Income Prospects of British Columbia University Graduates

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ABSTRACT

Using a new dataset which combines the 1982-1997 tax records and administrative records of British Columbia bachelors graduates from the classes of 1974-1996, I examine the real market income of graduates, focussing on changes in income between graduating cohorts, as well as differences across major fields of study. For men and women BC graduates, there has been a decline in real annual income received after graduation for more recent cohorts which is eventually offset by a higher growth rate in income. Also, annual incomes after graduation are relatively high for graduates with applied degrees such as in the engineering, education, and health fields, however, the range of incomes narrows as graduate cohorts age. The former finding is at odds with those of Beaudry and Green (1997) who found that weekly earnings declined across cohorts for male university graduates, with no offsetting rise in the growth rate (their results were more similar for women). Differences may be due to this paper's use of annual income as an outcome measure, or its focus on BC student's outcomes rather than national outcomes.

Keywords: Returns to education. JEL: I21, J31

Introduction

One question facing analysts and critics of the post secondary education system in Canada is: what are the returns to education? High school students ask: should I go on to university, college or a trade program, and what should I take? Governments and policy makers ask what kind of education they should be funding? Analysts of the macro-economy examine human capital investment and try to understand the connection between a country's brainpower and its aggregate growth rate and income inequality.

This paper informs these debates by providing a previously unobserved piece of information: what are the actual long-term market outcomes of university graduates. Using new data I examine the incomes of bachelors graduates of British Columbia universities for up to 23 years after they graduate. Twenty-three graduate cohorts of students are examined—those students graduating from a bachelor or equivalent certification between 1974 and 1996.

Many questions could be answered with this dataset. In this paper I attempt some broad analysis, leaving much more detailed work for the future. Specifically, I ask: (1) how do more recent cohorts of graduates fare relative to earlier graduates; and (2) how does income growth differ for graduates from different fields of study? I examine only graduates between the ages of 21 and 25 when they obtained their degree, thus individuals are at roughly the same starting points with respect to age and potential experience. I present results for each of eight major fields of study. A median regression technique is used to minimize the influence of outlying observations.

This data provides a unique perspective on the incomes of British Columbia bachelors graduates. However, one should not necessarily ascribe the income levels observed to the bachelor program. The graduate may continue on in studies in another province, perhaps in another program, and this cannot be known with certainty with this data. Hence, the results in this paper refer to the market prospects of graduates observed to be passing a common milestone—graduating from university with a specific major.

The main findings are:

- Median real market incomes for both men and women graduates are lower for more recent cohorts than past cohorts in the first years following graduation. However, the rate of growth in incomes is higher for more recent cohorts, so incomes eventually catch up, and indeed surpass those of past cohorts. This is in contrast to the findings of Beaudry and Green (1997), who examined weekly earnings and found a pronounced downward shift in the age-earnings profile for more recent cohorts of university educated men and no increase in the rate of growth in earnings to compensate. For women, their results were similar to this study. Important differences between this study and Beaudry and Green's—the use of annual income rather than weekly earnings, the use of BC data only in the present study, compared to nationally representative data used in Beaudry and Green, or other differences in methodology—may account for these differences.
- Median incomes for graduates from different fields of study converge (though not fully) as graduates age. Graduates from fields of study which start at lower median levels tend to narrow the gap

relative to their higher income counterparts. Incomes grow for both groups, but they grow at a faster rate for those that start out lower.

Background

Several studies which examine the future prospects of Canadian university graduates have been produced in recent years. These studies differ slightly in methods, data and outcome measures used.

One common approach is to examine age-earnings profiles—a curve which graphs the average level of earnings (or income) obtained at each level of age. Such a profile can be constructed using a single cross sectional survey where age and earnings are defined. Allen (1998) constructs these profiles for men and women high school non-completers, high school graduates and university graduates using data from the 1991 Census. He finds that male university graduates and women graduates older than 30 earn more than their non-university counterparts. Women university graduates in their 20s earn slightly less than non-university graduates, but pass them later in their careers. Allen also examined earnings for graduates from different fields of study. He found that among women there was substantial convergence for undergraduates from different fields, while for men, there was less convergence.[1]

One problem with analyses that use a single cross section of data to examine age-earnings profiles, is that one must look across outcomes from different graduating cohorts. For example, men in their 20s in 1991 graduated in the mid- to late 1980s, while those in their 50s may have graduated as much as 30 years earlier. There is no way of knowing if the incomes of the older men accurately reflect the future incomes of the younger men. If age-earnings profiles are shifting downward over time, the use of results from a single cross sectional survey will cause the age earnings profile to appear more steep than it is—predicting higher future incomes than will actually be realized.

One solution is to follow age cohorts through time using successive cross sectional surveys— commonly dubbed a synthetic cohort approach. This approach allows one to examine the outcomes of representative individuals from successive age cohorts and provide unbiased estimates. Beaudry and Green (1997) examine age-earnings profiles across synthetic cohorts and find that cross sectional results do overestimate the eventual incomes of male graduates. In fact, age-earnings profiles of successive graduates of men were shown to be shifting downward since the mid-1960s, implying that at every age level, recent graduates earned less than past graduates. For women, age earnings profiles appear to be pivoting. Recent women graduates also start out at a lower income level than past women graduates, but their earnings rise at a faster rate with age, suggesting a quick catch up and eventually higher incomes relative to past cohorts. Allen (1998) studied data from the 1970, 1980 and 1990 censuses and the SCF for 1995 for young men and women aged 25-29 in British Columbia and similarly found an erosion of real income for all education levels between 1980 and 1995. The decline for men was about 12% and for women it was about 5%. These declines were shared by young men and women of all education levels.

[1] Allen (1998) also examines occupation and unemployment outcomes, plus examines outcomes using the 1995 follow-up to the 1990 National Graduate Survey (NGS) in a manner similar to Finnie (2001).

Finnie (2001) examined earnings differentials by major field of study from the 1982, 1986 and 1990 National Graduates Surveys (NGS), and their respective two and five year follow up surveys. This set of surveys offers the possibility to examine two and five year outcomes across three cohorts of graduates using true (as opposed to synthetic) longitudinal data. Finnie examines bachelors graduates who, by two and five years out have not completed a second degree and are not enrolled in another program. Across cohorts, raw earnings were found to be falling for men (measured both two and five years out) and rising for women two years out but not five years out. Finnie also discovered substantial variation between majors, and earnings growth rates also varied by field of study. The various statistical reports from the NGS (HRDC 1997, 1999) provide useful background information on outcomes from this nationally representative survey.

Finally, Côté and Sweetman (1998) examined wage differentials across fields of study using the General Social Survey conducted in 1994. In that study a subtle point is made: that observed differences by field of study may not accurately represent the true differences in field of study since persons are not randomly selected into degree programs. In fact, persons choose programs best suited to their talents. Unadjusted results for men are shown to underestimate the inter-field differentials, while no evidence for this was found for women.

The present study is closest in spirit to Allen (1998) and Finnie (2001), but closest in approach to Beaudry and Green (1997).

Data

Data Sources and Matching

The dataset used in this study is created by augmenting graduate information obtained from the University Student Information System (USIS) with income data from the T1 Family File (T1FF).[2] USIS is a national database containing pertinent up-to-date information on student participation in and graduation from Canadian degree granting institutions obtained from administrative records provided at the individual level.[3] USIS data is available annually, from the 1974 graduating year to the most recent

[2] The T1 Family File is created and maintained by the Small Area and Administrative Data Division of Statistics Canada and is currently available from 1982 to 1997. Briefly, the T1FF comprises all the T1 tax records filed by Canadians, grouped into families. Children and non-filing spouses of tax filers are imputed records based upon information gleaned from the tax filer's T1 record. Thus, income from all sources including market and transfer income sources and the income tax bill can be tallied for each family along with its basic demographic profile and area of residence. The file is potentially large—containing over 29 million records in 1997. For the purposes of this study I link only the graduate, leaving analysis of the graduate's family to future work.

[3] USIS has two main components. The *enrolment* survey collects information on student counts, and requests information on a broad array of student and program characteristics including institution, province, gender, age, mother tongue, immigration status, country of citizenship and country of origin, full- or part-time status, type of qualification sought (e.g., bachelor, masters, etc., or none), field of study, year of study in program and Social Insurance Number. The *degrees* survey collects information on all students who have received a degree, diploma or certificate during the calendar year. The degrees survey has a more limited number of data elements than the enrolment survey. These datasets have been merged by the Education, Culture and Tourism Division of Statistics Canada, creating a third file commonly referred to as the *linkage* file. I use the linkage file in this analysis.

year available which is 1998. USIS identifies major field of study at a finely detailed level. I conduct the analysis at a highly aggregated level.

Specifically, I examine 8 major fields of study: (1) Education, Physical Education, Recreation and Leisure; (2) Fine and Applied Arts; (3) Humanities and Related; (4) Social Sciences and Related (includes Commerce); (5) Agriculture and Biological Sciences; (6) Engineering and Applied Sciences; (7) Health Professions and Occupations; and (8) Mathematics and Physical Sciences. USIS identifies graduates from diploma programs, bachelor and graduate degrees, but in this study I examine graduates from bachelor programs only.

There are 25 cohorts of graduates (1974-1998) and 16 years of T1 data (1982-1997) to be combined. The earliest graduates in 1974 can have outcomes observed as late as 1997, for a 23 year outlook on incomes of university graduates. I link graduates up to the 1996 cohort. For these graduates, only one year of outcomes is observed. The 1997 and 1998 cohorts are dropped since outcomes cannot be examined for these graduates yet. The matching key is the Social Insurance Number. Table 1 lays out the cohort patterns I link. The resulting datafile is longitudinal, but in this analysis I treat the data as a series of consecutive cross sections. The outcome I focus on is market income, defined as the sum of taxable earnings from employment and self-employment plus taxable income from assets. It is converted to real terms using the CPI (1992=100) as a deflator.

The quality of the results depends on the success rate of the match between USIS and the T1FF—data from both sources are required to answer the questions posed above. Not all graduates identified in USIS are successfully linked to the T1FF, which means that market income is missing for some graduates. The success rate of the match varies widely across provinces, and is highest in BC, prompting a focus on that province for the present study. For other provinces, representativeness may be obtained for some years. Possible explanations for non-matching include the incomplete or inaccurate reporting of the matching variable, and the non-filing of the tax return due to a lack of labour force participation, or leaving the country.

Figure 1 displays the numbers of university bachelors graduates in BC for each graduating year from 1974 to 1996. The annual number of graduates has roughly doubled over this period. On average, market income is obtained for 71% of BC graduates in each post graduation year between 1982 and 1997.

Representativeness

In the following analysis we examine only graduates for whom we have income information. For this data to be representative of the population of BC students, it is important that the demographic characteristics of graduates with income information resemble those of graduates without. The minimum to be done is to show that there are no large differences in the characteristics of graduates in and out of the sample. Figure 2a shows the number of graduates, averaged across graduation years by field of study (top panels). Both men and women graduate most often with a social sciences degree—more than 1,400 per year. Relatively few men and women graduate with fine arts degrees, and few women graduate with an engineering or math and physical sciences degree. Education, humanities and health degrees are more popular for women than men.[4] The lower panels of Figure 2a show the fraction of graduates with missing income information (averaged across each year following graduation). This varies from field to field for men and women, however, there does not appear to be any major under-representation of men or women for any field of study.

Figure 2a averaged results across graduate cohorts. In Figures 2b-2d I show the fraction of graduates with income information for each graduate cohort. The values in this graph mark the proportion of graduates with income information in each post-graduation tax year, averaged across post graduation tax years. There appears to be two phases in the data. In the first, lasting from 1974 through 1988, approximately 68% of graduates (measured cross-sectionally) have income information identified in the file, while after 1988 the fraction rises markedly to 79%. This change is due to an improvement in the reporting of matching keys by the universities after 1988. In what follows, I assume that income information is matched randomly across income levels.[5] To ensure that the improvement in the data following 1988 does not influence my results I estimate alternate models in Appendix 1 where covariates are interacted with a pre-1989 dummy variable. Results from these models confirm the other estimations in this paper.

The Final Sample

For the final sample, I select only graduates with positive market income who were between the ages of 21 and 25 in the years they graduated. Two thirds of graduates fall into this age range (21: 12.5%, 22: 20.9%, 23: 16.5%, 24: 10.6%, 25: 7.1%).This is done to control for the life-cycle position of graduates. All graduates in this analysis have approximately equal age and potential past work experience.[6]

A Note on the Interpretation of Results

For this study, I do not control for events that occur after graduation. This raises the important point that the future incomes of some graduates may derive from further study in some program other than the one in which they did their bachelors degree. For example, some sciences graduates may later get a law degree. That graduate may earn the income of a lawyer, but I measure him or her as having a background in sciences. This is a pitfall inherent in the data, caused by the inability to link bachelors graduates who go on to graduate studies in, for example, another province. Thus the results in this paper should be thought of as reflecting students at a specific point in their human capital accumulation and not as having necessarily completed their highest level of education.

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4 2.7% of graduates were dropped from the analysis since they did not have a major within these 8 fields.

5 The alternate approach which is to model the selection process using a sample selection model is prevented by the lack of covariates in this dataset which might be used to predict the probability of selection, which do not also influence the outcome in question.

6 In Appendix 1, I test the findings to a more restricted criterion that age at which income is measured is also at least 25. This is done in order to roughly approximate Beaudry and Green’s sample criteria. As with other sensitivity tests, it has little impact on the results of this study.

Another way to think of this is to distinguish between (1) the income of people who graduated from a particular program (in a particular year), and did not obtain any further education and; (2) the income of people who graduated from a particular program (in a particular year), no matter what further education they obtained. The former measure would be needed to identify the returns from a specific field of study. The latter is still useful since it speaks broadly to the question of the success of graduates from different fields, without making any claims as to the returns from these specific degrees.

Results

Descriptive Results

One of the challenges encountered in analyzing data that spans several cohorts of graduates measured at various levels of experience, and in different tax years is one of isolating *age* effects *cohort* effect and *year* effects. In this section, I provide a descriptive look at the data, while in the next section I develop a more rigorous statistical model.

While this paper mostly discusses changes in incomes, the results should be placed in a context of important structural changes in the composition of graduates, mainly by gender, but also by field of study. In the Figure 3a and 3b, I show the composition of the sample of graduates by major field of study. The largest change by field is towards more social sciences and humanities graduates, and away from education and phys-ed degrees. Figure 3c shows results by gender. Here the shifts are more pronounced, as the relative shares of men and women grads have completely reversed over the length of the panel from 60/40 in favour of men in the later 1970s to 60/40 in favour of women in the mid-1990s. (Changes in composition among all graduates are similar to these changes in this sample of graduates.)

Figure 4a and 4b show median income of graduates by year of graduation according to the number of years that have passed since graduation. In Figure 4a, 1 (the lowest line) to 10 years (the highest line) after graduation are shown. Common to all these lines are strong cyclical effects—outcomes are higher in good years of the business cycle. Less evident are cohort effects. Declining incomes across cohorts would appear in these lines as downwards slopes. Indeed, some of the lines appear to be sloped downward, but one would want to remove the year effects to be sure. Outcomes from 11 to 23 years following graduation are shown in Figure 4b. As before, median income rises with time, but the profiles become more jagged as the differences between outcome years declines, and any cohort effects become hard to see.

The underlying data could also be presented as a series of age-income profiles: a curve which graphs the median level of income for each level of age separately for each graduate cohort. This is done for the 1975, 1980, 1985, and 1990 graduate cohorts in Figure 5a. Age is measured as the number of years since graduation.[7] Age-income profiles have a shape similar to the familiar age-earnings profile, where earnings tend to increase quickly when young and more slowly when older. A shift downward (towards the x-axis) across cohorts would indicate that successive cohorts are achieving lower levels of income

[7] Strictly speaking these are not age-income profiles, but rather they reflect 'years since graduation'-income profiles. I use the common term "age-income profile" to avoid confusion.

for similar levels of experience. Any downward shifts are difficult to see in this presentation, and adding more cohorts to the graph would further obscure any findings. Furthermore, cohorts graduating in, say, 1990 would benefit from more favorable economic conditions than those available to those graduating in 1980, possibly obscuring shifts in this graph. Unemployment rates have roughly stabilized since 1990 in BC, so one could roughly compare, say, the 1989 and 1994 graduates. Age-income profiles for the 1989 and 1994 cohorts are in figure 5b. Here there is a small but distinct downward shift in the profile for the first few years following graduation, but also a potential convergence in the lines due to a faster growth in the income of the second cohort.

What of age-income profiles by gender and field of study? Figure 6a shows results averaged across cohorts for men, while Figure 6b contains profiles for women. Age-income profiles differ by gender. Women's profile is lower than men's, and displays a marked "dip" after 5 years which may be related to women reducing their labour market activity in order to have children in their late 20s and early 30s. Age-income profiles also diverge over time, with men's median income 1.4 times the rate of women's 1 year after graduation and 1.6 times after 23 years. This will be due both to differences between men and women in all fields of study, and differences in the choices of field of study made by men and women. Differences in age-income profiles are also apparent by field of study. For men, health and engineering graduates have the highest median outcomes. In addition, the difference between fields in the short run overstates the difference in the longer run, although the age- earnings profiles do not appear to fully converge over time (Figures 6c and 6d).[8] For women, there are few graduates in engineering or math and physical science graduates, lending an erratic nature to these time series. Women in the health and education fields tend to start off relatively high, but incomes in these fields tends to stabilize after three or four years with the results that graduates in other fields, except fine arts, tend to catch up (Figures 6e and 6f).

What does the preceding analysis tell us about our two main questions? There was some evidence that median income declined between the 1989 and 1994 cohorts, although it also appeared that the downward shift was temporary, being quickly nullified by faster income growth of the later cohort. Also, there does appear to be an income advantage associated with certain fields of study which declines, though not fully, over time.

A Statistical Analysis

I now turn to a statistical analysis of the data in order to provide a clearer representation of changes in incomes across cohorts. I estimate the following equation:

$$\ln(y)=\beta_0 + \beta_1 C + \beta_2 C^2 + \beta_3 T + \beta_4 T^2 + \beta_5 T^3 + \beta_6 T^4 + \beta_7 CT + \beta_8 UR \qquad (1)$$

where *ln(y)* is the log of median market income defined across 248 cohort-age groups. C is a cohort vector where $C=i$ for the graduating class of $1973+i$. b_1 captures the change across cohorts in income due to a shifting of the age-income profile, with negative values for b_1 indicating that the profile is shifting down over time. C^2 captures the possibility that cohort incomes are falling at an increasing or decreasing rate. T measures the number of years passed since graduation, and reflects potential post-graduate

[8] In Figures 6c-6f medians based on 50 or fewer observations are suppressed.

experience. T, T^2, T^3 and T^4 together represent a quartic age-income profile.[9] CT is an interaction term between cohort (C) and time since graduation (T). Positive values for b_7 indicate that the growth rate of income is increasing across cohorts, while negative values indicate that the growth rate for income is declining across cohorts. UR is the quadratically detrended unemployment rate for BC workers aged 45-54, and is included to capture cyclical effects on income.[10]

Equation (1) is estimated using weighted least squares where the weights are given by the number of observations in the cell. This approach follows Chamberlain (1991) and the results are expected median real income. This estimation approach makes the results insensitive to the presence of extreme or outlying values, and sidesteps the issue of having to estimate median regression on such large sample sizes.[11] y is measured in log form so coefficients can be interpreted as percentage deviation from the reference group. Estimation of (1) is not restricted to median values, and similar models could be estimated for other percentiles in order to decompose changes in the distribution of income.

Note that equation (1) is not estimating a causal model of income. It is simply a useful way of decomposing descriptive results into different components. For one thing, it lacks several important determinants of income, such as the unionization status, firm size and industry effects which one would normally want to control for to determine the effect of, say, major field of study on earnings. Second, (1) cannot tell us the causal effect of graduation from a particular field of study on future income since students are not randomly selected into different programs. These outcomes should not be interpreted as expected outcomes of a randomly selected student entering university. Also, as stated above, I cannot control for highest level of education attained, so these results apply to students at a particular point in their human capital accumulation—that is measured at the point of obtaining an undergraduate degree. Some of these students will continue to accumulate more human capital, sometimes in a different field of study.

9 Recall that graduates are restricted to being between 21 and 25 inclusively, so time since graduation equals approximate age. A model which uses actual age instead of years since graduation is discussed in Appendix 1. Adding actual age to the model does not alter the substantive conclusions. The quartic provided the best fit across all models, with the 4th term usually significant.

10 The detrended unemployment rate (UR_{di}), equals $\beta_0 + \varepsilon_i$ obtained from the OLS regression $UR_i = \beta_0 + \beta_1 TIME_i + \beta_2 TIME_i^2 + \varepsilon_i$, where UR_i is the unadjusted unemployment rate for men and women aged 45-54 in year i and $TIME_i$ indexes years. Actual and detrended unemployment rates are:

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
UR	8	9.1	10.5	10.3	9.1	8.6	8.1	7.1	5.4	6.6	7.4	7.4	6.3	5.6	6.4	5.8
UR_d	8.3	9.7	11.4	11.4	10.5	10.3	10.1	9.3	7.9	9.4	10.4	10.7	9.8	9.4	10.5	10.1

11 Thus, model estimation is performed on cell medians rather than individual observations. Using weighted least squares ensures that standard errors are unbiased. It also provides heteroskedastic consistent standard errors. Estimation using median regression on a subsample of micro data produced similar results. Estimation using OLS tends to be adversely influenced by outliers in this dataset. OLS estimates for C, C^2, and CT are closer to zero, and for women sometimes insignificant. The RREG procedure in STATA (StataCorp, 1997) provides coefficient estimates at the mean after down-weighting outliers. Results using this procedure on a subsample of the data are highly similar to the median estimates reported here. See Appendix 2 for a discussion of these issues.

Results for Men and Women

Results for equation (1) are shown in column 1 of Table 2 for men. A negative term for *C* indicates that cohort intercepts are declining while a positive term for C^2 means that they are declining at a decreasing rate. The interaction term *CT* is also positive indicating that while the intercept of the age-income profile is declining across time, the rate of return to experience for men is increasing. This suggests that changes in the age-income profile between cohorts may be better characterized as a change in shape, rather than a downward shift. That the profiles are shifting down at a decreasing rate suggests that larger declines occurred in the late 1970s and early 1980s compared to the early 1990s.

How large are the changes implied by these coefficients? Figure 7a shows raw results and Figure 7b shows predicted results for selected cohorts of men. Recent cohorts of graduating men started at lower levels of income than past cohorts, but incomes caught up and eventually surpassed previous cohorts. According to Figure 7b, the point of intersection—where incomes of recent cohorts begin to surpass those of past cohorts, is between 5 and 8 years following graduation. This suggests that studies using the National Graduates Survey, which only provided a 5 year outlook on incomes after graduation may not have seen this eventual catching up of incomes for more recent cohorts.

Column 2 of Table 2 shows results for women. Results are qualitatively similar as for men.[12] Women's starting incomes declined at a decreasing rate across cohorts. As for men, while graduates started at lower levels of income, income growth was faster for more recent cohorts, suggesting a catch up in incomes.

Figure 8a shows raw data and Figure 8b shows predicted values for selected cohorts of women. Like men, recent cohorts of graduating women also started out at lower income levels, but their incomes caught up and eventually surpassed earlier cohorts. The point intersection for women was earlier than for men—recent cohorts incomes began to surpass previous cohorts between 2 and 4 years. A second result for women that is apparent from the graph is that the characteristic slowdown in women's incomes starting about 5 years following graduation appears to be either lessening or being postponed until after more post-graduation experience has been obtained.

Results by Field of Study

The results reported in the previous section do not control for changes in the composition of graduates by field of study. One can easily alter equation (1) to control for field of study by including dummy variables for each of the 8 major fields of study. One field of study category must be omitted to estimate the model, and I omit the social sciences dummy variable, making the estimated coefficients for the rest of the field of study categories relative to social sciences. For these regressions, there are 1,984 observations of median income (by age, cohort and 8 major fields of study). Results are shown in Table 3 for men and women.

[12] A pooled men and women model which tests the hypothesis that the change in intercept and slope coefficients were different by gender shows that the changes experienced by men and were not significantly different (p-values on interactions between a gender dummy variable and C, C^2 and CT were all greater than 0.1).

Qualitatively the results are the same as if we had not controlled for field of study. The largest difference is that the decline in intercepts observed is larger than if one did not control for field of study, suggesting that some of the decline across cohorts has been offset by an increased tendency for students to graduate from fields of study with higher median returns. This is reflected in the larger size of the Cohort variable in Table 3 compared to Table 2.

Intercepts implied by the field of study variables reflect differences in expected outcomes by field of study. Do these differences increase or decline as the cohorts age? To answer this, I interact the seven field of study dummy variables with the years since graduation variable (T). Results for the field of study and interacted variables are given in Table 4, other coefficients being similar to those reported in Table 3.

A clear finding from Table 4 is that median incomes converge as graduates age and gain experience. Fields of study with higher expected median income, represented by positive and significant values for the field of study dummy variable, have below average growth rate, shown by a negative and significant value for the field of study by age interaction term. For example, men in education start at median income levels approximately 12% above social sciences graduates, but their incomes grow 1.3% slower each year. Women in health start at incomes 53% higher than women in social sciences, but their income grows 3.1% slower each year.

How much do median incomes converge? Table 5 shows predicted median incomes by sex and field of study, along with the mean prediction, the range of predictions (the maximum minus the minimum value), and the ratio of the range to the mean prediction.[13] The range of predictions represents the absolute amount of variance in incomes, while the ratio of the range to the mean reflects the amount of variation in incomes relative to the mean. In Table 5, cohort effects are removed by setting the cohort variable to its 1974 value.

Table 5 shows that the range of incomes (from maximum to minimum) is declining for men and women. After one year the highest paid field received income of 36,733 more for men and 29,005 for women. (Because estimates of incomes for women in engineering and math and physical sciences are based on few observations, and appear to be inaccurate, I exclude them in these calculations.) The corresponding figures after 20 years were 30,435 for men and 18,425 for women. This range also fell relative to mean incomes. For men and women, the range was roughly 25% larger than the mean income after one year (range/mean=1.29 for men and 1.25 for women), and about half of the mean by the 20th year.

Thus in terms of convergence in incomes as graduates age, there is a closing of the range of incomes for graduates from different fields of study.

Data from Table 5 are plotted in Figures 9a for men and 9b for women. The data is arranged in order to visually identify field of study groups that earn approximately equal median incomes. For example, in Figure 9a one sees that one year out from graduation, graduates from fine arts (indicated by a 2 on the

[13] A second model wherein the seven field of study dummy variables were interacted with T, T^2, T^3, and T^4 was used for the predictions in table 5. This was done in order to allow for more flexibility in the age earnings profiles and to allow for a better overall fit.

chart), humanities (3) and biological sciences (5) form a lower earnings group, social sciences (4), math and physical sciences (8) and education graduates (1) form a medium level earnings group, and health (7) and engineering (6) graduates form a higher earning group. By 15 years following graduation, one could classify fine arts into a low-median income group, engineering and health into a high income group, and the other fields into a medium income group.

For women, by 15 years out most fields fall into a narrow range of incomes, with only fine arts (group 2 on the graph) standing out as a relatively low-median income group (Figure 9b). Except for fine arts, predicted medians fell within a $6,500 range. As before, I omit inclusion of the engineering and math and physical sciences fields because of the small numbers of observations for women in these fields.

Note that the preceding discussion refers to median incomes only. It would also be interesting to know what the distributions of incomes are around these medians. Some fields of study may have higher variations than others, suggesting a closer link between the graduating program and actual outcomes. I leave this subject to future work.

Discussion

While explaining these effects would require more information, one can speculate as to plausible underlying factors. Declines in starting incomes for more recent graduates, particularly men, may reflect the well known decline in earnings for young men—a phenomenon thought to have begun in the early 1980s. However, a corresponding decline for women has not been uncovered in the literature, and the finding that recent cohorts of men catch-up to past cohorts disagrees with the current view that earnings have declined across cohorts (as shown in Beaudry and Green, 1997).[14]

Two possibilities for the difference between the literature and my results include the use of annual income rather than weekly earnings, and the use of BC data only in the present study.

An increased trend of bachelors graduates continuing on to graduate studies represents one possible explanation consistent with the change in the shape of the age-income profile found in this study. A shift towards more graduate studies would affect the shape of the age-income profile, presumably keeping it lower than corresponding profiles for non-graduate students at first, but eventually rising at a faster rate after completing graduate studies. In the present study, the impact of increased enrolment in graduate studies was not considered. This is because one cannot gauge with certainty whether a particular student continued on to graduate studies. Beaudry and Green's sample included students with "higher than bachelor" degrees, so while this explanation fits with my results, it does not reconcile the different findings.

According to the NGS, between 40% and 50% of bachelors graduates pursued additional qualifications within two years following graduation, a trend which declined between the 1986 and 1995 graduating

[14] Data in Figure 7b showed that between 1980 and 1990, predicted annual market income declined by 11%. A close examination of Beaudry and Green's Figure 5b: "Age Earnings Profiles Allowing Differing Slopes by Cohort-Males, University Educated" shows approximately a 5 to 7% drop in weekly earnings for age 26 across the same period. Thus, in terms of the magnitude of the cohort effects, these results are similar. The main difference is in the cohort-experience interaction term.

classes (HRDC, 1999). What is more critical to this analysis is to know what was happening in the late 1970s and early 1980s when the largest changes in post-graduation incomes were taking place. I am not aware of evidence available on this. Further examination of graduate studies enrolment rates using the USIS dataset may enlighten this subject.

The high incomes experienced by graduates of professional programs such as engineering and health may reflect the influence of the "applied" aspects of these programs. Graduates from these programs might be more ready for the workplace than graduates of other programs who need more experimentation with job matches, and to develop skills on the job. In light of this, the relative improvement of graduates in non-professional fields makes sense, as graduates from professional schools are expected to be more productive in the short term. Allen (1998) and Finnie (2001) also make this point. A related factor is that degree holders in "pure" as opposed to "applied" majors may be more likely to pursue graduate degrees, postponing higher incomes, and helping to explain a faster rate of income growth (from a lower starting level) following graduation.

Like this study, Allen (1998) saw a convergence of incomes of graduates from different fields of study. Using a single cross section from the 1991 Census, he finds that gaps between the mean incomes for women working full-year and full-time which are apparent when in their 20s, are largely gone by the time the women reach their 30s. For men, he sees incomes converge to two groups: a more successful group of engineers, social scientists, math and physical scientists, and commerce graduates; and a second tier of education, humanities and fine arts, and biology and other health graduates. My findings are qualitatively similar. By 15 years following graduation, most women's medians incomes by field of study are within a narrow range, after one excludes fine arts graduates who have lower incomes. For men at 15 years there is an upper group of graduates from engineering and health fields, a middle earning group of education, biological sciences math and physical sciences and social sciences graduates and a lower earning group of humanities and fine arts graduates. As usual these groupings represent median outcomes and do not represent the outcomes of all graduates from these fields.

Finnie (2001) found that expected outcomes declined two and five years out for recent cohorts of men, and rose two but not five years out for women. My findings are not inconsistent with these. For men, the point of intersection—where incomes of recent cohorts began to surpass those of past cohorts—is between five and eight years following graduation, suggesting that if Finnie had been able to look at longer outcomes, he may have seen incomes for recent cohorts of graduating men surpass those of prior cohorts. For women, the point of intersection is between two and four years which is consistent with Finnie's finding of no drop in incomes after five years, but not with his finding of a rise in incomes two years out. Finnie's focus on non-continuing students or this paper's focus on BC graduates only might explain this difference.

Finally, the results in this paper refer to median incomes. Investigating the dispersion of incomes is likewise interesting, and should be the subject of further analysis. While humanities graduates earned lower median incomes, it does not necessarily follow that humanities graduates in the top 25% of their field earn less then engineering graduates in the top 25% of their field.

Conclusion

Using a new dataset, I examine the median real market incomes of graduates from BC universities who completed their undergraduate degrees from 1974 through 1996. Incomes are observed from 1982 through 1997 and the analysis is done by gender and by 8 major fields of study. Two questions are addressed: (1) how do more recent cohorts of graduates fare relative to earlier graduates; and (2) how does income growth differ for graduates from different fields of study?

To answer the first question, median real market incomes for both men and women graduates are lower for more recent cohorts than past cohorts in the first years following graduation. However, the rate of growth in incomes is higher for more recent cohorts, so incomes catch up and eventually surpass those of past cohorts. This is true for both men and women graduates. For the second question, median incomes for graduates from different fields of study converge (but not fully) as graduates age. Graduates from fields of study which start at lower median levels tend to narrow the gap with their higher income counterparts. Incomes grow for both groups, but they grow at a faster rate for those that start out at lower levels.

The first finding is perhaps most interesting in the face of the evidence provided by Beaudry and Green (1997) which says that incomes shifted down for consecutive cohorts of men, with no eventual catching up. For women, Beaudry and Green's results were more similar to those found here, with women's weekly earnings starting lower but growing faster for recent cohorts. Analysis of other provinces is possible with this data, and should be undertaken in order to shed more light on this finding. It may be that trends are different for other regions of Canada.

Appendix 1: Sensitivity Tests

Results of sensitivity tests are presented in Table A1 for men and A2 for women. These tests ask the questions: what happens when I adopt an age specification more close to that of Beaudry and Green (1997); what happens when I use actual age rather than years from graduation to model the shape of the age-earnings profile; what happens when I include both actual age and years from graduation; what happens when I drop the first year following graduation; and what happens when I interact the slope parameters with a pre-1989 dummy variable. As in the main text, these models are estimated for men and women separately.

Men

Results in column 1 of Table A1 repeat the results reported in the main text in Table 2 for men. Column 2 reports estimates from a model which restricts the age of tax filers to at least 25. This is meant to make the sample more like that in Beaudry and Green where entry age to the mature labour market was assumed to occur at age 25. Comparing estimates from columns 1 and 2 one sees that the estimates remain significant, and that they are within 2 standard errors of each other.

Column 3 reports results from a model which uses actual age rather than years since graduation to shape the age-income profile. In this estimation, the cohort terms (C and C^2) are smaller, and the cohort-years from graduation interaction term is also smaller (CA as compared to CT in column 1). Adding both age and years from graduation (column 4) returns these effects back to the large size seen in column 1. Thus, measuring the age-earnings profile by age rather than years since graduation also appears to have little influence on the results for men.

Column 5 estimates the model after dropping observations from the first year after graduation. This year could be a “transitional” year when incomes are not reflective of later years. In fact the NGS first examines outcomes two years following graduation. As before, dropping this year’s observations does not affect the results.

Column 6 reports results from a model which interacts a pre-1989 dummy variable in order to allow for the possibility that the change in match rates between 1988 and 1989 affected results. The decline across cohorts (represented by coefficient C) appears to be somewhat understated, as revealed by the larger coefficient for C in column 6 compared to column 1.

Women

The results of these sensitivity tests are similar for women. One notable exception is in column 4 when we include both years since graduation and actual age in the model. For men, the age variables were insignificant compared to the years since graduation variables (Table A1, column 4). In contrast, for women the converse is true. For women, the shape of the age-income profile is better explained by the actual age of women, rather than the number of years following graduation. In the main text, I suggested that the shape of the earnings profile for women was determined in part by women to have children. This decision may be more closely related to the actual age of the woman than the number of years that have passed since graduation. In any case, the substantive conclusions are the same.

Appendix 2: Results Using Micro Data and Mean (OLS) Regression

The purpose of this subsection is to compare results obtained using the grouped median regression as discussed in the main text above with those from alternate regression techniques. Appendix Tables A3 and A4 re-estimate equation 1 for men and women respectively using: grouped mean regression; OLS regression on micro data; OLS regression in micro data with heteroskedasticity corrected standard errors; Median Regression on a 30% sample of micro data; and robust regression using STATA's RREG procedure on a 30% sample.

For men the results are consistent across models. Comparing grouped median results (model 1) with results obtained from the median regression estimation on a 30% sample of micro- observations (model 5) are very close in coefficients and standard errors. The most important effect of moving from median regression to mean regression, whether using grouped data (model 2) or micro data (models 3 and 4) is to reduce the size of the C, C^2 and CT coefficients. This is the result of influential outlying observations as evidenced by the results of model 6 which reduce the effect of outlying observations using STATA's RREG procedure. RREG is a mean regression procedure which gives coefficient estimates after down-weighting outlying observations. Results from the RREG estimation are similar to those obtained in median regression.

The use of regression techniques that are robust to outliers is even more important for women's results. Under mean-regression techniques the estimates for C and C^2 become insignificant and CT is reduced in magnitude by about 2 standard errors. Using mean regression using STATA's RREG procedure one obtains results again closer to those from median regression.

Table1: Cohort Structure

Graduating year	Outcome																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
	year outcome is observed in																						
1974								1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
1975							1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	
1976						1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997		
1977					1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997			
1978				1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997				
1979			1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997					
1980		1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997						
1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997							
1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997								
1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997									
1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997										
1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997											
1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997												
1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997													
1988	1989	1990	1991	1992	1993	1994	1995	1996	1997														
1989	1990	1991	1992	1993	1994	1995	1996	1997															
1990	1991	1992	1993	1994	1995	1996	1997																
1991	1992	1993	1994	1995	1996	1997																	
1992	1993	1994	1995	1996	1997																		
1993	1994	1995	1996	1997																			
1994	1995	1996	1997																				
1995	1996	1997																					
1996	1997																						
1997																							
1998																							

Table 2: Expected Changes in Age-Income Profiles for Men and Women

	men	women
Dependent Variable	ln(real market income)	ln(real market income)
Intercept	10.2543* (0.0472)	10.0764* (0.0595)
Cohort (C)	-0.0335* (0.0043)	-0.0232* (0.0053)
Cohort Squared (C^2)	0.0007* (0.0001)	0.0006* (0.0002)
Cohort*Years Since Graduation (CT)	0.0024* (0.0003)	0.0029* (0.0003)
Years Since Graduation (T)	0.2119* (0.0089)	0.2213* (0.0107)
Years Since Graduation Squared (T^2)	-0.0213* (0.0014)	-0.0313* (0.0016)
Years Since Graduation Cubed (T^3)	0.0010* (0.0001)	0.0017* (0.0001)
Years Since Graduation^4 (T^4)	0.0000* (0.0000)	0.0000* (0.0000)
Unemployment Rate (UR)	-0.0224* (0.0025)	-0.0285* (0.0031)
Number of Observations	248	248

* significant at the 1% level
~ significant at the 5% level

Table 3: Expected Changes in Age-Income Profiles for Men and Women Holding Composition of Graduates by Field of Study Constant

	men	Women
Dependent Variable	ln(Real Market Income)	ln(Real Market Income)
Intercept	10.2852* (0.0544)	10.1170* (0.0668)
Cohort (C)	-0.0431* (0.0049)	-0.0285* (0.0059)
Cohort Squared (C^2)	0.0012* (0.0002)	0.0008* (0.0002)
Cohort*Years Since Graduation (CT)	0.0024* (0.0003)	0.0029* (0.0003)
Years Since Graduation (T)	0.1870* (0.0103)	0.2197* (0.0120)
Years Since Graduation Squared (T^2)	-0.0164* (0.0016)	-0.0311* (0.0018)
Years Since Graduation Cubed (T^3)	0.0007* (0.0001)	0.0017* (0.0001)
Years Since Graduation^4 (T^4)	0.0000* (0.0000)	0.0000* (0.0000)
Unemployment Rate (UR)	-0.0194* (0.0028)	-0.0279* (0.0035)
Education and Phys -ed	-0.0058 (0.0091)	0.0093 (0.0081)
Fine and Applied Arts	-0.5167* (0.0148)	-0.4685* (0.0139)
Humanities	-0.3227* (0.0095)	-0.1762* (0.0094)
Biological Sciences	-0.2187* (0.0080)	-0.1091* (0.0096)
Engineering and Applied Sciences	0.2254* (0.0074)	0.2299* (0.0231)
Health	0.3361* (0.0115)	0.2687* (0.0108)
Math and Physical Sciences	0.0040 (0.0086)	0.1380* (0.0184)
Number of Observations	1984	1984

* significant at the 1% level
~ significant at the 5% level

Table 4: Do Expected Median Incomes Converge Over Time?

Model :	men	women
Dependent Variable	ln(Real Market Income)	ln(Real Market Income)
Intercept	10.3002* (0.0380)	10.0862* (0.0524)
Years Since Graduation (T)	0.1837* (0.0071)	0.2218* (0.0094)
Education and Phys-ed	0.1163* (0.0120)	0.1467* (0.0115)
Fine and Applied Arts	-0.7213* (0.0197)	-0.5823* (0.0196)
Humanities	-0.5080* (0.0120)	-0.2843* (0.0126)
Biological Sciences	-0.4297* (0.0105)	-0.2438* (0.0135)
Engineering and Applied Sciences	0.3548* (0.0095)	0.4055* (0.0319)
Health	0.5048* (0.0151)	0.5281* (0.0152)
Math and Physical Sciences	0.0712* (0.0110)	0.1071* (0.0253)
Education and Phys-ed * T	-0.0133* (0.0011)	-0.0156* (0.0012)
Fine and Applied Arts * T	0.0222* (0.0018)	0.0132* (0.0020)
Humanities * T	0.0215* (0.0012)	0.0139* (0.0014)
Biological Sciences * T	0.0234* (0.0010)	0.0153* (0.0014)
Engineering and Applied Sciences * T	-0.0156* (0.0010)	-0.0255* (0.0039)
Health * T	-0.0188* (0.0014)	-0.0310* (0.0016)
Math and Physical Sciences * T	-0.0078* (0.0011)	0.0040 (0.0028)
Number of Observations	1984	1984

* significant at the 1% level
~ significant at the 5% level

Table 5: Predicted Median Incomes, by Sex and Major Field of Study

	Years from graduation				
	1	5	10	15	20
Men					
Education and Phys-ed	32,270	44,726	50,412	54,270	58,271
Fine and Applied Arts	14,034	22,541	33,975	39,750	45,580
Humanities	15,751	29,126	41,939	48,528	54,435
Social Sciences	27,087	43,076	53,297	58,984	63,412
Biological Sciences	15,878	31,794	48,772	54,088	56,184
Engineering and Applied Sciences	42,685	55,035	61,787	67,306	74,228
Health	50,767	61,844	71,263	74,232	76,015
Math and Physical Sciences	28,841	44,854	52,192	55,780	60,035
Mean	28,414	41,625	51,705	56,617	61,020
Range	36,733	39,303	37,288	34,482	30,435
range/mean	1.29	0.94	0.72	0.61	0.50
Women					
Education and Phys-ed	26,100	32,670	28,140	30,058	41,548
Fine and Applied Arts	11,934	17,703	20,741	22,962	27,952
Humanities	14,546	25,468	28,329	30,019	37,775
Social Sciences	21,088	30,054	31,658	33,770	39,440
Biological Sciences	14,955	26,263	30,880	32,204	39,265
Engineering and Applied Sciences[1]					
Health	40,939	41,606	36,257	36,550	42,831
Math and Physical Sciences[1]					
mean[2]	23,184	30,871	31,099	32,434	40,018
range[2]	29,005	23,903	16,926	16,928	18,425
range/mean[2]	1.25	0.77	0.54	0.52	0.46

1: Since there were relatively few women in math and physical sciences and engineering, predicted values for these fields are omitted.
2: Excluding math and physical sciences and engineering.

Table A1: Sensitivity Tests, Men

	base model	age at least 25 when income measured	actual age rather than years since graduation	actual age and years since graduation	first year after graduation dropped	pre-1989 variable interacted
Dependent Variable	rmkt	rmkt	rmkt	rmkt	rmkt	rmkt
Intercept	10.2543* (0.0472)	10.4332* (0.0419)	9.7196* (0.0440)	9.7722* (0.0396)	10.2643* (0.0435)	10.2303* (0.0464)
Cohort (C)	-0.0335* (0.0043)	-0.0282* (0.0037)	-0.0194* (0.0035)	-0.0316* (0.0033)	-0.0303* (0.0037)	-0.0378* (0.0042)
Cohort Squared (C^2)	0.0007* (0.0001)	0.0005* (0.0001)	0.0002 (0.0001)	0.0007* (0.0001)	0.0006* (0.0001)	0.0010* (0.0001)
Cohort*Years Since Graduation (CT)	0.0024* (0.0003)	0.0022* (0.0002)		0.0033* (0.0004)	0.0023* (0.0002)	0.0029* (0.0003)
Years Since Graduation (T)	0.2119* (0.0089)	0.1106* (0.0087)		-0.0086 (0.0103)	0.1837* (0.0104)	0.2068* (0.0089)
Years Since Graduation Squared (T^2)	-0.0213* (0.0014)	-0.0073* (0.0013)		-0.0011 (0.0015)	-0.0168* (0.0015)	-0.0206* (0.0014)
Years Since Graduation Cubed (T^3)	0.0010* (0.0001)	0.0002* (0.0001)		0.0001 (0.0001)	0.0007* (0.0001)	0.0010* (0.0001)
Years Since Graduation^4 (T^4)	0.0000* (0.0000)	0.0000 (0.0000)		0.0000 (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)
Unemployment Rate (UR)	-0.0224* (0.0025)	-0.0174* (0.0021)	-0.0201* (0.0021)	-0.0224* (0.0019)	-0.0189* (0.0021)	-0.0215* (0.0023)
Cohort*Age (CA)			0.0013* (0.0002)	-0.0009* (0.0003)		
Age (A)			0.2761* (0.0087)	0.2999* (0.0116)		
Age Squared (A^2)			-0.0219* (0.0012)	-0.0242* (0.0015)		
Age Cubed (A^3)			0.0008* (0.0001)	0.0009* (0.0001)		
Age^4 (A^4)			0.0000* (0.0000)	0.0000* (0.0000)		
Pre-1989 Dummy						0.0885* (0.0191)
Cohort*Pre-1989 Dummy						-0.0005~ (0.0002)
number of observations	248	248	1240	1240	232	248

* significant at the 1% level
~ significant at the 5% level

Table A2: Sensitivity Tests, Women

	base model	age at least 25 when income measured	actual age rather than years since graduation	actual age and years since graduation	first year after graduation dropped	pre-1989 variable interacted
Dependent Variable	rmkt	rmkt	rmkt	rmkt	rmkt	rmkt
Intercept	10.0764* (0.0595)	10.2113* (0.0629)	9.7775* (0.0520)	9.8514* (0.0461)	10.0650* (0.0620)	10.0260* (0.0586)
Cohort (C)	-0.0232* (0.0053)	-0.0199* (0.0054)	-0.0159* (0.0041)	-0.0256* (0.0039)	-0.0240* (0.0052)	-0.0256* (0.0052)
Cohort Squared (C^2)	0.0006* (0.0002)	0.0006* (0.0002)	0.0001 (0.0001)	0.0004* (0.0001)	0.0006* (0.0002)	0.0009* (0.0002)
Cohort*Years Since Graduation (CT)	0.0029* (0.0003)	0.0025* (0.0003)		0.0006 (0.0005)	0.0028* (0.0003)	0.0036* (0.0003)
Years Since Graduation (T)	0.2213* (0.0107)	0.1354* (0.0127)		0.0915* (0.0122)	0.2116* (0.0142)	0.2115* (0.0108)
Years Since Graduation Squared (T^2)	-0.0313* (0.0016)	-0.0186* (0.0019)		-0.0108* (0.0017)	-0.0296* (0.0021)	-0.0296* (0.0017)
Years Since Graduation Cubed (T^3)	0.0017* (0.0001)	0.0010* (0.0001)		0.0006* (0.0001)	0.0016* (0.0001)	0.0016* (0.0001)
Years Since Graduation^4 (T^4)	0.0000* (0.0000)	0.0000* (0.0000)		0.0000* (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)
Unemployment Rate (UR)	-0.0285* (0.0031)	-0.0244* (0.0031)	-0.0263* (0.0027)	-0.0290* (0.0023)	-0.0256* (0.0030)	-0.0275* (0.0030)
Cohort*Age (CA)			0.0023* (0.0002)	0.0024* (0.0004)		
Age (A)			0.2704* (0.010)	0.2050* (0.0131)		
Age Squared (A^2)			-0.0322* (0.0014)	-0.0275* (0.0018)		
Age Cubed (A^3)			0.0016* (0.0001)	0.0013* (0.0001)		
Age^4 (A^4)			0.0000* (0.0000)	0.0000* (0.0000)		
Pre-1989 Dummy						0.110* (0.0222)
Cohort*Pre-1989 Dummy						-0.0009* (0.0003)
number of observations	248	248	1240	1240	232	248

* significant at the 1% level
~ significant at the 5% level

Table A3: Results Using Micro Data and Mean Regression (OLS), Men

	model 1	Model 2	model 3	model 4	model 5	model 6
	base model (grouped median regression)	Grouped mean regression	OLS	OLS with corrected standard errors	median regression on a 30% sample	robust regression on a 30% sample using STATA's RREG command
Dependent Variable	rmkt	Rmkt	rmkt	rmkt	rmkt	rmkt
Intercept	10.2543* (0.0472)	10.0119* (0.0439)	10.0117* (0.0318)	10.0117* (0.0309)	10.2000* (0.0341)	10.2806* (0.0384)
Cohort (C)	-0.0335* (0.0043)	-0.0234* (0.0040)	-0.0233* (0.0029)	-0.0233* (0.0029)	-0.0319* (0.0031)	-0.0389* (0.0035)
Cohort Squared (C^2)	0.0007* (0.0001)	0.0004* (0.0001)	0.0004* (0.0001)	0.0004* (0.0001)	0.0007* (0.0001)	0.0009* (0.0001)
Cohort*Years Since Graduation (CT)	0.0024* (0.0003)	0.0015* (0.0002)	0.0015* (0.0002)	0.0015* (0.0002)	0.0023* (0.0002)	0.0028* (0.0002)
Years Since Graduation (T)	0.2119* (0.0089)	0.1643* (0.0083)	0.1643* (0.0060)	0.1643* (0.0063)	0.2027* (0.0064)	0.1564* (0.0072)
Years Since Graduation Squared (T^2)	-0.0213* (0.0014)	-0.0088* (0.0013)	-0.0088* (0.0009)	-0.0088* (0.0010)	-0.0190* (0.0010)	-0.0119* (0.0011)
Years Since Graduation Cubed (T^3)	0.0010* (0.0001)	0.0002~ (0.0001)	0.0002* (0.0001)	0.0002* (0.0001)	0.0008* (0.0001)	0.0004* (0.0001)
Years Since Graduation^4 (T^4)	0.0000* (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)
Unemployment Rate (UR)	-0.0224* (0.0025)	-0.0222* (0.0023)	-0.0222* (0.0017)	-0.0222* (0.0016)	-0.0174* (0.0018)	-0.0189* (0.0020)
# obs : R-sq	248	248	382666 0.163	382666 0.163	114800	114800 0.267

* significant at the 1% level
~ significant at the 5% level

Table A4: Results Using Micro Data and Mean Regression (OLS), Women

	model 1	model 2	model 3	model 4	model 5	model 6
	base model (grouped median regression)	grouped mean regression	OLS	OLS with corrected standard errors	median regression on a 30% sample	robust regression on a 30% sample using STATA's RREG command
Dependent Variable	rmkt	rmkt	rmkt	rmkt	rmkt	rmkt
Intercept	10.0764*	9.6979*	9.7029*	9.7029*	10.2167*	10.1223*
	(0.0595)	(0.0661)	(0.0430)	(0.0411)	(0.0602)	(0.0486)
Cohort (C)	-0.0232*	-0.0037	-0.0040	-0.0040	-0.0320*	-0.0355*
	(0.0053)	(0.0059)	(0.0038)	(0.0038)	(0.0054)	(0.0043)
Cohort Squared (C^2)	0.0006*	-0.0001	0.0000	0.0000	0.0008*	0.0009*
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Cohort*Years Since Graduation (CT)	0.0029*	0.0023*	0.0023*	0.0023*	0.0036*	0.0036*
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Years Since Graduation (T)	0.2213*	0.2055*	0.2049*	0.2049*	0.1948*	0.1618*
	(0.0107)	(0.0119)	(0.0078)	(0.0074)	(0.0108)	(0.0088)
Years Since Graduation Squared (T^2)	-0.0313*	-0.0315*	-0.0315*	-0.0315*	-0.0284*	-0.0222*
	(0.0016)	(0.0018)	(0.0012)	(0.0012)	(0.0017)	(0.0013)
Years Since Graduation Cubed (T^3)	0.0017*	0.0018*	0.0018*	0.0018*	0.0016*	0.0012*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Years Since Graduation^4 (T^4)	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment Rate (UR)	-0.0285*	-0.0228*	-0.0229*	-0.0229*	-0.0310*	-0.0228*
	(0.0031)	(0.0034)	(0.0022)	(0.0022)	(0.0031)	(0.0025)
# obs :	248	248	355990	355990	106797	106797
R-sq			0.021	0.021		0.095

* significant at the 1% level
~ significant at the 5% level

Figure 1: Bachelors Graduates From BC Universities

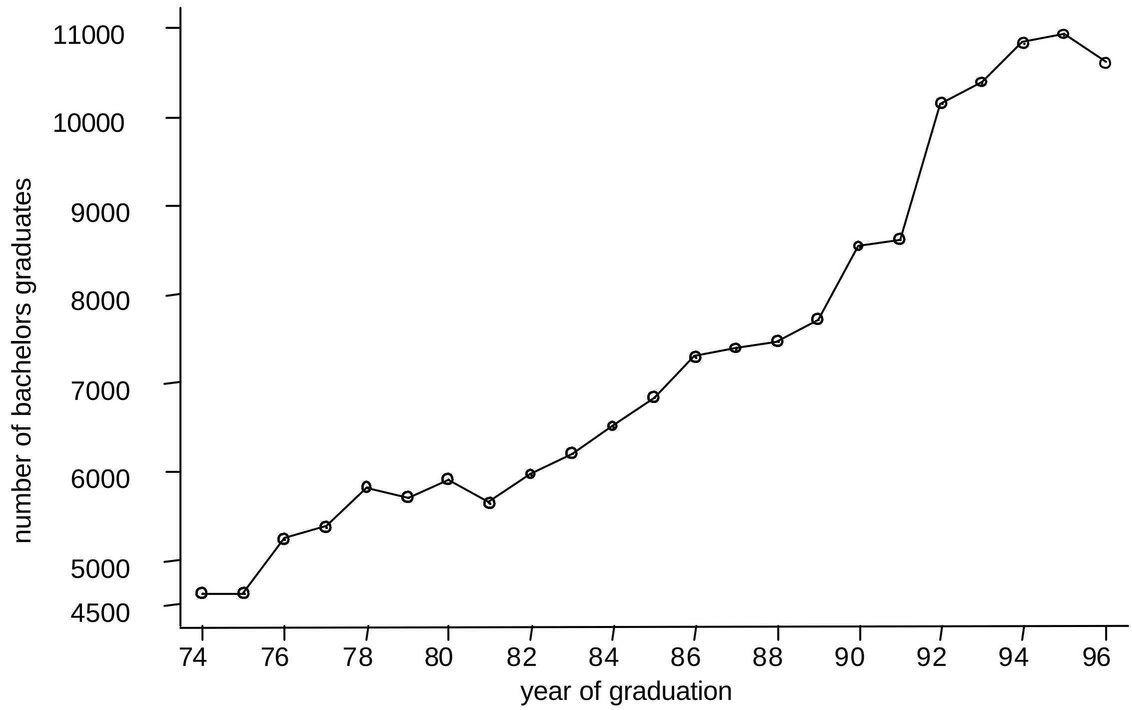


Figure 2a: Graduates by Field of Study

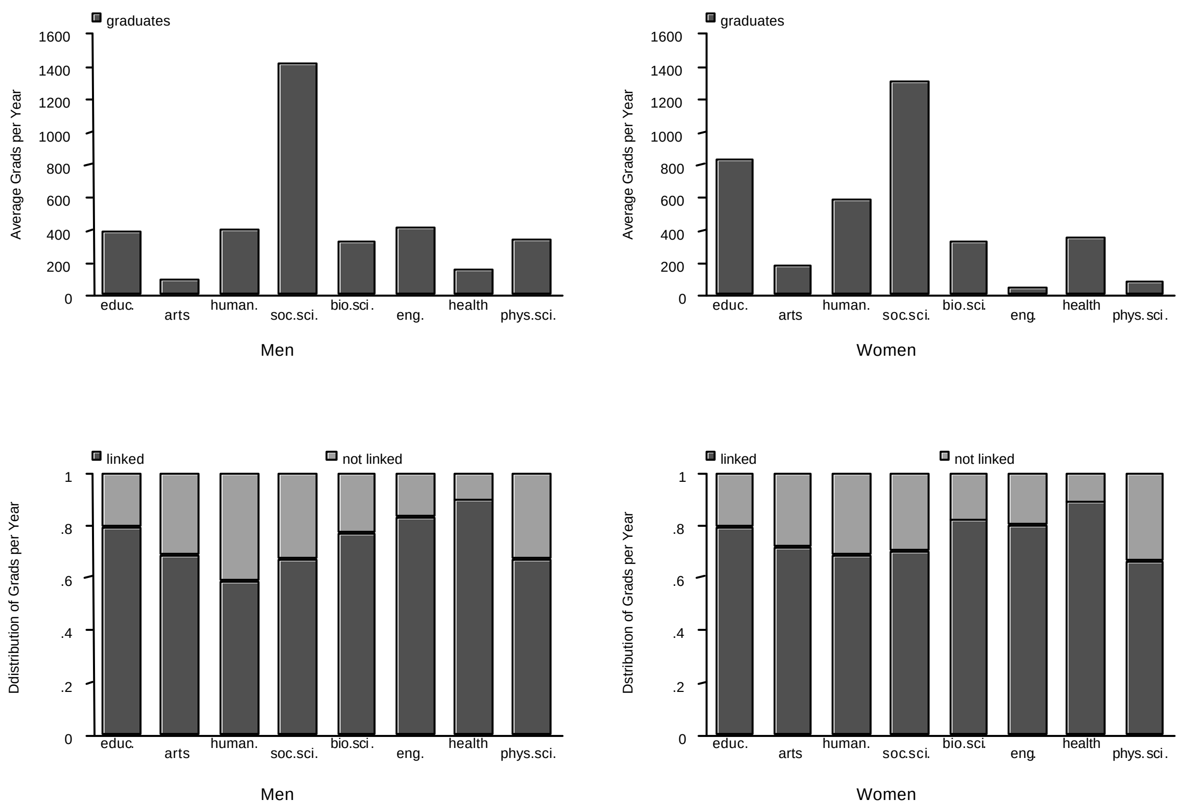


Figure 2b: Fraction of Graduates with Income Information

by field of study (a)

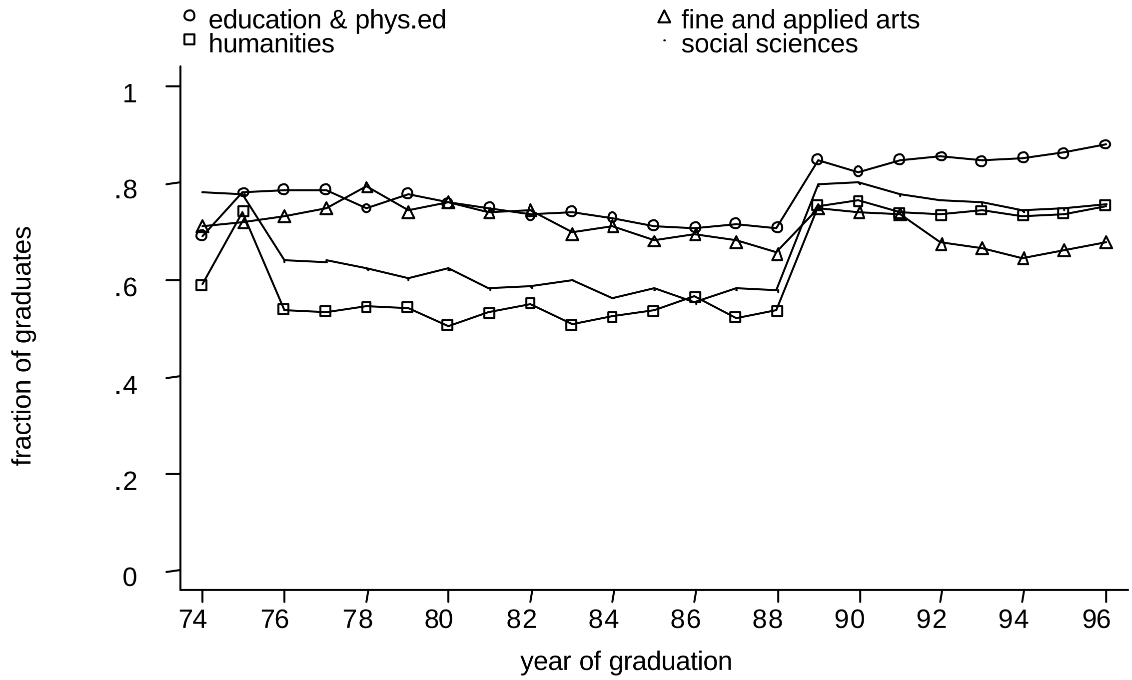


Figure 2c: Fraction of Graduates with Income Information

by field of study (b)

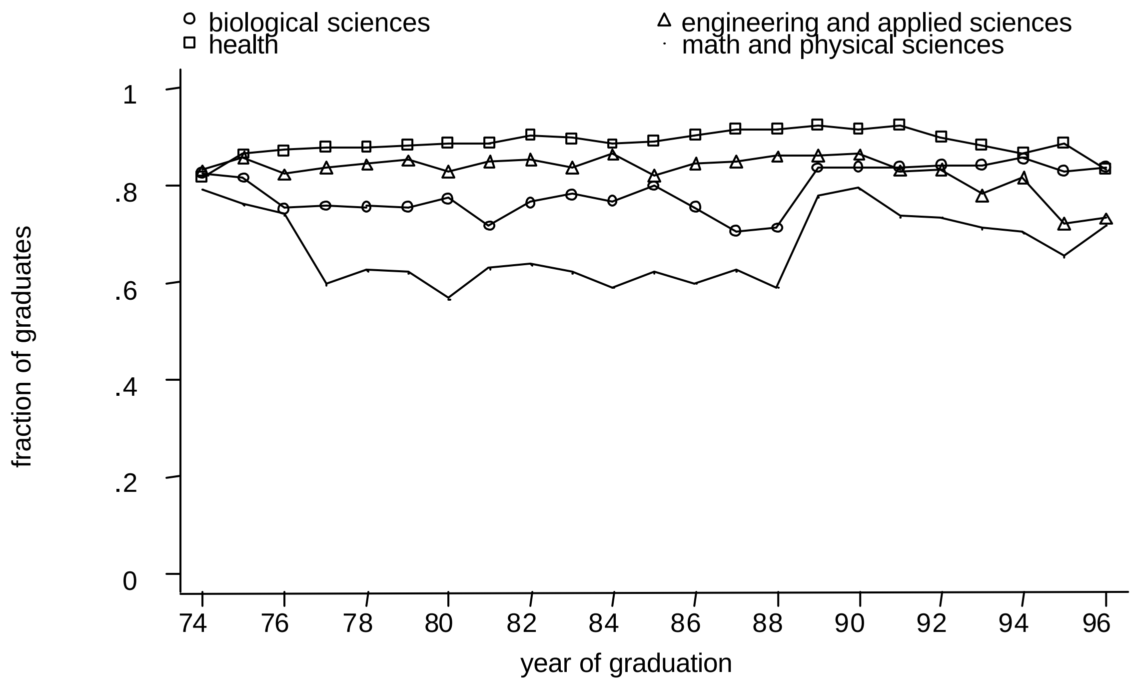


Figure 2d: Fraction of Graduates with Income Information

by Gender

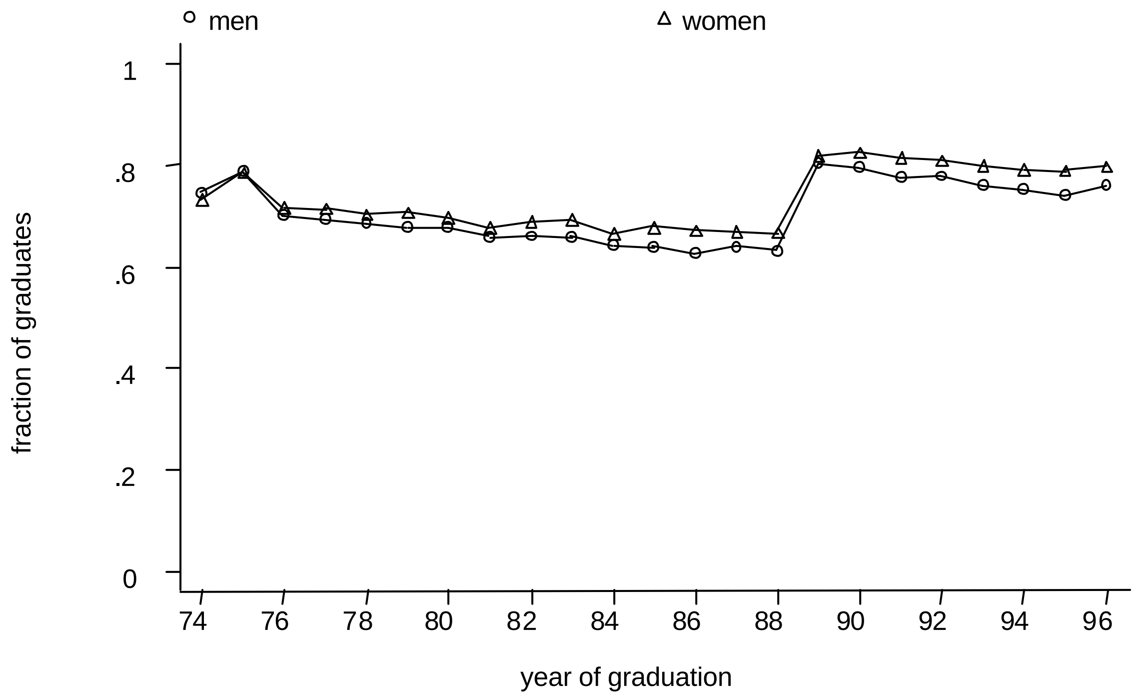


Figure 3a: Composition of Linked Graduates

by field of study (a)

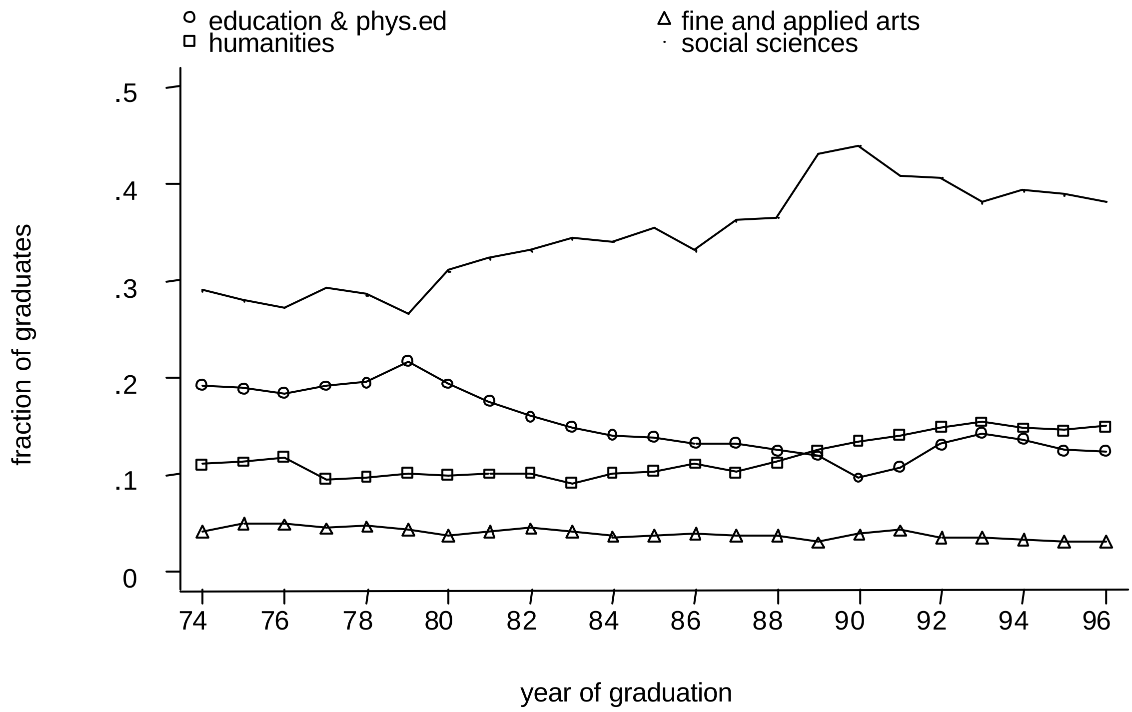


Figure 3b: Composition of Linked Graduates by field of study (b)

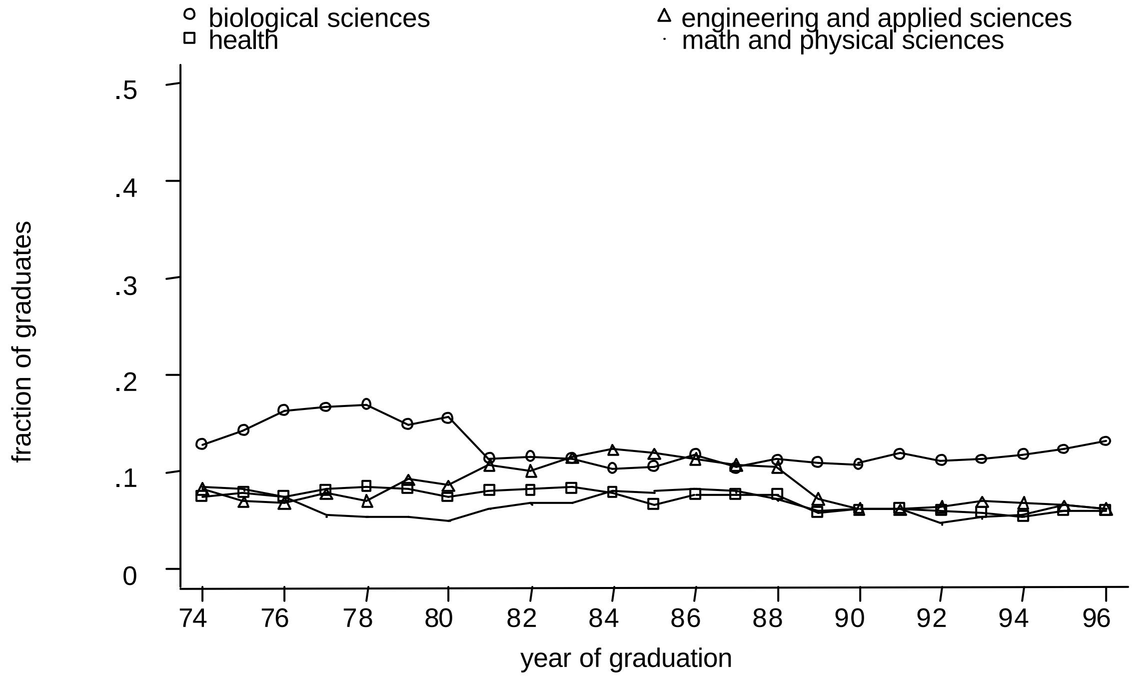


Figure 3c: Composition of Linked Graduates by Gender

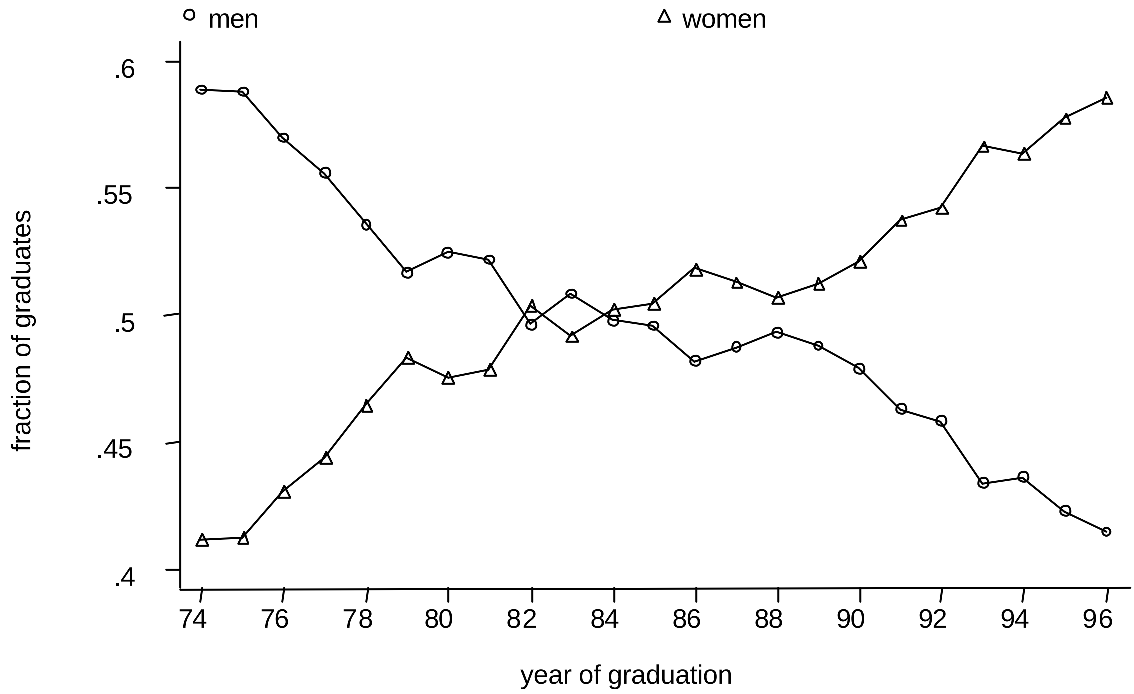


Figure 4a: Median Income of Graduates

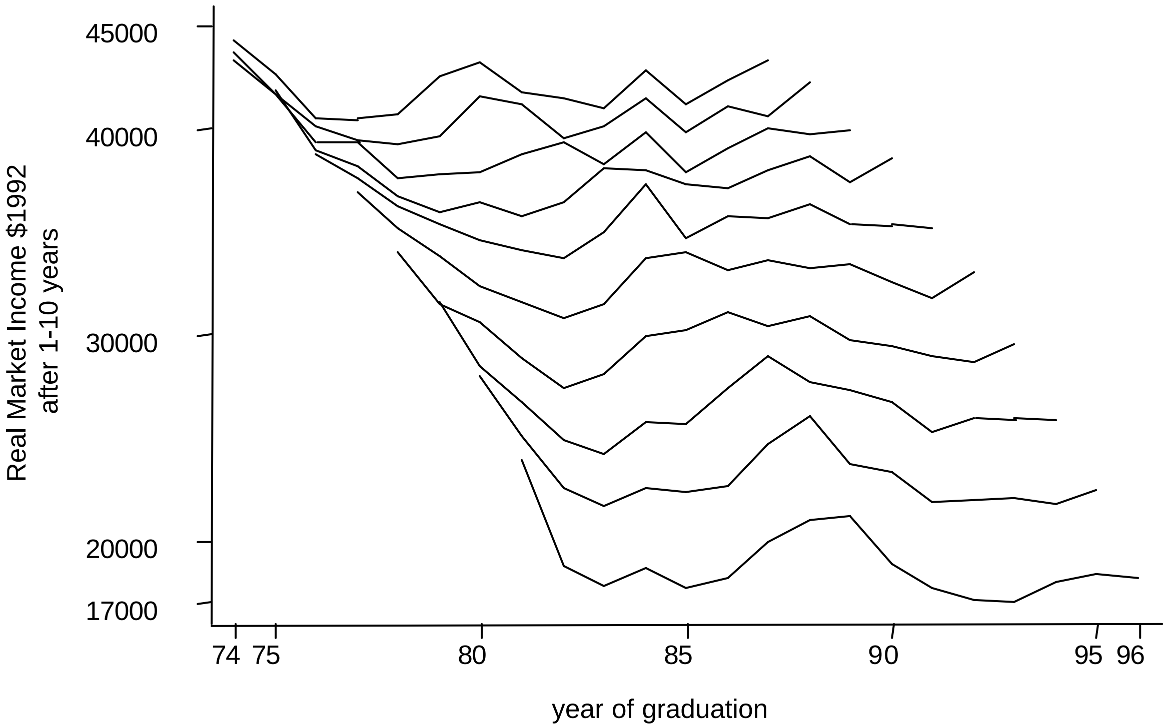


Figure 4b: Median Income of Graduates

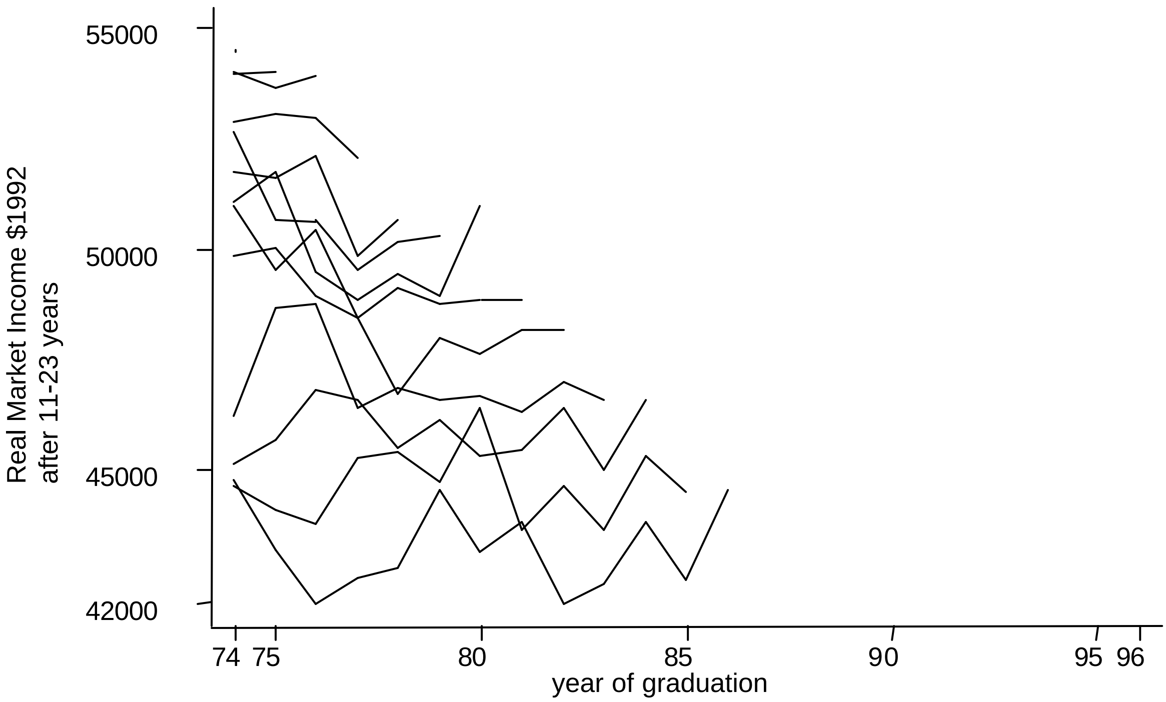


Figure 5a: Age-Income Profiles, Selected Cohorts

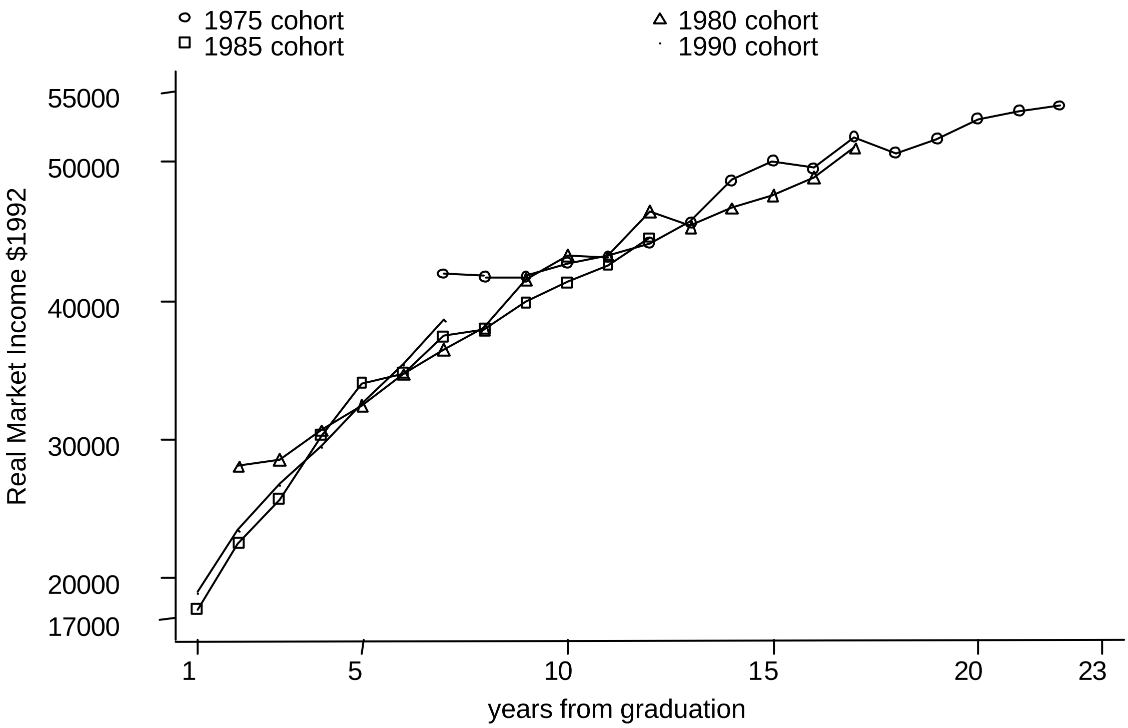


Figure 5b: Age-Income Profiles, Selected Cohorts

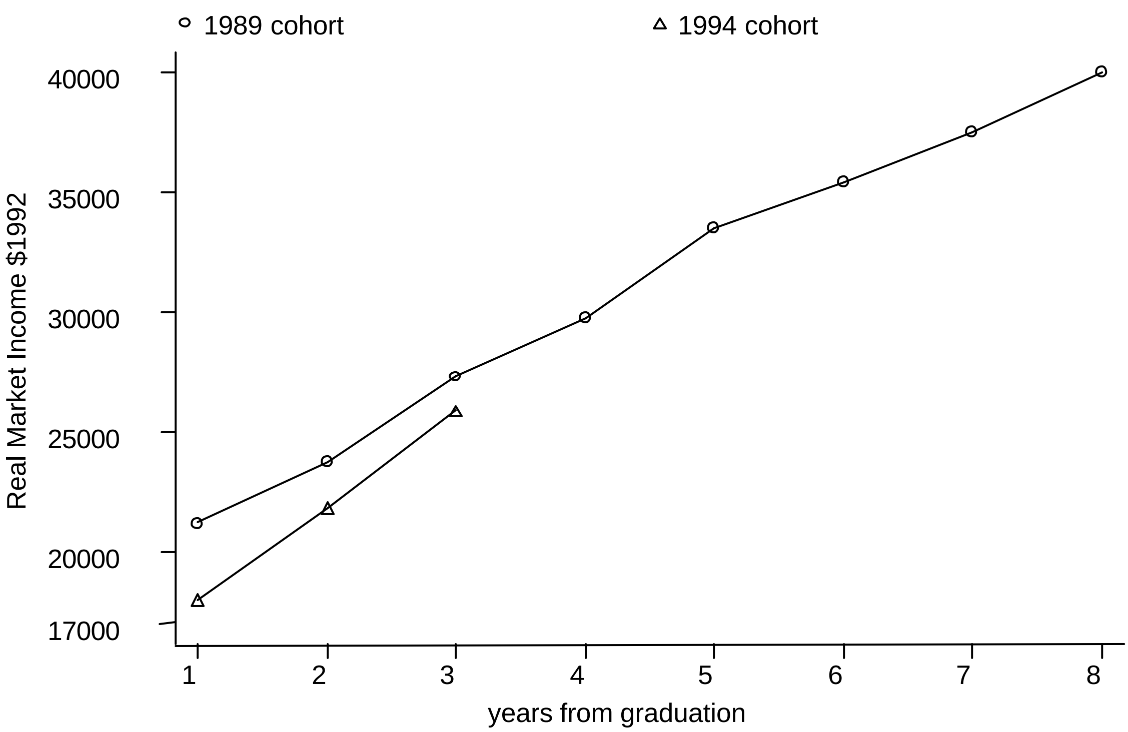


Figure 6a: Age-Income Profile (avg. across cohorts)

Men

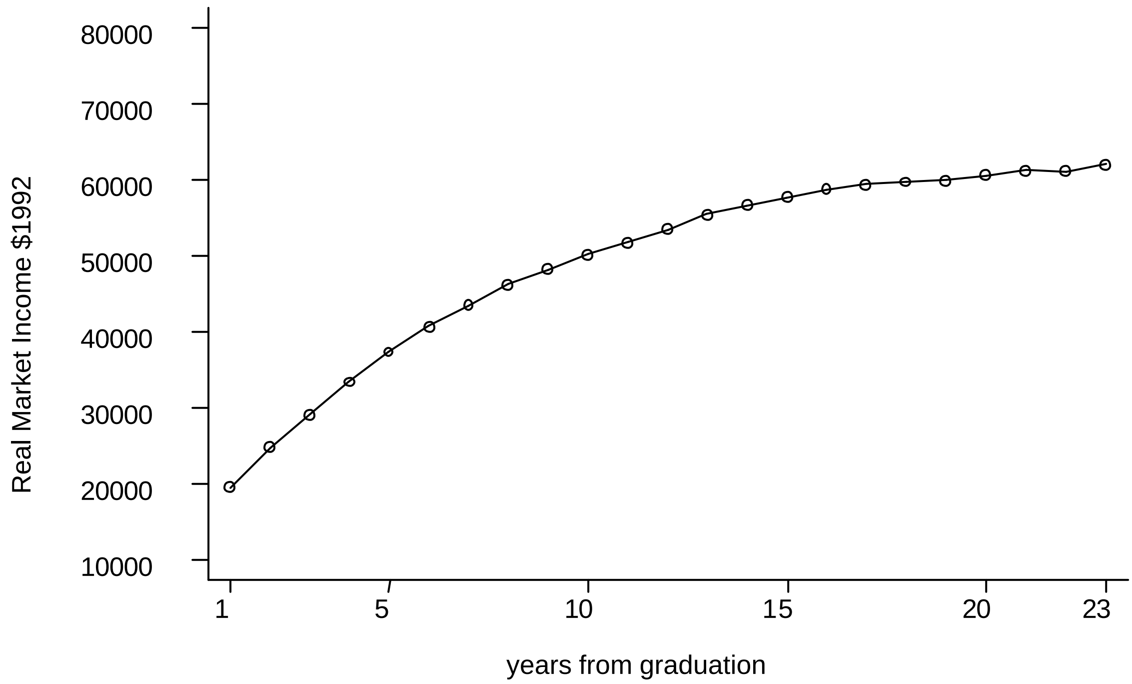


Figure 6b: Age-Income Profile (avg. across cohorts)

Women

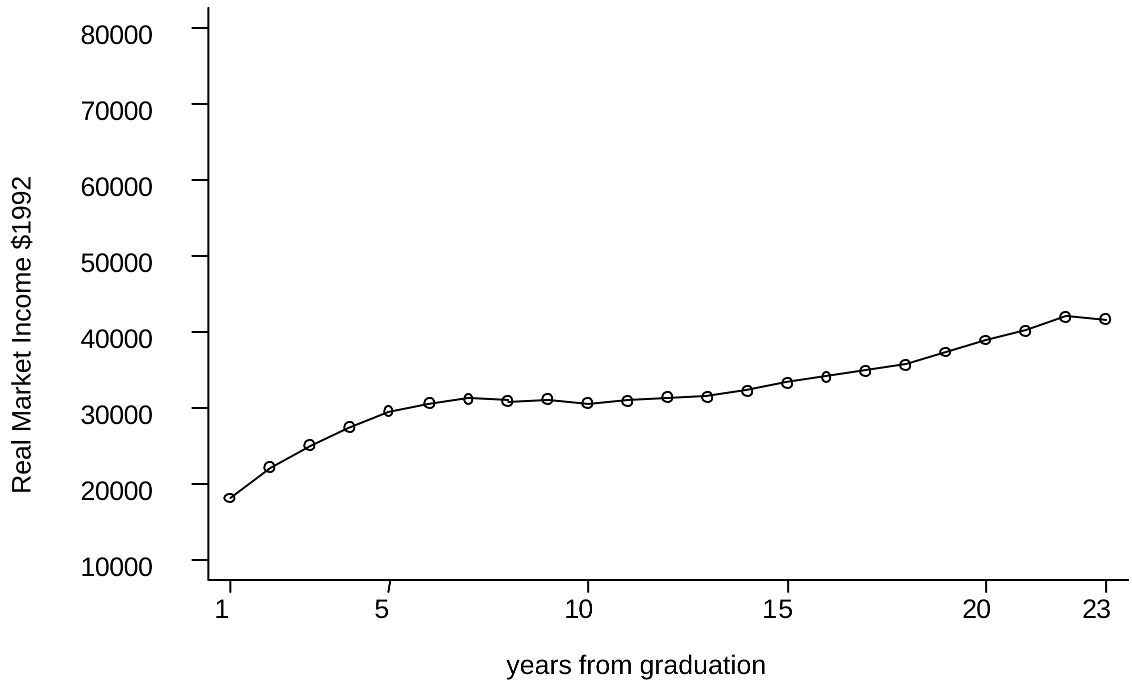


Figure 6c: Age-Income Profile (avg. across cohorts)
Men, by major field of study (a)

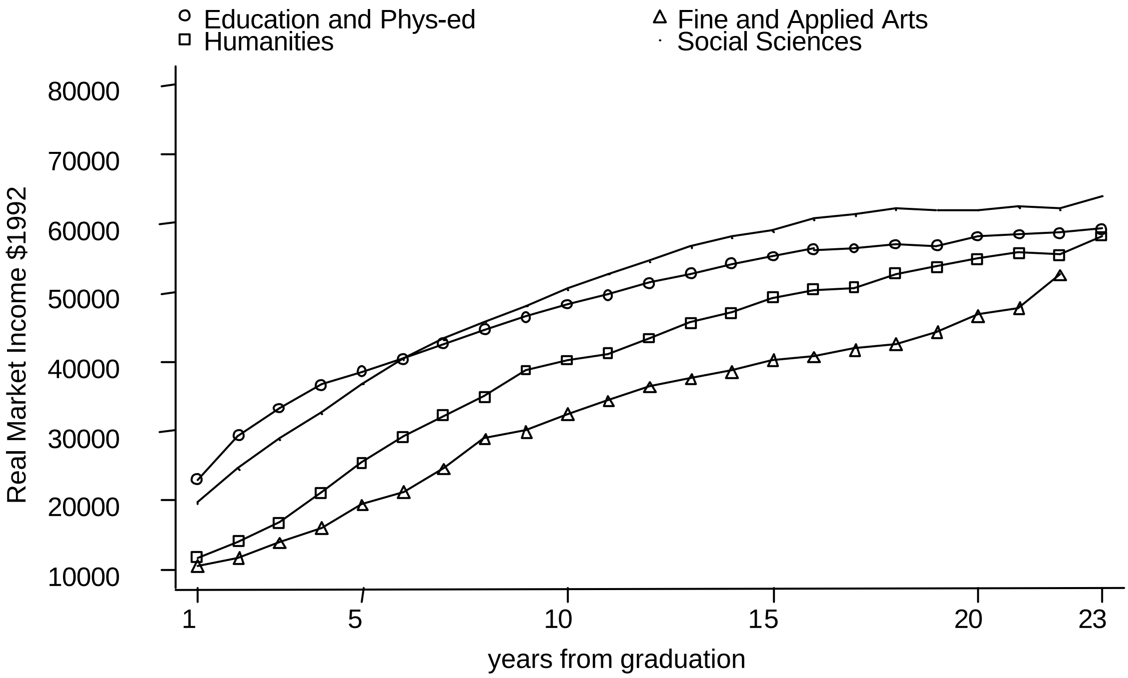


Figure 6d: Age-Income Profile (avg. across cohorts)
Men, by major field of study (b)

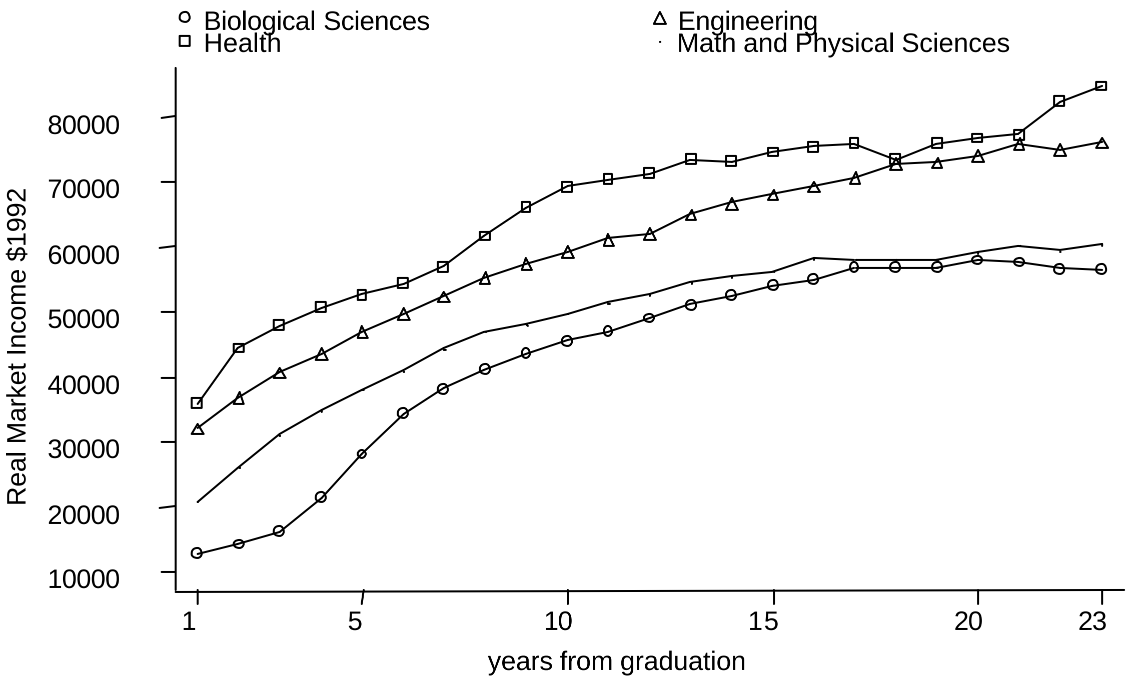


Figure 6e: Age-Income Profile (avg. across cohorts)
Women, by major field of study (a)

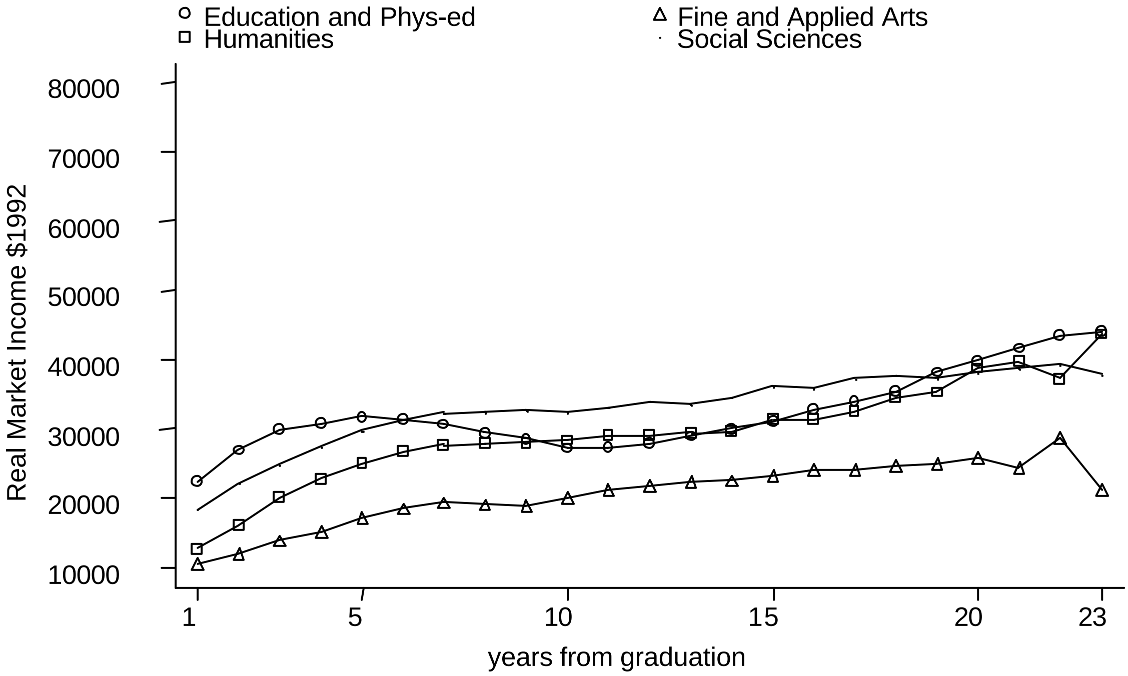


Figure 6f: Age-Income Profile (avg. across cohorts)
Women, by major field of study (b)

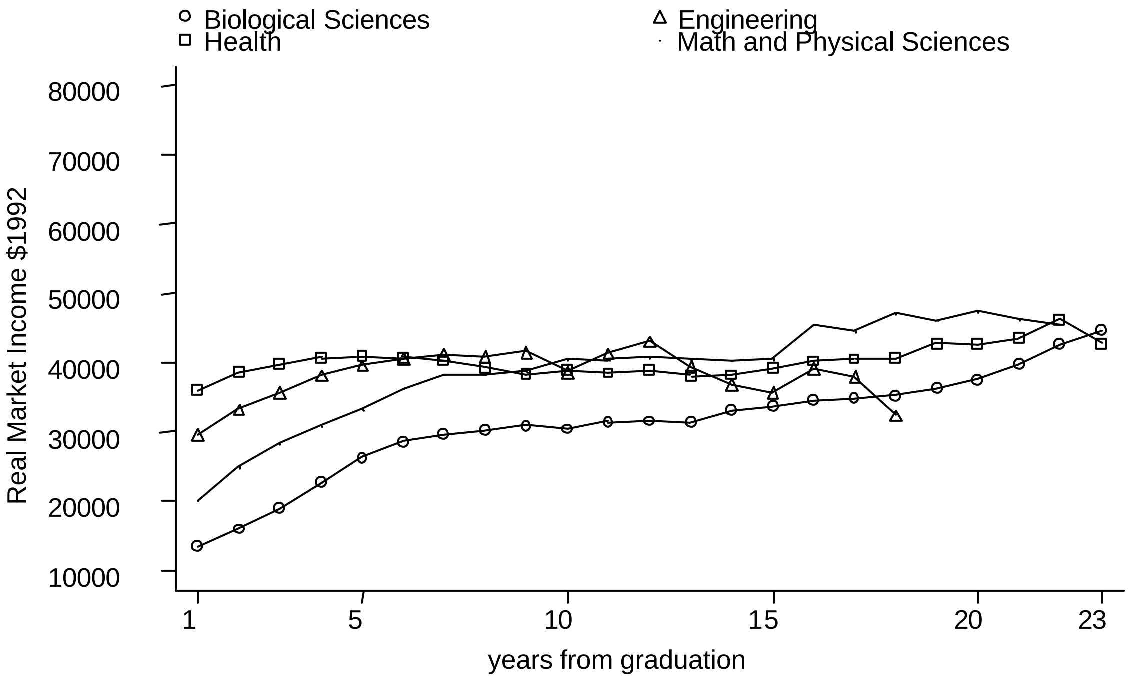


Figure 7a: Raw Age-Income Profiles, Men

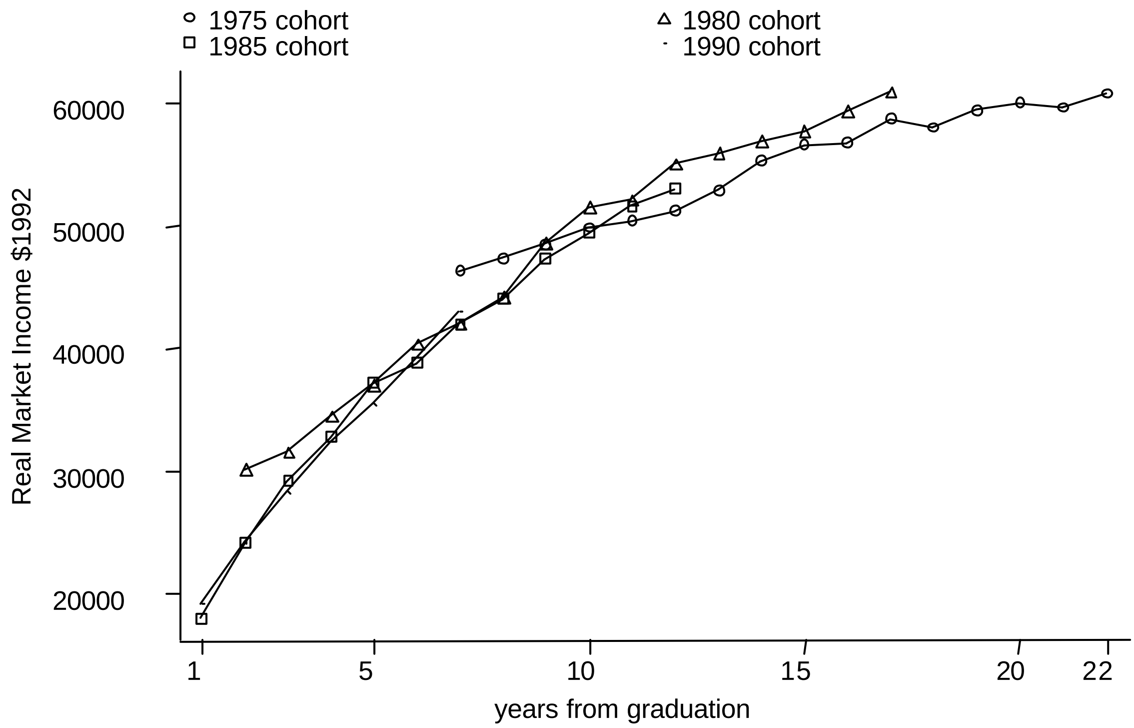


Figure 7b: Predicted Age-Income Profiles, Men

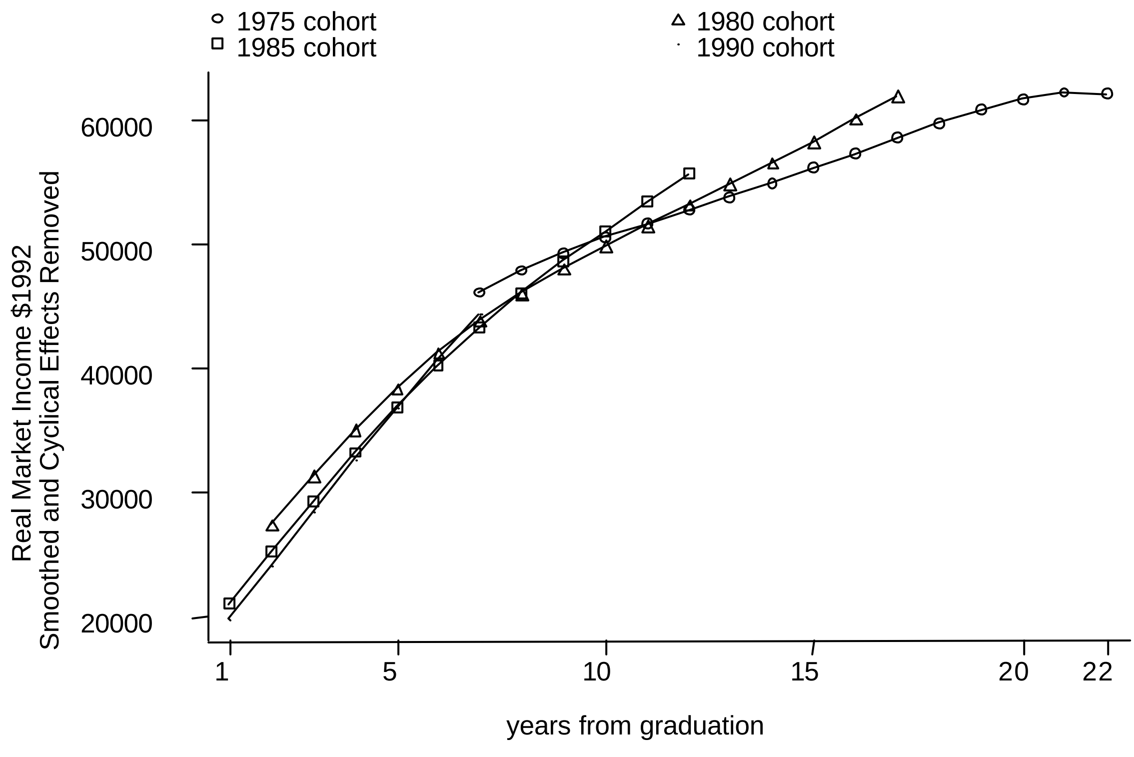


Figure 8a: Raw Age-Income Profiles, Women

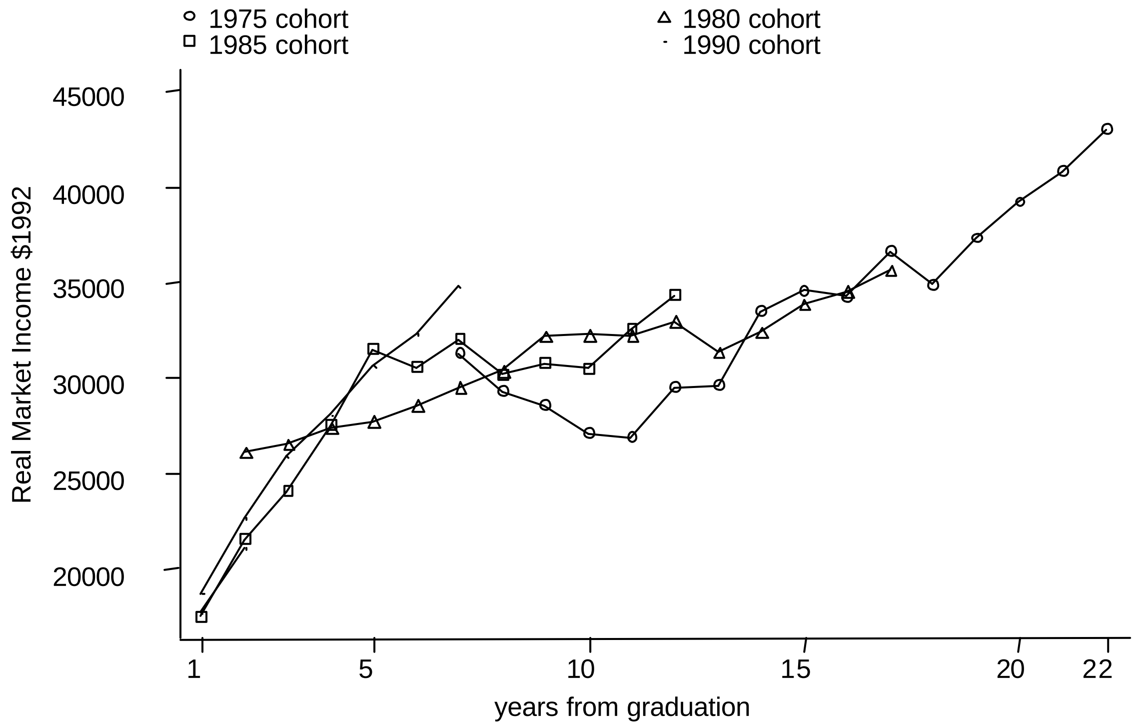


Figure 8b: Predicted Age-Income Profiles, Women

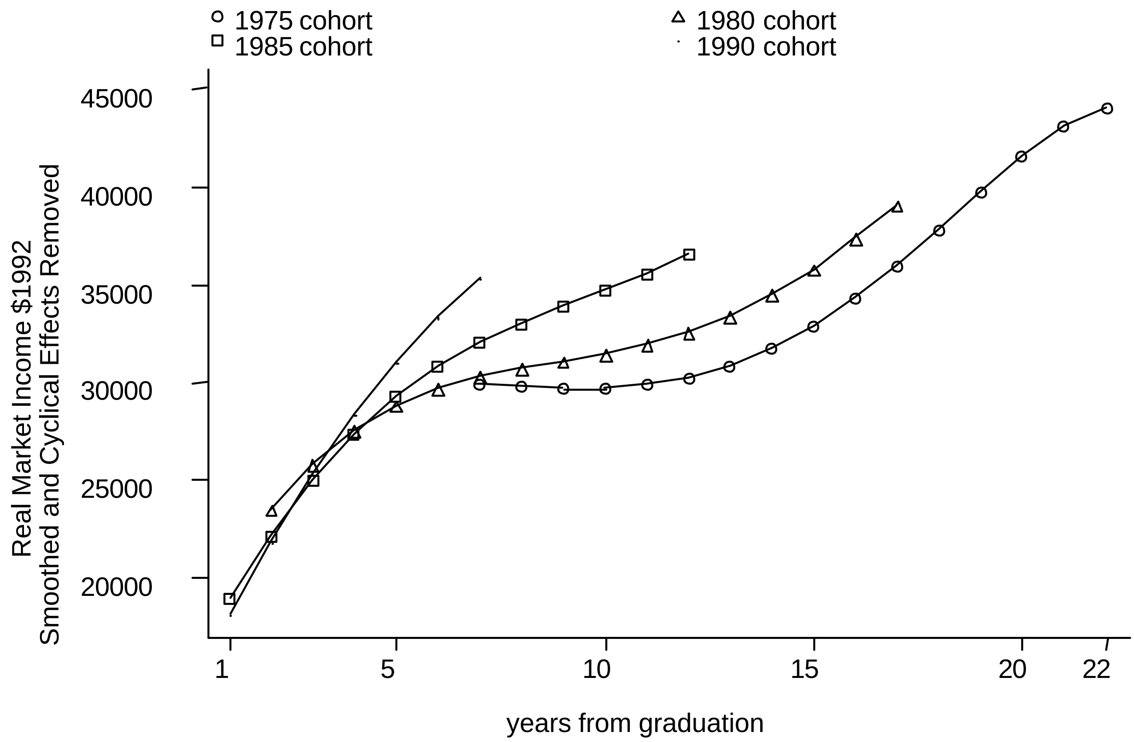
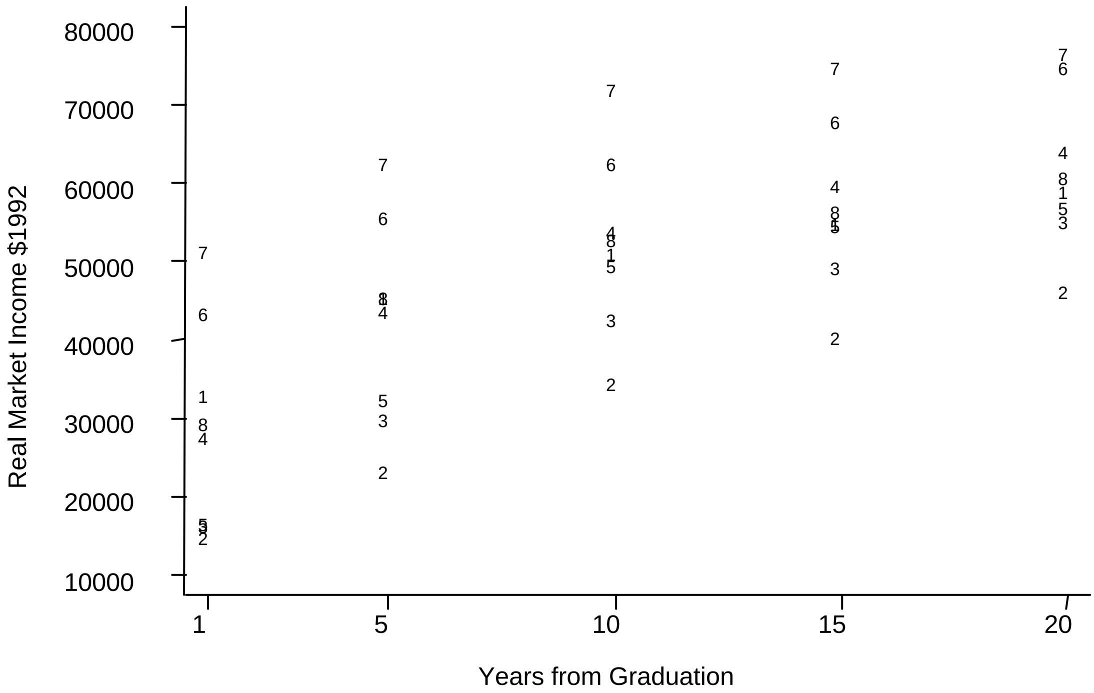


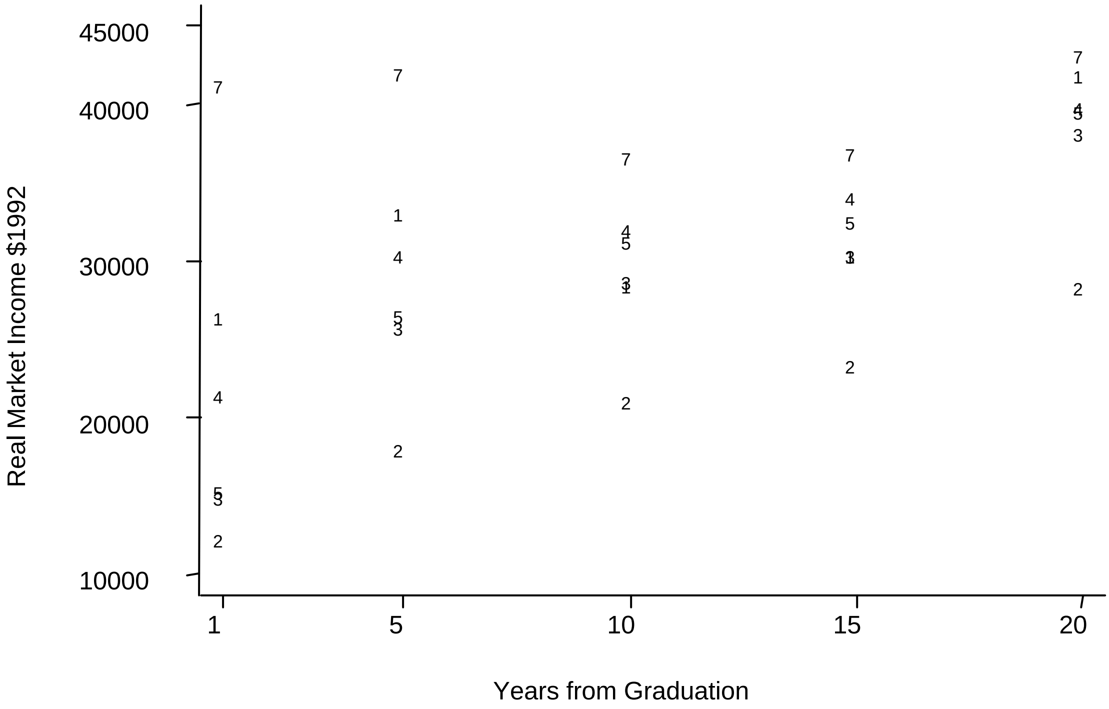
Figure 9a: Predicted Real Market Income, Men



The numbers in the above figure represent the expected median income for 8 fields of study where the numbers correspond to the following fields:

1 Education, Physical Education, Recreation and Leisure
2 Fine and Applied Arts
3 Humanities and related
4 Social Sciences and related
5 Agriculture and Biological Sciences
6 Engineering and Applied Sciences
7 Health Professions and Occupations
8 Mathematics and Physical Sciences

Figure 9b: Predicted Real Market Income, Women



The numbers in the above figure represent the expected median income for 8 fields of study where the numbers correspond to the following fields:

1 Education, Physical Education, Recreation and Leisure
2 Fine and Applied Arts
3 Humanities and related
4 Social Sciences and related
5 Agriculture and Biological Sciences
6 Engineering and Applied Sciences (omitted)
7 Health Professions and Occupations
8 Mathematics and Physical Sciences (omitted)

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