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

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This internet appendix contains the following materials:

- Theoretical appendix with additional derivations (Appendix A),
- Empirical appendix with institutional details, data description, and variance construction (Appendix B),
- Details on the solution, simulation, and estimation of the life cycle model (Appendix C),
- Additional results presented in figures and tables (Appendix D).

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Appendix A. Theoretical Appendix

A.1 Derivation of (2)

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

Appendix B. Empirical Appendix

B.1 Additional Institutional Details

Timing and collection of HELP repayments. Individuals can make compulsory HELP repayments, which are the repayments calculated according to the HELP repayment formula 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.[2] For most individuals, indexation occurs prior to the deduction of compulsory repayments because these repayments are deducted at the time of tax filing, which generally occurs between July 1st and October 31st. This is true even if an employer withholds repayments, as these repayments are not counted until the individual's tax return is filed.

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%.[3]

B.2 Data and Variable Construction

B.2.1 *ALife*

ALife provides access to a 10% random sample to approved projects. My code and analysis were tested on this sample, and then was executed on the population sample by research professionals at *ALife*. The remainder of this section provides additional details on variable definitions based on the underlying variables I construct. For description of these underlying variables, see the following link: `https://alife-research.app/research/search/list`. Variable definitions are presented in `Python 3.9`, where `df` refers to the underlying *ALife* dataset as a `Pandas DataFrame`. When variables are missing from *ALife* in a given year, they are replaced with zero unless otherwise mentioned in the text.

Age. Defined as `c_age_30_june`.

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

Female. An indicator variable that equals one if an individual is a female based on `c_gender`.

Salary & Wages. Defined as `i_salary_wage`.

Taxable Income. Defined as `ic_taxable_income_loss`.

HELP Income. The definition of HELP Income has changed since the introduction of HECS in 1989. For the 1989 to 1996 Australian tax years, HELP Income was equal to taxable income. Between 1996 and 1999 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.

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

Interest & Dividend Income.

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

Capital Income.

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

Net Deductions.

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

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

Superannuation balances. Defined as `sb_mem_bal`.

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

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

Other demographic variables. X.

B.2.2 MADIP

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

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

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

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

B.2.3 HILDA

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

Hourly flexibility: panel measure. Hourly flexibility is measured as the standard deviation of annual changes in log hours worked per week across all jobs, `jbhruc`. Before computing this measure at the occupation-level, I restrict the sample to individuals in the 2002-2019 HILDA Survey Waves that satisfy the following conditions: (i) report being employed; (ii) earn a positive weekly wage; (iii) do not switch occupations between two subsequent years; (iv) are between ages 23 and 64. Prior to computing the standard deviation, annual changes in log hours are winsorized at

1%-99%. The standard deviation within each occupation is computed using longitudinal survey weights.

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

B.3 Computation of Excess Bunching Mass Statistic, b

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

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

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

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

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

Appendix C. Structural Model Appendix

C.1 Model Solution and Simulation

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

Solution algorithm. The model has a finite horizon with a terminal condition and hence can be solved using backward induction in age starting with the terminal condition in the final year of life. There are two notable aspects of the solution algorithm that are crucial for getting the simulated minimum distance objective function to be smooth in the set of parameters in Figure A18. First, no choice variables are discretized, meaning I use continuous optimization routines rather than grid searches for find optimal policies. Second, I use Gauss-Hermite quadratures to integrate all continuous shocks, which means that continuous shocks are drawn from continuous distributions when I simulate from the model.

During retirement, I keep track of one value function that is a function of two states: wealth and age. The terminal condition for the model is that $E_{a_T - 1} V_{a_T}^{1-\gamma} = 0$, which embeds the assumption that $u_d^{1-\gamma} = 0$, where u_d is the utility upon death. This assumption is standard in life cycle models with recursive preferences.[5] Starting with this condition, I then solve the model in prior periods by finding the optimal consumption-savings choice using a Golden-Section search with boundaries set based on the borrowing constraint and positive consumption. I continue this backward induction until $a = a_R - 1$.

During working life, I keep track of two value functions that are solved separately for each $\mathcal{E}_i \in \{0, 1\}$. I describe how I solve for one of these, since the approach is the same, with the only difference that a different value of $\mathcal{E}_i$ changes the state transition equations. This backward induction during working life begins with the value function at retirement, $a = a_R$, as the terminal condition. At each age, for each of the grid points in the seven-dimensional state space that excludes the Calvo shock, I solve for optimal choices of savings and labor supply. I do this twice: once in the case when $\omega_a = 0$, in which case I solve for savings using a Golden-Section search and labor supply is held fixed, and once for the case in which $\omega_a = 1$, where I solve for savings *and* labor supply using a Nelder-Mead algorithm. The bounds for the Nelder-Mead algorithm are set based on the budget constraint for assets and between 0 and 10 for labor supply. The starting point is set equal to β times cash on hand for assets, and 1 for labor supply. I perform the Nelder-Mead up to three times, varying the starting point for labor supply, until the result passes a convergence check. When solving for these

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

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

optimal policy functions at a, I have to integrate V_{a+1} over θ_{a+1}, which depends on the stochastic shock, ν_{a+1}, and have to interpolate the value function in the continuous states. I perform the integration using a Gauss-Hermite quadrature with 9 nodes and use linear interpolation (and extrapolation, if necessary).[6] Linear interpolation is extremely accuracte in my setting, which allows me to use few grid points as long as choice variables are not discretized, because the Epstein-Zin value function is approximately linear in wealth. Having solved for optimal choices and hence the value function in the seven-dimensional state space at each age, I then integrate out ω_a and ϵ_a to obtain a value function that depends on five states for each age: past labor supply, debt, permanent income, liquid savings, and t.[7] I continue this backward induction until $a = a_0$ and perform it twice for each $\mathcal{E}_i \in \{0, 1\}$.

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

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

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

C.2 First-Stage Calibration

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.[8] 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

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

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

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

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.[9] 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.[10] 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 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

[9] 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

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

risk aversion and the elasticity of intertemporal substition. I set $\gamma = \sigma = 2.23$ based on the results in Choukhmane and de Silva (2023), so preferences are time-separable in the baseline. In counterfactuals, I consider the effect of moving risk and time preferences independently.

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

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

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

Student debt repayment function. When estimating the model, I use the HELP 2004 repayment function at $t < T^*$ and the HELP 2005 repayment function at $t \geq T^*$.[11] Formally, I set $d(y,i,D,a,t) = \mathbf{1}_{a<a_R} * \min\{HELP_t(y+\max\{i,0\}) * (y+\max\{i,0\}), (1+r_d)D\}$, where

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

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

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

Income and capital taxation. In Australia, income taxes are paid on taxable income, which aggregates both wage income and capital income. The marginal tax rate individuals pay increases in their income according to a schedule provided by the ATO.[12] 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

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

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

2003/04 Income Tax Formula at $t < T^*$ and the ATO 2004/05 Formula at $t \geq T^*$:

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

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

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

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

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

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

Unemployment benefits and net consumption floor. Unemployment benefits are set equal to the payments provided by the Newstart Allowance, which is the primary form of government-provided income support to individuals above 22 with low income due to unemployment. These benefits are means-tested based on income and assets. I use the formula for payments in 2005 for a single individual with no children.[13] 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:

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

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

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.

C.3 Second-Stage Simulated Minimum Distance Estimation

Construction of estimation targets. The set of estimation targets I use are:

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

In these definitions, y_{ia} refers to the value of Salary and Wages in *ALife* and i_{ia} refers to Capital Income defined in Appendix B.2. Due to data access restrictions, I construct the first six set of estimation targets using a 10% random sample of *ALife* data. This likely has little affect on my results because these moments are very precisely estimated and are not the primary moments responsible for identifying my structural parameters of interest. For these moments, I restrict to wage-earners between 22, the first age in my model, and 64, the age at which individuals retire in the model, and winsorize both y_{ia} and i_{ia} from above at 99.999% following Guvenen et al. (2014). When computing the moments based on y_{ia}, I restrict to individuals that have annual salary and wages that is greater than one-half the legal minimum wage times 13 full-time weeks following Guvenen et al. (2014). When calculating all estimation targets in the data, I also restrict to individuals who are age 22 between 1963 and 2019 to match the cohorts simulated in the model.

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

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

This choice follows Guvenen et al. (2021) and is made because I have many estimation targets that differ greatly in scale.[14] 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.

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

Calculation of 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

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

[14] 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.

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

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

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

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

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

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

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

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[15] 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).[16] The standard errors for Θ^* are then $\sqrt{N^{-1}\text{diag}(\hat{V})}$.

C.4 Description of 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. A 25-year fixed repayment contract corresponds to $a_S = a_0$, $a_E = a_0 + 20$, and $r_d = 0\%$

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

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

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

- US IBR: $\psi = 10\%$, $K = 1.5 * pov$, $\overline{T} = a_R$, $r_d = 0\%$
- US SAVE: $\psi = 5\%$, $K = 2.25 * pov$, $\overline{T} = a_R$, $r_d = 0\%$
- Constrained-Optimal Income-Contingent Loan: ψ and K chosen to solve (17), $\overline{T} = a_R$, $r_d = 0\%$

[15] 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.

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

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

where pov is 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.[17] For simplicity, I do not implement the restriction in the US that IBR payments cannot exceed payments under a fixed repayment contract. In practice, these repayment contracts also have forgieness after a fixed period of time. I do not implement this in order to make them more comparable to HELP contracts, but return to the effect of adding forgiveness separately.

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

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

where ψ is chosen to solve (17) with this alternative repayment contract. The value of $\$16,863$ corresponds to the phase-out point of unemployment benefits described in Appendix C.2.

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

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

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

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

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

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

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

The first contract corresponds to a smoothed version of the US IBR-style income-contingent loans considered above, in which repayments are a quadratic function of income. The latter two contracts make repayments conditional on age and debt, respectively. For each of these alternative contracts, I solve (17) to find the constrained-optimal values of $\{\psi_i\}$.

C.5 Computation of Welfare Metrics

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

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

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 25-Year Fixed repayment contract is computed as the fixed point of the following equation in π:

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

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

Consumption-equivalent welfare gain. Let $V_p(\mathbf{s}_0 \mid \mathcal{E}_i = E)$ 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 25-Year Fixed repayment contract is computed as the fixed point to the following equation in g:

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

This metric corresponds to the value of g that would make individuals with $\mathcal{E}_i = 1$ indifferent between having to (i) repay their debt under repayment policy p and (ii) repay their debt under 25-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.

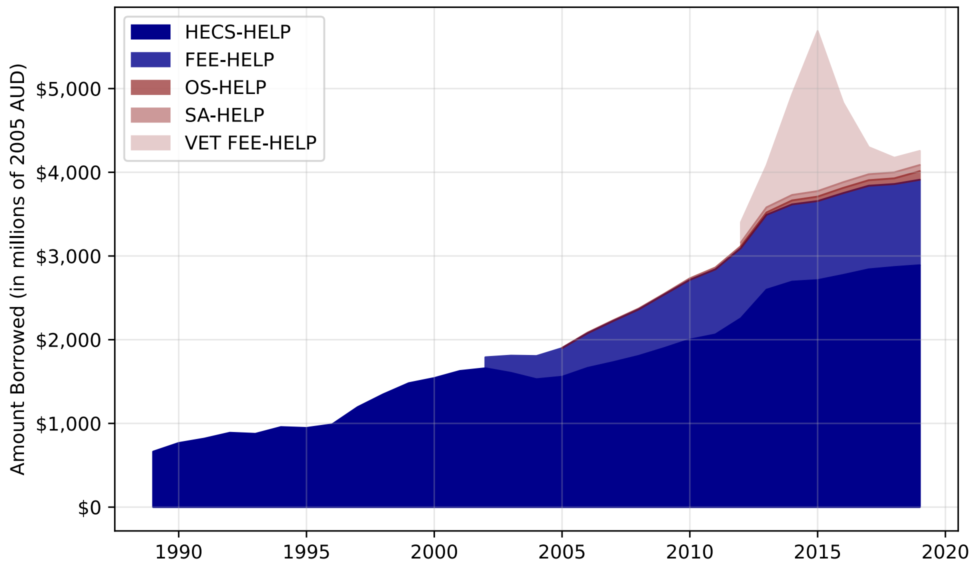
Net consumption-equivalent welfare gain. Due to computational constraints, some results (e.g., Figure 17) present *net* consumption-equivalent welfare gains, instead of consumption-equivalent welfare gains. These two are quantitatively very similar, but the former is significantly easier to compute because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

C.6 Computation of Constrained-Optimal Repayment Contracts

Solving (17) is numerically challenging, especially when considering higher-dimensional contracts, because it is a nonlinear constrained optimization problem in which the objective and constraints do not have closed-forms. I use a combination of a standard barrier method in numerical optimization (Nocedal and Wright 2006) and a global optimizer. Specifically, I set the objective function in (17) to an extremely large value in the event that first constraint, which corresponds to the government budget constraint, is violated by more than a tolerance of \$1. I then perform the minimization of this objective function using the TikTak optimizer from Arnoud et al. (2019).

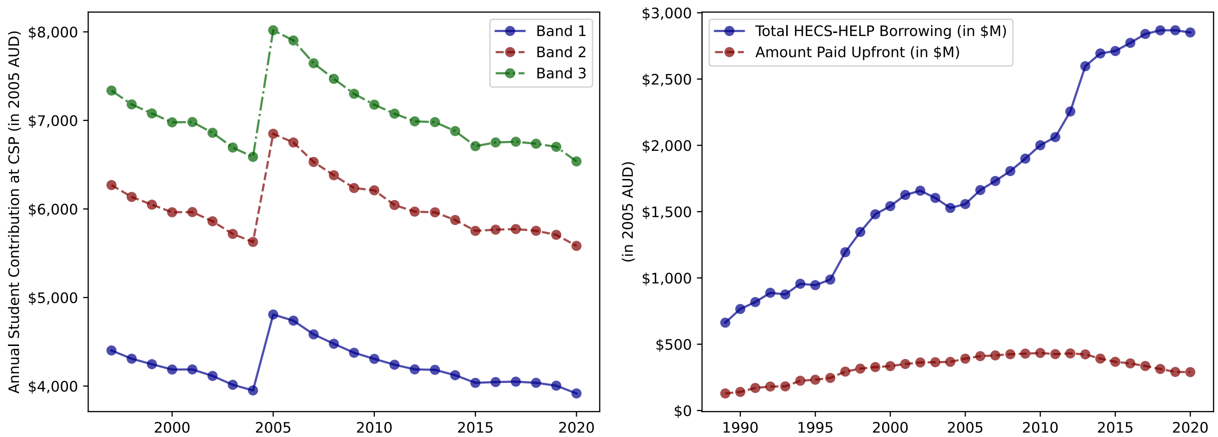
Appendix D. Additional Figures and Tables

Figure A1. Student Contributions and Aggregate HELP Borrowing over Time



Notes: This figure plots the time-series of the total amount borrowed each year among the five different HELP programs in millions of 2005 AUD. HECS-HELP refers to the primary HELP program that provides loans to cover student contribution amounts for Commonwealth Supported Places, which covers mostly undergraduate and postgraduate degrees at public institutions. FEE-HELP loans are used to cover the fees associated with degrees that are not Commonwealth Supported Places, such as undergraduate degrees at private institutions, and thus must be covered in full. FEE-HELP was introduced in 2005 and between 2002 and 2004 was formally called PELS. SA-HELP loans are used to pay student services and amenities fees. OS-HELP loans are used to cover expenses for students enrolled in a CSP that want to study overseas. VET FEE-HELP covers tuition fees for vocational education and training courses. VET FEE-HELP was closed on December 31st, 2016 and formally replaced by a different program called VET Student Loans on January 1st, 2017. The rapid increase in debt balances and subsequent closing of VET FEE-HELP was driven by fraud and corrupt behavior among vocational education provides (Australian National Audit Office 2016). A significant fraction of this debt has been written off in recent years (HELP Receiveable Report 2021, DESE Annual Report 2022). This data was obtained from Andrew Norton Higher Education Commentary.

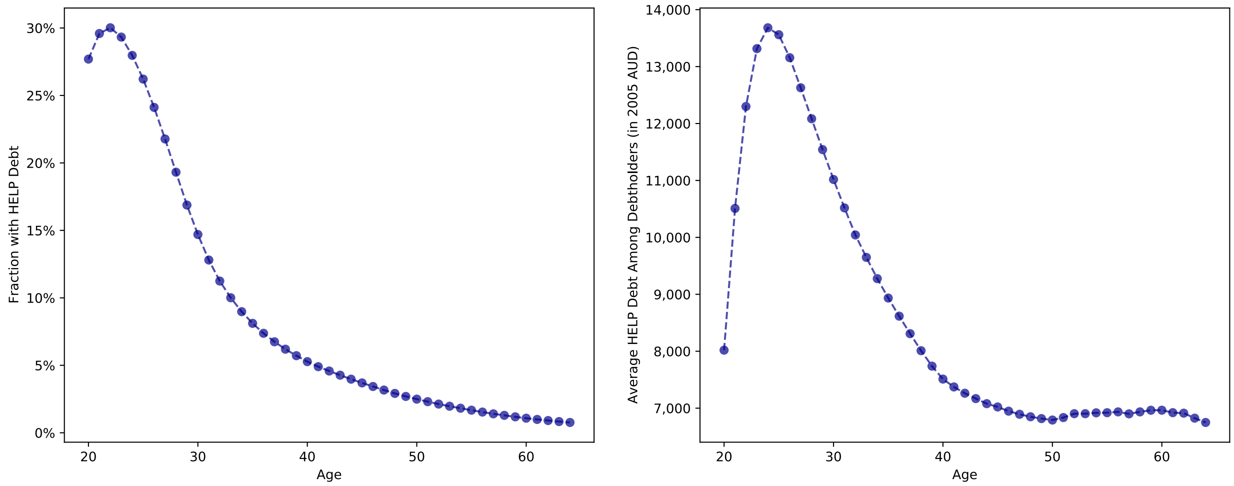
Figure A2. Student Contributions and Aggregate HELP Borrowing over Time



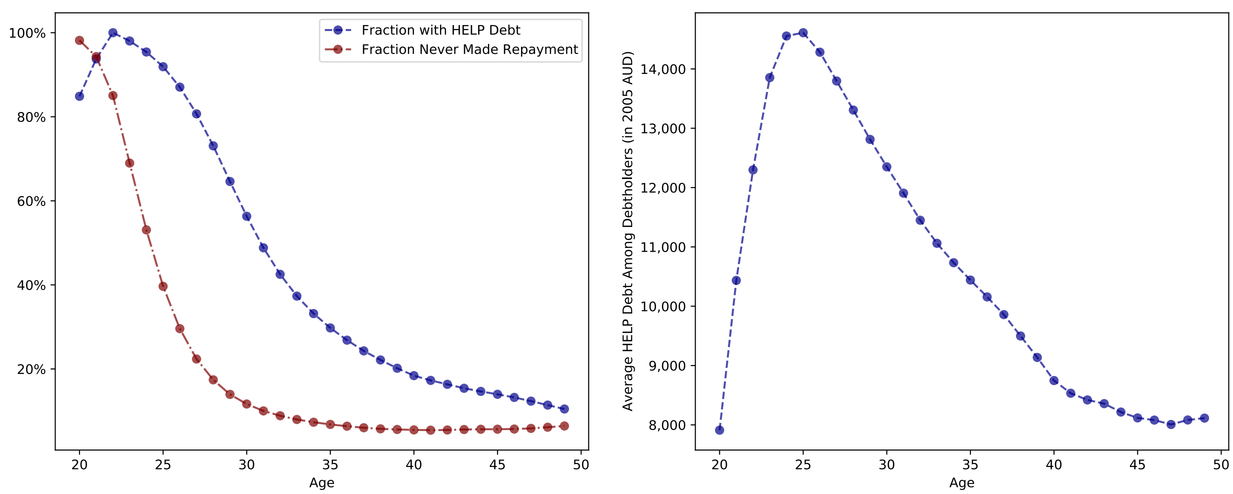
Notes: The left plot shows the time-series of student contributions in 2005 AUD for Commonwealth Supported Places (CSPs) based on the three separate bands of study classified by the Australian Government. These rates correspond to the cost of one year of coursework that must be covered with a HELP loan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

Figure A3. Average Debt Balances by Age

Panel A: All Individuals

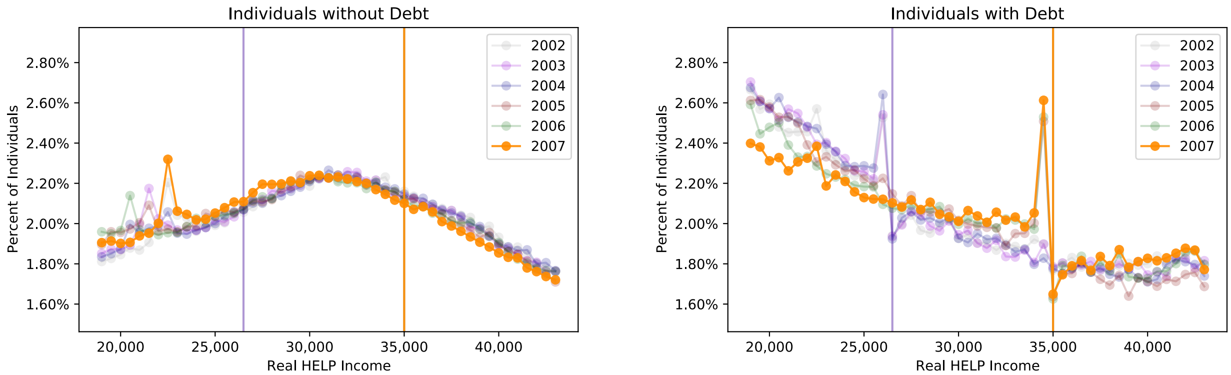


Panel B: Individuals with Positive Debt Balances at Age 22



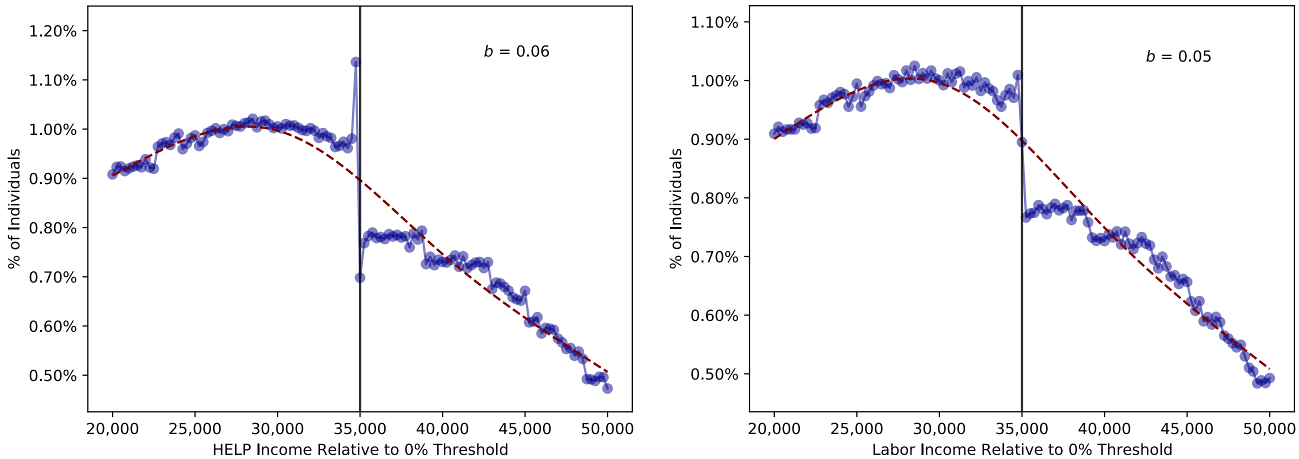
Notes: Panel A of this figure plots the fraction of individuals with HELP debt at each age in the left panel and the average HELP debt balance by age, in 2005 AUD, on the right. Panel B plots, in blue, the same quantities in Panel A among the subset of individuals who have positive debt balances at age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

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



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

Figure A5. Distributions of HELP Income and Labor Income



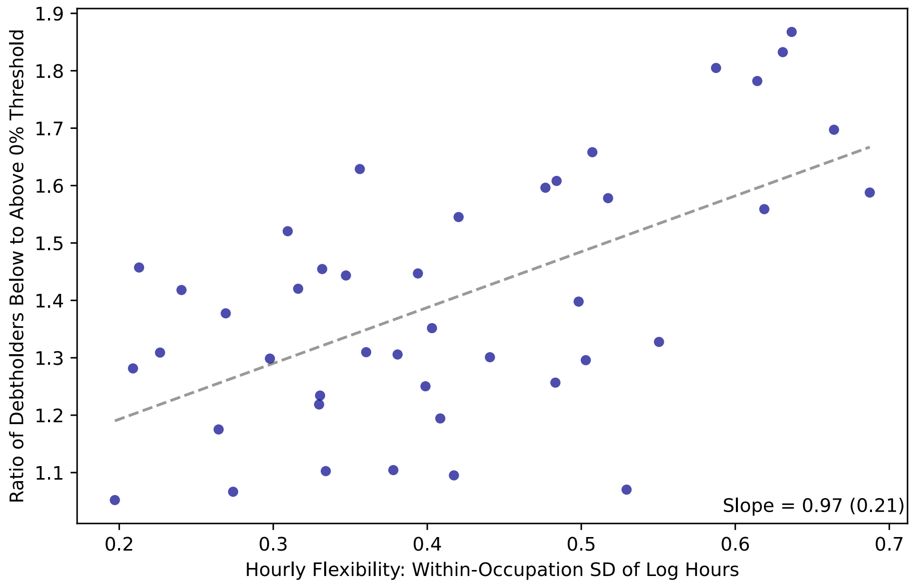
Notes: This figure plots the distribution of HELP and Labor Income in 2005 AUD relative to the repayment threshold after the policy change. This figure also plots the bunching statistic defined in (4) computed for the different distributions. Each bin corresponds to $250 AUD and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix B.3, and the counterfactual density estimated in this procedure is plotted in the dashed red line. The sample is the *ALife* sample defined in Section 2.4 between 2005 and 2018 after the policy change, restricted to individuals with have positive HELP debt balances and that have less than 1% of HELP Income from sources other than Labor Income.

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

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

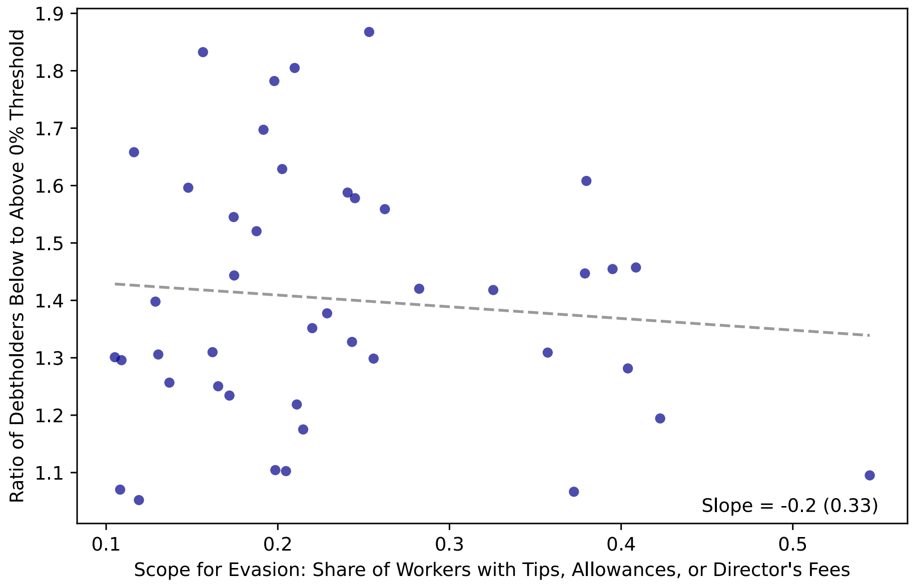
Notes: This table shows the measures of hourly flexibility at the 2-digit ANZSCO occupation-level used in Figure 4 and Figure A6. Hourly flexibility is measured as the standard deviation of annual changes, or the cross-sectional standard deviation, in log hours worked per week from HILDA.

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



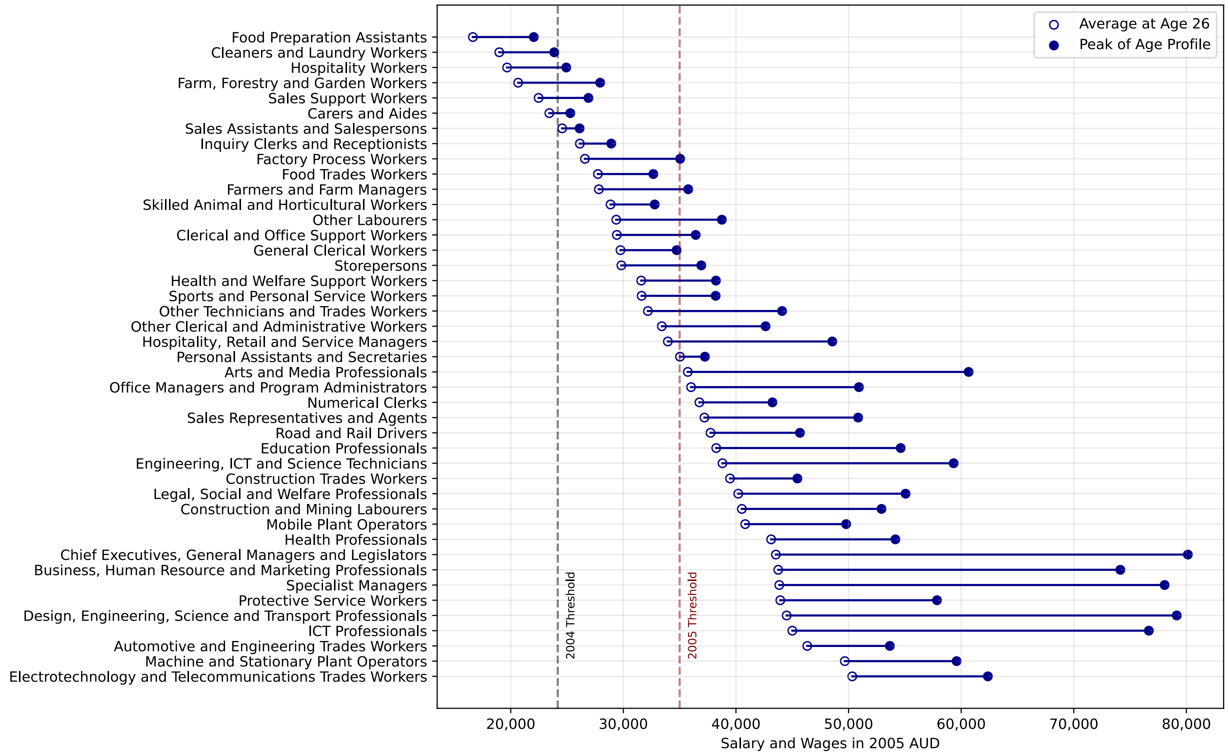
Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and an alternative measure of hourly flexibility by occupation. Each point represents a 2-digit ANZSCO occupation code reported in *ALife*. The amount of bunching is measured as the ratio of the number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

Figure A7. Variation in Bunching across Occupations based on Scope for Evasion



Notes: This figure replicates Figure 4 with a measure of evasion at the occupation-level instead of hourly flexibility on the horizontal axis. The measure of evasion is the fraction of individuals within each occupation that receive income from tips, allowances, or director's fees; see Appendix B.2 for additional details. This evasion measure is computed among the sample of individuals described in Figure A8.

Figure A8. Age Profiles of Wage Income across Occupations



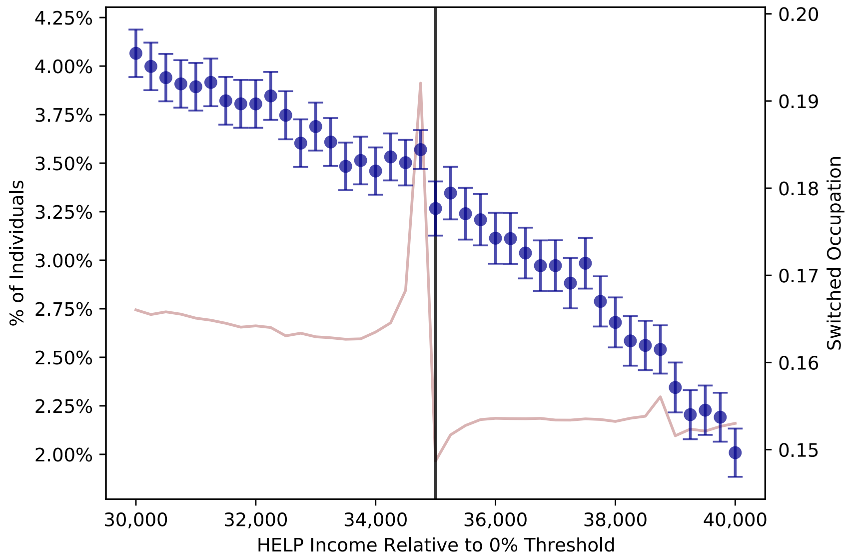
Notes: This figure plots characteristics of the age profile of salary and wages across 2-digit ANZSCO occupations. Occupation-specific age profiles are calculated by taking the average value of salary and wages across individuals in each occupation at a given age, after adjusting for inflation and removing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

Table A2. Correlates of Bunching across Occupations

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

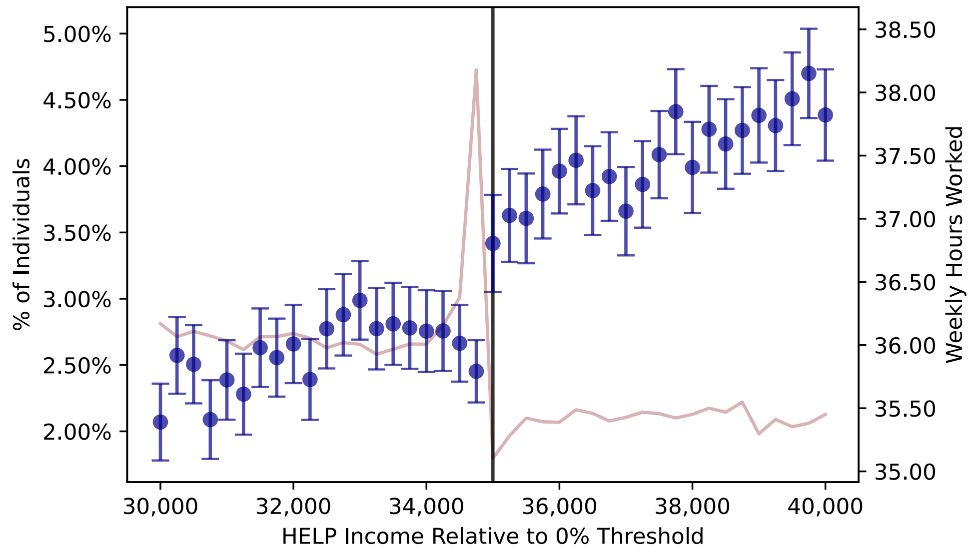
Notes: Each column of this table reports the results from an OLS regression run at the 2-digit ANZSCO occupation-level, with standard errors presented in paranthesis below coefficient estimates. The dependent variable in each column is the ratio of the number of debtholders within $2,500 below the repayment threshold to the number within $2,500 above the repayment threshold, as shown in Figure 4. Hourly Flexibility corresponds to the same measure used in Figure 4. Evasion corresponds to the share of all workers in each occupation that receive income from working in the form of allowances, tips, director's fees, consulting fees, or bonuses. Wage Slope corresponds to the occupation-specific average salary and wages at age 45, which is the age at which the pooled average of salary and wages reaches its maximum, divided by the average at 26 minus 1. Wage Peak corresponds to the maximum income in an occupation-specific age profile, normalized by the average value across all occupations. Salary and wages are adjusted for inflation and year fixed effects are removed prior to computing the occupation-specific age profiles used in the prior two measures. The Evasion, Wage Slope, and Wage Peak variables are calculated on the same sample of individuals used in Figure A8. Standard errors are computed using a heteroscedasticity-robust estimator.

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



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

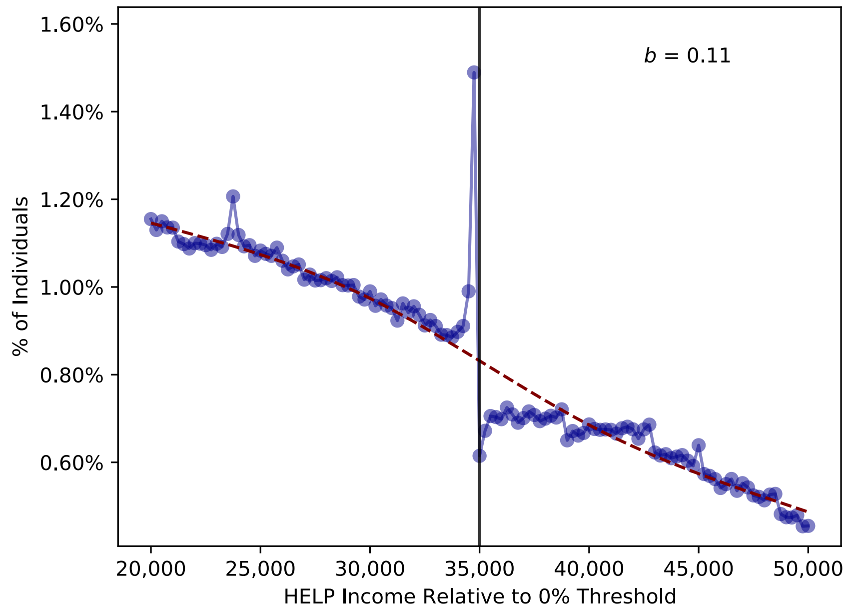
Figure A10. Self-Reported Hours Worked around Repayment Threshold: Positive Labor Income Individuals



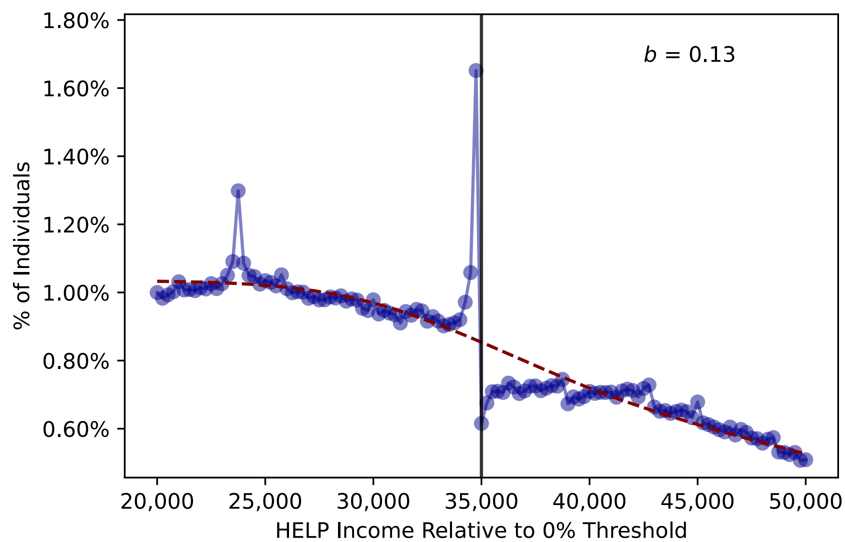
Notes: This figure replicates Figure 5 among the sample of individuals with positive Labor Income.

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

Panel A: ALife Sample in 2016

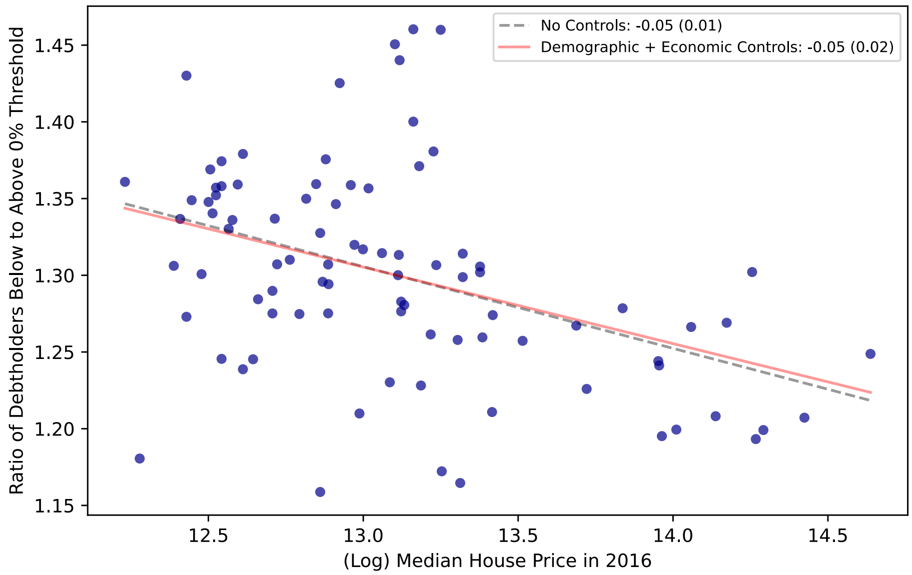


Panel B: MADIP Sample



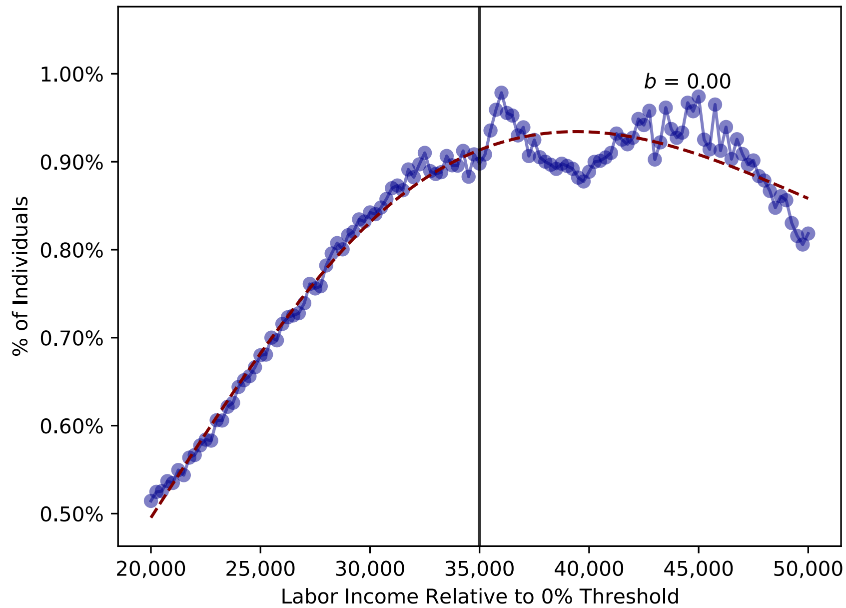
Notes: Panel A of this figure plots the distribution of HELP in 2005 AUD in 2016 relative to the repayment threshold and the bunching statistic defined in (4). Each bin corresponds to $250 AUD and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix B.3, and the counterfactual density estimated in this procedure is plotted in the dashed red line. The sample in this panel is the *ALife* sample defined in Section 2.4 in 2016, restricted to individuals with have positive HELP debt balances. Panel B performs the same analysis in the cross-sectional MADIP sample, restricting to individuals with positive HELP debt balances.

Figure A12. Variation in Bunching across Geographic Regions based on Housing Wealth



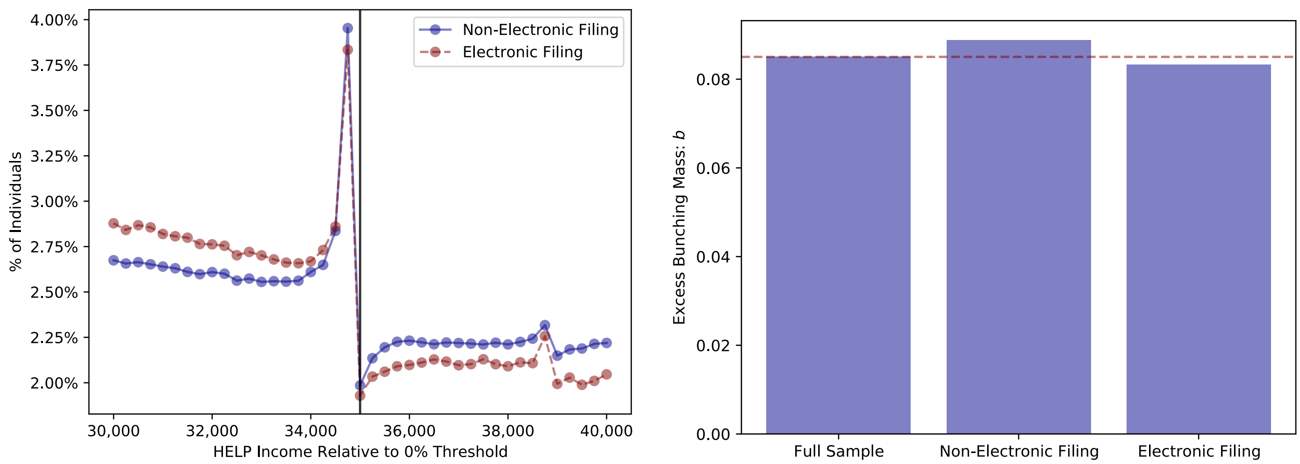
Notes: This figure plots the relationship between the amount of bunching below the repayment threshold and house prices by geographic region. Each point represents a geographic SA4 region reported in *ALife*. For each individual-year, *ALife* contains the location of individuals' home addresses by SA4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

Figure A13. Distribution of Labor Income among Individuals with Deductions



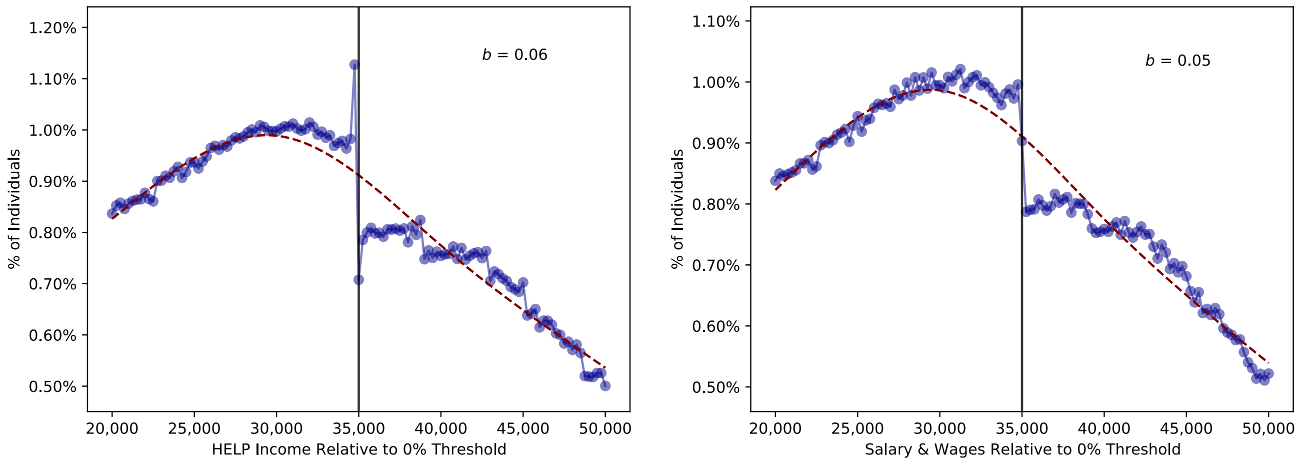
Notes: This figure plots the distribution of HELP Income in 2005 AUD relative to the repayment threshold after the policy change and the bunching statistic defined in (4). Each bin corresponds to $250 AUD and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of b is detailed in Appendix B.3, and the counterfactual density estimated in this procedure is plotted in the dashed red line. The sample is the *ALife* sample defined in Section 2.4 between 2005 and 2018 after the policy change, restricted to individuals with have positive HELP debt balances and that have at least $1,000 in Net Deductions.

Figure A14. Distribution of HELP Income by Tax Filing Method



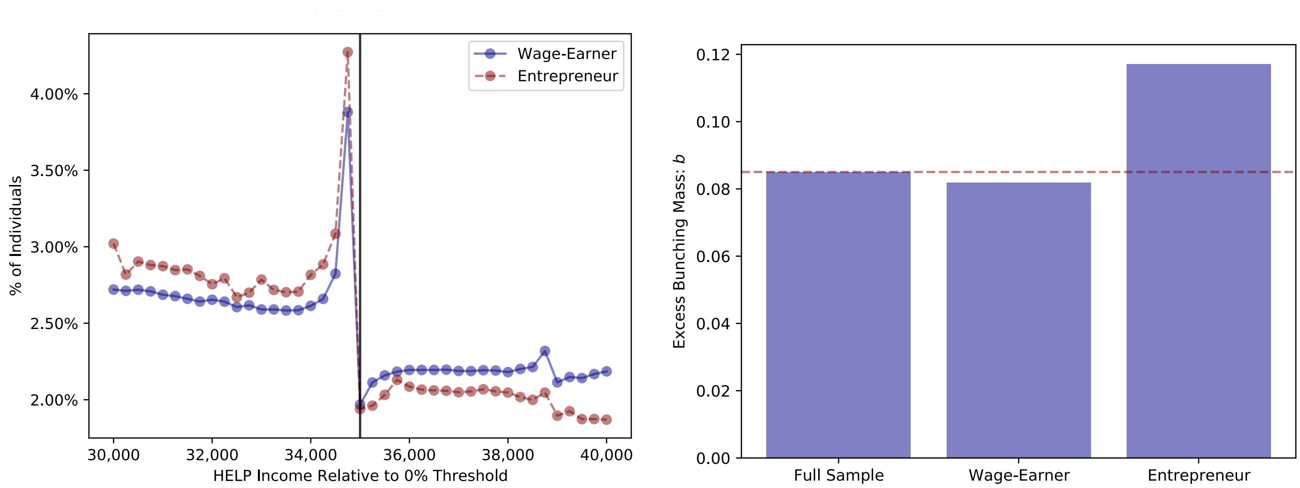
Notes: X.

Figure A15. Distributions of HELP Income and Salary and Wages



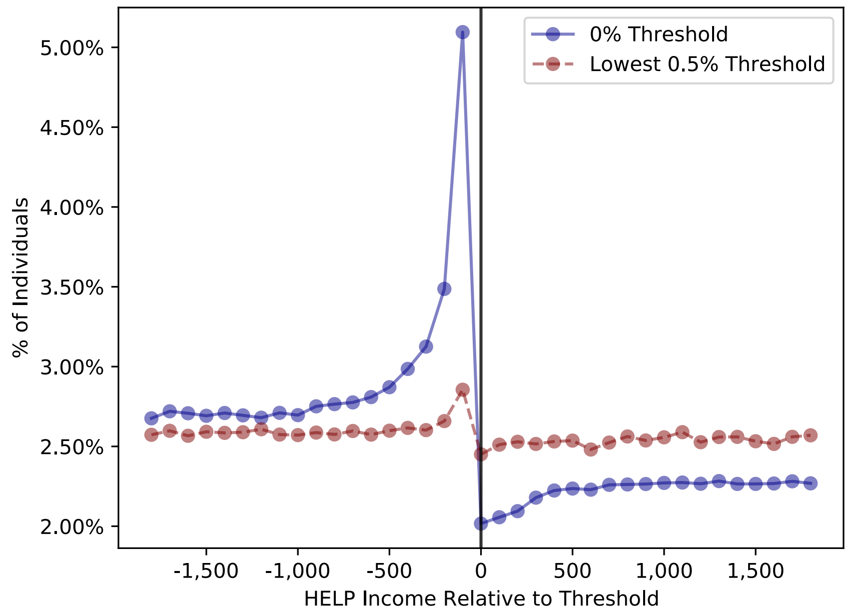
Notes: This figure replicates the analysis in Figure A5, replacing the right plot with Salary and Wages instead of Labor Income.

Figure A16. Distribution of HELP Income by Employment Type



Notes: X.

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



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

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

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

Notes: This table lists the set of estimation targets used in my simulated minimum distance estimation, along with the parameter(s) that each target was chosen to identify. Additional details on the calculation of each estimation target are presented in Appendix C.3.

Table A4. Elasticity of Estimation Targets with Respect to Parameters

Panel A: Income Distribution Before Policy Change

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

Panel B: Income Distribution After Policy Change

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

Panel C: Ratios Below to Above Repayment Thresholds

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

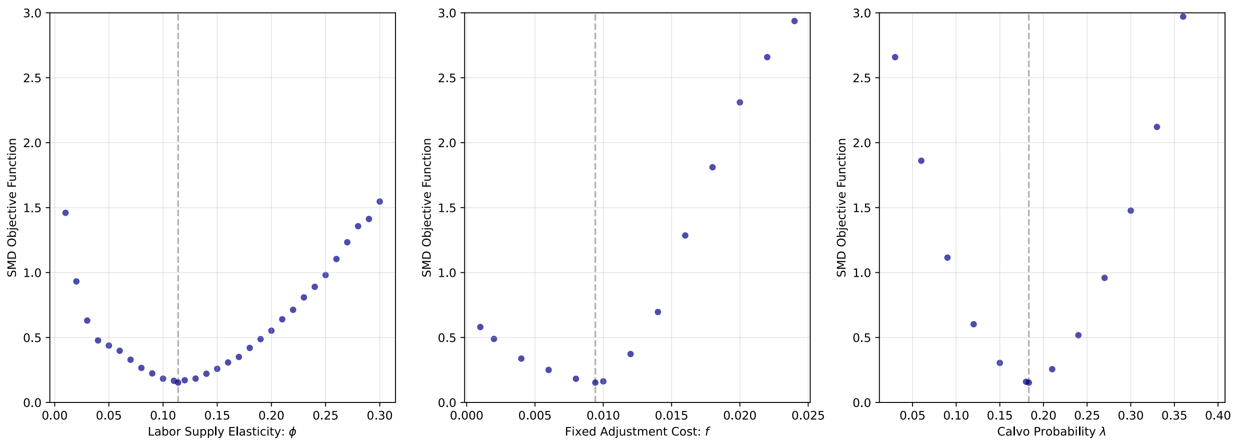
Table A4. Elasticity of Estimation Targets with Respect to Parameters (continued)

Panel D: Remaining Estimation Targets

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

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

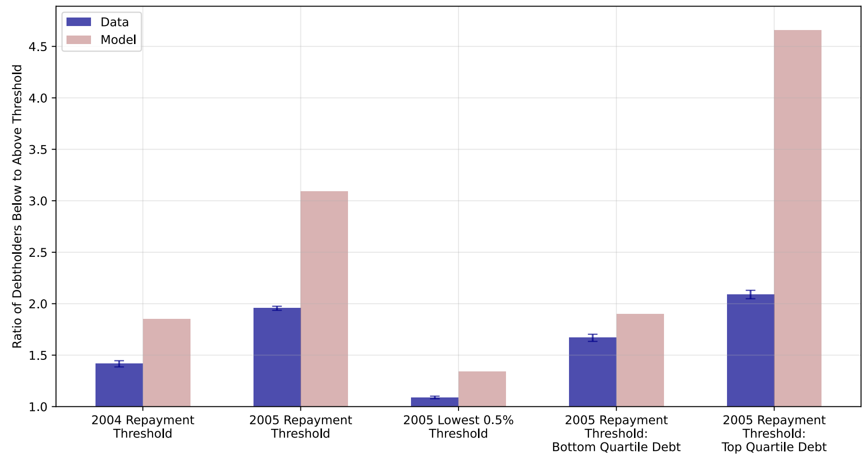
Figure A18. Local Identification of Labor Supply Parameters



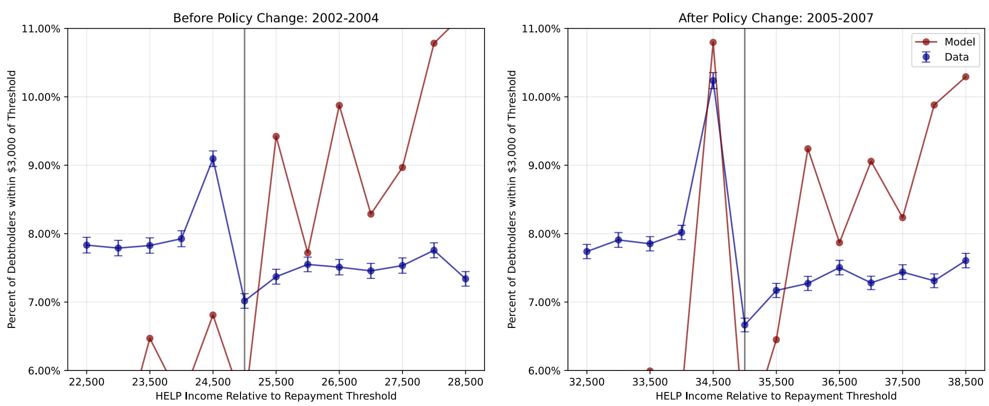
Notes: This figure plots the value of the simulated minimum distance objective function in the baseline estimation for different values of the three key parameters, ϕ, λ, and λ. Each point represent the objective function when solving the model at that parameter value, holding all other parameters fixed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

Figure A19. Model Fit: No Optimization Frictions

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



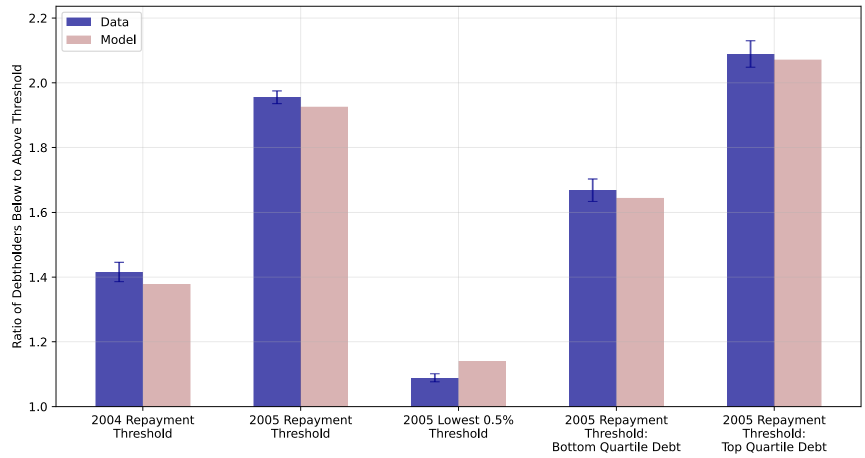
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	62169.068
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.304
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.403
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.533
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.661
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.319
Linear Age Profile Term	0.077	0.058
Quadratic Age Profile Term	−0.001	−0.002
Education Income Premium Constant	−0.574	−0.299
Education Income Premium Slope	0.023	0.033
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.913
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.945
90th Percentile of 1-Year Labor Income Growth	0.415	0.911
90th Percentile of 5-Year Labor Income Growth	0.698	0.928
Average Labor Supply	1.000	1.245
Average Capital Income between Ages 40 and 44	1338.846	8646.369

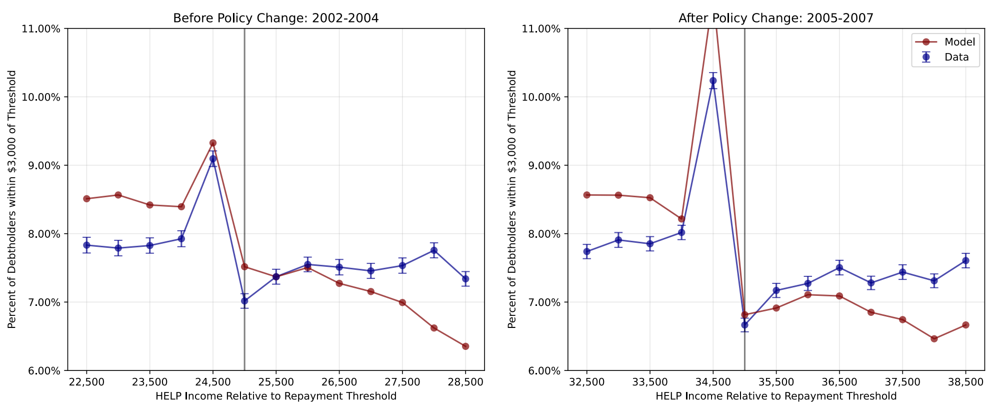
Notes: The results presented in this figure show the fit of the estimated model in column (2) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A20. Model Fit: No Calvo Adjustment

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



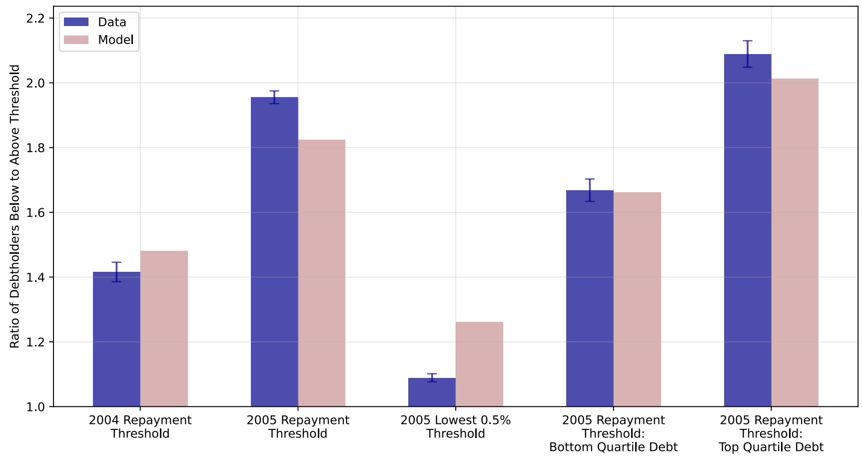
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	45691.108
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.483
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.493
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.523
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.584
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.648
Linear Age Profile Term	0.077	0.082
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.543
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.407
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.661
90th Percentile of 1-Year Labor Income Growth	0.415	0.411
90th Percentile of 5-Year Labor Income Growth	0.698	0.676
Average Labor Supply	1.000	1.247
Average Capital Income between Ages 40 and 44	1338.846	1295.642

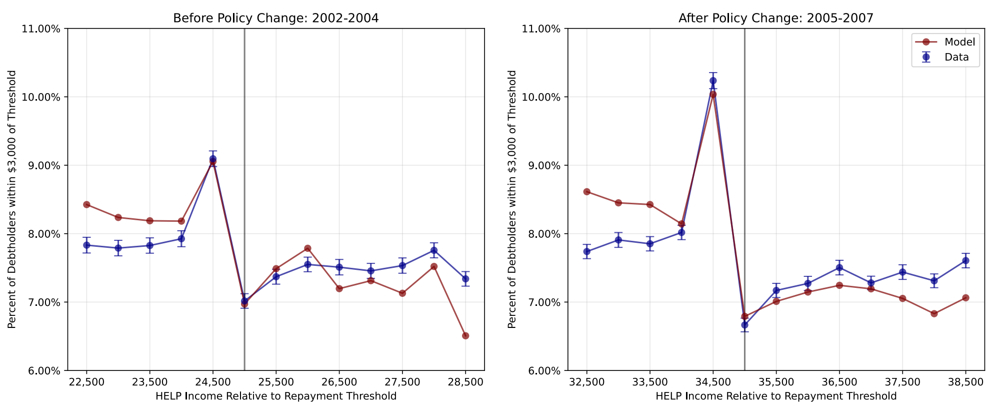
Notes: The results presented in this figure show the fit of the estimated model in column (3) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A21. Model Fit: No Fixed Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



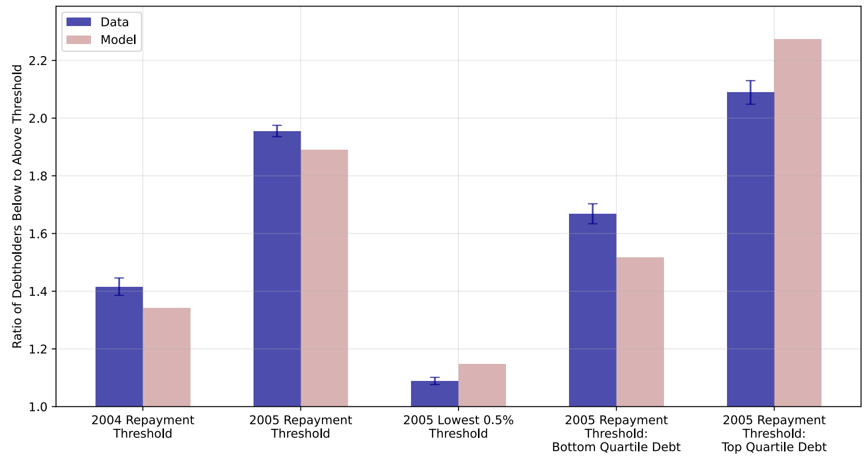
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	46896.491
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.474
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.507
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.537
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.585
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.641
Linear Age Profile Term	0.077	0.070
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.572
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.378
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.746
90th Percentile of 1-Year Labor Income Growth	0.415	0.379
90th Percentile of 5-Year Labor Income Growth	0.698	0.749
Average Labor Supply	1.000	0.991
Average Capital Income between Ages 40 and 44	1338.846	1301.442

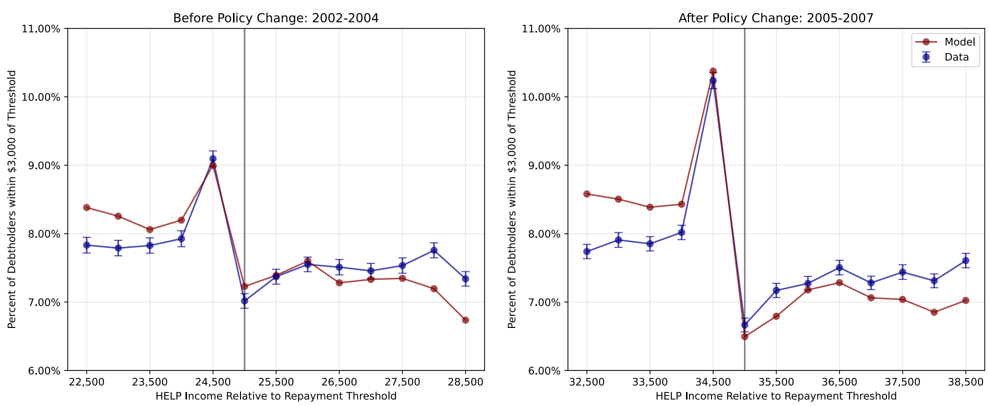
Notes: The results presented in this figure show the fit of the estimated model in column (4) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A22. Model Fit: Learning-by-Doing

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change



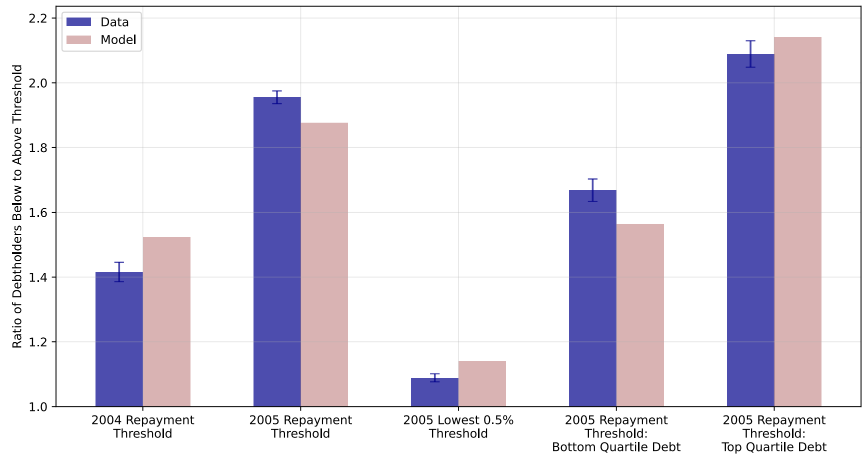
Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	48506.656
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.452
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.501
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.526
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.580
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.674
Linear Age Profile Term	0.077	0.075
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.581
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.401
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.787
90th Percentile of 1-Year Labor Income Growth	0.415	0.401
90th Percentile of 5-Year Labor Income Growth	0.698	0.790
Average Labor Supply	1.000	1.012
Average Capital Income between Ages 40 and 44	1338.846	1295.803

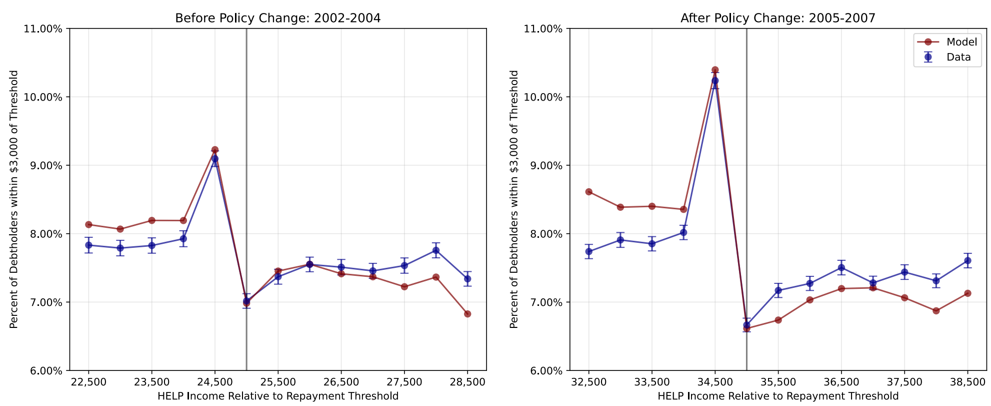
Notes: The results presented in this figure show the fit of the estimated model in column (5) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

Figure A23. Model Fit: Linear Adjustment Cost

Panel A: Bunching around Thresholds



Panel B: HELP Income Distribution around Policy Change

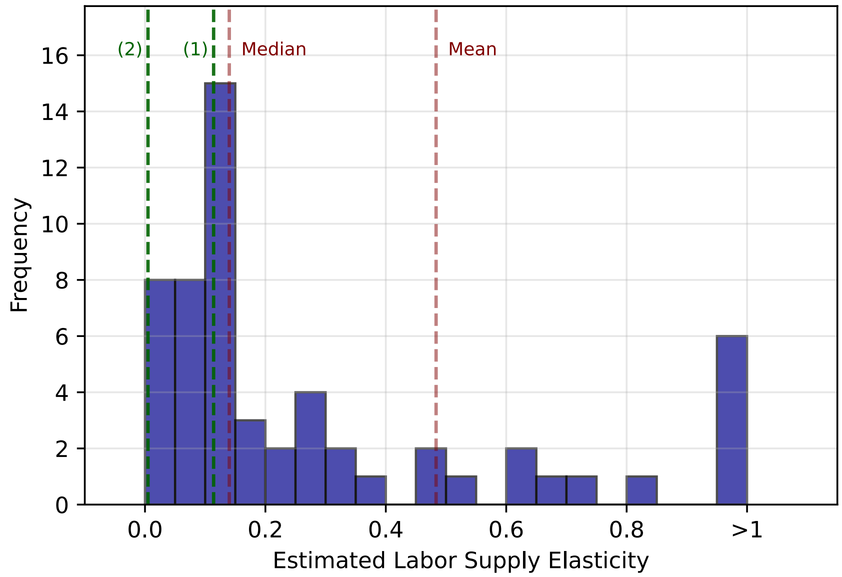


Panel C: Other Estimation Targets

Estimation Target	Data	Model
Average Labor Income	42639.373	49640.064
Cross-Sectional Variance of Log Labor Income at Age 22	0.453	0.461
Cross-Sectional Variance of Log Labor Income at Age 32	0.555	0.492
Cross-Sectional Variance of Log Labor Income at Age 42	0.577	0.525
Cross-Sectional Variance of Log Labor Income at Age 52	0.539	0.582
Cross-Sectional Variance of Log Labor Income at Age 62	0.608	0.662
Linear Age Profile Term	0.077	0.081
Quadratic Age Profile Term	−0.001	−0.001
Education Income Premium Constant	−0.574	−0.544
Education Income Premium Slope	0.023	0.022
10th Percentile of 1-Year Labor Income Growth	−0.387	−0.395
10th Percentile of 5-Year Labor Income Growth	−0.667	−0.774
90th Percentile of 1-Year Labor Income Growth	0.415	0.395
90th Percentile of 5-Year Labor Income Growth	0.698	0.778
Average Labor Supply	1.000	0.960
Average Capital Income between Ages 40 and 44	1338.846	1375.534

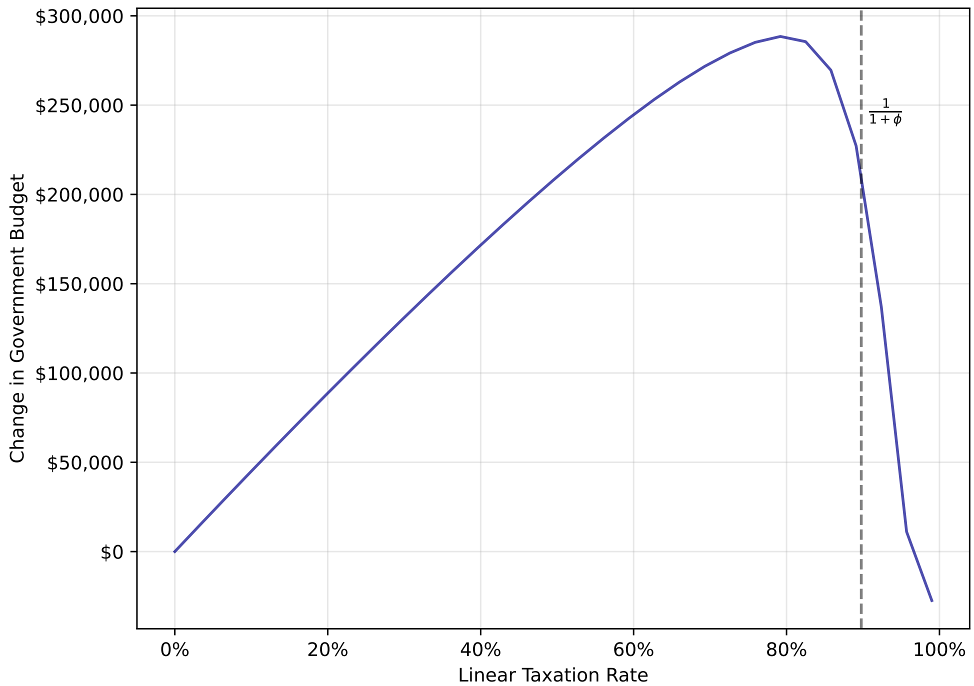
Notes: The results presented in this figure show the fit of the estimated model in column (6) of Table 3 on the set of estimation targets shown for the baseline model in Figure 9, Figure 10, and Table 4.

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



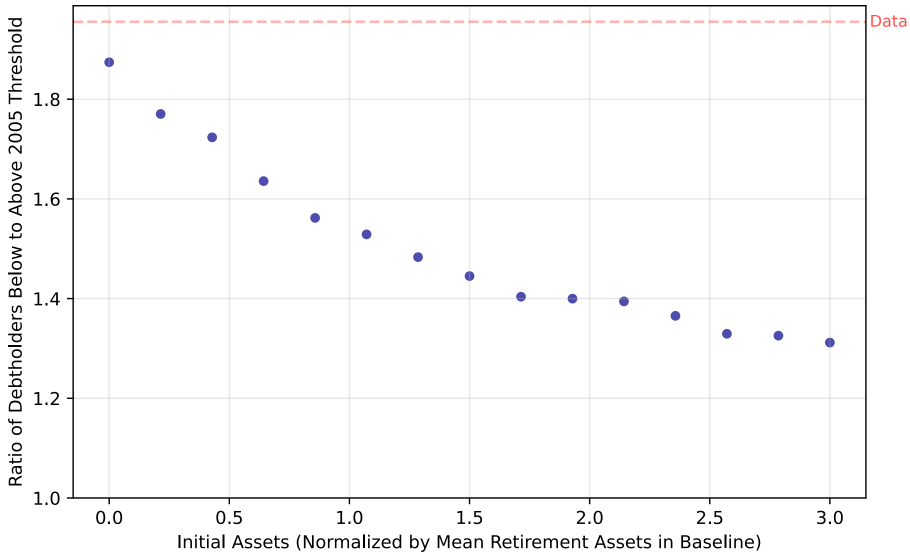
Notes: This figure plots a histogram of estimated intensive-margin labor supply elasticities in prior literature. I combine the estimates reported in Tables 6 and 7 of Keane (2011) and Table 1 of Chetty (2012). These estimates include intensive-margin Frisch (i.e., marginal utility-constant) and Hicksian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

Figure A25. Laffer Curve in Baseline Model



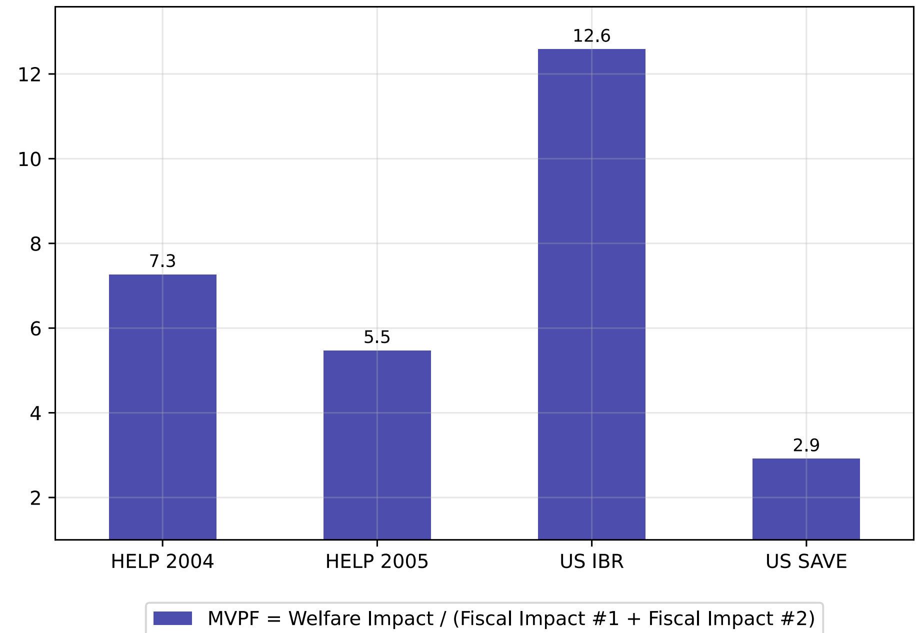
Notes: This figure plots the Laffer curve from a linear tax on income, τy_{ia}, in the baseline model. The horizontal axis corresponds to the value of the linear taxation rate, τ. The vertical axis shows that government revenue changes with respect to its value when $\tau = 0$. The vertical line corresponds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

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



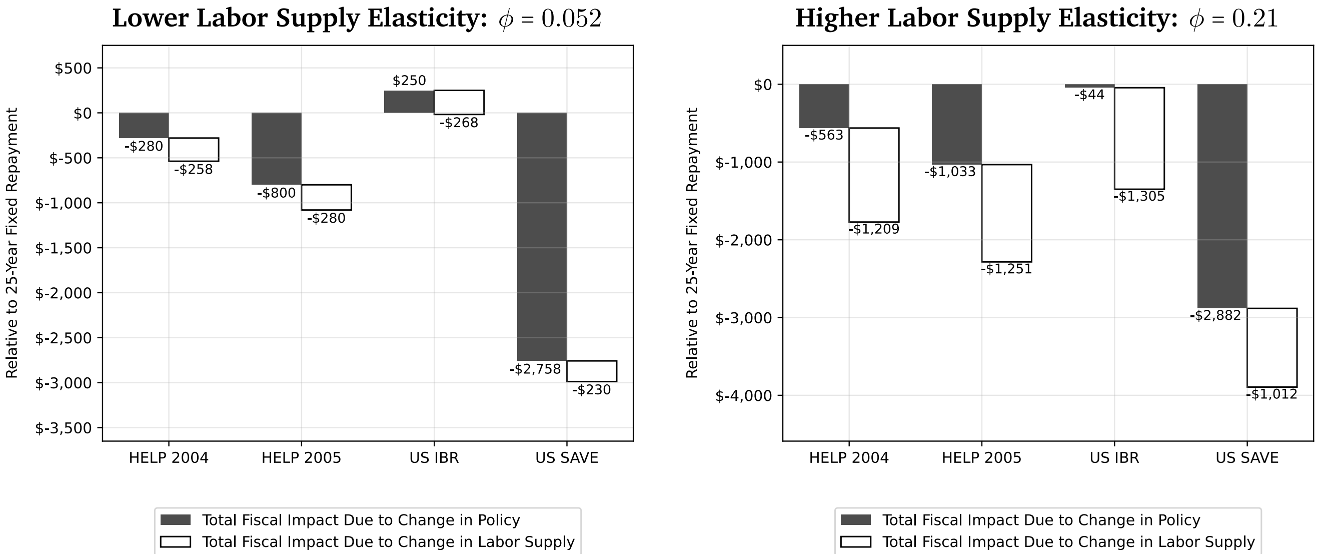
Notes: This figure plots the bunching below the 2005 repayment threshold between 2005 and 2018 as calculated in Figure 10 for different values of initial assets, A_0. The red dashed line in the plot corresponds to the value of this quantity in the data. For each value on the horizonal axis, I simulate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

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



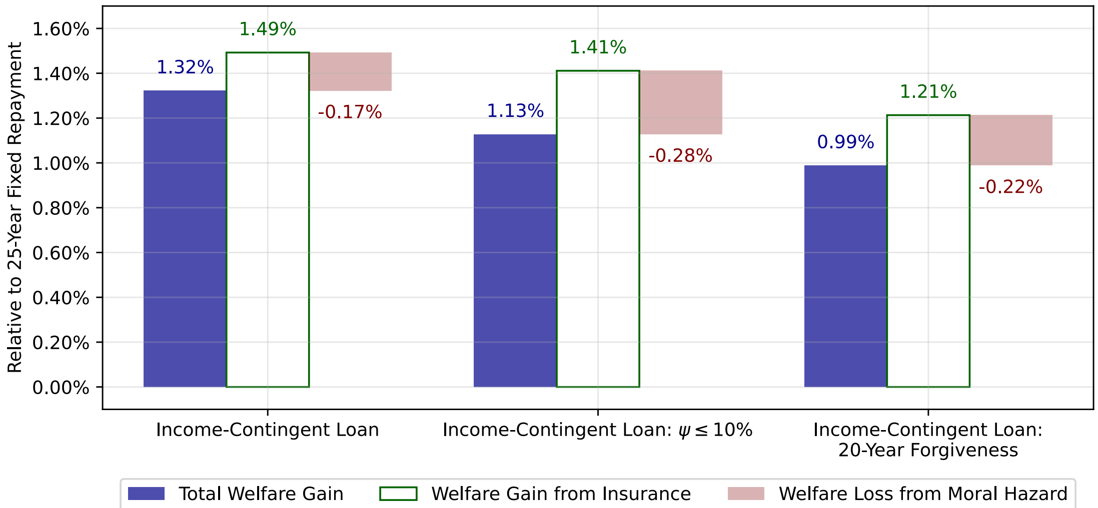
Notes: This figure plots the marginal value of public funds, defined by Hendren and Sprung-Keyser (2020), to moving from a 25-year fixed repayment contract to various existing income-contingent repayment contracts. This is computed by dividing the equivalent variation by the sum of the two fiscal impacts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

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



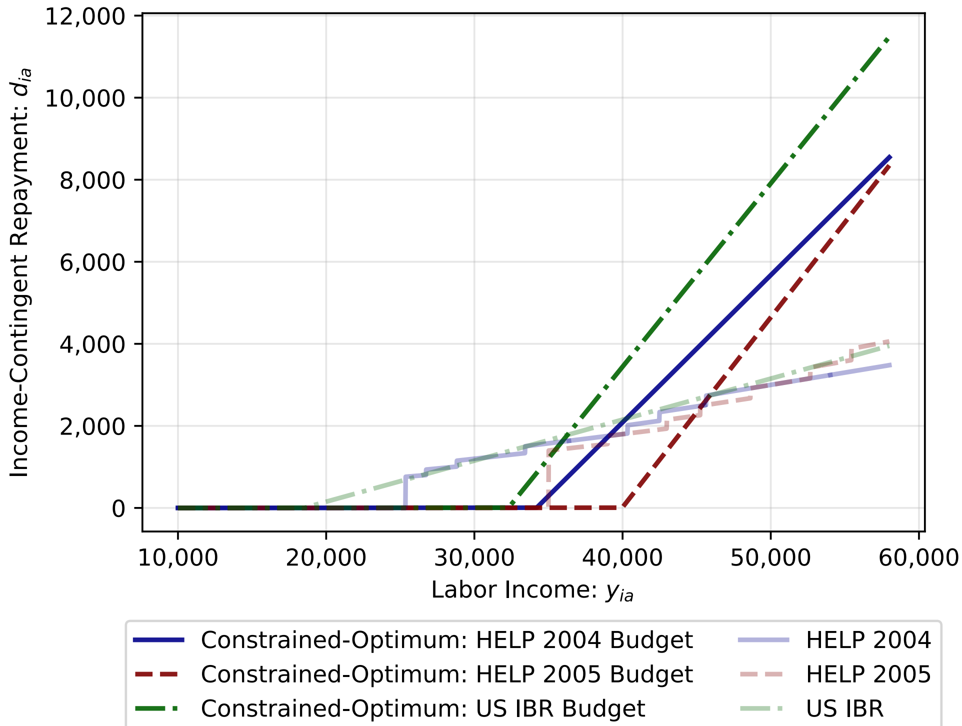
Notes: These two figures replicate the figure in the right panel of Figure 13 for two different values of the Frisch labor supply elasticity.

Figure A29. Welfare Gains from Alternative Constrained-Optimal Income Contingent Loans



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

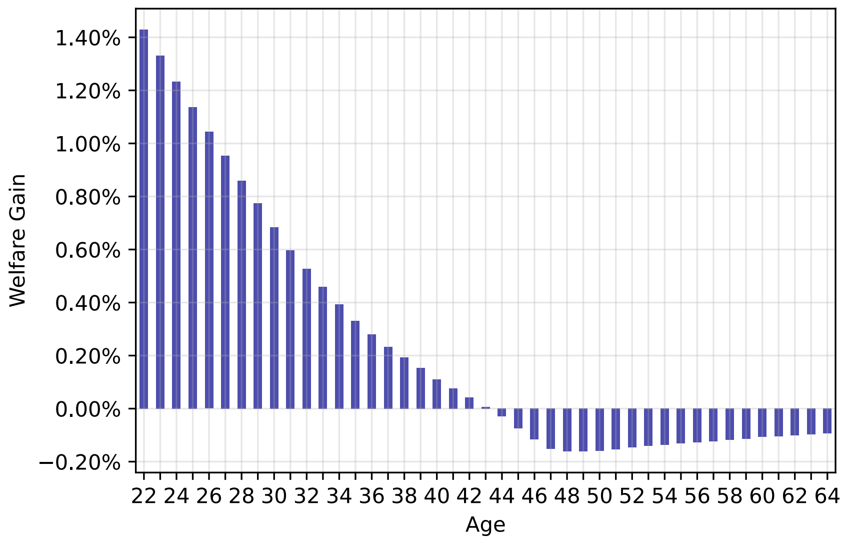
Figure A30. Comparison of Constrained-Optimal Income Contingent Loans with Existing Contracts



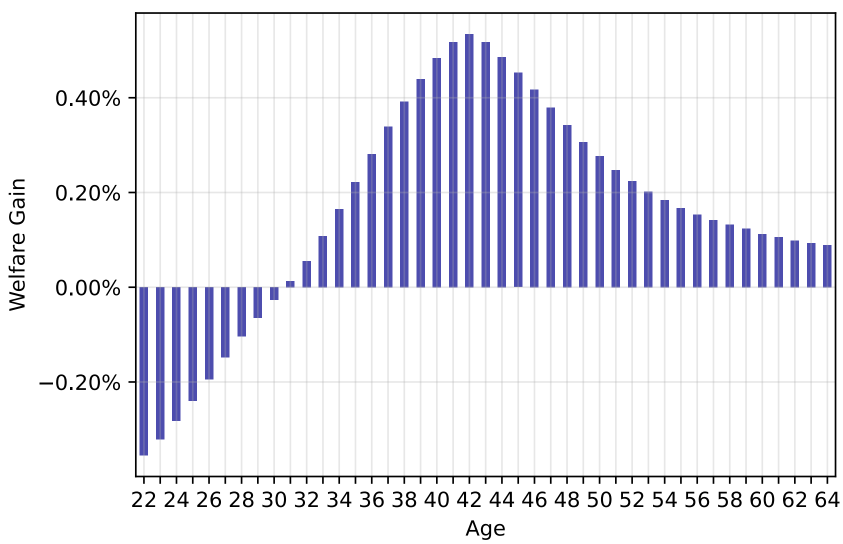
Notes: This figure shows the income-contigent repayments for several different repayment contracts. The light solid blue line is the 2004 HELP contract from Figure 2. The dark solid blue line corresponds to the constrained-optimal repayment contract in the baseline model that comes from solving (17)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

Figure A31. Heterogeneity in Welfare Gains by Age

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

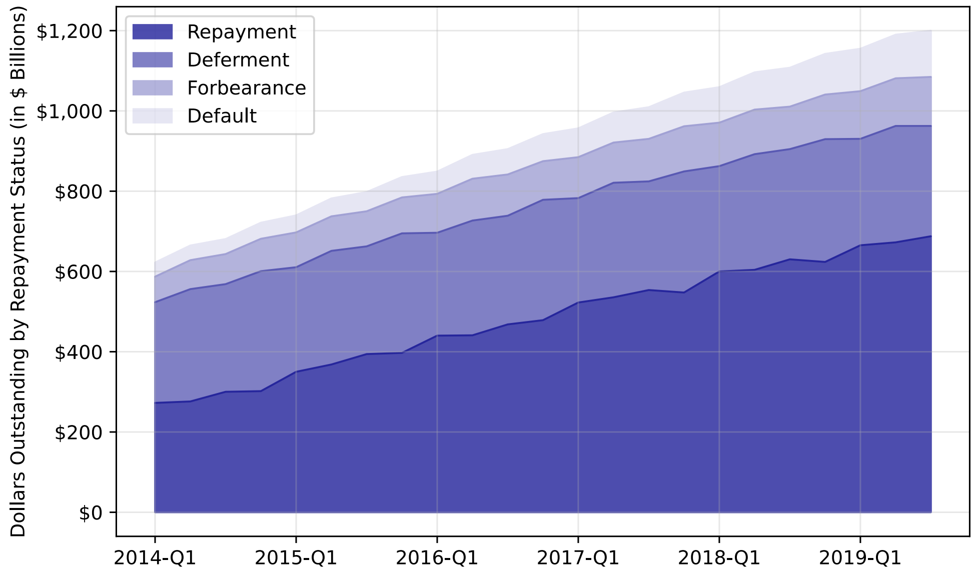


Panel B: Optimal Income-Contingent Loan with Forgiveness Relative to Optimal Income-Contingent Loan



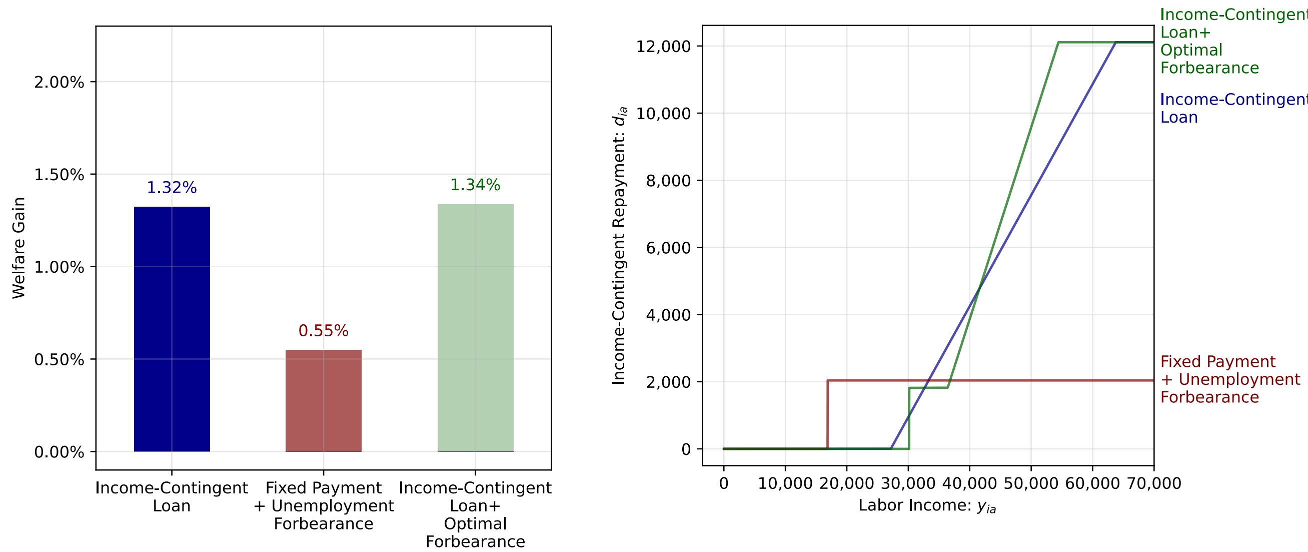
Notes: Panel A of this figure plots the average welfare gain at each age from the constrained-optimal income-contingent loan relative to 25-year fixed repayment. Panel B performs the same analysis for the welfare gain of the constrained-optimal income-contingent loan with forgiveness after 20 years relative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

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



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

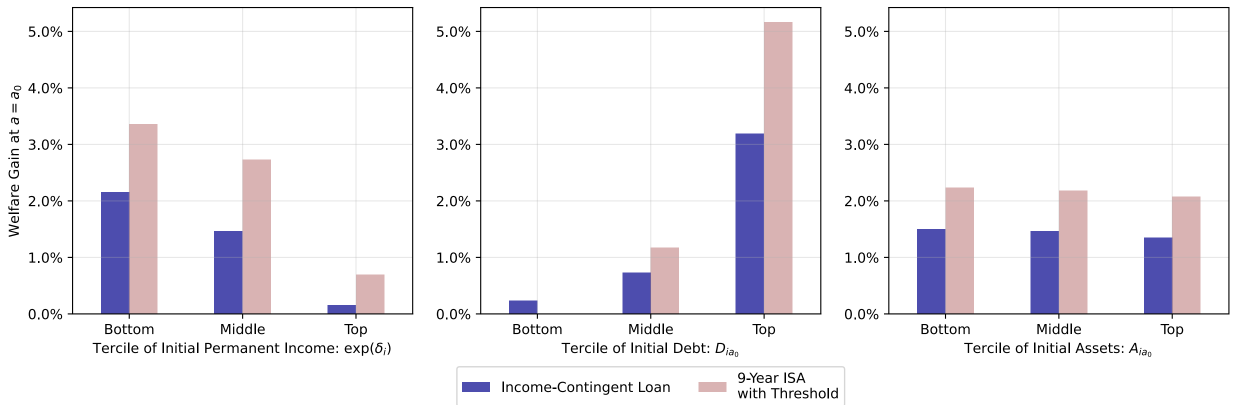
Figure A33. Welfare Gains from Adding Optimally-Chosen Forbearance to Income-Contingent Loan



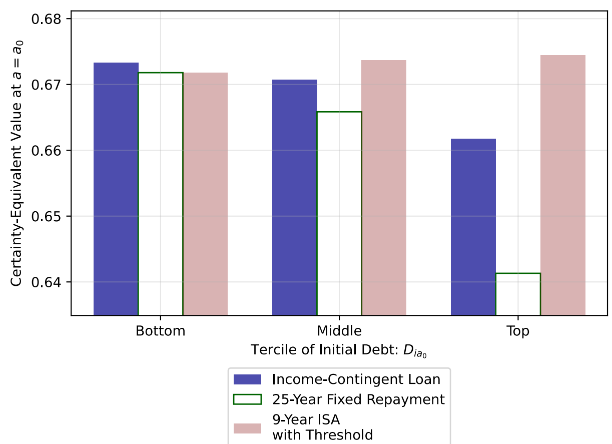
Notes: This figure plots the consumption-equivalent welfare gains relative to 25-year fixed repayment on the left from different constrained-optimal repayment contracts described in the text and shown on the right. The repayments are shown for an individual with median initial debt.

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

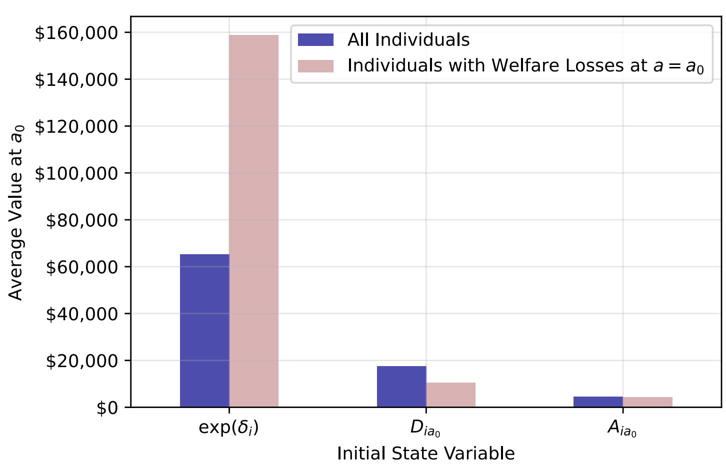
Panel A: Welfare Gains Across Initial States



Panel B: Variation in Certainty-Equivalents by Initial Debt



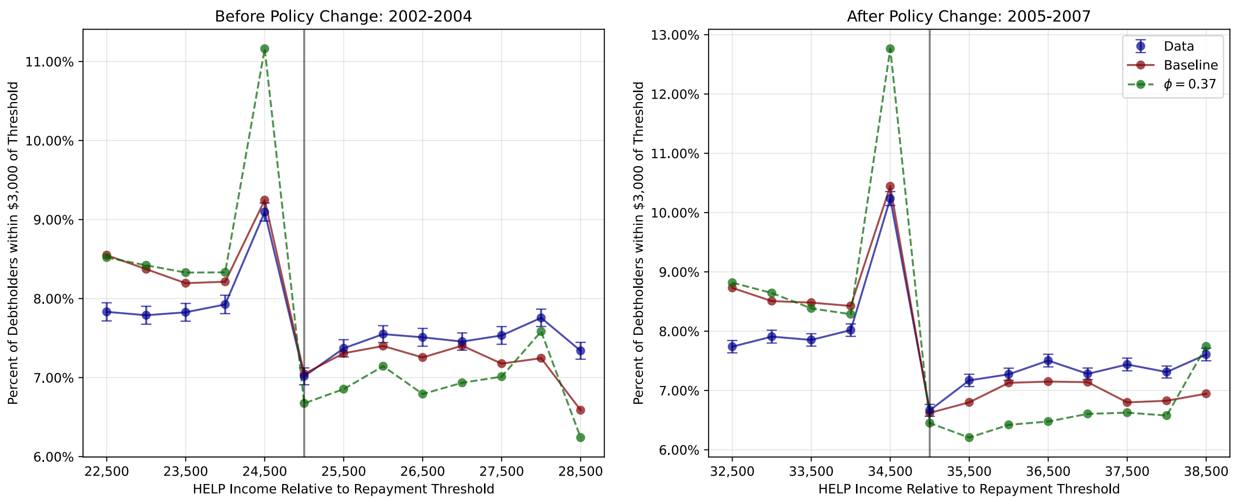
Panel C: Average Initial States by Welfare Gain from 9-Year ISA with Threshold



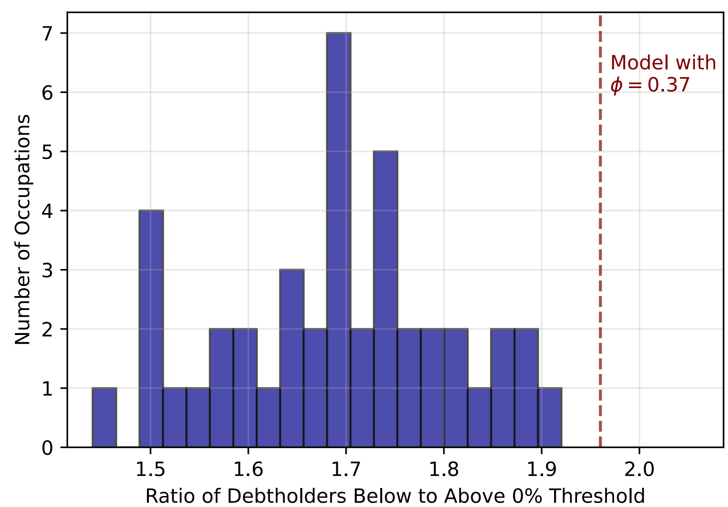
Notes: Panel A in this figure plots the welfare gains at a_0 computed in Figure 17 for different terciles of the three initial states that generate ex-ante heterogeneity in the model. Panel B plots the certainty-equivalent value at a_0 across terciles of initial debt. Panel C plots the average initial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

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

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

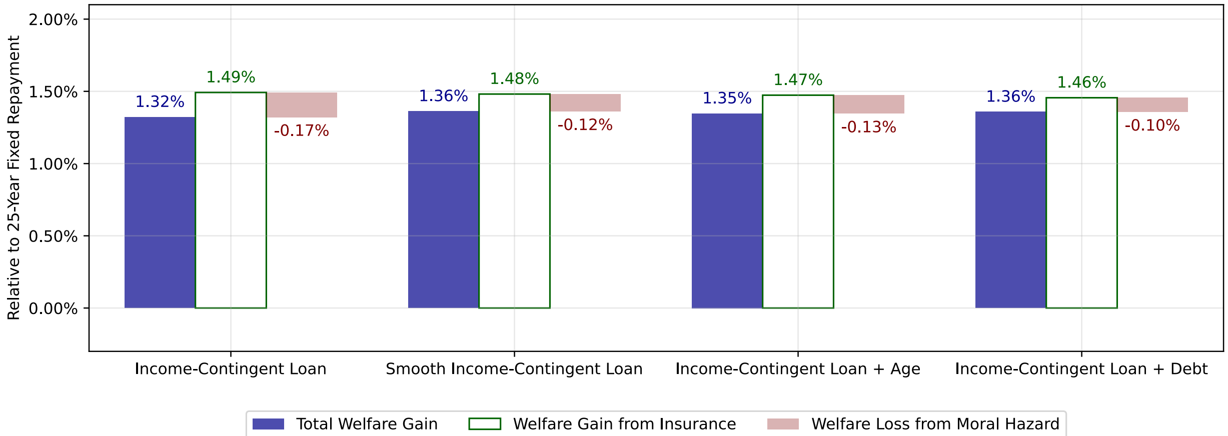


Panel B: Amount of Bunching Relative to Distribution Across Occupations



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

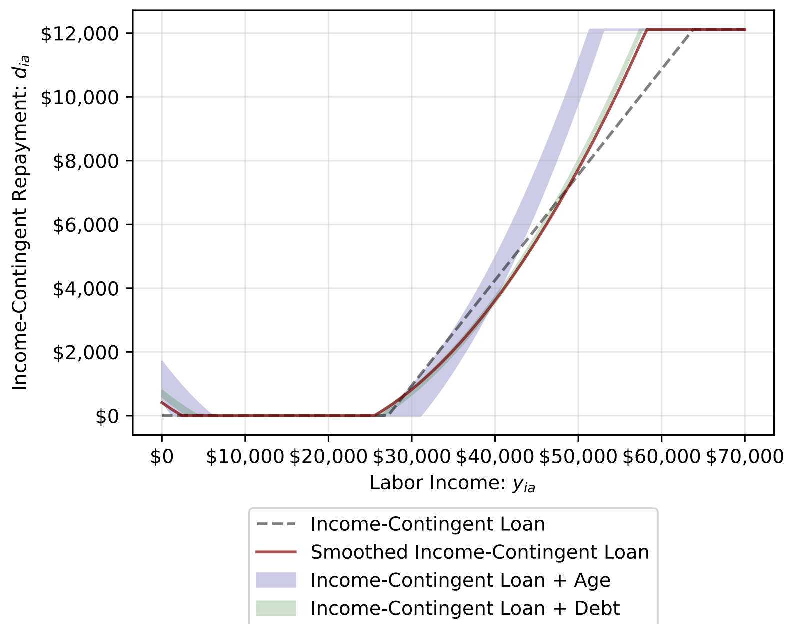
Figure A36. Welfare Gains from Alternative Forms of Income-Contingent Loans: Baseline Model



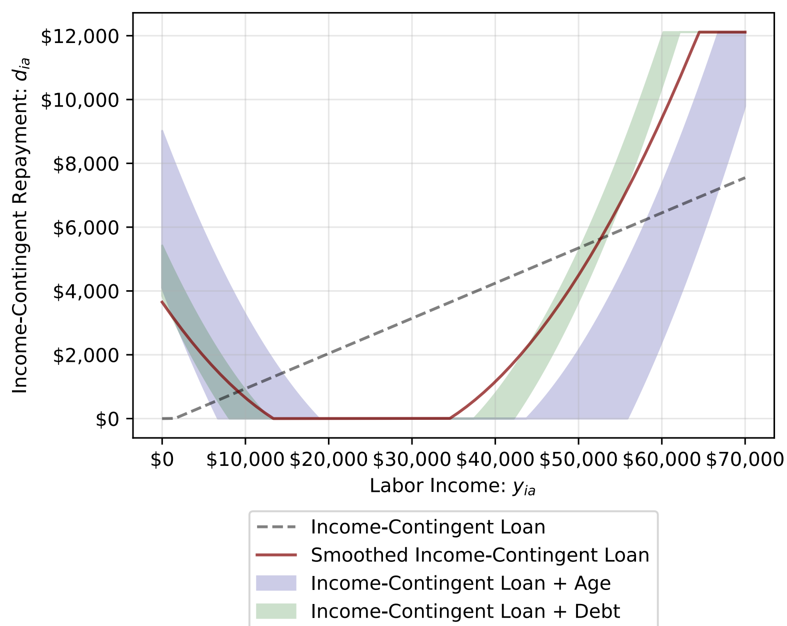
Notes: This figure plots the consumption-equivalent welfare gain relative to 25-year fixed repayment, along with the decomposition performed in Figure 14, for different constrained optimal repayment contracts described in the text. This analysis is performed with all parameters set at their estimated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

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

Panel A: Baseline Model



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



Notes: This figures plot the repayments as a function of income for the values of parameters for different classes of constrained-optimal repayment contracts described in the text that solve (17), assuming an individual has initial debt balances equal to the median. Panel A shows the results for the baseline model; Panel B shows the results for the baseline model with $\phi = 0.37$. The dashed gray line plots is a US-style income-contingent loan. The solid red line is the Smoothed Income-contingent Loan. The shaded blue region plots the range of payments on the Income-Contingent Loan + Age, where the boundaries of the region correspond to evaluating at $a = a_0$ and the 90th percentile of a among individuals that payoff their debt (or die) in the next period, respectively. The shaded green region plots the range of payments on the Income-Contingent Loan + Debt, where the boundaries of the region correspond to evaluating at $D_{ia} = 0$ and the 90th-percentile of D_{ia_0}, respectively. In the latter two plots, payments are increasing in age and debt, so the upper bounds of the shaded region correspond to the upper two evaluation points.

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