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

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**For Online Publication Only**

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# Appendix A. Institutional Details

## A.1 Additional Details on HELP

**Detailed description of HELP.** There are five HELP programs that provide income-contingent loans to Australian citizens for different purposes. The two largest programs are HECS-HELP and FEE-HELP, which historically have accounted for over $90\%$ of HELP borrowing. Figure A1 plots aggregate borrowing and discusses the details of the different HELP programs. HELP loans provided through these two programs can be used to finance tuition for undergraduate and graduate degree programs. Tuition at public institutions is controlled by the government and varies by degree, while private universities generally charge higher tuition. Most degrees at public institutions are classified as Commonwealth Supported Places (CSPs), in which the government provides a subsidy in the form of a contribution to the tuition owed by the student. The tuition remaining after the government's contribution is deducted is paid by the student and is called the student contribution. As of 2023, student contributions ranged from $4,124 to $15,142 AUD per year ($2,700 to $10,100 USD), with undergraduate degrees typically lasting 3–4 years. This is comparable to that for US in-state public undergraduate degrees, which averages $9,000 USD per year (Hanson 2023). The number of CSPs in Australia has generally been capped by the government, except for 2012–2017 (D'Souza 2018; Norton 2019).

Individuals who receive a CSP can either pay their student contribution upfront or borrow through the HECS-HELP program. Those who pursue degrees that are not CSPs are liable for full tuition and can either pay upfront or borrow through FEE-HELP. For borrowers who receive CSPs and access HECS-HELP, the largest program, their initial debt is equal to their student contribution. Given an average undergraduate student contribution of around $6,000 USD per year, tuition is comparable to that for US in-state public undergraduate degrees, which averages $9,000 USD per year (Hanson 2023). Figure A2 plots the time series of student contributions, aggregate HECS-HELP borrowing, and upfront payments.

Collection of HELP payments is integrated with the income tax system, which is crucial for HELP's success relative to other income-contingent loan programs (Barr et al. 2019). All individuals file tax returns in Australia, so $y_{it}$ refers to *individual* rather than household HELP income. For most borrowers, HELP repayments are withheld by their employer during the year and deducted from their debt after they file their tax returns. Individuals also have the option to make voluntary repayments at any time.[2] As in the US, HELP debt cannot be discharged in bankruptcy, implying borrowers cannot default on their loans. Nevertheless, borrowers could choose to avoid repayment

[2] I do not have access to micro-data on voluntary repayments. To the extent that borrowers make such repayments in the data, despite the zero interest rate, there are two likely explanations: (i) individuals are debt-averse or (ii) paying down debts has other benefits, such as helping with mortgage qualification.

by not lodging tax returns or lying about whether they have HELP debt. In addition to being illegal, doing so implies large penalties, such as administrative penalties of 95% and additional interest charges.

**Timing and collection of HELP repayments.** Individuals can make compulsory HELP repayments, which are the repayments calculated according to the HELP repayment schedule when the individual's tax returns are filed, or voluntary HELP repayments, which are additional repayments made at any time. If individuals are working, they are required to advise their employer if they have HELP debt. The employer will then withhold the corresponding compulsory repayment amounts from an individual's pay throughout the year based on the individual's wage or salary. Based on discussions with the ATO, most employers use an ATO-approved payroll software that calculates withholding amounts using the Tax Withheld Calculator, which effectively computes withholding amounts by converting the wage (or salary) paid from whatever frequency it is paid at to an annual frequency and applying the HELP repayment schedule. These withheld amounts are used to cover any compulsory repayments due when the tax return is filed. The tax year in Australia runs from July 1st to June 30th (e.g., the 2023 income tax year runs from July 1st, 2022 to June 30th, 2023), and tax returns must be filed by October 31st. After tax returns are filed, the difference between the total amount withheld and the actual amount due results in an amount that is paid or refunded. Additional payments are due by November 21st; most refunds are issued within 50 days of the tax lodgment. This withholding procedure is identical to the procedure used for income tax withholding.

On June 1st, HELP debts are subject to indexation, which refers to increasing the outstanding debts based on the indexation rate. The indexation rate is the nominal interest rate on HELP debt, which is based on the year-on-year quarterly CPI calculated using the March quarter CPI. It is calculated by dividing the sum of the CPI for the four quarters ending in March of the current year by the sum of the index numbers for the four quarters ending in March of the preceding year.[3] For most individuals, indexation occurs prior to the deduction of compulsory repayments because these repayments are deducted at the time of tax filing, which generally occurs between July 1st and October 31st. This is true even if an employer withholds repayments, as these repayments are not applied until the individual's tax return is filed.

**Salience of and motivation for policy change.** There are several reasons to believe that the HELP repayment function and the changes to it are salient to debtholders. First, the repayment function is indexed to inflation, which means that it updates every year. When it is published at the beginning of each tax year, the government ensures that the change receives press coverage.[4] Second, the policy change received media coverage at the time of its implementation (Marshall 2003). Finally, the fact that HELP income determines repayment rates and features a repayment

[3] See here for additional details.

[4] For an example of an announcement, see here.

threshold has not changed since the program's introduction in 1989, meaning that debtholders are likely to understand the program's structure.

Government policy documents and media articles suggest that the primary reason for the policy change was to provide relief for lower-income borrowers, whose payments were burdensome and contributed little to the total HELP budget (Nelson 2003). In addition to changing the repayment function, other changes were implemented in 2004–2005, such as the introduction of HELP loans for non-CSPs through FEE-HELP and a 25% increase in student contributions (see Figure A2). These other changes, discussed in detail by Beer and Chapman (2004), were primarily aimed at those entering their degree programs rather than those repaying HELP debt. The simultaneous implementation of these other changes with the change to the repayment threshold is not ideal for my analysis. However, it likely has a minimal effect, given that I focus on identifying ex-post moral hazard.

**Other changes to HELP repayment schedule.** Since HELP was introduced in 1989, there have been several changes to the repayment schedule detailed in Ey (2021). In the early years of the program, changes were more common: the schedule changed in 1991, 1994, 1996, and 1998. However, after 1998, there have been only two changes: the 2005 policy change that I study and a 2019 policy change that was phased in over two years. The fact that there have been several changes to the HELP repayment threshold is not ideal because it implies that the model will underestimate long-run labor supply responses: in the model, the policy change is unexpected and permanent, while empirically, individuals may expect other changes in the future that attenuate their responses. However, the size of this bias is likely small because news articles written at the time of the policy change suggest that the policy change was expected to last for several years (e.g., Marshall 2003). In contrast, empirically, I find that there is persistence of bunching below the repayment threshold for only around three years, likely shorter than individuals expected a subsequent policy change. The same logic applies if the policy change was anticipated: because there is little persistence in individuals' responses, it is likely that they would respond even if they expected a policy change in a few years.[5]

**Discount for upfront and voluntary payments.** In prior years, HELP provided discounts to individuals who paid their debt balances upfront and discounts for voluntary repayments. The upfront payment discount took the following values: 15% from 1989-1992, 25% from 1993-2004, 20% from 2005 to 2011, 10% from 2012 to 2016, and 0% after 2016. Unfortunately, *ALife* does not allow me to identify upfront payments, so I do not include this margin in the model. The fact that most upfront payments came from high-income individuals with family support (Norton 2018) suggests this is likely to bias my results in one of two ways. On the one hand, existing literature finds taxable income elasticities increase with income (e.g., Gruber and Saez 2002), which would

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

suggest the model understates the moral hazard created by income-contingent repayment. On the other hand, the probability of repayment is higher for high-income individuals. Given labor supply responses decrease with the probability of repayment, this suggests the model overestimates the moral hazard income-contingent repayment creates, reinforcing my qualitative conclusions. Nevertheless, the fact that aggregate upfront payments have been low and stable despite the variation in discounts (Figure A2) suggests any bias from omitting this margin is likely to be small.

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

**Wage-setting in Australia.** There are three wage-setting methods in Australia. The first method is through award-based wages, in which centralized bodies set the minimum terms and conditions for employment, including a minimum wage. The primary body responsible for setting these conditions is the Fair Work Commission, which operates at the national level. The second method is through enterprise agreements, which set a rate of pay and conditions for a group of employees through negotiation. This method of wage setting is analogous to that used by labor unions in the US. Finally, individual arrangements set wages and conditions for employees on an individual basis. Individual arrangements and enterprise agreements are the dominant forms of wage-setting, accounting for approximately 40% each of total wage-setting arrangements, while award-based wages make up approximately 20%.[6]

## A.2 Additional Discussion of Benefits of Studying Income-Contingent Repayment in Australia

In addition to the presence of high-quality administrative data, policy variation, and a repayment schedule with large incentives, there are several benefits to using HELP to identify labor supply responses to income-contingent repayment. First, there is limited selection on hidden information because HELP is the only government-provided student loan. In principle, individuals in Australia

[6]See, for example, here.

could seek external financing from a bank or university. However, there is little economic incentive to do so because the interest rate would exceed the zero real rate on HELP loans. The primary margin along which there is scope for selection is whether to pay upfront or borrow through HELP, but the zero interest rate on HELP loans again implies little incentive to pay upfront.[7]

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

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

## A.3 Comparison of Institutional Environments in Australia and US

This section describes similarities and differences between Australia and the US, summarized in Table A8. Although these countries are similar in many ways, some institutional differences are important when considering whether welfare gains from income-contingent repayment would generalize in the US.

The first notable difference is the cost of higher education: the student contribution at a public undergraduate institution for a Commonwealth Supported Place in Australia is around $6,400 USD after subtracting the government subsidy. This is comparable to the average undergraduate tuition at a 4-year in-state public institution in the US but much smaller than tuition for a 4-year (non-profit) private degree. Unlike in the US, where many students receive scholarships and grants that reduce tuition below the “sticker price”, this is extremely rare in Australia. In addition to differences in tuition, the cost of room and board and books and supplies are slightly higher in the US. These higher costs contribute to the second difference between Australia and the US: the amount individuals borrow from government-provided student loans. In Australia, this is around $20,000 on average, while in the US, it’s around $50,000 (Catherine and Yannelis 2023). The fact

[7] In earlier years of HELP, upfront payments were subject to a discount, which created a small incentive to pay upfront.

that debt balances are higher in the US means that the scope for welfare gains from optimizing contract design is even larger, as shown in Table A10. However, the higher loan balances also reflect that undergraduate degrees last a year longer in the US and, more importantly, that student loans in Australia can only be used to cover tuition.[8] Although the latter is useful for identification, as discussed in Section 1.3, it implies that borrowers in the US have more flexibility to adjust their borrowing using discretionary expenses, such as room and board. This introduces scope for ex-ante moral hazard, in which individuals who anticipate low incomes borrow more in anticipation of low repayment. Quantifying the strength of this force is an important task for future research because it could undermine the effectiveness of income-contingent repayment in the US. It is also especially relevant for the equity contracts studied in Section 4.2, which create large incentives to adjust initial debt balances.

As in Australia, the US government is the only provider of income-contingent loans and these loans are not dischargeable in bankruptcy. However, in the US, the government offers non-income-contingent contracts, and an active private market provides financing to high-income borrowers at lower rates (Bachas 2019). Both of these features are useful for my empirical analysis, as discussed in Section 1.3, and the former is not an issue for my normative analysis since I focus on the design of a single government-provided financing contract. In contrast, the presence of a private market implies that the degree of insurance that can be provided by income-contingent repayment in the US is limited: trying to collect repayments quickly from high-income borrowers to finance reduced payments from low-income borrowers may lead private lenders to cream-skim high-income borrowers with more favorable financing terms.

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

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

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

The bottom of Table A8 presents summary statistics on the income distribution and the social insurance system in Australia and the US. Median income and income inequality are lower in Australia: Australia has a Gini coefficient around halfway between France and the US. The personal income tax schedules are similar in terms of average level and progressivity, but Australia has a lower unemployment benefit replacement rate than the US, one of the lowest among OECD countries. Overall, Australia and the US are broadly similar in these aggregate statistics, suggesting differences in the institutional structure of higher education are more important when considering the applicability of my results to the US.

# Appendix B. Empirical Appendix

## B.1 Data and Variable Construction

### B.1.1 *ALife*

*ALife* provides access to a $10\%$ random sample for approved projects. My code and analysis were tested on this sample and then were executed on the population sample by research professionals at *ALife*. The remainder of this section provides additional details on variable definitions based on the underlying variables that I construct. For a description of these underlying variables, see

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

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

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.

**Data limitations.** The two main limitations of these data are that they do not allow me to identify any information on the source of borrowing, such as degree choice, and they aggregate debt across all the different HELP programs described in Appendix A.

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

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

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

**Taxable Income.** Defined as `ic_taxable_income_loss`.

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

```
df['help_income'] = np.maximum(df['ic_taxable_income_loss'], 0)
adds = ['help_income']
if yr >= 2000:
  adds += ['it_rept_fringe_benefit']
if yr >= 2006:
  adds += ['isn_fsi_exempt_empl']
if yr >= 2010:
```

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

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

**Labor Income and Wage-Earner.**

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

**Interest & Dividend Income.**

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

**Capital Income.**

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

**Net Deductions.**

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

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

**Superannuation balances.** Defined as `sb_mem_bal`.

**Occupation-level measure of evasion.** The sample of individuals used to calculate this measure of evasion is the *ALife* 10% random sample of individuals in the population *ALife* dataset who satisfy the sample selection criteria in Section 1, are wage-earners, and have annual salary and wages greater than one-half the legal minimum wage times 13 full-time weeks (Guvenen et al. 2014). The evasion measure is then computed as the share of all workers in each occupation, `c_occupation`, who receive income from working in the form of allowances, tips, directors' fees, consulting fees, or bonuses, which are reported jointly in `i_allowances`. This item is subject to the same reporting requirements as Salary & Wages.

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

### B.1.2 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 the same definition as in *ALife*.

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

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

### B.1.3 HILDA

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

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

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

## B.2 Computation of Excess Bunching Mass Statistic, $b$

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

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

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

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

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

## B.3 Additional Empirical Tests of Evasion

Several facts, in addition to the direct evidence of a labor supply response in Figure 5 and the lack of evidence for evasion in Figure A6, suggest evasion cannot explain all of the responses in Figure 3. First, Figure A13 shows that the distribution of salary and wages exhibits substantial bunching around the repayment threshold, which is generally interpreted as evidence of hours-worked responses (e.g., Chetty et al. 2013). This is because the literature on random audits finds that the majority of individual tax evasion comes from self-employment income, with an estimated noncompliance rate of less than 1% for items with withholding and substantial reporting information, such as salary and wages (Slemrod 2019). Second, Table A3 shows that the amount of bunching declines by only $4\%$ when I restrict to the sample of wage-earners, who have substantially less flexibility in reporting their income, and is almost identical between borrowers who file their tax returns electronically and nonelectronically. When taxes are filed electronically, pure evasion is more difficult because the sources of labor income are often prefilled by the employer and, if they are not, the ATO compares what the individual reports with the employer's payment summary. Finally, the sample of borrowers near the repayment threshold is around median income, unlike the evidence from prior literature that evasion is largest among high-income individuals, who have more avoidance opportunities (Slemrod and Yitzhaki 2002; Saez et al. 2012).

# Appendix C. Model of the Debt and Tax Effects of Income-Contingent Loans

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

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

subject to:

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

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

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

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

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

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

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

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

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

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

Given that the envelope theorem implies that

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

combining the last two lines gives the following result:

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

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

# Appendix D. Structural Model Appendix

## D.1 Recursive Formulation of Individual Decision Problem

Individuals solve a stochastic dynamic programming problem, which can be formulated recursively. There are five continuous states: $A_{ia}$ = beginning-of-period liquid assets, $\ell_{ia-1}$ = past labor supply, $D_{ia}$ = student debt, $\theta_{ia}$ = persistence component of wages, and $\epsilon_{ia}$ = transitory component of wages. There are four discrete states: $t$ = current year, $a$ = age, $\mathcal{E}_i$ = level of education, and $f_{ia}$ = fixed cost. Denote $\mathbf{s}_{ia}$ as the vector of these state variables for individual $i$ at age $a$ and $\mathbf{E}_a(\cdot) = E(\cdot \mid \mathbf{s}_{ia+1})$ as the conditional expectation over the three shocks, $\omega_{ia+1}$, $\nu_{ia+1}$, and $\epsilon_{ia+1}$. There are two controls: end-of-period liquid assets, $A_{ia+1}$, and labor supply, $\ell_{ia}$. Consumption, $c_{ia}$, is pinned down by the budget constraint.

Suppressing $i$ subscripts, individuals at age $a < a_R$ solve the following problem:

$$V_a(\mathbf{s}_a) = \max_{A_{a+1},\ell_a} \left\{ \mathcal{U}_a\left(c_a - f \times \mathbf{1}_{\ell_a \neq \ell_{a-1}}, \ell_a\right) + \beta m_a \mathbf{E}_a V_{a+1}(\mathbf{s}_{a+1}) \right\}$$

subject to: (4), (5), (7), (8), (10), (12), and

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

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

boundary conditions: (5), (6), (9), (11), and $\ell_{a_0-1} = \ell_{a_0}$

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

$$V_a(\mathbf{s}_a) = \max_{A_{a+1}} \left\{ \mathcal{U}_a(c_a, 0) + \beta m_a \mathbf{E}_a V_{a+1}(\mathbf{s}_{a+1}) \right\}$$

subject to: (10), (12), and $c_a + A_{a+1} = \overline{y}_R(A_{ia}) + A_a + i_a - \tau(0, i_a, t)$

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

boundary condition: $V_{a_T+1}(\mathbf{s}) = 0 \ \forall \mathbf{s}$

## D.2 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 on a grid with $101$ points that varies with age. The lower point of the grid linearly decreases from the minimum allowed value based on the borrowing constraint $a = a_R$ to $0$ at $a = a_T$. During working life, the grid has $31$ points, and the lower point on the grid is set to the lowest value allowed by the borrowing constraint. At all ages, the upper point of the liquid wealth grid is $100$ times the numeraire, which is $40,000 AUD in 2005, and the points are on a power grid with curvature parameter $0.2$.[11] Debt, $D_a$, is placed on 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, $\ell_a$, is placed on a grid with $25$ grid points. The grid is centered at $1$ and ranges from $0$ to $2$. The upper and lower halves of the grid are split into two and are power grids with curvature parameter $0.5$. The grid for $\theta_i$ 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 $\epsilon_a$ is computed as the nodes from a Gauss–Hermite quadrature with 7 nodes. The remaining states are age, which is discretized on a grid that is evenly spaced from $a_0$ to $a_T$ with increments of one; time, which takes two values $t \in \{2004, 2005\}$ to index before and after the policy change; the adjustment cost shock, which takes a value of zero or one; and $\mathcal{E}_i \in \{0, 1\}$.

**Solution algorithm.** The model has a finite horizon and a terminal condition, and hence can be solved by means of backward induction in age starting with the terminal condition in the final year of life. There are two notable aspects of the solution algorithm that are crucial for getting the SMD objective function to be smooth in the set of parameters. First, no choice variables are discretized, meaning I use continuous optimization routines rather than grid searches to find optimal policies. Second, I use Gauss–Hermite quadratures to integrate all continuous shocks, which means that continuous shocks are drawn from continuous rather than discretized distributions when I simulate from the model. Additionally, when solving the model, I work with the Epstein–Zin recursive generalization of (3) in Guvenen (2009b). With slight abuse of notation, I refer to this value function using the same notation as the value function in the main text.

For the period during retirement, I keep track of one value function that is a function of two states: wealth and age. The terminal condition for the model is that $E_{a_T-1} V_{a_T}^{1-\gamma} = 0$, which embeds the assumption that $u_d^{1-\gamma} = 0$, where $u_d$ is the utility upon death. This assumption is standard in life cycle models with recursive preferences.[12] Starting with this condition, I then solve the model

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

[12] With $\gamma > 1$, it implies that $u_d = \infty$. Bommier et al. (2020) point out some undesirable implications of this

in prior periods by finding the optimal consumption-saving choices 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 adjustment cost shock, I solve for optimal choices of savings and labor supply. I do this twice: once where I solve for savings using a golden-section search and labor supply is held fixed, and once 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 $\beta$ 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. The value function is then computed as the maximum from these two maximization problems, taking into account the fact that $f_a$ is only paid when $\ell_a$ is adjusted. When solving for these optimal policy functions at $a$, I have to integrate $V_{a+1}$ over $\theta_{a+1}$, which depends on the stochastic shock, $\nu_{a+1}$, and have to interpolate the value function in the continuous states. I perform the integration using a Gauss–Hermite quadrature with $9$ nodes and use linear interpolation (and extrapolation, if necessary).[13] Linear interpolation is extremely accurate, which allows me to use few grid points as long as choice variables are not discretized, because the Epstein–Zin value function is approximately linear in wealth. Having solved for optimal choices and hence the value function in the seven-dimensional state space at each age, I then integrate out $\omega_a$ and $\epsilon_a$ to obtain a value function that depends on five states for each age: past labor supply, debt, permanent income, liquid savings, and $t$.[14] I continue this backward induction until $a = a_0$ and perform it twice for each $\mathcal{E}_i \in \{0, 1\}$.

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

assumption in models where mortality is endogenous, which is not the case in my model.

[13] When solving the model with learning-by-doing, I add a constant of $0.001$ to $l_{ia-1}$ in (5) when integrating over $\theta_{a+1}$ to prevent numerical instability.

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

only $x$ observations for individuals with $\mathcal{E}_i = 1$, where $x$ is given by:

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

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

## D.3 First-Stage Calibration

This section provides a detailed description of the calibration of the parameters discussed in Section 3.2. Whenever possible, I calibrate parameters to match their observed values during the *ALife* sample period.

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

To compute equivalence scales, I use data from the HILDA Household-Level File on the number of 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 $\text{adults}_a$ and $\text{children}_a$. I then compute the equivalence scale at each age using the formula in Lusardi et al. (2017):

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

Finally, I normalize equivalence scales such that the average value is one, so that a household in the

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

model corresponds to the size of the average household in the data:

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

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

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

**Borrowing limit.** I calculate the age-specific borrowing limit, $\{\underline{A}_a\}_{a=a_0}^{a_T}$, using data on credit card borrowing limits from HILDA. I start from the combined household-level files from the 2002, 2006, 2010, 2014, and 2018 waves, which have Wealth modules that contain the total credit limit on all credit cards in the responding person's name, `crymbl`. Filtering the sample to individuals between 22 and 90, I deflate this variable to 2005 AUD and winsorize at 1%–99%. I then estimate a linear regression of this variable on a constant and a fourth-order polynomial in age using weighted least squares, where the weights are the cross-sectional survey weights normalized to weight each year equally. Finally, I use the predicted value from this regression for each age as $\underline{A}_a$. The resulting values are:

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

**Initial assets.** I calculate the parameters that govern the initial asset distribution using data on asset holdings from HILDA. I start from the combined household-level files from the 2002, 2006, 2010, 2014, and 2018 waves, which have Wealth modules that contain household-level information on asset holdings. Among individuals who are lone persons (`hhtype` = 24) between ages 18 and 22, I compute liquid assets as the sum of bank account balances (`hwtbani`), cash, money market, and

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

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

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 without HELP debt, who correspond to $\mathcal{E}_i = 0$. I then estimate the fraction of individuals with nonpositive asset balances, $p_A(\mathcal{E}_i)$. Among the individuals in each group with positive asset balances, I estimate $\mu_A(\mathcal{E}_i)$ and $\sigma_A(\mathcal{E}_i)$ by fitting a normal distribution to the distribution of positive asset balances among individuals in each group, adjusting for the cross-sectional survey weights that are normalized to weight each year equally. The resulting estimates are shown in Table 2. When simulating from this distribution, I impose an upper bound equal to the largest value that I observe empirically. Additionally, because $A_{ia}$ represents end-of-period savings, I scale $A_{ia_0}$ by $R^{-1}$ so that the liquid assets at $a = a_0$ in the model match the data.

**Preference parameters.** I set $\gamma = 2.23$ based on the results in Choukhmane and de Silva (Forthcoming).

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

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

**Initial student debt balances.** I calculate the parameters that govern the initial debt distribution using data on HELP debt balances from *ALife*. First, I deflate the debt balances for all individual–years to 2005 AUD and then calculate the year in which each individual had her maximum real debt balance. From these debt balances, I drop observations in which (i) individuals are not classified by *ALife* as having acquired new debt balances, (ii) the maximum occurs in the year 2019, which is the final year of data, and (iii) individuals are older than 26 years, 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 $\mu_d$ and $\sigma_d$ by fitting a normal distribution to the logarithm of these debt balances. When simulating from this distribution, I impose an upper bound equal to the largest value that I observe empirically.

**Student debt repayment function.** When estimating the model, I use the HELP 2004 repayment function at $t < T^*$ and the HELP 2005 repayment function at $t \geq T^*$.[18] Formally, I set $d(y, i, D, a, t) =$

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

$\mathbf{1}_{a<a_R} * \min\{HELP_t(y+\max\{i,0\}) * (y+\max\{i,0\}), (1+r_d)D\}$, 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 $\pi_{05}$ is the inflation rate used for the HELP indexation thresholds between 2004 and 2005. In counterfactuals, I consider alternative repayment contracts. In these counterfactuals, I consider repayments that are contingent only on wage income, $y_{ia}$, and not capital income, $i_{ia}$.

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

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

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

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

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

where $\pi_{05}$ 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 unconstrained Mirrlees solutions, which is unlikely to be the case for the actual ATO schedule:

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

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

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

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

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

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

In addition to unemployment benefits, individuals receive a net consumption floor payment. This

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

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

$$\underline{c}_a = \max\left\{\underline{c} - \Big(y_a + A_a + i_a - d_a - \tau(y_a, i_a, t) + ui(y_a, i_a, A_a)\Big), 0\right\},$$

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

**Retirement pension.** Individuals in retirement receive a retirement pension from the government that is based on the age pension, which is the primary form of government-provided income support for retirees in Australia. The age pension is available to individuals at age 65 and is means-tested based on assets and income. I use the formula for payments in 2005 for a single individual who is a homeowner and means-tested based on assets, but I exclude means-testing on income since individuals earn no labor income in retirement. This formula is:

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

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

## D.4 Second-Stage Simulated Minimum Distance Estimation

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

1. OLS estimates of $\beta_1$ and $\beta_2$ from estimating the following equation among employed individuals between ages 22 and 64:

$$\log y_{ia} = \beta_0 + \beta_1 a + \beta_2 a^2$$

2. OLS estimates of $\beta_0^E$ and $\beta_1^E$ from estimating the following equation among individuals who reach age 22 at $t \geq 1991$:[21]

$$\log y_{ia} = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_0^E \mathcal{E}_i + \beta_1^E \mathcal{E}_i a$$

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

3. Within-cohort cross-sectional variance of $\log y_{ia}$ at age 22, 32, 42, 52, and 62
4. 10th and 90th percentiles of $y_{ia+1} - y_{ia}$ and $y_{ia+5} - y_{ia}$
5. Average $\ell_{ia}$ among employed individuals between ages 23 and 64, which is normalized to 1 in the data
6. Real distribution of HELP income among debtholders aged 23 to 64 in 2002–2004 within \$3000 of the 2004 repayment threshold in bins of \$500
7. Real distribution of HELP income among debtholders aged 23 to 64 in 2005–2007 within \$3000 of the 2005 repayment threshold in bins of \$500
8. The following statistic, where quartiles of debt balances are calculated within each year and the number of debtholders is pooled from 2005–2018:

$$\frac{\frac{\text{\# of debtholders in top quartile of debt within \$500 below 2005 threshold}}{\text{\# of debtholders in top quartile of debt within \$500 above 2005 threshold}}}{\frac{\text{\# of debtholders in bottom quartile of debt within \$500 below 2005 threshold}}{\text{\# of debtholders in bottom quartile of debt within \$500 above 2005 threshold}}}.$$

9. Probability of bunching below the 2005 repayment threshold in 2005 conditional on bunching below the 2004 repayment threshold in 2004
10. Fraction of individuals who do not adjust their annual hours worked from HILDA
11. Kurtosis of annual changes in log hours worked from HILDA

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.1. Because of data access restrictions, I construct the first six sets of estimation targets using a 10% random sample of *ALife* data. This likely has little effect on the results because these estimation targets are very precisely estimated and are not the primary targets responsible for identifying the structural parameters of interest. For these estimation targets, I restrict to wage-earners between 22, the first age in the model, and 64, the age at which individuals retire in the model, and winsorize both $y_{ia}$ and $i_{ia}$ from above at $99.999\%$ following Guvenen et al. (2014). When computing the estimation targets based on $y_{ia}$, I restrict to individuals who have annual salary and wages greater than one-half the legal minimum wage times 13 full-time weeks following Guvenen et al. (2014). When calculating all estimation targets in the data, I also restrict to individuals who were age 22 between 1963 and 2019 to match the cohorts simulated in the model. To characterize bunching, I target the distribution within \$3,000 of the repayment thresholds so that these targets are primarily affected by the labor supply elasticity rather than wage profile parameters and use bins of \$500. For the final two moments from HILDA, I restrict the sample to data in two subsequent years among individuals who are employed, earning a positive weekly wage, non-business owners, and between age 22 and 64. I also adjust for longitudinal survey weights and compute hours worked using total reported hours worked across all jobs.

**Weighting matrix.** I choose the weighting matrix, $W(\Theta)$, such that the SMD 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.[22] I do not use the optimal weighting matrix because some of these targets are estimated from population-level data and thus have very small asymptotic variances that make the objective function unstable. I also follow Guvenen et al. (2021) and adjust $w(\Theta)$ so that the following blocks of estimation targets receive equal weight.

1. Block #1: Heterogeneity in bunching with debt balances, persistence of bunching below the repayment threshold, fraction of individuals immediately below and above repayment threshold prior to policy change, fraction of individuals immediately below and above repayment threshold after policy change.
2. Block #2: All remaining estimation targets.

This is done to ensure that the first block of moments, which are most important for the structural parameters of interest, receive equal weight to the remaining moments, even though there are fewer of them.

**Global optimization algorithm.** I compute the value of $\Theta$ that minimizes the SMD objective function using a variant of the TikTak algorithm from Arnoud et al. (2019). I start by evaluating the objective function at 8000 pseudorandom Halton points that cover the parameter space. I then take the top 10 candidate points and perform a Nelder–Mead optimization at each of these 10 points. Finally, I use the Nelder–Mead solutions at each of these 10 points to perform a second round of 10 additional Nelder–Mead optimizations. Specifically, I rank the 10 solutions from the first set of optimizations and start the first optimization of the second round at the best point. Then, to start each of the remaining $i = 2, \ldots, 10$ optimizations, I use as a starting point the weighted average of the current candidate optimum and the $i$th ranked point, with the weighting function and parameters chosen exactly as in Arnoud et al. (2019). In each of these Nelder-Meads, the convergence criteria

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

are a relative objective tolerance of $0.01$ or a maximum of $400$ iterations. In a final polishing phase, I perform a Nelder-Mead with a tolerance of $0.001$ and a maximum of $1000$ iterations.

**Calculation of standard errors.** To apply standard asymptotic theory to calculate standard errors, I rewrite the SMD objective function as

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

where

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

Denote the true value of the parameters, $\Theta$, as $\Theta_0$. Under standard regularity conditions (e.g., McFadden 1989; Duffie and Singleton 1993),

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

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

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

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

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

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

all multiplication and division in the definition of $\Lambda$ are performed element-wise, all quantities are evaluated at $\Theta_0$, and $c_0$ is a vector that accounts for the reweighting of the different blocks of estimation targets discussed above. The previous two equations define the asymptotic variance of $g(\Theta)$, denoted by $\Omega$, which is derived by means of the delta method and the asymptotic distribution of $\hat{m}$.

By the continuous mapping theorem, each component of $V$ can be estimated by replacing population quantities with sample analogs evaluated at the SMD estimate of $\Theta$. I estimate $\Omega_0$ via bootstrap assuming that all off-diagonal elements are zero[23] and compute $G$ using two-sided finite differentiation.[24] The standard errors for $\Theta^*$ are then $\sqrt{N^{-1}\text{diag}(\hat{V})}$.

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

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

## D.5 Model-Based Decomposition of Bunching

If borrowers chose their labor supply statically and treated repayments like an income tax, no borrowers would locate immediately above the repayment threshold because doing so would deliver less take-home pay and leisure. However, income-contingent repayment of debt differs from a tax in that it involves *dynamic*, in addition to static, trade-offs. For example, consider a borrower at $t = 0$ with a debt balance $D_0$ who is deciding between locating below versus above the 2005 repayment threshold. Locating below the threshold decreases her repayments at $t = 0$ by $1,400. However, under the assumption that this borrower's income at $t = 1$ will be high enough that the required payment is above $D_0$, this $1,400 repayment is simply transferred from $t = 0$ to $t = 1$. As a result, the present value of the reduction in repayments from locating below the repayment threshold is $\left(1 - \frac{p}{1+r}\right) \times \$1{,}400 = \frac{r+1-p}{1+r} \times \$1{,}400$, where $r$ is the real interest rate and $p$ is the probability of repayment at $t = 1$.[25]

As discussed in Section 1.2, the present value of bunching below the repayment threshold can be much different from the change in current repayments. To illustrate, assume that borrowers value repayments in two periods and discount cash flows in the second period with (net) interest rate $r$. Letting $p$ denote the probability of repayment in the second period, the net present value (NPV) of locating below the 2005 repayment threshold is

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

which is (weakly) smaller than the increase in liquidity.[26]

Motivated by (15), Figure A21 uses the estimated model to decompose the bunching below the 2005 repayment threshold into three distinct effects. The first effect is the bunching that arises from the difference between borrowers' discount rate and the debt interest rate (i.e., $r \neq 0$), which increases the NPV of bunching below the repayment threshold. Figure A21 shows that this has a negligible effect on the bunching below the repayment threshold. The second effect is that, even when $r = 0$, bunching below the repayment threshold has a positive NPV if borrowers do not anticipate repaying their debt (i.e., $p < 1$). The results in Figure A21 show that this channel accounts for the majority of the bunching: in a counterfactual where $p \approx 1$, bunching below the repayment threshold decreases by about $65\%$.[27] This model-based inference is consistent with the empirical evidence in Section 2 that the amount of bunching is larger among borrowers with a lower

[25] Technically, $r$ is the difference between the HELP interest rate and the borrower's private rate.

[26] Deriving this expression requires two additional assumptions: (i) $p$ is independent of bunching in the first period; (ii) the interest rate on outstanding debt is zero.

[27] Formally, this counterfactual does not correspond precisely to setting $p = 1$ because $p$ is an endogenous object in this dynamic model. Therefore, these results are a lower bound on the effect of $p$.

probability of repayment.

The remaining $35\%$ of the bunching that remains even when $r = 0$ and $p \approx 1$ in Figure A21 reveals that a third effect is a quantitatively important driver of bunching below the repayment threshold: a demand for liquidity. When $r = 0$ and $p = 1$, the NPV of locating below the repayment threshold is zero. Nevertheless, locating below the repayment threshold still increases borrowers' current liquidity, which they may value if they are liquidity-constrained. This importance of liquidity is empirically supported by evidence in Section 2 that the amount of bunching increases with proxies for liquidity constraints, complementing evidence that a demand for liquidity created by incomplete markets amplifies the moral hazard created by other forms of social insurance (Chetty 2008; Ganong and Noel 2023; Indarte 2023). Additionally, it illustrates an important way in which the incentives created by income-contingent repayment differ from those of an income tax. Because most borrowers anticipate repaying their debt with some probability, the labor supply response created by an income-contingent loan is larger than that of a tax for a given repayment function.

## D.6 Description of Repayment Contracts

**25-year Fixed Repayment.** For a borrower $i$ at age $a$, the required payment on a fixed repayment contract is:

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

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

**US Income-Contingent Loans.** For a borrower $i$ at age $a$, the required payment on the US-style income-contingent loans that I consider are:

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

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

- US IBR: $\psi = 10\%$, $K = 1.5 * pov$, $\overline{T} = a_R$, $r_d = 0\%$
- US SAVE: $\psi = 5\%$, $K = 2.25 * pov$, $\overline{T} = a_R$, $r_d = 0\%$
- US IBR + Forgiveness: $\psi = 10\%$, $K = 1.5 * pov$, $\overline{T} = a_0 + 20$, $r_d = 0\%$

- US SAVE + Forgiveness: $\psi = 5\%$, $K = 2.25 * pov$, $\overline{T} = a_0 + 20$, $r_d = 0\%$

where $pov$ is the 2023 US poverty line of $14,580 USD converted into AUD by adjusting for US CPI inflation from June 2005 to January 2023 and the exchange rate in June 2005.[28] The final two versions of these contracts that I consider are the US IBR + Fixed Cap and US SAVE + Fixed Cap. These correspond to the US IBR and US SAVE contracts defined above with the modification that $d_{ICL}(D_{ia}, y_{ia})$ cannot exceed $d_{Fixed}(a, D_{ia})$ for the 25-year fixed repayment contract.

**Purdue Income-Sharing Agreement.** For a borrower $i$ at age $a$, the required payment is:

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

In this expression, $T_{ISA}$ is the term of the ISA contract and $\psi$ is the income-share rate. For the Purdue ISA contract, I set $T = 9$ and $\psi = 4\%$, which closely matches that of the ISAs provided by Purdue University in 2016–2017 (Mumford 2022).

## D.7 Computation of Welfare Metrics

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

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

$$\int V_p(s_0 \mid \mathcal{E}_i = 1) dF(s_0 \mid \mathcal{E}_i = 1) = \int V_{\text{25-Year Fixed}}(s_0(\pi) \mid \mathcal{E}_i = 1) dF(s_0 \mid \mathcal{E}_i = 1).$$

The left-hand side of this equation corresponds to the expected utility of random consumption and labor supply streams under repayment policy $p$ to an agent with education level $\mathcal{E}_i = 1$ who is "behind the veil of ignorance" with respect to $s_0$ and views the realization of these states as risk. The right-hand side corresponds to the same quantity calculated under the 25-year fixed repayment contract when borrowers receive a deterministic cash transfer of $\pi$ at $a = a_0$. I compute this fixed point using a standard bisection root-finding algorithm.

**Consumption-equivalent welfare gain.** Let $V_p(s_0 \mid \mathcal{E}_i = E)$ and $F(\mathbf{s_0} \mid \mathcal{E}_i = E)$ denote the same

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

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

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

This metric corresponds to the value of $g$ that would make borrowers with $\mathcal{E}_i = 1$ indifferent between having to (i) pay their debt under repayment policy $p$ and (ii) pay their debt under 25-year fixed repayment *and* having their consumption increased by $g\%$ in every state during their lifetime. I compute this fixed point using a standard bisection root-finding algorithm. This metric takes the perspective of a hypothetical borrower who does not know her initial values of $D_{ia_0}$, $A_{ia_0}$, and $\delta_i$, and views the realization of these states as risk.

## D.8 Computation of Constrained-Optimal Repayment Contracts

Solving (14) is numerically challenging, especially when higher-dimensional contracts are considered, because it is a nonlinear constrained optimization problem in which the objective and constraints do not have closed forms. I use a combination of a standard barrier method in numerical optimization (Nocedal and Wright 2006) and a global optimizer. Specifically, I set the objective function in (14) to an extremely large value in the event that the first constraint, which corresponds to the government budget constraint, is violated by more than a tolerance of $1. I then perform the minimization of this objective function using the TikTak optimizer from Arnoud et al. (2019). Due to memory and computational constraints, I set $N$ = 50,000 when solving for constrained-optimal policies and only simulate individuals with $\mathcal{E}_i = 1$ (individuals with $\mathcal{E}_i = 0$ do not affect the planner's problem).

## D.9 Decomposition of Welfare Gains into Insurance and Redistribution

The planner's objective function in (14) combines two distinct objectives: (i) providing borrowers with insurance against the realization of ex-post shocks; (ii) redistributing across borrowers with different initial conditions. My baseline takes the perspective of a hypothetical borrower who does not know her initial states and views the realization of these states as risk. This perspective is natural because the initial states in the model are not primitive individual characteristics, but rather the outcomes of ex-ante borrowing and education decisions that are taken as given.[29] However, in reality, some of the variation in these states likely does not reflect risk and is probably driven by

[29] For example, upon entering college, individuals do not know what their income will be upon graduation. Therefore, to the extent that they are risk-averse, they will value insurance against realizations of it, even though it corresponds to an initial state in my model.

ex-ante heterogeneity in borrower types. In this case, the way the planner values redistribution *across* borrower types depends on society's social preferences and need not be the same as how she values redistribution *within* borrowers, which depends on borrowers' preferences.

To decompose welfare gains into insurance and redistribution, I take an approach analogous to Berger et al. (2025) and introduce lump-sum transfers that differ based on initial conditions.[30] I begin by discretizing the following initial states, which are continuous in the baseline model: $D_{ia_0}$, $A_{ia_0}$, and $\delta_i$. For each initial state $X$, I discretize it to take on one of two values, $X_-$ and $X_+$, so that the total number of initial states is $\mathcal{T} = 2^3 = 8$. I set these values as follows:

- $A_- = E(A_{ia_0}|A_{ia_0} \leq \text{median}(A_{ia_0})) = \$246.13$,
- $A_+ = E(A_{ia_0}|A_{ia_0} > \text{median}(A_{ia_0})) = \$8772.68$,
- $D_- = E(D_{ia_0}|D_{ia_0} \leq \text{median}(D_{ia_0})) = \$6859.07$,
- $D_+ = E(D_{ia_0}|D_{ia_0} > \text{median}(D_{ia_0})) = \$28026.08$,
- $\delta_-, \delta_+$ = gridpoints on a two-dimensional Gauss-Hermite quadrature grid that approximates $\delta_i$

This discretization of the initial states provides a parsimonious representation of the distribution of initial states while having the fewest possible number of values. In principle, the discretization could be finer, but each additional dimension makes the constrained-optimization problem that I solve significantly more complex by introducing another choice variable and constraint.

Given this discretization of the initial states, in the second step I resolve the constrained-planner's problem in (14) with two modifications. First, I introduce an additional $\mathcal{T}$ policy instruments that correspond to lump-sum transfers made at $a_0$ to borrowers based on their $\mathcal{T}$ possible initial states. Second, I introduce an additional $\mathcal{T}$ constraints, requiring that the government budget defined in (13) remains unchanged at each of the possible $\mathcal{T}$ initial states between a given repayment contract $p$ and the benchmark 25-year fixed repayment contract. To evaluate the government budget at a given initial state, I simply replace the unconditional expectation in (13) with the expectation taken over all individuals with the given initial state. As a result, the solution to this constrained-planner's problem with transfers does not involve any redistribution across initial states.

Table A9 shows that around half of the welfare gain from the constrained-optimal income-contingent loan comes from redistribution across initial states, while the other half comes from

[30] An alternative method to quantify the importance of redistribution separately from insurance would be to perform a decomposition in the spirit of Benabou (2002), Heathcote et al. (2017), or Abbott et al. (2019). However, these approaches are not feasible in my setting because they require computing certainty-equivalent consumption. Unlike Benabou (2002) and Heathcote et al. (2017), this cannot be done in closed form. Unlike Abbott et al. (2019), it is not computationally feasible to compute these certainty-equivalents numerically.

insurance. The second and fourth columns show that the welfare gain from solving (14) without the additional transfers is equivalent to a cash transfer of \$$4000$ or a $1\%$ increase in lifetime consumption. This differs slightly from the welfare gain in Table 5 because the distribution of initial states in this model is different from the baseline model due to the discretization. In contrast, the third and fifth columns show the welfare gain from solving (14) with the additional transfers is equivalent to a cash transfer of \$$1600$ or a $0.5\%$ increase in lifetime consumption. This implies that $40$-$48\%$ of the gains to moving from fixed repayment to the constrained-optimal income-contingent loan reflect insurance, while the remaining $52$-$60\%$ reflects redistribution across initial states. To the extent that the initial states reflect the realization of some risk, these estimates provide an upper bound on the fraction of gains that come from redistribution.

Most of the redistribution that occurs when moving from the benchmark contract to the constrained-optimal income-contingent loan occurs across initial wage levels among borrowers with large initial debt balances. Figure A22 shows the transfers made to each of the $\mathcal{T}$ initial states. Eliminating redistribution requires transfers of around \$$3000$ from borrowers with lower wages and higher debt, who gain the most from the income-contingent loan, to those with higher wages and higher debt. In contrast, there is much less redistribution across different initial debt or asset levels.

The final row of Table A9 attempts to perform the same decomposition for the ISA in the final row of Table 5, which has the largest welfare gain. However, I find that it is not possible to find transfers that balance the government budget at every initial state. Figure A22 shows that, in the initial states where the budget can be balanced, the transfers required are much larger than under the income-contingent loan. The direction of redistribution is also quite different: while an income-contingent loan primarily redistributes based on initial wages, the ISA primarily redistributes based on initial debt. This is because ISAs decouple repayments from debt balances, resulting in a large transfer from low– to high–debt borrowers that needs to be undone with transfers. The large redistribution created by ISAs suggests they are more likely to generate responses outside of the model, such as additional borrowing and selection, that might make income-contingent loans a more robust implementation of income-contingent repayment.

## D.10 Interaction Between Income-Contingent Loans and the Tax System

The analysis thus far has taken the tax and transfer system as given, which is an alternative way to redistribute and provide insurance. I view this as a reasonable starting point because the tax system is designed for the entire population and constrained by the political system. As a result, government agencies, such as the Congressional Budget Office, typically evaluate policies in isolation. Nevertheless, it is clearly desirable to study the joint determination of taxes, transfers, and education financing, as in Stantcheva (2017). Although this is outside the scope of this paper because it requires a model that (at a minimum) also has endogenous college entry, this section performs additional analyses to shed light on how income-contingent loans interact with and differ from changes in the tax system.

The first row in the second panel of Table A10 shows how the solution to (14) changes when the parametric income tax schedule that was calibrated to Australia is changed to match the US calibration in Heathcote et al. (2017). The shape and welfare gains of the constrained-optimal income-contingent loan are very similar. In the second row, I study how the results change when this tax schedule is optimized to maximize the expected utility of an individual who views all of her initial states as risk, including $\mathcal{E}_i$. With this optimized tax system, there is no gain from moving to income-contingent repayment.

Although the welfare gains from income-contingent repayment can be achieved through the tax system, the targeting of these two policy instruments is quite different. Figure A23 compares the distribution of the welfare gains across two policy experiments: (i) restructuring debt repayment from the baseline contract to the constrained-optimal income-contingent loan, holding taxes and transfers fixed; (ii) moving from the current to optimal tax system, holding the debt repayment fixed. These distributions differ in three ways. First, changing the tax system affects individuals of all education levels, while restructuring debt repayment only affects individuals who attend college. Second, higher-income individuals lose substantially from the change in the tax system because they have to make larger repayments throughout their lives. In contrast, repayments by these individuals are capped by their debt balances under income-contingent repayment. Finally, restructuring debt repayment more effectively targets individuals with high debt balances, who lose on average from the tax change. Given the policy discussion around student debt is particularly focused on highly-indebted individuals, this more precise targeting may be desirable.

## D.11 Sensitivity to Key Labor Supply Parameters

As with any counterfactual analysis, the key concern is whether the structural parameters are invariant to policy changes. The fact that the model is estimated using a policy change that did occur makes this more likely to be the case. Nevertheless, to assess this concern, I vary the four key parameters that govern labor supply responses–$\phi$, $\lambda$, $f_L$, $f_H$–and resolve (14) for this range of possible values, holding all other parameters at their estimated values from Table 3. Figure A24 plots the resulting consumption-equivalent welfare gains, $g_p$, of the constrained-optimal income-contingent loan.

The top left panel shows that the welfare gain from the constrained-optimal income-contingent loan is decreasing in the labor supply elasticity, $\phi$. This is natural: a higher $\phi$ increases the moral hazard created by income-contingent repayment, which reduces the amount of insurance that can be provided for a given fiscal cost. For the income-contingent loan to deliver a welfare loss relative to the benchmark fixed repayment contract, I estimate $\phi$ would need to be above $0.24$, which is well outside the confidence interval for its estimated value. Nevertheless, Appendix D.12 shows that using a richer contract space of income-contingent loans restores welfare gains even when $\phi = 0.24$. This is consistent with Shavell (1979): the gains from insurance are first-order while the losses from moral hazard are second-order.

The remaining three panels of Figure A24 show that the welfare gains from income-contingent loans are substantially less sensitive to the adjustment cost probability, $\lambda$, and the adjustment costs, $f_L$ and $f_H$. For all values of these parameters that I consider, which are well outside the range of their estimated values, the welfare gain is positive. This suggests that, although optimization frictions are important for individual-level labor supply responses, their precise values matter less for aggregate responses, which is what the planner cares about. This is not surprising because the responses that have the largest impact on the government budget are not year-to-year small adjustments, which are primarily controlled by frictions, but rather long-run steady-state responses, at which point the role of these frictions diminishes because the probability of labor supply adjustment approaches one. Nevertheless, distinguishing between different models of adjustment frictions is still quantitatively important: the top half of Table A10 shows how the welfare gains vary in the other models of adjustment frictions estimated in Table 3.

## D.12 Welfare Gains from using a Richer Contract Space

In this section, I consider the effects of solving (14) using the following three richer contract spaces:

1. Quadratic Income-Contingent Loan: $d_{ia}(\boldsymbol{\theta}) = \min\left\{\max\left\{\theta_1 + \theta_2 y_{ia} + \theta_3 y_{ia}^2, 0\right\}, D_{ia}\right\}$
2. Quadratic Income-Contingent Loan + Age: $d_{ia}(\boldsymbol{\theta}) = \min\left\{\max\left\{\theta_1 + \theta_2 y_{ia} + \theta_3 y_{ia}^2 + \theta_4 a, 0\right\}, D_{ia}\right\}$
3. Quadratic Income-Contingent Loan + Debt: $d_{ia}(\boldsymbol{\theta}) = \min\left\{\max\left\{\theta_1 + \theta_2 y_{ia} + \theta_3 y_{ia}^2 + \theta_4 D_{ia}, 0\right\}, D_{ia}\right\}$

The first contract corresponds to a smoothed version of the income-contingent loans considered in Section 4.2, in which repayments are a quadratic function of income. The latter two contracts make payments conditional on age and debt, respectively. For each of these alternative contracts, I solve the planner's problem in (14), optimizing over $\boldsymbol{\theta}$ instead of $\psi$ and $K$. Figure A25 shows the results. In the baseline model, using a quadratic repayment function has no effect on the welfare gain. While making payments debt-contingent also has no effect, making payments age-contingent increases the welfare gain to a $0.94\%$ equivalent increase in lifetime consumption. In the baseline model with a higher value of $\phi = 0.24$, where the baseline income-contingent loan leads to a welfare loss, the quadratic repayment function helps restore part of the welfare gain of income-contingent repayment. This is consistent with Shavell (1979), who shows that the unconstrained solution to

(14) features some insurance because the gains from insurance are first-order while the losses from moral hazard are second-order. However, making payments age-contingent helps even further, since this allows the planner to condition payments on a variable that is correlated with the marginal value of wealth but that cannot be manipulated.

## D.13 Sensitivity of Welfare Gains to Model Misspecification

This section describes the details of the various models shown in the bottom half of Table A10, which represent deviations from the baseline model shown in the first row and estimated in column (5) of Table 3.

**US tax system.** I change the parameters of the 2-parameter tax function defined in Appendix D.3 to the parameters defined in Section IIA of Heathcote et al. (2017).

**Optimized tax system.** I compute the optimized tax function by solving the constrained-planner's problem in (14) with two modifications. First, I change the objective function to be $\mathbf{E}_0(V_{ia_0})$, where the expectation is taken across all initial states. Second, I optimize over the parameters of the 2-parameter tax function from Heathcote et al. (2017) defined in Appendix D.3. The results with the optimized tax system then correspond to solving (14) with the parameters of the 2-parameter tax and transfer function already optimized.

**Alternative risk and time preferences.** To assess the effects of moving the RRA and EIS independently, I use the recursive generalization of (3) in Guvenen (2009b). I then change these two parameters independently, holding all others fixed.

**Wealth effects on labor supply.** Existing literature disagrees on the size of wealth effects on labor supply: Cesarini et al. (2017) find small wealth effects from lottery winnings in Sweden, while Golosov et al. (2023) find larger effects from lottery winnings in the US. To assess the importance of wealth effects, I adjust the flow utility in (3) to be

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

I set $\eta = 0.5$ following the calibration in Keane (2011).

**Persistence of income risk.** Because individuals can self-insure against transitory but not permanent shocks in incomplete markets, correctly estimating the persistence of income shocks is crucial for assessing the welfare impact of income-contingent repayment. Because estimates of this persistence vary between $0.8$ and close to $1$, depending on the degree of heterogeneity in income profiles (Guvenen 2009a), I consider alternative values of $\rho$, holding all other parameters fixed.

**US initial debt levels.** An important difference between the US and Australia is the level of initial debt that borrowers take on. In the 2019 Survey of Consumer Finances, the average initial debt among borrowers was $51,800 USD (Catherine and Yannelis 2023), while in the model, it is $17,400 in 2005 AUD ($20,500 in 2023 USD). I consider the effect of multiplying all initial debt balances by $2.51$, the ratio of the previous two values.

**Higher interest rate on debt.** In my analysis, I set the real interest rate on debt to zero, as in HELP. However, in the US, debt balances have historically been subject to interest accumulation (although the new SAVE plan changes this). Alternatively, I consider an interest rate of $2\%$ above the real interest rate, similar to the markup on student loans above Treasury bill rates in the US (Ji 2021) and above the Bank of England base rate in the UK (Britton and Gruber 2020).

**Government discount rate.** The model does not have aggregate risk, so the correct discount rate for debt repayments is the risk-free rate. I consider the effects of a higher discount rate, the risk-free rate plus a $2\%$ risk premium.

# Appendix E. Comparison with Existing Literature on Labor Supply

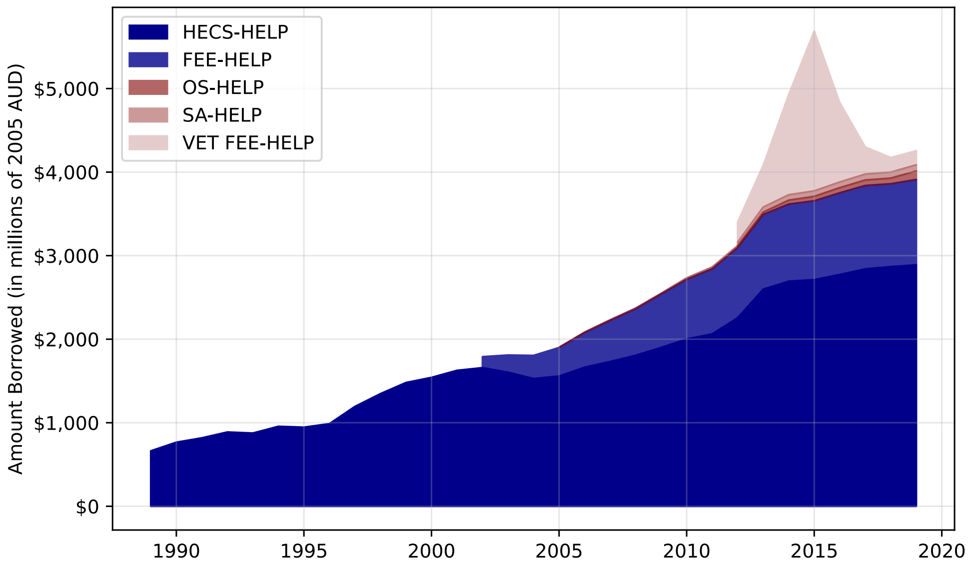
The literature on labor supply is extremely vast (see Blundell and MaCurdy 1999 and Keane 2011 for reviews) and can be divided into four strands (Chetty et al. 2012): the first uses data on hours worked to measure labor supply; the second uses income reported on tax returns to measure labor supply; the third also uses tax data, but focuses on top earners; and the fourth studies differences in hours worked in response to cross-sectional variation, such as variation in tax rates across countries. Because I identify $\phi$ using bunching in HELP income, it can also be interpreted as a reported income elasticity that aggregates both hours and non-hours responses (Feldstein 1999). Therefore, Figure A20 shows the distribution of labor supply elasticities estimated among studies in these first two strands of the literature, which have the closest structural interpretation to $\phi$. My baseline estimate of $0.15$ is similar to the median of these estimates, $0.14$. However, none of these studies explicitly account for optimization frictions, although some examine longer-run responses that might be less affected by such frictions. Assuming that these estimates do not account for frictions, the closer analog in my setting to these estimates would be my frictionless estimate of $0.003$, which is smaller than most estimates.

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

# Appendix F. Additional Figures and Tables

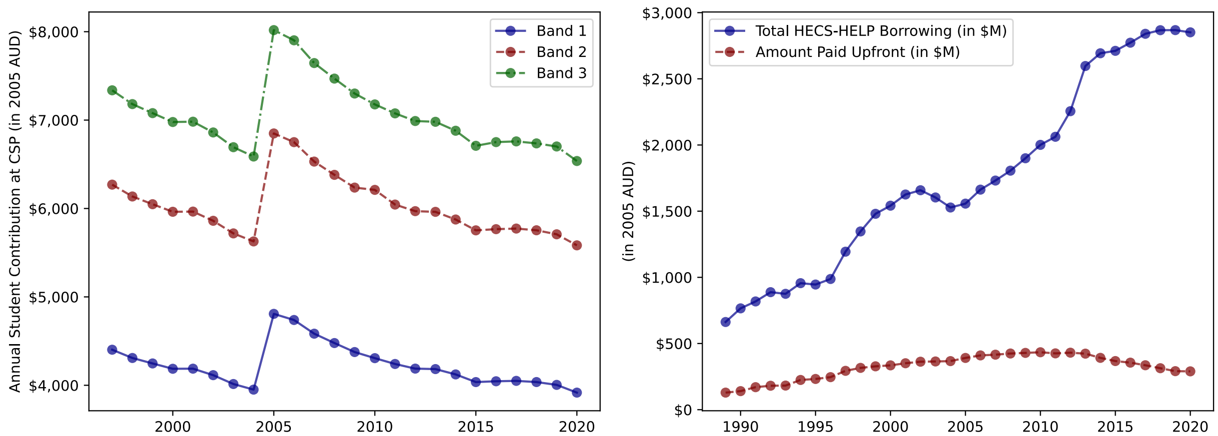
## F.1 Aggregate HELP Statistics

**Figure A1**. Student Contributions and Aggregate HELP Borrowing over Time




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

**Figure A2.** Student Contributions and Aggregate HELP Borrowing over Time

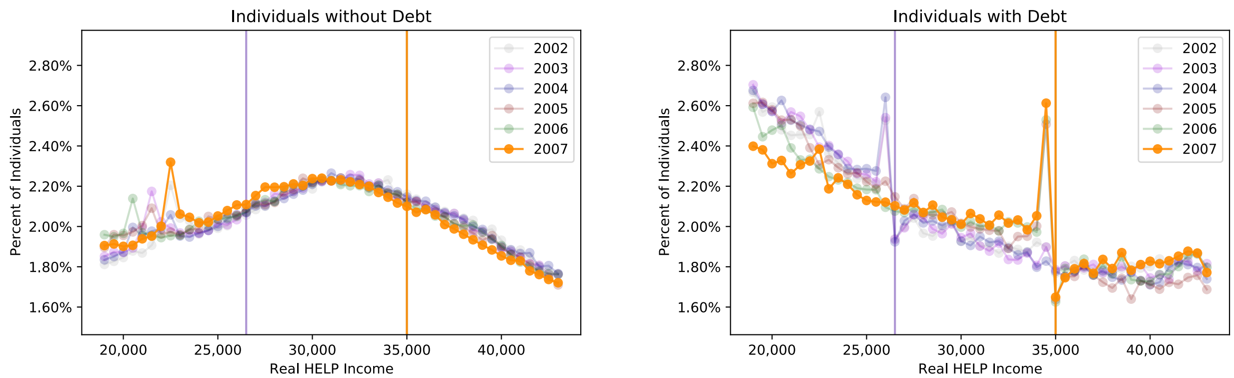



*Notes:* The left plot shows the time series of student contributions in 2005 AUD for Commonwealth Supported Places (CSPs) based on the three separate bands of study classified by the Australian government. These rates correspond to the cost of one year of coursework that must be covered with a HELP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

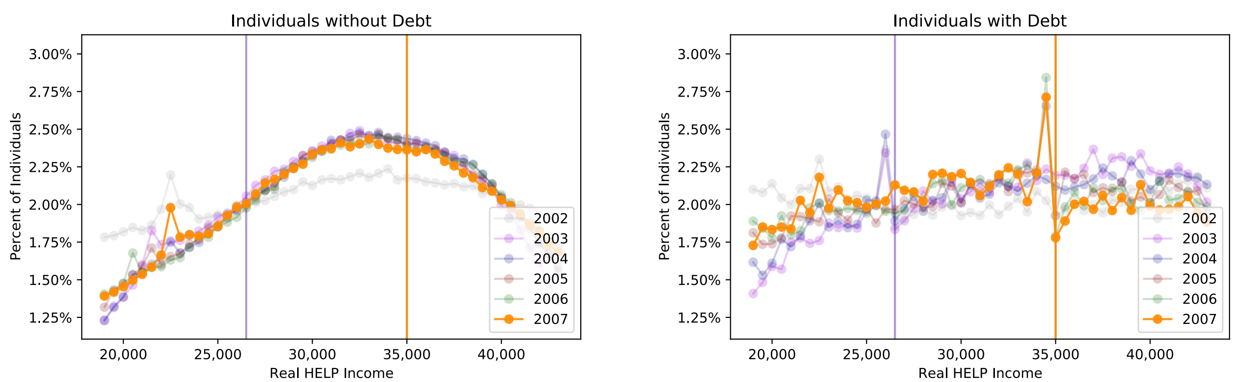
## F.2 Results Discussed in Section 2

**Figure A3**. Comparison of HELP Income Distribution for Debtholders and Non-Debtholders

*Panel A: Full Sample*

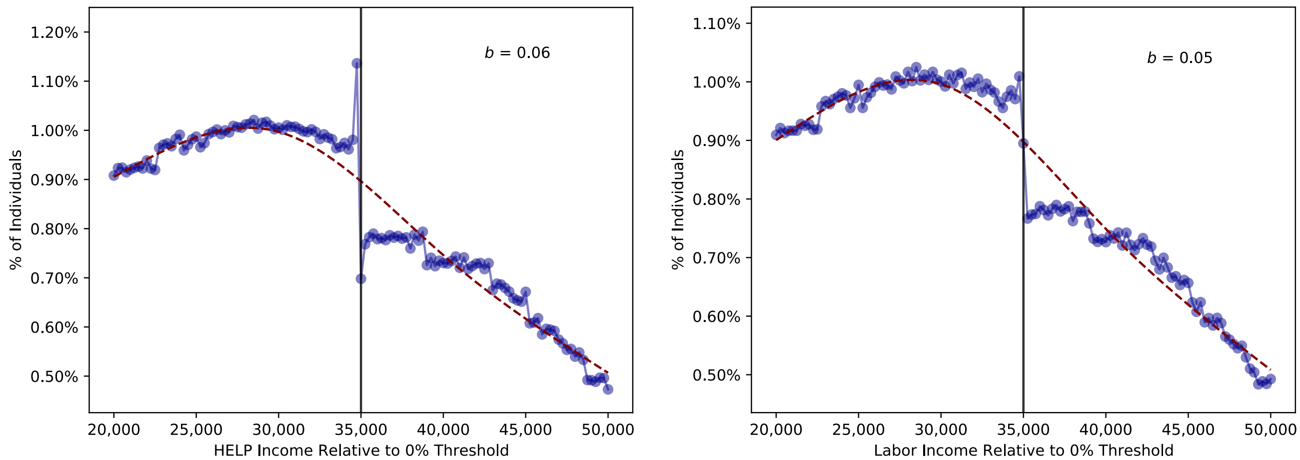



*Panel B: Sample of Borrowers Held Fixed from 2002*




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

**Figure A4**. Distributions of HELP Income and Labor Income



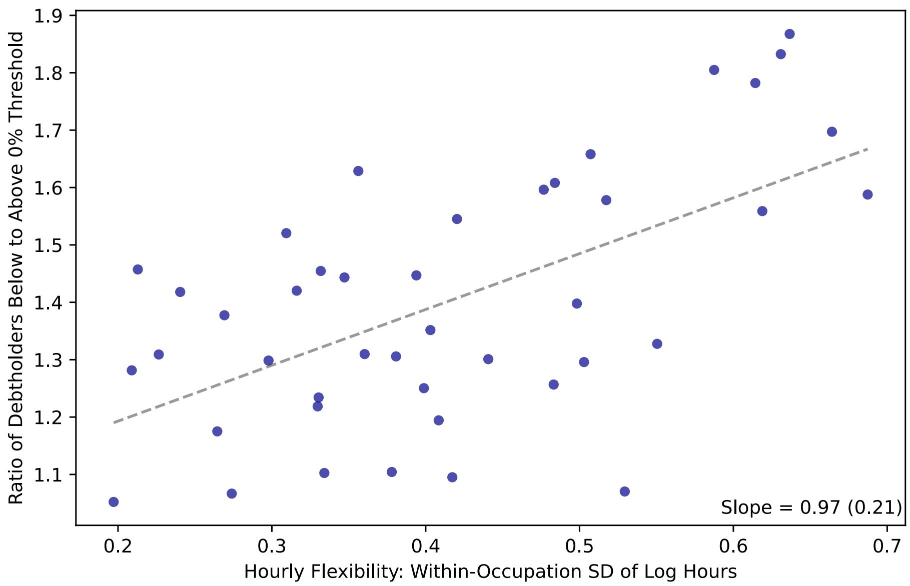

*Notes:* This figure plots the distributions of HELP and labor income (in 2005 AUD) relative to the repayment threshold after the policy change. This figure also plots the bunching statistic defined in (2) computed for the different distributions. Each bin corresponds to $250 AUD, and bins are chosen so that they center on the 2005 repayment threshold. The calculation of $b$ is detailed in Appendix B.2, and the counterfactual density estimated in this procedure is plotted in the dashed red line. The sample is the *ALife* sample defined in Section 1.4 for the period between 2005 and 2018 after the policy change, restricted to individuals with positive HELP debt balances and less than 1% of HELP income from sources other than labor income.

**Table 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 |

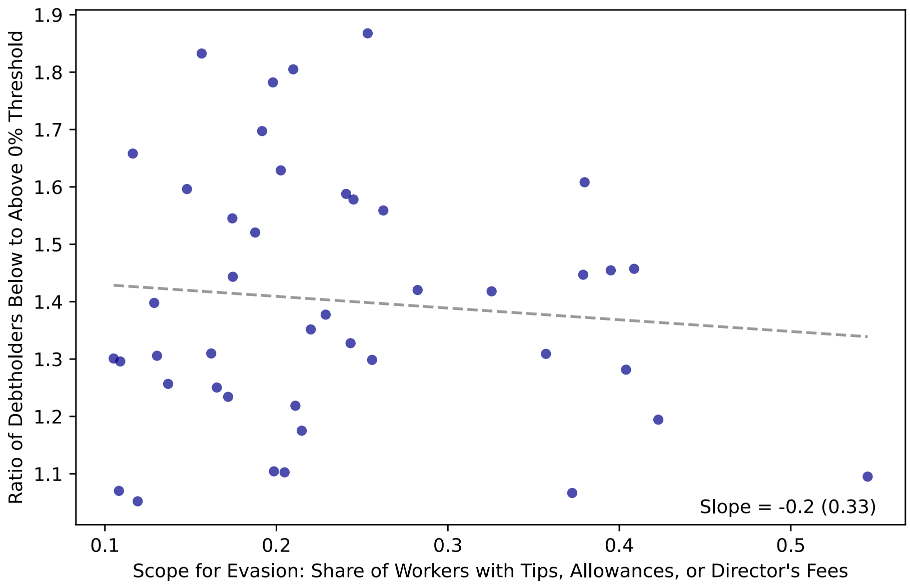
*Notes:* This table shows the measures of hourly flexibility at the 2-digit ANZSCO occupation-level used in Figure 4 and Figure A5. Hourly flexibility is measured as the standard deviation of annual changes, or the cross-sectional standard deviation, in log hours worked per week from HILDA.

**Figure A5**. Variation in Bunching across Occupations Based on Hourly Flexibility: Alternative Measure



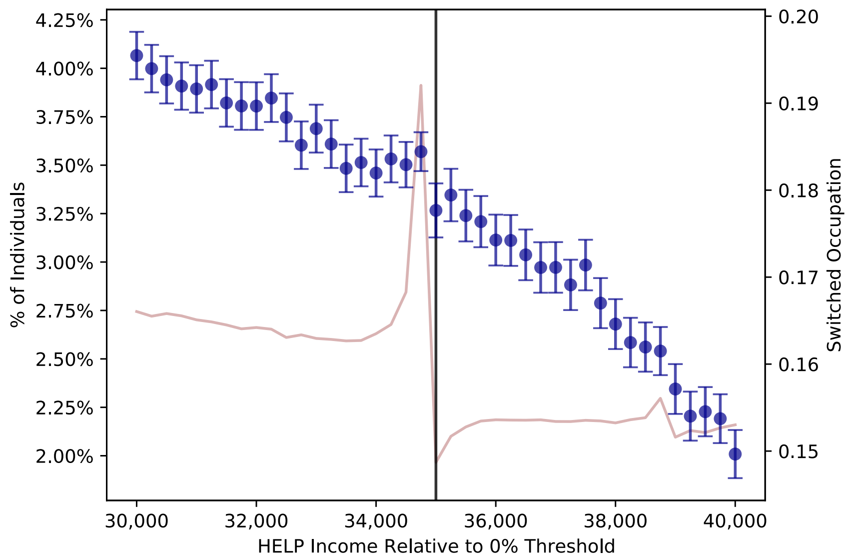

*Notes:* This figure plots the relationship between the amount of bunching below the repayment threshold and an alternative measure of hourly flexibility by occupation. Each point represents a 2-digit ANZSCO occupation code reported in *ALife*. The amount of bunching is measured as the ratio of the number of borrowers in that occupation within $2,500 below the repayment threshold to the number within $2,500 above the threshold for the period from 2005 to 2018. Hourly flexibility is measured as the cross-sectional standard deviation of log hours worked per week. The gray dashed line is the regression line with the estimated slope coefficient and standard error reported at bottom right. The sample is the *ALife* sample defined in Section 1.4, restricted to the subset of individual–years for which the borrowers are wage-earners.

**Figure A6**. Variation in Bunching across Occupations Based on Scope for Evasion



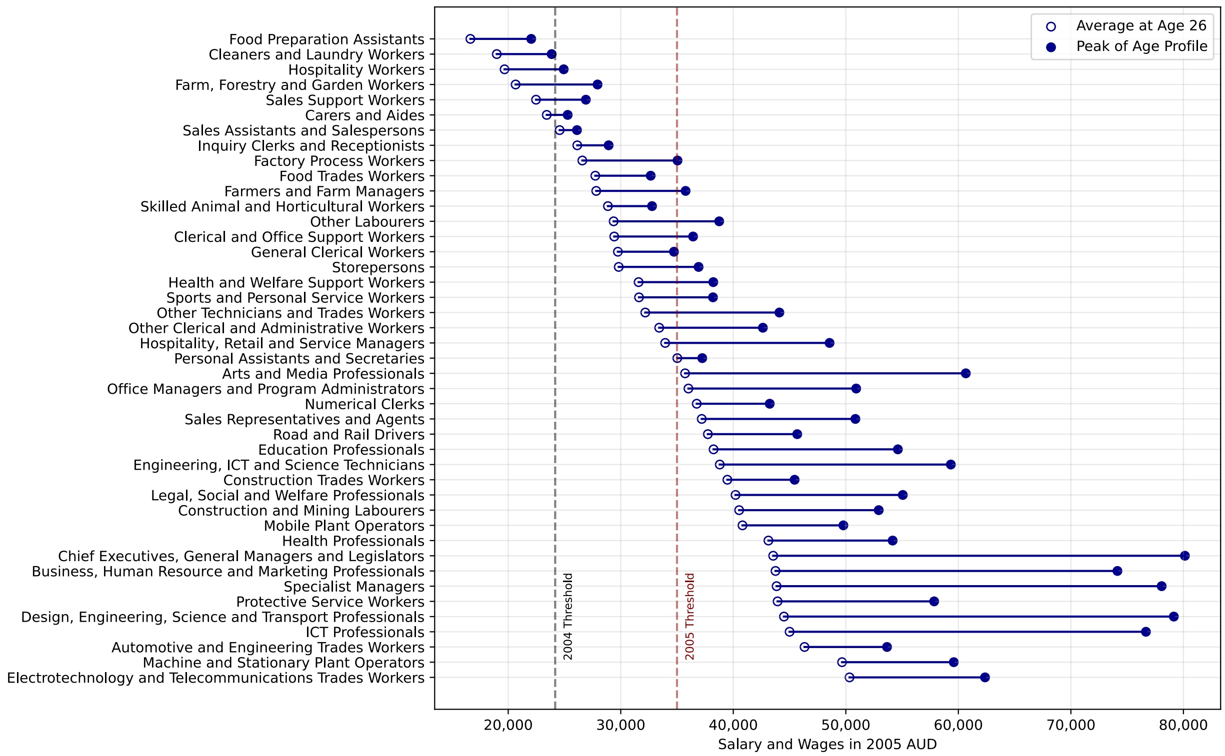

*Notes:* This figure replicates Figure 4 with a measure of evasion at the occupation-level, instead of hourly flexibility on the horizontal axis. The measure of evasion is the fraction of individuals within each occupation who receive income from tips, allowances, or director's fees; see Appendix B.1 for additional details. This evasion measure is computed for the sample of individuals described in Figure A8.

**Figure A7**. Probability of Switching Occupations around the Repayment Threshold in 2005–2018




*Notes:* This figure plots the real HELP income distribution between 2005 and 2018, in red and measured on the left axis. HELP income is deflated to 2005 with the HELP threshold indexation rate, which is based on the annual CPI. Each bin represents $250, and the plot focuses on borrowers within $5,000 of the repayment threshold. The bins are chosen so that they are centered on the 2005 repayment threshold. The blue points present the fraction of individual–years in each bin in which borrowers' 2-digit ANZSCO occupation code differs from that of the previous year, along with 95% confidence intervals. The sample is the *ALife* sample defined in Section 1.4, restricted to the subset of individual–years with positive HELP debt balances between 2005 and 2018.

**Figure A8**. Age Profiles of Wage Income across Occupations



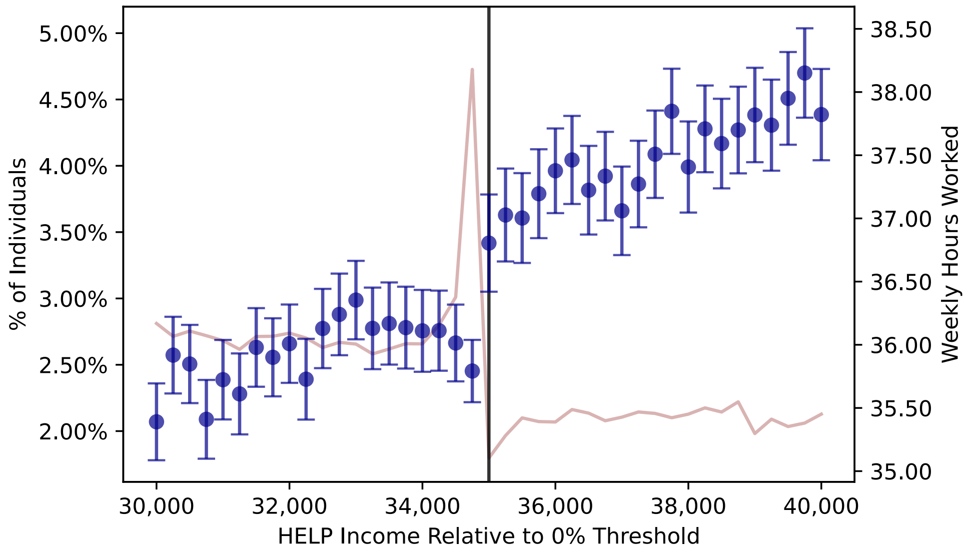

*Notes:* This figure plots characteristics of the age profile of salary and wages across 2-digit ANZSCO occupations. Occupation-specific age profiles are calculated by taking the average value of salary and wages across individuals in each occupation at a given age, after adjusting for inflation and 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 who satisfy the sample selection criteria in Section 1, are wage-earners, and have annual salary and wages greater than one-half the legal minimum wage times 13 full-time weeks (Guvenen et al. 2014).

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

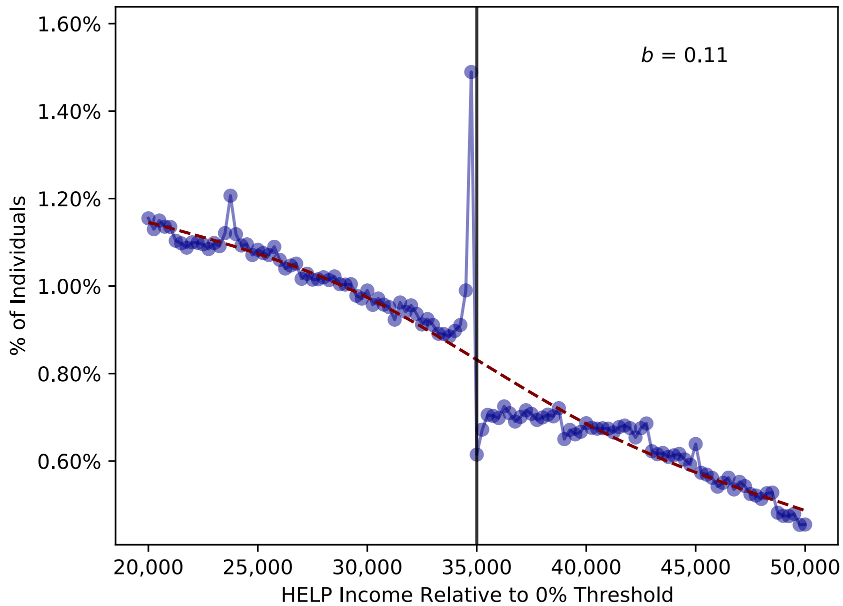
**Figure A9**. Self-Reported Hours Worked around the Repayment Threshold: Borrowers with Positive Labor Income



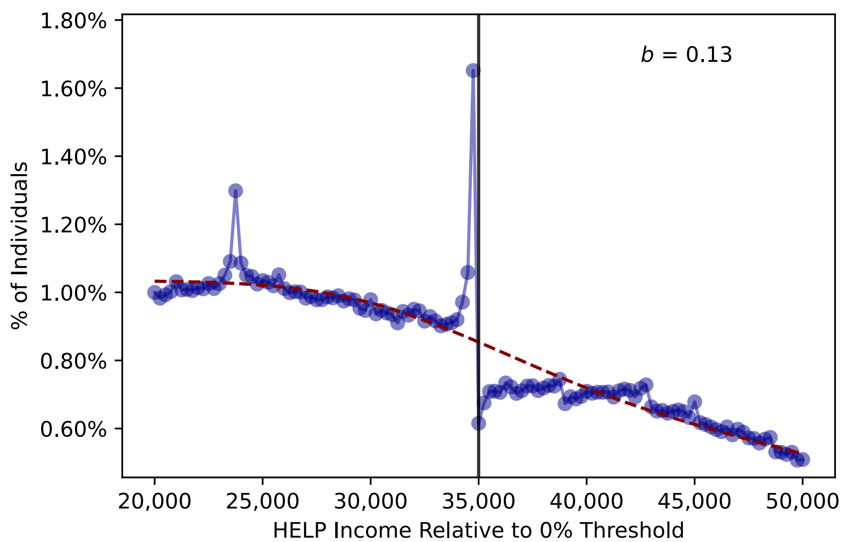

*Notes:* This figure replicates Figure 5 for the sample of borrowers with positive labor income.

**Figure A10**. Distribution of HELP Income in *ALife* versus MADIP Sample

*Panel A: ALife Sample in 2016*

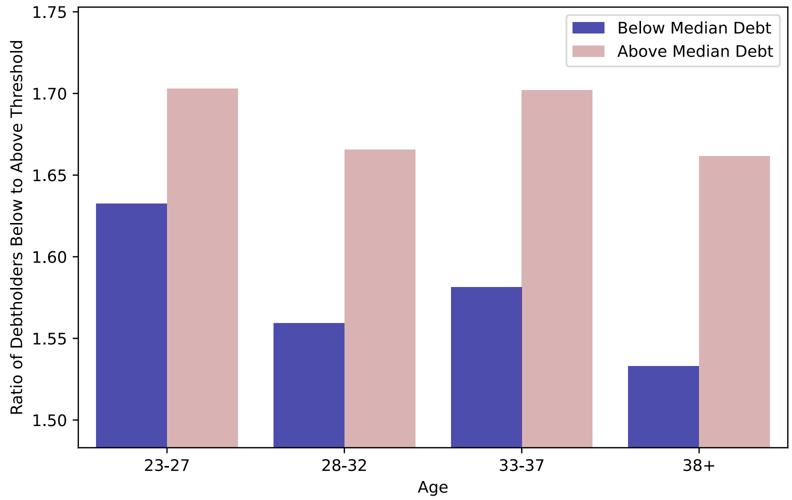



*Panel B: MADIP Sample*



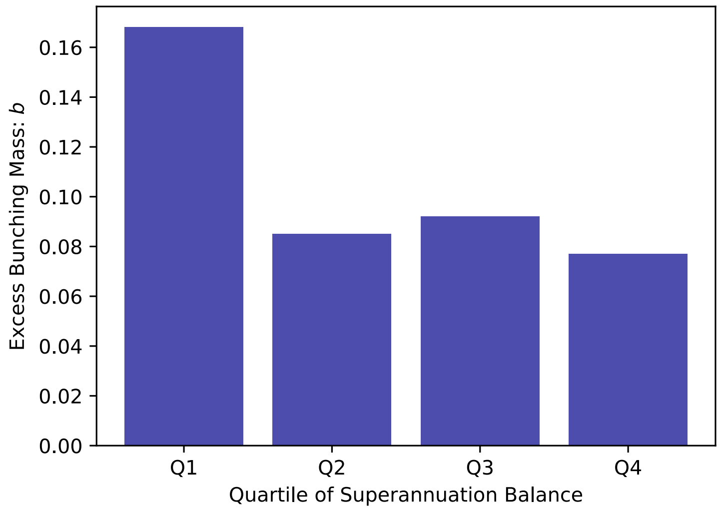

*Notes:* Panel A of this figure plots the distribution of HELP income (in 2005 AUD) in 2016 relative to the repayment threshold and the bunching statistic defined in (2). Each bin corresponds to $250 AUD, and bins are chosen so that they are centered around the 2005 repayment threshold. The calculation of $b$ is detailed in Appendix B.2, 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 1.4 in 2016, restricted to individuals with positive HELP debt balances. Panel B performs the same analysis in the cross-sectional MADIP sample, restricting to individuals with positive HELP debt balances.

**Figure A11**. Variation in Bunching by Debt Balances and Age: Ratio Measure




*Notes:* This figure shows the analogous plot to Figure 6 using the bunching measure used in Figure A16.

**Figure A12**. Bunching Heterogeneity by Superannuation Balances: Ages 20–29



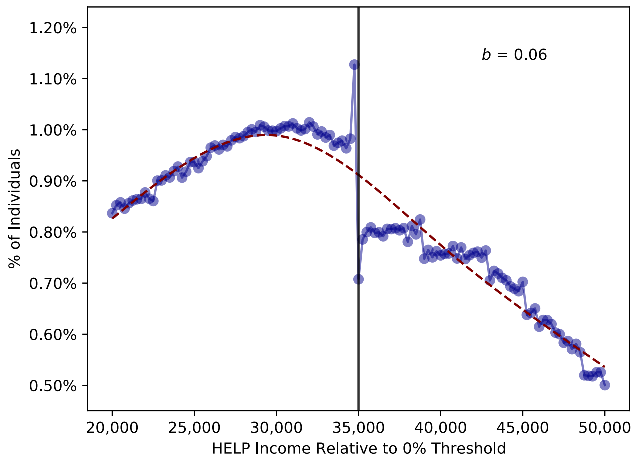

*Notes:* This figure replicates the analysis in the left panel of Figure 7 among borrowers who are ages 20–29.

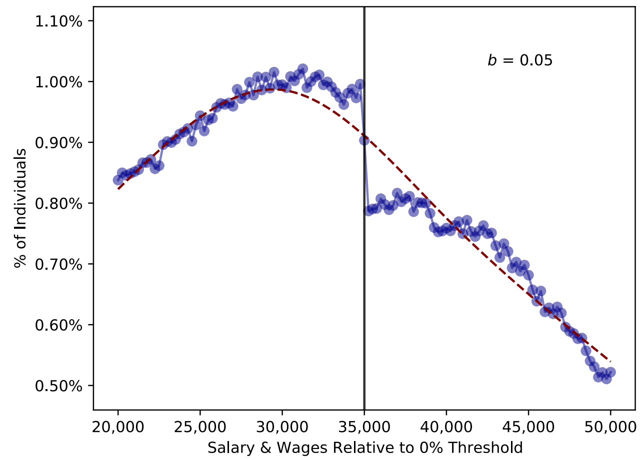
**Table A3.** Additional Sources of Heterogeneity in Bunching

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

*Notes:* This table shows the bunching statistic defined in (2) computed for different samples of debtholders. The calculation of $b$ is detailed in Appendix B.2. The sample in each row is the *ALife* sample defined in Section 1.4 for the period between 2005 and 2018 after the policy change, restricted to borrowers with positive HELP debt balances for whom the sample restrictions specified in each row are satisfied. The first two rows split borrowers based on whether they file their tax returns electronically; the third and fourth split the sample into wage-earners and non–wage-earners; the fifth and sixth split the sample based on gender; the seventh and eighth split the sample based on whether a borrower reports having a dependent child; and the ninth and tenth split the sample based on whether a borrower reports having a spouse.

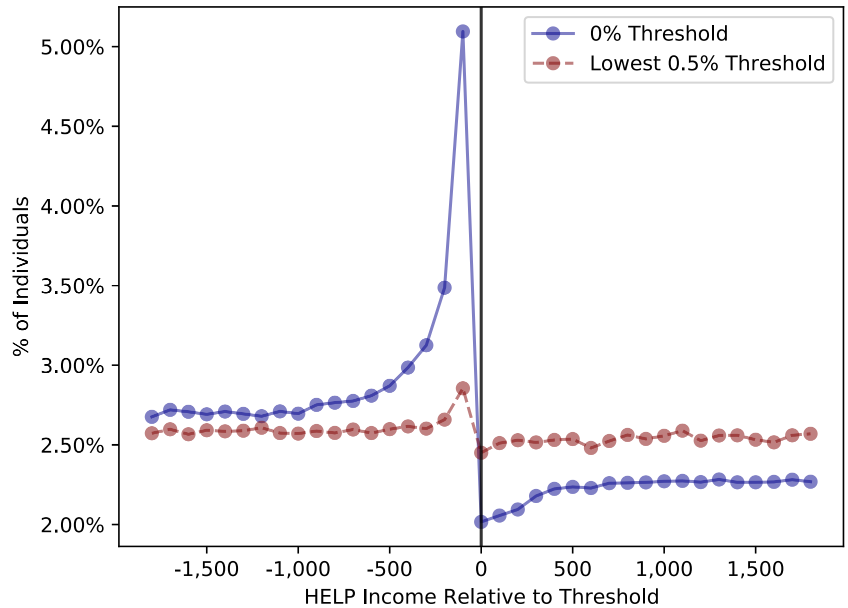
**Figure A13**. Distributions of HELP Income and Salary and Wages




*Notes:* This figure replicates the analysis in Figure A4, replacing the right plot with salary and wages instead of labor income.

**Figure A14**. Distribution of HELP Income at Repayment Threshold versus Lowest 0.5% Threshold




*Notes:* This figure plots the distribution of HELP income (in 2005 AUD) relative to the repayment threshold in solid blue and the lowest 0.5% threshold at $38,987 in dashed red. Each bin corresponds to $100 AUD, and bins are chosen so that they are centered around each threshold. The sample in this panel is the *ALife* sample defined in Section 1.4, restricted to individuals with positive HELP debt balances.

## F.3 Results Discussed in Section 3

**Table A4.** Elasticity of Estimation Targets with Respect to Parameters

*Panel A: Income Distribution Before the Policy Change*

| | $y$=22500 | $y$=23000 | $y$=23500 | $y$=24000 | $y$=24500 | $y$=25000 | $y$=25500 | $y$=26000 | $y$=26500 | $y$=27000 | $y$=27500 | $y$=28000 | $y$=28500 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\phi$ | 0.04 | 0.00 | 0.04 | 0.05 | 0.31 | -0.05 | -0.06 | -0.06 | -0.11 | -0.07 | -0.06 | -0.03 | -0.10 |
| $\lambda$ | 0.00 | -0.00 | -0.01 | 0.02 | 0.14 | -0.10 | -0.03 | -0.01 | -0.02 | -0.01 | -0.01 | 0.02 | -0.02 |
| $f_L$ | 0.01 | 0.00 | 0.00 | 0.01 | -0.06 | 0.05 | 0.01 | -0.01 | 0.01 | -0.00 | -0.00 | -0.02 | 0.02 |
| $f_H$ | -0.00 | -0.00 | -0.00 | -0.00 | -0.00 | 0.00 | 0.01 | 0.00 | -0.00 | 0.00 | 0.02 | -0.02 | -0.01 |
| $\beta$ | 0.07 | -0.03 | 0.19 | -0.12 | -0.87 | 0.68 | 0.05 | 0.25 | -0.03 | -0.00 | 0.17 | 0.09 | -0.32 |
| $\delta_0$ | -2.89 | -2.14 | -1.21 | -1.36 | -0.09 | 0.19 | -0.77 | 0.56 | 1.09 | 0.91 | 1.91 | 2.57 | 2.25 |
| $\delta_1$ | -0.57 | -0.53 | -0.39 | -0.29 | -0.03 | -0.21 | -0.04 | -0.05 | 0.04 | 0.82 | 0.66 | 0.38 | 0.46 |
| $\delta_2$ | -0.22 | -0.14 | -0.12 | -0.11 | -0.06 | -0.09 | 0.01 | 0.00 | 0.06 | 0.00 | 0.16 | 0.42 | 0.18 |
| $\delta_0^E$ | -0.01 | -0.28 | -0.12 | -0.25 | -0.04 | -0.02 | 0.25 | 0.25 | 0.11 | -0.08 | 0.03 | 0.15 | 0.08 |
| $\delta_1^E$ | -0.12 | -0.26 | -0.16 | -0.31 | -0.08 | 0.08 | 0.15 | 0.31 | 0.05 | 0.07 | 0.00 | 0.07 | 0.32 |
| $\rho$ | 1.15 | 0.65 | 0.84 | 0.07 | 0.33 | 0.01 | -0.26 | -0.40 | -0.41 | -0.43 | -0.02 | -1.15 | -0.78 |
| $\sigma_\nu$ | 0.14 | 0.15 | 0.08 | 0.03 | 0.02 | -0.04 | 0.01 | -0.01 | 0.03 | -0.09 | -0.10 | -0.17 | -0.10 |
| $\sigma_\epsilon$ | 0.01 | -0.00 | -0.03 | 0.02 | 0.04 | -0.01 | -0.04 | -0.03 | 0.04 | 0.01 | 0.02 | -0.02 | -0.00 |
| $\sigma_i$ | 0.10 | 0.06 | 0.01 | 0.14 | 0.06 | -0.07 | -0.01 | -0.17 | 0.08 | -0.13 | -0.01 | -0.04 | -0.06 |
| $\kappa$ | 0.04 | 0.02 | 0.02 | 0.01 | -0.03 | 0.02 | 0.02 | 0.00 | -0.00 | -0.01 | -0.03 | -0.04 | -0.02 |
| $\iota$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Panel B: Income Distribution After the Policy Change*

| | $y$=32500 | $y$=33000 | $y$=33500 | $y$=34000 | $y$=34500 | $y$=35000 | $y$=35500 | $y$=36000 | $y$=36500 | $y$=37000 | $y$=37500 | $y$=38000 | $y$=38500 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\phi$ | 0.06 | 0.01 | -0.01 | -0.04 | 0.25 | -0.06 | -0.08 | -0.08 | -0.05 | 0.02 | -0.05 | -0.07 | -0.01 |
| $\lambda$ | -0.02 | 0.01 | -0.00 | 0.01 | 0.26 | -0.13 | -0.11 | -0.08 | -0.07 | -0.04 | -0.03 | -0.01 | 0.06 |
| $f_L$ | 0.01 | 0.01 | 0.01 | 0.01 | -0.10 | 0.03 | 0.03 | 0.03 | 0.03 | 0.01 | 0.01 | -0.01 | -0.03 |
| $f_H$ | -0.01 | -0.00 | -0.00 | 0.00 | -0.02 | 0.01 | 0.00 | -0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.01 |
| $\beta$ | -0.10 | -0.07 | 0.05 | -0.29 | -0.90 | 0.18 | 0.72 | 0.19 | 0.22 | 0.40 | 0.16 | 0.02 | 0.00 |
| $\delta_0$ | -1.74 | -1.35 | -1.51 | -0.79 | 0.25 | 0.03 | -0.42 | -0.48 | 1.07 | 0.50 | 2.16 | 1.45 | 1.82 |
| $\delta_1$ | -0.67 | -0.21 | -0.45 | -0.33 | 0.41 | -0.23 | -0.26 | 0.34 | 0.27 | -0.04 | 0.24 | 0.40 | 0.67 |
| $\delta_2$ | -0.31 | -0.27 | -0.11 | -0.04 | 0.17 | -0.06 | -0.15 | -0.03 | 0.10 | 0.17 | 0.16 | 0.18 | 0.27 |
| $\delta_0^E$ | -0.09 | 0.09 | -0.06 | 0.05 | 0.04 | -0.23 | -0.30 | -0.04 | 0.35 | 0.12 | -0.22 | 0.06 | 0.19 |
| $\delta_1^E$ | -0.05 | -0.11 | -0.04 | -0.02 | -0.10 | -0.25 | 0.19 | -0.03 | -0.13 | 0.10 | 0.31 | 0.17 | 0.08 |
| $\rho$ | 0.94 | 0.19 | 0.11 | 0.56 | -0.84 | -0.09 | 0.45 | 0.11 | -0.03 | -0.06 | -0.69 | 0.09 | -0.64 |
| $\sigma_\nu$ | 0.03 | 0.00 | 0.07 | 0.04 | -0.05 | 0.02 | 0.03 | 0.02 | -0.01 | -0.04 | -0.03 | -0.13 | 0.03 |
| $\sigma_\epsilon$ | 0.00 | -0.03 | 0.03 | 0.03 | -0.02 | 0.05 | -0.05 | -0.01 | 0.01 | 0.02 | 0.01 | -0.02 | -0.04 |
| $\sigma_i$ | 0.03 | -0.04 | -0.16 | 0.12 | 0.04 | 0.08 | -0.03 | -0.01 | 0.03 | -0.10 | -0.00 | 0.05 | -0.01 |
| $\kappa$ | 0.02 | 0.02 | 0.01 | 0.01 | 0.04 | 0.01 | -0.01 | -0.02 | -0.02 | -0.01 | -0.03 | -0.03 | -0.01 |
| $\iota$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

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

*Panel C: Income Process Moments*

| | SD at 22 | SD at 32 | SD at 42 | SD at 52 | SD at 62 | $\beta_1$ | $\beta_2$ | P10 1-Yr | P10 5-Yr | P90 1-Yr | P90 5-Yr | $\beta_0^E$ | $\beta_1^E$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\phi$ | 0.27 | 0.24 | 0.25 | 0.28 | 0.31 | 0.01 | -0.02 | -0.03 | -0.07 | 0.03 | 0.07 | -0.14 | 0.14 |
| $\lambda$ | 0.04 | 0.03 | 0.04 | 0.05 | 0.05 | 0.01 | -0.01 | -0.01 | -0.02 | 0.01 | 0.02 | -0.04 | 0.03 |
| $f_L$ | 0.00 | -0.00 | -0.00 | -0.00 | -0.01 | 0.00 | -0.00 | 0.00 | 0.00 | -0.00 | -0.00 | 0.00 | -0.00 |
| $f_H$ | -0.04 | -0.03 | -0.03 | -0.03 | -0.05 | -0.01 | 0.02 | 0.01 | 0.02 | -0.01 | -0.02 | 0.02 | -0.02 |
| $\beta$ | -0.27 | -0.21 | -0.14 | -0.15 | -0.14 | 0.15 | -0.12 | 0.03 | 0.06 | -0.02 | -0.06 | 0.10 | -0.10 |
| $\delta_0$ | -1.06 | -0.64 | -0.82 | -1.13 | -0.50 | -0.36 | 0.43 | 0.02 | 0.06 | 0.02 | -0.04 | 0.27 | -0.35 |
| $\delta_1$ | -0.13 | -0.15 | -0.24 | -0.41 | -0.22 | 0.87 | 0.21 | 0.02 | 0.04 | 0.01 | -0.01 | 0.18 | -0.17 |
| $\delta_2$ | -0.10 | -0.08 | -0.15 | -0.24 | -0.04 | -0.11 | 1.27 | 0.02 | 0.04 | 0.00 | -0.01 | 0.10 | -0.10 |
| $\delta_0^E$ | -0.05 | 0.07 | 0.17 | 0.24 | 0.28 | -0.00 | 0.00 | -0.00 | -0.00 | 0.00 | -0.00 | 1.00 | -0.02 |
| $\delta_1^E$ | -0.05 | 0.08 | 0.28 | 0.50 | 0.71 | 0.08 | 0.02 | -0.00 | -0.01 | 0.00 | 0.01 | 0.06 | 0.95 |
| $\rho$ | 0.71 | 9.63 | 11.64 | 11.20 | 8.87 | -0.35 | 0.37 | 0.05 | -0.69 | -0.04 | 0.68 | -0.32 | 0.28 |
| $\sigma_\nu$ | 0.04 | 1.49 | 1.76 | 1.63 | 1.28 | -0.03 | 0.04 | -0.55 | -0.83 | 0.55 | 0.83 | -0.08 | 0.07 |
| $\sigma_\epsilon$ | 0.10 | 0.09 | 0.09 | 0.07 | 0.04 | -0.01 | 0.01 | -0.44 | -0.15 | 0.44 | 0.15 | 0.00 | -0.00 |
| $\sigma_i$ | 1.86 | 0.45 | 0.10 | 0.02 | 0.00 | -0.00 | 0.00 | -0.01 | -0.04 | 0.01 | 0.04 | -0.00 | 0.00 |
| $\kappa$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | -0.00 | -0.00 | -0.00 | 0.00 | 0.00 | -0.00 | 0.00 |
| $\iota$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Panel D: Remaining Estimation Targets*

| | Ratio: Q4 to Q1 Debt | Mean $\ell$ | Fraction No Adjustment | Kurtosis $\Delta \log \ell$ | Persistence 2004-2005 |
|---|---|---|---|---|---|
| $\phi$ | 0.22 | -0.20 | -0.05 | 0.29 | 0.06 |
| $\lambda$ | 0.19 | 0.01 | -0.02 | -0.03 | 0.36 |
| $f_L$ | 0.04 | -0.00 | 0.00 | 1.88 | -0.13 |
| $f_H$ | 0.02 | -0.01 | 0.02 | 1.56 | 0.01 |
| $\beta$ | 0.81 | 0.07 | 0.01 | -6.30 | 3.43 |
| $\delta_0$ | 1.77 | 1.54 | -0.11 | 9.16 | 6.03 |
| $\delta_1$ | 0.71 | 0.38 | -0.03 | 0.75 | -0.91 |
| $\delta_2$ | 0.15 | 0.22 | -0.02 | -1.06 | 0.44 |
| $\delta_0^E$ | 0.16 | 0.07 | -0.01 | 1.03 | 0.27 |
| $\delta_1^E$ | 0.32 | 0.11 | -0.01 | -5.83 | -0.00 |
| $\rho$ | -1.08 | -0.12 | -0.26 | 22.39 | -1.69 |
| $\sigma_\nu$ | -0.18 | -0.02 | -0.09 | 1.77 | -0.87 |
| $\sigma_\epsilon$ | -0.02 | 0.00 | -0.01 | 1.52 | -0.64 |
| $\sigma_i$ | -0.01 | -0.00 | -0.01 | -1.94 | 1.01 |
| $\kappa$ | -0.04 | -0.10 | 0.00 | -1.16 | -0.08 |
| $\iota$ | 0.00 | 0.00 | -0.87 | -3.33 | 0.00 |

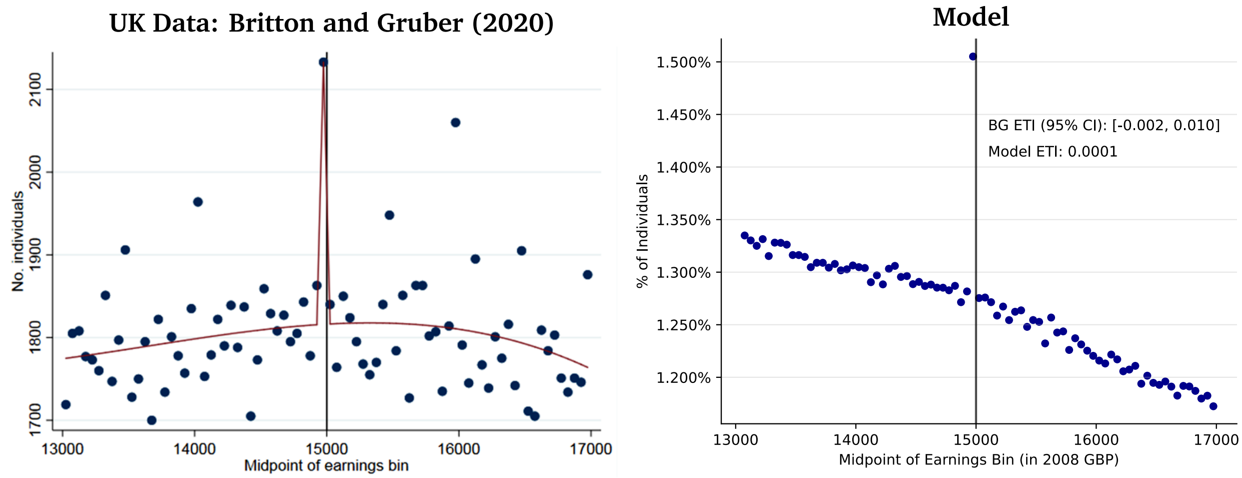
*Notes:* This table reports the elasticity of the simulated estimation targets with respect to the estimated structural parameters. The four panels present the results for different sets of estimation targets. In each panel, the entry in row $i$ and column $j$ is an estimate of the derivative of the log of the estimation target in column $j$ with respect to the log of the structural parameter in row $i$. I approximate this derivative locally around the estimated set of structural parameters in column (5) of Table 3 by central differencing. Since some estimation targets and parameters are negative, I take the absolute value before taking logarithms and then multiply the result by $-1$ if the parameter or estimation target is negative. The width between the lower and upper points in central differencing is set equal to the step size used in the Nelder–Mead optimization routine in estimating the model.

**Table A5**. Model Fit: Other Estimation Targets

| | Data | Model |
|---|---|---|
| Cross-Sectional Variance of Log Labor Income at Age 22 | 0.453 | 0.448 |
| Cross-Sectional Variance of Log Labor Income at Age 32 | 0.555 | 0.470 |
| Cross-Sectional Variance of Log Labor Income at Age 42 | 0.577 | 0.503 |
| Cross-Sectional Variance of Log Labor Income at Age 52 | 0.539 | 0.568 |
| Cross-Sectional Variance of Log Labor Income at Age 62 | 0.608 | 0.665 |
| Linear Age Profile Term | 0.077 | 0.071 |
| Quadratic Age Profile Term | −0.001 | −0.001 |
| Education Income Premium Constant | −0.574 | −0.559 |
| 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 | −0.702 |
| 90th Percentile of 1-Year Labor Income Growth | 0.415 | 0.407 |
| 90th Percentile of 5-Year Labor Income Growth | 0.698 | 0.706 |
| Average Labor Supply | 1.000 | 0.813 |
| Probability that Labor Supply Not Adjusted | 0.422 | 0.375 |
| Kurtosis of Changes in Log Hours | 5.637 | 5.721 |
| Bunching Ratio: Q4 Debt to Q1 Debt | 1.173 | 1.222 |
| Bunching Probability in 2005 Conditional on Bunching in 2004 | 0.020 | 0.020 |

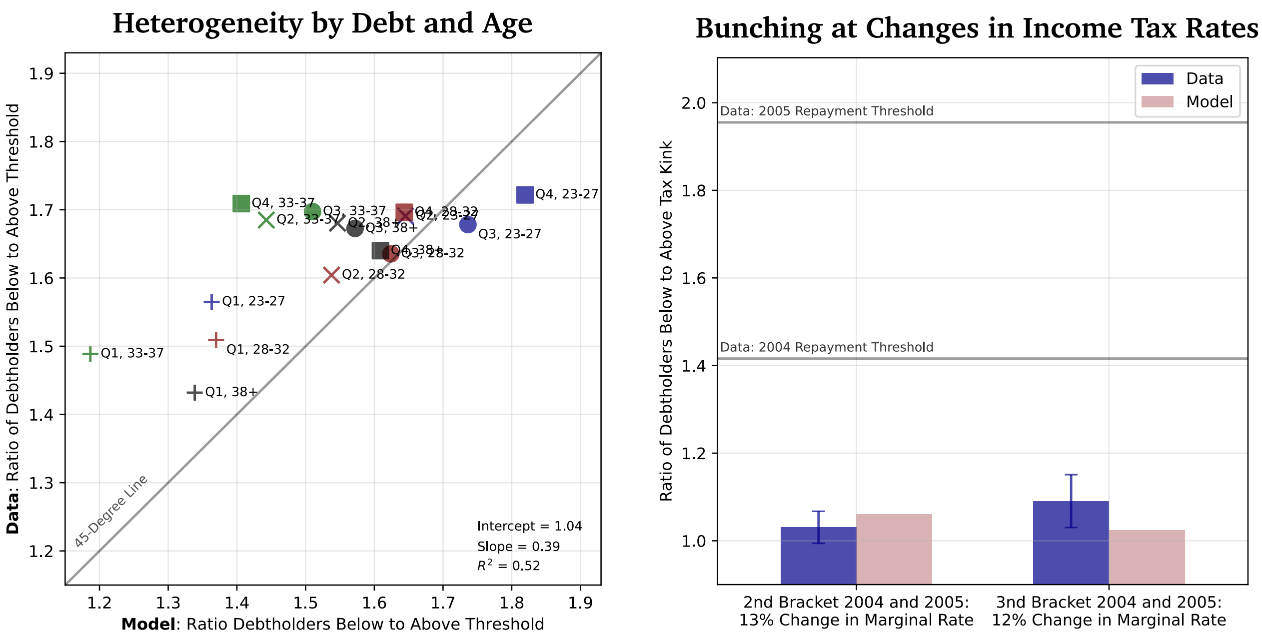
*Notes:* This table shows the value of the remaining estimation targets not shown in Figure 8 in the data and the model with parameters set at the estimated values in column (5) of Table 3.

**Figure A15**. Bunching around UK Income-Contingent Repayment Threshold



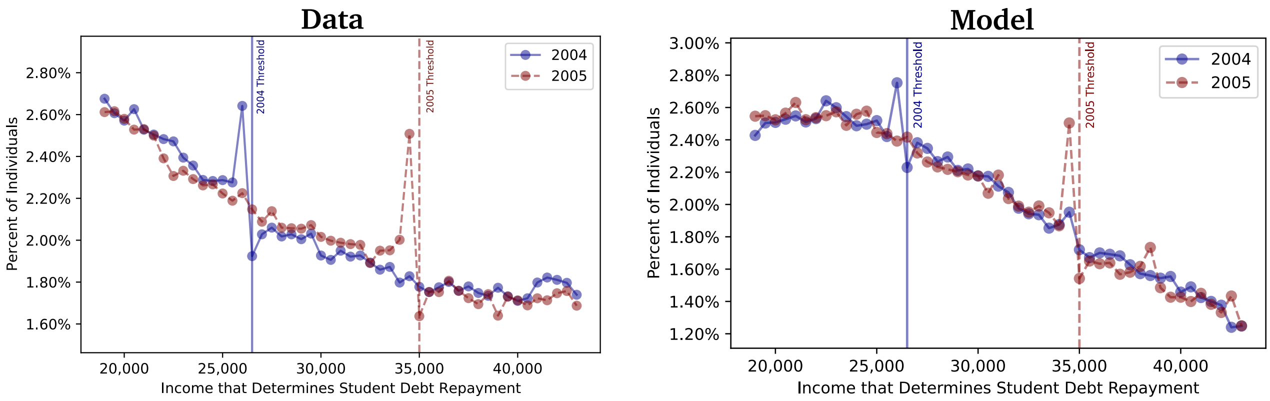

*Notes:* The left panel of this figure reproduces Figure 5 from Britton and Gruber (2020). This figure shows the income distribution in bins of £50 of student debtholders in years 2006-2012 around the £15,000 repayment threshold, at which the marginal repayment rate changes from 0% to 9% of taxable income. The sample is a 10% random sample of all students; see Britton and Gruber (2020) for additional details. The right panel shows the income distribution for debtholders generated by the model at the parameter values in column (5) of Table 3. To generate this plot, I change the debt repayment function in the model to be an income-contingent loan with a 9% marginal rate above $30,421 AUD, which corresponds to converting £15,000 from 2008 GBP to 2005 GBP using the CPI, and then adjusting to 2005 AUD using the exchange rate of 2.2 AUD/GBP, and an interest rate of $r_d = 1\%$, as is the case in the UK during this time period. The marginal tax rate at the repayment threshold in the model is 30% compared to 33% and 31% in the UK over this time period. The elasticity of taxable income (ETI) shown in the right panel for “BG” corresponds to the 95% confidence interval from Table 6 in Britton and Gruber (2020). The estimate for “Model” corresponds to applying the exact same approach on the model-generated data, adjusting for the differences in marginal income tax rate.

**Figure A16**. Fit of Model on Nontargeted Bunching Statistics



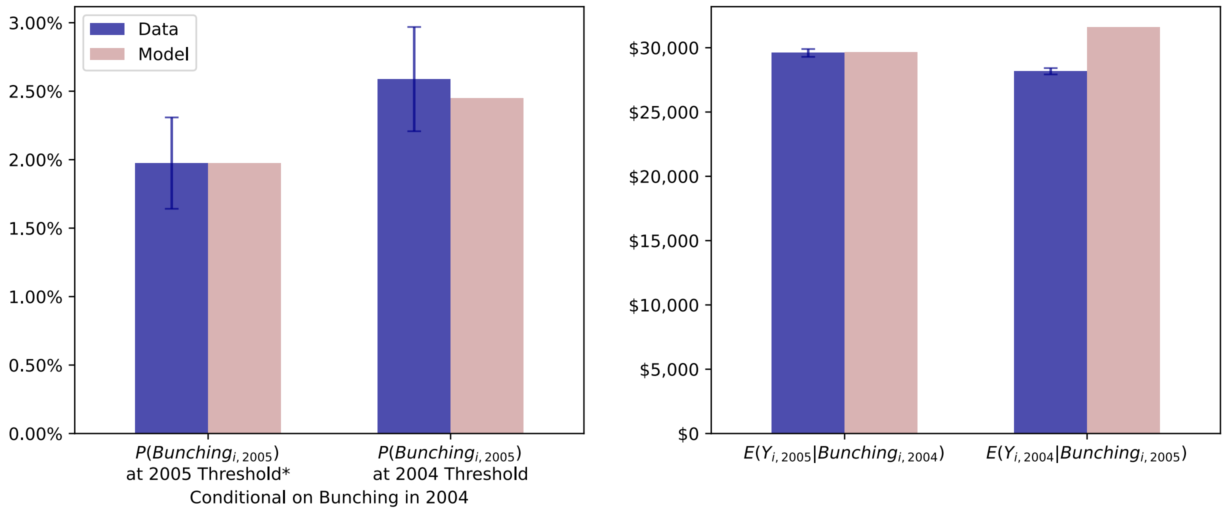

*Notes:* The left panel of this figure shows a scatterplot of bunching below the 2005 repayment threshold for different samples in the data versus the model. Each point corresponds to a different sample based on quartiles of debt and age labeled in the plot. The quartiles of debt are calculated in the data after taking out year fixed effects and adjusting for inflation. These same quartiles are used in the model. Each age group is plotted in a different color, and each quartile of debt has a differently shaped marker on the plot. For each sample, bunching is measured as the ratio of the number of debtholders with \$500 below to \$500 above different thresholds. The right panel shows the ratio of the number of debtholders with \$250 below to \$250 above different thresholds computed around two points with changes in marginal income tax rates in 2004 and 2005 using taxable income instead of HELP income in the data (there is no difference in the model). This panel also contains two horizontal lines at the values of the same bunching statistics computed around the two repayment thresholds for reference. Tax brackets are fixed in nominal terms, so when pooling 2004 and 2005, I adjust the thresholds and income using the HELP threshold indexation rate. Data values are presented in blue with 95% confidence intervals based on bootstrapped standard errors with 1000 iterations. Model values are presented in red. The sample is the *ALife* sample defined in Section 1.4 between 2005 and 2018, restricted to debtholders between 23 and 64. I impose the same sample filters in the model.

**Figure A17**. Fit of Model in Years Surrounding Policy Change




*Notes:* The left panel of this figure reproduces Figure 1. The right panel makes the analogous plot based on simulations from the baseline model with parameters set to the values in column (5) of Table 3.

**Figure A18**. Fit of Model on Within-Individual Moments around Policy Change




*Notes:* This figure shows how the model compares to the data on some panel-based moments in the years surrounding the policy change. In both panels, bunching is defined as individuals who are with $500 of the relevant threshold. The left panel restricts to individuals who are bunching below the 2004 repayment threshold in 2004, and plots two statistics: (i) the probability that they are bunching below the new 2005 repayment threshold in 2005, after the policy change; (ii) the probability that they remain bunching below the old 2004 repayment threshold in 2005, after the policy change. The right panel plots two statistics: (i) the average income in 2005, after the policy change, of individuals who were bunching below the 2004 repayment threshold before the policy change; (ii) the average income in 2004, before the policy change, of individuals that were bunching below the 2005 repayment threshold after the policy change. Data values are presented in blue with 95% confidence intervals; model values are presented in red. The * in the left panel indicates that this moment was targeted in estimation; all other moments were not targeted.

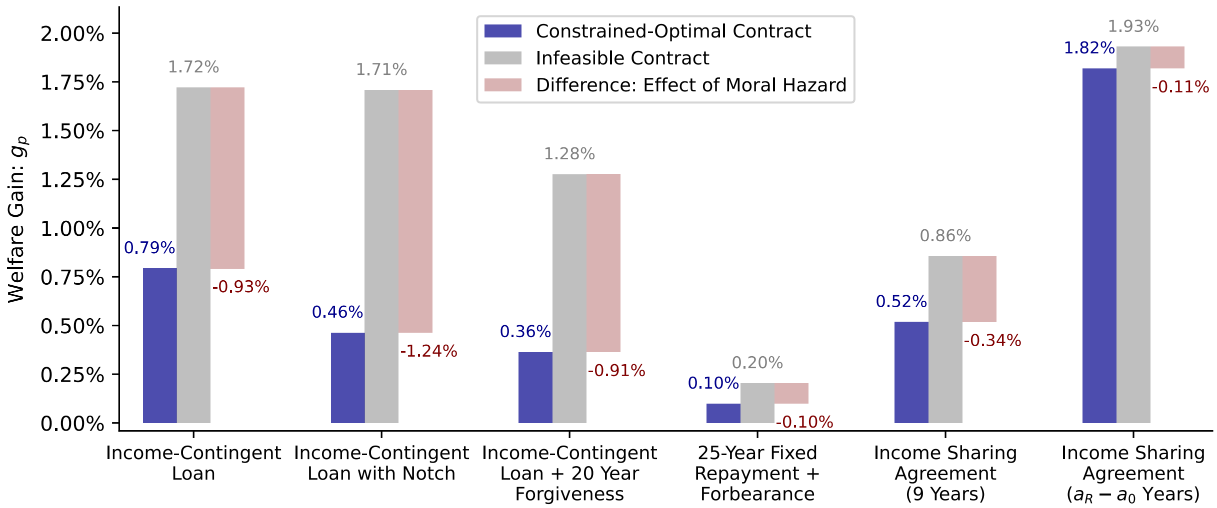
## F.4 Results Discussed in Section 4

**Table A6**. Fiscal Cost Decomposition of Moving from 25-Year Fixed Repayment to Alternative Contracts

| Policy: $p$ | $\Delta\mathcal{G}_p$ | $\Delta\mathcal{G}_p$ with $\ell$ Fixed | $\Delta\mathcal{G}_p$ from $\ell$ Response |
|---|---|---|---|
| HELP 2004 | -$983 | $261 | -$1,244 |
| HELP 2005 | -$1,635 | -$105 | -$1,529 |
| US IBR | -$516 | $679 | -$1,195 |
| US SAVE | -$3,111 | -$2,000 | -$1,111 |
| US IBR + Fixed Cap | -$1,453 | -$990 | -$463 |
| US SAVE + Fixed Cap | -$3,702 | -$2,992 | -$710 |
| US IBR + Forgiveness | -$1,745 | -$516 | -$1,228 |
| US SAVE + Forgiveness | -$5,370 | -$4,403 | -$967 |
| Purdue ISA | -$738 | $1,195 | -$1,933 |

*Notes:* This table decomposes the total fiscal cost associated with moving from the benchmark 25-year fixed repayment contract to alternative repayment contracts from the left panel of Figure 9 indicated in the first column. The second column repeats the same values in column (5) of Table 4. The third column computes the change in fiscal cost assuming that $\ell_{ia}$ remains fixed at its value under the benchmark contract for all $i$ and $a$. The final column reports the difference between the prior two columns, which represents the fiscal cost that comes from adjustments in labor supply.

**Figure A19**. Effect of Moral Hazard on Welfare Gains




*Notes:* This figure decomposes the welfare gains, $g_p$, from Table 5, repeated in the left blue bar for each contract, into two components. The middle gray bar corresponds to the welfare gain that would exist if the contract shown in the final two columns of Table 5 was implemented in the baseline model with endogenous labor supply. This contract is not feasible because it was the solution to (14) assuming that $\ell_{ia}$ remains fixed at its value under the benchmark contract for all $i$ and $a$. The right red bar plots the difference between the two bars, which corresponds to the loss from moral hazard.

**Table A7.** Parameters and Welfare Effects of Constrained-Optimal Contracts: Model with $f_H = \infty$

| Contract Space: $p$ | $\psi_p$ | $K_p$ | $\pi_p$ | $g_p$ | $\psi_p^{\ell \text{ fixed}}$ | $K_p^{\ell \text{ fixed}}$ |
|---|---|---|---|---|---|---|
| Income-Contingent Loan | 14% | \$31,055 | \$4,821 | 1.18% | 59% | \$62,022 |
| Income-Contingent Loan with Notch | 5.5% | \$37,704 | \$4,978 | 1.21% | 14% | \$67,315 |
| Income-Contingent Loan + 20 Year Forgiveness | 26% | \$27,877 | \$3,047 | 0.76% | 40% | \$42,285 |
| 25-Year Fixed Repayment + Forbearance | 0.17% | . | \$1,558 | 0.40% | 0.07% | . |
| Income Sharing Agreement (9 Years) | 3.4% | . | \$2,494 | 0.63% | 3.0% | . |
| Income Sharing Agreement ($a_R - a_0$ Years) | 0.52% | . | \$7,374 | 1.75% | 0.48% | . |

*Notes:* This table reproduces Table 5 in the model estimated in column (4) of Table 3.

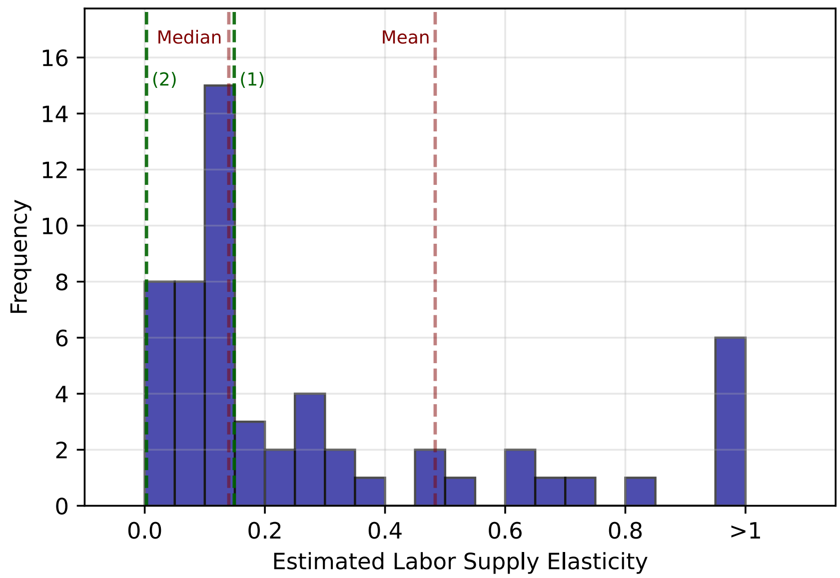
## F.5 Results Discussed in Online Appendix

**Table A8.** Comparison of Australia and US

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

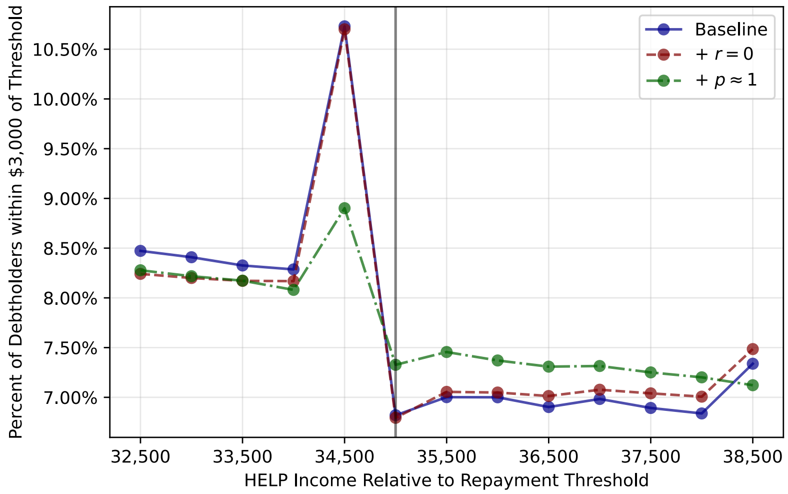
*Notes:* The sources for various statistics are shown as hyperlinks. All statistics are computed in the most recent year available.

**Figure A20**. Distribution of Estimated Labor Supply Elasticities from Prior Studies




*Notes:* This figure plots a histogram of the intensive margin labor supply elasticities estimated in prior literature. I combine the estimates reported in Tables 6 and 7 of Keane (2011) and Table 1 of Chetty et al. (2012). These estimates include intensive margin Frisch (i.e., marginal utility–constant) and Hicksian (i.e., wealth-constant) elasticities estimated among studies that measure labor supply using hours worked or taxable income, which have the closest structural interpretation to my estimates. This graph pools all studies, some using full populations, others using just men or women. See Keane (2011) and Chetty et al. (2012) for a detailed discussion of the underlying studies. In the histogram, all studies that estimate a value above one are placed into the last bar, but the mean and median, shown in dashed red lines, are calculated before these observations are trimmed. The two dashed green lines plot the estimates from columns (1) and (5) of Table 3, respectively.

**Figure A21**. Decomposition of Bunching Below the Repayment Threshold




*Notes:* This figure plots the income distribution in bins of $500 around the 2005 repayment threshold between 2005 and 2018 in three different models. The first model, Baseline, corresponds to the baseline model estimated in column (5) of Table 3 after the calibrated value of $R$ in Table 2 is replaced with $\beta^{-1}$. The second model, $+r = 0$, corresponds to additionally setting $r_d = \beta^{-1} - 1$ in the first model. The third model, $+p \approx 1$, corresponds to taking the second model and setting $D_0 = 4\% * \$35000 = \$1400$ for all borrowers. Then, for each year in which borrowers have debt in the second model, borrowers' debt balances in the third model are unanticipatedly reset to $\$1400$, regardless of whether they paid it off in the prior period. The purpose of this third model is to (approximately) make borrowers anticipate repayment with probability one, while ensuring the set of borrowers who have positive debt balances in each year are the same as in the second model.

**Table A9.** Welfare Effects Before and After Redistribution-Neutralizing Transfers

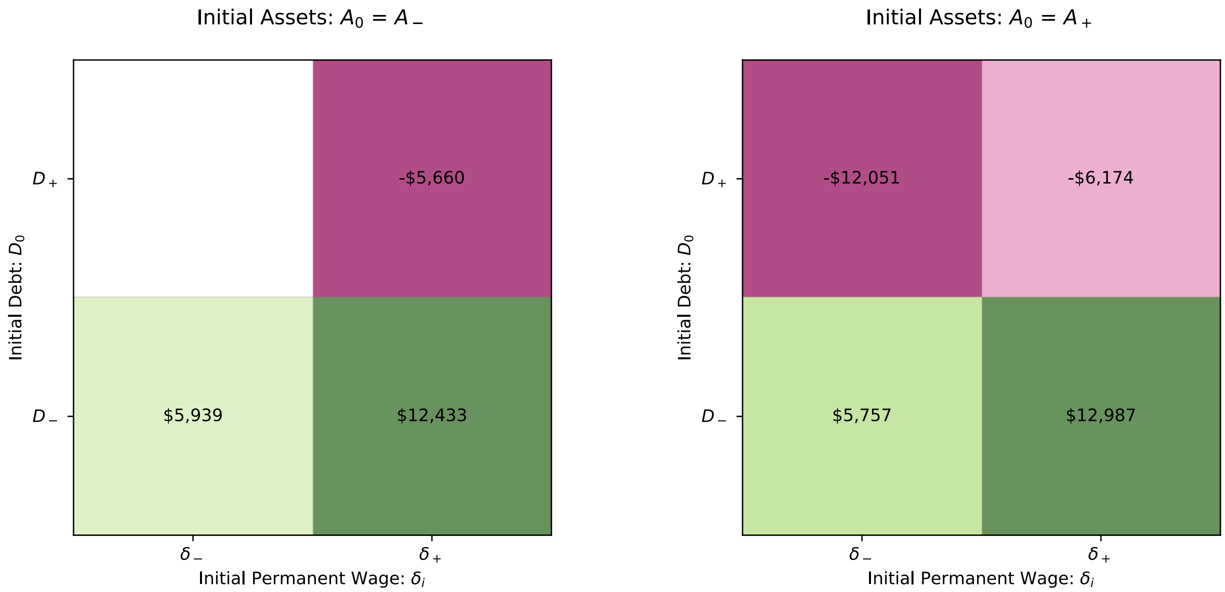
| Contract Space: $p$ | $\pi_p^{\text{Before}}$ | $\pi_p^{\text{After}}$ | $g_p^{\text{Before}}$ | $g_p^{\text{After}}$ |
|---|---|---|---|---|
| Income-Contingent Loan | \$4,012 | \$1,616 | 1.03% | 0.50% |
| Income Sharing Agreement ($a_R - a_0$ Years) | \$6,182 | . | 1.75% | . |

*Notes:* This table shows the effects of moving from the benchmark 25-year fixed repayment contract to constrained-optimal repayment contracts that solve (14) within the different contract spaces indicated in the first column. The second and third columns show the two welfare metrics, $\pi_p$ and $g_p$. These values differ from Table 5 because the set of initial conditions is different and has been discretized into $\mathcal{T}$ values. The final two columns show the same welfare metrics that come from solving (14) with lump-sum transfers made at $a_0$ to borrowers in each $\mathcal{T}$ possible initial state to ensure the government budget remains unchanged at each of these states. The values of these transfers are shown in Figure A22. See Appendix D.9 for additional details on this analysis.

**Figure A22**. Redistribution-Neutralizing Transfers for Constrained-Optimal Contracts

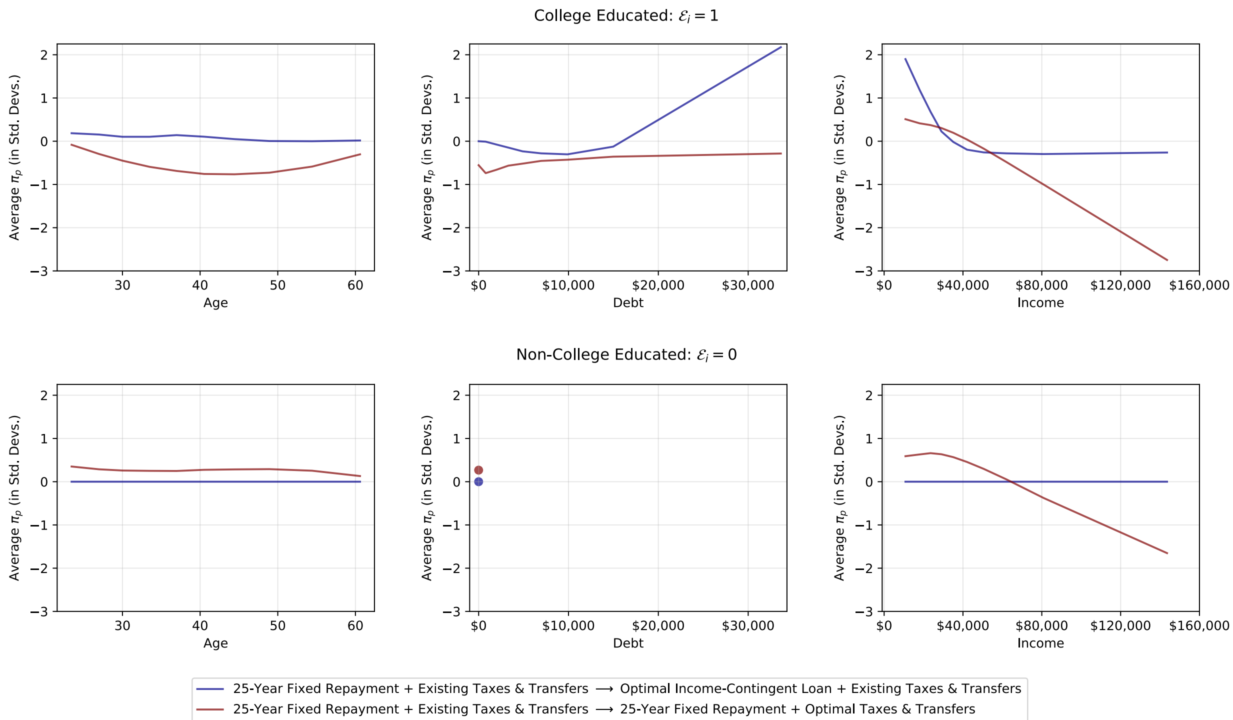
*Panel A: Income-Contingent Loan*


*Panel B: Income-Sharing Agreement ($a_R - a_0$ Years)*



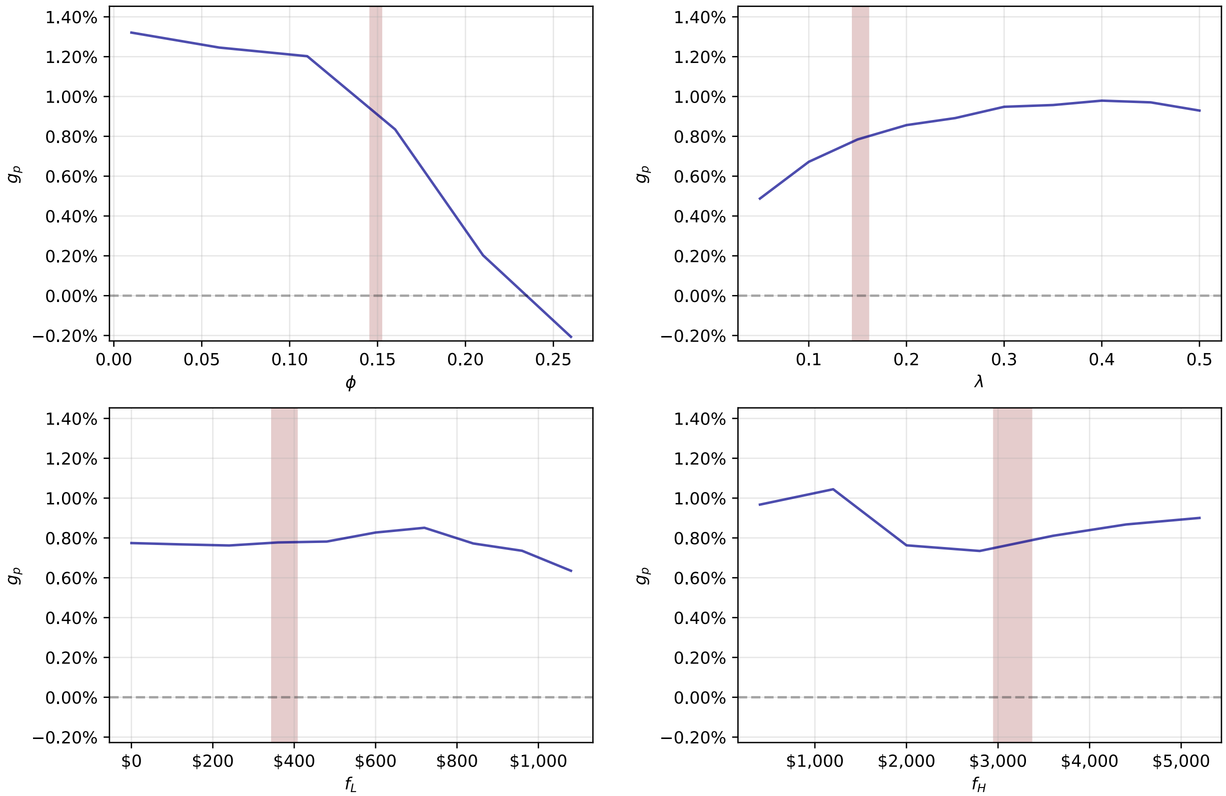

*Notes:* This figure shows the transfers in each of the $\mathcal{T} = 8$ initial states made to eliminate the redistributive effects of different constrained-optimal contracts described in Table A9. The missing value in Panel B corresponds to a case in which no transfer could be found to balance the government budget in that state. See Appendix D.9 for additional details and the discretized values of the three initial conditions.

**Figure A23**. Comparison of Debt Restructuring with Changing Taxes & Transfers




*Notes:* This figure compares the results from two experiments. The first experiment holds $\tau(\cdot)$ fixed and changes the debt repayment function from the benchmark fixed repayment contract to the constrained-optimal income-contingent loan in Table 5. The second holds the debt repayment function fixed and changes $\tau(\cdot)$. In the first experiment, $\tau(\cdot)$ is equal to the Heathcote et al. (2017) functional form calibrated to the Australian tax schedule, as described in Appendix D.3. In the second experiment, $\tau(\cdot)$ is equal to the Heathcote et al. (2017) functional form, where the two parameters of this tax function have been chosen to maximize the expected utility at $a = a_0$ of an individual that does not know any of her initial states and views their realizations as risk. In both experiments, the simulation procedure follows the same procedure used to estimate the model, where the policy change occurs at $t = T^*$. This figure then plots the average of $\pi_p$ in each experiment across all individuals that have the value of the state shown on the horizontal axis. The top axis focuses on individuals with $\mathcal{E}_i = 1$, while the bottom focuses on those with $\mathcal{E}_i = 0$. In all panels, the welfare gains shown are normalized by the standard deviation of $\pi_p$ across all states within each experiment so that the distribution of gains from the two experiments have similar magnitudes.

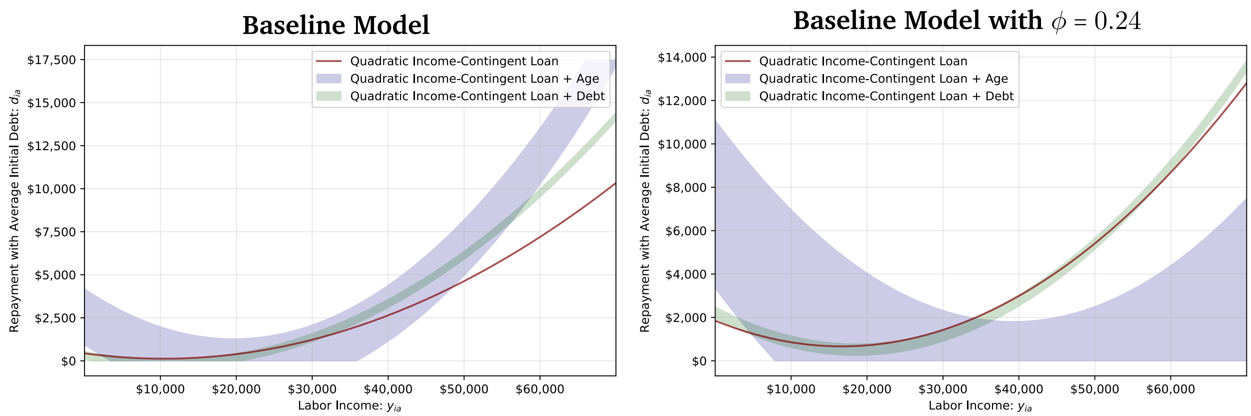
**Figure A24**. Welfare Gains from Income-Contingent Loan as a Function of Model Parameters




*Notes:* This figure shows the consumption-equivalent welfare gain from solving for the constrained-optimal income-contingent loan in the baseline model as a function of different model parameters. In each panel, the parameter on the horizontal axis is the only parameter that varies, while all other parameters are held fixed at their values in column (5) of Table 3. (14) is then resolved for each value of the parameter on the horizontal axis. The shaded red regions correspond to the 95% confidence intervals from column (5) of Table 3.

**Figure A25**. Welfare Gains from Smooth Repayment Contracts

*Panel A: Repayment Functions for Constrained-Optimal Contracts*




*Panel B: Parameters and Welfare Effects of Constrained-Optimal Contracts: Baseline Model*

| Contract Space: $p$ | $\theta_1$ | $\theta_2$ | $\theta_3 \times 1000$ | $\theta_4$ | $\pi_p$ | $g_p$ |
|---|---|---|---|---|---|---|
| Quadratic Income-Contingent Loan | $435 | -0.06 | 0.0029 | . | $2,524 | 0.73% |
| Quadratic Income-Contingent Loan + Age | $365 | -0.30 | 0.0075 | 0.005 | $3,399 | 0.94% |
| Quadratic Income-Contingent Loan + Debt | $25 | -0.09 | 0.0041 | 0.014 | $2,657 | 0.77% |

*Panel C: Parameters and Welfare Effects of Constrained-Optimal Contracts: Baseline Model with* $\phi = 0.24$

| Contract Space: $p$ | $\theta_1$ | $\theta_2$ | $\theta_3 \times 1000$ | $\theta_4$ | $\pi_p$ | $g_p$ |
|---|---|---|---|---|---|---|
| Quadratic Income-Contingent Loan | $1,850 | -0.14 | 0.0043 | . | $614 | 0.19% |
| Quadratic Income-Contingent Loan + Age | $1,993 | -0.47 | 0.0060 | 0.011 | $2,011 | 0.60% |
| Quadratic Income-Contingent Loan + Debt | $1,898 | -0.18 | 0.0049 | 0.016 | $805 | 0.25% |

*Notes:* Panel A of this figure shows repayments as a function of income for the richer contract spaces described in Appendix D.12. The shaded regions in this plot correspond to the repayments for individuals with initial debt balances between the 10th and 90th percentiles and with ages between the 10th and 90th percentiles at which the final debt repayment is made in the baseline model. Panels B and C show the corresponding welfare gains in the two different models used in Panel A: the baseline model, and the baseline model with $\phi = 0.24$ while all other parameters are held fixed.

**Table A10.** Welfare Gains from Constrained-Optimal Income-Contingent Loans in Alternative Models

| Estimated Models | $\psi_p$ | $K_p$ | $\pi_p$ | $g_p$ |
|---|---|---|---|---|
| Baseline Model | 16% | $19,188 | $2,778 | 0.79% |
| $f_L = f_H$ Model | 16% | $31,786 | $3,456 | 1.35% |
| $f_L = 0, f_H = \infty$ Model | 37% | $38,390 | $4,997 | 1.61% |
| $f_H = \infty$ Model | 14% | $31,055 | $4,821 | 1.18% |
| **Deviation from Baseline Model** | $\psi_p$ | $K_p$ | $\pi_p$ | $g_p$ |
| US Tax System | 15% | $18,539 | $2,599 | 0.65% |
| Optimized Tax System | 6% | $2,104 | $24 | 0.01% |
| Lower RRA = 1.5 | 14% | $18,565 | $1,429 | 0.44% |
| Higher RRA = 4 | 22% | $20,856 | $5,551 | 1.74% |
| Lower EIS = 0.25 | 18% | $18,524 | $2,404 | 0.84% |
| Higher EIS = 1.5 | 11% | $17,151 | $2,238 | 0.52% |
| Wealth Effects on $\ell$ | 33% | $34,083 | $3,129 | 0.76% |
| Less Persistence: $\rho$ = 0.8 | 33% | $37,518 | $2,963 | 0.83% |
| More Persistence: $\rho$ = 0.99 | 8% | $2,782 | $1,700 | 0.49% |
| US Initial Debt Levels | 27% | $16,994 | $9,838 | 3.03% |
| Higher Debt Interest Rate: $R_d = 2\%$ | 28% | $43,863 | $6,776 | 1.88% |
| Government Discount Rate = $R + 2\%$ | 33% | $33,095 | $5,044 | 1.43% |

*Notes:* This table shows results from repeating the analysis in the first row of Table 5. The top panel of the table shows the results in the baseline model, as well as the three additional models with optimization frictions estimated in Table 3. The bottom panel shows the results in the baseline model with the deviations stated in the first column and described in further detail in Appendix D.13.

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