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Falling Behind or Catching Up?
Cross-Country Evidence in Intra-Generational Wages Mobility through Pseudo-Panels

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Abstract

The paper aims to encompass evidence on wage distribution and inequality with micro-mobility measures for several countries in the 2000s, by applying pseudo-panel methodology to microdata from the LIS database. Hence, different paths in term of wage growth or stagnation, increasing or declining inequalities and wages convergence over time emerge from comparison across countries. Finally, cohort-based measures of micro-mobility are compared to the corresponding ones obtained from true panel component for some countries.

Keywords: Intra-generational Mobility, wage, inequality

JEL Codes: D31, J31, D63

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1 Introduction

The paper aims to provide some evidence on both wage inequality and intra-generational mobility in a comparative perspective for a set of fourteen countries from the LIS database for the period from 2000 to 2010.

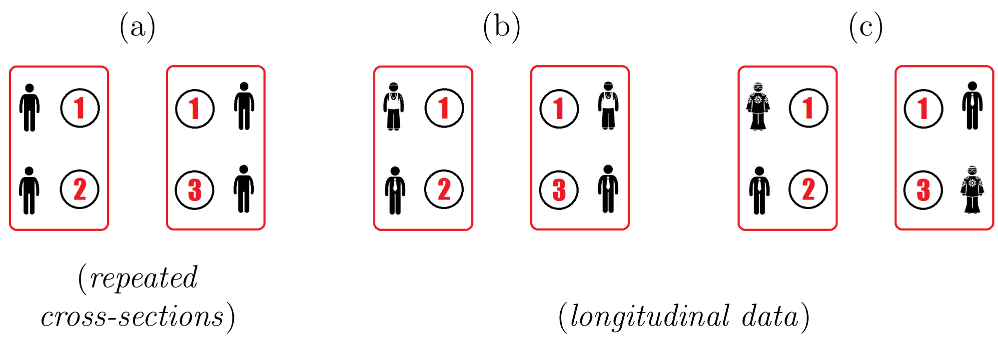
The increasing time dimension for many countries available in the LIS dataset - i.e. the growing number of waves for each country - opens a new opportunity for researchers interested in income distribution and its dynamics. With respect to the last point, research on mobility using LIS data has been prevented by the lack of any longitudinal dimension in the available datasets.

Nonetheless, many concerns about inequality levels and trends are somehow missing the dynamic features of income distribution. Let us make use of some simple illustrations as pictured in Figure 1, where a minuscule country with two only individuals is depicted in two different points in time: in the initial year one individual earns twice as much as that of the second one, while in the final year one individual income is three times bigger than the second one's. In such a case, any inequality metric would return a quite strong increase over time. What makes a difference in interpreting the inequality change is the impact on lifetime income profiles.

Working with repeated cross-sections corresponds to the situation represented in panel (a), where anonymous individuals do not allow to draw any conclusion on individual movements within the income distribution over time, i.e. intra-generational mobility; on the other hand, many scholars would be concerned by the sharp rise in inequality. The other two panels in Figure 1 refer to ability to track the individual income pattern that is usually allowed by longitudinal data, with two extreme cases in terms of intra-generational mobility. In particular, panel (b) shows a very divergent pattern for the society where the initially poorer worker is even more segregated at the end of the period, locked in its own intial condition; while an extreme convergence is pictured in panel (c) where people succeed to reverse their initial situation, like a geek who moved from working in his basement to be a world top CEO. Of course, all the worries coming from the increase in inequality would be exacerbated when looking at panel (b) or mitigated by the convergent pattern shown in panel (c). In the final section, we will come back to the importance of enriching the analysis of income distribution over time with some insights from longitudinal data.

Since the availability of micro datasets in the form of repeated cross-

Figure 1: Inequality and Intra-generational Mobility



sections grew considerably, different econometric techniques have been developed and adapted to these data structures to analyze changes over time. Indeed, even if observations for two different periods refer to different individuals, nothing prevents researchers to take advantage of the time dimension.

Of course, standard panel methodologies cannot be used and some "tricks" are needed aiming at *panelise* data, in particular the ones proposed by Deaton in the mid-80s and further developed in the last decades (Deaton, 1985; McKenzie, 2004), aiming at building pseudo-panels from repeated cross-sections of cohorts of individuals, who share some features over time.

Some Authors find the cohort-based approach to be more accurate in estimating intra-generational mobility than using the longitudinal data (Antman and McKenzie, 2007), other estimates referring to the probability of moving into poverty also tend to confirm the goodness of the pseudo-panel approach (Bourguignon, Goh and Kim, 2006; Martinez, 2013). Pseudo-panels are used here to propose measures of intragenerational wage micro-mobility to analyze wage dynamics, encompassing together the pseudo-panel based measures of wage mobility with the overall wage growth with the inequality profile. Findings highlight the coexistence of different paths over the period, countries ending up with a trade-off in terms of growth, final versus initial inequality and mobility of wages.

Whether the use of pseudo-panel methodology leads towards biased results will be addressed briefly in the last section through the comparison with the true longitudinal measures for a subset of countries. The cohorts-based mobility measures are found to be partly different from the ones obtained by using the longitudinal sub-sample in the microdata, for several reasons related to both the pseudo-panel and the true panel analyses. On one hand, pseudo-panels solve both the measurement error and the attrition problems that arise when using longitudinal data. On the other hand, as Fields et al. (2007) points out, the use of pseudo-panels might face some other limitations: there could be a different measurement error specific to the cohort and if it is varying over time it would end up with biased estimates; cohorts should be defined in order to group similar individuals and their size hsould be big enough; the within-cohort mobility - hopefully small - cannot be accounted by pseudo-panel estimates.

The remainder of this article is organized as follows. Section 2 gives account of data used for the following analyses and provides an overview on countries main features. The cohort-based approach through pseudo-panels is described in Section 3 along with the intra-generational mobility measures which have been chosen. Results are described and final considerations are given in Section 4.

2 Data

The need for encompassing inequality trends and mobility analysis drove the empirical strategy that has been implemented for several countries available in the LIS database. There are several data issues to be considered when comparing several countries for different points in time: some arise as a consequence of *ex post* harmonization of microdata coming from very different original surveys and administrative archives, while others stem from LIS template modifications which occur over time.

The paper uses LIS database [1] for 14 countries observed at the beginning and the end of the 2000s. LIS is a derived microdata archive available for researchers interested in comparative analyses on several socio-economic and policy issues. Comparability is ensured by ex post harmonization through template guidelines developed according to the international standards and country-specific institutional settings[2].

Nonetheless, full comparability across countries and over time could be halted, to many extents, by original data features. Since original surveys come with different sample and questionnaire designs, focus on different socio-economic aspects and employ different strategies to collect individual data, harmonized data could still reflect those differences. Moreover, original surveys vary in their ability to account for national figures in terms of major income sources: Endeweld and Alkemade (2014) provides a detailed overview of the bias for many datasets used here.

[1] The *Luxembourg Income Study Database* provide comparable microdata at personal and household level for several countries (48 at the moment) observed in some points in time called waves (9 waves at the moment from Wave 1 centered in 1980 to Wave IX centered in 2013) on demographics, labor market outcomes, market and transfers income as well as on redistribution by taxation and social contributions; new datasets are added on continuous basis, see the website http://www.lisdatacenter.org for more details and latest updates.

[2] For a critical review of the LIS project see Ravallion (2015).

Table 1: Data Features

Country	Features [a]	Sample		Cohorts		Average Age	
		$2000^{(b)}$	2010	Birthyears groups	cohorts: size $> s_t^{(c)}$	$2000^{(b)}$	2010
Canada	G - C	26587	20045	1 year	148	34.5	44.5
Finland	G - C	8732	7381	1 year	102	34.7	44.5
Germany	G - P	9306	8275	1 year	104	34.6	44.5
		$4048^{(e)}$					
Greece	$G^{(d)}$ - C	652	2698	3 years	0	34.5	44.6
Ireland	$G^{(d)}$ - C	2357	2324	3 years	23	34.5	44.5
Israel	G - C	4211	4715	3 years	43	37.1	44.5
Italy	N - P	4949	4578	3 years	53	34.8	44.5
		$576^{(e)}$					
Mexico	N - C	8494	18510	3 years	53	34.5	44.5
Netherlands	G - C	4106	9106	3 years	48	33.6	44.5
Russia	N - P	2444	4631	3 years	40	34.6	44.5
		$690^{(e)}$					
Slovenia	N - C	4259	3672	3 years	33	33.8	44.4
Spain	$G^{(d)}$ - C	2475	9183	3 years	46	34.5	44.5
United Kingdom	G - C	15609	15202	1 year	141	33.5	44.5
United States	G - C	45448	63386	1 year	178	34.5	44.5

(a): Wages are collected gross (G) or net (N) of taxes and social contributions; original survey used as repeated cross-sections (C) or panel data also (P).
(b): Initial year is 1999 for Netherlands slovenia and United Kingdom while it is 2001 for Israel.
(c): Number of cohorts which are bigger in size than a minimum threshold in both initial and final years.
(d): Gross wages for initial year were recovered from previous template PGWAGE variable.
(e): Panel subsample.

Table 2: Wage Distribution

Country	P25		P50		P75		P50 / P25		P75 / P50		P75 / P25		Gini	
	2000	2010	2000	2010	2000	2010	2000	2010	2000	2010	2000	2010	2000	2010
CA	15,265	23,000	32,972	42,000	52,510	67,500	2.2	1.8	1.6	1.6	3.4	2.9	0.43	0.42
FI	11,310	21,636	22,902	31,026	31,193	42,091	2.0	1.4	1.4	1.4	2.8	2.0	0.37	0.33
DE	11,607	14,125	25,553	27,600	37,790	41,000	2.2	2.0	1.5	1.5	3.3	2.9	0.40	0.40
GR	8,721	12,669	12,458	17,752	16,943	23,444	1.4	1.4	1.4	1.3	1.9	1.9	0.29	0.32
IE	13,478	17,035	23,700	33,227	33,184	52,890	1.8	2.0	1.4	1.6	2.5	3.1	0.37	0.41
IL	53,263	56,355	85,396	86,878	141,242	143,760	1.6	1.5	1.6	1.6	2.7	2.5	0.40	0.40
IT	11,605	12,594	15,473	16,800	19,341	20,000	1.3	1.3	1.3	1.2	1.7	1.6	0.25	0.25
MX	28,430	43,318	47,384	68,961	75,814	108,886	1.7	1.6	1.6	1.6	2.7	2.5	0.47	0.44
NL	14,344	20,587	26,780	34,196	36,968	48,828	1.9	1.7	1.4	1.4	2.6	2.4	0.35	0.36
RU	25,679	84,000	50,598	144,000	91,706	240,000	2.0	1.7	1.8	1.7	3.6	2.9	0.51	0.39
SI	5,726	9,058	7,832	11,735	10,389	15,416	1.4	1.3	1.3	1.3	1.8	1.7	0.29	0.25
ES	9,527	12,000	15,560	18,200	22,259	26,654	1.6	1.5	1.4	1.5	2.3	2.2	0.38	0.34
UK	11,171	13,988	18,112	22,828	27,048	34,996	1.6	1.6	1.5	1.5	2.4	2.5	0.37	0.40
US	18,386	21,000	32,832	38,000	53,036	60,000	1.8	1.8	1.6	1.6	2.9	2.9	0.45	0.44

With respect to data used here, the first stage selection was about countries and mainly driven by the need for having mid-term reference points around 2000 and 2010 as well as comparable and almost complete measures of dependent employment earnings at personal level[3].

Furthermore, as second stage selection the individuals that were born from 1951 to 1980[4], who reported a positive yearly wage[5], were included in the final sample.

As shown in Table 1, countries differ to some extents: selected countries samples vary from few hundreds to several thousands. As a consequence, cohorts were designed accordingly to the sample sizes. Cohorts are defined in terms of birth year, gender and education[6] according to a flexible principle to better exploit countries sample sizes. More in detail, if 1-year birth groups by gender and education were big enough then that was the first best cohort definition employed; when this solution was not possible because of small sample issues, then 3-years birth groups by gender and education applied. Moreover, a further selection as a minimum threshold for cohorts size was imposed[7]. Finally, if some countries failed to have a significant number of enough big 3-years birth cohorts, they have been kept in, including all the 60 3-year birth cohorts, although results could be biased because of the small sample issues[8]. Table 1 shows the final choice for cohorts size.

Wages are gross of taxes and social contributions in many datasets but there are few exceptions[9]; nonetheless, selected samples have quite similar age and gender profiles, while they differ a bit more in terms of education. Currency adjustments were made for those countries that have adopted the Euro over the period. Amounts are converted in 2010 real terms by using the indexes of consumer prices.

[3]Hence, some countries were excluded as the initial/final year was too distant from the reference one, other countries were not comparable over time in terms of individual wages (e.g. Poland in 2000 only provides wages lumped at household level, Luxembourg collected wages gross of taxation and social contribution in 2000 and net ones in 2010).

[4]Hence, individuals' age range from 20 to 59 over the period 2000-2010.

[5]In particular, we refer to the variable PILE ("paid employment income") from the flow variables section.

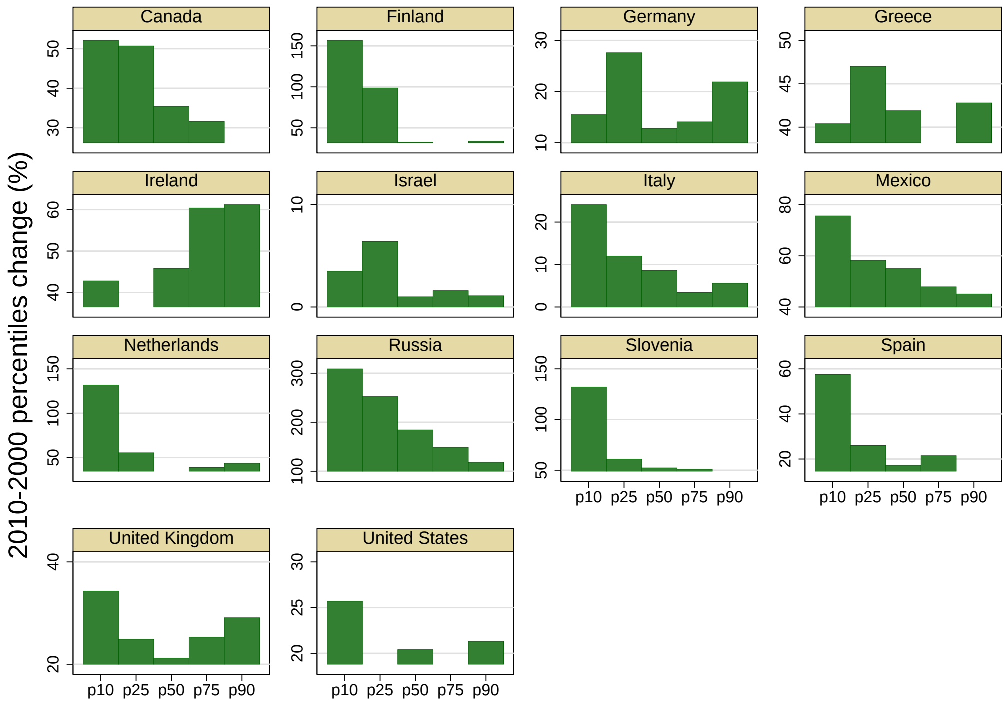
[6]Three levels - low, medium and high - for completed education, standardized across countries following the International Standard Classification of Education (ISCED).

[7]In particular, 1-year birth groups were defined for Canada, Finland, Germany, UK and US, while 3-years birtht groups were used in all the other countries.

[8]Greece, Ireland and Slovenia fall into this group.

[9]In particular, net wages are used in Italy, Mexico, Russia and Slovenia.

Figure 2: Wage distribution: percentiles real change



Real wage growth over the period was quite high, especially for middle-low income countries; in most of the countries wage growth was more effective for lower percentiles with few noticeable exceptions as shown in Figure 1. That turned into a decrease in the wage inequalities as measured by percentiles ratios and Gini index for many countries (see Table 2). As one might expect, $P75P50$ and $P50P25$ diminished more, maybe because of the effects of the financial crisis on young entrants in the labour market and low-paid/marginal jobs (ILO, 2010).

3 Cohort-based Intra-Generational Micro-Mobility

Intra-generational Micro-Mobility measures were introduced several decades ago (Lillard and Willis, 1978) as an individual-level based, time-dependence index of convergence or divergence[10]. Individuals distributions are compared in two or many different points in time to assess through a mobility measure whether the individuals who started with being at the bottom of the distribution succeeded in growing faster than the top ones or in reverting their initial conditions. The pseudo-panel approach overcomes the lack of a longitudinal dimension, moving from anonymous individuals available in the repeated cross-sections to new trackable *individuals*, i.e. the cohorts, who represent groups of similar persons in terms of some observable characteristics.

The paper uses measures of unconditional and conditional micro-mobility, in the latter case some individual characteristics are considered. Moreover, wages could be expressed both in absolute and relative terms, i.e. logarithms, depending on the addressed questions. These micro-mobility measures come from the estimations of the following equations:

$$\begin{array}{ll} \text{Unconditional:} & Y_{i,t} = \alpha + \beta_1 Y_{i,t-1} + \varepsilon_{i,t} \\ \text{Conditional:} & Y_{i,t} = \alpha + \beta_1 Y_{i,t-1} + \beta_2 x_{i,2} + ... + \varepsilon_{i,t} \end{array}$$

unconditional

- absolute (Y_t vs Y_{t-1}):
  whether lower incomes increased more (decreased less) than the higher ones

- relative ($log(Y_t)$ vs $log(Y_{t-1})$):
  whether lower incomes grew at a higher rate (diminished at a lower rate) than the higher ones

conditional

- absolute (Y_t vs Y_{t-1}):
  whether lower incomes increased more (decreased less) than the higher ones that were similar in terms of individual characteristics

[10] See Jäntti and Jenkins (2014) for a comphensive and detailed review on mobility.

- relative ($log(Y_t)$ vs $log(Y_{t-1})$):
  whether lower incomes grew at a higher rate (diminished at a lower rate) than the higher ones that were similar in terms of individual characteristics

The pseudo-panel approach has been proposed as a tool to overcome lack of longitudinal data (Deaton, 1985). Starting from the individual level specification used with longitudinal data, $Y_{i,t} = \alpha + \beta_1 Y_{i,t-1} + \varepsilon_{i,t}$, substituting cohorts averages and taking into consideration measurement errors and that the same individuals belonging to cohort c at time t cannot be observed at time $t-1$:

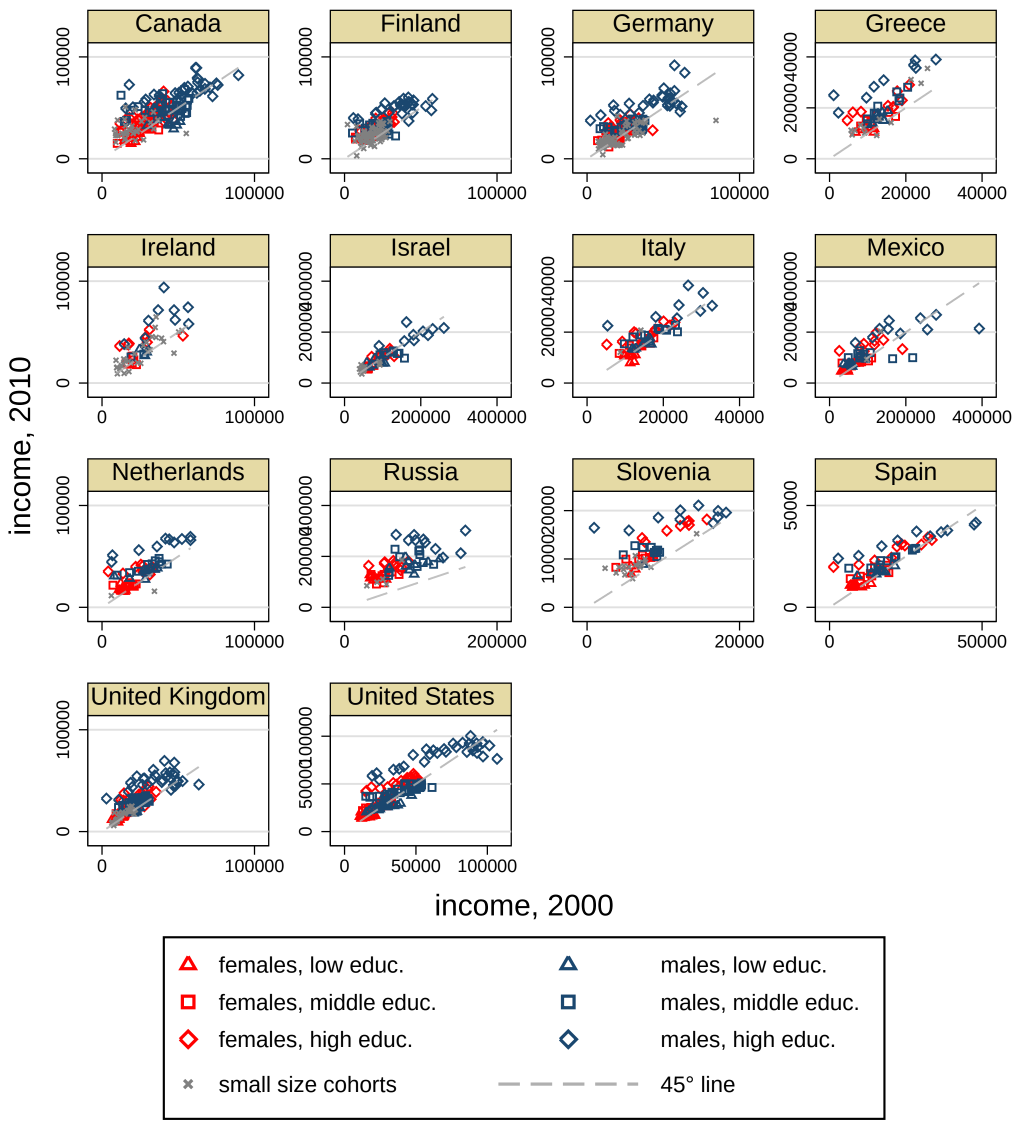
$$\bar{Y}_{c(t),t} = \alpha + \beta_1 \bar{Y}_{c(t-1),t-1} + \bar{\varepsilon}_{c(t),t} + \bar{u}_{c(t),t} - \beta \bar{u}_{c(t),t-1} + \beta(\bar{Y}_{c(t),t-1} - \bar{Y}_{c(t-1),t-1})$$

McKenzie (2004) shows that under certain conditions, the pseudo-panel approach is consistent with the longitudinal data one: in particular, if the number of individuals belonging to the cohort is big enough then $n_c \to \infty \quad \Rightarrow \quad \bar{u}_c \to 0, \quad \bar{Y}_{c(t),t-1} - \bar{Y}_{c(t-1),t-1} \to 0$, hence:

$$\bar{Y}_{c(t),t} = \alpha + \beta_1 \bar{Y}_{c(t-1),t-1} + \bar{\varepsilon}_{c(t),t}$$

Figure 2 shows the graphical interpretation of the unconditional micro-mobility measure proposed here, where cohort average wages at the end of the period are plotted against the initial ones. Different density of observations reflects the procedure adopted for cohorts definition. The slope of the scattered cohorts is the measure of absolute unconditional mobility; different colors and markers, which denote similar cohorts in terms of birth year, sex and education, account for part of the conditional vs unconditional differences, while wage growth is measured by the vertical distance of the points from the 45-degree line.

Figure 3: Cohort average wages, 2010 versus 2000



4 Main findings

Results offer a detailed picture on the wage dynamics in different labor markets during the first decade of the new century. A general caveat applies here, because of the differences in labor market institutions as well as with respect to the different challenges that the respective economies faced during that period. Overall wage growth, its distribution and the mobility measures are affected by several other factors out of the few described here. As mentioned in section 2, cohorts design accounted for country differences in sample sizes. Nonetheless, those differences could still have a small impact on the final figures.

National labor market performed very differently in term of cohorts wage dynamics: countries ranging from lowest Italian wage inequality to the Russian highest one at the initial year as measured by the Gini index, while the change over the period has been almost null for several countries and the highest increase and decrease occurred in UK and Russia respectively.

Moreover, relative change is negatively correlated to initial Gini measures. Indeed, even if Gini was almost constant for some countries, Table 2 and Figure 1 point to the changing shape of wage distribution through some percentiles figures.

Should we be worried about evidence on inequality? It would be worth to take into account the overall wage performance, to better answer to the above question. On the mentioned cases of Italy and Russia, while in the former the very low - almost stable - inequality goes along a negligible real growth, there has been a huge increase in Russian wages that matches with their - rapidly declining - higher inequality. US and Germany share a high stable inequality and modest wage increase: that would be less desirable than the Finland case - or Canada and Mexico to some extent - where robust wage growth took place along with a medium-high declining inequality.

How fast are the lower wage cohorts catching up with the higher ones? The unconditional mobility estimates in Tables 3 and 4 provide some additional evidence, cohorts wage increases were independent from initial positions in few medium-high inequality countries only, nonetheless they vary substantially in terms of cohorts performances as shown in figures 1 and 2.

It is worth noting that the more convergent profiles in terms of intergenerational wage mobility are more likely to be found in those countries where intra-generational mobility is higher and incomes/earnings are less dependent on parental backgrounds[11].

The figures are largely driven by the initial level of inequalities, since the more cohorts are distant in terms of initial wage the greater will be the increase needed for convergence, and by the inequality change during the period. As soon as we focus on the relative measure of intra-generational mobility, stronger convergence patterns arise, i.e. cohort wages at the bottom of the initial distribution grew at higher rates than the ones at the top in most of the countries. Although cohort wages were slightly converging in some countries, growth rates were negatively correlated to the initial positions everywhere. Most of the mobility - either the moderate convergence in levels or the more pronounced convergence in growth rates - took place between different cohorts in terms of educational attainments and gender, while birth-year does not play a significant role in many countries. The evidence of a stronger convergence among similar cohorts is also interesting for the emergence of convergence clubs that could even coexist with a divergence trend among them. Hence, most of cohort convergence is due to cohorts characteristics, i.e. convergence was mainly driven by between similar groups catching-up, in terms of age, sex and education. As a consequence of the patterns, some countries experienced that a major fraction of the population of employees were better off at the end of the period, althought that major increase or higher rate of growth did not always impact the initially lower wages, as shown in Figure 5.

Finally, it is difficult to answer the question about the reliability of cohort-based mobility measures. It has been possible to recover the longitudinal component for three countries in the sample (Germany, Italy and Russia), in order to compare the results obtained from the pseudo-panel approach with the ones from the true panel microdata. By comparing the two, we should be aware that the attrition and measurement errors[12] on one side and intra-cohort movements and size issues on the other make the comparison between longitudinal and pseudo-panel mobility partly pointless. Attrition is an issue that affects the countries differently[13], depending on the survey design and

[11] See D'Addio (2007) and OECD (2010) for some comparable evidence on several countries included in our analyses.

[12] By comparing pseudo-panel and true longitudinal Mexican data, Antman and McKenzie (2007) found that measurement errors explain most of the bias and account for unconditional mobility being overestimated by using longitudinal data.

[13] Among the workers with a positive yearly wage in the initial year, about 43% are still in the sample at the end of the period in Germany, 12% in Italy and 28% in Russia.

and its implementation. While cohorts size issues have been addressed in the cohorts definition procedure, the role played by intra-cohort mobility has not be tackled.

There are several reasons for analysing together wage inequality and mobility, as Paul Krugman wrote:

> There are two ways in which income mobility (...) could offset the proposition that inequality has increased sharply.
>
> First, if income mobility were very high, the degree of inequality in any given year would be unimportant, because the distribution of lifetime income would be very even.
>
> Second, if income mobility had increased over time, this could offset the increased inequality at each point in time. An increase in income mobility tends to make the distribution of lifetime income more equal (...)
>
> Unfortunately, neither of these possibilities actually characterizes the U.S. economy. (Krugman,1992)

When looking at cohort-based measures of micro intra-generational mobility, the more stable and less higher were the wage inequality profiles, the less convergent were over the period, providing evidence for Krugman argument: in a way we should be less worried by inequality changes over time as long as this evidence is supported.

Table 3: Unconditional Mobility, absolute terms

Y_t	Canada	Finland	Germany	Greece	Ireland
Y_{t-1}	0.660***	0.753***	0.898***	0.940***	0.975***
	(0.053)	(0.063)	(0.064)	(0.117)	(0.144)
constant	25306.1***	15828.6***	7472.3***	7853.1***	13383.5**
	(2315.0)	(1673.4)	(1940.2)	(1674.0)	(4223.5)
Obs.	148	115	118	60	60
Adj. R-sqr	0.51	0.56	0.62	0.52	0.43
F	153.1	144.0	193.6	64.8	45.6

Y_t	Israel	Italy	Mexico	Netherlands	Russia
Y_{t-1}	0.806***	0.808***	0.818***	0.804***	1.071***
	(0.069)	(0.086)	(0.071)	(0.108)	(0.204)
constant	26735.6**	4808.4***	36205.9***	17113.1***	103327.6***
	(8812.8)	(1377.5)	(6355.8)	(3077.3)	(16277.0)
Obs.	43	57	58	58	55
Adj. R-sqr	0.76	0.61	0.70	0.49	0.33
F	135.5	87.5	132.3	55.9	27.6

Y_t	Slovenia	Spain	United Kingdom	United States
Y_{t-1}	0.671***	0.699***	0.989***	0.826***
	(0.120)	(0.066)	(0.063)	(0.035)
constant	7076.0***	9199.5***	7492.3***	14044.6***
	(1112.9)	(1213.4)	(1491.0)	(1728.9)
Obs.	41	60	148	180
Adj. R-sqr	0.43	0.65	0.63	0.75
F	31.2	111.8	249.7	541.4

Table 4: Unconditional Mobility, relative terms

$log(Y_t)$	Canada	Finland	Germany	Greece	Ireland
$log(Y_{t-1})$	0.461***	0.425***	0.540***	0.266***	0.680***
	(0.044)	(0.046)	(0.059)	(0.070)	(0.104)
constant	5.96***	6.14***	4.83***	7.37***	3.62**
	(0.46)	(0.46)	(0.60)	(0.66)	(1.05)
Obs.	148	115	118	60	60
Adj. R-sqr	0.43	0.43	0.41	0.18	0.42
F	111.3	86.4	83.4	14.3	43.1

$log(Y_t)$	Israel	Italy	Mexico	Netherlands	Russia
$log(Y_{t-1})$	0.836***	0.611***	0.739***	0.330***	0.451***
	(0.070)	(0.088)	(0.064)	(0.076)	(0.079)
constant	1.94*	3.85***	3.20***	7.16***	7.05***
	(0.82)	(0.84)	(0.71)	(0.77)	(0.88)
Obs.	43	57	58	58	55
Adj. R-sqr	0.77	0.46	0.70	0.24	0.37
F	141.1	48.6	131.9	18.6	32.9

$log(Y_t)$	Slovenia	Spain	United Kingdom	United States
$log(Y_{t-1})$	0.221**	0.325***	0.689***	0.693***
	(0.078)	(0.062)	(0.049)	(0.036)
constant	7.45***	6.77***	3.38***	3.41***
	(0.70)	(0.59)	(0.49)	(0.38)
Obs.	41	60	148	180
Adj. R-sqr	0.15	0.31	0.57	0.68
F	8.1	27.7	197.0	377.1

Table 5: Conditional Mobility, absolute terms

Y_t	Canada	Finland	Germany	Greece	Ireland
Y_{t-1}	0.282***	0.369***	0.469***	0.455***	0.380*
	(0.076)	(0.080)	(0.081)	(0.099)	(0.166)
age	57.4	-40.4	-131.7	226.5**	134.0
	(125.0)	(74.7)	(88.9)	(67.3)	(187.1)
Middle Educ.	9008.5**	3466.5	.	4249.5***	4786.0
	(2680.9)	(6268.2)	.	(931.3)	(3616.3)
High Educ.	22689.8***	14828.5*	13461.0***	11763.0***	24336.0***
	(2901.4)	(6417.5)	(1364.2)	(984.2)	(3987.5)
Female	-16711.2***	-8028.3***	-11086.0***	-5598.8***	-12430.3***
	(1847.9)	(1145.1)	(1543.9)	(646.4)	(3024.2)
constant	27922.2***	22092.0**	26194.0***	564.5	15835.4*
	(4670.0)	(6859.8)	(2954.8)	(2300.5)	(7006.8)
Obs.	148	115	118	60	60
Adj. R-sqr	0.81	0.82	0.85	0.90	0.75
F	129.9	106.8	169.8	108.5	35.9

Y_t	Israel	Italy	Mexico	Netherlands	Russia
Y_{t-1}	0.351**	0.376***	0.284***	0.335***	0.370*
	(0.112)	(0.079)	(0.056)	(0.061)	(0.160)
age	325.6	47.9	-27.9	67.5	-2088.6***
	(451.5)	(37.5)	(256.5)	(81.9)	(361.1)
Middle Educ.	23581.8*	3559.2***	24856.3***	4294.2***	8033.2
	(10149.3)	(460.3)	(5247.8)	(1220.7)	(8260.7)
High Educ.	65715.6***	8918.3***	93576.7***	20382.0***	62456.9***
	(13169.2)	(707.8)	(7137.8)	(1391.7)	(8189.6)
Female	-37293.6***	-3797.2***	-28363.7***	-15559.7***	-63774.8***
	(8636.0)	(489.1)	(3845.6)	(1172.4)	(8634.0)
constant	37762.3*	7875.8***	63014.7***	23735.4***	241684.5***
	(16473.2)	(1089.4)	(9967.8)	(2906.2)	(16906.2)
Obs.	43	57	58	58	55
Adj. R-sqr	0.89	0.92	0.94	0.95	0.86
F	69.1	127.5	170.1	220.3	67.9

Y_t	Slovenia	Spain	United Kingdom	United States
Y_{t-1}	0.385***	0.357***	0.357***	0.453***
	(0.077)	(0.036)	(0.064)	(0.036)
age	-63.4*	72.0*	8.3	-99.0
	(28.3)	(32.3)	(55.0)	(63.8)
Middle Educ.	1568.6*	4350.9***	5945.7***	9070.4***
	(718.6)	(427.2)	(1393.8)	(1393.6)
High Educ.	6534.4***	12189.8***	20008.0***	29330.8***
	(859.3)	(557.1)	(1822.2)	(1801.5)
Female	-1553.7***	-4601.4***	-10100.6***	-12316.8***
	(283.6)	(408.4)	(897.6)	(1029.4)
constant	9899.3***	8898.6***	15886.2***	22585.5***
	(1242.5)	(1086.1)	(2491.9)	(2382.6)
Obs.	41	60	148	180
Adj. R-sqr	0.93	0.97	0.90	0.95
F	109.3	393.3	258.2	694.2

Table 6: Conditional Mobility, relative terms

$log(Y_t)$	Canada	Finland	Germany	Greece	Ireland
$log(Y_{t-1})$	0.235***	0.165***	0.127**	0.074*	0.284*
	(0.052)	(0.046)	(0.039)	(0.033)	(0.107)
age	-0.00	0.00	0.00	0.02***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Middle Educ.	0.24***	0.10	.	0.30***	0.15
	(0.05)	(0.17)	.	(0.04)	(0.09)
High Educ.	0.53***	0.47**	0.49***	0.67***	0.69***
	(0.06)	(0.17)	(0.03)	(0.04)	(0.10)
Female	-0.34***	-0.27***	-0.49***	-0.31***	-0.32***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.08)
constant	8.12***	8.59***	9.02***	8.12***	7.31***
	(0.45)	(0.42)	(0.35)	(0.24)	(0.95)
Obs.	148	115	118	60	60
Adj. R-sqr	0.83	0.83	0.91	0.91	0.79
F	142.7	114.7	290.4	127.0	46.2

$log(Y_t)$	Israel	Italy	Mexico	Netherlands	Russia
$log(Y_{t-1})$	0.197	0.191**	0.127**	0.105**	0.232***
	(0.118)	(0.063)	(0.047)	(0.031)	(0.056)
age	0.01	0.01**	-0.00	0.00	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Middle Educ.	0.29***	0.27***	0.36***	0.17***	0.03
	(0.08)	(0.03)	(0.04)	(0.03)	(0.04)
High Educ.	0.71***	0.56***	0.93***	0.62***	0.32***
	(0.11)	(0.04)	(0.06)	(0.04)	(0.04)
Female	-0.38***	-0.27***	-0.36***	-0.51***	-0.29***
	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)
constant	8.79***	7.54***	9.84***	9.17***	10.01***
	(1.22)	(0.53)	(0.47)	(0.26)	(0.60)
Obs.	43	57	58	58	55
Adj. R-sqr	0.92	0.92	0.97	0.94	0.90
F	103.0	125.9	340.6	195.4	98.3

$log(Y_t)$	Slovenia	Spain	United Kingdom	United States	
$log(Y_{t-1})$	0.110**	0.107***	0.224***	0.227***	
	(0.035)	(0.025)	(0.030)	(0.025)	
age	-0.00	0.01***	0.00	0.00*	
	(0.00)	(0.00)	(0.00)	(0.00)	
Middle Educ.	0.25***	0.30***	0.32***	0.38***	
	(0.06)	(0.03)	(0.04)	(0.02)	
High Educ.	0.67***	0.72***	0.80***	0.87***	
	(0.06)	(0.03)	(0.04)	(0.03)	
Female	-0.14***	-0.33***	-0.39***	-0.34***	
	(0.02)	(0.02)	(0.02)	(0.02)	
constant	8.19***	8.33***	7.70***	7.81***	
	(0.26)	(0.19)	(0.26)	(0.22)	
Obs.	41	60	148	180	
Adj. R-sqr	0.91	0.95	0.94	0.97	
F	84.5	222.7	475.5	1267.8	

Table 7: Cohort-based *versus* Panel Measures of Mobility

	Unconditional Mobility			
	absolute terms		relative terms	
	pseudo-panel	panel sub-sample	pseudo-panel	panel sub-sample
Germany	0.898	0.794	0.540	0.489
Italy	0.808	0.679	0.611	0.540
Russia	1.071	0.548	0.451	0.300

	Conditional Mobility			
	absolute terms		relative terms	
	pseudo-panel	panel sub-sample	pseudo-panel	panel sub-sample
Germany	0.470	0.715	0.127	0.417
Italy	0.376	0.564	0.191	0.438
Russia	0.370	0.493	0.232	0.281

Figure 4: Inequality and Mobility

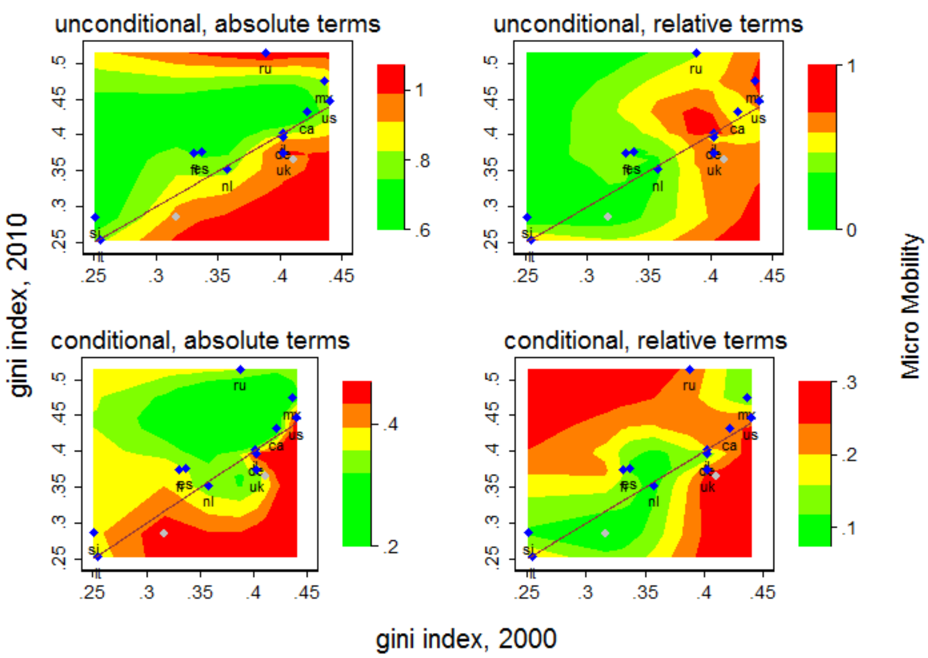
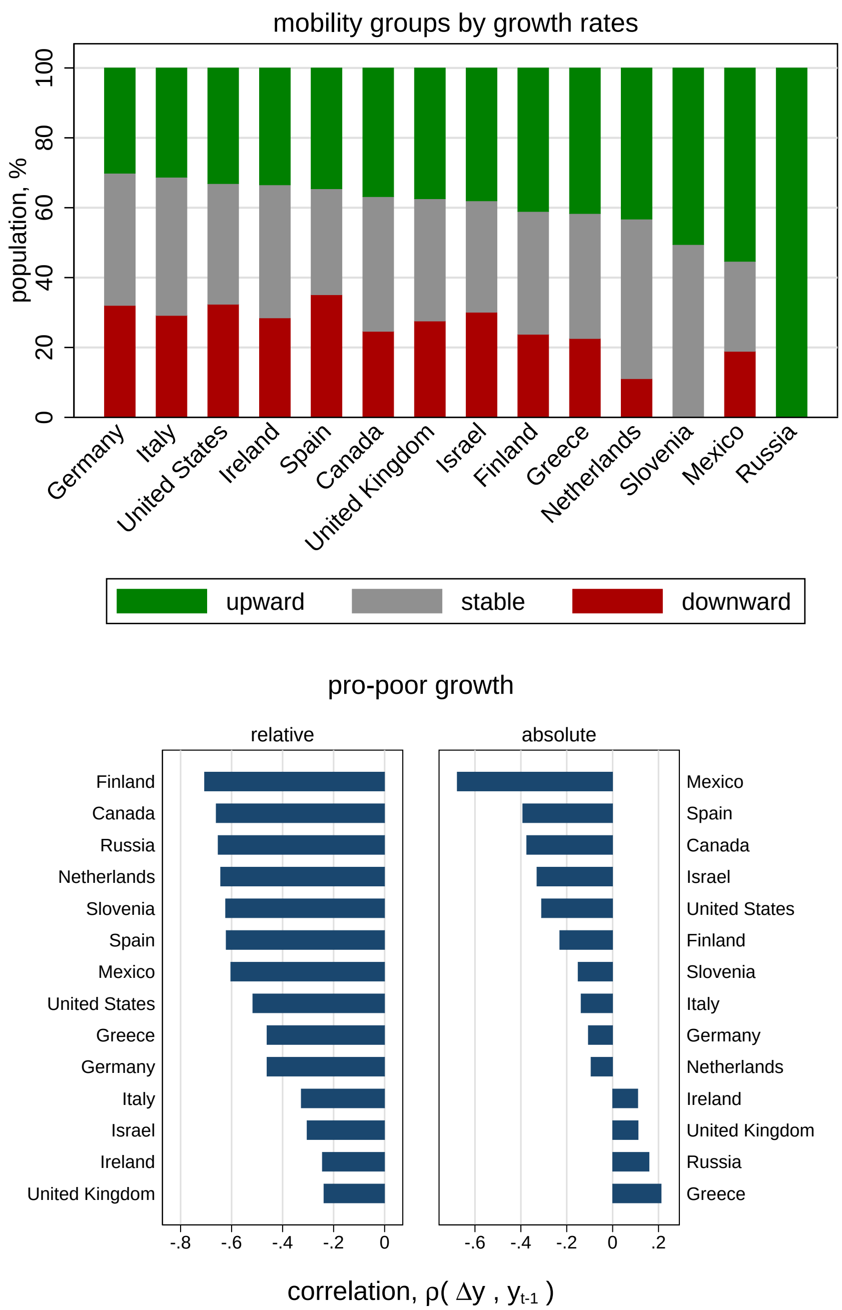


Figure 5: Mobility and Growth



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