Earnings dynamics, foreign workers and the stability of inequality trends in Luxembourg, 1988–2009[1]

Denisa M. Sologon[2]
CEPS/INSTEAD, Maastricht University/UNU-MERIT and IZA Bonn

Philippe Van Kerm[3]
CEPS/INSTEAD

January 2014

[1]This research is part of the "Earnings Dynamics and Microsimulation" project co-funded by the 'Fonds National de la Recherche' Luxembourg (AFR grant PDR893613) under the Marie Curie Actions of the European Commission (FP7-COFUND). It is also part of the InWIn project (*Information and Wage Inequality: Evidence on wage differences between natives, immigrants and cross-border workers in Luxembourg*) supported by the 'Fonds National de la Recherche' Luxembourg (contract C10/LM/785657). We are grateful to the Inspection Générale de la Sécurité Sociale of Luxembourg for providing the anonymized extracts from social security registers and to Isabelle Debourges, Tom Dominique, Béatrice Lepêcheur, Thierry Mazoyer and Raymond Wagener for their invaluable support. We also thank Robert A. Moffitt and Timm Bönke for providing their estimates for the international comparison. Comments on earlier drafts from Lorenzo Cappellari, Alessio Fusco, Stephen Jenkins, Gary Solon, Don Williams and from participants at the OECD-EDRC Technical seminar on inequalities and social mobility, Ministère de l'Economie et du Commerce Extérieur, Luxembourg (April 24, 2012) and the Workshop on Household Finance and Consumption, Banque Centrale du Luxembourg (June 26, 2013) are gratefully acknowledged.

[2]D. M. Sologon (corresponding author), CEPS/INSTEAD, 3 Av. de la Fonte, L-4364 Esch/Alzette, Luxembourg. E-mail: `denisa.sologon@ceps.lu`.

[3]P. Van Kerm, CEPS/INSTEAD, 3 Av. de la Fonte, L-4364 Esch/Alzette, Luxembourg. E-mail: `philippe.vankerm@ceps.lu`.

Abstract

This paper exploits a large-scale administrative dataset to analyze trends in male earnings inequality in Luxembourg over twenty years of rapid economic growth. A detailed error components model is estimated to identify persistent and transitory components of log hourly earnings variance. Given the importance of foreign labour in Luxembourg, models and inequality trends are distinguished between native, immigrant and cross-border workers. Surprisingly, we observe only a modest increase in overall hourly earnings inequality between 1988 and 2009. This apparent stability is however the net result of somewhat more complex underlying changes, with marked increases in persistent inequality (except among native workers), growing contribution of foreign workers, divergence across subgroups, and a decrease in earnings instability (primarily for native workers). Overall, we interpret these results as showing a surprising stability in the face of the industrial re-development, the changes in the size and structure of employment, and the fast growth that characterized the country's economy in this period. Such results possibly hint at the role of strict labour market regulations and collective bargaining institutions in holding back earnings inequality, at least in a period of fast economic growth and soaring demand for labour.

Keywords: earnings dynamics; persistent inequality; transitory inequality; Luxembourg; cross-border workers; immigrant workers

JEL classification codes: C23 ; D31 ; J15 ; J31

1 Introduction

The rise in inequality is a global policy concern. The World Economic Forum has identified income inequality as one of the "two most serious challenges" in the world today (World Economic Forum, 2011). The rise in *earnings* inequality has attracted particular attention for it has been identified as the key driver of the growth in family income inequality (OECD, 2008, 2011). Globalization and skill-biased technological change have amplified returns to skills and are typically identified as the main forces behind increasing earnings inequality in the last three decades (see, e.g., Freeman and Katz, 1994, Jaumotte et al., 2013). Additionally, a role for labour market institutions in curtailing inequality increases has been suggested to account for the different trends observed in the United States and continental Europe (Freeman and Katz, 1994, Acemoglu, 2002).

Following seminal analysis for the US by Gottschalk and Moffit (1994), much of the empirical literature has explored the extent to which long-term changes in earnings inequality reflect an increase in persistent wage differentials between workers or whether it reflects increased transitory earnings variations. The former is consistent with explanations related to increasing returns to skills and education—which are essentially permanent individual characteristics—while the former is associated with increased labour market risks and volatility (employment and earnings shocks) (see, e.g. Haider, 2001). Unlike an increase in persistent inequality, an increase in transitory inequality need not lead to higher inequality in long-term or life-time earnings and, to the extent that transitory variations can be insured and consumption can be smoothed out, trends in transitory inequality is sometimes viewed as an issue of second-order importance (Friedman and Kuznets, 1954).

Empirical strategies to decompose inequality trends into permanent and transitory components typically consist in exploiting dynamic error components models for (the logarithm of) individual earnings. Earnings dynamics processes incorporate both persistent terms (that affect earnings permanently) and transitory terms (that have short-lived impacts), and model parameter estimates are then used to additively decompose the overall earnings variance into permanent and transitory factors whose relative contributions can be tracked over time (see Meghir and Pistaferri, 2011, Jantti and Jenkins, 2013, for reviews). Consistently with the observed increasing returns to skills, most recent studies based on panel data with a long time-series dimension find that permanent inequality increased in most industrialized countries between the 1970s/1980s and the 1990s/2000s, both in Europe and in North America; see, among others, Haider (2001), Kopczuk et al. (2010), Moffitt and Gottschalk (2011), DeBacker et al. (2013) on the US, Baker and Solon (2003) on Canada, Dickens (2000) and Kalwij and Alessie (2007) on the UK, Cappellari (2004) and Cappellari and Leonardi (2013) on Italy, Bingley et al. (2013) on Denmark, and Bönke et al. (2013) on Germany. As a matter of exception, Gustavsson (2007) observes a decrease in persistent inequality in Sweden until 1990 and an increase thereafter.[1] Results on trends in transitory variance are somewhat more mixed. Moffitt and Gottschalk (2011) find a dramatic increase in transitory variance in the US in the 1980s, a levelling-off in the late 1980s, followed by a decrease in the 1990s and a further increase in the early 2000s. In Canada, most of the increase in earnings instability occurred during the early 1980s and early 1990s (Baker and Solon, 2003). Across Europe, a strong increase in transitory inequality was found by Kalwij and Alessie (2007) in the UK, by Cappellari and Leonardi (2013) in Italy, and by Bönke et al. (2013) in Germany.[2] Bingley et al. (2013) find an increase in earnings instability in Denmark starting with the mid 1990s, and this appears to be the trend across most other European countries, at least until the early 2000s (Sologon and O'Donoghue, 2012).

The present paper contributes to this literature with an analysis of trends in (permanent and transitory) earnings inequality among male workers in Luxembourg between 1988 and 2009. The originality of the analysis is three-fold. First we take advantage of a large-scale administrative dataset on earnings and employment which allows us to rely on a flexible model of earnings dynamics. Second, owing to the scale of our dataset, we are able to distinguish trends for native and foreign workers and identify their relative contributions to the overall long-term earnings inequality trends. Last, the Luxembourg case study is yet unexplored and is of interest *per se*. The industrial transition and the magnitude of the concurrent labour market changes that the country experienced in this period make inspection of inequality trends in Luxembourg particularly worthy of interest. We look at a period during which this small economy experienced sustained economic growth and an industrial re-development from an industry-driven economy to an economy dominated by the tertiary sector, the financial sector in particular (Annaert, 2004, Allegrezza et al., 2004, Fusco et al., 2014). The transition from the steel industry towards the specialization in financial and banking sectors recorded a strong upswing of GDP growth from the mid-90s. Sustained economic growth increased labour demand to levels that could not be matched by the resident population alone (especially for high skilled workers) and soaring labour demand led to a massive inflow of foreign workers—both of immigrants and of cross-border workers residing in Belgium, France and Germany (Amétépé and Hartmann-

[1] In a study of 15 EU countries based on relatively short panel, Sologon and O'Donoghue (2012) find that only Denmark stands out with the lowest and decreasing overall permanent variance in the 1990s/early 2000s.

[2] In the UK, while Kalwij and Alessie (2007) found that transitory inequality increased to a larger extent than permanent inequality, Dickens (2000) found similar increases in both components. The difference was attributed to the methodological advancements brought by Kalwij and Alessie (2007) which account for age, time and cohort effects in their model specification (see Section 5).

Hirsch, 2011). According to our calculations, the share of cross-border workers among male workers aged 20-57 recorded an increase from over 20 percent in the late 1980s to close to 45 percent in the late 2000s. By 2009, foreign workers represented 75 percent of workers in this group (see Section 2 *supra* for details). We conjecture that rising demand for high skill labour (in the financial sector in particular) and the limited supply of domestic workers put strong upward pressure on earnings inequality. However, this may have been mitigated by (i) a growth-induced general increase in the demand for labour across the overall skill distribution, (ii) the abundant supply of foreign labour from neighbouring countries, and (iii) relatively strong labour market institutions—in particular, influential collective bargaining institutions, a high statutory minimum wage and relatively strict employment protection regulation. The trends in earnings inequality in Luxembourg can therefore provide some empirical indication as to whether strong labour market regulation and large foreign labour supply can counterbalance otherwise strong inequality increasing pressures.

Recent research has also pointed towards the role of the financial sector *per se* in increased earnings inequality (Kaplan and Rauh, 2010, Kus, 2012, Bell and Van Reenen, 2013). The sheer importance of the sector and its expansion in the period covered by our analysis (from about 15 percent of the gross value added in the late 1980s to 30 percent in the late 2000s) is another incentive to examine earnings inequality trends in Luxembourg in detail.

This paper is one of the few studies to date based on a very large administrative dataset with complete coverage of the working-age population in the country—we analyze just under 370,000 men contributing more than 3 million person-year observations (see Section 2). To the best of our knowledge, only Blundell et al. (2014) exploit larger data for analyses of this type.[3] The data are derived from social security administration registers and provide annual information on earnings spanning 22 years about each person ever employed in Luxembourg at any point in time during this period. The size of the dataset both in the cross-section and time dimensions enables us to estimate a flexible earnings dynamics model that nests many specifications recently used in the literature (see Meghir and Pistaferri (2011) for a review).[4] Crucially, we are able to allow the variance of both permanent and transitory shocks to vary flexibly with workers' age—an essential feature emphasized in Blundell et al. (2014)—and to allow the relative weight of permanent and transitory factors to vary over calendar time and birth cohorts (see Section 5). Use of administrative data brings further advantages compared

[3]Other studies which have exploited administrative registers have generally analyzed smaller extracts (see, e.g., Baker and Solon, 2003, Cappellari, 2004, DeBacker et al., 2013).

[4]Reliable inference on flexible models earnings dynamics requires access to data with both a high number of observations and long time frame, as Doris et al. (2013) emphasize.

to survey data such as very low reporting or recollection error and the absence of selective attrition (other than trough migration or death). The drawback of our data is however the absence of information on educational achievements. Also information on earnings is affected by top-coding. To address this issue, we implement a multiple imputation procedure as proposed by Jenkins et al. (2011) and incorporate this in the process of estimating the parameters of our earnings dynamics model.

Finally, the scale of our data allows us to examine the contribution of foreign workers in detail by estimating models separately for native, immigrant and cross-border workers. We then use the separate model parameters to estimate the contributions of each of the subgroups to the overall inequality trends (and to its permanent and transitory components separately), disentangling trends in within-group inequality, in between-group differentials and in the relative share of each group in total employment. This is a distinctive feature of our analysis which reveals particularly informative given the magnitude of changes in the employment composition throughout the period and the different skill composition of these three groups of workers (Choe and Van Kerm, 2014, Fusco et al., 2014).

To preview our results, we find evidence of only a relatively modest increase in earnings inequality. However, this surprising stability in light of the drastic labour market changes in the period analyzed is the net result of somewhat more complex underlying changes, with marked increases in persistent inequality among cross-border workers and among immigrants, a growing contribution of foreign workers, divergence in persistent differentials between subgroups, and a decrease in earnings instability (but primarily for native workers). Native workers appear to have experienced a particularly favourable trends. Such results possibly hint at the role of strict labour market regulations and collective bargaining institutions in holding back earnings inequality, at least in a period of fast economic growth and soaring demand for labour.

The paper is structured as follows. Section 2 describes the data used in the analysis, our sample selection and the strategy implemented to address top-coding of earnings. Section 3 sets the scene by documenting the trends in mean earnings and in inequality observed in the data and Section 4 describes the general auto-covariance structure of earnings. Our model of earnings dynamics is detailed in Section 5. Section 6 exploits model estimates to disentangle persistent and transitory components in the variance of log earnings and reveals the long-run increase in persistent inequality and the contribution of foreign workers to these trends. Our main results are finally contrasted with comparable estimates from other countries in Section 7. Section 8 concludes.

2 Data

2.1 Data frame and sample description

Each person with a paid occupation in Luxembourg is registered to the social security administration (*Inspection Générale de la Sécurité Sociale*—IGSS) from the date of her first job in the country. Information is subsequently recorded on various aspects of individual employment histories for the purpose of calculating future pension entitlements.

Our analysis exploits a large-scale anonymized scientific-use extract from these registers. The dataset contains annual individual-level data on gross annual labour income, months, days or hours worked per year, occupational status, nationality, place of residence over the period 1950–2009.[5] Civil servants and white collars' hours or days worked per year are however only recorded from 1988 onwards. We therefore limit our analysis to the 22 years of data from 1988 to 2009.

The dataset provides information on the professional career profile of all people ever working for an employer based in Luxembourg in the period 1988–2009. Following the tradition of previous studies, our analysis focuses on men aged between 20 and 57 to avoid issues related to the labour market participation of women and of men at the end of their career. We consider individuals born in 41 yearly birth cohorts between 1940 and 1980 who have been recorded working in Luxembourg at least in one year between 1988 and 2009. The 41 cohorts are observed at least ten years over the time span of the data.[6] Individuals who experienced at least five years of inactivity gaps between 1950 and 2009 because of disability or who retired before the age of 57 with a disability benefit are disregarded. Individuals may exit and (re-)enter the dataset at any year due to death or migration. The resulting dataset (after some additional sample selection based on earnings described below) contains data on 369 288 men providing an unbalanced panel of 3 265 927 person-year observations with positive annual earnings.[7] Table 1 details the sample composition in persons and person-years, years observed, age range for

[5]Note that because of the purpose of these registers, it contains no information on potentially relevant variables such educational achievements, non-labour incomes and household-level contextual and demographic information.

[6]See Baker and Solon (2003) for the rationale of such a cohort selection rule in the context of error components model estimation.

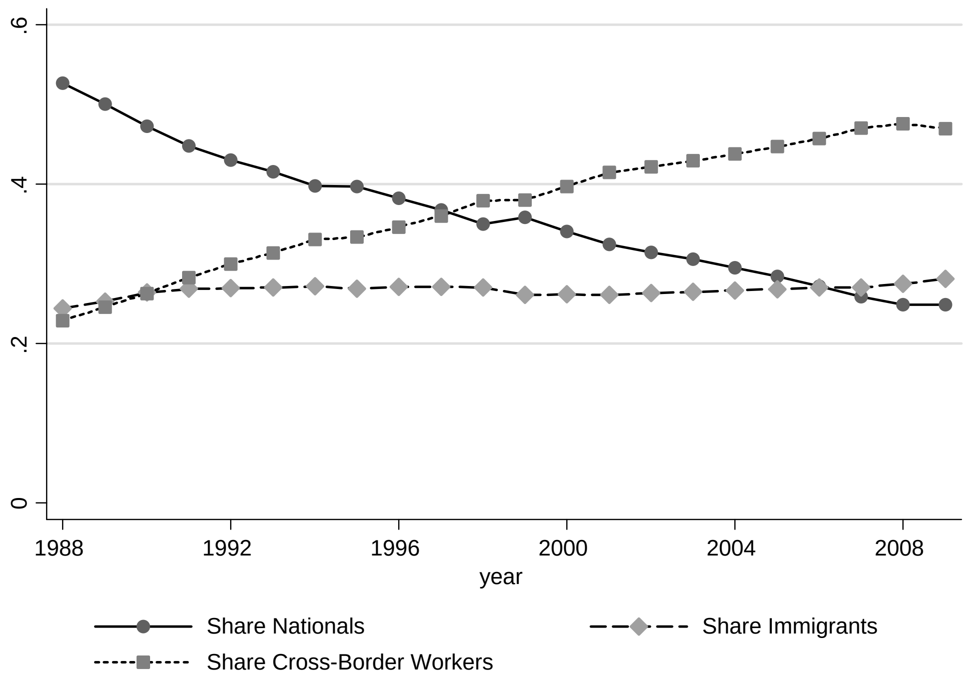
[7]This is a large sample in comparison to the sample sizes of 3 115, 2 988, 76 079, and 169 877 individuals used in similar studies in the US by Haider (2001) and Moffitt and Gottschalk (2002), in Sweden by Gustavsson (2008) and in the UK by Dickens (2000). Samples from administrative sources of smaller sizes are used by Cappellari (2004) for a study in Italy (67 768 individuals and 935 333 person-year observations) and by Baker and Solon (2003) for a study in Canada (31 105 individuals). Blundell et al. (2014) on the other hand analyze a dataset of 1 004 294 Norwegian men.

each of the 41 cohorts and type of worker (native, immigrant or cross-border worker).

The fifth column in Table 1 shows the share of individuals in each cohort remaining in the sample for the maximum number of years observed for each cohort. For example, from the cohort born in 1947, 54.4% of the people present in 1988 continued working until 2009. Similar levels of attrition are reported by Dickens (2000) for the UK. To complement this information, the sixth column of Table 1 shows, by cohort, the share of observed person-year observations in the theoretical person-year observations had all individuals been present in all years of each cohort (years observed multiplied by the number of persons by cohort). This share ranges from around 75% for the oldest cohorts to around 45% for the youngest cohort.

Table 2 shows, by year, the size of the sample, the age range, the share of observations whose income is top-coded (see below) and the distribution across native, immigrant and cross-border workers. While the share of immigrant workers in our sample remained stable throughout the period, the share of cross-border workers increased sharply over time; see Figure 1. As a result, the share of native workers fell from about 51% in 1988 to only 25% by 2009.

Figure 1: Share of nationals, immigrants and cross-border workers in the sample (men, aged 20 to 57, norn between 1940 and 1980, with positive earnings)



Tables A.1–A.3 in Appendix A display detailed sample information by worker type. Immigrants display rich longitudinal profiles. The share of immigrants active for all observed years

Table 1: Sample Size by Birth Cohort

Cohort born in	Persons	Person-years	Years observed	% Persons present in all years	% Observed person-years in theoretical person-years	Year range		Age range	
1940	1982	14832	10	68.57	74.83	1988	1997	48	57
1941	1996	15893	11	65.89	72.39	1988	1998	47	57
1942	2409	18984	12	64.10	65.67	1988	1999	46	57
1943	2629	21434	13	59.07	62.71	1988	2000	45	57
1944	2865	24957	14	60.14	62.22	1988	2001	44	57
1945	2972	27036	15	59.09	60.65	1988	2002	43	57
1946	3782	36983	16	55.81	61.12	1988	2003	42	57
1947	4320	42874	17	54.44	58.38	1988	2004	41	57
1948	4691	48846	18	53.25	57.85	1988	2005	40	57
1949	5038	54614	19	51.38	57.05	1988	2006	39	57
1950	5346	58017	20	49.78	54.26	1988	2007	38	57
1951	5643	64362	21	47.83	54.31	1988	2008	37	57
1952	6361	73236	22	46.53	52.33	1988	2009	36	57
1953	6531	75847	22	46.09	52.79	1988	2009	35	56
1954	7199	82420	22	46.63	52.04	1988	2009	34	55
1955	7377	82045	22	45.08	50.55	1988	2009	33	54
1956	7866	87893	22	44.80	50.79	1988	2009	32	53
1957	8517	94351	22	43.25	50.35	1988	2009	31	52
1958	8995	99613	22	42.60	50.34	1988	2009	30	51
1959	9842	106217	22	41.80	49.06	1988	2009	29	50
1960	10140	107828	22	41.32	48.34	1988	2009	28	49
1961	11145	116668	22	40.28	47.58	1988	2009	27	48
1962	11550	120733	22	40.18	47.51	1988	2009	26	47
1963	12604	130182	22	37.38	46.95	1988	2009	25	46
1964	13351	137151	22	37.09	46.69	1988	2009	24	45
1965	13636	136802	22	33.43	45.60	1988	2009	23	44
1966	13787	133288	22	29.92	43.94	1988	2009	22	43
1967	13949	132386	22	26.69	43.14	1988	2009	21	42
1968	14074	127501	22	22.41	41.18	1988	2009	20	41
1969	13886	120273	21	21.77	41.25	1989	2009	20	40
1970	13857	113777	20	21.27	41.05	1990	2009	20	39
1971	14097	112540	19	20.99	42.02	1991	2009	20	38
1972	13620	102807	18	21.40	41.93	1992	2009	20	37
1973	12978	91822	17	18.64	41.62	1993	2009	20	36
1974	12398	83094	16	18.77	41.89	1994	2009	20	35
1975	11834	75312	15	17.63	42.43	1995	2009	20	34
1976	11548	68404	14	18.40	42.31	1996	2009	20	33
1977	11489	64777	13	20.07	43.37	1997	2009	20	32
1978	11099	57668	12	22.47	43.30	1998	2009	20	31
1979	10971	53147	11	23.80	44.04	1999	2009	20	30
1980	10914	49313	10	26.91	45.18	2000	2009	20	29
Total	369288	3265927							

Notes: % Observed person-years in theoretical person-years = the ratio between the third column (Person-years) and the product between the second column (Persons) and the fourth column (Years observed). The sample size refers only to positive earnings.

Table 2: Sample Size by Year

Year	Persons	Age range		% Top-coded	Nationals	Immigrants	Cross-Border Workers
1988	74785	20	48	10.85	38675	18543	17567
1989	81609	20	49	10.58	40036	20999	20574
1990	89621	20	50	11.26	41363	24084	24174
1991	97504	20	51	10.31	42587	26641	28276
1992	104417	20	52	5.50	43698	28615	32104
1993	109890	20	53	4.92	44667	30090	35133
1994	116849	20	54	5.14	45647	32043	39159
1995	125868	20	55	4.54	49392	34115	42361
1996	133124	20	56	4.93	50563	36234	46327
1997	141196	20	57	4.47	51945	38357	50894
1998	149607	20	57	4.91	52360	40474	56773
1999	165208	20	57	5.21	59255	43119	62834
2000	174490	20	57	5.14	59428	45698	69364
2001	181030	21	57	5.43	58779	47229	75022
2002	183103	22	57	5.67	57840	48104	77159
2003	185291	23	57	5.08	56977	48901	79413
2004	187474	24	57	5.34	55749	49792	81933
2005	189317	25	57	5.38	54379	50625	84313
2006	192061	26	57	6.13	52946	51842	87273
2007	194849	27	57	5.97	51530	52626	90693
2008	196625	28	57	6.44	50088	54064	92473
2009	192009	29	57	5.96	48477	53805	89727
Total	3265927				1106381	876000	1283546

in each cohort ranges from close to 71% for the oldest cohort to over 33% for the youngest. The share of observed person-years in the theoretical person-year observations ranges from over 74% for the oldest cohort to close to 46% for the youngest. As expected, cross-borders have shorter observed profiles. Their share of observed person-years in the theoretical person-years ranges from 54% for the oldest cohort to over 38% for the youngest. The share of cross-borders present throughout the cohort's active years ranges from over 54% for the oldest cohort to over 14% for the youngest.

Note that cross-border workers pose a specific problem since their earnings are only recorded for the years worked in Luxembourg. While they are properly followed on re-entry into the data frame, no information is available in the years worked abroad. Similarly, migrant workers who leave the country are not tracked until they return in Luxembourg. This most likely underestimates the variability of earnings experienced by these two sets of individuals. However this does not prevent estimation of their contribution to the trends in persistent and transitory earnings inequality *in* Luxembourg, presented *supra*.

2.2 Hourly earnings calculation and adjustments for top-coding

Our analysis focuses on real gross hourly wage, which we will refer to as 'earnings'.[8] Hourly wage is computed by dividing gross annual earnings by the number of hours worked in the main job. Both wages and hours worked are available as annual amounts in our dataset and have been constructed on the basis of monthly reports by employers. Overtime hours and multiple jobs are disregarded. All earnings are inflated to 2009 prices using the consumer price index.

Earnings data are affected by top-coding. The monthly reports by employers are top-coded at 4 times the monthly minimum wage until 1991 and 5 times thereafter. This top-coding in the monthly employer reports translates in truncated annual earnings.[9] The fourth column of Table 2 gives the share of observations with top-coded earnings. The change in the legislation for reporting wages after 1991 is reflected by the share of top-coded which drops to almost half the value before 1992.

We address this issue by imputing simulated values for top-coded earnings. We follow Jenkins et al. (2011) and first conduct (censored) maximum likelihood estimation of a parametrically specified distribution for top incomes then multiply impute each top-coded earnings observation with m independent random draws from the estimated top income distribution. Multiple imputation allows us to account for the variability introduced by the stochastic nature of the imputation. As is now common (see, e.g., Atkinson and Piketty, 2010, Kopczuk et al., 2010, Atkinson et al., 2011, Alfons et al., 2013), we assume that the upper tail of the annual earnings distribution for each year is described by a Pareto distribution with cumulative distribution function

$$F_\theta(y) = 1 - \left(\frac{y}{y_0}\right)^{-\theta}, y \geq y_0 \tag{1}$$

where $y_0 > 0$ is a threshold beyond which data are assumed Pareto distributed and $\theta > 0$ is a parameter to be estimated.

We estimate the θ parameter independently for each year 1988–2009 by fitting a Pareto distribution to observations with earnings above or equal to y_0 set at 0.7 of the top-coding threshold. Estimation is conducted by maximum likelihood where, crucially, the likelihood

[8] Hourly wages are preferable to annual earnings for workers with incomplete employment in Luxembourg during a given year. Incomplete annual employment is common for cross-border workers and immigrants on their first job in Luxembourg. For other male workers, the difference between total annual earnings and annualized hourly wages is unlikely to be large since rates of unemployment and part-time employment were both particularly low among men in Luxembourg in the period covered by the analysis.

[9] The truncated monthly earnings are calculated by dividing annual earnings by the number of months worked. All observations with monthly earnings that concentrated around the ceiling in the upper tail of the distribution are considered as top-coded.

function accounts for the top-coding of observed earnings: the log-likelihood contribution of observation i is 0 if observed earnings y_i is below y_0 and is otherwise

$$\ln L_i = c_i ln[1 - F(y_i)] + (1 - c_i) ln[f(y_i)] \tag{2}$$

where $c_i = 1$ if i's earnings have been top-coded and $c_i = 0$ otherwise and f is the Pareto density function.

Parameter estimates $\hat{\theta}$ are then used to draw imputed values for top-coded earnings for each year using the inverse transform sampling method based on the standard formula for truncated distributions (Jenkins et al., 2011). To account for the imputation variance, we draw $m = 20$ imputed values for each top-coded observation and thereby generate 20 partially synthetic datasets composed of reported non top-coded data and an imputed value for all top-coded earnings. We finally retain in each of the synthetic datasets all observations with positive earnings and, following common practice (see, e.g. Moffitt and Gottschalk, 2011), we drop the highest and lowest 1% of hourly earnings to prevent outlying observations from driving our model and inequality estimates.

All calculations and estimations conducted in our analysis were subsequently replicated on each of the 20 synthetic datasets and the estimates reported in the paper were obtained using the combination formula proposed in Reiter (2003) as recommended in Jenkins et al. (2011):

$$\bar{q}_m = \sum_{j=1}^{m} \frac{q_j}{m} \tag{3}$$

where q_j is an estimate from data replication j ($j = 1, ..., m = 20$).[10]

This procedure ensures that we properly account for the variability introduced by the stochastic nature of the imputation process. As far as we know, this procedure has never yet been used in estimation of error components models of earnings dynamics.

3 Trends in the mean and variance of earnings

Before proceeding to the error components model and to the main part of our analysis, we first describe the broad empirical patterns observed in our data throughout the period. Figure

[10]The sampling variance of $\bar{q}_m$ can be estimated as

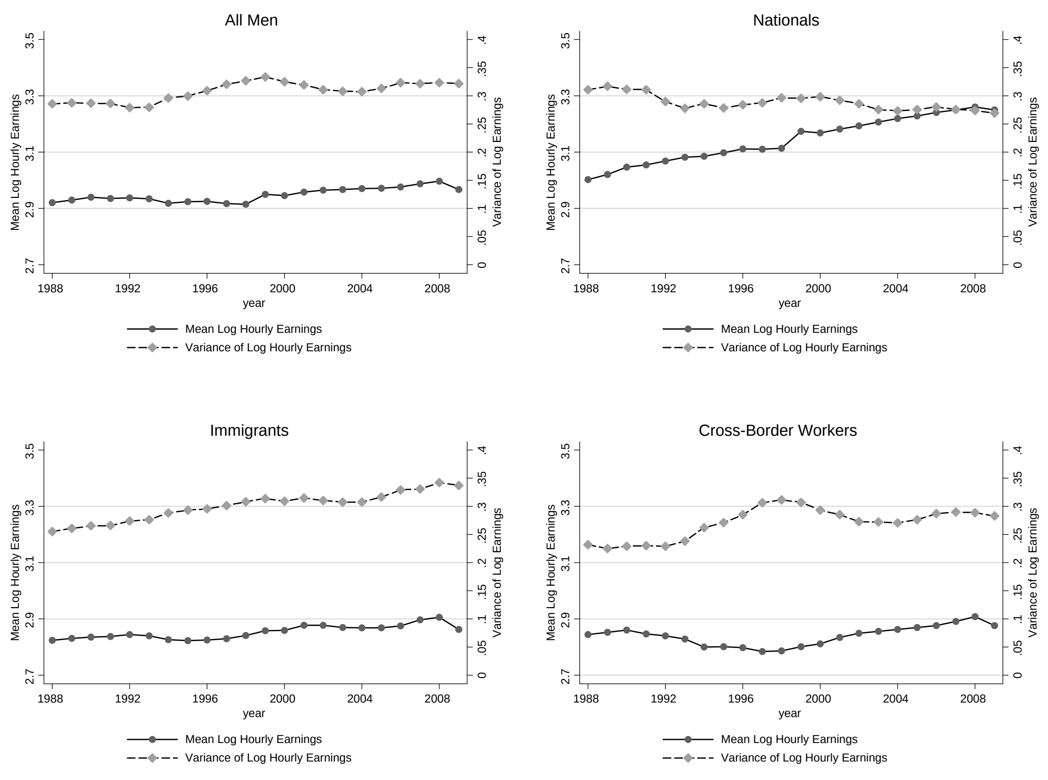
$$T_p = \frac{1}{m} \sum_{j=1}^{m} \frac{(q_i - \bar{q}_m)^2}{m-1} + \sum_{j=1}^{m} \frac{v_j}{m} \tag{4}$$

where v_j is an estimate of the sampling variance of q_j (Reiter, 2003).

2 shows the evolution of the variance and mean log hourly earnings in our sample of men aged between 20 and 57 and born between 1940 and 1980.

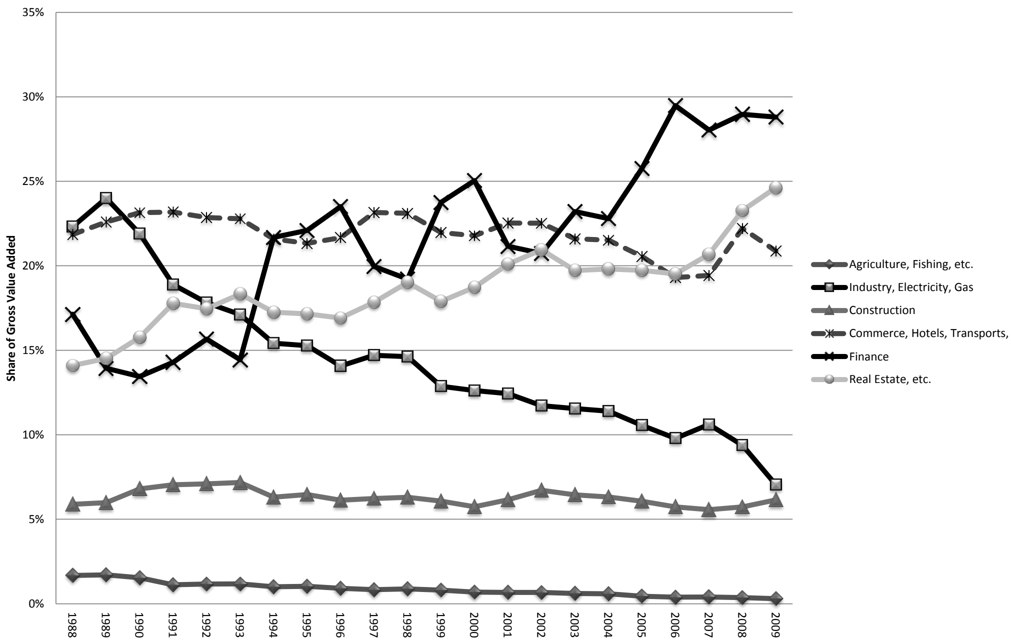
Throughout the period, there is an overall increase in both earnings inequality and mean earnings. Mean earnings is relatively stable between 1988 and 2000 (barring a jump between between 1998 and 1999 which is due to a sharp increase of 8% in the gross wage of civil servants). It then increases continuously from 2000 to 2008—a period during which Luxembourg's GDP grew by 4.3% annually on average. Mean earnings finally drops sharply in the recession year of 2009. The variance of log earnings appears to evolve less smoothly. It increased most sharply between 1993 and 1999 (when mean earnings was stable), declined until 2004 (when mean earnings was growing) and increased again until 2009. While both variables trended upwards throughout the 22 years, the patterns of change do not exhibit any systematic association. The long-run relative increase in the variance of log earnings is somewhat smaller than observed during the same overlapping period in the US (Moffitt and Gottschalk, 2011), the UK (Kalwij and Alessie, 2007), Italy (Cappellari and Leonardi, 2013), and Germany (Bönke et al., 2013), while being higher than in Sweden (Gustavsson, 2007, 2008).

Figure 2: The variance and mean of log hourly earnings, 1988–2009



The increase in inequality corresponds roughly to the timing of the development of the financial sector. Figure 3, which illustrates the industrial mix in Luxembourg GDP between 1988 and 2009, shows a sharp increase in the share of finance and services in the economy at the expense of the share of industry, especially from 1993 onwards.

Figure 3: Gross value added share contributed by sectors

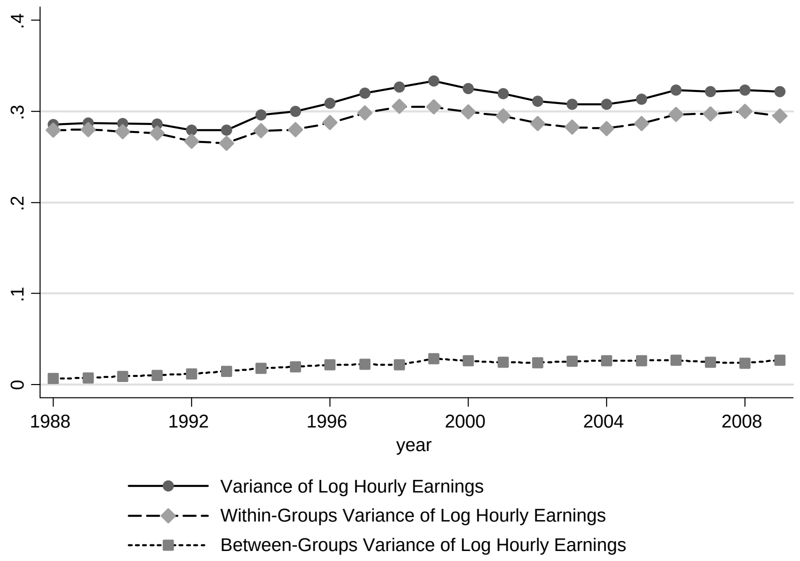


Note: Sectors are classified based on the NACE2 methodology.
Source: Calculations based on EUROSTAT data.

Figure 2 also distinguishes the trends for native, immigrant and cross-border workers. Patterns of change differ between the three groups. Mean earnings grew faster for nationals than for immigrants or cross-border workers (and fell less in the recession year of 2009). For cross-border workers, mean earnings decreased between the early 1990s and the late 1990s and increased fast thereafter. Inequality overall decreased among nationals, while it increased among immigrants and cross-border workers. Cross-border workers earnings exhibit less inequality than residents, but have had a steep rate of increase over a period during which their share of total employment increased significantly (see Figure 1). Their contribution to overall inequality trends has therefore become significant (see *supra*).

Figure 4 finally shows a decomposition of the trends in overall log earnings variance into trends in within-group variances (defined as the population-weighted average of within group variances shown in Figure 2) and in between-group variances (defined as the residual difference between total variance and within-group variance).[11] The increase in overall inequality was driven by an increase in both within and between-group components, most of the increase occurring between the late 1980s and the late 1990s. Within-group inequality was the dominant component throughout the period, following the pattern observed for the overall inequality. The increase in the within-group inequality was mostly driven by increasing inequality among cross-borders and immigrants. Between-groups differentials gradually increased from 1988 to 1999 but then remained stable afterwards.

Figure 4: Decomposition of the variance of log earnings by population subgroups: Native, immigrant and Cross-Border workers, 1988–2009



4 The auto-covariance structure of earnings

Taking advantage of our large-scale longitudinal data on long-term individual earnings profiles, we seek to ascertain whether the trends in the variance of log earnings primarily reflect an increase in short-run earnings variability or an increase in persistent, long-run earnings differences between workers. Answers to such a question are to be found in the auto-covariance structure of earnings and its development over time.

The long-run auto-covariance structure of hourly earnings for all workers is shown in Figure 5. (The patterns for residents and cross-border workers are reported in Appendix Figures

[11] These trends are consistent across different inequality indices. See for example Figure B.1 in Appendix B, which shows the decomposition for the mean log earning deviation index.

C.2 and C.3.) The auto-covariance structure of earnings is estimated for each cohort separately (adding up to 7513 sample moments).

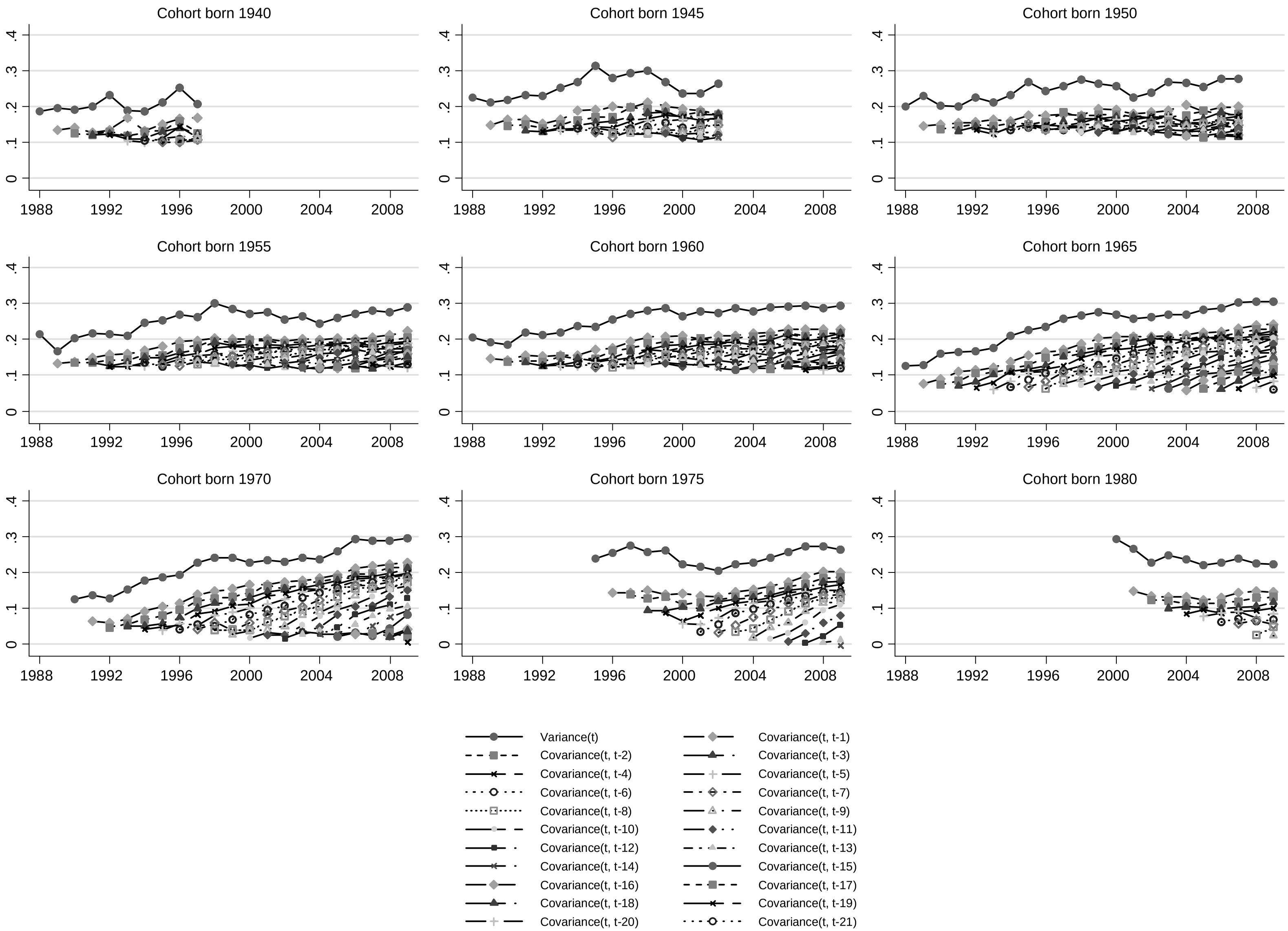
The auto-covariances display different patterns across cohorts. The variance of log hourly earnings increases over time for most cohorts, except the oldest and the rate of increase differs across cohorts. Similarly with the results of Dickens (2000) for the UK, the younger the cohort the faster the rise in the auto-covariances. The absolute magnitude of the auto-covariance structure has a hump-shaped pattern: the youngest cohorts have the lowest values, followed by the oldest and the middle-age cohorts.

For all cohorts, lag auto-covariances show a similar pattern as the variance. The distance between auto-covariances at consecutive lags falls at a decreasing rate. The biggest fall is registered by the lag-1 auto-covariance, after which the covariances appear to converge gradually at a positive level. As variances reflect both the permanent and the transitory components of earnings, and higher order covariances reflect the permanent component of earnings, the evolution of covariances at all orders suggests the presence of a permanent individual component of wages and a transitory component which is serially correlated. Figure 6 presents the variance-covariance structure by age for the selected years. (The patterns for residents and cross-border workers are reported in Appendix Figures C.4 and C.5.) All lag auto-covariances of log earnings show a similar pattern as the variance. They are positive and evolve parallel to the variance, yet at different rates over the life-cycle. They rise sharply until the late 30s and early 40s, after which the rate of increase slows down. (Note that for cross-border workers, the slowdown in the rate of increase after the late 30s is stronger compared with the other labour market groups.) The diminishing rate of increase of all lag auto-covariances observed from age 20 until late 50s is consistent with the presence of a permanent component of earnings that rises with age at a decreasing rate. Across years, the life-cycle profile of the auto-covariances become somewhat steeper. If the slope of the life-cycle profile is interpreted as the permanent increase in earnings, steeper slopes in later years imply increasing returns to the permanent component of earnings over time.

5 Persistent and transitory inequality in a model of earnings dynamics

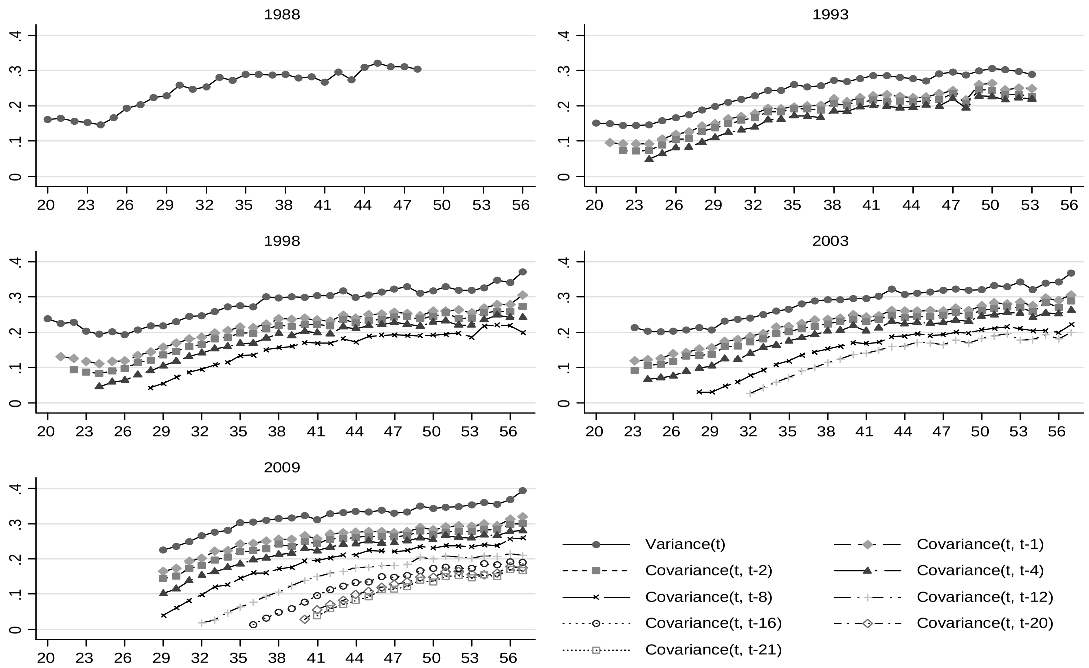
We consider a flexible error components model of earnings dynamics in order to fit the auto-covariance structure just described. To separate out life-cycle dynamics from secular changes in earnings inequality, earnings trajectories are analysed within each of the 41 birth-cohorts. Models are also estimated separately for natives, immigrants and cross-border workers to account for their different earnings dynamics and variances. Combining model parameter estimates then allow us to disentangle permanent and transitory components in the level and trends

Figure 5: Auto-covariance structure of log earnings for selected cohorts



Note: In the legend, ‘t’ stands for the year displayed on the horizontal axis.

Figure 6: Life-cycle auto-covariances of log earnings for selected years



Note: In the legend, ‘t’ stands for the age displayed on the horizontal axis.

of earnings inequality and the contribution of the different workers types to these trends.

5.1 Model specification

We first de-trend earnings and model earnings as zero-mean deviations from yearly cohort means:

$$r_{it} = Y_{it} - \bar{Y}_{c(i)m(i)t} \tag{5}$$

where Y_{it} is the natural logarithm of real hourly earnings of individual i in year t and $\bar{Y}_{c(i)m(i)t}$ is the average in year t of Y_{it} over all workers of the same cohort ($c(i)$) and of the same type ($m(i)$)—whether native, immigrant or non-resident—as individual i.[12] Individual-specific deviations from year-cohort means, r_{it}, are then assumed to be independently distributed across individuals, but autocorrelated over time. So, the structure of earnings differentials within each cohort and worker type is fully characterized by modelling the covariance structure of individual (demeaned) earnings: $E(r_{it}r_{it-s})$ for $t = t^0_{c(i)}, \ldots, (t^0_{c(i)} + T_{c(i)})$ and $s = 0, \ldots, t - t^0_{c(i)}$.[13]

For exposition clarity, we ignore indices for worker type throughout this section. All model parameters will be estimated separately for each of the three groups of workers. For the sake of exposition, we also denote simply by c instead of $c(i)$ the cohort of individual i.

As in much of the literature (Jantti and Jenkins, 2013), our model is an extension of the canonical model of earnings dynamics of Lillard and Willis (1978) in which r_{it} is assumed to be the sum of two orthogonal terms:

$$r_{it} = \mu_i + \upsilon_{it}, \quad \mu_i \sim iid(0, \sigma^2_\mu), \upsilon_{it} \sim iid(0, \sigma^2_\upsilon). \tag{6}$$

This canonical model decomposes earnings into a permanent, time-invariant individual specific component, μ_i, (reflecting labour market returns to innate ability and pre-labour market human capital accumulation) and a transitory component (reflecting any yearly deviation from the permanent component), υ_{it}. Both components in this model are independent both across individuals and over time. The implied covariance structure of earnings then takes the form:

$$Cov(r_{it}, r_{is}) = \begin{cases} \sigma^2_\mu + \sigma^2_\upsilon, & t = s \\ \sigma^2_\mu, & t \neq s \end{cases} \tag{7}$$

[12] Workers type is treated as a time-invariant status. Individuals are classified on the basis of their most frequent status. Individuals with multiple status are primarily cross-border workers who later migrate into Luxembourg. Only 11.07 percent of workers we classify as immigrants have multiple status over time. This causes 2.6 percent of person-year observations for immigrants to be effectively periods spent as cross-border worker. Similarly 2.68 percent of workers we classify as cross-border workers have multiple status over time. This causes 1.2 percent of person-year observations for this group to be effectively periods spent as resident.

[13] $t^0_{c(i)}$ is the first year at which the cohort of individual i is observed in the data (e.g., 1988 for the 1940 cohort) and $T_{c(i)}$ represent the total number of years the cohort is observed.

where σ^2_μ is the persistent dispersion of earnings (permanent earnings inequality) and σ^2_υ is the variance of transitory deviations. The variance of earnings at a given year t is given by $\sigma^2_r = \sigma^2_\mu + \sigma^2_\upsilon$ and deviates from the persistent dispersion by the variance of the transitory shocks. This canonical model obviously imposes severe restrictions on the covariance structure of earnings. More sophisticated specifications are now routinely estimated (see Meghir and Pistaferri (2011) for a comprehensive review).

We specify and estimate a model which accommodates fine details of the auto-covariance structure of earnings. As is conventional, we maintain the basic assumption that r_{it} is the sum of two orthogonal components, one persistent and one transitory, but we allow the relative weight of each of the two terms to vary over time and by cohort:

$$r_{it} = \gamma_{1c}\lambda_{1t}\mu_{it} + \gamma_{2c}\lambda_{2t}\upsilon_{it}. \tag{8}$$

Additionally we allow the permanent term μ_{it} to have a unit root and evolve as a random walk with age

$$\mu_{it} = \mu_{i(c+20)} \sim iid(0, \sigma^2_{\mu_{c+20}}) \qquad \textit{if } t = c+20 \tag{9}$$

$$\mu_{it} = \mu_{i,t-1} + \pi_{it} \qquad \textit{if } t > c+20 \tag{10}$$

$$\pi_{it} \sim iid(0, \sigma^2_{\pi_{t-c}}), E(\mu_{i,t-1}, \pi_{it}) = 0$$

and let the transitory term υ_{it} follow an ARMA(1,1) process:

$$\upsilon_{it} = \rho\upsilon_{i,t-1} + \epsilon_{it} + \theta\epsilon_{i,t-1} \tag{11}$$

$$\epsilon_{it} \sim (0, \sigma^2_{\epsilon_{ct}}), \upsilon_{i0} \sim (0, \sigma^2_{c0}).$$

It is now conventional to allow the covariance structure of earnings to vary over time by incorporating time-specific shifters on the two main components, λ_{kt}, $k = 1, 2$, that allow for the relative contributions of the permanent and transitory components to change over time (see, e.g., Dickens, 2000, Haider, 2001, Moffitt and Gottschalk, 2002, Baker and Solon, 2003, Ramos, 2003, Kalwij and Alessie, 2007, Cappellari, 2004, Biewen, 2005, Gustavsson, 2007, 2008, Sologon and O'Donoghue, 2012). $\lambda_{kt}, k = 1, 2$ is normalized to 1 in the first year (1988) for identification.

Allowing the relative contributions of the permanent and transitory components to vary also by cohort by incorporating cohort-specific loading factors, $\gamma_{kc}, k = 1, 2$, is as in Cappellari (2004), Kalwij and Alessie (2007), Gustavsson (2008) or Sologon and O'Donoghue (2012). $\gamma_{kc}, k = 1, 2$ is normalized to 1 for the cohort born in 1945.

Specification of a random walk in age for the permanent component of earnings follows MaCurdy (1982), Abowd and Card (1989), Moffitt and Gottschalk (1995), Dickens (2000), Baker and Solon (2003), Kalwij and Alessie (2007), Ramos (2003), Gustavsson (2008), Sologon and O'Donoghue (2012). This specification captures earnings shocks with permanent effects. While most studies restrict the innovation variance $\sigma^2_{\pi_{t-c}}$ to be constant, we estimate age-specific innovation variances (age is $a = t - c$) in a way similar to Dickens (2000), Gustavsson (2008) and Kalwij and Alessie (2007).[14] The importance of allowing for age-specific variances is emphasized in Blundell et al. (2014). This specification accommodates the highly persistent increase in earnings variance with age, as observed in Figure 5.

The ARMA(1,1) specification for the transitory component of earnings is as in MaCurdy (1982). The serial correlation parameter ρ captures the decreasing rate of decay of the covariances with the lag, the moving-average parameter θ captures the sharp drop of the lag-1 auto-covariance compared with the other auto-covariances, and ϵ_{ict} are white-noise mean-reverting transitory shocks. The cohort-specific variance σ^2_{c0} measures the volatility of shocks at the start of the sample period and the cohort-specific $\sigma^2_{\epsilon_{ct}}$ the volatility of shocks in subsequent years.

According to MaCurdy (1982), initial cohort transitory variances could be treated as additional parameters to be estimated. However, Ostrovsky (2010) and Moffitt and Gottschalk (2011) argue that treating the initial transitory variances of each cohort as unrestricted parameters is problematic because it affects the time trend for left-censored observations. They propose instead to introduce a parameter α which allows cohort-specific transitory variances in the first wave to deviate from what they would be if $\lambda_{2t} = 1$ for the years before the first wave, so

$$\sigma^2_{c0_{leftcensored}} = (1 + \alpha(a_{c0} - 20))\sigma^2_0, c = 1940, ..., 1980 \qquad (12)$$

where $a_{c0} = t^0_c - c$ is the age of the cohort in the first wave.

Finally, as recent studies found that the variance of the transitory component tends to be a U-shaped function of age or experience (Baker and Solon, 2003, Gustavsson, 2008), we allow for age-related heteroskedasticity in the transitory shocks too by letting a cohort-specific variance of ϵ_{it} vary as a polynomial in age:

$$\sigma^2_{\epsilon_{ct}} = \beta_0 + \beta_1(a_{ct} - 20) + \beta_2(a_{ct} - 20)^2 + \beta_3(a_{ct} - 20)^3 + \beta_4(a_{ct} - 20)^4 \qquad (13)$$

where $a_{ct} = t - c$ is the age of cohort c at time t.

This model specification allows for a wide range of dynamics: a high degree of individual heterogeneity by allowing for individual and age-specific characteristics in the permanent component via a random walk specification with age-specific innovation variances, a transitory

[14] In the application, age-specific innovation variances are estimated from age 21 to 49, after which innovation variances are allowed to vary every two years at age 50-51, 52-53, ..., 56-57. For cross-border workers the innovation variances only vary twice after age 39, namely for age 40–49 and 50–57.

component which evolves as an ARMA(1,1), with a correction for left-censoring for each cohort in the first year observed, and with age-specific heteroskedastic transitory variances. The non-stationary pattern of earnings is accommodated by time-specific loading factors on both earnings components. Cohort heterogeneity is accommodated by allowing both the permanent and the transitory component to vary by cohort. The model is similar to Kalwij and Alessie (2007), with added features from Baker and Solon (2003) (age-specific heteroskedastic transitory variances), and Ostrovsky (2010) and Moffitt and Gottschalk (2011) for the correction for left-censoring for each cohort in the first year observed.

5.2 Permanent versus transitory variance components

The earnings dynamics model determines a theoretical auto-covariance structure of earnings which allows separating out persistent and transitory components of inequality.

At the first period, and for cohort $c = c(i)$ of initial age $a_0 = 1988 - c$, the variance of log earnings is

$$Var(Y_{i0}) = E(r_{i0}r_{i0}) \tag{14}$$

$$= \underbrace{\sigma^2_{\mu 20} + \sum_{a=21}^{a_0} \sigma^2_{\pi_a}}_{\text{persistent inequality}} + \underbrace{Var(\upsilon_{i0})}_{\text{transitory inequality}} \quad . \tag{15}$$

In subsequent years, the theoretical covariance structure is:

$$Var(Y_{it}) = E(r_{it}r_{it}) \tag{16}$$

$$= \underbrace{\gamma^2_{1c}\lambda^2_{1t}\left[\sigma^2_{\mu 20} + \sum_{a=21}^{a_t} \sigma^2_{\pi_a}\right]}_{\text{persistent inequality}} + \underbrace{\gamma^2_{2c}\lambda^2_{2t}\left[\rho^2 Var(\upsilon_{i,t-1}) + \sigma^2_{\epsilon_t}(1 + 2\rho\theta + \theta^2)\right]}_{\text{transitory inequality}}$$

and

$$Cov(Y_{ict}, Y_{i,c,t-s}) = E(r_{ict}r_{i,c,t-s}) \tag{17}$$

$$= \gamma^2_{1c}\lambda^2_{1t}\left[\sigma^2_{\mu 20} + \sum_{a=21}^{a_{t-s}} \sigma^2_{\pi_a}\right] + \gamma^2_{2c}\lambda_{2t}\lambda_{2,t-s}\left[\rho Cov(\upsilon_{i,t-1}\upsilon_{i,t-s})\right]$$

$$\textit{if } s > 1$$

$$Cov(Y_{ict}, Y_{i,c,t-1}) = E(r_{ict}r_{i,c,t-1}) \tag{18}$$

$$= \gamma^2_{1c}\lambda^2_{1t}\left[\sigma^2_{\mu 20} + \sum_{a=21}^{a_{t-1}} \sigma^2_{\pi_a}\right] + \gamma^2_{2c}\lambda_{2t}\lambda_{2,t-s}\left[\rho Var(\upsilon_{i,t-1}) + \theta\sigma^2_{\epsilon_{t-1}})\right]$$

$$\textit{if } s = 1$$

We are therefore able from Equations (15) and (16) to decompose total earnings variance for any cohort into a permanent and a transitory component and track their respective share over time.

5.3 Estimation

Estimation of the model parameters is also based on the theoretical auto-covariance matrix. The full model specification determines a theoretical auto-covariance structure where each cell of the auto-covariance matrix is a function of model parameters. Parameters can then be estimated by fitting the theoretical covariance matrix onto the empirical covariance structure using minimum distance methods. If θ is the set of parameters to be estimated, the minimum distance estimator chooses $\hat{\theta}$ to minimize the distance function

$$D(\hat{\theta}) = [m - f(\hat{\theta})]W[m - f(\hat{\theta})]', \tag{19}$$

where m is a column vector of moments of dimension (7513×1). We take W to be the identity matrix, following Altonji and Segal (1996) and Clark (1996) and most empirical applications. For estimating the asymptotic standard errors of the parameter estimates, we apply the delta method, following Chamberlain (1984).

This methods of moments approach does not require additional modelling assumptions and is now the workhorse for estimation of such variance-covariance models; e.g., Abowd and Card (1989), Moffitt and Gottschalk (1995, 1998, 2002, 2011), Baker (1997), Dickens (2000), Baker and Solon (2003), Ramos (2003), Kalwij and Alessie (2007), Cappellari (2004), Biewen (2005), Gustavsson (2007, 2008), Meghir and Pistaferri (2011), Sologon and O'Donoghue (2012).

5.4 Assessing subgroup contributions

By estimating the error components model parameters separately for subgroups of workers—nationals, immigrants and cross-border workers—we are able to allow for different variances within each of the subgroup and to identify different trends. Applying simple variance decomposition arithmetics by subgroup, we use the model estimates to track the contribution of each of the subgroup to overall inequality.

Let $\bar{V}$ denote the average within-group log-earnings variance at time t (Chakravarty, 2001):

$$\bar{V} = \sum_{g=1}^{k} n_g V_g \tag{20}$$

where n_g and V_g are the population share and the permanent variance of group g. A basic decomposition takes the difference between the observed total variance V and $\bar{V}$ as a measure of the 'between-group' contributions

$$B = V - \bar{V}. \tag{21}$$

The evolution of V can then mechanically be linked to the evolution of the subgroup shares n_g, the subgroup variances V_g and the residual measure of between-group contributions B.[15]

In Section 6, we apply this simple mechanics to both the transitory variance and the permanent variance on the basis of model-based predictions for V_g as per Equations (15) and (16) and a model-based prediction for overall V estimated from the overall pooled sample of the three worker subgroups.

6 Results

We estimated the error components model outlined in Section 5 on the entire sample of employees and then separately on subgroups of workers: residents (nationals and immigrants pooled), nationals, immigrants and cross-border workers. Tables D.4 and D.5 in Appendix D report the estimates and the associated standard errors for all parameters. Parameter estimates are then used to decompose the variance of log-earnings in each year into its permanent and transitory components.[16]

Figure 7 displays the trends in inequality (observed and as predicted by the model parameters) and the absolute and relative contributions of the persistent and transitory component for all men. As in Baker and Solon (2003), to account for different age compositions over time, the variance of log-earnings is as predicted at the age of 40, which is approximately the middle of the active career.[17]

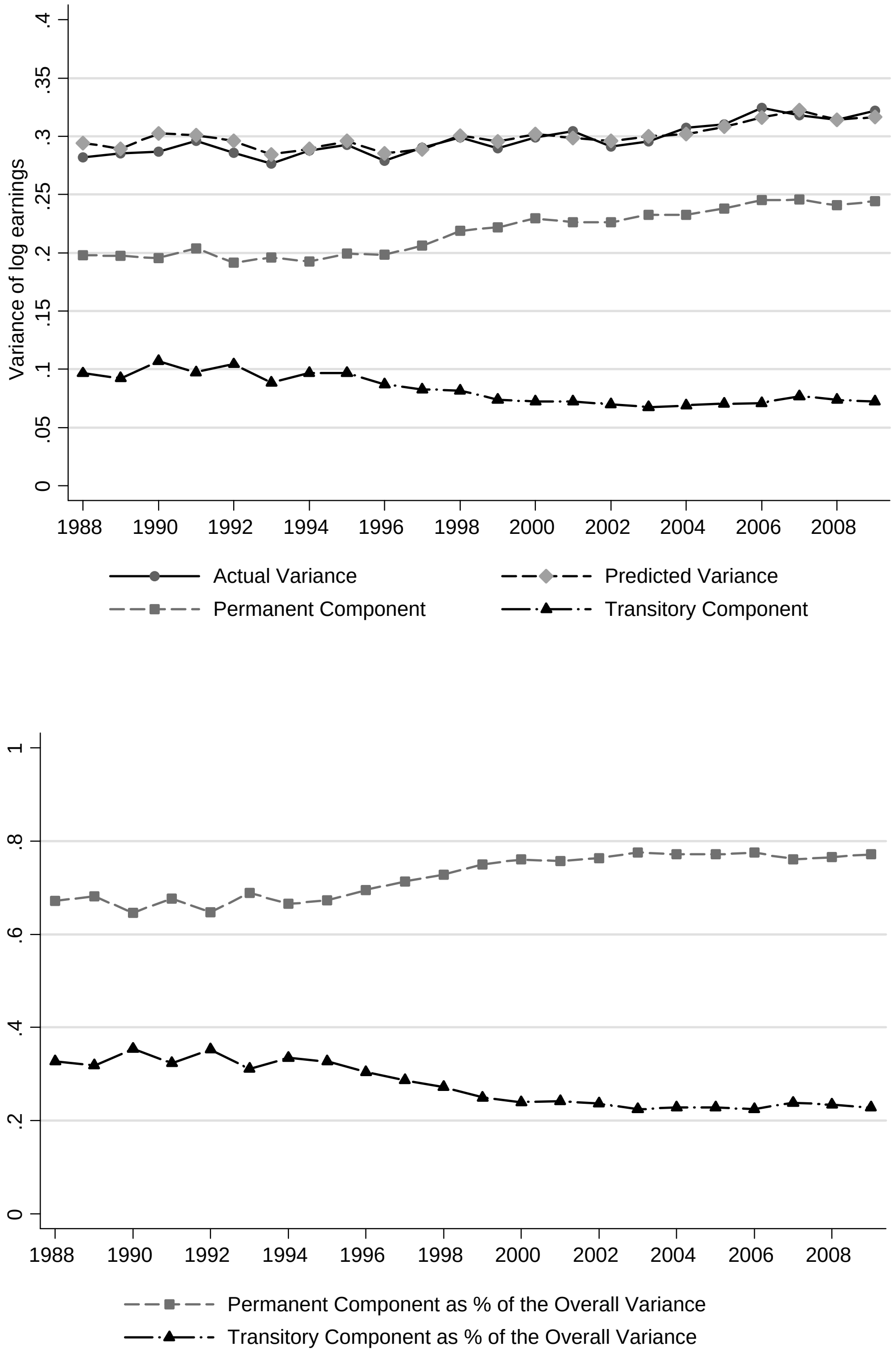
Note first the close coincidence of the trends in the observed and predicted variances for 40-year old men—an indication of the good fit of our parametric model. Note, second, that the trends in predicted variance at age 40 roughly follow the patterns outlined in Figure 2 for all age groups combined: inequality remained approximately constant from 1988 to 1993, after when it drifted upwards (although with temporary ups and downs—the increase in inequality at age 40 is not as marked during the between 1993 to 1999). Predicted trends at ages 30 and 50 exhibit similar patterns (see Figure E.6 in Appendix E).

[15]Semantics are important here since B is not a measure of between-group 'inequality'. That is, it is not equal to the overall variance of log earnings that would be observed if all earnings were set to equal to their subgroup means—the typical definition of a between-group inequality component (Shorrocks, 1984). The latter cannot be recovered from our model parameters since it is based on modelling the *logarithm* of earnings.

[16]Note that model parameters were estimated on each of the 20 synthetic datasets. Estimates of the persistent and transitory inequality were obtained by averaging over the 20 synthetic estimates as per Equation (3).

[17]Prediction at each year are based on the relevant combinations of period and birth cohort parameters.

Figure 7: Inequality decomposition all men at age 40



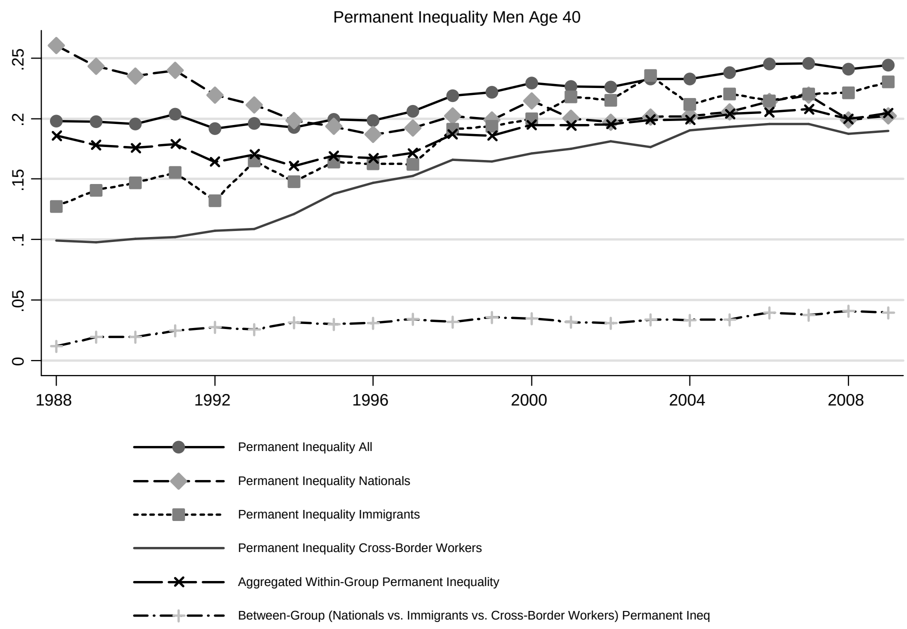
The modest increase in inequality since the middle of the 1990s turns out to be mainly driven by a relatively important increase in the persistent component of the model, alongside a reduction in the transitory component. We observe a fanning out of the two components from the mid-1990s, a period which coincided with the acceleration of the development of the financial sector and the contraction of the steel industry. Overall, persistent inequality increased by 23.4%, whereas transitory inequality decreased by 25.1% between the late-1980s and the late 2000s. These offsetting trends led to a modest increase in overall inequality of 7.5%. The share of persistent inequality in total inequality rose from over 60% in 1988 to close to 80% in 2009. These trends contrast with what has been observed elsewhere, e.g., in the US, the UK, Italy, and Germany where transitory variance increased faster than persistent inequality (Kalwij and Alessie, 2007, Moffitt and Gottschalk, 2011, Cappellari and Leonardi, 2013, Bönke et al., 2013). (We return to cross-national comparisons in Section 7.) This pattern suggests that the development of the financial sector and the decline of the steel industry increased returns to skills and other permanent characteristics but reduced earnings volatility.

The rise in persistent inequality from the mid-1990s may also be related to the changing structure of employment and the massive inflow of cross-border workers. The mid-1990s marks the period when the share of cross-border workers in the labour force overtook the share of nationals. To see this, we decompose the permanent inequality component using parameter estimates reported in Table D.4 to predict persistent inequality within each of the native, immigrant and cross-border worker subgroup. The predicted persistent inequalities for each group are then aggregated to obtain an estimate of overall within-group persistent inequality as $PV = \sum_{g=1}^{k} n_g PV_g$ where n_g and PV_g are the population share and the permanent variance of group g and the residual difference between overall persistent inequality and PV is a measure of between-group contribution to permanent inequality (see Section 5).

Figure 8 shows the decomposition of the trends in persistent inequality between cross-border workers, nationals and immigrants. Cross-border workers have the lowest persistent differentials throughout the period, signalling they are more homogeneous in terms of persistent earnings capacity than immigrants and nationals. Immigrants display the highest persistent differentials from the 2000s. This is consistent with the argument that Luxembourg immigrants have become concentrated on both ends of the skill distribution (see, e.g., Amétépé and Hartmann-Hirsch, 2011, Choe and Van Kerm, 2014, Fusco et al., 2014).

Trends in permanent inequality are more sharply marked within subgroups than for the total population. Cross-border workers recorded the largest relative increase in persistent inequality (+91.4%), followed by immigrants with a relative increase of +80.6%. Overall permanent inequality did not increase in similarly large proportions (+23.5%) because (i) persistent differentials decreased by 22.3% among nationals (in particular between 1988 and 1996 after

Figure 8: Permanent inequality subgroup decomposition: Nationals, immigrants and cross-border workers



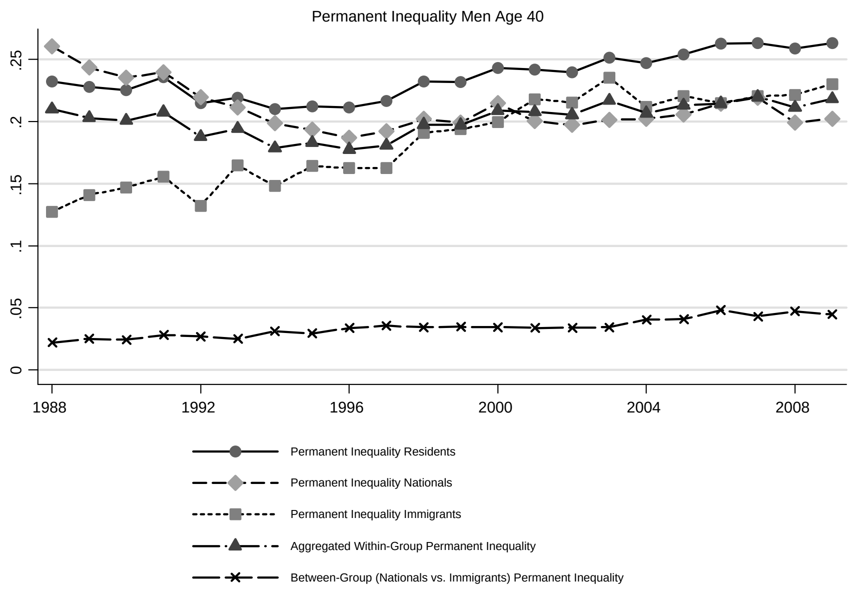
when it started to trend upwards too), (ii) the weight of nationals decreased during the period, and (iii) the weight of cross-border workers—which, despite the increase still have less inequality than the other groups—increased during the period.

The contribution of persistent differentials among cross-border workers to overall permanent inequality is compounded by the sharp increase in their share in the labour market. In 1988, persistent inequality among cross-border workers (weighted by their population shares) accounted for 10.9% of overall persistent inequality, against 19.1% by immigrants and 64% by nationals. The remaining 6% are claimed by persistent earnings differences between the three groups. By 2009, persistent inequality among cross-border workers accounts for the largest share in the overall persistent inequality (37.7%), followed by immigrants with 27.5% and by nationals with 18.5%. 16.3% are claimed by persistent earnings differences between the three groups.

An increase in between-group differentials also contributed to the overall growth in permanent inequality. While it contributed to about one tenth of overall permanent inequality in 1988, it contributes to close to one fifth by 2009. This increase in permanent between-group differentials suggests that the distribution of skills and job types have become increasingly heterogeneous across the three groups.

In order to isolate persistent earnings differentials among residents (between immigrants and nationals), we perform the subgroup decomposition only for the resident working population. Figure 9 shows that persistent inequality is higher among residents compared with the situation when cross-border workers are included (see Figure 8). The presence of cross-border workers therefore appears to have an equalizing effect on the distribution of persistent earnings. The increase in persistent inequality among residents is determined in proportion of 26.1% by the increase in the aggregated within-group persistent inequality and in proportion of 73.9% by the increase in persistent differentials between nationals and immigrants. The increase in persistent earnings differentials between nationals and immigrants signals that the distribution of skills and job types have become increasingly heterogeneous between the two groups.

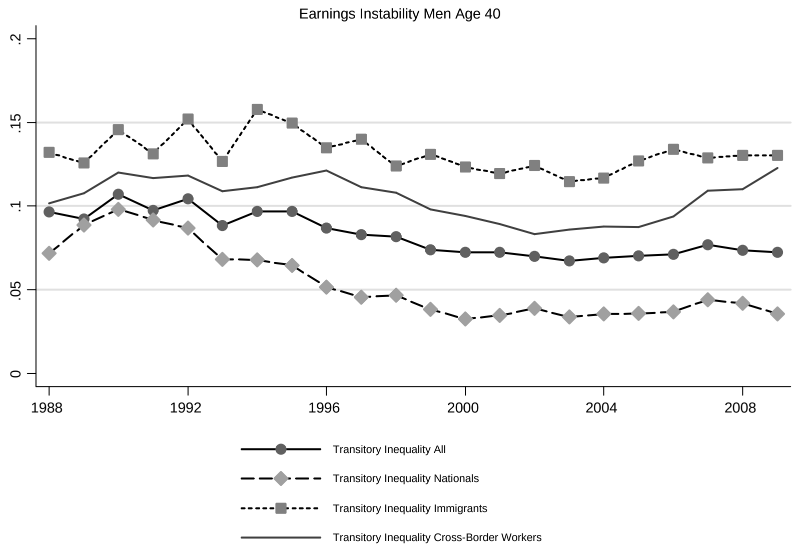
Figure 9: Permanent inequality subgroup decomposition: Nationals vs. immigrants at age 40



We finally turn to trends in the transitory components of inequality—earnings instability. As illustrated in Figure 10, earnings instability at age 40 changed little until the mid-1990s, then decreased until the mid-2000s.

Again, this relative stability hides contrasted levels and trends for population groups. Immigrants have had the highest transitory fluctuations in earnings throughout the period, followed by cross-border workers and nationals. Earnings instability for nationals decreased substantially over the whole period while the earnings instability of cross-border workers appears to increase sharply from 2005 and, by 2009, almost converged to the level observed for immigrants and was higher than in any previous year. (Bear in mind that earnings instability of cross-border workers is likely underestimated by not observing their potential wage trajectories outside of Luxembourg.) Note also that similar trends are predicted at age 50, but that the earnings instability predicted at age 30 have trended downwards until the mid-1990s but have been on the increase throughout the 2000s to reach levels in 2009 higher than in 1988.

Figure 10: Transitory inequality: National, immigrants and cross-border workers at age 40



In order to ascertain the significance of the estimated changes over time and whether these changes are linked to economic cycles, we follow Baker and Solon (2003) and regress the persistent and transitory inequality components on a linear trend and the growth rate in real GDP. Results are reported in Table 3. The point estimates for all men indicate a strongly significant positive trend for permanent inequality, and a less strong significant negative trend for transitory inequality. Coefficient estimates on GDP growth rate indicate that both permanent and transitory inequality are sensitive to the business cycle but in opposite directions, with high growth rates linked to increasing (resp. decreasing) permanent (resp. transitory) inequality. These findings are consistent for cross-border workers and immigrants, yet cross-border workers appear to be most sensitive to the business cycle. The picture for nationals only is, by contrast, one of a significant negative trend in both for permanent *and* transitory inequality with low association to the business cycle.

7 Cross-national comparisons

To put estimates into perspective, we compare the findings for Luxembourg with published estimates for other countries between 1988 and 2009. The benchmarks of our comparison are

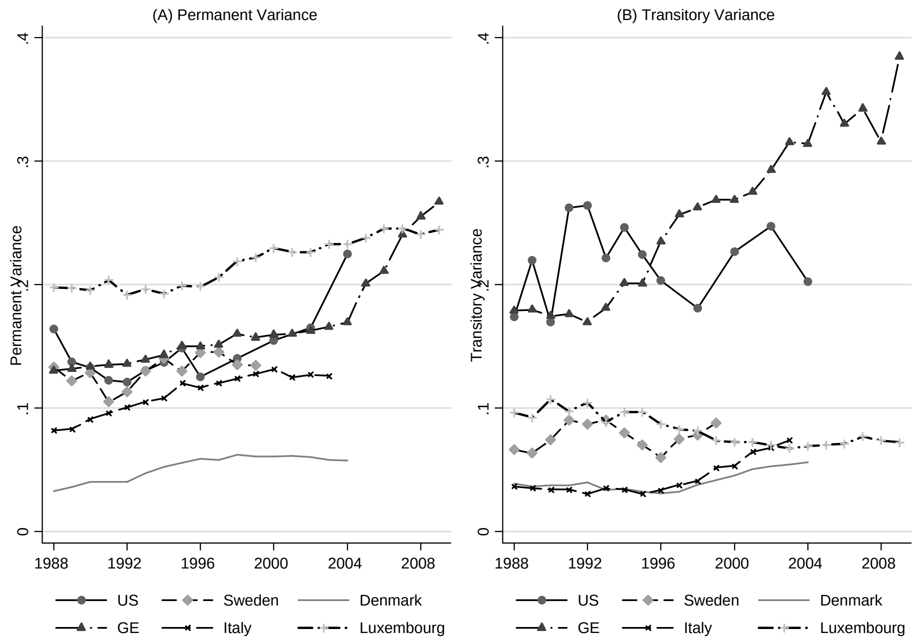
Table 3: Trend and cyclical variation of the persistent and transitory components

Models	Dependent Variable	Linear trend		Real GDP growth rate		Adjusted R^2
		Est	SE	Est	SE	
All Men	Permanent Variance	0.0032	0.0002	0.1417	0.0352	0.9331
	Transitory Variance	-0.0019	0.0002	-0.0995	0.0417	0.7876
Nationals	Permanent Variance	-0.0011	0.0006	0.1942	0.1063	0.3412
	Transitory Variance	-0.0030	0.0004	-0.0873	0.0812	0.7256
Immigrants	Permanent Variance	0.0053	0.0004	0.0934	0.0840	0.8820
	Transitory Variance	-0.0011	0.0004	-0.1360	0.0670	0.2590
Cross-Border Workers	Permanent Variance	0.0058	0.0003	0.1493	0.0641	0.9360
	Transitory Variance	-0.0012	0.0004	-0.1888	0.0745	0.2668

the countries with available information for the longest overlapping period. We report both the cross-national differences in levels (Figure 11) and the comparison of trends relative to 1988=100 (Figure 12). We compare the evolution of persistent and transitory inequality of annual earnings in the US between 1988 and 2004 based on the results in Moffitt and Gottschalk (2008), of annual earnings in Sweden between 1988 and 1990 based on Gustavsson (2008) and between 1991 and 1999 based on Gustavsson (2007), of hourly earnings in Denmark between 1988 and 2004 based on Bingley et al. (2013), of hourly earnings in Germany between 1988 and 2009 based on Bönke et al. (2013), and of weekly earnings in Italy between 1988 and 2003 based on Cappellari and Leonardi (2013), with the estimates for hourly earnings for Luxembourg between 1988 and 2009 based on Tables D.4 and D.5. Of course, the comparability of findings is affected by the definition of income, sample designs, data sources and especially earnings model specifications. Comparisons are therefore indicative and we focus on broad trends rather than more detailed analysis of levels.

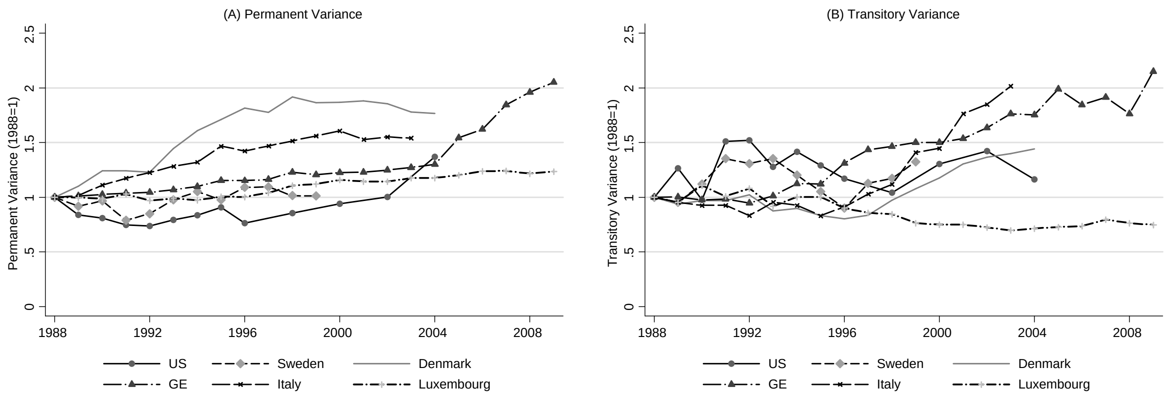
According to the model estimates compared, Luxembourg displays a significantly higher persistent inequality than the US, Germany until the early 2000s, Sweden, Italy and Denmark. However we do not observe such a strong increase in Luxembourg during the 1990s as in Denmark, Italy, and Germany, or during the 2000s as in Germany and the US. On the other hand, transitory inequality appears considerably larger in the US and in Germany than in Luxembourg, Sweden, Denmark and Italy. Moreover, while transitory inequality spikes upwards for Germany, Italy and Denmark, it tends to decrease in Luxembourg. This decline in transitory inequality therefore appears particularly at odds with international evidence. It may be related to the speed of economic growth and the comparatively very low unemployment rate observed in Luxembourg throughout the period. So, while total earnings inequality is lower in Luxembourg than in the US and Germany, it is considerably more persistent (at least until recent years). In addition, it appears much more stable over time in Luxembourg compared with the other countries. This is surprising given the major structural changes which have taken place

Figure 11: Evolution of (A) permanent and (B) transitory variance of log earnings for men in the US (1988-2004), Sweden (1988-1999), Denmark (1988-2004), Germany (1988-2009), Italy (1988-2003), and Luxembourg (1988-2009).



Source: Numbers for the US are based on Moffitt and Gottschalk (2011) for men age 40-49, Table A-3.
The numbers for Sweden are based on Gustavsson (2007, 2008) for men age 40, Table 2 and Figure 3.
The numbers for Germany are based on Bönke et al. (2013) for men age 40. The numbers for Danish men are based on Bingley et al. (2013), Figure 2.
The numbers for Italian men are based on Cappellari and Leonardi (2013), Figure 3.
The numbers for Germany are based on Bönke et al. (2013) for men age 40.
The numbers for Luxembourg are based on Tables D.4 and D.5, men age 40.

Figure 12: Relative evolution (1988=100) of (A) permanent and (B) transitory variance of log earnings for men in the US (1988-2004), Sweden (1988-1999), Denmark (1988-2004), Germany (1988-2009), Italy (1988-2003), and Luxembourg (1988-2009).



Source: Numbers for the US are based on Moffitt and Gottschalk (2011) for men age 40-49, Table A-3.
The numbers for Sweden are based on Gustavsson (2007, 2008) for men age 40, Table 2 and Figure 3.
The numbers for Germany are based on Bönke et al. (2013) for men age 40. The numbers for Danish men are based on Bingley et al. (2013), Figure 2.
The numbers for Italian men are based on Cappellari and Leonardi (2013), Figure 3.
The numbers for Germany are based on Bönke et al. (2013) for men age 40.
The numbers for Luxembourg are based on Tables D.4 and D.5, men age 40.

in the labour market throughout the period covered by our analysis. Bear in mind, however that the comparisons shown here are not all based on identical model specifications or data sources. Comparisons, especially of levels, must therefore be taken as indicative.

8 Summary and concluding remarks

This paper exploits longitudinal earnings and employment data from an unusually large extract from the Luxembourg social security administration registers to document the trends and sources of earnings inequality between 1988 and 2009. This has been a time when the country underwent a drastic industrial re-development towards the financial sector and sustained high economic growth. In this process, labour demand soared and the country experienced a massive expansion of its employment through an inflow of foreign labour, especially of cross-border workers residing in neighbouring countries Belgium, France and Germany. Relatively strict labour market regulations were however maintained (Fusco et al., 2014).

In spite of these major structural and employment changes, we observe only a small overall increase in earnings inequality. This surprising stability appears however to be the net result of somewhat more complex underlying changes. Taking advantage of the large scale of our data, we estimate a rich model of earnings dynamics to first distinguish between persistent and transitory components of inequality. This shows how inequality became remarkably more persistent (while earnings instability decreased), suggesting an overall increase in returns to skills throughout the 22 years of our data. Second, we distinguish trends for native workers, immigrants and cross-border workers in order to better capture the contribution of changes in employment composition. This reveals that (persistent) inequality did grow significantly *within* the cross-border and immigrant worker groups and *between* the three worker groups, but that *overall* inequality growth was contained by (i) a reduction in persistent differentials among nationals, (ii) the decreasing employment share of nationals, and (iii) the increasing employment share of cross-border workers—the group exhibiting the lowest, yet most rapidly rising, 'within group' persistent inequality. The increase in between-group differentials is an indication that the distribution of skills and jobs have become increasingly heterogeneous across the three groups. While earnings instability declined overall, immigrants still have higher transitory earnings variance while transitory earnings variance for cross-border workers sharply increased in the late 2000s. Overall our results show favourable trends for Luxembourg nationals among which both persistent and transitory inequality declined throughout the period.

In sum, a somewhat more complex pattern is observed behind the apparent stability of earnings inequality over the 22 years of major economic changes covered by our analysis. Nevertheless, our results can still be interpreted as showing a somewhat surprising stability in the face of the large changes in the size and structure of employment and the fast growth that the country experienced and in comparison with changes observed in other countries, such as Germany where both persistent and transitory inequality increased considerably. These results possibly hint at the role of relatively strict labour market regulations and collective bargaining institutions in holding back earnings inequality—yet not so much in holding back *persistent* inequality—, at least in a period of fast economic growth and soaring demand for labour. It is however beyond the scope of this paper to pin down the contribution of particular labour market institutions or regulations in this rather peculiar context.

On a technical note, this analysis illustrates the usefulness of access to large-scale administrative registers for detailed analysis of inequality trends. The limited sample size and length of most panel surveys, for example, prevent detailed analysis within population subgroups and/or impose restrictions on the sophistication of variance components models that can be fit and affect the reliability of inference (Doris et al., 2013). In line with Dickens (2000), Kalwij and Alessie (2007), Baker and Solon (2003) or Gustavsson (2008), our model estimates bring evidence against simple restrictions concerning the life-cycle and cohort variation in the two components of earnings dynamics and the relevance of these features when exploiting the covariance structure of earnings for inference regarding the evolution of permanent and transitory inequality.

References

Abowd, J. M. and Card, D. (1989), 'On the covariance structure of earnings and hours changes', *Econometrica* **57**(2), 411–445.

Acemoglu, D. (2002), 'Technical change, inequality, and the labor market', *Journal of Economic Literature* **40**(1), 7–72.

Alfons, A., Templ, M. and Filzmoser, P. (2013), 'Robust estimation of economic indicators from survey samples based on Pareto tail modelling', *Journal of the Royal Statistical Society: Series C (Applied Statistics)* **62**(2), 1–16.

Allegrezza, S., Heinrich, G. and Jesuit, D. (2004), 'Poverty and income inequality in Luxembourg and the Grande Région in comparative perspective', *Socio-Economic Review* **2**(2), 263–283.

Altonji, J. G. and Segal, L. M. (1996), 'Small sample bias in GMM estimation of covariance structures', *Journal of Business and Economic Statistics* **14**(3), 353–67.

Amétépé, F. and Hartmann-Hirsch, C. (2011), 'An outstanding positioning of migrants and nationals: The case of Luxembourg', *Population Review* **50**(1), 195–217.

Annaert, J.-L. (2004), A bright spot in the heart of Europe: what can we learn from the Luxembourg success story?, ECFIN Country Focus 1(15), European Commission's Directorate General for Economic and Financial Affairs.

Atkinson, A. B. and Piketty, T., eds (2010), *Top Incomes: A Global Perspective*, Oxford University Press.

Atkinson, A. B., Piketty, T. and Saez, E. (2011), 'Top incomes in the long run of history', *Journal of Economic Literature* **49**(1), 3–71.

Baker, M. (1997), 'Growth-rate heterogeneity and the covariance structure of life-cycle earnings', *Journal of Labor Economics* **15**(2), 338–375.

Baker, M. and Solon, G. (2003), 'Earnings dynamics and inequality among Canadian men, 1976-1992: Evidence from longitudinal income tax records', *Journal of Labor Economics* **21**(2), 289–321.

Bell, B. and Van Reenen, J. (2013), 'Extreme wage inequality: Pay at the very top', *American Economic Review* **103**(3), 153–157.

Biewen, M. (2005), 'The covariance structure of East and West German incomes and its implications for the persistence of poverty and inequality', *German Economic Review* **6**(4), 445–469.

Bingley, P., Cappellari, L. and Westergard-Nielsen, N. (2013), 'Unemployment insurance, wage dynamics and inequality over the life cycle', *Economic Journal* pp. 341–372.

Blundell, R., Graber, M. and Mogstad, M. (2014), Labor income dynamics and the insurance from taxes, transfers and the family, IFS Working Paper W14/01, Institute for Fiscal Studies, London.

Bönke, T., Giesecke, M. and Lüthen, H. (2013), 'The dynamics of earnings in Germany: Evidence from social security records'. Unpublished manuscript, Free University of Berlin, Germany.

Cappellari, L. (2004), 'The dynamics and inequality of Italian men's earnings', *The Journal of Human Resources* **39**(2), 475–499.

Cappellari, L. and Leonardi, M. (2013), Earnings instability and tenure, CESifo Working Paper 4145, CESifo, Munich, Germany.

Chakravarty, S. R. (2001), 'The variance as a subgroup decomposable measure of inequality', *Social Indicators Research* **53**(1), 79–95.

Chamberlain, G. (1984), Panel data, *in* Z. Griliches and M. D. Intriligator, eds, 'Handbook of Econometrics', Vol. 2 of *Handbook of Econometrics*, Elsevier, chapter 22, pp. 1247–1318.

Choe, C. and Van Kerm, P. (2014), Foreign workers and the wage distribution: Where do they fit in? Unpublished manuscript, CEPS/INSTEAD, Esch/Alzette, Luxembourg.

Clark, T. E. (1996), 'Small sample properties of estimators of non-linear models of covariance structure', *Journal of Business and Economic Statistics* **14**, 367–73.

DeBacker, J., Heim, B., Panousi, V., Ramnath, S. and Vidangos, I. (2013), 'Rising inequality: Transitory or persistent? New evidence from a panel of U.S. tax returns', *Brookings Papers on Economic Activity* **46**(1), 67–142.

Dickens, R. (2000), 'The evolution of individual male earnings in Great Britain: 1975-95', *Economic Journal* **110**(460), 27–49.

Doris, A., O'Neill, D. and Sweetman, O. (2013), 'Identification of the covariance structure of earnings using the GMM estimator', *Journal of Economic Inequality* **11**(3), 343–372.

Freeman, R. B. and Katz, L. F. (1994), Rising wage inequality: the United States vs. other advanced countries, *in* R. B. Freeman, ed., 'Working under different rules', Russel Sage Foundation, New York, pp. 29–62.

Friedman, M. and Kuznets, S. (1954), 'Income from Independent Professional Practice', *NBER, New York* .

Fusco, A., Van Kerm, P., Alieva, A., Bellani, L., Etienne-Robert, F., Guio, A.-C., Kyzyma, I., Leduc, K., Liégeois, P., Pi Alperin, M. N., Reinstadler, A., Sierminska, E., Sologon, D., Thill, P., Valentova, M. and Voicu, B. (2014), Luxembourg: Has inequality grown enough to matter?, *in* B. Nolan, N. B. Salverda, Wiemer, D. Checchi, I. Marx, A. McKnight, I. Tóth and H. Van de Werfhorst, eds, 'Changing Inequalities and Societal Impacts in Rich Countries: Thirty Countries Experiences', Oxford University Press. Forthcoming.

Gottschalk, P. and Moffit, R. (1994), 'The growth of earnings instability in the U.S. labour market', *Brookings Papers on Economic Activity* **1994**(2), 217–254.

Gustavsson, M. (2007), 'The 1990s rise in Swedish earnings inequality – persistent or transitory?', *Applied Economics* **39**(1), 25–30.

Gustavsson, M. (2008), 'A new picture of Swedish earnings inequality: persistent and transitory components, 1960-1990', *Review of Income and Wealth* **54**(3), 324–349.

Haider, S. (2001), 'Earnings instability and earnings inequlaity of males in the United States: 1967-1991', *Journal of Labor Economics* **19**(4), 799–836.

Jantti, M. and Jenkins, S. P. (2013), Income mobility, ISER Working Paper Series 2013-23, Institute for Social and Economic Research. Forthcoming in *Handbook of Income Distribution (Volume 2)* edited by A. B. Atkinson and F. Bourguignon, Elsevier-North Holland.
URL: *http://ideas.repec.org/p/ese/iserwp/2013-23.html*

Jaumotte, F., Lall, S. and Papageorgiou, C. (2013), 'Rising income inequality', *IMF Economic Review* **61**(2), 271–309.

Jenkins, S. P., Burkhauser, R. V., Feng, S. and Larrimore, J. (2011), 'Measuring inequality using censored data: a multiple imputation approach', *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **174**(1), 63–81.

Kalwij, A. and Alessie, R. (2007), 'Permanent and transitory wage inequality of British men, 1975-2001: Year, age and cohort effect', *Journal of Applied Econometrics* **22**, 1063–1093.

Kaplan, S. and Rauh, J. (2010), 'Wall Street and Main Street: What contributes to the rise in the highest incomes?', *Review of Financial Studies* **23**, 10041050.

Kopczuk, W., Saez, E. and Song, J. (2010), 'Earnings inequality and mobility in the United States: Evidence from social security data since 1937', *Quarterly Journal of Economics* **125**(1), 91–128.

Kus, B. (2012), 'Financialization and income inequality in OECD nations: 1995-2007', *Economic and Social Review* **43**(4), 477–495.

Lillard, L. A. and Willis, R. (1978), 'Dynamic aspects of earnings mobility', *Econometrica* **46**(5), 985–1012.

MaCurdy, T. E. (1982), 'The use of time series processes to model the error structure of earnings in a longitudinal data analysis', *Journal of Econometrics* **18**(1), 83–114.

Meghir, C. and Pistaferri, L. (2011), Earnings, consumption, and life cycle choices, *in* O. Ashenfelter and D. Card, eds, 'Handbook of Labor Economics', Vol. 4B, Amsterdam: Elsevier.

Moffitt, R. A. and Gottschalk, P. (2011), Trends in the transitory variance of male earnings in the U.S., 1970-2004, Working Paper 16833, National Bureau of Economic Research, Cambridge, MA.

Moffitt, R. and Gottschalk, P. (1995), Trends in the covariance structure of earnings in the United States: 1969-1987, Institute for Research on Poverty Discussion Papers 1001-93, Institute for Research on Poverty, University of Wisconsin.

Moffitt, R. and Gottschalk, P. (1998), Trends in the variances of permanent and transitory earnings in the U.S and their relation to earnings mobility, Technical Report 444, Boston College.

Moffitt, R. and Gottschalk, P. (2002), 'Trends in the transitory variance of earnings in the United States', *The Economic Journal* **112**(478), C68–C73.

Moffitt, R. and Gottschalk, P. (2008), Trends in the Transitory Variance of Male Earnings in the U.S., 1970-2004, Boston College Working Papers in Economics 697, Boston College Department of Economics.

OECD (2008), *Growing Unequal? Income Distribution and Poverty in OECD Countries*, OECD, Paris.

OECD (2011), *Divided We Stand: Why Inequality Keeps Rising*, OECD, Paris.

Ostrovsky, Y. (2010), 'Long-run earnings inequality and earnings instability among Canadian men revisited, 1985-2005', *The B.E. Journal of Economic Analysis and Policy* **10**(20), 1–34.

Ramos, X. (2003), 'The covariance structure of earnings in Great Britain, 1991-1999', *Economica* **70**(278), 353–374.

Reiter, J. P. (2003), 'Inference for partially synthetic, public use microdata sets', *Survey Methodology* **29**, 181–188.

Shorrocks, A. F. (1984), 'Inequality Decomposition by Population Subgroups', *Econometrica* **52**(6), 1369–1385.

Sologon, D. and O'Donoghue, C. (2012), Cross-national trends in permanent earnings inequality and earnings instability in Europe 1994–2001, UNU-MERIT Working Paper 2012-006, Maastricht University.

World Economic Forum (2011), *Global Risks 2011*, 6 edn, World Economic Forum, Geneva.

Appendix A Sample sizes by worker type

Table A.1: Sample Size by Birth Cohort - Nationals

Cohort born in	Persons	Person-years	Years observed	% Persons present in all years	% Observed person-years in theoretical person-years	Year range		Age range	
1940	997	8618	10	72.64	86.44	1988	1997	48	57
1941	985	9237	11	72.29	85.25	1988	1998	47	57
1942	1280	11199	12	67.51	72.91	1988	1999	46	57
1943	1248	12012	13	63.85	74.04	1988	2000	45	57
1944	1296	13336	14	65.30	73.50	1988	2001	44	57
1945	1240	13591	15	65.12	73.07	1988	2002	43	57
1946	1502	18469	16	64.28	76.85	1988	2003	42	57
1947	1547	20488	17	62.23	77.90	1988	2004	41	57
1948	1563	21510	18	60.08	76.46	1988	2005	40	57
1949	1551	23305	19	59.92	79.08	1988	2006	39	57
1950	1589	25079	20	59.49	78.91	1988	2007	38	57
1951	1679	28112	21	57.07	79.73	1988	2008	37	57
1952	1825	32016	22	57.10	79.74	1988	2009	36	57
1953	1870	33438	22	59.67	81.28	1988	2009	35	56
1954	1914	34725	22	60.82	82.47	1988	2009	34	55
1955	1943	34966	22	61.91	81.80	1988	2009	33	54
1956	1952	35369	22	63.01	82.36	1988	2009	32	53
1957	2152	38998	22	61.38	82.37	1988	2009	31	52
1958	2208	40492	22	62.75	83.36	1988	2009	30	51
1959	2230	41792	22	64.80	85.19	1988	2009	29	50
1960	2147	40564	22	66.28	85.88	1988	2009	28	49
1961	2199	41909	22	68.14	86.63	1988	2009	27	48
1962	2129	40850	22	69.53	87.22	1988	2009	26	47
1963	2245	43228	22	67.48	87.52	1988	2009	25	46
1964	2288	43912	22	66.63	87.24	1988	2009	24	45
1965	2235	42799	22	63.84	87.04	1988	2009	23	44
1966	2129	40408	22	60.43	86.27	1988	2009	22	43
1967	2160	40227	22	56.06	84.65	1988	2009	21	42
1968	2039	37268	22	50.94	83.08	1988	2009	20	41
1969	1957	33670	21	46.78	81.93	1989	2009	20	40
1970	1829	30111	20	48.22	82.32	1990	2009	20	39
1971	1882	29159	19	45.81	81.55	1991	2009	20	38
1972	1666	24321	18	44.78	81.10	1992	2009	20	37
1973	1460	19973	17	39.32	80.47	1993	2009	20	36
1974	1438	18243	16	37.98	79.29	1994	2009	20	35
1975	1409	16630	15	36.17	78.68	1995	2009	20	34
1976	1384	14932	14	37.22	77.06	1996	2009	20	33
1977	1477	14790	13	39.91	77.03	1997	2009	20	32
1978	1488	13552	12	47.64	75.90	1998	2009	20	31
1979	1464	12102	11	47.26	75.15	1999	2009	20	30
1980	1506	10981	10	46.53	72.92	2000	2009	20	29
Total	71102	1106381							

Notes: % Observed person-years in theoretical person-years = the ratio between the third column (Person-years) and the product between the second column (Persons) and the fourth column (Years observed). The sample size refers only to positive earnings.

Table A.2: Sample Size by Birth Cohort - Immigrants

Cohort born in	Persons	Person-years	Years observed	% Persons present in all years	% Observed person-years in theoretical person-years	Year range		Age range	
1940	441	3274	10	70.56	74.24	1988	1997	48	57
1941	490	3623	11	60.42	67.22	1988	1998	47	57
1942	493	3865	12	65.20	65.33	1988	1999	46	57
1943	612	4804	13	57.37	60.38	1988	2000	45	57
1944	739	6356	14	60.57	61.43	1988	2001	44	57
1945	775	7001	15	59.35	60.22	1988	2002	43	57
1946	994	9403	16	55.81	59.12	1988	2003	42	57
1947	1170	11143	17	55.53	56.02	1988	2004	41	57
1948	1296	13437	18	56.93	57.60	1988	2005	40	57
1949	1376	14962	19	56.26	57.23	1988	2006	39	57
1950	1397	15397	20	49.75	55.11	1988	2007	38	57
1951	1438	15822	21	48.18	52.39	1988	2008	37	57
1952	1596	17011	22	47.08	48.45	1988	2009	36	57
1953	1691	18366	22	43.84	49.37	1988	2009	35	56
1954	1906	20721	22	45.97	49.42	1988	2009	34	55
1955	1949	20087	22	40.96	46.85	1988	2009	33	54
1956	2104	21809	22	42.07	47.12	1988	2009	32	53
1957	2301	23574	22	41.16	46.57	1988	2009	31	52
1958	2505	25461	22	38.28	46.20	1988	2009	30	51
1959	2636	26829	22	35.18	46.26	1988	2009	29	50
1960	2887	27941	22	32.83	43.99	1988	2009	28	49
1961	3119	29936	22	31.53	43.63	1988	2009	27	48
1962	3411	32800	22	32.26	43.71	1988	2009	26	47
1963	3587	34568	22	28.96	43.80	1988	2009	25	46
1964	3878	36997	22	31.46	43.36	1988	2009	24	45
1965	3996	36552	22	25.28	41.58	1988	2009	23	44
1966	3970	35496	22	23.12	40.64	1988	2009	22	43
1967	4091	35469	22	22.21	39.41	1988	2009	21	42
1968	4180	35117	22	17.67	38.19	1988	2009	20	41
1969	4212	33996	21	21.37	38.43	1989	2009	20	40
1970	4029	30860	20	21.65	38.30	1990	2009	20	39
1971	4163	31408	19	22.75	39.71	1991	2009	20	38
1972	4029	29301	18	25.68	40.40	1992	2009	20	37
1973	4053	27653	17	23.05	40.13	1993	2009	20	36
1974	3823	24606	16	24.25	40.23	1994	2009	20	35
1975	3704	23107	15	22.79	41.59	1995	2009	20	34
1976	3752	21622	14	24.22	41.16	1996	2009	20	33
1977	3479	19504	13	25.33	43.12	1997	2009	20	32
1978	3330	16991	12	25.28	42.52	1998	2009	20	31
1979	3214	15185	11	28.32	42.95	1999	2009	20	30
1980	3035	13946	10	33.34	45.95	2000	2009	20	29
Total	105851	876000							

Notes: % Observed person-years in theoretical person-years = the ratio between the third column (Person-years) and the product between the second column (Persons) and the fourth column (Years observed). The sample size refers only to positive earnings.

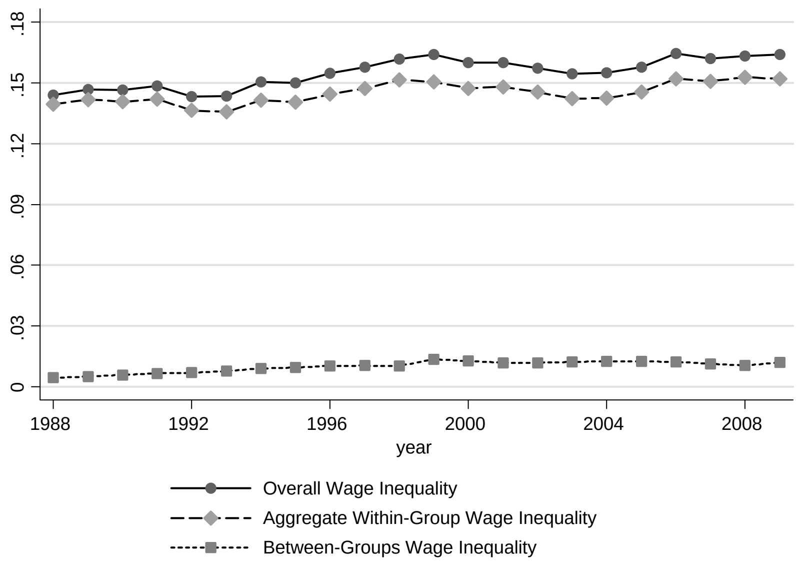
Table A.3: Sample Size by Birth Cohort - Cross-Border Workers

Cohort born in	Persons	Person-years	Years observed	% Persons present in all years	% Observed person-years in theoretical person-years	Year range		Age range	
1940	544	2940	10	54.42	54.04	1988	1997	48	57
1941	521	3033	11	52.95	52.92	1988	1998	47	57
1942	636	3920	12	53.27	51.36	1988	1999	46	57
1943	769	4618	13	48.42	46.19	1988	2000	45	57
1944	830	5265	14	46.53	45.31	1988	2001	44	57
1945	957	6444	15	46.09	44.89	1988	2002	43	57
1946	1286	9111	16	38.63	44.28	1988	2003	42	57
1947	1603	11243	17	39.16	41.26	1988	2004	41	57
1948	1832	13899	18	39.11	42.15	1988	2005	40	57
1949	2111	16347	19	34.75	40.76	1988	2006	39	57
1950	2360	17541	20	35.92	37.16	1988	2007	38	57
1951	2526	20428	21	34.85	38.51	1988	2008	37	57
1952	2940	24209	22	32.17	37.43	1988	2009	36	57
1953	2970	24043	22	28.91	36.80	1988	2009	35	56
1954	3379	26974	22	28.87	36.29	1988	2009	34	55
1955	3485	26992	22	26.33	35.21	1988	2009	33	54
1956	3810	30715	22	25.79	36.64	1988	2009	32	53
1957	4064	31779	22	22.57	35.54	1988	2009	31	52
1958	4282	33660	22	21.63	35.73	1988	2009	30	51
1959	4976	37596	22	20.95	34.34	1988	2009	29	50
1960	5106	39323	22	21.60	35.01	1988	2009	28	49
1961	5827	44823	22	20.07	34.96	1988	2009	27	48
1962	6010	47083	22	20.23	35.61	1988	2009	26	47
1963	6772	52386	22	18.10	35.16	1988	2009	25	46
1964	7185	56242	22	17.72	35.58	1988	2009	24	45
1965	7405	57451	22	15.97	35.27	1988	2009	23	44
1966	7688	57384	22	12.65	33.93	1988	2009	22	43
1967	7698	56690	22	8.65	33.47	1988	2009	21	42
1968	7855	55116	22	6.15	31.89	1988	2009	20	41
1969	7717	52607	21	6.03	32.46	1989	2009	20	40
1970	7999	52806	20	5.68	33.01	1990	2009	20	39
1971	8052	51973	19	6.00	33.97	1991	2009	20	38
1972	7925	49185	18	7.28	34.48	1992	2009	20	37
1973	7465	44196	17	6.54	34.83	1993	2009	20	36
1974	7137	40245	16	6.72	35.24	1994	2009	20	35
1975	6721	35575	15	5.61	35.29	1995	2009	20	34
1976	6412	31850	14	5.63	35.48	1996	2009	20	33
1977	6533	30483	13	7.08	35.89	1997	2009	20	32
1978	6281	27125	12	8.14	35.99	1998	2009	20	31
1979	6293	25860	11	10.17	37.36	1999	2009	20	30
1980	6373	24386	10	14.39	38.26	2000	2009	20	29
Total	192335	1283546							

Notes: % Observed person-years in theoretical person-years = the ratio between the third column (Person-years) and the product between the second column (Persons) and the fourth column (Years observed). The sample size refers only to positive earnings.

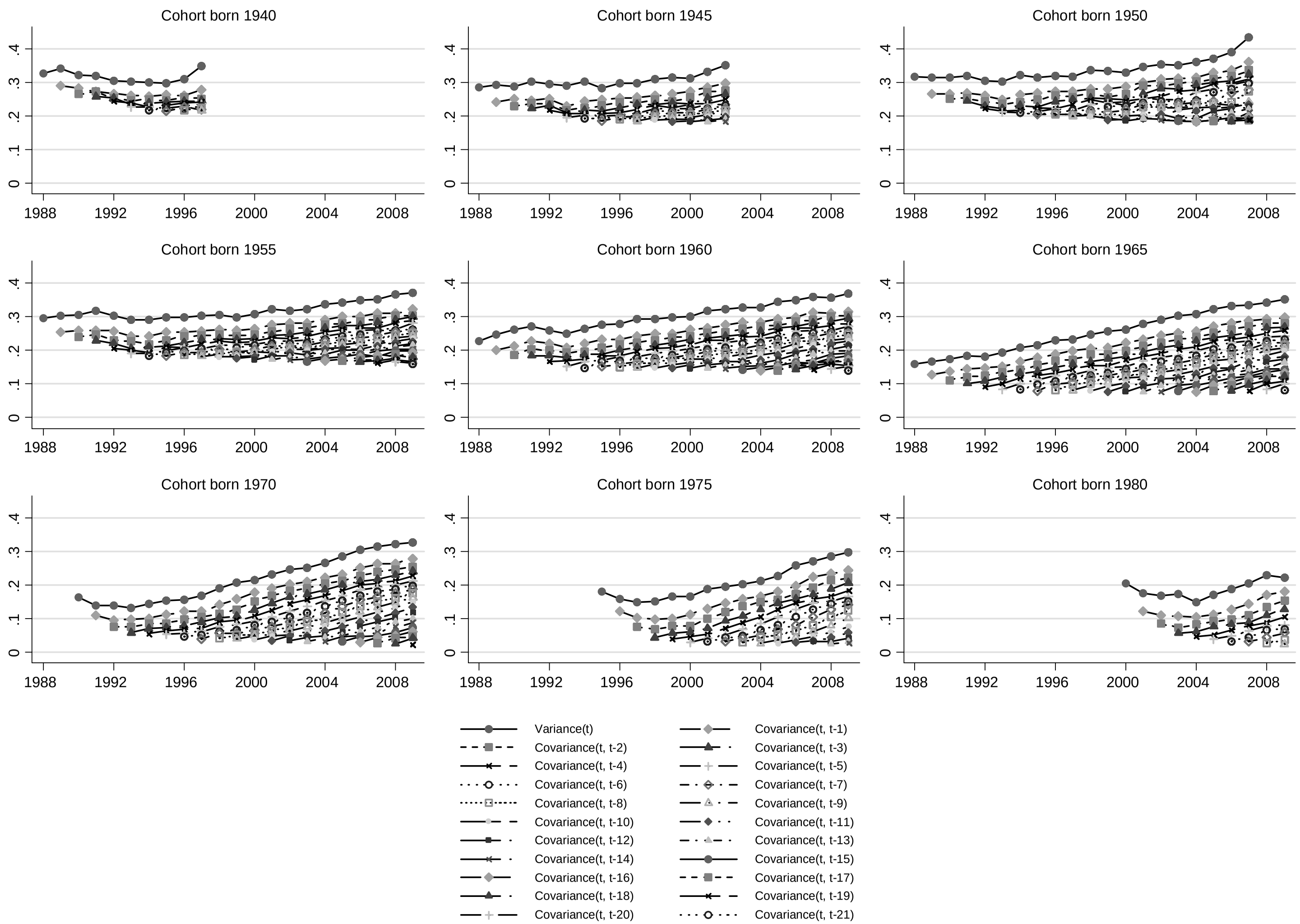
Appendix B Decomposition of the mean log earnings deviation by population subgroups

Figure B.1: Decomposition of the mean log earnings deviation by population subgroups: natives, immigrants and cross-border workers, 1988–2009



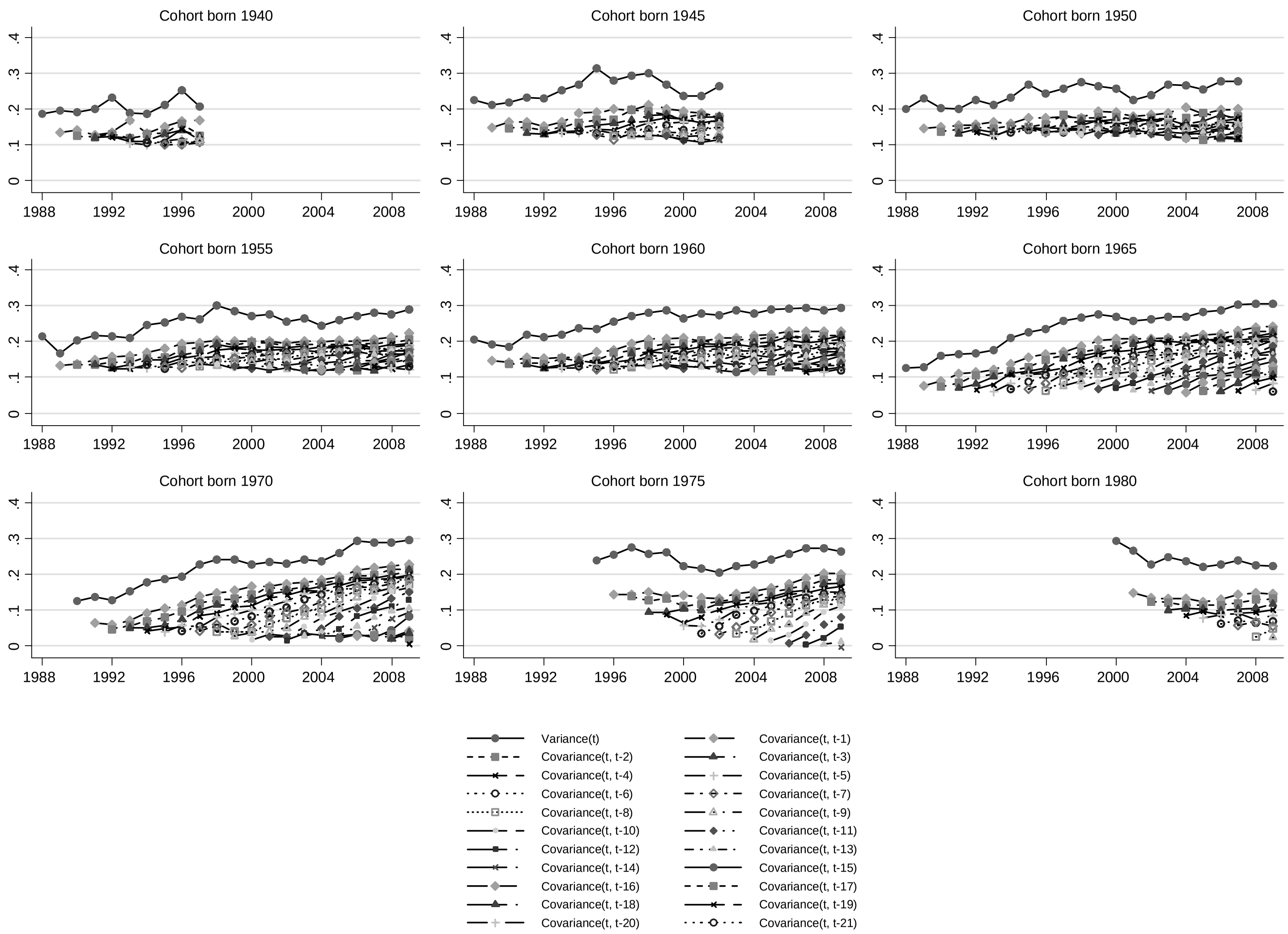
Appendix C Autocovariance structure of earnings for population sub-groups

Figure C.2: Auto-covariance structure of log earnings for selected cohorts - Residents



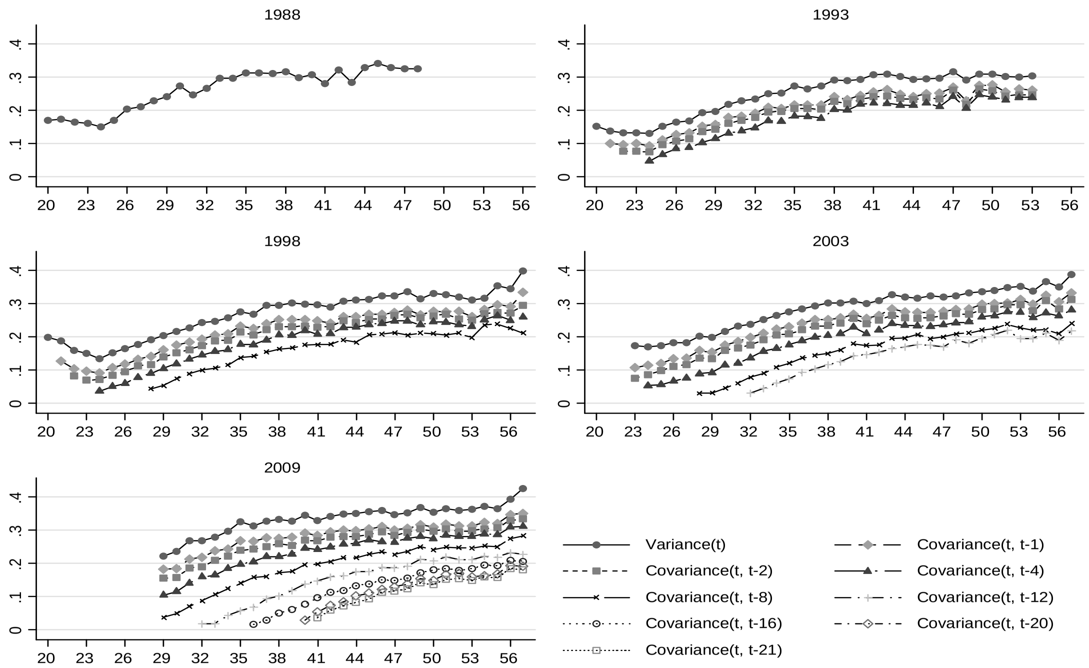
Note: In the legend, ‘t’ stands for the year displayed on the horizontal axis.

Figure C.3: Auto-covariance structure of log earnings for selected cohorts - Cross-Borders



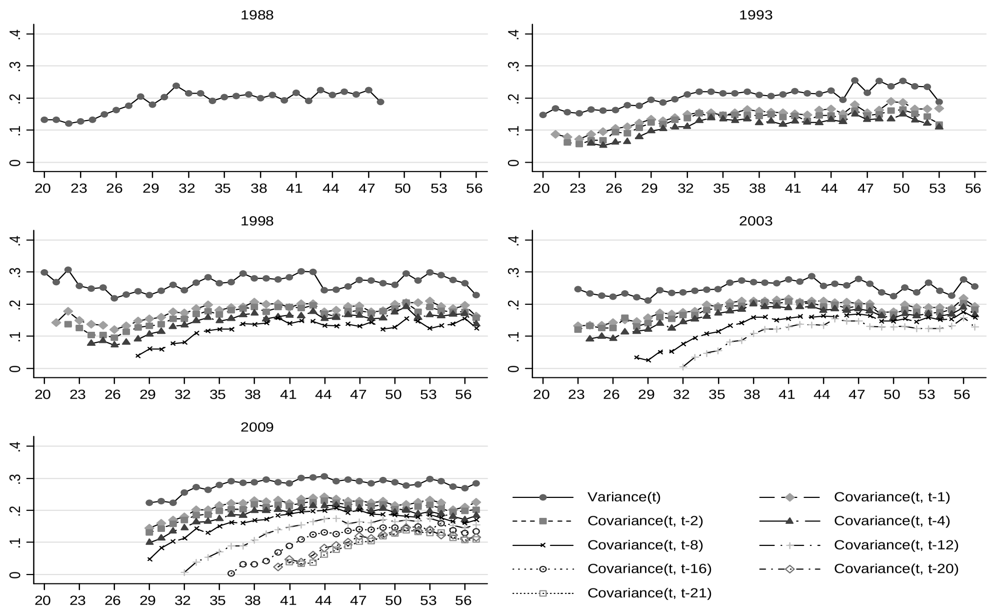
Note: In the legend, ‘t’ stands for the year displayed on the horizontal axis.

Figure C.4: Life-cycle auto-covariances of log earnings for selected years - Residents



Note: In the legend, ‘t’ stands for the age displayed on the horizontal axis.

Figure C.5: Life-cycle auto-covariances of log earnings for selected years - Cross-Border workers.



Note: In the legend, ‘t’ stands for the age displayed on the horizontal axis.

Appendix D Model parameter estimates

Table D.4: Error Component Model Estimates - Permanent Component

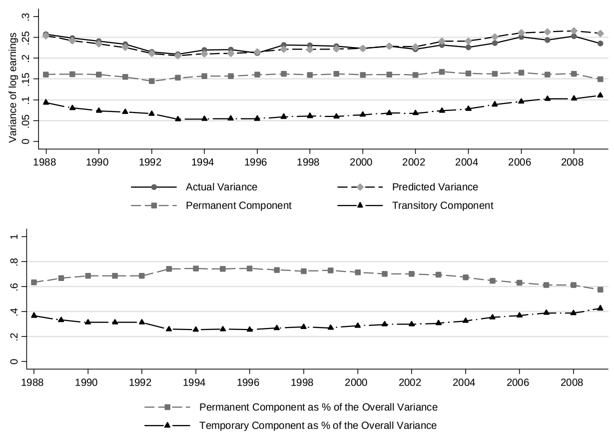
	Base Model All Men			Base Model Residents			Base Model Nationals			Base Model Immigrants			Base Model Cross-Border Workers		
Permanent Component	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate
Exp(estimate) = $\sigma^2_{\mu_{20}}$	-4.086	[0.060]	0.0168	-4.211	[0.067]	0.0148	-3.711	[0.081]	0.0245	-4.736	[0.194]	0.0088	-4.911	[0.271]	0.0074
Exp(estimate) = $\sigma^2_{\pi_{21}}$	-4.715	[0.081]	0.0090	-4.753	[0.086]	0.0086	-4.587	[0.121]	0.0102	-5.482	[0.318]	0.0042	-5.054	[0.271]	0.0064
Exp(estimate) = $\sigma^2_{\pi_{22}}$	-4.672	[0.071]	0.0094	-4.622	[0.073]	0.0098	-4.550	[0.107]	0.0106	-4.737	[0.161]	0.0088	-5.288	[0.264]	0.0051
Exp(estimate) = $\sigma^2_{\pi_{23}}$	-4.711	[0.068]	0.0090	-4.747	[0.075]	0.0087	-4.787	[0.118]	0.0083	-4.600	[0.151]	0.0100	-4.670	[0.180]	0.0094
Exp(estimate) = $\sigma^2_{\pi_{24}}$	-4.515	[0.060]	0.0109	-4.552	[0.067]	0.0105	-4.547	[0.098]	0.0106	-4.407	[0.139]	0.0122	-4.620	[0.170]	0.0099
Exp(estimate) = $\sigma^2_{\pi_{25}}$	-4.560	[0.060]	0.0105	-4.550	[0.066]	0.0106	-4.524	[0.095]	0.0108	-4.323	[0.136]	0.0133	-4.910	[0.179]	0.0074
Exp(estimate) = $\sigma^2_{\pi_{26}}$	-4.753	[0.065]	0.0086	-4.692	[0.069]	0.0092	-4.774	[0.108]	0.0085	-4.461	[0.137]	0.0116	-5.136	[0.190]	0.0059
Exp(estimate) = $\sigma^2_{\pi_{27}}$	-4.685	[0.062]	0.0092	-4.602	[0.067]	0.0100	-4.550	[0.094]	0.0106	-4.658	[0.146]	0.0095	-5.145	[0.187]	0.0058
Exp(estimate) = $\sigma^2_{\pi_{28}}$	-4.787	[0.067]	0.0083	-4.672	[0.071]	0.0094	-4.611	[0.100]	0.0099	-4.732	[0.153]	0.0088	-5.458	[0.218]	0.0043
Exp(estimate) = $\sigma^2_{\pi_{29}}$	-4.852	[0.071]	0.0078	-4.761	[0.077]	0.0086	-4.725	[0.109]	0.0089	-5.090	[0.196]	0.0062	-5.475	[0.214]	0.0042
Exp(estimate) = $\sigma^2_{\pi_{30}}$	-4.960	[0.079]	0.0070	-4.865	[0.084]	0.0077	-4.982	[0.137]	0.0069	-5.135	[0.209]	0.0059	-5.629	[0.245]	0.0036
Exp(estimate) = $\sigma^2_{\pi_{31}}$	-4.961	[0.083]	0.0070	-4.775	[0.082]	0.0084	-4.716	[0.116]	0.0090	-5.107	[0.204]	0.0061	-5.757	[0.268]	0.0032
Exp(estimate) = $\sigma^2_{\pi_{32}}$	-5.053	[0.093]	0.0064	-4.837	[0.091]	0.0079	-4.887	[0.139]	0.0076	-5.151	[0.220]	0.0058	-6.489	[0.541]	0.0016
Exp(estimate) = $\sigma^2_{\pi_{33}}$	-5.044	[0.095]	0.0065	-4.917	[0.100]	0.0073	-4.832	[0.140]	0.0080	-5.288	[0.252]	0.0051	-6.031	[0.341]	0.0024
Exp(estimate) = $\sigma^2_{\pi_{34}}$	-5.223	[0.114]	0.0054	-4.989	[0.110]	0.0068	-4.908	[0.150]	0.0074	-5.833	[0.439]	0.0029	-7.815	[5.312]	0.0006
Exp(estimate) = $\sigma^2_{\pi_{35}}$	-5.085	[0.107]	0.0062	-4.799	[0.100]	0.0082	-4.736	[0.138]	0.0088	-5.489	[0.343]	0.0041	-8.454	[29.445]	0.0004
Exp(estimate) = $\sigma^2_{\pi_{36}}$	-5.102	[0.113]	0.0061	-4.895	[0.112]	0.0075	-4.698	[0.138]	0.0091	-6.585	[1.014]	0.0014	-6.758	[0.662]	0.0012
Exp(estimate) = $\sigma^2_{\pi_{37}}$	-5.207	[0.131]	0.0055	-4.977	[0.127]	0.0069	-4.860	[0.166]	0.0078	-5.545	[0.363]	0.0039	-7.047	[1.433]	0.0010
Exp(estimate) = $\sigma^2_{\pi_{38}}$	-5.348	[0.150]	0.0048	-5.118	[0.144]	0.0060	-5.276	[0.245]	0.0051	-7.244	[2.040]	0.0007	-7.729	[2.632]	0.0006
Exp(estimate) = $\sigma^2_{\pi_{39}}$	-5.127	[0.127]	0.0060	-4.909	[0.125]	0.0074	-5.011	[0.191]	0.0067	-5.241	[0.295]	0.0053	-9.000	[219.952]	0.0004
Exp(estimate) = $\sigma^2_{\pi_{40}}$	-5.215	[0.142]	0.0055	-4.891	[0.125]	0.0075	-4.935	[0.187]	0.0072	-5.573	[0.411]	0.0038	no change		
Exp(estimate) = $\sigma^2_{\pi_{41}}$	-5.452	[0.181]	0.0043	-5.208	[0.172]	0.0055	-5.237	[0.253]	0.0054	-8.519	[7.777]	0.0002	no change		
Exp(estimate) = $\sigma^2_{\pi_{42}}$	-5.193	[0.145]	0.0056	-4.946	[0.137]	0.0071	-5.071	[0.214]	0.0063	-5.212	[0.310]	0.0054	no change		
Exp(estimate) = $\sigma^2_{\pi_{43}}$	-5.266	[0.160]	0.0052	-4.919	[0.137]	0.0073	-4.928	[0.187]	0.0073	-5.842	[0.558]	0.0029	no change		
Exp(estimate) = $\sigma^2_{\pi_{44}}$	-5.167	[0.152]	0.0057	-4.849	[0.135]	0.0079	-4.979	[0.208]	0.0069	-5.489	[0.416]	0.0041	no change		
Exp(estimate) = $\sigma^2_{\pi_{45}}$	-5.077	[0.148]	0.0063	-4.774	[0.134]	0.0085	-4.619	[0.155]	0.0099	-7.118	[2.235]	0.0008	no change		
Exp(estimate) = $\sigma^2_{\pi_{46}}$	-4.968	[0.140]	0.0070	-4.659	[0.125]	0.0095	-4.638	[0.162]	0.0097	-5.768	[0.619]	0.0031	no change		
Exp(estimate) = $\sigma^2_{\pi_{47}}$	-5.165	[0.170]	0.0057	-4.869	[0.152]	0.0077	-4.827	[0.193]	0.0080	-5.913	[0.699]	0.0027	no change		
Exp(estimate) = $\sigma^2_{\pi_{48}}$	-5.040	[0.157]	0.0065	-4.778	[0.144]	0.0084	-4.802	[0.192]	0.0083	-6.039	[0.846]	0.0024	no change		
Exp(estimate) = $\sigma^2_{\pi_{49}}$	-4.904	[0.140]	0.0075	-4.593	[0.125]	0.0102	-4.632	[0.165]	0.0098	-5.917	[0.744]	0.0027	no change		
Exp(estimate) = $\sigma^2_{\pi_{50-51}}$	-4.748	[0.125]	0.0087	-4.474	[0.119]	0.0114	-4.585	[0.163]	0.0102	-6.323	[1.177]	0.0018	-6.675	[0.946]	0.0013
Exp(estimate) = $\sigma^2_{\pi_{52-53}}$	-4.269	[0.091]	0.0140	-3.987	[0.091]	0.0186	-4.003	[0.117]	0.0183	-5.703	[0.684]	0.0033	no change		
Exp(estimate) = $\sigma^2_{\pi_{54-55}}$	-4.409	[0.126]	0.0122	-4.226	[0.135]	0.0146	-4.148	[0.167]	0.0158	-6.832	[2.547]	0.0011	no change		
Exp(estimate) = $\sigma^2_{\pi_{56-57}}$	-4.124	[0.139]	0.0162	-3.982	[0.155]	0.0187	-3.743	[0.175]	0.0237	-6.652	[3.176]	0.0013	no change		
Time shifters ($\lambda_{1,1988} = 1$)															
$\lambda_{1,1989}$	1.006	[0.005]		0.997	[0.005]		0.997	[0.005]		1.023	[0.013]		1.000	[0.015]	
$\lambda_{1,1990}$	0.977	[0.005]		0.958	[0.006]		0.948	[0.006]		1.005	[0.016]		1.024	[0.017]	
$\lambda_{1,1991}$	0.972	[0.006]		0.950	[0.006]		0.942	[0.007]		1.013	[0.018]		1.037	[0.018]	
$\lambda_{1,1992}$	0.934	[0.006]		0.905	[0.007]		0.887	[0.008]		0.997	[0.020]		1.036	[0.019]	
$\lambda_{1,1993}$	0.931	[0.007]		0.897	[0.007]		0.870	[0.009]		1.011	[0.023]		1.067	[0.021]	
$\lambda_{1,1994}$	0.941	[0.008]		0.900	[0.008]		0.873	[0.009]		1.012	[0.025]		1.120	[0.023]	
$\lambda_{1,1995}$	0.932	[0.008]		0.883	[0.008]		0.846	[0.010]		1.030	[0.028]		1.134	[0.025]	
$\lambda_{1,1996}$	0.937	[0.009]		0.885	[0.009]		0.849	[0.010]		1.039	[0.031]		1.160	[0.027]	
$\lambda_{1,1997}$	0.931	[0.009]		0.876	[0.009]		0.840	[0.011]		1.039	[0.033]		1.177	[0.028]	
$\lambda_{1,1998}$	0.935	[0.009]		0.878	[0.010]		0.842	[0.011]		1.067	[0.036]		1.204	[0.029]	
$\lambda_{1,1999}$	0.945	[0.010]		0.877	[0.010]		0.825	[0.011]		1.089	[0.039]		1.226	[0.031]	
$\lambda_{1,2000}$	0.936	[0.010]		0.871	[0.010]		0.825	[0.012]		1.082	[0.041]		1.225	[0.031]	
$\lambda_{1,2001}$	0.942	[0.011]		0.878	[0.011]		0.832	[0.013]		1.116	[0.044]		1.242	[0.033]	
$\lambda_{1,2002}$	0.935	[0.011]		0.870	[0.011]		0.822	[0.013]		1.101	[0.045]		1.243	[0.033]	
$\lambda_{1,2003}$	0.921	[0.011]		0.856	[0.011]		0.803	[0.013]		1.089	[0.046]		1.232	[0.033]	
$\lambda_{1,2004}$	0.919	[0.011]		0.857	[0.011]		0.806	[0.013]		1.102	[0.048]		1.235	[0.034]	
$\lambda_{1,2005}$	0.921	[0.012]		0.859	[0.012]		0.807	[0.014]		1.110	[0.050]		1.241	[0.034]	
$\lambda_{1,2006}$	0.929	[0.012]		0.863	[0.012]		0.812	[0.014]		1.118	[0.052]		1.266	[0.035]	
$\lambda_{1,2007}$	0.919	[0.012]		0.855	[0.012]		0.807	[0.014]		1.117	[0.053]		1.259	[0.035]	
$\lambda_{1,2008}$	0.919	[0.012]		0.854	[0.012]		0.804	[0.014]		1.120	[0.054]		1.264	[0.036]	
$\lambda_{1,2009}$	0.913	[0.012]		0.845	[0.012]		0.785	[0.014]		1.086	[0.054]		1.266	[0.036]	
Cohort shifters ($\gamma_{1,1940} = 1$)															
$\gamma_{1,1941}$	1.030	[0.028]		1.025	[0.031]		1.041	[0.042]		0.999	[0.065]		1.083	[0.107]	
$\gamma_{1,1942}$	1.045	[0.028]		1.041	[0.031]		1.036	[0.041]		1.076	[0.070]		1.119	[0.105]	
$\gamma_{1,1943}$	1.075	[0.028]		1.084	[0.032]		1.079	[0.043]		1.067	[0.069]		1.111	[0.100]	
$\gamma_{1,1944}$	1.069	[0.027]		1.087	[0.031]		1.074	[0.042]		1.076	[0.064]		1.112	[0.100]	
$\gamma_{1,1945}$	1.022	[0.026]		1.034	[0.029]		1.007	[0.040]		0.989	[0.061]		1.081	[0.095]	
$\gamma_{1,1946}$	1.075	[0.026]		1.101	[0.030]		1.113	[0.042]		1.024	[0.061]		1.116	[0.094]	
$\gamma_{1,1947}$	1.073	[0.026]		1.092	[0.029]		1.075	[0.039]		1.010	[0.060]		1.198	[0.098]	
$\gamma_{1,1948}$	1.092	[0.026]		1.129	[0.030]		1.151	[0.043]		0.960	[0.058]		1.110	[0.091]	
$\gamma_{1,1949}$	1.084	[0.026]		1.122	[0.030]		1.116	[0.041]		0.988	[0.059]		1.101	[0.090]	
$\gamma_{1,1950}$	1.111	[0.026]		1.161	[0.030]		1.154	[0.041]		1.026	[0.061]		1.093	[0.090]	
$\gamma_{1,1951}$	1.141	[0.026]		1.198	[0.031]		1.173	[0.042]		1.047	[0.062]		1.087	[0.088]	
$\gamma_{1,1952}$	1.151	[0.026]		1.200	[0.031]		1.191	[0.042]		0.981	[0.062]		1.115	[0.089]	
$\gamma_{1,1953}$	1.169	[0.027]		1.223	[0.031]		1.192	[0.042]		1.080	[0.065]		1.091	[0.087]	
$\gamma_{1,1954}$	1.145	[0.026]		1.194	[0.031]		1.151	[0.041]		1.022	[0.064]		1.095	[0.087]	
$\gamma_{1,1955}$	1.176	[0.027]		1.223	[0.031]		1.173	[0.042]		1.059	[0.066]		1.153	[0.091]	
$\gamma_{1,1956}$	1.167	[0.027]		1.217	[0.032]		1.148	[0.042]		1.044	[0.067]		1.164	[0.091]	
$\gamma_{1,1957}$	1.197	[0.028]		1.244	[0.032]		1.178	[0.043]		1.043	[0.068]		1.170	[0.092]	
$\gamma_{1,1958}$	1.229	[0.029]		1.285	[0.033]		1.204	[0.043]		1.102	[0.070]		1.194	[0.093]	
$\gamma_{1,1959}$	1.224	[0.029]		1.287	[0.034]		1.220	[0.044]		1.088	[0.072]		1.166	[0.091]	
$\gamma_{1,1960}$	1.257	[0.030]		1.326	[0.035]		1.267	[0.045]		1.111	[0.075]		1.191	[0.092]	
$\gamma_{1,1961}$	1.241	[0.030]		1.311	[0.035]		1.213	[0.045]		1.126	[0.076]		1.187	[0.091]	
$\gamma_{1,1962}$	1.249	[0.030]		1.318	[0.036]		1.218	[0.045]		1.134	[0.078]		1.207	[0.092]	
$\gamma_{1,1963}$	1.287	[0.031]		1.372	[0.037]		1.261	[0.046]		1.199	[0.082]		1.202	[0.092]	
$\gamma_{1,1964}$	1.289	[0.031]		1.360	[0.037]		1.258	[0.047]		1.123	[0.079]		1.244	[0.095]	
$\gamma_{1,1965}$	1.301	[0.032]		1.376	[0.038]		1.268	[0.048]		1.138	[0.082]		1.248	[0.095]	
$\gamma_{1,1966}$	1.310	[0.032]		1.393	[0.039]		1.286	[0.049]		1.115	[0.083]		1.232	[0.094]	
$\gamma_{1,1967}$	1.324	[0.033]		1.407	[0.040]		1.308	[0.050]		1.130	[0.085]		1.237	[0.094]	
$\gamma_{1,1968}$	1.311	[0.033]		1.396	[0.041]		1.253	[0.050]		1.130	[0.086]		1.208	[0.092]	
$\gamma_{1,1969}$	1.320	[0.034]		1.407	[0.041]		1.263	[0.050]		1.152	[0.088]		1.215	[0.093]	
$\gamma_{1,1970}$	1.310	[0.034]		1.392	[0.041]		1.228	[0.050]		1.152	[0.089]		1.213	[0.093]	
$\gamma_{1,1971}$	1.314	[0.034]		1.397	[0.041]		1.272	[0.051]		1.119	[0.086]		1.212	[0.093]	
$\gamma_{1,1972}$	1.310	[0.034]		1.407	[0.042]		1.269	[0.051]		1.145	[0.088]		1.197	[0.092]	
$\gamma_{1,1973}$	1.340	[0.035]		1.420	[0.042]		1.226	[0.052]		1.208	[0.092]		1.245	[0.095]	
$\gamma_{1,1974}$	1.323	[0.034]		1.405	[0.042]		1.183	[0.051]		1.230	[0.093]		1.212	[0.093]	
$\gamma_{1,1975}$	1.322	[0.035]		1.432	[0.043]		1.219	[0.052]		1.209	[0.093]		1.153	[0.090]	
$\gamma_{1,1976}$	1.331	[0.035]		1.407	[0.043]		1.223	[0.053]		1.144	[0.090]		1.169	[0.092]	
$\gamma_{1,1977}$	1.314	[0.035]		1.414	[0.044]		1.231	[0.054]		1.169	[0.094]		1.121	[0.088]	
$\gamma_{1,1978}$	1.322	[0.036]		1.439	[0.045]		1.274	[0.055]		1.116	[0.094]		1.059	[0.086]	
$\gamma_{1,1979}$	1.266	[0.036]		1.373	[0.044]		1.260	[0.056]		1.025	[0.092]		0.974	[0.082]	
$\gamma_{1,1980}$	1.253	[0.036]		1.399	[0.045]		1.307	[0.056]		0.963	[0.095]		0.916	[0.081]	

Table D.5: Error Component Model Estimates - Transitory Component

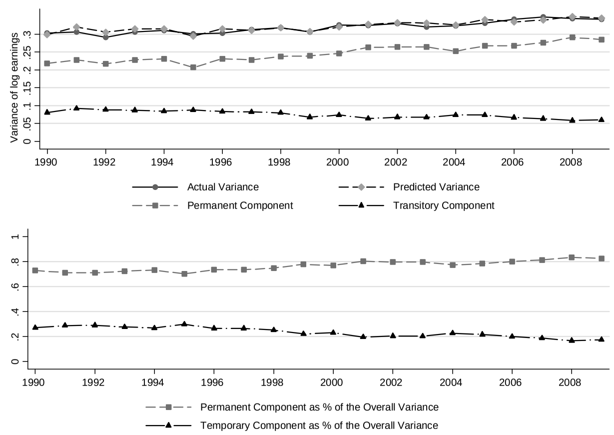
	Base Model All Men			Base Model Residents			Base Model Nationals			Base Model Immigrants			Base Model Cross-Border Workers		
Transitory Component	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate	Estimate	SE	Variance Estimate
Exp(estimate) = σ_0^2	-2.716	[0.171]	0.0661	-2.481	[0.216]	0.0839	-1.679	[0.251]	0.1870	-3.718	[0.218]	0.0243	-2.458	[0.306]	0.0857
α	0.008	[0.007]		-0.006	[0.007]		-0.027	[0.003]		0.129	[0.027]		0.006	[0.012]	
ρ	0.683	[0.008]		0.652	[0.010]		0.634	[0.013]		0.829	[0.012]		0.841	[0.008]	
θ	-0.301	[0.003]		-0.226	[0.006]		-0.208	[0.010]		-0.284	[0.005]		-0.371	[0.002]	
Exp(estimate) = σ_ϵ^2															
β_0	0.045	[0.007]		0.034	[0.006]		0.075	[0.018]		0.021	[0.004]		0.088	[0.025]	
β_1	-0.008	[0.001]		-0.006	[0.001]		-0.009	[0.002]		-0.006	[0.001]		-0.017	[0.005]	
β_2	0.001	[0.000]		0.001	[0.000]		0.001	[0.000]		0.001	[0.000]		0.002	[0.001]	
β_3	-0.000	[0.000]		-0.000	[0.000]		-0.000	[0.000]		-0.000	[0.000]		-0.000	[0.000]	
β_4	0.000	[0.000]		0.000	[0.000]		0.000	[0.000]		0.000	[0.000]		0.000	[0.000]	
Time shifters ($\lambda_{2,1988} = 1$)															
$\lambda_{2,1989}$	1.092	[0.011]		1.094	[0.015]		1.131	[0.020]		0.945	[0.015]		1.023	[0.013]	
$\lambda_{2,1990}$	1.178	[0.016]		1.164	[0.024]		1.226	[0.032]		0.914	[0.021]		1.054	[0.017]	
$\lambda_{2,1991}$	1.214	[0.019]		1.170	[0.027]		1.230	[0.036]		0.900	[0.025]		1.053	[0.022]	
$\lambda_{2,1992}$	1.245	[0.021]		1.186	[0.029]		1.219	[0.037]		0.903	[0.028]		1.056	[0.026]	
$\lambda_{2,1993}$	1.182	[0.022]		1.073	[0.027]		1.094	[0.033]		0.852	[0.029]		1.052	[0.031]	
$\lambda_{2,1994}$	1.181	[0.024]		1.070	[0.029]		1.061	[0.034]		0.845	[0.029]		1.056	[0.036]	
$\lambda_{2,1995}$	1.172	[0.026]		1.050	[0.032]		1.036	[0.036]		0.830	[0.030]		1.076	[0.041]	
$\lambda_{2,1996}$	1.140	[0.029]		1.018	[0.034]		0.987	[0.038]		0.800	[0.030]		1.060	[0.047]	
$\lambda_{2,1997}$	1.127	[0.032]		1.010	[0.038]		0.968	[0.042]		0.777	[0.032]		1.048	[0.052]	
$\lambda_{2,1998}$	1.112	[0.035]		0.991	[0.041]		0.956	[0.045]		0.744	[0.032]		1.037	[0.058]	
$\lambda_{2,1999}$	1.037	[0.035]		0.936	[0.041]		0.904	[0.045]		0.688	[0.032]		0.964	[0.059]	
$\lambda_{2,2000}$	1.027	[0.037]		0.938	[0.043]		0.922	[0.049]		0.669	[0.033]		0.929	[0.061]	
$\lambda_{2,2001}$	1.004	[0.039]		0.921	[0.045]		0.888	[0.049]		0.637	[0.033]		0.908	[0.064]	
$\lambda_{2,2002}$	1.008	[0.041]		0.947	[0.049]		0.934	[0.054]		0.639	[0.035]		0.906	[0.068]	
$\lambda_{2,2003}$	1.029	[0.045]		0.977	[0.053]		1.000	[0.061]		0.636	[0.037]		0.926	[0.073]	
$\lambda_{2,2004}$	1.025	[0.047]		0.967	[0.055]		1.000	[0.064]		0.609	[0.037]		0.939	[0.078]	
$\lambda_{2,2005}$	1.015	[0.049]		0.965	[0.058]		0.994	[0.068]		0.597	[0.038]		0.954	[0.084]	
$\lambda_{2,2006}$	0.991	[0.051]		0.953	[0.060]		1.019	[0.073]		0.583	[0.039]		0.955	[0.089]	
$\lambda_{2,2007}$	0.979	[0.053]		0.922	[0.062]		1.007	[0.077]		0.554	[0.039]		0.984	[0.096]	
$\lambda_{2,2008}$	0.930	[0.053]		0.886	[0.063]		0.913	[0.077]		0.550	[0.041]		0.969	[0.100]	
$\lambda_{2,2009}$	0.927	[0.056]		0.898	[0.067]		0.993	[0.086]		0.548	[0.042]		0.962	[0.104]	
Cohort shifters ($\gamma_{2,1940} = 1$)															
$\gamma_{2,1941}$	1.070	[0.047]		1.099	[0.061]		1.090	[0.087]		1.158	[0.083]		1.014	[0.075]	
$\gamma_{2,1942}$	1.038	[0.044]		1.026	[0.056]		1.008	[0.078]		1.023	[0.077]		1.015	[0.069]	
$\gamma_{2,1943}$	1.092	[0.047]		1.072	[0.060]		1.047	[0.084]		1.100	[0.079]		1.100	[0.076]	
$\gamma_{2,1944}$	1.079	[0.045]		1.025	[0.057]		0.966	[0.082]		1.117	[0.075]		1.049	[0.073]	
$\gamma_{2,1945}$	1.112	[0.047]		1.051	[0.060]		0.971	[0.086]		1.111	[0.075]		1.148	[0.078]	
$\gamma_{2,1946}$	1.115	[0.048]		1.086	[0.061]		0.964	[0.083]		1.242	[0.084]		1.032	[0.072]	
$\gamma_{2,1947}$	1.120	[0.048]		1.063	[0.060]		0.916	[0.079]		1.218	[0.080]		1.059	[0.075]	
$\gamma_{2,1948}$	1.119	[0.049]		1.087	[0.064]		0.909	[0.082]		1.232	[0.082]		1.027	[0.075]	
$\gamma_{2,1949}$	1.104	[0.050]		1.048	[0.063]		0.948	[0.083]		1.212	[0.082]		1.035	[0.079]	
$\gamma_{2,1950}$	1.164	[0.054]		1.099	[0.067]		0.948	[0.085]		1.311	[0.090]		1.063	[0.084]	
$\gamma_{2,1951}$	1.109	[0.054]		1.033	[0.066]		0.927	[0.084]		1.242	[0.088]		1.054	[0.086]	
$\gamma_{2,1952}$	1.135	[0.057]		1.060	[0.069]		0.917	[0.086]		1.316	[0.094]		1.064	[0.091]	
$\gamma_{2,1953}$	1.109	[0.058]		1.035	[0.070]		0.908	[0.086]		1.265	[0.096]		1.029	[0.092]	
$\gamma_{2,1954}$	1.165	[0.063]		1.108	[0.076]		0.936	[0.090]		1.418	[0.106]		1.042	[0.097]	
$\gamma_{2,1955}$	1.176	[0.066]		1.099	[0.079]		0.935	[0.091]		1.403	[0.109]		1.052	[0.103]	
$\gamma_{2,1956}$	1.146	[0.067]		1.041	[0.078]		0.879	[0.089]		1.382	[0.111]		1.092	[0.110]	
$\gamma_{2,1957}$	1.132	[0.069]		1.030	[0.080]		0.841	[0.088]		1.449	[0.118]		1.062	[0.112]	
$\gamma_{2,1958}$	1.141	[0.072]		1.037	[0.083]		0.863	[0.092]		1.423	[0.120]		1.060	[0.117]	
$\gamma_{2,1959}$	1.163	[0.075]		1.063	[0.087]		0.825	[0.090]		1.582	[0.133]		1.088	[0.123]	
$\gamma_{2,1960}$	1.162	[0.078]		1.046	[0.089]		0.747	[0.085]		1.579	[0.137]		1.109	[0.130]	
$\gamma_{2,1961}$	1.189	[0.082]		1.077	[0.094]		0.800	[0.092]		1.633	[0.145]		1.106	[0.135]	
$\gamma_{2,1962}$	1.164	[0.083]		1.069	[0.097]		0.806	[0.094]		1.659	[0.151]		1.071	[0.135]	
$\gamma_{2,1963}$	1.119	[0.083]		1.005	[0.095]		0.701	[0.085]		1.602	[0.153]		1.066	[0.139]	
$\gamma_{2,1964}$	1.137	[0.087]		1.015	[0.098]		0.718	[0.088]		1.691	[0.162]		1.062	[0.145]	
$\gamma_{2,1965}$	1.160	[0.092]		1.061	[0.106]		0.726	[0.091]		1.797	[0.177]		1.044	[0.147]	
$\gamma_{2,1966}$	1.193	[0.098]		1.071	[0.111]		0.718	[0.091]		1.891	[0.193]		1.080	[0.157]	
$\gamma_{2,1967}$	1.257	[0.106]		1.139	[0.120]		0.795	[0.102]		1.950	[0.206]		1.131	[0.170]	
$\gamma_{2,1968}$	1.295	[0.112]		1.191	[0.129]		0.855	[0.111]		1.976	[0.217]		1.154	[0.179]	
$\gamma_{2,1969}$	1.282	[0.111]		1.149	[0.125]		0.789	[0.103]		1.975	[0.217]		1.217	[0.189]	
$\gamma_{2,1970}$	1.325	[0.115]		1.207	[0.131]		0.851	[0.110]		1.986	[0.219]		1.206	[0.186]	
$\gamma_{2,1971}$	1.366	[0.118]		1.202	[0.131]		0.840	[0.110]		2.023	[0.221]		1.296	[0.199]	
$\gamma_{2,1972}$	1.365	[0.118]		1.192	[0.130]		0.815	[0.107]		1.996	[0.220]		1.310	[0.201]	
$\gamma_{2,1973}$	1.423	[0.123]		1.224	[0.134]		0.894	[0.117]		1.944	[0.218]		1.424	[0.219]	
$\gamma_{2,1974}$	1.467	[0.127]		1.229	[0.135]		0.873	[0.114]		1.945	[0.218]		1.493	[0.229]	
$\gamma_{2,1975}$	1.561	[0.135]		1.273	[0.140]		0.912	[0.120]		2.070	[0.232]		1.634	[0.250]	
$\gamma_{2,1976}$	1.624	[0.141]		1.306	[0.144]		0.918	[0.121]		2.218	[0.246]		1.757	[0.268]	
$\gamma_{2,1977}$	1.677	[0.145]		1.403	[0.155]		1.002	[0.132]		2.333	[0.258]		1.693	[0.259]	
$\gamma_{2,1978}$	1.680	[0.146]		1.360	[0.150]		0.915	[0.120]		2.446	[0.272]		1.779	[0.272]	
$\gamma_{2,1979}$	1.741	[0.150]		1.428	[0.157]		0.990	[0.129]		2.430	[0.271]		1.797	[0.275]	
$\gamma_{2,1980}$	1.721	[0.149]		1.390	[0.153]		0.887	[0.116]		2.590	[0.288]		1.758	[0.270]	

Appendix E Inequality trends and decomposition predicted at ages 30 and 50

Figure E.6: Inequality Decomposition, All Men Age 30 and 50



Age 30



Age 50