Progressive Income-Contingent Student Loans*

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Abstract

Progressive income-contingent loans (ICLs), where repayment rates rise with income, provide college students with insurance against post-graduation income risks. We study how ICL progressivity shapes repayment dynamics, educational choices, and welfare. Using Australian longitudinal survey data, we estimate income processes and parsimoniously parameterize ICL repayment rules to isolate how repayment size and progressivity affect repayment dynamics over the lifecycle. We then construct a heterogeneous-agent life-cycle model, estimated using the method of simulated moments, to evaluate policy responses of educational attainment and welfare. We find that optimal repayment sizes are negatively associated with progressivity. Existing ICL policies in several developed economies are generally more progressive than is optimal, given their repayment sizes. Welfare can be improved by either increasing average per-period repayments or reducing progressivity, with the optimal ICL combining moderate progressivity with gradual repayment.

Keywords: Student loans, income-contingent loans, progressivity, heterogeneous-agent life-cycle model

JEL Classification: E24, D15, H52, I22, J24

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1 Introduction

Income-contingent loans (ICLs) serve two key roles in financing higher education. First, like traditional student loans, they relax borrowing constraints while students are enrolled in college. Second, they provide insurance against post-graduation income risks, as required repayments fall when income is low and rise when income is high. Neither function is readily available in private credit markets, given that prospective students typically lack collateral. As a result, ICLs have become a central policy instrument for financing higher education in many developed economies.

The insurance role of ICLs has become more important as higher education increasingly exhibits high cost, high risks, but also high returns. Over the past thirty years, tuition fees have quadrupled in the US and tripled in both the UK and Australia. Dropout rates remain substantial, at around 30%. Even after receiving their degrees, graduates still face employment and earnings risks in the labor market. Despite these costs and risks, college attendance has continued to increase in developed economies, as college premium remains high – between 1.5 and 2.0. A growing share of young adult population with college experience – but not necessarily college degrees as some may drop out – now hold large amounts of student debt, which many struggle to repay.

In this study, we analyze the effects of ICL progressivity – i.e., how the share of income devoted to repayment changes with income level – on educational choices and welfare. Progressivity in ICLs enhances the insurance role of ICLs: higher-income borrowers devote a larger share of income to repayment while lower-income borrowers devote less. We show that progressive ICL, combined with the right level of average repayment per period, provides the highest social welfare.

We use Australian data to study the role of progressivity in ICLs, while providing insights relevant to other developed economies. In recent decades, countries such as the United Kingdom, the United States, and Canada have all transitioned from non-contingent student loans to ICLs. In Australia, where our analysis is based, student loans have always been income-contingent since their introduction in 1989. Repayments in Australia have also always been progressive and have become increasingly so, following successive reforms documented in Section 2.2. Australian data therefore provides a useful benchmark for evaluating both existing progressive ICLs and potential policies, which may be optimal but have not yet been implemented.

Our main results show that the optimal ICL is progressive, but less so than existing ICLs in Australia and the United Kingdom. The optimal ICL also features smaller and slower repayments and must be supported by higher income taxes to remain revenue neutral. Under the optimal ICL, borrowers repay a smaller share of their income and often do not finish repaying the loan until they are in their forties. Such a policy design helps borrowers smooth consumption in the presence of borrowing constraints, which are most binding early in the working life.

While there is extensive literature on progressivity in the context of income taxation (e.g., Heathcote, Storesletten and Violante (2017)), progressivity in the case of ICLs differs in a crucial dimension – unlike taxable income, the total amount of debt to be repaid is fixed.[1] As a result, progressivity in ICLs also affects the timing of repayments, with higher-income borrowers finishing repaying sooner than lower-income ones. Repayment timing subsequently affects welfare, both because the present value of total repayments may vary with timing due to subsidized interest rates and, more importantly, because the tightness of borrowing constraints varies over the lifecycle.

We start by documenting reforms in the Australian ICL systems and their impact on educational attainment. We show that, with each reform, tuition fees have increased and repayment schedules have become more progressive.

In order to understand how the ICL repayment rules transform stochastic income process into stochastic repayments over the lifecycle, we estimate the income processes using longitudinal household survey data – 20 waves of HILDA survey from 2001-2020 (Summerfield et al., 2021). Using the estimated income process, we then parameterize the repayment rules using the formulation of Heathcote, Storesletten and Violante (2017), which separates the roles of repayment size and progressivity. The stylized repayment function matches well with empirical ICL rules used in the countries we are interested in.

In order to study the response of private savings, education choices and, ultimately, welfare to ICL policy changes, we develop a Huggett (1996)-style heterogeneous-agent lifecycle model with (i) endogenous decisions on education, consumption and saving/borrowing;

[1] This is generally true unless borrowers never earn enough throughout their working lives to complete repayment. In the case of Australia, this is estimated to be around 20% of the outstanding loans (Ey, 2017).

(ii) exogenous income process, student debt repayment, and parental transfer; and (iii) individual heterogeneity in schooling taste and income shocks. The setup is similar to Abbott et al. (2019), except that we abstract from general equilibrium and endogenous parental linkages. Instead, we fully characterize the income dynamics and the income-contingent repayment regime, which is what our research question calls for.

We estimate the model using a combination of census and HILDA survey data. We adopt a two-stage estimation process commonly used in literature (Arellano, Blundell and Bonhomme, 2017; De Nardi, French and Jones, 2016; Gourinchas and Parker, 2002). First, we estimate income process and policy parameters directly from observed data. Then, we use the method of simulated moments (MSM) to estimate deep, structural parameters, such as psychic costs of schooling and preferences for saving at the end of working life.

We then test alternative income-contingent repayment designs on the estimated model by varying the size and progressivity parameters. We evaluate education attainment, tax rate required for revenue neutrality, and aggregate welfare under both existing and potential policies. We also numerically solve for the optimal repayment function – the combination of size and progressivity parameters that provide the highest aggregate welfare.

1.1 Related literature

Our paper falls within the growing literature that uses Huggett (1996)-style heterogeneous-agent, life-cycle models to study student loans. Ionescu (2009) and Lochner and Monge-Naranjo (2011) are among the first to study the US federal student loans (FSL), with the former focusing on default risks and the latter on human capital investment. Abbott et al. (2019) use a rich model to show that general equilibrium effects and crowding-out of parental transfer are key to evaluating loans and grants. Luo and Mongey (2019) focus on job search and job-related amenities and finds that FSL borrowers choose higher-paying jobs with worse amenities. Hua (2023) endogenizes fertility and finds a negative impact of FSL on fertility among borrowers. Moschini, Raveendranathan and Xu (2022) consider over-optimism in college decisions, which causes FSL to reduce welfare. Kim and Kim (2023) decompose the rise in student debts in the US from 1979 and finds that rising college fees and default rates contributed to debt accumulation. This paper adds to the literature by focusing on the heterogeneity responses of borrowers to progressivity in income-contingent loans.

We also complement the literature on ICLs across countries and methodologies. In the US, where the share of borrowers opting-in the income-contingent plan instead of the default non-contingent plan is low, Mueller and Yannelis (2022) find in a field experiment that prefilling applications forms dramatically increases the take-up rate of IDR plan. Using a life-cycle OLG model, Matsuda and Mazur (2022) simulate the introduction of ICL in the US and found that it increased welfare in the US, with only mild costs from moral hazard. Hanushek, Leung and Yilmaz (2014) highlight the tradeoff between efficiency and inequality for loans and grants and finds ICL to be on the optimal frontier.

We contribute to this strand of literature in two ways. First, we focus on the role played by the shape of the repayment function, including the repayment size and progressivity. Second, we calibrate the model to match the Australian economy using microdata from the HILDA panel study.

As we numerically solve for an optimal repayment schedule, our quantitative results complement the theory literature on dynamic optimal taxation. For example, Stantcheva (2017) shows that, in a model with risky human capital accumulation over the lifecycle, income-contingent loans can achieve the optimum. Solving a Mirrlees (1971)-type economies, Findeisen and Sachs (2016) show that optimal tax design resembles a non-progressive ICL while Farhi and Werning (2013) show that it resembles an age-dependent tax. Paluszynski and Yu (2023) combine the optimal design of student loans with pensions. We numerically compare student loans with various contingency designs and show that ICLs are preferable to non-contingent counterfactuals, which is in line with theory results.

Our results also complement existing empirical studies on income-contingent loans, such as Higgins and Sinning (2013) on the case of Australia; Dearden et al. (2008) on the UK; Cox, Kreisman and Dynarski (2020) on the US. Chapman, Higgins and Stiglitz (2014) provide an overview of theory, practice, and analysis of income-contingent student loan designs across different countries.

The remainder of this paper is organized as follows. Section 2 presents institutional background of the Australian education and ICL system. Section 3 estimates income and repayment dynamics and parameterizes the ICL repayment function. Section 4 introduces the life-cycle model. Section 5 describes the model parameterization and estimation using the method of simulated moments. Section 6 analyzes how the size and progressivity of income-contingent loans affect education choices and welfare. Section 7 concludes with a discussion of policy implications and directions for future research.

2 Institutional Background

We focus our study on the case of Australia, which has a relatively long history of a universal progressive ICL system, with multiple reforms over the past thirty years. Like many other developed countries in recent decades, Australia has also experienced dramatic changes in both the institutional background and the labor market impacts of higher education.

2.1 Student loans in Australia

The income-contingent student loan scheme in Australia, known as the Higher Education Contribution Scheme (HECS), was established in 1989. It is characterized by near-universal take-up rate, zero real interest rate, and repayment rates that increase with income.

Prior to 1989, higher education was free of charge in Australia, but the free education system became incompatible with increasing demand for higher education. The HECS system was established to let students bear some of the cost without having to pay upfront. All students pursuing bachelor's degrees and above are automatically enrolled into the ICL, with upfront payment (i.e. not taking the loans) remaining an option. The loans offer a zero real interest rate, with outstanding debt indexed by the price level. After graduation, repayment is automatically collected by the Australian Tax Office during tax returns, with the ICL repayment schedule announced each year.

The average size of student loans in Australia, while not as large as in the United Kingdom or the United States, is significant. In 2019, total outstanding student debt was \$29 billion Australian dollars, or 5% of Australia's GDP.[2] In 2023/24, the average debt per borrower is \$27,641 Australian dollars. As the median income for a two-person household is around \$70,000, for a household consisting of two college graduates, repaying all of their student debts would cost around 80% of their annual income. In 2023/24, it took an average

[2]See "Higher Education Loan Program (HELP) debt statistics—2018–19": https://www.aph.gov.au/About_Parliament/Parliamentary_departments/Parliamentary_Library/Research/FlagPost/2019/October/HELP_statistics_2018-19

of 10 years after graduation to fully repay student debt under the ICL system.

2.2 Reforms in the Australian ICL system

Since being established in 1989, the Australian ICL system has undergone three major reforms — in 1997, 2004, and 2019[3] — which simultaneously increased tuition fees and made the repayment schedule more progressive.

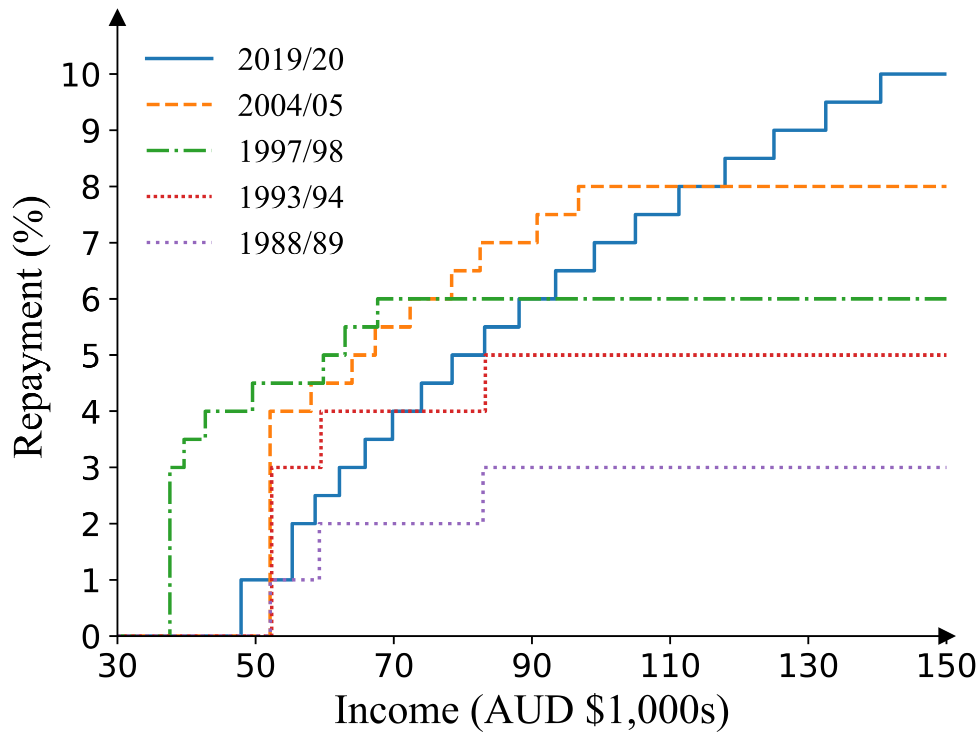

Figure 1: Repayment schedule across reforms

Note. Data from Australian Taxation Office (2022). Income is adjusted for inflation and in units of thousands of 2022 Australian dollars. The years selected in this figure are those immediately after a reform.

Figure 1 illustrates the major changes in the repayment schedules from 1989 until 2022. When it was first introduced in 1989, the repayment schedule consisted of a simple three-tiered structure, with repayment rates ranging from 1% to 3% of income. While the original repayment schedule was progressive (since repayment rates increased with income), it was

[3] Appendix B provides more detailed information about each reform relevant to this paper. Higgins (2019) provides a policymakers' narrative of the 1997 and 2005 reforms.

not too different from a linear ICL. Over the past three decades, the range of repayment rates has increased substantially. The largest change occurred in the most recent reform in 2019, shown as the solid blue line in Figure 1, where the range of variation widened to between 1% and 10%. It is difficult to evaluate the impact of this reform in reduced form, since most students under this scheme have graduated only recently. Therefore, we adopt a structural approach, which also provides guidance on the long-run impact of the newest reform.

Average tuition fees have increased with each reform. From the introduction of the ICL system in 1989 to the latest reform in 2020, tuition fees have more than doubled, from around $4,000 to $10,000 Australian dollars. However, between each reform, tuition fees have remained relatively stable. In our analysis, we mainly use data between 2000 to 2019, where tuition fees remained stable at the 2004/05 reform level. Therefore, we do not focus on the effect of tuition fee increase in our empirical and structural analysis. Instead, we mainly focus on the changes in progressivity of the repayment scheme. Appendix B describes changes in tuition fees in further detail.

3 Income and Repayment Dynamics

Before studying behavioral responses of individuals, such as schooling choices and private borrowing, we first examine how repayment schedules directly affect actual repayments as a stochastic process. As the repayment schedule is essentially a deterministic function applied to the stochastic income process, we conduct this analysis in three steps. First, in Section 3.1, we estimate the stochastic income process as an AR(1) process following data cleaning and estimation procedures similar to previous literature (Guvenen, 2009; Guvenen et al., 2021; Heathcote, Perri and Violante, 2010). Second, in Section 3.2, we parameterize all existing and potential repayment schedules with a two-parameter function based on Heathcote, Storesletten and Violante (2017). Finally, in Section 3.3, we study how repayment parameters affect actual repayment amounts as a stochastic process.

3.1 Estimating income process

We assume the income process depends on cohort, experience, and education level. Specifically, we assume income processes separately for four educations levels: Year 10 or below, Year 11-12, vocational education, and higher education. The log income, denoted $\ln y^e_{i,t,s}$, for individual i in cohort s, with experience t and education level e, follows the stochastic process below:

$$\ln y^e_{i,t,s} = \alpha^e_s + \ln \bar{y}^e_t + \gamma^e X_{i,t,s} + \nu_{i,t} \tag{1}$$

$$\nu_{i,t} = \rho^e \nu_{i,t-1} + \epsilon_{i,t} \tag{2}$$

$$\epsilon_{i,t} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^e_\epsilon) \tag{3}$$

where α^e_s is the education-specific cohort effect, $\bar{y}^e_t$ is the education-specific income profile over experience, $X_{i,t,s}$ are control variables,[4] and $\nu_{i,t}$ is the idiosyncratic income shock. In equation (2), we parameterize $\nu_{i,t}$ as an AR(1) process, with persistence $\rho^e \in (0, 1)$[5] and normally-distributed innovations $\epsilon_{i,t}$ with standard deviation σ^e_ϵ.

We assume that the initial individual income shock upon entering the labor market, i.e., $t = 0$, to be normally distributed with variance parameter σ_η.

$$\nu_{i,0} = \eta \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^e_\eta) \tag{4}$$

We use the HILDA panel survey data, which includes around 30,000 individual-year earnings observations from 2000 to 2020.[6] We exclude capital income because it is expected to be small, especially among student debt holders, and because it is typically subject to different taxation rules than earnings. Table 1 reports summary statistics of our sample for selected years. It can be seen that key characteristics, including marital status, education, and occupation, remain stable over the time period, with the exception of trends of population aging and increasing education attainment.

Following previous literature, we first estimate the common cohort effects α^e_s and income-

[4] We include marital status, region, and Aboriginal status as controls.

[5] We tested the hypothesis of $\rho^e = 1$, i.e., that the income process is a random walk, and found it rejected for all four education levels.

[6] We provide details of our data cleaning process in Appendix C.1.

Table 1: Summary statistics for selected years

	2001	2010	2020
Demographics			
Age	34.5	37.5	42.5
% Married	70.6	73.0	79.7
Family size	3.2	3.1	3.1
Education			
% Bachelor and above	16.9	19.4	22.6
% Below Year 12	27.2	24.2	16.5
Location			
% Major city	58.9	59.4	56.5
% All city	84.6	84.5	79.2
Occupation			
% Managers	14.7	16.0	22.2
% Professionals	20.1	20.0	20.4
% White collar	49.1	48.5	52.4
Observations	992	1605	1308

Note. Marriage includes both legal marriage and de facto relationships. Family size is defined as the number of individuals, including both children and adults. White-collar occupation includes (i) managers, (ii) professionals, (iii) clerical and administrative workers, and (iv) sales workers.

experience profiles $\bar{y}_t^e$, before estimating the AR(1) process of residual earnings $\nu_{i,t}$. To estimate cohort effects and experience–income profile, we run OLS regressions separately for the four education groups – Year 10, Year 12, vocational education, and higher education. For each education group, we regress income on cohort dummies, fractional polynomials of experience, and control variables.

We consider cohort effects because previous studies such as Meghir and Pistaferri (2004) found significant cohort effect in the US between 1980 and 2000. In our OLS estimates, we also found significant cohort effects for workers without post-secondary education, but no such effects for workers with either vocational or higher education. We illustrate this difference in cohort effect for college and non-college types in Figure 2, where we decompose the age-income profile by birth cohort and calendar year. For college workers, the age-income profile only slightly increases over cohort. As a result, profiles controlling for cohort, controlling for time, and using the pooled sample are all similar to one another. On the other hand, the non-college profiles increase significantly over cohorts. The cross-sectional profile, depicted by the red dashed line, is much flatter than the longitudinal profile, depicted by the blue solid line.

After controlling for cohort effects α_s^e and demographics $X_{i,t,s}$, we fit the residual earnings using education-specific profiles. In Figure 3, we compare the fitted profile with the data average for each age-education cell. We use fractional polynomials as our functional forms because of their flexibility in fitting both the sharp increase in income at the beginning of the career and flattening at the end. For all four education groups, income increases in the first five to ten years of entering the labor market and remains relatively stable throughout the rest of the working life. Unlike patterns observed in the US data, we do not observe a substantial decline in income even in the years close to retirement.

Finally, we estimate the AR(1) process of the residual income $\nu_{i,t}$ using the generalized method of moments (GMM). We choose GMM over maximum likelihood estimation (MLE) for two reasons. First, it is less reliant on the assumption of log-normality, which has been shown to be inconsistent with empirical results regarding income dynamics (Guvenen et al., 2022). Second, it allows us to better match qualitative features of income volatility, such as the initial dispersion and the increase in variance with age. We believe these qualitative features to be important for studying the lifecycle effects of ICLs.

We target three moments: the variance of income for workers with less than five years

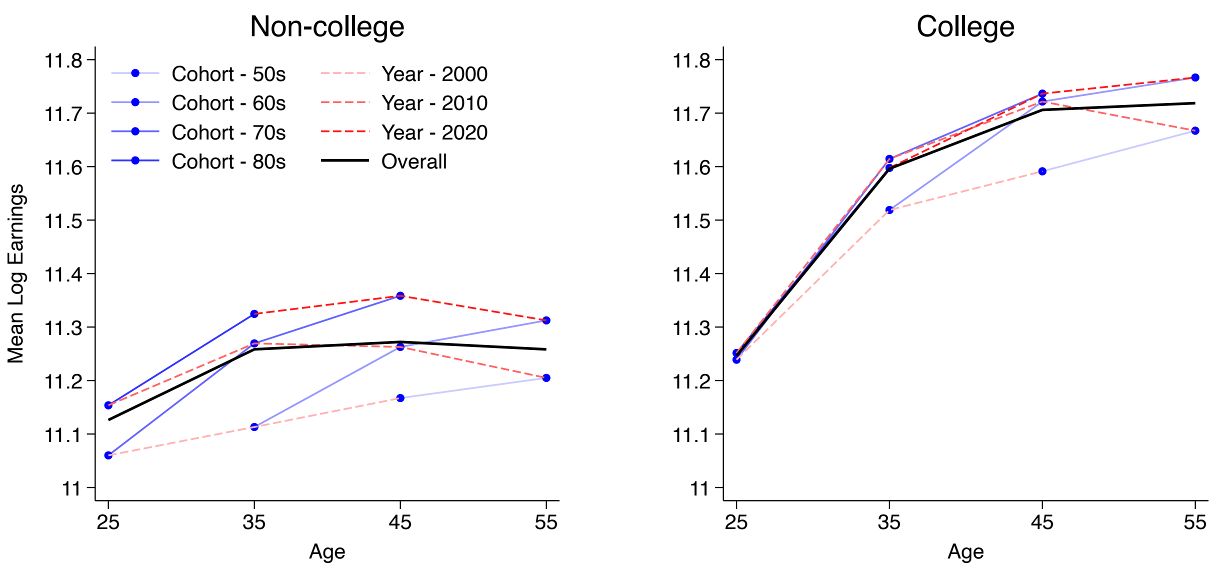

Figure 2: Log Income by age, cohort, and time

Note. Each dot represents a within-group mean for a cohort-age group. The blue solid lines connect all dots for the same cohort group. The red dashed lines connect all dots with the same average calendar year of observation. The "overall" line represents within-group average not controlling for time or cohort. The left panel labelled "non-college" include individuals with less than two years of post-secondary education. The right panel labelled "college" includes individuals with at least two years of post-secondary education, either vocational or higher education. The unit is log of 2020 Australian dollars. Data source: HILDA data, waves 1-20, all male full-time workers aged 25-55.

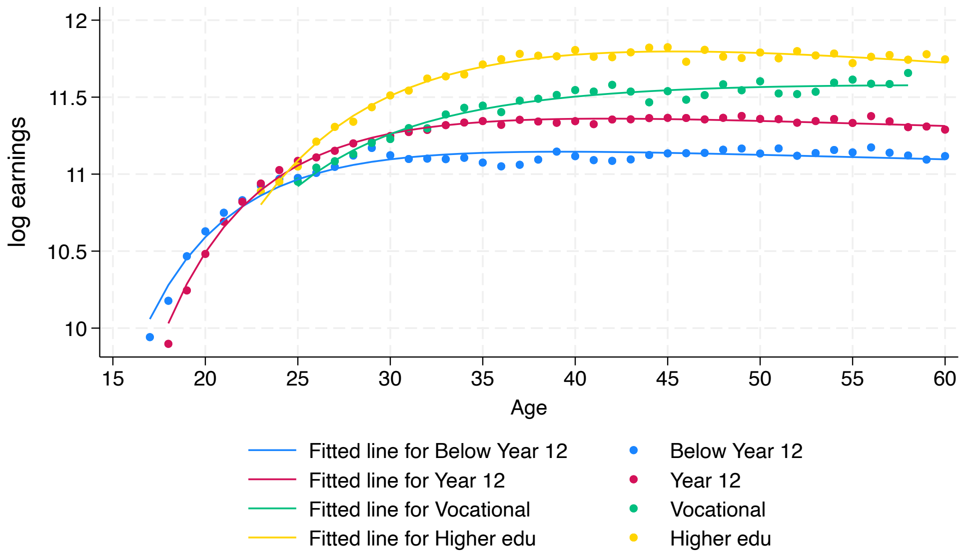

Figure 3: Fit for age-income profile by education

Note. We use fractional polynomial fit. Log earnings are residual earnings after controlling for marital status, region, and cohort. The unit is log of 2020 Australian dollars. Source: HILDA data, waves 1-20, all male full-time workers aged 25-55.

of experience, the variance of income for workers with 25 to 35 years of experience, and the covariance between current income and income in the previous year. These targeted moments are summarized in Table 2.

We have the same number of moments and parameters and are able to match the targeted moments exactly. Table 3 summarizes the estimated parameters of the AR(1) process described in equations (2) - (4). Figure 4 compares the simulated standard deviations of income from the AR(1) process with those directly measured in the data.

Table 2: Targeted moments in GMM estimation

	Variance		Covariance
	0-5 yrs exp	25-35 yrs exp	
Below Year 12	0.20	0.18	0.17
Year 12	0.22	0.19	0.18
VET	0.24	0.17	0.17
Higher Ed	0.19	0.24	0.22

Note. Estimated variances and covariances of the income process by education group. First two columns show variances of income for those with 0-5 years and 25-35 years of experience. The third column shows covariance between current income and income in the previous year. We use log residual earnings after controlling for marital status, region, and cohort. The unit is log of 2020 Australian dollars. Data source: HILDA data, waves 1-20, all male full-time workers aged 25-55.

Table 3: Estimated AR(1) parameters

	Initial dispersion σ_η	AR(1) shock σ_ϵ	Persistence ρ
Below Year 12	0.45	0.16	0.93
Year 12	0.49	0.18	0.91
VET	0.52	0.16	0.92
Higher Ed	0.43	0.10	0.98

Note. Estimated values of AR(1) parameters.

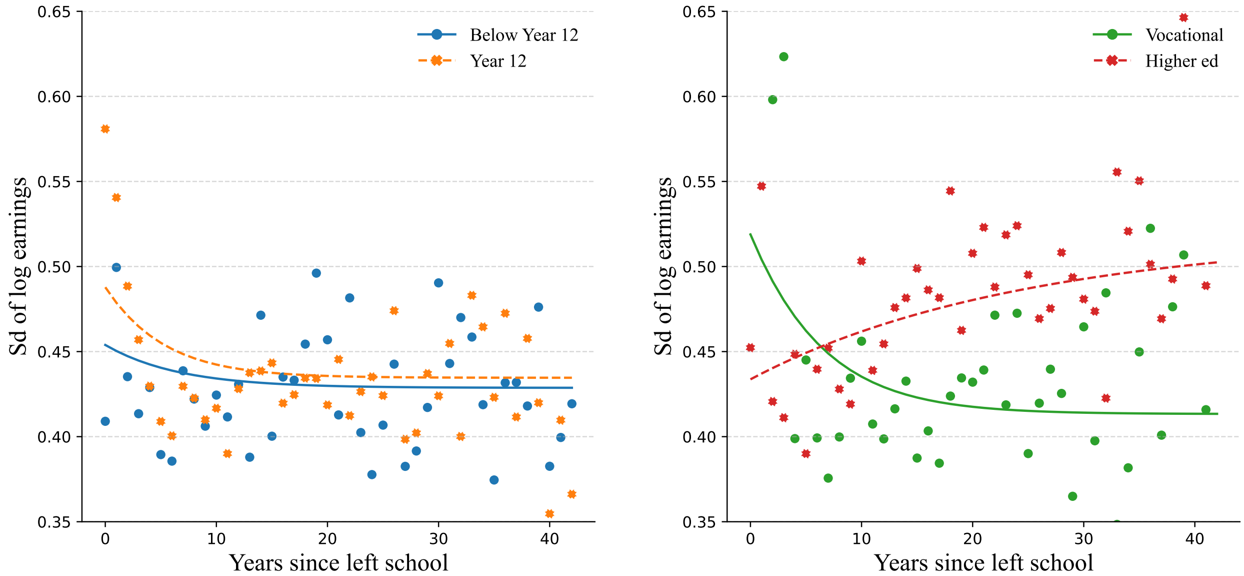

Figure 4: Model & data standard deviations by age and education

Note. The scatter plots show standard deviations for each education-age group, estimated using HILDA sample. We omit education-age groups with less than 10 observations. The line plots are unconditional standard deviations generated by the AR(1) process.

The estimated income processes exhibit high persistence across all education levels. Yet the patterns of income volatility differ by education. Only individuals with higher education experience income volatility that increases with experience, due to higher persistence of the income process. For individuals with Year 10, Year 12, and vocational education, income volatility is the highest when they first enter the labor market, and is either decreasing or nearly constant over their working life.

3.2 Repayment function

For income-contingent student loans, borrowers make payments $R(y_t)$ that depends on the level of income y_t at time t. They continue repaying until the discounted sum of repayments equals the initial loan amount. The function R, also called repayment rules or repayment schedule, is our focus in this section.

In Section 2, we have shown the exact repayment rules used in Australia across various reforms, in Figure 1. We now adopt a more generic, parameterized function that helps us separate the roles of progressivity and repayment size. Following Heathcote, Storesletten and Violante (2017)'s formula for an analytical tax function, we use a two-parameter function to represent the repayment rules of ICLs. Specifically, the amount of repayment R at income level y is defined as

$$R(y|\lambda,\tau) \equiv y - \lambda y^{1-\tau} \tag{5}$$

where τ governs the progressivity of ICL and λ (inversely) governs the size of repayment required each period. Another way to understand the role of the two parameters is to look at after-tax income $y - R(y) = \lambda y^{1-\tau}$, which is proportional to λ and exhibits increasing curvature in τ.

The key difference between progressive repayment – which we study here – and progressive taxation – which has been studied in the literature – is that repayment ends once all debt has been repaid, whereas taxes are always levied. To see this concretely, we define the law of motion for ICL debt d_t at time t with income y_t to be:

$$d_{t+1} = d_t - \tilde{R}(y_t, d_t|\lambda,\tau), \quad \tilde{R}(y_t, d_t|\lambda,\tau) = \min\Big\{d_t, \max\big\{0, R(y_t|\lambda,\tau)\big\}\Big\} \tag{6}$$

where $\tilde{R}(y_t, d_t)$ is the truncated repayment that is both non-negative and not exceeding total remaining debt. In the original formulation by Heathcote, Storesletten and Violante (2017), negative taxes are allowed and equivalent to receiving subsidies. Here, we do not allow repayments to be negative because there is no empirical counterpart to negative repayments.

Both the size and progressivity parameters affect the number of years required to fully repay. To see this, since the present value of all repayments must equal the total loan amount,

$$\sum_{t=1}^{\tilde{T}} \frac{\tilde{R}(y_t, d_t|\lambda,\tau)}{1+\tilde{r}_t} = \phi, \tag{7}$$

where $\tilde{T}$ is the total number of years required for full repayment, $\tilde{r}_t$ is the interest rate for the ICL (which may differ from the prevailing market rate)[7], and ϕ is the total loan amount.

$\tilde{T}$ depends both on income stream $y^t = (y_1, y_2, \cdots)$ and ICL parameters λ and τ. A borrower with a series of high income will finish repaying faster under lower λ, i.e higher repayment size, or higher τ, i.e. more progressive repayments. Therefore, repayment param-

[7]ICLs often carry have lower interest rates due to being subsidized by governments. In the Australian case, $\tilde{r}_t = 0$ because the ICL there carries no real interest.

eters λ and τ not only affect welfare while repaying, but also when repayment is completed. We will further describe how changing λ and τ affects $\tilde{T}$ empirically in Section 3.3.

3.2.1 Identifying repayment parameters

To illustrate how well the theoretical repayment function defined in equation (5) represents existing repayment schedules in different countries, we run OLS regressions of log income after repayment on log income before repayment. Taking logs on both sides of equation (5), the relationship between the two variables is characterized by

$$\log[y - R(y)] = \log(\lambda) + (1 - \tau)\log(y). \tag{8}$$

Therefore, we can identify λ and τ from the intercept and slope coefficients of a simple OLS regression on income post- and pre-repayment.

Unlike Heathcote, Storesletten and Violante (2017), who use self-reported taxes and transfers to determine after-tax income, we directly calculate ICL repayments using official repayment rules. We prefer this approach because, unlike taxes and benefits, repayment rules are universal, straightforward, and applied automatically rather than requiring individuals to submit applications. Therefore, we do not need to consider complications such as variation across regions or uptake rates (which is close to one in our case).

We use the sample of male full-time workers, same as in Section 3.1, and calculate income after repayments under three different Australian repayment schedules – the 1998, 2005, and 2019 reforms – using official repayment rates, illustrated by the step functions in Figure 1. Furthermore, we also consider repayment rules used in the United Kingdom and the United States for comparison. Even though the UK an US rules have never actually been implemented in the Australian sample, we believe it's useful to see how the parameterized function fit other plausible repayment rules. The repayment rules in the UK and the US are defined as follows.

UK (flat-rate). A fixed rate of repayment at 9% is applied to income above a minimum threshold of 51,100 Australian dollars. Borrowers do not need to repay if income falls below the threshold

$$R^{\text{UK}}(y) = \begin{cases} 0 & \text{if } y < 51.1, \\ 0.09 \cdot (y - 51.1) & \text{if } y \geq 51.1. \end{cases} \tag{9}$$

US (mortgage-style). A fixed amount of repayment per period is required over 15 years. The corresponding repayment schedule is

$$R^{\text{US}}(y) = \min \left\{ \frac{\phi}{15}, y \right\}, \tag{10}$$

where ϕ is the total outstanding debt, taken to be the average cost of college in Australia. We assume the borrower repays all income when income is below the monthly repayment required. Thus, repayment never exceeds income. To simplify our analysis, we do not model default, which affects around 10% of student borrowers in the US.

Using the common definition of progressivity–where the marginal repayment rate always exceeds average repayment rate–the UK rule is progressive, while the US rule is regressive. For the UK rule, while the marginal repayment rate is fixed at 9%, the average repayment rate is lower because part of income is exempt. For the US rule, the marginal repayment rate is always zero.

Table 4: Estimated parameters for existing ICL policies

Policy	λ	τ	R^2	$y_{\min}$
AU 1997/98	1.080	0.030	1.000	13.519
	(0.001)	(0.000)		
AU 2004/05	1.180	0.050	0.999	27.209
	(0.001)	(0.000)		
AU 2019/20	1.210	0.055	0.999	32.352
	(0.002)	(0.000)		
UK	1.133	0.036	1.000	33.591
	(0.001)	(0.000)		
US	0.757	-0.056	0.999	-
	(0.003)	(0.001)		

Note. Standard errors in parenthesis. The fifth column titled $y_{\min}$ shows the minimum income, $y_{\min} = \lambda^{1/\tau}$, for repayment to be positive, in unit of thousands of 2020 Australin dollars. This column does not apply to the estimated US policy as it is regressive, with $\tau < 0$, with positive repayment begins at 0.

Table 4 reports the OLS estimation results, as specified in equation (8), for existing repayment policies. As expected, both λ and τ increase for Australian policies from 1997 to 2020 as repayments become larger and more progressive. Moreover, τ is positive for the UK policy and negative for the US policy, consistent with the actual policy rules. We also report the income threshold $y_{\min} = \lambda^{1/\tau}$ where $T(y) = 0$. Under a progressive ICL ($\tau > 0$), borrowers face no repayment until their income exceeds $y_{\min}$. Repayment determined by the theoretical function is negative for lower incomes and positive for higher incomes if ICL is progressive, i.e., $\tau > 0$.

Despite its simple parameterized form, the theoretical function fits empirical data very well. The R^2 values are very close to 1 for all policy rules. This is because existing ICLs are typically simple step or linear functions without kinks, large jumps, or changes in curvature. The US standard repayment rule, which is a constant function with a large jump at income 0, provides the worst fit but still yields $R^2 > 0.995$.

3.3 Repayment dynamics

We now study repayment dynamics by applying the deterministic function (6) to the stochastic income process. We defer the analysis of behavioral responses to ICL, such as education and private saving, to Section 4, where a heterogeneous-agent life-cycle model is introduced.

First, we study separately how the two parameters in the repayment function – λ, which governs the size of the recurring repayment, and τ, which governs the progressivity – affect the dynamics of repayment and disposable income after repayment. We show that λ primarily affects the timing of repayment, while τ affects the dispersion in the time required to finish repayment.

In Figure 5, we show how λ and τ affects income after repayment, average annual repayment, and probability of finishing repaying in a given year after graduation. We use the Australian 2004/05 ICL rules, i.e., $\lambda = 1.18$ and $\tau = 0.05$, as our benchmark. We then vary each of the two parameter values and compare the resulting repayment outcomes.

In panels (a) and (b), we illustrate how the (log) ICL repayment function changes when we vary τ and λ, respectively. We plot log income before repayment on the horizontal axis and log income after repayment on the vertical axis. The relationship between log

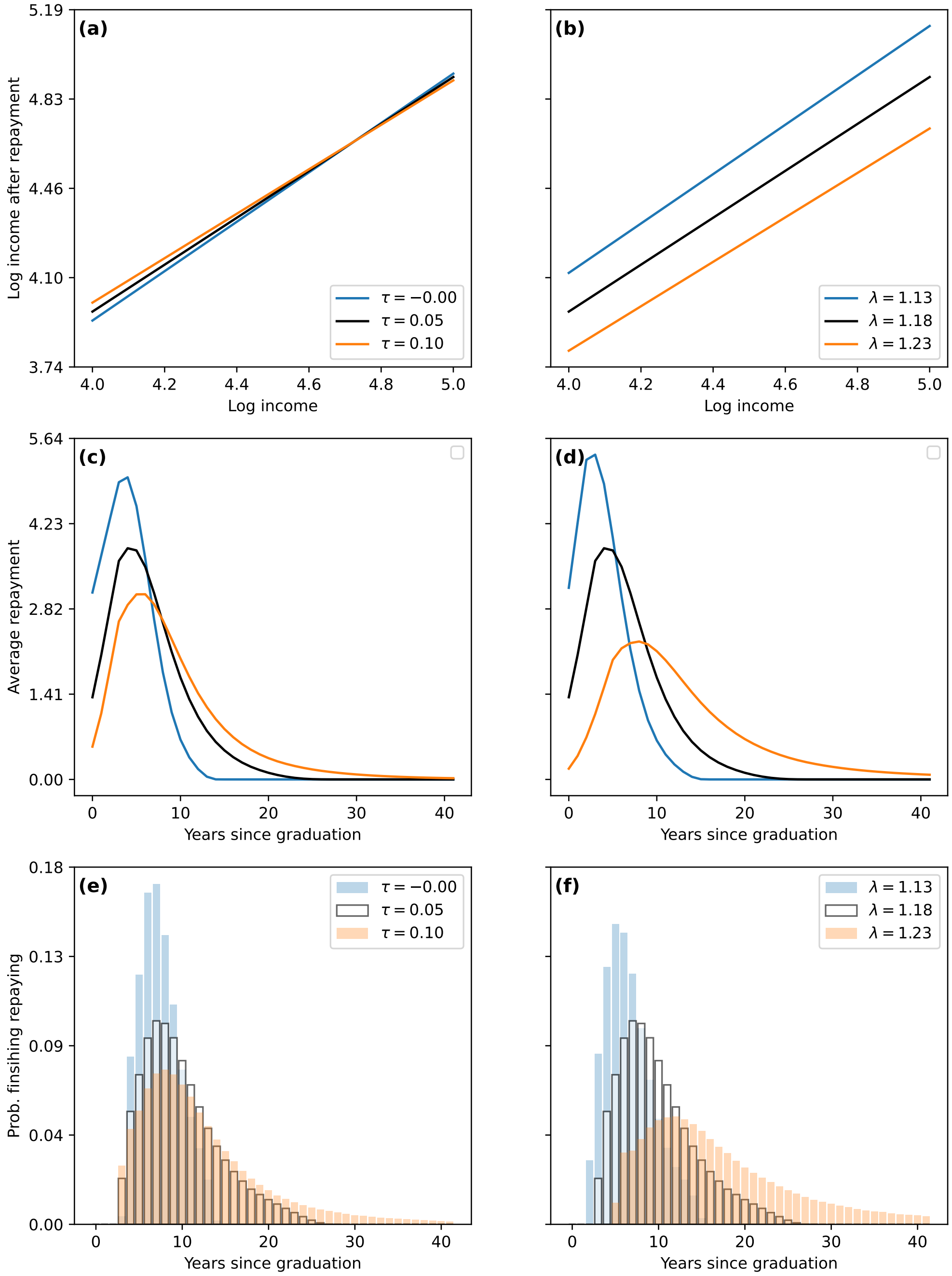

Figure 5: Effects of changing τ and λ on repayment dynamics

Note. Black lines and bars with black outlines represent repayment dynamics under the benchmark Australian 2004/05 policy. The blue and orange lines and bars represent dynamics after slightly varying τ and λ. In panels (a)-(d), the unit of account is log of thousands of 2020 Australian dollars. In panels (c) and (d), repayment is averaged over all borrowers, regardless of whether they have already finished repaying all debt.

income before and after repayment is always linear, as characterized in equation (8), with λ representing the vertical intercept and τ the slope.

In the left-hand panels (a), (c), and (e), we focus on changing progressivity τ, while adjusting λ to keep repayment at the median income for higher education[8] fixed. Therefore, in panel (a), increasing τ is illustrated by rotating the lines anti-clockwise. In the right-hand panels (b), (d), and (f), we focus on changing λ while keeping τ fixed, so that repayment is proportionally higher at every income level.

We see from panels (c) and (e) that increasing progressivity τ causes greater dispersion in repayments without shifting the overall timing of repayment. Average repayments are more spread out over the lifecycle, but they remain concentrated in 5 to 10 years after graduation, regardless of progressivity.

On the other hand, panels (d) and (f) show that changing the size of repayment at all income levels shifts the overall timing of repayment. A smaller λ leads to larger repayments at all income levels, which causes average repayments to increase more quickly after graduation, as seen in panel (d). Average repayment also decreases more sharply after more borrowers completely repay their debt sooner. As seen in panel (f), the distribution of years taken to finish repayment shifts to the left and becomes more concentrated.

We summarize that higher progressivity reduces the dispersion of per-period repayment, while increasing the dispersion of overall repayment time. Higher repayment size mainly reduces both overall repayment time and the dispersion of repayment time. Next, we study how changes in repayment dynamics translate to behavioral responses by the households.

4 Life-Cycle Model

To examine the implications of the ICL repayment function on education attainment and welfare, we now build a heterogeneous life-cycle model with endogenous education and consumption-savings decisions and study the effects of ICL progressivity through the lens of the model.

[8]The median income conditional on having higher education is around 112,850 Australian dollars in our data sample.

We model individuals from age 16, when they begin to make secondary and post-secondary schooling decisions, to 65, the retirement age in Australia.[9] Each time period corresponds to one year. We divide the lifecycle into two stages – student stage and worker stage. We provide a brief summary of each stage here, with full details to follow in Sections 4.1 and 4.2.

Student. Starting from age 16, a student receives parental transfers and education preference shocks, and then makes a two-stage education decision. First, the student chooses whether or not to finish high school. If the student decides not to finish, they become a *high school dropout* (*hd*) type and enter the worker stage immediately. If the student decides to finish high school, then a second education choice is made at age 18, between three education levels – *high school graduates* (*hg*), *vocational education* (*ve*), and *higher education* (*he*).

We assume that only students in vocational and higher education are eligible for student loans.[10] We also abstract from voluntary upfront payments and repayment, where students do not take the full loan amount or repay more than the requirement amount. Students who make upfront payments and voluntary repayments account for less than 10% of all eligible students. In the model, since the ICL–modeled after the Australian system–carries a zero real interest rate, it is not optimal for students to make upfront payment or voluntary repayments.

Worker. A student enters the worker stage immediately after graduation. Depending on the education level, the worker stage starts between the age of 16 and 22 and ends at the age of 65. Workers receive income that is exogenous and stochastic, repay debt, and make consumption-savings decisions in each period. They don't choose whether to participate in the labor market or adjust hours of work.

We do not endogenize labor supply because we believe modeling it credibly would be beyond the scope of this paper. Endogenizing labor supply requires accurately estimating labor supply elasticities while accounting for differences across age, gender, and education. To our knowledge, there is still no consensus on such estimates for the Australian economy. We take comfort in the fact that an elasticity of zero is often within the range of existing estimates (Dandie and Mercante, 2007), and that previous studies report the effects of moral

[9]Individuals could begin to draw age pension at the age of 65 until 2017. The age limit gradually increased from 65 to 67 between 2014 and 2017.

[10]This has been the case since 2007, when vocational students became eligible for ICLs as part of the 2005 reform. Before 2007, only higher education students are eligible for ICLs.

hazard in the context of student loans are generally small (Chatterjee and Ionescu, 2012; Matsuda and Mazur, 2022).

We describe the choices, shocks, and full optimization problems in the student stage and the worker stage below. While double-indexing is typically used for life-cycle models, we suppress the time index because we do not explore time trends here. Throughout the section, we use x_α to denote a variable x associated with an individual who is aged α. We assume the model is invariant over time, so no time index is needed.

4.1 Student stage

In the student stage, the student receives parental transfers and realizes their preference shocks for education. They then make education decisions sequentially, once at age 16 and again at age 18. This two-stage setup is common in literature on educational policy using life-cycle models such as Fuchs-Schündeln et al. (2022) and Abbott et al. (2019). It also captures the idea that attending college entails a fixed cost in the form of two additional years of high school education and foregone earnings.

4.1.1 At age 16

At age 16, a student receives parental transfers b and a vector of taste shocks for education levels, $\epsilon_1 = (\epsilon_{1,1}, \epsilon_{1,2})$. Conditional on these two state variables, the student then chooses between dropping out and finishing high school. Their corresponding value function is written as:

$$V_{16}^S(b, \epsilon_1) = \max \Big\{ \underbrace{\Big[\mathbb{E}_y \tilde{V}_{16}^W(hd, b, y_{16}, d_{16} = 0)\Big] + \epsilon_{1,1}}_{\text{Leave high school}}, \quad \underbrace{\tilde{V}_{16}^S(b) + \epsilon_{1,2}}_{\text{Finish high school}} \Big\}. \tag{11}$$

$$\epsilon_{1,k} \sim EV(-\gamma, \sigma_1) \text{ for } k \in \{1, 2\}. \tag{12}$$

where $\tilde{V}_{16}^W(hd, b, y_{16}, d_{16} = 0)$ is the lifetime value function of a high school dropout (hd)-type worker, with asset b, initial income y_{16} and no student debt ($d_{16} = 0$), to be specified in Section 4.2. The expectation is taken over income y_{16}, according to equation (4). $\tilde{V}_{16}^S$ is the lifetime value associated with finishing high school, to be specified later in equation (13).

Parental transfers b follows a distribution estimated externally, which we describe in

Section 5.2. γ is the Euler–Mascheroni constant, and σ_1 is a parameter to be estimated internally using MSM.

If the student has chosen to finish high school at age 16, they remain in school for two more years. They pay an annual psychic cost ψ for each additional year in school. Moreover, they choose how much to consume, c_α, and save, $a_{\alpha+1}$. As a high school student, they cannot borrow at this stage, as shown by the inequality (16). Their optimization problem conditional on finishing high school is

$$\tilde{V}^S_{16}(b) = \max_{c,a} \left[u(c_{16}) - \psi\right] + \beta \left[u(c_{17}) - \psi\right] + \beta^2 V^S_{18}(a_{18}), \tag{13}$$

subject to

$$c_{16} + a_{17} = b, \tag{14}$$

$$c_{17} + a_{18} = (1 + r)a_{17}, \tag{15}$$

$$a_{17}, a_{18} \geq 0. \tag{16}$$

where ψ is estimated internally using MSM, and V^S_{18} is the lifetime value to be specified in equation (17).

4.1.2 At age 18

A student who has chosen to finish high school graduates at age 18 and makes a second choice among three education levels – high school graduate (hg), vocational education (ve), and higher education (he) – by solving a discrete choice problem specified below.

$$V^S_{18}(a_{18}) = \max \Big\{ \underbrace{\mathbb{E}_y \left[\tilde{V}^W_{18}(hg, a_{18}, y_{18}, d_{18} = 0)\right] + \epsilon_{2,1}}_{\text{Year 12}}, \underbrace{\tilde{V}^S_{18}(ve, a_{18}) + \epsilon_{2,2}}_{\text{Vocational}}, \underbrace{\tilde{V}^S_{18}(he, a_{18}) + \epsilon_{2,3}}_{\text{Higher edu}} \Big\}, \tag{17}$$

$$\epsilon_{2,k} \sim EV(-\gamma, \sigma_2) \text{ for } k \in \{1, 2, 3\}. \tag{18}$$

where $\tilde{V}^W_{18}(hg, a_{18}, y_{18}, d_{18} = 0)$ is the lifetime value function for a high school graduate-type worker, with assets a_{18}, income y_{18}, and no student debt ($d_{18} = 0$), to be specified in Section

4.2. The expectation is taken over income y_{18}. $\tilde{V}_{18}^S(ve, a_{18})$ and $\tilde{V}_{18}^S(he, a_{18})$ are the lifetime values associated with choosing vocational and higher education, to be specified in equations (19) and (23).

If the student has chosen vocational education, they remain in school from age 18 to 20. During this period, they receive capital income ra_α, accumulate student debt $d_{\alpha+1}$, and choose consumption c_α. They cannot borrow privately, as shown by the borrowing constraint (21). Their optimization problem at age 18 is

$$\tilde{V}_{18}^S(ve, a_{18}, \psi) = \max_{c_\alpha} \Big\{ [u(c_{18}) - \psi] + \beta [u(c_{19}) - \psi] + \beta^2 \mathbb{E}_{y_{20}} \left[V_{20}^W(ve, a_{20}, y_{20}, d_{20}) \right] \Big\}, \quad (19)$$

subject to the budget constraint (20), the borrowing constraint (21), and debt accumulation (22):

$$c_\alpha + a_{\alpha+1} = (1 + r)a_\alpha \quad (20)$$

$$a_{\alpha+1} \geq 0, \quad (21)$$

$$d_{20} = \phi^{ve}, \quad (22)$$

for $\alpha \in \{18, 19\}$.

Similarly, if the student has chosen higher education, they stay in school from age 18 to 22 and face an analogous optimization problem, specified as

$$\tilde{V}_{18}^S(he, a_{18}, \psi) = \max_{c_\alpha} \left\{ \sum_{\alpha=18}^{21} \beta^{\alpha-18} [u(c_\alpha) - \psi] + \beta^4 \mathbb{E}_{y_{22}} \left[V_{22}^W(he, a_{22}, y_{22}, d_{22}) \right] \right\}, \quad (23)$$

subject to

$$c_\alpha + a_{\alpha+1} = (1 + r)a_\alpha, \quad (24)$$

$$a_{\alpha+1} \geq 0, \quad (25)$$

$$d_{22} = \phi^{he}, \quad (26)$$

for $\alpha \in \{18, 19, 20, 21\}$.

4.2 Worker stage

The student becomes a worker at the age of graduation, which varies depending on their schooling choices. A worker receives exogenous, stochastic income net of ICL repayments and chooses consumption and savings.

A worker at age α with education e, assets a_α, and student debt d_α solves the consumption–savings problem specified below:

$$V_\alpha^W(e, a_\alpha, y_\alpha, d_\alpha) = \max_{c_\alpha} \left\{ u(c_\alpha) + \beta \mathbb{E}_y \left[V_{\alpha+1}^W(e, a_{\alpha+1}, y_{\alpha+1}, d_{\alpha+1}) | y_\alpha \right] \right\}, \tag{27}$$

subject to

$$a_{\alpha+1} + c_\alpha + (d_\alpha - d_{\alpha+1}) = (1+r)a_\alpha + y_\alpha \tag{28}$$

$$d_\alpha - d_{\alpha+1} = \tilde{R}(y_\alpha) \tag{29}$$

$$a_{\alpha+1} \geq -L. \tag{30}$$

where expectation $\mathbb{E}_y$ is taken over future income $y_{\alpha+1}$, conditional on current income y_α.

In equation (29), the worker's student loan debt is automatically deducted by the amount of repayment $\tilde{R}(y_\alpha)$, where $\tilde{R}(\cdot) = \min\{d_\alpha, \max\{0, R(\cdot)\}\}$ is the non-negative portion of the repayment function defined by equation (5). The worker can borrow privately up to an exogenous borrowing limit L, which is set externally in Section 5.2.

4.3 Terminal period

Our model ends at age 65, which was the starting age for collecting pension until 2017. We do not model pension or retirement explicitly. Instead, we adopt a warm-glow utility function, $g(a_{65})$, where the worker's utility g is increasing and concave in their asset position a_{65} at age 65. This specification is consistent with the literature on savings, retirement, and bequests (De Nardi, 2004; De Nardi and Fella, 2017; Kaplan, Mitman and Violante, 2020).

The optimization problem faced by a worker aged 64, one period before retirement, is characterized as follows:

$$V_{64}^{W}(e, a_{64}, y_{64}, d_{64}) = \max_{c_{64}} \; u(c_{64}) + g(a_{65}), \tag{31}$$

subject to

$$a_{65} + c_{64} + \min\{d_{64}, \tilde{R}(y_{64})\} = (1+r)a_{64} + y_{64} + \omega^R(e) \tag{32}$$

$$a_{65} \geq -L. \tag{33}$$

where $\omega^R(e) = \omega^R - T(e)$ is the education-specific net transfer from the government. Any remaining student debt after repayment $\tilde{R}(y_{64})$ is cancelled and does not enter the warm-glow utility function g.

4.4 Goverment

Since the ICL carries a zero real interest rate, the sum of the present value of repayments is always lower than the total loan amount. Therefore, the government must levy taxes in order to balance the budget. We assume government collects education-specific, proportional income tax, $\tau^{\text{inc}}(e)$, for every period in the working stage. Tax rates $\tau^{\text{inc}}(e)$ for four education groups, $e \in \{he, ve, hg, hd\}$, satisfy the following equations.

For those with higher education, i.e., $e = he$,

$$\mathbb{E}_\epsilon \left[\sum_{t=22}^{64} \frac{\tau^{\text{inc}}(he) y_t^{he}}{(1+r)^t} \right] = \phi^{he} \sum_{t=18}^{21} \frac{1}{(1+r)^t} - \mathbb{E}_\epsilon \left[\sum_{t=22}^{64} \frac{R(y_t^{he})}{(1+r)^t} \right]. \tag{34}$$

Similarly, for those with vocational education, i.e., $e = ve$,

$$\mathbb{E}_\epsilon \left[\sum_{t=20}^{64} \frac{\tau^{\text{inc}}(ve) y_t^{ve}}{(1+r)^t} \right] = \phi^{ve} \sum_{t=18}^{19} \frac{1}{(1+r)^t} - \mathbb{E}_\epsilon \left[\sum_{t=20}^{64} \frac{R(y_t^{ve})}{(1+r)^t} \right]. \tag{35}$$

The left-hand sides of the two equations are the present values of income tax revenues from all workers in each education group. The right-hand sides are the difference between the present values of the tuition fees and the aggregate repayments collected from workers.

The expectation is taken unconditionally over income risks ϵ, as described in equations (1) – (4).

There are two differences between the two equations for vocational and higher education groups. First, the higher education group spends two more years in education than the vocational group. Second, the tuition fee ϕ^{ve} is lower than that for higher education, ϕ^{he}.

Those with Year 10 and Year 12 education do not take out loans and therefore do not pay tax, so $\tau^{\text{inc}}(hg) = \tau^{\text{inc}}(hd) = 0$.

Even though education-specific taxes are not carried out in reality, we believe this simplifying assumption is suitable for our analysis for two reasons. First, it ensures there is no redistribution across educational groups. We tax only those with higher and vocational education the difference between the present value of their loan and repayments. We do not tax those without post-secondary education, who also do not benefit from ICLs. A uniform tax across education groups would imply a redistribution from lower-education groups to higher-education groups, which would be regressive in nature.

Second, educational specific tax is more tractable because the tax rates can be calculated without solving the equilibrium. Imposing a uniform tax rate across educational group would imply the tax rate depends on the share of each education group, which is endogenously determined.

5 Model Parametrization

In this section, we describe how we choose the functional forms and parameters used in the life-cycle model presented in Section 4. We adopt functional forms commonly used in the existing literature on life-cycle models and determine external parameters using publicly available information or statistics. For the remaining parameters that are only meaningful within the model, we use the method of simulated moments (MSM) to estimate them jointly to match conceptually relevant data moments.

5.1 Functional forms

Preferences. We assume individuals have CRRA utility over consumption:

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}. \tag{36}$$

Last-period asset holding. We assume the same functional form for the warm-glow terminal value as in De Nardi (2004). In particular, the value associated with having assets a at age 65 is

$$g(a) = g_1 \left(1 + \frac{a}{g_2}\right)^{1-\sigma}, \tag{37}$$

where $g_1 < 0$ (for $\sigma > 1$, which is the empirically relevant case) and $g_2 > 0$. We calibrate g_1 and g_2 using MSM to match mean asset holdings around age 65, both for the pooled sample and for the higher education group separately.

Income-contingent loans. As described in Section 3.2, we adopt the Heathcote, Storesletten and Violante (2017) formulation of the ICL, with repayment $R(y) = y - \lambda y^{1-\tau}$. We further impose that repayments cannot be negative, defining $\tilde{R}(y) = \max\{0, R(y)\}$. Since our observed period spans 2000-2020, we use the 2004/05 Australian policy rule, which was in place for most of this period (2005-2019). Using OLS regressions of income before and after repayment (see Table 4), we estimate $\lambda = 1.18$ and $\tau = 0.05$.

5.2 Externally chosen parameters

We choose some parameter values to match those frequently used in the literature. We set the risk-aversion parameter σ to 2, a value commonly used in life-cycle literature (Abbott et al., 2019; Lochner and Monge-Naranjo, 2016). A higher σ would imply that individuals are more risk averse and thus have stronger incentives to accumulate precautionary saving. Our parameterization allows for a moderate role of precautionary savings.

We choose other parameter values to represent relevant statistics that are directly measured elsewhere. The exogenous borrowing constraint during the working stage is set to $L = 23$, i.e., \$23,000 Australian dollars, which corresponds to the average unsecured personal loan size according to an Australia financial platform[11]. We set the deposit interest rate r to 4%, the average value for commercial banks in Australia in recent years. Finally, we take the household discount rate to be $\beta = 1/(1+r)$, so households are neither more patient nor more impatient than the market.

We choose policy parameters, such as public transfers and tuition fees, based on publicly available policy rules and official statistics. We set the public transfer received by students and workers, ω^S and ω^W to half of the poverty line in Australia, which is around $13,000 Australian dollars. We take the retirement age to be 65, which was the eligibility age for the Age Pension before it was gradually increased to age 67 after 2017. For individuals at age 65, we set the public transfer ω^R to approximate a full pension payment for a single pensioner, which amounts to about $30,000 Australian dollars in 2024.

We set the fees for vocational and higher education, ϕ^{ve} and ϕ^{he} to $15,000 and $36,000 Australian dollars, respectively, which are typical values of a 2-year diploma and a 4-year Bachelor's program. Table 5 summarizes all parameters chosen or estimated externally.

Table 5: Parameters estimated externally

Parameter	*Value*	*Description*
σ	2	Intertemporal elasticity of substitution = 0.5
r	4%	Average deposit rate
β	0.96	Imposing $\beta(1+r) = 1$
ω^S	13	Annual transfer, students
ω^W	13	Annual transfer, workers
ω^R	30	Annual transfer, retirees
L	23	Borrowing constraint for adults
ϕ^{ve}	15	Average fee for a two-year vocational diploma
ϕ^{he}	36	Average fee for a three-year bachelor's degree
T^r	65	Retirement age

Note. Table 5 lists all parameters chosen or estimated without solving the model. The unit used for all monetary values are $1,000s of Australian dollars in 2012.

We estimate the distribution of initial assets at age 16, represented by b in equation (11), directly from the wealth module of the HILDA survey. We use the pooled sample every four years from 2002 to 2014. We then estimate a Gaussian kernel density function

[11] https://www.money.com.au/personal-loans/personal-loan-statistics

via maximum likelihood and use the discretized probabilities as the initial asset distribution in the life-cycle model.

5.3 Internally estimated parameters

We estimate the remaining five parameters – $\psi, \sigma_1, \sigma_2, g_1, g_2$ – using the method of simulated moments (MSM). All are parameters that do not have straightforward interpretations outside the structural model. Therefore, we select data moments that are most relevant to the roles played by these parameters and find parameter values that minimize the distance between model-generated and data moments.

Formally, let $\theta = (\psi, \sigma_1, \sigma_2, g_1, g_2)$. The MSM estimator solves

$$\hat{\theta} = \arg\min_{\theta} \left[M^{\text{data}} - M^{\text{model}}(\theta)\right]' W \left[M^{\text{data}} - M^{\text{model}}(\theta)\right], \tag{38}$$

where M^{data} and $M^{\text{model}}(\theta)$ are the vectors of empirical and simulated moments, respectively. W is taken to be the identity matrix.

Out of the five parameters, ψ represents the psychic utility cost incurred for each year of staying in school. Therefore, it directly affects education choices. σ_1 and σ_2 are the standard deviations of taste shocks for schooling choices at age 16 and 18, respectively. They determine how sensitive schooling choices are to initial assets. We use the population shares of high school dropouts, high school graduates, and vocational education (with higher education as the omitted reference group) to target these three parameters.

Lastly, g_1 and g_2 are parameters governing the warm-glow utility function used in the terminal age of 65. They affect individuals' desire to leave positive assets in the final period. Therefore, we use the asset distribution, both independent of and conditional on education level, as our targeted moment.

The MSM method requires us to solve the model repeatedly for different combinations of parameter values. Moreover, due to the complexity of the fully structural model, gradients cannot be calculated for the moments we use. We therefore use the endogenous grid method (EGM) to solve the model, which is the most computationally efficient approch given the large state space generated by both private asset a and student loans d. The computational method used to solve the model is further described in Appendix D.

Table 6: MSM Estimated Parameters

Parameter	Estimated Value	Moment	Data	Model
ψ	-0.01	Year 10 share	0.34	0.37
σ_1	0.04	Year 12 share	0.37	0.38
σ_2	0.02	VET share	0.08	0.10
g_1	-2.54	Mean Asset at age 65	0.74	0.79
g_2	37.22	Mean Asset at age 65, higher edu	1.15	1.13

Table 6 reports the estimated values for these parameters, as well as the moments to which they are conceptually linked. The model-generated moments match closely with those observed in the data.

5.4 Validation

After verifying that the targeted moments in the model match those in the data, we also assess how the parameterized model reproduces untargeted but key features of the data. This includes the distribution of schooling probabilities, and age profiles such as consumption and savings.

Schooling probabilities. Figure 6 shows the probabilities of choosing each of the four education levels conditional on initial assets at age 16. The probabilities add up to one. As described in Section 4.1, individuals make education choices at most twice – first, whether to finish high school at age 16; and second, whether to enter vocational or higher education at age 18. The figure reports the ex-ante probabilities of being in one of the four education groups at the beginning of age 16, before the individual has made the first choice.

While the schooling probabilities unconditional on initial assets – i.e., the levels of each line – are targeted moments (see Section 5.3), the trends of each line are not targeted. The model-generated probabilities exhibit trends that conform to both the data and economic intuition. As initial asset increases, the probabilities for choosing vocational and higher education increase, while those for Year 10 and Year 12 education decrease.

Age profiles. Figure 7 shows the age profiles of average consumption, average saving,

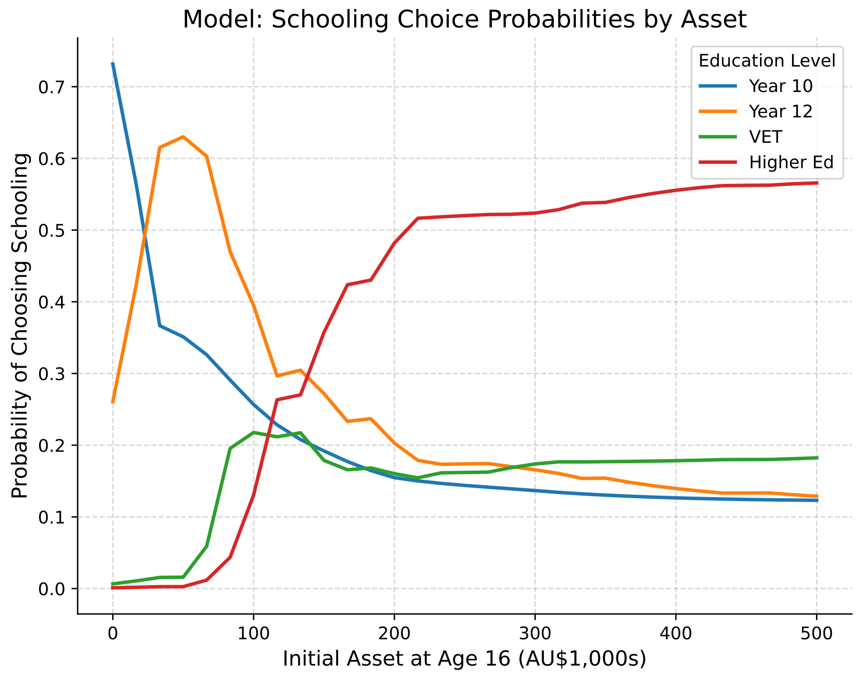

Figure 6: Model-generated, ex-ante education probabilities by initial asset at age 16.

the probability of being borrowing-constrained, and average income across the four education groups. Overall, the simulated life-cycle patterns align well with expectations, indicating that the behaviors and circumstances of heterogeneous individuals in the model are consistent with economic intuition.

The consumption-age profiles (top-left panel) for all four education groups exhibit the expected hump shape – rising at the beginning of working life due to borrowing constraints and remaining relatively flat toward the end of working life. The consumption profile for the higher-education group decreases toward the end of working life because income variance increases with age (see Figure 4), thereby raising the need for precautionary savings. In contrast, the consumption profiles for all the other three groups remain slightly increasing, as income variance decreases with age.

The asset-age profiles (top-right panel) also display the familiar pattern of borrowing at the beginning of the working period, followed by saving as individuals age. There is very little indebtedness among those without post-secondary education (Year 10 and 12) because they begin their working period with non-negative assets. This occurs because we do not allow

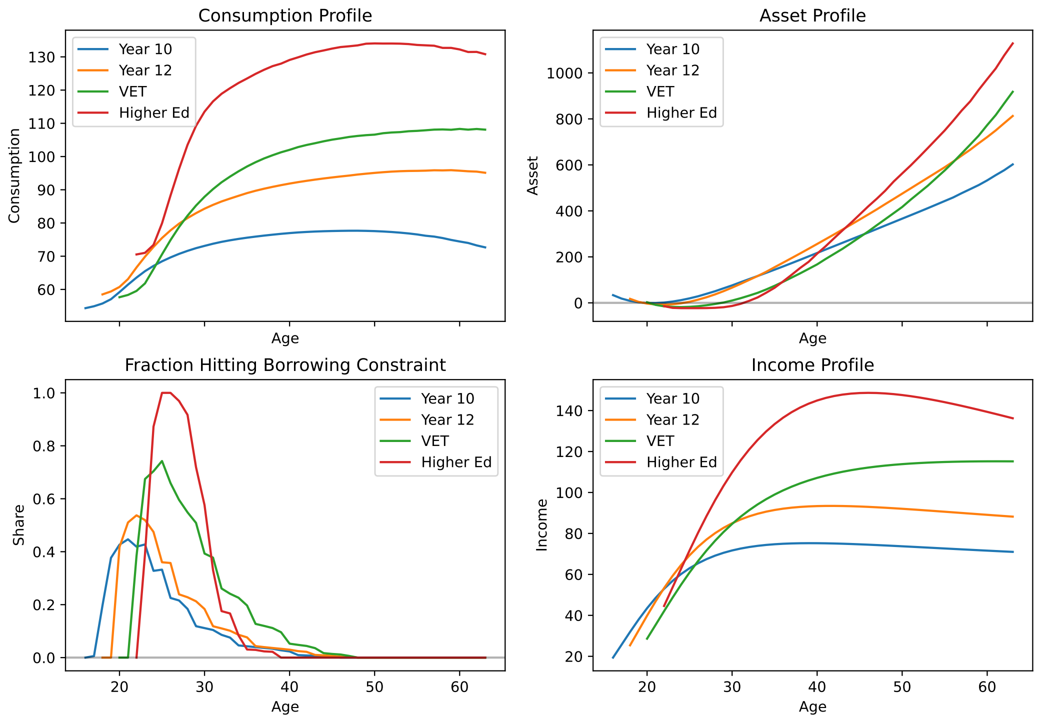

Figure 7: Simulated life-cycle profiles of consumption, assets, income, and borrowing constraint, disaggregated by education level.

private borrowing during student stage in the model. As expected, the higher-education group remains indebted for the longest on average because their fees are the highest.

While not targeted in the MSM estimation, the overall share of individuals who are borrowing constrained in the model is around 15%, which fits well with the average for the Australian economy. The age profiles of the fraction constrained (bottom-left panel) show that individuals are more likely to be constrained earlier in working life, as they borrow against future income as much as possible. The fraction constrained is much higher for the higher-education type than for others, indicating that while student loans help finance college, they also increase financial burdens after graduation. However, the fraction also decreases more rapidly for the college type than for others, indicating that the constraint is only temporary.

In the bottom-right panel, we show the age–income profile for all education groups. Since income is exogenous in our model, the profiles are generated by the AR(1) process described in Section 3 and do not depend on the life-cycle model itself. We include them here to provide a comparison with consumption and asset profiles.

6 Policy Analysis

In this section, we present how ICL repayment size and progressivity parameters, λ and τ, defined in equation (5), jointly affect consumer behavior and welfare. We solve the model equilibrium repeatedly for different combinations of λ and τ while adjusting the tax rate to maintain revenue neutrality and calculate changes in consumption, education, tax rates, and aggregate welfare.

For our measure of welfare, we use the ex-ante lifetime utility at the beginning of age 16, before individuals have received any preference shocks or made any education decisions. We also aggregate over the initial asset distribution at age 16, i.e., $\int\int V_{16}^{S}(b,\epsilon_1)dbd\epsilon_1$, so that each policy parameter pair (λ,τ) is associated with a single welfare value.

We impose revenue neutrality in this policy exercise by adjusting income tax rates. For each (λ,τ), we calculate the tax rates needed to balance the government budget using equations (34) and (35) for the higher education and vocational education groups, respectively.

The solid lines in Figure 8 are iso-cost lines that represent the combinations of λ and τ that require levying the captioned tax rates.

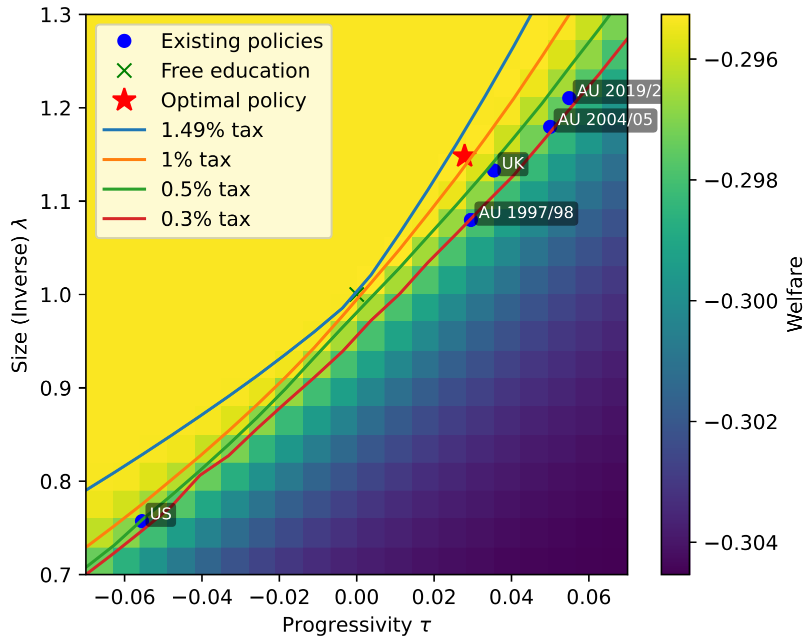

Figure 8: Average welfare under combinations of policy parameters λ and τ

Figure 8 shows the average welfare for each pair of (λ, τ), with brighter colors representing higher welfare. Here, free education is represented by the central point with $\lambda = 1$ and $\tau = 0$. Under this specification, "borrowers" never have to repay, since $R(y) = y - \lambda y^{1-\tau} = 0$ for all values of y. Tuition fees will be funded completely by income tax. Such a scheme would require an income tax rate of 1.5% on the higher education group and 0.7% on the vocational education group, which are the highest out of all possible parameter combinations.

ICL functions in the upper-left regions have smaller repayments and lower progressivity, i.e., larger λ and smaller τ. They generate higher welfare in general, represented with brighter colors. The ICL functions above the 1.49% tax iso-cost line, do not trigger repayment at almost all realized income levels and are supported almost entirely by income tax. Therefore, they are very similar to free education when carried out in reality. However, free education and those policies similar to it, while generating high welfare, do not maximize welfare due to the high tax rate needed to maintain revenue neutrality.

The optimal ICL, represented by the red star sign, is progressive and has small per-period repayments. It requires $\lambda = 1.15$ and progressivity $\tau = 0.027$, which is less progressive and imposes smaller and slower repayments than existing ICL policies in Australia and the UK. Optimal ICL also needs to be funded by a higher income tax rate, around 1.2%, than those for existing ICLs, around 0.3-0.4%.

Table 7 presents statistics on educational attainment, welfare, and tax rate for the optimal and existing ICL policies. Progressive ICLs, such as the Australian and UK plans, provides similar welfare compared to regressive ICLs, such as the US standard plan. They also induce slightly lower attainment rates for higher education. This is mainly due to progressive ICLs triggering higher repayments five to ten years after graduation.

Table 7: Model-generated statistics under various policies

Policies	Educational attainment (%)				Welfare	Tax (%)
	Year 10	Year 12	Vocational	Higher Edu		
Optimal	35.9	34.7	11.9	17.5	74.6	1.2
AU 1997/98	36.9	38.5	9.2	15.4	74.1	0.3
AU 2004/05	36.9	38.1	9.8	15.2	74.1	0.3
AU 2019/20	36.9	37.9	9.9	15.3	74.1	0.3
UK	36.5	36.8	10.6	16.1	74.4	0.4
US	36.7	37.3	8.9	17.1	74.3	0.4

Note. Welfare is calculated using annual consumption equivalence in units of $1,000s of 2020 Australian dollars. Therefore, a welfare of 100 represents consuming $100,000 every year throughout the lifecycle. Tax rates listed here are those levied on the higher education group.

In Figure 9, we compare the changes in consumption-age profile under the benchmark policy (Australia 2004/05) and other existing policies. Under the UK and US policies, which provides higher welfare, consumption is higher before age 30 and is only slightly lower between age 30 and 40.

7 Conclusions

In this paper, we study how the size and progressivity parameters of ICLs affect debt repayment flows, educational attainment, and welfare as measured by consumption equivalence.

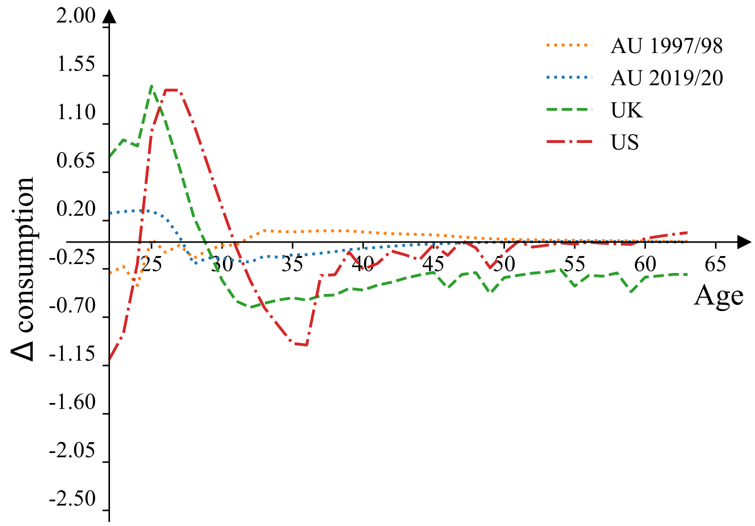

Figure 9: Consumption differences under counterfactual policies against benchmark

Notes: The unit of y-axis is thousands of Australian dollars in 2012.

We adopt a structural approach by constructing a heterogeneous-agent life-cycle model with rich idiosyncratic exogenous shocks and endogenous choices, which we match to patterns in microdata. To our knowledge, we are the first paper to use this approach to evaluate the welfare implications for the size–progressivity combinations under both existing and potential ICL policies.

We find that the optimal size and progressivity of repayments are negatively correlated: more progressive ICLs should be combined with smaller average repayments. Moreover, smaller and more progressive ICLs yield slightly higher welfare than larger, less progressive ones. Existing ICLs in the US, the UK, and Australia are close to the optimal combination, but the UK and Australian policies are larger than optimal, conditional on their relative progressivity.

We contribute to the quantitative literature on student loan design by constructing a model that incorporates the details of ICLs alongside rich educational choices. We also complement the theoretical literature on optimal policy by numerically evaluating the optimal size–progressivity combinations of ICLs. Moreover, our study provides practical policy implications for governments choosing ICL parameters which, to our knowledge, hasn't been done in previous research.

When constructing the life-cycle model, we abstract from several features commonly included in the literature, because we believe they would not significantly affect the main result. First, we do not consider general equilibrium effects, such as changes in the college premium, because altering the repayment function without changing overall fees does not induce large enough shifts in college enrollment. Second, we abstract from labor supply. This is supported by previous studies that find small labor supply elasticities (Dandie and Mercante, 2007). Moreover, accounting for potential moral hazard in labor supply under ICLs would likely reinforce our main results that existing policies are more progressive than optimal.

The quantitative model we have constructed also lays the foundation for several meaningful extensions. First, it would be interesting to consider how ICLs affect marriage and gender differences, since married women are more likely to exit the labor market and thus may not have high enough income to trigger repayment. Second, given that the life-cycle changes in consumption and borrowing behavior are prominent in our analysis, it may also be worthwhile to study how an age- or experience-dependent repayment rule 0– which may be easier than ICLs to implement – approximate ICL rules in affecting individual behaviors and welfare.

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Appendix A Glossary

Table 8 provides a list of all variables used in the life-cycle model in Section 4.

Table 8: Glossary of variables

Notation	Meaning
$a_{j,t}$	Asset position indexed by age and time
b_t	Parental transfer received at age 16
$c_{j,t}$	Consumption indexed by age and time
$d_{j,t}$	Remaining student debt indexed by age and time
e	Education level (four categories)
g	Warm glow terminal utility function
g_1, g_2	Parameters governing function g
r	Real interest rate
T	Tax at retirement age
$y_{j,t}$	Earnings indexed by age and time
γ	Euler-Mascheroni constant
δ_1, δ_2	Std of taste shock - education
ϵ_1, ϵ_2	Taste shock - education
λ	ICL repayment parameter, size
τ	ICL repayment parameter, progressivity
τ^{inc}	Income tax
ϕ^{ve}, ϕ^{he}	Monetary cost of education
φ	Aggregate distribution
χ	Generic vector of state variables
ψ	Psychic utility cost of education
$\omega^S, \omega^W, \omega^R$	Net transfers

Appendix B Additional empirical findings

Tuition fees. Tuition fees increased during all four reforms and remained stable between each reform, as shown in Figure 10. Tuition fees doubled in 1997 and increased by about 20% in both 2005 and 2021. As it usually takes three years to complete a bachelor's degree in Australia, the typical amount of student debt for a bachelor graduate was between \$20,000 and \$50,000 Australian dollars in 2020. At the same time, total education expenditure per student by universities has remained stable at around $25,000 Australian dollars since 2000.[12] This implies that the private share of education has increased.

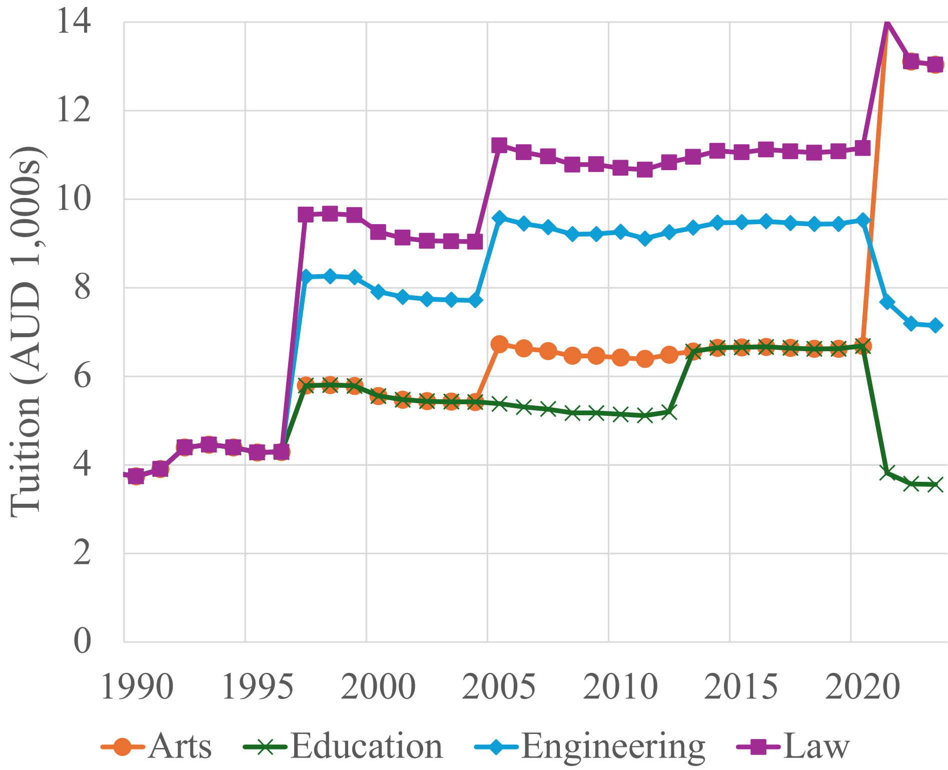

Figure 10: Tuition fee by discipline

Statistics taken from news article "From free university to $15,000 a year for an arts degree". Tuition fee is defined as the government-mandated minimum annual student contribution and deflated to 2020 Australian dollars. Universities can charge up to 30% higher than the minimum.

Education attainment. The size of the higher education sector in Australia ballooned into significance starting from the 1980s. Using both repeated cross-sections from the census (Australian Bureau of Statistics, 2016) and panel data from HILDA (Watson and Wooden, 2012), we find large increases in college education attainment. In 1981, only 5% of Australians aged 25-34 hold a bachelor's degree. Today, more than 30% do.

Figure 11 shows the increase in educational attainment in Australians aged 25-34 from 1981 to 2016. There is a large increase in the share of population with post-secondary education, matched by the decrease in those with less than 12 years of education. The shares of

[12] Figure 15 in the Appendix shows the time trend using OECD data.

younger population holding certificates and bachelor degrees both expanded notably, whereas the shares for other levels of post-secondary education either only slight increased or remained stable.

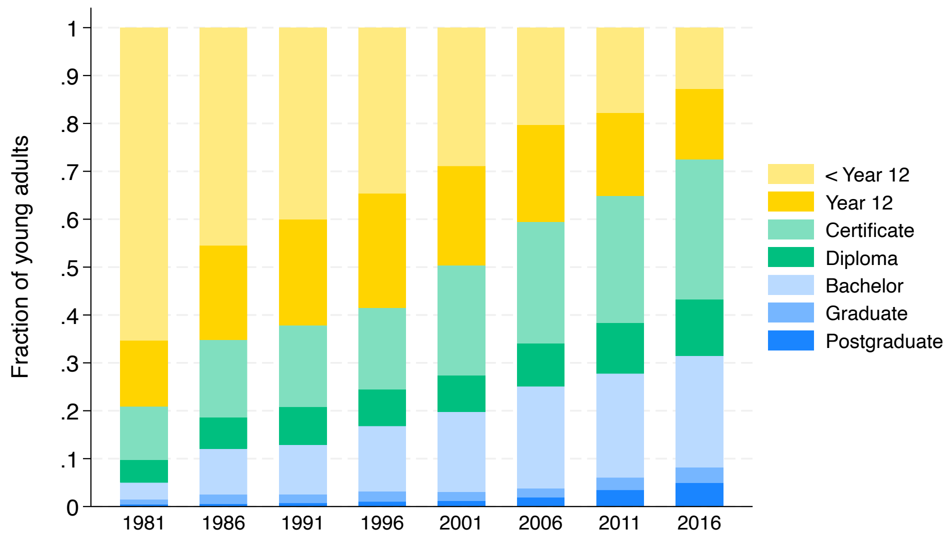

Figure 11: Educational attainment in Australia, 1981-2016

Notes: Data from Census of Population and Housing 1981-2016, 1% sample. Non-citizens or individuals born outside of Australia are excluded. Young adults include individuals aged 25-34.

Figure 12 shows similar trends in educational composition as Figure 11 using the annual HILDA dataset from 2001 to 2020 (Waves 1-20) to that in Figure 11. The left panel contains all individuals in working age (aged 25-60), whereas the right shows those aged between 25 and 34, same as in Figure 11. The composition shown in the right panel is consistent with that in Figure 11, using census data. With annual instead of five-year data, we can see that the increase in educational attainment for young workers is faster in 2001-2005 than the rest of the time period.

Although there are many education levels officially recognized in Australia, as seen in Figure 11, we categorize individuals into four groups based on their eligibility for ICLs and the difference in their income processes during entering the labor market. The four groups are Below Year 12, Year 12, Vocational Education, and Higher Education.

It is common in Australia for high school students to leave school at Year 10 or 11, at around the age of 16, if they do not intend to go to college. Even in 2020, more than 10%

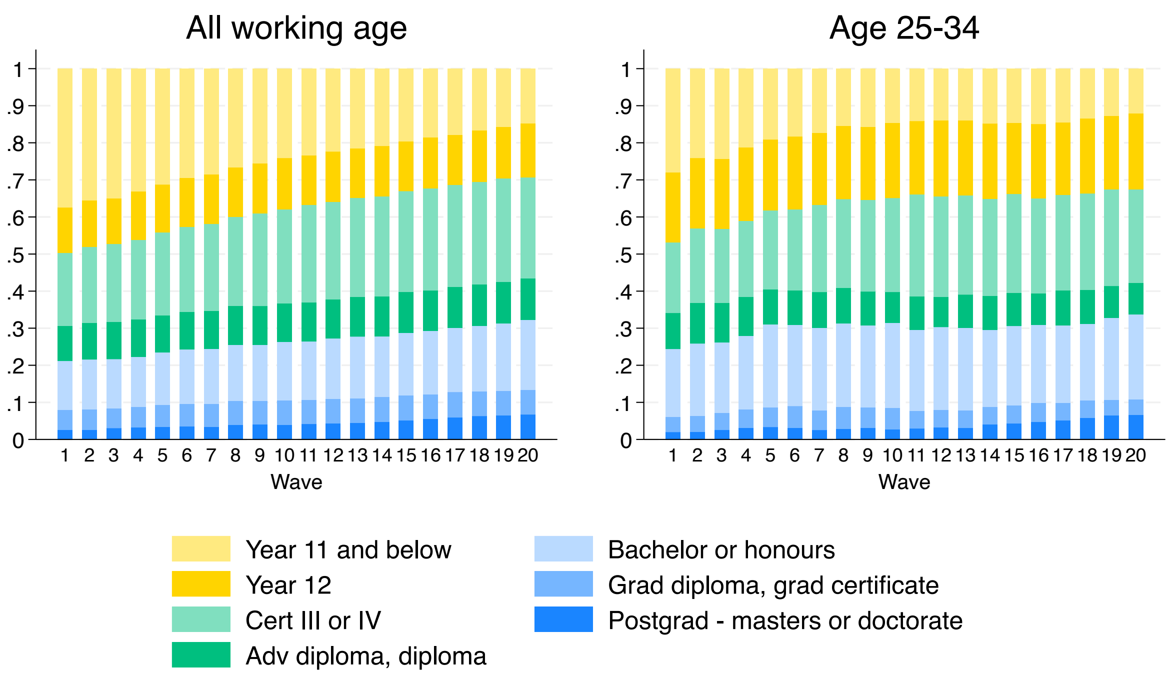

Figure 12: Trends in educational attainment using HILDA Wave 1-20

Notes: Sample from HILDA. We include all individuals born in Australia. We use cross-sectional individual weights for each wave. High school dropout is defined as those who completed year 11 or below; high school graduate as completed year 12; vocational as completed certificate or diploma; higher education as completed bachelor and above.

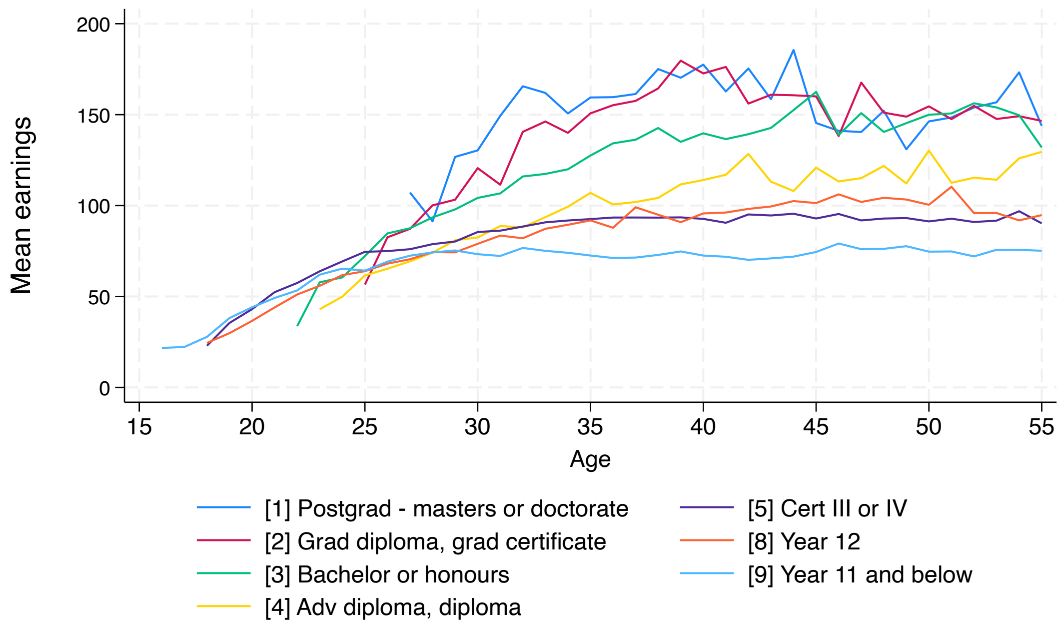

Figure 13: Age-income profile for different education levels

Notes: Sample here include all male full-time workers in HILDA Waves 1-20. The unit used is thousands of Australian dollars in 2012. Education category is based on highest level completed. We drop estimates where there are less than 10 observations in an age-education cell.

of individuals leave college before Year 12.[13] Their income is also notably lower than those with twelve years of education or above, as shown in Figure 13. Therefore, we consider them as a separate education group and model the decision of staying through Year 12 explicitly in our life-cycle model in Section 4.

The vocational education sector in Australia is sizable. About 10% of adults aged 25-34 hold a vocational degree that takes two or more years to complete, such as a diploma or a Certificate III or IV. Before the reform in 2005, they were not eligible for ICLs. In the 2005 reform, it was announced that vocational students are included in the ICL scheme starting 2007.

Completion rates. College dropout rates have remained stable since 2005. While less than half of all bachelor students at Australian universities graduate in four years, more than 70% manage to do so in nine.[14] Enrollment has increased since the 2000s while college premium has remained stable. Figure 14 shows the 4-year, 6-year, and 9-year completion rates for bachelor students in Australian universities. Although there is a slight decline in the completion rates, the levels remain relatively stable over the 14-year period observed.

Total educational expenditure. Using OECD data, we can observe total expenditure as US dollars per student per year from 2000 to 2020. We convert US dollars to Australian dollars in 2020 using market exchange rate and CPI in Australia. Figure 15 shows the trend in college expenditure since 2005. Total expenditure remains stable at around $25,000 dollars, with a slight decrease before 2012 and a slight increase after 2012.

HECS reforms. Since its establishment in 1989, the HECS system has experienced three major reforms – in 1997, 2003, and 2019.

In 1997, the newly elected administration announced a HECS reform with three main features. Firstly, student contribution level was increased by about 40%. Secondly, contribution level changed from a uniform price to three levels by course of study, with subjects such as humanities and education being the lowest and those such as law and medicine being the highest. Lastly, income thresholds for repayment were reduced. Chapman (2006) studied the 1997 reform and found no adverse effects for students of any background despite the large changes.

[13] See Figure 12 in the Appendix.

[14] Although the official length of study for Australian universities are three to four years, a fraction of students have some form of interruption in their studies.

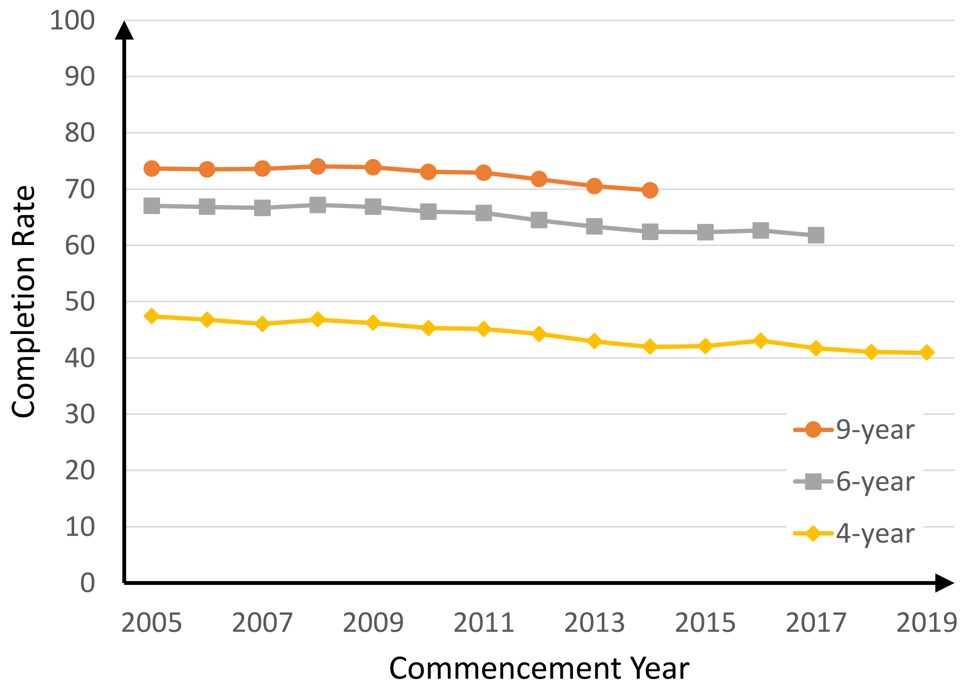

Figure 14: Trends in completion rates

Notes: Statistics from "Completion Rates of Higher Education Students - Cohort Analysis, 2005-2022" published by the Australian Department of Education. Sample includes all domestic students studying in institutions designated as universities by the DoE. Completion rates differ the length of time periods observed, i.e. the 4-year completion rate in 2019 represents the percentage of students graduating by 2023.

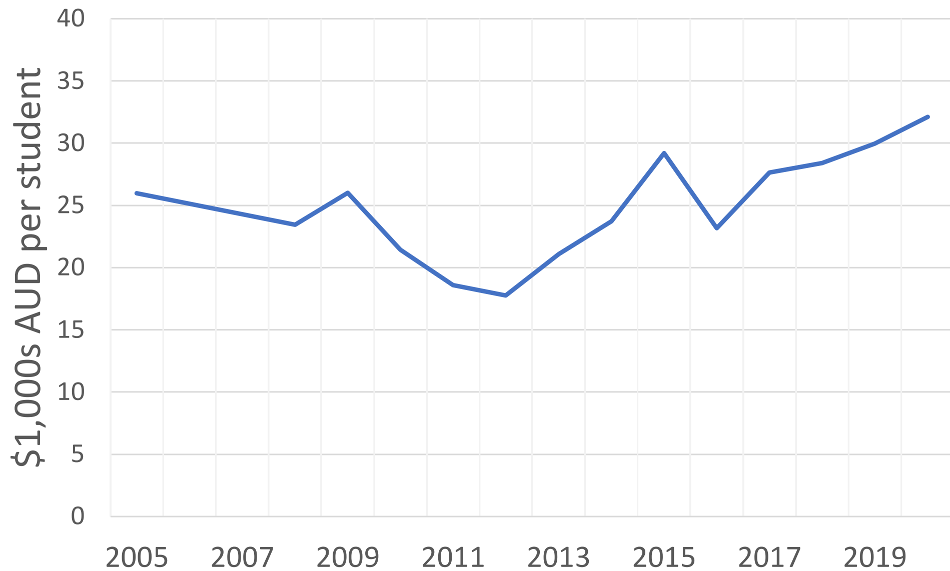

Figure 15: Total expenditure on tertiary education

Notes: Data from OECD, Education at a glance. Author's own conversion from US dollars

The Higher Education Support Act (HESA) in 2003 introduced several changes to HECS. First, the uniform student contribution level is replaced by a range, where each school can set its own level. Secondly, the income threshold for repayment is increased. Thirdly, HECS is incorporated into the new Higher Education Loan Program (HELP), which also includes graduate-level studies and professional training. Nelson (2003) provided a summary of changes included in HESA 2003.

After the 2003 reform, higher education institutions were able to set their own fees up to 30% higher than the pre-reform level. The ceiling set by the government is binding for at least some universities. Most notably, Go8, the group of the eight top universities of Australia, all charge fees either equal to, or close to the upper bound.

In May 2017, Australian government announced a more progressive repayment schedule with a higher minimum repayment threshold and a higher top repayment rate. The proposed thresholds and rates did not start until 2019-20. The minimum repayment threshold for 2019-20 moved to $45,881, and the thresholds will be indexed in the years after 2019-20.

Appendix C Estimating income dynamics

C.1 Data cleaning

To estimate the parameters of the income process, we use the HILDA survey data from 2000 to 2020. We select all male respondents born in Australia. We keep only full-time workers aged between 25 and 55, as we do not wish to account for the wage loss from health shocks which commonly occurs after age 55.

Consistent with the rest of the paper, we divide individuals into four education groups – (1) Individuals with bachelor degrees or above (*Higher Education*); (2) individuals with vocational degrees that take at least one year to finish, such as Diploma and Certificate II or IV, but no higher education degrees (*Vocational Education* or *VET*); (3) individuals with 12 years of schooling who do not belong to the first two groups (*Year 12*); and (4) individuals with less than 12 years of schooling (*Less Than Year 12*). Higher education or vocational education dropouts will therefore be classified as *Year 12*. We have checked empirically that their income profiles are similar to those who never enrolled in post-secondary education.

For our measure of income, we use financial year gross wages and salary (variable name "wsfes"), which measures income before tax. We deflate income using CPI to 2020 dollars. We drop observations with income below \$7,500 or above \$750,000, as well as those with abnormal growth (i.e. with log difference bigger than 4 or smaller than -2 between two consecutive years).

C.2 Estimating age-income profiles

When estimating the age-income profiles $\bar{y}^e_t$, we run the following regression:

$$y^e_{t,i} = f(t|e) + X_{i,t} + \nu_{i,t}, \tag{39}$$

where $y^e_{t,i}$ is the log income of individual i with education group e at time t. $f(t|e)$ is a fractional polynomial with two terms, each with powers between -2 and 2. $X_{i,t}$ include control variables including marital status, cohort group, and geographical region. We do not control for individual fixed effects because we want to measure the initial dispersion in residual income $\epsilon_{i,t}$. $\nu_{i,t}$ is the residual term which we will use to estimate the AR(1) process in the next section.

Appendix D Computation of the life-cycle model

In this section, we describe how the life-cycle model described in Section 4 is solved numerically.

The individual problem is solved backwards from the age of 65 to 16. Except for the ages when schooling choices are made (16 and 18), the problems for other ages are versions of consumption-savings decisions under credit constraint and income risks (Huggett, 1996), which I solve using the endogenous grid method (EGM), first introduced by (Carroll, 2006).

To illustrate, consider the individual problem at working age α. we drop both the age and time subscript and use primes to indicate variables in the latter period. The value function can be simplified into

$$V_\alpha(e,a,y,d) = \max_c u(c) + \beta\mathbb{E}_y\left[V_{\alpha+1}(e,a',y',d')|y\right], \tag{40}$$

subject to

$$a' + c + (d - d') = (1+r)a + y \tag{41}$$

$$d - d' = \min\{d, R(y)\} \tag{42}$$

$$a' \geq -L. \tag{43}$$

We construct (exogenous) grids over (a', y, d). This also allows us to calculate next period debt $d' = \max\{0, d - R(y)\}$ using the repayment rule. Moreover, we have calculated eacf $\mathbb{E}_yV$ and $\mathbb{E}_y\partial V_{\alpha+1}/\partial a'$ associated with (a', y, d') in the previous iteration, for age $\alpha + 1$. Using the first order condition, we can find a closed-form, interior solution for c,

$$c = (u')^{-1}\left\{\beta\mathbb{E}_y\left[\frac{\partial V_{\alpha+1}}{\partial a'}\right]\right\}. \tag{44}$$

Then, we can back out this period asset a using the budget and the credit constraint:

$$a = \max\left\{-L, \frac{a' + c + (d - d') - y}{1 + r}\right\}. \tag{45}$$

This equation yields endogenous grids a associated with (a', y, d), which is why this method is call Endogenous Grid Method. For both the corner solution, i.e. $a = -L$, and interior solution, i.e. $a > -L$, we can also calculate V_α using equation (40) and $\partial V_\alpha / \partial a$ using the Envelop condition, $\partial V_\alpha / \partial a = u'(c)$, which will be used for the next iteration, for age $\alpha - 1$.

Lastly, we interpolate V_α and $\partial V_\alpha / \partial a$, currently on the endogenous grids of a, onto exogenous grids set ahead of time. This step is the most computationally costly step and needs to be done only once for each age, instead of for each age and combination of states (a', y, d), as is required in other methods such as Value Function Iteration or Policy Function Iteration.