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

PETER HAAN
Public Economics Department, DIW Berlin and FU Berlin

DANIEL KEMPTNER
German Federal Ministry of Labour and Social Affairs

VICTORIA PROWSE
Department of Economics, Purdue University

MAXIMILIAN SCHALLER
Public Economics Department, DIW Berlin and Berlin School of Economics

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.

Peter Haan: phaan@diw.de
Daniel Kemptner: daniel.kemptner@web.de
Victoria Prowse: vprowse@purdue.edu
Maximilian Schaller: mschaller@diw.de

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:

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

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:

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

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:

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

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:

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

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:

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

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 $(\phi^s_1,...,\phi^s_6)$ 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

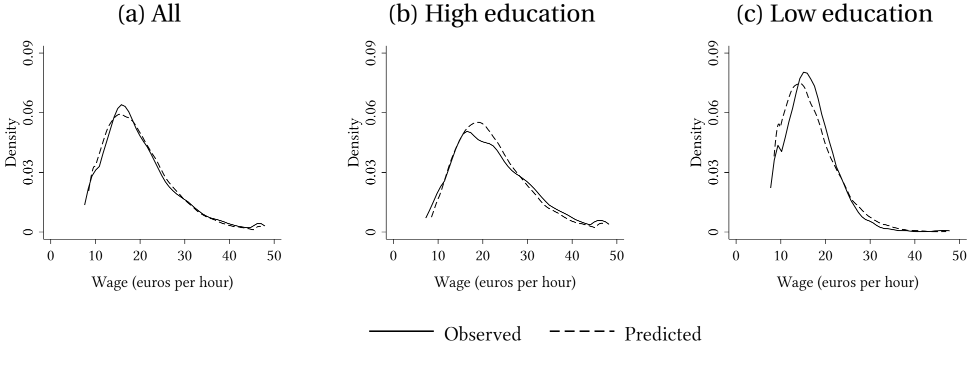

FIGURE S.1. Observed and predicted distributions of wages. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. Employed individuals aged 20–59 years inclusive.

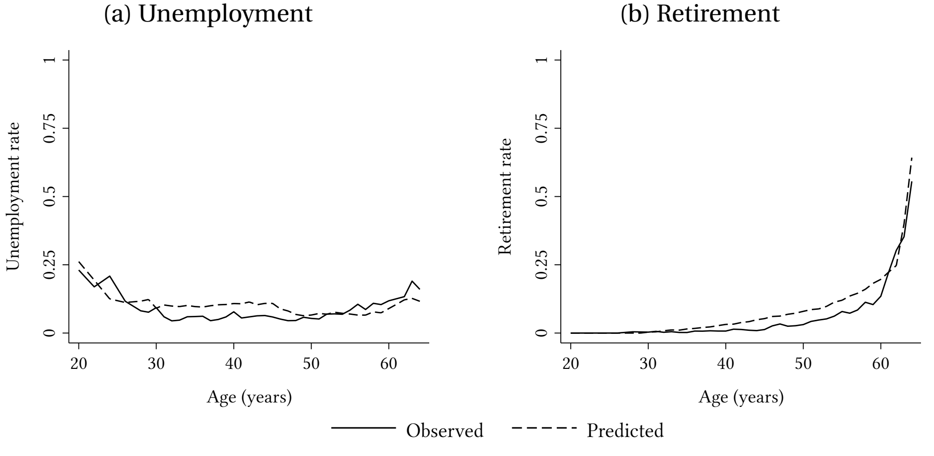

FIGURE S.2. Observed and predicted age profiles of unemployment and retirement. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4.

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.

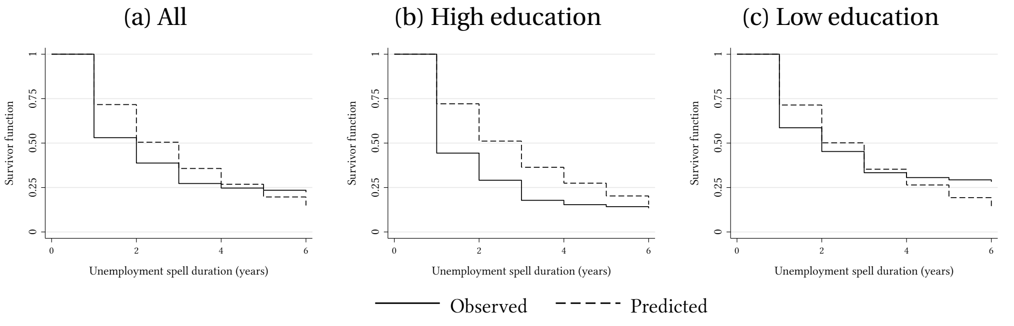

FIGURE S.3. Unemployment survivor functions. *Note:* Estimated survivor functions of unemployment durations derived from discrete-time logistic hazard models. Failure events given by transitions from unemployment to employment. Observed survivor functions were estimated using the estimation sample. Predicted 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	$\geq$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.

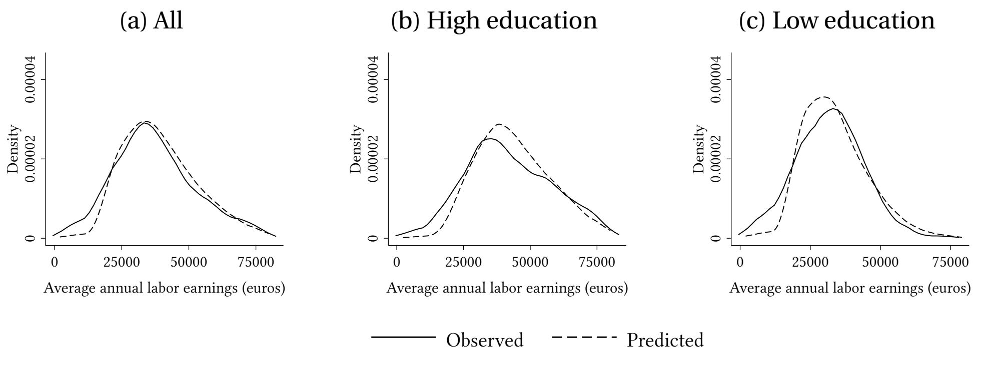

FIGURE S.4. Observed and predicted persistence in labor earnings. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. 'Average annual labor earnings' is the individual-level average of annual 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.

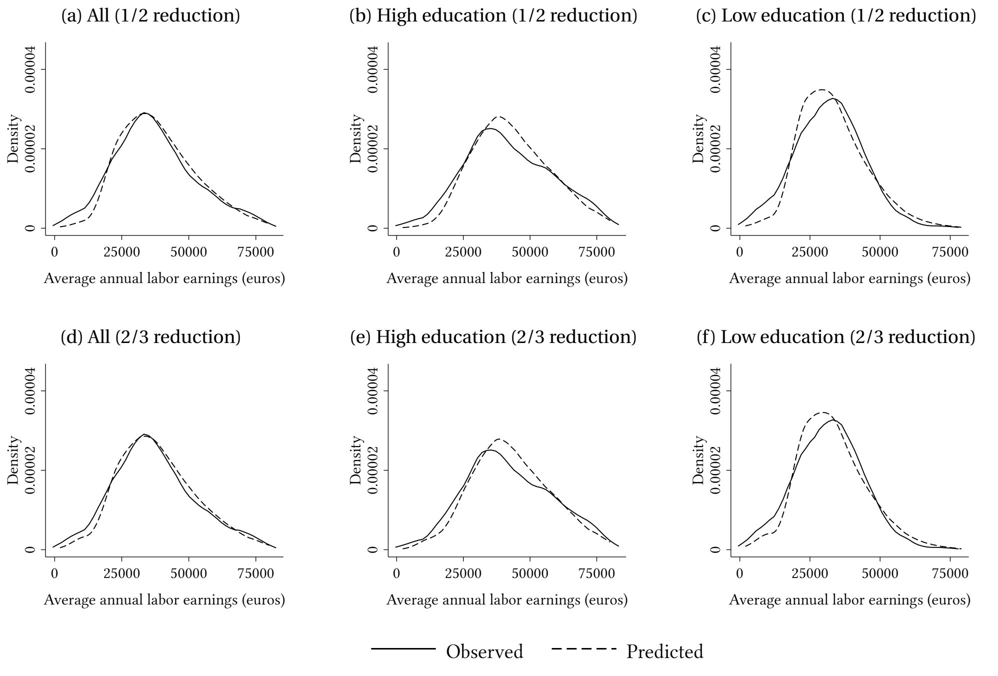

FIGURE S.5. Observed and predicted persistence in labor earnings with labor earnings lowered for reduced working hours. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4, with the exception 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.

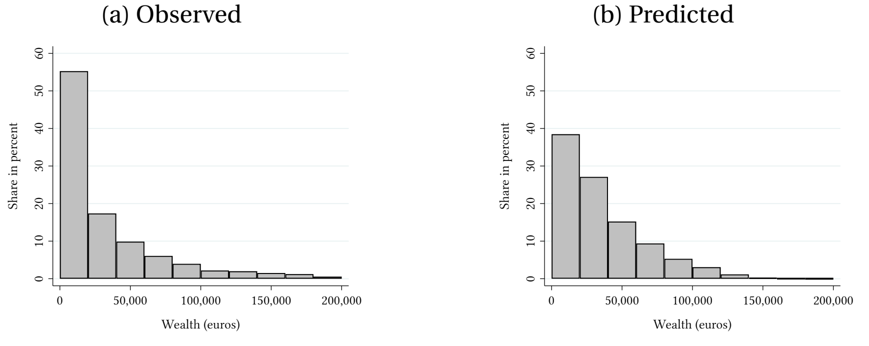

FIGURE S.6. Distributions of observed and predicted wealth. *Note:* Observed values are calculated from cross-sectional wealth data of SOEP wave 2007. Predicted values were obtained using the simulated subsample described in the notes to Figure 4. To maintain comparability, predicted values were calculated 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.

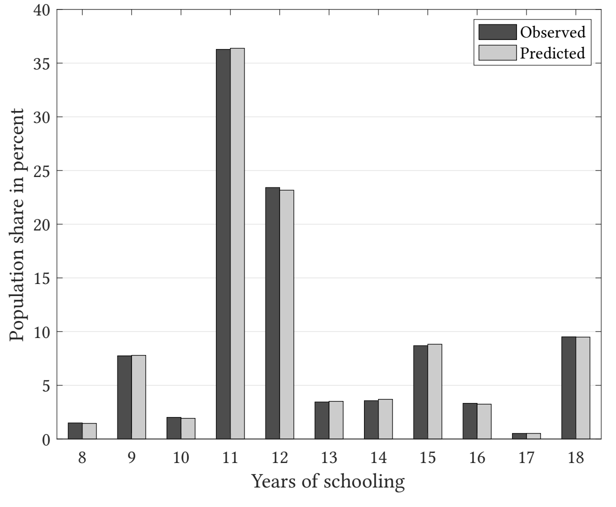

FIGURE S.7. Distributions of observed and predicted years of education. *Note:* Observed values were calculated using the estimation sample. Predicted values were obtained using the simulated subsample described in the notes to Figure 4.

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).

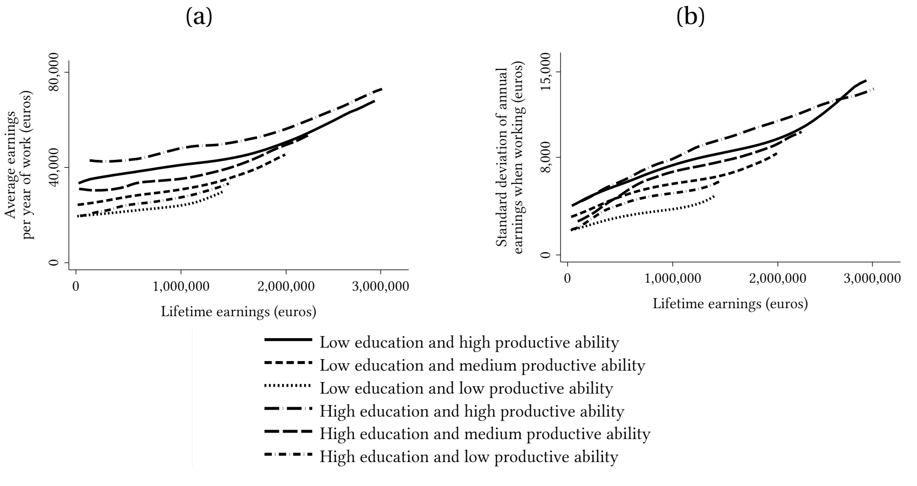

FIGURE S.8. Insurance effects of taxation. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample described in the notes to Table 6. 'Low education' refers to eleven years of education, and 'high education' refers to fourteen years of education.

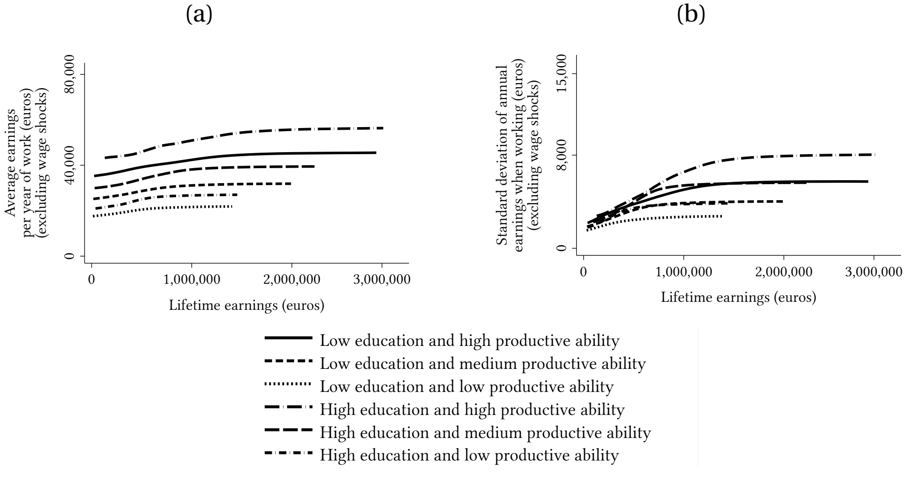

FIGURE S.9. Insurance effects of taxation without wage shocks. *Note:* Smoothed Nadaraya-Watson kernel regressions estimated using the simulated sample described in the notes to Table 6. 'Low education' refers eleven years of education and 'high education' refers to fourteen years of education.

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 $\times$ 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	Δ Within-skill-group inequality: Decreased job offer rate	Δ Within-skill-group inequality: 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.

References

Albers, Thilo, Charlotte Bartels, and Moritz Schularick (2022), "Wealth and its distribution in Germany, 1895-2018." CESifo Working Paper No. 9739. [16]

Bennett, Loris, Bernd Melchers, and Boris Proppe (2020), "Curta: A general-purpose high-performance computer at ZEDAT, Freie Universität Berlin." URL http://dx.doi.org/10.17169/refubium-26754. [7]

Berndt, E., B. Hall, R. Hall, and J. Hausman (1974), "Estimation and inference in nonlinear statistical models." *Annals of Economic and Social Measurement*, 3 (4), 653–665. [7]

Bönke, Timm, Giacomo Corneo, and Holger Lüthen (2015), "Lifetime earnings inequality in Germany." *Journal of Labor Economics*, 33 (1), 171–208, URL http://EconPapers.repec.org/RePEc:ucp:jlabec:doi:10.1086/677559. [2]

Bowlus, Audra J. and Jean-Marc Robin (2004), "Twenty years of rising inequality in U.S. lifetime labor income values." *Review of Economic Studies*, 71 (3), 709–743. [2]

Flinn, Christopher (2002), "Labour market structure and inequality: A comparison of Italy and the U.S." *Review of Economic Studies*, 69 (3), 611–645. [2]

Goebel, Jan, Markus M. Grabka, Stefan Liebig, Martin Kroh, David Richter, Carsten Schröder, and Jürgen Schupp (2019), "The german socio-economic panel (soep)." *Jahrbücher für Nationalökonomie und Statistik*, 239 (2), 345–360, URL https://doi.org/10.1515/jbnst-2018-0022. [2]

HMD (2024), "Human Mortality Database. Max Planck Institute for Demographic Research (Germany), University of California, Berkeley (USA), and French Institute for Demographic Studies (France). Available at www.mortality.org (data downloaded on April 15, 2024)." [8]

Keane, Michael and Kenneth Wolpin (1994), "The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence." *Review of Economics and Statistics*, 76 (4), 648–672. [5]

Kroh, Martin and Hannes Kröger (2020), "Soep-core v35 - lifespell: Information on the pre- and post-survey history of soep-respondents." SOEP Survey Papers 887, Berlin, URL https://hdl.handle.net/10419/222844. [8]

Kroll, Lars Eric and Thomas Lampert (2009), "Soziale Unterschiede in der Lebenserwartung: Datenquellen in Deutschland und Analysemöglichkeiten des SOEP." 3 (1), 3–30. [8]

Montez, Jennifer Karas, Robert A. Hummer, Mark D. Hayward, Hyeyoung Woo, and Richard G. Rogers (2011), "Trends in the Educational Gradient of U.S. Adult Mortality From 1986 Through 2006 by Race, Gender, and Age Group." *Research on Aging*, 33 (2), 145–171, URL http://journals.sagepub.com/doi/10.1177/0164027510392388. [8]

Pijoan-Mas, Josep and José-Víctor Ríos-Rull (2014), "Heterogeneity in Expected Longevities." *Demography*, 51 (6), 2075–2102, URL https://doi.org/10.1007/s13524-014-0346-1. [8]

SOEP (2011), "Socio-Economic Panel (SOEP), data for years 1984-2010, version 27." doi:10.5684/soep.v27. [2]

SOEP (2017), "Socio-Economic Panel (SOEP), data for years 1984-2016, version 33." doi:10.5684/soep.v33. [2]

SOEP (2019), "Socio-Economic Panel (SOEP), data for years 1984-2018, version 35." doi:10.5684/soep.v35. [2, 8]

Wagner, Gert, Joachim Frick, and Juergen Schupp (2007), "The German Socio-Economic Panel Study (SOEP) - Scope, evolution and enhancements." *Schmollers Jahrbuch*, 127 (1), 139–169. [2]