liquidity comes from exploiting geographical variation in household wealth. For each individual-year, *ALife* contains the location of individuals' home addresses by SA4 region, which are non-overlapping geographic regions that cover Australia.[47] Similar to Figure 5, I measure the amount of bunching by SA4 region as the ratio of the number of individuals that are within $2,500 below to the number that are above the repayment threshold, so that a ratio of one indicates no bunching.

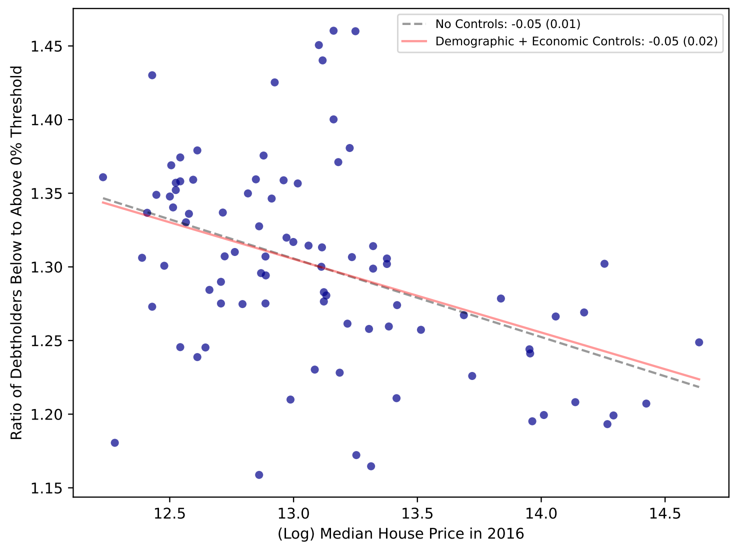
Figure 14 plots the relationship between this measure of bunching and house prices from CoreLogic by SA4 region. I use house prices as a proxy for household wealth because housing represents the largest form of household wealth in Australia (Australian Council of Social Service 2018). The results show the amount of bunching is lower in regions with higher house prices, which tend to

[46]In untabulated results, I show this difference is similar even within individuals younger than 30.

[47]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.

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. This finding is consistent with the importance of liquidity in driving labor supply responses because individuals in areas with lower house prices likely have less wealth and thus place a higher value on reducing repayments.

Figure 14. Bunching and Housing Wealth by Geographic SA4 Region



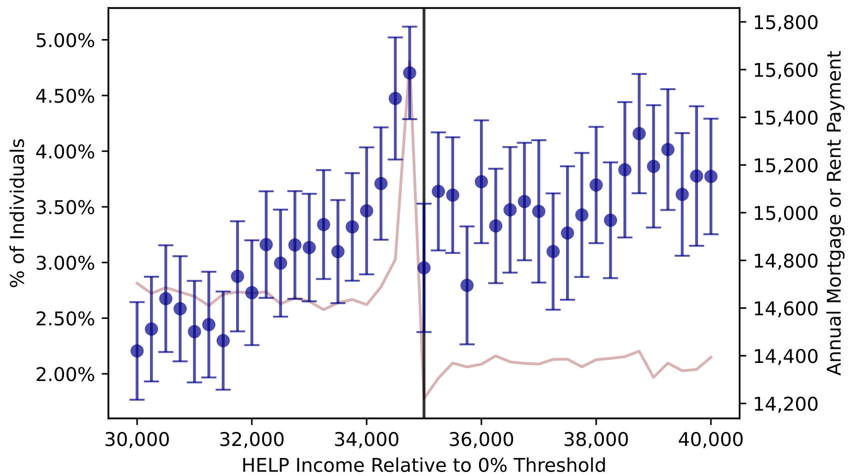
Notes: The horizontal axis corresponds to the (log) median transacted residential established house price in 2016 calculated by CoreLogic and reported by the ABS in the Data by Region Release. The gray dashed line corresponds to the line from a regression with no controls, while the red solid line corresponds 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.

My third 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. Figure 15 shows this pattern holds in the data: individuals immediately below the repayment threshold tend to have larger housing payments by around \$500 (i.e., 3-4%).

5.2 Income-Contingent Loans Generate Different Responses than Taxes

I next use my model to study how labor supply responses to income-contingent loans differ from that of income taxes. An extensive literature has characterized the mechanisms through which labor supply responds to taxes (Keane 2011; Saez, Slemrod, and Giertz 2012). There are two key differences between an income-contingent loan and an income tax in a dynamic model. First, when the interest rate on the income-contingent loan is lower than the interest rate on borrowing,

Figure 15. Housing Payments around Repayment Threshold in 2016



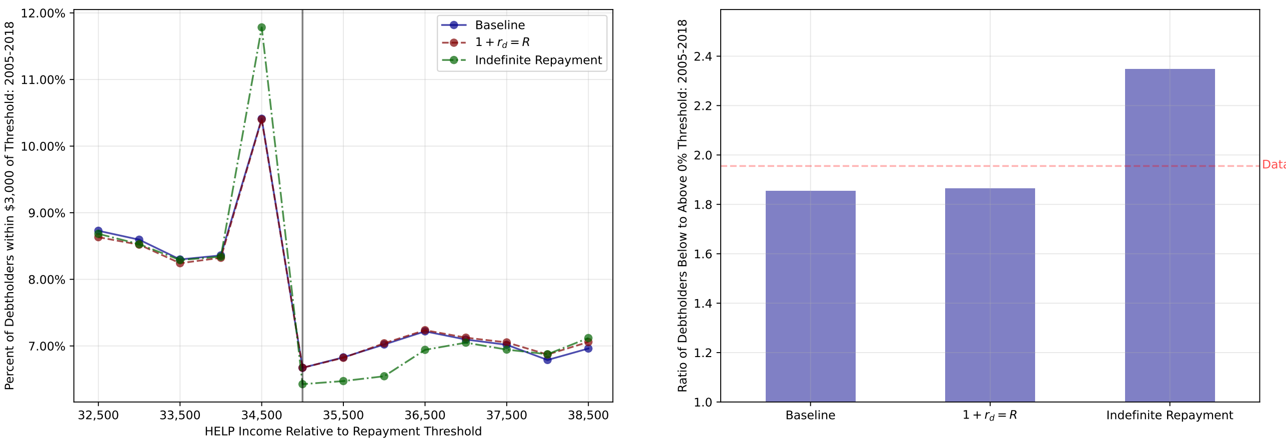
Notes: The figure uses the MADIP sample, which is smaller because it only covers 2016.

income-contingent loans provide an additional incentive to reduce labor supply because doing so effectively allows individuals to borrow at a lower rate. Second, payments on income-contingent loans capped based on individuals' initial debt balances. This reduces the incentive to reduce labor supply because the reduction in payments from doing so partly reflects a transfer over time rather than solely a permanent reduction.

Figure 16 quantifies the importance of these two channels by plotting the bunching around the repayment threshold in two counterfactuals. The first counterfactual eliminates the interest rate wedge between debt and liquid assets by setting $1 + r_d = R$. Comparing these results with the baseline, the results show the amount of bunching is basically unchanged. The second counterfactual eliminates the constraint that repayments are set to zero after an individuals' debt balance is paid off, but uses the same HELP repayment formula. This effectively makes income-contingent loan repayments an income tax, or equity contract, where payments continue indefinitely. This counterfactual has a large effect on labor supply responses, generating almost twice as bunching below the repayment threshold.

In sum, the results in Figure 16 suggest the labor supply distortions created by income-contingent loans are affected by the likelihood of eventual debt repayment in a quantitatively important way. Empirically, this result is consistent with the fact that bunching increases in debt balances (Figure 9) and highlights an important way in which the effects of income-contingent loans on labor supply differ from those of income taxes.

Figure 16. Decomposition of Difference between Income-Contingent Loan and Tax



Notes: The right panel plots the number of debtholders within $250 below divided by the fraction of debtholders within $250 above the repayment threshold over years 2005-2018.

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 subsidized repayment contract, holding fixed borrowing and education choices. This problem of choosing a single repayment contract is faced by governments that do not offer multiple contracts, such as Australia and the UK. Additionally, this choice reflects the fact that my model does not endogenize borrowing choices and is not designed to capture endogenous contract selection across borrowers, which are both limited in Australia. For most of the analysis in this section, I focus on subsidized repayment contracts with a zero interest rate, as in Australia.[48]

6.1 Welfare and Fiscal Impacts of Existing Income-Contingent Loans

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.[49] This fixed repayment contract corresponds to a standard debt contract in which individuals make constant repayments over the 25 years post-graduation to repay their loan principal and interest. 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.

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

[49] Additional details on the exact implementation of each contract are presented in Appendix I.

6.1.1 Definition of Government Budget

Measuring the fiscal impact of alternative repayment contracts requires a definition of the 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.[50] 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.[51] $\mathcal{R}_a$ 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 preference 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 is focused 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.[52] In my baseline model, the average value of $\mathcal{R}_a$ for $a \in (a_0, a_R)$ is 1.03.

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, Storesletten, and Violante (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

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

[51] 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 I consider budget-neutral repayment policies in subsequent analyses because it ensures a reasonable path for budget deficits in the transition between two policies, without the difficulties associated with fully characterizing transition dynamics. In particular, this definition ensures that if the government were to immediately start giving loans to people graduating from college under two policies with equal values of $\mathcal{G}$, there would be no change in expected costs to this group of individuals.

[52] Calculating the proper discount rate would require aggregate risk, which my model abstracts from.

Schedule.[53] I also adopt a smoothed specification of the ATO unemployment benefit formula used in estimation; see Appendix G for additional details.

6.1.2 Results

The left panel of Figure 17 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:[54] "*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 welfare 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 next two columns show the results for the income-based repayment (IBR) contract currently used in the US and the new IBR contract proposed by the Biden administration (known as "SAVE"), in which individuals make repay a fixed rate of income earned above a certain threshold.[55] These two columns show that the two US IBR contracts deliver similar welfare gains to HELP contracts, but differ in terms of their 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 larger, which reflects the higher repayment threshold and lower repayment rate in this policy. Dividing the welfare benefit 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 A23) is highest for US IBR and is on the high-end for policies targeting adults reported by Hendren and Sprung-Keyser (2020).

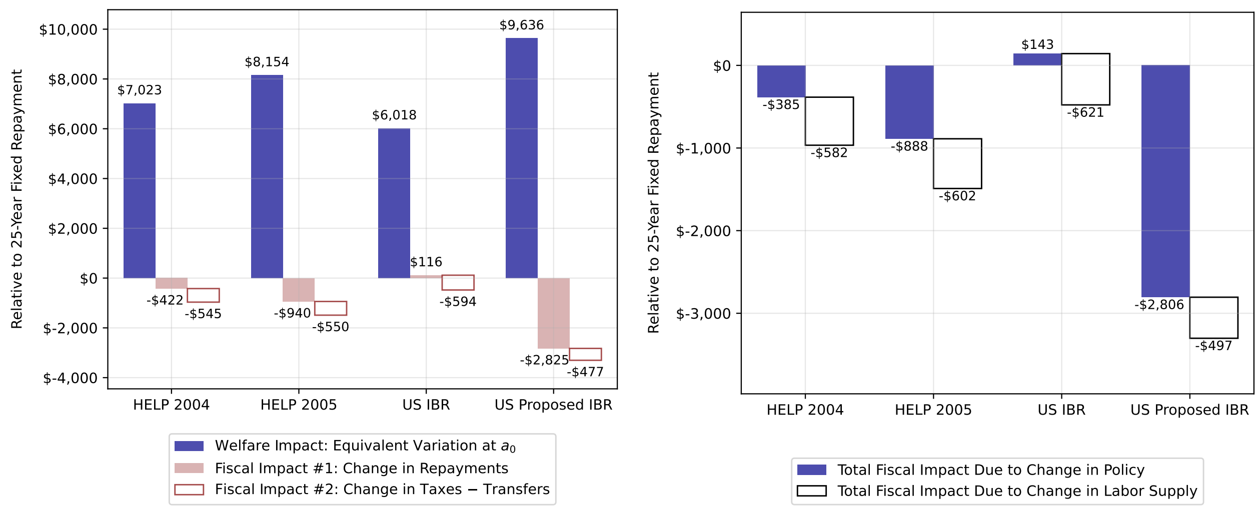
The right panel of Figure 17 decomposes the total fiscal cost associated with moving from 25-year fixed repayment to income-contingent loans, which is the sum of the two fiscal impacts shown in the left panel, into two components. The first component, shown in the top black component of each bar, is 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

[53] By "unconstrained optimal policies", here I mean policies that are unconstrained in their functional form but informationally-constrained to be a function of only individual earnings á la Mirrlees (1974).

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

[55] 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 17. Effects of Moving from Fixed Repayment to Income-Contingent Loans



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 accounts for only 15% of the fiscal cost, which reflects the fact 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 A24 reproduces the right panel of Figure 17 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 Can Income-Contingent Loans Generate Welfare Gains at the Same Fiscal Cost?

The evidence in Section 6.1 shows the that the welfare gains of income-contingent loans are large relative to their fiscal costs. The objective of this section is to assess whether income-contingent loans can generate welfare improvements with the requirement that they have the same fiscal cost.

6.2.1 Constrained Planner's Problem

I consider a social planner that maximizes the welfare of borrowers 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: threshold at which repayment begins, K and a repayment rate of income above the threshold, ψ.[56] 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).[57]

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.[58] The first constraint requires that the fiscal revenue from the chosen repayment contract is at least $\overline{\mathcal{G}}$. I set $\overline{\mathcal{G}}$ equal to the revenue raised from a 25-year fixed repayment contract, which serves as a natural benchmark to an income-contingent loan given it has a similar repayment duration and is currently available to borrowers in the US. The second and third constraints capture the informational and parametric restrictions on the repayment contract.

Solving (17) is numerically challenging, especially when I consider higher-dimensional contracts in Section 6.4, 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.

6.2.2 Results

Solution to planner's problem. The red solid line in Figure 18 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

[56] I choose to use US-style instead of Australia-style loans because the latter have many more parameters.

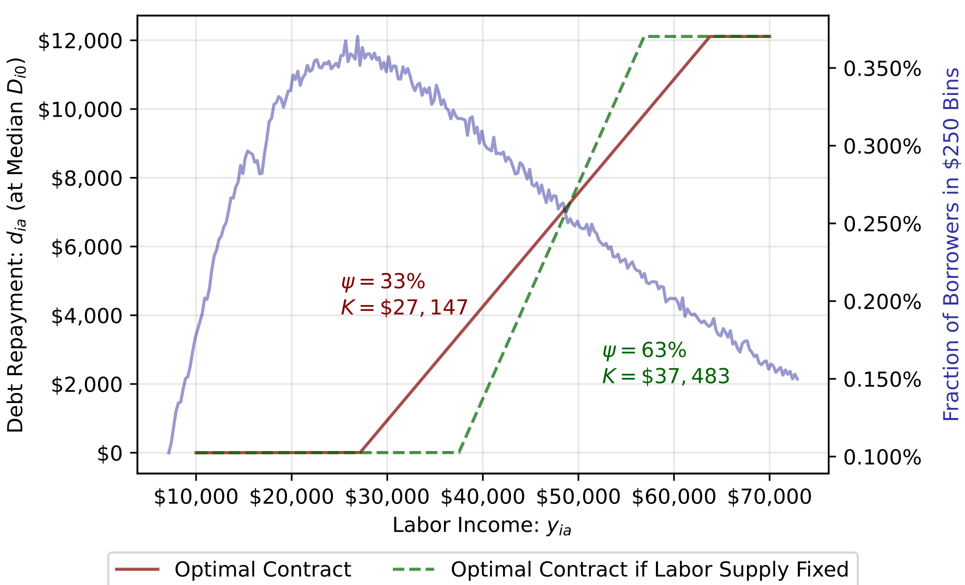
[57] See Stantcheva (2017) for an analysis of Mirrleesian optimal policies in a similar environment.

[58] As in Section 6.1, I focus only on the welfare of college-educated individuals, $\mathcal{E}_i = 1$, because they are the ones with debt balances.

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 contracts, K is set equal to 1.5 times the US federal poverty line, which corresponds to 1.5$*$\$12,320 = \$18,480 in 2005 AUD, or 68% of the optimal value of K.[59]

In order to collect sufficient revenue with a relatively high repayment threshold, the constrained-optimal contract has a repayment rate of ψ = 33%, which is around 3 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 blue. This small amount 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 locating below the threshold do not receive an increase in their cash on hand, which eliminates liquidity effect discussed in Section 5.1. This relatively small bunching is consistent with the findings in Britton and Gruber (2020), who find limited bunching in the UK where the repayment threshold changes the marginal repayment rate.

Figure 18. Constrained-Optimal Income-Contingent Loans



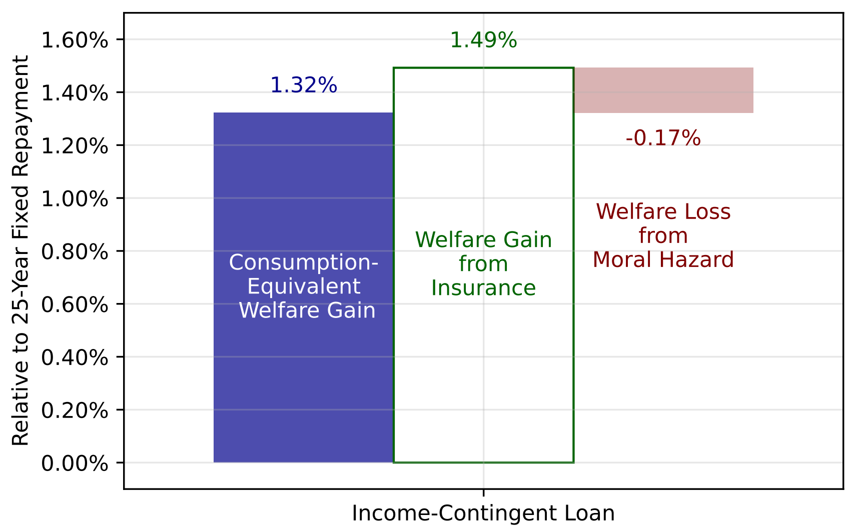
Effect of moral hazard. To isolate the impact of moral hazard on the design of income-contingent loans, the dashed green line in Figure 18 plots the contract that solves (17) in a model

[59]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 coverting 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.

where individuals' labor supply is fixed at its value under the baseline 25-year fixed repayment contract.[60] The results show this alternative contract provides even more insurance than the contract in my baseline model, with both a higher repayment rate and threshold. This reflects the fact 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 in turn 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 repayment rate to induce a smaller behavioral response.

Welfare gains. The left panel of Figure 19 plots the welfare gain from the constrained-optimal income-contingent loan in my baseline model. To measure welfare gains, I use a consumption-equivalent welfare metric commonly-used by existing literature (e.g., Benabou 2002; Lucas 2003; Abbott et al. 2019).[61] This metric answers the following question: "*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 bars in Figure 19 show that the optimal income-contingent loan provides a welfare gain equivalent to a 1.32% increase in lifetime consumption relative to 25-year fixed repayment. This corresponds to 47% of the welfare gain from forgiving debt balances entirely (which is clearly not budget neutral).

Figure 19. Welfare Gains from Constrained-Optimal Income-Contingent Loans



The right two bars in the left panel of Figure 19 decompose the total welfare gain shown in the first bar into the gain that comes from providing insurance and loss that comes from moral hazard.

[60]In this model, I exclude disutility from labor supply from welfare since it is not being chosen by individuals.
[61]See Appendix J for additional details the calculation of this welfare metric.

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 the welfare gains from it 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 welfare gain of this wage-contingent loan and the constrained-optimal income-contingent loan. The results show that the welfare cost of moral hazard is relatively small, accounting for 0.17pp or a 13% reduction in the total welfare gain.

As discussed above, the repayment rate on the constrained optimal income-contingent loan is higher than those in the US. Figure A25 shows how imposing the constraint that $\psi \leq 10\%$, the current repayment rate on US IBR contracts, affects the results in Figure 19. Imposing this constraint reduces the total welfare gain by 0.19pp or 14%. Around half of this loss comes from the fact that a lower repayment rate requires 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 welfare loss from moral hazard.

Heterogeneity in welfare gains. Figure A26 plots the distribution of welfare gains and losses at $a = a_0$ from the constrained optimal income-contingent loan. Relative to 25-year fixed repayment, this contract generates welfare gains for around 70% of individuals, while the remaining 30% of individuals experience small welfare losses. In other words, moving from fixed repayment to this optimal contract is not a Pareto improvment. However, these small welfare losses are concentrated among high-income individuals, who are required to repay their loans back faster under income-contingent relative to fixed repayment. Given these individuals have low marginal utility, these losses have little effect on the overall welfare gain in Figure 19.

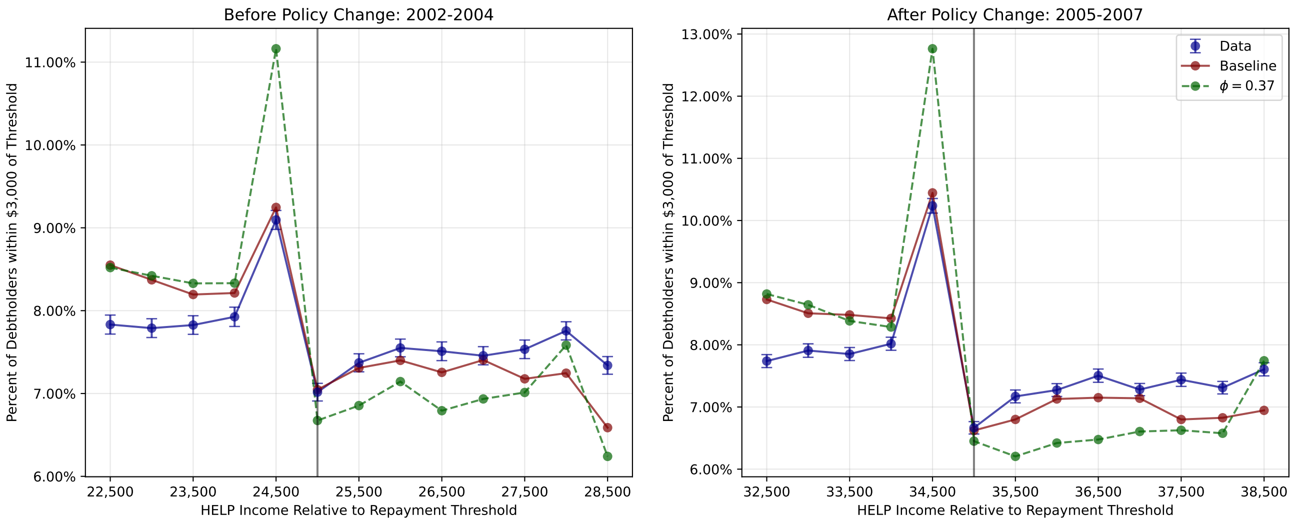
6.3 Under What Conditions Would Fixed Repayment Contracts Be Optimal?

The relatively small welfare cost of moral hazard in income-contingent loans crucially depends on the labor supply elasticity in my estimated model. To illustrate this point, the right panel of Figure 19 replicates the analysis in the left panel within an alternative model where the labor supply elasticity, ϕ, has been increased until the total welfare gain from a constrained-optimal income-contingent loan is zero, which corresponds to setting $\phi = 0.37$ and leaving all other parameters unchanged.[62] This reflects the fact that the changes in labor supply caused high payments under a fixed repayment contract are more costly. However, the welfare loss from moral hazard is over 10 times as large because a higher labor supply elasticity implies a larger response by borrowers to income-contingent repayment.

[62]The welfare cost of moral hazard is monotonically increasing my model for values of $\phi \in (0, 1)$.

[Figure 20] plots the fit 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 a significantly more amount of bunching that both the baseline model and the data. Quantitatively, the number of individuals below relative to above the threshold is around 70% larger, over 60 standard errors from its estimated value and larger than what is observed within any occupation (Figure A27).

Figure 20. Fit of Model Required for Fixed Repayment to be Optimal



Notes: Bars represent 95% confidence intervals based on bootstrapped standard errors with 1000 iterations.

6.4 Alternative Constrained-Optimal Repayment Contracts

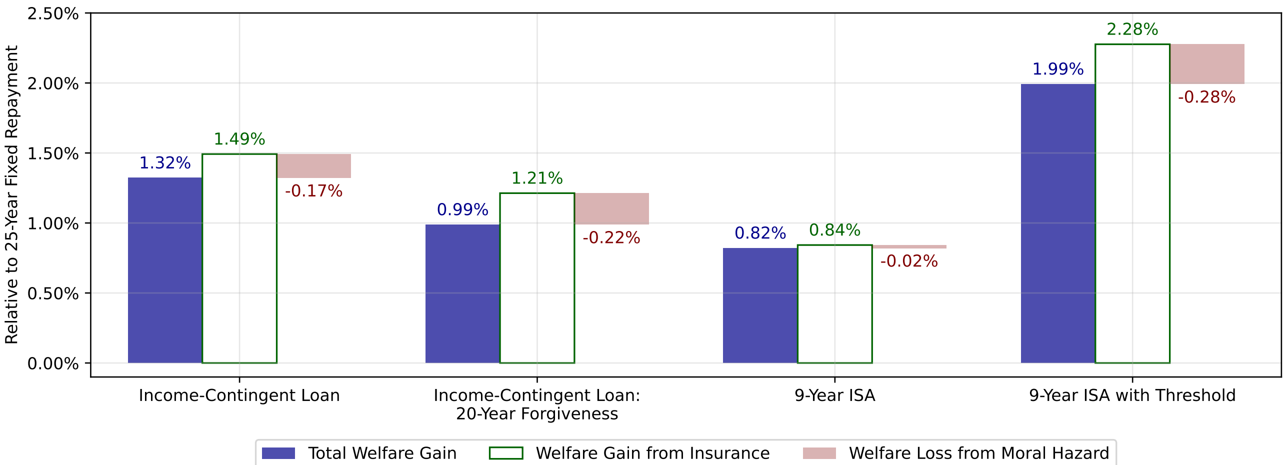
This section considers the welfare impact of alternative contrained-optimal repayment contracts to the income-contingent loans studied in the previous section. For each of these contracts, which have different parameters than the baseline income-contingent loan, I solve (17) to determine the constrained-optimal value of these parameters.

6.4.1 Income-Contingent Loans with Forgiveness

I next consider the effects of adding forgiveness to income-contingent loans, as in the US and UK. The second column of Figure 21 shows the welfare gain from a constrained-optimal income-contingent loan that has forgiveness at $a_0 + 20$, as in the currently available US IBR contracts. This contract generates a welfare gain of 0.99%, around 0.33pp lower than the contract with forgiveness repeated in the first column.[63]

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

Figure 21. Welfare Gains from Income-Contingent Loan with Forgiveness and Income-Sharing Agreements



Notes:

The reduction in the welfare 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 but a similar repayment rate of ψ = 34%. 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 (see Figure A28). This reduces the welfare gain from insurance, shown in green in Figure 21, 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 welfare gain from forgiveness is that a finite forgiveness horizon increases the welfare loss from moral hazard, shown in red in Figure 21. 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 at some point later in their life cycle.

6.4.2 Income-Sharing Agreements

The development of income-contingent loans was motivated by Friedman (1955), who advocated the use of income-sharing agreements (ISAs) in which individuals repay a percentage of their income for a fixed repayment period. The challenge with these contracts is that they induce substantial adverse selection (Herbst and Hendren 2021). Setting aside issues with adverse selection, I use my model to assess the desirability of income-sharing agreements as a mandatory government-provided financing contract. I model ISAs after those provided by Purdue University in 2016-2017, in which individuals repay a constant fraction of their income for nine years (Mumford 2022).

The third column of Figure 21 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 welfare gain is around 40% (or 0.5pp) lower than the gain from the constrained-optimal income-contingent loan. This occurs for a similar reason that forgiveness generates smaller welfare gains: 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.

The final column of Figure 21 shows that a modified ISA, which is offered by Purdue, does significantly better. In the 9-Year ISA + Threshold, borrowers only make payments when their income exceeds a certain threshold, which is chosen jointly with the repayment 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 agreeement, these payments are uncapped and thus can be used to finance even lower repayments from low-income individuals. This manifests itself in a similar repayment rate of $\psi = 35\%$ but higher repayment threshold of K =\$46,821.

Figure 22 shows the welfare gains from the constrained-optimal income-contingent loan and income-sharing agreement with a threshold across the three different initial states that are heterogeneous in my model: initial permanent income, debt, and assets. The income-contingent loan provides redistribution from high- to low-income and low- to high-debt individuals, but limited redistribution across initial assets. However, the redistribution is even larger for the ISA. The redistribution across debt balances is sufficiently large that it actually generates a reversal in the ranking of certainty-equivalent values across terciles of initial debt (see Figure A29). In sum, although ISAs with a repayment threshold generate larger welfare gains, they are also more likely to generate ex-ante responses because the distribution of welfare gains across initial debt balances is significantly more dispersed (see Figure A30 for the distribution of welfare gains).

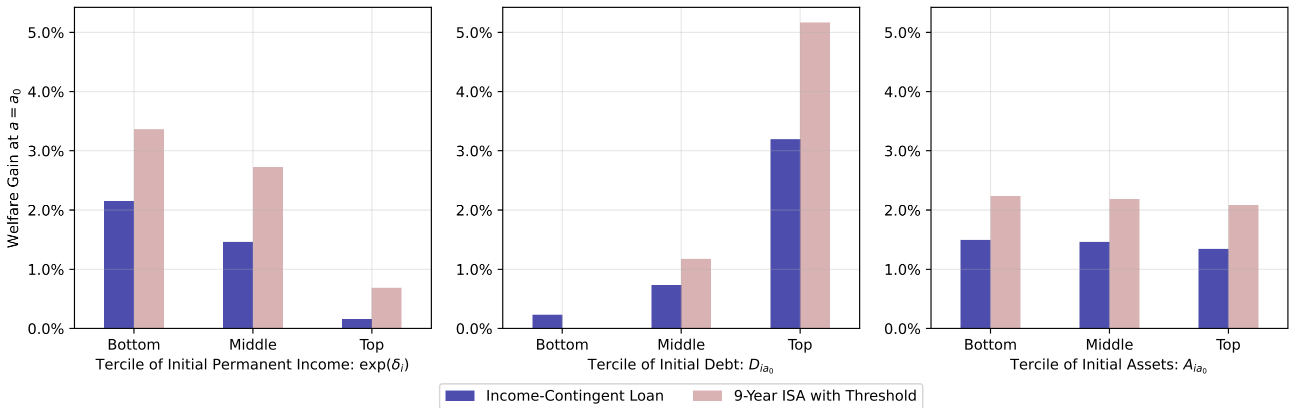
6.4.3 Age and Debt-Dependent Income-Contingent Loans

The final contracts I consider are the following alternative forms of income-contingent loans:

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

The first contract corresponds to 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

Figure 22. Heterogeneity in Welfare Gains across Initial States



Notes: The welfare gain shown in this figure differs slightly from the welfare gain shown in other figures.

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 23 shows the welfare gains from these contracts in my baseline model in Panel A and the model with $\phi = 0.37$, in which the US IBR-style income-contingent loan delivers zero gain relative to 25-year fixed repayment, in Panel B. The results in Panel A show all three of these contracts deliver almost identical welfare gains to the income-contingent loan considered in previous sections. This result reflects the fact 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 18.

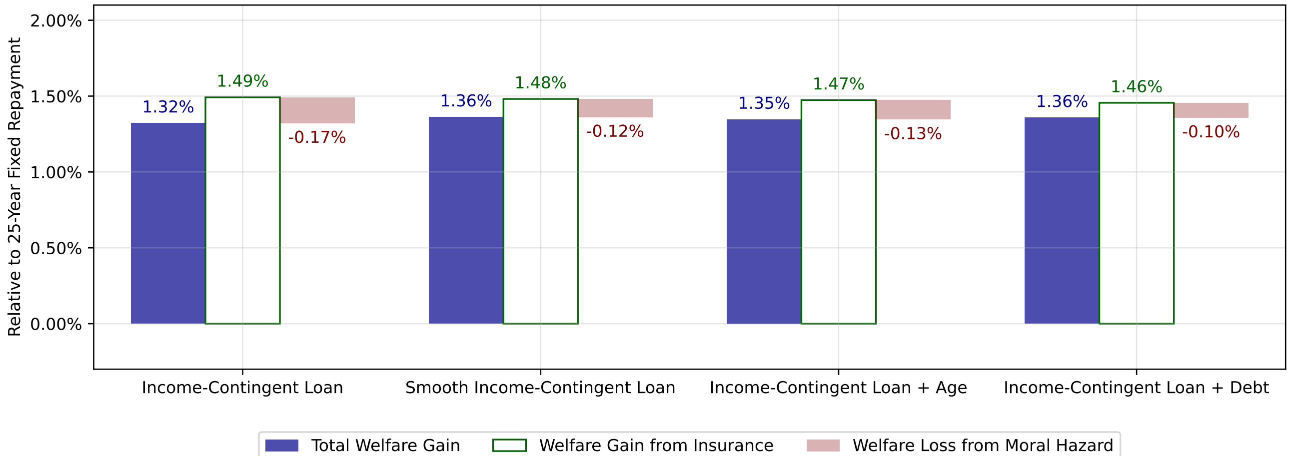
In contrast, Panel B shows that all three of these contracts generate larger welfare gains in the model with $\phi = 0.37$. These large gains come entirely from reducing the welfare cost of moral hazard: the smooth income-contingent loan generates a **X**pp reduction in this cost, while the age- and debt-contingent contracts generate additional **X**pp and **X**pp reductions, respectively. Figure A31 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 generates 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 labor supply today.

6.5 Extensions and Robustness

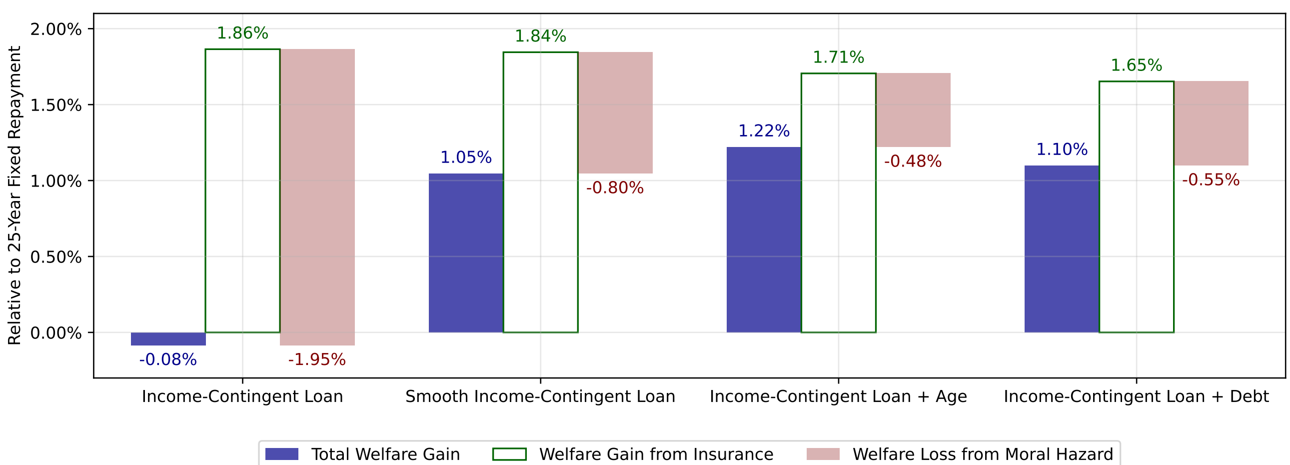
This section assess the robustness of the welfare gains from the constrained optimal income-contingent loans that solve (17) to several model extensions and alternative values of calibrated parameters. The results are presented in the different rows in Table 6 and discussed individually

Figure 23. Welfare Gains from Alternative Forms of Income-Contingent Loans

Panel A: Baseline Model



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



below.

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

	Deviation from Baseline	Welfare Gain	=	Insurance	+	Moral Hazard	ψ^*	K^*
(1)	RRA = 7.5	3.52%		4.00%		−0.48%	50%	$27,607
(2)	EIS = 1.5	0.57%		0.7%		−0.13%	42%	$30,905
(3)	RRA = 7.5, EIS = 1.5	1.87%		2.29%		−0.43%	49%	$28,641
(4)	No Ex-Post Uncertainty	0.58%		0.76%		−0.17%	27%	$18,098
(5)	No Uncertainty	−0.17%		0.15%		−0.32%	21%	$26,906
(6)	Occupation Heterogeneity	0.28%		0.33%		−0.05%	22%	$25,639
(7)	Learning-by-Doing	1.68%		·		·	35%	$36,615
(8)	Wealth Effects on Labor Supply	0.82%		1.05%		−0.23%	37%	$30,307
(9)	$\rho = 0.8$	0.90%		1.14%		−0.23%	42%	$34,244
(10)	$\rho = 0.99$	1.35%		1.63%		−0.28%	35%	$18,949
(11)	Non-Normal Permanent Shocks	1.14%		1.43%		−0.30%	28%	$26,933
(12)	$r_d = 2\%$	1.96%		2.14%		−0.18%	38%	$47,731
(13)	US Tax System	1.18%		1.36%		−0.19%	38%	$28,838
(14)	$\mathcal{R}_a = R$	1.06%		1.41%		−0.35%	29%	$22,696
(15)	$\mathcal{R}_a = R + 4\%$	1.60%		1.65%		−0.05%	46%	$34,441
	Baseline Model	**1.32%**		**1.47%**		**0.15%**	**33%**	**$27,147**

Notes: 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.

Risk and time preferences. ?? shows the effect of moving the coefficient of relative risk aversion, γ, and the elasticity of intertemporal substition, 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). The results show this has a minimial effect on the welfare gains from delaying repayments with 10-Year/10-Year Fixed, but increases the welfare gain from US IBR by a factor of X. This result is analogous to Schmidt (2016), who shows that persistent idiosyncratic shocks carry high prices of risk with Epstein-Zin preferences due to their effects on future certainty equivalents. Next, I increase $\sigma^{-1} = 1.5$ to that γ and σ match the baseline calibration in Bansal and Yaron (2004). The primary effect is to eliminante the welfare gain from delaying repayments, which reflects the fact that a higher EIS reduces the cost of imperfect consumption (and labor supply) smoothing over time. However, in both of these alternative calibrations, my qualitative finding that income-contingent loans provide significant welfare gains relative to fixed repayment contracts is unchanged.

Level, uncertainty, and redistributive effects. In general, the consumption-equivalent welfare gain of a policy reform is the sum of three effects: (i) level effects due to changes 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.[64] To assess the importance of each of these terms, I instead compare the welfare gain in

[64]An alternative decomposition that can be implemented numerically is presented in Abbott et al. (2019). I cannot

the baseline model with the welfare 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 welfare gain of the latter model should be due to level effects, while the difference between the two captures redistributive effects. The results from these two models are shown in Table 6, which shows around **X**% comes from level effects **X**% from redistributive effects. The size of uncertainty effects can then be estimated by comparing the baseline model to the model with no ex-post uncertainty, which shows around **X**% comes from these effects. In sum, these results suggest **X**.

Occupation-level heterogeneity. Figure 5 shows a significant amount of occupation-level heterogeneity in labor supply responses that is not present in my baseline model. To assess the importance of this heterogeneity, I consider an extension in my model where there are two types of educated individuals with different values of the Calvo parameter, λ. To assess robustness with respect to an extreme amount of heterogeneity, I assume these groups have $\lambda = 0$ and $\lambda = 1$ respectively. I then calibrate the fraction of each type so that the model generates the same fit on the amount of bunching around the 2005 0% repayment threshold. Row **X**of Table 6 shows that incorporating this heterogeneity **X**.

Learning-by-doing.

Wealth effects on labor supply. There is quite a bit of disagreement in exisiting 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, Graber, Mogstad, and Novgorodsky (2023) find larger effects from lottery winnings in the US. To assess the importance of wealth effects, I adjust the flow utility in (5) to be:

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

I follow Keane (2011) and consider $\eta = 0.5$.

Persistence of income risk. My estimation could overstate the presence of permanent shocks (Guvenen 2009a). I set $\rho = 0.8$ and $\rho = 0.99$ following the two estimations in Guvenen (2009a).

Non-normal income risk. A recent body of empirical evidence using administrative datasets on individuals' incomes highlights the importance of non-normal income shocks (Guvenen et al. 2014, 2021; Braxton et al. 2021), which has been shown to have implications for portfolio choice (Catherine 2022), asset prices (Schmidt 2016), and mortgage contract design (Campbell et al. 2021). I omit these shocks from my baseline model for tractability.

perform this decomposition in my model because I do not discretize initial states. This would require me to calculate consumption-equivalents for many states, which is not computationally-feasible since each consumption-equivalent requires solving a fixed point. The approach I pursue avoids this problem, but lacks analytical results guaranteeing it generates accurate estimates of the three effects.

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 are subject to interest accumulation. As a result, I consider an alternative 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).

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 welfare gains using the tax and transfer system from Heathcote et al. that provides an approximation to the US system.

Discount rates for government budget. My model does not have aggregate risk, so the proper discount rate for debt repayments is the risk-free rate. However, in reality, student loan repayments likely should be discounted at a higher rate, given they are income-dependent and thus are correlated with the business cycle. To address this, I consider an alternative term structure of discount rate: the Treasury yield curve plus a constant credit risk premium equal to that of non-investment-grade corporate borrowers.

7 Conclusion and Additional Discsussion

This paper studies the trade-off in government-financed student loans between providing insurance against income risk and disincentivizing labor supply. Using policy variation from the Australian student loan system, I show borrowers adjust their labor supply to reduce repayments on income-contingent loans. These responses are larger among borrowers with high debt balances, who have a lower likelihood of eventual repayment, and among those who are more liquidity-constrained, for whom the repayment reduction is valuable. I then estimate a structural model and find this evidence is consistent with a Frisch labor supply elasticity of 0.11, but also substantial frictions that limit labor supply adjustment. In the model, a constrained-optimal income-contingent loan generates a welfare gain relative to a 25-year fixed repayment contract equivalent to 1.3% of lifetime consumption with the same fiscal cost. Of this gain, 1.5% comes from improved insurance, while -0.2% comes from labor supply responses that reduce the amount of insurance this contract can provide at a given cost. These findings suggest that income-contingent repayment creates labor supply responses that affect contract design, but these responses are too small to justify fixed repayment contracts.

My analysis focuses on the trade-off between providing individuals with insurance against income risk and the distortions in labor supply such insurance creates. For tractability, my structural model omits several forces that could influence the welfare impacts of different repayment contracts to focus on the main forces of interest. I conclude by discussing the relevance of some unmodeled ingredients and how they are likely to affect my normative results.

Endogenous college attendance and major choice. Hampole (2022) shows student debt can affect major choices. This generates scope for an additional fiscal externality.

Occupation choice.

Strategic default. You only would need this for fixed repayment contracts. If you add it, follow Gomes et al. 2023, which does it more simply than Ji (2021).

Additional debt accumulation. The model I present focuses on student debt to finance undergraduate education, as all borrowers are born with debt and cannot acquire debt in subsequent periods.

Endogenous early repayment.

Adverse selection and endogeneous contract selection. High-income borrowers selecting into non-income-contingent contracts or refinancing in private market (Bachas 2019).

Extensive margin labor supply decisions. Note that this model abstracts from extensive margin labor supply decisions, although individuals can in principle choose $\ell_{ia} = 0$. I do this for tractability, but view it as unlikely to affect my results for two reasons. First, the typical micro-foundation of an extensive margin decision is a fixed disutility cost of working. However, its unlikely this cost is larger than the post-repayment income of a median income individual, as this would make the counterfactual prediction that many unemployed individuals would earn median income upon labor market entry. Secondly, in the context of taxation, extensive margin labor supply decisions matter primarily for the bottom part of the transfer schedule (Saez 2002), which not the focus in my analysis.

Labor market general equilibrium effects.

Wealthy hand-to-mouth behavior. Starting with Kaplan and Violante (2014), a growing body of literature shows how two-asset models provide a better fit to the high estimated marginal propensities to consume out of transitory income shocks by generating a group of "wealthy hand-to-mouth agents" with high illiquid but low liquid wealth. Because the welfare costs of holding low liquid balances and limiting short-term consumption smoothing are second-order relative to the first-order gain of a higher return in the illiquid asset, individuals find it optimal to accumulate low liquid wealth and hence have high marginal propensities to consume. Although omitting an illiquid asset is likely to understate the welfare gains from income-contingent loans, I suspect it would not qualitatively change my conclusions for several reasons. First, the presence of an illiquid asset helps match high-frequency consumption behavior in response to transistory income shocks. In contrast, I consider policy changes that generate welfare gains primarily by affecting individuals' ability to smooth permanent income shocks. Second, I'm primarily interested in the properties of consumption at longer horizons. In most calibrations of illiquid asset models, individuals receive adjustment opportunities quarterly or monthly, meaning the properties of consumption in these models are likely not too different from my model over the longer horizons I consider. For example, Figure 2 in Auclert, Rognlie, and Straub (2018) and Figure 5 in Kaplan and Violante (2022) show that the MPC out of a transitory income shock in a two-asset model converges to that of a one-asset model at horizons of around one-year.[65]

[65] In the calibration in Section 4.1.2 of Kaplan and Violante (2022), 9% of households rebalance each quarter, which implies around one-third of households will rebalance each year.

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.

Abel, Andrew B., Janice Eberly, and Stavros Panageas (2013), "Optimal Inattention to the Stock Market With Information Costs and Transactions Costs." *Econometrica*, 81, 1455–1481.

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.

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*, w26340.

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*, 14.

Auclert, Adrien, Matthew Rognlie, and Ludwig Straub (2018), "The Intertemporal Keynesian Cross." *National Bureau of Economic Research*, 1–58.

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

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

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

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

Baker, Scott R. (2018), "Debt and the response to household income shocks: Validation and Application of linked financial account data." *Journal of Political Economy*, 126, 1504–1557.

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.

Belley, Philippe and Lance Lochner (2007), "The Changing Role of Family Income and Ability in Determining Educational Achievement." *Journal of Human Capital*, 1, 37–89.

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

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*.

Blundell, Richard, Luigi Pistaferri, and Ian Preston (2008), "Consumption Inequality and Partial Insurance." *American Economic Review*, 98, 1887–1921.

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

Bornstein, Gideon and Sasha Indarte (2022), "The Impact of Social Insurance on Household Debt." *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.

Braxton, J. Carter, Kyle Herkenhoff, Jonathan Rothbaum, and Lawrence D. W. Schmidt (2021), "Changing income risk across the US skill distribution: Evidence from a generalized Kalman filter." *Working Paper*.

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

Caballero, Ricardo J. and Eduardo M. R. A. Engel (1999), "Explaining Investment Dynamics in U.S. Manufacturing: A Generalized (S, s) Approach." *Econometrica*, 67, 783–826.

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*.

Caplin, Andrew and John Leahy (2010), "Economic Theory and the World of Practice: A Celebration of the (S , s) Model." *Journal of Economic Perspectives*, 24, 183–202.

Caplin, Andrew and Daniel F. Spulber (1987), "Menu Costs and the Neutrality of Money." *Quarterly Journal of Economics*, 102, 703–726.

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 (1997), "Buffer-Stock Saving and the Life-Cycle/Permanent Income Hypothesis." *The Quarterly Journal of Economics*, 112, 12–26.

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*.

Caucutt, Elizabeth M. and Lance Lochner (2020), "Early and late human capital investments, borrowing constraints, and the family." *Journal of Political Economy*, 128, 1065–1147.

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.

Chapman, Bruce and Tony Salvage (2001), "Australian Postgraduate Financing Options." *Agenda - A Journal of Policy Analysis and Reform*, 8.

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 (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.

Chetty, Raj, Adam Looney, and Kory Kroft (2009), “Salience and taxation: Theory and evidence.” *American Economic Review*, 99, 1145–1177.

Choukhmane, Taha (2021), “Default Options and Retirement Saving Dynamics.” *Working Paper*, 1–78.

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

Cocco, João F., Francisco J. Gomes, and Pascal J. Maenhout (2005), “Consumption and portfolio choice over the life cycle.” *Review of Financial Studies*, 18, 491–533.

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

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 and Amy Finkelstein (2011), “Selection in Insurance Markets: Theory and Empirics in Pictures.” *Journal of Economic Perspectives*, 25, 115–138.

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.

Ey, Carol (2021), “The Higher Education Loan Program (HELP) and related loans: A chronology.” Technical report, Parliament of Australia.

Fagereng, Andreas and Marius Alexander Kalleberg Ring (2021), “Financial Frictions and the Non-Distortionary Effects of Delayed Taxation.” *SSRN Electronic Journal*.

Federal Reserve Board (2023), “Federal Reserve Statistical Release: Consumer Credit- G.19.”

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 (2022), "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*.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen P. Utkus (2021), "Five Facts About Beliefs and Portfolios." *American Economic Review*, 115, 1481–1522.

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, 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.

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*.

Imai, Susumu and Michael P. Keane (2004), “Intertemporal Labor Supply and Human Capital Accumulation*.” *International Economic Review*, 45, 601–641.

Indarte, Sasha (2023), “Moral Hazard versus Liquidity in Household Bankruptcy.” *Working Paper*.

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.

Kaplan, Greg and Giovanni L. Violante (2014), “A Model of the Consumption Response to Fiscal Stimulus Payments.” *Econometrica*, 82, 1199–1239.

Kaplan, Greg and Giovanni L Violante (2022), “The Marginal Propensity to Consume in Heterogeneous Agent Models.” *Annual Review of Economics*, 57.

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.

Keane, Michael P. (2016), “Life-cycle Labour Supply with Human Capital: Econometric and Behavioural Implications.” *The Economic Journal*, 126, 546–577.

Keane, Michael P. and Kenneth I. Wolpin (1997), “The Career Decisions of Young Men.” *Journal of Political Economy*, 105, 473–523.

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.

Lucas, Robert E. (2003), “Macroeconomic Priorities.” *American Economic Review*, 93, 1–14.

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.

Makris, Miltiadis and Alessandro Pavan (2021), “Taxation under Learning by Doing.” *Journal of Political Economy*, 129, 1878–1944.

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.

Medhora, Shalailah (2018), “From next year you’ll be paying back your student loans sooner.” *ABC News*.

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

Mian, Atif, Kamalesh Rao, and Amir Sufi (2013), “Household Balance Sheets, Consumption, and the Economic Slump*.” *The Quarterly Journal of Economics*, 128, 1687–1726.

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*.

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.

Schmidt, Lawrence D. W. (2016), "Climbing and Falling Off the Ladder: Asset Pricing Implications of Labor Market Event Risk." *Working Paper*.

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.

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

Student Loans Company (2023), "National statistics: Outstanding income contingent student loans balance."

Verner, Emil and Gyozo Gyöngyösi (2020), "Household Debt Revaluation and the Real Economy: Evidence from a Foreign Currency Debt Crisis." *American Economic Review*, 110, 2667–2702.

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*.

Zeldes, Stephen P. (1989), "Optimal consumption with stochastic income: Deviations from certainty equivalence." *Quarterly Journal of Economics*, 104, 275–297.

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.[66] 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.[67] 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:

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

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 $t+1$[68], and D_{it+1}^{new} 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_{it}^{new}. *ALife* does, however, have a flag for when D_{it}^{new} is positive. Under the assumption that individuals do not make voluntary repayments when they accumulate new HELP debt, I can estimate voluntary repayments as:

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

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

[66]See here for additional details.

[67]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.

[68]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%.[69]

[69] 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*.[70] 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 (Ey 2021). 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',
```

[70]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, Kepner, Byun, Samsi, Arcand, Bestor, Bergeron, Gadepally, Houle, Hubbell, Jones, Klein, Milechin, Mullen, Prout, Rosa, Yee, and Michaeleas 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.[71] 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.[72] 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.[73] 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

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

[72] 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

[73] 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 endogeneous 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 $t \geq T^*$.[74] 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

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

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

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

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.[75] 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 $t \ge T^*$:

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

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

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

where π_{05} is the inflation rate used for the HELP indexation thresholds between 2004 and 2005. For individuals in retirement with $a \ge a_R$, 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

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

for payments in 2005 for a single individual with no children.[76] 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.

[76] 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 following 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 main structural parameters of interest.

When calculating these 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 $W(\Theta) = \text{diag}\left(w(\Theta)\right)$, where

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

This choice follows Guvenen et al. (2021) and is made because I have many estimation targets that differ greatly in scale.[77] 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 $G = \frac{\partial}{\partial\Theta} g(\Theta)$,

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

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

[77] 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[78] 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). The standard errors for Θ^* are then $\sqrt{N^{-1}\text{diag}(\hat{V})}$.

[78] 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.

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:

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

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.[79] For simplicity, I do not implement the restriction in the US that IBR payments cannot exceed payments under a fixed repayment contract.[80]

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.[81] 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 $\psi_{ISA} = 4\%$.

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

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

[81] 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:

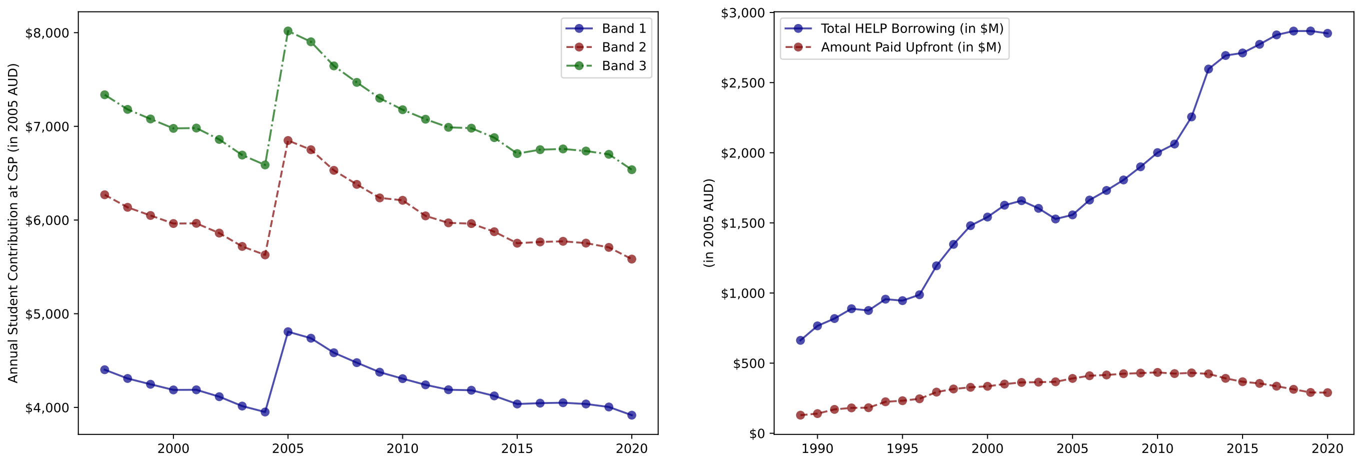
$$\left[\int V_p(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}} = \left[\int V^g_{\text{10-Year Fixed}}(\mathbf{s}_0 \mid \mathcal{E}_i = 1)^{1-\gamma} dF(\mathbf{s}_0 \mid \mathcal{E}_i = 1)\right]^{\frac{1}{1-\gamma}}.$$

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: 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 HELP borrowing and upfront payments in 2005 AUD. *Source:* Andrew Norton Higher Education Commentary.

Figure A2. Marginal HELP Repayment Rates

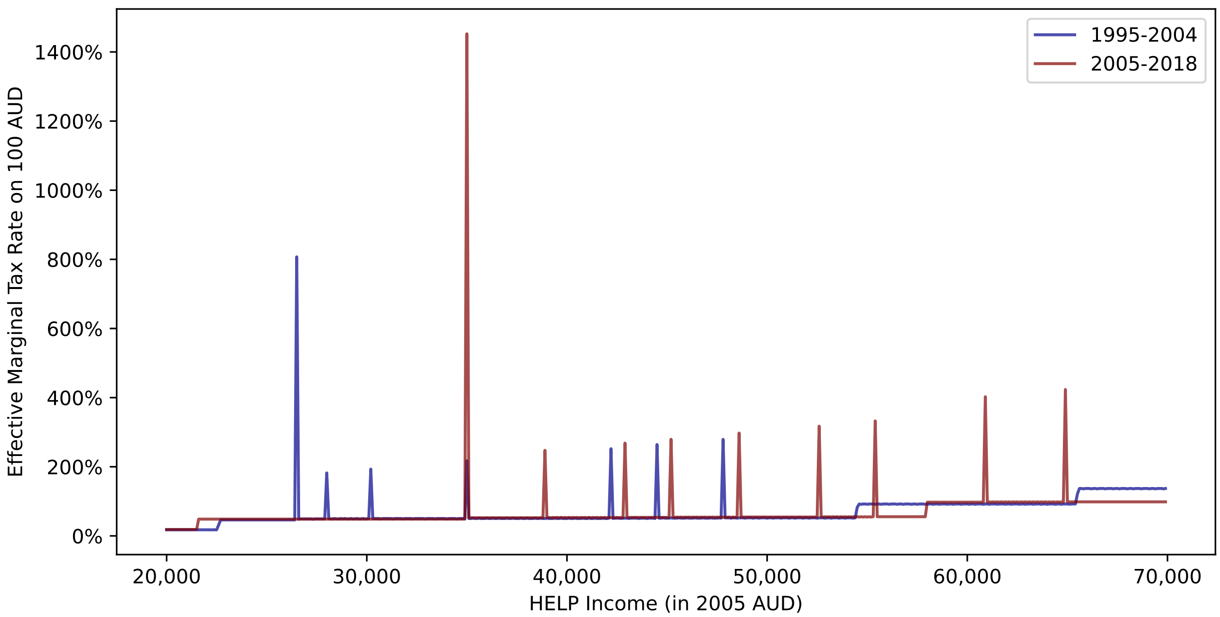


Figure A3. Rise in Education Costs in Australia

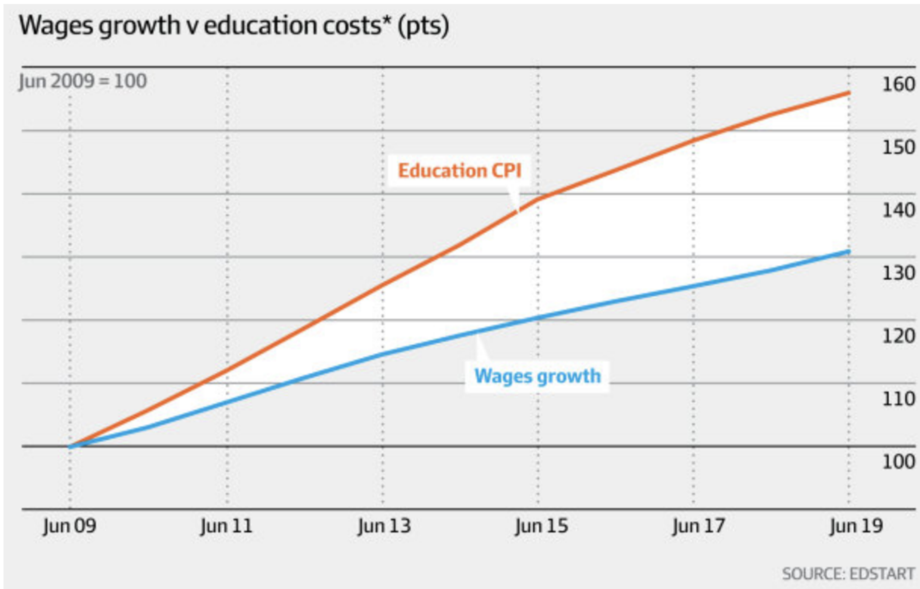
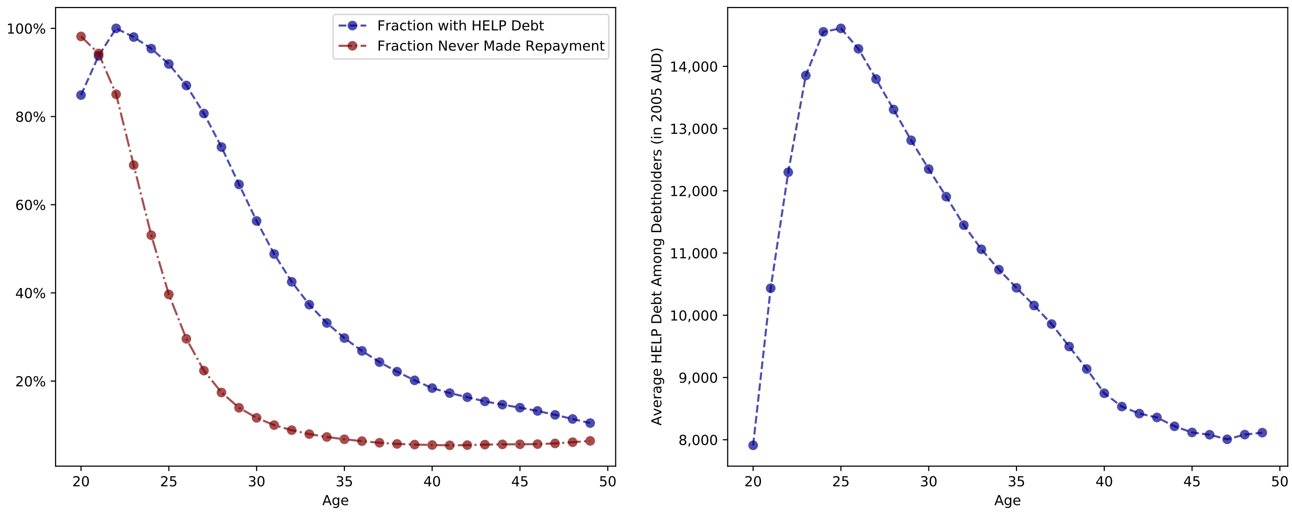


Figure A4. Debt Balances by Age

Panel A: Individuals with Positive Debt Balances at Age 22



Panel B: All Individuals

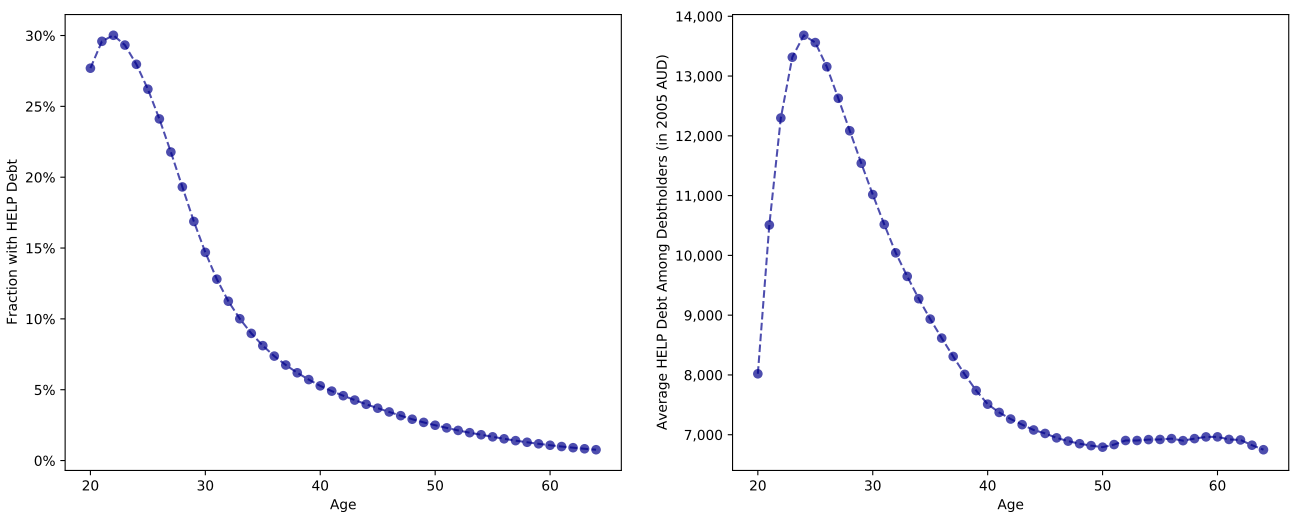


Figure A5. Real HELP Income Distribution in 2002-2008

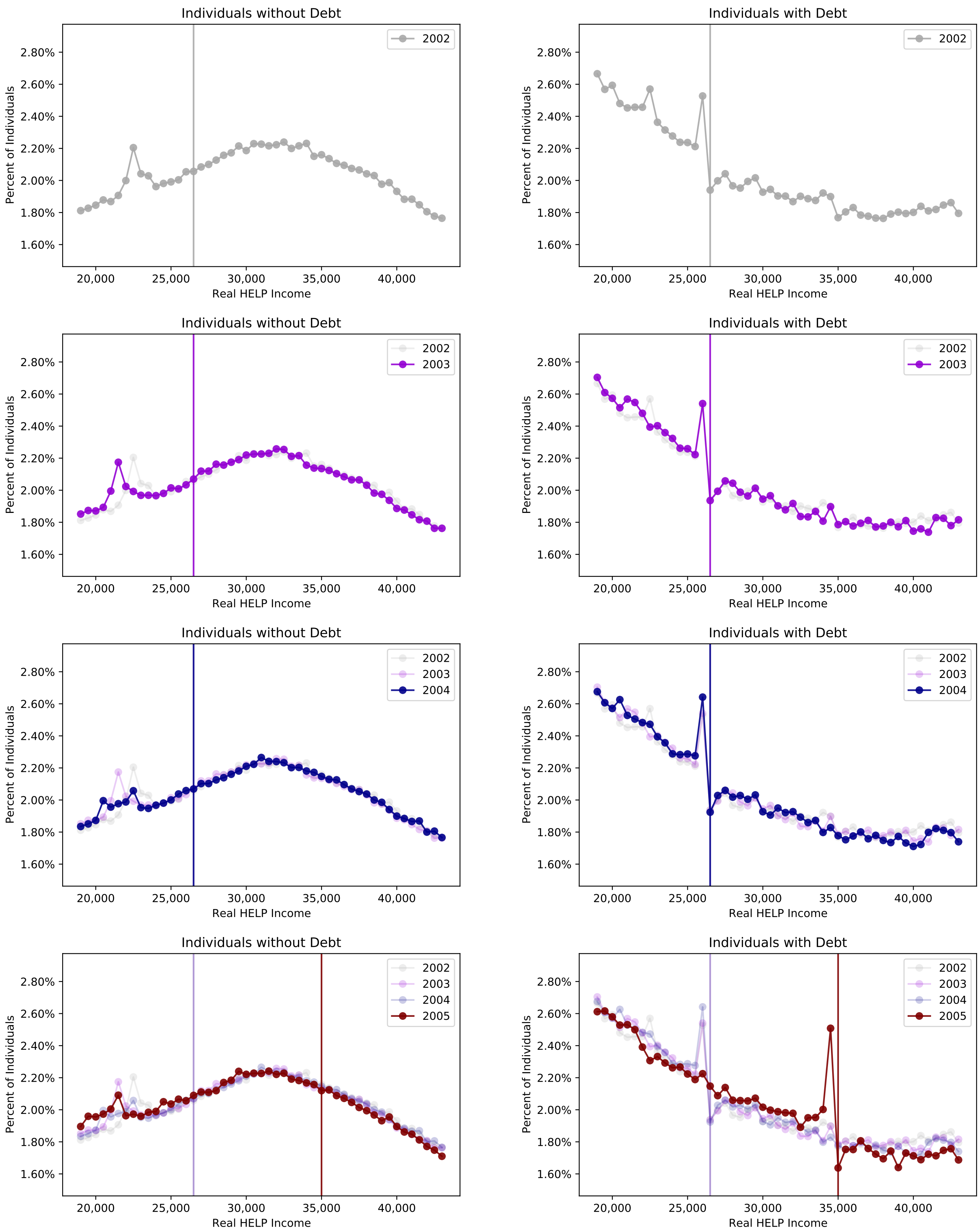


Figure A5. Real HELP Income Distribution in 2002-2008 (Continued)

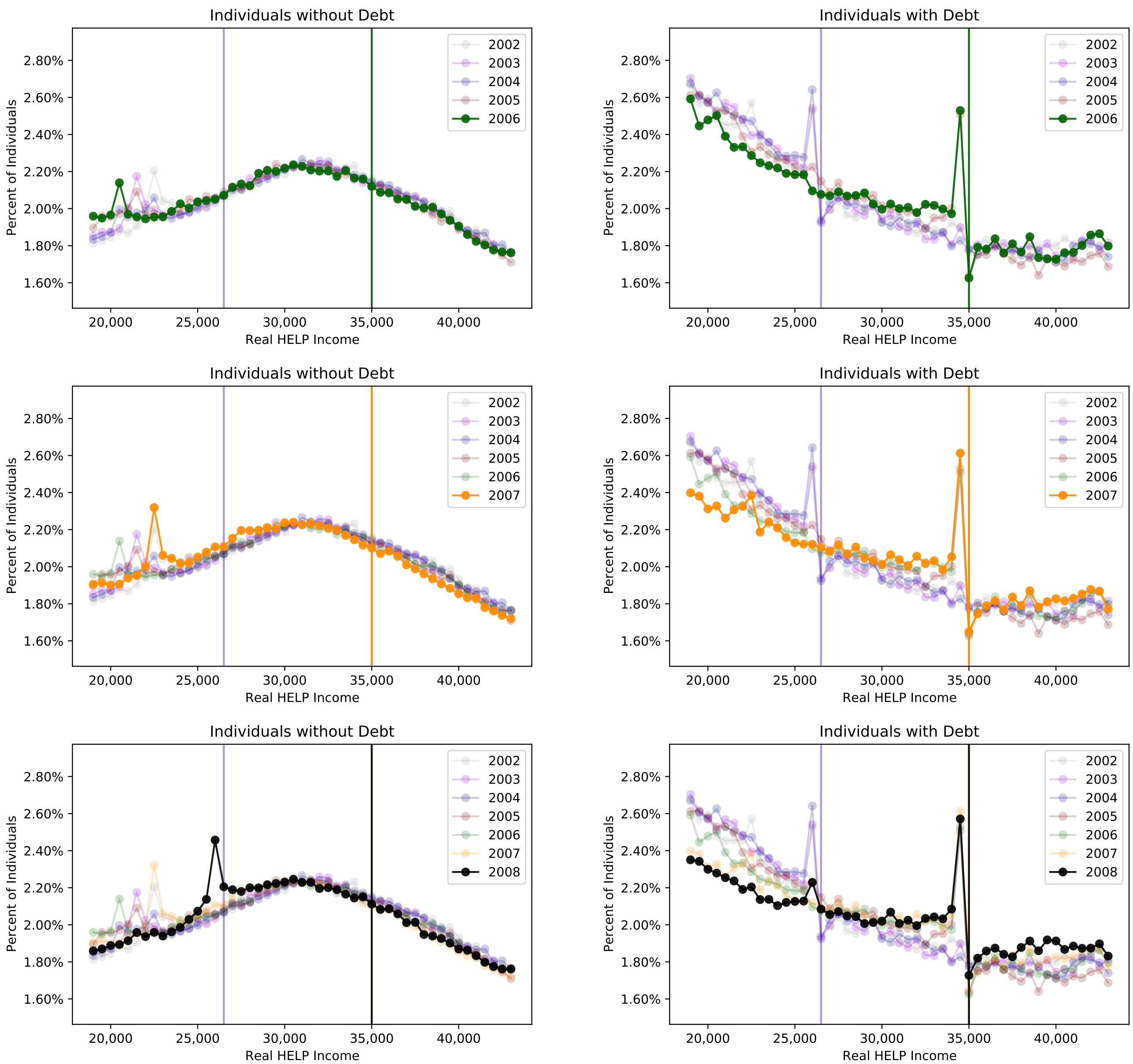


Table A1. Hours Flexibility Measures by 2-Digit ANZSCO Occupation

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

Figure A6. Average Hours Worked around Repayment Threshold in 2016: Individuals with Positive Labor Income

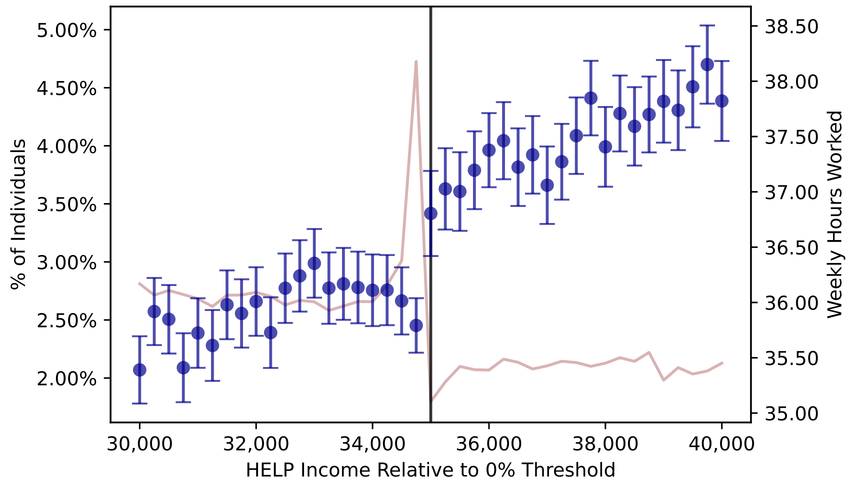
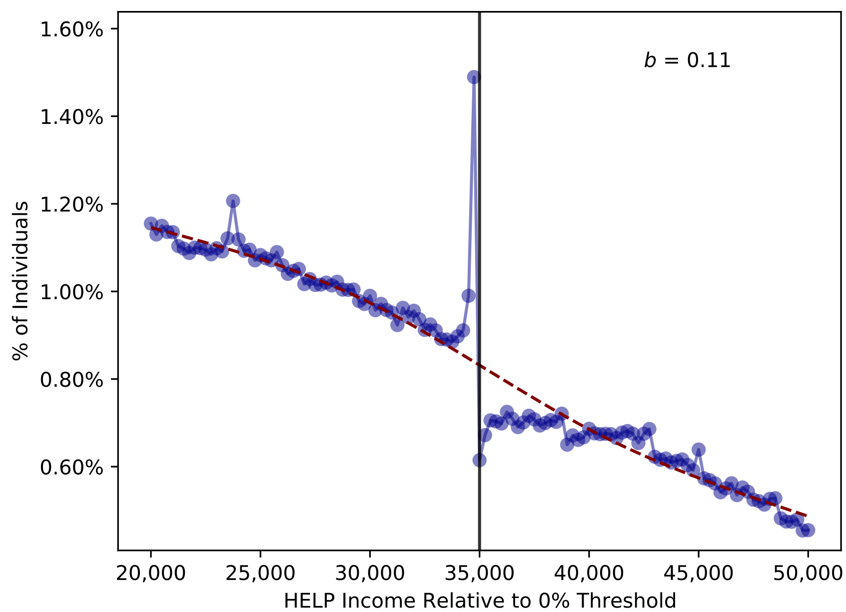


Figure A7. Distribution of Real HELP Income in *ALife* and MADIP Samples in 2016

Panel A: ALife Sample



Panel B: MADIP Sample

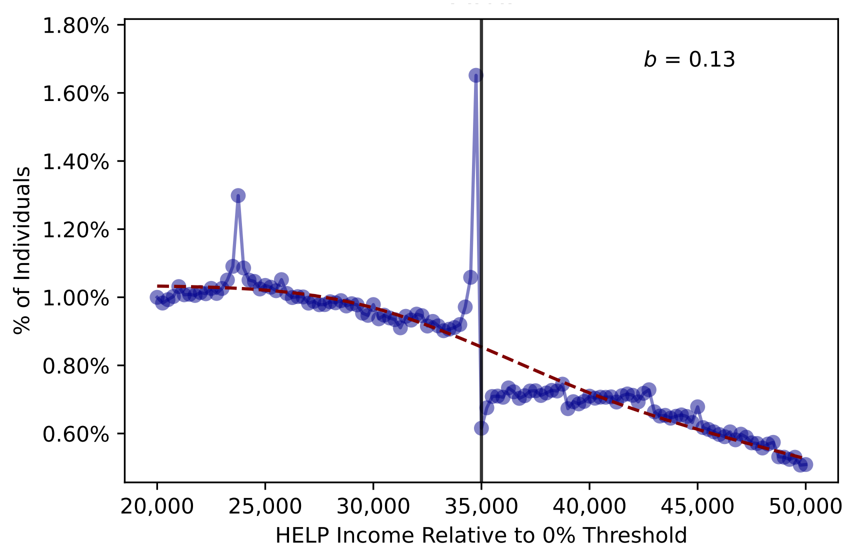


Figure A8. Distribution of Real Labor Income among Individuals with Net Deductions > $1,000 in 2005-2018

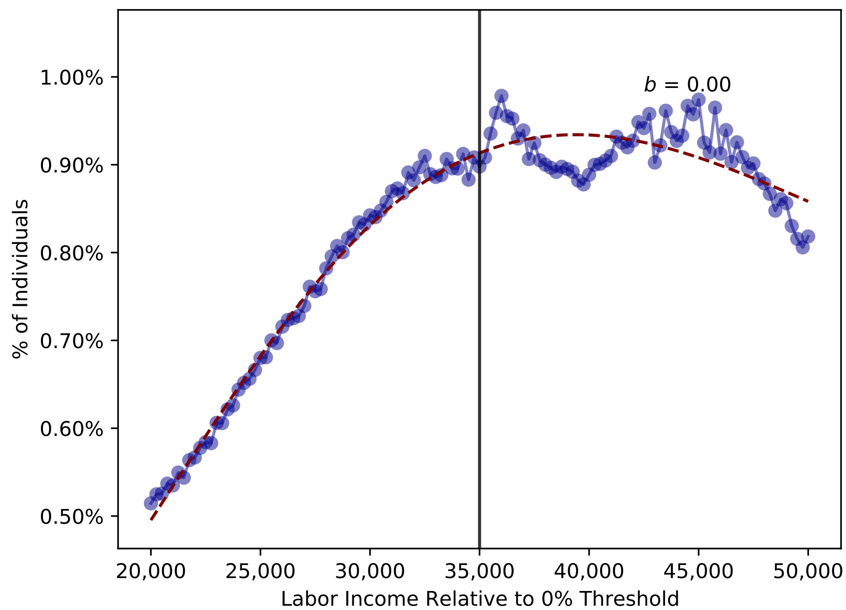


Figure A9. Probability of Switching Occupations around Repayment Threshold in 2005-2018

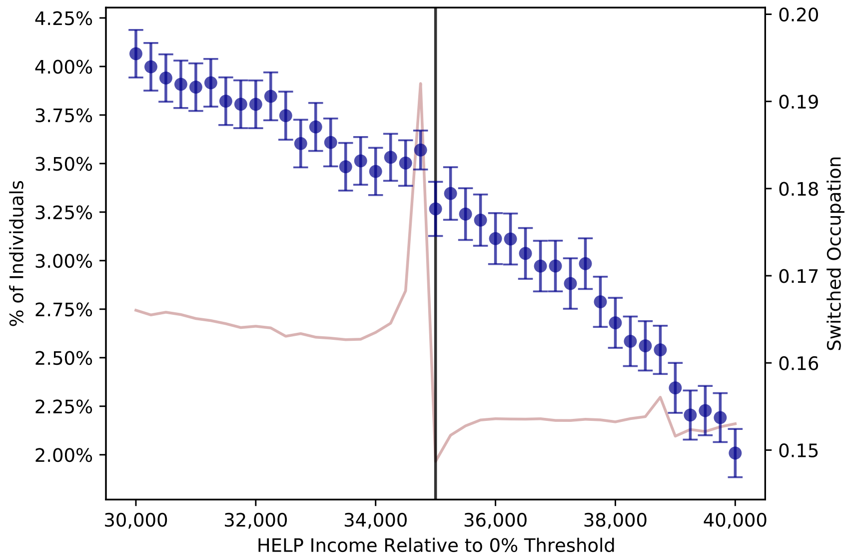


Figure A10. Real HELP Income Distribution by Tax Filing Method in 2005-2018

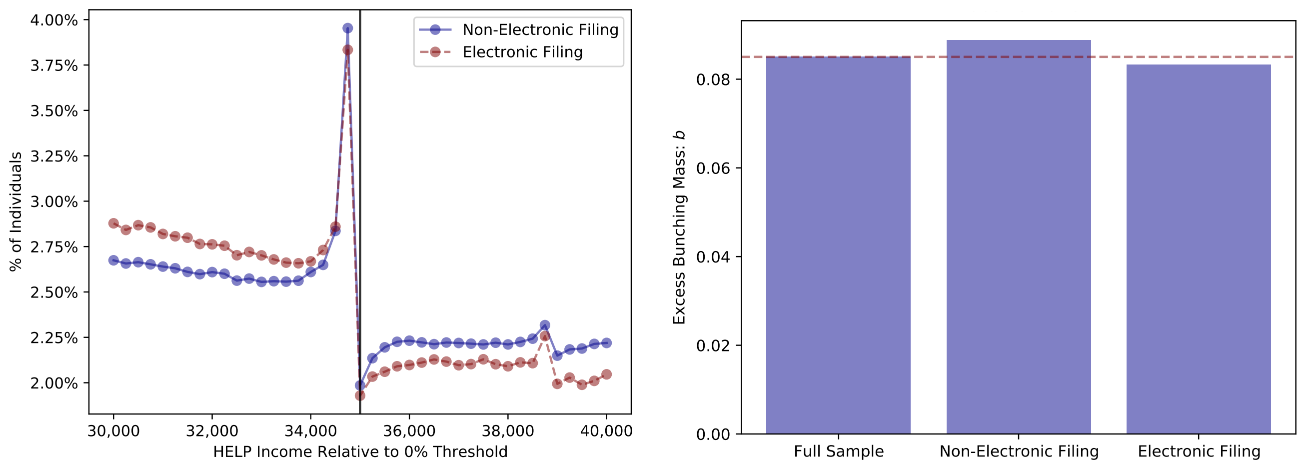


Figure A11. Distributions of Real HELP Income and Salary and Wages in 2005-2018

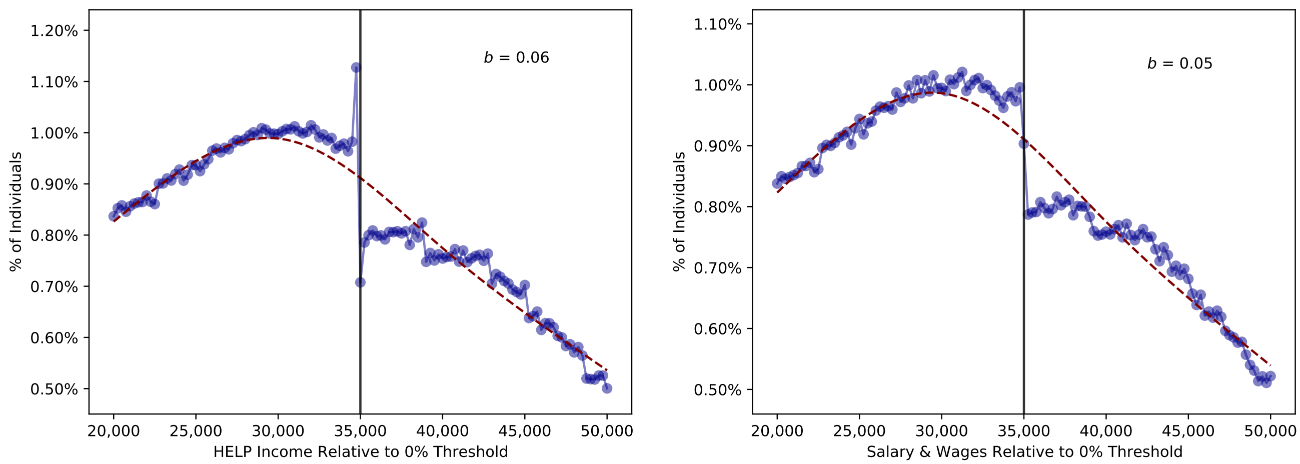


Figure A12. Real HELP Income Distribution by Employment Type in 2005-2018

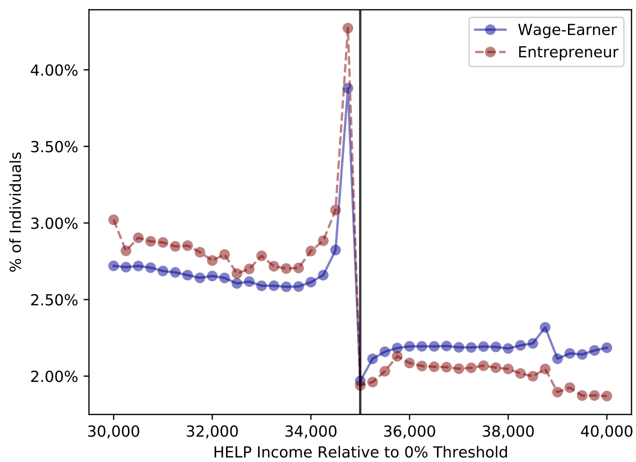


Figure A13. Real HELP Income Distribution by Age in 2005-2018

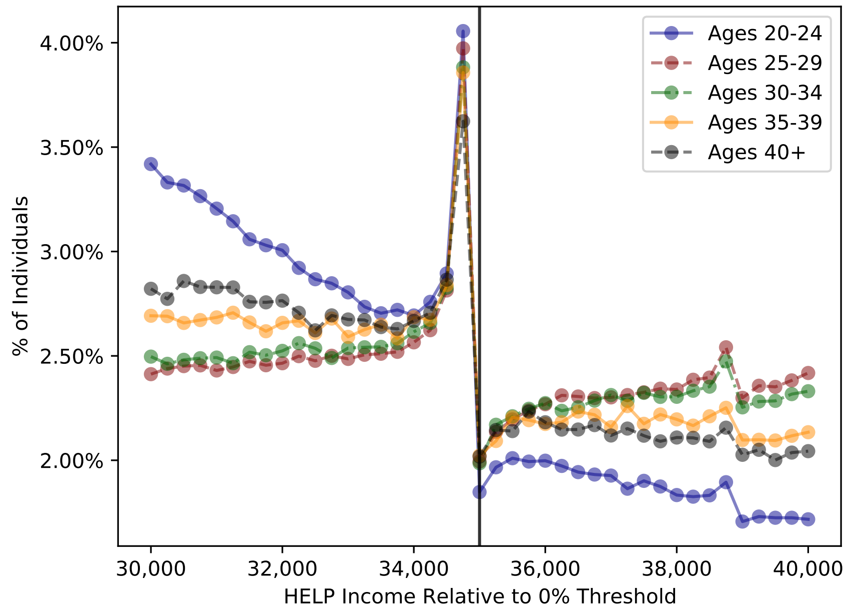


Figure A14. Real HELP Income Distribution by Quartiles of Debt in 2005-2018

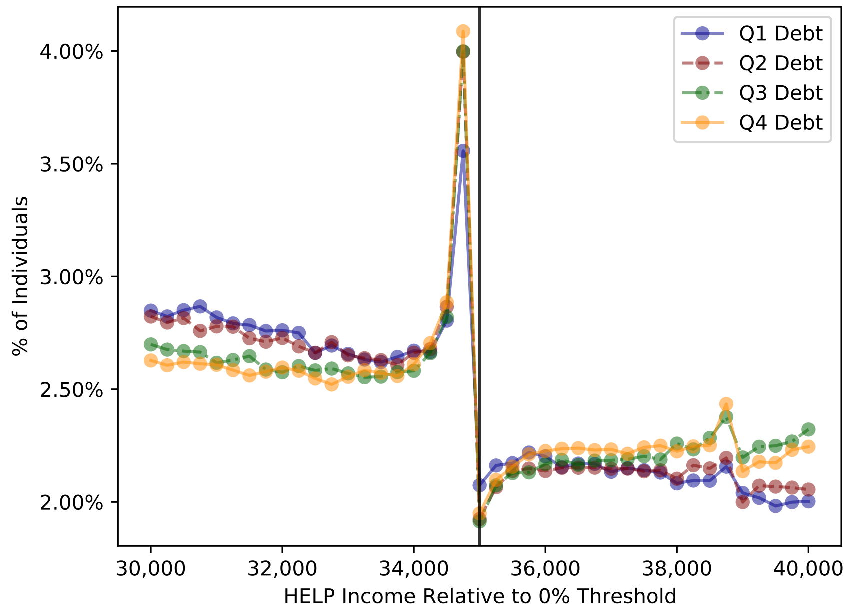
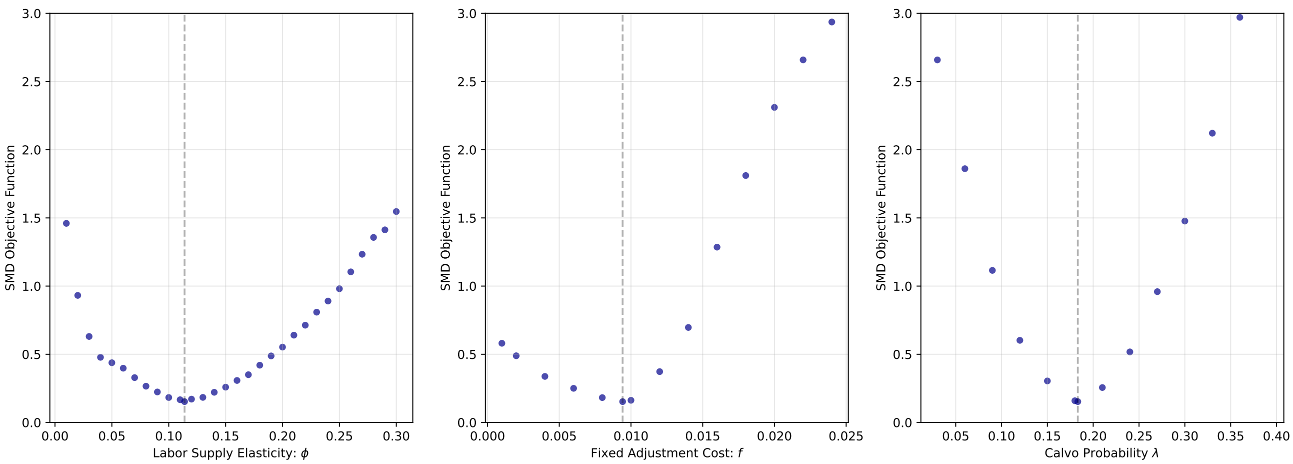


Table A2. Estimated Bunching Statistic, b, by Age Group and Debt in 2005-2018

	HELP Debt	
Age Group	Below Median	Above Median
20-24	0.079	0.118
25-29	0.078	0.095
30-34	0.066	0.102
35-39	0.080	0.080
40+	0.058	0.078

Figure A15. Local Identification of Labor Supply Parameters



Notes: This figure plots the value of the SMD objective function in the baseline estimation for different values of the three labor supply parameters in my model. 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 4. The vertical gray dashed line indicates the estimated value of each parameter.

Table A3. 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 A3. Elasticity of Estimation Targets with Respect to Parameters (continued)

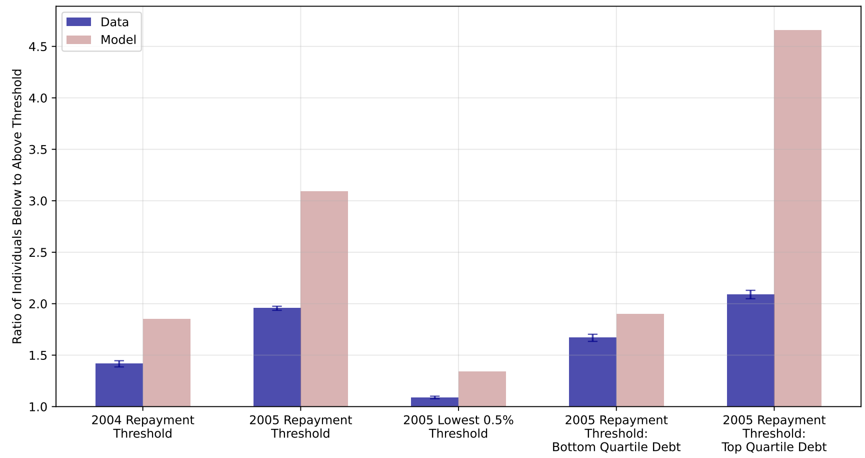
Panel D: Remaining Estimation Targets

	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

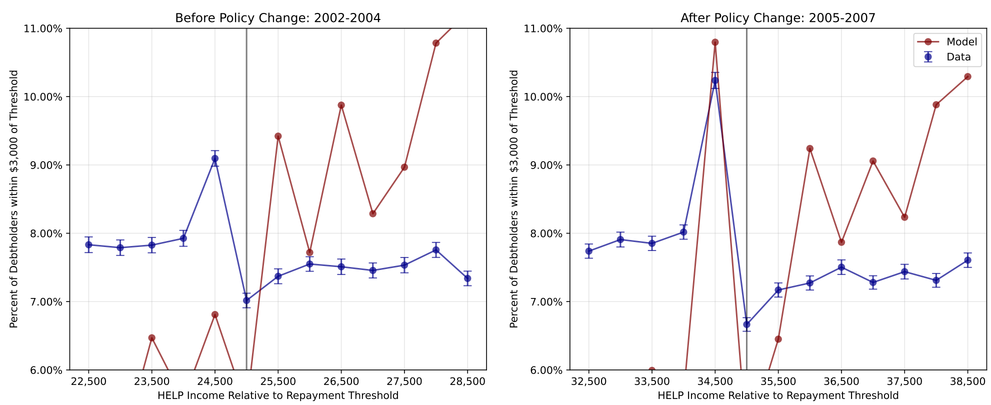
Notes: This table reports the elasticity of simulated estimation targets with respect to my estimated structural parameters. The four panels present the results for different sets of estimation targets. In each panel, the entry in row i and column j is an estimate of the derivative of the log of the 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 4 by central differencing. Since some moments 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 fraction on individuals in each $500 income bin before and after the policy change, respectively, shown in Figure 10. Panel C provides the results for the moments in Figure 11. Panel D provides the results for the remaining set of estimation targets shown in Table 5.

Figure A16. Model Fit: No Adjustment Frictions

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change

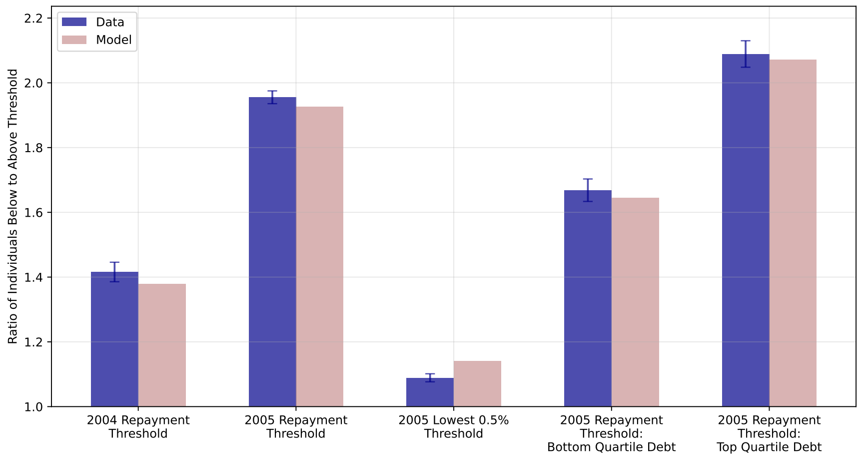


Panel C: Other Estimation Targets

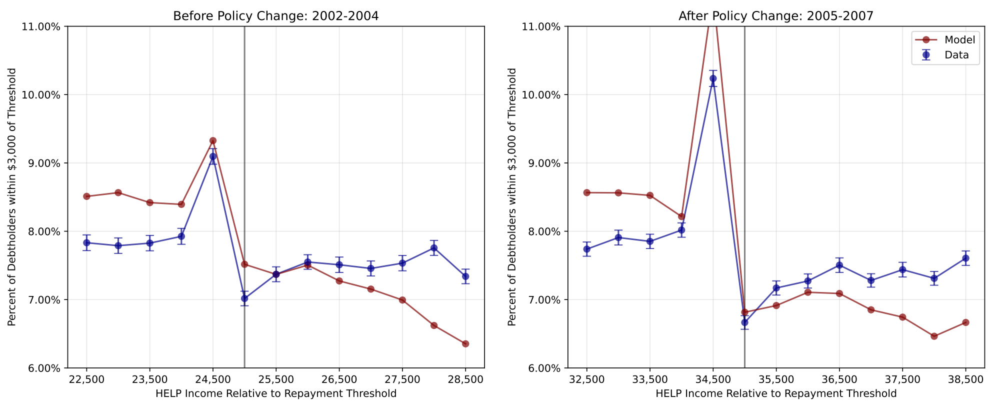
Estimation Target	Data	Model
Average Labor Income	42639.373	62169.068
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.304
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.403
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.533
Cross-Sectional Variance of Log 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

Figure A17. Model Fit: No Calvo Adjustment

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change

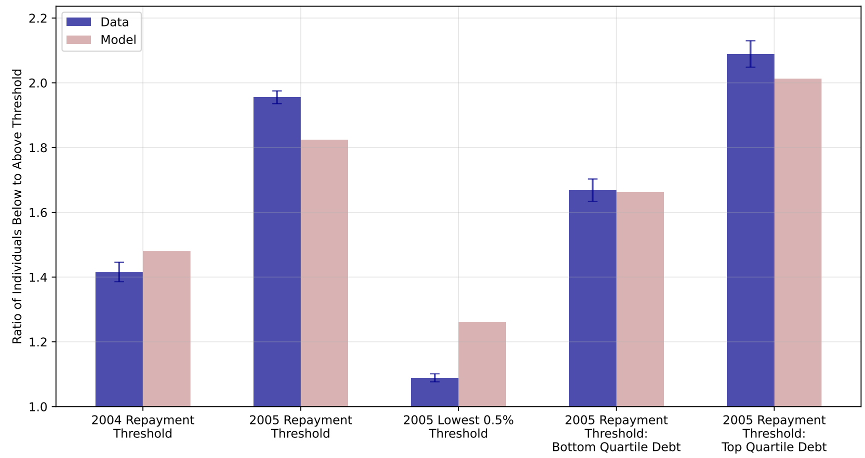


Panel C: Other Estimation Targets

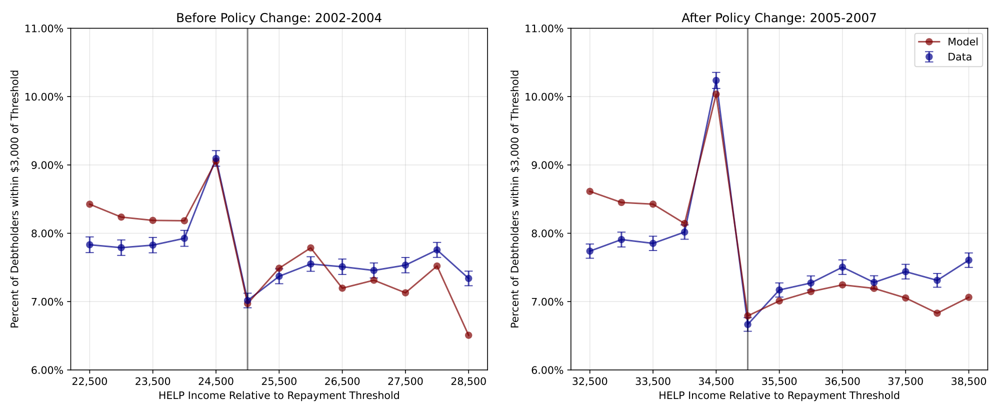
Estimation Target	Data	Model
Average Labor Income	42639.373	45691.108
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.483
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.493
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.523
Cross-Sectional Variance of Log 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

Figure A18. Model Fit: No Fixed Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change

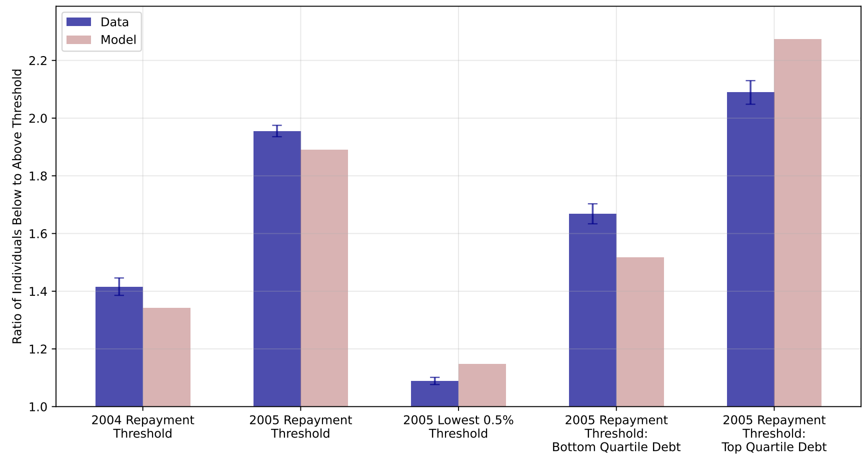


Panel C: Other Estimation Targets

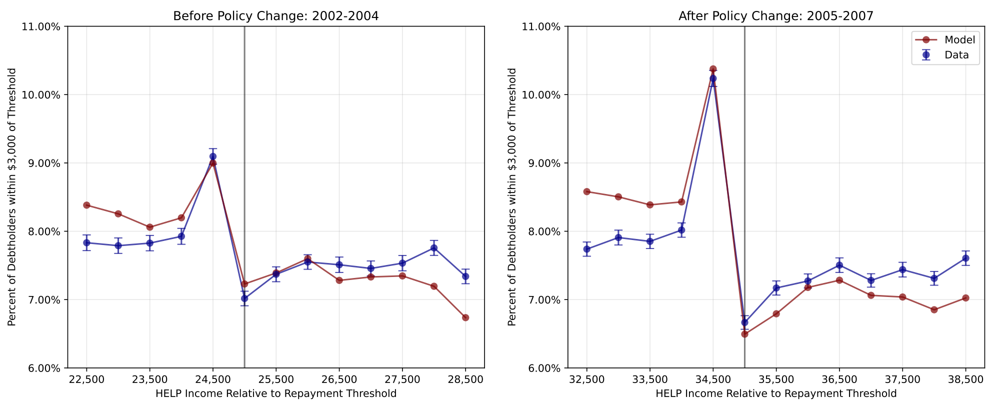
Estimation Target	Data	Model
Average Labor Income	42639.373	46896.491
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.474
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.507
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.537
Cross-Sectional Variance of Log 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

Figure A19. Model Fit: Learning-by-Doing

Panel A: Bunching around Thresholds



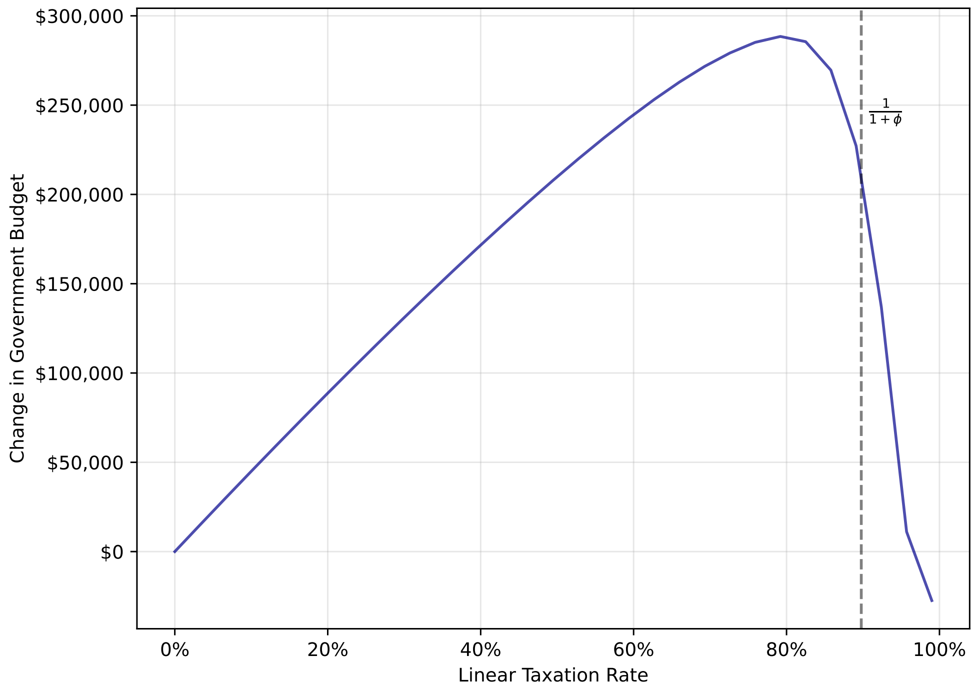
Panel B: HELP Income Distribution around Policy Change



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

Figure A20. Laffer Curve from Linear Taxation in Model



Notes: This figure plots the Laffer curve from a linear tax on income, τy_{ia}, in my 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 a canonical static frictionless model of labor supply (Saez 2001; Piketty and Saez 2013) evaluated at my estimate of ϕ in column (1) of Table 4. 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 A21. Bunching Below Repayment Threshold and Liquidity

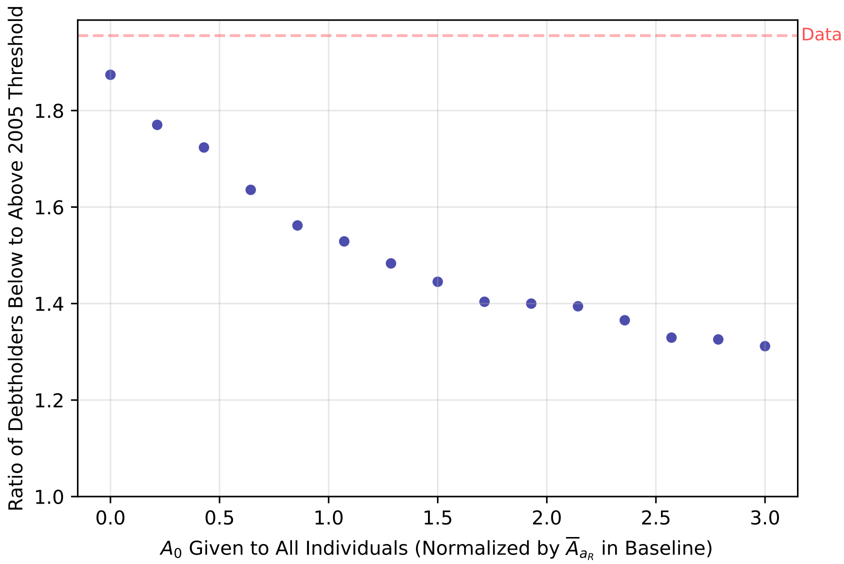


Figure A22. Real HELP Income Distribution by Quartiles of Superannuation Balances in 2005-2018

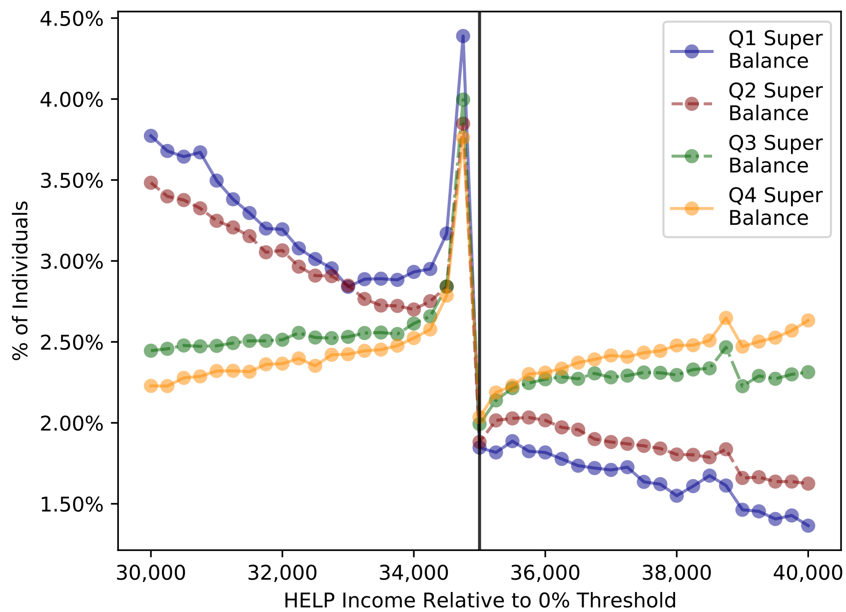


Figure A23. Marginal Value of Public Funds from Alternative Repayment Contracts

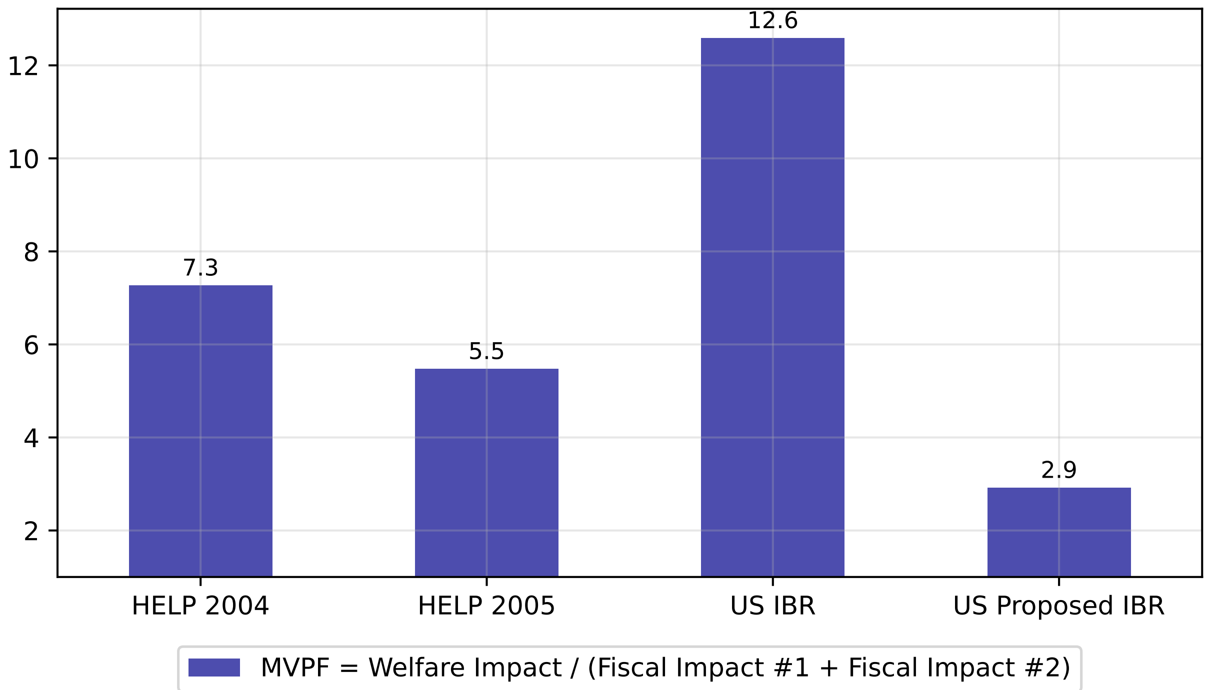


Figure A24. Fiscal Impact of Income-Contingent Loans under Alternative Labor Supply Parameterizations

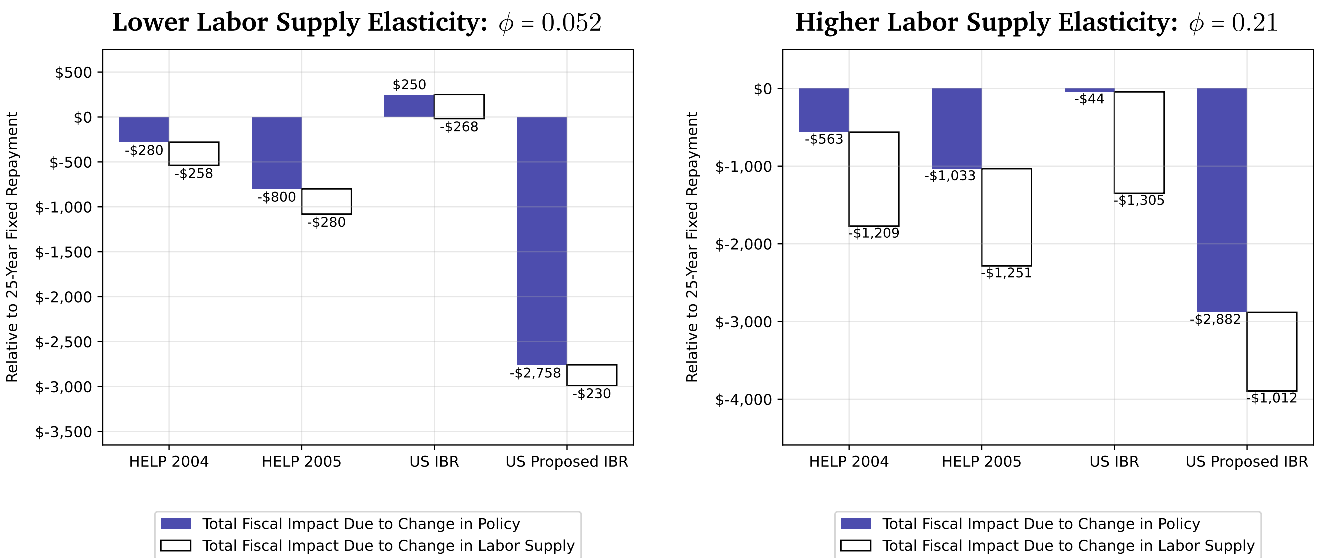


Figure A25. Welfare Gains from Constrained-Optimal Income Contingent Loan with $\psi \leq 10\%$

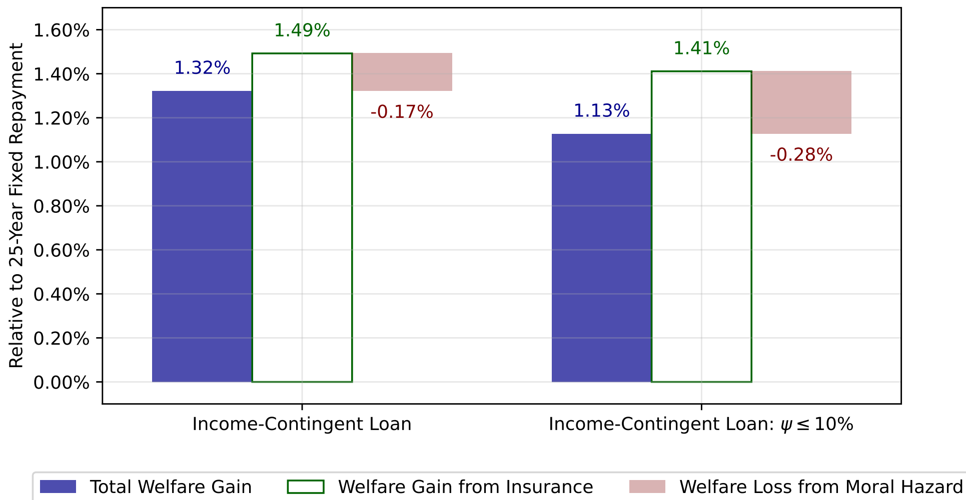
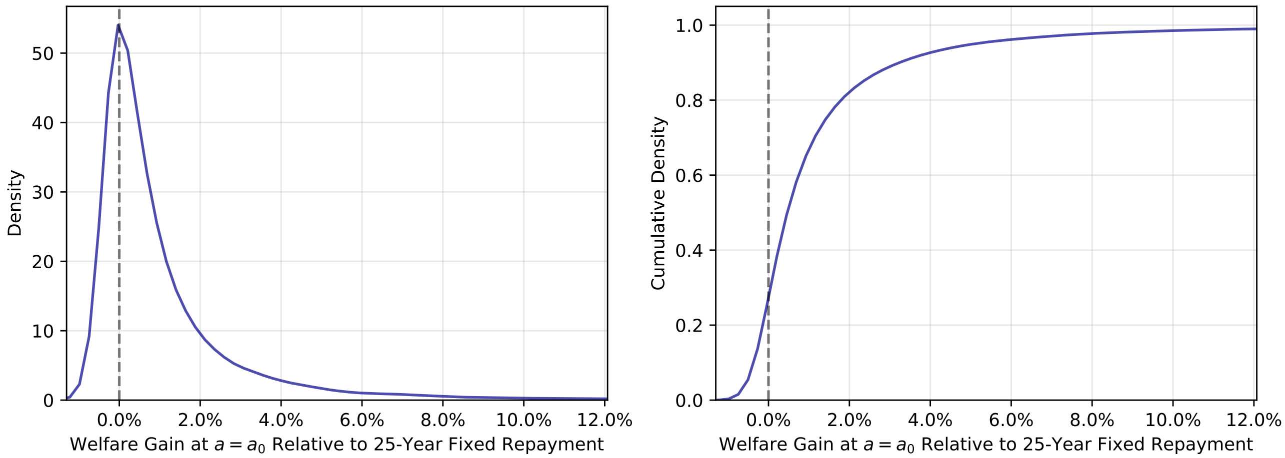


Figure A26. Heterogeneity in Initial Welfare Gains from Constrained Optimal Income-Contingent Loan

Panel A: Distribution of Net Consumption-Equivalent Welfare Gains



Panel B: Average Initial States by Net Consumption-Equivalent Welfare Gain

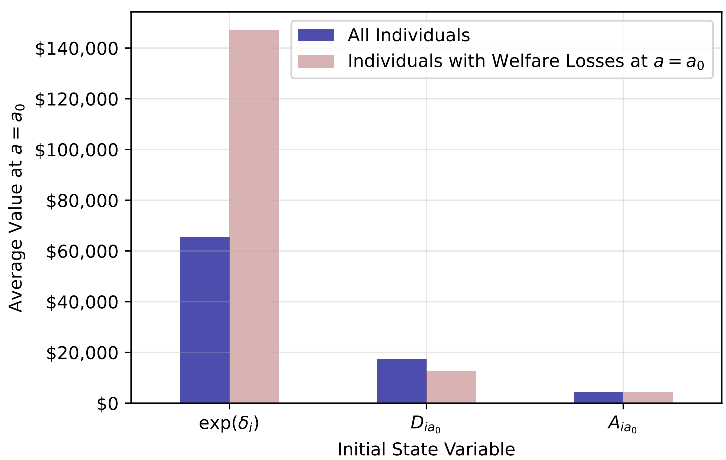
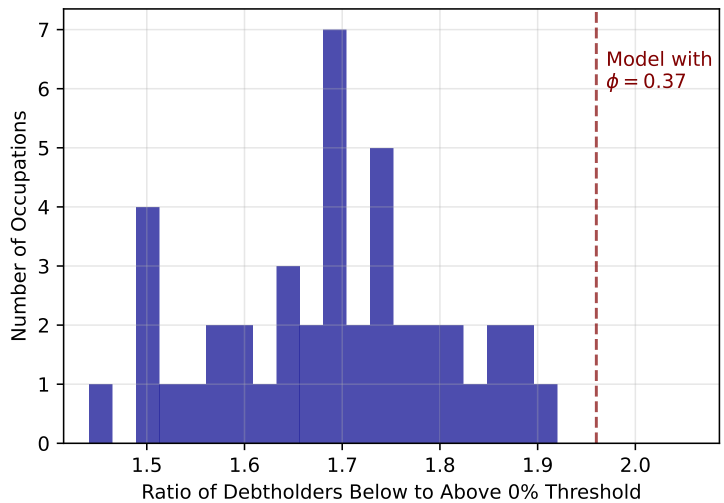


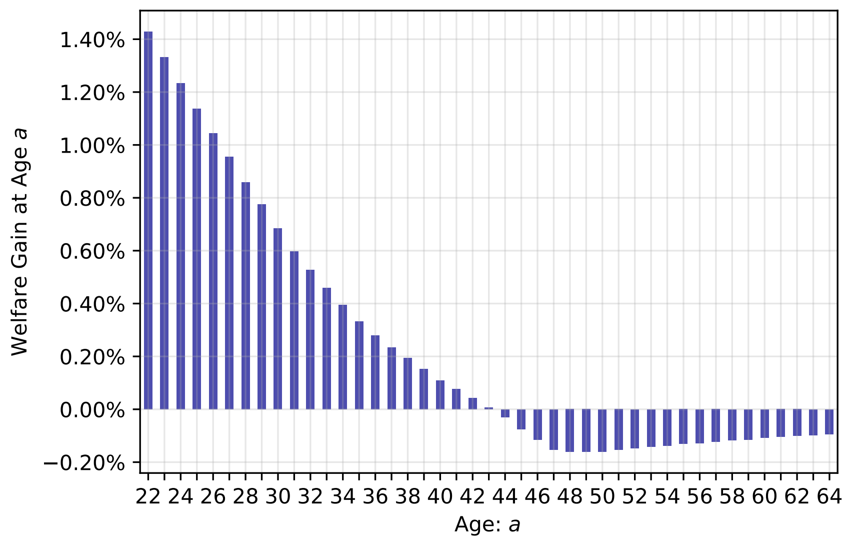
Figure A27. Bunching in Model with $\psi = 0.37$ Compared to Distribution by Occupation



Notes: This figure plots the distribution of the ratio of the number of debtholders within $500 below the 0% repayment threshold to the number within $500 above it between 2005 in 2018 in blue bars. The red line corresponds to the same statistic computed within the model among individuals with $D_{ia} > 0$ and $a > a_0$.

Figure A28. 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 20-Year Forgiveness Relative to Optimal Income-Contingent Loan

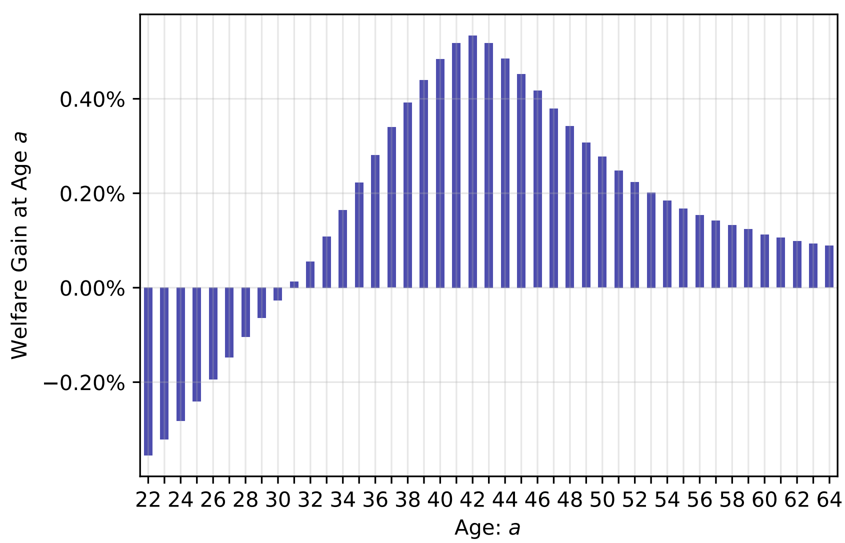


Figure A29. Heterogeneity in Certainty-Equivalents across Terciles of Initial Debt

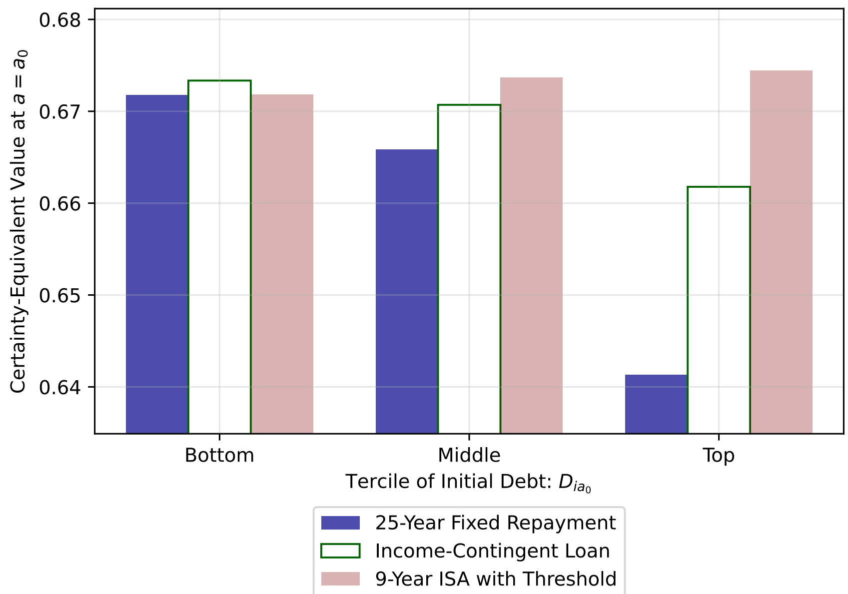
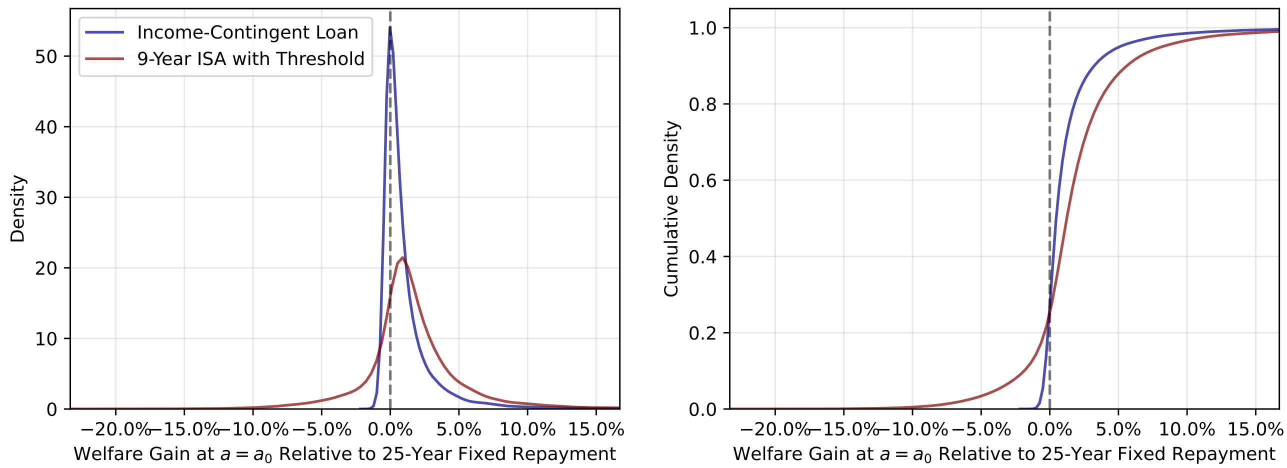


Figure A30. Heterogeneity in Initial Welfare Gains from Constrained Optimal Income-Sharing Agreement

Panel A: Distribution of Net Consumption-Equivalent Welfare Gains



Panel B: Average Initial States by Net Consumption-Equivalent Welfare Gain

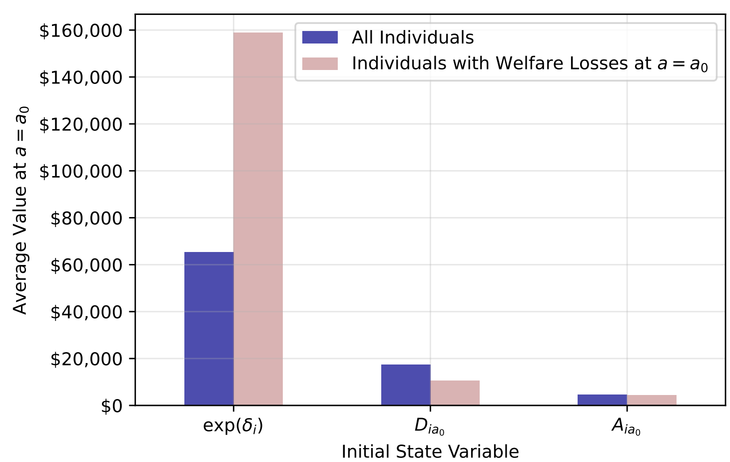
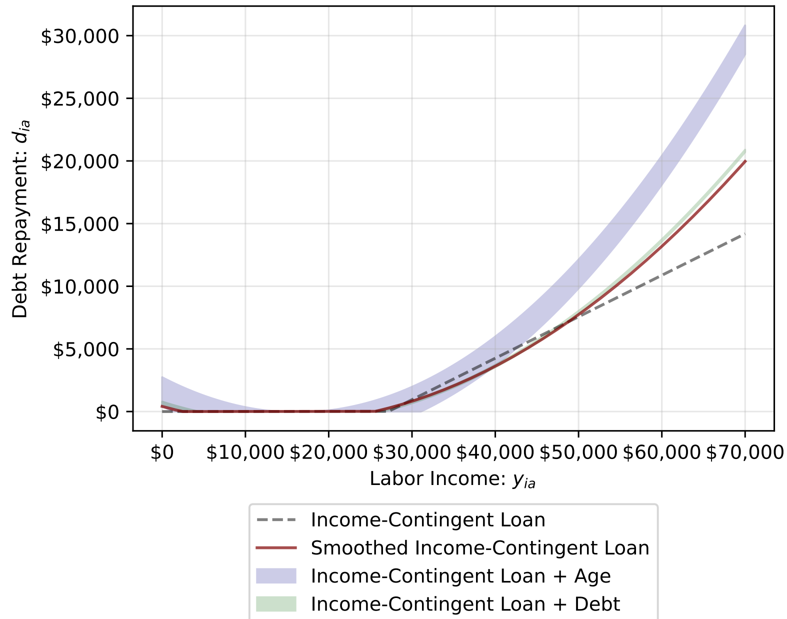
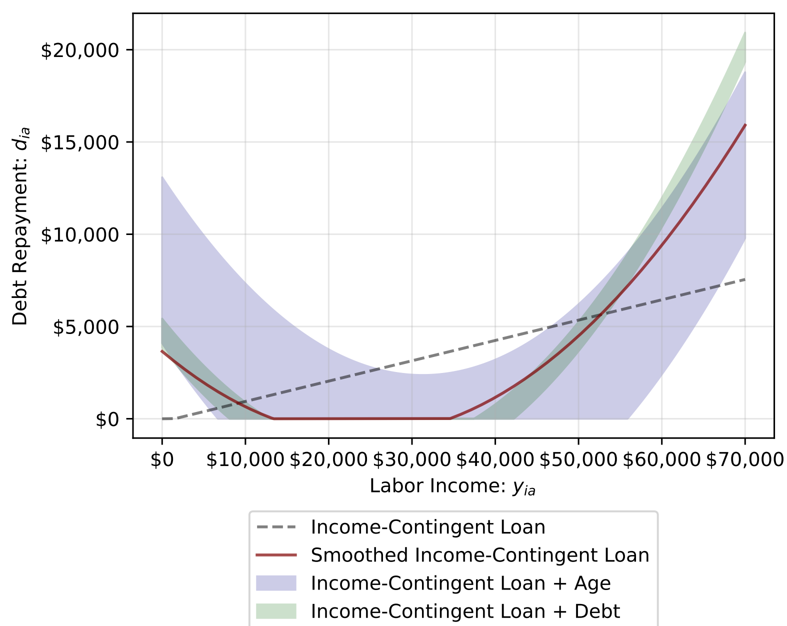


Figure A31. Constrained-Optimal Smoothed Income-Contingent Loans

Panel A: Baseline Model



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



Notes: This figures plot the repayments, d_{ia}, as a function of income, y_{ia}, for the values of parameters for each repayment contract that solve (17). The solid red line plots the smoothed income-contingent loan. The shaded blue region plots the range of payments on income-contingent loan with age-contingent repayment, where the boundaries of the region correspond to evaluating at $a = a_0$ and $a = a_R$, respectively. The shaded Green region plots the range of payments on income-contingent loan with debt-contingent repayment, where the boundaries of the region correspond to evaluating at $D_{ia} = 0$ and the 90th-percentile of D_{ia_0}, respectively. Panel A reports results from the baseline model, while Panel B reports results from the baseline model with $\phi = 0.37$.