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Working Paper

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Working Paper, No. 2008:14

Provided in Cooperation with:

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Suggested Citation: Gustavsson, Magnus (2008) : A longitudinal analysis of within-education-group earnings inequality, Working Paper, No. 2008:14, Uppsala University, Department of Economics, Uppsala,
<http://nbn-resolving.de/urn:nbn:se:uu:diva-86784>

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Working Paper 2008:14

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A Longitudinal Analysis of Within-Education-Group Earnings Inequality

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Working paper 2008:14
December 2008
ISSN 1653-6975

LONGITUDINAL ANALYSIS OF WITHIN-EDUCATION-GROUP EARNINGS INEQUALITY

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A Longitudinal Analysis of Within-Education-Group Earnings Inequality*

December 5, 2008

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Abstract

Using a large Swedish longitudinal database for the period 1982–2005, I estimate and compare within-group inequality in persistent and transitory earnings among men with high-school and college degrees. Analyses of inequality over the life cycle reveal that experience-variance profiles of persistent earnings are very similar across the two education groups and also consistent with standard human capital models of on-the-job training. Transitory earnings shocks display a marked U-shaped variance pattern over the life-cycle for both groups, but are clearly larger for high-school graduates and also account for a larger proportion of their overall variance. Analyses of changes in within-group inequality over time, holding life-cycle effects constant, show that high-school and college graduates have been subject to similar trend growths in both persistent and transitory earnings differentials between 1982 and 2005.

Keywords: Permanent inequality; Earnings instability; Life-cycle earnings; Schooling

JEL classifications: C33, D31, J39

* I am thankful for comments and suggestions from Per-Anders Edin and seminars participants at Uppsala University, SOFI, and the ESOP-Workshop on Wage Inequality in Oslo. Financial support from the Jan Wallander and Tom Hedelius Foundation is gratefully acknowledged.

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1. Introduction

It is well established that pay differentials within rather than between education groups account for most of the variation in earnings. Results from Mincerian earnings equations across time and countries have demonstrated that differences across workers in educational attainment, controlling for labor market experience, generally only explain around one third of the overall variance. Within-education-group inequality, or “residual inequality”, also explains the bulk of the rise in earnings dispersion observed in many OECD-countries during the 1980s and 1990s, including that of Sweden and the US (see e.g. Katz and Autor, 1999; Autor *et al*, 2005; Domeij, 2008).

However, even though a thorough knowledge of pay differentials among workers with the same educational attainment is a prerequisite for a full understanding of inequality in the labor market, very little is actually known about the longitudinal properties of these differentials. With a longitudinal perspective on inequality, earnings dispersion at a single point in time can be decomposed into two markedly different components: one that captures systematic and persistent pay differences across individuals and another that simply reflects individuals’ transitory and stochastic earnings fluctuations (see e.g. Atkinson *et al*, 1992). The relative weight of these two components is obviously crucial for interpretations and comparisons of within-education-group inequality; while persistent differentials imply enduring and systematic differences in labor market outcomes, short term earnings fluctuations simply reflect temporary luck.

The aim of this paper is to increase our knowledge of the longitudinal properties of within-education-group inequality. Utilizing a large Swedish longitudinal dataset spanning the period 1982–2005, I estimate detailed experience- and time-varying covariance models of persistent and transitory earnings separately for men with high-school and college degrees. This approach – made possible by the large dataset – allows me to estimate persistent and transitory inequality at each stage of workers’ life-cycles. It also allows me to decompose year-to-year changes in cross-sectional inequality into its persistent and transitory components while at the same time holding life-cycle effects constant. Though several previous studies have utilized high-quality longitudinal data and covariance models to separate life-cycle effects from time effects in the year-to-year evolution of persistent and transitory inequality

for all workers grouped together, this paper is (to my knowledge) the first to perform such an analysis for inequality among individuals with the same educational attainment levels.¹ In addition, this paper also shows how comparisons of results across two groups of individuals can be simplified by a straightforward re-formulation of the econometric specification used in previous studies.

Previewing the main results, experience-variance profiles of persistent earnings are very similar across high-school and college graduates, and are generally upward sloping with the steepest increase at the end of workers' careers. The minimum distance estimates underlying these profiles show that individuals' life-cycle earnings are consistent with predictions from human capital models of on-the-job training: men with lower initial earnings have rapid early earnings growth, which in turn is associated with more curvature in the earnings profile later on. Transitory earnings fluctuations, on the other hand, display a marked U-shaped variance pattern over the life-cycle for both education groups, but are clearly larger for high-school graduates and also make up a larger share of their overall variance. The analysis of changes in inequality over time, holding life-cycle effects constant, shows that high-school and college graduates in Sweden have experienced marked and similar trend-increases in persistent and transitory earnings differentials during the period 1982–2005.

Previous studies of the longitudinal properties of within-education-group inequality are scarce. Most of what is known is from the US study by Gottschalk and Moffitt (1994). In their work, persistent earnings are defined as an individual's average earnings over a 9-year period and transitory earnings are the year-specific deviations from this 9-year average. Based on the survey PSID for the years 1970–87, they find a negative relationship between earnings instability and schooling but no stable correlation between schooling and persistent inequality.² Their limited sample size does however not allow them to estimate how the two inequality components vary with labor market experience or to draw any inference about

¹ Pioneer studies in using covariance models to decompose inequality into persistent and transitory components include Lillard and Weiss (1979), Hause (1980), and MaCurdy (1982). More recent studies include Moffitt and Gottschalk (1995, 2002), Baker (1997), and Haider (2001) for the US; Dickens (2000), Ramos (2003), and Kalwij and Alessie (2007) for the UK; Baker and Solon (2003) for Canada; Cappellari (2004) for Italy; Gustavsson (2007, 2008) for Sweden; Doris *et al* (2008) for Ireland; Myck *et al* (2008) for Germany; and Daly and Valetta (2007) for Germany, UK, and US.

² A recent study by Drewianka (2008), which focuses solely on transitory inequality, confirms the negative relationship between educational attainment and earnings instability in the US labor market. Gottschalk and Moffitt's research also indicates higher levels of persistent and transitory inequality among all education groups in the 1980s than in the 1970s.

individuals' underlying earnings processes. Where comparable, the conclusions in this paper regarding persistent and transitory inequality across education groups are well in line with the results in Gottschalk and Moffitt (1994).

The rest of this paper proceeds as follows. The next section describes the data and the sample construction. Section 3 describes the parametric models and the estimation method. Section 4 contains the results. The paper ends with concluding remarks.

2. Data and sample construction

The data come from the Swedish longitudinal database LINDA, constructed to be cross-sectionally representative of the Swedish population each year (Edin and Fredriksson, 2000). The database is large; it contains 3.35 percent of the Swedish population, amounting to around 300,000 individuals. All information, including educational attainment, is based on administrative registers, which confers several advantages compared to an analysis based on survey data. First, there is no outflow apart from death or migration, so the data are free of the kind of sample attrition common in surveys. Second, the data is highly reliable; information from administrative registers is likely to be better than the recall of individuals.

The measure of earnings used in the analysis contains earnings from all jobs, including self-employment, held by an individual during a calendar year. Information on individuals' earnings stems from employers' mandatory reports to government tax authorities.

For the analysis, I include men who have either a high-school school degree ("gymnasium examen") or a college degree. The restriction to males is because of large changes in female labor force participation rates during the sample period and because of women's weaker attachment to the labor force due to child bearing and parental leave; the exclusion of women is standard in the literature on earnings dynamics.

Separately for the two education groups, individuals are categorized into three-year birth cohorts and followed over the period 1982–2005.³ For men with a high-school degree (*high-*

³ The LINDA database stretches back to 1968, but prior to 1982 only contains earnings for individuals obligated to fill a tax report. As the tax threshold is quite high in some years (see Gustavsson, 2008), it is more likely that a

school henceforth), I include cohorts who are between the ages of 20 and 59 for at least 7 years between 1982 and 2005. For men with a collage degree (*college* henceforth), the same procedure is applied with the difference that they have to be at least 25 years old.⁴ Cohorts can be present in the sample between 7 and 24 years depending on their date of births. In total, there are 17 cohorts for *high-school* and 16 for *college*.

The goal is to include only individuals with a constant educational attainment level in the sample. That is, individuals with an observed switch between high-school and college (or some other change) are excluded altogether from the analysis. However, unobserved changes of individuals' highest educational attainment may occur prior to 1991, since this is the first year that high quality data on schooling is available in LINDA; the level of schooling in 1991 therefore have to be merged to the 1982–90 data.

All positive earnings observations for each individual are included in the analysis, allowing individuals to re-enter the panel if they do exit.⁵ The end result is an unbalanced sample as some individuals die or migrate abroad during the sample period and some do not have positive earnings for all years.⁶

For each cohort, Table 1 presents the sample period, initial level of potential labor experience, and sample size; potential labor market experience is calculated as years since age 20 and 25 for *high-school* and *college*, respectively. In total, the *high-school* and *college* samples consist of 34,343 and 17,352 individuals, respectively; this should be compared to the total sample size, i.e. all education groups pooled together, of 2,730 individuals from PSID used in the most comparable US study by Gottschalk and Moffitt (1994). Table 1 also contains

college than a high-school educated individual was obligated to fill a tax report. Since this selection would confound a comparison of the two groups, I choose to start the analysis in 1982 as this still gives 24 years of earnings.

⁴ To demonstrate the procedure, for *high-school*, the youngest cohort is aged 20–22 years in 1997 (born 1975–77), the next youngest is aged 20–22 in 1994 (born 1972–74), and so on down to the oldest cohort, aged 50–52 in 1982 (born 1930–32).

⁵ As explained in Haider (2001), including the zeros would combine the analysis of earnings with the dynamics associated with the extensive and intensive margins of working during a year, making the results harder to interpret. As the analysis is based on the log of earnings, there is also the mechanical difficulty associated with using logarithms with zeros. Excluding the zeros is also standard in the literature.

⁶ As variances and covariances are sensitive to outliers, I have excluded very low levels of annual earnings from the sample. Based on the separate year-specific distributions for the two education groups, earnings below the lowest 0.1 percentile have been excluded from the analysis in each year. In general, this affects individuals with annual earnings below 1000 real SEK in 2005 value, corresponding to approximately 100 euro and 120 dollars. As it turns out, however, this exclusion does not alter any conclusion but results in somewhat more precise estimates. Results from estimates where all earnings are included are available on request.

Table 1: Cohorts included in the sample

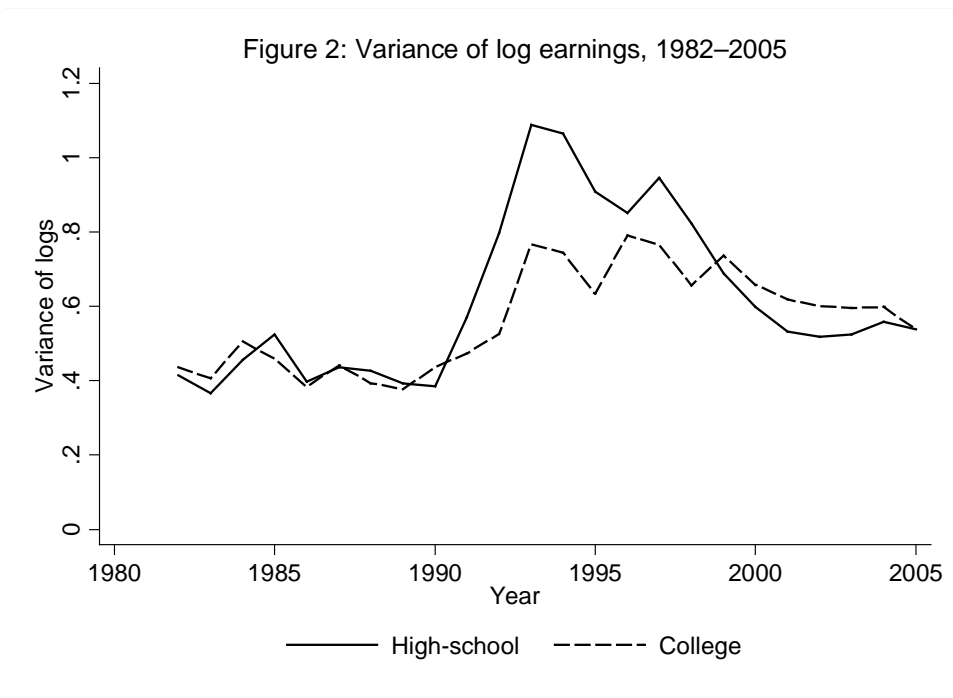
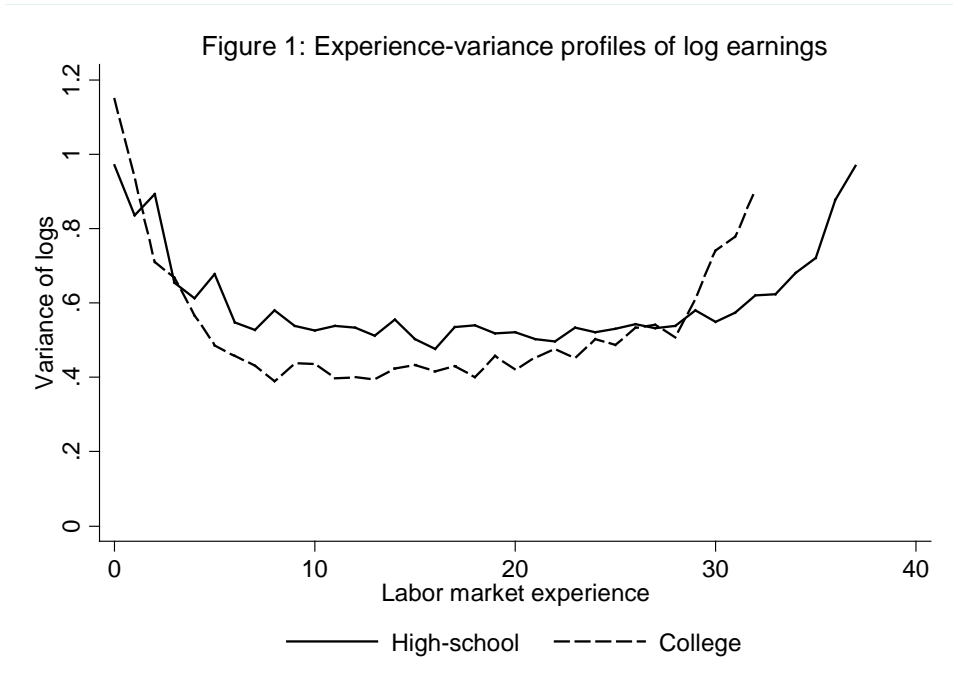
<i>Birth year</i>	High-School						College					
	Years observed	Experience in initial year	Sample size	% included all years	% included all but 1 year	% included all but 2 year	Years observed	Experience in initial year	Sample size	% included all years	% included all but 1 year	% included all but 2 year
1930–32	1982–89	30	1,122	89.57	4.99	1.16	1982–89	25	526	94.68	2.28	0.95
1933–35	1982–92	27	1,162	87.44	4.56	2.32	1982–92	22	621	94.36	3.22	0.64
1936–38	1982–95	24	1,289	80.14	6.98	4.27	1982–95	19	743	89.23	4.44	3.77
1939–41	1982–98	21	1,535	78.57	7.30	3.39	1982–98	16	816	85.91	4.17	2.70
1942–44	1982–01	18	2,177	80.29	6.11	3.17	1982–01	13	1,305	84.98	5.36	2.91
1945–47	1982–04	15	2,363	77.32	6.52	3.98	1982–04	10	1,402	84.88	5.28	2.14
1948–50	1982–05	12	2,302	77.98	6.69	2.87	1982–05	7	1,439	84.92	5.56	3.34
1951–53	1982–05	9	2,206	78.29	7.52	3.31	1982–05	4	1,399	87.92	5.22	2.07
1954–56	1982–05	6	2,234	78.11	7.07	3.76	1982–05	1	1,349	84.88	7.19	2.22
1957–59	1982–05	3	2,336	77.83	7.62	3.55	1984–05	0	1,241	85.25	7.49	2.42
1960–62	1982–05	0	2,392	76.00	9.07	3.93	1987–05	0	1,142	86.43	6.92	2.89
1963–65	1985–05	0	3,017	76.07	9.55	4.47	1990–05	0	1,136	88.03	5.37	2.99
1966–68	1988–05	0	3,022	79.95	9.07	3.44	1993–05	0	1,306	83.38	8.27	3.75
1969–71	1991–05	0	2,808	76.21	10.72	4.52	1996–05	0	1,373	85.07	8.08	3.50
1972–74	1994–05	0	2,560	73.40	13.01	5.94	1999–05	0	1,554	84.88	8.49	2.77
1975–77	1997–05	0	2,289	78.37	11.75	4.33	-	-	-	-	-	-
<i>Total</i>			34,343						17,352			

Note: Experience is defined as years since age 20 and 25 for *high-school* and *college*, respectively.

information on the percentage of individuals in each cohort that are, in turn, included in all their potential sample years, all but one year, and all but two years. For instance, for *high-school* and the cohort born 1930–32, 89.57 percent fulfill the requirement of being alive, living in Sweden, and having positive earnings in all their sample years (1982–89), 4.99 percent fulfills these requirements in all but one year, and 1.16 percent in all but two years. Compared to studies that use long panels of individual earnings collected through surveys, the share of individuals with consecutive earnings observations in my sample must be considered very high. For instance, in the U.K. study of earnings dynamics by Dickens (2000) it is reported that *half* of the individuals in a given cohort have *permanently* disappeared from the sample after 20 years. Fitzgerald *et al* (1998) also testify to extensive sample attrition in the PSID. It should however be noted that Table 1 reports more missing observations among *high-school* than *college*. The difference is moderate though, and it appears unlikely that it should have any profound effect on the final results.

Besides men with a high-school or a college education, it can perhaps be argued that those with only a compulsory education (9 years of schooling) should be added as a third group to the analysis. There are however two technical reasons for excluding these individuals. First, very few born in Sweden after the 1950s have compulsory education as their highest attainment level, making it hard to calculate reliable sample moments to be used in the minimum distance estimation. Second, younger individuals with compulsory education are much more prone to have records of zero earnings; only between 25 and 50 percent of these individuals have positive earnings during all their potential sample years (numbers are not shown but are available on request). This extent of intervening years with zero earnings makes it hard to interpret and compare the final results: while variances in year t and $t-s$ will be based on all individuals with positive earnings in each of these years, the auto-covariance for these two years will be based only on those individuals with positive earnings in both years. With many missing values, the calculated variances and auto-covariances may thus be based on individuals with markedly different labor market attachments.

To investigate the properties of the used sample and to get an overview of earnings inequality in Sweden, Figure 1 displays the experience-variance relationship of log earnings in the samples; the numbers are obtained by calculating experience-specific variances for each cohort and then averaging these over all cohorts. The variances are similar across the two



groups, with a strong initial decline followed by a roughly constant dispersion up to the last years of experience after which it rises again.

Figure 2 further depicts the full variance of the log of annual earnings over time for the two samples, i.e. calculated across all experience levels. Both groups display larger inequality in 2005 than in 1982. Most notable is the sharp rise in inequality during the first years of the 1990s. This is to a large extent a reflection of the rapid rise in Swedish unemployment during

this time, with total unemployment increasing from 1.6 to 8.2 percent between 1990 and 1993.¹ Unemployment and the Swedish economy rebounded around 1997, with unemployment hovering around 4 percent from 2000 onwards.

3. Econometric model and estimation method

Let $Y_{ibt,e}$ denote the log of earnings in year t for individual i born in year b with educational attainment e . Then

$$(1) \quad Y_{ibt,e} = \mu_{bt,e} + y_{ibt,e},$$

expresses $Y_{ibt,e}$ as the cohort specific mean $\mu_{bt,e}$ for education category e in year t plus an individual specific deviation $y_{ibt,e}$ from that mean. The variable of interest in this study is relative earnings $y_{ibt,e}$.

To decompose inequality into persistent and transitory components, I use the following underlying model for y_{ibt} (for ease of exposition, the subscript e is dropped in what follows):

$$(2) \quad y_{ibt} = p_t(\alpha_i + \beta_i exp + \gamma_i exp^2) + \varepsilon_{ibt},$$

$$(3) \quad \varepsilon_{ibt} = \rho \varepsilon_{ib,t-1} + \lambda_i v_{ibt},$$

with

$$(4) \quad Var(v_{ibt}) = \delta_0 + \delta_1 exp + \delta_2 exp^2 + \delta_3 exp^3 + \delta_4 exp^4.$$

In equation (2), persistent relative earnings are captured by the product of an individual-specific quadratic function of potential experience $(\alpha_i + \beta_i exp + \gamma_i exp^2)$ and the year-specific factor loading p_t . A frequent interpretation is that the heterogeneous term

¹ For a detailed account of Swedish unemployment and non-employment, see Holmlund (2006).

$(\alpha_i + \beta_i exp + \gamma_i exp^2)$ is determined by skills, perhaps through differential human capital investment, and that p_t is the time-varying price of these skills; this choice of specification for persistent earnings is discussed in more detail below. Equation (3) models transitory earning as an autoregressive process with year-specific factor loadings λ_t on the idiosyncratic random shock v_{ibt} . The specification in (3) is motivated by overwhelming evidence from the literature that earnings fluctuations are serially correlated and that this can be captured by a low order autoregressive process (see e.g. Baker and Solon, 2003). Based on results in several previous studies (Baker and Solon, 2003; Gustavsson, 2007, 2008), equation (4) also allows for experience-heteroscedasticity in transitory earnings shocks. To clarify, the main statistical properties of the employed model for individual earnings are:²

$$(5) \quad E(\alpha_i \varepsilon_{ibt}) = E(\beta_i \varepsilon_{ibt}) = E(\gamma_i \varepsilon_{ibt}) = 0,$$

$$(6) \quad (\alpha_i, \beta_i, \gamma_i) \sim [(0, 0, 0); (\sigma_\alpha^2, \sigma_\beta^2, \sigma_\gamma^2, \sigma_{\alpha\beta}, \sigma_{\alpha\gamma}, \sigma_{\beta\gamma})],$$

$$(7) \quad \varepsilon_{ibt} \sim (0, \sigma_{\varepsilon, bt}^2).$$

The specification in (2) for persistent earnings assumes that experience-earnings profiles vary across individuals in a systematic way – a specification usually referred to as the “random profile model” (RPM) or “random growth model”. This specification is not uncontroversial though. An alternative, competing specification used in some studies is the “random walk model” (RWM), where individual’s persistent earnings instead are governed by stochastic permanent shocks over the work-life (see e.g. Moffitt and Gottschalk, 1995). I use the RPM for three reasons. First, a recent study by Guvenen (2007) indicates that the RPM is more consistent with individual consumption behavior than the RWM. Second, while the RWM has an atheoretical flavor to it, the RPM model can be motivated by well-established economic models, including human capital models of on-the-job training with heterogeneity in ability and investments across individuals (Mincer, 1974) or models with variations in earnings profiles for the purposes of effort extraction (Lazear, 1979, 1981). And third, the chi-squared

² See Moffitt and Gottschalk (1995) and Baker and Solon (2003) for a more detailed account of these kind of models.

goodness of fit statistic proposed by Newey (1985) suggests that RPM offers a better fit to the data in this study.³

Previous studies in the earnings dynamics literature that use the RPM have generally employed the linear version ($\alpha_i + \beta_i exp$).⁴ I use the more flexible quadratic specification for two reasons. First, Mincer's (1974) model of on-the-job training that motivates a quadratic function of experience in models of mean earnings – i.e. standard Mincerian earnings equations – also predicts that individual longer-term deviations from this mean should be governed by individual-specific quadratic functions of experience (Lillard and Reville, 1999). Second, the quadratic specification provides more information about individuals' life-cycle profiles. In particular, it is possible to learn more about the correlation between individuals' initial earnings, initial earnings growth, and the curvature of the earnings profile; information that in turn can be contrasted against predictions from basic human capital models of on-the-job training.

The parameters common to all individuals and the variances of the individual specific variables in equations (2)–(4) can be obtained by applying a minimum distance estimator (Chamberlain, 1984; Abowd and Card, 1989). In practice, this means that the theoretical expressions for the variance and auto-covariance of the underlying earnings model are fitted to the empirical counterparts.

Two issues need to be addressed before the minimum distance approach can be implemented in practice though. Firstly, the auto-regressive process for transitory earnings requires the estimation of initial transitory variances, i.e. parameters that capture the value of the transitory variance at the start of each cohort's sample period. I here follow the approach of Baker and

³ This statistic always favors the RPM over the RWM, even when a very flexible version of the RWM is used where the variance of the innovation process is only restricted to be the same for two years at a time, i.e. individuals with 1 and 2 years of experience have one variance, those with 3 and 4 years of experience have another variance, and so forth; see Gustavsson (2008) for an example of such a model. That is, even though this specification allows the covariance structure of persistent earnings to be determined by 18 and 16 parameters for *high-school* and *college*, respectively, where some parameters/variances even are (wrongly) allowed to be negative, the chi-square statistic still favors the covariance structure implied by the 6-parameter version of the RPM; these results are available on request. It should however be noted that Gustavsson (2008) reports a better fit for the flexible version of the RWM based on Swedish data for the period 1960–90. However, the earnings data used in that study is both top-coded and censored from below, and the age range of the included individuals is also much narrower; these features are likely to be the main explanation for the different result.

⁴ Two exceptions are Baker (1997) and Baker and Solon (1999), which both contain a brief discussion of results from a quadratic specification.

Solon (2003) and allow each cohort to have their own initial transitory variance. Since cohorts enter the sample at different experience levels and years, this set-up is necessary in order for the model to be fully consistent with experience heteroscedasticity in transitory shocks as well as with time variation in the dispersion of transitory earnings.

Secondly, when estimating the model in equations (2)–(4), it is not possible to separately identify the values of the factor loadings p_t and the covariance elements for α_i , β_i , and γ_i . Previous studies have therefore used a re-specified version of equation (2) along the lines of

$$(8) \quad y_{ibt} = \frac{p_t}{p_1} (p_1 \alpha_i + p_1 \beta_i \text{exp} + p_1 \gamma_i \text{exp}^2) + \varepsilon_{ibt} = \eta_t (\tilde{\alpha}_{i,1} + \tilde{\beta}_{i,1} \text{exp} + \tilde{\gamma}_{i,1} \text{exp}^2) + \varepsilon_{ibt},$$

where p_1 is the factor loading corresponding to the first sample year, $\eta_t = p_t / p_1$, and $\tilde{\alpha}_{i,1} = p_1 \alpha_i$, and so forth. This specification is, however, not ideal for making comparisons across two groups of individuals. Any straightforward comparison of, for instance, the evolution of persistent inequality over the life-cycle with accompanied statistical tests will be hard to conduct since the obtained estimates that pertain to variations in earnings profiles, $\sigma_{\tilde{\alpha}_i}^2 = \text{Var}(p_1 \alpha_i)$, $\sigma_{\tilde{\beta}_i}^2 = \text{Var}(p_1 \beta_i)$, and so forth, only are valid for the ‘price of skills’ in the first sample year. Only if the factor loadings for the two education groups display equal year-to-year changes will the comparison based on such estimates be straightforward for the whole period 1982–2005. As it turns out, however, this assumption is strongly rejected (see section 4).

To obtain comparable estimates that pertain to all sample years, I instead use the following re-specified version of equation (2):

$$(9) \quad y_{ibt} = \frac{p_t}{\bar{p}} (\bar{p} \alpha_i + \bar{p} \beta_i \text{exp} + \bar{p} \gamma_i \text{exp}^2) + \varepsilon_{ibt} = \pi_t (\bar{\alpha}_i + \bar{\beta}_i \text{exp} + \bar{\gamma}_i \text{exp}^2) + \varepsilon_{ibt},$$

where \bar{p} is the mean value of p_t over the sample period, $\pi_t = p_t / \bar{p}$ capture changes relative to the mean, and $\bar{\alpha}_i = \bar{p} \alpha_i$, and so forth. The resulting empirical factor loadings will capture

changes relative to the mean of the p_i factor loadings. The estimates of the variances and auto-covariances of $\bar{\alpha}_i$, $\bar{\beta}_i$, and $\bar{\gamma}_i$ will be an equally weighted function of all year-specific factor loadings over the sample period, since $\sigma_{\bar{\alpha}}^2 = Var(\bar{p}\alpha_i)$. This formulation of the model removes the arbitrariness associated with choosing a single year as ‘base year’. It also produces direct estimates of the variance in earnings profiles that are valid for all sample years, in the sense that they reflect averages over the period 1982–2005. In practice, the specification in equation (9) is implemented by imposing the restriction that the empirical factor loadings should have a mean equal to unity.

The same approach as in equation (9) is also used for the factor loading on the transitory shocks, λ_i . The estimates of the parameters in equation (4) will therefore reflect averages for the period 1982–2005, and will be denoted $\bar{\delta}_0, \bar{\delta}_1, \dots, \bar{\delta}_4$.

In the actual estimation, I follow the modern literature and use the equally weighted minimum distance estimator because of the poor finite sample properties of the optimally weighted counterpart (Altonji and Segall, 1996). To obtain the dependent variables, I calculate variances and auto-covariances separately for each education specific three-year birth cohort, which gives 2,991 and 2,499 distinct covariance elements for the high-school and college categories, respectively. Robust standard errors are calculated as outlined in Chamberlain (1984).⁵ As a measure of the goodness-of-fit, the chi-squared statistic proposed in Newey (1985) is reported for each model.⁶

4. Results

The model outlined in the previous section results in 73 estimated parameters for the *high-school* sample and 72 parameters for the *college* sample. Table 2 presents the estimates for the

⁵ Let the vector $\boldsymbol{\theta}$ contain all the parameters of the earnings model. Standard errors are then obtained from the formula $(\mathbf{G}'\mathbf{G})^{-1}\mathbf{G}'\mathbf{V}\mathbf{G}(\mathbf{G}'\mathbf{G})^{-1}$, where \mathbf{G} is the gradient matrix $\partial f(\boldsymbol{\theta})/\partial C$ evaluated at $\hat{\boldsymbol{\theta}}$ and \mathbf{V} is a block diagonal matrix containing the estimated covariance matrices for each cohort.

⁶ The chi-squared goodness-of-fit is computed as $\mathbf{u}\mathbf{Q}'\mathbf{u}' \sim \chi^2(df)$, where \mathbf{u} contains the residuals from the minimum distance estimation, and \mathbf{Q}' is a generalized inverse of $\mathbf{Q} = \mathbf{W}\mathbf{V}\mathbf{W}'$ with $\mathbf{W} = \mathbf{I} - \mathbf{G}(\mathbf{G}'\mathbf{G})^{-1}\mathbf{G}'$. Note however, that a general result in the earnings dynamics literature is that the null of a correctly specified model is rejected with this test, and this is especially true for studies that use large sample sizes (see e.g. Baker, 1997; Baker and Solon, 2003).

Table 2: Estimates of earnings dynamics: time and cohort invariant parameters

	High school	College	P-value, equal parameters
<i>Persistent component</i>			
$\sigma_{\bar{\alpha}}^2$	0.1629 (0.0115)	0.2054 (0.0177)	0.044
$\sigma_{\bar{\beta}}^2$	0.0018 (0.0002)	0.0029 (0.0004)	0.015
$\sigma_{\bar{\gamma}}^2 \cdot 10^4$	0.0112 (0.0018)	0.0238 (0.0042)	0.005
$\sigma_{\bar{\alpha}\bar{\beta}}$	-0.0044 (0.0016)	-0.0113 (0.0026)	0.026
$\sigma_{\bar{\beta}\bar{\gamma}} \cdot 10^2$	-0.0037 (0.0007)	-0.0076 (0.0013)	0.008
$\sigma_{\bar{\alpha}\bar{\gamma}} \cdot 10^2$	-0.0063 (0.0054)	0.0208 (0.0090)	0.009
<i>Transitory component</i>			
ρ	0.3952 (0.0049)	0.4668 (0.0086)	0.000
$\bar{\delta}_0$	0.6516 (0.0231)	0.6206 (0.0309)	0.130
$\bar{\delta}_1$	-0.0788 (0.0082)	-0.1185 (0.0122)	0.007
$\bar{\delta}_2$	0.0061 (0.0009)	0.0107 (0.0015)	0.006
$\bar{\delta}_3 \cdot 10$	-0.0021 (0.0003)	-0.0041 (0.0007)	0.007
$\bar{\delta}_4 \cdot 10^3$	0.0027 (0.0005)	0.00581 (0.0010)	0.001
Chi-square	5,266	3,592	

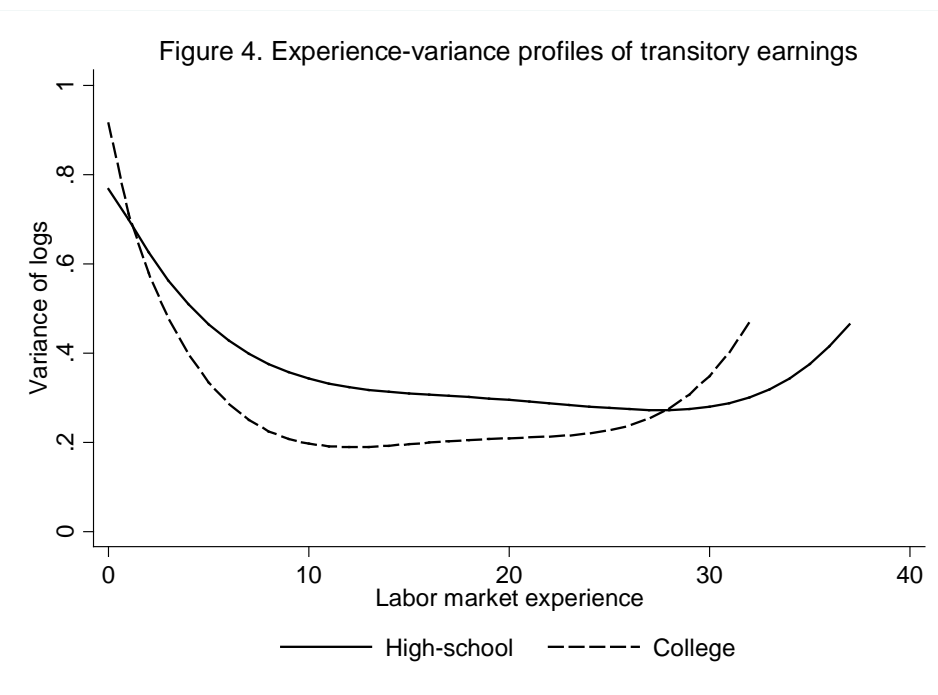
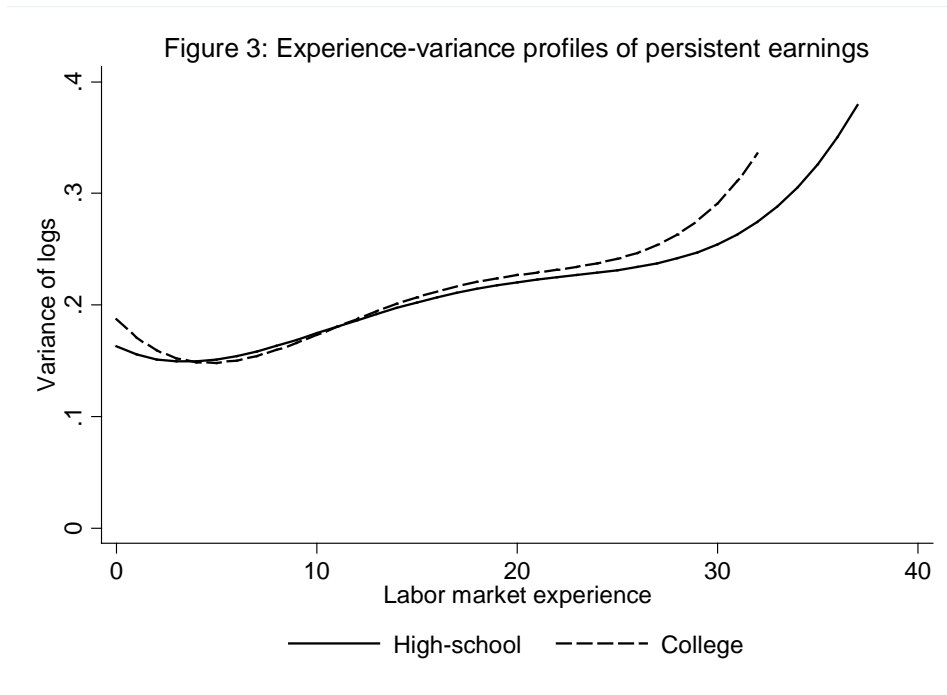
Notes: Each model is estimated by minimum distance and also includes year-specific factor loadings on the permanent component and on the transitory innovation, as well as initial cohort-specific transitory variances; these estimates are reported in Tables A1 and A2 in Appendix. Heteroscedasticity and auto-correlation robust standard errors are in parentheses. The estimates for high-school are based on 2,991 auto-covariance elements which in turn are based on 34,343 individual specific earnings observations. The estimates for college are based on 2,499 auto-covariance elements which in turn are based on 17,352 individual specific earnings observations.

time and cohort invariant parameters. First are the variances and covariances pertaining to the individual specific life-cycle profiles of persistent earnings: $\bar{\alpha}_i$, $\bar{\beta}_i$, and $\bar{\gamma}_i$. All these are statistically significantly different between *high-school* and *college*, as can be seen by the reported p-value from a standard F-test in the last column. Also, since most studies in the literature use a linear specification of individuals' life-cycle earnings, it should be observed that Wald-tests for both groups strongly reject the assumption $\sigma_{\bar{\gamma}}^2 = \sigma_{\bar{\alpha}\bar{\gamma}} = \sigma_{\bar{\beta}\bar{\gamma}} = 0$. Or in other words, statistical tests indicate that the linear specification is too restrictive.

The estimates of $\sigma_{\bar{\alpha}}^2$, $\sigma_{\bar{\beta}}^2$, and $\sigma_{\bar{\gamma}}^2$ – the variances in initial earnings and in the linear and quadratic earnings growth coefficients – are all larger for *college*. The estimated covariance between initial earnings and initial earnings growth, $\sigma_{\bar{\alpha}\bar{\beta}}$, is negative for both samples; this is consistent with human capital models of on-the-job training where workers face a trade-off between initial earnings and initial earnings growth. The estimate of $\sigma_{\bar{\beta}\bar{\gamma}}$ is negative for both groups. Within the framework of Mincer’s (1974) on-the-job training model, this implies that individuals with faster initial earnings growth on average also have more curvature in their life-cycle profiles.⁷ As explained by Lillard and Reville (1999), a negative $\sigma_{\bar{\beta}\bar{\gamma}}$ is also to be expected from Mincer’s model: more training early on in the career should be associated with a stronger initial earnings growth but also more curvature in the earnings profile later on. The estimate of $\sigma_{\bar{\alpha}\bar{\gamma}}$ is insignificantly different from zero for *high-school* but positive for *college*. Again, a positive value is consistent with the basic human capital model, since high initial earnings should be associated with less curvature in the earnings profile (through the slower initial earnings growth). The insignificant estimate of $\sigma_{\bar{\alpha}\bar{\gamma}}$ for *high-school* is thus the only estimate that is not fully supportive of the basic human capital model of on-the-job training. But since it is insignificantly different from zero, it can neither be taken as evidence against it.

The larger estimates of $\sigma_{\bar{\alpha}}^2$, $\sigma_{\bar{\beta}}^2$, and $\sigma_{\bar{\gamma}}^2$ for *college* is not enough to conclude that this groups has a larger dispersion in persistent earnings, since one must also take account of the contribution from the covariance elements $\sigma_{\bar{\alpha}\bar{\gamma}}$, $\sigma_{\bar{\alpha}\bar{\beta}}$, and $\sigma_{\bar{\beta}\bar{\gamma}}$. Figure 3 therefore depicts the full dispersion in persistent earnings over the life-cycle, using all variances and covariances of $\bar{\alpha}_i$, $\bar{\beta}_i$, and $\bar{\gamma}_i$ while holding factor loadings p_i at their mean value during 1982–2005, i.e.

⁷ To see clearly why a smaller value of $\bar{\gamma}_i$ is associated with more curvature, remember that individual i ’s full earnings are $Y_{ibt} = \mu_{bt} + y_{ibt}$. For simplicity, assume no cohort effects in Y_{ibt} and that $p_i = \bar{p}$. Mincer’s (1974) on-the-job training model then corresponds to $Y_{it} = (\bar{\alpha} + \bar{\alpha}_i) + (\bar{\beta} + \bar{\beta}_i)exp + (\bar{\gamma} + \bar{\gamma}_i)exp^2 + \varepsilon_{it}$, where $\bar{\alpha}$, $\bar{\beta}$, and $\bar{\gamma}$ are parameters that determine the average life-cycle profile of earnings, i.e. parameters in a standard Mincerian earnings equation. Since one of the most robust empirical result in economics is that $\bar{\beta} > 0$ and $\bar{\gamma} < 0$ – which also holds for the data in this study – a negative value of $\bar{\gamma}_i$ implies that individual i ’s earnings profile has more curvature than that of the average profile.



factor loadings are held constant at \bar{p} . It is clear that persistent inequality is in fact very similar across the groups. With the exception of the experience interval 29–32 years, the series are also statistically insignificantly different from each other at the 0.05-level (exact p-values are available on request). Except for the very lowest levels of experience, the experience–variance profiles are upward sloping with the steepest increase at the end of workers’ careers.

In Table 2, the estimates of the autoregressive parameter ρ and the parameters that allow for age heteroscedasticity in the variance of transitory innovations, $\bar{\delta}_0 \dots \bar{\delta}_4$, together make up the variance of transitory earnings over workers' careers through the auto-regressive process outlined in equations (3) and (4). Figure 4 graphs the predicted life-cycle profiles of this variance, again holding the factor loadings p_i constant at their mean value \bar{p} .⁸ Both groups have a marked U-shaped profile, similar to what is reported in Baker and Solon (2003) and Gustavsson (2007, 2008) based on samples where all education groups are pooled together. The variances are however clearly larger for *high-school* at all but the smallest and largest levels of experience; the differences across the two education groups are also statistically significant at all but 1, 2, and 27–29 years of experience.⁹ It should however be noted that the estimates of the autoregressive parameter ρ indicate that transitory shocks are less enduring for *high-school*; the estimate for *high-school* implies that 40 percent of a transitory shock remains after 1 year and that 6.4 percent remains after 3 years, while the estimate for *college* instead implies that 48 percent remains after 1 year and 11.1 percent after 3 years.

The predicted persistent and transitory variances in Figures 3 and 4 can be used to inform about their relative contributions to the total variance at different stages of workers' careers. Figures 5 and 6 display the experience-variance profiles of persistent and transitory earnings together with their sum (the total variance) for *college* and *high-school*, respectively. For both groups, it is clear that the notable U-shape of the total variance is largely attributable to stochastic and transitory earnings fluctuations. For *high-school*, transitory earnings makes up between two thirds and half of the total variance, except in the very first years on the labor market when it is larger. For *college*, transitory earnings also dominates the initial years but is then of roughly the same importance as the persistent variance.

⁸ Since transitory earnings follow an autoregressive process, a starting value of the transitory variance, i.e. a variance for individuals with zero years of experience, is needed in the predictions. As was discussed in section 3, the estimated models incorporate cohort-specific initial transitory variances; see Table A2 in Appendix for these estimates. As a starting value, I therefore use the average of the initial variances for those cohorts that enter the sample with zero years of potential experience. For *high-school*, this average is based on the estimates that pertain to cohorts born in the period 1960–77, whereas it for *college* pertain to cohorts born in the period 1957–74; see Table 1. This approach distracts – as far as possible – from time and cohort heterogeneity in the calculations.

⁹ Since the transitory variance is a non-linear combination of estimated parameters, standard errors have been calculated by the delta method.

Figure 5: Decomposition of the experience-variance profile of log earnings:
High-school

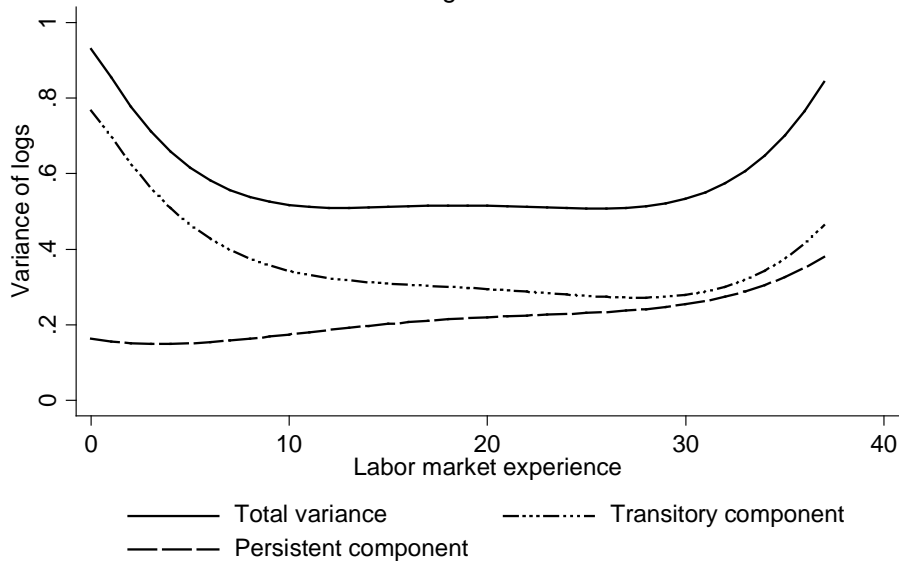
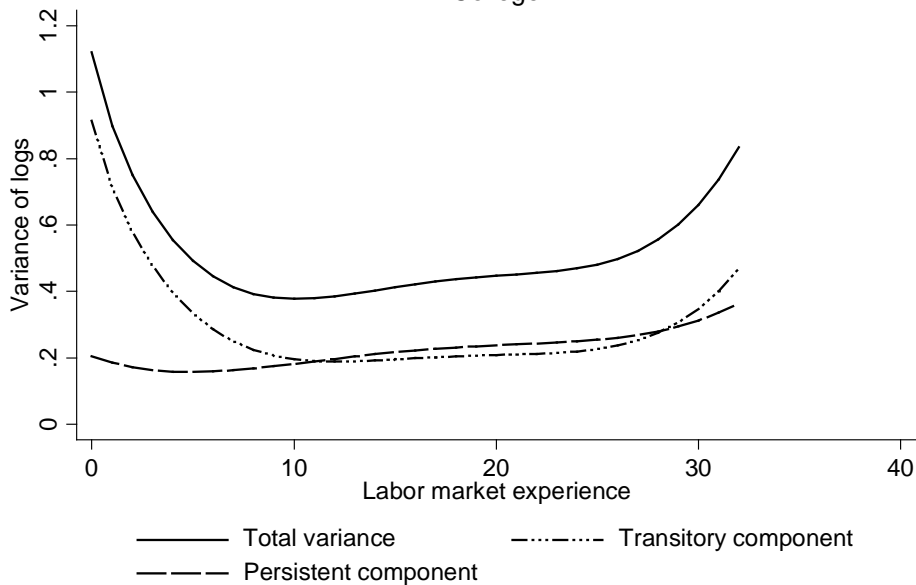
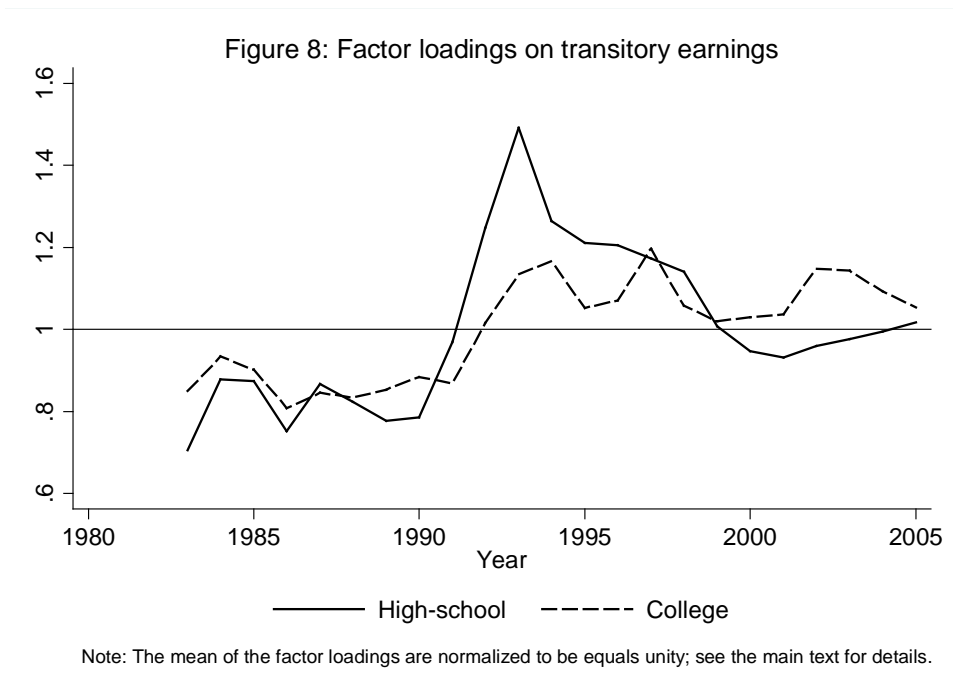
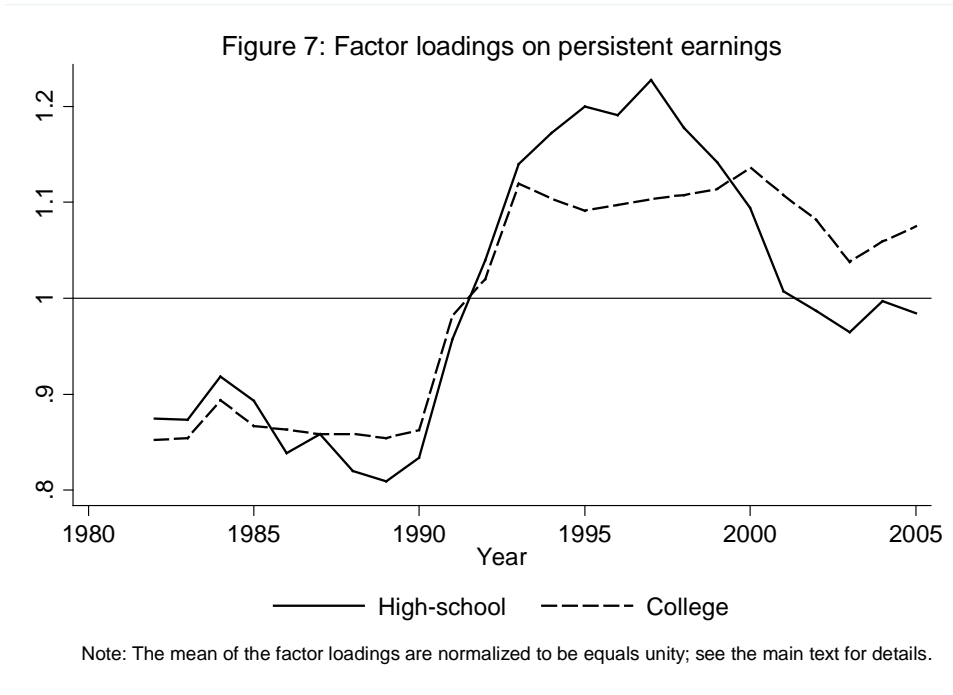


Figure 6: Decomposition of the experience-variance profile of log earnings:
College



While the analysis up to now have discussed persistent and transitory inequality over the life-cycle in terms of averages for the period 1982–2005, I next turn to the year-to-year evolution of these two components with life-cycle effects held constant. Table A1 in Appendix displays the factor loadings for the persistent component; all of these are precisely estimated. For identification, the mean of the factor loadings is normalized to unity, as was discussed in Section 2. Figure 7 provides time-series graphs of the estimates. Both groups display a clear upward shift in persistent inequality following the Swedish economic crisis of the early



1990s, suggesting important changes in the functioning of the labor market that have affected both groups.

Figure 8 displays a time-series graph of the factor loadings on the transitory innovation. Note that there are no estimates for 1982 because the innovation variance in this year must be left unrestricted in order to identify the initial variances of the cohorts, i.e. the transitory variance in a cohort's initial year is estimated by a single, separate parameter; see Table A2 in

Figure 9: Decomposition of the variance of log earnings, 1982–2005:
High-school, 20 years of experience

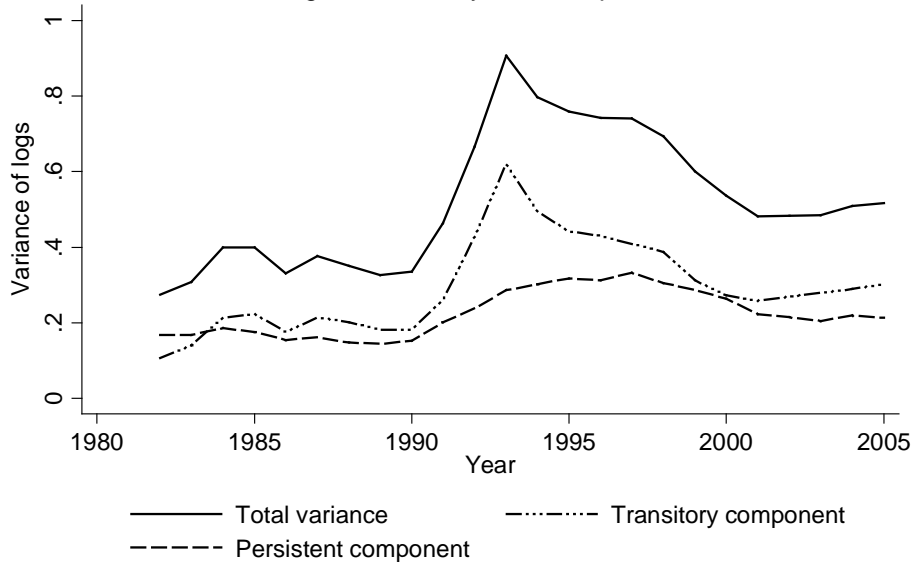
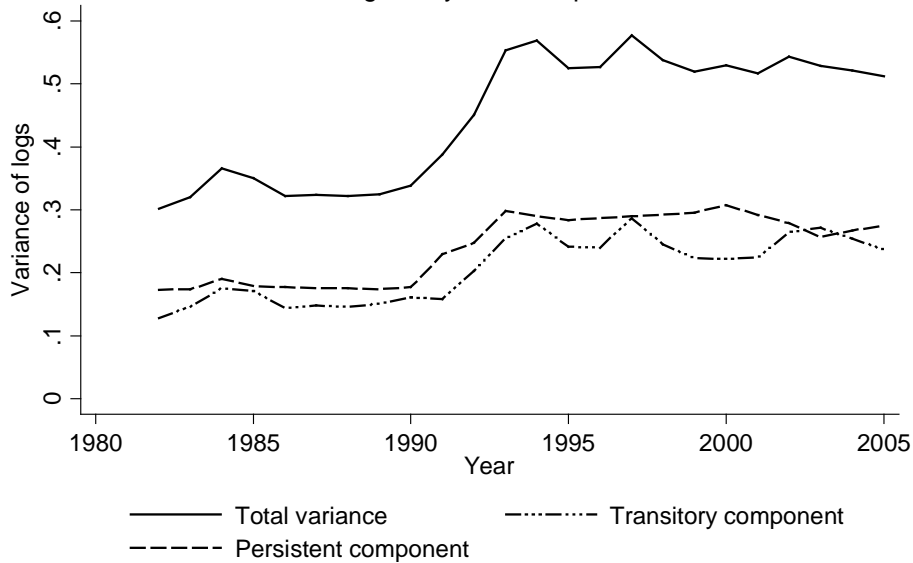


Figure 10: Decomposition of the variance of log earnings, 1982–2005:
College, 20 years of experience



Appendix. Interestingly, the time-series patterns of the factor loadings are similar to those on the persistent component, with upward shifts during the 1990s. There is however a more cyclical pattern for *high-school*, with a stronger increase during the recession of the early 1990s followed by a marked fall during the recovery in the second half of the 1990s.

The estimates in Tables 2, A1, and A2 can be used to predict the relative contribution of persistent and transitory earnings to the year-to-year changes in cross-sectional inequality, as

for instance is done in Baker and Solon (2003). To deduct from life-cycle variation, I predict inequality among men with 20 years of experience. This should paint a picture valid for men who are in the prime of their working career. Figures 9 and 10 display the predictions for *college* and *high-school*, respectively. In moving from year-to-year the factor loadings on each component change, and so do the cohort specific parameters.¹⁰

Figure 9 shows that variations in transitory earnings have been the major determinant of year-to-year changes in cross-sectional inequality among high-school graduates, whereas Figure 10 indicates that variations in permanent and transitory earnings have been equally important among college graduates; similar conclusions are also reached if the predictions are done for men with 10 or 30 years of experience (results are not shown but are available on request). Consistent with the results for the factor loadings, both groups have experienced a shift upward in both persistent and transitory inequality during the 1990s.

5. Concluding remarks

In this paper, I investigate and compare the longitudinal nature of within-group inequality among Swedish men with high-school and college degrees. Based on register data spanning the period 1982–05 combined with minimum distance estimates, it is shown that experience-variance profiles of persistent earnings are very similar across the two groups and also consistent with standard human capital models of on-the-job training. Earnings fluctuations displays a marked U-shaped variance pattern over the life-cycle for both groups, but are clearly larger for high-school graduates and also make up a larger part of their overall variance. The analysis of changes in inequality over time, holding labor market experience constant, shows that both groups have been subject to marked and similar trend growths in persistent and transitory earnings differentials between 1982 and 2005.

The very similar levels and life-cycle evolutions of persistent inequality among high-school and college graduates imply that longer-term labor market outcomes are equally heterogeneous across the two groups. Comparisons based on cross-sectional measures do

¹⁰ In fact, the cohort specific parameters change every third year. For example, predictions for *high-school* and the years 1982–84 employ the cohort specific estimate for the cohort born 1942–44, as members of this three-year birth cohort have 20 years of potential experience these years. For 1985–87, the estimate for the cohort born 1945–47 is used, and so forth.

hence not carry over to a longitudinal analysis, since such ‘snapshots’ instead indicate more heterogeneity among high-school graduates. However, this is not to say that the dispersion in transitory earnings is irrelevant. With workers who seek to smooth their consumption, uninsurable transitory earnings shocks will reduce individual welfare. Hence, to the extent that individuals are unable to insure against shocks, the lower inequality in transitory earnings among college graduates suggest that they, in addition to having higher average earnings than high-school graduates, also benefit from being less exposed to earnings instability.

An important finding in this paper is the very similar trend growths in persistent inequality across the education groups between 1982 and 2005. Given the marked increases in the returns to observable worker characteristics in Sweden during the 1990s (e.g. Domeij and Ljungqvist, 2006; Gustavsson, 2006), it is tempting to point towards a general rise in the price of unobserved worker skills as a likely explanation for this across-the-board rise. This, in turn, would be consistent with skill biased technical change along the lines discussed in Acemoglu (2002). This hypothesis also gains support for Sweden in Lindquist (2005) and in Domeij and Ljungqvist (2006). On the other hand, Nordström Skans *et al* (2008) show that most of the 1990s rise in Swedish earnings dispersion has occurred between rather than within firms, and they hypothesize that the move towards decentralized wage setting in Sweden has increased the importance of industry specific factors in individual earnings. That is, institutional changes in Sweden during the 1990s are another potential explanation for the trend-increase in persistent within-education-group inequality.

Suggesting hypotheses for the similar trend-growths in transitory inequality among high-school and college graduates is harder. But that persistent and transitory inequality tend to move in tandem could mean that the same underlying factors influence both short- and long-term inequality. In that case, skill biased technological change and decentralized wage bargaining could also be two explanations for the rise in earnings instability. Close to nothing is known about the relevance of such explanations for changes in transitory inequality though, and this is clearly an area that merits further attention.

References

- Abowd, J. and D. Card (1989), “On the Covariance Structure of Earnings and Hours Changes”, *Econometrica*, 57, 411–445.
- Acemoglu, D. (2002), “Technical Change, Inequality, and the Labor Market”, *Journal of Economic Literature*, 40, 7–72.
- Altonji, J. and L. Segal (1996), “Small-Sample Bias in GMM Estimation of Covariance Structures”, *Journal of Business and Economic Statistics*, 14, 353–366.
- Atkinson, A., F. Bourguignon and C. Morrisson (1992), *Empirical Studies of Earnings Mobility*, Harwood Academic Publishers, Chur.
- Autor, D., L. Katz and M. Kearney (2005), “Rising Wage Inequality: The Role of Composition and Prices”, Working Paper 11628, NBER.
- Baker, M. (1997), “Growth Rate Heterogeneity and the Covariance Structure of Life-Cycle Earnings”, *Journal of Labor Economics*, 15, 537–579.
- Baker, M. and G. Solon (1999), “Earnings Dynamics and Inequality among Canadian Men, 1976–1992: Evidence from Longitudinal Tax Records”, Working Paper 7370, NBER.
- Baker, M. and G. Solon (2003), “Earnings Dynamics and Inequality among Canadian Men, 1976–1992: Evidence from Longitudinal Tax Records”, *Journal of Labor Economics*, 21, 289–321.
- Cappellari, L. (2004), “The Dynamics and Inequality of Italian Men’s Earnings: Long-term Changes or Transitory Fluctuations?”, *Journal of Human Resources*, 39, 475–499.
- Chamberlain, G. (1984), “Panel Data”, in Z. Griliches and M. Intriligator, eds., *Handbook of Econometrics*, Vol. 2, Elsevier Science B.V., Amsterdam.
- Daly, M. and R. Valetta (2007), “Cross-National Trends in Earnings Inequality and Instability”, *Economics Letters*, 99, 2015–219.
- Dickens, R. (2000), “The Evolution of Individual Male Earnings in Great Britain: 1975–95”, *Economic Journal*, 110, 27–49.
- Domeij, D. (2008), “Rising Earnings Inequality in Sweden: The Role of Composition and Prices”, *Scandinavian Journal of Economics*, 110, 609–634.
- Domeij, D. and L. Ljungqvist (2006), “Wage Structure and Public Sector Employment: Sweden versus the United States 1970–2002”, Working Paper Series in Economics and Finance 638, Stockholm School of Economics.
- Doris, A., D. O’Neill and O. Sweetman (2008), “Does Growth Affect the Nature of Inequality? Ireland 1994–2001”, Discussion Paper 3701, IZA.

- Drewianka, S. (2008), “Cross-Sectional Variation in Individual’ Earnings Instability”, mimeo, University of Wisconsin-Milwaukee.
- Edin, P.-A. and P. Fredriksson (2000), “LINDA – Longitudinal Individual Data for Sweden” Working Paper 2000:19, Department of Economics, Uppsala University.
- Fitzgerald, J, P Gottschalk and R Moffitt (1998), “An Analysis of Sample Attrition in Panel Data: The Michigan Study of Income Dynamics”, *Journal of Human Resources*, 33, 251-299.
- Gottschalk, P. and R. Moffitt (1994), “The Growth of Earnings Instability in the U.S. Labor Market”, *Brookings Papers on Economic Activity*, 1994 (2), 217–272.
- Gustavsson, M. (2006), “The Evolution of the Swedish Wage Structure: New Evidence for 1992–2001”, *Applied Economics Letters*, 13, 279–286.
- Gustavsson, M. (2007), “The 1990s Rise in Swedish Earnings Inequality – Persistent or Transitory?”, *Applied Economics*, 39, 25–30.
- Gustavsson, M. (2008), “A New Picture of Swedish Earnings Inequality: Persistent and Transitory Components, 1960–90”, *Review of Income and Wealth*, 54, 324–349.
- Guvenen, F. (2007), “Learning Your Earning: Are Labor Income Shocks Really Very Persistent?”, *American Economic Review*, 97, 687–712.
- Haider, S. (2001), “Earnings Instability and Earnings Inequality of Males in the United States: 1967–1991”, *Journal of Labor Economics*, 19, 799–836.
- Hause, J. (1980), “The Fine Structure of Earnings and the On-the-Job Training Hypothesis”, *Econometrica*, 48, 1013–1029.
- Holmlund, B (2006), “The Rise and Fall of Swedish Unemployment”, in M. Werding, ed., *Structural Unemployment in Western Europe: Reasons and Remedies*, MIT Press, Cambridge.
- Kalwij, A. and R. Alessie (2007), “Permanent and Transitory Wages of British Men, 1975–2001: Year, Age and Cohort Effects”, *Journal of Applied Econometrics*, 22, 1063–1093.
- Katz, L and D Autor (1999), “Changes in the Wage Structure and Earnings Inequality” in O Ashenfelter and D Card (eds), *Handbook of Labor Economics*, Vol. 3A, Elsevier Science B.V., Amsterdam.
- Lazear, E. (1979), “Why is there Mandatory Retirement?”, *Journal of Political Economy*, 87, 1261–1264.
- Lazear, E. (1981), “Agency, Earnings Profiles, Productivity, and Hours Restrictions”, *American Economic Review*, 71, 606–620.

- Lillard, L. and R. Reville (1999), “Life Cycle Human Capital Investment: New Evidence on an Old Issue”, mimeo, University of Michigan.
- Lillard, L. and Y. Weiss (1979) “Components of Variation in Panel Earnings Data: American Scientists 1960–70”, *Econometrica*, 47, 437–454.
- Lindquist, M. (2005) “Capital-Skill Complementarity and Inequality in Sweden”, *Scandinavian Journal of Economics*, 107, 711–735.
- MaCurdy, T. (1982), “The Use of Time Series Processes to Model the Error Structure of Earnings in Longitudinal Data Analysis”, *Journal of Econometrics*, 18, 83–114.
- Mincer, J. (1974), *Schooling, Experience and Earnings*, Columbia University Press, New York.
- Moffitt, R. and P. Gottschalk (1995), “Trends in the Covariance Structure of Earnings in the U.S.: 1969–1987”, mimeo, Johns Hopkins University.
- Moffitt, R. and P. Gottschalk (2002), “Trends in the Transitory Variance of Earnings in the United States” *Economic Journal*, 112, 68–73.
- Myck, M., R. Ochmann and S. Qari (2008), “Dynamics of Earnings and Hourly Wages in Germany”, Discussion Paper 3751, IZA.
- Newey, W. (1985), “Generalized Method of Moments Specification Testing” *Journal of Econometrics*, 29, 229–256.
- Nordström Skans, O., P.-A. Edin and B. Holmlund (2008), “Wage Dispersion Between and Within Plants: Sweden 1985–2000, forthcoming in E. Lazear and K. Shaw (Eds.), *An International Comparison of the Structure of Wages*, University of Chicago Press, Chicago.
- Ramos, X. (2003), “The Covariance Structure of Earnings in Great Britain, 1991–1999”, *Economica*, 70, 353–374.

Appendix: Additional tables

Table A1: Estimates of earnings dynamics: year-specific factor-loadings

<i>Year</i>	High school		College	
	<i>Persistent component</i>	<i>Transitory component</i>	<i>Persistent component</i>	<i>Transitory component</i>
1982	0.8745 (0.0181)		0.8525 (0.0268)	
1983	0.8737 (0.0172)	0.7062 (0.0182)	0.8545 (0.0250)	0.8507 (0.0372)
1984	0.9184 (0.0185)	0.8781 (0.0208)	0.8938 (0.0254)	0.9339 (0.0405)
1985	0.8932 (0.0170)	0.8738 (0.0205)	0.8669 (0.0222)	0.9016 (0.0353)
1986	0.8388 (0.0159)	0.7527 (0.0162)	0.8630 (0.0221)	0.8085 (0.0335)
1987	0.8585 (0.0164)	0.8669 (0.0186)	0.8586 (0.0217)	0.8459 (0.0374)
1988	0.8200 (0.0146)	0.8234 (0.0184)	0.8585 (0.0192)	0.8341 (0.0347)
1989	0.8091 (0.0140)	0.7769 (0.0168)	0.8544 (0.0201)	0.8535 (0.0402)
1990	0.8338 (0.0149)	0.7865 (0.0166)	0.8628 (0.0202)	0.8845 (0.0461)
1991	0.9573 (0.0161)	0.9689 (0.0207)	0.9816 (0.0221)	0.8691 (0.0372)
1992	1.0397 (0.0183)	1.2479 (0.0197)	1.0198 (0.0243)	1.0154 (0.0413)
1993	1.1397 (0.0203)	1.4918 (0.0205)	1.1192 (0.0270)	1.1337 (0.0452)
1994	1.1719 (0.0198)	1.2643 (0.0214)	1.1038 (0.0263)	1.1666 (0.0406)
1995	1.1999 (0.0204)	1.2105 (0.0206)	1.0912 (0.0247)	1.0522 (0.0401)
1996	1.1907 (0.0218)	1.2054 (0.0221)	1.0971 (0.0257)	1.0707 (0.0449)
1997	1.2276 (0.0222)	1.1722 (0.0218)	1.1034 (0.0281)	1.1971 (0.0397)
1998	1.1776 (0.0214)	1.1412 (0.0222)	1.1076 (0.0266)	1.0575 (0.0395)
1999	1.1414 (0.0214)	1.0068 (0.0212)	1.1139 (0.0252)	1.0195 (0.0429)
2000	1.0939 (0.0201)	0.9477 (0.0195)	1.1362 (0.0266)	1.0305 (0.0355)
2001	1.0071 (0.0187)	0.9316 (0.0199)	1.1075 (0.0264)	1.0365 (0.0353)
2002	0.9869 (0.0197)	0.9593 (0.0221)	1.0816 (0.0274)	1.1482 (0.0414)
2003	0.9648 (0.0191)	0.9766 (0.0216)	1.0381 (0.0260)	1.1435 (0.0407)
2004	0.9970 (0.0203)	0.9942 (0.0214)	1.0592 (0.0271)	1.0926 (0.0396)
2005	0.9845 (0.0212)	1.0172 (0.0228)	1.0749 (0.0281)	1.0542 (0.0418)

Notes: The mean of the factor loadings are normalized to be equals unity; see the main text for details.

Table A2: Estimates of earnings dynamics: Initial cohort-specific transitory variances

<i>Birth years</i>	High school	College
1930–32	0.2000 (0.0538)	0.1036 (0.0657)
1933–35	0.1459 (0.0382)	0.0914 (0.0553)
1936–38	0.1833 (0.0480)	0.1284 (0.0461)
1939–41	0.1877 (0.0482)	0.1508 (0.0572)
1942–44	0.1068 (0.0315)	0.1283 (0.0417)
1945–47	0.1661 (0.0331)	0.1902 (0.0391)
1948–50	0.1438 (0.0323)	0.3221 (0.0535)
1951–53	0.1853 (0.0319)	0.3571 (0.0539)
1954–56	0.2337 (0.0318)	0.4345 (0.0492)
1957–59	0.2789 (0.0325)	0.6405 (0.0628)
1960–62	0.4068 (0.0342)	0.5573 (0.0571)
1963–65	0.5133 (0.0406)	0.5932 (0.0625)
1966–68	0.3433 (0.0320)	1.1425 (0.0893)
1969–71	0.6412 (0.0522)	1.4182 (0.0919)
1972–74	1.4638 (0.0757)	1.1349 (0.0844)
1975–77	1.2342 (0.0721)	-

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