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Insurance, Redistribution and the Inequality of Lifetime Income

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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 the tax-and-transfer system offsets 45% of lifetime earnings inequality attributed to differences in productive abilities and education. Additionally, the system insures against 47% of lifetime earnings risk. Implementing a lifetime tax reform that links annual taxes to prior employment could enhance the system's insurance function, though it may involve tradeoffs in terms of employment and overall welfare.

KEYWORDS. Lifetime earnings, lifetime income, tax-and-transfer system, taxation, disability benefits, social assistance, inequality, redistribution, insurance, education, productive ability, risk, dynamic life-cycle model, welfare.

JEL CLASSIFICATION. D63, H23, I24, I38, J22, J31.

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 body of literature has

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started documenting 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 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 can 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 labor supply 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 47% 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 or 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 annually-assessed 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 employment histories. Social assistance is the most important transfer program for both insurance and redistribution of lifetime earnings. 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 suggest that the tax-and-transfer system insures 60–64% 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 the inequality in lifetime earnings due to job offer risk is noticeably smaller at 40%. 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. The motivation for this reform is to target disparities in earnings resulting from differences in employment histories. 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, overall, the reform also leads to a decrease in the employment rate and an increase in the frequency of unemployment spells. After accounting for changes in labor supply and other behaviors, the welfare effects of the reform are mixed: approximately one-third of individuals benefit, while the majority experience a reduction in welfare.

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 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 skills established early in life are important determinants of lifetime earnings (e.g., Heckman and Kautz (2012), Bhuller et al. (2017), Nybom (2017), Gill and Prowse (2024)).

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 (2014, 2024) 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)). The lifetime tax reform we examine is similar to the system proposed by Vickrey (1939, 1947), which substitutes annual taxes with a progressive tax on cumulative lifetime earnings to prevent penalizing individuals for year-to-year income fluctuations. Our policy analysis is also related to a large literature on optimal dynamic taxation over the life cycle (e.g., Golosov et al. (2003), Farhi and Werning (2013)). In particular, our lifetime tax reform makes the progressivity of current taxation depend on past earnings, a feature that aligns with the findings of several papers in the literature on optimal dynamic taxation, such as Golosov et al. (2016) and Kapička (2022). However, we do not go as far as characterizing the optimal dynamic tax system. Indeed, the richness of the institutional details we incorporate, along with individual differences in education, health, and preferences, makes it infeasible to apply existing methods to determine the optimal dynamic tax system.

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. The Supplemental Appendix (Haan et al. (2025)) collects details on the estimation sample, auxiliary estimation results, formalities of the model solution, analysis of the in-sample fit and robustness checks.

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:

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

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:

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

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 earnings 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 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]

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[1]The model also includes pension benefits for individuals in old-age retirement (see Supplemental 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 (2024) for a study of the welfare effects of social assistance and unemployment insurance with benefit non-take-up.

[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 modelled in less detail.

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

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

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.

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:

$$\mathcal{T} = \begin{cases} 0 & \text{if} \quad \text{LaborEarn} \leq 8652, \\ (993.62 * y + 1400) * y & \text{if} \quad 8653 \leq \text{LaborEarn} \leq 13669 \quad \text{where} \quad y = \frac{\text{LaborEarn} - 8652}{10000}, \\ (225.4 * y + 2397) * y + 952 & \text{if} \quad 13670 \leq \text{LaborEarn} \leq 53665 \quad \text{where} \quad y = \frac{\text{LaborEarn} - 13669}{10000}, \\ (0.42 \times \text{LaborEarn}) - 8394 & \text{if} \quad 53666 \leq \text{LaborEarn}. \end{cases} \tag{1}$$

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 thresh-

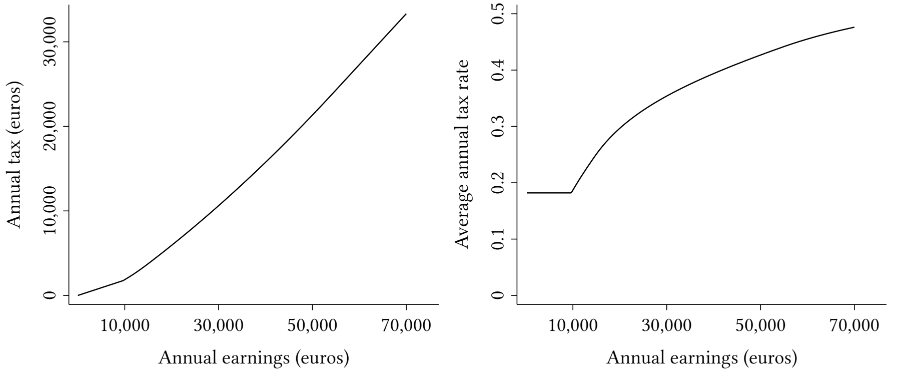
where α is a parameter that controls the generosity of disability benefits, $\overline{W}_R$ is the individual's disability-benefit-eligible annual earnings averaged over all years of employment prior to retirement, DBPenalty_R is a penalty that reduces the individual's annual disability benefit by 3.6% 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.

[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.

old of 801 euros is taxed at a flat rate of 25%. Supplemental Appendix I describes how pension income is taxed.

Figure 1a shows how the combined annual tax increases with annual earnings (assuming all earnings are from employment). Figure 1b 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.



(a) (b)

FIGURE 1. Annual taxes.

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. The model also allows us to simulate the implications of a counterfactual tax system featuring elements of lifetime taxation.

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.[7] The model incorporates three mutually exclusive labor supply states: employment, unemployment, and retirement.[8] The individual's labor supply choice depends on wages and preferences and is constrained by job offers. While receiving a job offer is a prerequisite for employment, an unemployed individual may reject a job offer due to an unfavorable wage offer or personal preference. Similarly, an employed individual may voluntarily transition out of employment despite receiving a job offer. A detailed description of the model can be found in Sections 3.1-3.8, with the solution to the labor supply problem presented in equation (9) in Section 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, $\mathrm{Educ}_i \in \{8, ..., 18\}$. 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 or age $8 + \mathrm{Educ}_i$, assuming seven years of pre-school and the mandatory completion of one year of military or civil service. 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 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 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.

[7]Given that we model annual employment transitions, our analysis will not capture some temporary employment situations, such as short spells of unemployment. As a result, our analysis is most relevant for understanding the effects of risks that impact employment for a year or longer.

[8]In the model, employment is defined as working 40 hours per week, which aligns with the observed median workweek duration for employees in the estimation sample. Part-time work is excluded from the model, as only 0.98% of the observations in the estimation sample correspond to individuals working fewer than twenty hours per week. For the purposes of our model, unemployment includes two groups: those unwilling to work at their market wage and those willing to work at their market wage but unable to secure a job offer.

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:

$$\mathrm{Prob}(\mathrm{GoodHealth}_{i,t} = 1) = G_t\big(\mathrm{HighEduc}_i, \mathrm{GoodHealth}_{i,t-1}\big), \tag{2}$$

where $\mathrm{GoodHealth}_{i,t}$ is an indicator of the individual being in good health at age t, $\mathrm{HighEduc}_i$ 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.[9]

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

$$p(t+1|t) = S_t\big(\mathrm{HighEduc}_i, \mathrm{GoodHealth}_{i,t}\big), \tag{3}$$

where $p(t+1|t)$ 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 uncertainty about job offers. In particular, individuals can choose to be employed in the current year only if they receive a job offer. The probability of such an offer depends on the individual's employment status in the previous year. If the individual was unemployed in the previous year, they receive a job offer in the current year with probability $\Phi^o_{i,t}$. If the individual was employed in the previous year, they receive a job offer in the current year if and only if they are not subjected to an involuntary job separation, which occurs with probability $\Phi^s_{i,t}$. The probabilities of an unemployed individual receiving a job offer and of an employed individual experiencing an involuntary job separation are expressed as follows:

$$\Phi^h_{i,t} = \Lambda\left(\phi^h_1 + \phi^h_2 \mathrm{HighEduc}_i + \phi^h_3 \mathrm{GoodHealth}_{i,t} + \phi^h_4 \mathbb{1}_{t\geq 50} + \phi^h_5 \mathbb{1}_{t\geq 55} + \phi^h_6 \mathbb{1}_{t\geq 60}\right)$$
$$\text{for} \quad h \in \{o, s\}, \tag{4}$$

where $\Lambda(\cdot)$ denotes the logistic distribution function. Irrespective of their previous employment status, an individual who receives job offers faces further uncertainty about the value of the offered wage. Section 3.5 explains the wage determination process for individuals who receive a job offer.

[9]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.

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*

For previously employed and previously unemployed individuals who receive a job offer, the log hourly wage is given by:

$$\log(W_{i,t}) = \psi_1 \mathrm{Educ}_i + \left(\psi_2 \mathrm{Exper}_{i,t} + \psi_3 \mathrm{Exper}_{i,t}^2\right) \times \mathrm{LowEduc}_i + \left(\psi_4 \mathrm{Exper}_{i,t} + \psi_5 \mathrm{Exper}_{i,t}^2\right) \times \mathrm{HighEduc}_i + \psi_6 \mathrm{GoodHealth}_{i,t} + \eta_i + \kappa_{i,t}, \quad (5)$$

where $\mathrm{Exper}_{i,t}$ denotes experience, defined as the number of years that the individual was employed during his life prior to the current year, $\mathrm{LowEduc}_i$ is an indicator of the individual having 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:

$$\kappa_{i,t} = \delta \kappa_{i,t-1} + \nu_{i,t}, \quad (6)$$

where $\nu_{i,t} \sim \mathcal{N}(0, \sigma_\nu^2)$ 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.[10] Given that employed individuals receive a new job offer each year (unless subject to an involuntary job separation), this wage process implies that employed workers receive annual wage shocks.

Since employment entails 40 hours of work per week (see footnote 8), 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 $\mu_{i,t} \sim \mathcal{N}(0, \sigma_\mu^2)$ and occurs independently over time.

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:

$$A_{i,t} = (1+r)\, A_{i,t-1} + \mathrm{LaborEarnings}_{i,t} - \mathrm{Taxes}_{i,t} + \mathrm{Transfers}_{i,t} - c_{i,t}, \quad (7)$$

[10] In the steady state $\kappa_{i,t} \sim \mathcal{N}(0, \sigma_\nu^2/(1-\delta^2))$.

where $c_{i,t}$ denotes the annual consumption of individual i at age t and r is assumed to be equal to 0.01. The individual is allowed to borrow up to a limit of 20,000 euros.[11,12]

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:

$$U(c_{i,t}, l_{i,t}, \boldsymbol{\epsilon}_{i,t}) = \begin{cases} \alpha_1 \dfrac{c_{i,t}^{1-\gamma} - 1}{1-\gamma} & + \varepsilon_{i,t}^1 \quad \text{if } l_{i,t} = \text{retired}, \\[2ex] \alpha_1 \dfrac{(c_{i,t}(1 + \alpha_{2,1}\mathrm{BH}_{i,t} + \alpha_{2,2}\mathrm{GH}_{i,t}))^{1-\gamma} - 1}{1-\gamma} & + \varepsilon_{i,t}^2 \quad \text{if } l_{i,t} = \text{employed}, \\[2ex] \alpha_1 \dfrac{(c_{i,t}(1 + \alpha_{3,1}\mathrm{BH}_{i,t} + \alpha_{3,2}\mathrm{GH}_{i,t}))^{1-\gamma} - 1}{1-\gamma} & + \varepsilon_{i,t}^3 \quad \text{if } l_{i,t} = \text{unemployed}. \end{cases} \tag{8}$$

For individuals in bad health (BH), $\alpha_{2,1}$ 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 (GH) are $\alpha_{2,2}$ and $\alpha_{3,2}$. $\gamma \equiv 1.5$ is the coefficient of relative risk aversion (see footnote 25 for evidence on robustness to this calibration). The preference shocks $\varepsilon_{i,t}^1$, $\varepsilon_{i,t}^2$ and $\varepsilon_{i,t}^3$ are assumed to be type-1 extreme value distributed and independent over labor supply states and over time. $\boldsymbol{\varepsilon_{i,t}}$ 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, choosing to obtain $k \in \{8, \ldots, 18\}$ years of education entails a cost of $\lambda_k + \varepsilon_i(k)$, incurred at age 15. The term λ_k represents the systematic component of the cost of choosing k years of education, encompassing the portions of, e.g., tuition, subsistence, and psychological study costs that are constant across individuals. The systematic component of educational investment costs is estimated non-parametrically, allowing λ_k to take a different value for each level of k (with λ_8 normalized to zero for identification). The terms $\varepsilon_i(8), \ldots, \varepsilon_i(18)$ represent the idiosyncratic components of educational investment costs, assumed to follow a type-1

[11]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.

[12]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.

extreme value distribution and to be mutually independent. These idiosyncratic cost components capture individual differences in educational costs, such as differences in the psychological cost of studying, and enable the model to explain why some high-ability individuals choose lower levels of education while some low-ability individuals choose higher levels.

3.8 *Optimal behavior*

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

$$\{c^*_{i,t}, l^*_{i,t}\} = \underset{\{c,l\}\in\mathbb{D}(\boldsymbol{s}_t)}{\arg\max} \left\{U(c,l,\boldsymbol{\varepsilon}_{i,t}) + p(t+1|t,\boldsymbol{s}_{i,t})\beta\mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{i,t+1})|\boldsymbol{s}_{i,t},c,l]\right\}. \tag{9}$$

In the above, $\beta \equiv 0.99$ is the discount factor (see footnote 25 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:

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

where $\mathrm{JS}_{i,t}$ and $\mathrm{JO}_{i,t}$ are indicators of the individual receiving, respectively, an involuntary job separation and a job offer at age t.[13,14] We note that the model includes three mechanisms that may generate voluntary transitions from employment to unemployment: wage shocks, preference shocks, and health shocks. These same shocks also influence transitions from unemployment to employment. However, transitions into employment are constrained by the availability of job offers.

At age 15, the individual chooses his years of education $k \in \{8, ..., 18\}$ to maximize the expected present discounted value of his lifetime utility, which captures the effect of education on the timing of labor force entry, for the benefits of increased earning

[13]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.

[14]We note that the solution to the individual's labor supply problem implicitly defines the reservation wage. In Supplemental Appendix III, we use this solution to derive the probability of the current labor supply conditional on past labor supply and other observed elements of the state space. These derivations show, for example, that the probability of a transition from unemployment to employment, conditional on observed characteristics, depends on the job offer rate, the distribution of wages in the event of an offer, and the probability of the individual accepting the job offer. The job acceptance probability depends on the distribution of preference shocks. Unemployment durations can be calculated through repeated application of this calculation. Since education affects wages and job offer rates, the model can account for different transition rates out of unemployment and variations in unemployment durations by education.

potential once in the labor force, and the costs associated with education. Formally, the decision rule for years of education is given by:

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

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:

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

$R(\eta_i,k)$ is 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 the time of labor force entry beyond age 20, and impacting health risk, mortality risk and employment opportunities. We note that the model explicitly accounts for earnings starting from either age 20 or the age at which the individual completes their education, whichever comes later. For educational choices where education is completed before age 20, any earnings prior to age 20 are incorporated into the educational cost parameters.

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).[15] Our estimation sample contains 3,280 distinct individuals and a total of 20,840 individual-year observations from 2004–2016.[16] In each year of the sample, individuals are classified as employed or unemployed based on whether they were working and their average weekly hours at the time of the annual survey. This classification, which reflects individuals' status

[15] Wagner et al. (2007) and Goebel et al. (2019) describe the SOEP. The datasets that we use are SOEP (2011, 2017, 2019).

[16] 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.

at the time of the annual survey, aligns with the model's annual decision-making frequency. However, it may overlook some temporary changes in employment status. Consequently, our analysis is most suited to examining the effects of risks that influence employment over periods of a year or longer. Supplemental Appendix II provides further details on how individuals are classified as employed or unemployed, along with information on the other variables used in the analysis.

We estimate the model in two stages. First, we estimate the health transition probabilities in (2), the heterogeneous survival probabilities in (3), and the involuntary job separation probabilities in (4). 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 HMD (2024) 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 Appendix IV.1. An employed individual is determined to have experienced an involuntary job separation if he transitions from employment into unemployment due to the end of a fixed-term contract, a dismissal or a firm closure. The involuntary job separation probabilities are estimated using Maximum Likelihood.

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 for previously unemployed individuals, along with the educational investment cost parameters. The formalities of the estimation are provided in Appendix III, which discusses how we approximate the value function, presents the likelihood function, and describes how we maximize the likelihood function.

We highlight some important aspects of the estimation. First, the model includes sufficient flexibility to fit the empirical frequencies of voluntary transitions out of employment and transitions from unemployment to employment while also fitting the wage data. In particular, in the estimation, the weight on the systematic utility from consumption and leisure relative to the preference shocks (i.e., the parameter α_1) can be adjusted to fit the rate of voluntary transitions and involuntary separations in the data. Similarly, job offer probability for previously unemployed individuals can be adjusted to match the empirical transition rate from unemployment to employment. Second, unemployment durations are implicitly used when estimating the model, as each individual's contribution to the likelihood function includes the joint probability of their annual labor supply outcomes during the sample period. The model includes several features that the estimation may use to fit observed persistence in unemployment, most importantly, limited job offers for unemployed individuals and persistent observed and unobserved wage heterogeneity. Third, 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.

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 36.7% of consumption for individuals in good health and 30.3% for individuals in bad health. Meanwhile, the estimated cost of unemployment amounts to 65.9% of consumption for individuals in good health and 21.1% 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 0.871. 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 30.5% are endowed with high productive ability (type H), 51.3% are endowed with medium productive ability (type M), and the remaining 18.2% 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 portions of tuition and subsistence costs and psychological costs (or benefits) of studying that are common across individuals. This explains the non-monotonic pattern of the coefficients by years of education. 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 0.13 between years of education and productive ability.[17]

[17]For context, Belzil and Hansen (2002) estimate a correlation of 0.28 between years of schooling and market ability. Additionally, Cascio and Lewis (2006) find that an extra year of schooling is associated with

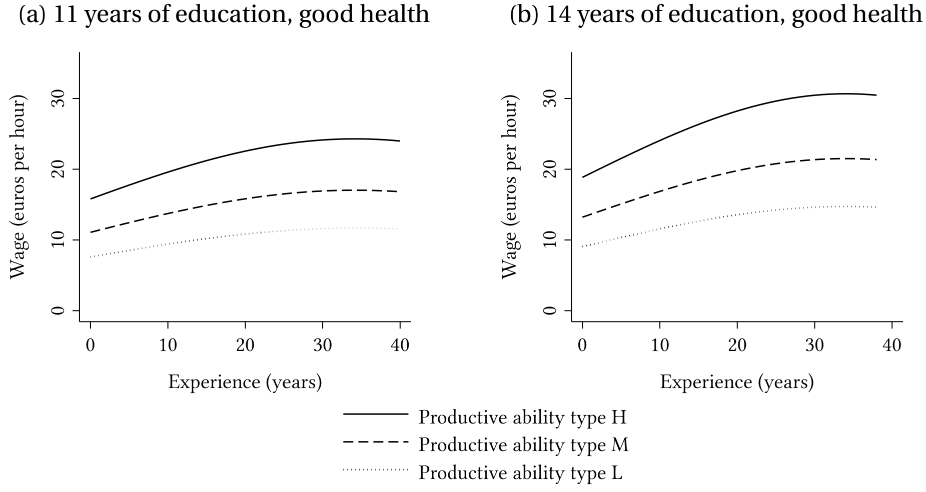


FIGURE 2. Estimated wage profiles (excluding wage shocks).

4.2.2 *Health shocks and mortality risk* Figures 3a and 3b 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 3c 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%.

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 S.4 (see Appendix IV.3). 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

an increase in performance on the AFQT of 0.31 to 0.32 standard deviations, and Zagorsky (2007) reports a correlation of 0.62 between years of schooling and AFQT scores. However, we argue that making quantitative comparisons between the schooling-ability correlation implied by our estimated model and the results from the literature is not particularly meaningful. First, the magnitude of this correlation likely depends on the specifics of the education system. In Germany, post-secondary education is generally free, which may weaken the correlation between education and ability. Second, the extent of selection into education will also depend on labor market returns to education, which is again context-specific. Third, the concept of ability varies across studies. In our model and in the approach of Belzil and Hansen (2002), ability is treated as a latent variable, whereas some other studies, including Cascio and Lewis (2006) and Zagorsky (2007), use direct measures of ability, such as the AFQT score.

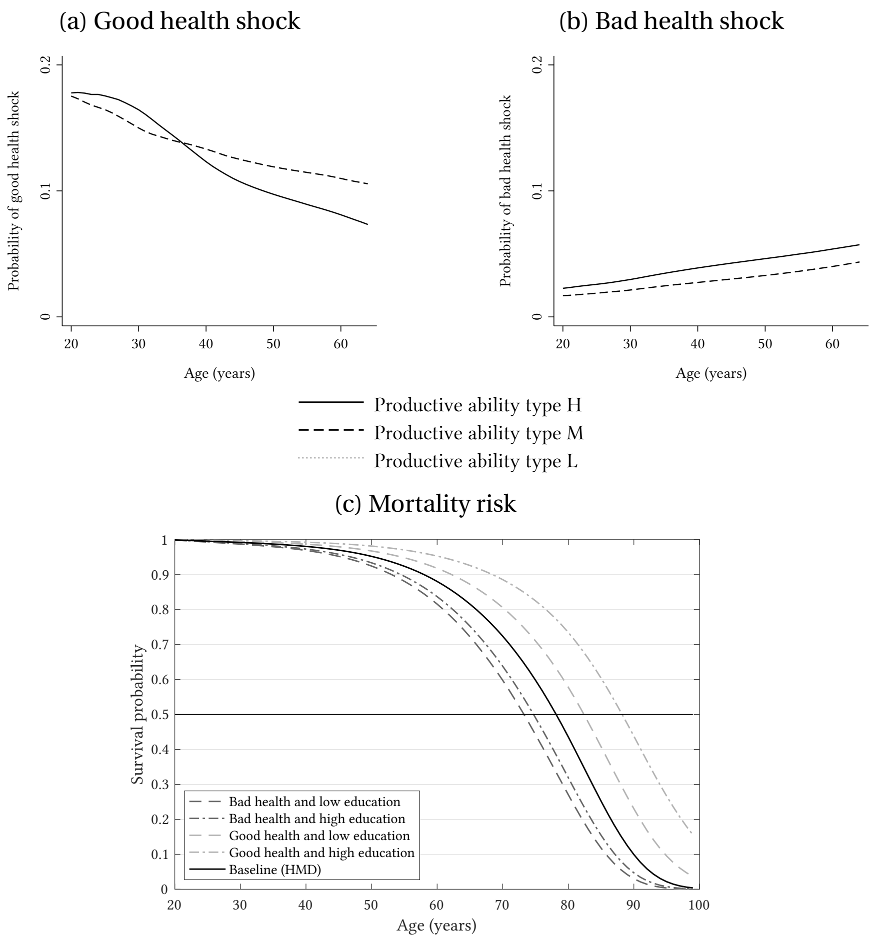


FIGURE 3. Health shocks and mortality risk. The Baseline survival probabilities in Figure 3c were obtained by averaging life table mortality risks (HMD, 1992–2016). See Appendix IV.1 for further results on the survival model.

low education. These patterns match the differences in labor supply by education in the estimation sample. For example, the model predicts that 82.8% of high-educated individuals and 69.8% of low-educated individuals will never experience unemployment. These figures closely match the estimation sample, where the corresponding percentages are 85.1% and 76.3%, respectively.[18]

[18]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 4a 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 4b 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 4c 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.

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 the 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 0.879 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.

Supplemental Appendix IV.3 provides additional evidence of the in-sample fit of the estimated model. We summarize this evidence here. Figure S.1 demonstrates that the model's predictions align with the observed distribution of gross hourly wages by education. Figure S.2 shows that the model replicates unemployment and retirement patterns by age. Figure S.3 shows that the model fits the survivor function for the duration of unemployment by education. Table S.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 S.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 S.4 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 S.6 shows that the model fits the cross-sectional distribution of wealth. Figure S.7 shows the model replicates the observed distribution education. Table S.6 shows that the model fits the

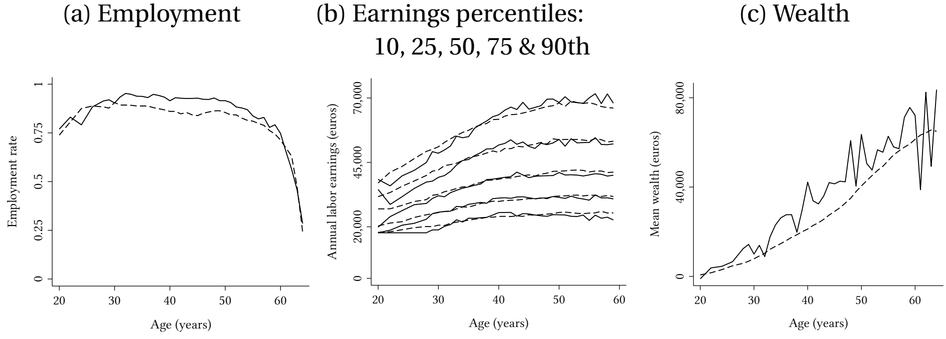


FIGURE 4. Observed and predicted age profiles of employment, earnings and wealth. *Note:* Observed values were calculated using the estimation sample. Predicted values were calculated using a simulated subsample, obtained by simulating a sample of 50,000 individual life cycles and then drawing a subsample 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 $8 + \mathrm{Educ}_i$. 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 3,280 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.

incidence of involuntary job separations among transitions into unemployment by age and 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 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 Appendix II): both samples exclude civil servants, self-employed individuals, East Germans, and women. Third, we restrict our simulated sample to exclude individuals aged 60 years or above again matching Bönke et al. (2015).[19]

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 0.222 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 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.

[19] 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.

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	0.871	0.0381
$\alpha_{2,1}$	Disutility of employment, bad health	−0.303	0.0454
$\alpha_{2,2}$	Disutility of employment, good health	−0.367	0.0384
$\alpha_{3,1}$	Disutility of unemployment, bad health	−0.211	0.0522
$\alpha_{3,2}$	Disutility of unemployment, good health	−0.659	0.0220
	Panel II: Wage equation		
η^H	Intercept for productive ability type H	2.098	0.0384
η^M	Intercept for productive ability type M	1.743	0.0388
η^L	Intercept for productive ability type L	1.365	0.0411
ψ_1	Educ/10	0.589	0.0254
ψ_2	Exper/10, low education	0.252	0.0147
ψ_3	Exper/10, high education	0.286	0.0142
ψ_4	Exper^2/1000, low education	−0.368	0.0321
ψ_5	Exper^2/1000, high education	−0.420	0.0332
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	0.0008
	Panel III: Productive ability type probabilities		
ρ_H	Probability of productive ability type H	0.305	0.0193
ρ_M	Probability of productive ability type M	0.513	0.0192
ρ_L	Probability of productive ability type L	0.182	0.0150
	Panel IV: Systematic education cost components		
λ_8	8 years of education	*Reference category*	
λ_9	9 years of education	1.279	0.1581
λ_{10}	10 years of education	−0.464	0.1940
λ_{11}	11 years of education	2.010	0.1597
λ_{12}	12 years of education	1.010	0.3077
λ_{13}	13 years of education	−1.498	0.3121
λ_{14}	14 years of education	−2.008	0.3163
λ_{15}	15 years of education	−1.611	0.3252
λ_{16}	16 years of education	−3.013	0.3591
λ_{17}	17 years of education	−5.253	0.4472
λ_{18}	18 years of education	−2.672	0.4044

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

TABLE 2. Joint distribution of years of education and productive ability.

	Productive ability type							
	High		Medium		Low		All	
Years of education								
8	0.21	(14.29)	0.64	(42.86)	0.64	(42.86)	1.49	(100.00)
9	1.59	(20.47)	3.69	(47.64)	2.47	(31.89)	7.74	(100.00)
10	0.52	(25.76)	0.95	(46.97)	0.55	(27.27)	2.01	(100.00)
11	10.27	(28.32)	18.20	(50.17)	7.80	(21.51)	36.28	(100.00)
12	8.20	(35.03)	11.98	(51.17)	3.23	(13.80)	23.41	(100.00)
13	1.19	(34.51)	1.80	(52.21)	0.46	(13.27)	3.45	(100.00)
14	1.25	(35.04)	1.86	(52.14)	0.46	(12.82)	3.57	(100.00)
15	2.90	(33.33)	4.63	(53.33)	1.16	(13.33)	8.69	(100.00)
16	1.04	(31.19)	1.92	(57.80)	0.37	(11.01)	3.32	(100.00)
17	0.18	(35.29)	0.27	(52.94)	0.06	(11.76)	0.52	(100.00)
18	3.23	(33.97)	5.30	(55.77)	0.98	(10.26)	9.51	(100.00)
All	30.58		51.25		18.17		100.00	

Note: 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 0.1257.

TABLE 3. Job offer and involuntary job separation probabilities

		Age<50	Age 50–54	Age 55–59	Age≥60
Panel I: Job offer probabilities for unemployed individuals					
Low education	Bad health	0.198	0.132	0.156	0.132
		(0.0159)	(0.0150)	(0.0165)	(0.0197)
	Good health	0.365	0.262	0.301	0.261
		(0.0140)	(0.0204)	(0.0213)	(0.0297)
High education	Bad health	0.177	0.117	0.139	0.117
		(0.0148)	(0.0138)	(0.0154)	(0.0179)
	Good health	0.334	0.236	0.273	0.235
		(0.0121)	(0.0189)	(0.0201)	(0.0276)
Panel II: Involuntary job separation probabilities for employed individuals					
Low education	Bad health	0.044	0.035	0.032	0.055
		(0.0067)	(0.0064)	(0.0077)	(0.0173)
	Good health	0.022	0.017	0.016	0.027
		(0.0022)	(0.0029)	(0.0041)	(0.0098)
High education	Bad health	0.020	0.016	0.014	0.025
		(0.0035)	(0.0032)	(0.0039)	(0.0090)
	Good health	0.010	0.008	0.007	0.012
		(0.0011)	(0.0014)	(0.0020)	(0.0048)

Note: Reported probabilities were obtained by evaluating equation (4) using the parameter estimates of the employment risk models reported in Table S.3 of Appendix IV.2. Standard errors in parentheses.

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	0.879	0.844	0.813	0.785	0.755

Note: 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.

TABLE 5. Gini coefficients for annual and lifetime labor earnings.

	Simulation using estimated model	Administrative social security records	Estimation sample (from SOEP)
Annual labor earnings	0.351	0.336	0.316
Lifetime labor earnings	0.222	0.212	–

Note: 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 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.

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:

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

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 half the squared coefficient of variation, the mean logarithmic deviation and the variance of the natural logarithm. Compared to the Theil index, the half-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.[20]

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:

$$\begin{matrix}\text{Inequality of}\\ \text{lifetime income}\end{matrix} = \begin{matrix}\text{Within-skill-group}\\ \text{inequality of lifetime income}\end{matrix} + \begin{matrix}\text{Between-skill-group}\\ \text{inequality of lifetime income}\end{matrix}. \quad (10)$$

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

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

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

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 0.16% of individuals (82 out of 50,000 individuals). In Panel IV of Table S.9 in 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.

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.[21]

We quantify each component of (10) 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.[22] 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 earnings (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.[23]

The second and third columns of Table 6 explore this result. We see that taxes and transfers combined offset 47% of the within-skill-group inequality of lifetime earnings, i.e., close to half of the 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

[21] 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.

[22] 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).

[23] The model also implies that taxes and transfers reduce the Gini coefficient for annual income by 0.094 (a 27% decrease). 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)	8.78	4.28	4.50	0.51
Income (Earnings − taxes + transfers)	4.72	2.26	2.47	0.52
Share of earnings inequality offset by the tax-and-transfer system	0.46	0.47	0.45	

Note: 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).

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.[24,25]

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 identify the specific programs that account for

[24]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.

[25]In Supplemental Appendix VII, we report the results of several robustness checks of the results in Tables 6 and Table 7: Table S.8 shows robustness to excluding capital income from the inequality decomposition; Table S.9 that our results continue to hold if inequality is measured using half the squared coefficient of variation, the mean logarithmic deviation or the variance of the natural logarithm, instead of the Theil index; Tables S.10 and S.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	0.03	0.02
Disability benefits	0.08	0.16	0.01
Social assistance	0.13	0.17	0.09

Note: 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.

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 a further 23% (giving 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 8% of the inequality of lifetime earnings, respectively.[26]

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.

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

[26]Table S.9 in 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 half the squared coefficient of variation, the mean logarithmic deviation or the variance of the natural logarithm instead of the Theil index.

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 5a 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 2,500,000 euros, pay 37% 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 400%, the proportion of lifetime earnings these lifetime rich individuals pay in taxes is only 5 percentage points or 16% higher. A similar pattern holds for the other skill groups.

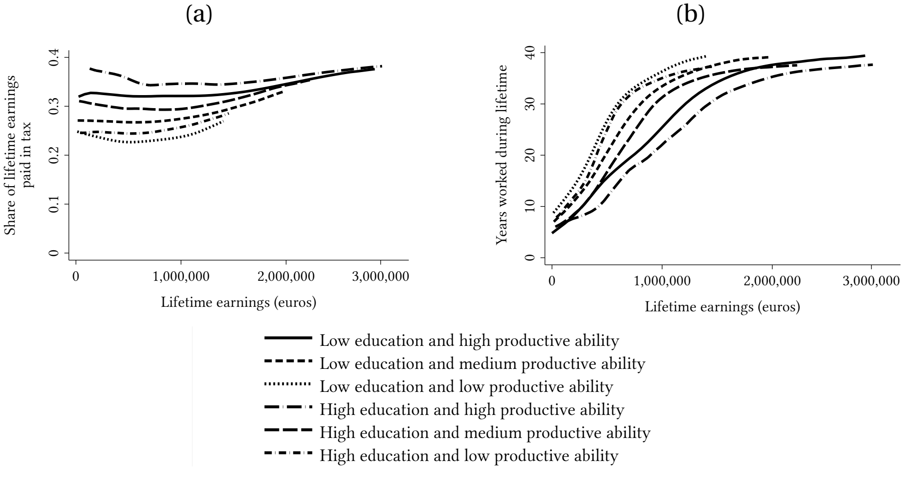


FIGURE 5. Insurance effects of taxation. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. 'Low education' refers to eleven years of education, and 'high education' refers to fourteen years of 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 5b 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 77.8% 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.[27]

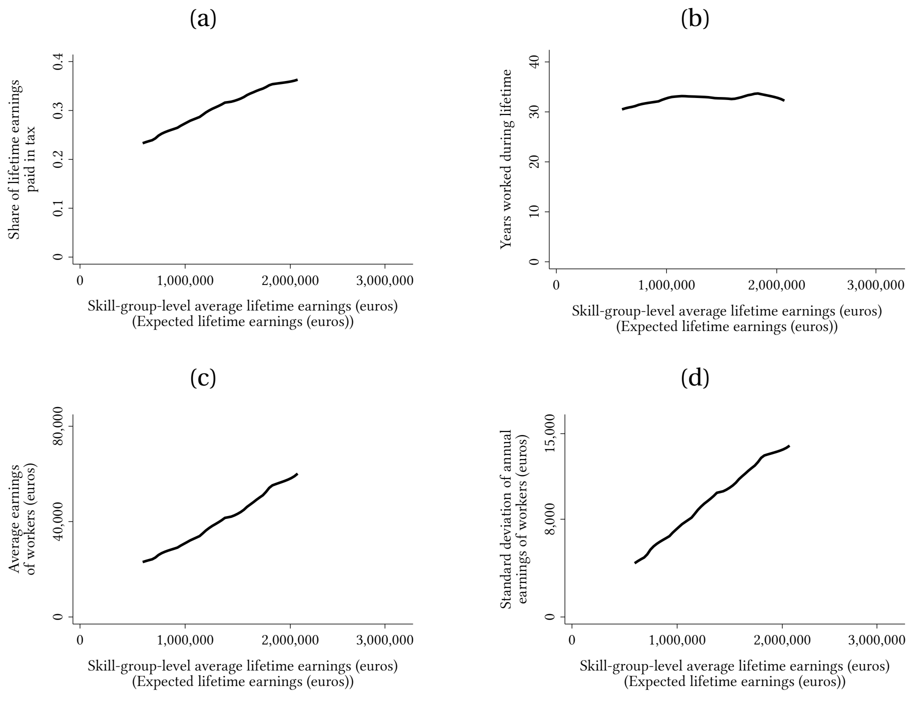


FIGURE 6. Redistributive effect of taxation. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types. All dependent variables are skill–group-level averages.

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 6a 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 earnings in taxes. From a

[27]In Appendix V, we show that annual earning taxes provide partial insurance against the remaining 22.2% of the within-skill group inequality of lifetime earnings that is not due to differences in years worked during the life cycle.

comparison of Figure 5a and Figure 6a, 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 6b, we find that essentially none of the between-skill-group inequality in lifetime earnings is due to between-individual differences in years worked.[28] 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 6c). 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 6d shows that workers with higher expected lifetime earnings have more variability in their earnings.[29]

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 counterintuitive: 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

[28] Differences between groups in the average number of years that individuals work during their lifetimes explains only 2.6% of the between-skill-group inequality in lifetime earnings.

[29] 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.

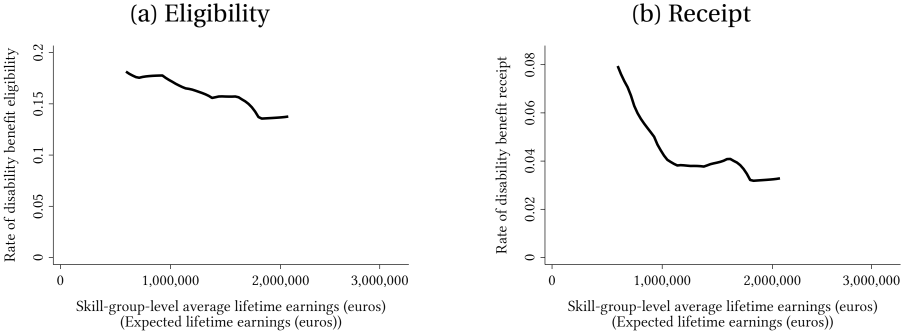


FIGURE 7. Redistributive effect of disability benefits. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Skill groups are specified as all possible combinations of the eleven possible years of 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.

insurance is mildly redistributive. Specifically, Table 7 shows that unemployment insurance eliminates two 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?* Table 7 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 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.

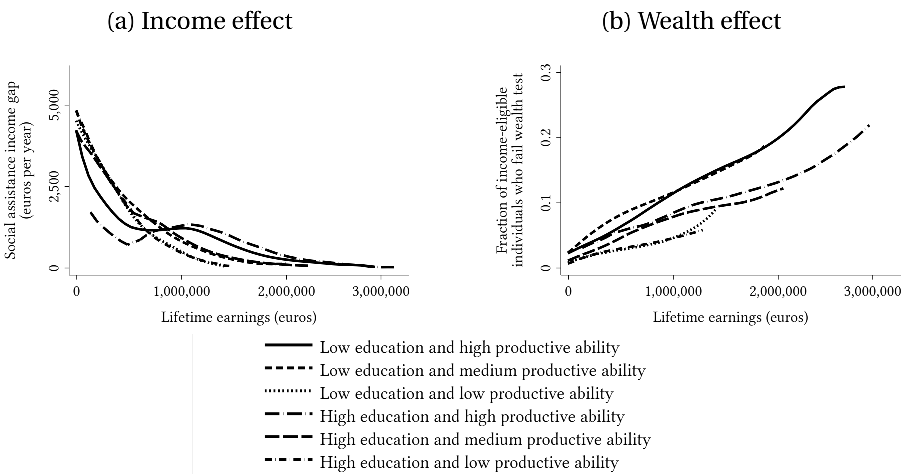


FIGURE 8. Insurance effect of social assistance. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5, and restricting to individual-year observations where the individual was eligible for social assistance 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.

We first consider the insurance effect of social assistance. We focus on the same six groups as considered in Figure 2. Figure 8a 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 experience many years with low income, i.e., low-income status is highly persistent. Figure 8b 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 9a 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 strongly 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 9b 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.

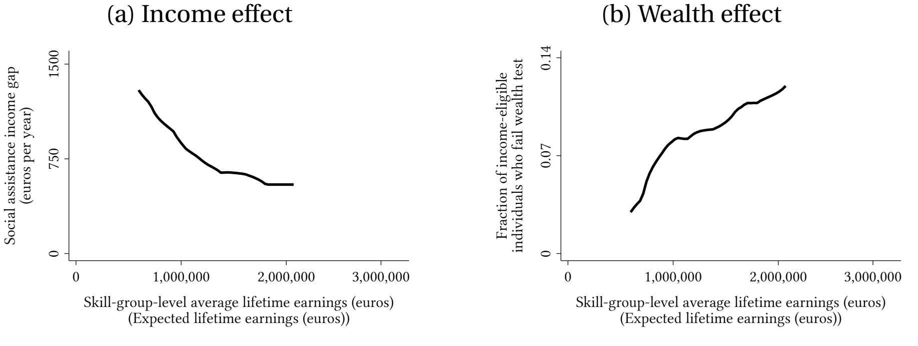


FIGURE 9. Redistributive effect of social assistance. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample of 50,000 life-cycle trajectories described in the notes to Table 5. Skill groups are specified as all possible combinations of the eleven possible years of education with the three productive ability types. Dependent variables are skill–group-level averages of the variables defined in the notes to Figure 8.

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 reduce the job offer likelihood for unemployed individuals by one-fourth; 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

	Baseline	Counterfactual risk environment		
		Increased job separation risk	Decreased job offer rate	Increased risk of bad health shocks
Average years of education	12.41	13.05	12.59	12.34
Employment rate	0.82	0.77	0.81	0.77
Average unemployment spells per person	1.10	1.37	0.67	1.24
Average unemployment spell duration (years)	2.90	2.90	3.35	3.08
Rate of bad health	0.16	0.15	0.16	0.36
Average bad health spells per person	1.00	0.96	0.99	2.20
Average bad health spell duration (years)	6.21	6.16	6.19	6.34

Note: 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 reduce the job offer likelihood for unemployed individuals by one-fourth; 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.[30] 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

[30] Long unemployment durations are characteristic of the German labor market, where long-term unemployment is relatively common despite the moderate unemployment rate. For example, OECD (2017) reports that in Germany in 2016 (the last year of our sample), the unemployment rate was 4.2%, with 41.2% of unemployed workers having been unemployed for 12 months or longer. In the same year, the unemployment rate in the US was similar at 4.9%, but only 13.3% of unemployed workers had been unemployed for 12 months or longer.

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.

		Δ Within-skill-group inequality in counterfactual		
	Within-skill-group inequality in baseline	Increased job separation risk	Decreased job offer rate	Increased risk of bad health shocks
Lifetime earnings (Labor earnings + capital income)	4.28	1.33 [31%]	0.82 [19%]	1.73 [40%]
Lifetime income (Earnings − taxes + transfers)	2.26	0.48 [21%]	0.49 [22%]	0.70 [31%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.64	0.40	0.60

Note: 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.[31] 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 60% 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

[31]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.

40% 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. 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	0.15	0.09
Unemployment insurance	0.04	-0.01	0.03
Disability benefits	0.27	0.10	0.25
Social assistance	0.22	0.15	0.24

Note: 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.

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 job separation and health risks in similar ways: insurance is obtained predominantly 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 relies only slightly more on transfers rather than taxation. 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 becomes ineffective as an insurance mechanism, reflecting 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.[32]

[32]Table S.12 in Appendix VII explores the robustness of the results in Table 9 and 10 to measuring inequality using half the squared coefficient of variation, the mean logarithmic deviation and the variance

7. Policy simulation

In Section 5.1 we noted the limited capacity of annual taxation to mitigate inequalities in lifetime earnings, as it cannot target inequalities arising from differences in total years worked during a lifetime. In particular, under annual taxation, individuals with identical annual earnings are taxed equally, regardless of disparities in their employment histories. Here, we shift our focus to the effects of a 'lifetime tax reform' that increases annual taxes for individuals with strong employment histories and decreases them for those with weak employment histories. As a result, between two individuals with the same annual earnings, the one with the stronger work history would face higher taxes in the current year. The motivation for this reform is to mitigate a key source of lifetime income risk: disparities in earnings resulting from differences in employment histories. However, in addition to examining the inequality-reducing effects of this reform, we also analyze its impact on labor supply and welfare. The reform we consider shares similarities with the lifetime tax system proposed by Vickrey (1939, 1947), which replaces annual taxes with a progressive tax on cumulative lifetime earnings to avoid penalizing individuals for year-to-year fluctuations in earnings.[33]

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 all 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:

$$\mathcal{T}'_{i,t} = \mathcal{T}_{i,t} \times \Big(1 + \pi_1(H_{i,t} - \bar{H}_t) \times \mathbb{1}[H_{i,t} \geq \bar{H}_t] - \pi_2(\bar{H}_t - H_{i,t}) \times \mathbb{1}[H_{i,t} < \bar{H}_t]\Big)\,, \tag{11}$$

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 below-average years for their age group.

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.

[33]We argue that implementing the lifetime tax 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.

For the following analysis, we set $\pi_2 = 1.0$ and calibrate π_1 to ensure the reform is revenue neutral.[34]

Table 11 shows the effects of this reform on inequality and employment. 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 0.57 achieves revenue neutrality. Since we assume that individuals 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 0.87 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 effects of the reform on behavior is provided in 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 1.10 to 1.21 per person.[35] 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 8.78 to 8.52, a decrease of approximately 3%. 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 the employment rate for individuals with stronger working histories while having little overall effect on the employment rate for those with weaker working histories.[36]

We find that incorporating behavioral adjustments enhances 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

[34]The criterion for assessing the revenue neutrality of the reform is the total sum of all taxes paid on labor earnings and capital income, combined with contributions to health and unemployment insurance, minus all transfers received between the ages of 20 and 59.

[35]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.

[36]See Figure S.10 in Appendix VI.

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	8.78	4.28	4.50
Lifetime income	4.72	2.26	2.47
Share of earnings inequality offset by:			
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	0.13	0.17	0.09
Labor supply behaviors:			
Employment rate	0.82		
Average unemployment spells per person	1.10		
Panel II: Lifetime tax reform with behavior fixed to the baseline environment ($\pi_1 = 0.5676, \pi_2 = 1$)			
Inequality (100 × Theil index):			
Lifetime earnings (same as Panel I by construction)	8.78	4.28	4.50
Lifetime income	4.54	2.09	2.45
Share of earnings inequality offset by:			
Tax-and-transfer system	0.48	0.51	0.46
... Taxes	0.26	0.17	0.34
... Unemployment insurance	0.02	0.02	0.02
... Disability benefits	0.08	0.16	0.01
... Social assistance	0.12	0.16	0.09
Panel III: Lifetime tax reform with behavioral adjustments ($\pi_1 = 0.8734, \pi_2 = 1$)			
Inequality (100 × Theil index):			
Lifetime earnings	8.52	4.12	4.40
Lifetime income	4.36	2.00	2.36
Share of earnings inequality offset by:			
Tax-and-transfer system	0.49	0.51	0.46
... Taxes	0.27	0.19	0.34
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.07	0.14	0.01
... Social assistance	0.12	0.16	0.09
Labor supply behaviors:			
Employment rate	0.81		
Average unemployment spells per person	1.21		

Note: 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.

implementing the tax reform without behavioral changes. With behavioral changes accounted for, the share rises to 49%. 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. Therefore, the inequality-reducing effects of the lifetime tax reform are driven by changes in the function of taxation alone. We also note 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 income. In other words, the lifetime tax reform enhances the tax system's effectiveness in insuring against lifetime earning risk.[37]

Table 12 presents the welfare effects of the lifetime tax reform, measured by equivalent variation (expressed as a percentage of baseline consumption) and the share of "winners" – individuals whose expected lifetime utility under the lifetime tax reform exceeds that under the baseline tax system. Welfare effects are presented for all individuals, as well as for subgroups based on productive ability, education, and lifetime employment history. Panel I in Table 12 shows that, with behavior held constant (i.e., unchanged from the baseline environment), the reform benefits 43% of individuals and, across all individuals, yields an increase in expected lifetime utility equivalent to 0.26% of baseline consumption. Additionally, the equivalent variation is positive for all subgroups except for those with strong employment histories. These findings highlight the potential welfare benefits of using tax policy to mitigate inequalities in lifetime earnings by linking taxation to past employment.

However, Panel II in Table 12 shows that the welfare effects become less favorable once behavioral responses to the lifetime tax reform are taken into account. While individuals mechanically benefit from adjusting their behavior in response to policy changes, the lifetime tax reform induces a reduction in employment, necessitating higher taxes to preserve revenue neutrality. After adjusting for revenue neutrality and accounting for behavioral changes, 36% of individuals benefit from the reform. This percentage rises to 76% among those with weak lifetime employment histories. Nevertheless, for the population as a whole, the reform leads to a reduction in expected lifetime utility equivalent to 1.33% of baseline consumption. The equivalent variation is negative for all subgroups except for individuals with weak lifetime employment histories. These results highlight the incentive costs of the lifetime tax reform and leave open the question of how to design tax policies that mitigate lifetime earnings risk without introducing offsetting distortions.

Finally, we connect our lifetime tax reform analysis to the literature on optimal dynamic taxation. The foundational contribution of Golosov et al. (2003) characterized optimal savings and indirect taxes when agents' skills are private information and evolve

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

TABLE 12. Welfare effects of lifetime taxation.

		Productive ability			Education		Employment history	
	All	High	Medium	Low	High	Low	Strong	Weak
Panel I: Lifetime tax reform with behavior fixed to the baseline environment ($\pi_1 = 0.5676, \pi_2 = 1$)								
Equivalent variation (% of consumption)	0.26	0.38	0.25	0.14	0.24	0.28	-1.34	2.66
Share of winners (%)	42.77	42.25	42.78	43.58	40.97	44.75	13.83	90.82
Panel II: Lifetime tax reform with behavioral adjustments ($\pi_1 = 0.8734, \pi_2 = 1$)								
Equivalent variation (% of consumption)	-1.33	-2.02	-1.09	-1.01	-1.54	-1.12	-3.83	2.49
Share of winners (%)	36.16	34.48	37.77	34.48	35.69	36.68	12.44	75.54

Note: Equivalent variation refers to the percentage change in baseline consumption that equalizes expected lifetime utility between the baseline and the lifetime tax reform scenarios. The share of winners represents the percentage of individuals with higher expected lifetime utility under the lifetime tax reform compared to the baseline tax system. An individual is classified as having a weak (strong) lifetime employment history if their employment history is below (above) the sample mean in more than half of the years between ages 20 and 59. The strength of employment history is measured by the fraction of years the individual has been employed since entering the workforce after completing their education.

over time. Building on this, several studies have extended the analysis in various directions. For instance, Kocherlakota (2005) examines optimal capital taxes in the presence of aggregate shocks, while Farhi and Werning (2013) and Golosov et al. (2016), among others, apply the methodology of Kapička (2013) to characterize the dynamics of optimal labor distortions. Additionally, Stantcheva (2017) and Kapička and Neira (2019) investigate how labor taxes and subsidies can be optimally designed to encourage risky investments in human capital. For a comprehensive review of recent developments in dynamic taxation, see Stantcheva (2020).

In contrast to the models typically used to study optimal dynamic taxes, our life-cycle model incorporates individual differences in education, health, preferences, and earnings, as well as factors such as unemployment insurance, social assistance, disability benefits, pensions, and employment risk. These elements are central to analyzing the impact of tax and transfer systems on lifetime earnings. However, they also preclude the use of existing methods to determine the optimal dynamic tax system. Nevertheless, it is worth noting that our lifetime tax reform introduces history dependence into income taxation through progressivity in current taxation based on past earnings. This feature aligns with the findings of several papers in the literature on optimal dynamic taxation, such as Golosov et al. (2016) and Kapička (2022).

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 earnings. 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. In particular, the system 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 tax-and-transfer system has limited capacity to address lifetime earnings inequalities stemming from differences in employment histories. Motivated by this, we examine the impact of a lifetime tax reform that adjusts individuals' current tax rates based on their employment records. This reform reduces lifetime income inequality, primarily by improving the tax system's ability to provide insurance against lifetime earnings risk. However, our results reveal an important tradeoff: while the reform decreases lifetime income inequality, it also lowers the employment rate. The welfare effects are mixed. While the reform benefits about one-third of all individuals and more than three-quarters of those with weak lifetime employment histories, it results in an overall welfare loss equivalent to a 1.33% reduction in lifetime consumption.

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.

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Supplement to "Insurance, Redistribution and the Inequality of Lifetime Income"

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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:

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

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.

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Appendix II: Data and estimation sample

Our estimation sample is from the German Socio-Economic Panel (SOEP). The SOEP is a representative longitudinal study of households in Germany. Each year since 1984, the SOEP has collected data about households' socio-demographic characteristics, including education, employment, wages, health, and wealth.[1] Our estimation sample is an unbalanced annual panel sample of men from the SOEP and covers the years 2004–2016.[2] The sample excludes individual-year observations from individuals who, in the year of observation, were younger than 20 or older than 65, in education, resident in former East Germany, in self-employment, or working for the civil service.[3] The estimation sample contains 3,280 distinct individuals and a total of 20,840 individual-year observations.

Table S.1 provides descriptive statistics for each variable used in the analysis. Here, we explain how each variable is constructed using SOEP data. We calculate the years of education by summing the years an individual reports having spent in formal education and occupational training. Observations of years of education below eight are recoded to eight to match the lower bound of years of education in the model.

Regarding labor market outcomes, the SOEP collects data on the average hours worked per week (including overtime) for all individuals who were in work when they completed the annual survey (the survey instrument does not specify the period over which the individual should calculate their average hours). Using this information, along with additional data on pension income, we classify each individual as employed, unemployed, or retired for the survey year.

Specifically, individuals are classified as retired if they report receiving income from old-age or disability pensions. Since old-age and disability pensions are permanent, this classification aligns with the model's assumption that retirement is an absorbing state. Next, individuals are classified as employed if they do not meet the criteria for being classified as retired, were in work at the time of the survey, and worked an average of at least twenty hours per week. The median of average hours worked per week among those classified as employed (and who meet other sample selection criteria) is forty, which again matches the model. All remaining individuals are classified as unemployed. Therefore, individuals classified as unemployed are those who are not classified as retired and were either: i) not in work when they completed the survey, or ii) in work when they

[1] Wagner et al. (2007) and Goebel et al. (2019) describe the SOEP. The datasets that we use are SOEP (2011, 2017, 2019).

[2] 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.

[3] 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.

completed the survey but working an average of less than twenty hours per week (i.e., part-time workers).

Part-time work is rare in the sample, and therefore, classifying part-time workers as unemployed does not meaningfully impact key descriptive statistics on employment behavior. Specifically, out of the 20,840 individual-year observations in the estimation sample, only 204 (0.98%) correspond to individuals working less than twenty hours per week. Dropping these observations would raise the employment rate from 0.874 to 0.883, reduce the average number of unemployment spells per person from 0.162 to 0.147, and shorten the average duration of unemployment from 1.609 to 1.580 years. The minor impact of part-time work on unemployment duration reflects not only the rarity of part-time work but also its transitory nature. Of the 204 individual-year observations of part-time work, only 28 involved individuals who were in part-time work for the entire observation period.

For individuals who moved out of work or changed jobs between one year and the next, the SOEP collects data on the reason for the transition. The survey instrument does not account for multiple transitions within the same one-year period, and only the first reason provided was recorded if an individual gave multiple reasons for a year-to-year transition. We construct an indicator for an involuntary separation, defined as a transition out of employment due to the end of a fixed-term contract, dismissal, or firm closure. All individuals who moved out of work or changed jobs between one year and the next are asked the same survey questions, regardless of whether they are currently looking for work. Therefore, an individual who was involuntarily separated but is not currently seeking work will still be asked why they left employment and should report an involuntary separation. We construct an indicator for good health, defined as neither being officially disabled nor self-assessing health as 'bad' or 'very bad'. For each individual-year observation, the health indicator is based on self-reported information and reflects the individual's health status at the time of the annual survey.

For individual-year observations where the individual is classified as employed, the hourly wage is calculated by dividing pre-tax weekly earnings by the average hours worked per week. Wealth data were compiled from individuals' net asset holdings, which include real and financial assets as well as debts, thereby aligning with the model's omnibus wealth variable (see Section 3.6). This information was only collected in the 2007 and 2012 survey waves. To maintain a consistent measure of wealth, we use the cross-sectional wealth data from 2007 and combine it with annual information on saving behavior and losses from capital investments to impute wealth in line with the life-cycle model's assumptions. Specifically, we assume individuals receive interest returns at a real rate of 1% and can borrow at the same rate. Unemployed individuals who are not eligible for either social assistance or unemployment insurance are assumed to dissave up to the annual minimum income guarantee. We left-censor the wealth distribution at the borrowing limit imposed by the life-cycle model and right-censor wealth observations that are inconsistent with the model's savings possibilities. Specifically, we right-censor observations with wealth values exceeding the age-specific maximum level the model can generate. Importantly, while we do not attempt to fit wealth when estimating the model, we use these data to determine eligibility for social assistance. All wealth-related

TABLE S.1. Descriptive statistics for the SOEP sample.

Variable	Observations	Mean	Minimum	Maximum
Age (years)	20,840	45.763	20	64
Employed	20,840	0.874	0	1
Unemployed	20,840	0.074	0	1
Retired	20,840	0.052	0	1
Experience (years)	20,840	22.476	0	49
Wage (euros per hour)	18,223	19.992	8.5	47.01
Education (years)	20,840	12.376	8	18
Health	20,840	0.831	0	1
Involuntary job separation	20,840	0.015	0	1
Wealth (euros)	2,476	40,159	-20,000	522,317

Note: Wages and wealth are expressed in 2016 prices.

goodness-of-fit evaluations for the estimated model are based on comparisons to the observed cross-sectional data from 2007 only.

APPENDIX III: MODEL SOLUTION & ESTIMATION

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

Appendix III.1: Value function approximation

We derive analytic expressions for the value function that appears in Eq. (9) of the main text, starting from the following choice-specific value functions:

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

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:

$$V_t(c_{i,t}, l_{i,t}, \boldsymbol{s}_{i,t}) = \overline{V}_t(c_{i,t}, l_{i,t}, \boldsymbol{x}_{i,t}) + \epsilon_{i,t}(c_{i,t}, l_{i,t}) \text{ for } t = 20, ..., T. \tag{S.2}$$

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:

$$\mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{i,t+1})|\boldsymbol{s}_{i,t}, c_{i,t}, l_{i,t}] = \sum_{\boldsymbol{x}_{t+1}} \log\left(\sum_{\{c,l\}\in\mathbb{D}(\boldsymbol{x}_{t+1})} \exp(\overline{V}_{t+1}(c, l, \boldsymbol{x}_{i,t+1}))\right) \times \\ q(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t, c_{i,t}, l_{i,t}) \text{ for } t = 20, ..., T-1, \tag{S.3}$$

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.

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:

$$\mathcal{L}_i(\boldsymbol{\theta}, \boldsymbol{\rho}|z_i) = \mathcal{P}(\text{Educ}_i, \boldsymbol{W}_i^*, \boldsymbol{l}_i, |\boldsymbol{z}_i, \boldsymbol{\theta}, \boldsymbol{\rho}), \tag{S.4}$$

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:

$$\begin{aligned}\mathcal{L}_i(\boldsymbol{\theta}, \boldsymbol{\rho}|z_i) &= \sum_{j\in\{H,M,L\}} \rho_j \times \mathcal{P}(\text{Educ}_i, \boldsymbol{W}_i^*, \boldsymbol{l}_i, |\eta_i = \eta^j, \boldsymbol{z}_i, \boldsymbol{\theta}), \\ &= \sum_{j\in\{H,M,L\}} \rho_j \times \mathcal{P}_e(\text{Educ}_i|\eta_i = \eta^j, \boldsymbol{\theta}) \times \mathcal{P}_{wl}(\boldsymbol{W}_i^*, \boldsymbol{l}_i, |\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{z_i}, \boldsymbol{\theta}).\end{aligned} \tag{S.5}$$

The educational choice probability in (S.6) characterizes the endogenous self-selection of individuals into education based on productive ability and takes the following form:

$$\mathcal{P}_e(k|\eta_i = \eta^j, \boldsymbol{\theta}) = \frac{\exp\left(R(\eta^j, k) + \lambda_k\right)}{\sum_{k'=8}^{18} \exp\left(R(\eta^j, k') + \lambda_k'\right)} \quad \text{for} \quad k = 8, \ldots, 18, \tag{S.6}$$

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 (S.6) can be written using Bayes' law:

$$\begin{aligned}\mathcal{P}_{wl}(\boldsymbol{W}_i^*, \boldsymbol{l}_i|\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{z}_i, \boldsymbol{\theta}) = \prod_{t=\underline{t}_i}^{\bar{t}_i} \Big[& f(W_{i,t}^*|\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{W}_{i,t-1}^*, \boldsymbol{l}_{i,t-1}, \boldsymbol{z}_i, \boldsymbol{\theta}) \times \\ & \mathcal{P}_l(\boldsymbol{l}_{i,t}|\eta_i = \eta^j, \text{Educ}_i, \boldsymbol{W}_{i,t}^*, \boldsymbol{l}_{i,t-1}, \boldsymbol{z}_i, \boldsymbol{\theta})\Big].\end{aligned} \tag{S.7}$$

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:

$$P(l_{i,t}|\boldsymbol{x}_{i,t},\boldsymbol{\theta}) = \sum_m \frac{\exp\left(\overline{V}_t(m,l_{i,t},\boldsymbol{x}_{i,t})\right)}{\sum\limits_{\{c,l\}\in\mathbb{D}(\boldsymbol{x}_{i,t})} \exp\left(\overline{V}_t(c,l,\boldsymbol{x}_{i,t})\right)}, \tag{S.8}$$

where $\overline{V}_t()$ is the systematic component of the choice-specific value function given by (S.2), $\boldsymbol{x}_{i,t}$ denote the age-t state variables excluding the preference shocks, and the sum is over the possible consumption choices (see footnote 13). 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:

$$\begin{aligned}\mathcal{P}_l(\boldsymbol{l}_{i,t}|\eta_i = \eta^j, \mathrm{Educ}_i, \boldsymbol{W}^*_{i,t}, \boldsymbol{l}_{i,t-1}, \boldsymbol{z}_i, \boldsymbol{\theta}) = \\ \int\int P(l_{i,t}|\boldsymbol{x}_{i,t},\boldsymbol{\theta}) dF(\mathrm{JO}_{i,t}|\mathrm{Educ}_i,\boldsymbol{z}_i) g(W_{i,t}|\boldsymbol{W}^*_{i,t},\boldsymbol{l}_{i,t-1},\boldsymbol{z}_i) dW^*_{i,t},\end{aligned} \tag{S.9}$$

where $F(\mathrm{JO}_{i,t}|\mathrm{Educ}_i,\boldsymbol{z}_i)$ 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.

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 the 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.[4]

[4]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)).

Appendix IV: Estimation results & in-sample fit

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.[5] We proceed in two steps.

First, we estimate the heterogeneity in mortality risk 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 (SOEP (2019), Kroh and Kröger (2020)). 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 Appendix II. Table S.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.[6] 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 S.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 3c in the main text.

TABLE S.2. Relative mortality risk.

	Estimate	Standard error
Bad health and low education	1.606	0.063
Bad health and high education	1.402	0.082
Good health and low education	0.673	0.036
Good health and high education	0.379	0.030
Individual-by-year observations	194,542	
Individuals	23,051	
Deaths	1,854	
Log-likelihood	-1,302.77	
Chi-squared statistic	6,056.49	

Note: 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.

[5]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).

[6]Life tables are obtained from the Mortality Database (HMD (2024)). Max Planck Institute for Demographic Research (Germany), University of California, Berkeley (USA), and French Institute for Demographic Studies (France). Available at www.mortality.org.

Appendix IV.2: Employment risk estimates

TABLE S.3. Parameter estimates: employment risks.

			Estimate	Standard error
		Panel I: Job offers		
ϕ_1^o	Intercept		-1.398	0.1003
ϕ_2^o	High-education		-0.138	0.0473
ϕ_3^o	Good-health		0.846	0.1103
ϕ_4^o	Age ≥ 50		-0.486	0.1052
ϕ_5^o	Age ≥ 55		0.195	0.1508
ϕ_6^o	Age ≥ 60		-0.197	0.1933
		Panel II: Involuntary job separations		
ϕ_1^s	Intercept		-3.081	0.1605
ϕ_2^s	High-education		-0.811	0.1340
ϕ_3^s	Good-health		-0.725	0.1516
ϕ_4^s	Age ≥ 50		-0.248	0.1752
ϕ_5^s	Age ≥ 55		-0.093	0.1873
ϕ_6^s	Age ≥ 60		0.577	0.1938
Individual-by-year observations		18,373		
Individuals		2,954		
Involuntary job separations		323		
Log-likelihood		-1574.02		
Chi-squared statistic		107.78		

Note: 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.

Appendix IV.3: Additional in-sample fit analysis

This appendix contains additional analyses of the model's in-sample fit. Throughout this appendix, 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.

Appendix IV.3.1: Employment and earnings Figure S.1 shows that the estimated model fits the distribution of wages, both overall and when we split the samples based on years of education. Figure S.2 shows that the estimated model accurately captures the life-cycle profiles of unemployment and retirement.

Next, we use four analyses to show that the estimated model accurately reflects the observed dynamics 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 S.4 shows that the estimated model reproduces the patterns of persistence in employment and unemployment observed in the estimation sample. 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.

The bottom panel of Table S.4 shows the fit of the mean unemployment duration for all individuals and split by education. The estimated model fits the observed unemployment durations reasonably well, although the estimated model predicts slightly longer mean unemployment durations compared to what we observed in the estimation sample. For example, across all individuals, the model predicts a mean unemployment duration of 2.16 years, compared to a mean observed duration of 1.61 years. This difference is consistent with the annual frequency of transitions in our model. As discussed in Section 4.1, because we model employment transitions on an annual basis, our analysis will not capture some temporary employment situations, such as short spells of unemployment. Figure S.3 shows the fit of the distribution of unemployment spell durations for the full sample and by education. Broadly speaking, the estimated model fits the observed distribution of unemployment durations, again with a slight tendency to overstate the unemployment durations compared to the sample.

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 calculate the fraction of individuals transitioning between these quintiles from one employment year to the next, omitting any years of unemployment in between. Table S.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, the good fit of the estimated model is evident in the close alignment between the observed and predicted shares of involuntary separations among all transitions into unemployment, as shown in Table S.6. This alignment holds consistently across education and age groups.

Fourth, we extend Table 4 in the main text to provide further evidence of the estimated model's ability to capture persistence in labor earnings, considering both earnings mobility among employed individuals and labor supply persistence. To measure labor earnings persistence, we use average annual labor earnings over the years that individuals were part of the estimation sample. Figure S.4 presents the observed and predicted distributions of average annual labor earnings. Overall, the estimated model successfully matches the observed distribution of average labor earnings in the sample, though there is a slight discrepancy at the lower tail, where the model underestimates the proportion of individuals with low average earnings. To investigate this issue further, we note that the model assumes full-time employment for all working individuals, while 3% of employed individuals in the sample work fewer than 30 hours per week. To address this, we created two adjusted simulated samples, identical to the original, except that a random 3% of individuals work reduced hours. In one adjusted sample, these individuals earn half of their potential full-time earnings, while in the other, they earn one-third. As shown in Figure S.5, both adjustments bring the predicted distribution of average annual earnings closer to the observed data, with the one-third earnings adjustment effectively eliminating the under-prediction of low average earnings. Importantly, as shown in Table S.16, the lifetime inequality decomposition results discussed in Section 5 continue to hold in the adjusted samples. Thus, the omission of a small proportion of workers with reduced hours is not critical for the decomposition results based on the estimated model

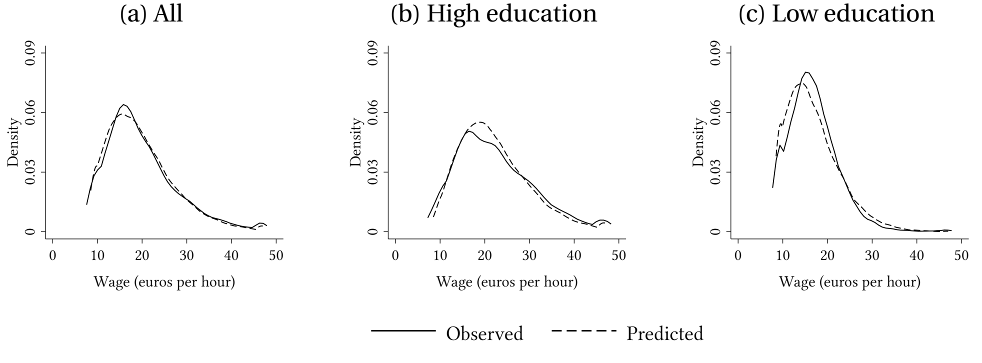

FIGURE S.1. Observed and predicted distributions of wages. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. Employed individuals aged 20–59 years inclusive.

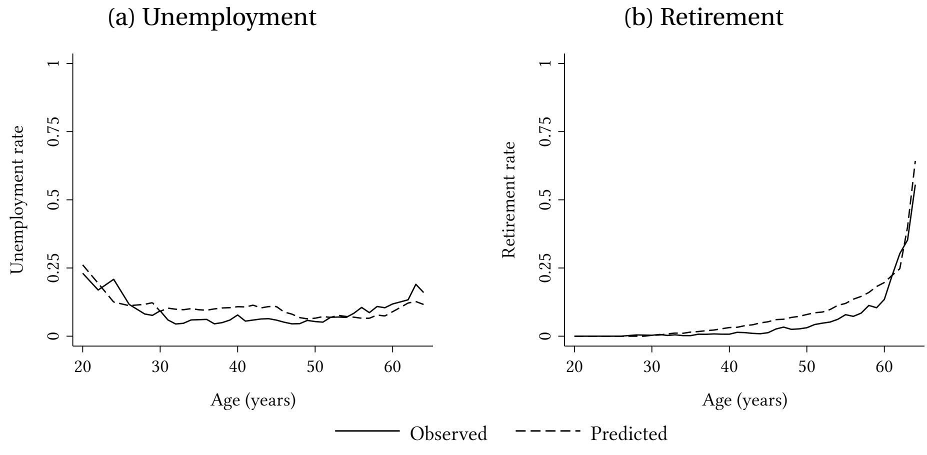

FIGURE S.2. Observed and predicted age profiles of unemployment and retirement. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4.

TABLE S.4. Observed and predicted persistence in labor supply.

	Employment					
	All		High education		Low education	
Percentage of time	Observed	Predicted	Observed	Predicted	Observed	Predicted
$= 0$	7.42	8.17	5.66	5.23	9.42	11.50
≤ 25	8.50	9.67	6.46	6.30	10.82	13.50
≤ 50	11.94	14.16	8.68	9.51	15.63	19.43
≤ 75	16.64	21.04	12.37	14.41	21.49	28.56
≤ 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
$= 0$	81.00	76.68	85.11	82.77	76.34	69.78
≤ 25	88.65	87.32	91.75	90.56	85.14	83.64
≤ 50	93.95	94.32	95.32	95.67	92.39	92.80
≤ 75	95.45	96.83	96.37	97.46	94.42	96.11
≤ 100	100.00	100.00	100.00	100.00	100.00	100.00
Mean spells	0.16	0.18	0.12	0.12	0.21	0.24
Mean spell length (years)	1.61	2.16	1.49	2.24	1.69	2.12

Note: 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. Unemployment spells in the estimation sample and in the simulated subsample are right censored if the spell is ongoing when the individual is last observed in the estimation sample. The mean unemployment duration is shorter in the simulated subsample used for the goodness-of-fit exercise than in the simulated sample of full life-cycle trajectories used for the employment risk analysis reported in Table 8. This difference arises because restricting the simulated sample to the ages at which individuals were observed in the estimation sample mechanically leads to disproportionate right-censoring of longer unemployment spells.

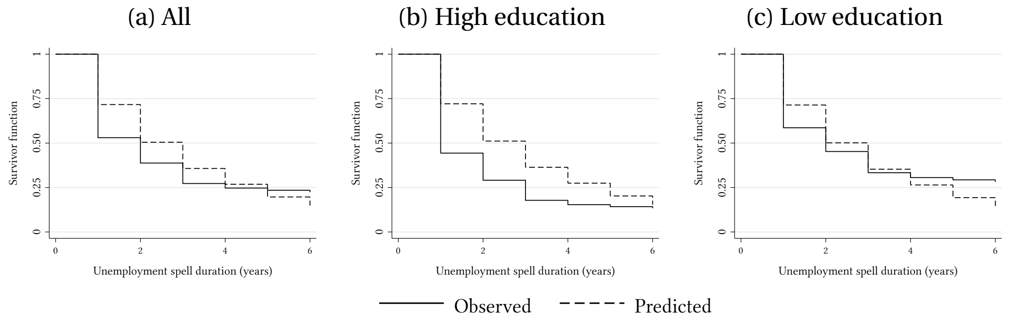

FIGURE S.3. Unemployment survivor functions. *Note:* Estimated survivor functions of unemployment durations derived from discrete-time logistic hazard models. Failure events given by transitions from unemployment to employment. Observed survivor functions were estimated using the estimation sample. Predicted survivor functions are based on the simulated subsample described in the notes to Figure 4. Individuals aged 20-64 years inclusive.

TABLE S.5. Observed and predicted labor earnings transition matrices for employed individuals.

(a) Observed

$t \setminus t'$	Q1	Q2	Q3	Q4	Q5
Q1	0.731	0.205	0.046	0.015	0.003
Q2	0.178	0.561	0.213	0.040	0.008
Q3	0.047	0.184	0.541	0.200	0.027
Q4	0.013	0.047	0.171	0.601	0.167
Q5	0.006	0.012	0.022	0.134	0.826

(b) Predicted

$t \setminus t'$	Q1	Q2	Q3	Q4	Q5
Q1	0.729	0.230	0.037	0.004	0.000
Q2	0.201	0.467	0.272	0.056	0.004
Q3	0.026	0.239	0.429	0.272	0.034
Q4	0.003	0.047	0.235	0.480	0.235
Q5	0.000	0.002	0.027	0.202	0.770

Note: 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.

TABLE S.6. Observed and predicted shares of involuntary separations among transitions into unemployment.

		Education		Age group (years)			
	All	High	Low	20-49	50-54	55-59	≥60
Observed (%)	46.81	40.91	50.47	52.83	56.76	48.84	27.04
Predicted (%)	44.08	43.03	44.70	47.43	59.82	48.07	18.82

Note: Share of involuntary job separations among all transitions into unemployment. Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. Individuals aged 20-64 years inclusive.

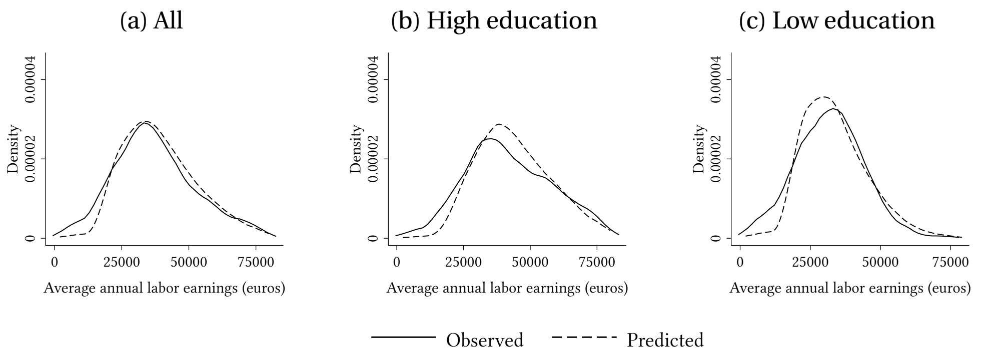

FIGURE S.4. Observed and predicted persistence in labor earnings. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. 'Average annual labor earnings' is the individual-level average of annual 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 S.4, across all individuals, the observed and predicted fractions of individuals with zero average annual labor earnings are 7.4% and 8.2%, respectively. The corresponding figures are 5.7% and 5.2% for individuals with at least twelve years of education, and 9.4% and 11.5% for individuals with fewer than twelve years of education. Individuals aged 20–59 years inclusive.

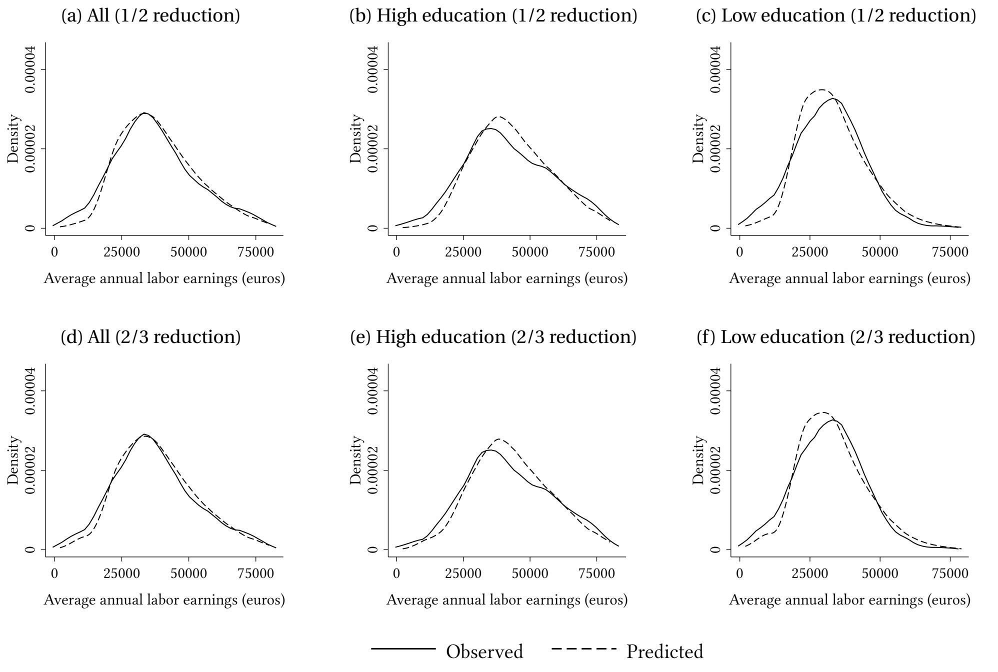

FIGURE S.5. Observed and predicted persistence in labor earnings with labor earnings lowered for reduced working hours. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4, with the exception that we assume 3% of employed individuals work reduced hours. This percentage corresponds to the share of employed individuals working fewer than 30 hours per week in the estimation sample. For the reduced worked hours category, we reduce simulated labor earnings by either one-half (panels a-c) or two-thirds (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.

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 S.6 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.

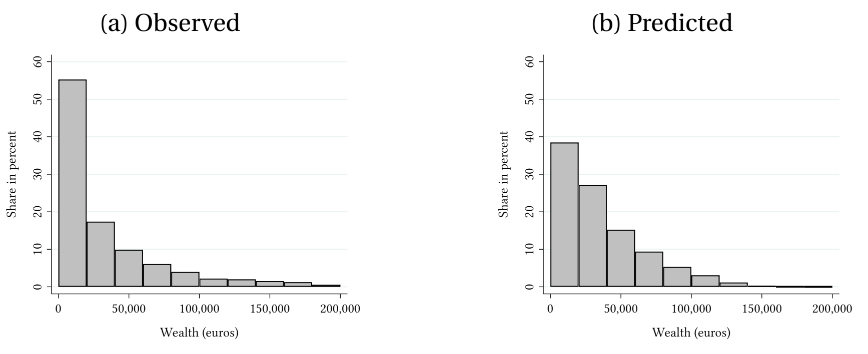

FIGURE S.6. Distributions of observed and predicted wealth. *Note:* Observed values are calculated from cross-sectional wealth data of SOEP wave 2007. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. To maintain comparability, predicted values were calculated based on the age values at which wealth was observed in the SOEP. Left-censored at zero. Consistency restrictions are applied as discussed in Appendix II. Individuals aged 20–59 years inclusive.

Appendix IV.3.3: Education Figure S.7 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.

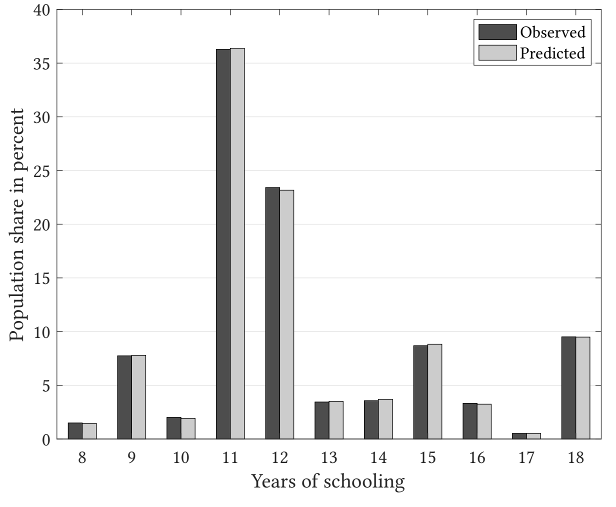

FIGURE S.7. Distributions of observed and predicted years of education. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4.

Appendix V: Further results

Annual earning taxes provide insurance against 22.2% 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 S.8a–S.8b show that both channels operate in practice. The increase in average earnings per year of work with lifetime earnings shown in Figure S.8a 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 S.8b. 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 S.9).

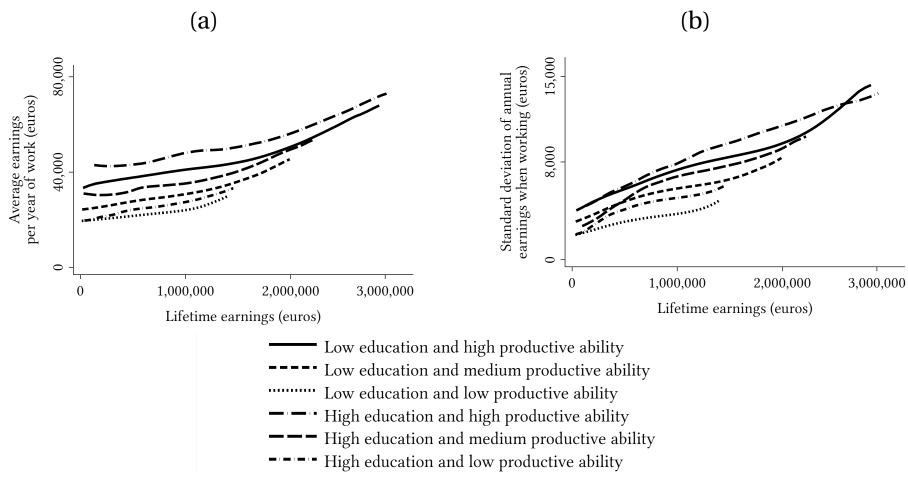

Figure S.8. Insurance effects of taxation. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample described in the notes to Table 6. 'Low education' refers to eleven years of education, and 'high education' refers to fourteen years of education.

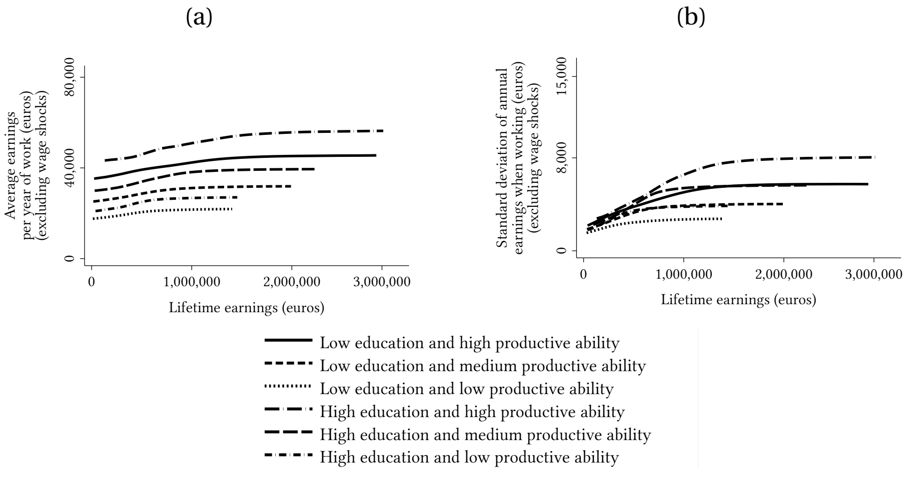

FIGURE S.9. Insurance effects of taxation without wage shocks. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample described in the notes to Table 6. ‘Low education’ refers eleven years of education and ‘high education’ refers to fourteen years of education.

Appendix VI: Behavioral effects of the lifetime tax reform

Table S.7. Behavioral effects of the lifetime tax reform

	Baseline	Lifetime tax reform (with behavioral adjustments)
Average years of education	12.41	12.54
Employment rate	0.82	0.81
Average unemployment spells per person	1.10	1.21
Average unemployment spell duration (years)	2.90	2.97
Rate of bad health	0.16	0.16
Average bad health spells per person	1.00	1.00
Average bad health spell duration (years)	6.21	6.20

Note: 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) equivalent to the lifetime tax reform with $\pi_1 = \pi_2 = 0$.

Figure S.10. Labor supply effects of the lifetime tax reform over the life cycle. *Note:* An individual is classified as having a weak (strong) lifetime employment history if their employment history is below (above) the sample mean in more than half of the years between ages 20 and 59. The strength of employment history is measured by the fraction of years the individual has been employed since entering the workforce after completing their education.

APPENDIX VII: ROBUSTNESS CHECKS

TABLE S.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	8.70	4.22	4.47	0.51
Lifetime income	4.61	2.19	2.42	0.52
Share of earnings inequality offset by TTS	0.47	0.48	0.46	
... Taxes	0.24	0.13	0.34	
... Unempl. insurance	0.02	0.03	0.02	
... Disability benefits	0.08	0.16	0.01	
... Social assistance	0.13	0.17	0.09	

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

	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: Half the squared coefficient of variation				
Lifetime earnings	8.36	3.88	4.47	0.54
Lifetime income	4.57	2.12	2.46	0.54
Share of earnings inequality offset by TTS	0.45	0.46	0.45	
... Taxes	0.25	0.16	0.34	
... Unempl. insurance	0.02	0.03	0.02	
... Disability benefits	0.07	0.13	0.01	
... Social assistance	0.11	0.14	0.08	
Panel II: Mean logarithmic deviation				
Lifetime earnings	10.76	6.06	4.70	0.44
Lifetime income	5.35	2.83	2.52	0.47
Share of earnings inequality offset by TTS	0.50	0.53	0.46	
... Taxes	0.20	0.10	0.33	
... Unempl. insurance	0.02	0.03	0.02	
... Disability benefits	0.11	0.18	0.01	
... Social assistance	0.17	0.22	0.10	
Panel III: Variance of the natural logarithm				
Lifetime earnings	27.42	16.83	12.98	0.47
Lifetime income	12.63	7.54	6.39	0.51
Share of earnings inequality offset by TTS	0.54	0.55	0.51	
... Taxes	0.18	0.09	0.32	
... Unempl. insurance	0.02	0.03	0.02	
... Disability benefits	0.13	0.20	0.02	
... Social assistance	0.20	0.23	0.15	
Panel IV: Theil index with correction for negative and zero values (see table notes)				
Lifetime earnings	8.67	4.28	4.39	0.51
Lifetime income	4.53	2.16	2.37	0.52
Share of earnings inequality offset by TTS	0.48	0.50	0.46	
... Taxes	0.24	0.13	0.34	
... Unempl. insurance	0.02	0.02	0.02	
... Disability benefits	0.08	0.15	0.01	
... Social assistance	0.14	0.19	0.09	

Note: 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 S.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	8.45	4.13	4.32	0.51
Lifetime income	4.58	2.19	2.39	0.52
Share of earnings inequality offset by TTS	0.46	0.47	0.45	
... Taxes	0.24	0.13	0.34	
... Unempl. insurance	0.02	0.02	0.02	
... Disability benefits	0.08	0.16	0.01	
... Social assistance	0.12	0.16	0.08	
Panel I: $\beta = 0.97, \gamma = 1.5$				
Lifetime earnings	7.98	3.84	4.14	0.52
Lifetime income	4.41	2.09	2.32	0.53
Share of earnings inequality offset by TTS	0.45	0.46	0.44	
... Taxes	0.24	0.13	0.35	
... Unempl. insurance	0.02	0.02	0.01	
... Disability benefits	0.08	0.15	0.01	
... Social assistance	0.11	0.15	0.07	
Panel III: $\beta = 0.99, \gamma = 1.25$				
Lifetime earnings	8.74	4.07	4.67	0.53
Lifetime income	4.74	2.17	2.57	0.54
Share of earnings inequality offset by TTS	0.46	0.47	0.45	
... Taxes	0.23	0.12	0.33	
... Unempl. insurance	0.02	0.03	0.02	
... Disability benefits	0.08	0.15	0.01	
... Social assistance	0.12	0.17	0.09	
Panel IV: $\beta = 0.99, \gamma = 1.75$				
Lifetime earnings	9.26	4.71	4.56	0.49
Lifetime income	4.87	2.41	2.46	0.51
Share of earnings inequality offset by TTS	0.47	0.49	0.46	
... Taxes	0.22	0.12	0.33	
... Unempl. insurance	0.02	0.02	0.02	
... Disability benefits	0.09	0.17	0.02	
... Social assistance	0.14	0.18	0.10	

Note: Following procedures described in footnote 25, 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 S.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	8.31	3.85	4.46	0.54
Lifetime income	4.56	2.08	2.48	0.54
Share of earnings inequality offset by TTS	0.45	0.46	0.44	
... Taxes	0.24	0.13	0.34	
... Unempl. insurance	0.02	0.03	0.02	
... Disability benefits	0.07	0.15	0.01	
... Social assistance	0.12	0.16	0.08	
Panel II: $\beta = 0.98, \gamma = 1.75$				
Lifetime earnings	8.66	4.41	4.25	0.49
Lifetime income	4.65	2.31	2.34	0.50
Share of earnings inequality offset by TTS	0.46	0.48	0.45	
... Taxes	0.23	0.12	0.34	
... Unempl. insurance	0.02	0.02	0.01	
... Disability benefits	0.09	0.17	0.01	
... Social assistance	0.12	0.16	0.08	
Panel III: $\beta = 0.97, \gamma = 1.25$				
Lifetime earnings	7.90	3.61	4.28	0.54
Lifetime income	4.40	1.99	2.41	0.55
Share of earnings inequality offset by TTS	0.44	0.45	0.44	
... Taxes	0.25	0.13	0.34	
... Unempl. insurance	0.02	0.03	0.02	
... Disability benefits	0.07	0.14	0.01	
... Social assistance	0.10	0.15	0.07	
Panel IV: $\beta = 0.97, \gamma = 1.75$				
Lifetime earnings	8.05	4.03	4.02	0.50
Lifetime income	4.42	2.17	2.26	0.51
Share of earnings inequality offset by TTS	0.45	0.46	0.44	
... Taxes	0.24	0.13	0.35	
... Unempl. insurance	0.02	0.02	0.01	
... Disability benefits	0.02	0.02	0.01	
... Social assistance	0.11	0.15	0.07	

Note: See the notes to Table S.10.

TABLE S.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: Half the squared coefficient of variation				
Lifetime earnings	3.88	1.20 [31%]	0.64 [17%]	1.66 [43%]
Lifetime income	2.12	0.49 [23%]	0.45 [21%]	0.70 [33%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.59	0.30	0.58
... Taxes		0.12	0.17	0.12
... Unemployment insurance		0.05	-0.02	0.03
... Disability benefits		0.25	0.07	0.25
... Social assistance		0.18	0.08	0.18
Panel II: Mean logarithmic deviation				
Lifetime earnings	6.06	1.97 [32%]	1.48 [24%]	2.41 [40%]
Lifetime income	2.83	0.49 [17%]	0.61 [22%]	0.78 [27%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.75	0.59	0.68
... Taxes		0.09	0.13	0.07
... Unemployment insurance		0.04	0.01	0.03
... Disability benefits		0.30	0.15	0.22
... Social assistance		0.32	0.30	0.35
Panel III: Variance of the natural logarithm				
Lifetime earnings	16.83	5.61 [33%]	4.87 [29%]	6.60 [39%]
Lifetime income	7.54	0.96 [13%]	1.59 [21%]	1.86 [25%]
Share of extra within-skill-group inequality offset by the tax-and-transfer system		0.83	0.67	0.72
... Taxes		0.07	0.12	0.07
... Unemployment insurance		0.04	0.02	0.03
... Disability benefits		0.33	0.17	0.22
... Social assistance		0.38	0.36	0.40

Note: 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 S.13. Robustness of the results in Table 11 to measuring inequality using half 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	8.36	3.88	4.47
Lifetime income	4.37	1.92	2.45
Share of earnings inequality offset by:			
Tax-and transfer system	0.48	0.51	0.45
... Taxes	0.28	0.22	0.34
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.07	0.13	0.01
... Social assistance	0.10	0.12	0.08
Panel II: Lifetime tax reform with behavioral adjustments			
Inequality:			
Lifetime earnings	8.17	3.80	4.37
Lifetime income	4.20	1.85	2.36
Share of earnings inequality offset by:			
Tax-and-transfer system	0.49	0.51	0.46
... Taxes	0.30	0.24	0.35
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.06	0.12	0.01
... Social assistance	0.11	0.13	0.09

Note: 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 S.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	10.76	6.06	4.70
Lifetime income	5.16	2.65	2.51
Share of earnings inequality offset by:			
Tax-and transfer system	0.52	0.56	0.47
... Taxes	0.23	0.15	0.34
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.11	0.18	0.01
... Social assistance	0.16	0.21	0.10
Panel II: Lifetime tax reform with behavioral adjustments			
Inequality:			
Lifetime earnings	10.28	5.68	4.60
Lifetime income	4.98	2.56	2.42
Share of earnings inequality offset by:			
Tax-and-transfer system	0.52	0.57	0.48
... Taxes	0.24	0.16	0.35
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.09	0.16	0.01
... Social assistance	0.16	0.20	0.10

Note: 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 S.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	27.42	16.83	12.98
Lifetime income	12.23	7.13	6.44
Share of earnings inequality offset by:			
Tax-and transfer system	0.55	0.58	0.50
... Taxes	0.20	0.13	0.32
... Unemployment insurance	0.02	0.03	0.02
... Disability benefits	0.13	0.20	0.02
... Social assistance	0.20	0.22	0.15
Panel II: Lifetime tax reform with behavioral adjustments			
Inequality:			
Lifetime earnings	25.74	15.48	12.96
Lifetime income	11.86	6.94	6.28
Share of earnings inequality offset by:			
Tax-and-transfer system	0.54	0.55	0.52
... Taxes	0.21	0.13	0.32
... Unemployment insurance	0.03	0.03	0.02
... Disability benefits	0.12	0.18	0.02
... Social assistance	0.19	0.21	0.15

Note: 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 S.16. Robustness of the results in Table 6 to lowered labor earnings due to reduced working hours.

	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 individuals with labor earnings reduced to one-half				
Lifetime earnings	9.24	4.74	4.50	0.49
Lifetime income	5.18	2.72	2.47	0.48
Share of earnings inequality offset by TTS	0.49	0.52	0.45	
Panel II: 3% of individuals with labor earnings reduced to one-third				
Lifetime earnings	9.69	5.18	4.50	0.46
Lifetime income	5.63	3.16	2.47	0.44
Share of earnings inequality offset by TTS	0.51	0.56	0.45	

Note: 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 S.5 describe the procedure implemented to account for lowered labor earnings due to reduced working hours.

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