Permanent and transitory earnings dynamics and lifetime income inequality in Sweden*

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Abstract

This paper studies the role of permanent- and transitory earnings variability for lifetime income inequality in Sweden. We fit a permanent–transitory error component model to the autocovariance structure of earnings using administrative data for 2002–2015 and minimum distance estimation. We find that permanent earnings inequality increased during the first decade and that the financial crisis of 2008 temporarily heightened earnings volatility. Using this model, we simulate pensions and study lifetime income inequality. We find that permanent earnings differences generally contributes the most to lifetime income inequality. We conclude that the Swedish pension system provides some insurance against earnings risk, but accentuates the role of permanent earnings differences in explaining lifetime inequality.

JEL Classification $J31 \cdot J62 \cdot H55 \cdot I24$

1 Introduction

In the 1990s, Sweden carried out a major structural reform of its public pension system. One of the key changes was the replacement of the defined benefit system with a notional defined contribution (NDC) system as the main pension pillar. Whereas the previous system linked benefits to top-income years, the NDC pension computes benefits based on lifetime contributions.[1] The increased earnings-dependence of pension income implies a tighter link between earnings dynamics, pension income, and ultimately, lifetime income. In the aggregate, the reform created a direct link between earnings dynamics and lifetime income inequality, as earnings variability carries over to the dispersion of pension income in a systematic way.

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[1] Several countries, including Italy, Poland, and Mongolia, have followed Sweden and introduced notional accounts to their pension systems.

The present paper studies the role of earnings dynamics for earnings-, pension-, and lifetime inequality in Sweden. We estimate a model of life-cycle earnings dynamics for Swedish employees using microdata from administrative registers for the years 2002–2015. This period allows us to study how recent macroeconomic events such as the great recession of 2008/2009 and the lingering euro debt crisis affected the structure of earnings inequality. Unlike previous studies using Swedish data, we analyze earnings dynamics and lifetime inequality for both men and women. We use our estimated model to simulate lifetime income profiles to analyze how the structure of earnings inequality contributes to the distribution of pension income entitlements and lifetime income.

We follow an extensive literature on income inequality that assumes income to be determined by a permanent and a transitory component (see, e.g., Moffitt and Gottschalk, 1995; Haider, 2001; Baker and Solon, 2003; Gustavsson, 2007, 2008; Doris et al., 2013; Kässi, 2014). Permanent inequality refers to systematic income differences between individuals, while transitory inequality relates to short-term income fluctuations. Increased permanent inequality could, for example, arise due to labor demand shifts from increased offshoring or new technological paradigms. Changes in transitory inequality could, in turn, be explained by variations in job instability due to labor market competition or hiring–firing restrictions. While an increase in permanent inequality might be counteracted by policies targeting human capital investments over the life-cycle or redistributive taxation, transitory inequality is commonly remedied by social security measures.

The Swedish institutional setting is interesting for studying income inequality. The extensive public sector and collective wage bargaining are expected to distort incentives for human capital investments and for exerting effort in the labor market, reducing the human capital premium (Edin and Topel, 1997). Additionally, the employment protection act (last hired–first fired) can reduce the earnings risk for workers with longer tenure and increase the number of temporary employment schemes, contributing to labor market segmentation. While there is no legal uniform minimum wage, union contracts induce a wage floor covering most of the labor market. Since 1998, such contracts are negotiated on a highly coordinated basis between union- and employer organizations.

We fit a parsimonious earnings profile specification that is serially correlated by an ARMA(1,1) process. Our results suggest that income shocks are of moderate persistence with an AR-parameter in the range of [0.627,0.704] for women, and [0.693,0.74] for men.

Our findings show that permanent earnings inequality has increased between 2002–2010 for both men and women. Since 2010, both permanent inequality and transitory inequality have decreased. This suggests that the trend in increased permanent inequality during the 1990s documented by Gustavsson (2007) continued throughout the first decade of the new millennium, but has since reversed. The financial crisis implied a temporary increase in transitory earnings inequality for both men and women, which is likely explained by an increased variation in hours worked or short-term unemployment spells. This is interesting since the crisis is mainly argued to have affected export industries in the private sector, while stable public finances prevented any major shocks on the public sector (Gottfries, 2018). Given that women to a larger extent are employed in the public sector than men, one could hypothesize that the financial crisis had a larger impact on the structure of male earnings inequality. Our results suggest that the gender differences in the dynamic properties of earnings are mainly characterized by an overall lower persistence of shocks for women, and lower permanent earnings variability.

Simulating lifetime income as the present value of earnings and pension income, we find that permanent earnings shocks contribute more than transitory shocks to the pension income variance and the lifetime income variance. Although we find earnings shocks to be mean-reverting, changes in the AR(1) parameter affect the pension income distribution as lifetimes are finite. We also find that earnings risk can reduce the inequality in pension entitlements from the Swedish income pension system. Although this pension system provides some insurance from earnings risk, it also accentuates the role of permanent earnings differences in determining lifetime income inequality.

The remainder of the paper is outlined as follows. We survey the literature in Section 2. Section 3 describes the data and descriptive statistics. We introduce the empirical model in Section 4, followed by an outline of the estimation method in Section 5. Results for the estimation of the earnings model are presented in Section 6. Section 7 contains the simulations of lifetime income inequality. Section 8 concludes.

2 Literature review

Lillard and Willis (1978), Lillard and Weiss (1979), and MaCurdy (1982) made early and substantial contribution to the earnings dynamics literature, but find evidence for different permanent-transitory model specifications. While Lillard and Weiss (1979) suggests an empirical model of fixed and time-varying observable individual characteristics with stationary earnings shocks (the heterogenous income profile (HIP) model), MaCurdy (1982) rejects the inclusion of individual heterogeneity in earnings growth in favor of a model specification where the earnings process is governed by a unit root (the restricted income profile (RIP) model).

More recent contributions to the literature have estimated models with both individual fixed and time-varying effects and a unit-root component (see, e.g., Baker and Solon, 2003; Hryshko, 2012). Kässi (2014) briefly discusses the implications of such a model in his study of Finnish data, but questions its interpretability. Hoffmann (2019) show the potential upward bias on the dispersion of returns to education if not controlling for age-dependent heteroscedasticity in earnings shocks. He ultimately stresses the difficulty to statistically distinguish between the existence of profile heterogeneity and the presence of a unit root component.[2] This is typical of the debate in the literature.[3]

Following the seminal paper by Moffitt and Gottschalk (1995), the standard approach augments the permanent–transitory model framework with time factor loadings. This allows the researcher to study how permanent and transitory earnings variability changes over time. The factor analysis approach has since been extended to allow for both time and birth cohort factor loadings (see, e.g., Ramos, 2003; Kalwij and Alessie, 2007; Bingley et al., 2013).

Our paper closely relates to Storesletten et al. (2004) who estimates a permanent–transitory error components model to study how income risk varies over the business cycle and the relative importance of permanent and transitory income shocks in explaining life-

[2]Furthermore, analyses striving beyond inference from the autocovariance structure can allow for more rigorous models of individual earnings processes (see, e.g., Meghir and Pistaferri, 2004; Browning et al., 2010). While more detailed models can explain the underlying drivers of permanent and transitory earnings components, they go beyond the scope of this paper.

[3]Guvenen (2007, 2009) shows that if individuals are modeled to gradually learn about their earnings process in a Bayesian fashion, the autocovariance structure of the stationary HIP process resembles the observed patterns of a RIP process. Guvenen (2009) further finds that residual earnings inequality evolves in a convex fashion over the life-cycle, which is better fitted by the HIP process than the RIP specification. Hryshko (2012) rejects earnings growth heterogeneity and deems the results of Guvenen (2009) as non-robust to any minor change in error specifications.

time income uncertainty. By simulating lifetime earnings variance, they study the relative importance of permanent and transitory income shocks for total lifetime income uncertainty. While we do not study the role of business cycles, we also estimate a permanent–transitory error components model to simulate lifetime income. A novel feature of our study is that we define lifetime income as the present value of the sum of both earnings and pension income instead of just earnings.

Little work has been done on the decomposition of the evolution of earnings inequality in Sweden. Gustavsson (2008) examines the period 1960–1990. Sweden famously experienced a substantial wage gap compression in the 1970s, which subsequently widened during the 80s and 90s. He employs data from the LINDA register database and concludes that the permanent earnings inequality began to decrease before the introduction of the solidarity wage policy, possibly even before 1960. While a noticeable increase in earnings inequality coincided with the aftermath of the abandonment of central wage bargaining in the early 1980s, Gustavsson finds this to have been driven by increased earnings volatility rather than human capital dispersion. This could be considered a somewhat counter-intuitive finding as the solidarity wage policy was believed to have had discouraging effects on human capital investments, which should have reversed when the policy was abandoned. Gustavsson (2007) observed that the recession 1991–1994 led to an increased earnings dispersion. He finds that the increased dispersion was almost entirely driven by permanent earnings differences. Both Gustavsson (2007) and Gustavsson (2008) use RIP models.

Gustavsson and Österholm (2014) uses approximately median-unbiased estimation to approach the question of stationary/non-stationary earning processes. Their results suggest a median parameter value for the autoregressive process in the range of [0.6,0.65] when including an individual earnings trend, and [0.68,0.76] when only including an individual intercept term. Furthermore, they find a negative correlation between initial earnings and earnings growth, which is inconsistent with the predictions of a unit-root model.

In this paper, we seek to extend the existing literature on earnings dynamics by analyzing how the earnings process interacts with the Swedish pension system and ultimately affects lifetime inequality. A secondary contribution of this paper is that we study how the earnings inequality in Sweden has evolved after the 1990s. We also go beyond the existing Swedish literature by analyzing the earnings process for both men and women. Furthermore, it is not obvious whether the earnings dynamics process in Sweden is stationary or non-stationary. We, therefore, seek new evidence on which model best represents the evolution of life-cycle earnings. As such, our paper makes a clear contribution to the literature on earnings dynamics and lifetime inequality.

3 Data

We employed Swedish register data from the ASTRID database. Our data-set included longitudinal data for 7,478,807 individuals observed 2002–2015. ASTRID is a database linking geographical and socioeconomic information with information from tax records for the Swedish population for birth cohorts 1936—1997. It was compiled by Statistics Sweden (SCB) and hosted by the Department of Geography and Economic History at Umeå University (Stjernström, 2011).

The main variable of interest was annual earnings defined as cash gross salary measured in 100 SEK, including wage and other compensations for labor, such as holiday allowances, profit shares, travel reimbursements, and similar compensations. There was no top coding of income in this data.[4] The sources of information were administrative records, which have several advantages over survey data.[5] While register data has been used in previous studies of the Swedish labor market (i.e., Gustavsson, 2007, 2008), this is to our knowledge the first time ASTRID data was used in this context.

Only employees were considered during the years they were employed.[6] It is standard within the earnings dynamics literature to focus on employed workers.[7] The self-employed

[4]An issue in the frequently employed U.S. Panel Study of Income Dynamics (PSID) and some registers (see, e.g., Kässi, 2014).

[5]Administrative records are free from non-stochastic sample attrition, apart from migration or death, meaning that they do not suffer from the same attrition issues that are common in survey data. Furthermore, since tax record information does not rely on the memory of the participants, such data should be less prone to suffer from measurement error due to misreporting. Employers are also legally obliged to report earnings amounting to more than 100 SEK to the Swedish tax agency (Skatteverket, 2019).

[6]Employed in both the public and the private sectors. Some, such as Bingley et al. (2013), exclude employees in the public sector and part-time workers from their analyses. Due to institutional factors, such as collective bargaining being the norm in Sweden, we argue that the labor market functioning is relatively similar in the public and private sectors. We do not exclude part-time workers since our analysis focus on earnings, and not wages. However, our selection did not include individuals who might have suffered shocks that push them into long-term unemployment.

[7]See Meghir and Pistaferri (2011) For example Baker (1997), Haider (2001), Baker and Solon (2003), Gustavsson (2007) and Doris et al. (2013) only consider those employed all years in their respective samples while Moffitt and Gottschalk (1995), Kässi (2014) and Lochner and Shin (2014)

workers were not considered during the years of self-employment.[8] Additionally, seamen were excluded from the sample.[9] Any zero earnings reported were treated as missing observations.[10] Variation across as well as within cohorts was exploited for the estimation of the parameters of interest, which increases the importance of the definition of sample selection criteria by year of birth. To ensure sufficiently long time series for each cohort we required at least ten years of viable observations for each cohort. A consequence of this was that only individuals born 1956–1981 were considered in the analysis. Individuals were allowed to leave and enter the data on a year-to-year basis depending on whether they fulfill the criteria during the specific period.[11] This approach partially mitigated the problem of including women in the analysis since any maternal leave longer than one year was treated as a missing observation, like long-term unemployment (Kässi, 2014). It is relatively uncommon to analyze both women and men in the literature, which instead primarily focuses solely on male earnings. Men and women were analyzed separately since their earnings processes are expected to differ and to increase the comparability of our results with the previous literature. Further discussion of the selection criteria can be found in Appendix A.

Men and women were separated into groups based on their year of birth and education. We calculated the empirical moments separately for these groups. The education groups were: individuals with less than high school education (7–9 years of education), with high school education (11–12 years of education), with at least some college education (13–14 years of education), and with a college degree (15–17 years of education).[12] We analyzed these groups separately as the labor market characteristics may differ between groups, for

only consider employees the years they have positive earnings or are employed.

[8]This was due to tax incentives for defining earnings as capital gains rather than labor income and the possibility of private consumption veiled as corporate expenses. Meghir and Pistaferri (2004), Kalwij and Alessie (2007) and Bingley et al. (2013) are other examples of studies solely considering employees.

[9]Their earnings are not necessarily registered in Sweden and therefore may not appear in our tax record data.

[10]This was a result of the logarithm of earnings being used for the analysis. Daly et al. (2016) raise the concern that earnings registered before and after missing observations are likely the result of transitions in and out of employment. These earnings are found to be more volatile and considerably lower than typical earnings observations.

[11]This feature is sometimes referred to as the panel being "revolving." Haider (2001) introduced the terminology of the "revolving unbalanced panel" sometimes used in the literature to describe panels in which all cohorts are not observed for all periods and where individuals may enter and exit freely.

[12]We did not analyze individuals who have participated in doctoral studies (19–21 years of education). Stipends for educational purposes are not classified as taxable income in Sweden, and would therefore not be included in our measure of earnings. This was also a relatively small group, especially among the younger birth year cohorts.

example, in terms of the type of jobs available and the substitutability of labor.

We utilized three data selection processes. The main selection is referred to as the *strict* sample. We have also estimated the model using two other sets of sample criteria to check the robustness of our results. These are referred to as the *lenient*- and *top-coded* sample. The strict sample used a set of data selection criteria based on those found in the literature. This makes it easier to compare our findings with the previous literature. The lenient sample serves as a control giving a measure of the sensitivity of the results to some potential selection effects. The top-coded sample was similar to the strict sample, but instead of truncating the extremes of the earnings distribution, we put a cap on income that binds at a frequency similar to the PSID (see for example Haider, 2001). The strict sample only considers prime-age workers between 25–55 years old for whom there were valid data on educational attainment. This age span was chosen as we wanted to focus on individuals with a relatively stable labor supply. Following Bingley et al. (2013), we required valid earning observations for at least five consecutive years for an individual to be included in the strict sample. The top and bottom 0.5% of the yearly income distribution was removed to reduce the influence of outliers.[13] The lenient sample required that individuals have valid data on education, were at least 25 years old and were born between 1956–1981. This meant that the range of ages observed increased to 25–59. There were no other requirements for this sample. The restrictions for the lenient sample were made to allow for comparability of the results with the strict counterpart. Overall, the strict criteria reduced the sample size to 1,328,440 men and 1,340,851 women. Compared with the literature, this can still be considered a relatively large sample.[14] Table 1 in Appendix A shows sample sizes in total and for each education group and gives further details on the selection and how the different criteria affected the sample. The additional criteria for the strict sample disproportionately affected the less educated population, which could potentially be a sign of non-monetary returns to education, such as job security and smoother transitions between jobs or between employment and unemployment.

Figure 1 depicts yearly average log earnings for the period 2002–2015 by education group for men and women. This period includes recent macroeconomic events, such as the aftermath

[13] This has been done in e.g. Kalwij and Alessie (2007), Bingley et al. (2013) and Lochner and Shin (2014)

[14] Gustavsson (2008) analyzed data for 76,079 Swedish individuals and the sample utilized in Haider (2001) consisted of only 3,115 individuals drawn from the PSID. Blundell et al. (2015) analyzed data for 934,704 Norwegian men and is thus a study that uses a panel with comparable scope.

of the dot-com bubble of 2001 and the 2008 financial crisis. For both men and women, there are differences in average log earnings across education groups. The most pronounced are the difference between people without high school education and workers with more education.

Figure 2 presents the variance of real log earnings 2002–2015. From this figure, we find that earnings differences have been relatively stable over the period. We also find a slight downward trend in variances for college educated-workers.

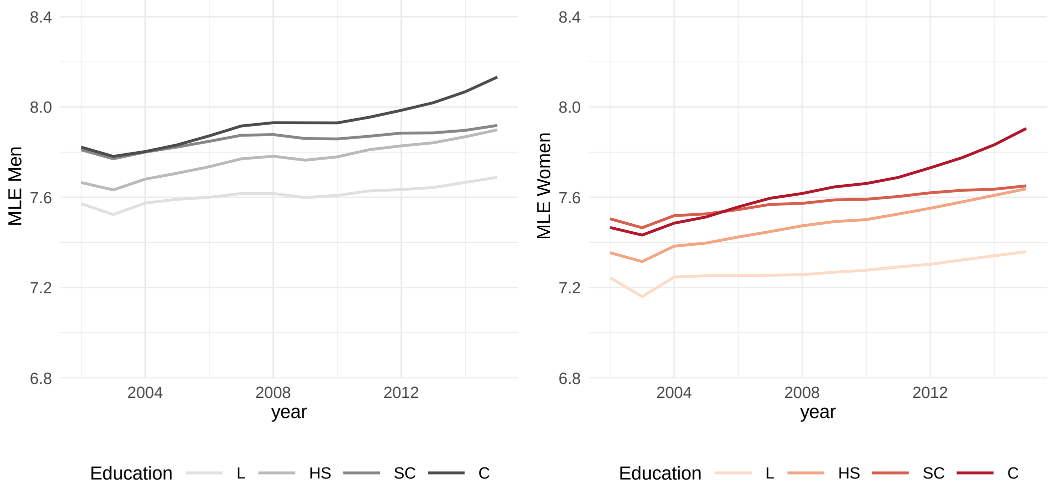

Figure 1: Average real log earnings 2002-2015 for workers aged 25–55.
Note: The education groups are: less than high school (L), high school (HS), some college (SC), and college (C). Earnings are deflated to 2002 SEK.

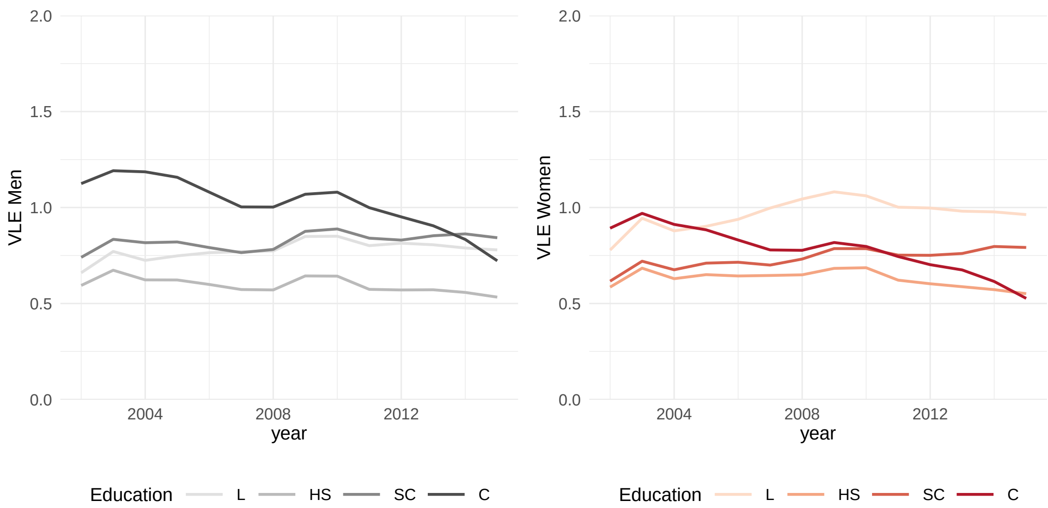

Figure 2: Variance log real earnings 2002-2015 for workers aged 25–55.
Note: the education groups are: less than high school (L), high school (HS), some college (SC) and college (C). Earnings are deflated to 2002 SEK.

Figures 3 and 4 show the variance and first three autocovariances for men and women in the strict sample. The tendency of decreasing variances in earnings over the life-cycle observed in the data was an unexpected finding. Most of the literature, the permanent income hypothesis, and both the standard HIP and RIP models suggest that variances increase with age.[15] We found similar patterns for the other samples (see Appendix B).

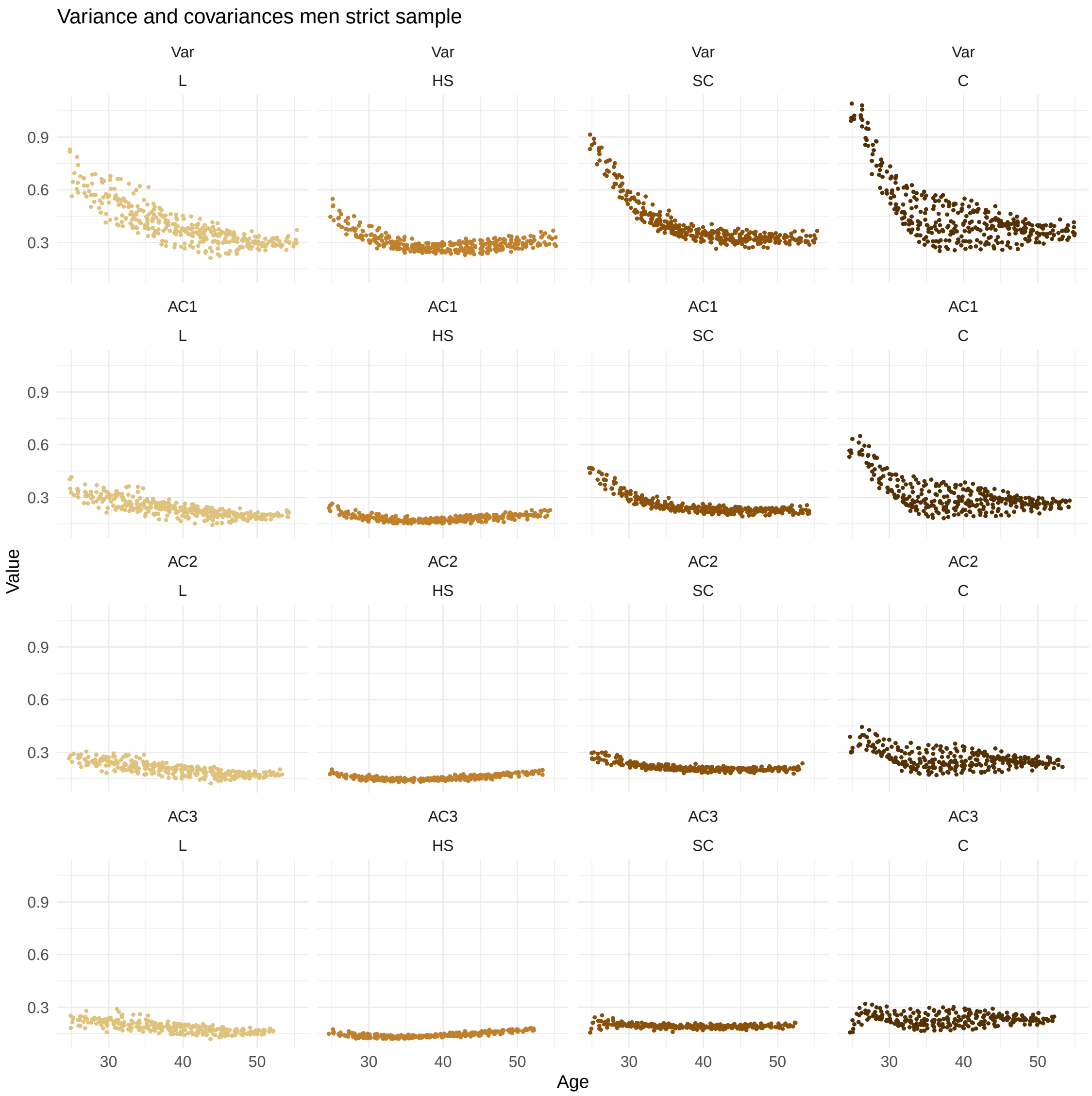

Figure 3: Variance and first to third lag autocovariance of residual log earnings for men in the strict sample. Each data point represents the empirical variance, or autocovariance, of earnings for a specific birth year cohort at a certain age.
Note: Plots for the variance and first three autocovariances for all selection criteria can be found in Appendix B. Education groups are: less than high school education (L), high school education (HS), some college education (SC), and college education (C).

[15] Hoffmann (2019) shows that such a pattern can be consistent with the predictions of conventional HIP and RIP models once age-heteroscedasticity is accounted for. We return to this discussion when introducing the model in section 4.

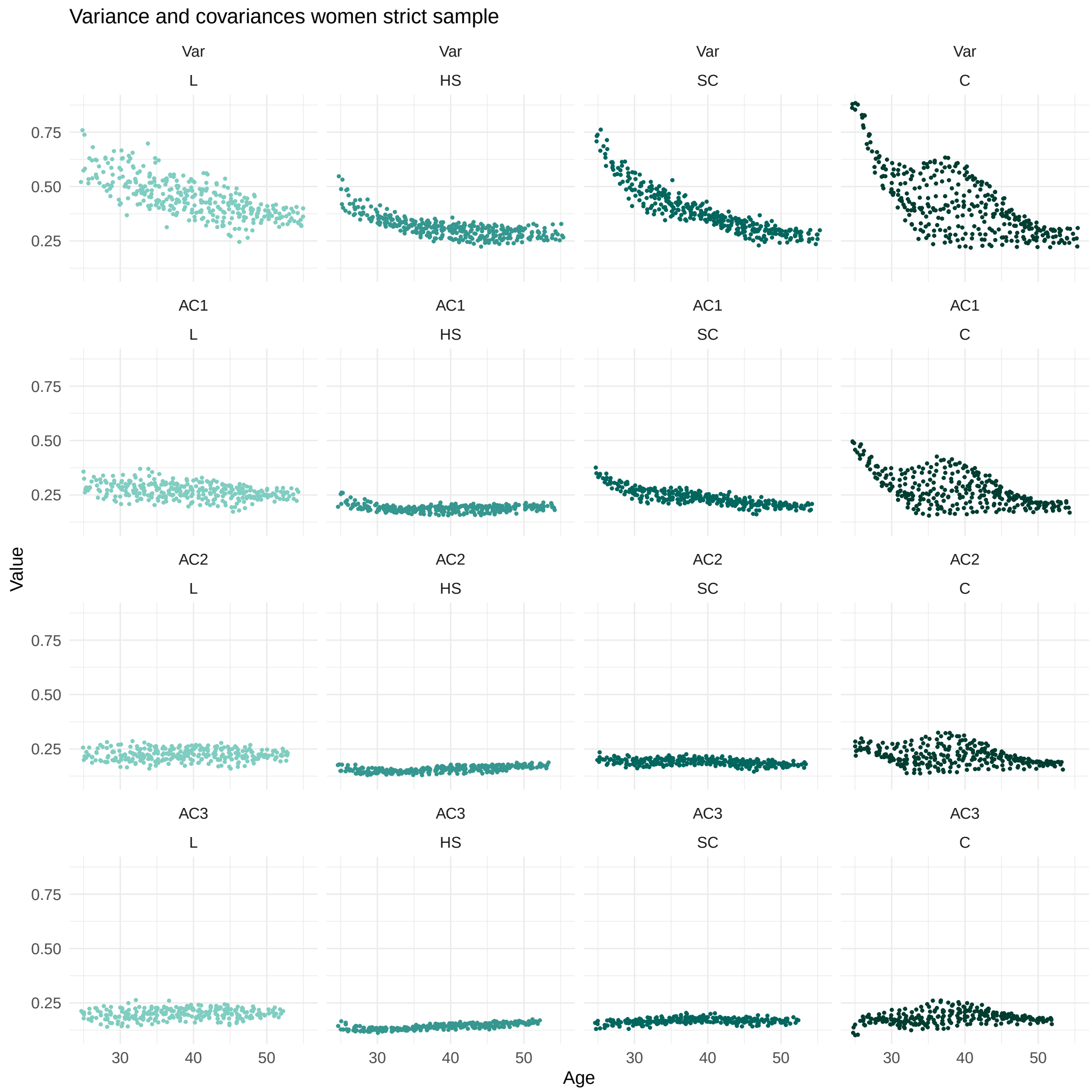

Figure 4: Variance and first to third lag autocovariance of residual log earnings for women in the strict sample. Each data point represents the empirical variance, or autocovariance, of earnings for a specific birth year cohort at a certain age.
Note: Plots for the variance and first three autocovariances for all selection criteria can be found in Appendix B. Education groups are: less than high school education (L), high school education (HS), some college education (SC), and college education (C).

Deaton and Paxson (1994) found that inequality in earnings increased with age in Great Britain, the United States, and Taiwan. Blundell et al. (2015) found upward trends in the variance of earnings over the life-cycle for low- and medium-skilled male workers in Norway. For high-skilled workers they found a steep downward trend in the early stages, followed by a period of relative stability with fairly small changes in earnings variance. This pattern is similar to that found in our data. In his analysis of Finnish earnings, Kässi (2014) found upward trends in earnings variance over the life-cycle for men, and downward but less pronounced trends among women. A common observation in the literature is that variances in earnings increase as individuals approach retirement. A plausible explanation for this is that labor supply becomes more variable during the later parts of the working life.

4 Model

In this paper, we analyzed the dynamic properties of residual log earnings. Many of the social security systems in Sweden determine benefits based on income rather than wages.[16] This makes earnings dynamics relevant from a policy perspective. The facts that collective bargaining is the norm and that Sweden has a rigid wage structure (Gottfries, 2018) provide further arguments for analyzing earnings. By analyzing earnings rather than wages, one captures both variabilities in wages and hours worked (Kässi, 2014).

4.1 Calculation of residual earnings

The residuals, $\hat{y}_{cide}$, were calculated by removing the yearly means for each birth cohort- and education group in the data. This "de-meaning" approach to estimate residual earnings follows from Baker and Solon (2003). As the covariance structure of earnings is the focus of our analysis, the residual earnings were sufficient for identifying the parameters of interest. In this paper, the residuals were defined as:

$$\hat{y}_{cide} = Y_{cide} - \overline{y}_{cde}, \tag{1}$$

where Y_{cide} is the observed log of earnings calendar year d for individual i born in year c with education e, and $\overline{y}_{cde}$ is the year- and group-specific sample mean. An alternative method for estimating the residual earnings is to run a separate first-stage regression using observable characteristics (e.g., Lillard and Weiss, 1979; Meghir and Pistaferri, 2004) sometimes including polynomials in potential experience or age (see Haider, 2001; Blundell et al., 2015). We chose to follow the approach of Baker and Solon (2003) as it flexibly captures the macro, age, and cohort effects on earnings levels we wished to control for.

[16] Some examples are pension entitlements, unemployment benefits, and parental allowances.

4.2 Model specification

We propose an empirical model with a parsimonious individual lifetime earnings profile. This model can be seen as an augmentation of the one proposed by Lillard and Willis (1978).[17] We define the transitory component in our model as an ARMA(1,1) process with cohort- and time factor loadings and a separate labor market entry shock.

$$\hat{y}_{cidt} = \lambda_c \gamma_d \alpha_i + \mu_c \pi_d \tau_{it} \tag{2}$$

$$\tau_{i0} = \xi_i \tag{3}$$

$$\tau_{i1} = \rho \xi_i + \epsilon_{i1} \tag{4}$$

$$\tau_{it} \ = \rho \tau_{it-1} + \epsilon_{it} + \theta \epsilon_{it-1} \tag{5}$$

$$[\alpha_i, \epsilon_{it}, \xi_i] \sim \big([0,0,0],\ [\sigma^2_\alpha, \sigma^2_\epsilon, \sigma^2_\xi]\big)$$

The indexation for education, e, has been dropped to ease the notation. In Equation (2), λ_c and μ_c are cohort-specific factor loadings scaling the permanent and transitory variances between cohorts. Cohort factor loadings have been used in e.g., Ramos (2003), Cappellari (2004), Kalwij and Alessie (2007), Bingley et al. (2013), and can account for any potential dispersion of unobserved labour quality between birth cohorts (Katz et al., 1999). The variables γ_d and π_d correspond to time factor loadings that allow for scaling from calendar year-specific macro shocks. In this model, index t corresponds to potential experience measured as years since labor market entry.[18]

The permanent component is specified as a fixed-effects parameter α_i. This parameter is assumed to be distributed with mean zero and variance σ^2_α. As there was no clear trend of earning variances increasing with age, neither linearly nor in a convex manner, the conventional RIP and HIP specifications of the permanent wage would impose structures on the data that do not match the observed patterns. This made it difficult to justify the use of these types of models.[19] Effects of human capital are partially controlled for by a separate analysis

[17] The inclusion of cohort- and time factor loadings, a separate shock for the first period upon entering the labor market and a transitory component modeled as an ARMA separates our residual earnings model from that of Lillard and Willis (1978).

[18] Defined as $age - 25$ in this model.

[19] Hoffmann (2019) shows that HIP and RIP models can account for non-increasing variances over time once age-heteroscedasticity is accounted for. To address this issue, we have estimated an alterna-

of different education groups and α_i. We allow for some heterogeneity in the permanent component through the factor loadings.

The transitory component, τ_{it}, is modeled as an ARMA(1,1) where ρ denotes the autoregressive (AR(1)) parameter, θ represents the moving average (MA(1)) parameter and the innovation term is defined as ϵ_{it}. The error term is assumed to adhere to earnings shocks which are distributed with a mean of zero and variance σ^2_ϵ.[20] We aim to capture the initial drop in the variance of log earnings observed in the data by including a shock upon initial entry into the labor market ξ_i. This initial shock will have some persistence through the AR(1) process and is assumed to have a zero mean distribution with variance σ^2_ξ.

5 Estimation method

The properties of life-cycle earnings are commonly identified by drawing inference from the observed covariance structure of earnings. We used the method of moments (MM) and minimum distance estimation. This is a common estimation method in the literature.[21] There are numerous reasons why MM is so widely adopted within the literature. Most prominently, the method can cope with endogenous regressors and over-identification and relies on a relatively sparse set of statistical assumptions. The basic principle is to match the information observed in the data (the empirical moments) with the predictions made from a theoretical model (the population moments) so that the distance between them is as small as possible. An advantage of MM over the alternative maximum likelihood (ML) approach is that it does not have to rely on distributional assumptions for the underlying unobserved counterpart. As the first order moments are 0 by construction, its utilization does not require any assumptions regarding the distribution of shocks, which previous evidence suggests is not normal.[22]

The empirical moments used in this paper were the estimated second-order moments of the

tive model specification with year and age factor loadings. We prefer this specification over assuming a functional form for age heterogeneity as in Hoffmann (2019) and Gustavsson (2008). This is further discussed in Section 6.3.

[20]See Appendix C for an explanation of the potential bias introduced by including an additional measurement error.

[21]See Baker and Solon (2003), Gustavsson (2008), Bingley et al. (2013), Kässi (2014) and Blundell et al. (2015) for examples of similar studies employing MM in their estimation.

[22]Lillard and Weiss (1979) observe slightly left-skewed, fat-tailed errors, and Horowitz and Markatou (1996) also concludes non-normally distributed innovations.

residual logarithm of earnings. The cohorts included in the samples were observed for 10–14 periods yielding 55–105 second-order moments per cohort. Estimates of empirical moments based on fewer than 30 observations were disregarded from the analysis. More details on the estimation procedure and the moments used for identification are presented in Appendix D. Standard errors were calculated using the delta method. This method uses a first-order Taylor approximation and the asymptotic normality of the estimator to approximate the variance of the estimates (see Oehlert, 1992 for a review of the method).

6 Parameter estimates

For men and women in the strict samples, the core parameters of the residual earnings model are presented in Table 1 while cohort- and time factor loadings are presented in Figures 5–6. The corresponding results for the lenient and top-coded samples can be found in Appendix E while point estimates for time- and cohort factor loadings are in Appendix F. The fit of the model is presented in Appendix G.[23]

6.1 Core model

Table 1 shows that the variance of the heterogeneous intercepts, σ_α^2, is higher for the more educated workers, with the highest variance for workers with a college education. We can observe that the permanent variance increases with education for men, while this relationship is less systematic for women. When comparing men and women within the same education group, we find that the variance is larger for men. The gender difference across and within education groups is a bit puzzling but could potentially be a result of factors such as the choice of fields of education or line of business differing between men and women at an aggregate level. For instance, women are to a larger extent than men hired in the public sector (Statistics Sweden, 2019). These sectors have a more compressed wage structure than the private sector in Sweden (Statistics Sweden, 2018).

Analyzing the AR(1) parameter estimates, we find that the estimates range from 0.627 to 0.704 for women and 0.693 to 0.74 for men. These estimates are significantly smaller than

[23]We present both the residual between the observed- and predicted moments for each analyzed subsample as well as separate plots for some key moments.

	ρ	θ	σ^2_α	σ^2_ϵ	σ^2_ξ	Prop. perm	MSE
Less than HS Men	0.74***	-0.413***	0.091***	0.136***	0.134*	0.685	0.0003
	(0.131)	(0.009)	(0.023)	(0.029)	(0.081)	(0.024)	
Less than HS Women	0.704***	-0.346***	0.089***	0.168***	0.161**	0.669	0.0004
	(0.147)	(0.039)	(0.014)	(0.038)	(0.062)	(0.019)	
High School Men	0.732***	-0.406***	0.106***	0.158***	0.17***	0.712	0.0001
	(0.027)	(0.007)	(0.01)	(0.012)	(0.009)	(0.000)	
High School Women	0.684***	-0.326***	0.079***	0.166***	0.164***	0.704	0.0001
	(0.044)	(0.025)	(0.01)	(0.005)	(0.023)	(0.000)	
Some College Men	0.693***	-0.309**	0.137***	0.156***	0.157***	0.729	0.0004
	(0.155)	(0.132)	(0.012)	(0.016)	(0.000)	(0.007)	
Some College Women	0.627***	-0.228**	0.094***	0.141***	0.145***	0.724	0.0002
	(0.122)	(0.098)	(0.012)	(0.008)	(0.000)	(0.003)	
College Men	0.733***	-0.282***	0.192***	0.179***	0.135***	0.702	0.0009
	(0.057)	(0.048)	(0.005)	(0.019)	(0.03)	(0.003)	
College Women	0.637***	-0.14***	0.114***	0.19***	0.202***	0.686	0.0004
	(0.02)	(0.012)	(0.015)	(0.011)	(0.004)	(0.000)	

Table 1: Results core parameters for strict samples.
Note: $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$. *All hypothesis tests are two-sided. Standard errors are presented in parentheses beneath parameter estimates. Prop. perm measures the mean ratio between predicted permanent variance and the sum of predicted permanent- and transitory variances. MSE is mean squared error between predicted and observed empirical moments.*

unity and suggest that earnings shocks are of moderate persistence. Compared to previous literature on Swedish earnings, the estimates for the male samples are within the range of 0.679–0.760 found in Gustavsson and Österholm (2014), for the model specification without individual earnings trends. Gustavsson (2007) finds an AR(1) of 0.555, and Gustavsson (2008) finds an AR(1) parameter of 0.8190 for the years 1960–1967 and 0.5726 for 1968–1990. It is, however, important to note the difference in the model specifications as we do not include a unit root.

The estimated MA(1) coefficients range between -0.140 and -0.346 for women, and -0.282 to -0.413 for men. In absolute value, the parameter values are seemingly decreasing with education. This suggests that individuals with less education are more likely to experience rapidly mean-reverting shocks to earnings. This could, for example, be the result of short spells of unemployment or hourly employments being more common for workers with lower education.

The proportion of overall variability attributable to the permanent inequality $Prop.perm$ informs that permanent differences contribute more to overall earnings inequality than transitory shocks. Within education groups, we find permanent earnings to contribute less to the earnings inequality of women than men.

6.2 Factor loadings

The cohort factor loadings describe the size of the permanent- or transitory components for a specific cohort relative to workers born in 1956. The time factor loadings describe the relative size of the permanent- and transitory components of a specific year with 2002 as the reference.

Figure 5 shows that younger cohorts have more volatile earnings than older cohorts. Furthermore, younger workers with at least a high school education have smaller permanent differences in earnings. This could be explained by younger workers being more mobile between workplaces, both voluntarily and due to hiring/firing restrictions. The timing of labor market entry relative to the financial crisis could also have contributed to this trend. Mainly as the unemployment risk for young workers increased more relative to other groups during the financial crisis (Statistics Sweden, 2014). Since we are unable to control for hours worked, we should also expect the presence of individuals working part-time to financially support their educational commitments to inflate the estimates of earnings volatility among younger cohorts.[24]

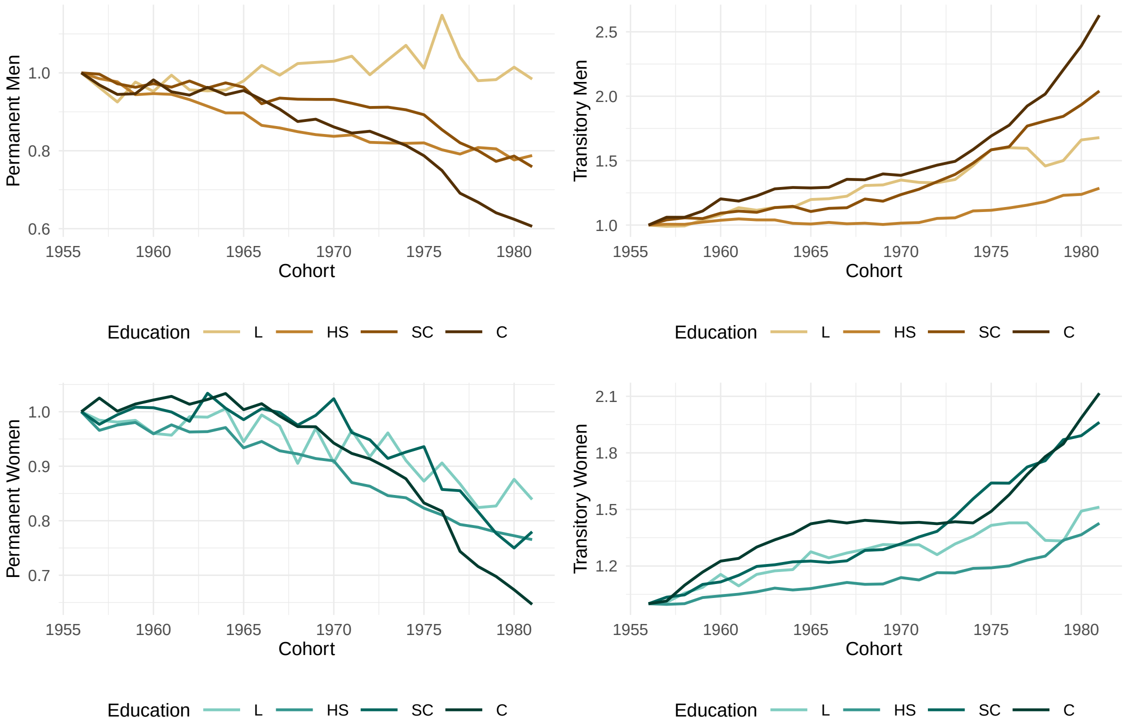

Figure 5: Cohort factor loadings strict samples.
Note: The education groups are: less than high school (L), high school (HS), some college (SC) and college (C).

Figure 6 presents the time factor loadings. Our findings show that the increase in permanent inequality documented in Gustavsson (2007) continued throughout the first decade for both men and women but then decreased throughout 2010–2015. The variation in the impact of the financial crisis was found to be mainly driven by differences in education level, rather than in gender. Specifically, we find an increase in transitory inequality among all education groups except for workers with a college education.

[24]This expectation is further supported by Björklund (1993) who concludes that the correlation between annual income and lifetime income is lower for younger than for older workers.

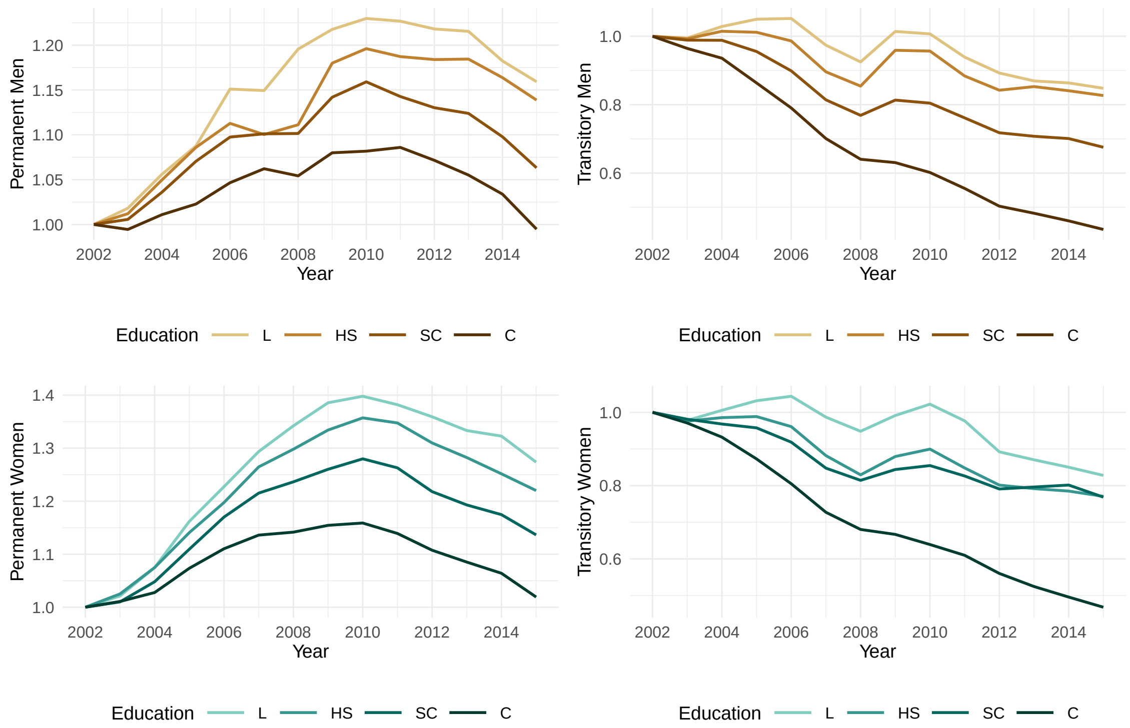

Figure 6: Time factor loadings strict samples.
Note: The education groups are: less than high school (L), high school (HS), some college (SC) and college (C).

6.3 Robustness checks

We tested the robustness of our results in two ways. First, we estimated the model based on two data sets constructed using alternative sample criteria.[25] The results from these analyses can be found in Appendix E and F. Second, we estimated an alternative model specification with age- and year factor loadings to see how age heteroscedasticity affects our estimates. The results from this analysis are presented in Appendix H.

From the selection criteria analysis, we find that most of our results are qualitatively similar. However, we do find some changes for our parameter estimates. First, the estimated AR(1) parameter values are smaller for both the lenient and top-coded samples. The lower AR(1) parameter estimates for these data sets suggest that workers in the lower end of the earnings distribution face less persistent earnings shocks. Since the model framework does not capture transitions in and out of employment, this result could partly be driven by some workers receiving negative shocks ending up in long-term unemployment. One way of alleviating this limitation is by focusing the analysis on workers that are more established

[25]For further explanation, see Section 3.

in the labor market. Another finding is that earnings are more variable in these data sets, with larger permanent differences and higher variances for the earnings shocks. Finally, we find the parameter estimates in the lenient and top-coded samples to be less precise than the estimates from our main analysis.

From the analysis of the alternative model specification with age and year factor loadings, we find that the choice of model specification affects some of our parameter estimates. First, when comparing the AR(1) parameter estimates from the robustness check with the main analysis, we find that estimates are higher for workers without any college education and lower for college-educated workers. There is more variability in estimates between groups with the alternative model specification with AR(1) parameter estimates ranging from 0.546 to 0.948. We also find more variability between education groups. For men with high school education, we find that permanent earnings differences contribute very little to overall earnings inequality. This finding is robust across all data selection criteria. Comparing the MSE for our preferred specification and the robustness check, we find that the fit to the data is better for the cohort- and year factor loading specification.

7 Pension entitlements and lifetime income

In this section, we study pension- and lifetime inequality. First, we use our model to simulate individual life-cycle earnings for different cohorts, genders, and education groups. We compute individual pension contributions from the simulated earnings accounting for key features of the Swedish public pension scheme and calculate pension entitlements at age 66. Second, we conduct a sensitivity analysis to illustrate how the different parts of our model affect the accumulation of pension entitlements and lifetime inequality. Finally, to describe how the Swedish public pension system insure against earnings risk, we assess the relative importance of permanent and transitory shocks for the variance of pension- and lifetime incomes.

The Swedish public pension scheme underwent a major structural reform in the 1990s from a defined benefit plan to a combined pay-as-you-go notional defined contribution (income pension), financial defined contribution (premium pension), and defined benefit scheme (guaranteed pension). Income- and the premium pension are financed through earmarked income-based contributions, while general tax revenue finances the guaranteed pension.

Every year, 18.5% of pensionable income is allocated to the public pension system.[26] Pensionable income consists of several income types, including earnings, parental allowance, unemployment benefits, and sickness and activity allowance, and is also subject to an upper- and lower limit. The upper limit is 7.5 times the so-called income base amount, and pension contributions cannot exceed this limit. The lower limit corresponds to 42.3% of the so-called price base amount. Income falling short of this does not contribute to the public pension system. Both base amounts are time-variant. Individuals also pay a pension fee of 7% on their pensionable income.

The earlier pension system combined a flat-rate basic income pension ("folkpensionen"), and an earnings-based defined benefit pension ("allmän tilläggspension", ATP). This system was partially earnings-based as pension income was determined from only the top 15 income years. The pension reform increased the link between lifetime earnings and pension income (Palmer et al., 2000) making lifetime earnings central for any predictions of entitled pension wealth.

7.1 Simulation procedure

We conduct cohort-specific simulations for each gender and education group based on the parameter estimates from the strict sample. All cohorts are integrated into the post-reform pension system. For each group, we simulate 10000 individual life-cycle income profiles. Individuals are assumed to enter the labor market at age 25, full-time retire at age 66, and remain retired until death at age 80. Following the unisex annuity divisor utilized by the Swedish Pensions Agency, we use the same life expectancy for men and women. For simplicity, we only simulate income pensions as premium pension benefits rely on the performance of financial markets.

We simulate log earnings and transform them into levels to determine pensionable income. In line with Storesletten et al. (2004), all shocks to log earnings are assumed to be normally distributed. Furthermore, we assume homoscedastic shocks for all years.[27] Pensionable

[26]For income registered after 1995, 16 percentage points go towards the income pension pillar, and 2.5 percentage points towards the premium pension pillar. For income registered before 1995, all goes towards the income pension pillar.

[27]An alternative approach would be to combine our time factor loadings with estimates from previous studies on Swedish data. Since our model specification differs from that of Gustavsson (2007) and Gustavsson (2008), we disregarded this option.

income is defined as 93% of earnings and is truncated using the previously described limits. The contribution rate is 18.5% of pensionable income registered before 1995 and 16% after. We divide total pension wealth by the number of years in retirement to obtain annuity amounts. We use GDP projections from MIMER[28] and predict future values for the price and income base amounts using extrapolations from the projected GDP/capita growth. Future mean earnings are predicted using an OLS regression model including GDP/capita, education dummies, and cohort dummies. The oldest cohort to register their first earnings within the reformed pension system is the 1970 birth cohort. Therefore they serve as the baseline for many of the simulations.

Following the above simulation procedure and using a standard discount factor $\Upsilon(h) = \frac{1}{(1+\upsilon)^h}$ with constant discount rate υ, we calculate the present value of an individual's pension income (Y^p):

$$\text{PV Pension income} = \sum_{h=66}^{80} \Upsilon(h) Y^p_{c,i,h}, \tag{6}$$

and lifetime income:

$$\text{PV Lifetime income} = \sum_{h=25}^{65} \Upsilon(h) \exp(\hat{y}_{c,i,h}) + \sum_{h=66}^{80} \Upsilon(h) Y^p_{c,i,h}. \tag{7}$$

Given Equations (6)–(7), we systematically study how the different earnings shocks contribute to pensions and lifetime income.

For out-of-sample validation, Table 2 presents observed statistics for pensionable income for 2017 and 2019. The observed statistics come from the Swedish pensions agency (Pensionsmyndigheten, 2021). Simulated statistics were weighted using the strict sample sizes (see Table 1, Appendix A).

Our model does not capture all features of the income process. There is a difference between observed and simulated quartile values. This could be explained by true earnings shocks being asymmetrically skewed, or that the distribution of taxable benefits differs from that of the earnings distribution. Overall the simulations are more accurate for men than

[28] MIMER is a general equilibrium model with overlapping generations employed by the Swedish Ministry of Finance (*Finansdepartementet*). While MIMER does not explicitly account for business cycle fluctuations, it does integrate demographic change, which is a common predictor of business cycle fluctuations as in Röstberg et al. (2005). For a detailed description of MIMER, see Almerud (2018).

2017	Mean	Median	1st Quartile	3rd Quartile
Male sim.	367 146	394 962	262 384	489 800
	(359 246)	(391 600)	(300 300)	(461 250)
Female sim.	304 171	288 184	185 227	459 105
	(318 152)	(325 500)	(249 000)	(416 650)
2019	Mean	Median	1st Quartile	3rd Quartile
Male sim.	384 869	415 256	275 882	514 000
	(378 280)	(413 400)	(315 700)	(483 000)
Female sim.	324 391	310 802	198 191	494 894
	(337 824)	(345 600)	(264 000)	(447 300)

Table 2: Simulated and observed pensionable income (SEK).
Note: Simulations concern men and women born in 1970. Each sample is weighted such that the number of individuals of each education group corresponds to the strict sample found in Appendix A, Table 1. Observed values are presented in parentheses.

women. There are several possible explanations for this. Women are more prone to spells of labor market absence and have a larger variation in hours worked. It could also be that taxable benefits, like parental allowances, are more important for determining pensionable income for women or that shocks to female earnings are drawn from a different distribution than men.

7.2 Pension inequality

We begin by studying the within-education group distributions of annual income pension payments. Figure 7 presents the simulated distributions of the first pension entitlement for men and women born in 1970. Figure 8 shows the simulated distributions of lifetime income as a reference. We consider two different scenarios. First, we simulate pension contributions following the rules that limit pensionable income. Then, we repeat the simulation treating all labor income as pensionable. This allows us to illustrate how the limits to pensionable income affect the distributions of pension entitlements. To give equal weight to earnings and pension income, we set $v = 0$.

For men, we find that pension entitlements of both college groups are more prone to truncation at the upper limits to pensionable income. This reduces the overall variability of pension entitlements. We find that workers with less than high school education display a higher variability of entitlements than both high school educated and college-educated groups. Since individuals with less than high school education have lower average earnings, they experience fewer years when earnings exceed the upper limit to pensionable income. If all earnings qualify as pensionable income, we find that the distributions of pension entitlements resemble the log-normal distribution of lifetime income found in Figure 8 and that more educated workers get higher variances in pension entitlements.

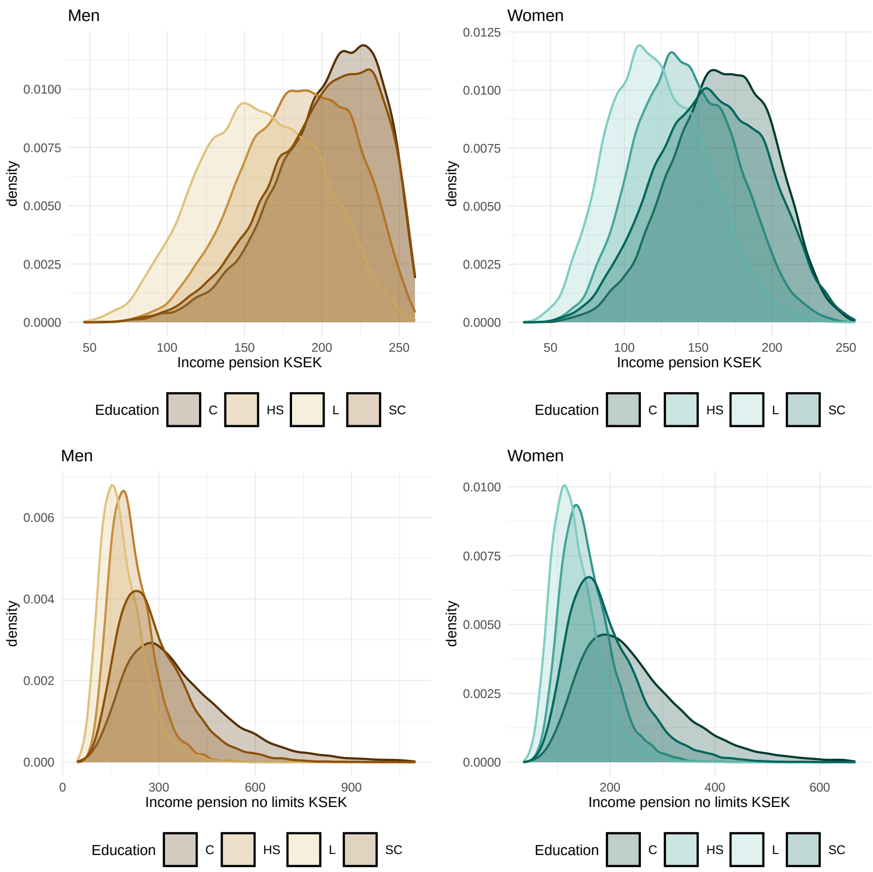

Figure 7: Distribution of male and female pension entitlements across education groups (birth cohort 1970) in thousands of SEK (KSEK).
Note: The education groups are: less than high school (L), high school (HS), some college (SC), and college (C). Top figures depict pension income when pensionable income is truncated. Bottom figures depict pension income when pensionable income is not truncated. For readability, we cut the top 0.1% of the unbounded pension income distribution.

The pension entitlements for men and women follow the same overall pattern. However, college-educated women are not as affected by the upper limit to pensionable income as their male counterparts. Ultimately, the differences in pension income variances between education groups are less pronounced for women than for men.

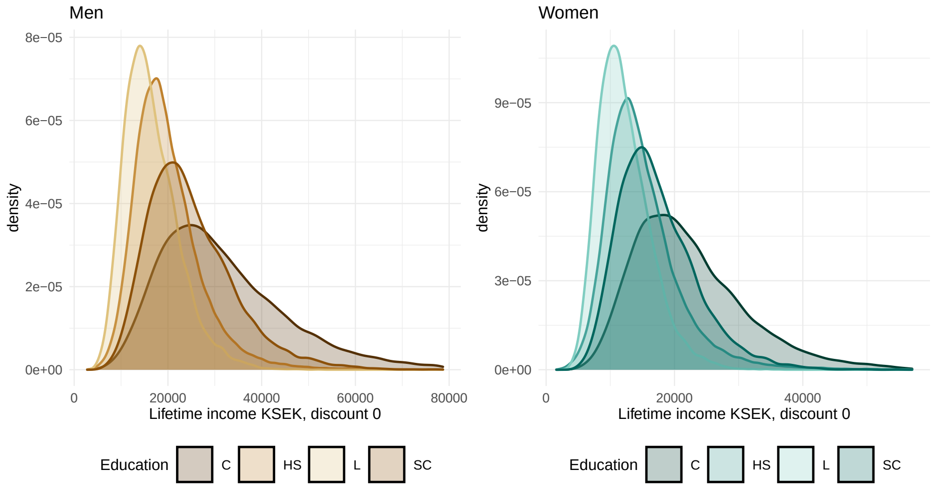

Figure 8: Distribution of male and female lifetime income across education groups birth cohort 1970) in thousands of SEK (KSEK).
Note: The education groups are: less than high school (L), high school (HS), some college (SC) and college (C). For readability, we cut the top 0.1% of these distributions.

7.3 Sensitivity

In this section, we study how the parameter values of our model affect the distributions of pension entitlements and lifetime income by varying parameter values of our model. We use high school-educated men and women born in 1970 for these simulations. Figure 9 illustrates the results.

We start by studying the effects of changing the variances of the permanent and transitory shocks. We consider three values for the variances, ranging from "low" to "high:" [0.05,0.2,0.4]. Since pension entitlements are derived from lifetime earnings, we expect permanent earnings differences to contribute more to the distribution of entitlements than transitory earnings. For men, we find that an increased permanent variability widens the distribution of pension entitlements, while an increased transitory variability contracts the distribution. This can be explained by the limits to pensionable income. If the variability of shocks increases, individuals with earnings above the upper limit of pensionable income will more often face negative shocks large enough to push their earnings below the upper truncation. The result is that more individuals will register earnings within the range qualifying as pensionable income. An increased transitory variance does not contract the distribution of pension entitlements of women to the same extent as men. This is reasonable since women have lower average earnings.

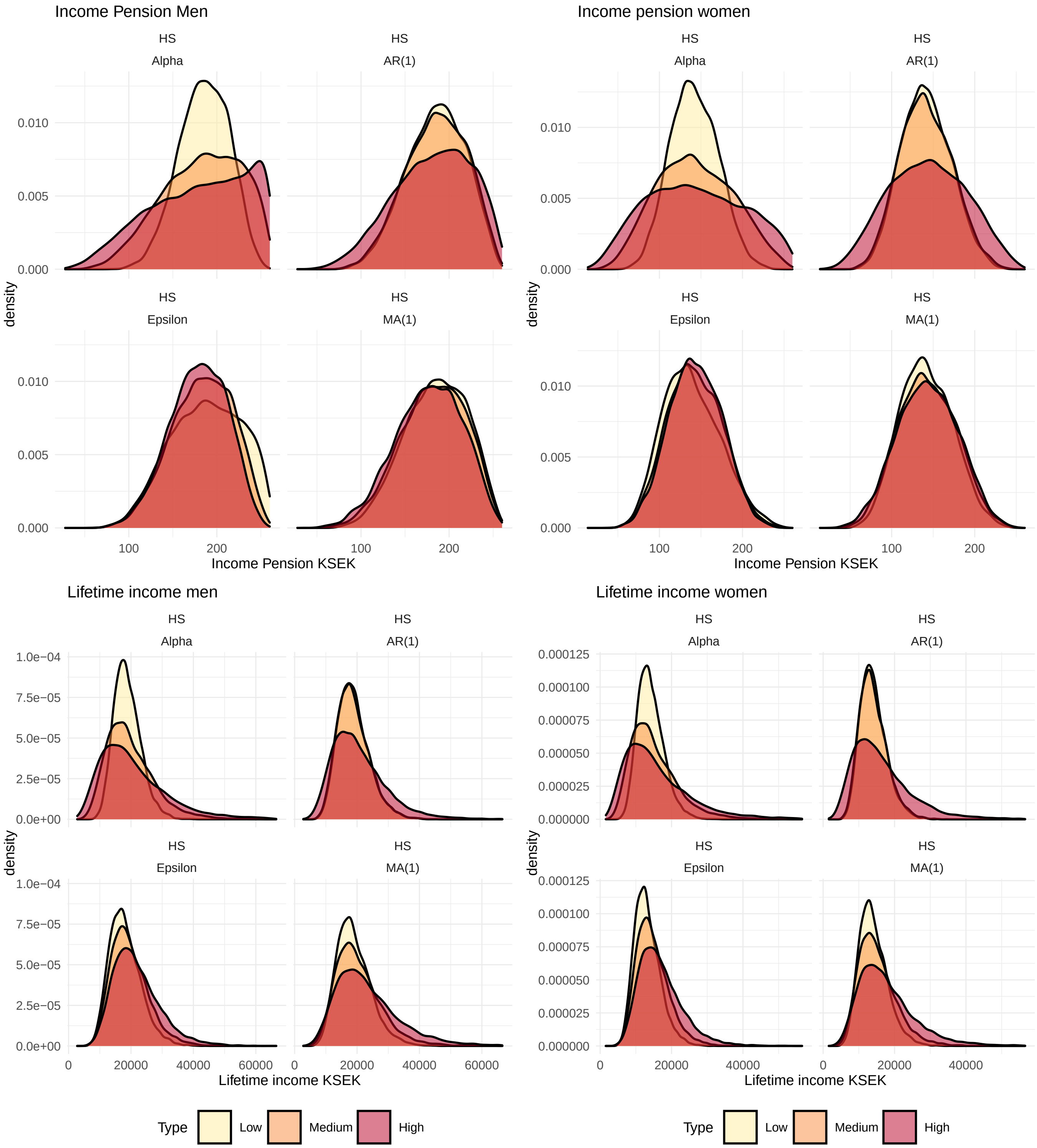

Figure 9: Pension- and lifetime income sensitivity birth cohort 1970) in thousands of SEK (KSEK).

Note: The top 0.1% of lifetime income distributions have been truncated. Alpha = variance in permanent component, AR(1) = autoregressive parameter, Epsilon = variance of transitory shocks, MA(1) = moving average parameter. Baseline parameterization follows from the strict selected male and female samples of the 1970 birth cohort with high school education. For Alpha and Epsilon: Low = 0.05, Medium = 0.2, High = 0.4. For AR(1): Low = 0.1, Medium = 0.5, High = 0.9. For MA(1): Low = -0.5, Medium = 0, High = 0.5.

We find that an increased permanent- or transitory earnings variance increases the lifetime inequality for both men and women. Since earnings constitute the largest share of lifetime income in our income measure, the increase in earnings inequality dominates the equalizing effect of an increased transitory variance on the distribution of pension entitlements.

Studying the effects of changes to the ARMA parameters, we vary ρ between the following values: [0.1,0.5,0.9]. Our analysis shows that even mean-reverting shocks affect the accumulation of pension entitlements. When the persistence of shocks is high enough, the distribution of pension entitlements and lifetime income is characterized by fatter tails, with a more distinct censoring at higher entitlement amounts. This results from a finite working life.

The effects of changing θ are less obvious. To interpret the results, we note that the sign of θ matters for the size of the variance of the transitory component. Our estimates suggest that θ is negative. In this sensitivity analysis, we will modify both the size and the sign of θ. We consider the following values: [-0.5,0,0.5]. If $\rho > |\theta|$, a negative θ will reduce the variance of the transitory component.[29] As a result, a lower value of θ results in a lower variability of lifetime income.

7.4 Lifetime inequality

This section studies the relative importance of permanent earnings differences and earnings volatility in explaining pension- and lifetime uncertainty. We present a variance decomposition based on total lifetime uncertainty in the spirit of Storesletten et al. (2004), but with the addition of simulated pension income in the lifetime income measure. From equation (7), the variance of the present value of the future income of individual i of birth cohort c becomes:

$$\text{Var}\left[\sum_{h=25}^{65} \Upsilon(h)\exp(\hat{y}_{c,i,h}) + \sum_{h=66}^{80} \Upsilon(h) Y^{p}_{c,i,h}\right]. \tag{8}$$

First, we decompose lifetime variance and then the variance of pension income. For each decomposition, we run three simulations based on Equation (9). In the first simulation, we set the variance of the permanent component to zero. We repeat the simulation with the variances for the transitory component set to zero. Then we compute the ratio of the

[29] See Appendix D, equation (16).

variances produced by these simulations with the total variance to calculate their relative contribution to lifetime inequality. Following Storesletten et al. (2004) we set the discount rate $\upsilon = 4\%$. The results are presented in Table 3.

	1956	1960	1965	1970	1975	1980
Less than HS Men	85.6	82.4	80.4	78.6	61.2	57.8
	(87.5)	(85.4)	(84.5)	(84)	(79.5)	(78.6)
Less than HS Women	80.3	77	73.1	70.4	54.1	50.4
	(83.1)	(78.7)	(76)	(73.8)	(68.9)	(68)
High School Men	86.3	84.2	83.5	82.5	72.2	62.8
	(89.7)	(88.4)	(87.9)	(87.1)	(84.5)	(81.1)
High School Women	79.5	80	78.1	75.5	62.1	49.4
	(84.3)	(82.4)	(81)	(79.2)	(73.6)	(68)
Some College Men	87.6	86.3	85.8	82.1	60.2	36.4
	(91.9)	(90.5)	(90.3)	(88.3)	(84.2)	(77.6)
Some College Women	87.4	85.2	82.3	81.6	58.3	35
	(88.9)	(87.6)	(85.9)	(86.1)	(80.7)	(70.8)
College Men	84	84.5	79.1	72.7	62	7.1
	(90.6)	(88.6)	(84.9)	(79.6)	(74.2)	(59.2)
College Women	83.1	77.8	72	69.3	43.6	13.4
	(86.5)	(83.7)	(80.7)	(78.7)	(75)	(60.4)

Table 3: Relative contribution (%) of permanent shocks to lifetime income variance and pension income variance, for specific birth year cohorts in the strict samples.
Note: Relative contributions to pension income are presented within parentheses. The contribution of transitory shocks are by construction 1 - the contribution of permanent earnings.

For most groups, we find that the permanent earnings differences contribute relatively more to lifetime income variance than earnings risk. For men, the transitory component only dominates among college-educated born in 1980. For women, the transitory component also dominates among individuals with high school education born in 1980, and among the college-educated born in 1975. We find the permanent component to contribute less to lifetime inequality among women than men when comparing education and birth cohort samples.

For all groups, permanent earnings contribute more to pension income variability than to lifetime income variability. The relative contributions vary across groups. For people born in 1980, the contribution of earnings risk to pension income uncertainty ranges from 18.9-40.8% for men. The corresponding range for women is 29.2-39.6%.

For men with less than high school education born in 1956 the contribution of the permanent component to the lifetime income uncertainty is 85.6%. For pension income uncertainty, the contribution is 87.5%. Taking the ratio, we conclude that earnings risk contributes 2.2% less to pension income uncertainty than to lifetime income inequality. Performing the same calculation for college-educated men born in 1980, we find that earnings risk contributes 89.5% less to pension income uncertainty than to lifetime income inequality. This difference could be explained by younger workers being more mobile between workplaces. Due to part-time work during the school years, young college-educated workers also have a larger variation in hours worked.

We conclude that the pension system reduces the impact of earnings risk, but accentuates the role of permanent earnings differences in determining lifetime income variability. However, the impact of earnings risk on pension income uncertainty is not negligible, especially among the younger cohorts.

8 Conclusions

This paper studies the role of permanent- and transitory earnings for earnings-, pension-, and lifetime inequality in Sweden. We estimate an error components model using earnings data from administrative records for Swedish workers born in 1956-1981 over the years 2002–2015. We then simulate life-cycle income to study how the different components of the earnings process contribute to the distribution of pension- and lifetime income.

Our results suggest that earnings shocks are of moderate persistence, with the AR(1)-parameter in the range of [0.627,0.704] for women, and [0.693,0.74] for men. Although our model is parsimonious, it manages to explain the patterns found in the data and yields parameter estimates that are consistent across different education groups, sample selection criteria, and gender.

From simulations of pension and lifetime income, we find that transitory earnings volatility contributes less to the variance of pension income than to the variance of earnings and lifetime income. We find that earnings volatility can narrow the pension income distribution. Furthermore, we find that the within-group variability of pension entitlements is lower among the college-educated workers than less-educated groups. Both findings can be explained by pension contributions being truncated by an upper limit within the Swedish pension system. Our findings suggest that the pension system provides some insurance against earnings risk, but accentuates the role of permanent earnings differences in determining lifetime inequality.

Our results on earnings inequality show that permanent earnings inequality increased between 2002–2010 for men and women. The trend of increased permanent inequality during the 1990s documented by Gustavsson (2007) may have continued up until the aftermath of the financial crisis. The financial crisis implied a temporary increase in earnings risk, except for workers with a college education. We find that both permanent and transitory inequality decreased between 2010–2015.

The model we use only captures the earnings dynamics among individuals in employment. A suggestion for future studies is to extend the model of earnings dynamics to include transitions between employment and unemployment. Such a model could be used to study how long-term unemployment spells affect pension income inequality and lifetime inequality.

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