The Changes in the Linkage between Current and Lifetime Earnings over the Life-Cycle

Mustafa U. Karakaplan*

Abstract:

In their influential article, Haider and Solon (2006) reassess the suitability of the textbook errors-in-variables model and find that it does not correctly describe current earnings as a proxy for lifetime earnings. In this paper, I utilize their model with a more recent and significantly larger US data set, and examine the sensitivity of their findings by analyzing four birth cohorts of each gender and comparing my estimates with Böhlmark and Lindquist's (2006) and Brenner's (2009) findings. My results demonstrate statistically significant cohort, gender and country specific differences in the life-cycle bias.

I. Introduction

In the literature, it is common practice to use current income as a proxy for lifetime income, mainly due to the lack of data on lifetime earnings. Empirical studies which do not consider the difference between current and lifetime income mostly assume the standard errors-in-variables model. There are many studies that have focused on the errors-in-variables biases that arise from the use of current income as a proxy for long-run income. Modigliani and Brumberg (1954) and Friedman (1957) are two famous examples of studies that have considered the attenuation bias that arises from the use of current rather than lifetime income variables as the regressors. In intergenerational income mobility studies, lifetime income variables are used as both dependent variables and regressors. Solon's (1999) survey has shown that the association between incomes of the father and the son is underestimated when current income variables are used as proxy for lifetime income variables. Grawe (2006) uses Jenkins (1987) to construct a model and presents that the average age of fathers significantly affects the intergenerational link.

Recent studies by Haider and Solon (2006) and Böhlmark and Lindquist (2006) have found that the association between current and lifetime earnings changes over the life-cycle and therefore the bias of estimates obtained by following this practice is well beyond the one suggested by the standard errors-in-variables model. Haider and Solon estimate of the association between current and lifetime earnings over the life-cycle for men born between 1931 and 1933 in the United States. Their estimates show the existence of life-cycle bias, and thereby indicate that the use of current income as a proxy for lifetime income leads to inconsistent parameter estimates even in the case of measurement error in the dependent variable. Their estimates also provide useful information on the size and direction of the life-cycle bias at each age from ages 19 to 59. They suggest that their evidence on departures from the textbook errors-in-variables model can be used by applied researchers to better analyze and correct for the life-cycle bias.

Böhlmark and Lindquist (2006) are concerned with the generality of the results provided by Haider and Solon (2006). They apply Haider and Solon's generalized errors-in-variables model to Swedish income tax data to figure out the country specific differences in the association between current and lifetime earnings. By comparing the estimates for three different cohorts of men and women, they also try to answer if there are any significant cohort and gender differences in estimated associations. Their results indicate remarkable similarities for the comparable cohorts of Swedish and American men but they also found significant cohort and gender differences in the estimated association.

Furthermore, a very recent study by Brenner (2009) examines the same case for German natives and guest workers. Brenner's study shows that Swedes and Germans have more similar results compared to the results for American men. Brenner also presents further evidence for the significant differences in the estimated linkage of population groups such as groups with different immigration status.

My main goal in this paper is to test the generalizability of Haider and Solon's (2006) results by examining whether Haider and Solon's estimates of the life-cycle variations in the association between current and lifetime earnings for the United States apply to other cohorts of men, and women. I follow Haider and Solon's estimation method in order to make the results of my study comparable to theirs. The proposed contributions of my study are as follows: First, by using a more recent and significantly larger data set from the same source, namely Social Security records, I revisit the main results of Haider and Solon and see if their results are sensitive to the augmentation of the data set. By estimating and comparing the association between current and lifetime income for four birth cohorts of men, I examine whether there are any cohort differences in life-cycle bias for men. Then I analyze the link between current and lifetime income for American women, and compare the estimated associations between four different birth cohorts of women to see if there are any significant cohort differences for women. In addition to that, I compare the estimated associations for men and women to see if there are any significant gender differences. Moreover, since Haider and Solon's study includes only one cohort and only one gender, Böhlmark and Lindquist (2006) and Brenner (2009) were able to make a comparison with the United States for only a single birth cohort of men. By making the omitted results for cohorts and genders available, my study provides more room to see if there are any country specific similarities or differences for both men and women.

Section II presents the model developed by Haider and Solon (2006) and discusses the reasons for and implications of life-cycle bias. Section III describes the data set and econometric methods. The results are provided in Section IV, and Section V summarizes the findings.

II. The Generalized Errors-in-Variables Model of Haider and Solon (2006)

In the literature, lifetime income variable is extensively used in regression analysis as both dependent variable and explanatory variable. In the cases where lifetime income variable is used as a dependent variable and it is replaced by a proxy of current income due to lack of life-cycle earnings, left-side measurement error arises. On the other hand, right-side measurement error occurs when current income variable is used as a proxy for an explanatory lifetime income variable. Intergenerational income mobility studies in which log of son's lifetime earnings are regressed on log father's lifetime earnings are good examples to illustrate life-cycle bias arising in both right-side and left-side measurement error cases (see Böhlmark and Lindquist (2006)).

Assume that we estimate the following model to measure intergenerational mobility in income between fathers and sons.

$$(1) \qquad y_i = \beta x_i + \varepsilon_i$$

where x_i represents the log of fathers' lifetime earnings and y_i represents the log of sons' lifetime earnings. Random disturbance term, ε_i, is uncorrelated with x_i and the coefficient β measures the intergenerational income mobility.

Assume that we have an appropriate measure on the father's lifetime earnings but have observations on the earnings of the son for only a short period of his career and therefore lack information on the son's true lifetime income. In this case the common practice in the literature is to use current income of the son, y_{it}, as a proxy for his lifetime income, y_i. Unlike standard errors-in-variables model, Haider and Solon's (2006) generalized errors-in-variables model allows the relation between current and lifetime income to vary over the life-cycle. Then, the association between the son's current and lifetime income is given by

$$(2) \qquad y_{it} = \lambda_t y_i + u_{it}$$

where y_{it} and y_i are the logs of current and lifetime income respectively, λ_t is the relation between current and lifetime income at age t, and u_{it} is the error term. Thus, when current income of the son is used as a proxy for his lifetime income, we will have the following regression function:

$$(3) \qquad y_{it} = \beta x_i + \eta_{it}$$

where η_{it} is equal to $(\lambda_t - 1)\beta x_i + \lambda_t \varepsilon_i + u_{it}$, and the probability limit of the estimated slope coefficient $\hat{\beta}$ is equal to $\lambda_t \beta$.

According to the standard errors-in-variables model, the OLS estimate of β is unbiased since λ_t is assumed to be equal to 1 over the life-cycle. However, once λ_t is allowed to vary over ages, the estimate of intergenerational income mobility is biased and the bias varies with age at which earnings are observed. Both Haider and Solon (2006) and Böhlmark and Lindquist (2006) warn that controlling for age alone does not remove life-cycle bias since life-cycle earnings profiles are not parallel across individuals as high skilled workers have steeper profiles than do low skilled workers.

Now suppose that we know the sons' lifetime incomes but lack an appropriate measure for fathers' lifetime incomes and therefore fathers' current incomes are used as proxies for their lifetime incomes. In this case, the probability limit of the estimate of β is equal to $\theta_t \beta$, where

$$(4) \qquad \theta_t \equiv \frac{Cov(y_{it}, y_i)}{Var(y_{it})} = \frac{\lambda_t Var(y_i)}{\lambda_t^2 Var(y_i) + Var(u_{it})}$$

In the case of the right-side measurement error, OLS estimate of β is biased even under the assumption of standard errors-in-variables model. When λ_t is assumed to be equal to 1 throughout the life-cycle, the estimated β would be biased downwards since θ_t would be less than 1. This bias is known as attenuation bias. In the generalized model proposed by Haider and Solon (2006), the size and direction of the bias depends on λ_t. When $\lambda_t < 1$ and the ratio $Var(u_{it})/Var(y_i)$ is small, θ_t can exceed 1 that indicates amplification rather than attenuation bias. If current incomes are used to proxy for both sons' and fathers' lifetime incomes, the probability limit of the estimates of β is given by $\lambda_t \theta_t \beta$.

Haider and Solon (2006) note that life-cycle bias arising from the use of current income as a proxy for lifetime income can be summarized by two parameters, λ_t and θ_t. λ_t can be obtained by regressing log of current income on log of lifetime income and θ_t is the slope coefficient in the regression of lifetime income on current income:

(5) $$y_{it} = \lambda_t y_i + \mu_{it}$$

(6) $$y_i = \theta_t y_{it} + v_{it}$$

Haider and Solon (2006) estimate those two parameters for 821 men born in the USA between 1931 and 1933 to examine how they vary over the life-cycle. Böhlmark and Lindquist (2006) get estimates of λ_t and θ_t for three different cohorts of men and women using Swedish income tax data to figure out the gender and cohort specific differences in the association between current and lifetime earnings in Sweden. They also provide country specific differences between the USA and Sweden. Brenner (2009) uses German data to find the estimates of λ_t and θ_t for men and women of German natives and guest workers. My paper searches for the generality of the estimated association between current and lifetime earnings in the USA, and provides estimates of two parameters for four cohorts of men and women. I also make comparison of life-cycle variations in the estimated association in the USA, Sweden and Germany.

III. Data Properties and Econometric Methods

a. Data Properties

The results I report in this paper are obtained by using the Social Security earnings and benefit data. My data consists of a 1 percent random, representative sample of records of Old-Age, Survivors, and Disability Insurance beneficiaries who were entitled to receive a Social Security (OASDI) benefit. The earnings data contains information on the annual Social Security taxable earnings for the beneficiary for each of the years 1951 through 2003 and an aggregate earnings measure for earnings between 1937 and 1950 for the older cohorts. The total number of beneficiaries is 473,366, and this includes retirees and their spouses, surviving children and spouses, and disabled workers and their dependents.

The 1 percent representative sample of social security administrative records have several advantages over other survey based data sets. The main advantage of the data is that it provides annual earnings information over the major portion of the life-cycle for a very large number of individuals born between the late 1920s and the early 1940s. The other main strength of the data is that the Social Security earnings records are more accurate than the earnings reports collected by survey methods. However, the data also has some weaknesses. The earnings in the data are measured only up to the maximum amount subject to Social Security tax. If the income of an individual in any year is higher than the taxable maximum amount, his/her earning in that year is shown by taxable maximum amount. Therefore, the data is censored from the right. The percent of people censored from the right differs greatly by year and age. The taxable maximum becomes more severe problem in 1960s and 1970s during which the taxable limit is low relative to the general earnings distribution. The degree of censorship lessens after 1980s as the threshold amount is progressively increased. The percent of people above taxable limit depends also on age of individuals as the average earnings are low at early years and grow over the careers of workers as they accumulate human capital. Average earnings then start falling after age 45 or 50. Therefore, very few individuals have earnings above taxable limit when they are young, the percent of the earnings above the threshold is high for those aged between 30 and 45 or 50, and it falls once people get older. In the sample data, the percent above threshold amount reaches maximum of 69% in year 1965 for individuals aged 44.

Using the earnings data from the same source, Social Security Records, Haider and Solon (2006) estimate the two parameters for men, who were born between 1931 and 1933, that is, who were 19 years old in the beginning of the 1951-1991 earnings period and about 59 at the end. Their sample contains 821 men. The more recent data allows us to get estimates of life-cycle bias for four cohorts of both men and women, and in addition to this, my data contains more than ten thousand observations for each cohort of men and women. In my study, the men and women in the first cohort were born between 1931 and 1933, and the three other younger birth cohorts were born between 1934 and 1936, between 1937 and 1939, and between 1940 and 1942 respectively. By having data for different birth cohorts and genders, I am able to answer potential cohort and gender differences in the association between current and lifetime earnings. Additionally, my study provides detailed information on country specific differences by comparing the evolution of life cycle bias in the USA with the results for Sweden and Germany.

b. Methodology

As mentioned earlier, life-cycle bias arising from the use of current income as a proxy for lifetime income can be summarized by two parameters, λ_t and θ_t. If the earnings data was not right censored, these two parameters could be estimated by simply running OLS on equations (5) and (6). Since the earnings data is right censored, actual values of earnings cannot be observed if they are above the taxable maximum. Furthermore, without knowing actual earnings of individuals, their lifetime earnings cannot be calculated. Therefore, OLS method cannot be applied to estimate equation (5) and (6). Due to censorship problem, instead of following Björklund's (1993) methodology, I follow Haider and Solon's (2006) approach, and use a three step procedure to estimate λ and θ. This way, my results become more comparable to their findings.

In the first step, I use limited dependent variable model to estimate joint distribution of log annual earnings. The main assumption is that log annual earnings follow a multivariate normal distribution. In order to get the estimates of the joint distribution over the corresponding earning time period, I estimate means and standard deviations of log earnings for each year as well as cross-year autocorrelations of log earnings for each pair of years. Table 1 shows the average estimated autocorrelations from various other studies for comparison.

In my estimation I only include those with at least ten years of positive annual earnings. I apply the Tobit regression method separately for each year to get estimates of means and standard deviations. Moreover, I use two-limit Tobit model as the earnings below \$50 are left-censored at \$50 and taxable limit serves as the right-censorship value. To get year specific means and variances, I utilized the intercept as regressor. In order to obtain autocorrelations between each pair of year, I employ bivariate Tobit regression method separately for each of the $41 \times 40/2 = 820$ pair of years. By obtaining the estimates of means and standard deviations of log earnings for each year and autocorrelations of log earnings for each pair of years, I get estimates of the joint distribution of uncensored log earnings over 41 years.

In the second step, I take 4,000 random draws from the estimated joint distribution to obtain 41 years of uncensored annual log earnings. In the main estimation, I use personal consumption expenditures (PCE) deflator to convert nominal earnings to real earnings. Then, for each of the simulated earnings histories, I calculate present discounted value of lifetime earnings using a 2 percent real discount rate.

Finally, I estimate λ and θ by applying OLS on equations (5) and (6) using 4,000 simulated log real annual earnings over 41 years and measure log lifetime earnings for each 4,000 draws. Then, the evolution of λ and θ over 41 years from the age of 19 to 59 provide information on life-cycle bias due to the use of current income as a proxy for lifetime income.[1]

IV. Estimation Results and Implications

a. Revisiting Haider and Solon (2006)

In Figure 1, I plot and compare my estimates, and Haider and Solon's (2006) estimates of the slope coefficient, λ_t in the regression of log annual earnings at t on the log of the present value of lifetime earnings for the men born between 1931 and 1933. In order to concentrate on the life-cycle pattern, approximate age on the horizontal axis is calculated by subtracting 1932 from the year.[2] Contrary to the assumption of $\lambda_t = 1$ over the life-cycle, my findings show that $\hat{\lambda}_t$ is somewhere around 0.3 in the beginning at age 19, increases gradually and becomes 1 at around age 30, then follows a volatile pattern between ages 30 and 47 in a range of 1.3 and 0.7, and stays relatively stable after age 47 at 0.7. Therefore, in contrast to what is suggested by the textbooks, the use of current income as a proxy for lifetime income can produce significant errors-in-variables

---

[1] See Haider and Solon (2006) for the details of their estimation procedure

[2] A similar procedure to find the approximate age is followed for the rest of the figures in this study.

biases. The degree of downward divergence from $\lambda_t = 1$ assumption is the most in the early twenties. Hence using the current income in the early twenties as a proxy would cause the biggest attenuation bias. However, if the current income between ages 30 and 47 is used as a proxy, then $\lambda_t = 1$ assumption would be somewhat sensible, and the bias would be smaller.

Moreover, when compared to Haider and Solon's (2006) estimates, my estimates show a fairly similar pattern. However my estimated λ_t is relatively bigger and closer to $\lambda_t = 1$ at every point before age 33. Therefore, my findings suggest that although using the current income in the early twenties as a proxy would definitely cause attenuation bias, it would not be as large as asserted in Haider and Solon. In addition to this, my $\hat{\lambda}_t$ is smaller than Haider and Solon's estimates at every age after 45 telling that the divergence from the assumption of $\lambda_t = 1$ after age 45 is even more than what is presented in their study.

Figure 2 plots my estimates of θ_t, the life-cycle trajectory of the reliability ratio, which is the appropriate parameter for measuring the errors-in-variables bias due to postulating log current income as a proxy for log lifetime income. $\hat{\theta}_t$ is 0.3 in the beginning. It increases to 0.6 as the age is 25, and then stays relatively stable in the range between 0.6 and 0.8 until age 47. After age 47, it begins decreasing constantly, and at the end, it is very close to 0.2. As can be seen in the figure, if the current income in the early twenties is used, the bias is very large. However, my results also show that it is not as large as in Haider and Solon (2006). Although there is relatively less volatility between ages 25 and 47, the errors-in-variables bias is still sizeable in the array. The bias gets larger and larger after age 47, and it is even more substantial than that of Haider and Solon.

b. Cohort Differences for Men

Figure 3 presents my estimates of λ_t, the slope coefficient, for four different cohorts of men, namely those who were born between 1931 and 1933, and three other younger cohorts: those who were born between 1934 and 1936, those who were born between 1937 and 1939, and those who were born between 1940 and 1942. In the figure, the estimates of λ_t for the cohorts look vastly similar, and as it can also be implied from the patterns, it is statistically very difficult to tell the difference between the estimates. However, there are some statistically significant variations in the structure of the patterns of $\hat{\lambda}_t$ of different cohorts of men. Although, $\hat{\lambda}_t$ for different cohorts of men all begin at around 0.3 at age 19, and keep increasing until the peak at 1.2, the values reach their peaks at different ages. $\hat{\lambda}_t$ of men born between 1940 and 1942 reach its peak at age 29; $\hat{\lambda}_t$ of men born between 1937 and 1939 reach its peak at age 32; $\hat{\lambda}_t$ of men born between 1934 and 1936 reach its peak at age at age 35; and $\hat{\lambda}_t$ of men born between 1931 and 1933 reach its peak at age at age 38.[3] This, I believe, is due to the socio-economic conditions in 1970 in the US. The relative scarcity of young men due to the drafts for the ongoing Vietnam war possibly results in a higher demand for men from older cohorts in these years. Therefore, different cohorts of men

---

[3] The $\hat{\lambda}_t$ of men born between 1931 and 1933 reaches the 1.2 level twice: First at age 32 (in year 1964), and then at age 38. The first peak in this cohort's $\hat{\lambda}_t$ is expected considering high earnings for men at their early thirties. The peak in this cohort's $\hat{\lambda}_t$ in this particular year, 1964, is somewhat mirrored by the younger cohorts in the same year but with less intensity. Hence, these "peaks" are not well-representative of a year specific change in $\hat{\lambda}_t$, and for the sake of the discussion, I talk about the differences and similarities between the "second peaks" in the $\hat{\lambda}_t$ patterns.

reaches the peak in the same period but at different ages, resulting in significantly disparate trajectories of estimated λ_t.

Moreover, the younger cohorts' $\hat{\lambda}_t$ dips to the 0.8 level sooner than the older cohorts' $\hat{\lambda}_t$. Hence, it can be said that younger cohorts start earning high incomes earlier than older cohorts, and their incomes decrease sooner than the older cohorts. However, after age 50, while the youngest cohort's $\hat{\lambda}_t$ stays around 0.9, the oldest cohort's $\hat{\lambda}_t$ is around 0.7, and the other two cohorts' $\hat{\lambda}_t$ are at around 0.8. The most important implication is that although it is the case that regardless of the cohorts of men, annual earning differences generally underestimate the lifetime earnings when they are at their twenties or older than 40, and overestimate the lifetime earnings when these men are in a certain age period in their thirties, the age interval in which there is an overestimation or underestimation, and the degree of the bias change significantly by cohorts. Therefore, correction for life-cycle biases of the men in general based on only one cohort of men would be utterly wrong.

My estimates of θ_t for different cohorts of men are shown on Figure 4. Except in the early twenties, the patterns of $\hat{\theta}_t$ for the cohorts are very similar to each other. They all begin at around 0.3-0.4 range, increase to 0.6, and stay in the band of 0.5-0.8 till mid-forties, and then decrease to 0.2 at the end. However, between ages 20 and 25, $\hat{\theta}_t$ of the younger cohorts are a lot bigger than the oldest cohort. Compared to Haider and Solon's (2006) $\hat{\theta}_t$ in Figure 2, where it dips to 0.1 ($t = 21$), my estimates of θ_t for younger cohorts of men are at 0.5-0.6 level. The implication of this difference is that although the bias is substantial for every cohort of men, supporting the general assertion that the method of utilizing current income in place of lifetime income is inaccurate, if the current income of the younger cohorts of men in the early twenties is used as a proxy for their lifetime income, the bias would not be as big as what Haider and Solon determined.

c. Cohort Differences for Women

Figure 5 reports my estimates of λ_t for four different cohorts of women: Women, who were born between 1931 and 1933, between 1934 and 1936, between 1937 and 1939, and between 1940 and 1942, respectively. As shown in the figure, the patterns of $\hat{\lambda}_t$ for the four cohorts of women are almost the same. They all begin at around 0.35; increase steadily until they reach to 1.1 towards their late twenties, and then decline smoothly to 0.5 as they get older. Thus, my findings for different cohorts of women verify that regardless of the cohorts, using log current earnings of women as a proxy for their log lifetime earnings induces errors-in-variables bias. However, the assumption of $\lambda_t = 1$ would be rather reasonable if one uses current earnings of women between ages 25 and 40, due to the fact that the bias would be relatively smaller in that range.

In Figure 6, I plot the estimated reliability ratio θ_t, of the cohorts of women. The trajectories are essentially identical. They all start from 0.16 and keep increasing until they hit the 0.4 level at around age 50. Then they start decreasing to somewhere between 0.1 and 0.3. These findings further confirm that, regardless of the cohorts of women, there is an attenuation bias if the current earnings of women are used as a proxy for lifetime earnings. Moreover, the bias is exceptionally large for women at almost every point, because $\hat{\theta}_t$ is smaller than 0.4 for every cohort of women at every age.

d. Gender Differences

Figure 7 and Figure 8 compares the estimates of λ_t and θ_t of the men and women, who were born between 1931 and 1933.[4] In Figure 7, my estimates of λ_t display a significantly different pattern for men than for women. Especially between ages 19 and 32, $\hat{\lambda}_t$ of men increase from 0.3 to over 1.2 with a more or less increase rate, but $\hat{\lambda}_t$ of women increase from 0.35 to 1.2 with a rather decreasing rate. Hence, there is a wide gap between the $\hat{\lambda}_t$ of men and women in this period. Remembering from Figure 1 that Haider and Solon's (2006) $\hat{\lambda}_t$ for men is plotted even lower than my $\hat{\lambda}_t$ for men within this age range. Therefore, it is important to point out the statically significant difference between the linkage of current and lifetime incomes of men, and women. Since women have a smoother lifetime trajectory of $\hat{\lambda}_t$, and men display more variety in their lifetime supply of labor and income profiles, I suggest that the life-cycle bias is a more severe predicament for American men than for American women.

My $\hat{\theta}_t$ for women and men also exhibit a significantly distinct patterns. As shown in Figure 8, over the life-cycle, while $\hat{\theta}_t$ of women moves evenly in the small band between 0.1 and 0.4, $\hat{\theta}_t$ of men is very volatile between 0.1 and 0.8. Especially between ages 25 and 50, there is a huge difference between the $\hat{\theta}_t$ of men and women. To summarize, although there is life-cycle bias for both men and women, I present that the degree of life-cycle bias of men is not well-representative of that of women.

[4] I specifically presented this cohort's gender comparison, so that it could be easier for the reader to compare the results with Haider and Solon's (2006) results.

e. Country Comparison

In Figure 9, I compare my findings for men with that of Böhlmark and Lindquist (2006) and Brenner (2009). Brenner's study includes an analogous comparison figure but the US and European cohorts Brenner uses are mismatching due to the unavailability of a matching cohort from Haider and Solon (2006). Since Haider and Solon's cohort lags a decade, Brenner states that the dissimilarity found between countries can to some extent be an outcome of the different birth cohorts under examination. In this study, I provide results for a better matching cohort, namely men, who were born between 1940 and 1942. Hence, my study offers an improved insight into the international comparison of the linkage.

The top part of Figure 9 shows that the estimates of λ_t for Swedish men and German men are noticeably similar to each other, and they are significantly different than the estimates of λ_t for American men. Unlike Brenner (2009), my figure demonstrates that the difference between $\hat{\lambda}_t$ of the European and American men is almost at every age, and their 95% confidence bands hardly overlap.

The estimates of θ_t for men are presented at bottom part of Figure 9. Correspondingly, $\hat{\theta}_t$ of Swedish men and German men resembles each other, and the estimates for American men are significantly different than that of Europeans'. Until age 35, the attenuation bias in the USA is very weak compared to Sweden and Germany, but especially after age 50, the attenuation bias in the USA gets stronger compared to the Sweden and Germany. However, all of the $\hat{\theta}_t$ trajectories are below unity.

The cohort effects, which cause Brenner (2009) to be cautious about the interpretations of the similarities between Sweden and Germany, are mostly eliminated in my study since I provide a better matching birth cohort of American men. Thus, my findings fortify the idea that the similarities between the profiles of Sweden and Germany are a consequence of their more similar educational systems and labor market organizations compared to the USA.

Furthermore, since Haider and Solon's (2006) study is conducted only for men, Böhlmark and Lindquist (2006) and Brenner (2009) cannot compare their findings for women with American women. I fill this gap by comparing my results of women, who were born between 1940 and 1942, with their corresponding findings. The top portion of Figure 10 displays the $\hat{\lambda}_t$ profile of the American, Swedish and German women. To my surprise, the eye-catching similarity is between the profiles of American and German women. The trajectories are concave shaped, and there is almost no volatility in the trajectories of American and German women, compared to the volatile trajectory of Swedish women. However, after age 30, $\hat{\lambda}_t$ of American women decreases sharply, resulting in increased attenuation biases, whereas $\hat{\lambda}_t$ of German women stays relatively constant at around 1.1, resulting in stable amplification biases.

The bottom portion of Figure 10 presents the $\hat{\theta}_t$ of American, Swedish and German women. Similarly, my findings show that the reliability ratios of German women are more similar to that of American women. Concave shapes of the reliability ratios German and American women are roughly the same, peaking at around age 47, hitting 0.5 and 0.4 respectively. The estimates of θ_t for Swedish women follow a significantly different path than that of American and German women. The Swedish trajectory is very volatile over the whole life-cycle with several local peaks, the highest of which is 0.73. Although there are differences between the profiles of $\hat{\theta}_t$, the estimates are never close to unity, and therefore they are always biased.

As stated in Brenner (2009), the volatility in the life-cycle patterns of Swedish women compared to American and German women is probably attributable to the different structure of Swedish labor market supply of mothers. If the Swedish women having young children generally prefer reducing the hours worked to exiting the labor market, and if the American and German counterparts prefer exiting the labor market relatively more frequently, then the results would be reasonable. Boca et al. (2003) supports this notion further.

Furthermore, one very significant difference between Sweden and the USA is that for Sweden, there are large variations in λ_t across cohorts of men; but for the USA, the difference in λ_t across cohorts of men is not as striking as Sweden's.[5] This difference between Sweden and the USA is even more evident in the case of generations of women: In Sweden's case, the difference between the estimates of λ_t across generations of women is quantitatively important and statistically significant. However, in the US case, there is almost no difference between the estimates of λ_t across generations of women. The same conclusion applies to the estimates of θ_t. $\hat{\theta}_t$ does not vary much across generations of American men, or women; on the contrary, $\hat{\theta}_t$ significantly varies across generations of Swedish men, or women. This difference between Sweden and the USA would be due to the relatively more stable structure of the labor markets in the USA and relatively more dynamic and changing labor markets in Sweden across the birth cohorts.

Yet, life-cycle bias problem for American people seems to be as serious as for Swedish and German people. The problem can be even more severe for American people considering the certain age ranges within generations of men and women. However, as acknowledged in Böhlmark

[5] The comparison in this paragraph is made between my results presented in Figure 3, 4, 5 and 6, and Böhlmark and Lindquist's (2006) results presented in their Figure 3 and 4. Since Brenner (2009) does not have results for different birth cohorts of men and women, I am unable to incorporate Germany to this discussion.

and Lindquist (2006), I also think that the resemblance between my estimates and theirs, Brenner's (2009), and Haider and Solon's (2006) is as remarkable as the dissimilarities.

V. Conclusion

In this study, my main objective has been to generate estimates of the linkage between the annual and lifetime earnings, so that I can test the magnitude and the course of the bias if it exists. In order to achieve my goal, I first applied Haider and Solon's (2006) generalized errors-in-variables model to a more up to date and a considerably larger data set from the same source that is Social Security records. This way, I assessed the sensitivity of their results to an enlargement in the data. I also tested the generalizability of Haider and Solon's results by investigating if Haider and Solon's estimates of the life-cycle variations in the association between current and lifetime earnings for the United States match other cohorts of men, and to women. Moreover, my study made estimates for other cohorts of men and women available, providing the opportunity of comparison with the results of Böhlmark and Lindquist (2006) and Brenner (2009) for different cohorts of men and women.

I obtained significantly problematic life-cycle trajectories in the linkage between annual and lifetime earnings, indicating that the common exercise of annual earning as a proxy of lifetime earning causes life-cycle bias even the dependent variable is set to be the proxy. My results show astonishing similarities with the comparable cohort of Haider and Solon (2006). However, in addition to the similarities, I found noticeable differences between estimates of different cohorts of men and women, which imply distinct life-cycle biases for different generations and genders. Moreover, as well as some astounding resemblance, I presented the significant dissimilarities with the Böhlmark and Lindquist's (2006), and Brenner's (2009) estimates for different cohorts and genders in Sweden and in Germany respectively, which suggest quantitatively important and statistically significant variation between the life-cycles biases of Sweden, Germany and the USA. The evidence provided in my study informs the researchers further in various terms about the deviations from the errors-in-variables model and the sensitivity of the bias profiles to gender, birth cohort and country, so that the analyses of, and the adjustments for the estimation biases can be made with a better enlightened background.

References

Björklund, Anders. 1993. "A Comparison between Actual Distributions of Annual and Life-time Income: Sweden 1951-89." Review of Income and Wealth 39(4):377-86.

Boca, Daniela Del, Rolf Aaberge, Ugo Colombino, John Ermisch, Marco Francesconi, Silvia Pasqua, and Steinar Strøm. 2003. "Labour Market Participation of Women and Fertility: The Effect of Social Policies." Paper presented at the FRDB CHILD Conference, Alghero.

Böhlmark, Anders, and Matthew J. Lindquist. 2006. "Life-Cycle Variations in the Association between Current and Lifetime Income: Replication and Extension for Sweden." Journal of Labor Economics 24(4): 879-96.

Brenner, Jan. 2009. "Life-Cycle Variations in the Association between Current and Lifetime Earnings: Evidence for German Natives and Guest Workers." Labour Economics, doi: http://dx.doi.org/10.1016/j.labeco.2009.03.006

Friedman, Milton. 1957. "A Theory of the Consumption Function." Princeton, NJ: Princeton University Press.

Grawe, Nathan D. 2006. "Lifecycle Bias in Estimates of Intergenerational Earnings Persistence." Labour Economics 13(5):551-70.

Haider, Steven, and Gary Solon. 2006. "Life-Cycle Variation in the Association between Current and Lifetime Earnings." The American Economic Review 96(4):1308-20.

Jenkins, Stephen. 1987. "Snapshots versus Movies: 'Lifecycle Biases' and the Estimation of Intergenerational Earnings Inheritance." European Economic Review 31(5):1149-58.

Modigliani, Franco, and Richard Brumberg. 1954. “Utility Analysis and the Consumption Function: An Interpretation of Cross-Sectional Data.” In Post-Keynesian Economics, ed. K. K. Kurihara. New Brunswick, NJ: Rutgers University Press.

Solon, Gary. 1999. "Intergenerational Mobility in the Labor Market," In Handbook of Labor Economics, Volume 3A, eds. Orley C. Ashenfelter and David Card, 1761-1800. Amsterdam: Elsevier Science, North-Holland.

Table 1: Average estimated autocorrelations from various studies

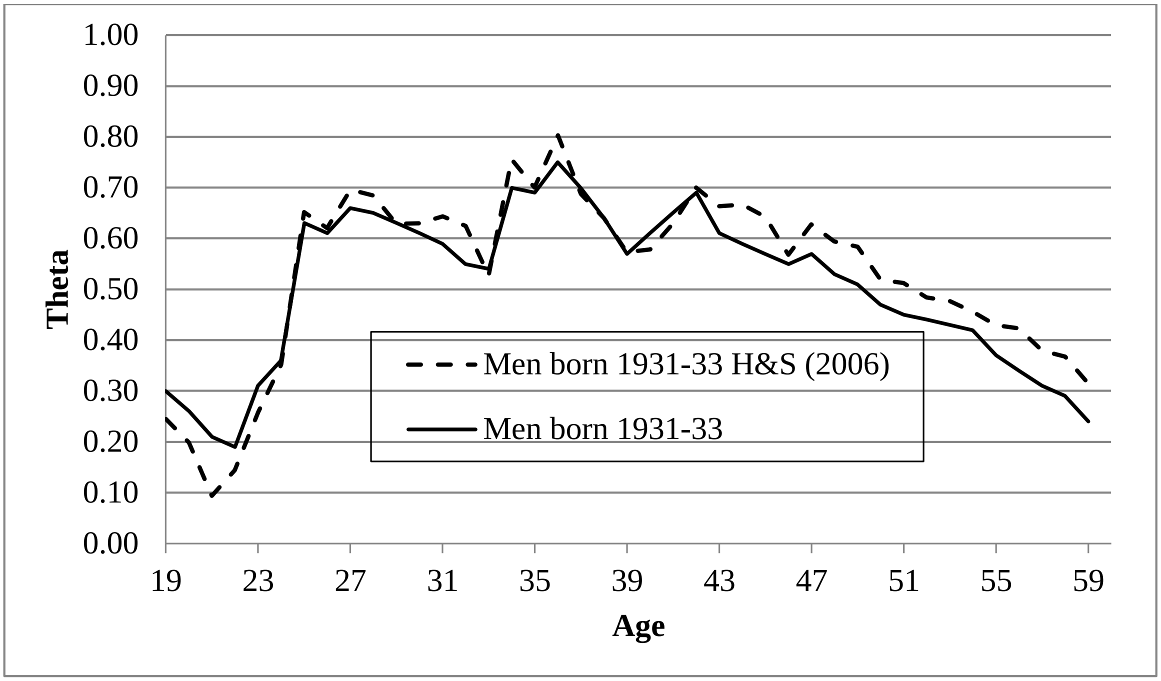
Order of Autocorrelation	American Men Born 1931-33 Age 42-53	American Men Born 1931-33 Age 42-53	Swedish Men Born 1929-33 Age 42-55	American Men Born 1940-42 Age 42-53	Swedish Men Born 1939-43 Age 42-55	German Men Born 1939-44 Age 43-52
1	0.87	0.89	0.84	0.85	0.79	0.86
2	0.81	0.82	0.79	0.78	0.70	0.82
3	0.75	0.78	0.80	0.73	0.66	0.79
4	0.70	0.75	0.73	0.69	0.64	0.77
5	0.66	0.72	0.72	0.65	0.64	0.74
6	0.62	0.69	0.69	0.62	0.63	0.71
Source:	My results	H&S (2006)	B&L (2006)	My results	B&L (2006)	Brenner (2009)

Notes: Haider and Solon (2006) is abbreviated as H&S (2006) and Böhlmark and Lindquist (2006) is abbreviated as B&L (2006).

Figure 1: Estimates of lambda for men born in 1931-33.

Note: Haider and Solon (2006) is abbreviated as H&S (2006)

Figure 2: Estimates of theta for men born in 1931-33.



Note: Haider and Solon (2006) is abbreviated as H&S (2006)

Figure 3: Estimated lambda for men of different cohorts.

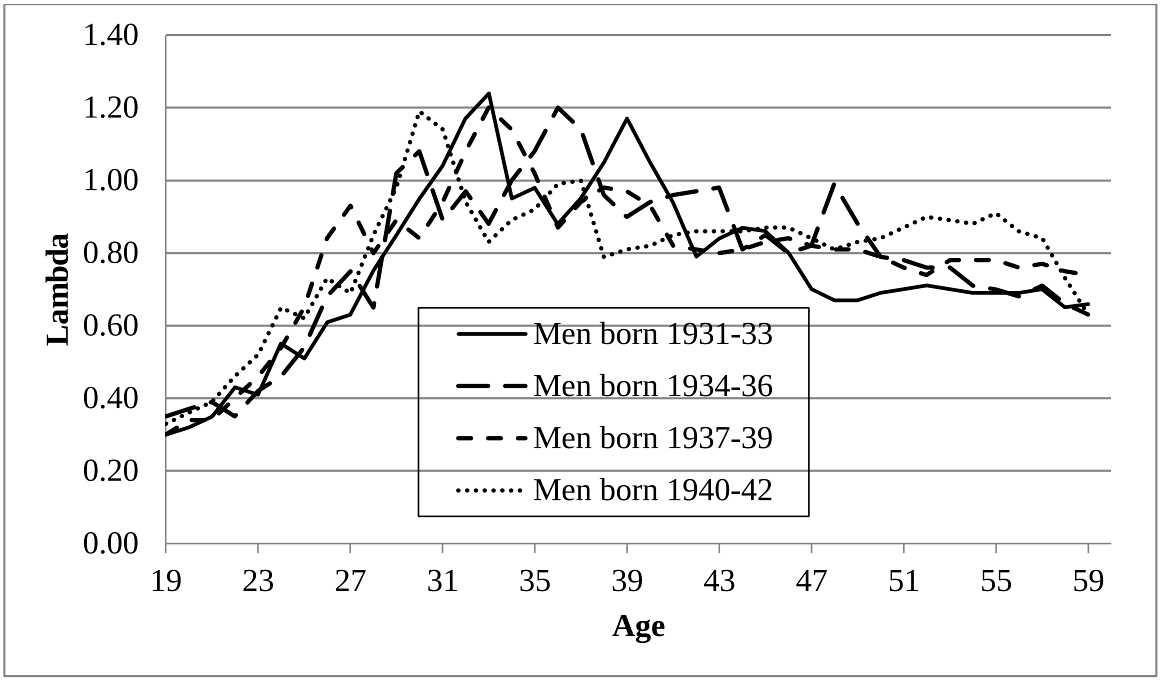


Figure 4: Estimated theta for men of different cohorts.

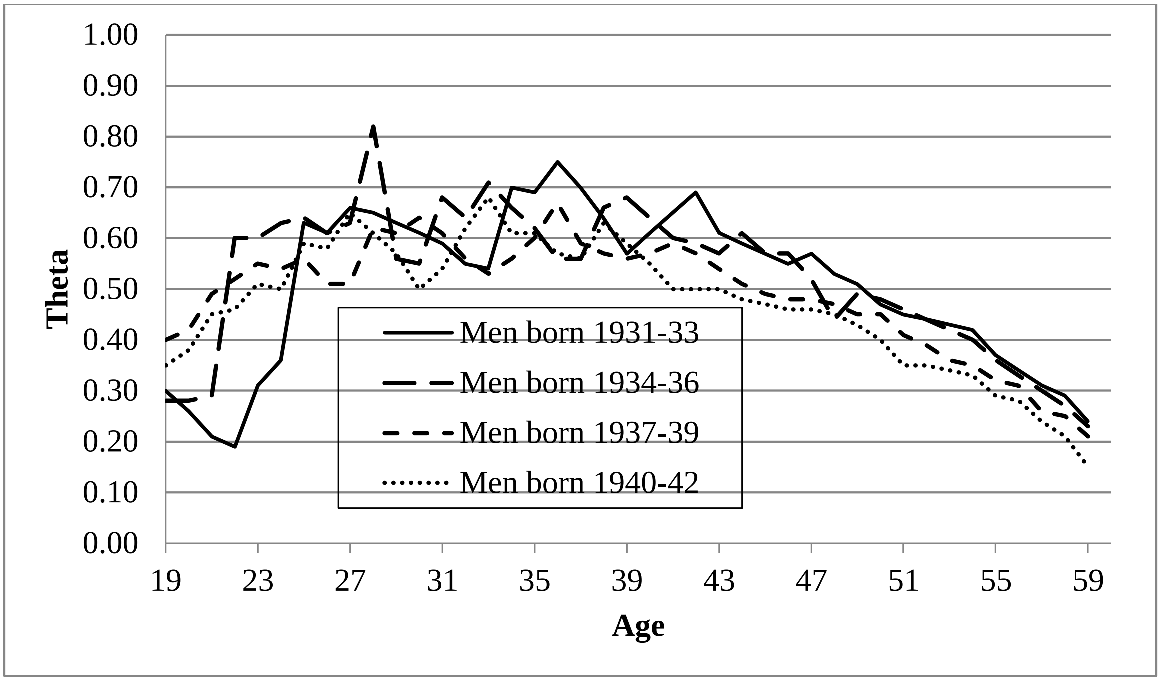


Figure 5: Estimated lambda for women of different cohorts.

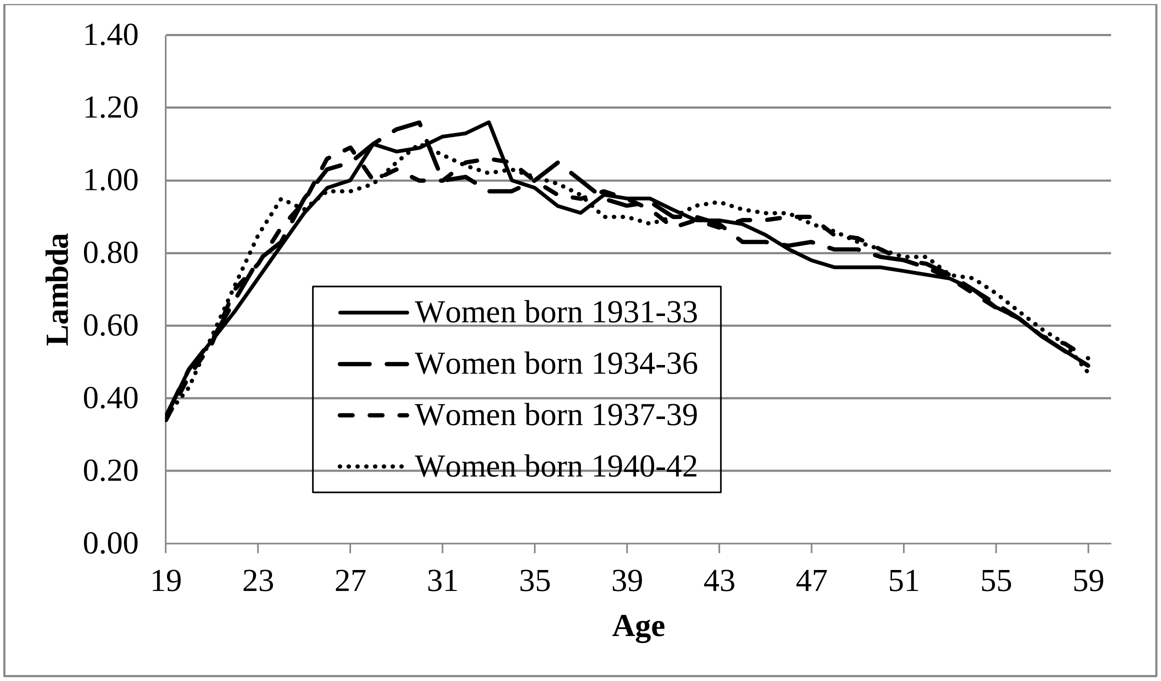


Figure 6: Estimated theta for women of different cohorts.

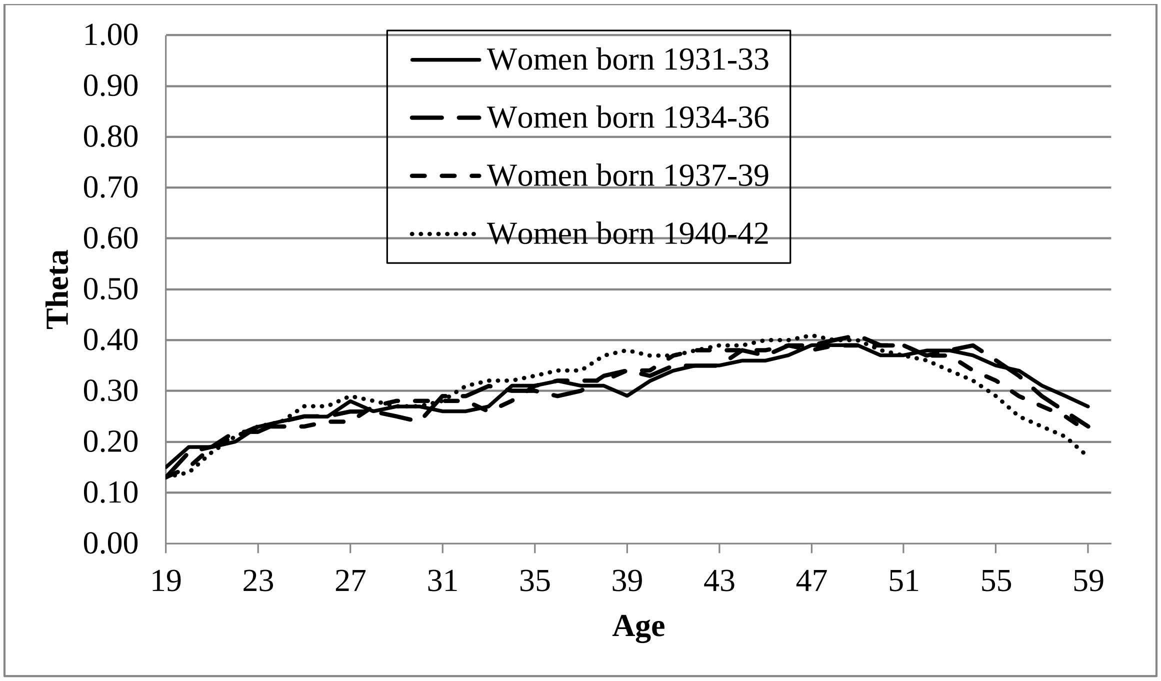


Figure 7: Estimated lambda for men and women born in 1931-33.

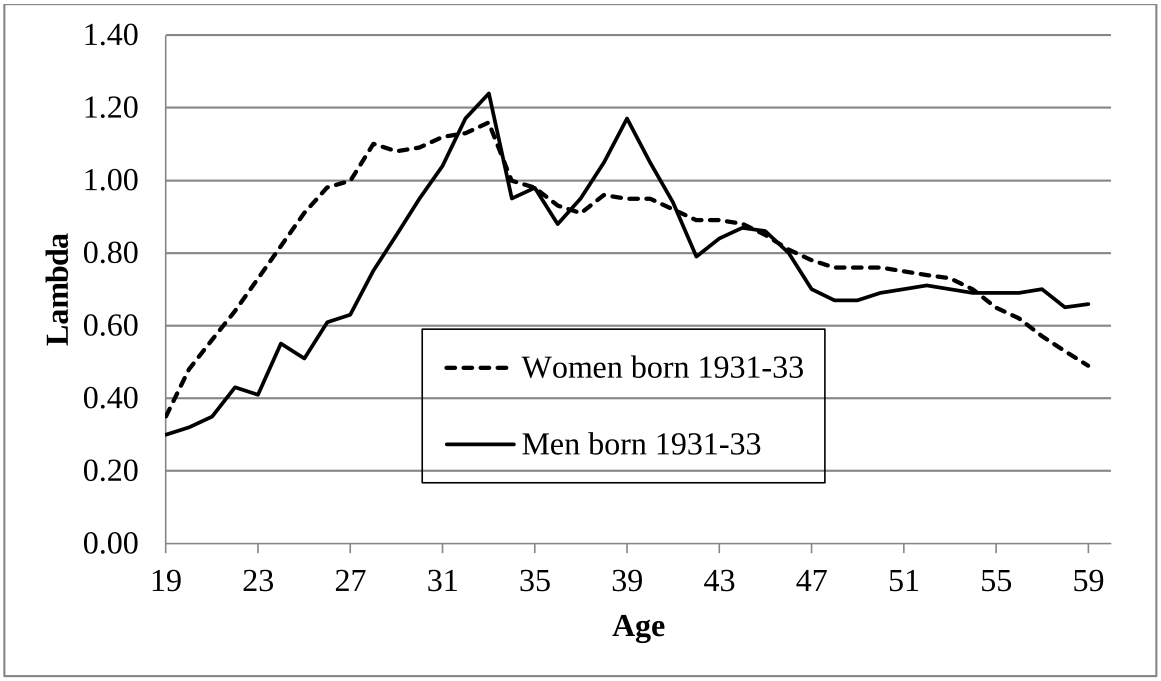


Figure 8: Estimated theta for men and women born in 1931-33.

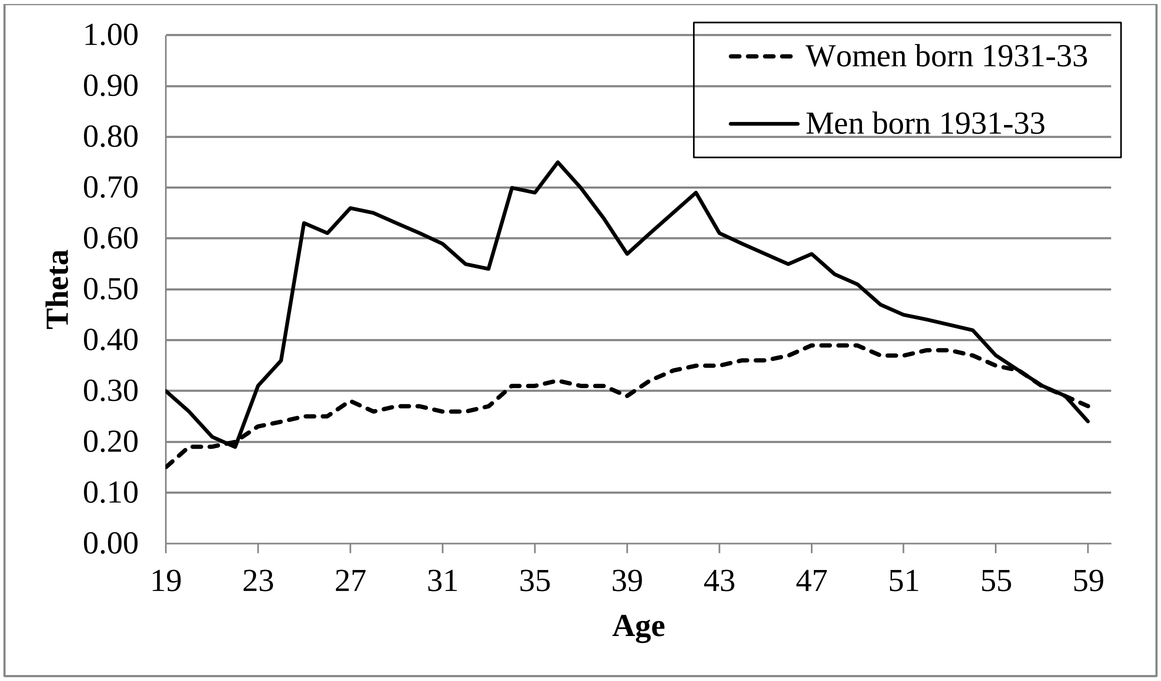
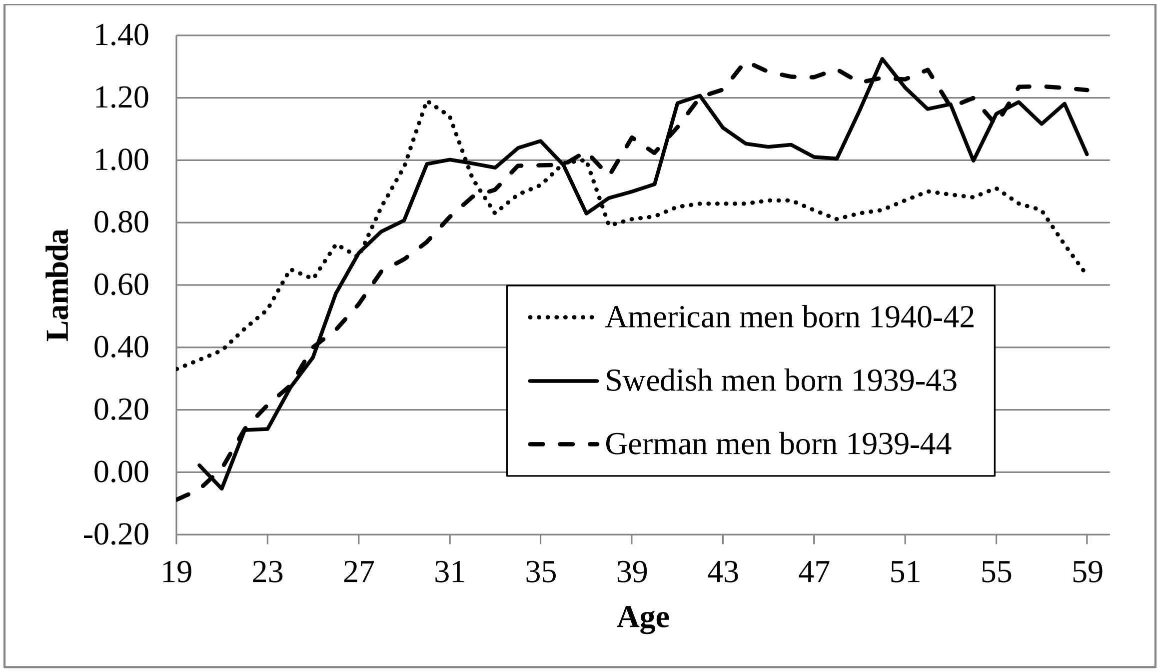
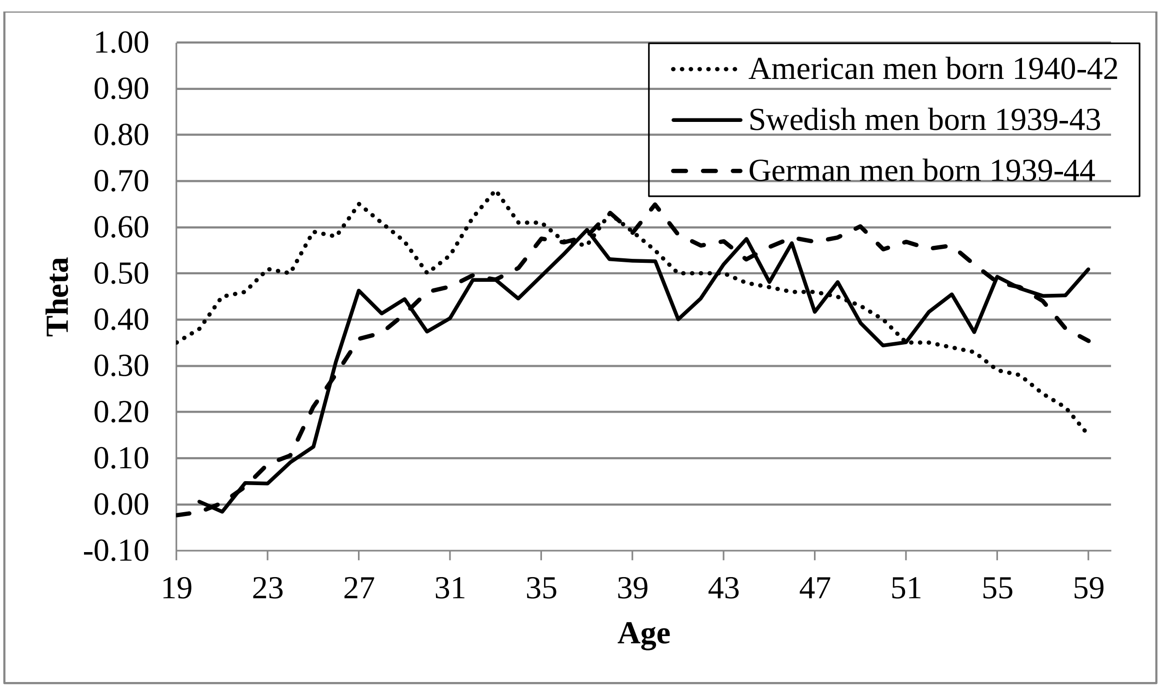


Figure 9: Estimates of parameters for men of different countries.

Panel A:



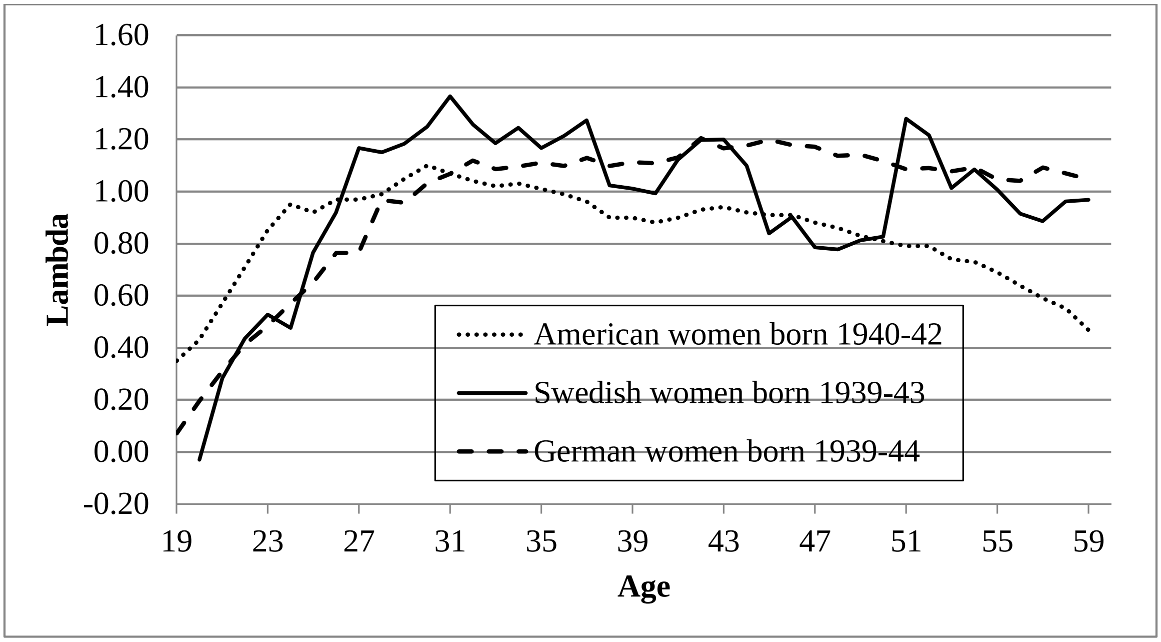
Panel B:



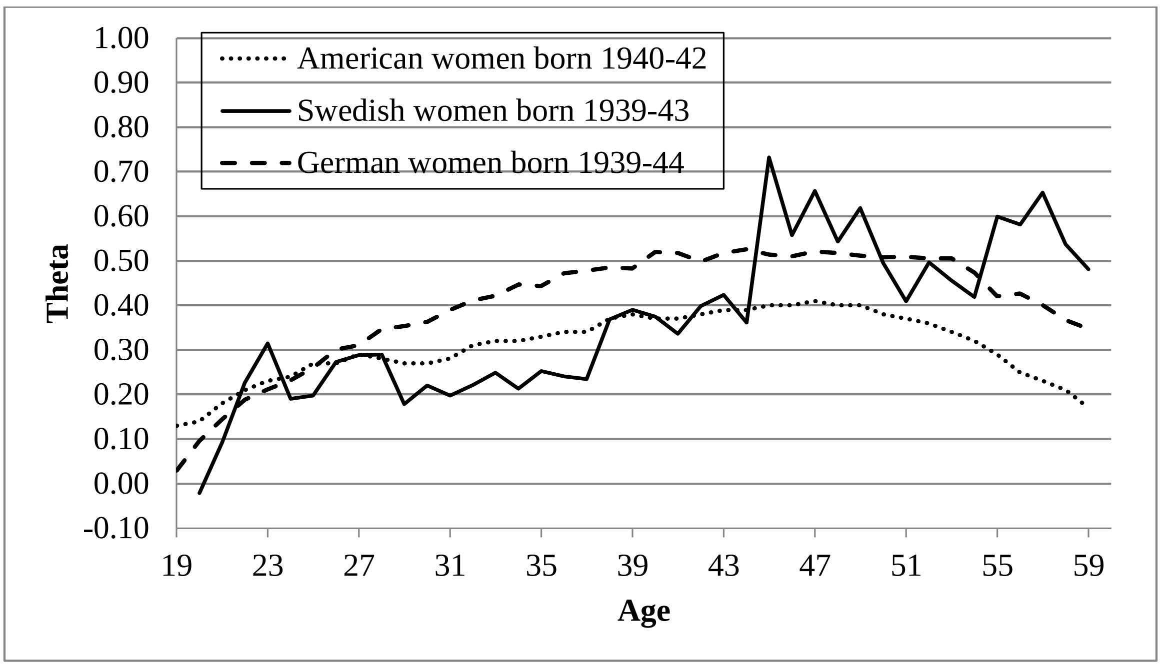
Sources: Böhlmark and Lindquist (2006) for Swedish men, and Brenner (2009) for German men.

Figure 10: Estimates of parameters for women of different countries.

Panel A:



Panel B:



Sources: Böhlmark and Lindquist (2006) for Swedish women, and Brenner (2009) for German women.