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# Cohort Effects in Age-Earnings Profiles for Women: Implications for Forensic Analysis

Matthew J. Cushing and David I. Rosenbaum
123D Kauffman Center, University of Nebraska-Lincoln, Lincoln, NE 68588-0690, USA.
E-mail: drosenbaum@unl.edu

Forensic economists typically estimate age-earnings profiles using cross-sectional data from one point in time. This approach leads to inaccurate predictions for younger women. Cohorts of younger women have more education and better access to higher paying jobs than their predecessors. Consequently as they age, their earnings experience is likely to be different than the cohorts of women preceding them. We measure the divergence between estimates using the traditional approach and those obtained when accounting for cohort effects. While the divergence is relatively small early in women's careers, it becomes more pronounced — more than 10 percent — as women move into the later parts of their working lives.
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**JEL:** J31; K30; K13

## INTRODUCTION

Forensic economists are frequently asked to value the economic loss when someone is injured or killed in an accident. In a personal injury case, a large component of that loss can be lost earning capacity. In a wrongful death case, it is generally lost contribution to the family. Typically, predicting economic losses in either case involves estimating future earnings. For a younger person, however, there may be little or no employment record on which to base an estimate of lost earning capacity or economic contribution. Consequently, a forensic economist may have to rely upon broader Bureau of Labor Statistics data to estimate an age-earnings profile that maps expected earnings over a person's lifetime.

The traditional method for developing an age-earnings profile is to use a cross-section from one year of average or median earnings for individuals in a variety of age groups. For example, 2007 Current Population Survey (CPS) data might be used to look at earnings of women aged 25 to 29, 30 to 34 and so on in 2007. The earnings from each age group would be graphed against age to create an age-earnings profile. Projected earnings would be adjusted for expected wage inflation and real earnings growth and appropriately discounted to arrive at the present value of the economic loss. This cross-sectional method captures age effects: older workers tend to have higher earnings.

Using cross-sectional data to estimate lifecycle earnings will miss significant cohort effects if younger generations will have fundamentally different labor market experiences than older generations. These cohort effects may be especially pronounced for women. Recent cohorts of women entering the job market tend to be better educated and have greater access to higher paying occupations than the cohorts that entered the job market before them. More extensive education and greater access mean they are likely to experience higher average salaries than the cohorts of women preceding them. One consequence will be that the traditional practice of projecting lifecycle earnings based on the current cross-sectional age-earnings profile, which ignores these potentially important cohort education and access effects, will underestimate future earnings for young women. The relative earnings of women who are 55 in 2007 may be a very poor guide to the earnings that women currently in their twenties will have when they eventually turn 55. In this article we attempt to quantify these underestimates. We focus on relatively straightforward empirical methods that are suitable for use in a forensic setting.

We examine these cohort effects from three different perspectives. We first examine the impact that educational attainment has had on women's earnings. The traditional approach, in effect, assumes that when the cohort of women just entering the labor market eventually turns 50, the education levels of that cohort will be the same as the education levels of women who are currently age 50. More likely, the level of education that will be attained by these young women will be considerably higher than those of past cohorts. We account for this by predicting eventual educational attainment and earnings by education for the cohort of women just entering the labor market and using those predictions to form a cohort-adjusted age-earnings profile. Our results show that the projected age-earnings profile is well above the profile traditionally developed using cross-sectional estimates based on age alone. For women aged 45 to 64, cohort-adjusted earnings are from 8 to 12 percent above the traditional cross-sectional estimates.

We next examine the impact that greater access to the job market has had on women's earnings. The traditional approach, in effect, assumes that when the cohort of women just entering the labor market eventually turns 50, the occupation mix of that cohort will be the same as the occupation mix of workers who are currently age 50. However, the projected occupation mix of these young women differs from those of past cohorts. There has been a trend towards women entering higher paid occupations. Adjusting for projected occupational mix leads to a 5 to 10 percent upward shift in the age-earnings profile.

In the first two subsections we focused on the impacts that education and then access have on earnings. These two are undoubtedly inter-related. There are also other factors that will affect younger women's potential for lifetime earnings. In the third empirical subsection, we examine overall cohort effects using time series analysis. To do this, we rely on data showing the gap between male and female earnings. Historical data show that for any age group, the gap has been closing over time as women of any particular age in more recent cohorts are earning at rates closer to men than women at that same age in less recent cohorts. Our analysis forecasts wage gaps and shows that for women entering the job market in 2007, expected gaps are smaller when cohort effects are accounted for. Using traditional cross-sectional analyses, women aged 25 to 29 in 2007 would expect to earn 77 percent of male earnings by the time they reach the age 50–54. In contrast, once cohort effects are accounted for, the same women would earn almost 85 percent of their male counterparts' earnings. Using the traditional cross-sectional approach underestimates women's earnings by more than 10 percent.

The next section discusses recent literature related to age-earnings profiles. It points to several factors that have allowed women's labor market experiences to evolve. In the subsequent section, we empirically examine the implications of this evolution. There are three subsections looking at the implications of education, age, and overall cohort effects. The analysis is followed by a conclusion in the last section.

## THE ISSUES CONFRONTED

A problem in using cross-sectional data to create an age-earnings profile is the difficulty of disentangling cohort effects from age and period effects. Rodgers et al. [1996], for example, identified several cohort-related influences, including the size of a cohort (labor supply *vs* demand), varying rates of inflation, and varying rates of productivity growth, both for individuals and the economy. The cohort problem can be especially pronounced for women. Women entering the labor market nearer to the close of the 20th century had greater access to education, greater access to professions, increased societal acceptance of women having careers, and faced less of a starting wage differential than women in cohorts entering before them. These cohort effects can potentially skew a typical cross-sectional age-earnings profile.

Rodgers et al. [1996] explored age-earnings profiles along racial, gender, and educational lines. In their empirical analysis, among other things, they showed that there is a correlation between more education and higher earnings expectations. Once again, if women in younger cohorts are taking advantage of educational opportunities at a greater rate than women in older cohorts, this should impact their access to the labor market and their earnings.

A variety of current research reinforces these cohort distortions. Gohmann et al. [1998] explored the dynamics of age-earnings profiles. Their findings showed that women are closing the earnings gap with respect to men's earnings. The narrowing of the gender gap implies that the experiences of older women may not be good predictors for younger women's future earnings and thus it may be misleading to directly extrapolate earnings data from older women and apply it to their younger counterparts. In Gohmann et al.'s words, "[i]t is unlikely that a 20-year-old female today will in 30 years have the same labor market experience and wages as a 50-year-old woman today" [Gohmann et al. 1998, p. 173]. Gohmann et al. go on to do some empirical analysis, comparing age-earnings profiles calculated using 1979 cross-sectional data to profiles calculated using 1989 cross-sectional data. They showed that a change of only 10 years can have a profound effect on earnings. Two results are of particular interest. First, they showed that college-educated women did better in the later sample than in the earlier sample. This finding is consistent with our hypothesis that younger women have greater access than older women to higher paying jobs in the labor market. Second, they showed that earnings for women, and younger women in particular, were catching up to those of men over the 10-year period.

Polachek [2004] viewed the narrowing of the gender gap as a function of human capital formation, particularly investments in education. He argued that "the human capital model links expected lifetime labor force participation to one's incentive to acquire marketable training. In turn, this training, acquired in school and on the job, determines earnings potential. Thus expected lifetime work history is the most important motivating ingredient in one's ability to eventually achieve high earnings" [Polachek 2004, p. 3]. His model of human capital formation reinforced the contention that cohort effects may be important as younger cohorts have very different expectations, and consequently experiences, than older cohorts.

Perhaps the strongest indication that cohorts matter comes from Goldin [2004]. She found that

> [t]he only reason we can have meaningful discussion of "women at the top" is because a quiet revolution took place about thirty years ago. … We can observe it in a number of social and economic indicators. … Sharp breaks or turning points are apparent in the data presented on labor market expectations, college graduation rates, professional degrees, labor force participation rates, and the age at first marriage. Turning points are also evident in most of the series for college majors and occupations. The inflection or break points in almost all of these series occur from the late 1960s to the early 1970s and for cohorts born during the 1940s. [Goldin 2004, p. 1].

Goldin's point is that by the mid-1970s, women were gaining very different backgrounds and forming very different expectations than their older counterparts.

Weinberger and Kuhn [2010] examined the impacts that cohort effects have on the narrowing of the gender earnings gap. Borrowing from Blau and Kahn [2000] and Goldin [1989], they posited that the literature demonstrates a lessening of the gap, in part due to women's greater commitment to the labor market and their concomitant acquisition of job market experience more on par of that gained by men. Weinberger and Kuhn then use longitudinal data to test this hypothesis and examine its root causes. They document that the narrowing of the gender gap is primarily due to improved access to higher paid employment by successive cohorts of young women. They show that the majority of the between-cohort improvements are already apparent among young workers in their 20s, soon after initial entry to the labor force. Reliable predictions of future earnings are therefore possible even when only early career earnings and occupations can be observed.

## EMPIRICAL ANALYSIS

For the first parts of this analysis, we use micro data from the March CPSs for the years 1991 to 2007. Each survey contains detailed information on earnings, occupation, age, and educational attainment of from 20,000 to 30,000 women between the ages of 25 and 64 who worked full time year round. The data are then divided into age cohorts. These age cohorts are composed of 5-year intervals with the relevant age cohorts 25 to 29, 30 to 34, 35 to 39, 40 to 44, 45 to 49, 50 to 54, 55 to 59, and 60 to 64. Information about employment and earnings for women in each age cohort can be further categorized based on education and occupation.

Using this data, we first examine the relationship between educational attainment and women's earnings. Using the historical data we predict young women's lifetime educational attainment and we predict earnings by education. The predictions are then combined to create a weighted average age-earnings profile. In the second subsection we examine the relationship between job market access and women's earnings. Using a technique similar to that used for education, we project occupation mix and earnings by occupation, and then combine them to create a weighted average age-earnings profile. In the third empirical subsection we examine overall cohort effects using time series analysis of the gap between male and female earnings.

## Impact of education

In this subsection we focus on the effects that greater levels of educational attainment have on estimating age-earnings profiles. Table 1 shows educational attainment for women in different age groups based on year 2007 data. The results are rather telling of the progress that women have made in the educational realm. The right-hand column of Table 1 shows that 17 percent of women employed year round full time between the ages of 60 and 64 earned a college degree. Moving leftward to women in younger and younger age groups, the percentage with college degrees keeps rising. Almost 30 percent of women in the youngest age group are college educated. Clearly, younger women are seeking higher education at greater rates than their older counterparts. This conclusion is reinforced when looking at the percentage of women either not finishing or having high school as their terminal degree. It falls from almost 70 percent of the women in the oldest group to just over 60 percent of women in the youngest.

The educational mix in Table 1 probably misrepresents the education levels that will be attained by the cohort of women aged 25 to 29 in 2007. This misrepresentation can bias a predicted age-earnings profile. However, we can use historical data to adjust their future expected educational mix and its impact on earnings. Our correction for this birth cohort effect follows three steps. The first step uses historical data to predict the relative mix of degrees that women just entering the labor force will possess as they age. In the second step, we use regression analysis on data from the 2007 CPS to predict earnings as a function of age and education level. In the third step, we weight predicted earnings in each age/education group by the projected proportions of women holding those degrees to create a projected age-earnings profile.

### *Predicting educational attainment*

We begin by looking at the subset of women holding graduate or professional degrees. Table 2 shows by age group, the percentage of women employed full time year round who had advanced degrees in a variety of years. The upper left-hand cell in the table shows that in 1992, 5.1 percent of the women aged 25 to 29 had advanced degrees. The lower right-hand cell shows that in 2007, 13.3 percent of women aged 60 to 64 had advanced degrees. It is clear from these results that more women are seeking advanced degrees. For almost every age group, the proportion of women with advanced degrees is increasing for newer cohorts.

Recall that the traditional methodology in forensic economics is to treat the columns in Table 2 (the cross-sectional data) as revealing the lifecycle pattern of educational attainment. Reading down the last column highlights a peculiar result.

**Table 1** Educational attainment by age group for women working full time year round

| | *Age in 2007* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| No high school (%) | 5.7 | 5.9 | 7.7 | 7.0 | 6.1 | 5.5 | 6.1 | 6.4 |
| High school (%) | 55.2 | 53.5 | 54.6 | 58.9 | 60.4 | 58.3 | 59.2 | 62.8 |
| College (%) | 29.3 | 25.7 | 23.1 | 22.5 | 22.5 | 21.6 | 20.3 | 17.4 |
| Graduate/Professional (%) | 9.8 | 14.9 | 14.6 | 11.5 | 11.0 | 14.6 | 14.4 | 13.3 |

**Table 2** Percent of women working full time year round with profession or graduate degrees: selected years

| *Age* | *Year* | | | |
|---|---|---|---|---|
| | *1992 (%)* | *1997 (%)* | *2002 (%)* | *2007 (%)* |
| 25–29 | 5.1 | 7.5 | 7.3 | 9.8 |
| 30–34 | 6.4 | 8.6 | 10.2 | 14.9 |
| 35–39 | 8.3 | 8.4 | 9.6 | 14.6 |
| 40–44 | 11.7 | 9.3 | 9.8 | 11.5 |
| 45–49 | 11.2 | 11.6 | 11.6 | 11.0 |
| 50–54 | 11.4 | 12.1 | 15.7 | 14.6 |
| 55–59 | 8.3 | 10.1 | 13.3 | 14.4 |
| 60–64 | 7.1 | 10.0 | 10.1 | 13.3 |

The percent attaining an advanced degree peaks at age 30 to 34 and then falls to a low at age 45 to 49. It then increases, but never attains the earlier peak. This does not appear consistent with a lifecycle pattern of women's educational experience. After all, individuals do not lose advanced degrees as they age and women with advanced degrees are at least as likely as other women to remain in the full-time year round labor force. For men working full time year round, the percentage holding advanced degrees increases monotonically with age. We attribute the peculiar result for women to a birth cohort effect.

To see this we create pseudo cohort data by rearranging the columns of Table 2. The columns in Table 3 refer to the year in which cohorts of women were in the job market as 25- to 29-year olds. The column "1992," for example, tracks the women who were aged 25 to 29 in 1992. Reading down that column gives the percentage of women working full time year round who held professional and graduate degrees at ages 25 to 29 in 1992, became ages 30 to 34 in 1997, 31 to 35 in 2002 and so on.

Table 3 shows that, following birth cohorts, the percentage of women with advanced degrees generally increases with age. That is, the cross-sectional results from Table 2 give a misleading indication of the likely cohort pattern of educational attainment for women.

To get a better estimate of the future mix of educational attainment for women, we create a set of pseudo birth cohorts from the CPS micro sample which is available from 1991 to 2007. We compute the change in the educational attainment across age groups for women working full time year round for each year from 1996 to 2007. The average change over the sample is reported in Table 4. The upper left-hand cell in Table 4 shows that for the age group 30 to 34, on average, the percentage of women with advanced degrees was 4.1 percentage points higher than the percentage attained by the age group 25 to 29 five years earlier.

Over these pseudo cohorts, the percentage with advanced degrees increases throughout their lifecycles, except for a small decline from ages 50 to 54 to ages 55 to 59. The percentage with college degrees initially falls, and then rises thereafter. This is consistent with a pattern of college-educated women obtaining advanced degrees. The percentage holding either only a high school degree or no high school degree falls. This is consistent with these groups either leaving the labor force, or obtaining college or high school degrees.

The information in Table 4 can be used to project the lifecycle relative mix of degrees held by the cohort of women turning 25to 29 in 2007. These projections are

**Table 3** Percent of women with advanced degrees by starting cohort year

| *Age* | *Year of entry into job market* | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | *1957 (%)* | *1962 (%)* | *1967 (%)* | *1972 (%)* | *1977 (%)* | *1982 (%)* | *1987 (%)* | *1992 (%)* | *1997 (%)* | *2002 (%)* | *2007 (%)* |
| 25–29 | | | | | | | | 5.1 | 7.5 | 7.3 | 9.8 |
| 30–34 | | | | | | | 6.4 | 8.6 | 10.2 | 14.9 | |
| 35–39 | | | | | | 8.3 | 8.4 | 9.6 | 14.6 | | |
| 40–44 | | | | | 11.7 | 9.3 | 9.8 | 11.5 | | | |
| 45–49 | | | | 11.2 | 11.6 | 11.6 | 11.0 | | | | |
| 50–54 | | | 11.4 | 12.1 | 15.7 | 14.6 | | | | | |
| 55–59 | | 8.3 | 10.1 | 13.3 | 14.4 | | | | | | |
| 60–64 | 7.1 | 10.0 | 10.1 | 13.3 | | | | | | | |

**Table 4** Change in percentage of women with various education levels from one age group to next

| *Age* | *Type of degree* | | | |
|---|---|---|---|---|
| | *Advanced degree (%)* | *College (%)* | *High school (%)* | *No high school (%)* |
| 30–34 | 4.1 | −3.2 | −1.5 | 0.7 |
| 35–39 | 1.7 | −1.6 | −0.1 | −0.1 |
| 40–44 | 1.5 | 0.6 | −1.2 | −0.9 |
| 45–49 | 1.3 | 2.1 | −2.6 | −0.8 |
| 50–54 | 2.0 | 0.6 | −2.0 | −0.7 |
| 55–59 | −0.1 | 0.6 | −0.1 | −0.4 |
| 60–64 | 0.7 | 0.0 | −0.1 | −0.6 |

**Table 5** Projected percent of women who entered workforce in 2007

| *Age* | *Type of degree* | | | |
|---|---|---|---|---|
| | *Advanced degree (%)* | *College (%)* | *High school (%)* | *No high school (%)* |
| 25–29 | 9.8 | 29.3 | 55.2 | 5.7 |
| 30–34 | 13.9 | 26.1 | 53.7 | 6.4 |
| 35–39 | 15.6 | 24.5 | 53.6 | 6.3 |
| 40–44 | 17.1 | 25.1 | 52.5 | 5.4 |
| 45–49 | 18.4 | 27.2 | 49.9 | 4.6 |
| 50–54 | 20.4 | 27.8 | 47.9 | 3.9 |
| 55–59 | 20.3 | 28.4 | 47.8 | 3.5 |
| 60–64 | 21.1 | 28.3 | 47.7 | 2.9 |

shown in Table 5. The first row of Table 5 shows the actual percentage of women aged 25 to 29 holding each type of degree. These percentages are changed by the figures in Table 4 to project the degree mix thought this cohort's working life. By the time this cohort reaches ages 60 to 64, we project that over 21 percent will hold an advanced degree. Fewer than 3 percent will have no degree.

The figures in Table 5 for women with advanced degrees can be compared to the figures in the last column of Table 2. Again, Table 2 shows the cross-sectional results for all women in the labor force in 2007. According to Table 2, approximately

13 percent of women aged 60 to 64 in 2007 held advanced degrees. Table 5 shows that by the time women who are 25 to 29 in 2007 reach ages 60 to 64, over 21 percent of them will hold advanced degrees.

*Predicting earnings*

In this subsection we want to predict earnings for women as a function of age and educational attainment. To do this we start with the 2007 CPS micro subsample of women working full time year round. The traditional practice has been to estimate the profile from a cross-sectional regression of earnings on age of all full-time female workers in the sample year:

$$Earnings_i = \sum_{n=1}^{N} \alpha_n Age_i^n + e_i \tag{1}$$

where $Earnings_i$ represents the earnings of individual $i$ and $Age_i^n$ is a dummy variable taking a value of 1 if individual $i$ is in age category $n$ and 0 otherwise.[1]

Because education is clearly an important determinate of earnings, we augment (1) by including the interactions of the $Age_i^n$ variables with a set of dummy variables, $Educ_i^j$, taking a value of 1 if individual $i$ is in education category $j$ and 0 otherwise:

$$Earnings_i = \sum_{j=1}^{4} \sum_{n=1}^{N} \beta_{j,n} Age_i^n Educ_i^j + e_i \tag{2}$$

Table 6 reports the coefficient estimates from equations (1) and (2). Standard errors are in parentheses below each coefficient estimate. All of the coefficient estimates are statistically significant. The first row contains the $\hat{\alpha}_n$ from equation (1) and the next four rows contain the $\hat{\beta}_{j,n}$ from equation (2). Reading down any column of Table 6 shows that at any age, projected income is increasing in educational attainment.

There is a simple relationship between the two estimated sets of coefficients reported in Table 6. Let $\Psi_{j,n}$ represent the proportion of women in age group $n$ with educational attainment $j$ in 2007. These are the cross-sectional proportions reported in Table 1. Computationally, it can be shown that,

$$\hat{\alpha}_n = \sum_{j=1}^{4} \hat{\beta}_{j,n} \Psi_{j,n} \tag{3}$$

**Table 6** Estimated full time earning of women in 2007 by age and education

| | *Age in 2007* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| All women | $32,756 | $38,530 | $41,740 | $41,521 | $42,958 | $44,506 | $42,199 | $39,890 |
| | (613) | (598) | (563) | (537) | (534) | (582) | (680) | (959) |
| No high school | $18,067 | $17,995 | $20,399 | $21,097 | $20,454 | $21,182 | $21,755 | $22,100 |
| | (2,410) | (2,298) | (1,901) | (1,893) | (2,019) | (2,313) | (2,576) | (3,538) |
| High school | $27,592 | $30,799 | $32,206 | $34,183 | $35,361 | $35,574 | $34,796 | $33,548 |
| | (771) | (765) | (712) | (654) | (642) | (713) | (827) | (1,132) |
| College | $39,151 | $46,029 | $54,121 | $52,049 | $56,573 | $54,646 | $52,738 | $50,699 |
| | (1,058) | (1,105) | (1,094) | (1,058) | (1,052) | (1,171) | (1,411) | (2,149) |
| Graduate degree | $51,162 | $61,597 | $68,930 | $71,079 | $69,373 | $74,084 | $66,430 | $64,215 |
| | (1,829) | (1,451) | (1,376) | (1,483) | (1,506) | (1,426) | (1,676) | (2,458) |

**Table 7** Projected full time earning: women entering workforce in 2007

| | *Age* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| Predicted earnings using predicted weights ($\tilde{\Psi}_{j,n}$) | \$32,756 | \$38,230 | \$42,549 | \$44,267 | \$46,685 | \$48,158 | \$45,859 | \$44,536 |
| Estimated earnings using cross-sectional weights ($\Psi_{j,n}$) | \$32,756 | \$38,530 | \$41,740 | \$41,521 | \$42,958 | \$44,506 | \$42,199 | \$39,890 |
| Ratio | 1.000 | 0.992 | 1.019 | 1.066 | 1.087 | 1.082 | 1.087 | 1.116 |
| SE of ratio[a] | | 0.0005 | 0.0008 | 0.0026 | 0.0035 | 0.0033 | 0.0047 | 0.0096 |

[a]These standard errors are conditional on the weighting matrices. To the extent that the projected weights are not known with certainty, they overstate the confidence we have in our projections.

In other words, the estimated average earnings of women at age $n$ (the first row of Table 6) are the weighted averages of the estimated earnings of women at age $n$ across education levels (the next four rows of Table 6) with weights given by the cross-sectional proportions from year 2007.

*Projecting age-earnings profile*
We can now estimate lifecycle earnings using the predicted educational attainment figures from Table 5 and the earnings projections from Table 6. Let $\tilde{\Psi}_{j,n}$ represent the predicted proportion of women in age group $n$ who have attained education level $j$ as seen in Table 5. Then predicted earnings for age group $n$, $\tilde{\alpha}_n$, can be estimated as:

$$\tilde{\alpha}_n = \sum_{j=1}^{4} \hat{\beta}_{j,n} \tilde{\Psi}_{j,n} \tag{4}$$

These predicted earnings are shown in the first row of Table 7. They range from \$32,756 for younger women to a peak of \$45,859 for women aged 55 to 59. For comparison, the estimated earnings using the traditional cross-sectional weights ($\Psi_{j,n}$) are shown in the second row of Table 7. For all age groups, the estimates using predicted educational attainment are above the estimates using the cross-sectional education weights. The third row in Table 7 shows the ratio of the estimates and the last row shows the standard error of that ratio. All but one of the ratios is statistically greater than one at the 95 percent confidence level or greater. These results indicate that once educational mix is accounted for, young women entering the workforce in 2007 will earn from 8 to almost 12 percent more than would be predicted by using traditional cross-sectional age-earnings projections.

## Impact of occupation

In this subsection we focus on the effects that occupation choices can have on estimating women's age-earnings profiles. Similar to the previous subsection, this prediction process occurs in three steps. The first step uses historical data to predict the relative mix of occupations that women just entering the labor force will possess as they age. In the second step, we use regression analysis on data from the 2007 CPS micro sample to predict earnings as a function of age and occupation. In the third step, we weight predicted earnings in each age/occupation group by the projected proportions of women holding those occupations to create a projected age-earnings profile.

*Predicting occupational mix*

Table 8 shows, by age group, the percentage of women in each of six major CPS occupation groupings. The percentage of women in professional occupations peaks for women aged 30 to 34 at 29.7 percent and falls to 25.9 by the time they reach ages 60 to 64. The percentage of women in management peaks at ages 45 to 49 and then falls thereafter. In contrast, the percentage of men in these high paying occupations steadily increases with age. We think the decline in the percentage of women in high paying occupations is a consequence of using cross-sectional data to predict what is really a cohort effect, and suggest that the occupation mix of the birth cohort ages 25 to 29 in 2007 is likely to be different than the mix suggested by the data in Table 8.

Table 9 gives our projected occupational mix. Generally, we construct this projection just like we did in the education section: create a set of pseudo birth cohorts from the CPS micro sample which is available from 1991 to 2007 and compute the change in the occupation mix across age groups for women working full time year round for each year from 1996 to 2007. However, the occupation codes used by the CPS changed so that the occupation categories for the 1991 to 2001 panels are not compatible with the occupation categories for the 2002 to 2007 panels. We therefore construct our pseudo cohorts using only the 2002 and 2007

**Table 8** Occupation in 2007 by age group

| | *Age in 2007* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| Management (%) | 14.0 | 16.2 | 16.3 | 16.8 | 17.7 | 17.3 | 16.6 | 16.1 |
| Professional (%) | 27.4 | 29.7 | 28.7 | 27.4 | 27.0 | 29.0 | 28.1 | 25.9 |
| Service (%) | 17.5 | 15.0 | 15.1 | 15.4 | 15.2 | 14.0 | 13.5 | 13.8 |
| Sales(%) | 11.9 | 9.6 | 8.9 | 8.2 | 8.7 | 7.3 | 8.0 | 9.4 |
| Office support(%) | 23.4 | 22.5 | 21.9 | 23.0 | 22.7 | 24.6 | 25.3 | 26.0 |
| Other(%) | 5.9 | 7.0 | 9.1 | 9.2 | 8.9 | 7.8 | 8.6 | 8.9 |

**Table 9** Projected occupational mix of women who entered workforce in 2007

| *Age* | *Occupation* | | | | | |
|---|---|---|---|---|---|---|
| | *Management (%)* | *Professional (%)* | *Service (%)* | *Sales (%)* | *Office support (%)* | *Other (%)* |
| 25–29 | 14.0 | 27.4 | 17.5 | 11.9 | 23.4 | 5.9 |
| 30–34 | 17.4 | 30.1 | 15.8 | 11.4 | 20.1 | 5.2 |
| 35–39 | 17.9 | 33.0 | 15.1 | 10.7 | 17.8 | 5.6 |
| 40–44 | 18.4 | 36.3 | 15.1 | 9.1 | 15.8 | 5.2 |
| 45–49 | 19.8 | 37.7 | 15.7 | 9.5 | 13.0 | 4.3 |
| 50–54 | 19.8 | 39.8 | 15.1 | 8.3 | 13.6 | 3.4 |
| 55–59 | 19.6 | 40.3 | 15.0 | 8.3 | 13.4 | 3.3 |
| 60–64 | 20.5 | 39.9 | 13.8 | 9.0 | 13.5 | 3.3 |

panels. That is, we calculate the change in occupations for the 30 to 34 age group in 2007 relative to the occupations for the 25- to 29-year age group five years earlier, and so on for other age groups. We then use these changes to project how the occupational mix will evolve over the lifecycle of the current 25- to 29-year-old cohort of workers. The results in Table 9 show much more consistent growth in the management and professional occupations and a steady decline in the remaining four occupation groups over the projected lifecycle.

*Predicting earnings*

In this subsection we predict earnings for women as a function of age and occupation. As done previously, we start with the 2007 CPS micro sample of women working full time year round. We run regressions similar to equations (1) and (2) above, but substitute a set of occupation rather than education control variables. Table 10 reports the coefficient estimates with standard errors in parentheses below. All of the coefficients are statistically significant. The first row contains the $\hat{\alpha}_n$ from the first equation and the next six rows contain the $\hat{\beta}_{j,n}$. For any age group, women working in management and professional occupations earn substantially more than women working in service, sales, office support, or other occupations.

*Projecting age-earnings profile*

We can now estimate lifecycle earnings using the predicted occupation mix and earnings projections. Similar to before, let $\Omega_{j,n}$ represent the cross-sectional proportion of women of age $n$ in occupation $j$ in 2007. Let $\tilde{\Omega}_{j,n}$ represent the predicted proportion of women in age group $n$ who are in occupation $j$ as seen in Table 9. Then predicted earnings can be estimated using equation (4) above. Predictions using the predicted weights ($\tilde{\Omega}_{j,n}$) are shown in the first row of Table 11. They range from \$32,756 for younger women to a peak of \$45,341 for women aged 55 to 59 and are similar to results in the previous subsection. For comparison, the estimated earnings using the cross-sectional occupation weights ($\Omega_{j,n}$) are shown in the second row of Table 11. For all age groups, the estimates using the predicted

**Table 10** Estimated full time earning of women in 2007 by age and occupation

| | *Age in 2007* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| All women | \$32,756 | \$38,530 | \$41,740 | \$41,521 | \$42,958 | \$44,506 | \$42,199 | \$39,890 |
| | (613) | (598) | (563) | (537) | (534) | (582) | (680) | (959) |
| Management | \$44,779 | \$51,600 | \$59,889 | \$60,626 | \$64,759 | \$63,947 | \$62,734 | \$57,928 |
| | (1,550) | (1,407) | (1,319) | (1,241) | (1,203) | (1,324) | (1,583) | (2,264) |
| Professional | \$40,744 | \$47,550 | \$50,869 | \$50,479 | \$49,838 | \$55,353 | \$51,562 | \$50,211 |
| | (1,110) | (1,041) | (995) | (972) | (973) | (1,023) | (1,215) | (1,787) |
| Service | \$22,035 | \$27,220 | \$25,485 | \$24,425 | \$25,550 | \$26,873 | \$25,035 | \$23,318 |
| | (1,388) | (1,461) | (1,374) | (1,298) | (1,297) | (1,473) | (1,751) | (2,447) |
| Sales | \$28,879 | \$36,212 | \$40,528 | \$37,253 | \$40,979 | \$34,080 | \$34,992 | \$34,967 |
| | (1,686) | (1,827) | (1,785) | (1,773) | (1,718) | (2,044) | (2,283) | (2,972) |
| Office support | \$28,581 | \$30,086 | \$33,092 | \$34,857 | \$35,375 | \$35,794 | \$34,490 | \$33,335 |
| | (1,200) | (1,196) | (1,139) | (1,061) | (1,062) | (1,111) | (1,282) | (1,782) |
| Other | \$23,268 | \$24,624 | \$29,342 | \$28,958 | \$29,705 | \$29,896 | \$28,350 | \$27,226 |
| | (2,395) | (2,140) | (1,762) | (1,675) | (1,698) | (1,970) | (2,197) | (3,048) |

**Table 11** Projected full time earning by occupation for women entering workforce in 2007

| | Age | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| Predicted earnings using predicted weights ($\tilde{\Omega}_{j,n}$) | \$32,758 | \$39,058 | \$43,171 | \$43,604 | \$45,389 | \$47,459 | \$45,341 | \$43,660 |
| Estimated earnings using cross-sectional weights ($\Omega_{j,n}$) | \$32,756 | \$38,530 | \$41,740 | \$41,521 | \$42,958 | \$44,506 | \$42,199 | \$39,890 |
| Ratio | 1.000 | 1.014 | 1.034 | 1.050 | 1.057 | 1.066 | 1.074 | 1.094 |
| SE of Ratio[a] | | 0.0016 | 0.0024 | 0.0033 | 0.0040 | 0.0044 | 0.0060 | 0.0100 |

[a]As in the previous section, these standard errors are conditional on the predicted weights. The same caveat applies.

occupation mix are above the estimates using the cross-sectional occupation mix. The third row in Table 11 shows the ratio of the estimates and the last row shows the standard error of that ratio. All but one of the ratios are statistically greater than one at the 95 percent confidence level or greater. These results indicate that because of greater access to occupations, young women entering the workforce in 2007 will earn more than would be predicted by using traditional cross-sectional age-earnings projections. The difference ranges from 5 to 10 percent more as they move into the second half of their working lives.

## Overall cohort effects

The previous analyses focused on specific aspects of women's evolution in the labor market. In this last subsection, we examine women's earnings prospects when the aggregate of cohort effects are considered. To do this, we use time series forecasts of women's wages relative to men's. Table 12 shows the earnings of women relative to men by age group for the last 30 years. The upper left-hand cell in the table shows that in 1977, for people working full time year round, women aged 25 to 29 earned 72.2 percent of men's earnings. Conversely, the gap between men's and women's earnings for women aged 25 to 29 was 22.6 percent. In all years the disparity between men's and women's earnings is considerably lower at younger than older ages. Notice that for any age, the disparity has been steadily decreasing over time.

Data and analysis from the previous section as well as the literature review suggest that causes for the gap in earnings between genders include occupational and education choices. These choices have been evolving. As such, the lifecycle earnings differences faced by young women entering the labor market in 2007 may not be well proxied by the differences faced by older cohorts of women.

Table 13 rearranges the data from Table 12 into pseudo cohorts. The columns in Table 13 refer to the year in which the cohort of women was from ages 25 to 29. Comparing Tables 13 and 12 reveals that the lifecycle relative earnings faced by cohorts of female workers have been considerably closer to men's earnings than the naïve cross-sectional estimates indicate. For 1977, the cross-section method from Table 12 has the ratio falling from 72.2 percent at ages 25 to 29 to 54.9 percent at ages 55 to 59. Table 13 reveals that the actual average relative earnings faced by a typical female worker in the 1977 birth cohort rose to 72.4 percent at ages 55 to 59. Applying the cross-section method would have grossly underestimated the relative earning of women in later years.

**Table 12** Ratio: median income of full-time female workers to male workers

| *Age* | *Year* | | | | | | |
|---|---|---|---|---|---|---|---|
| | *1977 (%)* | *1982 (%)* | *1987 (%)* | *1992 (%)* | *1997 (%)* | *2002 (%)* | *2007 (%)* |
| 25–29 | 72.2 | 75.7 | 76.8 | 90.1 | 88.6 | 92.6 | 90.0 |
| 30–34 | 61.5 | 69.5 | 72.6 | 78.3 | 82.4 | 82.8 | 86.4 |
| 35–49 | 55.7 | 61.6 | 65.9 | 73.8 | 73.8 | 75.5 | 77.0 |
| 40–44 | 51.7 | 56.7 | 63.5 | 66.8 | 71.5 | 70.5 | 72.4 |
| 45–49 | 51.0 | 54.8 | 59.4 | 65.3 | 70.8 | 70.1 | 74.1 |
| 50–54 | 52.5 | 56.5 | 56.9 | 62.9 | 66.4 | 70.9 | 76.9 |
| 55–59 | 54.9 | 58.3 | 57.0 | 62.3 | 64.1 | 66.9 | 72.4 |
| 60–64 | 54.7 | 58.0 | 58.5 | 67.7 | 66.6 | 67.0 | 66.9 |

**Table 13** Ratio: median income of full-time female workers to male workers by cohort year

| *Age* | *Year of entry into job market* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *1947* | *1952* | *1957* | *1962* | *1967* | *1972* | *1977* | *1982* | *1987* | *1992* | *1997* | *2002* | *2007* |
| 25–29 | | | | | | | 72.2 | 75.7 | 76.8 | 90.1 | 88.6 | 92.6 | 90.0 |
| 30–34 | | | | | | 61.5 | 69.5 | 72.6 | 78.3 | 82.4 | 82.8 | 86.4 | |
| 35–49 | | | | | 55.7 | 61.6 | 65.9 | 73.8 | 73.8 | 75.5 | 77.0 | | |
| 40–44 | | | | 51.7 | 56.7 | 63.5 | 66.8 | 71.5 | 70.5 | 72.4 | | | |
| 45–49 | | | 51.0 | 54.8 | 59.4 | 65.3 | 70.8 | 70.1 | 74.1 | | | | |
| 50–54 | | 52.5 | 56.5 | 56.9 | 62.9 | 66.4 | 70.9 | 76.9 | | | | | |
| 55–59 | 54.9 | 58.3 | 57.0 | 62.3 | 64.1 | 66.9 | 72.4 | | | | | | |
| 60–64 | 58.0 | 58.5 | 67.7 | 66.6 | 67.0 | 66.9 | | | | | | | |

Of course, the cohort data for 1977 are of little direct use in a contemporary forensic setting. We would like to know the lifecycle relative earnings that are likely to be faced by a worker who is entering the labor force in 2007. In effect, this requires obtaining estimates of the missing entries in the '2007' column.

One way to supply the missing information is to assume that the trends in the female to male income ratios observed in each age group over the past 30 years will persist up to a limit of equality. In particular, let $R_{a,t}$ denote the female to male income ratio for age group '$a$' for the cohort that is 25 to 29 years old in year $t$. Letting $t$ equal 0 for 1975, 1 for 1976 and so on, we can model then estimate a regression of the form:

$$R_{a,t} = 1 - e^{\alpha_a + \beta_a t + \varepsilon_{a,t}} \tag{5}$$

For $\beta_a < 0$, the expected ratio will approach 1. Converting equation (5) to logs,

$$\log(1 - R_{a,t}) = \alpha_a + \beta_a t + \varepsilon_{a,t} \tag{6}$$

We model the error term in equation (6) as a first-order serially correlated process, $\varepsilon_{a,t} = \rho_a \varepsilon_{a,t-1} + \eta_{a,t}$ and estimate (6) for each age group using data on female to male median income ratios from 1975 to 2007. Results for each age group ($a$) are shown in Table 14. Coefficients are shown with their standard errors below. All coefficients are negative, as expected, and highly statistically significant. The negative coefficients indicate that over time, the female/male wage gap is shrinking for all age groups. Notice that the absolute value of the coefficients is greater for younger

**Table 14** Estimates of equation by age group

| | *Age group* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| $\alpha_a$ | −1.111 | −0.963 | −0.817 | −0.730 | −0.655 | −0.689 | −0.677 | −0.863 |
| Std. Err. | 0.114 | 0.038 | 0.030 | 0.036 | 0.019 | 0.043 | 0.033 | 0.018 |
| $\beta_a$ | −0.046 | −0.030 | −0.023 | −0.021 | −0.021 | −0.022 | −0.016 | −0.008 |
| Std. Err. | 0.009 | 0.002 | 0.001 | 0.002 | 0.001 | 0.003 | 0.003 | 0.001 |
| $\rho_a$ | 0.600 | 0.282 | 0.328 | −0.021 | 0.396 | 0.557 | 0.532 | −0.065 |
| | 0.077 | 0.139 | 0.263 | 0.001 | 0.135 | 0.161 | 0.100 | 0.108 |
| $R^2$ | 0.896 | 0.906 | 0.936 | 0.959 | 0.959 | 0.921 | 0.854 | 0.529 |

**Table 15** Projected female/male income ratios: women entering workforce in 2007

| | *Age* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *25–29* | *30–34* | *35–39* | *40–44* | *45–49* | *50–54* | *55–59* | *60–64* |
| Projected female/male earnings ratio | 0.900 | 0.876 | 0.830 | 0.815 | 0.828 | 0.844 | 0.813 | 0.750 |
| Cross-sectional female/male earnings ratio | 0.900 | 0.864 | 0.770 | 0.724 | 0.741 | 0.769 | 0.724 | 0.669 |
| Difference | 1 | 1.013 | 1.078 | 1.125 | 1.117 | 1.098 | 1.123 | 1.121 |
| Standard error[a] | | 0.016 | 0.018 | 0.036 | 0.015 | 0.033 | 0.039 | 0.036 |
| Projected earnings | $32,305 | $36,719 | $41,393 | $41,694 | $42,682 | $44,332 | $45,395 | $42,805 |
| Cross-sectional earnings | $32,305 | $36,233 | $38,410 | $37,047 | $38,211 | $40,383 | $40,433 | $38,171 |

[a]The standard errors are obtained by Monte Carlo methods and take into account uncertainty in the estimated coefficients from Table 14.

than older women. This indicates that the rate of shrinkage is greatest for the younger age cohorts.

The estimated equation from Table 14 can be used to project the future ratios of female to male earnings for each age group when cohort effects are considered. The ratios are shown in the first row of Table 15. For comparison, traditional ratios using cross-sectional earnings data are shown in the second row of Table 15. The percentage differences between the ratios are shown in the third row and the standard errors of the differences are shown in the fourth. For all age groups, the cohort-adjusted predicted ratios are above the ratios using the cross-sectional data. The difference in ratios shows that by the time women reach ages 40 to 44, the cohort-adjusted ratios are at least 10 percent greater than the cross-sectional ratios. In aggregate, cohort effects seem to matter. Using a traditional cross-sectional age-earnings profile significantly underestimates women's expected lifetime earnings.

Practicing forensic economists can readily use the results in Table 15 to estimate a young woman's age-earnings profile. First, collect year 2007 CPS data on male earnings by age group. Then multiply those figures by the ratios in the first row of Table 15. The projected earnings are shown in the penultimate row of Table 15.[2] Median income steadily rises from $32,305 at ages 25 to 29 to $45,395 through ages 55 to 59. It then falls somewhat at ages 60 to 64. For comparison, the last row in Table 15 shows women's median earnings using the traditional cross-sectional approach. It is apparent that the traditional approach underestimates earnings by four to five thousand dollars per year in the later parts of women's careers.

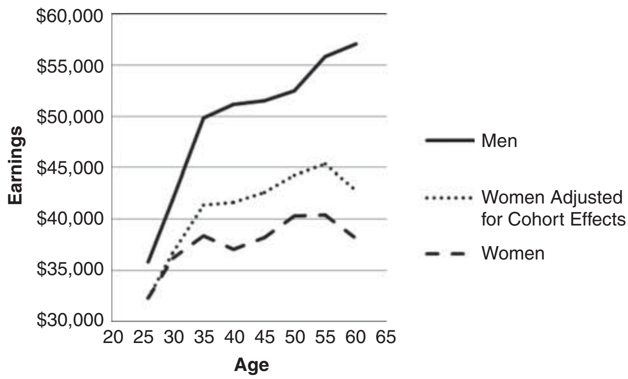


**Figure 1.** Expected earnings by age for cohort entering job market in 2007.

Figure 1 shows projected earnings for the cohort of women aged 25 to 29 in 2007 using male earnings and the estimated ratios of female to male earnings. The upper-most curve is the lifecycle earnings projection for men. The lower-most curve is the traditional cross-sectional lifecycle earnings function for women. The center curve shows women's expected earnings when those earnings are adjusted for cohort effects. This cohort adjustment significantly increases expected earnings and helps close the male-female earnings gap. However, the gap is not completely closed. The results in Figure 1 may be very relevant to forensic economists who use male earnings to estimate lifecycle earnings for women in younger cohorts. It clearly shows that doing so would overestimate women's lifecycle earnings. Women are catching up to men, but these estimates suggest that they still have a way to go.

## CONCLUSION

Traditional cross-sectional age-earnings analyses assume that as women age, they take on the labor market characteristics of women in older age cohorts. Data show that this is not the case. Cohorts of younger women are relatively better educated than their older counterparts. They also have access to and participate to a greater extent in higher paying occupations. Ignoring women's evolution in the workplace can significantly underestimate an age-earnings profile. In this article we compare age-earnings estimates generated using the traditional cross-sectional approach to estimates that predict earnings when accounting for cohort effects. This cohort adjustment produces a far more realistic projection of a woman's expected earnings.

The analysis begins by adjusting for women's growing levels of educational attainment. We use CPS data to predict lifetime educational attainment and to predict earnings by education for women that are aged 25 to 29 in the year 2007. The predictions are combined to develop an education-adjusted age-earnings profile. This profile is compared to a profile developed using traditional cross-sectional methods. The results indicate that young women entering the workforce in 2007 will be relatively better educated than their older counterparts and from ages 45 to 64 will earn from 8 to almost 12 percent more than would be predicted by using traditional cross-sectional techniques. We then use a similar method to compare earnings profiles when occupation access is considered. These results indicate that because of greater participation in higher paying occupations, young women entering the workforce in 2007 will earn more than would be predicted by using traditional cross-sectional age-earnings projections. The difference ranges from 5 to 10 percent more as they move into the second half of their working lives.

Our third analysis accounts for cohort effects more comprehensively. To do this we examine trends in women's earnings relative to men's. A time series model is developed that estimates expected future gaps between women's and men's earnings at specific ages as we look at successive cohorts. These expected gaps are used to form a cohort-adjusted age-earnings profile for women. This adjusted profile shows that women entering the job market more recently can expect to earn significantly more than predicted by traditional cross-sectional estimates. All three estimation approaches support the conclusion that, for women aged 25 to 29 in 2007, their earnings can adjust upward by as much as 12 percent once cohort effects are considered.

Women's experiences in the labor market have evolved greatly over the last 30 years. How the educational mix, occupational mix, and wage gaps will change over the next 30 years cannot be known with certainty. However, forensic economists are forced to make some prediction about how these characteristics will evolve when they arrive at appropriate damage estimates. We argue that the traditional estimates based on cross-sectional age-earnings profiles are likely to underestimate by a substantial margin the earnings potential of young women. When overall cohort effects are considered, the traditional age-earnings profile can underestimate women's expected earnings by more than 10 percent. Sometime in the future, as current birth cohorts work their way through their lifecycles, the problems pointed out by this paper may disappear. For now, however, forensic economists need to rethink their approach to estimating age-earnings profiles.

## Acknowledgements

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## Notes

1. In the equation, the $\alpha_n$ are the average earnings from the cross-sectional data for all women in age group $n$.
2. Note that the values in Table 15 are in year 2007 dollars and do not account for wage inflation over time.

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