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Dynamics of Earnings and Hourly Wages in Germany*

Michał Myck† Richard Ochmann‡ Salmai Qari§

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Abstract

There is by now a lot of evidence showing a sharp increase in cross-sectional wage and earnings inequality during the 2000s in Germany. Our study is the first to decompose this cross-sectional variance into its permanent and transitory parts for years beyond 2000. Using data from the German Socio-Economic Panel on full-time working individuals for years of 1994 to 2006, we do not find unambiguous empirical support for the frequent claims that recent increases in inequality have been driven mainly by permanent disparities. From 1994 on, permanent inequality increases continuously, peaks in 2001 but then declines in subsequent years. Interestingly the decline in the permanent fraction of inequality occurs at the time of most rapid increases in cross-sectional inequality. It seems therefore that it is primarily the temporary and not the permanent component which has driven the strong expansion of cross-sectional inequality during the 2000s in Germany.

Keywords: Variance Decomposition, Covariance Structure Models, Earnings Inequality, Wage Dynamics.
JEL Classification: C23, D31, J31

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1 Introduction

The evolution of wage inequality in Germany has been perceived to approach the dynamics of the U.S. labour market in recent years. The literature on cross-sectional wage and earnings inequality in Germany has found that the distributions, while relatively stable during the 1980s, begun to reflect increasing inequality from about in the mid-1990s with an accelerated rise in the 2000s (Gernandt and Pfeiffer, 2007; Müller and Steiner, 2008).[1] However, the documented changes in cross-sectional inequality are not very informative about the mechanisms determining the observed dynamics, and tell us very little about the nature of the changing inequality. A rise in cross-sectional inequality over time might result from an increasing role of transitory shocks or from growing permanent differences in wages and earnings between individuals, and appropriate policy response to changes in inequality should take these respective driving forces into account.

This paper is, to our best knowledge, the first study which applies covariance structure models to longitudinal German data over a period between 1994-2006, i.e. covering the recent years of changes in the German wage structure. The results of our analysis are to a large extent surprising and indicate that the trend of increasing permanent inequality in Germany breaks in 2000/2001. Previous studies focus on the 1990s and therefore are unable to observe this break. For example, Daly and Valletta (2008) use a heterogeneous growth model to compare Germany, UK and the USA during the 1990s and find substantial convergence in the permanent and transitory parts of inequality. This convergence is mainly a consequence of an increase in permanent inequality in Germany and a decline of permanent inequality in the United States. Our analysis confirms their results for the 1990s but we find a decreasing role of permanent inequality after 2001, i.e. at the time of a steep rise in cross-sectional inequality. It seems therefore that transitory factors have played a very important role in recent changes in earnings and wage inequality in Germany.

The analysis in this paper is conducted using thirteen years of data from the German Socio-Economic Panel (GSOEP) for years 1994-2006. Over this period the cross-sectional residual variance in our sample increases –depending on the specification– by 20 to 50 percent. Consistent with previous research, our sample shows that the increase is much steeper in the 2000s. In fact, most of the increase occurs between 1999 and 2006, while from 1994 to 1999 the cross-sectional variance remains relatively stable. Secondly, the

[1] While there is agreement on the expansion of inequality during the 1990s, there is some disagreement about the 1980s. In a recent paper Dustmann et al. (2009) "show that the common perception that Germany's wage structure has remained largely stable during the 1980s is inaccurate [and] find that wage inequality has increased in the 1980s, but mostly at the top half of the distribution."

rise in the cross-sectional variance is accompanied by an increase and then a reduction in the fraction of its permanent component. Interestingly, this reversal of the evolution of permanent inequality occurs around the years 2000/2001, when cross-sectional inequality begins to rise steeply. The fraction of the permanent inequality increases from 1994, peaks in 2001 and then declines by approximately 20 percentage points. This implies that the strong expansion of cross-sectional inequality during the 2000s can be increasingly attributed to transitory inequality.

In the following section we describe the dataset we use for our analysis. Section 3 presents the method for separating the permanent and temporary components of the variance. Here we build on existing literature which focuses mainly on the UK (Dickens, 2000; Ramos, 2003), the United States (Haider, 2001; Moffitt and Gottschalk, 2002) or Canada (Baker and Solon, 2003).[2] Section 4 provides details on the estimation procedure. We then present and discuss our main results in Section 5 and conclude in Section 6.

2 Data

The analysis uses data from the German Socio-Economic Panel (GSOEP). The GSOEP is a panel study for Germany, which started in 1984 as a longitudinal survey of households and individuals in West Germany and was expanded in 1990 to cover the population of the former East Germany.[3] The GSOEP is also used in the recent analysis by Daly and Valletta (2008), which is in terms of methodology very close to our paper. Other studies using GSOEP data either focus on household inequality (Biewen, 2005) or use index-based measures to analyse the evolution of inequality (Burkhauser and Poupore, 1997; Maasoumi and Trede, 2001).

We use a fully balanced subsample of the GSOEP for the years 1994-2006 to ensure that any changes in the distribution of wages and earnings do not result from compositional changes. Applying usual age restrictions we include individuals aged 20-60 who report to be employed in all 13 years covered by the analysis and who are full-time employees during the entire period.[4] These two sample restrictions imply that we focus

[2]For earlier examples, see Lillard and Willis (1978), Lillard and Weiss (1979), as well as Abowd and Card (1989). For a study covering Italy, see Cappellari (2000). Gustavsson (2007) provides a recent study for Swedish data. Using a similar approach, Biewen (2005) analyses the evolution of disposable household income inequality in Germany for the years 1990-1998.

[3]For further details on the data, see Haisken-DeNew and Frick (2005) and Wagner et al. (2007).

[4]In the analysis we do not apply sampling weights as any existing weights do not account for our sampling conditions.

on individuals with stable employment histories and as a result we may underestimate the degree of transitory dispersion for the whole workforce. Our results are particularly interesting in light of this, since we find increasing importance of the transitory component, which is at odds with the conjecture of underestimation.

Individuals need to report 'full-time' employment status and weekly hours above 19 to be classified as full-time employees. For these individuals, we analyse monthly gross individual labour income as reported for the month prior to the interview. Earnings are deflated by Consumer Price Index to the base of year 2000. We apply common restrictions to outliers in the data and truncate the distribution of monthly earnings in our balanced sample at the 0.5th percentile from below and at the 99.5th percentile from above.[5]

Hourly wages are generated from reported weekly hours actually worked (including hours of paid overtime) and monthly earnings (including overtime pay), and computed as $wage = monthly\ earnings/(4.35 * weekly\ hours\ worked)$. After dropping some observations due to incomplete information on the necessary characteristics we end up with a sample of 952 individuals (women and men), i.e. 12,376 individual-year observations. For the purpose of robustness checks the analysis is also conducted on a limited sample restricted to men only which includes 728 individuals (9,464 individual-year observations). The small number of women in our full sample (24%) is a consequence of restricting it to individuals observed in full-time employment over the entire period of 13 years. Table 1 displays the number of individual-year observations by gender, nationality, location as well as by age and education groups for our balanced panel for the full and the restricted samples, while Table 2 gives descriptive statistics on monthly gross earnings and hourly wages in the full sample.

[5] Although the GSOEP is not generally top-coded with respect to the income distribution, it nevertheless includes only a small number of individuals with high incomes in the sample applied here, c.f. Dustmann et al. (2009), Bach et al. (2007) as well as Bach et al. (2008). These authors moreover conclude that the GSOEP covers the distribution of market income quite well up to the 99th percentile. Bach et al. (2007) also find that a large share of the total market income is actually labour income, in 2001 a share of 83.1 percent on average was wage income and an additional 11.4 percent was income from business activity. We conclude that by analysing labour earnings we capture the main part of market income which is representative for the income distribution in Germany, except for the very rich.

Table 1: Sample Composition by Demographics

	Full Sample		**Male Only**	
	Obs.	Frac.	Obs.	Frac.
Gender				
female	2,912	.24	0	0
male	9,464	.76	9,464	1.0
Nationality				
non-German	969	.08	800	.08
German	11,407	.92	8,664	.92
Location				
West	8,591	.69	7,162	.76
East	3,785	.31	2,302	.24
Age				
age 20 - 30	1,026	.08	765	.08
age 31 - 40	4,455	.36	3,523	.37
age 41 - 50	5,106	.41	3,765	.40
age 51 - 60	1,789	.14	1,411	.15
Education				
10 and less	1,047	.08	817	.09
10 - 13	8,134	.66	6,114	.65
13 - 15	1,202	.10	950	.10
15 - 18	1,993	.16	1,583	.17
Total	12,376	1.0	9,464	1.0

Notes: Education in years. Observations are individual-year observations.

Source: Own calculations using the GSOEP data (1994-2006).

Table 2: Summary Statistics for Earnings and Wages

	Monthly Earnings		Hourly Wages	
year	mean	sd	mean	sd
1994	2,385	1,112	13.09	5.61
1995	2,494	1,143	13.69	5.69
1996	2,620	1,171	14.36	5.87
1997	2,648	1,149	14.42	5.71
1998	2,695	1,194	14.70	5.88
1999	2,748	1,214	14.90	6.03
2000	2,852	1,420	15.49	6.61
2001	2,885	1,380	15.63	6.55
2002	2,932	1,346	16.03	6.73
2003	3,080	1,603	16.78	7.43
2004	3,062	1,453	16.73	7.07
2005	3,049	1,498	16.70	7.33
2006	3,036	1,563	16.55	7.71
Total	2,807	1,354	15.31	6.62

Notes: Earnings are gross earnings, deflated by Consumer Price Index to the base of year 2000. Hourly wages generated from earnings and reported hours, see text.

Source: Own calculations using the GSOEP data (1994-2006).

3 Modelling the Dynamics of Earnings and Wages

We assume that real log-earnings (log-wages, respectively) can be modelled by

$$Y_{it} = x'_{it}\beta_t + u_{it} \tag{1}$$

for individuals $i = 1, ...N$ and periods $t = 1, ...T$, with x_{it} denoting a $K \times 1$-vector of individual-specific characteristics including a time-varying constant, β_t denoting a $K \times 1$ time-varying parameter vector, and u_{it} the error term. This model is computed for every $t = 1, ...T$ in two variants. In the first variant, $x_{it} \equiv 1$, so that log earnings are only regressed on a time-varying constant. In the second variant, x_{it} contains several individual-specific covariates, i.e. log-age, log-age-squared, region of residence (East or West Germany), years of education in four groups, and gender (for sample statistics, see Table 1).

For each variant, we decompose the residuals u_{it} into a permanent (μ_i) and a transitory (v_{it}) part. Throughout the entire paper we assume that these two parts are uncorrelated, i.e. $Cov(\mu_i, v_{it}) = 0$.

Our simplest model is the "enhanced canonical" permanent-transitory model with year-specific factor loadings p_t and λ_t on the two components. It assumes that there is no serial correlation among transitory shocks, i.e $Cov(v_{it}, v_{it-s}) = 0$ for $s \neq 0$:

$$u_{it} = p_t\mu_i + \lambda_t v_{it} \tag{2}$$

Intuitively, $x'_{it}\beta_t$ defines the population's mean profile and the term μ_i introduces individual heterogeneity, which allows the individuals to deviate from the mean profile. The variance of this individual heterogeneity constitutes the source for permanent inequality and the respective factor loadings allow changes of the permanent component over time.

The variance of the residual of log-earnings or log-wages in this model, given independence of the permanent and the transitory component, is:

$$Var(u_{it}) = p_t^2\sigma_\mu^2 + \lambda_t^2\sigma_v^2 \tag{3}$$

An increase in either factor loading in period t leads to an increase in the cross-sectional variance of period t. The interpretation of such an increase, however depends crucially on which factor changes. An increase in p_t can be interpreted as an increase in the returns to unobserved individual-specific permanent components, e.g. ability. On the other hand, an increase in λ_t without an increase in p_t can be interpreted as an increase in year-to-year volatility due to short-term factors, such as e.g. temporarily powerful labour unions or demand shocks affecting specific sectors of the economy, without any shifts in the permanent component of earnings.

The canonical model relies on a rather arbitrary assumption that residuals which are sufficiently far apart are not correlated. To remove this assumption, we consider two specific models for the transitory component. The first model is an AR(1) process. In this case, the transitory part of the residuals is equal to:

$$v_{it} = \rho v_{it-1} + \varepsilon_{it} \tag{4}$$

In the second model, the transitory component is assumed to follow an ARMA(1,1) process:

$$v_{it} = \rho v_{it-1} + \gamma \varepsilon_{it-1} + \varepsilon_{it} \tag{5}$$

Under the assumptions that $E[\mu_i] = E[v_{it}] = E[\varepsilon_{it}] = 0$ and $E[\mu_i \varepsilon_{it}] = E[\varepsilon_{it}\varepsilon_{js}] = 0$ for all i and j and for all $t \neq s$, the covariance matrix of residuals is given by:

$$cov(u_{it}, u_{it-s}) = p_t p_{t-s} \sigma_\mu^2 + \lambda_t \lambda_{t-s} E[v_{it} v_{it-s}] \tag{6}$$

where p_t, p_{t-s}, λ_t, and λ_{t-s} are time specific factor loadings and $E[v_{it}v_{it-s}]$ is equal to:

$$E[v_{it}v_{it-s}] = \begin{cases} \sigma_{v0}^2 & ,t=0, s=0 \\ \rho^2\sigma_{v0}^2 + \sigma_\epsilon^2 & ,t=1, s=0 \\ \rho^2 E[v_{it-1}v_{it-1}] + (1+\gamma^2+2\rho\gamma)\,\sigma_\epsilon^2 & ,2 \leq t, s=0 \\ \rho^{s-1}(\rho E[v_{it-s}v_{it-s}] + \gamma\sigma_\epsilon^2) & ,s+1 \leq t, 1 \leq s \leq T-1 \end{cases} \tag{7}$$

In Equation (7), $\sigma_\mu^2 = var(\mu_i)$ and $\sigma_\varepsilon^2 = var(\varepsilon_{it})$. $\sigma_{v_0}^2 = var(v_{i0})$ is the initial condition for the ARMA-process.[6] In Equation (7), the AR(1) specification is nested with $\gamma = 0$. Summarising, we consider three different specifications:

$$\text{(S-CAN)} \quad u_{it} = p_t\mu_i + \lambda_t v_{it} \tag{8}$$

$$\text{(S-AR)} \quad u_{it} = p_t\mu_i + \lambda_t(\rho v_{it-1} + \varepsilon_{it}) \tag{9}$$

$$\text{(S-ARMA)} \quad u_{it} = p_t\mu_i + \lambda_t(\rho v_{it-1} + \gamma\varepsilon_{it-1} + \varepsilon_{it}) \tag{10}$$

Specification (S-CAN) is the “enhanced canonical” model with factor loadings. Specification (S-AR) models the transitory component as an AR(1) process, while specifica-

[6]The initial condition is needed for an unbiased estimation of the parameters of the ARMA-process, c.f. MaCurdy (1982).

tion (S-ARMA) models the transitory component as an ARMA(1,1) process. (S-CAN) is nested in (S-AR) which in turn is nested in (S-ARMA).

4 Estimation

The estimation is conducted in two steps. In the first step, we obtain an estimate of u_{it}, which is just the vector of residuals from the regression model $Y_{it} = x_{it}'\beta_t + u_{it}$. From these residuals, we construct an empirical covariance matrix (which is provided in Tables B.1 to B.8 in the Appendix). In the second step, we estimate the parameters of our theoretical covariance matrix by fitting the implications of specifications (S-CAN), (S-AR), and (S-ARMA) to the empirical covariance matrix.

Formally, let the vector C collect all distinct elements of the empirical covariance matrix obtained from the first stage. For each specification, we can express the corresponding theoretical moments in Equations (6)-(7) as a function $f(\theta)$, where the vector θ collects all parameters which are needed to construct these moments. For example, in specification (S-AR), θ collects the initial variance, as well as the permanent variance, the year-to-year variance, the persistence parameter of the AR(1) process, and the factor loadings for the permanent and transitory components. This results in 27 parameters for specification (S-AR) and 28 for specification (S-ARMA), respectively.[7] The model's parameters are estimated by the generalised method of moments (Chamberlain, 1984); that is the estimate $\hat{\theta}$ minimises the distance between the empirical and the theoretical moments:

$$\hat{\theta} = \arg\min_{\theta} \left[C - f(\theta)\right]' W \left[C - f(\theta)\right] \tag{11}$$

We follow the recent literature and use the identity matrix as the weighting matrix W.[8] This approach, called "equally weighted minimum distance estimation" (Baker and Solon, 2003), boils down to using nonlinear least squares to fit $f(\hat{\theta})$ to C.

[7]Note that p_{1994}, λ_{1994} and λ_{1995} are normalised to unity in order to identify the parameters of the stochastic process.

[8]While an asymptotically optimal choice of W is the inverse of a matrix that consistently estimates the covariance matrix of C (Chamberlain, 1984), Altonji and Segal (1996) as well as Clark (1996) provide Monte Carlo evidence of potentially serious finite sample bias in $\hat{\theta}$ using this approach.

5 Results

The estimation results for the full sample are compiled in Table 3. It shows the 27 (28, respectively) parameter estimates for the specifications (S-AR) and (S-ARMA). Instead of discussing the results for the different specifications one after another, we present all results side by side for ease of comparison.

The distribution of working hours for full-time employees is fairly constant over time. As a consequence, the evolution of earnings dynamics in our sample closely resembles the one for wage dynamics. We therefore focus on the results for wages here. We first discuss the economic meaning of key parameters like the variance estimates and then calculate the fraction of permanent and transitory wage dispersion.

In specification (S-AR), the variance of the transitory part (σ_ε^2) for wages is estimated to be between one third and two thirds of the permanent variance (σ_μ^2). Transitory shocks are reduced quite quickly. An estimate for ρ of 0.57 implies that already after two periods almost 70% of a shock disappear.

The same findings emerge in the (S-ARMA)-specification, with estimates for ρ of about 0.85 and an estimate for γ of about -0.48. As in specification (S-AR), this implies that a shock is reduced to about 31% after two periods. The evolution of the factor loadings (p_t) suggests that the permanent component becomes increasingly important during the years 1994 to 2001. In line with that, the factor loadings of the transitory part (λ_t) are initially only slightly below unity and decline continuously until the year 2001. From 2001 to 2006 they grow sharply and reach values slightly above unity. Hence, the evolution of the factor loadings indicates that during the 2000s the sharp increase in cross-sectional inequality is due largely to the growing role of *transitory* wage and earnings dispersion.

Using Equation (6) we calculate the fraction of the permanent variance from our parameter estimates as $(\hat{p}_t^2 \cdot \hat{\sigma}_\mu^2) \ / \ var(\hat{u}_{it})$, where $var(\hat{u}_{it})$ denotes the variance of the predicted residuals in period t.

Figure 1 shows the evolution of this fraction for wages regressed on the full set of covariates for all three specifications, while the respective results when fitting just an intercept are relegated to the Appendix (Figure A.1). Figure 1 additionally shows the cross-sectional variance $var(u_{it})$. The plots show a clear break in the years 2000/2001. From 1994 to 1999, the cross-sectional variance is more or less unchanged, followed by a sharp increase starting in 2000. This sharp increase in cross-sectional inequality is in line with previous research as mentioned earlier. However, the permanent part of the variance increases sharply only in the first time frame. The estimated parameters of

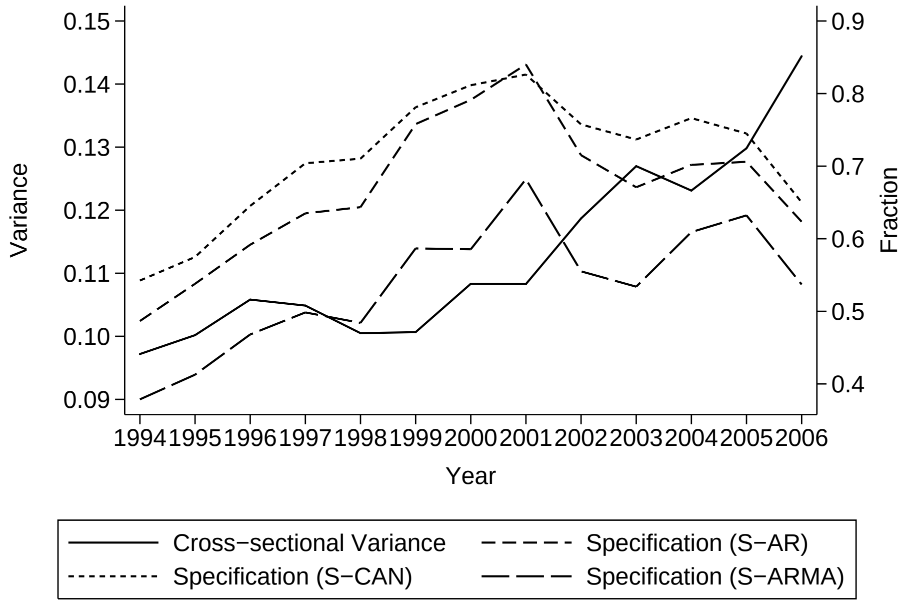
Table 3: Parameter Estimates - Full Sample

	AR(1)				ARMA(1,1)			
	Earnings		Wages		Earnings		Wages	
	constant	covariates	constant	covariates	constant	covariates	constant	covariates
$\sigma^2_{v_0}$	0.092	0.064	0.093	0.063	0.054	0.035	0.054	0.034
	(0.015)	(0.014)	(0.021)	(0.019)	(0.006)	(0.005)	(0.006)	(0.005)
σ^2_{μ}	0.109	0.048	0.108	0.047	0.098	0.037	0.095	0.037
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
σ^2_{ε}	0.026	0.024	0.032	0.029	0.033	0.032	0.036	0.034
	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
ρ	0.618	0.663	0.572	0.574	0.839	0.887	0.842	0.873
	(0.021)	(0.022)	(0.024)	(0.025)	(0.027)	(0.015)	(0.027)	(0.021)
γ					-0.431	-0.444	-0.483	-0.486
					(0.032)	(0.017)	(0.029)	(0.021)
p_{1995}	1.034	1.066	1.030	1.060	1.033	1.053	1.035	1.065
	(0.011)	(0.023)	(0.014)	(0.027)	(0.008)	(0.018)	(0.009)	(0.020)
p_{1996}	1.061	1.139	1.046	1.137	1.079	1.155	1.066	1.156
	(0.012)	(0.025)	(0.014)	(0.028)	(0.012)	(0.026)	(0.012)	(0.027)
p_{1997}	1.078	1.149	1.073	1.181	1.097	1.156	1.094	1.198
	(0.013)	(0.026)	(0.015)	(0.030)	(0.013)	(0.029)	(0.014)	(0.031)
p_{1998}	1.094	1.188	1.058	1.162	1.108	1.180	1.072	1.155
	(0.013)	(0.028)	(0.015)	(0.031)	(0.014)	(0.033)	(0.015)	(0.035)
p_{1999}	1.131	1.256	1.110	1.251	1.152	1.259	1.139	1.270
	(0.015)	(0.031)	(0.017)	(0.034)	(0.018)	(0.039)	(0.018)	(0.040)
p_{2000}	1.161	1.340	1.139	1.330	1.169	1.272	1.159	1.313
	(0.015)	(0.034)	(0.017)	(0.037)	(0.018)	(0.054)	(0.020)	(0.057)
p_{2001}	1.204	1.383	1.169	1.358	1.222	1.427	1.204	1.414
	(0.018)	(0.038)	(0.019)	(0.039)	(0.023)	(0.062)	(0.023)	(0.054)
p_{2002}	1.123	1.313	1.115	1.321	1.137	1.292	1.143	1.336
	(0.015)	(0.034)	(0.017)	(0.036)	(0.018)	(0.051)	(0.021)	(0.054)
p_{2003}	1.162	1.333	1.134	1.331	1.183	1.312	1.171	1.359
	(0.015)	(0.033)	(0.017)	(0.036)	(0.019)	(0.053)	(0.021)	(0.057)
p_{2004}	1.154	1.339	1.121	1.344	1.191	1.368	1.177	1.433
	(0.014)	(0.032)	(0.016)	(0.036)	(0.019)	(0.054)	(0.022)	(0.057)
p_{2005}	1.165	1.368	1.137	1.379	1.208	1.420	1.201	1.495
	(0.014)	(0.032)	(0.016)	(0.035)	(0.020)	(0.055)	(0.023)	(0.059)
p_{2006}	1.191	1.355	1.171	1.376	1.230	1.372	1.230	1.454
	(0.014)	(0.030)	(0.016)	(0.034)	(0.019)	(0.053)	(0.022)	(0.056)
λ_{1996}	0.884	0.951	0.919	0.976	0.858	0.922	0.911	0.976
	(0.062)	(0.069)	(0.069)	(0.073)	(0.032)	(0.027)	(0.032)	(0.030)
λ_{1997}	0.828	0.909	0.858	0.930	0.822	0.891	0.889	0.956
	(0.071)	(0.076)	(0.075)	(0.078)	(0.038)	(0.031)	(0.038)	(0.035)
λ_{1998}	0.780	0.881	0.822	0.900	0.814	0.890	0.892	0.952
	(0.076)	(0.081)	(0.078)	(0.080)	(0.044)	(0.034)	(0.041)	(0.037)
λ_{1999}	0.609	0.753	0.629	0.736	0.705	0.827	0.758	0.854
	(0.090)	(0.087)	(0.091)	(0.087)	(0.056)	(0.041)	(0.051)	(0.044)
λ_{2000}	0.709	0.761	0.672	0.711	0.814	0.911	0.812	0.887
	(0.086)	(0.093)	(0.091)	(0.094)	(0.054)	(0.045)	(0.054)	(0.051)
λ_{2001}	0.413	0.582	0.539	0.617	0.666	0.730	0.726	0.776
	(0.127)	(0.113)	(0.106)	(0.104)	(0.069)	(0.061)	(0.060)	(0.056)
λ_{2002}	0.830	0.868	0.843	0.869	0.889	0.925	0.931	0.963
	(0.077)	(0.086)	(0.080)	(0.085)	(0.046)	(0.039)	(0.045)	(0.042)
λ_{2003}	0.954	1.008	0.931	0.971	0.979	1.014	0.986	1.023
	(0.077)	(0.086)	(0.080)	(0.084)	(0.045)	(0.038)	(0.044)	(0.042)
λ_{2004}	0.946	0.982	0.893	0.913	0.935	0.956	0.909	0.925
	(0.076)	(0.085)	(0.079)	(0.084)	(0.045)	(0.038)	(0.045)	(0.043)
λ_{2005}	0.978	1.017	0.903	0.927	0.953	0.968	0.910	0.920
	(0.076)	(0.085)	(0.078)	(0.084)	(0.046)	(0.037)	(0.046)	(0.043)
λ_{2006}	1.143	1.191	1.067	1.114	1.092	1.101	1.058	1.089
	(0.081)	(0.091)	(0.081)	(0.087)	(0.050)	(0.040)	(0.048)	(0.044)
N	91	91	91	91	91	91	91	91

Notes: See Section 3 for the full list of covariates.

Source: Own calculations using the GSOEP data (1994-2006).

Figure 1: Cross-sectional Variance and its Permanent Component, for **Wages** in the specification with **covariates** on the full sample



Notes: See Section 3 for the full list of covariates.

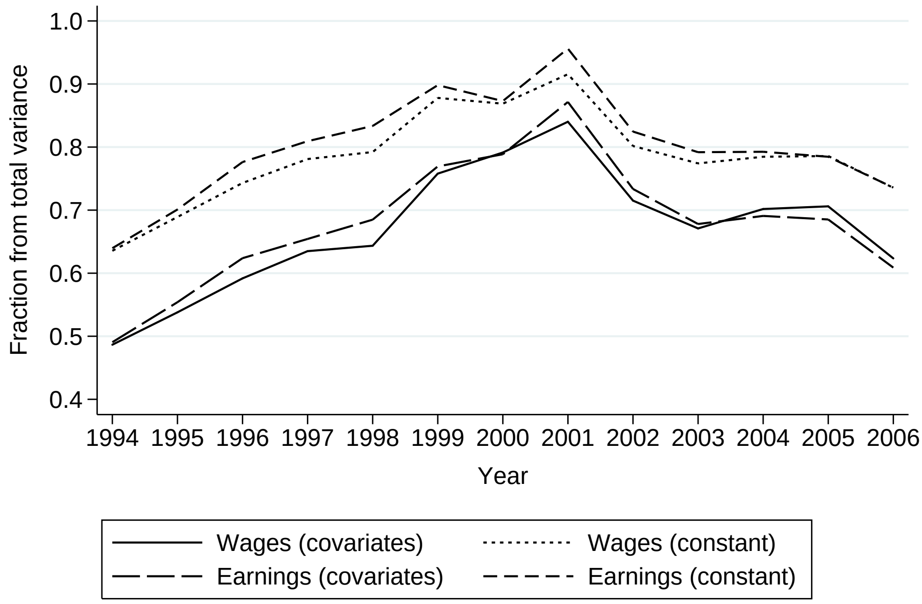
specification (S-AR) set the fraction of permanent inequality to roughly 50% in 1994. For the subsequent years, permanent inequality firstly climbs up, peaks with over 80% in 2001, and then declines to roughly 60% in 2006. These two findings imply that it is an increasing fraction of the *transitory* variance which is primarily driving the sharp increase in cross-sectional inequality from 2001 to 2006.

This pattern is very similar for the other two specifications and reflects the robustness of the estimated factor loadings across the specifications. Although these qualitative findings emerge in all specifications, the exact level of the estimated inequality fractions varies across the models we apply. As one could expect the more flexible treatment of the transitory component in the (S-ARMA) specification allows the estimation to assign a larger share of the variance to transitory causes (see Figure 1).

Figure 2 compares wage and earnings dynamics. It uses the parameter estimates from Table 3 for the (S-AR) specification and shows the resulting fraction of permanent inequality (as a fraction from the total variance) for both wages and earnings. The evolution of factor loadings is virtually identical for earnings and wages in both variants, regressed on a constant and on the full set of covariates. Figure A.4 in the Appendix depicts the corresponding results for the (S-ARMA) specification.

All the estimated models and all specifications reflect an increase in the fraction of

Figure 2: Evolution of the Fraction of the Permanent Variance Component, in specification (S-AR) on the full sample



Notes: In the specifications of a constant and of covariates. See Section 3 for the full list of covariates.

permanent inequality starting in 1994, a peak in 2000/2001 and a decline in subsequent years. While all specifications find this pattern, the exact level of permanent inequality depends on the underlying model. In the Appendix we present results of a robustness check, which repeats the analysis on the subsample of men. The results from these additional regressions, given graphically in Figures A.5 and A.6, confirm our findings on the full sample presented above.

Our results, in the same way as other studies which apply similar methodology, are subject to the caveat, that by its nature the analysis is limited to individuals who can be followed throughout the period we look at. This feature of the method implies that we cannot take into account the changes in wages of those who did not work at some point during the time frame covered, and so necessarily excludes the cohorts who entered or exited the labour market during the period. But as already discussed this selection mechanism usually leads to an underestimation of transitory dispersion, because only individuals with stable employment histories remain in the sample. Hence, our estimates of transitory inequality may be a conservative *lower* bound.

Table 3 shows that controlling for individual characteristics leads to qualitatively similar results as fitting just a constant. This is another important robustness check and implies that our conclusions hold for both between- and within-groups residual inequality. By including age we control for cohort and experience effects and the remaining variables (gender dummy, education, region) control for the different wage levels of these groups. It is obvious that controlling for these factors reduces the level of dispersion, as the fraction of explained variance from the first stage regression (see Section 3) is larger.

Figure 2 provides a direct comparison of the two sets of results. The variance after controlling for individual characteristics shrinks by about 20 percentage points. However, apart from this level effect, the same pattern emerges: rising relevance of permanent inequality from 1994 to 2000/2001, followed by a decline thereafter.

6 Concluding Remarks

There is by now a lot of evidence showing a sharp increase in cross-sectional wage and earnings inequality during the 2000s in Germany. However, cross-sectional studies are not very informative over the changing nature of inequality and over mechanisms which are likely to drive it. It is often claimed that the growth of inequality has been predominantly due to permanent factors which in turn is sometimes used in policy discussions as an argument for a greater role of government regulation concerning the determination of wages and earnings. Our study is the first to take the variance decomposition approach and apply it to German data over a period covering years beyond 2000. Using data on full-time working individuals in Germany from the GSOEP dataset for the years of 1994 to 2006, we do not find unambiguous empirical support for the claim that recent increases in inequality have been driven mainly by permanent disparities.

By decomposing the cross-sectional variance into a permanent and a transitory part, we find that the fraction of permanent inequality in 2006 is greater compared to what it was in 1994. However, this fraction declines by approximately 20 percentage points from 2001 to 2006, at the time of rapidly growing cross-sectional inequality. This implies that from about 2000 onward it is the year-to-year transitory volatility which becomes the increasingly important element of the growing cross-sectional inequality of wages and earnings in Germany.

Since there is already evidence for an increase in permanent inequality in the United States during the 2000s (Moffitt and Gottschalk, 2008), our results suggest that the degree to which permanent factors are responsible for determining the observed cross sectional earnings structures in the US and Germany begins to be diverging. This is in contrast to the path of convergence observed for these two countries during the 1990s (Daly and Valletta, 2008). The end of this convergence is rather unexpected and the mechanisms responsible for it deserve further analysis. Importantly - also for German policy makers - the growing transitory fraction of earnings dispersion in Germany in recent years implies that cross sectional inequality is over time partially offset by increasing earnings mobility.

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A Figures

Figure A.1: Cross-sectional Variance and its Permanent Component, for **Wages** in the specification with **a constant** on the full sample

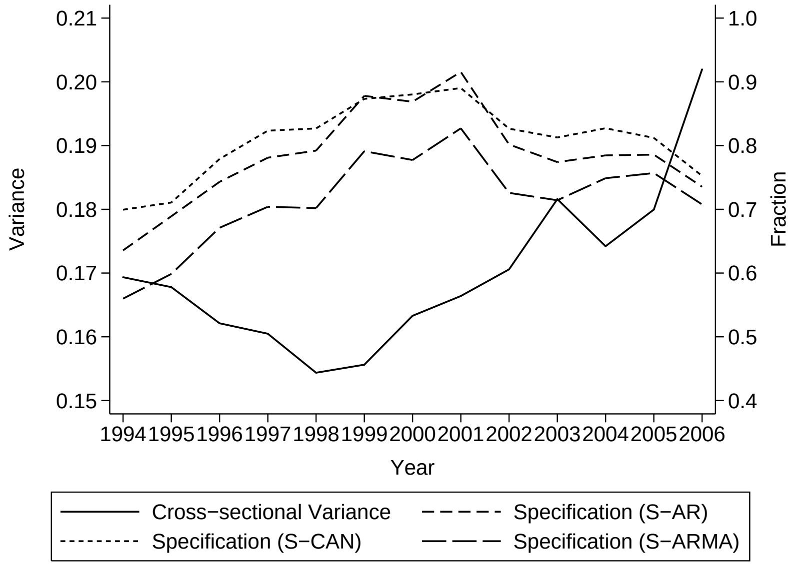
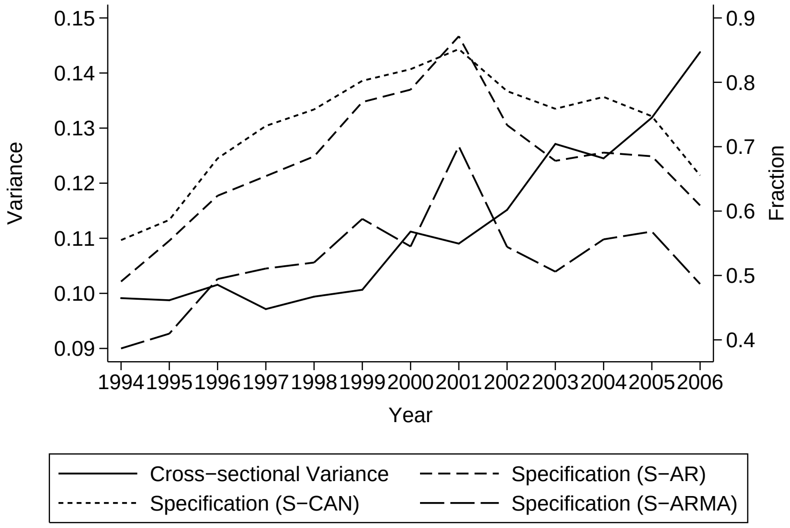


Figure A.2: Cross-sectional Variance and its Permanent Component, for **Earnings** in the specification with **covariates** on the full sample



Notes: See Section 3 for the full list of covariates.

Figure A.3: Cross-sectional Variance and its Permanent Component, for **Earnings** in the specification with **a constant** on the full sample

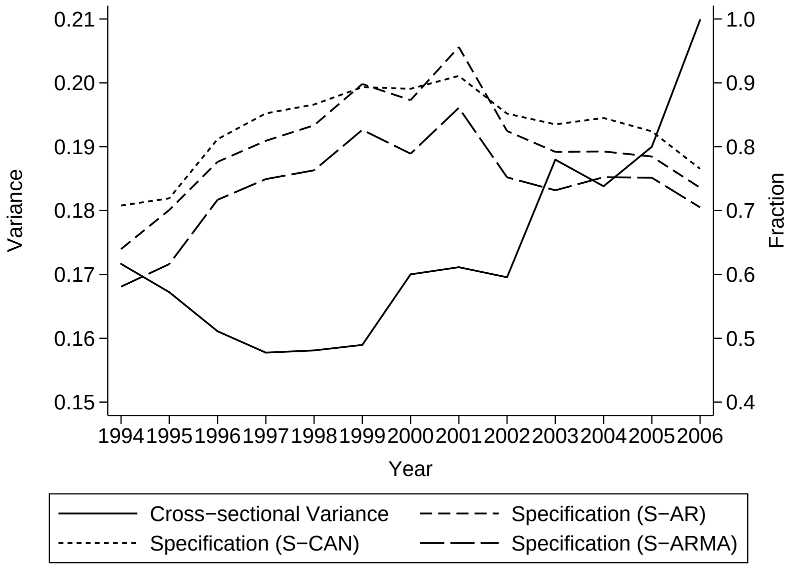
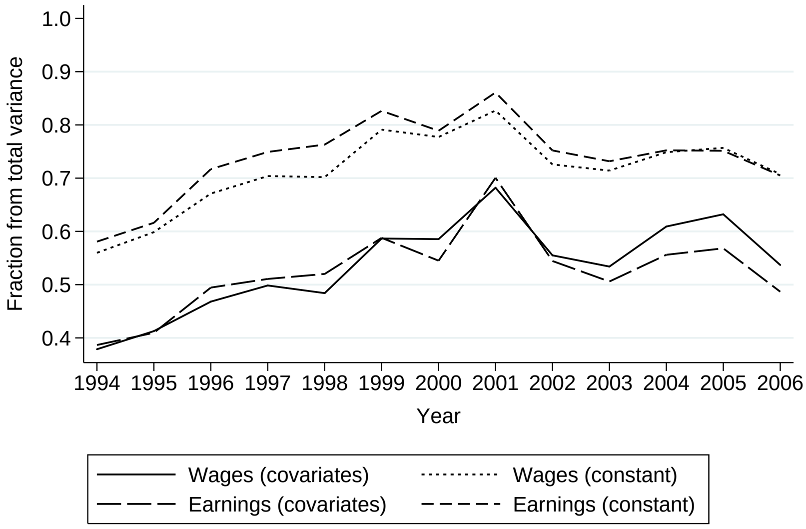
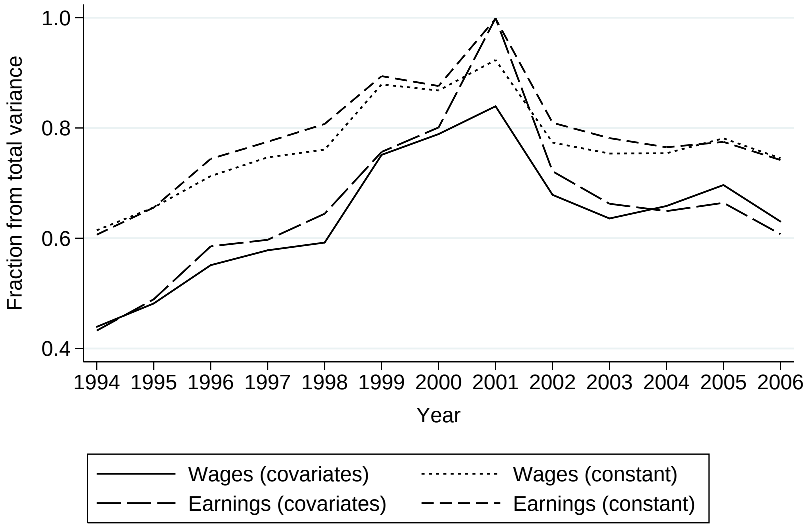


Figure A.4: Evolution of the Fraction of the Permanent Variance Component, in specification (S-ARMA) on the full sample



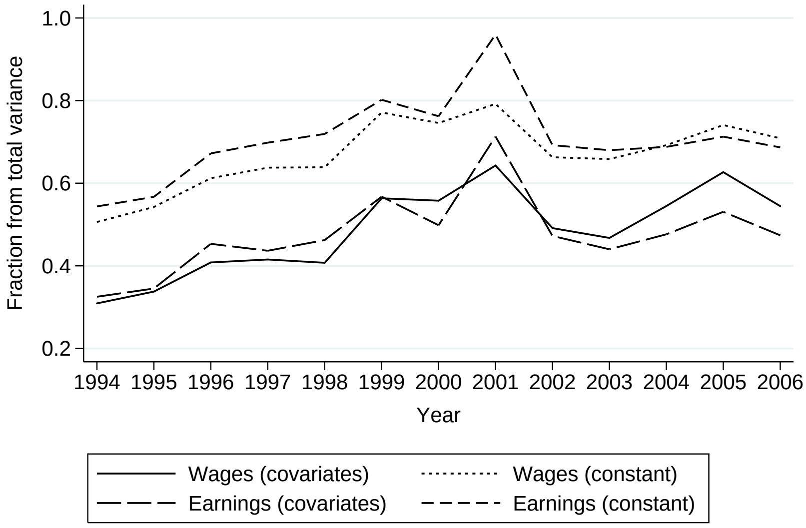
Notes: In the specifications of a constant and of covariates. See Section 3 for the full list of covariates.

Figure A.5: Evolution of the Fraction of the Permanent Variance Component, in Specification (S-AR) on the reduced sample (male only)



Notes: In the specifications of a constant and of covariates. See Section 3 for the full list of covariates.

Figure A.6: Evolution of the Fraction of the Permanent Variance Component, in Specification (S-ARMA) on the reduced sample (male only)



Notes: In the specifications of a constant and of covariates. See Section 3 for the full list of covariates.

B Tables

Table B.1: Variance-Covariance Matrix - **Earnings** in the specification with **a constant** on the full sample

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.1716												
1995	.148	.1672											
1996	.1341	.1425	.1611										
1997	.1324	.1399	.1422	.1577									
1998	.131	.136	.1398	.1421	.1581								
1999	.129	.133	.1372	.1392	.1422	.159							
2000	.1299	.1346	.1399	.1453	.1466	.1518	.17						
2001	.1334	.138	.1423	.143	.1453	.1503	.1581	.1711					
2002	.1227	.1278	.1346	.1352	.1379	.1428	.1489	.1532	.1696				
2003	.1293	.1341	.1352	.1396	.1418	.1461	.1525	.1559	.156	.188			
2004	.1255	.1312	.1333	.1357	.1397	.1457	.1512	.1555	.1536	.1677	.1838		
2005	.124	.1306	.1351	.1385	.141	.1464	.1505	.1548	.1552	.1644	.1688	.19	
2006	.1251	.1306	.1366	.1401	.143	.1493	.1542	.157	.1554	.1672	.1719	.1772	.2099

Notes: Number of observations for computing covariances is 952.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.2: Variance-Covariance Matrix - **Earnings** in the specification with **covariates** on the full sample

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.0991												
1995	.0784	.0987											
1996	.0703	.0796	.1016										
1997	.0685	.0767	.0822	.0971									
1998	.0683	.0738	.0807	.0825	.0994								
1999	.0682	.0723	.0787	.0799	.0839	.1007							
2000	.0656	.0709	.0782	.0825	.0848	.0896	.1112						
2001	.0679	.0728	.0794	.079	.0822	.0869	.0977	.109					
2002	.0634	.0683	.0762	.0755	.0789	.0834	.0926	.0952	.1151				
2003	.0661	.071	.0733	.0763	.0794	.0836	.0928	.0947	.0987	.1271			
2004	.0639	.0693	.0723	.0734	.0781	.0836	.0922	.095	.0968	.1076	.1245		
2005	.0622	.0684	.0741	.0763	.0794	.0842	.092	.0946	.0988	.1048	.1101	.1319	
2006	.0606	.0654	.0716	.0739	.0777	.0836	.0909	.0922	.0949	.1031	.1089	.1147	.1438

Notes: Number of observations for computing covariances is 952. See Section 3 for the full list of covariates.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.3: Variance-Covariance Matrix - **Wages** in the specification with **a constant** on the full sample

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.1694												
1995	.1465	.1678											
1996	.1303	.1381	.1621										
1997	.1303	.1384	.139	.1605									
1998	.1257	.1311	.1331	.1373	.1544								
1999	.1263	.1287	.1313	.135	.1352	.1556							
2000	.124	.1274	.1346	.1395	.1373	.145	.1633						
2001	.128	.1323	.1369	.1387	.1362	.1415	.1497	.1664					
2002	.1198	.1243	.1297	.1302	.1306	.1375	.1442	.1479	.1706				
2003	.1234	.1291	.1279	.1339	.1317	.1382	.1446	.148	.15	.1816			
2004	.1203	.1247	.1268	.1292	.1292	.1377	.1434	.1468	.1465	.1576	.1742		
2005	.1199	.1246	.1285	.1325	.1307	.1379	.1423	.1471	.1505	.155	.1562	.18	
2006	.1219	.1256	.1299	.1351	.1344	.1434	.147	.1492	.1513	.1582	.1599	.1639	.202

Notes: Number of observations for computing covariances is 952.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.4: Variance-Covariance Matrix - **Wages** in the specification with **covariates** on the full sample

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.0972												
1995	.0774	.1002											
1996	.0684	.0772	.1058										
1997	.0688	.0778	.0831	.1049									
1998	.0652	.0716	.0781	.0826	.1005								
1999	.0671	.07	.0761	.0799	.0811	.1007							
2000	.0624	.0666	.0771	.0819	.0808	.0873	.1083						
2001	.0649	.0697	.0781	.0798	.0783	.0827	.0933	.1083					
2002	.0622	.0667	.0744	.0747	.0759	.0816	.091	.0933	.1187				
2003	.0635	.0695	.071	.0767	.0754	.0813	.09	.0921	.0971	.127			
2004	.0634	.0676	.0721	.0741	.0749	.0821	.0905	.0926	.0952	.1047	.1231		
2005	.0627	.0672	.0738	.0775	.0764	.0822	.0898	.0931	.0993	.1024	.1056	.1298	
2006	.0615	.0647	.0707	.0758	.0759	.0838	.0897	.0907	.0962	.1013	.1051	.1096	.1444

Notes: Number of observations for computing covariances is 952. See Section 3 for the full list of covariates.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.5: Variance-Covariance Matrix - **Earnings** in the specification with **a constant** on the reduced sample (male only)

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.1606												
1995	.1401	.1627											
1996	.1268	.1387	.1612										
1997	.125	.1346	.1386	.1558									
1998	.1261	.1331	.1389	.1411	.1613								
1999	.1242	.1295	.1364	.1378	.1428	.1617							
2000	.1242	.1305	.1384	.1443	.1474	.1539	.1733						
2001	.1281	.1336	.1401	.1402	.1452	.1514	.159	.1724					
2002	.1151	.1208	.1314	.1303	.1365	.1416	.1475	.1516	.1698				
2003	.1188	.1261	.1304	.1342	.1385	.1431	.1502	.1528	.151	.1828			
2004	.1155	.1233	.1278	.1291	.1362	.1432	.1485	.1523	.1486	.162	.1808		
2005	.1155	.1231	.1315	.1338	.1395	.1457	.1499	.1529	.1521	.1581	.1664	.1863	
2006	.1143	.1201	.1303	.1328	.1403	.1474	.1529	.154	.1504	.162	.168	.1733	.1967

Notes: Number of observations for computing covariances is 728.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.6: Variance-Covariance Matrix - **Earnings** in the specification with **covariates** on the reduced sample (male only)

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.0921												
1995	.0717	.0936											
1996	.0656	.0766	.1042										
1997	.0625	.071	.08	.0951									
1998	.0639	.07	.0805	.0807	.1011								
1999	.063	.0672	.078	.0771	.0824	.1009							
2000	.0604	.066	.0774	.0804	.0838	.0896	.1125						
2001	.064	.0689	.0789	.0763	.0816	.0873	.0976	.1104					
2002	.0576	.0625	.0749	.071	.0772	.0814	.0905	.0938	.1153				
2003	.0578	.0644	.0709	.0715	.0761	.0803	.0901	.0921	.0944	.1232			
2004	.056	.0626	.069	.0672	.0741	.0804	.0889	.0921	.0922	.1027	.1222		
2005	.055	.0615	.0721	.0714	.077	.0824	.09	.0923	.0952	.0984	.1076	.1275	
2006	.0522	.0564	.0675	.0671	.0749	.0815	.0895	.0901	.091	.0993	.1063	.1115	.1329

Notes: Number of observations for computing covariances is 728. See Section 3 for the full list of covariates.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.7: Variance-Covariance Matrix - **Wages** in the specification with **a constant** on the reduced sample (male only)

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.1623												
1995	.1406	.1639											
1996	.126	.1358	.1655										
1997	.126	.1346	.1372	.1601									
1998	.1225	.1285	.1323	.1356	.1576								
1999	.125	.1268	.1322	.1354	.1371	.1617							
2000	.1205	.1244	.1344	.1387	.1377	.1491	.1671						
2001	.1238	.1284	.1354	.1358	.1349	.1433	.151	.1666					
2002	.1141	.1176	.1272	.1242	.1283	.1375	.1437	.1453	.17				
2003	.1154	.1219	.1238	.1277	.1273	.137	.143	.1435	.1441	.1769			
2004	.1128	.1175	.1227	.1231	.1254	.1371	.1421	.1439	.1418	.1526	.1727		
2005	.1139	.1182	.1268	.1287	.1284	.1392	.1429	.1459	.1475	.1488	.1538	.1774	
2006	.114	.1167	.125	.129	.1312	.1441	.1477	.146	.1468	.1531	.1567	.1607	.1915

Notes: Number of observations for computing covariances is 728.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.8: Variance-Covariance Matrix - **Wages** in the specification with **covariates** on the reduced sample (male only)

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1994	.0913												
1995	.0704	.0937											
1996	.0634	.0731	.1088										
1997	.063	.0711	.0799	.102									
1998	.0601	.0658	.0755	.0781	.1005								
1999	.0629	.0644	.0745	.0766	.0789	.1021							
2000	.0567	.0604	.0748	.0777	.0774	.087	.1077						
2001	.0596	.064	.0757	.0749	.0744	.0817	.0913	.1066					
2002	.0557	.0588	.071	.0669	.071	.0785	.0872	.0886	.1155				
2003	.0553	.0614	.0665	.0688	.0689	.0776	.0854	.0857	.0894	.121			
2004	.0557	.0596	.0677	.0665	.069	.079	.0867	.0883	.0888	.0985	.1208		
2005	.0555	.0591	.0711	.0715	.0713	.0802	.0868	.0895	.0938	.0941	.1013	.1245	
2006	.0535	.055	.0654	.0681	.0708	.0822	.0877	.0861	.0903	.0952	.1013	.1049	.1339

Notes: Number of observations for computing covariances is 728. See Section 3 for the full list of covariates.
Source: Own calculations using the GSOEP data (1994-2006).

Table B.9: Parameter Estimates - Reduced Sample (Male Only)

	AR(1)				ARMA(1,1)			
	Earnings		Wages		Earnings		Wages	
	constant	covariates	constant	covariates	constant	covariates	constant	covariates
$\sigma^2_{v_0}$	0.080	0.060	0.084	0.062	0.046	0.033	0.056	0.035
	(0.015)	(0.014)	(0.022)	(0.020)	(0.006)	(0.005)	(0.007)	(0.005)
σ^2_μ	0.097	0.039	0.101	0.040	0.086	0.029	0.083	0.028
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.005)	(0.003)
σ^2_ε	0.029	0.025	0.034	0.031	0.038	0.034	0.039	0.036
	(0.004)	(0.004)	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)
ρ	0.652	0.655	0.590	0.574	0.868	0.897	0.867	0.880
	(0.024)	(0.024)	(0.027)	(0.027)	(0.028)	(0.015)	(0.027)	(0.022)
γ					-0.418	-0.437	-0.497	-0.494
					(0.032)	(0.020)	(0.027)	(0.022)
p_{1995}	1.046	1.077	1.030	1.052	1.041	1.062	1.040	1.060
	(0.014)	(0.030)	(0.017)	(0.033)	(0.011)	(0.027)	(0.013)	(0.028)
p_{1996}	1.099	1.231	1.071	1.205	1.113	1.263	1.100	1.245
	(0.015)	(0.033)	(0.018)	(0.037)	(0.016)	(0.043)	(0.017)	(0.040)
p_{1997}	1.111	1.198	1.085	1.203	1.121	1.193	1.113	1.228
	(0.016)	(0.034)	(0.019)	(0.038)	(0.017)	(0.046)	(0.020)	(0.045)
p_{1998}	1.153	1.283	1.085	1.207	1.158	1.266	1.105	1.206
	(0.017)	(0.037)	(0.019)	(0.040)	(0.019)	(0.054)	(0.022)	(0.051)
p_{1999}	1.205	1.376	1.172	1.357	1.219	1.395	1.225	1.427
	(0.018)	(0.040)	(0.022)	(0.045)	(0.024)	(0.066)	(0.029)	(0.060)
p_{2000}	1.242	1.495	1.193	1.434	1.231	1.377	1.227	1.453
	(0.019)	(0.045)	(0.023)	(0.048)	(0.028)	(0.084)	(0.032)	(0.081)
p_{2001}	1.322	1.661	1.213	1.454	1.377	1.633	1.263	1.553
	(0.018)	(0.043)	(0.024)	(0.051)	(0.032)	(0.115)	(0.035)	(0.079)
p_{2002}	1.176	1.433	1.132	1.373	1.160	1.354	1.165	1.409
	(0.019)	(0.044)	(0.021)	(0.046)	(0.025)	(0.077)	(0.031)	(0.077)
p_{2003}	1.203	1.427	1.142	1.367	1.196	1.358	1.187	1.413
	(0.018)	(0.043)	(0.021)	(0.045)	(0.025)	(0.078)	(0.032)	(0.080)
p_{2004}	1.192	1.420	1.135	1.400	1.203	1.416	1.206	1.529
	(0.018)	(0.041)	(0.020)	(0.045)	(0.024)	(0.079)	(0.032)	(0.082)
p_{2005}	1.217	1.466	1.168	1.456	1.243	1.527	1.263	1.662
	(0.018)	(0.041)	(0.020)	(0.046)	(0.024)	(0.084)	(0.035)	(0.092)
p_{2006}	1.232	1.446	1.193	1.449	1.257	1.478	1.285	1.611
	(0.017)	(0.040)	(0.020)	(0.044)	(0.024)	(0.080)	(0.034)	(0.082)
λ_{1996}	0.875	0.959	0.932	1.008	0.859	0.938	0.941	1.015
	(0.062)	(0.070)	(0.074)	(0.078)	(0.034)	(0.034)	(0.034)	(0.033)
λ_{1997}	0.822	0.918	0.873	0.957	0.818	0.908	0.921	0.990
	(0.070)	(0.077)	(0.080)	(0.083)	(0.039)	(0.036)	(0.041)	(0.038)
λ_{1998}	0.778	0.892	0.844	0.934	0.805	0.907	0.927	0.991
	(0.075)	(0.082)	(0.083)	(0.085)	(0.044)	(0.041)	(0.045)	(0.041)
λ_{1999}	0.574	0.731	0.603	0.728	0.676	0.804	0.754	0.858
	(0.089)	(0.087)	(0.102)	(0.094)	(0.057)	(0.053)	(0.062)	(0.051)
λ_{2000}	0.647	0.699	0.646	0.692	0.769	0.909	0.818	0.886
	(0.088)	(0.097)	(0.102)	(0.109)	(0.062)	(0.055)	(0.065)	(0.060)
λ_{2001}	-0.076	-0.046	0.485	0.593	0.316	0.679	0.745	0.794
	(0.103)	(0.114)	(0.124)	(0.115)	(0.140)	(0.097)	(0.070)	(0.065)
λ_{2002}	0.791	0.835	0.850	0.881	0.866	0.935	0.961	0.985
	(0.077)	(0.087)	(0.085)	(0.090)	(0.049)	(0.047)	(0.050)	(0.048)
λ_{2003}	0.882	0.956	0.906	0.965	0.921	0.998	0.993	1.036
	(0.076)	(0.086)	(0.084)	(0.089)	(0.048)	(0.046)	(0.050)	(0.047)
λ_{2004}	0.916	0.980	0.900	0.940	0.909	0.966	0.937	0.962
	(0.076)	(0.087)	(0.084)	(0.089)	(0.048)	(0.046)	(0.050)	(0.048)
λ_{2005}	0.910	0.978	0.858	0.897	0.886	0.932	0.873	0.882
	(0.076)	(0.087)	(0.084)	(0.089)	(0.049)	(0.046)	(0.053)	(0.054)
λ_{2006}	1.007	1.090	0.969	1.035	0.953	1.010	0.964	1.014
	(0.079)	(0.091)	(0.085)	(0.089)	(0.051)	(0.046)	(0.053)	(0.049)
N	91	91	91	91	91	91	91	91

Notes: See Section 3 for the full list of covariates.

Source: Own calculations using the GSOEP data (1994-2006).