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Age-adjusted measures of earnings inequality in the United States, 1980-2010

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Abstract

I demonstrate a simple procedure for creating age-adjusted earnings distribution statistics, using US data and recentered influence function regression methods. As the baby boom generation has moved toward the latter part of their career, earnings distribution statistics for the working age population have emphasized within-cohort disparities that are largest at older ages. As such, the aging of the US population has placed upward pressure on standard measures of earnings inequality. Results suggest the increase in the 90-10 log differential has been overstated by 8 percent when the changing age structure of the population is accounted for.

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1. Introduction

It is common knowledge that income inequality has increased substantially over the past three decades in the United States. As earnings are the largest source of family and individual income, researchers have devoted considerable time to understanding the sources of earnings inequality. A general consensus developed, suggesting large increases in the returns to skill are driving large increases in inequality (see Lemieux 2008).

As with several measures of economic, social, or physical well-being, however, we may want to account for the changing age structure of the population when measuring trends. With earnings inequality, this is particularly important if we believe individuals judge their position in society as relative to their peers rather than the population as a whole.

Previous studies have accounted for the population's age structure as one of several factors that may affect the distribution of earnings (for example Daly and Valetta 2006; Fortin and Schirle 2006, Lu et al. 2011, Lemieux 2006). These studies, however, do not examine the experience of individuals within their birth cohorts over time or provide measures of inequality that explicitly account for changes in the age structure of the population separate from other factors. For example, Lemieux (2006) uses the reweighting methods of Dinardo et al. (1996) to account for the skill composition of the labour force (age and education). However, the reweighting methods do not easily allow for a separate accounting of the effects of age structure – primarily because the counterfactual distribution statistics will depend on the sequence in which factors are accounted for. Previous studies have examined the extent to which changes in age demographics influences inequality measures and propose alternative age-adjusted measures. Recently, Almas et al. (2011) propose an age adjusted Gini coefficient, measuring inequality trends in Norway.

In this study, I document trends in US earnings inequality and demonstrate a simple procedure for creating several age-adjusted measures of inequality. Using US data on weekly earnings, I document recent trends in unadjusted aggregate measures of earnings inequality. An examination of birth cohorts' earnings over time indicates that part of the increase in earnings inequality over the past three decades has represented the aging of the baby boom generation and the earnings disparity typically experienced within a cohort with age.

I then demonstrate how age-adjusted distribution statistics are easily constructed. The age-adjusted measures of inequality are created using the recentered influence function (RIF) regression methods developed in Firpo et al. (2009). Age-adjusted measures of earnings inequality (Gini, 90-10, 90-50 and 50-10 differentials) demonstrate that unadjusted measures slightly overstate the extent to which earnings inequality has increased over time.

I begin in section 2 by describing the data used in this study and the measurement of earnings inequality. In this section I also outline how age-adjusted measures of earnings inequality may be computed. In section 3 I present results describing the changes in the US earnings distribution since 1980. Finally, I offer some concluding remarks.

2. Data and Methods

2.1. CPS MORG Extracts

I use the Monthly Outgoing Rotation Group (MORG) extracts of the Current Population Survey's Basic Monthly Data files, available from the NBER. These files include the records from survey months when usual hours worked and weekly earnings are reported. I use samples from each year 1980-2010. I restrict the analysis to the weekly earnings of individuals that work 30-55 hours per week and have positive earnings. Earnings are adjusted for inflation using the consumer price index, presented in 2010 constant dollars.

2.2. Measuring earnings inequality and birth cohorts

To characterize the distribution of earnings in each year I present the 90-10, 90-50, and 50-10 log earning differentials and the Gini coefficient. In characterizing the distribution of earnings over time, I restrict the analysis to individuals age 25-64. This allows me to abstract from concerns about delayed entry to the labour force related to rising education levels over time. This is important given the importance of education and the returns to skill in explaining large changes in the distribution of income. Historical changes in retirement behavior may be a contributing factor to inequality that is not accounted for here.[1]

To characterize within-cohort earnings over time, I first divide the population into five-year birth cohorts, beginning with the 1945-49 birth cohort. I then prepare earnings inequality statistics representing the earnings distribution within each cohort within each year 1980-2010

2.3 Creating age-adjusted measures of earnings inequality

Age-adjusted measures of earnings inequality are easily constructed using the Recentred Influence Function (RIF) regressions developed by Firpo et al. (2009). I briefly outline these methods here. Fortin et al. (2011) provide greater detail regarding the implementation of these methods.

As a first step, I use a RIF-regression to estimate the effect of age on the earnings distribution statistics for each year of the data 1980-2010 (based on the sample of 25-64 year olds described in section 2.1). Recognizing the importance of changes in education and the returns to education (Card and Lemieux 2001), I control separately for education in the regression. This regression model is analogous to ordinary least squares, except that the dependent variable for income is replaced by its recentered influence function. Firpo et al. (2009) have defined this as equal to the distribution statistic of interest plus the

[1] Evidence from Schirle (2008) suggests rising education levels in the US are an important factor driving up labour force participation among older men. As such, we might expect selection into early retirement primarily by lower wage workers, shifting up the earnings distribution.

influence function for that distribution statistic. The expected value of the recentered influence function is the distribution statistic itself.

Four RIF-regressions are completed for each year, estimating the effect of age on the distribution statistic of interest (90th percentile, 50th percentile, 10th percentile and the Gini coefficient).[2] The only covariates are indicators for each 5-year age group.

The conditional expectation of the RIF is modeled as a linear function of the covariates, and can be stated as

$$\mathrm{E}[\mathrm{RIF}(Y_t; \nu)|A_t] = \gamma_{0t} + A_t\gamma_t + Educ_t\delta_t \tag{1}$$

where ν is the statistic of interest for the distribution of income Y_t. (or the natural logarithm of income in the case of percentiles). A_t is a vector of indicators for each five year age group. In this analysis, the youngest group (age 25-29) is the omitted group and the oldest age group is age 60-64. $Educ_t$ is a vector of indicators for educational attainment.

The second step uses the RIF regression results to construct a counterfactual distribution statistic (ie. the 90th, 50th, or 10th percentiles) for each year 1981-2010:

$$\nu_{ct} = \hat{\gamma}_{0t} + \bar{A}_{1980}\hat{\gamma}_t + \overline{Educ_t}\hat{\hat{\delta}}_t \tag{2}$$

The distribution statistic ν_{ct} characterizes the distribution of income in year t had the age structure of the population (represented by the portion of individuals in each age group, $\bar{A}$) not changed after 1980.

3. Results

Historical trends in measures of inequality are presented in Figure 1. We see steady increases in the 90-10 and 90-50 log differentials and the Gini coefficient as the earnings distribution widens over time. The 50-10 log differential, however, has not changed substantially since the early 1990s. Overall, these indicators describe a widening of the top half of the earnings distribution that is consistent with the literature. The 90-50 log differential increased by 0.017 (or 27%) over the 1980-2010 period. The 50-10 log differential increased by 0.066 (or 10%) over the 1980-2010 period and most of that increase occurred in the 1980s.

Trends in within-cohort inequality measures are presented in Figure 2 for three birth cohorts – 1945-49, 1955-59, and 1965-69.[3] In Figure 2, the vertical line marks the year in which the birth cohort begins turning 40.

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[2] I have made use of the Stata rifreg.ado file made available by Nicole Fortin at http://faculty.arts.ubc.ca/nfortin/datahead.html.

[3] Trends within all cohorts are available upon request, and are consistent with the description here.

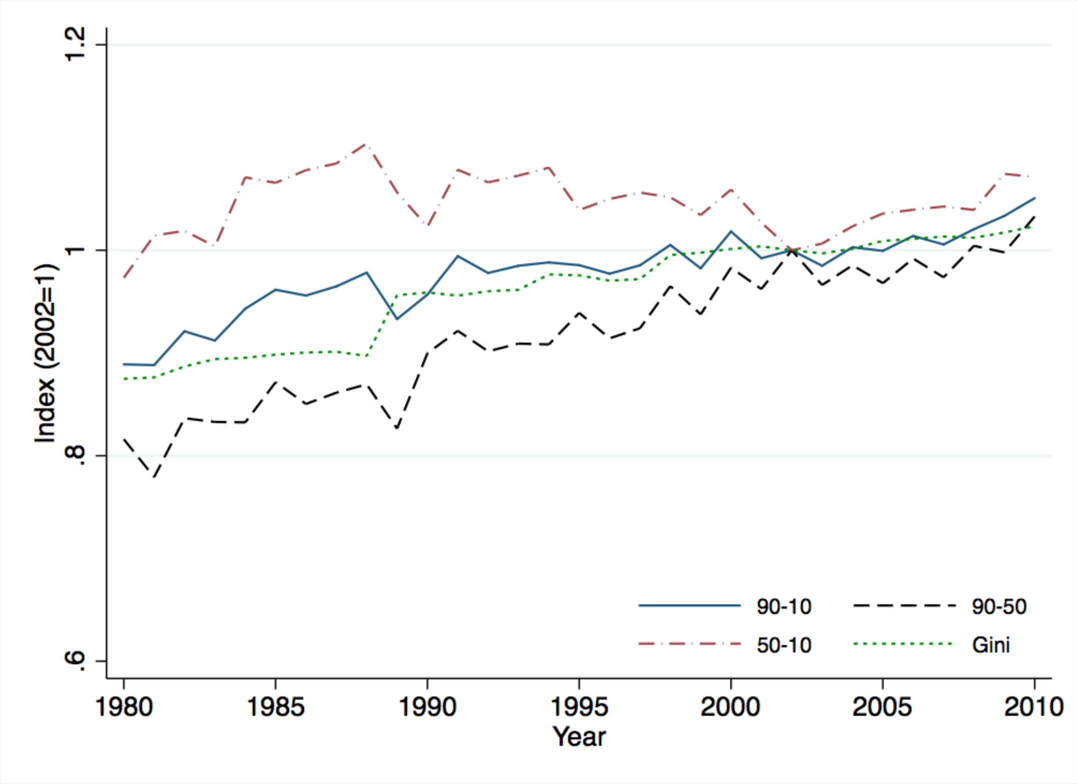

Figure 1. Measures of Earnings Inequality, 1980-2010.
Source: Authors' tabulations from CPS MORG files. Sample includes individuals with positive earnings and usual hours between 30 and 55 hours per week. Log differentials in percentiles are presented.

The most interesting result from Figure 2 is that once a cohort starts turning 40, the 50-10 log differential trend starts to flatten. This reflects the fact that earning profiles for relatively less educated workers (likely to be positioned in the lower part of the earnings distribution) start to flatten around age 40 – so that the median and 10th percentiles grow at roughly the same rate as the cohort continues to age. The earnings of university-educated workers, on the other hand, typically continue to increase after age 40 – driving up the 90th percentile of earnings within a birth cohort relative to the 50th or 10th percentiles. As a result, we see the 90-50 and 90-10 log differentials continue to increase as a cohort ages.

When relative cohort size is not constant over time, relatively large birth cohorts will tend to dominate the trends in aggregate inequality statistics. Given the relative size of the birth cohorts representing the baby boomers, it appears the aggregate inequality statistics have in part reflected where the baby boomers are in terms of their age-earnings profiles. In 2010, those aged 51-65 (born in 1945-59) represented 26% of the earners in the United Stated while the comparable age group in 1990 (born 1925-39) only represented 15% of the population.

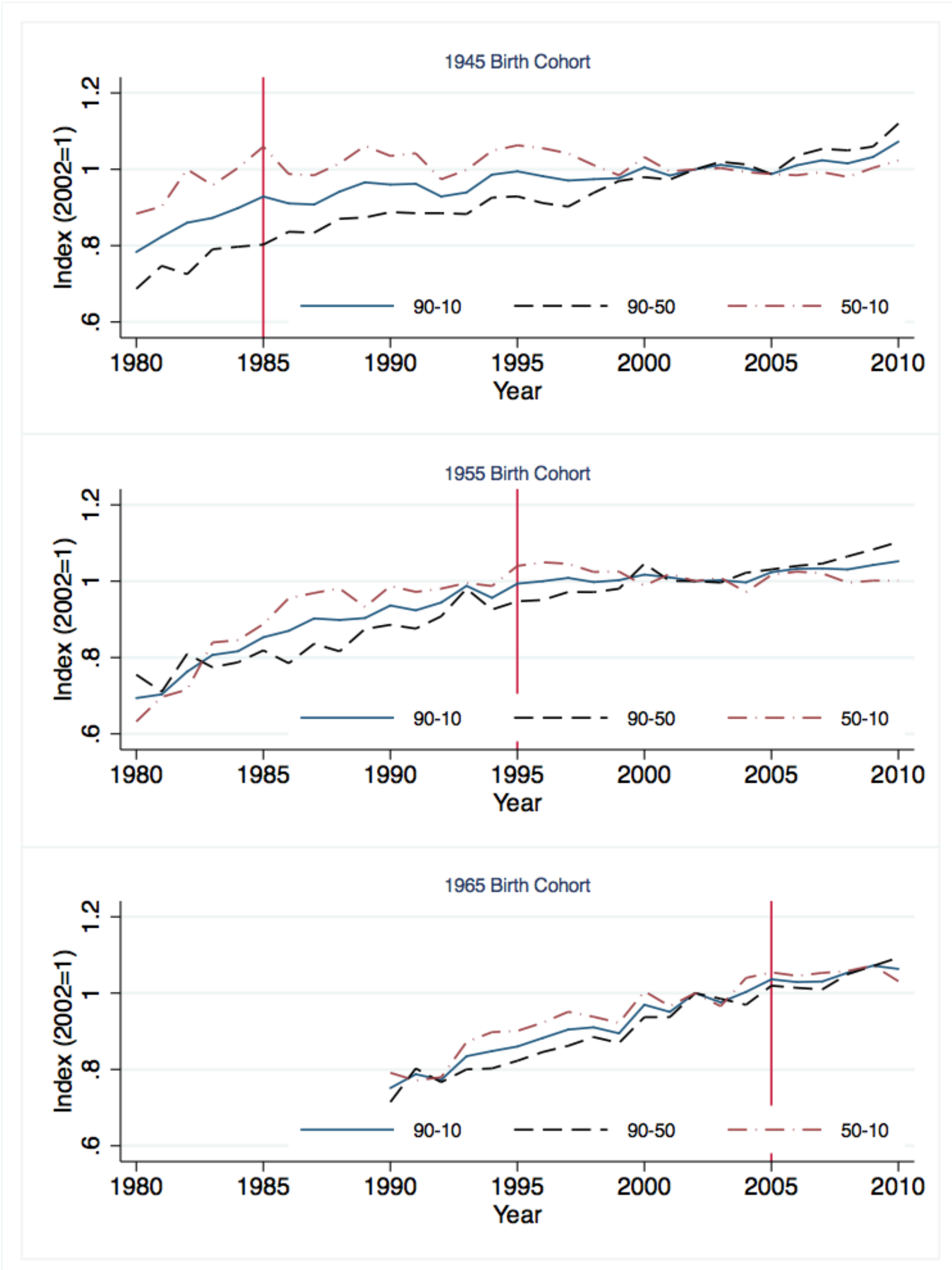

Figure 2. Measures of Earnings Inequality, Within 5-Year Birth Cohort, 1980-2010
Source: Authors' tabulations from CPS MORG files. Sample includes individuals with positive earnings and usual hours between 30 and 55 hours per week.
Note: The 1945 birth cohort includes individuals born 1945-49. The vertical line marks the year in which the birth cohort begins turning 40.

The age-adjusted earnings inequality measures, based on the results represented by equation (2), are presented in Table I and demonstrate the importance of accounting for age structure when presenting inequality trends. For all earnings inequality measures, the aging of the baby boomers has resulted in higher aggregate measures of earnings inequality. For example, increases in the 90-10 log differential appear smaller (by 0.019) when adjustments are made to account for the changing age structure. Relative to the observed increase in the 90-10 between 1980 and 2010, the unadjusted measures overstate the increase in inequality by 8%. Intuitively, when we remove the emphasis effectively placed on the disparity between late-career baby boomers in recent trends for the 90th percentile, we don't see as much of an increase in the 90th percentile relative to the 10th percentile of the overall earnings distribution.

Table I. Observed and Age-Adjusted Measures of Earnings Inequality

	1980	1990	2000	2010	Difference (2010- 1980 observed)
90-10 differential					
Observed	1.295	1.405	1.505	1.562	0.267
Age-adjusted	.	1.404	1.490	1.539	0.248
Difference	.	0.000	0.015	0.022	
90-50 differential					
Observed	0.632	0.709	0.780	0.827	0.195
Age-adjusted	.	0.712	0.775	0.816	0.185
Difference	.	-0.003	0.004	0.011	
50-10 differential					
Observed	0.663	0.696	0.725	0.735	0.072
Age-adjusted	.	0.692	0.714	0.724	0.063
Difference	.	0.004	0.011	0.011	
Gini Coefficient					
Observed	0.277	0.306	0.321	0.331	0.053
Age-adjusted	.	0.307	0.320	0.329	0.052
Difference	.	0.000	0.001	0.002	

Source: Authors' tabulations from CPS MORG files. Sample includes individuals with positive earnings and usual hours between 30 and 55 hours per week. RIF-regression results are available upon request.

4. Concluding Remarks

The analysis presented here has demonstrated the importance of using age-adjusted measures of earnings inequality when comparing such measures over time. Only slightly more complex than age-adjusted measures of well-being based on averages, the RIF-regression methods provide us with a similar simple procedure for the creation of age-adjusted distribution statistics.

Overall, the evidence presented here demonstrates the influence of cohort size on distribution statistics for the United States. Given the baby boom generation is nearing the end of their careers, current earnings distribution statistics tend to emphasize the earnings disparity that exists between the individuals within a birth cohort at the latest stages of their careers, when the within-cohort earnings inequality appears largest.

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