Insurance, Redistribution, and the Inequality of Lifetime Income

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Abstract

Individuals vary considerably in how much they earn during their lifetimes. This study examines the role of the tax-and-transfer system in mitigating such inequalities, which could otherwise lead to disparities in living standards. Utilizing a life-cycle model, we determine that taxes and transfers offset 45% of lifetime earnings inequality attributed to differences in productive abilities and education. Additionally, the system insures against 48% of lifetime earnings risk. Implementing a lifetime tax reform linking annual taxes to previous employment could improve the system's insurance capabilities, albeit at the cost of a lower employment rate.

Key words: Lifetime earnings; lifetime income; tax-and-transfer system; taxation; unemployment insurance; disability benefits; social assistance; inequality; redistribution; insurance; education; productive ability; risk; dynamic life-cycle models.

JEL classification: D63; H23; I24; I38; J22; J31.

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1 Introduction

The inequality of lifetime earnings is a key barometer of disparities in living standards. Indeed, to the degree that individuals can save and borrow, the inequality of lifetime earnings captures fundamental economic disparities more accurately than the inequality of annual earnings. Motivated by this observation, a growing literature has started to document the inequality of lifetime earnings. Despite the mobility of individuals in the earnings distribution, the inequality of lifetime earnings is substantial: Bönke et al. (2015) find that the distribution of the lifetime earnings of German men has a Gini coefficient around 0.2, and Guvenen et al. (2017) find that the 75th percentile of the lifetime earnings of American workers is around three times higher than the 25th percentile. Based on decompositions of the inequality of lifetime earnings, several studies have shown that the inequality in lifetime earnings is due to a combination of differences in skills that are established early in life and chance differences in the shocks that individuals experience during their lifetimes (e.g., Bowlus and Robin, 2004, Huggett et al., 2011).

In this paper, we examine the effectiveness of the tax-and-transfer system in offsetting inequalities in lifetime earnings that stem from skills established early in life. Additionally, we demonstrate how this system mitigates disparities in lifetime earnings arising from health and employment shocks. We call the former effect the redistributive effect of the tax-and-transfer system, and we call the latter effect the insurance effect of the tax-and-transfer system. While previous studies have shown that the inequality of lifetime after-tax-and-transfer earnings (i.e., lifetime income) is lower than that of lifetime earnings, we separately study how the tax-and-transfer system redistributes lifetime earnings and how it insures lifetime earnings risk. As in Bowlus and Robin (2004) and Huggett et al. (2011), we focus on men and set aside considerations of household formation. Consequently, our analysis does not aim to address questions about inequality in the aggregate economy.

There are three reasons why it is important to separate the insurance and redistributive effects of the tax-and-transfer system on lifetime income. First, information about the redistributive effect of the tax-and-transfer system speaks to how well taxes and transfers mitigate increases in the inequality of lifetime earnings that are driven by economic shifts that increase the returns to productive ability and education. Relevant shifts include changes in the pattern of international trade that drive up the wage premium for a college degree and technological change that favors high-ability workers Second, studying how well taxes and transfers insure lifetime earnings risk highlights additional benefits from taxation, social assistance (or 'welfare') programs, and social insurance programs, such as unemployment insurance and disability benefits, compared to benefit calculations that focus on the effects of these programs on annual income or other short-term income measures. Third, by documenting the insurance and redistributive effects of the tax-and-transfer system, we are able to identify directions for policy reforms to taxes and social assistance that may improve the lifetime insurance and redistributive effects of the tax-and-transfer system.

Our empirical analysis is centered on Germany. Consistent with the systems in most developed countries, Germany's tax-and-transfer system incorporates progressive taxes, disability benefits for individuals facing health issues, unemployment insurance for temporary income replacement after job loss, and social assistance offering long-term support to low-income individuals with limited wealth. To investigate the relationship between lifetime earnings, taxes, transfers, and lifetime income, we embed a tax-and-transfer system based on the German system into a dynamic life-cycle model of educational choices, labor supply and consumption behavior. The model generates individual-level trajectories for earnings and after-tax-and-transfer income over the life cycle. Consequently, the model provides the necessary information to calculate lifetime earnings and income for each individual. The model includes two key drivers of disparities in lifetime earnings: differences in skills established early in life, specifically education and productive ability, and differences in the employment, health, and wage shocks that individuals encounter during their lifetimes.

A crucial aspect of our model is its capability to capture the ways in which forward-looking individuals adjust their labor supply, educational choices, and savings as a form of self-insurance against risks like job loss and health shocks. Consequently, it offers insights into the role of the tax-and-transfer system as a protective mechanism, while also accounting for the self-insurance individuals secure through modifications in their behavior based on their current and anticipated future circumstances. To understand the importance of such adjustments, consider one of the questions addressed in this paper: how does the risk of job loss influence income inequality? Utilizing our life-cycle model, we can conduct a counterfactual analysis that not only imposes an elevated risk of job loss but also captures how individuals choose to self-insure, for instance, by increasing their working hours in anticipation of potential job loss or re-entering the workforce more rapidly following a job loss. Relying instead on an exogenous labor supply process would hide this self-insurance and would thereby tend to overstate the insurance effect of taxes and transfers.

We estimate the parameters of the life-cycle model by using a Maximum Likelihood procedure that targets the patterns of educational choices, labor supply and earnings that we observe in a sample of men taken from the German Socio-Economic Panel (SOEP). We demonstrate that the estimated model has a good in-sample fit. We also perform a validation exercise that shows that the inequality in lifetime earnings predicted by the estimated model matches the inequality in lifetime earnings observed in a comparable administrative dataset that was not used for estimation. We find that the tax-and-transfer system is strongly progressive on a lifetime basis, despite taxes and transfers being based on annual earnings. Both insurance and redistribution contribute to the progressive effect of the tax-and-transfer system on lifetime income. In particular, we find that the tax-and-transfer system mitigates 48% of the inequality in lifetime earnings that is due to shocks that individuals experience during their lives. Meanwhile, our results on redistribution suggest that the tax-and-transfer system absorbs 45% of any additional inequality in lifetime earnings that is generated by skill-biased technological change or other economic shifts that increase the returns to education and productive ability.

We break down the overall effect of the tax-and-transfer system on the inequality of lifetime income into the effects of its constituent elements: taxes, unemployment insurance, disability benefits, and social assistance. Our findings indicate that taxes are more effective at redistributing lifetime income than at insuring against lifetime earnings risk. This limited insurance capability of taxes stems from their inability to address inequalities in lifetime earnings caused by differences in the number of years that individuals work during their lifetimes, compounded by the fact that most lifetime earnings inequality among those with the same skills is due to differences in work behavior. Social assistance is the most important transfer program for both insurance and redistribution of lifetime income. Disability benefits are important for insurance, but their redistributive effect is negligible. Unemployment benefits, on the other hand, have a limited role in both insurance and redistribution.

In our subsequent analysis, we investigate how the tax-and-transfer system mitigates three specific sources of lifetime earnings risk: job separation risk, job offer risk, and health risk. Our findings reveal that the tax-and-transfer system insures 61–65% of the increased inequality in lifetime earnings resulting from an increase in job separation risk or health risk. Conversely, the mitigating effect of the tax-and-transfer system on job offer risk is noticeably smaller at 22%. This difference can be partly attributed to individuals opting to use their labor supply more extensively as a self-insurance mechanism against job offer risk, compared to health risk or job separation risk. We also find that individuals mitigate job separation risk and job offer risk by increasing their years of education, which leads to small improvements in health.

Our results point to potential policy reforms that could improve the insurance and redistributive functions of the tax-and-transfer system, though possibly at the cost of reduced employment or other economic inefficiencies. In the final section of the paper, we explore the effects of a revenue-neutral tax reform linking annual taxes to past employment. This 'lifetime tax reform' increases annual taxes for individuals with stronger employment histories and decreases them for those with weaker employment histories. Consequently, among two individuals with the same annual earnings, the one with the stronger employment history will face higher taxes in the current year. Our simulation based on the estimated model suggests that this reform could reduce the inequality of lifetime earnings. The reform achieves this through both direct means—by specifically targeting higher taxes for those with stronger employment histories—and indirect means, by prompting labor supply adjustments that reduce lifetime earnings inequality. However, the reform also leads to a decrease in the overall employment rate and an increase in the frequency of unemployment spells over individuals' working lives.

Our interest in the inequality of lifetime income is based on studies that document substantial inequities in lifetime earnings using administrative datasets (Björklund, 1993, Kopczuk et al., 2010, Aaberge and Mogstad, 2015, Bönke et al., 2015, Guvenen et al., 2017), statistical models (Bonhomme and Robin, 2009), or behavioral economic models (Bowlus and Robin, 2004, Bowlus and Robin, 2012, Brewer et al., 2012). Our focus on the insurance and redistributive effects of the tax-and-transfer system is motivated by a related literature that shows that both risk and skill endowments contribute to the inequality of lifetime outcomes (e.g., Keane and Wolpin, 1997, Flinn, 2002, Bowlus and Robin, 2004, Storesletten et al., 2004, Huggett et al., 2011). The importance of risk in explaining disparities in lifetime earnings is consistent with studies that show that individuals are subject to persistent earnings, health, and employment shocks (e.g., Meghir and Pistaferri, 2011). The role of skill endowments in driving lifetime earnings aligns with studies showing that education and non-cognitive skills are important determinants of lifetime earnings (e.g., Bhuller et al., 2017, Nybom, 2017).

Several papers have looked at the reallocative effect of taxes and transfers on a lifetime basis (e.g., Falkingham and Harding, 1996, Nelissen, 1998, Björklund and Palme, 2002, Pettersson and Pettersson, 2007, Ter Rele et al., 2007, Bovenberg et al., 2008, Bartels, 2012, Levell et al., 2017). This literature systematically finds that the reallocation of lifetime earnings through the tax-and-transfer system partially offsets disparities in lifetime earnings. Levell et al. (2017), for example, find that the inequality of lifetime income in the UK is about 25% lower than the inequality of lifetime earnings. Levell et al. (2017) further show that in-work benefits and out-of-work benefits are equally effective at reducing the inequality of lifetime income. Other papers have taken a longitudinal perspective by looking at the dynamics of earnings and income at the individual level. In this vein, Blundell et al. (2015) show that taxes and transfers moderate the impact of transitory and permanent earnings shocks, and Brewer and Shaw (2018) show that the marginal tax rate that individuals face varies more within the life cycle than across individuals. However, in contrast to our analysis, the previous literature has not separately considered how the tax-and-transfer system targets inequalities in lifetime earnings that are due to risk and how taxes and transfers mitigate the inequality in lifetime earnings that is attributable to skills established early in life.

Our life-cycle model of education, labor supply and consumption is in the spirit of the models introduced by Eckstein and Wolpin (1989), Keane and Wolpin (1997), Imai and Keane (2004) and Belzil and Hansen (2002). Since we require information about lifetime income, as well as lifetime earnings, we follow, e.g., Low et al. (2010), Hoynes and Luttmer (2011), Shaw (2014), Low and Pistaferri (2015), Haan and Prowse (2015), and Blundell et al. (2016) by embedding a tax-and-transfer system into a life-cycle model. This literature has considered individuals' willingness to pay for particular elements of the tax-and-transfer system and, in many cases, has differentiated willingness to pay by education or other skill endowments. In contrast, we focus on the implications of taxes and transfers for the inequality of lifetime income. In doing so, we make a connection to a literature that links inequality to broader economic and socio-economic outcomes (see, e.g., Kelly, 2000, Panizza, 2002, Cramer, 2003).

This paper proceeds as follows. In Section 2 we introduce our definitions of lifetime earnings and lifetime income. In Section 3 we describe the life-cycle model that we use to derive lifetime earnings and lifetime income. In Section 4 we discuss our parameter estimates and present the results of a model validation exercise. In Section 5 we explore the insurance and redistributive effects of the tax-and-transfer system. In Section 6 we show how the tax-and-transfer system insures job separation risk, job offer risk, and health risk. In Section 7 we explore the implications of a lifetime tax reform. In Section 8 we conclude by discussing some implications of our results.

2 Earnings and income concepts

We start with our definitions of earnings and income. An individual's annual earnings is composed of annual labor earnings and annual capital income derived from current net wealth. Using i to index individuals and t to denote age (measured in years), we have:

$$\text{Earnings}_{i,t} = \text{LaborEarnings}_{i,t} + \text{CapitalIncome}_{i,t}. \tag{1}$$

We define the individual's annual income at age t to be equal to his annual earnings, defined above, minus annual taxes plus the annual value of any government transfers:

$$\text{Income}_{i,t} \quad = \quad \text{Earnings}_{i,t} - \text{Taxes}_{i,t} + \text{Transfers}_{i,t}. \tag{2}$$

In other words, we use the term income to refer to after-tax-and-transfer earnings. Summing the individual's annual earnings over the life cycle yields the individual's lifetime earnings. Likewise, the individual's lifetime income is obtained by summing the individual's annual income over the life cycle.

While the exact nature of tax and transfer programs varies from country to country, there are some broad similarities in how countries organize these programs. First, taxes are generally based on annual income and are progressive on an annual basis. Second, transfer programs typically include provisions for people experiencing bad health or disabilities, unemployment insurance that provides temporary income replacement following a job loss, and social assistance (i.e., welfare) that provides support to low-income, wealth-poor individuals, irrespective of their earnings history. Since these transfer programs support individuals when they experience low income, they are also progressive on an annual basis. Our analysis considers a tax-and-transfer system that includes progressive annual taxation, unemployment insurance, disability benefits and social assistance. To align with our data, the tax-and-transfer system that we model is based on the German system for 2005–2016.[1,2] Sections 2.1 and 2.2 provide further details.

2.1 Transfers

Transfers include unemployment insurance, disability benefits and social assistance.

Unemployment insurance: An individual who enters unemployment from employment receives unemployment insurance for one year. Unemployment insurance is equal to sixty percent of the

[1]The model also includes pension benefits for individuals in old-age retirement (see Web Appendix I). Our model of transfers abstracts from some details but, overall, is a relatively complete representation of the German transfer system (see, e.g., OECD, 2020 or Bundesministerium für Arbeit und Soziales, 2023). In particular, we include all relevant unemployment benefits (unemployment assistance, a program for the long-term unemployed, was discontinued in 2004, and, therefore, it is irrelevant in our study). Housing benefits are modeled as part of social assistance. We also omit the housing allowance (a program for low-income households) and work-entry assistance since these are smaller programs with individually assessed benefits.

[2]In our analysis, we operate under the assumption of full take-up of transfers and full compliance with the tax system. Thus our focus is to examine the implications of the established rules rather than potential deviations from them. Two considerations mitigate the importance of non-take-up of transfers. First, most instances of non-take-up usually involve smaller benefit amounts. Second, to the extent that take-up rates may be influenced by factors such as claiming costs or stigma, the nominal value of the benefits that are not claimed will overstate the actual value of those benefits to the individual. See Haan and Prowse (2023) for a study of the welfare effects of social assistance and unemployment insurance with benefit non-take-up.

individual's after-tax labor earnings in the year before he entered unemployment.[3]

Disability benefits: An individual in bad health may choose to enter disability-based retirement, irrespective of his age. Once in disability-based retirement, an individual receives disability benefits each year for the rest of his life. Disability benefits increase with earnings prior to retirement and include an experience credit of one year for each year that the individual entered disability-based retirement before age 63 years.[4]

Social assistance: Social assistance guarantees every individual a minimum annual income (comprising of income support and housing assistance). In particular, if an individual's combined annual income from labor earnings, capital income, unemployment insurance and disability benefits is below the annual minimum income guaranteed by social assistance, then the individual receives a social assistance transfer to increase his annual income to the level of the annual minimum income guarantee. The annual minimum income guarantee ranges from 8,400 euros per year if the individual has no assets to zero if the individual is sufficiently wealthy. In more detail, the annual minimum income guaranteed by social assistance is equal to:

$$\max\left\{8,400 - \max\left\{A_{i,t} - 10,000 - 500 \times (t-20), 0\right\}, 0\right\},$$

where $A_{i,t}$ denotes the individual's net assets at age t. Intuitively, the annual minimum income guarantee is adjusted downwards by one euro for each euro of assets in excess of an age-specific disregard. The age-specific disregard starts at 10,000 euros for an individual aged 20 years and increases by 500 euros with each year of age.

[3] According to German regulations, eligibility for unemployment insurance depends on two factors: the applicant's employment history and the circumstances surrounding their departure from their previous job. The employment history requirement stipulates that individuals employed for the past twelve months are eligible for unemployment insurance. This rule is accurately reflected in our model. Regarding the circumstances of job loss, individuals who voluntarily leave their jobs may be banned from receiving unemployment insurance for up to three months; however, they regain eligibility once the ban concludes. In our analysis, we abstract from temporary unemployment insurance bans because they are of minor importance in our setting. First, they impact only a small proportion of individuals. Specifically, during the time frame of our estimation sample, only 2.8% of unemployed individuals who satisfied the work history requirement were temporarily banned from receiving unemployment insurance benefits due to the circumstances of their job loss (Bundesagentur für Arbeit, 2023). Second, given the annual specification of our model, a maximal-length ban of three months affects only one-quarter of an individual's benefits. Garnero et al. (2019) propose a useful approach to account for the pattern of unemployment insurance receipt when benefit rules are modeled in less detail.

[4] Specifically, an individual who enters retirement in bad health at age R receives an annual disability benefit of:

$$\alpha \times \overline{W}_R \times \text{DBPenalty}_R \times \left(\text{Exper}_R + \text{Credit}_R\right),$$

where α is a parameter that controls the generosity of disability benefits, $\overline{W}_R$ is the individual's disability-benefit-eligible annual earnings averaged over all years of employment prior to retirement, DBPenalty_R is a penalty that reduces the individual's annual disability benefit by 3.6% for each year that he retired before the age of 63 years (up to a maximum reduction of 10.8%), Exper_R denotes the individual's experience at retirement (i.e., the number of years that the individual was employed during his life), and Credit_R is an experience credit of one year for each year that the individual is entered disability-based retirement before the age of 63 years. Only annual earnings below 72,374 euros are considered when calculating disability benefits.

2.2 Taxes

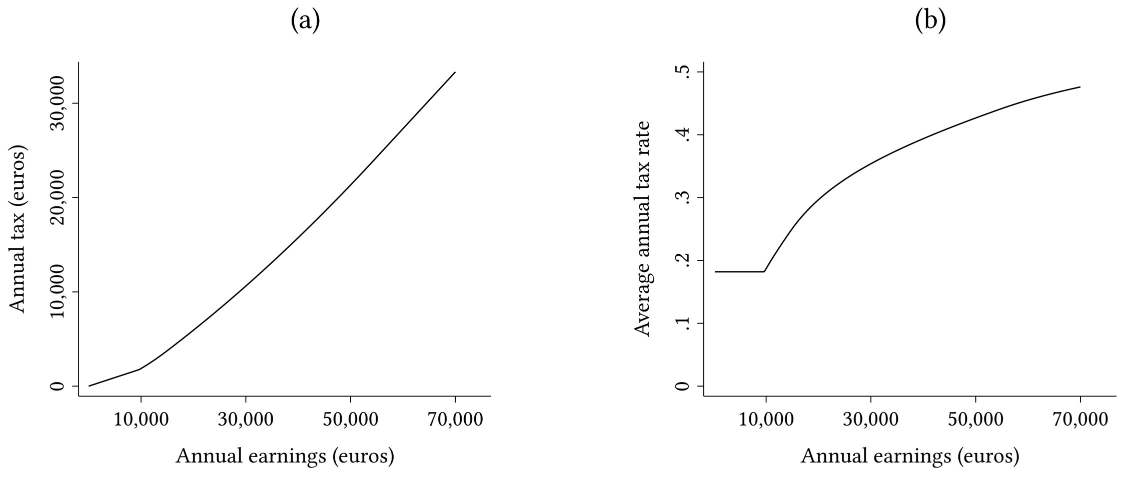
We model the three main income taxes faced in Germany. First, individuals pay a tax on annual labor earnings[5]: annual labor earnings above 8,652 euros are taxed according to a progressive tax schedule with a marginal tax rate that increases smoothly from 14% at annual labor earnings of 8,652 up to 42% at annual labor earnings above 53,666 euros. Specifically, the tax ($\mathcal{T}$) on labor earnings is given by:

$$\mathcal{T} = \begin{cases} 0 & \text{if} \quad \text{LaborEarnings} \leq 8652, \\ (993.62 \times y + 1400) \times y & \text{if} \quad 8653 \leq \text{LaborEarnings} \leq 13669 \quad \text{where} \quad y = \frac{\text{LaborEarnings}-8652}{10000}, \\ (225.4 \times y + 2397) \times y + 952 & \text{if} \quad 13670 \leq \text{LaborEarnings} \leq 53665 \quad \text{where} \quad y = \frac{\text{LaborEarnings}-13669}{10000}, \\ (0.42 \times \text{LaborEarnings}) - 8394 & \text{if} \quad 53666 \leq \text{LaborEarnings}. \end{cases} \tag{3}$$

Second, individuals pay a social security tax for health, unemployment and pension benefits. The social security tax is a flat rate tax of 18.2% (7.35% for health benefits, 1.5% for unemployment benefits, and 9.35% for pension benefits) on labor earnings below a cap of 74,400 euros per year.[6] Third, annual capital income above an exemption threshold of 801 euros is taxed at a flat rate of 25%. Web Appendix I describes how pension income is taxed.

Figure 1(a) shows how the combined annual tax increases with annual earnings (assuming all earnings are from employment). Figure 1(b) shows that the average annual tax rate increases with annual earnings. Overall, taxation is strongly progressive on an annual basis: the average tax rate varies from 18.2% for individuals with labor earnings below 8,583 euros per year to 48% for individuals with labor earnings of 70,000 euros per year.

Figure 1: Annual taxes



[5]The tax base is derived from gross annual labor earnings by deducting an additional lump-sum allowance for income-related expenses of 1000 euros.

[6]Individuals pay a further tax (Solidaritaetszuschlag) of 5.5% of their tax liability on labor earnings and capital income, included in the model.

3 A model of lifetime income

Our analysis of the effect of taxes and transfers on lifetime income inequality necessitates individual-level data about earnings, taxes, and transfers for each year of the life cycle. Furthermore, to distinguish between the insurance and redistributive effects of the tax-and-transfer system, we need to link the individual-level measures of earnings and income with the respective individual's skills established early in life. We derive the required information about earnings, income and skills from a dynamic life-cycle model. This model enables us to study how taxes and transfer programs provide insurance against employment and health risks, while also accounting for the self-insurance that individuals obtain through optimal adjustments to their education, labor supply and savings behavior in response to changes in the risks they encounter. Moreover, using the model, we can simulate the implications of a counterfactual tax system featuring elements of lifetime taxation (refer to Section 7 for more details).

In the model, the skills established early in life comprise productive ability and years of education. In particular, the individual first observes their productive ability and then makes a decision about their years of education (k). Subsequently, each year, each individual selects a labor supply state (l) and a level of consumption (c) to maximize the discounted present value of their lifetime utility. The model incorporates three mutually exclusive labor supply states: employment, unemployment, and retirement.[7] Our model accounts for four types of lifetime risk: employment (originating from job separation and offer risks), wage, health, and longevity. By including taxes and transfers, the model provides us with a framework to investigate how the tax-and-transfer system mitigates lifetime earnings risk and facilitates the redistribution of lifetime earnings. A detailed description of the model can be found in Sections 3.1-3.8.

3.1 Productive ability and education

Each individual is endowed with a certain level of productive ability. We categorize productive abilities into three types: high, medium, and low, represented by unobserved productivities of η^H, η^M, and η^L, respectively. For individual i, the productive ability, η_i, takes the value η^j with probability ρ_j for $j \in \{H, M, L\}$. As we describe below, productive ability affects potential earnings and, therefore, the likelihood of employment.

The individual's educational attainment is determined by a one-time forward-looking educational investment decision made at age 15. Specifically, at this age, the individual chooses years of education, $\text{Educ}_i \in \{8, \ldots, 18\}$. This decision occurs after the individual has observed their productive ability but prior to entering the labor market. The individual then enters the labor market at the later of age 20 and age $8 + \text{Educ}_i$. It is important to note that productive ability will be a factor in the individual's educational investment decision because the return on education depends on the likelihood of

[7] In the model, employment equates to 40 hours of work per week, aligning with the observed median workweek duration for employees. The incidence of part-time work is negligible. In the estimation sample, only around 3% of employees work fewer than 30 hours per week. For our purposes, unemployment encompasses two groups: individuals who are unwilling to work at their market wage and those who are willing to work at their market wage but do not receive a job offer.

employment, which is influenced by productive ability. This link allows a correlation between unobserved labor market abilities and educational attainment to arise endogenously from the model. We describe the educational investment decision in more detail below in Section 3.8.

By combining the eleven possible values of years of education with the three types of productive ability, we generate thirty-three distinct skill groups. As we explain below, these skills can influence the health, longevity, and employment risks individuals encounter over their life cycles. Consequently, the model captures between-skill-group inequality in lifetime earnings.

3.2 Health and longevity risk

Health risk arises from shocks to the individual's health status. In particular, starting from good health at the time of labor market entry, health evolves stochastically over the life cycle. Each year presents a possibility of a negative health shock for those in good health, moving them into a state of bad health, while those in bad health may encounter a positive health shock, restoring them to good health. The health transition probabilities depend on age, health status, and years of education as follows:

$$\text{Prob}(\text{GoodHealth}_{i,t} = 1) = G_t\big(\text{HighEduc}_i, \text{GoodHealth}_{i,t-1}\big), \tag{4}$$

where $\text{GoodHealth}_{i,t}$ is an indicator of the individual being in good health at age t, HighEduc_i is an indicator of the individual having been endowed with at least twelve years of education (high education), and $G_t(\cdot)$ is an age-dependent nonparametric function. See Section 4.2.2 for further details.[8]

The model allows for longevity risk through age-specific survival probabilities that depend on years of education and health status. In particular:

$$p(t+1|t, s_{i,t}) = S_t\big(\text{HighEduc}_i, \text{GoodHealth}_{i,t}\big), \tag{5}$$

where $p(t+1|t, s_{i,t})$ denotes the probability of survival to age $t+1$, conditional on being alive at age t, and $S(\cdot)$ is an age-dependent survivor function. The maximal life span is assumed to be 100 years.

3.3 Employment risk

Employment risk stems from the uncertainties surrounding job offers and involuntary separations. The individual can only secure employment in the current year if they receive a job offer. The probability of such an offer is influenced by the individual's employment status from the previous year. For instance, if the individual was either unemployed in the previous year, they stand a chance to receive a job offer in the current year with a probability denoted as $\Phi^o_{i,t}$. However, those who

[8] Based on the findings of Adda et al. (2009) and O'Donnell et al. (2015), which report negligible or weak effects of income and wealth on health when conditioned on education, we opt to exclude income and wealth variables from the health process in our model. We note that this omission means that we may be underplaying the role of social benefits.

were employed in the previous year will receive a job offer in the current year only if they are not subjected to an involuntary job separation, which occurs with a probability of $\Phi^s_{i,t}$. Once retired, the individual does not receive job offers. The probabilities of receiving a job offer and experiencing an involuntary job separation are expressed as follows:

$$\Phi^h_{i,t} = \Lambda\left(\phi^h_1 + \phi^h_2 \text{HighEduc}_i + \phi^h_3 \text{GoodHealth}_{i,t} + \phi^h_4 \mathbb{1}_{t\geq 50} + \phi^h_5 \mathbb{1}_{t\geq 55} + \phi^h_6 \mathbb{1}_{t\geq 60}\right) \quad \text{for} \quad h \in \{o, s\}, \quad (6)$$

where $\Lambda(\cdot)$ denotes the logistic distribution function.

3.4 Retirement

The individual may retire only if he meets certain health- or age-based criteria. In particular, the individual may retire only if he is age 30 or older and in bad health (disability-based retirement) or if he is age 63 years or older (old-age retirement). Retirement is compulsory at age 65 years, and once retired, the individual remains retired for the rest of his life.

3.5 Wages and labor earnings

The log hourly wage is given by:

$$\begin{aligned} \log(W_{i,t}) \quad = \quad & \psi_1 \text{Educ}_i + \left(\psi_2 \text{Exper}_{i,t} + \psi_3 \text{Exper}^2_{i,t}\right) \times \text{LowEduc}_i + \\ & \left(\psi_4 \text{Exper}_{i,t} + \psi_5 \text{Exper}^2_{i,t}\right) \times \text{HighEduc}_i + \psi_6 \text{GoodHealth}_{i,t} + \eta_i + \kappa_{i,t}, \end{aligned} \quad (7)$$

where $\text{Exper}_{i,t}$ denotes experience, defined as the number of years that the individual was employed during his life prior to the current year, LowEduc_i is an indicator of the individual eleven or fewer years of education (low education), η_i is the individual's productive ability (see Section 3.1), and $\kappa_{i,t}$ is an autocorrelated wage shock. If the individual was employed in the previous year, then the autocorrelated wage shock evolves according to:

$$\kappa_{i,t} = \delta \kappa_{i,t-1} + \nu_{i,t}, \quad (8)$$

where $\nu_{i,t} \sim \mathbb{N}(0, \sigma^2_\nu)$ and is independent over time. Meanwhile, if the individual was in education or unemployed in the previous year, then $\kappa_{i,t}$ is a draw from the steady-state distribution of the autocorrelated wage shock.[9] Since employment entails 40 hours of work per week (see footnote 7), the annual labor earnings of employed individual i at age t are equal to $W_{i,t} \times 40 \times 52$. Sample log wage observations additionally include measurement error and are given by $\log(W^*_{i,t}) = \log(W_{i,t}) + \mu_{i,t}$ where $\mu_{i,t} \sim \mathbb{N}(0, \sigma^2_\mu)$ and occurs independently over time.

[9] In the steady state $\kappa_{i,t} \sim \mathbb{N}(0, \sigma^2_\nu/(1-\delta^2))$.

3.6 Inter-temporal budget constraint

We use a single variable, $A_{i,t}$, to denote the combined value of the individual's net real and financial wealth. Each year, the individual receives a real return on their wealth of $r \times A_{i,t}$, representing the combined real value of all sources of capital income (including interest income, dividends, rents and so forth). Wealth is accumulated according to:

$$A_{i,t} \quad = \quad (1 + r)\, A_{i,t-1} + \text{LaborEarnings}_{i,t} - \text{Taxes}_{i,t} + \text{Transfers}_{i,t} - c_{i,t}, \tag{9}$$

where $c_{i,t}$ denotes the annual consumption of individual i at age t ad r is assumed to be equal to 0.01. The individual is allowed to borrow up to a limit of 20,000 euros.[10,11]

3.7 Consumption and preferences

An individual who has entered the labor market derives utility from consumption and leisure according to a per-period utility function that is given by:

$$U(c_{i,t}, l_{i,t}, \epsilon_{i,t}) = \begin{cases} \alpha_1 \dfrac{c_{i,t}^{1-\gamma} - 1}{1-\gamma} + \epsilon^1_{i,t} & \text{if } l_{i,t} = \text{retired}, \\[2ex] \alpha_1 \dfrac{(c_{i,t}(1 + \alpha_{2,1}\text{BadHealth}_{i,t} + \alpha_{2,2}\text{GoodHealth}_{i,t}))^{1-\gamma} - 1}{1-\gamma} + \epsilon^2_{i,t} & \text{if } l_{i,t} = \text{employed}, \\[2ex] \alpha_1 \dfrac{(c_{i,t}(1 + \alpha_{3,1}\text{BadHealth}_{i,t} + \alpha_{3,2}\text{GoodHealth}_{i,t}))^{1-\gamma} - 1}{1-\gamma} + \epsilon^3_{i,t} & \text{if } l_{i,t} = \text{unemployed}. \end{cases} \tag{10}$$

For individuals in bad health, $\alpha_{2,1}$ and $\alpha_{3,1}$ measure the utility of employment and unemployment, respectively, relative to retirement, expressed as a fraction of consumption, with negative values corresponding to disutility relative to being retired. The corresponding preference parameters for individuals in good health are $\alpha_{2,2}$ and $\alpha_{3,2}$. $\gamma \equiv 1.5$ is the coefficient of relative risk aversion (see footnote 22 for evidence on robustness to this calibration). The preference shocks $\epsilon^1_{i,t}$, $\epsilon^2_{i,t}$ and $\epsilon^3_{i,t}$ are assumed to be type-1 extreme value distributed and independent over labor supply states and over time. $\boldsymbol{\epsilon_{i,t}}$ is a vector containing the individual's age-t preference shocks. Finally, α_1 is the weight on the systematic utility from consumption and leisure relative to the preference shocks.

In addition to the utilities derived after entering the labor market, the individual incurs a cost from the one-shot educational investment decision that they make at age 15 before entering the labor market. In particular, a choice to obtain $k \in \{8, \ldots, 18\}$ years of education entails a cost of $\lambda_k + \varepsilon_i(k)$,

[10] This borrowing constraint is designed to enable households to partially self-insure by leveraging credit markets to smooth consumption. The credit constraint we implement is consistent with prior research, such as Stoltenberg and Uhlendorff (2022) who estimate that households can borrow up to 42% of their net household income. We note that, since households are limited in their borrowing, social assistance and unemployment insurance still offer insurance.

[11] We do not explicitly incorporate out-of-pocket health care expenses. Such expenses are relatively unimportant in Germany where health insurance covers medical costs, irrespective of income or wealth. While there are out-of-pocket expenses for long-term care, these costs are borne by the social assistance program for eligible households. Since our focus is specifically on the implications of the tax-and-transfer system for individuals under the age of 60—who typically present a low risk for long-term care—the impact of out-of-pocket costs and the related effects of social assistance is of minor relevance. See De Nardi et al. (2010) for a study of the interplay between longevity risk, medical expenses and Medicaid.

which is incurred at age 15. λ_k represents the systematic component of the cost of choosing k years of education, including tuition and subsistence costs, psychological costs (or benefits) of studying and forgone earnings. The systematic component of the educational investment cost is estimated fully non-parametrically, i.e., λ_k is allowed to take a different value of each value of k (with λ_8 normalized to zero for identification). $\varepsilon_i(8), \ldots, \varepsilon_i(18)$ are the idiosyncratic components of educational investment costs and are assumed to be type-1 extreme value distributed and mutually independent.

3.8 Optimal behavior

The individual's optimal consumption and labor supply choice at age t is given by:

$$\{c^*_{i,t}, l^*_{i,t}\} = \underset{\{c,l\}\in\mathbb{D}(\boldsymbol{s}_t)}{\arg\max} \left\{U(c, l, \epsilon_{i,t}) + p(t+1|t, \boldsymbol{s}_{i,t})\beta\mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{i,t+1})|\boldsymbol{s}_{i,t}, c, l]\right\}. \tag{11}$$

In the above, $\beta \equiv 0.99$ is the discount factor (see footnote 22 for evidence on robustness to this calibration), $\mathbb{D}(\boldsymbol{s}_t)$ is the set of choices that is available to the individual at age t (the choice set is determined by involuntary job separations, job offers, wealth and the age- and health-based restrictions on eligibility for retirement), $p(t+1|t, \boldsymbol{s}_{i,t})$ is the probability of survival to age $t+1$ conditional on being alive at age t, $V_{t+1}(\boldsymbol{s}_{i,t+1})$, is the value function, i.e., the expected maximal discounted present value of lifetime utility at age $t+1$, and $\boldsymbol{s}_{i,t}$ denotes the state variables. The state variables are as follows:

$$\boldsymbol{s}_{i,t} \equiv \left\{\text{Educ}_i, \eta_i, t, \text{GoodHealth}_{i,t}, \text{Exper}_{i,t}, A_{i,t}, l_{i,t-1}, \kappa_{i,t-1}, \nu_{i,t}, \text{JS}_{i,t}, \text{JO}_{i,t}, \epsilon_{i,t}\right\}, \tag{12}$$

where $\text{JS}_{i,t}$ and $\text{JO}_{i,t}$ are indicators of the individual receiving, respectively, an involuntary job separation and a job offer at age t.[12]

At age 15, the individual chooses his years of education $k \in \{8, \ldots, 18\}$ to maximize the expected present discounted value of his lifetime utility, accounting for the benefits of increased earning potential and the costs associated with education. Formally, the decision rule for years of education is given by:

$$\text{Educ}_i = \underset{k\in\{8,\ldots,18\}}{\arg\max} \{R(\eta_i, k) + \lambda_k + \varepsilon_i(k)\}. \tag{13}$$

In the above, $\lambda_k + \varepsilon_i(k)$ is the cost of choosing k years of education, as discussed above in Section 3.7, and $R(\eta_i, k)$ denotes the expected maximized value of the individual's year-by-year utilities after entering the labor market, discounted back to age 15 values. Since the individual enters the labor market at age $t' = \max\{8+k, 20\}$ (see Section 3.1) we have:

$$R(\eta_i, k) = \beta^{t'-15}\mathbb{E}_{15}\left[V_{t'}(\boldsymbol{s}_{i,t'}) \mid \eta_i, \text{Educ}_i = k\right]. \tag{14}$$

[12]We operationalize the model by assuming that the individual chooses a level of saving, and thus a level of consumption, from a finite set of alternatives. An employed individual chooses annual savings (in euros) from the set {−5000, −2500, −1000, −500, 0, 500, 1000, 2500, 5000, 7500, 10000, 12500, 15000}. An unemployed individual chooses annual savings (in euros) from the set {−15000, −12500, −10000, −7500, −5000, −2500, −1000, −500, 0, 500, 1000, 2500, 5000}. A retired individual dis-saves the annuity value of his wealth.

I.e., $R(\eta_i, k)$ the expectation of the individual's value function at the time of labor market entry, conditional on productive ability and the individual's choice of years of education, discounted by the number of years between the time of the education choice (age 15) and the time of labor market entry. The education choice affects $R(\eta_i, k)$ by increasing wages, delaying labor market entry, and impacting health risk, mortality risk and employment opportunities.

4 Empirical implementation of the model

In Section 4.1, we describe our sample and discuss our approach for estimating the parameters of the life-cycle model. Section 4.2 details our parameter estimates. Section 4.3 provides a summary of the good in-sample fit of the model and validates the estimated life-cycle model by demonstrating the close match between the model's predictions regarding annual and lifetime earnings inequality and the inequality levels observed in a comparable administrative dataset not used in the estimation process.

4.1 Sample and estimation procedure

We estimate the parameters of the life-cycle model using an unbalanced annual panel sample of men from the German Socio-Economic Panel (SOEP).[13] Our estimation sample contains 3,281 distinct individuals and a total of 20,843 individual-year observations from 2004–2016.[14] Web Appendix II describes the sample in more detail.

We estimate the model in two stages. First, we estimate the health transition probabilities in (4), the heterogeneous survival probabilities in (5), and the involuntary job separation probabilities in (6). Specifically, to calculate the health transition probabilities, we compute the empirical probability of good health for each combination of age, health status, and educational category (high or low). We then smooth the age profiles of the empirical health probabilities using a Nadaraya-Watson kernel regression (Nadaraya, 1964, Watson, 1964) with an Epanechnikov kernel and the rule-of-thumb bandwidth (Fan and Gijbels, 1996). The heterogeneous survival probabilities are calculated using the approach of Kroll and Lampert (2009). In particular, we use the population life tables from the Human Mortality Database to translate information about heterogeneity in mortality in the SOEP data into health-by-education group survival curves. A detailed discussion on this approach is provided in Web Appendix IV.1. The involuntary job separation probabilities are estimated as the empirical transition rates from employment into unemployment due to the end of a fixed-term contract, a dismissal or a firm closure.

In the second stage of the estimation, we use a Maximum Likelihood procedure that targets the patterns of education, labor supply and wages that we observe in the sample to estimate the parameters that appear in the utility function, the wage equation, and the job offer probabilities,

[13] Wagner et al. (2007) and Socio-Economic Panel (2013) describe the SOEP.

[14] The estimation uses information on individuals' outcomes in the years 2005-2016. Information from 2004 is used only to determine lagged employment states for the year 2005, which is necessary to seed the estimation.

along with the educational investment cost parameters. It is widely acknowledged that household wealth data collected from surveys often contain significant measurement error. For example, in their discussion of the SOEP data we employ, Albers et al. (2022) observe that the aggregate household wealth recorded in the survey falls substantially short of macroeconomic aggregates from other data sources, especially in the categories of financial and business assets. Due to these inaccuracies, we follow, e.g., Low et al. (2010) by not attempting to fit information about wealth when estimating the model. We do, however, use these data to examine the goodness-of-fit of the estimated model. Web Appendix III explains how we approximate the value function, presents the likelihood function, and describes how we maximize the likelihood function.

4.2 Parameter estimates

4.2.1 Preferences and wages

Panel I of Table 1 reports our estimates of the parameters of the utility function. We estimate the disutility of employment relative to retirement to be 38.2% of consumption for individuals in good health and 34.5% for individuals in bad health. Meanwhile, the estimated cost of unemployment amounts to 68.0% of consumption for individuals in good health and 23.3% for individuals in bad health. The weighting factor of systematic utility derived from consumption and leisure choices relative to the preference shocks is estimated at 0.833. Panel II of Table 1 reports our estimates of the parameters of the wage equation. We find that wage shocks have a standard deviation of 0.071 and are highly persistent, with 93.3% of a wage shock carrying through to the following year. The standard deviation of the wage measurement error is equal to 0.107. To aid in interpreting the remaining wage parameters, Figure 2 illustrates estimated wage profiles (excluding wage shocks) for six of the thirty-three skill and education groups we model. We find that wages vary strongly with education and productive ability. We also find positive returns to experience (with a minor exception for individuals with close to the maximal level of experience). However, for the purpose of interpreting our later results, it is important to note that the variation in wages with experience within a group is small and is much lower than the variation in wages between different groups. The effect of health status on wages is negligible in magnitude (being in good health instead of bad health increases the wage by 1.5%). The small effect of health on wages that we find is similar to the estimates of French (2005).

Panel III of Table 1 shows the estimated probabilities of productive ability types. We estimate that 30.3% are endowed with high productive ability (type H), 51.7% are endowed with medium productive ability (type M), and the remaining 18.0% are endowed with low productive ability (type L).

Panel IV of Table 1 reports the estimates for the systematic component of the educational investment cost. As explained in Section 3.7, the systematic component includes tuition and subsistence costs, psychological costs (or benefits) of studying and forgone earnings. This explains the non-monotonic pattern of the coefficients by years of education. Recall, before entering the labor market, individuals observe their productive ability and then make a forward-looking educational investment decision that determines their years of education. Since the returns to education depend on produc-

Table 1: Parameters of the utility function, wage equation and type probabilities

		Estimate	Standard error
	Panel I: Utility function		
α_1	Weight on utility from consumption and leisure	0.833	0.0374
$\alpha_{2,1}$	Disutility of employment, bad health	−0.345	0.0389
$\alpha_{2,2}$	Disutility of employment, good health	−0.382	0.0382
$\alpha_{3,1}$	Disutility of unemployment, bad health	−0.233	0.0507
$\alpha_{3,2}$	Disutility of unemployment, good health	−0.680	0.0208
	Panel II: Wage equation		
η^H	Intercept for productive ability type H	2.089	0.0384
η^M	Intercept for productive ability type M	1.734	0.0387
η^L	Intercept for productive ability type L	1.353	0.0411
ψ_1	Educ/10	0.594	0.0255
ψ_2	Exper/10, low education	0.253	0.0147
ψ_3	Exper/10, high education	0.287	0.0142
ψ_4	Exper^2/1000, low education	−0.370	0.0320
ψ_5	Exper^2/1000, high education	−0.422	0.0333
ψ_6	Good health	0.015	0.0056
δ	Autocorrelation of wage shocks	0.933	0.0038
σ_ν	St.d. of wage shocks	0.071	0.0014
σ_μ	St.d. of wage measurement error	0.107	0.0009
	Panel III: Productive ability type probabilities		
ρ_H	Probability of productive ability type H	0.303	0.0192
ρ_M	Probability of productive ability type M	0.517	0.0191
ρ_L	Probability of productive ability type L	0.180	0.0147
	Panel IV: Systematic education cost components		
λ_8	8 years of education	*Reference category*	
λ_9	9 years of education	1.287	0.1580
λ_{10}	10 years of education	−0.443	0.1937
λ_{11}	11 years of education	2.046	0.1590
λ_{12}	12 years of education	1.268	0.3013
λ_{13}	13 years of education	−1.243	0.3065
λ_{14}	14 years of education	−1.757	0.3115
λ_{15}	15 years of education	−1.366	0.3214
λ_{16}	16 years of education	−2.773	0.3562
λ_{17}	17 years of education	−4.965	0.4407
λ_{18}	18 years of education	−2.448	0.4026

Notes: 'Educ' is years of education, and 'Exper' is years of experience. Standard errors were derived from the Hessian of the log-likelihood function at its maximum and using the delta method where required.

Figure 2: Estimated wage profiles (excluding wage shocks)

(a) 11 years of education, good health

(b) 14 years of education, good health

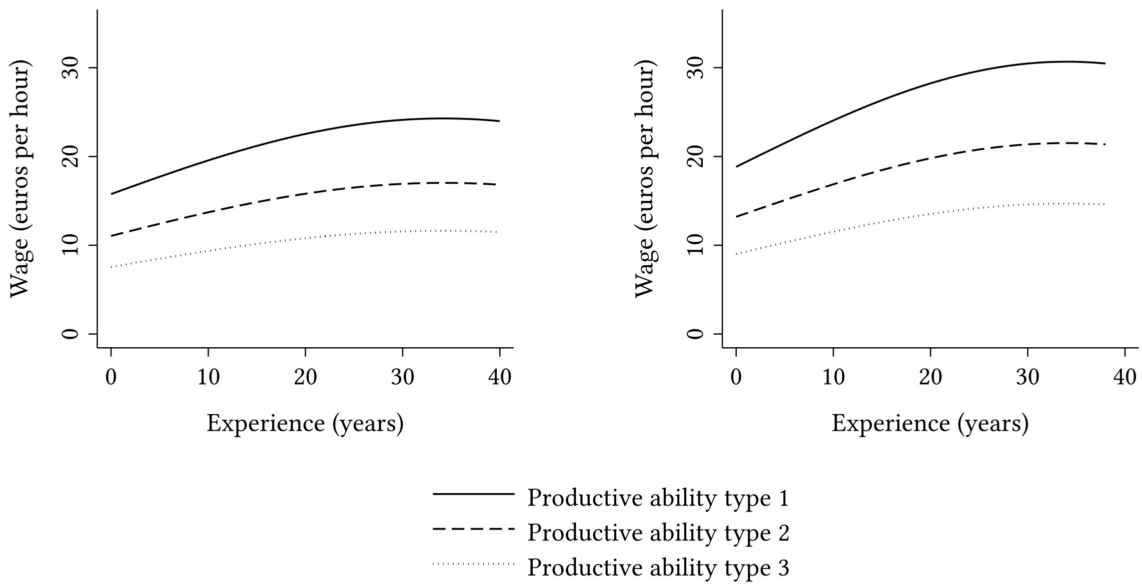


Table 2: Joint distribution of years of education and productive ability

	Productive ability type							
	High		Medium		Low		All	
Years of education								
8	0.24	(16.33)	0.70	(46.94)	0.55	(36.73)	1.49	(100.00)
9	1.46	(18.90)	3.78	(48.82)	2.50	(32.28)	7.74	(100.00)
10	0.46	(22.73)	1.01	(50.00)	0.55	(27.27)	2.01	(100.00)
11	10.18	(28.07)	18.53	(51.09)	7.56	(20.84)	36.27	(100.00)
12	7.99	(34.11)	12.19	(52.08)	3.23	(13.80)	23.41	(100.00)
13	1.19	(34.51)	1.83	(53.10)	0.43	(12.39)	3.44	(100.00)
14	1.19	(33.33)	1.89	(52.99)	0.49	(13.68)	3.57	(100.00)
15	2.93	(33.68)	4.66	(53.68)	1.10	(12.63)	8.69	(100.00)
16	1.13	(33.94)	1.80	(54.13)	0.40	(11.93)	3.32	(100.00)
17	0.18	(33.33)	0.30	(55.56)	0.06	(11.11)	0.55	(100.00)
18	3.20	(33.65)	5.24	(55.13)	1.07	(11.22)	9.51	(100.00)
All	100.00	(30.14)	100.00	(51.94)	100.00	(17.92)	100.00	(100.00)

Notes: Percentage shares of productive ability types within each education group are reported in parentheses. The correlation between years of education and productive ability is equal to 0.1189.

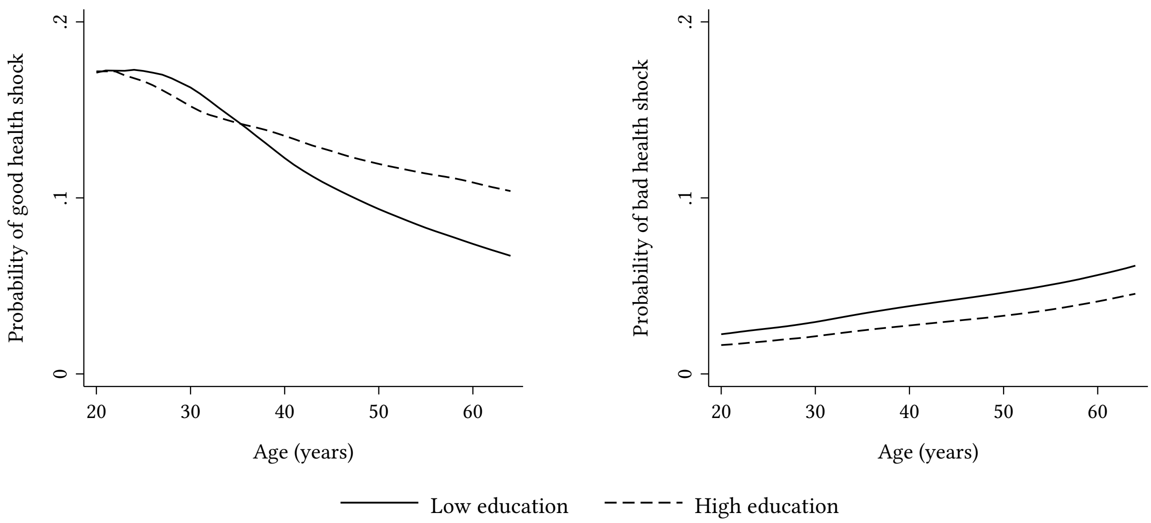
tive ability, individuals self-select into education based on their productive ability. To help quantify the relationship between productive ability and educational attainment, Table 2 presents the joint distribution of years of education and productive ability implied by the estimated model. Our results indicate that individuals tend to self-select into education based on their productive ability, leading to a positive correlation of 0.12 between years of education and productive ability. This implication of the estimated model is consistent with Belzil and Hansen (2002), who estimate a correlation of 0.28 between market ability and schooling, and supports the general idea of a positive ability bias in estimates related to the return on education.

4.2.2 Health shocks and mortality risk

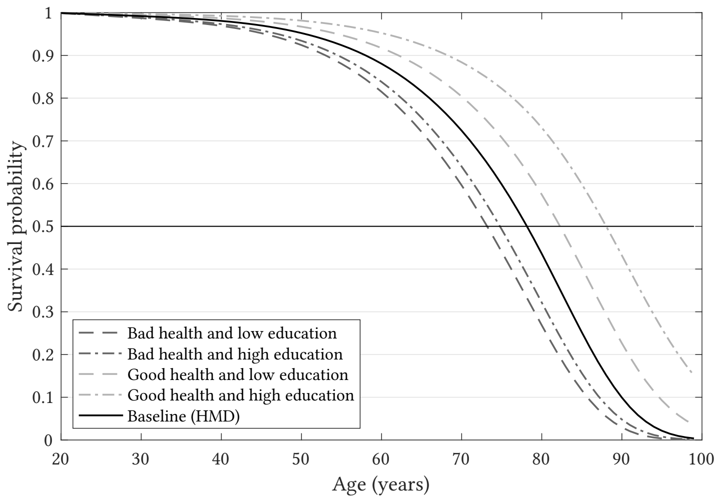
Figures 3(a) and 3(b) show the estimated health risk profile over the life cycle. We see that education is an important determinant of health. In particular, being highly educated decreases the likelihood of a bad health shock and increases the likelihood of a good health shock. Reflecting a general deterioration in health status over the life cycle, the probability of a bad health shock increases with age. Figure 3(c) illustrates the estimated survival curves for groups distinguished by health and education. For the baseline (i.e., the whole population), the probability of surviving to the age of 80 years is 0.5. For men in good health and with high education, the probability is 80%, while for men in poor health and with low education, the probability is only 20%.

Figure 3: Health shocks and mortality risk

(a) Good health shock (b) Bad health shock



(c) Mortality risk



Notes: The Baseline survival probabilities in Figure 3(c) were obtained by averaging life table mortality risks (HMD, 1992–2016). See Web Appendix IV.1 for further results on the survival model.

4.2.3 Employment risk

Table 3 shows the estimated job offer and involuntary job separation probabilities. While the job offer rate does not vary strongly with education, the likelihood of involuntary job separation decreases with a high level of education. Consequently, the estimated model suggests that the rates of unemployment and employment differ substantially by education. We explore this further in Table SWA.4 in Web Appendix IV.3.1. In summary, the model predicts that high-educated individuals are both more likely to be always employed and less likely to be always unemployed compared to those with low education. These patterns match the differences in labor supply by education in the estimation sample. For example, the model predicts that 82.6% of high-educated individuals and 71.7% of low-educated individuals will never experience unemployment. These figures closely match the estimation sample, where the corresponding percentages are 85.0% and 76.3%, respectively.[15]

Table 3: Job offer and involuntary job separation probabilities

		Age<50	Age 50–54	Age 55–59	Age≥60
Panel I: Job offer probabilities					
Low education	Bad health	0.207	0.139	0.164	0.147
		(0.0162)	(0.0153)	(0.0169)	(0.0207)
	Good health	0.367	0.264	0.304	0.280
		(0.0138)	(0.0199)	(0.0209)	(0.0292)
High education	Bad health	0.184	0.122	0.145	0.131
		(0.0150)	(0.0140)	(0.0157)	(0.0188)
	Good health	0.334	0.237	0.274	0.251
		(0.0119)	(0.0184)	(0.0196)	(0.0271)
Panel II: Involuntary job separation probabilities					
Low education	Bad health	0.030	0.024	0.020	0.026
		(0.0041)	(0.0043)	(0.0048)	(0.0076)
	Good health	0.020	0.016	0.014	0.017
		(0.0018)	(0.0026)	(0.0033)	(0.0055)
High education	Bad health	0.014	0.011	0.010	0.012
		(0.0023)	(0.0023)	(0.0025)	(0.0039)
	Good health	0.010	0.008	0.006	0.008
		(0.0010)	(0.0013)	(0.0017)	(0.0028)

Notes: Reported probabilities were obtained by evaluating equation (6) using the parameter estimates of the employment risk models reported in Table SWA.3 of Web Appendix IV.2. Standard errors in parentheses.

[15]One possible reason for the absence of an increase in job offer probability with education could be that some individuals categorized as unemployed are actually in early retirement, a situation potentially more common among highly educated individuals. However, if this were the case, we would expect a growing gap in job offer probabilities between high- and low-educated individuals as they age, given that early retirement becomes more prevalent at older ages. As we do not observe this trend, we conclude that the similarity in the job offer probabilities for high- and low-educated individuals is unlikely attributable to early retirement being misclassified as unemployment.

4.3 In sample-fit and model validation

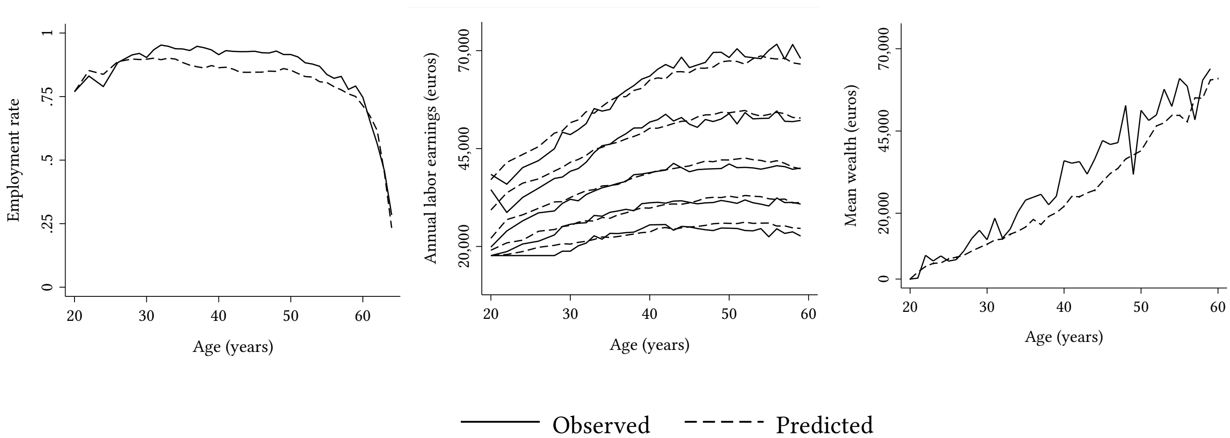
In this section, we summarize the estimated model's ability to accurately replicate key behaviors observed in the sample. We also present a validation exercise in which we compare the estimated inequality of labor earnings with the labor earnings inequality observed in a comparable sample that was not used for estimation.

4.3.1 In-sample fit

First, we examine how the estimated model fits the observed age profiles of employment, earnings, and wealth. Figure 4(a) demonstrates that the model accurately replicates the observed life-cycle pattern of employment, including the pronounced decline in the employment rate beginning around age 50. Figure 4(b) shows that the model also successfully fits the evolution of the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of cross-sectional earnings over the life cycle. This includes fitting the growing dispersion of earnings with age. Finally, we turn to wealth. Although wealth is not a targeted variable in the estimation, the model allows us to simulate life-cycle wealth trajectories. Figure 4(c) shows that the estimated model accurately captures the observed growth in mean wealth, which rises from near zero at age 20 to approximately 60,000 euros by age 60.

Figure 4: Observed and predicted age profiles of employment, earnings and wealth

(a) Employment | (b) Earnings percentiles: 10, 25, 50, 75 & 90th | (c) Wealth



Notes: Observed values were calculated using the estimation sample. Predicted values were calculated using a simulated subsample, obtained by simulating a sample of 50,000 individual life cycles and then drawing a subsample of individual-age observations from the simulated sample to match the age structure observed in the estimation sample. We construct the simulated sample using the estimated life-cycle model with the parameter values reported in Section 4.2. Each individual in the simulated sample is endowed with a productive ability, obtained by drawing from the estimated distribution of productive ability (see Panel III of Table 1). Each individual then chooses their years of education using the forward-looking decision rule described in Section 3.1. Subsequently, individuals enter the labor market at the later of age 20 and age 8 + Educ_i. Given their productive ability and years of education, individual life-cycle trajectories of labor supply, wages, wealth, health, and retirement are simulated up to age 100. Job offer probabilities at labor market entry are calibrated to fit the empirical employment rates in the early phase of the life cycle. We draw the subsample of individual-age observations from the simulated sample. In particular, for each of the 3,281 individuals in the estimation sample, we randomly select five individuals from the simulated sample who have the same years of education as the individual in the estimation sample, preserving the estimated within-education-level distribution of productive ability types. We then retain the observations corresponding to the ages when the individual was observed in the estimation sample. The earning percentiles in Panel (b) are conditional on employment.

Next, we explore how the model fits the persistence in labor earnings, taking into account both earnings mobility for employed individuals and employment dynamics. To this end, we compute rank correlation of labor earnings between two distinct years, spaced one to five years apart. Individuals who are not in employment are included with zero labor earnings. Table 4 shows that the estimated model accurately captures the high persistence in observed labor earnings: the rank correlation between labor earnings in adjacent years is 0.882 in the estimation sample and 0.890 in a sample simulated from the estimated life-cycle model. Table 4 also highlights the model's ability to reflect the rise in earnings mobility when longer time intervals are considered.

Table 4: Rank correlations between annual labor earnings in different years

	Time interval				
	1 year	2 years	3 years	4 years	5 years
Observed	0.882	0.855	0.832	0.813	0.795
Predicted	0.890	0.863	0.839	0.813	0.791

Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. Individuals who are not in employment are included with zero labor earnings. If multiple observations in a year have the same value, they are assigned the average of the ranks that would have been given to those tied values if they had been slightly different. Note that mobility within the earnings distribution is inversely related to the rank correlation. The analysis includes individuals aged 20 to 59 years inclusive.

Web Appendix IV.3 provides additional evidence of the in-sample fit of the estimated model. We summarize this evidence here. Figure SWA.1 demonstrates that the model's predictions align with the observed distribution of gross hourly wages, both overall and when splitting by education. Table SWA.4 shows that the model accurately replicates the observed labor supply persistence. For example, 12.0% of individuals in the sample are employed for less than half of their time in the sample, compared to the model prediction of 14.6%. Similarly, the fractions of individuals who spend less than half of their time in the sample in unemployment are 93.9% and 94.3% in the observed data and the model predictions, respectively. Table SWA.5 reports the observed and predicted transition rates between quintiles of the distribution of annual labor earnings for employed individuals. Again, the estimated model fits the observed pattern. As a further measure of persistence in labor earnings, Figure SWA.3 shows that the model fits the distribution of the individual-level average of annual labor earnings, which combines information about employment persistence and wage earnings over the life cycle. Figure SWA.5 shows that the model fits the cross-sectional distribution of wealth. Figure SWA.6 shows the model replicates the distribution of years of education.

4.3.2 Validation

We validate the estimated model by comparing the inequality in labor earnings that is predicted by the estimated model with the labor earnings inequality observed in a comparable sample that was not used for estimation. In particular, we use the estimated model to simulate a sample of life-cycle

Table 5: Gini coefficients for annual and lifetime labor earnings

	Sample simulated using estimated model	Sample of administrative social security records	Estimation sample (from SOEP)
Annual labor earnings	0.351	0.336	0.316
Lifetime labor earnings	0.227	0.212	–

Notes: The simulated sample is constructed by simulating a sample of 50,000 individual life cycles using the method described in the notes to Figure 4. To account for longevity risk, each simulated full life-cycle trajectory is complemented by a trajectory of survival indicators simulated from the mortality profile associated with the individual's education choice and health status. Post-mortem observations and observations from individuals aged 60 years or older are then removed from consideration. The sample of administrative social security records was taken from the VSKT sample and is described in Bönke et al. (2015). The estimation sample from the SOEP is described in Web Appendix II. Gini coefficients for the sample of administrative social security records are taken from Bönke et al. (2015, Figure 1) and pertain to the 1949 birth cohort. The Gini coefficient for annual labor earnings for the estimation sample was calculated using re-weighting to replicate the (uniform) age distribution in the other two samples. Observations of individuals aged 60 years or older are excluded from all calculations.

labor earnings profiles. We then compare the inequality of annual and lifetime labor earnings in the simulated sample to Bönke et al. (2015)'s calculations of the inequality of annual and lifetime labor earnings based on a sample of lifetime labor earnings histories taken from administrative social security records for Germany. We take several steps to ensure a reasonable degree of comparability between the predictions of our model and the sample used by Bönke et al. (2015). First, in both cases, the measures of inequality pertain to labor earnings before taxes and transfers. By looking at before tax-and-transfer labor earnings, we minimize any mismatch between the tax-and-transfer system in our model and the various systems that are applied to the members of Bönke et al. (2015)'s cohort during their lives. Second, the sample selection criteria used by Bönke et al. (2015) closely match the rules used for constructing our estimation sample (see Web Appendix II): both samples exclude civil servants, self-employed individuals, East Germans, and women. Third, we restrict our simulated sample to exclude individuals age aged 60 years or above again matching Bönke et al. (2015).[16]

Table 5 reports the results of our validation exercise. The first row of this table shows that the inequality of annual labor earnings implied by the estimated model closely matches that observed in the sample of administrative social security records (the Gini coefficients are equal to 0.351 and 0.336, respectively). Of particular relevance for our later analysis, the second row of Table 5 shows that the inequality of lifetime labor earnings predicted by the estimated model also closely matches that observed in the sample of administrative social security records (the Gini coefficients are equal to 0.227 and 0.212, respectively). It follows that the estimated model replicates Bönke et al. (2015)'s finding that the inequality of lifetime labor earnings is around two-thirds of the inequality of annual labor earnings.

We also note that the inequality of annual labor earnings in the estimation sample is similar to

[16]Corneo (2015) reports further results from analysis of Bönke et al. (2015)'s sample. For further comparisons of the inequality of annual and lifetime earnings using administrative datasets of lifetime earnings, see Kopczuk et al. (2010) and Guvenen et al. (2017) for the US, Björklund (1993) for Sweden, and Aaberge and Mogstad (2015) for Norway.

the inequality of annual labor earnings in the simulated sample, which provides further support for the in-sample fit of the estimated model. The inequality of annual labor earnings in the estimation sample is also similar to the inequality of annual labor earnings in a sample of administrative social security records; this finding provides empirical support for the argument that the estimation sample and the sample of administrative social security records are comparable.

5 Taxes, transfers & the inequality of lifetime income

Before proceeding, we must consider the measurement of inequality. Our question requires us to work with an inequality measure that is additively decomposable into within- and between-skill-group components. The rules out using the Gini coefficient (see Cowell and Flachaire, 2015). Instead, our primary analysis focuses on the Theil index, which is a special case of the generalized entropy index. The Theil index for a sample of earnings (incomes) $\{y_i\}_{i=1}^N$ is given by:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}}\ln\left(\frac{y_i}{\bar{y}}\right), \tag{15}$$

where $\bar{y}$ denotes the sample mean of earnings (income).

We check the robustness of our results by reevaluating inequality using three alternative measures, namely the squared coefficient of variation, the mean logarithmic deviation and the variance of the natural logarithm. Compared to the Theil index, the squared coefficient of variation gives less weight to inequality at the lower end of the distribution. On the other hand, the mean logarithmic deviation and the variance of the natural logarithm place more weight on inequality experienced at the distribution's lower end. Despite these differences, we show that our qualitative results hold irrespective of the inequality measure used.[17]

5.1 Insurance and redistributive effects of taxes and transfers

Using the Theil index, we have the following decomposition of the inequality of lifetime income:

$$\begin{matrix}\text{Inequality of}\\ \text{lifetime income}\end{matrix} = \begin{matrix}\text{Within-skill-group}\\ \text{inequality of lifetime income}\end{matrix} + \begin{matrix}\text{Between-skill-group}\\ \text{inequality of lifetime income}\end{matrix}. \tag{16}$$

[17] The squared coefficient of variation, the mean logarithmic deviation and the variance of the natural logarithm are given by, respectively,

$$\frac{\sum_{i=1}^{N}(y_i-\bar{y})^2/N}{\bar{y}^2},\quad \frac{1}{N}\sum_{i=1}^{N}\ln\left(\frac{y_i}{\bar{y}}\right)\quad\text{and}\quad \frac{1}{N}\sum_{i=1}^{N}\left(\ln y_i-\overline{\ln y}\right)^2.$$

When computing measures that involve logarithms, we exclude individuals with zero or negative lifetime earnings. These instances might occur for those who are seldom or never employed or who assume debt to smooth consumption. However, in our baseline simulation, this affects only 0.15% of individuals (77 out of 50,000 individuals). In Panel IV of Table SWA.9 in Web Appendix VII, we show that our findings continue to hold when we include these individuals and augment the lifetime earnings of all individuals by the value of one year's worth of minimum wage labor earnings. This adjustment ensures that all individuals have strictly positive lifetime earnings and income.

The between-skill-group inequality of lifetime income is a summary measure of the differences in average lifetime income between individuals with different levels of education and productive ability. We define the redistributive effect of the tax-and-transfer system as the difference between the between-skill-group inequality of lifetime earnings and the between-skill-group inequality of lifetime income. The within-skill-group inequality of lifetime income reflects differences in lifetime income among individuals with the same level of education and productive ability. The within-skill-group inequality of lifetime income is, therefore, a summary measure of the lifetime income consequences of risks. We assess the insurance function of taxes and transfers by looking at how the tax-and-transfer system affects the within-skill-group inequality of lifetime income.[18]

We quantify each component of (16) using a sample of life-cycle income trajectories simulated from the estimated model. We repeat this exercise using earnings instead of income (the notes to Table 5 describe how we use the estimated model to simulate earnings and income trajectories). These calculations reveal the effect of taxes and transfers on the inequality of lifetime income or, equivalently, the share of lifetime earnings inequality that is offset by taxes and transfers. Throughout this exercise, we continue to focus on the earnings and incomes of individuals younger than 60 years. In doing so, we abstract from the effects of old-age retirement and pensions on income inequality.[19] However, we account for differential mortality. In particular, in addition to simulating life-cycle earnings and income trajectories, we also simulate an indicator of survival based on the mortality risk associated with the individual's education and health status. Post-mortem observations are then removed from consideration.

Table 6 summarizes our findings. Interestingly, although taxes and transfers are based on annual earnings, the first column of Table 6 shows that the tax-and-transfer system is strongly progressive on a lifetime basis. In particular, our calculations show that taxes and transfers eliminate 46% of the inequality of lifetime income (see, e.g., Brewer et al., 2012, and Bengtsson et al., 2016, for similar findings). This is an important result because: i) the inequality of lifetime earnings is substantial (the inequality of lifetime earnings is around two-thirds as large as the inequality of annual earnings, see Table 5); and ii) inequalities in lifetime earnings represent cross-individual differences that people cannot mitigate by saving and borrowing.[20]

The second and third columns of Table 6 explore this result. We see that taxes and transfers combined offset 48% of the within-skill-group inequality of lifetime earnings, i.e., close to half of the

[18]Hoynes and Luttmer (2011) and Shaw (2014) adopt similar definitions of insurance and redistribution in the context of willingness to pay calculations. We note that the separation of the insurance and redistributive effects of taxes and transfers is contingent on our assumptions about individuals' knowledge of the earnings process at the start of the life cycle. In particular, the within-skill-group inequality of lifetime earnings can only be interpreted as lifetime income risk if shocks are truly unforeseen. Likewise, the effect of taxes and transfers on the between-skill-group inequality of lifetime income can only be interpreted as redistribution if individuals are fully informed about the expected consequences of their level of education and ability.

[19]For a discussion about the distributional effects of pensions see, e.g., Conesa and Krueger (1999), Huggett and Parra (2010), Coronado et al. (2011), and Feldstein and Liebman (2002).

[20]The model also implies that taxes and transfers reduce the Gini coefficient for annual income by 0.185. This result aligns with previous studies, which have shown large mitigating effects of taxes and transfers on the inequality of annual income (see, e.g., Piketty and Saez, 2007, Heathcote et al., 2010, Fuchs-Schuendeln et al., 2010, Wang et al., 2012, DeBacker et al., 2013, and Bengtsson et al., 2016).

Table 6: Insurance and redistributive effects of the tax-and-transfer system

	Inequality of lifetime earnings and lifetime income (100 × Theil index)			Ratio of between-skill-group inequ. to total inequ.
	Total	Within-skill-group	Between-skill-group	
Earnings (Labor earnings+ capital income)	8.94	4.44	4.50	0.50
Income (Earnings−taxes+transfers)	4.79	2.32	2.47	0.52
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.48	0.45	

Notes: All calculations are based on the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types. Taxes include a progressive tax on annual labor earnings, a progressive tax on annual capital income, and social security taxes for health and unemployment benefits. Transfers include unemployment insurance, disability benefits, and social assistance (see Section 2).

inequality in lifetime earnings that arises from differences between the lifetime earnings of individuals with the same level of education and productive ability is mitigated by taxes and transfers. Taxes and transfers together also offset a similar percentage (45%) of the between-skill-group inequality of lifetime earnings. In other words, little below half of the inequality in lifetime earnings that arises from education and productive ability is offset by taxes and transfers. Together these results show that the tax-and-transfer system provides substantial insurance against lifetime earnings risk and is strongly redistributive on a lifetime basis. We note that since around half of the inequality in lifetime earnings is attributable to differences between skill groups (see the first row of Table 6), the insurance and redistributive effects of taxes and transfers are similar in absolute terms.[21,22]

We disaggregate the effects of the four programs that comprise the tax-and-transfer system (namely taxes, unemployment insurance, disability benefits, and social assistance). This allows us to understand which programs are most effective at reducing the inequality of lifetime income and to

[21]Our estimate of the share of the inequality of lifetime earnings that is explained by the level of education and productive ability is similar to that found by Huggett et al. (2011) (about 60%) and Storesletten et al. (2004) (about 50%). However, the estimated share is lower than that reported in Keane and Wolpin (1997), who attribute 90% of the inequality of lifetime earnings to skill endowments. Huggett et al. (2011) discuss how the different findings are related to the specification of the skill endowments and the modeled sources of risk.

[22]In Web Appendix VII, we report the results of several robustness checks of the results in Tables 6 and Table 7: Table SWA.8 shows robustness to excluding capital income from the inequality decomposition; Table SWA.9 that our results continue to hold if inequality is measured using the squared coefficient of variation, the mean logarithmic deviation or the variance of the natural logarithm, instead of the Theil index; Tables SWA.10 and SWA.11 show that our results are robust to variations in the calibration of the discount factor and risk aversion parameters. For this latter analysis, we re-estimate the model for each combination of discount factor values (0.97, 0.98, 0.99) and risk aversion parameter values (1.25, 1.5, 1.75). We then use the estimation results to re-simulate lifetime earnings and income trajectories using the method described in the notes to Table 5. Finally, we replicate the analyses from Tables 6 and 7 using the new simulated samples.

Table 7: Shares of lifetime earnings inequality offset by taxes and transfer programs

	Total	Within-skill-group (Insurance)	Between-skill-group (Redistribution)
Taxes	0.23	0.12	0.33
Unemployment insurance	0.02	0.02	0.02
Disability benefits	0.09	0.16	0.01
Social assistance	0.13	0.17	0.09

Notes: All calculations are based on the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Shares are calculated from inequality as measured using the Theil index. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types.

identify the specific programs that account for the insurance and redistributive effects of the tax-and-transfer system. A complication arises here because the effect of each program depends on the order in which the programs are considered. We deal with this issue by using the permutation-based method of Shorrocks (2013) to derive the contribution of each program to income inequality in a way that is robust to ordering effects. According to this method, the order-robust effect of a program on income inequality is obtained by calculating the program's effect on income inequality for each of the twenty-four (i.e., four factorial) possible orders of the four programs and then averaging over the twenty-four possible program orders.

The first column of Table 7 shows that taxes reduce the inequality of lifetime income by 23% while the three transfer programs combined (unemployment insurance, disability benefits, and social assistance) reduce the inequality of lifetime income by 24% (giving, after rounding, the aforementioned combined mitigating effect of the tax-and-transfer system on the inequality of lifetime income of 46%). Among the three transfer programs, social assistance is by far the most important program for reducing the inequality of lifetime income: social assistance offsets 13% of the inequality of lifetime earnings while unemployment insurance and disability benefits offset 2% and 9% of the inequality of lifetime earnings, respectively.[23]

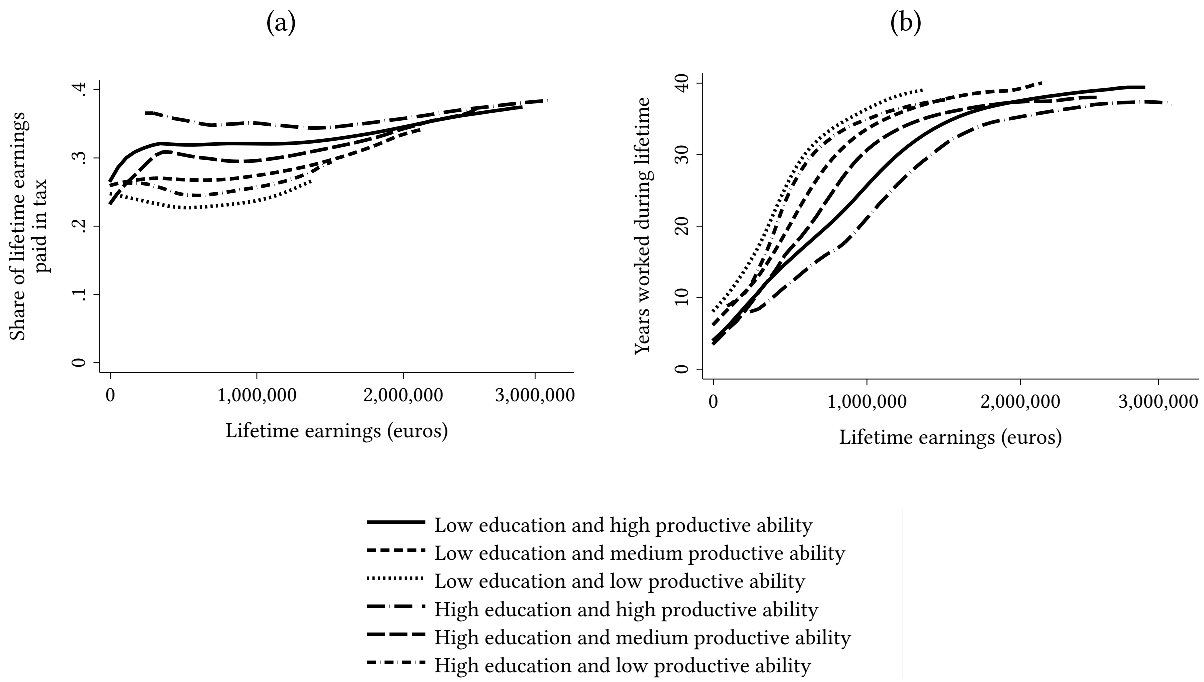
The second and third columns of Table 7 report the effects of taxes and each of the three transfer programs on the within- and between-skill-group inequality of lifetime income. These results, which we discuss in Sections 5.1.1-5.1.4, raise the following four questions about the insurance and redistributive effects of taxes and transfers. Why are taxes more effective at redistributing lifetime income than at insuring lifetime earnings risk? Why do disability benefits fail to redistribute lifetime earnings? What drives the redistributive effect of unemployment insurance? What makes social assistance the most important transfer program for insuring lifetime earnings risk and redistributing lifetime income? We address each question in turn.

[23]Table SWA.9 in Web Appendix VII shows that social assistance becomes more important as the inequality measure gives more weight to the bottom of the income distribution. Despite this, we find that the pattern of effects reported in Table 7 continues to hold when inequality is measured using the squared coefficient of variation, the mean logarithmic deviation or the variance of the natural logarithm instead of the Theil index.

5.1.1 Why are taxes more effective at redistributing lifetime income than at insuring lifetime earnings risk?

Table 7 shows that taxes reduce the between-skill-group inequality of lifetime income by 33%. In contrast, taxes reduce the within-skill-group inequality of lifetime income by only 12%. Thus, the insurance effect of taxes is around one-third of the size of the redistributive effect of taxes. Figure 5(a) explores the insurance effects of taxes in more detail by plotting the share of lifetime earnings paid in tax against lifetime earnings for each of the six groups as shown in Figure 2. We find that within each skill group, the share of lifetime earnings paid in tax increases modestly with lifetime earnings. Consider, e.g., individuals with eleven years of education (low education) and high productive ability. Within this group, lifetime poor individuals, e.g., those with lifetime earnings of around 500,000 euros, pay 32% of their lifetime earnings in taxes. Meanwhile, lifetime rich individuals in the same group, e.g., those with lifetime earnings of around 3,000,000 euros, pay 38% of their lifetime earnings in taxes. In other words, even though the lifetime earnings of the lifetime rich individuals in this group surpass those of the lifetime poor by over 500%, the proportion of lifetime earnings these lifetime rich individuals pay in taxes is only 6 percentage points or 19% higher. A similar pattern holds for the other skill groups.

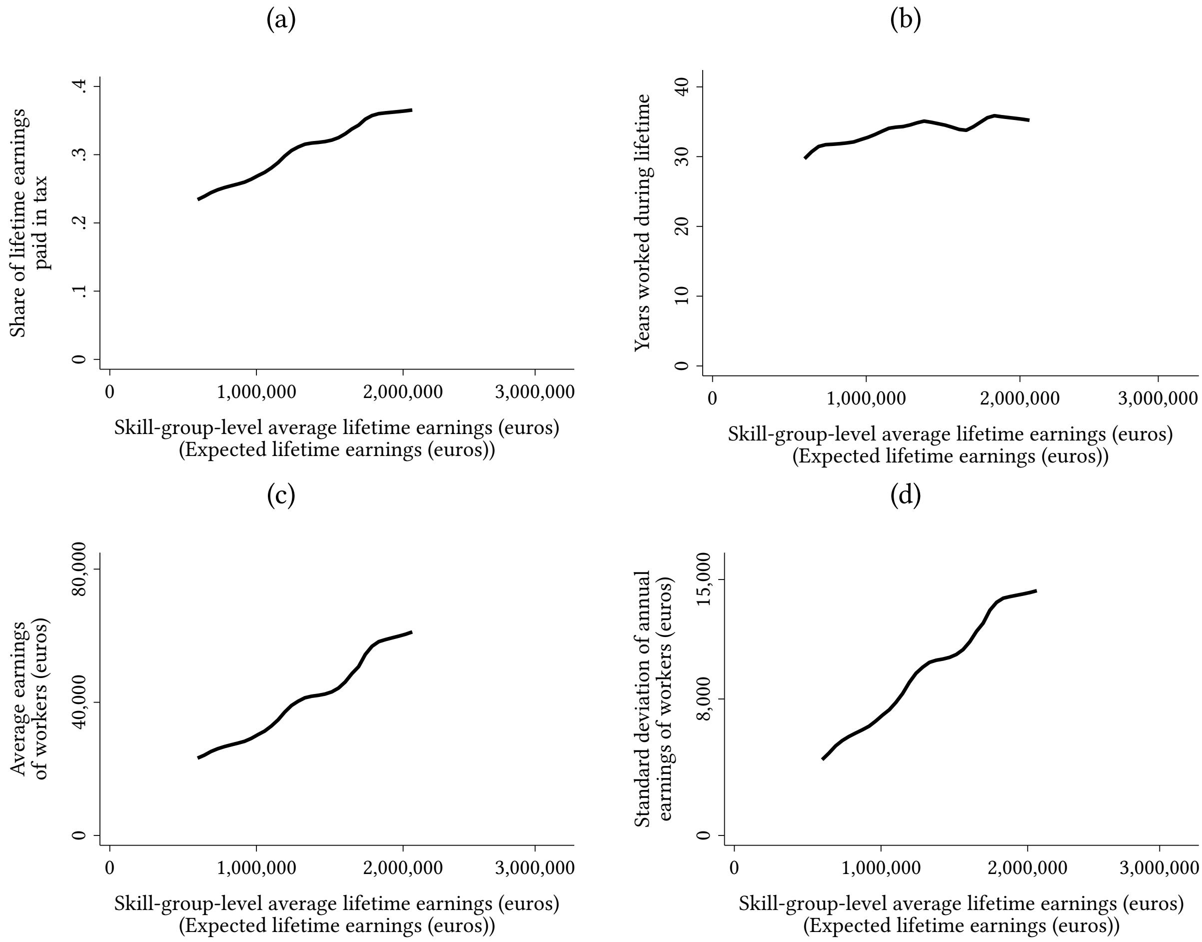
Figure 5: Insurance effects of taxation



Notes: Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. 'Low education' refers to eleven years of education, and 'high education' refers to fourteen years of education.

The key to understanding why taxes have a limited insurance effect is to note that annual taxes do not adjust for earnings in previous years of the individual's life. It follows that taxes based on annual earnings can not mitigate lifetime earnings differences that arise from differences in the number of years that individuals work during their lives. To help understand how differences in years worked during the life cycle contribute to our finding of a modest insurance effect of taxation, Figure 5(b)

Figure 6: Redistributive effect of taxation



Notes: Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types. All dependent variables are skill-group-level averages.

shows the average number of years worked during the life cycle against lifetime earnings for six of the thirty-three skill groups in the model. Within each skill group, the number of years worked during the life cycle increases strongly with lifetime earnings. Aggregating over all skill groups, we find that differences in years worked during the life cycle explain 77.9% of the within-skill-group inequality of lifetime earnings (measured using the Theil index). This important role of years of work in determining lifetime earnings strongly limits the potential for annual taxes to provide insurance against lifetime earnings risk.[24]

Next, we explore the redistributive impacts of annual taxation, providing an explanation as to why it serves as an effective mechanism for redistributing lifetime income among individuals with varying levels of education and productivity. Figure 6(a) shows that the share of lifetime earnings paid in tax increases strongly with the skill-group-level average of lifetime earnings. Individuals in the lowest-earning skill group contribute an average of 22% of their lifetime earnings in taxes. Conversely, individuals in the highest-earning group contribute an average of 38% of their lifetime

[24]In Web Appendix V, we show that annual earning taxes provide partial insurance against the remaining 22.1% of the within-skill group inequality of lifetime earnings that is not due to differences in years worked during the life cycle.

earnings in taxes. From a comparison of Figure 5(a) and Figure 6(a), it is apparent that the correlation between lifetime taxation and lifetime earnings is far more pronounced between skill groups than within them.

Three factors contribute to the large redistributive effect of annual taxes. First, annual taxes cannot address the between-skill-group inequality in lifetime earnings that is due to differences across individuals in years of work. However, as shown in Figure 6(b), we find that essentially none of the between-skill-group inequality in lifetime earnings is due to between-individual differences in years worked.[25] Second, a progressive annual tax will be more redistributive the more strongly the group-level average earnings of workers increase with the group-level average of lifetime earnings. The high wage returns to education and productive ability that we find lead the skill-group-level average annual earnings to increase strongly with the skill-group-level average of lifetime earnings (see Figure 6(c)). Third, due to the convexity of progressive annual taxes, the redistributive effect of annual taxes increases with the year-to-year variability in workers' earnings. Figure 6(d) shows that workers with higher expected lifetime earnings have more variability in their earnings.[26]

5.1.2 Why do disability benefits fail to redistribute lifetime earnings?

Table 7 shows that disability benefits decrease the between-skill-group inequality of lifetime income by one percentage point. This is a small effect compared to the 45% reduction in the between-skill-group inequality of lifetime income achieved by the composite tax-and-transfer system.

At first sight, the lack of a sizable redistributive effect from disability benefits seems counter-intuitive: given that education increases expected lifetime earnings and increases the likelihood of good health, which in turn decreases eligibility for disability benefits, we would anticipate that disability benefits could reduce inequality in lifetime income. However, disability benefits fail to redistribute lifetime earnings because the rate of disability benefit receipt decreases with expected lifetime earnings only up until those earnings reach 1,000,000 euros (see Figure 7). Beyond this threshold, there is no discernible relationship between benefit receipt and expected lifetime earnings. This pattern can be partially attributed to the interactions between social assistance and disability benefits. Specifically, the value of disability benefits increases with lifetime earnings, while social assistance guarantees individuals a minimum annual income, regardless of past earnings. Consequently, as expected lifetime earnings increase, so does the proportion of individuals who find disability benefits more beneficial than social assistance.

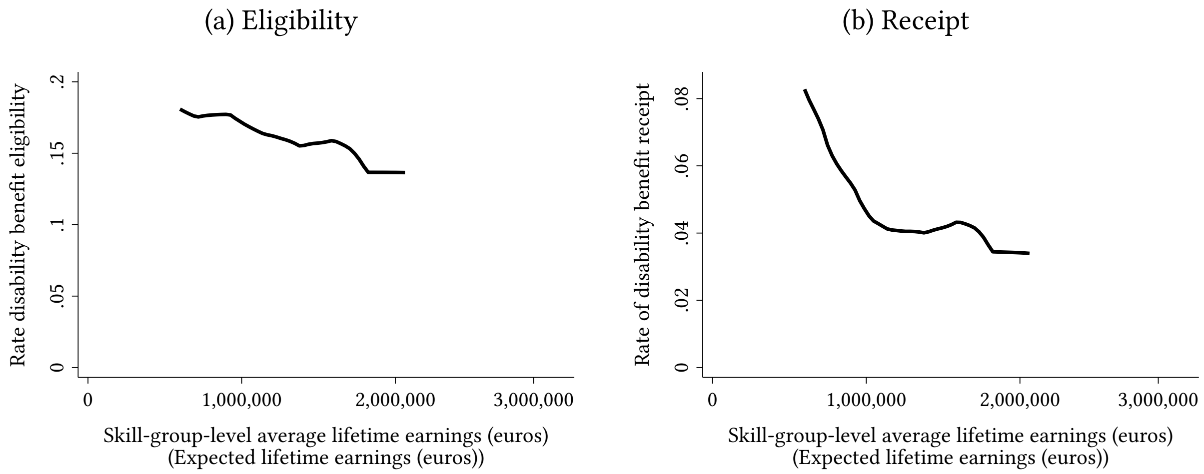
5.1.3 What drives the redistributive effect of unemployment insurance?

Unemployment insurance is designed to provide short-term insurance against job loss, and is not generally considered to be a redistributive program. However, we find that unemployment insurance is mildly redistributive. Specifically, Table 7 shows that unemployment insurance eliminates two

[25] Differences between groups in the average number of years that individuals work during their lifetimes explains only 2.5% of the between-skill-group inequality in lifetime earnings.

[26] Indeed, if the year-to-year variability of earnings increases with expected lifetime earnings, an annual tax may be more redistributive than an equally progressive tax on lifetime earnings.

Figure 7: Redistributive effect of disability benefits



Notes: Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types The dependent variable in Panel (a) is the skill-group-level average of an individual-year-level indicator of eligibility for disability benefits (an individual is eligible for disability benefits in a given year if he is in bad health in that year). The dependent variable in Panel (b) is the skill-group-level average of an individual-year indicator of disability benefit receipt.

percent of the between-skill-group inequality of lifetime income. This result is driven by the decrease in the risk of a job separation with education, both directly and via the effect of education on health (see Table 3). This pattern of employment risk leads unemployment insurance receipt to be concentrated among individuals with low expected lifetime earnings. In particular, in our simulated sample, individuals with expected lifetime earnings below 600,000 euros receive unemployment insurance for an average of 1.8 years between the ages of 20 and 60, while individuals with expected lifetime earnings above 2,000,000 euros receive unemployment insurance for an average of 0.6 years during the same time period.

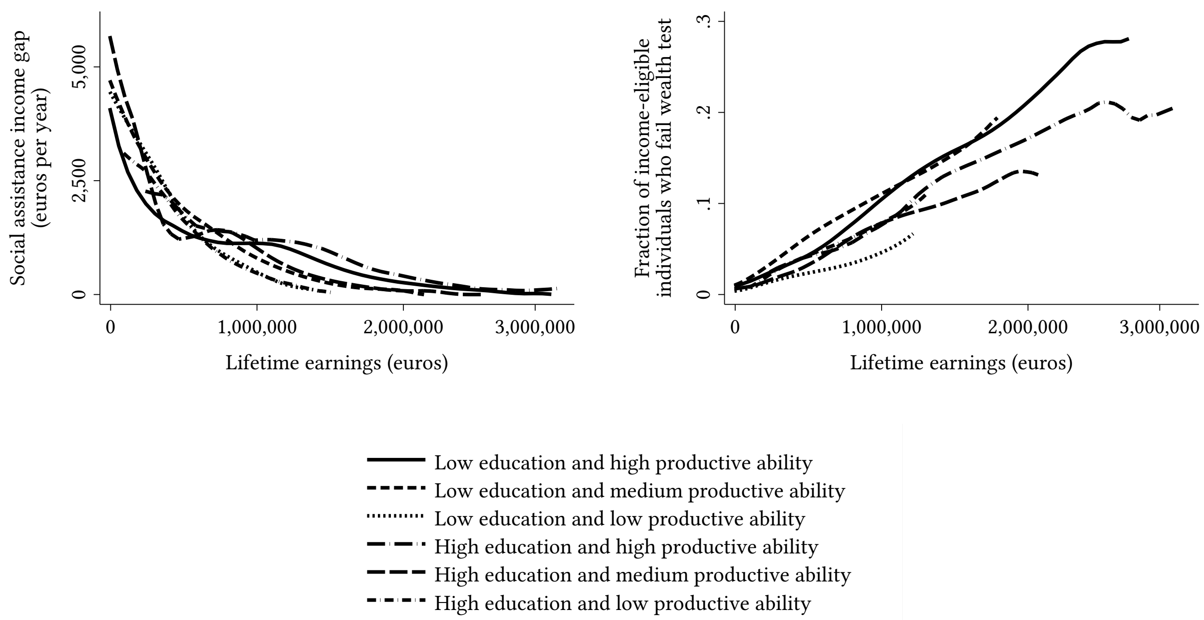
5.1.4 What makes social assistance the most important transfer program for insurance and redistribution?

Among the three transfer programs, social assistance has the largest effect on the inequality of lifetime income: Table 7 shows that social assistance eliminates 13% of the inequality of lifetime income, while unemployment insurance and disability benefits eliminate, respectively, 2% and 9% of the inequality of lifetime income. Table 7 further shows that social assistance is important for insuring lifetime earnings risk and redistributing lifetime income. In particular, social assistance offsets 17% of the within-skill-group inequality of lifetime earnings and mitigates 9% of the between-skill-group inequality of lifetime earnings. The insurance and redistributive effects of social assistance exceed those of unemployment insurance and disability benefits.

To understand why social assistance has large insurance and redistributive effects, we must consider the rules that are used to calculate social assistance. As explained in Section 2.1, social assistance makes up the difference between an individual's income from all other sources and the

Figure 8: Insurance effect of social assistance

(a) Income effect (b) Wealth effect



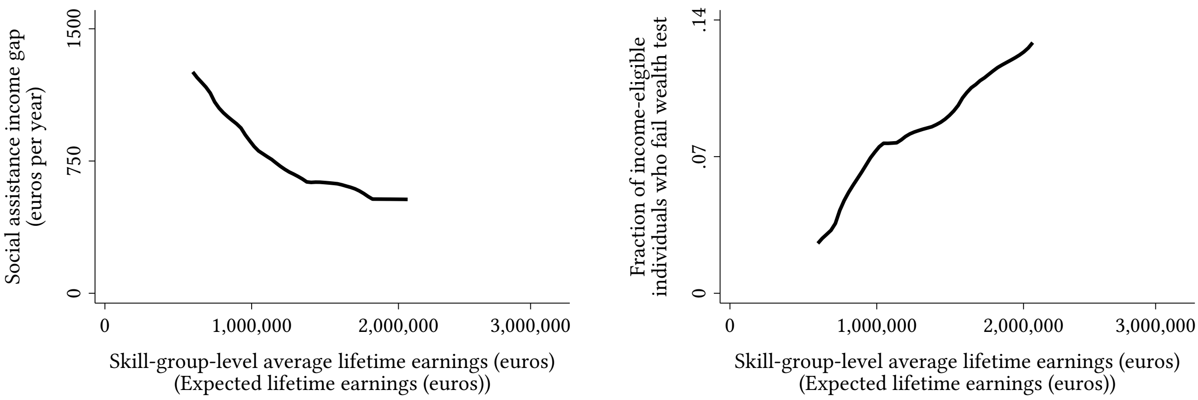
Notes: Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5, and restricting to individual-year observations where the individual was eligible for social assistance on the basis of income. The dependent variable in Panel (a) is equal to the difference between the non-wealth-adjusted annual minimum income guarantee and an individual's annual income before social assistance (this variable is censored at zero and thus is equal to zero if the individual's annual income before social assistance is greater than the non-wealth-adjusted annual minimum income guarantee). The dependent variable in Panel (b) is an indicator for an individual's annual social assistance income being reduced to zero by the wealth-based adjustment to the annual minimum income guarantee. 'Low education' refers to eleven years of education, and 'high education' refers to fourteen years of education.

minimum income guarantee. The minimum income guarantee decreases with wealth and is zero for individuals who are sufficiently wealthy. We explore the effects of social assistance by separating the income-based determinants of social assistance from the effect of the wealth-based adjustment to the minimum income guarantee. In particular, we learn about the income-based determinants of social assistance by studying the 'social assistance income gap', defined as the difference between the non-wealth-adjusted minimum income guarantee and an individual's annual income before social assistance. We parse out the effect of the wealth-based social assistance rules by studying how often the wealth-based adjustment to the minimum income guarantee reduces the social assistance received by income-eligible individuals to zero, i.e., we study the fraction of income-eligible individuals who fail the social assistance wealth test.

We first consider the insurance effect of social assistance. We focus on the same six groups as considered in Figure 2. Figure 8(a) shows that within each skill group the social assistance income gap decreases rapidly with lifetime earnings, indicating that the income-based social assistance rules make social assistance an effective insurance device. This occurs because the income-based rules for social assistance focus the benefit on individuals with low annual income from other sources and, among individuals with the same level of education and ability, those with low lifetime earnings

Figure 9: Redistributive effect of social assistance

(a) Income effect (b) Wealth effect



Notes: Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types. Dependent variables are skill-group-level averages of the variables defined in the notes to Figure 8.

experience many years with low income, i.e., low-income status is highly persistent. Figure 8(b) shows the fraction of income-eligible individuals who fail the social assistance wealth test against lifetime income for the six selected groups. Overall, within each group, there is an increasing pattern, with individuals with the lowest lifetime earnings being the least likely to fail the wealth test. Individuals with the lowest lifetime earnings rarely work and therefore are unlikely to have accumulated sufficient wealth to make them ineligible for social assistance.

We now turn to the redistributive effect of social assistance. We again separate the effects of the income-based and wealth-based determinants of social assistance. Figure 9(a) shows that the social assistance income gap is modest and below 750 euros per person per year for individuals with expected lifetime earnings above 1,000,000 euros. However, the social assistance income gap increases sharply as expected lifetime earnings decrease below this level and reaches about 1,200 euros per person per year for individuals with the lowest level of expected lifetime earnings. This pattern implies that the income-based rules for social assistance are strongly redistributive. Intuitively, social assistance targets the incomes of individuals with low expected lifetime incomes because the income-based rules for social assistance focus the benefit on individuals with low annual income (before social assistance), and individuals with low expected lifetime earnings tend to experience many years of low income during their lives. Figure 9(b) shows an upwards-sloping relationship between ineligibility for social assistance on the basis of wealth and expected lifetime earnings, showing that the wealth-testing of social assistance increases the redistributive effect of the program.

6 Insurance of lifetime employment and health risks

In the following, we demonstrate how employment risk and health risk affect the inequality of lifetime earnings. We also explore how the tax-and-transfer system provides insurance against these risks. This analysis leverages the estimated life-cycle model to project how individuals adjust their education, labor supply, and savings behavior in response to changes in risk exposure. By accounting for the behavioral responses to changes in risk, we study the insurance effect of the tax-and-transfer system while accounting for the self-insurance individuals secure through adjustments in their behavior. This is important because the self-insurance that individuals obtain through behavioral adjustments is likely to reduce the insurance provided by the tax-and-transfer system.

We consider four risk environments: a baseline environment and three counterfactual risk environments in which individuals face an increased risk of adverse employment or health events. In the baseline environment, health shocks, job offers, and involuntary job separations occur at the rates given by the estimated life-cycle model. In the three counterfactual scenarios, we modify these rates: first, we double the risk of involuntary job separation for employed individuals; second, we halve the job offer likelihood for unemployed individuals; and third, we double the risk of bad health shocks for those in good health. The risk changes are anticipated by individuals, thus enabling them to proactively modify their behavior to self-insure against the increased risk of unfavorable events in the future.

Table 8: Employment risk and health risk environments

		Counterfactual risk environment		
	Baseline	Increased job separation risk	Decreased job offer rate	Increased risk of bad health shocks
Average years of education	12.40	12.95	12.54	12.32
Employment rate	0.82	0.78	0.81	0.77
Average unemployment spells per person	1.08	1.35	0.64	1.21
Average unemployment spell duration (years)	2.85	2.88	3.31	3.00
Rate of bad health	0.16	0.15	0.16	0.36
Average bad health spells per person	0.99	0.96	0.98	2.19
Average bad health spell duration (years)	6.24	6.17	6.21	6.38

Notes: Calculations for all three risk environments are based on samples of 50,000 life-cycle trajectories of individuals aged 20–59 years inclusive, simulated from the estimated model (the notes to Table 5 describe how we use the estimated model to simulate employment trajectories). In the baseline scenario, risks are realized as the rates given by the estimated life-cycle model. In three counterfactual scenarios, we modify these rates: first, we double the risk of involuntary job separation for employed individuals; second, we halve the job offer likelihood for unemployed individuals; and third, we double the risk of bad health shocks for those in good health. In each environment, job offer probabilities at labor market entry are calibrated to fit the empirical employment rates in the early phase of the life cycle.

Table 8 summarizes education, employment, and health outcomes in the four risk environments. As the risk changes we study are not revenue-equivalent, our discussion concentrates on the directional similarities and differences in how behaviors adapt to these changes. The employment rate is lower in each of the counterfactual environments compared to the baseline. The effects of the increases in job separation risk and health risk on employment behavior are qualitatively similar: the average duration of unemployment spells is largely unaffected, yet the average number of unemployment spells increases. On the other hand, a decrease in the job offer rate results in a longer average unemployment spell duration and a decrease in the average number of unemployment spells per person. This latter change reflects that employed individuals, anticipating a lower job offer rate should they become unemployed, are less likely to leave their current jobs. This can be viewed as a form of self-insurance through labor supply. Individuals also mitigate job separation risk and job offer risk by increasing their years of education which, in turn, entails small positive effects on health outcomes. However, when faced with an increased risk of a bad health shock, average years of education decrease. This is because the increased insurance value of education is outweighed by a reduced likelihood that the individual can reap the benefits of their education by working.

Table 9: Insurance of employment risk and health risk

	Within-skill-group inequality in baseline	Δ Within-skill-group inequality in counterfactual: Increased job separation risk	Decreased job offer rate	Increased risk of bad health shocks
Lifetime earnings (Labor earnings+capital income)	4.44	1.18 [27%]	0.47 [11%]	1.73 [39%]
Lifetime income (Earnings−taxes+transfers)	2.32	0.43 [19%]	0.36 [16%]	0.67 [29%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.64	0.22	0.61

Notes: Inequality is measured using (100×) the Theil index. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types. 'Δ Within-skill-group inequality' is the increase in within-skill-group inequality from the baseline environment. The percentage increases in inequality from the baseline are shown in brackets. Also see the notes to Table 8.

Table 9 summarizes the effects of the risk increases on the within-skill-group inequality of lifetime earnings and lifetime incomes. As anticipated, the within-skill-group inequality of lifetime earnings increases following each risk increase.[27] The tax-and-transfer system proves comparably effective in mitigating the surge in lifetime earnings risk due to the increases in job separation and health risk. It absorbs 64% and 61% of the increased within-skill-group inequality in lifetime earnings that results from these respective risk increments. In contrast, the mitigating effect of the tax-and-transfer system is notably smaller when it comes to a decrease in job offer rates, absorbing only 22% of the extra within-skill-group inequality. This pattern aligns with the relatively low frequency of unemployment spells in this risk scenario, as individuals adjust their employment behavior to self-insure against the increased difficulty of finding a job while unemployed.

Table 10 details the contribution of each component of the tax-and-transfer system to the overall ability of the system to insure individuals against employment and health risks. The system mitigates

[27] As in Section 5.1, we define 33 skill groups, based on all possible combinations of productive ability and years of education in the baseline environment. In counterfactual risk environments, individuals may change their educational attainment. This adjustment is a form of self-insurance, as it will affect the individual's earnings potential as well as the employment and health risks they face over the life cycle. To ensure that group membership is constant across the baseline and counterfactual environments, we continue to classify individuals into skill groups based on their years of education in the baseline environment.

Table 10: Shares of additional within-skill-group lifetime earnings inequality offset by taxes and transfer programs

	Increased job separation risk	Decreased job offer rate	Increased risk of bad health shocks
Taxes	0.10	0.19	0.09
Unemployment insurance	0.04	-0.04	0.02
Disability benefits	0.26	-0.01	0.27
Social assistance	0.23	0.08	0.23

Notes: Inequality is measured using the Theil index. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types. Also see the notes to Table 8.

job separation and health risks in similar ways: insurance is primarily obtained from transfers rather than taxes, and among the transfer programs, social assistance and disability benefits each counteract roughly a quarter of the additional lifetime earning risk, with unemployment insurance providing a modest supplement. Two factors explain why disability benefits are not more effective against health risk compared to job separation risk. First, although poor health qualifies an individual for disability benefits, not all eligible individuals claim these benefits, as it would preclude future employment; indeed, some may prefer social assistance or self-insurance to retain the option of working. Second, disability benefits, despite not being their primary function, offer protection against job separation risk, with employed individuals in poor health opting to claim these benefits only if they lose their jobs.

In contrast, insurance against job offer risk primarily stems from taxation rather than transfers. In fact, among the three transfer programs, only social assistance mitigates the additional inequality in lifetime earnings, albeit modestly, offsetting only 8% of the extra inequality. Disability benefits become a less effective insurance mechanism because a decrease in the job offer rate increases the likelihood of extended periods of unemployment, which in turn diminishes the value of disability benefits.

Unemployment insurance also becomes a less effective insurance mechanism. This reflects two features of unemployment insurance: firstly, it does not offer long-term income replacement. This diminishes its efficacy in mitigating the lifetime earnings risk brought about by the longer average duration of unemployment spells ensuing from a decreased job offer rate. Secondly, unemployment insurance benefits are triggered when an individual becomes unemployed. However, since the decrease in the job offer rate results in individuals experiencing fewer instances of unemployment on average throughout their working lives, these individuals have fewer opportunities to become eligible for unemployment insurance.[28]

7 Policy simulation

In Section 5.1, we noted the limited capacity of annual taxation to address inequalities in lifetime earnings, as it cannot target inequalities arising from differences in total years worked during a lifetime. Indeed, under annual taxation, people with identical annual earnings pay the same annual tax, irrespective of any differences in their employment histories. In this analysis, we turn our attention to the effects of a tax reform that ties annual taxation to past employment. The core principle of this 'lifetime tax reform' is to raise annual taxes for individuals with stronger employment histories and lower them for those with weaker employment histories. Consequently, among two individuals with identical annual earnings, the one with a stronger work history will face higher taxes in the current year. This reform is in the spirit of the lifetime taxation system discussed by Vickrey (1939, 1947). We show that, despite being revenue neutral, the lifetime tax reform enhances the insurance function of the tax system. The reform leads to behavioral adjustments, including in labor supply. While these adjustments reduce lifetime earnings inequality, they also lower the employment rate.[29]

The specifics of the lifetime income tax reform we consider are as follows. We summarize the strength of the individual's employment history by the fraction of years an individual has been employed since entering the workforce after completing their education. The tax reform then involves adjusting the individual's annual tax burden depending on the strength of their personal employment history compared to the average employment history of same-aged individuals. Letting $H_{i,t}$ denote the strength of individual i's employment history at age t and using $\bar{H}_t$ to denote the average employment history strength of all individuals of age t, the individual tax liability under the reformed system is given by:

$$\mathcal{T}'_{i,t} = \mathcal{T}_{i,t} \times \left(1 + \pi_1(H_{i,t} - \bar{H}_t) \times \mathbb{1}[H_{i,t} \geq \bar{H}_t] - \pi_2(\bar{H}_t - H_{i,t}) \times \mathbb{1}[H_{i,t} < \bar{H}_t]\right), \tag{17}$$

where $\mathcal{T}_{i,t}$ is the individual's tax liability calculated using the rules in the baseline system and π_1, and π_2 are weakly positive parameters. The parameter π_1 modulates the extent to which the tax reform increases taxes for individuals who have worked above-average years for their age group. Conversely, π_2 modulates the degree to which the tax reform reduces taxes for individuals who have worked

[28] Table SWA.12 in Web Appendix VII explores the robustness of the results in Table 9 and 10 to measuring inequality using the squared coefficient of variation, the mean logarithmic deviation and the variance of the natural logarithm instead of the Theil index. Irrespective of the measure of inequality, the tax-and-transfer system offers essentially equal insurance against the two different employment risks. The amount of insurance increases as we move to inequality measures that give more weight to the bottom of the income distribution, reflecting that the tax-and-transfer system is relatively effective at mitigating increases in the inequality of lifetime earnings among the lifetime poor.

[29] We argue that implementing this reform would be practical, as the required information on employment histories is already being collected for the administration of disability benefits and public pensions. Additionally, the idea of linking current tax to events in an individual's past is not novel and is exemplified by existing carryover provisions, e.g., the U.S., the UK, and Canada allow taxpayers to carry forward capital losses to offset future capital gains. By exploring how taxation affects lifetime income inequality and life-cycle behaviors, we highlight some of the tradeoffs that would likely factor into an optimality-based policy recommendation. However, we stress that, since we do not consider optimality, we are not making policy recommendations.

below-average years for their age group. For the following analysis, we set $\pi_2 = 1.0$ and calibrate π_1 to ensure the reform is revenue neutral.[30]

[30]The criterion used to assess revenue neutrality of the reform is the total of all taxes paid on labor earnings and captial income, along with all contributions made towards health and unemployment insurance benefits, minus all transfers received within the age bracket of 20 to 59 years.

Table 11: Insurance and redistribution with lifetime taxation

	Total	Within-skill-group (ins.)	Between-skill-group (redist.)
Panel I: Baseline tax system			
Inequality (100 × Theil index):			
Lifetime earnings	8.94	4.44	4.50
Lifetime income	4.79	2.32	2.47
Share of earnings inequality offset by:			
Tax-and-transfer system	0.46	0.48	0.45
... Taxes	0.23	0.12	0.33
... Unemployment insurance	0.02	0.02	0.02
... Disability benefits	0.09	0.16	0.01
... Social assistance	0.13	0.17	0.09
Labor supply behaviors:			
Employment rate	0.82		
Average unemployment spells per person	1.08		
Panel II: Lifetime tax reform with behavior fixed to match the baseline environment ($\pi_1 = 0.6605, \pi_2 = 1$)			
Inequality (100 × Theil index):			
Lifetime earnings (same as Panel I by construction)	8.94	4.44	4.50
Lifetime income	4.61	2.15	2.46
Share of earnings inequality offset by:			
Tax-and-transfer system	0.48	0.52	0.45
... Taxes	0.25	0.17	0.33
... Unemployment insurance	0.02	0.02	0.02
... Disability benefits	0.09	0.17	0.01
... Social assistance	0.12	0.16	0.09
Panel III: Lifetime tax reform with behavioral adjustments ($\pi_1 = 1.2430, \pi_2 = 1$)			
Inequality (100 × Theil index):			
Lifetime earnings	8.85	4.39	4.45
Lifetime income	4.45	2.06	2.38
Share of earnings inequality offset by:			
Tax-and-transfer system	0.50	0.53	0.46
... Taxes	0.27	0.19	0.35
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.08	0.16	0.01
... Social assistance	0.13	0.16	0.09
Labor supply behaviors:			
Employment rate	0.81		
Average unemployment spells per person	1.22		

Notes: Calculations from samples of 50,000 life-cycle trajectories of individuals aged 20–59 years inclusive, simulated from the estimated model (the notes to Table 5 describe how we use the estimated model to simulate employment trajectories). The baseline tax system (Panel I) is equivalent to the lifetime tax reform with $\pi_1 = \pi_2 = 0$. Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types.

Table 11 examines the effects of this reform. In Panel I, we recap our earlier findings on the inequality-reducing effects of the baseline tax-and-transfer system. Panel II presents the implications of the lifetime income tax reform under the assumption that individuals cannot adjust their behavior. With behavior fixed to match the baseline environment, setting π_1 equal to 0.6605 achieves revenue neutrality. Since we assume the individual cannot adjust their behavior in response to the reform, the inequality of lifetime earnings is the same as under the baseline tax system (Panel I). However, the lifetime tax reform increases the percentage of the inequality in lifetime earnings that is mitigated by the tax-and-transfer system from 46% to 48%.

While Panel II of Table 11 depicts the direct effect of the lifetime tax reform on lifetime income inequality, it fails to incorporate potentially significant indirect effects that arise from individuals adjusting their education, labor supply, and savings behaviors in response to the reform. To understand the impact of these behavioral adjustments, we utilize the life-cycle model to derive individuals' behavior in the post-reform policy environment. We then recalculate the value of π_1, accounting for behavioral adjustments (iterating until we find the value of π_1 that makes the reform revenue neutral after further behavioral changes in response to the updated value of this parameter). Setting π_1 equal to 1.2430 ensures revenue neutrality for the lifetime tax reform after allowing for behavioral adjustments.

Panel III of Table 11 shows the effects of the revenue-neutral lifetime tax reform, allowing for both the direct effect of the reform on lifetime income and the indirect effects that arise from changes in behavior. Summary measures of labor supply behavior are included in this table, while more detailed information on the effect of the reform on behavior is provided in Web Appendix VI. The lifetime tax reform reduces the overall employment rate from 0.82 to 0.81 and increases the average number of unemployment spells from 1.08 to 1.22 per person.[31] However, at the same time, the lifetime tax reform reduces the inequality of lifetime earnings. In particular, the lifetime tax reform reduces (100 $\times$) the Theil index for lifetime earnings from 8.94 to 8.85, a decrease of approximately 1%. Notably, the reform decreases both within-skill-group and between-skill-group disparities in lifetime earnings. The decrease in within-skill-group inequality reflects the tendency of the reform to reduce earnings for individuals with stronger working histories while having little overall effect on the employment rate for those with weaker working histories.[32]

We find that incorporating behavioral adjustments doubles the inequality-reducing effect of the lifetime tax reform. Specifically, under the baseline tax-and-transfer system, the share of earnings inequality that is offset is 46%. This share increases to 48% when implementing the tax reform without behavioral changes. With behavioral changes accounted for, the share rises to 50%. Finally, Table 11 decomposes the overall effect of the tax-and-transfer system into the effects of income taxation and the three different transfer programs. These results show that the lifetime tax reform does not appreciably affect the inequality-reducing effects of unemployment insurance, disability benefits, or social assistance on income inequality. Therefore, the inequality-reducing effects of the lifetime

[31]This decline in employment explains why achieving revenue neutrality with behavioral adjustments necessitates a higher value of π_1 compared to when behavior is fixed to match the baseline.

[32]See Figure SWA.9 in Web Appendix V.

tax reform are driven by changes in the function of taxation alone. We also highlight that, while the baseline taxation system is essentially equally effective at targeting within and between skill-group inequality in lifetime earnings, the lifetime tax reform increases the effect of the tax system on within-skill-group inequality in lifetime earnings. In other words, the lifetime tax reform enhances the tax system's effectiveness in insuring against lifetime earning risk.[33]

8 Conclusion

In this paper, we have examined the dual roles of Germany's tax-and-transfer system in reducing inequalities in the lifetime incomes of German men, namely by providing insurance against lifetime earnings risk and redistributing lifetime income. We find that the system significantly redistributes lifetime earnings among individuals based on differences in skills established early in life. Specifically, our analysis shows that approximately half of the inequality generated by skill disparities is offset by the current tax-and-transfer system. This finding has important implications for the conversation around skill-biased technological change, suggesting that such shifts may not fully translate into increased income inequality due to the redistributive mechanisms in place. We also find that the tax-and-transfer system serves as a substantial insurance mechanism against lifetime earnings risk. It effectively cushions around 60% of the earnings disparities arising from job loss and health shocks, primarily through income social assistance and disability benefits.

We find that the current system has limited ability to mitigate earnings inequalities arising from differences in employment histories. Motivated by this, we explore the effects of a lifetime tax reform that adjusts an individual's current tax rates based on their past employment record. The lifetime tax reform reduces the inequality of lifetime income, primarily by enhancing the ability of the tax system to insure against lifetime earnings risk. However, our results highlight an important tradeoff: while the lifetime tax reform reduces the inequality of lifetime income, it also decreases the employment rate.

In summary, our research serves as a foundation for further analysis aimed at understanding how the tax-and-transfer system affects inequalities in lifetime income. Our findings specifically indicate that reforms designed to mitigate the long-term impacts of job loss could be particularly effective, given the current system's shortcomings in addressing employment-related uncertainties. Importantly, our work underscores the necessity of accounting for behavioral responses when designing such reforms. These behavioral adjustments can influence the reform's overall impact on the inequality of lifetime income and must be understood to provide a complete picture of the reform.

[33]Tables SWA.13, SWA.14 and SWA.15 in Web Appendix VII show that the results in Table 11 to are qualitatively robust to measuring inequality using the squared coefficient of variation, the mean logarithmic deviation and the variance of the natural logarithm, instead of the Theil index.

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Supplementary Web Appendix

(Intended for Online Publication)

Web Appendix I: Pensions

Individuals in old-age retirement (i.e., individuals who retired at age 63 or above in good health) receive pension benefits each year for the remainder of their lives. The annual pension benefit received by an individual who entered old-age retirement at age R is given by:

$$\text{Pension} = \zeta \times \overline{W}_R \times \text{PenPenalty}_R \times \text{Exper}_R, \tag{18}$$

where ζ is a parameter that controls the generosity of pension benefits, $\overline{W}_R$ is the individual's annual pension-benefit-eligible labor earnings averaged over all years of employment before retirement, Exper_R is the individual's experience (in years) at retirement, and PenPenalty_R is a penalty that reduces the individual's annual pension by 3.6% for each year that he retired before the age of 65 years. Only annual labor earnings below 72,374 euros are considered when calculating pension benefits.

Fifty percent of annual pension benefit income above an exemption threshold of 17,306 euros is taxed on the same basis as taxable labor earnings. We account for the taxation of pension benefits, along with all other taxes, when estimating the model and when using the estimated model to simulate datasets. However, because we focus on individuals younger than 60 years, the taxation of pension benefits does not affect the decompositions presented in Sections 5 and 6.

Web Appendix II: Estimation sample

The estimation sample comprises an unbalanced annual panel of males from the German Socio-Economic Panel (SOEP) covering the years 2004–2016. The sample excludes individuals younger than 20 or older than 65, those in education, individuals from former East Germany, self-employed individuals, and civil servants.[34] Table SWA.1 provides definitions and descriptive statistics for the variables used in the analysis.

Observations on wealth were compiled from individual net asset holdings, encompassing real and financial assets and debts (thereby matching the omnibus wealth variable in the model, see Section 3.6). This information was collected only in the 2007 and 2012 survey waves. We left-censor the wealth distribution at zero (note, individuals with zero or negative wealth are included in the sample). We exclude wealth observations inconsistent with the savings possibilities in the life-cycle model. In particular, we drop observations with wealth values that exceed the maximum wealth amount the model can generate. Importantly, we do not attempt to fit wealth when we estimate the model; however, we do use these data to impute eligibility for social assistance and to examine the goodness-of-fit of the estimated model.

[34]While exploring the implications for self-employed individuals and civil servants would be insightful, such an examination falls outside the scope of this paper. Self-employed individuals face distinct transfer programs and risk profiles compared to employees. For this reason, we follow Flinn (2002), Bowlus and Robin (2004), and Bönke et al. (2015) by excluding self-employed individuals from our study. In Germany, civil servants also face distinct transfer systems and risk profiles compared to employees. Bönke et al. (2015), who also work with German data, exclude civil servants from their analysis. We use the same restriction for our sample.

Table SWA.1: Descriptive statistics for the SOEP sample

Variable	Observations	Mean	Minimum	Maximum
Age (years)	20,843	45.760	20	64
Employed	20,843	0.874	0	1
Unemployed	20,843	0.074	0	1
Retired (disability-based or old-age retirement)	20,843	0.052	0	1
Education (years)	20,843	12.362	7	18
Health	20,843	0.832	0	1
Involuntary job separation	20,843	0.022	0	1
Experience (years)	20,843	22.474	0	49
Wage (euros per hour)	18,225	19.993	8.5	47.01
Wealth (euros)	3,909	39,117	0	575,857

Notes: Individuals working at least 20 hours per week are classified as employed. A small number of men working fewer than 20 hours per week are classified as unemployed. The median work week for those classified as employed is 40 hours. Years of education include time spent in formal education and occupational training. The health indicator signifies good health, defined as neither being officially disabled nor self-assessing health as 'bad' or 'very bad'. Involuntary job separations include transitions to unemployment due to the end of a fixed-term contract, dismissal, or firm closure. Experience is defined as years spent in employment. The wage refers to the pre-tax hourly wage, which is only observed for employed individuals. Cross-sectional wealth refers to the net value of financial and real assets based on information collected from the 2007 and 2012 SOEP surveys. Both wages and wealth are expressed in 2016 prices.

Web Appendix III: Model solution & estimation

In Web Appendix III.1 we explain how we approximate the value function, in Web Appendix III.2 we present the likelihood function, and in Web Appendix III.3 we describe how we maximize the likelihood function.

Web Appendix III.1: Value function approximation

We derive analytic expressions for the value function that appears in (11), starting from the following choice-specific value functions:

$$V_t(c_{i,t}, l_{i,t}, \boldsymbol{s}_{i,t}) = U(c_{i,t}, l_{i,t}, \epsilon_{i,t}) + p(t+1|t, \boldsymbol{s}_{i,t})\beta\mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{i,t+1})|\boldsymbol{s}_{i,t}, c_{i,t}, l_{i,t}] \quad \text{for} \quad t = 20, \ldots, T, \tag{19}$$

where $\mathbb{E}_t[V_{T+1}(\boldsymbol{s}_{i,T+1})|\boldsymbol{s}_{i,T}, c_{i,T}, l_{i,T}] = 0$ (since period T is the last period of the individual's life). Let $\boldsymbol{x}_{i,t}$ denote the age-t state variables excluding the preference shocks. We decompose the choice-specific value functions into a systematic component and a random component, which corresponds to the preference shock:

$$V_t(c_{i,t}, l_{i,t}, \boldsymbol{s}_{i,t}) = \overline{V}_t(c_{i,t}, l_{i,t}, \boldsymbol{x}_{i,t}) + \epsilon_{i,t}(c_{i,t}, l_{i,t}) \quad \text{for} \quad t = 20, \ldots, T. \tag{20}$$

Given the distributional assumptions about preference shocks (see Section 3.7), we have the following analytic expression for the expected age $t+1$ value function:

$$\mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{i,t+1})|\boldsymbol{s}_{i,t}, c_{i,t}, l_{i,t}] = \sum_{\boldsymbol{x}_{t+1}} \log\left(\sum_{\{c,l\}\in\mathbb{D}(\boldsymbol{x}_{t+1})} \exp(\overline{V}_{t+1}(c, l, \boldsymbol{x}_{i,t+1}))\right) \times q(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t, c_{i,t}, l_{i,t}) \quad \text{for} \quad t = 20, \ldots, T-1, \tag{21}$$

where $q(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t, c_{i,t}, l_{i,t})$ denotes the joint probability mass function of the state variables $\boldsymbol{x}_{i,t+1}$ conditional on the state variables $\boldsymbol{x}_{i,t}$ and conditional on the individual's consumption and labor supply outcome at age t (since the choice set does not depend on preference shocks, $\mathbb{D}(\boldsymbol{x}_t) \equiv \mathbb{D}(\boldsymbol{s}_t)$).

We approximate the value function using recursive interpolation, working backward from age T (see Keane and Wolpin, 1994). In more detail, for each age, we evaluate the value function at a set of grid points. The evaluation grid includes all possible values of health, labor supply outcome in the previous year, and unobserved productive type. The evaluation grid also includes 9 values of wealth (-20000, 0, 10000, 20000, 30000, 50000, 100000, 150000, 700000), 6 values of experience (0, 10, 20, 30, 40, 50), 4 values of education (7, 11, 12, 18), 5 values of lagged log(hourly wage) (2, 2.5, 3, 3.5, 4), and 5 values of draws from the standard normal distribution for the calculation of the wage shocks (-2, -1, 0, 1, 2), giving a total of 64,800 grid points. We then use a linear interpolation function to predict the value function at values of the state variables that are not included in the evaluation grid. The results are insensitive to increasing the number of grid points and changing the interpolation method.

Web Appendix III.2: Likelihood function

Each individual contributes to the likelihood the joint probability of their observed wage (i.e., their market wage perturbed by measurement error) and labor supply outcome in each year between entering and leaving the sample and their educational choice. Assuming independence of all unobservables over individuals, the likelihood function for the sample is the product of the individual likelihood contributions.

In more detail, individual i's contribution to the likelihood is given by:

$$\mathcal{L}_i(\boldsymbol{\theta}, \boldsymbol{\rho}|z_i) \quad = \quad \mathcal{P}(\text{Educ}_i, \boldsymbol{W}_i^*, \boldsymbol{l}_i, |\boldsymbol{z}_i, \boldsymbol{\theta}, \boldsymbol{\rho}), \tag{22}$$

where $\boldsymbol{\theta}$ denotes the parameters in preferences, the wage equation and the job offer probability, $\boldsymbol{\rho}$ denotes the productive ability type probabilities, $\boldsymbol{W}_i^*$ and $\boldsymbol{l}_i$, are vectors that contain the values of the individual's observed wage and labor supply outcome in each year they are in the sample, and z_i is a vector of condition variables, including the individual's observed wage and labor supply outcome in the year before they enter the sample, and their age, wealth, job separation status and health status in each year they are in the sample.

Given the finite mixture structure of productive ability, where an individual's productivity takes the values η^H, η^M and η^L with probabilities ρ^H, ρ^M and ρ^L, respectively, we have:

$$\begin{aligned} \mathcal{L}_i(\boldsymbol{\theta}, \boldsymbol{\rho}|z_i) &= \sum_{j\in\{H,M,L\}} \rho_j \times \mathcal{P}(\text{Educ}_i, \boldsymbol{W}_i^*, \boldsymbol{l}_i, |\eta_i = \eta^j, \boldsymbol{z}_i, \boldsymbol{\theta}), & (23) \\ &= \sum_{j\in\{H,M,L\}} \rho_j \times \mathcal{P}_e(\text{Educ}_i|\eta_i = \eta^j, \boldsymbol{\theta}) \times \mathcal{P}_{wl}(\boldsymbol{W}_i^*, \boldsymbol{l}_i, |\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{z_i}, \boldsymbol{\theta}). & (24) \end{aligned}$$

The educational choice probability in (24) characterizes the endogenous self-selection of individuals into education based on productive ability and takes the following form:

$$\mathcal{P}_e(k|\eta_i = \eta^j, \boldsymbol{\theta}) = \frac{\exp\left(R(\eta^j, k) + \lambda_k\right)}{\sum_{k'=8}^{18} \exp\left(R(\eta^j, k') + \lambda_k'\right)} \quad \text{for} \quad k = 8, ..., 18, \tag{25}$$

where λ_k is the systematic component of the cost of choosing k years of education and $R(\eta^j, k)$ denotes the expected maximized value of the individual's year-by-year utilities after entering the labor market for an individual with probability ability η^j, discounted back to age 15 values (see Section 3.8).

The conditional joint probability of observed wages and labor supply outcomes in (24) can be written using Bayes' law:

$$\begin{aligned} \mathcal{P}_{wl}(\boldsymbol{W}_i^*, \boldsymbol{l}_i|\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{z}_i, \boldsymbol{\theta}) = \prod_{t=\underline{t}_i}^{\bar{t}_i} & \left[f(W_{i,t}^*|\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{W}_{i,t-1}^*, \boldsymbol{l}_{i,t-1}, \boldsymbol{z}_i, \boldsymbol{\theta}) \times \right. \\ & \left. \mathcal{P}_l(\boldsymbol{l}_{i,t}|\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{W}_{i,t}^*, \boldsymbol{l}_{i,t-1}, \boldsymbol{z}_i, \boldsymbol{\theta}) \right]. \end{aligned} \tag{26}$$

In the above, $\underline{t}_i$ and $\bar{t}_i$ denote the times when the individual entered and left the sample, $f()$ denotes the conditional density of the individual's observed wage in year t, $\mathcal{P}_l()$ denotes the conditional probability of the individual's labor supply outcome in year t, and $\boldsymbol{W}_{i,\tau}^*$ ($\boldsymbol{l}_{i,\tau}$) denotes the individual's wage observations (labor supply outcomes) in each year from year $\underline{t}_i$ to year τ.

Since all unobserved wage components are normally distributed, $f()$ is a normal density function with a mean and a variance that follow from the distributional assumptions given in Section 3.5. We derive the conditional probability of the individual's labor supply outcome, $\mathcal{P}_l()$, in two steps. First, note that under the distributional assumptions on preference shocks in Section 3.7 the probability of an individual's labor supply outcome in year t is given by:

$$P(l_{i,t}|\boldsymbol{x}_{i,t},\boldsymbol{\theta}) \quad = \quad \sum_m \frac{\exp\left(\overline{V}_t(m,l_{i,t},\boldsymbol{x}_{i,t})\right)}{\sum_{\{c,l\}\in\mathbb{D}(\boldsymbol{x}_{i,t})}\exp\left(\overline{V}_t(c,l,\boldsymbol{x}_{i,t})\right)}, \tag{27}$$

where $\overline{V}_t()$ is the systematic component of the choice-specific value function given by (20), $\boldsymbol{x}_{i,t}$ denote the age-t state variables excluding the preference shocks, and the sum is over the possible consumption choices (see footnote 12). Second, we integrate over the elements of the state space that are unobserved to the econometrician. In particular, since wage shocks and job offer status are the only state variables in $\boldsymbol{x}_{i,t}$ that are unknown to the econometrician, given past and current observations of wages, and past labor supply outcomes and the conditioning variables, we have:

$$\begin{aligned}&\mathcal{P}_l(\boldsymbol{l}_{i,t}|\eta_i=\eta^j,\text{Educ}_i,\boldsymbol{W}^*_{i,t},\boldsymbol{l}_{i,t-1},\boldsymbol{z}_i,\boldsymbol{\theta}) = \\ &\qquad\int\int P(l_{i,t}|\boldsymbol{x}_{i,t},\boldsymbol{\theta})dF(\text{JO}_{i,t}|\text{Educ}_i,\boldsymbol{z}_i)g(W_{i,t}|\boldsymbol{W}^*_{i,t},\boldsymbol{l}_{i,t-1},\boldsymbol{z}_i)dW^*_{i,t},\end{aligned} \tag{28}$$

where $F(\text{JO}_{i,t}|\text{Educ}_i,\boldsymbol{z}_i)$ denotes the cumulative distribution function for job offers (see Section 3.3) and $g()$ denotes the density of the individual's market wage in year t conditional on past observations of wages, past observed labor supply outcomes and the conditioning variables.

Web Appendix III.3: Maximization of the likelihood function

We maximize the likelihood function using a maximum likelihood procedure that utilizes the numerical gradient and the BHHH Hessian (Berndt et al., 1974). The health transition probabilities and the parameters of the separation probabilities ($\phi_1^s, ..., \phi_6^s$) are estimated separately in a first step and, then, taken as given in the estimation of the full model. Furthermore, in order to obtain good starting values for the wage process and the type probabilities, we estimate the wage process together with the type probabilities separately first and, subsequently, use these estimates as starting values in the estimation of the full model. Based on these starting values as well as starting values for the utility function and the parameters of the offer probabilities that are within a reasonable range, the ML procedure converges quickly.[35]

[35]We gratefully acknowledge the computing time on the high-performance computing cluster CURTA provided by Zentraleinrichtung für Datenverarbeitung (ZEDAT) of Freie Universität Berlin (Bennett et al., 2020).

Web Appendix IV: Estimation results & in-sample fit

Web Appendix IV.1: Heterogenous survival risk estimates

This appendix explains how we use the approach of Kroll and Lampert (2009) to calculate survival probabilities that vary with health and education, as well as age.[36] We proceed in two steps.

First, we estimate the heterogeneity in mortality risk pattern by health and education based on an exponential survival model that includes health-by-education-group indicators as covariates. For this exercise, we use information from death records in the SOEP *Lifespell* dataset (Kroh and Kröger, 2019). Due to the low number of deaths in any given year, we employ an extended sample of West German men observed between 1992 and 2016. However, we continue to use the occupational sample restrictions and variable definitions described in Web Appendix II. Table SWA.2 reports the results of this analysis. In summary, poor health and low education are associated with higher mortality risk, with the effects of health outweighing those of education.

Second, we use the population life tables to translate the information about heterogeneity in mortality in the SOEP data into health-by-education group survival curves. By supplementing the SOEP with information from the life tables, we ensure that we match overall longevity in the population.[37] Specifically, we take the baseline (population) hazard rates from the life tables for each year between 1992 and 2016 and adjust them according to the mortality risk estimates for each health-by-education group, as reported in Table SWA.2. These adjusted rates are then transformed into survival probabilities and averaged over the years. The final survival curves for each health-by-education group are shown in Figure 3(c) in the main text.

Table SWA.2: Relative mortality risk

	Estimate	Standard error
Bad health and low education	1.615	0.064
Bad health and high education	1.393	0.079
Good health and low education	0.681	0.037
Good health and high education	0.385	0.030
Individual-by-year observations	195,056	
Individuals	23,164	
Deaths	1,856	
Log likelihood	-1,318.66	
Chi-squared statistic	6,042.17	

Notes: Estimates are expressed as hazard ratios indicating relative differences in mortality risk compared to the sample average. Standard errors are robust with clustering at the individual level. The model also includes a linear age trend.

[36] Evidence on the relationship between socioeconomic indicators and mortality is provided by, e.g., Montez et al. (2011) and Pijoan-Mas and Ríos-Rull (2014).

[37] Life tables are obtained from the Human Mortality Database. Max Planck Institute for Demographic Research (Germany), University of California, Berkeley (USA), and French Institute for Demographic Studies (France). Available at www.mortality.org.

Web Appendix IV.2: Employment risk estimates

Table SWA.3: Parameter estimates: employment risks

		Estimate	Standard error
	Panel I: Job offers		
ϕ_1^o	Intercept	−1.344	0.0987
ϕ_2^o	High-education	−0.147	0.0464
ϕ_3^o	Good-health	0.799	0.1091
ϕ_4^o	Age ≥ 50	−0.480	0.1016
ϕ_5^o	Age ≥ 55	0.195	0.1458
ϕ_6^o	Age ≥ 60	−0.117	0.1829
	Panel II: Involuntary job separations		
ϕ_1^s	Intercept	−3.467	0.1574
ϕ_2^s	High-education	−0.757	0.1315
ϕ_3^s	Good-health	−0.415	0.1505
ϕ_4^s	Age ≥ 50	−0.249	0.1725
ϕ_5^s	Age ≥ 55	−0.154	0.1840
ϕ_6^s	Age ≥ 60	0.227	0.1914
Observations	20,843		
Individuals	3,281		
Involuntary job separations	323		
Log likelihood	−1634.86		
Chi-squared statistic	65.18		

Notes: Parameter estimates for the job offer probability equation (Panel I) are obtained from a FIML procedure. The reduced form risk model of involuntary job separations (Panel II) is estimated separately by standard maximum likelihood and accounting for cluster-robust standard errors.

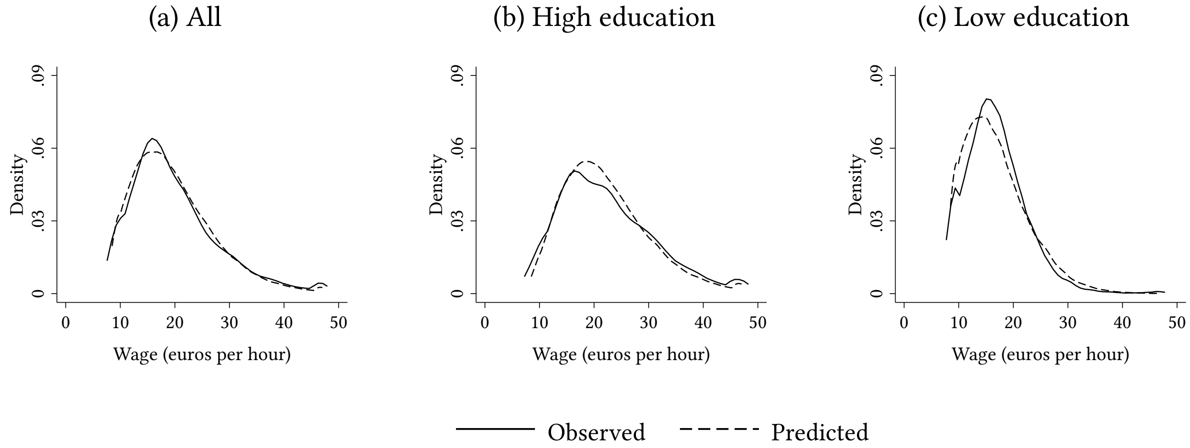
Web Appendix IV.3: Additional in-sample fit analysis

The appendix contains additional analyses of the model's in-sample fit. Throughout this section, we compare behaviors observed in the estimation sample with predicted behaviors in a sample simulated using the estimated model. Details about the simulated sample are provided in the notes to Figure 4.

Web Appendix IV.3.1 Employment and earnings

Figure SWA.1 shows that the estimated model fits the distribution of wages, both overall and when we split the samples based on years of education. Figures SWA.2(a)-(b) show that the estimated model captures accurately the life-cycle profiles of unemployment and retirement.

Figure SWA.1: Observed and predicted distributions of wages



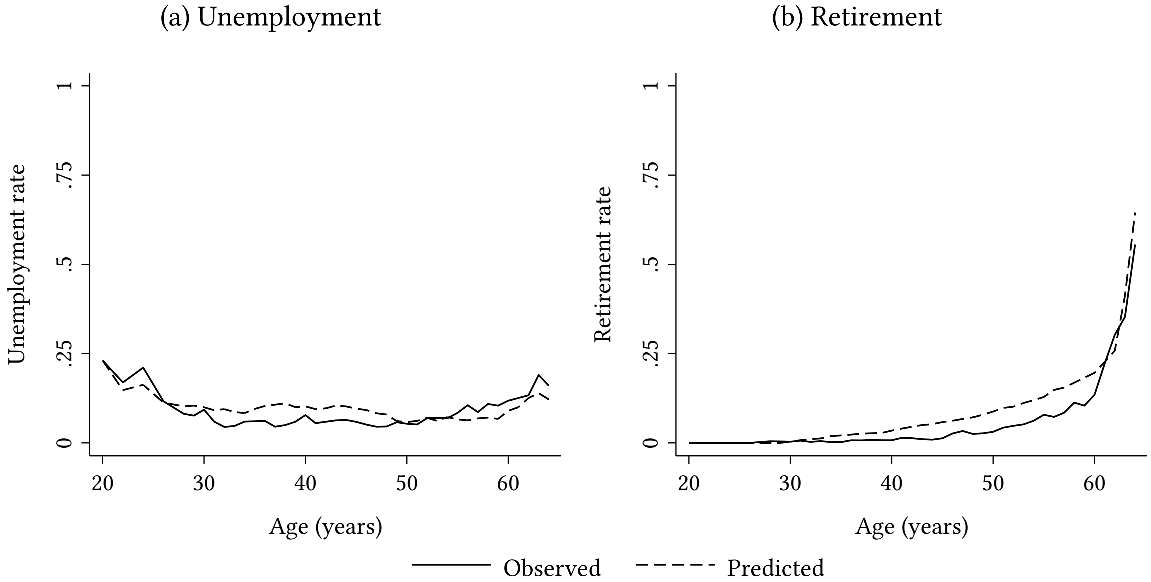
Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. Employed individuals aged 20–59 years inclusive.

Next, we use three different analyses to show that the estimated model accurately reflects the observed persistence in labor supply and earnings. First, we investigate the ability of the estimated model to accurately predict the observed persistence in employment and unemployment. We define employment persistence as the fraction of time an individual is employed while part of the sample. For example, employment persistence would be 33% for an individual who is in the sample for 6 years and employed for 2 of those years. We measure unemployment persistence in the same way. Table SWA.4 shows that the estimated model reproduces the patterns of persistence in employment and unemployment observed in the estimation sample.

Also, when we split the we split the samples based on years of education, the model continues to fit the persistence in employment and unemployment. In particular, the estimated model replicates the higher employment persistence among high-educated individuals. This result is driven by differences in the average number of unemployment spells during work life. While the average length of unemployment spells is very similar between education groups, individuals with less than 12 years of education experience unemployment episodes roughly 80% more often.

Second, we assess the model's capacity to capture earnings mobility for employed individuals. To do this, we divide the labor earnings distribution of employed individuals into quintiles. We then

Figure SWA.2: Observed and predicted age profiles of unemployment and retirement



Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4.

calculate the fraction of individuals transitioning between these quintiles from one employment year to the next, omitting any years of unemployment in between. Table SWA.5 reveals that the model's predictions largely align with observed patterns in the estimation sample. The largest deviations occur in persistence within quintiles 2-4, where the model tends to under-predict. This under-prediction is balanced by an over-prediction in the rates of transition to adjacent quintiles. Importantly, the model accurately predicts persistence in the bottom quintile, where interactions with the transfer system are the largest.

Third, we extend on Table 4 in the main text and provide further evidence on the estimated model's proficiency in capturing persistence in labor earnings, taking into account both earnings mobility among employed individuals and labor supply persistence. For this purpose, we measure labor earning persistence using average annual labor earnings over the years that the individual was in the estimation sample. Figure SWA.3 shows the observed and predicted distributions of average annual labor earnings. Overall, the estimated model is successful at matching the observed distribution of average labor earnings in the estimation sample, although there is a slight discrepancy at the lower tail. Specifically, the model underestimates the proportion of individuals with low average earnings.

To examine this issue more closely, we note that the model assumes full-time employment for everyone, while 3% of employed individuals in the estimation sample work fewer than 30 hours per week. We created two part-time adjusted simulated samples, identical to the original simulated sample, except that a random 3% of employed individuals work part-time. In one adjusted sample, part-time workers earn two-thirds of their potential full-time earnings, while in the other, they earn one-half of their potential full-time earnings. As shown in Figure SWA.4, both adjustments bring the distribution of average annual earnings closer to that in the estimation sample, with the under-prediction of low average labor earnings essentially eliminated by the one-half adjustment.

Table SWA.4: Observed and predicted persistence in labor supply

	Employment					
	All		High education		Low education	
Percentage of time	Observed	Predicted	Observed	Predicted	Observed	Predicted
= 0	7.45	8.75	5.72	5.66	9.42	12.27
≤ 25	8.53	10.22	6.52	6.68	10.82	14.24
≤ 50	11.96	14.61	8.73	9.68	15.63	20.20
≤ 75	16.67	21.07	12.42	14.34	21.49	28.70
≤ 100	100.00	100.00	100.00	100.00	100.00	100.00

	Unemployment					
	All		High education		Low education	
Percentage of time	Observed	Predicted	Observed	Predicted	Observed	Predicted
= 0	80.97	77.51	85.05	82.60	76.34	71.74
≤ 25	88.62	87.80	91.70	90.98	85.14	84.20
≤ 50	93.92	94.38	95.26	95.57	92.39	93.04
≤ 75	95.42	96.89	96.31	97.37	94.42	96.36
≤ 100	100.00	100.00	100.00	100.00	100.00	100.00
Mean spells	0.12	0.13	0.09	0.10	0.16	0.17
Mean spells length (years)	1.42	2.12	1.38	2.11	1.45	2.12

Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. Persistence in a given labor market state is defined at the individual level as the fraction of time an individual is observed in that labor supply state within the sample. Individuals aged 20–59 years inclusive.

Importantly, Table SWA.16 shows that the lifetime inequality decomposition results, discussed in Section 5, continue to hold in the part-time adjusted samples. Thus, the omission of a small amount of part-time work is not critical for our decompositions based on the estimated model.

Table SWA.5: Observed and predicted labor earnings transition matrices for employed individuals

(a) Observed

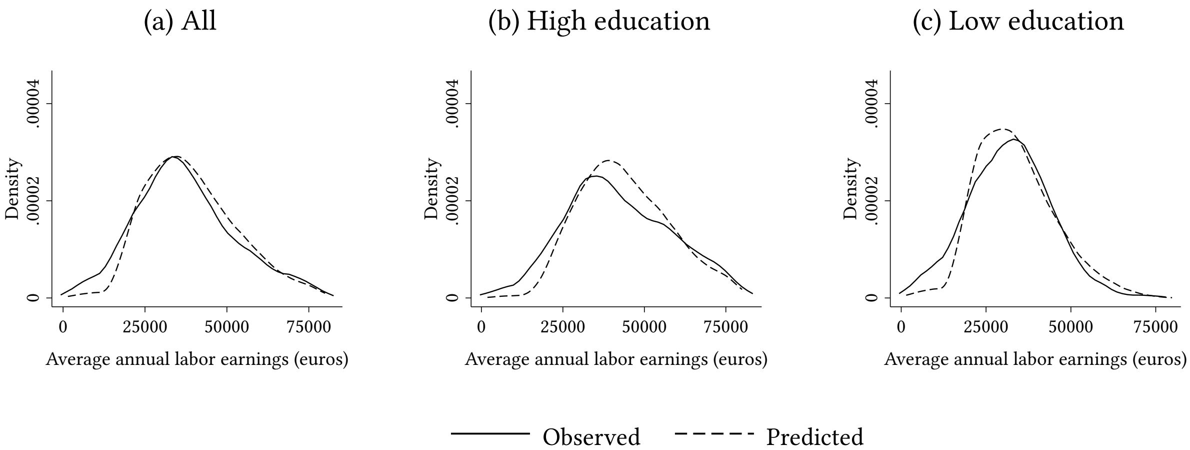
$t \setminus t'$	Q1	Q2	Q3	Q4	Q5
Q1	0.772	0.173	0.035	0.011	0.008
Q2	0.146	0.604	0.202	0.042	0.006
Q3	0.036	0.182	0.557	0.201	0.026
Q4	0.018	0.038	0.178	0.606	0.161
Q5	0.013	0.008	0.020	0.124	0.835

(b) Predicted

$t \setminus t'$	Q1	Q2	Q3	Q4	Q5
Q1	0.730	0.231	0.035	0.001	0.000
Q2	0.193	0.471	0.273	0.060	0.003
Q3	0.025	0.234	0.433	0.270	0.038
Q4	0.002	0.046	0.241	0.477	0.233
Q5	0.000	0.003	0.029	0.203	0.765

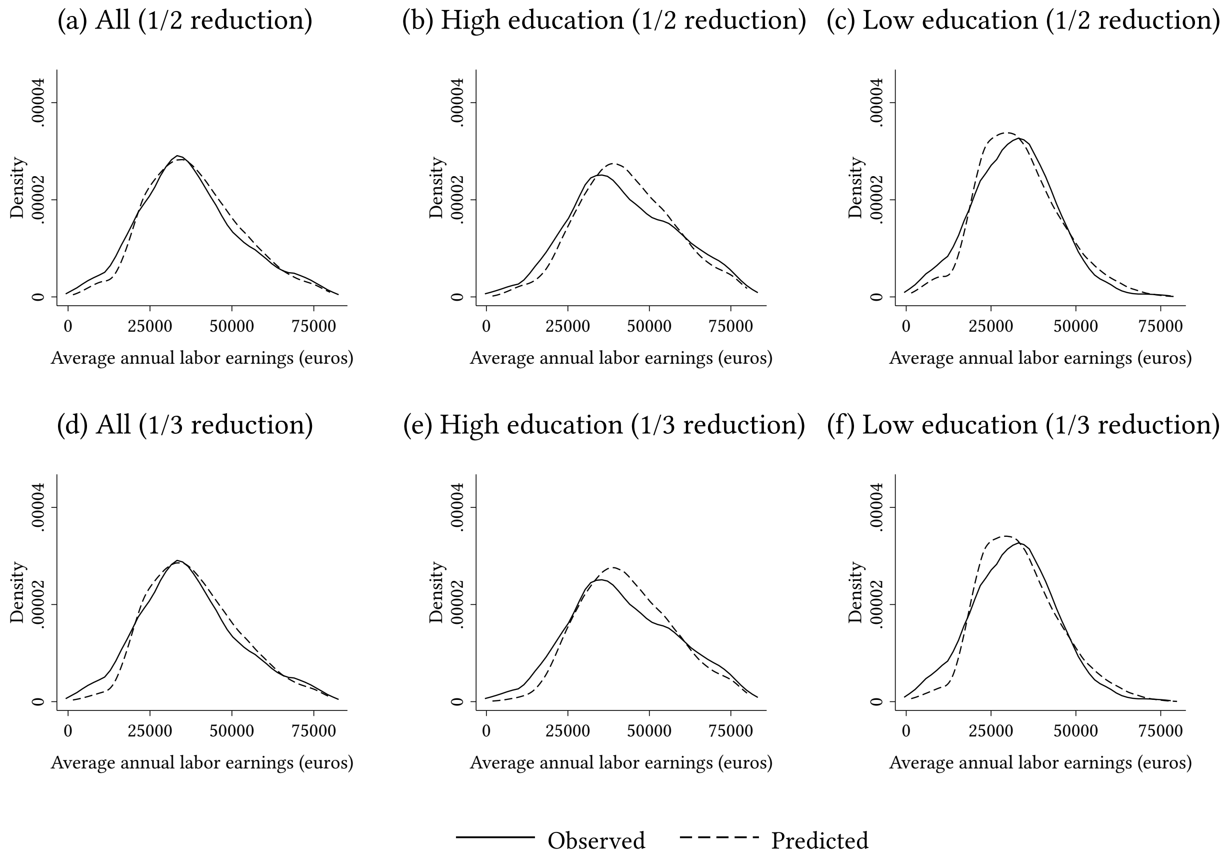
Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. Q1-Q5 refer to quintiles 1-5 of the cross-sectional distribution of labor earnings of employed individuals. Transition matrices display the proportion of employed individuals within each quintile at age t who move to each corresponding quintile in their subsequent year of employment at age t'. Employed individuals aged 20–59 years inclusive.

Figure SWA.3: Observed and predicted persistence in labor earnings



Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. 'Average annual labor earnings' is the individual-level average of annual labor earnings over the years that the individual was in the sample. Individuals with zero average annual labor earnings (i.e., those individuals who never worked during the sample period) are excluded. As reported in Table SWA.4, across all individuals, the observed and predicted fractions of individuals with zero average annual labor earnings are 7.5% and 8.8%, respectively. The corresponding figures are 5.7% and 5.7% for individuals with at least twelve years of education, and 9.4% and 12.3% for individuals with fewer than twelve years of education. Individuals aged 20–59 years inclusive.

Figure SWA.4: Observed and predicted persistence in labor earnings with labor earnings reduced for part-time work



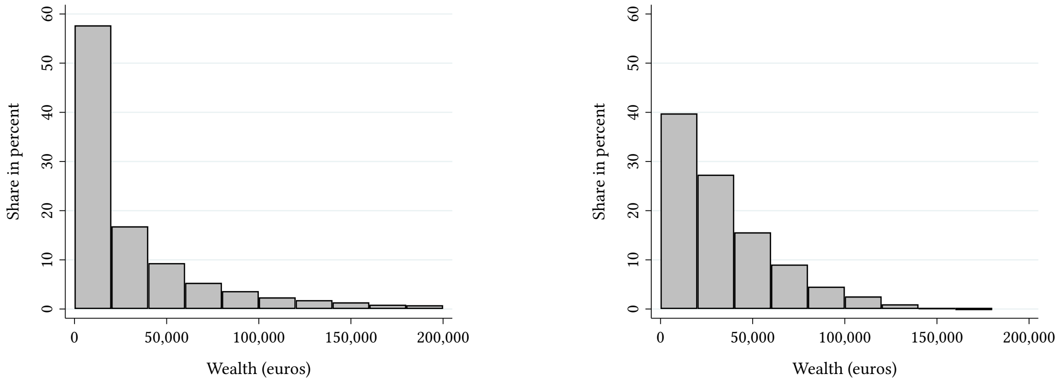
Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4, with the exception that we assume 3% of employed individuals work part-time. This percentage is consistent with the observed share of individuals working fewer than 30 hours per week in the estimation sample. For the part-time category, we reduce simulated labor earnings by either one-half (panels a-c) or one-third (panels d-e) of the baseline value. To maintain comparability, predicted values were calculated based on the age values at which individuals were observed in the estimation sample. 'Average annual labor earnings' is the individual-level average of annual labor earnings over the years that the individual was in the sample. Individuals with zero average annual labor earnings (i.e., those individuals who never worked during the sample period) are excluded. Individuals aged 20–59 years inclusive.

Web Appendix IV.3.2 Wealth

Here, we compare the distribution of wealth from the SOEP sample with that generated through simulations using our estimated model. Figure SWA.5 illustrates that the model successfully predicts both the low modal values and the right-skewed distribution of observed wealth. However, the model overestimates the proportion of individuals with moderate wealth and underestimates the proportion with low wealth. These discrepancies are not surprising, given the challenges associated with measuring wealth in the SOEP survey. Specifically, Albers et al. (2022) provide evidence of underreporting certain asset classes in the SOEP, which might account for the higher frequency of low wealth levels in the SOEP compared to the model's predictions.

Figure SWA.5: Distributions of observed and predicted wealth

(a) Observed (b) Predicted

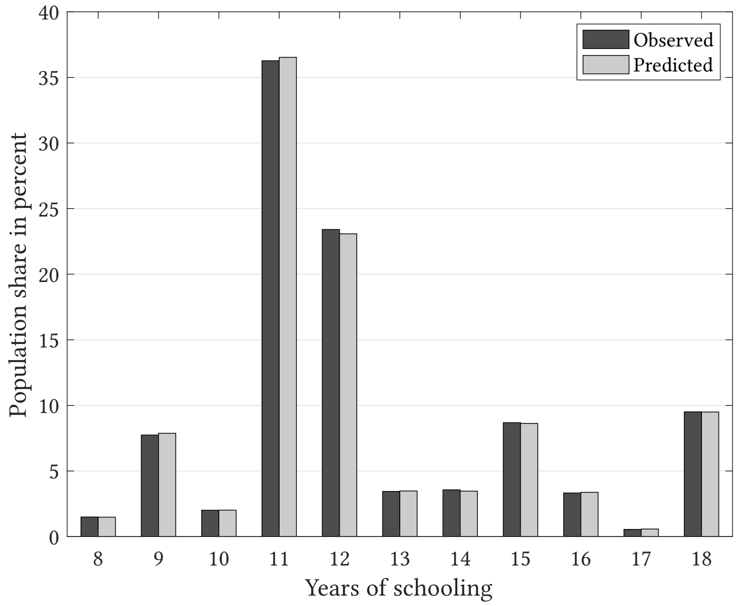


Notes: Observed values are calculated from cross-sectional wealth data of SOEP waves 2007 and 2012. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. To maintain comparability, predicted values were calculated based on the age values at which wealth was observed in the SOEP. Left-censoring and consistency restrictions are applied as discussed in Web Appendix II. Individuals aged 20–59 years inclusive.

Web Appendix IV.3.3 Education

Figure SWA.6 illustrates the observed and predicted percentages of individuals with each number of years of education. Deviations for any education alternative are within one percentage point for all values of years of education.

Figure SWA.6: Distributions of observed and predicted years of education



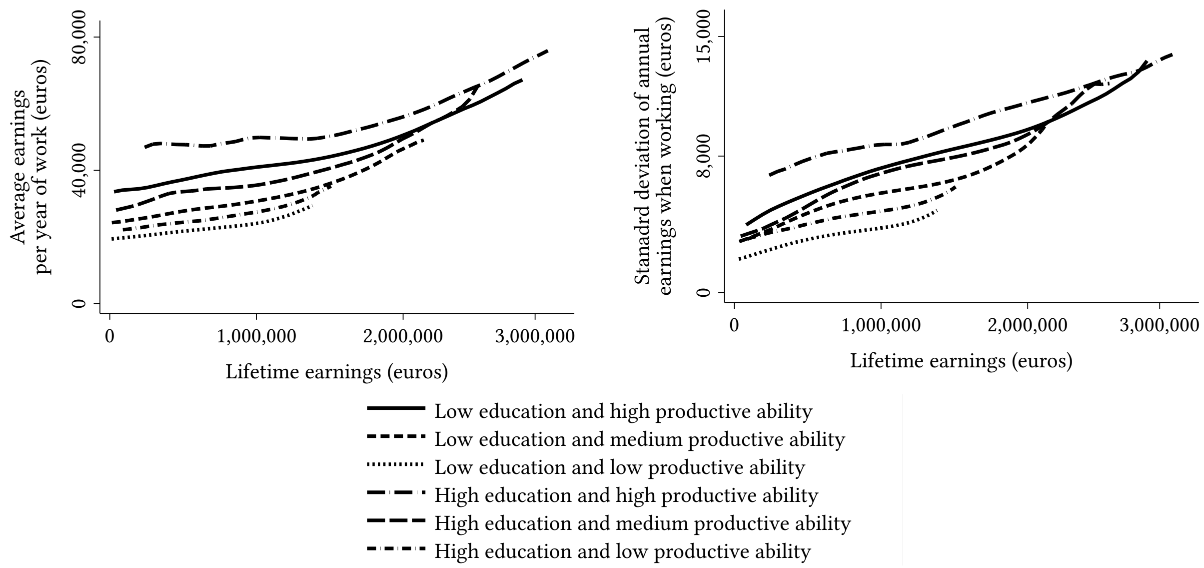
Notes: Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4.

Web Appendix V: Further results

Annual earning taxes provide insurance against 22.1% of the within-skill group inequality of lifetime earnings that is not due to differences in years worked during the life cycle. Insurance may operate through two channels. First, if average earnings per year of work increase with lifetime earnings among individuals with the same level of education and productive ability, then a progressive annual tax will translate into a progressive tax on lifetime earnings. Second, if the year-to-year variation in annual earnings across years of work increases with lifetime earnings for individuals in the same skill group, then, due to the convexity of the progressive annual tax function, annual taxes will again be progressive on a lifetime basis. Figures SWA.7(a)–SWA.7(b) show that both channels operate in practice. The increase in average earnings per year of work with lifetime earnings shown in Figure SWA.7(a) reflects both the returns to experience and persistent wage shocks. Similarly, both the wage returns to experience and persistent wage shocks contribute to the increase in the standard deviation of annual earnings with lifetime earnings shown in Figure SWA.7(b). Further analysis shows that most of the insurance effect of annual taxes is driven by persistent wage shocks rather than returns to experience (see Figure SWA.8).

Figure SWA.7: Insurance effects of taxation

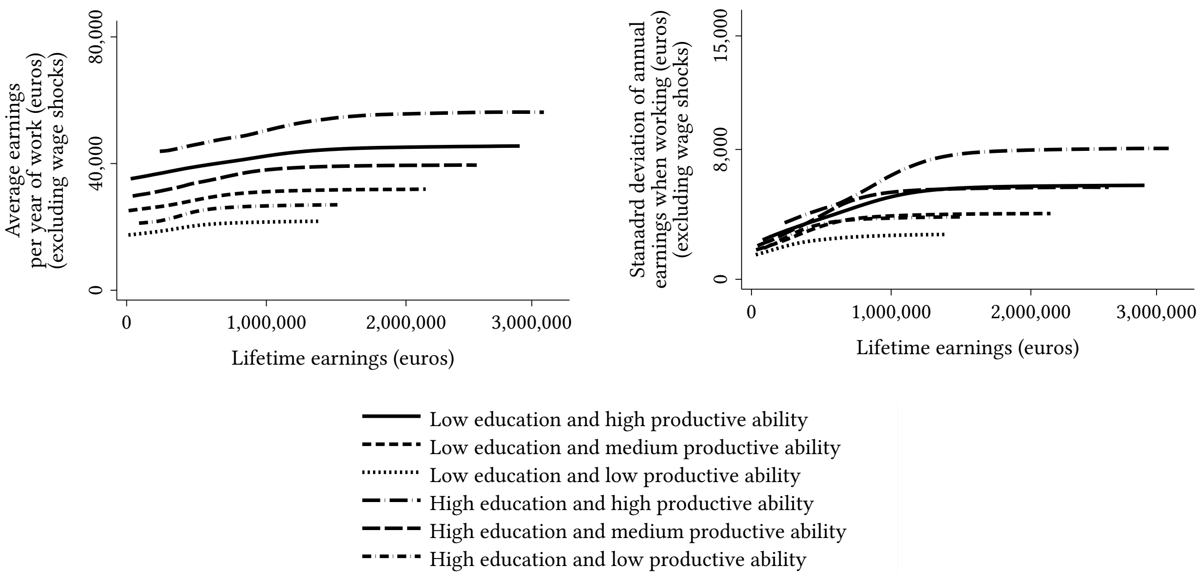
(a) (b)



Notes: Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample described in the notes to Table 6. 'Low education' refers to eleven years of education, and 'high education' refers to fourteen years of education.

Figure SWA.8: Insurance effects of taxation without wage shocks

(a) (b)



Notes: Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample described in the notes to Table 6. 'Low education' refers eleven years of education and 'high education' refers to fourteen years of education.

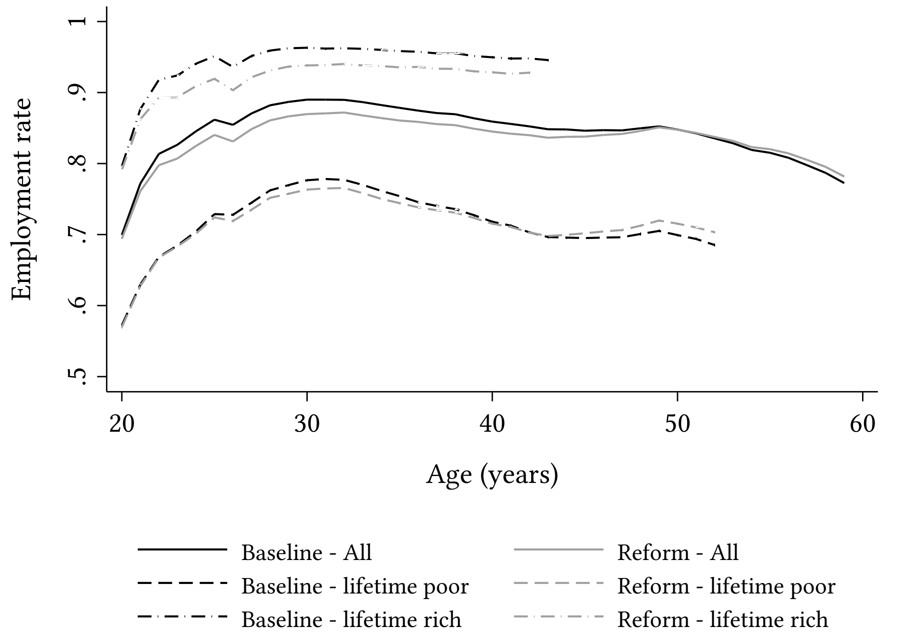
Web Appendix VI: Behavioral effects of the lifetime tax reform

Table SWA.7: Behavioral effects of the lifetime tax reform

	Baseline	Lifetime tax reform (with behavioral adjustments)
Average years of education	12.40	12.56
Employment rate	0.82	0.81
Average unemployment spells per person	1.08	1.22
Average unemployment spell duration (years)	2.85	2.93
Rate of bad health	0.16	0.16
Average bad health spells per person	0.99	0.99
Average bad health spell duration (years)	6.24	6.23

Notes: Calcualtions from samples of 50,000 life-cycle trajectories of individuals aged 20–59 years inclusive, simulated from the estimated model (the notes to Table 5 describe how we use the estimated model to simulate employment trajectories). The baseline tax system (Panel I) equivalent to the lifetime tax reform with $\pi_1 = \pi_2 = 0$.

Figure SWA.9: Labor supply effects of the lifetime tax reform over the life cycle



Notes: Individuals are classified as lifetime poor or rich based on the strength of their employment history baseline simulation (i.e., the fraction of years an individual has been employed since entering the workforce after completing their education). If this is below the sample mean for more than half of the years between ages 20 and 59, they are classified as poor. If it is above the mean for more than half of these years, they are classified as rich.

Web Appendix VII: Robustness checks

Table SWA.8: Robustness of the results in Tables 6 and 7 to excluding capital income

	Inequality of lifetime earnings and lifetime income (100 × Theil index)			Ratio of between-skill-group inequ. to total inequ.
	Total	Within-skill-group	Between-skill-group	
Lifetime earnings	8.86	4.39	4.47	0.50
Lifetime income	4.68	2.26	2.42	0.52
Share of earnings inequality offset by the tax-and-transfer system	0.47	0.49	0.46	
... Taxes	0.23	0.13	0.34	
... Unemployment insurance	0.02	0.02	0.02	
... Disability benefits	0.09	0.17	0.01	
... Social assistance	0.13	0.17	0.09	

Notes: In this table, earnings are defined as the labor earnings only (capital income is excluded). Income is defined as labor earnings net of all taxes and transfers (capital income is excluded). For further details, see the notes to Tables 6 and 7.

Table SWA.9: Robustness of the results in Tables 6 and 7 to alternative measures of inequality

	Inequality of lifetime earnings and lifetime income (100 × Inequality index)			Ratio of between-skill-group inequ. to total inequ.
	Total	Within-skill-group	Between-skill-group	
Panel I: Squared coefficient of variation				
Lifetime earnings	8.47	3.99	4.48	0.53
Lifetime income	4.63	2.17	2.47	0.53
Share of earnings inequality offset by the tax-and-transfer system	0.45	0.46	0.45	
... Taxes	0.25	0.16	0.34	
... Unemployment insurance	0.02	0.03	0.02	
... Disability benefits	0.07	0.14	0.01	
... Social assistance	0.11	0.13	0.08	
Panel II: Mean logarithmic deviation				
Lifetime earnings	11.09	6.41	4.58	0.42
Lifetime income	5.44	2.92	2.52	0.46
Share of earnings inequality offset by the tax-and-transfer system	0.51	0.54	0.46	
... Taxes	0.20	0.10	0.33	
... Unemployment insurance	0.02	0.03	0.02	
... Disability benefits	0.12	0.19	0.01	
... Social assistance	0.17	0.23	0.10	
Panel III: Variance of the natural logarithm				
Lifetime earnings	28.64	18.13	13.48	0.47
Lifetime income	12.87	7.80	6.54	0.51
Share of earnings inequality offset by the tax-and-transfer system	0.55	0.57	0.51	
... Taxes	0.17	0.09	0.32	
... Unemployment insurance	0.02	0.03	0.02	
... Disability benefits	0.14	0.21	0.03	
... Social assistance	0.21	0.25	0.15	
Panel IV: Theil index with correction for negative and zero values (see table notes)				
Lifetime earnings	8.84	4.46	4.38	0.50
Lifetime income	4.60	2.22	2.37	0.52
Share of earnings inequality offset by the tax-and-transfer system	0.48	0.50	0.46	
... Taxes	0.23	0.13	0.34	
... Unemployment insurance	0.02	0.02	0.02	
... Disability benefits	0.09	0.16	0.01	
... Social assistance	0.14	0.19	0.09	

Notes: Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. For further details, see the notes to Table 6. In Panel IV, we include individuals with zero or negative lifetime earnings and augment the lifetime earnings of all individuals by the value of one year's worth of minimum wage labor earnings. This adjustment ensures that all individuals have strictly positive lifetime earnings and income.

Table SWA.10: Robustness (Part 1) of the results in Tables 6 and 7 to the calibration of the discount factor and risk aversion parameters

	Inequality of lifetime earnings and lifetime income (100 × Theil index)			Ratio of between-skill-group inequ. to total inequ.
	Total	Within-skill-group	Between-skill-group	
Panel I: $\beta = 0.98, \gamma = 1.5$				
Lifetime earnings	8.63	4.28	4.35	0.50
Lifetime income	4.66	2.25	2.41	0.52
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
... Taxes	0.23	0.12	0.34	
... Unemployment insurance	0.02	0.02	0.02	
... Disability benefits	0.09	0.17	0.01	
... Social assistance	0.12	0.16	0.08	
Panel I: $\beta = 0.97, \gamma = 1.5$				
Lifetime earnings	8.21	4.03	4.19	0.51
Lifetime income	4.51	2.16	2.35	0.52
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
... Taxes	0.24	0.13	0.34	
... Unemployment insurance	0.02	0.02	0.01	
... Disability benefits	0.09	0.16	0.01	
... Social assistance	0.11	0.15	0.07	
Panel III: $\beta = 0.99, \gamma = 1.25$				
Lifetime earnings	8.80	4.18	4.62	0.52
Lifetime income	4.77	2.22	2.55	0.53
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
... Taxes	0.23	0.12	0.33	
... Unemployment insurance	0.02	0.03	0.02	
... Disability benefits	0.08	0.16	0.01	
... Social assistance	0.12	0.17	0.09	
Panel IV: $\beta = 0.99, \gamma = 1.75$				
Lifetime earnings	9.28	4.80	4.48	0.48
Lifetime income	4.89	2.46	2.43	0.50
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
...Taxes	0.22	0.12	0.33	
...Unemployment insurance	0.02	0.02	0.02	
...Disability benefits	0.10	0.18	0.02	
...Social assistance	0.13	0.17	0.10	

Notes: Following procedures described in footnote 22, the model is re-estimated for the indicated calibration values of discount and risk aversion parameters. The model's in-sample fit and external validity are similar across the calibrations. Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. For further details see the notes to Table 6.

Table SWA.11: Robustness (Part 2) of the results in Tables 6 and 7 to the calibration of the discount factor and risk aversion parameters

	Inequality of lifetime earnings and lifetime income (100 × Theil index)			Ratio of between-skill-group inequ. to total inequ.
	Total	Within-skill-group	Between-skill-group	
Panel I: $\beta = 0.98, \gamma = 1.25$				
Lifetime earnings	8.44	3.97	4.48	0.53
Lifetime income	4.62	2.13	2.48	0.54
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
... Taxes	0.24	0.13	0.34	
... Unemployment insurance	0.02	0.03	0.02	
... Disability benefits	0.08	0.15	0.01	
... Social assistance	0.12	0.16	0.08	
Panel II: $\beta = 0.98, \gamma = 1.75$				
Lifetime earnings	8.87	4.57	4.30	0.48
Lifetime income	4.73	2.37	2.37	0.50
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
... Taxes	0.23	0.12	0.34	
... Unemployment insurance	0.02	0.02	0.01	
... Disability benefits	0.10	0.18	0.02	
... Social assistance	0.12	0.16	0.08	
Panel III: $\beta = 0.97, \gamma = 1.25$				
Lifetime earnings	8.06	3.75	4.32	0.54
Lifetime income	4.47	2.04	2.43	0.54
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
... Taxes	0.25	0.13	0.34	
... Unemployment insurance	0.02	0.02	0.01	
... Disability benefits	0.08	0.15	0.01	
... Social assistance	0.11	0.15	0.07	
Panel IV: $\beta = 0.97, \gamma = 1.75$				
Lifetime earnings	8.33	4.26	4.07	0.49
Lifetime income	4.53	2.25	2.28	0.50
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	
... Taxes	0.23	0.13	0.35	
... Unemployment insurance	0.02	0.02	0.01	
... Disability benefits	0.10	0.18	0.01	
... Social assistance	0.11	0.15	0.07	

Notes: See the notes to Table SWA.10.

Table SWA.12: Robustness of the results in Tables 9 and 10 to alternative measures of inequality

	Within-skill-group inequality in baseline	Δ Within-skill-group inequality		
		Increased job separation risk	Decreased job offer rate	Increased risk of bad health shocks
Panel I: Squared coefficient of variation				
Lifetime earnings	3.99	1.06 [27%]	0.34 [9%]	1.66 [42%]
Lifetime income	2.17	0.44 [20%]	0.32 [15%]	0.68 [31%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.59	0.07	0.59
... Taxes		0.12	0.21	0.12
... Unemployment insurance		0.05	-0.06	0.03
... Disability benefits		0.23	-0.07	0.28
... Social assistance		0.18	-0.02	0.17
Panel II: Mean logarithmic deviation				
Lifetime earnings	6.41	1.78 [28%]	0.93 [15%]	2.39 [37%]
Lifetime income	2.92	0.44 [15%]	0.48 [16%]	0.74 [25%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.75	0.49	0.69
... Taxes		0.08	0.17	0.07
... Unemployment insurance		0.03	-0.01	0.03
... Disability benefits		0.30	0.08	0.25
... Social assistance		0.33	0.25	0.34
Panel III: Variance of the natural logarithm				
Lifetime earnings	18.13	5.11 [28%]	3.08 [17%]	6.33 [34%]
Lifetime income	7.80	0.86 [12%]	1.32 [17%]	1.71 [22%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.83	0.57	0.73
... Taxes		0.07	0.15	0.06
... Unemployment insurance		0.04	0.01	0.03
... Disability benefits		0.33	0.11	0.25
... Social assistance		0.39	0.30	0.38

Notes: Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. For further details, see the notes to Table 6. 'Δ Within-skill-group inequality' is the increase in within-skill-group inequality from the baseline environment. The percentage increases in inequality from the baseline are shown in brackets. Also see the notes to Table 8.

Table SWA.13: Robustness of the results in Table 11 to measuring inequality using the squared coefficient of variation

	Total	Within-skill-group (ins.)	Between-skill-group (redist.)
Panel I: Lifetime tax reform with behavior fixed to match the baseline environment			
Inequality:			
Lifetime earnings	8.47	3.99	4.48
Lifetime income	4.44	1.98	2.46
Share of earnings inequality offset by:			
Tax-and transfer system	0.48	0.50	0.45
... Taxes	0.28	0.21	0.34
... Unemployment insurance	0.02	0.02	0.02
... Disability benefits	0.07	0.14	0.01
... Social assistance	0.10	0.12	0.08
Panel II: Lifetime tax reform with behavioral adjustments			
Inequality:			
Lifetime earnings	8.42	3.99	4.42
Lifetime income	4.27	1.90	2.38
Share of earnings inequality offset by:			
Tax-and-transfer system	0.49	0.53	0.46
... Taxes	0.30	0.24	0.35
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.07	0.13	0.01
... Social assistance	0.11	0.13	0.09

Notes: Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. For further details see the notes to Table 6.

Table SWA.14: Robustness of the results in Table 11 to measuring inequality using the mean logarithmic deviation

	Total	Within-skill-group (ins.)	Between-skill-group (redist.)
Panel I: Lifetime tax reform with behavior fixed to match the baseline environment			
Inequality:			
Lifetime earnings	11.09	6.41	4.68
Lifetime income	5.26	2.75	2.51
Share of earnings inequality offset by:			
Tax-and transfer system	0.53	0.57	0.46
... Taxes	0.22	0.14	0.34
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.12	0.19	0.01
... Social assistance	0.16	0.22	0.10
Panel II: Lifetime tax reform with behavioral adjustments			
Inequality:			
Lifetime earnings	10.87	6.22	4.65
Lifetime income	5.08	2.65	2.43
Share of earnings inequality offset by:			
Tax-and-transfer system	0.53	0.57	0.48
... Taxes	0.24	0.15	0.35
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.11	0.18	0.01
... Social assistance	0.17	0.22	0.10

Notes: Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. For further details see the notes to Table 6.

Table SWA.15: Robustness of the results in Table 11 to measuring inequality using the variance of the natural logarithm

	Total	Within-skill-group (ins.)	Between-skill-group (redist.)
Panel I: Lifetime tax reform with behavior fixed to match the baseline environment			
Inequality:			
Lifetime earnings	0.29	0.18	0.13
Lifetime income	0.12	0.07	0.07
Share of earnings inequality offset by:			
Tax-and transfer system	0.56	0.51	0.59
... Taxes	0.19	0.12	0.31
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.14	0.21	0.03
... Social assistance	0.21	0.24	0.15
Panel II: Lifetime tax reform with behavioral adjustments			
Inequality:			
Lifetime earnings	0.28	0.17	0.13
Lifetime income	0.12	0.07	0.06
Share of earnings inequality offset by:			
Tax-and-transfer system	0.56	0.59	0.52
... Taxes	0.20	0.13	0.32
... Unemployment insurance	0.03	0.03	0.02
... Disability benefits	0.13	0.20	0.03
... Social assistance	0.20	0.23	0.15

Notes: Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. For further details see the notes to Table 6.

Table SWA.16: Robustness of the results in Table 6 to including part-time employment

	Inequality of lifetime earnings and lifetime income (100 × Theil index)			Ratio of between-skill-group inequ. to total inequ.
	Total	Within-skill-group	Between-skill-group	
Panel I: 3% of employed individuals work part-time with labor earnings reduced by one-half				
Lifetime earnings	9.40	4.90	4.49	0.48
Lifetime income	5.25	2.78	2.46	0.47
Share of earnings inequality offset by the tax-and-transfer system	0.49	0.53	0.45	
Panel II: 3% of employed individuals work part-time with labor earnings reduced by one-third				
Lifetime earnings	9.84	5.35	4.49	0.46
Lifetime income	5.69	3.23	2.46	0.43
Share of earnings inequality offset by the tax-and-transfer system	0.51	0.57	0.45	

Notes: Earnings are defined as the sum of labor earnings and capital income. Income is defined as earnings net of all taxes and transfers. For further details, see the notes to Table 6. The notes to Figure SWA.4 describe the procedure implemented to account for part-time employment.