STEPPIN' OUT: An analysis of the education experiences and early labour market outcomes of a panel of recent science and non-science university graduates.

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TABLE OF CONTENTS

EXECUTIVE SUMMARY

The research reported on here provides a descriptive analysis of a sample of bachelors-level university graduates derived from the Follow-Up of 1982 Graduates database, with an emphasis on comparisons between NSE and non-NSE graduates, and men versus women. The unique nature of the data and the mix of cross-tabulations and regression analysis covering many different aspects of the education programme and early labour market experiences gives a perspective on the school-to-work transition which did not previously exist. This is especially useful for the evaluation of the Canada Scholarships Program which encourages university graduates to enrol in engineering and the sciences.

The results from the crosstabulations may be summarized as follows:

• Most graduates were working or back in school five years after leaving university, although some passed through an initial period of joblessness before finding employment. Activity rates vary considerably by field of study and sex, with ENG and MATHSCI graduates having higher rates of full-time employment, and women likelier to be found in part-time jobs.

• ENG and MATHSCI graduates appear to have been more concerned with developing specialised knowledge and job skills and improving their career prospects when choosing their education programme; non-NSE graduates put greater weight on the acquisition of general communication, social, and reasoning skills; while AGBIOSC graduates resemble the non-NSE group more than the other science graduates. Women claim to have been generally more concerned with all the criteria than men, but it is not clear if this reflects different choices, more careful decision making, or simply the manner in which they respond to the questions.

• Satisfaction with the different aspects of the programmes corresponds to the preferences cited: ENG and MATHSCI graduates were happier with the narrower career aspects of their programmes; non-NSE men and women expressed greater satisfaction with the more general developmental aspects; while the AGBIOSC group was less happy than the other NSE groups in terms of the job-specific aspects of the programme, below the non-NSE group in terms of general developments, and generally the least satisfied with their programmes. The groups expressed similar opinions in terms of the importance of the learning satisfaction aspect of the programme, and all were more-or-less equally satisfied on this count.

• The job-education match was closest for Eng and MATHSCI graduates, followed by the non-NSE group, the AGBIOSC men and women next, and the SOCSCI graduates having the weakest job-education matches of all. There was a general movement into jobs more closely related to the programme of study over time for all groups, which is further evidence of the gradual or step-wise nature of the integration into the labour market for many of these graduates. Match patterns were similar for men and women.

• These graduates generally expressed high levels of satisfaction with their jobs overall, but were less content with their earnings. The AGBIOSC graduates were the least satisfied in this regard, the MATHSCI group was the happiest, and the non-NSE and ENG men and women lay between. There were no gender patterns in these outcomes.

• The overall evaluation of the programme — would it be chosen all over again if given the chance? — roughly followed the job evaluation patterns, with the ENG and MATHSCI graduates most likely to respond in the affirmative, followed by the general non-NSE group, then the AGBIOSC graduates, and the SOCSCI men and women the least likely to give this overall approval of their programme. Patterns were generally similar for men and women. While approval rates were around three-quarters at the highest, a full 40 percent of the least-satisfied groups said they would have preferred another programme, although virtually no-one seemed to regret their general decision to have gone to university. Approval ratings are clearly correlated with having a full-time job or being back in school, which suggests that there is perhaps a role for the simple policy of helping students identify fields where they are more likely to find good employment opportunities (although the issue is obviously more complicated than this).

• Not surprisingly, the ENG and MATHSCI graduates were clustered in a couple of occupations and industries, while the other groups were more widely distributed. Mean earnings and the rate of part-time work vary significantly by occupation and industry. Women were more likely to be in part-time jobs's and their mean earnings were almost everywhere lower than men's — and sometimes *much* lower, meaning that there are significant gender gaps even after controlling for field of education *and* the industry and occupation where the graduate finds employment.

• ENG and MATHSCI men and women earned significantly more than their non-science counterparts in 1984, and AGBIOSC men and women made considerably less. But by 1987 — just three years later — the ENG and MATHSCI men had *lower* mean earnings than the non-NSE group, while the women in these fields actually had a slightly *increased* advantage relative to the non-NSE comparison group.

• Looked at differently, the gender earnings gap was relatively uniform across all education groups in 1984 — around 10 percent when part-time workers are included. The gap then increased everywhere by 1987 — but by much less among the ENG and MATHSCI graduates than others. Thus the advantage of the ENG and MATHSCI women must be seen in terms of their not falling as far behind the men in their field as occurred elsewhere. Five years after graduation, the gender earnings gap was 20-25 percent for the non-NSE and AGBIOSC graduates, and just over 10 percent for the ENG and MATHSCI men and women.

• It is interesting to contrast these gender earnings gaps with the similar levels of satisfaction regarding remuneration expressed by men and women mentioned above. It could be that women are happy to be in the jobs they are, and are indeed fairly paid; alternatively, they might not like their jobs, but feel the pay is fair under the circumstances; or it could be that they are resigned to making less than men, and thus the satisfaction they express is within the context of a general resignation to pay inequity.

• The gender earnings gap appears to be related to family responsibilities, in that it is greater among men and women who are married or who have children as compared to singles. The regression analysis will follow up on these questions in a more detailed and rigorous manner.

The regression analysis may be summarized as follows:

• The general possibilities and limits of regression analysis were established, and the work reported here should be thought of as descriptive.

• The nature of analyses of the gender earnings gap of this type were put in the context of always choosing between: i) wanting to add explanatory variables to the regressions which can rightfully account for male-female differences in earnings, and ii) concern that such "controls" might themselves be the *outcomes* of discrimination processes, thus leading to overstatements of the portion of the gap which can be "explained" (and thus underestimating the share which might be due to discrimination). The procedure adopted here was to start with very simple models in order to establish an initial overview of the gender earnings gap, and to then add variables in order to provide a decomposition of these differences.

• In 1984, ENG and MATHSCI men and women had substantially higher earnings than the non-NSE graduates — on the order of 16 and 11 percent respectively — while AGBIOSC graduates earned almost 10 percent *less* than the non-NSE group.

• These early earnings differences by field of study were very similar for men and women, and were partly related to differences in job attachment, as seen by the role of accumulated experience and part-time versus full-time work status in the earnings patterns.

• The overall gender earnings gap was around 14 percent in 1984. A significant portion of this gap was associated with marriage and the presence of children: the initial results indicated that married men and those with children had substantially higher earnings than single and childless men, while for women the effects were much weaker. These effects accounted for about one-half of the gender gap which remained after the different fields of study had been controlled for, and almost all of the gap which could be explained by the variables available in the data.

• A good portion of these marriage and children effects can, in turn, be related to differences in labour market attachment. In particular, marriage and children are associated with more experience and higher rates of full-time work for men. The remaining *direct* effects of the family status variables are small, but significant. Interpretations of causality must be made with caution.

• The job-education match was an important determinant of earnings for all groups in 1984. Women in jobs directly related to their education fared particularly well, and there was actually no gap between the earnings of these women and men in similar situations.

• Occupation and industry play little role in explaining the gender earnings gap, but are — naturally — related to differences by field of study.

• Adding a full set of interaction variables to allow for different relationships between the explanatory variables and earnings for men and women added to the explanatory power of the 1984 earnings model, but did not change the principal results of interest in any way.

• By 1987, the sex-education patterns of earnings had changed substantially: while the ENG and MATHSCI men had lost most of the earnings premiums they enjoyed over non-NSE men less than three years earlier, the advantages of the ENG and MATHSCI women relative to non-NSE women actually *increased* (slightly) over this same period. The earnings of the AGBIOSC graduates lagged behind the non-NSE group about as much as in the earlier period. Once again, these patterns were significantly related to differences in the accumulation of experience and the incidence of part-time work across fields.

• The overall gender earnings gap rose from 14 percent in 1984 to 24 percent in 1987. Thus earnings differences were very substantial for this group of university graduates just five years after the completion of their schooling. The gap was smaller among the ENG and MATHSCI graduates due to the extra advantages of women in these fields, but they lagged behind all the same — just not *as much* as elsewhere.

- About two-fifths of the 1987 gender earnings gap as related to the marriage and children variables, suggesting that a major factor in these male-female earnings differences was the different impacts of family responsibilities on men's and women's earnings. A good portion of these effects were related to differences in job attachment (*i.e.* experience, part-time versus full-time status, *etc.*).

- As in 1984, the job-education match was strongly related to earnings; unlike the earlier year, the gender gap was pretty similar across all categories of match.

- The results were generally very robust across a variety of specifications, including separate regressions by education, sex, and even education-sex group. The only exception was that the marriage and children effects appeared to vary by field of study, although some of the sample sizes were fairly small. There is no clear explanation of why this might be, and future research might pursue these observations further.

- Fixed effects models were implemented to control for certain unobservable individual characteristics which might bias the coefficient estimates — especially the marriage and children effects. The findings suggest that such bias is indeed quite strong in these samples. In particular, while the previous results generally suggested that men who were married and had children had higher earnings than others, while women's earnings were more mixed in this respect, the fixed effects results suggested that men's earnings were largely *unaffected* by marriage and parenthood, while women's earnings were *much lower* as a result.

These results are not only interesting, but also relevant to policy. In particular, while the analysis is limited in what it can say about actual beneficiaries of the existing Canada Scholarships Program which encourages university students to enter the sciences and engineering, it certainly paints a picture of these fields which is perhaps at odds with the common presumptions which underlie the programme. Most simply, if there is such a demand for NSE graduates, why aren't their earnings higher? This is especially true for the agricultural and biological sciences, where earnings are uniformly lower than not only the other NSE groups, but also relative to the non-NSE graduates. How does current policy square with this? For example, with fifty percent of the scholarships reserved for women, and the majority of NSE women in the AGBIOSC fields, are women being encouraged to enter fields where they are likely to have disappointing careers? And earnings are by no means the sole measure of success used here. Quite the contrary, as these results hold across almost the full array of measures employed, both subjective and objective, regarding evaluations of the education experience, as well as the record of labour market achievement.

The news is by no means all bad. The ENG and MATHSCI men and women — that is, four of the six NSE sex-education groups — have considerably higher earnings than others two years after graduation, and this must be considered as at least somewhat affirming of the Canada Scholarship Program. Further, the ENG and MATHSCI *women's* advantages hold as strongly a full five years after graduation — which would seem to at least partly validate the stated goal of encouraging female NSE students in particular, and the policy instrument of reserving one-half of the scholarships for women. The down side is that the ENG and MATHSCI men are characterised by only average or slightly above average earnings in the later year, while the AGBIOSC men and women have the consistently lower earnings, as mentioned above. Thus four of the six scholarship recipient groups do not do any better than other graduates in the longer term, and two of these have decidedly dismal performances across the board.

This does not necessarily mean that the scholarship programme is not working. In fact, the high-achieving students who obtain the scholarships might do very well in all of these fields — and better than they would have fared elsewhere. This we cannot tell from these data. Nor can we conjecture what the societal returns to the federal government's investment in the Canada Scholarships Program has been, given that the market rates of return may not reflect societal rates of return to investments in these areas of study. Also, the data employed here follow the graduates only five years after graduation and cover only a single cohort, whereas the longer term record or that for another cohort might be very different. What is required is data on the scholarship recipients themselves, and, ideally, being able to follow them over a longer period of time.

Nevertheless, the findings presented here should cause one to pause and think. Then, perhaps some more research, or perhaps a fine-tuning of the Canada Scholarships Program to ensure that the money is used to encourage students to enter into areas where they will be able to make a significant contribution to Canada's economic well-being and at the same time enjoy more successful and personally rewarding careers. It is hoped that this study has made a contribution to this review process. In the meantime, a dissemination of these findings would, by better informing students, allow them to make better education and career choices for themselves.

I. Introduction

Graduating from university and moving into the labour force is an important transition, but we really don't know very much about it. A sampling of interesting, important, and largely unanswered questions might include the following. How many people find employment in the years following graduation? What do earnings patterns look like? How many university graduates are in jobs directly related to their schooling, and do such individuals have higher earnings than those who do not? What is the level of job satisfaction — in terms of earnings, and more globally? How do graduates evaluate their programmes of study, with respect to the intellectual experience as well as career preparation? How many would choose the same programme again? How do these patterns compare across field of education? Are there significant differences by sex? In particular, is there a gender earnings gap for recent university graduates? If so, what is its magnitude and what are the associated factors, such as differences in job attachment versus the direct effects of marriage and children?

We lack answers to these and other questions regarding the school-to-work transition largely due to the lack of suitable data. The research possibilities have, however, been significantly enhanced with the release of a new and interesting database, "The Follow-Up of 1982 Graduates", which is a representative panel of 1982 graduates of Canadian universities, colleges, and trade schools, based on interviews in 1984 and 1987. The research reported here uses these data to study the education experiences and early labour market outcomes of Canadian university graduates at the bachelors level, with a focus on the comparison of science versus non-science graduates and men versus women.

The Graduates database is particularly well suited to this analysis of the school-to-work transition because this is precisely the event upon which it is structured, and it is very rich in information regarding the education experience and the labour market outcomes which unfold in the five years following graduation. The panel nature of the Graduates data is especially advantageous, not only for the detailed and dynamic profile of the post-graduation experience which it provides, but also by facilitating the implementation of certain econometric procedures, such as the estimation of fixed effect ("panel") estimators. In short, the general structure of the database, the interesting variables available, and its panel nature present the opportunity for an original contribution to our understanding of the education experience and entry into the labour market of Canadian university graduates.

The emphasis on the comparison of science versus non-science graduates is largely motivated by the general perception that we need to add more — and better — technically oriented graduates to the labour force, which has resulted in the implementation of new programmes which are intended to encourage students to choose the associated majors. For example, the "Canada Scholarships in Science and Engineering" programme awards a minimum of 2,500 scholarships of $2,000 per year (increasing to $2,500 in 1993-94) to university students entering into the relevant fields, with renewals possible through the following three years of university enrolment if academic performance is maintained. In 1992-93 the programme was expanded to include technicians and technologists in colleges and institutes. But while annual scholarship disbursements are substantial (in the order of seventeen million dollars in 1993), this policy — which was implemented in response to a recommendation by the National Advisory Board on Science and Technology — is being implemented without really knowing how these students evaluate their education experiences, or what happens after graduation.[1]

Thus to evaluate this general push for more science graduates and the specific policy initiatives which have been adopted it would be useful to know more about the comparative university and early labour market experiences of natural science and engineering ("NSE") graduates versus others. For example, do NSE graduates have higher post-graduation employment rates than others? Do they earn more? How do the subjective evaluations of their education programmes compare across field? Are NSE graduates more or less satisfied with their jobs? Given the choice, would they choose the same education again? Do these patterns vary *within* the broad NSE grouping — that is, the agricultural and biological science ("AGBIOSC") graduates versus the engineers ("ENG"), versus the mathematics and physical science ("MATHSCI") graduates?

The second point of emphasis — men versus women — also has a pair of motivations, and again one is more general, while the other is more policy-specific. Regarding the former, it would be interesting to compare the education and early work experiences of male and female bachelors-level graduates generally, and doing this along the demarcation of a traditionally male-dominated area versus others adds an interesting dimension to the analysis. As for policy, approximately fifty percent of the Canada Scholarships are reserved for women. Thus it would also be useful to know how the science versus non-science patterns vary by sex, and to compare the male and female graduates in the targeted fields to those in other disciplines.

Finally, the results reported here should be of interest not only to academics, university administrators, and policy makers, but also to students themselves — especially those about to

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[1] Gilbert and Pomfret [1991] use data on students at Guelph University to study why individuals choose to enter the sciences and how they evaluate their university experiences, with the same basis of comparison — science versus non-science and men versus women — as is used here. The two studies are thus very complementary. Following the Guelph students in the post-university years is a project currently under consideration by this author and Gilbert and Pomfret.

choose which field of study to enter. If students were better apprised of the outcomes associated with different fields of study, they could take this into consideration when making their choices. Providing better information is often a very useful and cost-effective policy, and this report could provide a small but significant contribution in this regard. The potential efficacy of such information is indicated by the finding that there is a significant correlation between post-university employment status and the overall evaluation of the education programme. Thus providing information on outcomes by field of study might lead to better choices and more satisfying careers.

The report is organized as follows. The next section describes the Graduates data and the construction of the samples used in the analysis. The third section presents a descriptive analysis based on a series of cross-tabulations regarding the various aspects of the education programme and early labour market experiences. The fourth section documents the findings of a more detailed econometric analysis of earnings patterns. The report ends with a short concluding section.

II. The Data

This section describes the Follow-Up of 1982 Graduates data used in the empirical analysis reported on in Sections III and IV below. The first part describes the general characteristics of the database, while the second part outlines the construction of the specific samples used in the empirical work. The discussions include an evaluation of the strengths and weaknesses of the data for the purposes of this present study.

II.1 The Follow-Up of 1982 Graduates Database

In 1984, the Department of Secretary of State and Employment and Immigration Canada jointly sponsored a Statistics Canada survey of 1982 graduates of Canadian universities, colleges, and trade schools. The purpose of the "National Graduates Survey" was to provide information on the integration of recent graduates into the labour market and the match between education/training and labour market outcomes. The usefulness of the information contained in the National Graduates Survey prompted EIC to sponsor a follow-up of the original sample, from which evolved the full "Follow-Up of 1982 Graduates Survey" which is used in this analysis.

The target population of the surveys was those individuals who successfully finished a programme and received a diploma or certificate from a credited Canadian university, college, or trade school (or similar teaching institution) in 1982. A stratified random sample design was employed, with stratifications according to province, level of education (trade school, college, BA, MA, Ph.D), and field of study, based on data provided by the educational institutions on their graduates.[2] Two telephone interviews were conducted, one in May/June 1984, the second in March, 1987, by which means the basic information provided by the schools was augmented

[2] The sample weights regarding province and field of study were not employed in the analysis, and therefore strictly speaking one cannot say that the results are representative of the general population of Canadian BA graduates. This route was chosen for several reasons. First, using weights is a somewhat cumbersome exercise, and therefore it is advantageous to avoid the procedures if it is thought reasonably safe to do. Second, the given weights no longer apply when subsamples are created, such as when the analysis is restricted to those with current jobs only, or those not missing any of the relevant information needed for a particular part of the analysis. Using the weights provided by Statistics Canada is therefore not likely to result in a truly proper correction even when they are used. Third, the stratification effects will often be implicitly controlled for by the nature of the analysis. Most important in this regard is that most of the cross-tabulations and regressions focus on — and allow for differences in — outcomes by field of study. Further, regression coefficient estimates will be unbiased if the model is correctly specified and the stratification variables are included in the models — for example, including region of residence as a regressor should control for the differences associated with the stratification by province. Finally, and perhaps most importantly, certain cross-tabulations and regressions were done with the weights as adjusted for the actual samples used, and the results were similar to those obtained with the unweighted samples.

with that furnished by the graduates themselves. The remainder of this section deals only with the BA university graduates found in the sample.[3]

Of the 13,131 undergraduates selected into the original sample, representing an underlying population of 91,538 graduates, 10,589 (80.6 percent) were successfully located in 1984, and 9,527 were found again in 1987 (90 percent of the 1984 sample), for a total response rate of 72.6%, which is quite good for a survey of this type.[4] On the other hand, the sample is probably not perfectly representative of the target population of BA graduates it is meant to represent, and most likely overrepresents "successful" graduates, who are more likely to be located and willing to cooperate with the interviewer.

The following is a brief description of the important characteristics of these files as they relate to the present study. First, there is detailed information on the nature of the BA programme and the education experience of the individual, some of which was provided by the educational institutions, the rest determined during the interviews. This includes objective data such as field of study, and also some very interesting subjective information, such as the importance the individual attached to various factors in the choice of the programme — for example, the satisfaction of mastering a specific field of knowledge versus career preparation. Second, the data include considerable detail on the first five years in the labour market, including the characteristics of the jobs held at the time of the two interviews (earnings, occupation, industry, full-time versus part-time, job satisfaction, *etc.*), and labour market status at two precise points between graduation in 1982 and the 1984 interview and at another specific inter-interview date in 1986.

Third, there is a set of variables directed explicitly at the school-to-work transition and the evaluation of the education experience from this perspective. For example, we know whether or not the current job was related to the education programme graduated from; the individual's evaluation of the education programme by the same criteria as those affecting the choice (see above); and whether or not the individual would choose the same education programme if given the chance to do it all over. Fourth, there is standard personal and family information, such as age, marital status, the number of children, and region of residence. Unfortunately, the database lacks any information on the spouse, and has nothing on the individual's family of origin except the parents' level of education.

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[3] See Statistics Canada [1989] for full documentation of the Graduates database.

[4] Unfortunately there is no documentation of the response rate by field of study.

As with any database, there are some aspects of the Follow-Up of 1982 Graduates which limit the analysis. First, there is no wage variable as such, and annual earnings must suffice. This is not an overly serious limitation, however, in that earnings are still an entirely interesting outcome in themselves, and the relevant literature is replete with studies which use wages, total income, *or* annual earnings as the variable of interest.[5] Second, there is no total labour market experience variable (*i.e.* the total amount of time spent working), and one cannot be constructed from the variables available in the database. This is a potentially serious problem because labour market experience is typically a key variable in economists' analyses of earnings patterns, and usually figures quite prominently in econometric earnings models of the type to be estimated here. As a solution, the series of variables indicating part-time or full-time work at the various precise points in time have been used as proxies for labour market experience. More will be said on this in Section III.

Finally, the data cover a period of time when the economy was first in the recession of 1982 — the time of graduation — and then moving into a period of quite strong growth through the 1987 interview date. We are therefore unable to separate the observed changes over time into the component due to the normal integration into the labour market from that due to the changing economic conditions over the period covered by the data. Replicating the analysis with the panel of 1986 graduates which has just been released would be an interesting exercise in this respect. We should keep in mind that the panel nature of the Graduates data means that we are still far ahead of what any cross-section data can show in terms of permitting us to observe the dynamics of the school-to-work transition.

II.2 The Construction of the Samples Used in the Empirical Analysis

The specific samples used in the empirical analysis were constructed in the following manner. First, only graduates who were interviewed in both 1984 and 1987 were included. While another option would have been to include individuals who were interviewed in 1984 but not in 1987 (the reverse case does not hold), it was decided that it would be better to keep the sample constant over the two years so that the tracking of outcomes over time would not mix the effects of a changing sample with the actual dynamics we are interested in. For similar reasons, the record had to identify the basic activity of the individual (*e.g.* work versus school) at the time of both interviews. Further, basic identifying information used throughout the analysis had to be included (*e.g.* field of study, sex). Next, all individuals who completed a

[5] Individuals in jobs not lasting the full-year were asked how much they *would* earn on an annual basis.

higher degree (M.A. or Ph.D) from 1982 to 1987 were excluded, to limit the study to BA graduates as such. These restrictions left a basic sample of about 7,000 graduates, as seen in the initial tables of cross-tabulations.

Beyond this, the various cross-tabulations are based on different subsamples, depending on the particular group being investigated in each table (*e.g.* all graduates together in the first tables, only those with current jobs in other places, only full-time workers elsewhere) and the obvious requirement that the record had to have the information required for the particular table in question (*e.g.* the job satisfaction information had to be there for the observation to be included in the tables which look at this outcome). The notes which accompany each table may be referred to regarding the specific details of the samples used. The regressions work from the basic samples of those holding jobs at the time of the interviews in 1984 and/or 1987 (not necessarily both), where information on earning was provided, and there was no missing information on any of the other variables included in the models. This resulted in samples of just under 5,000 for the 1984 earnings models, and around 5,600 in 1987.

III. Cross-Tabulation Results

This section presents and discusses the cross-tabulations which have been performed with the sample of bachelors-level university graduates described above. The tables and discussions cover the following topics: activity rates; the distribution of the graduates across field of study; the importance of various factors in the choice of the education programme and the evaluation of the programme by these same criteria; the relationship of the job to the education programme; job satisfaction — overall, and in terms of earnings in particular; overall evaluation of the education programme, including a breakdown by labour force status; the distribution of graduates by industry and occupation and the associated earnings patterns and incidence of part-time work; overall earnings levels by sex and field of study; the job-education match and earnings; and the relationship between marriage, children and earnings. The emphasis throughout is on two sets of comparisons: i) science versus non-science graduates, and ii) men versus women within each field of study; while the longitudinal nature of the data is exploited by presenting the outcomes for 1984 and 1987 — thus tracking the graduates two and five years after graduation from university. All tables are located at the end of the text.

III.1 Activity Rates

Tables 1 and 2 give the basic activity rates of the graduates for 1984 and 1987 by sex and field of study. The shaded first column indicates the education categories which are used throughout this study, with the top half representing the three NSE groups of agricultural and biological sciences ("AGBIOSC"), Engineering ("ENG"), and maths and physical sciences ("MATHSCI"); and the bottom part first giving the NSE total, then all non-NSE graduates as a group, and finally the social science graduates as a specific group within the general non-NSE category. (The social science graduates are also included within the general non-NSE grouping; thus the NSE total and the non-NSE group comprise all the graduates in the sample.) To be perfectly explicit, AGBIOSC includes agriculture (animal, plant, and soil science, *etc.*), biochemistry, biology, biophysics, and botany; ENG ("and applied sciences") is engineering and architecture; MATHSCI is comprised of computer science, mathematics, chemistry, geology and related, metallurgy and materials science, meteorology and climatology, oceanography and water studies, and physics. These classifications conform to the standard University Student Information System (USIS), and conform to the organization of the Graduates data. The only exception in this regard is that SOCSCI includes economists, who are classified with law and commerce students in the standard system.

The tables give the number of graduates in the sample by field of education and sex (the first column in Table 1), and the distribution of these groups across activity: employed full-time or part-time, unemployed, and those not in the labour force, with the latter split into students and non-students. This gives a very useful overview of what the graduates of 1982 were doing in 1984 and 1987 — that is, two and five years after graduation. It is prudent to first note that some of the groups are fairly small (*e.g.* just under 100 for the ENG women in particular), and even smaller for some of the more specific tables presented below (*e.g.* full-time workers only). This should be kept in mind throughout the analysis, although anything in the hundreds should be pretty reliable for our purposes, and the statistical tests which accompany most of the tables take the sample sizes into account when identifying significant differences in outcomes by sex or education.

There is considerable variation in the activity rates by both sex and field of study. For example, full-time employment rates run from a low of 60 percent for AGBIOSC women to 87 percent for ENG men in 1984, while unemployment ranges from 5 percent for MATHSCI women to 14 percent for their AGBIOSC sisters.[6] The ENG and MATHSCI graduates are generally more integrated into the labour market in terms of having full-time jobs, while the AGBIOSC men and women more closely resemble the non-NSE graduates than the other NSE groups, and actually have the lowest full-time employment rates — although this is partially due to their higher enrolment rates, and their unemployment rates are not noticeably higher than others'.

These patterns show that treating the NSE graduates as a single group would result in important within-NSE differences being missed and some significant aspects of the NSE versus non-NSE comparisons being blurred. For example, the comparisons of "NSE TOTAL" versus "Non-NSE" could be mistakenly taken to indicate that initial labour market experiences are similar across these two broad groupings of graduates, whereas in fact there are considerable differences when one looks at the NSE groups individually or compares these to the non-NSE category. This is not only an interesting result, but also has direct relevance to policy initiatives which seek to attract students into the broad NSE category of disciplines. Perhaps the fields should be targeted more precisely, or at least information could be provided regarding the different outcomes which characterize the AGBIOSC versus ENG versus MATHSCI areas of specialisation. This importance of differentiating the NSE groups is reinforced at almost every

[6] These are not "unemployment rates" by the standard definition: those without jobs who would like to work as a proportion of those *in the labour market*. Those would be higher than the rates shown.

point in the study, where the "NSE TOTAL" results are seen to reflect a combination of quite disparate outcomes across the specific NSE groups.

The general increases in full-time employment and reductions in unemployment from 1984 to 1987 indicate a difficult but ultimately successful move into the labour market for a significant number of these graduates. It should be kept in mind that the move from unemployment into a job might be due to an improvement in job offers *or* the lowering of aspirations. The different part-time patterns in Tables 1 and 2 are also interesting. Part-time work could be a preferred choice, or it could be the result of not being able to find full-time work. Either way, we see that it is much less common for the ENG and MATHSCI graduates, and more prevalent for women than men (except engineering, with the small sample of women). The fact that part-time employment rates are roughly stable from 1984 to 1987 while unemployment rates generally fall might indicate that part-time status is in fact largely a matter of choice. That is, with improved job opportunities driving the unemployment rates down, we might expect part-time employment to fall as well if it is similarly driven by a lack of job opportunities. On the other hand, there might be a queuing process whereby individuals move from unemployment into to a part-time position, and finally to a full-time job. A much more complete analysis would be necessary to resolve these issues.

One quite positive aspect of these data is that if we define as "inactive" those individuals who are neither employed nor in school, these rates are around 8-10 percent for the men in the sample in 1984, and down to 4-5 percent by 1987 (except for the slightly higher 7 percent among the social science graduates). We can thus conclude that around 95 percent of these male university graduates are engaged in some sort of productive activity five years after graduation, which seems like a good rate of "success" — even as the term is defined in a rather conservative manner (*i.e.* including part-time work). The ambiguity of the "not in the labour force - not working" category makes the same calculation less meaningful for women. For example, the proportion rises from 1984 to 1987, which undoubtedly largely represents women leaving the labour force due to family responsibilities.

III.2 The Distribution of the Graduates Across Field of Study

Tables 3 and 4 pull back from the overview of outcomes to look at the distribution of graduates in the sample. The first table shows the male-female proportion of graduates in each field, and illustrates that MATHSCI and especially ENG were indeed the most male dominated fields in 1982, while the AGBIOSC group was evenly split. This means that we need to be careful in lumping all the NSE fields together in terms of labels such as "male dominated", and adds an interesting dimension to our inspection of outcomes across the three NSE areas. Of the other fields, only commerce and law also had a majority of male graduates, while all others had more women than men. The social science group is 56 percent female. Table 4 gives the percentages in the other direction: the distribution of men and women across the various fields. See how a mere 2 percent of the female graduates came from engineering and 5 percent were in the maths and sciences, versus 18 percent and 13 percent respectively for men. It is figures like these which have prompted the introduction of programmes to encourage women to enter the NSE fields, which altogether represent a full 40 percent of the male graduates, but only 16 percent of the women.[7]

III.3 The Choice and the Evaluation of the Education Programme

The 1984 questionnaire of the Graduates survey asked the respondents to rate the importance of four factors in the choice of the educational programme: "To acquire specialized knowledge and skills required in a particular occupation"; "To improve career prospects"; "To acquire general communication, social, and reasoning skills"; and "To have the satisfaction of learning and understanding an academic discipline". Individuals were given a choice of numerical codes, with 1 representing "not important", 4 corresponding to "very important", and 2 and 3 as intermediate choices. A similar set of questions asked about the success of the programme by these same criteria, with 1 representing "not at all successful", 4 indicating "very successful", and 2 and 3 again being intermediate. The responses to these questions are presented in Tables 5-10, with one table for each education group (the three NSE groups, all NSE combined, all non-NSE, social science graduates). The tables also report the "Mean Score" for each question, which is the average of the numerical responses as calculated by the author; higher scores thus indicate a more important factor, or one judged to have been more successfully met by the programme.

In addition, the distribution of responses for each of the NSE groups is tested against the non-NSE graduates of the same sex, while within each education group gender comparisons are also made. For example, is the distribution of responses regarding the importance of "specialized knowledge" significantly different for AGBIOSC men versus non-NSE men? Are

[7] As noted above, these figures do not employ the sample weights, and so the actual distributions could be somewhat different than those shown, since the sample was stratified by field of study. The male-female comparisons within each field should, however, not be affected.

the distributions different for AGBIOSC men and women? This exercise identifies the significant sex-education patterns in these variables. An asterisk in the "Mean Score" column in Tables 5-8 indicates that the distribution of men's or women's responses is statistically different from the distribution for non-NSE graduates (as given in Table 9) of the same sex.[8] For the social science graduates reported in Table 10, the change sign (Δ) indicates that the distribution of responses is significantly different from that of all other graduates taken together (including NSE graduates). In a similar fashion, the pairs of female biological signs indicate that the distributions are significantly different for the men and women of the given education group. The mean score is thus a general indicator of the direction of any differences in the distributions of response, but there could also be differences in the distribution of responses even with *no* differences in the means — or *vice versa* — so, properly speaking, the mean scores and statistical tests should be read together.

For example, Table 5 initially suggests that AGBIOSC women generally took the specialized knowledge the programme would provide into greater consideration than did the AGBIOSC men — as indicated by the higher mean score (3.43 versus 3.29), and that this gender difference held for the other factors as well. But on closer inspection it is clear that the only male-female difference which is statistically significant is for the importance of learning satisfaction. A more mixed pattern holds for the successfulness of the programme given on the right hand side of the table, but again the only significant difference is a more positive evaluation of the programme in terms of learning satisfaction. On the other hand, the asterisks almost everywhere indicate that the distributions are significantly different for the AGBIOSC men and women versus the non-NSE graduates, with the mean scores indicating the direction of the differences.

There are a lot of numbers in these tables, and while they provide an interesting and useful set of detailed reference tables, Table 11 better facilitates the principal comparisons we wish to make by presenting the mean scores and statistical test results (as represented by *, Δ, and ♀) for all the groups together. The following discussion focuses on this table. Before proceeding, there is one important caveat: these numbers are only indicative and have no clear absolute interpretation. For example, it is not entirely clear as to how one should evaluate these subjective responses to begin with — for example, will some individuals justify the choice

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[8] See Degroot [1975] regarding the χ^2 test for distributions of discrete values employed here. Naturally, the power of the test depends on the number of observations in the two distributions. This discrete distribution test is more appropriate than a standard χ^2 test of the means, since the latter is based on continuous distributions. The tests are at a 5% significance level.

already made by responding more positively than is truly the case, while others perhaps have a more negative attitude? Still, the patterns are interesting.

The figures in Table 11 show, first, that the ENG and MATHSCI men and women appear to have been more narrowly career oriented when choosing their education programmes, as judged by the higher scores for the first two factors ("specialized knowledge" and "help career") relative to the non-NSE graduates. Conversely, the non-NSE men and women claimed the development of "general skills" to have been more important than did the NSE graduates. Finally, the importance of "learning satisfaction" was pretty similar across these groups.[9] The evaluations of the programmes on the right hand side of the table follow a very similar pattern: the ENG and MATHSCI men and women were more satisfied with the specialized knowledge and career advantages of their programmes than were the non-NSE graduates; the latter gave a higher approval rating regarding the more general skills they obtained; and there is no clear pattern in terms of learning satisfaction.

The AGBIOSC men and women have the most mixed set of responses. They appear to have been less concerned with getting specialized knowledge and directly helping their careers than the other NSE graduates, and in some cases are seen to have been even less directly career-oriented (by these measures) than the non-NSE graduates. Their evaluations follow a similar pattern: definitely less satisfied with the direct career aspects than the other NSE graduates, and generally less content than the non-NSE graduates as well. Regarding the acquisition of more general skills, the initial orientation of the AGBIOSC men and women was more like the other NSE students — less concerned with this factor than the non-NSE students; in turn, they were less satisfied with their programmes by this criterion as well. Finally, learning satisfaction was about as important as for the other groups, and in this regard their programmes were judged to have served them about as well as is the case for the other groups.[10]

The social science graduates were the least concerned of all with respect to specific job skills and the likelihood of the programme to help their careers, but the *most* interested in obtaining general skills. They were in turn the least satisfied of all groups with the more direct

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[9] Not all of these differences are statistically significant, but the relative magnitudes all run in the indicated directions, and a good number of the differences are indeed statistically significant. Further, the relatively small number of engineering women means that these differences are unlikely to be statistically significant.

[10] Note that there are some differences which are seen to be statistically significant, but very small. These should be taken as just that, and judged to be not very important in an evaluative sense. This is reflected in the discussion in the text.

career aspects of their education, and the most content in terms of the general skills they acquired. The learning satisfaction category is again similar to that of other graduates.

Thus these university graduates tended to be more satisfied with their programmes along the criteria which figured most importantly in their education choices, with the ENG and MATHSCI graduates looking to develop direct career skills, and the non-NSE and social science groups more concerned with developing general talents. The similarity across all groups in terms of overall learning satisfaction is consistent with this view of things more or less working out as — in some sense — planned. It is interesting to ponder the fact that the graduates seem to have been generally more satisfied with their programmes in terms of overall learning satisfaction than the skills development aspects — does this indicate that university education tends to be more interesting than it is useful in terms of a career? This is not necessarily a bad thing, although the choice factors in the left side of the table suggest that students entertained no clear preferences in this regard when making their education decisions. The greatest outlier group in all of this is the AGBIOSC graduates: their choice patterns were mixed, while they were generally the least satisfied with their programmes.

As for gender patterns, the most remarkable finding is that every factor seems to have figured more importantly in the choice of the education programme for women than men — without exception (although not all of the differences are significant). This can mean either that women really do take more factors into account when choosing their careers — in terms of both direct job skills and more general learning goals — or they simply say that they do after the fact. The caveats offered above concerning the interpretation of these results are particularly relevant here. As for the evaluation of the programmes, the gender patterns are quite mixed, and few are statistically significant. The only exception to this is for the MATHSCI group, where the women express greater satisfaction with the programme on every count — but, on the other hand, none of the underlying pairs of distributions are statistically significant.

If we use the totals of the mean scores across all four criteria as a crude overall measure of satisfaction with the education programme, we arrive at the following calculations: AGBIOSC men and women: 11.70, 11.89; ENG: 12.44, 12.55; MATHSCI: 12.19, 12.52; non-NSE: 11.95, 12.17; and SOCSCI: 11.47, 11.80. Thus the ENG and MATHSI graduates were the most content, followed by the non-NSE group overall, then the AGBIOSC graduates, and the SOCSCI men and women at the bottom. This same pattern holds whether or not the learning satisfaction criterion is included in the calculation. The female graduates express greater overall satisfaction with their programmes in every field. One must keep in mind the caveat mentioned above regarding the interpretation of these results, since these are very subjective responses to somewhat imprecise sets of questions. For example, the individuals presumably expressed their satisfaction relative to their expectations, but we do not really know what these were. Still, the numbers are there, differences exist, and many of these are statistically significant — and this is interesting.

III.4 The Job-Education Match

The principle reason for creating the Graduates data was to investigate the match between education programmes and jobs, and certain questions were designed to do this in an explicit fashion. Two of these were: "Was the education programme you completed in 1982 intended to prepare you for this job?" and "Do you use any of the skills acquired through the education programme completed in 1982 [in your job]?" A single "job-education relationship" variable was then created by Statistics Canada: if the individual responded yes to both questions, the variable was coded 1 ("Directly Related"); if the person answered yes to just one of the questions (usually no to the first and yes to the second) the variable was coded 2 ("Partly Related"); if the answer was no to both questions, the variable was coded 3 ("Unrelated"). The distribution of this variable for the jobs held at the time of the 1984 and 1987 interviews is shown in Table 12, while a later table will look at the associated earnings patterns.

Tests for differences in the distributions across sex-education groups were again performed, and the asterisks continue to indicate that the distributions are significantly different for the NSE men or women versus the non-NSE graduates; the change signs indicate differences between the social science graduates and all others; and the female biological signs indicate that the distributions are significantly different for the men and women of the same education group.[11] "Mean Score" is once again the average of the responses as calculated by the author. Note that lower numerical values indicate a stronger job-education relationship. For this table and others which follow which are related to jobs and earnings, the sample was further restricted to those who were working as of the relevant interview date and for whom earnings were given, while those who were enrolled as full-time students or who were missing information on any of these selection variables or the variable treated in the table were dropped.

Table 12 shows that there were markedly closer job-education links in 1987 than 1984 for all of the sex-education groups (summarized in the lower mean scores in the later year), indicating that an important aspect of the early labour market dynamics for these university

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[11] See the discussion above for a more detailed description of the tests used. A 5% significance level was again employed.

graduates is a movement into jobs which are more directly related to the education programme graduated from — which is in addition to the changes in labour force status seen in Tables 1 and 2 above. The second major point is that the distributions across field generally conform to expectations, with ENG graduates having the closest job-education matches, followed fairly closely by the MATHSCI group, the non-NSE group third, followed by the AGBIOSC group, and the SOCSCI graduates a little after them. As for job-education patterns by sex, the interesting finding is that there do not appear to be any, and although some of the mean scores are numerically fairly different, the male-female differences in distributions are statistically different for only one group (MATHSCI in 1984). This finding of no significant gender differences in the job-education match is an interesting equality.

The AGBIOSC finding is probably the most surprising, and perhaps explains some of the disappointment with the education programme in terms of career preparation which this group expressed in the previous tables. After all, this is generally thought to be a career-oriented field of education — but in fact it seems to be fairly weak in terms of actually leading to related jobs. This has clear implications for the policies aimed at directing students into NSE specialisations, since these are founded on the presumption that there is a need for such graduates in the labour market, and that the graduates will indeed find work in their field. Quite simply, this does not appear to be the case for the AGBIOSC group — which make up one-third of the total NSE graduates in this sample, and a full 56 percent of the female NSE graduates in particular. Also, this should be put in the context of one-half of the scholarships in the "Canada Scholars in Science and Engineering" programme being reserved for women.

Thus it is possible that a significant number of these scholarships might be rewarding students to enter fields of study where they are actually *less* likely to find a related job upon graduation, and *especially* so for women. The issues are more complicated than this, and it could be the case, for example, that the high-quality students which the scholarships programme attracts do in fact fare very well in the sciences. Still, the patterns of job-education matches revealed here are of interest in that they at least challenge the underlying premise for the programme in many instances, and thus would seem to suggest that more research is required to learn what happens to scholarship recipients in the AGBIOSC fields in particular.

III.5 Job Satisfaction

"Considering all aspects of your job, how satisfied are you with it?". This is an interesting question, the responses to which are summarized in Table 13. The structure of the table and the statistical tests are similar to those which have gone before, with lower values indicating greater job satisfaction. In general, these recent graduates seem remarkably content with their jobs, with around 85 percent and upwards claiming to be either "very satisfied" or "quite satisfied" in 1984, and even more in 1987. There are no clear patterns by education group or sex, except perhaps the lower levels of satisfaction for the social science graduates in 1984 — who then largely catch up by 1987. There are a few significant movements, however: AGBIOSC and ENG men become significantly less satisfied with their jobs than non-NSE men from 1984 to 1987, while MATHSCI women become significantly *more* satisfied than both MATHSCI men and the non-NSE women over the same period.

A similar question was asked regarding satisfaction with earnings in particular: "Considering the duties and responsibilities of your job, how satisfied are you with the money you make?". The responses are reported in Table 14. The graduates generally express less satisfaction with their earnings than with the general evaluation of their jobs. Even still, those who were either very satisfied or quite satisfied with their earnings ranged from 73 to 87 percent in the two years. Patterns appear to be quite stable over time, except that the MATHSCI graduates seem to be a little more content in the latter year, and the AGBIOSC graduates less so. The MATHSCI graduates also express the greatest satisfaction in general, while the AGBIOSC and SOCSCI group are the least content. Men and women exhibit generally similar patterns of job satisfaction — keep this in mind for when we turn to look at gender earnings patterns below. One must keep in mind how the question was put: "*considering the duties and responsibilities of your job...*". It could be that those who are disappointed with their jobs nevertheless feel fairly paid — *given* the nature of the job.

III.6 Overall Evaluation of the Education Programme

A summary evaluation of almost anything undertaken in life is whether or not you would do it again if given the chance. There was an interesting question of this sort asked in the 1984 interview: "Given your experience, which educational programme would you have selected?" with the choice of responses being "the same programme", "a different programme", or "no programme". The responses are presented in Table 15, with a lower mean score indicating a higher approval rating. By this measure, the engineers are the most satisfied, followed by the MATHSCI group, then the non-NSE graduates, the AGBIOSC group, and finally the SOCSCI men and women — which is approximately the same pattern as was found for the general job satisfaction variable discussed above.

Thus while the majority of graduates of each education group would choose the same programme again, one would certainly hope this was easily the case, and in fact around 40 percent of the AGBIOSC women and SOCSCI graduates appear to regret their choices. For the other groups, around one-quarter to one-third would choose another programme. Thus while we previously saw generally high levels of satisfaction with the jobs held, this does not directly translate into a general satisfaction with the education choices made. It is interesting to note that the number of graduates who say they would have taken no programme at all is negligible, which could be taken as a strong vote of confidence for the value of a bachelors degree in general. Finally, note that the question was not asked in 1987, whereas it is possible that responses would have changed over this time period.

Table 16 gives provides some insight into these patterns by showing the relationship between approval ratings and current activity. (Only the mean scores are shown.) Not surprisingly, those in full-time jobs or enrolled in school are most likely to say they would choose the programme again, while part-time and unemployed workers express less satisfaction with their education choices. This makes it clear that the ensuing labour market outcomes are a strong determinant of how graduates feel about their education programmes. Thus in a perfect world we could perhaps make graduates happier by ensuring that there were jobs for all who wanted them. On the other hand, we could try to prevent disappointments by better informing young people about the career prospects attached to each field of study.

III.7 Patterns by Occupation and Industry

How are these graduates distributed across occupation and industry, and what are the associated earnings and part-time work patterns? Tables 17 and 18 present the record as of the 1987 interview date, and the patterns are interesting.[12] One first notices the relative concentration of the ENG and MATHSCI graduates in the NSE and business administration occupations, versus the wide distribution of the AGBIOSC and non-NSE graduates.[13] This reflects the job-education match patterns seen in previous tables, and once again the AGBIOSC group is an outlier relative to the other NSE graduates. Second, the occupation distributions are fairly similar for men and women in each of the education groups, although this is not at all

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[12] Results for 1984 are available from the author, who also has a research project which includes an assessment of the importance of changes in occupation and industry to earnings growth over the 1984-87 period.

[13] The wider distributions of the non-NSE graduates is not surprising; these reflect the different distributions *across* field of study as well as any gender differences *within* a *given* field.

apparent in the aggregate NSE category ("NSE TOTAL") which reflects the different male-female distributions across the three NSE specialisations. Third, there is considerable variation in earnings by occupation for all sex-education groups.

Fourth, female graduates earn less than men of the same education group in the same occupation in almost every pair-wise comparison in the table, and the differences are often considerable. This suggests that any explanation of the gender earnings gap will have to address within-occupation earnings differences as well as those which exist across occupation. This is significant because the differences in how men and women are distributed across occupation can often explain a large portion of the gender earnings gap, whereas in this case substantial earnings differences exist *within* occupation groups. (This will be followed up on in the regressions analysis.) Finally, there is considerable variation in part-time work habits across occupation, women are much more likely to be part-time workers than are men, and these are clearly important factors in the observed earnings patterns.

In Table 18 we see that there is even a wider distribution of graduates by industry than by occupation. This makes sense: one can, for example, be an engineer in any number of different industries, while one's occupation obviously remains that of engineer. As expected, the distributions remain more tightly grouped for the ENG and MATHSCI graduates than others. Reflecting the pattern found with occupation, there is a wide distribution of earnings across industry for the graduates of a given field. Men earn more than women of the same education group in the same industry, but the differences seem to be smaller than the differences by occupation. Part-time work patterns are again varied, with the expected female overrepresentation.

III.8 Earnings Patterns by Sex and Field of Study

We now turn to focus on earnings patterns by sex and education, and this theme will take up the rest of the section. Tables 19 and 20 begin the analysis by showing mean earnings for all workers, for full-time workers only, and the gender earnings ratios for each of these by education group for 1984 and 1987. The asterisks indicate that the mean earnings of the NSE men or women are significantly different from those of non-NSE graduates, the change signs indicate significant differences between the SOCSCI graduates and others, and the pairs of female biological signs indicate a statistically significant difference in earnings for men and women of the same education group.[14]

Table 19 presents mean earnings for 1984. The first thing to notice is the patterns by field of study. They are generally not surprising: the ENG and MATHSCI graduates earn more than the non-NSE graduates, the AGBIOSC group earns less, as do the SOCSCI men and women in the sample. Most of these differences relative to the non-NSE graduates are statistically significant, and on the order of a few thousand dollars on earnings which generally range from the mid- to upper-twenties. (All dollar figures have been converted into 1987 values.) Restricting the view to full-time workers does not change the patterns very much, although of course mean earnings are everywhere higher than when all workers were considered. We saw above that differences in the distribution of male and female graduates by occupation and industry cannot explain the gender earnings gaps; neither can part-time versus full-time work patterns.

The gender earnings ratios for the different education groups are all around .90 when all workers are considered, and up to as high as .97 for full-time workers only. While these gender earnings differences are almost all statistically significant they are not huge, and are indeed quite a bit smaller than what is typically found in a broad sampling of workers — and very far from the famous ".60" which is often cited as the overall gender earnings ratio. On the other hand, this is what we should expect, since these are all recent university graduates and thus resemble each other in some important earnings-determining dimensions. In fact, we would probably have been quite surprised to find large gender earnings gaps for these relatively homogeneous groups of male and female workers.

The 1987 earnings shown in Table 20 — just three years later — present quite a different situation. First, male ENG and MATHSCI graduates now have (slightly) *lower* mean earnings than the non-NSE group — the opposite of what was found for 1984. Conversely, the female ENG graduates continue to have significantly *higher* earnings than their non-NSE sisters — indeed, even more so than in 1984. Finally, AGBIOSC men and women continue to lag behind the others, as do the SOCSCI graduates. More precisely, the ratios of mean earnings (all workers) of the AGBIOSC, MATHSCI, and ENG women versus the non-NSE group go from .89, 1.11, and 1.11 respectively in 1984, to .90, 1.14, and 1.14 in 1987 — that is, the relative earnings patterns are pretty stable, with a smallish rise in the relative earnings of the ENG and

[14] The tests thus resemble those previously presented, only now they are based on standard χ^2 tests for continuous distributions. The 5% significance level continues to be employed.

MATHSCI graduates. For men, however, the comparable ratios move from .88, 1.13, and 1.09 in 1984 to .93, .99, and .97 in 1987. There are thus some very different earnings dynamics in the early years: ENG and MATHSCI men initially earn significantly more than non-NSE men, but this advantage has completely disappeared just three years later; ENG and MATHSCI women earn more than non-NSE women initially, and this advantage *grows* a little in the following years; and the relative patterns of the AGBIOSC and non-NSE graduates are roughly stable across the two years for both men and women.

The second major point is the general increase in the gender earnings gaps from 1984 to 1987, and the differences in the gap by education group which emerge over the period. For example, the female-male earnings ratio for the non-NSE graduates (all workers) falls from .91 in 1984 to .77 in 1987, and even for full-time workers it drops from .93 to .79. Similar patterns hold for the AGBIOSC and SOCSCI groups. On the other hand, for the ENG and MATHSCI graduates the gender earnings gaps widen only slightly from 1984 to 1987, with the earnings ratio around .90 in the later year. This of course simply mirrors the maintained earnings advantages for the ENG and MATHSCI women in these early years versus the declines for men, as seen just previously. In short, the gender earnings gaps grow everywhere, and for some groups rather astoundingly over such a relatively short period — while the widening is much less dramatic for the ENG and MATHSCI graduates.

These results are quite relevant to the evaluation of the policies designed to encourage students to enter the sciences, and in this regard the comments offered here largely follow in the vein established above. In short, science graduates do indeed have higher earnings in many cases, but this is by no means a general rule across groups or over time. For men, ENG and MATHSCI graduates have higher earnings two years after graduation, while three years later they earn about the same as non-NSE graduates; for the AGBIOSC men, earnings are lower in both periods. Thus across the board the NSE men have some early earnings advantages, but taken as a group they actually appear to make a little *less* than non-NSE graduates five years after graduation. For women, the story is different, in that the early advantages of the ENG and MATHSCI women continue, and even strengthen a little over time, whereas the lower earnings of the AGBIOSC women are equally stable. Taken as a group the NSE women have mean earnings which are very similar to those of non-NSE women in both 1984 and 1987.

Thus the scholarships programme is largely attracting individuals into fields where earnings are higher than elsewhere in two of the three fields (ENG and MATHSCI), but lower in the other (AGBIOSC), and the identified earnings advantages are relatively short-lived for men, but more enduring for women. The clearly-benefitting ENG and MATHSCI women comprise only about one-half of the full group of NSE women in the sample, with the lower-earning AGBIOSC group making up the rest; and these ENG and MATHSCI women represent a mere 13 percent of *all* the NSE (male *and* female) graduates in the sample. Thus there are perhaps not a great number of clear winners from a programme which encourages men and women to enter into the sciences.

It is, however, important to keep the caveats offered earlier in mind. In particular, it is probable that those who receive the scholarships do in fact earn more than the average in the NSE fields, and it is quite possible that these individuals are better off than they would have been in other disciplines. Finally, it could well be that the scholarships programme is achieving its goal of encouraging more — and better quality — students to go into the sciences. This gets into the complex question of programme choice and related estimation issues, which will be discussed further in the econometric section below. But the evidence does raise some issues with which policy makers should be concerned, and points out the need for further research on what happens to NSE graduates generally, and scholarship recipients in particular. Finally, there is the whole issue of social rates of returns to these investments, and how well these are reflected in the earnings patterns observed in these data.

III.9 The Job-Education Match and Earnings

The pattern of job-education matches was shown in Table 12. Tables 21 and 22 follows up on this by showing the mean earnings by the job-education match for each sex-education group for 1984 and 1987. The asterisks now indicate that mean earnings are significantly different for those in jobs which are partly- or directly-related to their education versus those in jobs with no such link, while the female biological signs indicate significant differences for men and women of the same job-education match type and education group. Direct comparisons of earnings by type of job-education match and by gender are facilitated by the earnings ratios shown in the last two columns of the tables.

The results are not surprising. ENG men and women are most likely to be in jobs matched to their education, followed by the non-NSE group, the AGBIOSC graduates, and those in the SOCSCI field — as was seen in the earlier table. Second, earnings are everywhere higher where the job is more closely linked to the education programme, but no clear patterns over time or across field are apparent. Finally, the gender earnings ratios all follow the general patterns established just above, but there is again no clear pattern as to the gap being higher or lower where jobs are better or worse matches with the education programme. We might therefore simply conclude that those in jobs related to their education do indeed have higher earnings, and sometimes quite significantly so, but beyond this there is little we can say. The issue will, however, be returned to in the regression analysis reported on in Section IV.

III.10 Marriage, Children, and Earnings

The remaining tables in this section investigate the relationship between marriage, the presence of children, and earnings. This focus reflects the important role these relationships usually play in the earnings gender gap — as we shall see is the case here as well. This discussion also helps set the stage for the more rigorous and detailed econometric analysis of the male-female earnings differences presented below. Tables 23 and 24 show the mean earnings by the presence of children, with asterisks indicating that mean earnings are significantly different for men or women with children versus those without, while the pairs of female biological signs indicate that earnings are significantly different for men and women in the same presence of children category. The ratio of mean earnings for men or women with children versus those without, and the gender earnings ratio by the presence of children for each education group are shown in the last two columns of the tables to simplify the analysis of earnings patterns by child status, and the associated gender earnings gaps. Due to the dearth of sufficient observations for certain categories in 1984, the discussion will focus on the findings for 1987 found in Table 24.

The first thing to notice is that men with children have higher earnings than those without in all three NSE groups — although the difference is statistically significant only for the engineers. Second, the pattern is more mixed for NSE women, where the differences are nowhere statistically significant and in the case of the ENG women there are not enough women with children to make a reliable estimate. Nevertheless, in the final column we see that the net result is that the gender earnings gaps for these NSE graduates are greater for men and women with children than those without — that is, for the AGBIOSC and MATHSCI groups for which these can be compared. Thus for the NSE graduates, having children is generally associated with higher earnings for men, a more mixed pattern for women, and wider gender earnings gaps. The non-NSE men with children also have higher mean earnings than their childless brethren — but so too do non-NSE women. The same holds for the SOCSCI group. The net outcome is gender earnings gaps which are roughly comparable for those with and without children for the non-NSE group as a whole, and a *lower* gap for men and women with children for the SOCSCI group. This perhaps counter-intuitive result is followed up on in the regression section, where econometric models are employed to separate the effects of individual characteristics correlated with the presence of children from the influence of children earnings *per se*.

Table 25 repeats the exercise of Table 24 ,but treats marriage instead of the presence of children (only the figures for 1987 are presented). Married men have higher mean earnings than unmarried men in almost every education group (AGBIOSC is the exception), and the differences are mostly statistically significant. For women there is no such clear pattern, but the net effect is that the gender earnings gap is everywhere greater for those who are married relative to singles.

Finally, Table 26 puts marriage and children together, and presents the earnings patterns for those men and women who are married and have children versus those individuals who have never been married and have no children. For men, the married-with-children groups have higher earnings than the singles in every case except the AGBIOSC graduates, and for the others the differences are all at least 10 percent. Once again the record is mixed for women, but the resulting gender earnings gaps are in every case notably greater for those with family responsibilities than those without — excepting the SOCSCI group once again. Note also how it is important to look at the NSE groups one at a time to discern these underlying patterns, since the aggregated figures present a very misleading picture. We conclude simply by saying that it seems clear that marriage and the presence of children seem to be significant factors in the emerging gender gaps for these university graduates, which becomes even clearer in the regression analysis which follows.

III.11 Summary and Conclusion

The major findings of this section may be summarized as follows.

- Most graduates were working or back in school five years after leaving university, although some passed through an initial period of joblessness before finding employment. Activity rates vary considerably by field of study and sex, with ENG and MATHSCI graduates having higher rates of full-time employment, and women likelier to be found in part-time jobs.

- ENG and MATHSCI graduates appear to have been more concerned with developing specialised knowledge and job skills and improving their career prospects when choosing their education programme; non-NSE graduates put greater weight on the acquisition of general communication, social, and reasoning skills; while AGBIOSC graduates resemble the non-NSE group more than the other science graduates. Women claim to have been generally more concerned with all the criteria than men, but it is not clear if this reflects different choices, more careful decision making, or simply the manner in which they respond to the questions.

• Satisfaction with the different aspects of the programmes corresponds to the preferences cited: ENG and MATHSCI graduates were happier with the narrower career aspects of their programmes; non-NSE men and women expressed greater satisfaction with the more general developmental aspects; while the AGBIOSC group was less happy than the other NSE groups in terms of the job-specific aspects of the programme, below the non-NSE group in terms of general developments, and generally the least satisfied with their programmes. The groups expressed similar opinions in terms of the importance of the learning satisfaction aspect of the programme, and all were more-or-less equally satisfied on this count.

• The job-education match was closest for Eng and MATHSCI graduates, followed by the non-NSE group, the AGBIOSC men and women next, and the SOCSCI graduates having the weakest job-education matches of all. There was a general movement into jobs more closely related to the programme of study over time for all groups, which is further evidence of the gradual or step-wise nature of the integration into the labour market for many of these graduates. Match patterns were similar for men and women.

• These graduates generally expressed high levels of satisfaction with their jobs overall, but were less content with their earnings. The AGBIOSC graduates were the least satisfied in this regard, the MATHSCI group was the happiest, and the non-NSE and ENG men and women lay between. There were no gender patterns in these outcomes.

• The overall evaluation of the programme — would it be chosen all over again if given the chance? — roughly followed the job evaluation patterns, with the ENG and MATHSCI graduates most likely to respond in the affirmative, followed by the general non-NSE group, then the AGBIOSC graduates, and the SOCSCI men and women the least likely to give this overall approval of their programme. Patterns were generally similar for men and women. While approval rates were around three-quarters at the highest, a full 40 percent of the least-satisfied groups said they would have preferred another programme, although virtually no-one seemed to regret their general decision to have gone to university. Approval ratings are clearly correlated with having a full-time job or being back in school, which suggests that there is perhaps a role for the simple policy of helping students identify fields where they are more likely to find good employment opportunities (although the issue is obviously more complicated than this).

- Not surprisingly, the ENG and MATHSCI graduates were clustered in a couple of occupations and industries, while the other groups were more widely distributed. Mean earnings and the rate of part-time work vary significantly by occupation and industry. Women were more likely to be in part-time jobs's and their mean earnings were almost everywhere lower than men's — and sometimes *much* lower, meaning that there are significant gender gaps even after controlling for field of education *and* the industry and occupation where the graduate finds employment.

- ENG and MATHSCI men and women earned significantly more than their non-science counterparts in 1984, and AGBIOSC men and women made considerably less. But by 1987 — just three years later — the ENG and MATHSCI men had *lower* mean earnings than the non-NSE group, while the women in these fields actually had a slightly *increased* advantage relative to the non-NSE comparison group.

- Looked at differently, the gender earnings gap was relatively uniform across all education groups in 1984 — around 10 percent when part-time workers are included. The gap then increased everywhere by 1987 — but by much less among the ENG and MATHSCI graduates than others. Thus the advantage of the ENG and MATHSCI women must be seen in terms of their not falling as far behind the men in their field as occurred elsewhere. Five years after graduation, the gender earnings gap was 20-25 percent for the non-NSE and AGBIOSC graduates, and just over 10 percent for the ENG and MATHSCI men and women.

- It is interesting to contrast these gender earnings gaps with the similar levels of satisfaction regarding remuneration expressed by men and women mentioned above. It could be that women are happy to be in the jobs they are, and are indeed fairly paid; alternatively, they might not like their jobs, but feel the pay is fair under the circumstances; or it could be that they are resigned to making less than men, and thus the satisfaction they express is within the context of a general resignation to pay inequity.

- The gender earnings gap appears to be related to family responsibilities, in that it is greater among men and women who are married or who have children as compared to singles. The regression analysis will follow up on these questions in a more detailed and rigorous manner.

From a moral standpoint, the results raise serious questions about policies which encourage students to enter the NSE disciplines. From a societal point of view, if we presume that market rates of return reflect social rates of return to education investments in the NSE areas, the results raise questions regarding the efficacy of these human resource development policies. Of the six groups, both men and women in the agricultural and biological sciences have consistently *lower* earnings than non-NSE graduates; men in engineering and maths and sciences earn more than non-NSE graduates two years out, but no more than the non-NSE graduates just three years later; and it is only women in engineering and mathematics and the physical sciences who seem to have consistently higher earnings than non-NSE graduates. It has been noted, however, that the issues are more complex than this, and it is likely that the better students who win the scholarships do indeed go on to have higher earnings than other NSE graduate; that they also earn more than they would have earned in a non-NSE discipline; and that the programme has indeed caused some of them to enter into an NSE field. Further, there are obviously other outcomes which which we might wish to take into consideration when evaluating the outcomes associated with different programmes. Nevertheless, the questions remain regarding the wisdom of encouraging entry into the NSE disciplines.

IV. The Econometric Analysis

This section presents the findings of a regression analysis of the earnings of NSE and non-NSE graduates which has been carried out with the Graduates data described above. The emphasis is on the gender earnings gap which is seen to emerge over the early years in the labour market observed with these data, and the association of these gender earnings differences with marriage and child-bearing patterns represents an important leitmotif of the section. The presentation begins with a general explanation of regression analysis which those who are not particularly at ease with this approach — or those who could use a short refresher — might find useful. This is followed by an overview of what generally can and cannot be learned about the gender earnings gap with an analysis of this sort. A more specific guide to how to read the regression results is then presented, including how to interpret the coefficient estimates and associated statistical tests, followed by a discussion of the special class of categorical (as opposed to continuous) variables in this regard. It is intended that these opening sections will make the presentation of the regression results accessible to all readers, no matter what the technical background. Other readers will be able to skim over these parts more quickly.

After these preambular discussions, the samples used in the regression analysis are briefly reviewed, and the variables are explained. This leads into the regression results for earnings in the jobs held as of the 1984 interview date, which are presented in two sections: first a set of simpler models, and then fuller equations (*i.e.* more variables included in the models). The results for 1987 earnings follow in like fashion. Some disaggregated models are then presented, followed by a number of tables which summarize the earnings patterns by sex and field of study. The third to last and penultimate sections present fixed effects models, which represent an alternative econometric approach which can resolve certain problems likely to be associated with the more standard models passing before. There is a final summarizing and concluding section.

IV.1 Introduction to Regression Analysis: The General Interpretation of Results

The great advantage of regression analysis is that one can analyse simultaneously the various factors which affect earnings, and thus observe the effect of each variable of interest while others are "held constant". For example, one can identify the relationship between the level of earnings and having an AGBIOSC (or other NSE) degree while various labour supply or productivity factors (*e.g.* whether the job is part-time or full-time, or accumulated labour market experience) are controlled for via the appropriate variables being included in the regression.

The standard approach which is followed here assumes that earnings are determined according to the following model:

$$\ln Y_i = X_i\beta + \epsilon_i$$

where $\ln Y_i$ is the natural log of earnings of individual *i*, X represents a set of explanatory variables which characterise the individual, *t* is the year of observation, β is a series of parameters corresponding to X, and ϵ is an error term which captures all the factors which are not included in the $X\beta$ relationship. The empirical work consists of regressing the log of earnings on the relevant variables for which we have empirical measures to estimate the parameters represented in β. The models are estimated for 1984 and 1987 — the two years for which there is information on earnings and other job characteristics for the sample of graduates. The variables included in the models are discussed in sub-section IV.5 below.

One very important word of caution needs to be kept in mind throughout this section: regression analysis is a statistical exercise, and cannot generally differentiate between *correlation* and *causality*. In the present case, we need to be careful about saying that a certain factor *affects* earnings in the manner suggested by the regression coefficient. For example, if earnings are on average found to be (say) ten percent higher for engineering graduates relative to non-NSE graduates, this does not necessarily mean that going to engineering school has *caused* these individuals' earnings to be ten percent higher than they otherwise would have been — it is possible that the engineers' earnings would have been higher than others' even if they had *not* chosen this particular field of endeavour. Or on the other hand, their earnings might have been boosted even *more* than the indicated ten percent.

The fundamental problem is that we do not know what earnings would have been had the individuals chosen a different field of study, and the choice of field might be correlated with unobserved factors which affect earnings — including unobserved individual characteristics. For example, perhaps engineering attracts individuals who are more diligent in completing tasks, which would lead to higher earnings even without going to engineering school: the coefficient on engineering will reflect these effects, and thus overstate the actual effect of having completed an engineering degree on earnings.

This problem is a standard omitted variables problem — which in this specific form has come to be known as the problem of "omitted individual heterogeneity" — and is inherent in most statistical studies of this type. It should be noted that these problems plague cross-tabulations and other simple procedures as much as more sophisticated statistical approaches, including regression analysis; it is fundamentally a data problem, rather than a weakness of any specific statistical approach. There are established ways of attempting to resolve these problems — and some examples of these will be applied and presented below — but the data are usually limited in what they can reveal, and one is left needing to be very careful in how the results are interpreted. The key point is that one should generally think in terms of "associations" between various factors and earnings, rather than the *effect of* the variables *on* earnings, although at times the term "the effect" will be used and should be interpreted to mean no more than the statistical relationship observed in the data (unless otherwise noted).

A second related issue is that even when we do observe the "effect" of a certain variable on earnings, it is not necessarily true that the effect would be the same for other individuals. For example — and ignoring the issues of causality just addressed for the moment — suppose we found that going to engineering school *has* in fact raised the earnings of those graduates by ten percent. It is quite likely that the individuals who chose to go to engineering school had greater potential in this area of specialisation, and thus their earnings were boosted more from the experience than would be the case for others — *i.e.* those who in fact chose another field of study. This problem of simultaneity in the context of omitted heterogeneity has come to be known as "the selection problem": those who are likely to gain the most are more likely to have undertaken the activity — in this case going to engineering school. Again, methods may be employed to take these factors into account and will be reported on below, but such procedures rarely produce definitive results, and the best approach in the present case is to again to exercise caution in the interpretation of results.

It is not necessary for the reader to fully grasp the complex and subtle natures of these issues regarding "simultaneity", "selection", "omitted individual heterogeneity", *etc.*, to profit from reading the results of the regression analysis which follow. The key point to understand is that with the standard ordinary least squares ("OLS") regressions which are depended upon most heavily below we are essentially summarizing the empirical relationships which are observed to exist between earnings and the variables which are included in the regressions, as estimated over this sample of NSE and non-NSE university graduates. These empirical correlations may or may not be "causal", or may measure causal effects which hold for one group of individuals but which would not generalize to others — but the fact remains that the empirical relationships indicated by the regression coefficients do exist, and are of interest. It is only for the results to be appropriately interpreted.

IV.2 The Statistical Analysis of the Gender Earnings Gap

A good deal of attention is paid to the gender earnings gap in this study, and some cautionary remarks are warranted in this respect. First, it needs to be understood that statistical analyses of this type can rarely tell us if there is "discrimination" by the standard definition that equally qualified women in a given job situation are being paid less than men. The basic problem is one of incomplete information: we cannot observe *all* the factors which affect earnings, and to the degree any omitted factors are correlated with earnings *and* gender, it could appear that there is "discrimination" when in fact there is simply a missing (or badly measured) variable which could explain the difference. For example, while variables representing accumulated labour market experience are included in the regression models presented below in order to control for the related effects on earnings (*i.e.* people with more job experience should have higher earnings), if these variables are less than perfect measures of "human capital investments" and other factors, they will not fully capture the influence of these factors on earnings. For example, if experience tends to be undermeasured, and men tend to have more accumulated experience than women, it could appear that women are being inappropriately paid less than men — in that for "equal" levels of experience women receive lower earnings — when the earnings difference is really due to the unaccounted for differences in experience.

Again, this is the situation with virtually all empirical analyses of the gender earnings gap, and the present study is at no special disadvantage in this regard. In fact, quite the contrary, in that by looking at a reasonably homogeneous group of individuals — men and women who graduated from university the same year — many factors which can lead to male-female earnings differences do not exist. Further, the panel nature of the data (represented in the two post-graduation years for which we have job and earnings information) is exploited to implement methods which control for certain unobservable factors which could affect the assessment of the gender gap. Thus the present data afford a very interesting perspective of the gender gap and how it unfolds over the first years following graduation for this particular group of university graduates. Nevertheless, the caveat mentioned above should be kept in mind throughout the analysis.

The second main point regarding the gender earnings gap, and somewhat converse to the first — *i.e.* regarding the need to control for various factors which affect earnings in determining the true gender gap — is that one must be very precise with the definition of "discrimination" employed, and be careful regarding which factors *should* be "controlled for" via their inclusion in the earnings regressions. On the one hand, one might wish to control for not only field of education, but also accumulated labour market experience (for the reasons discussed above) and other productivity factors which affect earnings, to see if there is any residual difference in earnings between men and women. Labour supply variables (*e.g.* full-time versus part-time employment status) could also be included in the regressions by this rationale.

This is a reasonable approach, but it must be understood that the variables which are included in the regressions determine the definition of discrimination being analysed. For example, if a long list of explanatory variables is included in the regressions we might be left with a definition which says essentially that "after controlling for differences in education, labour market experience, occupation, industry *(etc.)*, there is a difference in men's and women's earnings of x percent" — while recognizing that the greater the number of variables included in the regressions, the smaller tends to be the residual earnings gap.[15] This is an intuitively appealing idea: if we control for more and more factors which affect earnings, the *remaining* "unexplained" gender gap is likely to get smaller, precisely because we are controlling for the factors which affect earnings generally, and thus play a role in the gender earnings differences which we observe. Again, this is fine; the interpretation just needs to be clear.[16]

An alternative conceptual and empirical approach is to control for very few factors — or even none. This gives a fine perspective of the "overall" gender gap, which is a good starting point for an analysis of gender differences in earnings patterns. As variables are then added to the regression models, one is able to observe what happens to the gap. If the residual ("unexplained") gap diminishes with the addition of a certain variable or group of variables, we can say that — in a statistical sense — differences in these factors "explain" that portion of the gender earnings gap. On the other hand, for each variable which is added and found to "explain" the gap, one needs to ask from whence came the associated male-female differences which drive the result. For example, if the residual gender earnings gap was seen to fall substantially with the addition of labour market experience variables to the regression, these differences in experience could *themselves* be the *outcome* of discrimination, and thus we would be "over-controlling" for productivity factors in our analysis of the gender earnings gap — and thus understating "discrimination".

There are methods which permit a researcher to attempt to go further in trying to pin down "discrimination", but once more the data are limited, and in this case the question

[15] The residual earnings gap does not *necessarily* diminish as variables are added to the regression. This depends on the correlation between earnings and the variable in question and how the variable is distributed among men and women in the sample.

[16] See Cain [1986] for a thorough discussion of these and other issues discussed in this sub-section.

generally remains extremely problematic even at the conceptual level. The issue hinges largely on the source of discrimination one wishes to investigate. For example, there might be very little *direct* labour market discrimination, in that women and men with the same qualifications and characteristics tend to have the same levels of earnings, but at the same time there could be labour market discrimination in terms of *obtaining* these qualifications — including entry into certain occupations or industries, the accumulation of experience, or being hired into a certain specific job. On another level, even in the absence of labour market discrimination *per se*, there could be appalling inequality with respect to responsibilities within the household — which would have implications for one's situation in the labour market, and thus indirectly contribute to the gender gap. Finally, the choice of field of education is itself partly the outcome of discrimination processes in the education system and society more generally.[17] These are all different types of discrimination, and the analysis of each one would require a different approach.

The key point is that the present study comprises a statistical analysis which cannot tell us very much regarding "discrimination" at any of these levels *per se*. For example, if it is found that differences in labour market experience or full-time versus part-time job status "explain" a significant portion of the gender earnings gap, can we say that this indicates the absence of discrimination? Not at all. We *could* say that there is perhaps little evidence of *direct* labour market discrimination of the type defined earlier, but there could be other structures of discrimination which underlie this apparent "equality".

The present analysis is, again, little different from any other of this type, and going further would essentially require the full investigation of all the processes which give rise to male-female differences in the factors which affect earnings. The goal of this study is much more modest: to observe the male-female differences in earnings which exist in the years following graduation, and to identify the factors which seem to be most important in the emergence of the gender earnings gap. While we will be able to make no dramatic pronouncements regarding "discrimination", we will be able to say quite a lot about the structure and source of the gender earnings *gap*.

The general approach used here is to start with regressions which provide an overall view of the gender earnings gap, and then add variables and pay careful attention to the interpretation.

[17] See Gilbert [1991] for an analysis of male and female university students' perception of the university experience in this regard, especially with respect to the sciences. For example, he finds that the influences which caused students to choose the sciences, or to abandon after starting, were significantly different for men and women.

In this way we obtain an excellent *description* of the gender earnings gap, without risking definitive statements regarding the *nature* of nature of these differences. That is, we will effectively decompose the gender earnings gap, but pass little judgement beyond what the data reveal. This is not out of any particular trepidation on the part of the author to take a stand, but rather out of a keen respect for what the data can and cannot reveal, and a desire to inform the debate rather than communicate a particular set of normative judgements.

IV.3 How to Read the Regression Results

Table R1 presents a series of simple regression models for all NSE and non-NSE graduates together to give an overview of the differences in earnings for those with jobs in 1984 by field of education and sex. The regressions are represented as the columns in the table, with the variables listed along the left hand side entering the regressions whenever there is a corresponding coefficient indicated in the table. Thus the first regression shown in column one has only an intercept and an indicator of whether or not the individual is female, the second regression adds a general NSE indicator, while other regressions have other combinations of the variables shown.

The dependent variable in every case is the natural log of earnings, which is the standard form for empirical earnings equations. This convention comes from both theory and the fact that this functional form tends to fit the data well.[18] The other advantage of the log-earnings specification is that the coefficient estimates have a simple interpretation: the relative amount by which earnings vary with a change in the value of the explanatory variable. Shifting the decimal point on the coefficient two places to the right thus gives this effect in percentage terms. For example, the first equation shows a coefficient of -.140 on the variable "Female", indicating that on average the women in the sample have earnings which are 14 percent lower than men's.[19]

Each coefficient is interpreted in terms of "holding the other factors constant", but in the first equation there are no other variables (except the intercept), so the coefficient reduces to the overall male-female difference in earnings for the recent university graduates in this sample.

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[18] Mincer [1974] is the classic work on the origins of the log-earnings specification, whereby the form comes from individuals maximizing the lifetime flow of consumption in the presence of human capital investments. On the other hand, once the simple theoretically-derived empirical model developed by Mincer is departed from, this particular functional form no longer necessarily holds. In any event, it is the standard specification, and is employed throughout this analysis.

[19] This percentage interpretation is actually an approximation, since the relationship holds exactly only for small changes at the margin. This is a minor technical point, however, and the percentage interpretation is always used.

The gap of 14 percent is smaller than is typically found, but this is to be expected, since we are looking at a relatively homogeneous group of workers for whom earnings *should* be quite similar.

Note that the coefficients represent *average* effects — this is the nature of regression analysis. In doing a regression we effectively instruct the computer to compare all the correlations between the dependent variable (*i.e.* earnings) and the explanatory variables of interest. The stronger the correlation, the larger and more statistically significant the coefficient. That is, if an explanatory variable tends to be correlated with higher (or lower) earnings, this systematic relationship is summarized in the coefficient estimate, such as the 14 percent for women in the first regression. This does not mean that *all* women have earnings which are this much lower than men's, but only that this is the *average* situation in the data. Finally, regressions generate *estimates* of the actual underlying parameters. That is, there is some true relationship between earnings and the explanatory variables, while the estimated coefficient is simply a "best guess" of that true effect. Thus we refer to "coefficient estimates", or the "estimated effects" or the "estimated relationship". Naturally we hope that our estimates are as close to the true parameters as possible.

The intercept term which enters each equation is a sort of general starting point for the dependent variable. The value of 10.15 in the first log-earnings equation translates into about $26,000 (in 1987 dollars) which is reasonable for the sample. The other variables then represent factors which are associated with different earnings levels relative to this base level. For example, the coefficient of -.14 for women indicates an earnings level approximately $3,580 lower than this on average (*i.e.* .14 * 26,000). In general, the intercept is not particularly interesting to the analysis, and will be different depending on the particular arrangement of the variables of the regression, and will therefore generally not enter the discussions below.

In addition to reporting the coefficient estimates, standard conventions are followed in also reporting "absolute t-statistics" (in the parentheses under each coefficient estimate). These are measures of the statistical significance of the coefficient estimates. t-tests take the specific form of reflecting the probability that the parameter estimate is significantly different from zero. A large t-value means there is a greater chance this is so — or, in popular terms, the coefficient estimate is "significant", while a smaller t-statistic means the opposite. There is a functional relationship between the *size* of the coefficient estimate and the t-statistic, but a smaller coefficient estimate can easily be more statistically significant than one which is larger — it all depends on the strength of the underlying relationship, and the ease with which this can be identified in the data.[20]

In general, then, the coefficient estimate is the best guess of the underlying parameter which summarizes the relationship of interest (*i.e.* between earnings and the explanatory variable in question); while the t-statistic is a guide to how reliable the coefficient estimate is. The larger the coefficient estimate, or "point estimate", the greater the effect is estimated to be; the larger the t-statistic, the more sure we can be sure that the effect is indeed different from zero, and the generally more "precise" the coefficient estimate is. A large coefficient with a large t-statistic means, roughly speaking, that the effect is both large and statistically significant (*i.e.* relatively precisely measured). A small coefficient with a small t-statistic suggests a small effect, perhaps not even different from zero in reality. A small coefficient estimate with a large t-statistic suggests a small effect which is quite precisely estimated. Finally, a large coefficient estimate with a small t-statistic suggests that the true effect *might* be large, but might also be small — the parameter is not precisely estimated, and the large coefficient estimate could be more due to random variation in the data than a reflection of the true effect.

To aid the reader, the statistical significance of the coefficient estimates is indicated in two ways in the tables. First, every coefficient has the t-statistic shown in parentheses underneath. A commonly-used rule of thumb is that a t-statistic of greater than 2 suggests we can be pretty confident that it is indeed different from zero — *i.e.* the coefficient is "significant". In addition, the asterisks indicate two specific levels of statistical significance in this regard, one asterisk indicating that we can be 95 percent confident that the parameter is indeed different from zero, and two asterisks indicating we can be 99 percent confident.[21] The relevant statistical issues are much more complicated than this, but the above gives the reader sufficient understanding for reading and interpreting the empirical results contained in the tables.

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[20] The statistic is, formally, the coefficient estimate divided by the standard error of the coefficient estimate, the latter essentially reflecting the precision of the coefficient estimate.

[21] The remaining margins of error of 5% and 1% respectively come from the random elements in the data, by which the true effect could really be nil even though the data seems to suggest the opposite. The 95% and 99% levels should technically be referred to as 5% and 1% levels of significance.

IV.4 The Special Case of Categorical Variables

Most of the variables used in this analysis are of the categorical type — as opposed to continuous. For example, individuals are (obviously) either men or women, and the "Female" variable takes the value one when the individual is a woman, and zero otherwise. The associated coefficient estimate reflects the relationship between earnings and being a woman — relative to the omitted category of men. A similar one-or-the-other possibility underlies the "NSE" variable which is added in the second equation of Table R1, which therefore also takes a value of 0 or 1, with the coefficient representing the effect of being an NSE graduate — this time relative to the omitted non-NSE group. Scanning the column which lists the variables included in the regressions in Table R1 denotes a whole series of such variables, representing sex, field of education, marital status, and the presence of children. Combinations of these variables also appear in the regressions. For example, in the fifth regression there are variables which represent "interactions" between field of study and Female, which is simply to say that these indicator variables take the value one when the individual is both a woman *and* an NSE graduate.

The structure of these categorical variables and the interpretation of their associated coefficient estimates can get somewhat complex, but it is all quite simple once the basic principles are understood. The general rule is that where there is a categorical variable, "dummy" variables are created, with each taking a value of one for a specific category, and zero otherwise. As many such dummy variables may be created as there are values for the particular categorical variable, less one. This is because one of the categories must be omitted from the regression to act as a reference group against which the effects of the other categories are compared. For example, there are two possible categories of sex, and thus we create the "Female" variable; including this indicator variable in the regressions yields a coefficient which estimates the effect on earnings of being a woman — versus the reference group of men. A similarly simple definition holds for the NSE variable: two categories exist (NSE vs. non-NSE), one indicator variable is created and entered in the regression, and the coefficient represents the relationship between earnings and being an NSE graduate — versus the omitted category of non-NSE graduates.

An example of the case of multiple categories is seen in the fourth equation in Table R1, where four education possibilities are considered: each of the three NSE types, and non-NSE. Three dummy variables are created — one for each of the three NSE groups — with the non-NSE group thus left as the reference category. The NSE variables yield regression coefficients which measure the associated differences in earnings relative to the non-NSE graduates. In this case we have simply split up the previous combined NSE group into its component groups, while retaining the same reference (omitted) category. Different levels of detail with regard to the categories can be represented in the regressions in this way.

Similar principles apply to the interactions of categories. For example, including both AGBIOSC (which indicates whether or not the individual is an agricultural or biological science graduate) and AGBIOSC*Female in equation 4 of Table R1 allows for the possibility that there is i) a general AGBIOSC effect, and ii) a *different* AGBIOSC effect for women. Similar constructions are made for marriage and children status in the final equation in Table R1. As we previously added the "Female" variable to allow for a different general level of women's earnings relative to men's, the Female*marriage interaction allows for a different marriage effect. And as we would have taken a nonsignificant coefficient on Female to indicate that there was no general shift for women's earnings relative to men's, a nonsignificant coefficient on Female*marriage would indicate there was no different marriage effect for women relative to men. It should now be clear that while the construction of the categorical variables can get complicated, the principles remain the same.

We can use equation 5 in Table R1 to demonstrate the interpretation of a series of these variables. For example, the general gender earnings gap is reflected in the -10.4 percent indicated by the coefficient on Female. What are the earnings differences associated with being an AGBIOSC graduate? For male AGBIOSC graduates, a general effect of -.116 applies (*i.e.* versus non-NSE graduates), while for AGBIOSC women the .007 effect associated with the AGBIOSC*Female interaction must also be considered. Thus in regression 5 the earnings differences associated with being an AGBIOSC graduate are estimated to be -11.6 percent for men, and -10.9 percent for women — each relative to non-NSE men and women.

The nature of the "nestings" of the comparisons must be kept in mind. For example, the results just reported do not mean that male and female AGBIOSC graduates have almost the same earnings — but rather that the effect of being an AGBIOSC graduate is comparable for men and women. One must recall that the "Female" effect applies equally to *all* women, including AGBIOSC graduates. Thus the gender earnings gap is approximately the same for AGBIOSC graduates as non-NSE graduates — just over 10 percent. In like manner, other pair-wise comparisons can be made; one need only be careful about what is being compared at each point. This will become more clear as the results are discussed below.

IV.5 The Data and the Variables Included in the Regressions

The Graduates data have been discussed in Section II, but a few remarks pertaining to the regression analysis in particular are appropriate here. First, the reader is reminded that the earnings measure is the actual yearly total for those with full-year jobs, while for those with less than full-year jobs the amount is what the individual said annual earnings would be on an annual basis. (Everything is in 1987 dollars.) Also recall that there are no conventional measures of labour market experience, so a series of variables indicating indicate part-time or full-time work (versus not working) at various particular dates between graduation and the interview dates are used instead.[22] This is not an unreasonable procedure, because experience is simply the sum of a series of participation decisions, and while the measures utilised only comprise an approximation of these accumulations, they also have the advantage of differentiating between part-time and full-time work, which is not usually done in conventional experience variables. In any event, these experience measures have proved to work quite well in other work with these data, and bear out quite well once again in the present work.[23]

The samples used for the estimation of the models consist of all individuals with non-zero earnings who were not full-time students as of the relevant interview date and for whom there was no missing information for the variables included in the regressions.[24] The principal variables of interest include the field of education: those in the natural sciences and engineering ("NSE") versus others ("non-NSE"); as well as the three specific groups within the NSE category: agricultural and biological sciences ("AGBIOSC"), engineering ("ENG"), and maths and sciences graduates ("MATHSCI"). Of equal interest are the comparative earnings patterns of men and women, and so the variable "Female" enters the models in a variety of forms. Related to the gender patterns, marital status (married or "unmarried" versus single) and the presence of children (some versus none) also figure prominently in the analysis. Finally, indicators of the job being either partly- or directly-related to the education programme are included to see how the job-education match is related to earnings.

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[22] Job status as of January and October 1983 are used in the 1984 regressions, while these dates plus the status as of the 1984 interview and as of January 1986 are used in the 1987 regressions.

[23] See Cain and Finnie [1992] and Finnie and Martel [1993] for other work which successfully employs this alternative experience measure; see the latter for comparisons across different particular constructions of the proxy.

[24] Student status as of the 1984 interview date is not given in the data, so status as of October 1983 was used instead. Various checks of student and work status in 1986 and 1987 indicated that this was a reasonable procedure for eliminating full-time students from the sample used in the 1984 earnings equations. For 1987, student status as of the interview date was available.

Other control variables included in the regressions are: the series of part-time and full-time work variables used to proxy labour market experience, part-time versus full-time work status in the current job, an indicator of (part-time) student status, age and age squared, a variable which identifies graduates who were in the labour market before being enrolled in the BA programme which was graduated from (to control for previous experience and related factors), "mother" tongue (English, French, other), and geographical region (four categories). These variables are omitted from the "simple" models reported below, while they are included in the "full" models.

IV.6 The Simple Earnings Models for 1984

Table R1 provides an overview of the 1984 earnings patterns by sex and field of education. Equation 1 indicates that on average, the female graduates in the sample have earnings 14 percent lower than their male counterparts, while this difference drops slightly in equation 2 when the NSE indicator is included, which is itself statistically significant, with a point estimate of .068. Thus while earnings appear to be lower for women than men, the drop in the Female coefficient from -.140 in equation 1 to -.123 in equation 2 along with the positive NSE coefficient estimate in equation 2 suggests that the overall earnings disadvantage of women is partly because there are higher earnings associated with being an NSE graduate, and men are evidently more represented in this group. This is the appropriate interpretation of the observation that after controlling for the positive NSE effect, the Female coefficient estimate drops — *i.e.* becomes a smaller negative coefficient. (This sort of reasoning is used extensively throughout the ensuing discussion to provide a more complete view of the earnings differences by field of education and sex among these university graduates.)

In equation 3, a separate NSE effect for women is introduced (NSE*Female), and found to be negative and statistically significant — that is, the NSE effect appears to be different for men and women. The coefficient estimates suggest that while men with NSE specialisations earn 9.6 percent more than their confreres, the effect for women is a much smaller 1.7 percent (*i.e.* the effect of the general NSE variable plus the extra effect for women: .096 - .079 = .017, or 1.7 percent). While we cannot test the significance of this 1.7 percent directly, since this comprises a joint test of two parameters simultaneously (*i.e.* is .096 - .079 significantly different from zero?), the effect is certainly not large, whether it is statistically significant or not.[25]

The fourth equation takes one step backwards and one ahead, in that it allows for different NSE effects by particular specialisation, but does not allow for different effects by sex. The results are quite dramatic in terms of the different effects found for the three NSE groups: strongly negative for AGBIOSC graduates, and strongly positive for ENG and MATHSCI. The overall NSE effect of 6.0 percent seen in equation 2 is now seen to be quite misleading in that it does not describe the relationship for any of the three NSE groups — each lying either quite above or below this figure.

Allowing for yet more flexibility by re-introducing different NSE effects for men and women in equation 5 affirms that the earnings of AGBIOSC graduates are considerably lower than the earnings of non-NSE graduates and the earnings for those in engineering and maths and sciences are quite a bit higher, while also showing that there is no evidence of different effects for men and women in any of the NSE specialisations. Thus the different male-female NSE effects found in equation 4 appear to be an artifact of men and women being distributed unequally across the three groups rather than any different effects by gender *per se*. In summary, the findings suggest there is an overall gender earnings gap of around 10 percent, AGBIOSC men earn 11.6 percent less than non-NSE male graduates, ENG and MATHSCI men earn 16.1 and 11.1 percent more than the non-NSE group respectively, these NSE effects are very similar for the women in these fields, and thus the overall gender earnings gap is pretty uniform across the three education groups.

These results also clearly show that it is very important to look at the three NSE groups individually — as was found throughout the cross-tabulations of Section III. Failing to do so would result in missing the important differences within the broader classification which are

[25] Such joint tests are conceptually very straight forward, but more cumbersome than the direct test represented by a t-statistic, since the covariance between the two parameters needs to be taken into account in the joint test. There are always various ways of constructing a series of dummy variables in a regression, each with its own set of direct and indirect tests. For example, separate variables for men's and women's NSE effects could have been constructed — as opposed to the general effect plus the women's additional effect — which would have generated *exactly* the same net coefficients of .096 for men and .017 for women, and provided direct tests as to whether each of these was significantly different from zero via the t-statistic. On the other hand, the direct test on the *difference* between the male and female NSE effects which exists in the current specification would have been lost, and a joint test would be required to make this determination. In this research, the male-female effects are specified as a general effect (which applies to men and women both) and an additional female effect, as represented by the interactions of the variables with the Female variable, as seen in the regressions of Table R1 and discussed above. This is done to provide the direct tests for the differences of effects between men and women, which was deemed to be most useful in the present study.

found here, distort the comparisons between the NSE and non-NSE graduates, and confuse the gender earnings patterns.

Finally, equation 6 adds marital status and the presence of children to the model, and lets these effects be different for men and women (as seen in the relevant marriage and children variables and the interactions of these with Female). The most dramatic effect is that the overall gender gap drops by about one-half (*i.e.* the coefficient on Female goes from -.104 to -.058), which is to say that the variations in earnings associated with marriage and children for men and women explain much of the previously unaccounted for differences in their earnings. More concretely, the coefficient estimates suggest that men who are married, "unmarried" (separated, divorced, widowed), or who have children, have significantly higher earnings than their single and childless brethren — indeed, being both married *and* having children is associated with earnings being on average a full 27 percent higher than for single men.

The coefficients on the interactions of Married and Children with Female are both negative (-.071 and -.051) and statistically significant, indicating that these effects are different by sex — as we might expect. The point estimates indicate that earnings are 2.2 percent higher for married women versus the reference group of single women, and 12.1 percent higher for women with children versus those without.[26] These positive effects are perhaps somewhat surprising — especially the strong positive correlation between children and earnings — since empirical studies usually find single women to have the highest earnings, and for reasons which we can understand. This pattern has been broken in recent empirical work, however, and so the results are by no means complete outliers. The issue of marriage and children effects will be returned to at various points throughout the rest of this section.

A word might be offered on the R^2 values at this point. The R^2 represents the proportion of the variation in the dependent variable which is associated with the explanatory variables included in the model, and must therefore lie between 0 and 1. Some of the R^2 in these simple models are fairly low, but this is not a problem. As Goldberger [1991] puts it: "The important thing about R^2 is that it is not important in the CR [classical regression] model" (p. 177). This

[26] These are arrived at as follows. The estimated effect of marriage for women is the general effect (shared with men) of .093 plus the additional effect for women as represented in the coefficient of -.071 on the Married*Female interaction: .093 - .071 = .022, or 2.2 percent higher earnings relative to the reference group of single women. Similarly, the estimated effect of children for women is .177 - .056 = .121, or 12.1 percent higher earnings. These contrast to the estimated effects for men, which are read directly off the Married and Children coefficient estimates. In general, adding a Female interaction to a variable essentially frees the effects of that variable to be different for men and women, with the coefficient on the original variable representing the effect for men, and the interaction representing the difference in the effects between men and women, and along with the general component also providing the estimated effect for women.

is because the classical regression model is principally about testing hypotheses regarding the relationships between the explanatory and dependent variables. Thus it is the coefficient estimates and t-statistics which are most important, with the R^2 playing the modest role of measuring the "goodness of fit" of the model. And in fact, we see in the fuller models in the next sub-section that the models do in fact fit the data pretty well. No more needs to be said about R^2.

IV.7 The Full Earnings Models for 1984

Moving to Table R2, we are still dealing with 1984 earnings equations, but these are "full" models in that numerous other explanatory variables are included in the regressions: the series of labour market participation variables for the periods before the 1984 interview date as controls for labour market experience, whether the individual was a full-time or part-time worker, age, age squared, whether or not the individual was working for at least a couple of years before enroling in the bachelors programme which was graduated from, an indicator of (part-time) student status, "mother" tongue, and region of residence. These variables generally performed quite well but are not the focus of this study, so the relevant coefficient estimates and t-statistics for these variables are not presented in the tables.

The reason for including these additional explanatory variables is to see what happens to the education and gender effects as a result. Note that the first equation in Table R2 does not allow for the different marriage and fertility effects for men and women which were included in the last equation of Table R1, while the second equation re-introduces this structure. This provides two useful perspectives. First, a comparison of the second equation of Table R2 — including the marriage/children effects — with the last equation in Table R1 shows that the additional variables drive the coefficient on Female from -.058 down to -.036, thus leaving a reduced, and small, but still statistically significant residual gender earnings gap.

This reduction in the Female coefficient across the equations indicates that some of the unaccounted for difference in earnings previously captured in the Female coefficient in the regressions of Table R1 are associated with male-female differences in the variables which have been added. In particular, it is the labour market experience and part- versus full-time variables which are most important in this regard (results not shown). That is, men have more experience, work full-time more often, and so on. When these effects are not accounted for, as in the regressions of Table R1, the associated gender earnings differences are captured in the

Female variable. Adding the variables then reduces the Female coefficient to the earnings differences *net* of these factors.

There are at least two possible interpretations of these results. First, if the male-female differences in the levels of the added explanatory variables are freely chosen, then we can say that these differences *explain* the portion of the residual gender earnings gap represented in the drop in the Female coefficient estimate from -.058 to -.036. On the other hand, if the male-female differences in experience, work status, *etc.* are themselves the result of discrimination in the labour market, then the larger coefficients on the Female variable seen in Table R1 are a better indicator of the portion of the overall gender earnings gap attributable to labour market discrimination. Whether these male-female differences in work attributes are the result of labour market discrimination or choice is beyond the scope of this paper — as it is for most other studies of this type. On the other hand, this is a useful decomposition of the gender earnings gap. For example, the findings indicate that men and women with similar individual characteristics and work histories have earnings which differ by only a few percentage points on average, and thus *direct* labour market discrimination does not seem to play a very important role in the overall gender gap of 14 percent for these university graduates.

Well...not exactly, since equation 2 of Table R2 also includes the marriage/children variables. This means that the regression takes into account how earnings vary with these factors, with different effects permitted for men and women (as seen in the interactions of Female with these variables). It is clear that adding the additional explanatory variables results in a large diminution of the marriage and children effects relative to those seen in equation 6 of Table R1. For example, married men now have earnings only 4.3 percent higher than single men, while fathers have earnings just 4.5 percent higher than others, for a combined effect of 8.8 — versus the 27 percent effect found previously. This suggests that a large part of why men who are married and have children earn more than others is linked to the fact that they have more work experience, are more likely to work full-time, *etc.* relative to single and childless men.

These differences in experience, work status, *etc.* might themselves result from being married and having children (*i.e.* such men need more to work more to provide for dependents), and could therefore be considered as part of the *total* effect of marriage and children on earnings. Alternatively, these might be noncausal correlations (*e.g.* married men are the "type" who would be working more anyway) in which case it would be the new, smaller direct effects represented in the coefficients of Table R2 which are the true effects of marriage and children — and the previous figures would be overestimates which result from the spurious correlations between these variables and the labour market profiles. Finally, the marriage and children coefficients might reflect *reverse* causality *from* earnings *to* marriage and children. We are not able to disentangle these competing hypotheses at this point, but these questions will be returned to later. Again, even if we are limited in what we can conclude in any definitive manner, at least the decomposition of these earnings patterns is useful. For example, it is interesting to know that most of the earnings differences associated with men's marital status and fatherhood are associated with the associated differences in labour market characteristics, rather than the direct effects of these variables.

The marriage effects for women seen in equation 2 of Table R2 are significantly smaller than those found for men, and don't appear to be very different from zero, while the children effects appear to be similarly unimportant once the additional controls are added in. As was the case for men, these effects are significantly diminished relative to those found in equation 6 of Table R1, which suggests a similar conclusion that the differences in women's earnings associated with marriage and children are largely related to labour market experience and work status. On the other hand, it still remains to be explained why the overall marriage and children effects of Table R1 are strongly positive — as are the remaining (diminished) effects of Table R2. This will be investigated further below.

Regarding the NSE effects, adding the additional explanatory variables leaves the same general pattern of coefficient estimates as those which held in the last equation of Table R1: negative for AGBIOSC, positive for ENG and MATHSCI, and not significantly different for men and women. The fact that the effects are all somewhat reduced from previously (from -.085 to -.064 for AGBIOSC, from .188 to .149 for ENG, and from .145 to .125 for MATHSCI) indicates that part of the overall effects of field of education on earnings is via the associated steadiness of employment, part-time versus full-time status, *etc.* enjoyed by the higher-earning graduates.

Alternative interpretations are once again possible. If these patterns are because ENG and MATHSCI specialisations generate greater opportunities regarding employment patterns, then the larger estimated effects of Table R1 represent the total benefits of being a graduate of these fields, and the fuller models of Table R2 only illustrate how some of the indirect effects unfold. On the other hand — and by the same logic as with the marriage and children effects discussed above — if these work patterns are voluntary, and are not a *result* of the education programme followed, the associated earnings differences are not really ascribable to the NSE specialisations *per se* (*e.g.* ENG and MATHSCI graduates would have worked more anyway), and it is the smaller coefficients of equation 2 which should be considered as the true effects of the programmes, while the coefficients of Table 1 represent over-estimates.[27] Again, we have no good way of testing these competing hypotheses with these data. Nevertheless, the patterns are interesting.

The second major perspective provided by equation 2 in Table R2 is that comparing it with the first equation in the same table identifies the portion of the gender earnings gap associated with the effects of marriage and children — *after* controlling for the various labour market and other factors included in these regressions. This is akin to the similar exercise conducted in going from equation 5 to equation 6 in Table R1; the difference is that in Table R2 the additional control variables of the "full" model are present throughout. The results are generally comparable to those found in the earlier exercise, in that the coefficient on Female drops in size (from -.067 to -.036) and statistical significance, meaning that a significant portion of the part of the earnings gap which is unaccounted for in the first equation is associated with these marriage and children effects.

The third regression in Table R2 add the relationship between the job and the education programme graduated from to the model. As explained in Section II, "Directly Related" means that the individual's programme was meant to prepare one for a job, *and* that the job was indeed related to the programme. "Partly related" means either one or the other of these conditions held, with most of these being where the education was not really intended to prepare the student for a particular career, but there was a link between the schooling and job anyway. The omitted comparison group is where the programme was not intended to prepare the student for a particular job, and the job was in fact not related to the programme of study. Interactions of these variables with Female also enter the regressions to allow these relationships to have different effects on earnings for men and women.

The job-education match variables are unusual, and provide an interesting opportunity to investigate the role of the job-education link in earnings structures in general, and its relationship to differences in earnings by field of education and sex in particular. The effects are found to be strong. For men, a partly- or directly-related job is associated with 15.9 and 18.6 percent higher earnings than those with no such job-education link. The partly-related effect is fairly similar for women, but the directly-related effect is significantly stronger, and is associated with 30.3 percent higher earnings than women with no such link (.186 + .117). We

[27] Any increased labour market participation which is voluntary, but which is based on the higher earnings associated with ENG or MATHSCI, should also be considered as part of the effects of these specialisations of earnings, even if these labour supply factors are in fact "endogenous". Technically, one is simply doing the reduced form estimation of the total effects of a more general structural model which traces the various avenues by which field of specialization affects earnings.

must again be careful in the interpretation of these correlations, but the patterns are interesting, and suggest that an important aspect of the school-to-work transition might be different for these male and female university graduates.

The figures also indicate that the gender earnings gap for men and women who are in jobs directly related to their education is approximately nil: the general Female effect of -.111 offset by the .117 advantage of women in jobs directly related to their studies. "Career-oriented" women (by this simple definition) thus appear to earn as much as similarly directed men. On the other hand, the larger Female coefficient in equation 3 suggests that women who have not completed education programmes which are intended to lead to a specific career and who are indeed not in an education-related job have earnings 11.1 percent lower than similar men. Thus the gender earnings gap is negatively related to the strength of the job-education match.

We also see that adding the job relationship variables results in a moderate diminution in the education effects — which makes sense. That is, the net ENG and MATHSCI effects of regression 3 are smaller than those found in the preceding equation because some of the higher earnings associated with these fields are evidently due to the career orientation of the field and the greater probability that graduates will indeed find work in their domains. The opposite holds for AGBIOSC men and women.

By including occupation and industry variables, the fourth equation of Table R2 controls for some very specific aspects of the individual's work situation. It is thus not surprising that many of the regression coefficients change, since many of the effects operate via their relationship with occupation and industry. For example, being an engineering graduate means the individual is likely to wind up as an engineer in an engineering industry. Thus once we control for the latter, the remaining direct effect of field of education is likely to be diminished. In fact, the addition of the occupation and industry variables leaves many of the coefficients rather difficult to interpret — especially those representing education.

What is more interesting is the male-female comparisons, since it is often thought that women choose to go into different careers upon graduation, and that controlling for this could lead to a much diminished residual gap. As was intimated by the cross-tabulations, this is not borne out in these data, and the general Female coefficient drops only a little when the occupation and industry variables are added.

The last two equations of Table R2 return to the form of the second equation — that is, without the education-job or occupation/industry variables — and add more flexibility to the model by including interactions of the explanatory variables with Female. Each time a variable is interacted with Female, the effect of the variable is allowed to be different for men and women. In equation 5 the series of variables which control for job experience plus the indicator of part-time work are treated in this way, while in the last equation of Table R2 *all* variables are given this flexibility, which is actually equivalent to doing two separate regressions for men and women while retaining the convenience of the direct comparisons which are possible in the single equation. What is most noticeable is how much the results for the variables of interest resemble those of the second regression.

Probably most interesting is that the coefficient estimate for the simple Female shift variable does not drop when the Female interactions are added, whereas it did decline when the interactions with marriage and children were included previously. This means that even allowing for different returns to labour market experience for men and women, different earnings patterns for part-time work status, and so on, there is still a significant gender earnings gap. Well, sort of...since the Female coefficient loses its statistical significance once all the interactions are added. On the other hand, this is not surprising, since the precision with which a coefficient is estimated generally falls as variables with which it is correlated are added to the model — as is the case when we add the additional female interactions. So while we must say that the coefficient estimate on Female is not significantly different from zero, we can also note that the estimate is actually larger than before.

IV.8 The Simple Earnings Models for 1987

A series of regressions for 1987 like those just seen for 1984 are given in Tables R3 and R4. The advantage of the panel nature of the data is that by tracking the same fixed group of graduates over time we can observe the evolution of the earnings patterns in a way which is not possible with cross-section data.[28] The first equation in Table R3 is very striking in that it shows the overall gender earnings gap for these university graduates to have grown from 14.0 percent two years after graduation to 24.8 percent three years later.

[28] The samples used in the regressions for 1984 and 1987 are not identical, in that the selection criteria were applied to each year independently, and thus some individuals who were included in the 1984 regressions were excluded from the 1987 regressions, and vice versa.

As for the importance of field of education, moving across the columns in Table R3 reveals rather different patterns than those found in Table R1 for 1984. For example, the coefficient on the general NSE variable in equations 2 and 3 is not very large, does not appear to be different for men and women, and has no impact on the Female coefficient — all of which are the opposites of what was found for the earlier year. Regarding different effects by particular field, the fourth equation suggests that the AGBIOSC effect is still negative, while ENG and MATHSCI are again associated with higher earnings — but none of these effects are as strong as in 1984.

Equation 5 is the most interesting, however. It indicates that by 1987 the NSE education effects were quite different for male and female graduates, with NSE specialisations working decidedly more to the advantage of women than men. Earnings are 8.3 percent higher for male engineering graduates compared to the non-NSE group, which is considerably less than the advantage of 16.1 percent in 1984; while female engineering graduates have earnings which are a full 18.0 percent higher than the non-NSE comparison group, which is a (slightly) *wider* difference than the 16.5 percent of before.[29] A similar pattern holds for the MATHSCI graduates: men's earnings are 5.0 percent higher than the non-NSE group in 1987, a sharp decline from the 14.5 percent advantage in 1984; while female graduates earn 15.2 percent more than the non-NSE group — up slightly from the 13.6 percent in 1984. Finally, while AGBIOSC is associated with lower earnings for men and women both, the effect might be a little less negative for women (*i.e.* AGBIOSC*Female is positive, but not statistically significant), although the best summary would be that the AGBIOSC effects do not generally appear to be much changed from 1984.

These are important results. They suggest that there are general advantages to being in ENG and MATHSCI for men and women alike, but that these advantages diminish over time with men, while they hold steady or even increase for women. Another way of looking at this is that the gender earnings gap is quite uniform across all graduates in 1984, but by 1987 the gap is considerably smaller for these NSE graduates than others, especially in engineering and maths and sciences. Indeed this is precisely what the positive coefficients on the field-Female interactions indicate: the gender gap in the NSE fields are smaller than the gap which holds for

[29] It needs to be noted that the t-statistic on the ENG*Female interaction is only 1.49, meaning that the supplementary ENG effect for women is not very precisely estimated, could be considerably different than the 9.7 percent point estimate, and might even be not different from zero in reality. On the other hand, this range of estimate is maintained across other regressions, including different poolings of the sample (see below), which is an indicator that one can have some confidence in the estimate.

non-NSE graduates.[30] At the same time, the overall FEMALE intercept in equation 5 indicates that the general gender earnings gap is 24.1 percent in 1987, meaning that women still earn considerably less than men even in the NSE areas — just not *as* much less as for the non-NSE graduates.[31] Indeed, with the general gap being much higher in 1987 than 1984 (*i.e.* the 24.1 percent versus 10.4 percent, from equation 5 in each table), the gender earnings gap is actually greater in 1987 than 1984 for all education groups, including NSE graduates — again, it is just that the widening of the gap is not as drastic for the NSE graduates as compared with the others.

Finally, this discussion of the gender earnings gap and women's lower earnings should not confuse the fact that women in engineering and maths and sciences have significantly higher earnings than *non*-NSE female graduates, and that this advantage is greater in 1987 than 1984, while for the AGBIOSC graduates earnings are about as much lower as they were in 1984 — and further, that these NSE-associated earnings differences are greater than those which hold for male NSE graduates in the case of engineering and maths and sciences. It need only be kept in mind that we are making two sets of comparisons: men versus women, and NSE versus non-NSE (plus of course the relative changes from 1984 to 1987.)

In short, women do worse than men; ENG and MATHSCI graduates generally do better than non-NSE graduates; the ENG and MATHSCI advantages are greater for women than men; and AGBIOSC graduates do worse than not only NSE graduates, but also have lower earnings than non-NSE graduates. Three different fields, three different stories regarding the earnings differences associated with being an NSE graduate, and three different gender earnings gaps.

Equation 6 adds the marriage and children effects to the specification, and the most striking result is that the coefficient on Female drops from -.241 to -.150, which is to say that about two-fifths of the overall gender earnings gap is related to male-female differences in the rate of marriage and the number of children and how earnings vary with marriage and children.

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[30] Conversely, a FEMALE-field interaction coefficient close to zero would indicate that the gender wage gap is about the same in the particular NSE field as for non-NSE graduates, which was uniformly the case for the 1984 regressions.

[31] That is, women in the NSE fields face the general -24.1% which applies to all women in the sample, but the positive coefficients on the Female-NSE interactions mean the gender gap is reduced in these areas. Consider a male and a female engineer as an example. The woman is characterised by the -24.1% general female earnings disadvantage, the 8.3% positive effect of being in engineering, which is shared with men, and an additional 9.7% which reflects the experience of women engineering graduates in particular. The engineering men will have only the 8.3% effect. Thus comparing the male and female engineers yields: -24.1 + 8.3 + 9.7 versus 8.3 which yields a gender earnings gap in engineering of 14.4%. This is simply the general gender gap minus the extra advantage women have for being engineering graduates relative to their male counterparts. This is the general method for determining the gender gap in any particular field.

Men who were married or had children had higher earnings than others, as in 1984, with the combined effect amounting to 18.8 percent more than the comparison group of single men. For women, marriage is not associated with any difference in earnings, while mothers appear to have slightly lower earnings than others. These compare with the positive effects found in 1984, which could be due to i) a higher proportion of lower-earning women getting married or having children from 1984 to 1987, thus changing the composition of these groups, ii) the negative impact of marriage and children on women's careers becoming greater over time, or — and most probably — iii) a mixture of these two effects. These questions will be pursued in more detail below. The other major point to note in equation 6 is that the education effects do not change a great deal with the addition of the marriage and children variables.

Finally, it should be noted that these regression results do not completely jibe with the cross-tabulation results seen in Section III. There, ENG and MATHSCI men appeared to have mean earnings no different from those of non-NSE graduates in 1987, while the regressions indicate their earnings are higher, even though not as much higher as in 1984. This is due to a rather technical point: when the log of earnings is used as the dependent variable, the *shape* of the earnings distributions becomes more important. Without going into the details, if two distributions have the same means, but one is more tightly distributed than the other (*i.e.* a smaller standard error), then the mean of the *log* of that distribution will be *higher*.[32] This is precisely the case here: the ENG, MATHSCI, and non-NSE male graduates have similar mean earnings, but the former two are more tightly distributed, and so their coefficients in the simple log earnings models are positive.[33] Which is best? No clear answer. These are simply two different representations of the different distributions. Most economists would probably prefer the log earnings regression representation, due to the well-established nature of the log approach, but the matter is essentially one of preference. The point is not, however, all that important, in that the story is roughly the same in the two presentations — the only difference being whether or not by 1987 ENG and MATHSCI earnings have dropped (relatively) to be about the same level as non-NSE graduates, or still remain a little ahead.

[32] This is essentially because the upper end of the distribution is compressed, as represented in the natural log transformation, and the distribution with more upper (and lower) observations will have a lower mean of the logs.

[33] Doing a regression of the levels of earnings rather than the logs of course generates the same results as the cross-tabulations: the ENG and MATHSCI men appear to have earnings no different from the non-NSE group.

IV.9 The Full Earnings Models for 1987

Table R4 presents a series of regressions for 1987 similar to those found in Table R2 for 1984 — all the regressions include the extra variables mentioned previously, such as the labour market experience variables, part-time versus full-time status, *etc.*. The first two regressions indicate that adding the extra explanatory variables leaves the NSE effects reduced in size, but with the same signs as in the simple regressions of Table R3. This suggests that a significant portion of the overall earnings differences by field are associated with the accumulation of labour market experience and full- or part-time employment status in the current job.[34] The comments regarding causality versus correlation offered in the discussion of the results of Tables R1 and R2 are equally appropriate here, and should be kept in mind for what follows as well — that is, whether or not these are truly *effects of* or simply *correlated with* the field of education cannot be determined with these data. These are descriptive regressions, not necessarily structural ones.

Next, comparing equation 2 of Table R4 with equation 6 of Table R3 shows that adding the extra variables does not change the overall Female intercept very much, meaning that the previously unexplained portion of the gender earnings gap is not significantly accounted for by taking into account the male-female differences in experience, full-time work, and so on. On the other hand, the marriage and children variables do change in the later equation. In particular, the higher earnings for men who are married and have children are significantly reduced from what was found in Table R3, which means that the overall earnings differences in this regard are largely due to differences in work patterns — as was found in the 1984 earnings equations. For women, the marriage and children effects are around zero in both regressions, but the fixed effects models presented below tell quite a different story in this regard.

Comparing equations 1 and 2 in Table R4 again demonstrates what happens when the different women's marriage and children variables are added in the presence of the full set of explanatory variables. The Female coefficient drops, as expected, but not as much as from equation 5 to equation 6 in Table R3 because the different experience variables included in Table R4 already capture some of the earnings differences associated with marriage and children.

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[34] That is, the portion of the field of education effects due to the labour force attachment and other added variables is the difference between the coefficients in Table R3 versus the coefficients in Table R4, since the associated labour market effects will be captured by the education variables in the first table, but are split out in the second. For example, for engineering men one can compare the coefficient in equation 6 in Table R3 with that of equation 2 in Table R4: .097 is the overall effect, while adding the additional explanatory variables leaves a coefficient of .044. Thus of the 9.7 percent higher earnings associated with ENG for men, 5.3 of this (or 55 percent of the total effect) is associated with the variables which have been added in the second regression.

One may summarize the marriage and children effects as follows. First, differences in earnings associated with marriage and children explain a significant portion of the overall gender earnings gap for this sample of recent graduates — and almost all of the portion of the gap which can be explained by the factors considered in the regressions.[35] Second, this is largely due to married men and fathers having higher earnings than single men, rather than married women and mothers having lower earnings than single women.[36] Third, a good portion of these advantages of men who are married and have children are due to their greater attachment to the labour market.[37] And finally, the coefficient on Female alone indicates that adding controls for labour market attachment has little effect on the earnings gap between unattached women and men, which remains around 14 percent.[38]

The job-education match variables which enter the third equation in Table R4 are again (as in 1984) strongly associated with earnings. What is different from 1984, however, is that the effects of having a job which is "Directly Related" to one's education are no longer greater for women than men, and thus the gender wage gap is as great for these women as others — whereas there was effectively no earnings gap for such comparable men and women in 1984. On the other hand, one must remember that the NSE field effects are now stronger for women than men, which was not the case in 1984, so comparisons have to be made with care. In any event, having a job partly related to one's education is associated with earnings being 16.5 percent higher than for those in jobs with no such association, while a directly-related job is associated with earnings 25.8 percent higher. (These figures are the general effects which, strictly speaking, are the estimated effects for men, but the relationships are very similar for women.)

Next, adding the occupation and industry variables in equation 4 changes the variables of interest surprisingly little. In particular, the education effects remain qualitatively unchanged, and the gender earnings gaps remain roughly the same as in the preceding equations. Finally,

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[35] That is, the overall gender earnings gap after controlling for field of education is 24.1 percent (Table R3, equation 5). Adding the male and female marriage and children variables reduces this to 15 percent (equation 6), while adding the other explanatory variables diminishes it only slightly further to 13.9 percent (Table R4, equation 2). Thus the 9.1 points of the gap explained by the marriage and children variables constitute 37.8 percent of the total gap, and 89 percent of the portion of the gap which is explained by the variables included in the regressions.

[36] That is, the marriage and children effects are estimated to be positive for men, and around zero for women.

[37] As seen in the reduction in the marriage and children coefficients from equation 6 in Table R3 to equation 2 in Table R4.

[38] As seen in the only slight reduction in the Female coefficient from equation 6 in Table R3 to equation 2 in Table R4.

allowing for additional differences in the relationships between the explanatory variables and earnings by adding interactions of Female with the labour force attachment variables in equation 5, and interactions with all remaining variables in equation 6, again leaves results relatively unchanged from those of equation 2. Thus the education effects are quite robust, and with the specification of equation 2 we are pretty much already at the limit of our ability to explain the gender wage gap in these data.

IV.10 Differences in Earnings Effects By Sex and Education Group: The Principles

Regression coefficients reflect the correlations between the explanatory variables and the dependent variable as these are averaged over all the individuals included in the regression. If there are two (or more) different "types" of individuals, in that the earnings relationships varies across the two types (*e.g.* the effect of experience on earnings is different for the two groups) a single pooled regression (*i.e.* with both groups included together) will estimate the weighted average of the two different effects.[39] For example, it was seen in Table R1 that the coefficient on a single NSE variable was very misleading, because the NSE effects were in fact quite different for men and women, as well as across the particular NSE fields. More interesting results were obtained by allowing for these different effects in the regressions. In general, whenever there are significantly different effects by some defining characteristic (*e.g.* sex, field of education) these should be allowed for in the regression model. If this is not done, the coefficient estimates will be misleading, not only for the variables with the different relationships, but also for all the other coefficients estimated in the regression.[40]

The general solution is to introduce the potentially different effects into the regression. This was done extensively in the models estimated above in terms of allowing for male-female differences in the earnings model. First, a simple intercept shift was added — the Female variable — which constrained the differences to be of a very simple form: a single, constant difference in earnings between men and women holding equally across all situations. Then, interactions of Female with the NSE and marriage and children variables were added to allow the relationships between these variables and earnings to differ as well. This treatment was then

[39] This will be done for all variables together, but it is heuristically useful to think in terms of a single variable in this regard.

[40] This is because the whole set of correlations among all variables enters into every coefficient estimate. That is, once one variable is in trouble, the whole regression is also (potentially) in trouble, and one cannot ignore the problem on the grounds that the problems are limited to variables in which little special interest is held.

extended to the job-education match variables, the labour market attachment variables, and finally to the entire list of regressors included in the equation. This latter specification was in fact equivalent to doing two separate regressions for men and women — since all the effects were allowed to differ by gender. It should now be clear why it was important to verify that the results of interest held across these more flexible specifications: this verified that the findings of interest were not due to male-female differences in the structure of the earnings model which had not been accounted for.

There are standard tests for assessing the need to allow for different effects by group. These consist of doing the "constrained" regression where the different effects are not allowed for, doing the "unconstrained" version which allows for the differences, and then comparing the two with a standard log-likelihood or F-test. If the added variables which allow for the different effects make a significant contribution to the fit of the model, this will be revealed (within the usual sort of margin of error). One does not, however, always find this sort of rigour in the published literature. With respect to the case at hand, male-female differences are not always tested for, and restrictions are often simply imposed, with a mention along the lines of "Differences in earnings between men and women are allowed for by including a variable indicating the sex of the individual." As mentioned above, this introduces flexibility of a very limited nature, and in fact men and women should usually *not* be pooled in the same earnings regressions. As for differences across education groups, the prior understanding we bring to the issue is typically very limited, and it thus seems prudent to pursue the issue in this regard as well.

The strategy adopted thus far was to start with a pooled model, then introduce flexibility in a step-wise fashion. One reason for this approach was to allow us to effectively decompose the gender earnings gap, such as identifying the direct versus indirect effects of marriage and children on the earnings of men and women. Another reason was to keep the model as simple as possible — partly because this made the results easier to report and analyse. For example, where there was no difference in the effects of a given variable on earnings for men and women, only a single coefficient had to be estimated, reported, and discussed, and this parameter could obviously play no role in the gender earnings gap. Finally, and more formally, statistical theory tells us that introducing additional variables when unnecessary reduces the efficiency of the estimators. That is, the data is being asked to identify two different parameters when only one actually exists. In practical terms, this means coefficient estimates are less precise — standard errors rise, and t-statistics fall.

In fact, most of the more flexible specifications presented above did in fact perform better than the more restrictive ones; the earnings structures are indeed generally different for these male and female graduates. This was roughly indicated by the change in the coefficient estimates on the original variables (which then came to represent the effects for men), the significance of the newly-added variables which were giving the model greater flexibility (*i.e.* the interactions with Female), and the movements in the F statistics and log-likelihoods of the equations. Various formal tests were also performed to verify these impressions, but were not reported. The key results for our purposes were that i) allowing for different education and marriage and children effects was important, while ii) introducing additional flexibility in terms of allowing for male-female differences in the effects of other variables on earnings variables (*e.g.* the labour market attachment variables, and finally the *entire* set of variables) did not further change the results of interest in any significant way. This is not to say that the additional flexibility did not improve the model — because it did (as indicated by the coefficient estimates, t-statistics, and F and log-likelihood values). It simply means that these changes did not affect the variables which are of most interest in this report.

While we may thus have confidence in the robustness of our results in terms of allowing for differences in the male-female structure of earnings, this is not yet the case for differences by education group. Therefore the following section reports results for separate regressions by education group. (This could have been done within a pooled equation by adding full sets of interactions of the education identifiers with all the variables, but these equations would obviously get very cumbersome, especially if we wanted to retain the separate female effects at the same time.) This seems worth doing, since it seems very possible that the differences in earnings between NSE and non-NSE graduates could be greater than the single dummy variables allow for. For example, earnings might rise differently with experience across fields, and this could affect any of the coefficient estimates in the model. It turns out that some interesting patterns across education groups do emerge, especially for the marriage and children effects and the role they play in the gender earnings gap.

IV.11 Differences in Earnings Effects By Sex and Education Group: The Results

We begin, however, with some separate regressions by sex. Although these have already been done implicitly and reported above, this separate-equation presentation allows us to read off some of the more important effects directly, instead of having to add the general and women-specific effects together as in the pooled equations. The equations in Table R5 are equivalent to the last equations in Tables R1 and R3, in that there is full allowance for the different education effects by sex and field, and the marriage and children effects are permitted to be different for men and women. (No other variables are included in these "simple" models.) The results in this table nicely illuminate the differences in earnings by NSE field for men and women; again, most interesting is how the ENG and MATHSCI advantages hold from 1984 to 1987 for women, while they drop for men — which is now perhaps more obvious than in Tables R1 and R3. The different marriage and children effects by sex are also clearly revealed.[41]

The disadvantage of the separate equations by sex is that one cannot observe the gender earnings differences directly, as *was* possible in the pooled equations, and there are no direct tests on the different effects by gender — which proved useful above. In short, each presentation has its advantages and disadvantages, and we can profit by looking at both. Table R6 extends this exercise by reporting separate equations for men and women for the full models (*i.e.* the full set of regressors listed in Table R2), which therefore correspond to the last equations in Tables R2 and R4.

Turning to the other dimension of importance, different regressions by education group are shown Tables R7 through R10. Obviously the education effects are not shown directly in these results, since the differences exist *across* the equations, but these separate equations are useful for looking at other differences in the structure of earnings by education group. The first two tables present simple models which include only the Female shift and the marriage and children variables for 1984 and 1987 for each education group, and significant differences do seem to exist in this regard. For example, in 1984 (Table R7) the marriage effects are strongly positive for AGBIOSC and non-NSE men, but weak for other males, while in 1987 (Table R8) the effects are strong for all but the AGBIOSC men. Similarly varying patterns are found for the presence of children, and for the interactions of these marriage and children effects for women. These will be summarized and discussed below. More interesting at the moment is the lead-in this provides for the next tables.

Tables R9 and R10 present full models (with the full set of regressors) with and without separate marriage and children effects for men and women. This allows us to observe the importance of the marriage and children effects in explaining the gender earnings gap — after

[41] It is worth emphasizing that these results are *exactly* the same as those implied in the earlier pooled equations. For example, the AGBIOSC effects in 1984 are -.085 for men, and -.088 for women by the separate models reported in the first two equations in Table R5. Equation 5 in Table R1 has the same -.085 coefficient on the AGBIOSC variable, and this applies to men; while this coefficient plus the -.003 coefficient on AGBIOSC*Female generate the same -.088 effect found for women in the separate regression. This exact equivalence holds whenever precisely the same flexibility in earnings effects is represented in the two equations. Changing either the pooled or separate regressions (*e.g.* adding a variable to the separate regressions without allowing for the different effects in the pooled regression) would represent a departure from this exact equivalence.

all other factors have been controlled for. The pairs of regressions for 1984 in Table R9 show that the inclusion of the separate marriage and children variables significantly cuts into the residual gender gap only for the Non-NSE group — seen in the diminution of the Female coefficient from -.066 to -.025. The results for 1987 in Table R10 are very different. The residual gap for the AGBIOSC group drops from 16.6 percent to 7.9 percent; for the ENG group it actually rises a little; for the MATHSCI group the gender earnings gap is reduced from 10.6 percent to practically nil; while the gap narrows from 17.3 percent to 13.6 percent for the non-NSE group.

In summary, while marriage and children effects were seen to play a generally important role in explaining the gender earnings gap in the pooled regressions of Tables R1-R4, it now appears that these vary quite substantially by education group and across time. For example, the ability of the marriage and children effects to explain a significant portion of the gender earnings gap in 1984 is driven almost entirely by the non-NSE group alone. Just three years later the association between earnings and marriage and children appears to directly explain none of the gender gap for engineers, virtually the entirety of the gap among MATHSCI graduates, and between these extremes for the AGBIOSC and non-NSE groups. There is no obvious set of explanations for these patterns, but the patterns are certainly interesting, and might be something worth pursuing further in a later stage of research.

Finally, a series of separate regressions by sex *and* education group were also estimated, to check further for any differences arising from the pooling of men and women in the same regressions by education group. The problem is that we begin to get down to some very small samples, such as around just fifty female ENG graduates. These results were, however, generally very consistent with those reported above, and so the detailed regressions are not reported and need not be discussed further.

IV.12 Some Summarizing Tables

Tables R11 through R15 summarize some of the more important relationships found in the analysis. First, Table R11 shows the differences in earnings associated with the three NSE specialisations versus the non-NSE graduates, for men and women. These are based on the equations of Tables R1 through R4, with the columns corresponding to the different groups of explanatory variables included in the source regressions (see the notes to the table). The key points are as follows. First, the AGBIOSC field is associated with lower earnings and ENG and MATHSCI with higher earnings for both men and women in 1984 and 1987. Second, the effects are very generally similar for men and women (in percentage terms) in 1984. Third, the positive ENG and MATHSCI effects are considerably weaker in 1987 than 1984 for men, but a little stronger for women, and thus over time there emerges a greater advantage to specializing in these fields for women than men. Fourth, for the most part the education effects are not greatly changed when marriage and children effects are added to the regressions, but are significantly reduced when the full set of regressors is included. This means that the overall effects of the field of education on earnings are partly related to the labour market attachment variables (in particular); for example, part of the higher earnings of ENG and MATHSCI graduates is due to their quicker insertion into the labour market and higher rate of full-time jobs.

Table R12 switches the perspective, and summarizes the overall gender earnings gaps by field of education in 1984 and 1987, based on the simple models of equation 5 in Tables R1 and R3 which include only variables for the field of education and sex. First, the gender earnings gaps are uniformly much greater in 1984 than 1987 — *i.e.* women's earnings fall much farther behind men's over the period. Second, while they are quite similar across the education groups in 1984, by 1987 the gaps are distinctly smaller for the ENG and MATHSCI graduates, and somewhat reduced for the AGBIOSC group as well — all relative to the non-NSE group. (The comparisons to the non-NSE group are shown explicitly in the third and fourth columns of the table.) Thus while being an AGBIOSC graduate has been seen to be associated with lower earnings for men and women alike, the gender gap is nevertheless smaller there. On the other hand, earnings are higher for ENG and MATHSCI graduates relative to the non-NSE types, *and* by 1987 the gender gap is smaller as well. It would be another endeavour altogether — and an interesting one — to attempt to ascertain *why* the gender gaps have this pattern across fields.

In the earlier parts of this section we saw that the marriage and children effects play an important role in explaining the overall gender earnings gap in the pooled regressions. We now look at these relationships by field of study. Table R13 shows the overall gender gaps from Table R12 plus the gaps which remain after controlling for, first, marriage and children effects (only); and second, after adding other explanatory variables to the separate regressions by field.[42] This is done to summarize the role of earnings differences associated with marriage and children in the gender earnings gaps across the different fields of specialisation. A comparison of columns 1 and 2 with columns 3 and 4 shows the contribution of these marriage

[42] The overall gaps shown in columns 1 and 2 are based on the pooled regressions of Tables R1 and R3, but there is sufficient flexibility in these simple models that the exact same results would be obtain in regressions separated by field which contained only a Female intercept. That is, even though columns 3 through 6 are based on separate regressions by field of education, while the first two columns come from pooled regressions, the results are in fact directly comparable.

and children effects on the overall gender earnings gaps, and we again see that the results vary by year and by field. (This is a somewhat different set of comparisons to those which were presented previously; both presentations are useful, and these two views simply offer alternative perspectives of the same set of relationships.) The marriage and earnings effects are seen to be very important to the overall earnings differences in 1984 for the non-NSE and AGBIOSC groups, but less so for the others. By 1987, marriage and children are associated with large portions of the gender gap for all but the ENG graduates. Finally, a comparison of columns 3 and 4 with 5 and 6 shows that once we control for these marriage and children effects, not much more of the gap is explainable by the variables available in the data. In summary, the variations in men's and women's earnings associated with marriage and children generally play a large and increasingly important role in the overall gender earnings gaps, but the patterns vary by field. The clear outlier is engineering graduates, which is the group for which we have the fewest number of women and therefore for whom the coefficients are the least precisely estimated.

Table R14 extends the analysis of marriage and children by summarizing the earnings differences associated with these variables, as implied by the coefficient estimates of the pooled equations of Tables R1 and R3, for men and women in 1984 and 1987. Columns 1 and 3 give the overall patterns between marriage and children and earnings — that is, based on regressions which include only the education, sex, and marriage and children variables. Columns 2 and 4 give the remaining direct effects after the additional explanatory variables have been added to the regressions. First, we see that for men the effects are almost everywhere positive, and sometimes very strong. Second, for women they are mostly positive — but weaker. Third, the effects are generally much weaker where the additional regressors have been added to the regression models, meaning that a good portion of the overall effects is related to differences in labour force attachment and other factors correlated with marriage and parenthood. Fourth, since the effects are generally sizably positive for men while they are close to zero for women, it must be the higher earnings of married men and fathers relative to single men, rather than lower earnings of married women and mothers, wherein lies the power of these variables to explain a significant portion of the gender gap, as seen in the preceding table. Finally, the effects are generally smaller in 1987 than 1984, and the women's children effects change from positive to negative. This is probably due to shifts in the type of person who is married or is a parent in the years following graduation and the correlation of the associated unobserved characteristics with earnings, as well as the effects of marriage and children *per se*.

Finally, Table R15 lists the marriage and children effects by education group for women. Whereas we saw above that these variables seem to play quite different roles in the overall earnings gaps for the various education groups, we see here that the effects themselves vary considerably by field. These results should be read with caution, however, because some of these effects are not very precisely estimated. Nevertheless, it is interesting that the pattern of effects is so varied across field and over time. For example, while married women in engineering have earnings 13.4 percent higher than their unmarried sisters in 1987, marriage is *negatively* associated with earnings for AGBIOSC and MATHSCI graduates. The children effects are all negative, but vary widely. As before, there is no obvious explanation for this, and further work might be warranted in this area.

IV.13 Fixed Effect Estimators: The Theory

Another significant advantage of panel data is that they facilitate the use of fixed effect estimators. With this approach, one takes advantage of the repeated observations on individuals over time to implicitly control for omitted individual heterogeneity and thereby eliminate the associated bias in the coefficient estimates. That is, there are certain to be unobserved individual characteristics which affect the earnings of the individuals in the sample, and to the degree this heterogeneity is correlated with variables included in the regression models, standard OLS estimation methods will generate biased coefficient estimates. To the degree these effects are fixed — in that they have the same effect on earnings each period — the panel estimator purges the estimators of this bias. One way of implementing this method is to regress the observed change in earnings over time on changes in the explanatory variables. By this procedure, the omitted fixed (or at least "persistent") effects drop out; by assumption they affect earnings equally in the two periods, and are therefore cancelled when the *change* in earnings — rather than the level — is used as the dependent variable.

In the context of the Graduates data, which include observations on earnings and other information in 1984 and 1987, we can present the model as:

$$\ln E_{i87} = X_{i87}\beta + \theta_i + \epsilon_{i87}$$

$$\ln E_{i84} = X_{i84}\beta + \theta_i + \epsilon_{i84}$$

and therefore

$$\ln E_{i87} - \ln E_{i84} = (X_{i87} - X_{i84})\beta + (\epsilon_{i87} - \epsilon_{i84})$$

where all terms have been previously defined, except for the unobserved fixed effect θ_i. If we estimate either the 1984 or 1987 earnings models by standard OLS methods, any correlation between θ_i and the explanatory variables included in the regressions will generate biased coefficient estimates. Conversely, in the fixed effects difference equation these omitted effects cancel out — thus eliminating the associated bias on the coefficient estimates.[43]

For example, if unobserved individual characteristics which affect earnings are correlated with fatherhood ("fathers tend to be more stable individuals"), standard OLS methods will generate biased estimates of the effects of being a father on earnings, since the coefficient estimate will reflect the influence of the unobserved factors along with the effects of fatherhood *per se*. The fixed effect estimator, on the other hand, will relate the *changes* in earnings associated with the *movement into* fatherhood for *given* individuals, and thus the omitted factors cancel out — the more stable individual who is more likely to be a father (as the story goes) will be more stable and therefore have higher earnings both prior to and during fatherhood, so the changes in earnings at the point of fatherhood will reflect only the effects of fatherhood itself.[44] This is a simple, intuitively appealing, and powerful estimation method which can be used when panel data are available.

The fixed effects model is implemented here by constructing the first difference measures indicated above: the change in log earnings from 1984 to 1987 as the dependent variable, plus a set of change variables associated with the explanatory variables in the model. Two approaches are pursued. The first is to adopt a standard generalization of the model into a form which allows for different growth rates in earnings by various fixed characteristics as well as constructing some very simple change variables which correspond to the marriage and children

[43] It is worth emphasizing that the fixed effects models provide estimates of the same coefficients we are attempting to estimate with the OLS models, even though the form of the estimation model changes. In a more general framework this relationship might not hold exactly, but one can always go back and forth between an OLS and a fixed effects model, and this approximation suits the purposes at hand. See Finnie and Martel [1993] for further discussion of these issues in the context of the graduates data and the estimation of the effects of childbearing on women's earnings.

[44] Of course if individuals *become* "more stable", *etc. because of* fatherhood, this effect will be reflected in the fixed effects coefficient estimate — as it should, since this is indeed part of the effects of fatherhood.

effects which are included in the earnings models estimated above. That is, the change in log earnings is regressed on variables such as Female and the field of education, plus dummy variables which indicate changes from being single to becoming married, or becoming a new parent in the period between the interviews in 1984 and 1987.

The second approach is to include a more complete set of state and change variables regarding marital status and parenthood. For marriage, the omitted reference category is those who were single in both periods, while the regressors included in the models are: married both periods, "unmarried" both periods, newly married between the interview dates, newly divorced, and a residual category for all the other possible but infrequent combinations. Regarding children, the omitted reference category is those who had no children either period, while the regressors are: the same number of children both periods, becoming a new parent between 1984 and 1987, having additional children over the period, and allowance for the few observations with fewer children from one period to the next.

IV.14 Fixed Effect Estimators: The Results

Table F1 presents the results for a number of variants of the simpler model, and the results can be compared to the level equations presented in Tables R1 and R3. The intercept of .239 in the first equation indicates that the overall mean rate of growth of earnings over the 1984-87 period was 23.9 percent — a reasonable number for this group of recent graduates. But actually this is the rate for men only, since the Female intercept has a coefficient of -.082, meaning that earnings grew only 15.7 percent on average for the female graduates in the sample. Hence the widening of the overall gender earnings gap from 1984 to 1987, as seen in Tables R1-R4. Equations 2 and 3 repeat the exercises of Tables R1 and R3 by introducing the NSE variables, but equation 4 is more interesting, as it permits different growth rates for men and women of each field of education. The coefficients on the NSE variables should be interpreted as the differences in the 1984-87 rate of growth of earnings for the NSE graduates versus the non-NSE group. The results indicate that growth rates are about the same for AGBIOSC graduates and the non-NSE group; male engineers perhaps have lower growth rates than non-NSE men (the coefficient is negative, but small and not statistically significant), while women engineers enjoy greater growth than both other women and male engineers; and a similar dynamic holds for MATHSCI graduates. These results are all consistent with what has been seen above.

We now consider the estimates on the marriage and children variables, where the full power of the fixed effects approach is employed. The marriage and children effects in equation 4 of Table F1 are best compared with the OLS estimates of equation 6 in Tables R1 and R4. First, the effects of marriage and children for men are still positive, but much smaller by the fixed effects estimators than was found previously. This is strong evidence that the earlier estimates were biased upwards due to correlation between marriage and the presence of children and unobserved individual characteristics associated with higher earnings. Second, the marriage effects are now moderately negative for women, versus the slightly positive effects seen in Tables 3 and 5, while the presence of children is seen to be *strongly* negative — as opposed to the positive effects found for 1984 and the only slightly negative association found in the 1987 equation. Thus the standard regression models appear to seriously underestimate the negative earnings effects associated with being married and having children for women.

The regressions reported in Table F2 offer a more complete perspective of the earnings effects associated with marriage and parenthood — with and without controls for labour market experience. For men, the marriage and children effects in the first equation are almost uniformly nonsignificant — the sole exception being a somewhat curious negative effect for men with the same number of children in both years. For women, the results suggest that the earnings of women who marry fall 5.8 percent behind what would have held had they remained single, while for continuously married women earnings lag an additional 2.7 percent over the three year inter-interview period (although the latter estimate has a large standard error).

Concerning motherhood, the earnings effects are -14.7 percent for women who had their first child between 1984 and 1987; -17.8 percent for those who gave birth to an additional child over the period; and -5.4 percent for mothers with the same number of children in 1984 and 1987. These results thus suggest that having children is associated with immediate earnings losses; the penalty rises substantially with each new arrival; and these disadvantages worsen over time. Thus mothers fall farther and farther behind women without children, and men in general. These patterns are very different from those suggested by the OLS models, whose coefficient estimates are now seen to be seriously biased by correlation between the presence of children and omitted individual characteristics which are positively related to earnings.[45]

The second regression in Table 16 adds the labour force attachment variables to the fixed effects models. For men, the results are little changed from the first equation, while it is not

[45] See Finnie and Martel [1993] regarding the properties of the fixed effect approach in the context of estimating the effects of children on women's earnings, including a full set of empirical estimates.

surprising to find that the marriage and children effects for women are significantly attenuated by the added variables. This means that a significant portion of the earnings losses associated with being married and having children is related to the associated weaker labour force attachment of these women. The direct effects of marriage remain negative, however, including an effect of -4.0 percent for those newly married; while the children effects remain sizeable and significant: -6.9 percent for a first birth, -12.0 percent for an additional child, and -5.4 percent for women who have the same number of children over the period. In summary, while the fixed effects estimators might themselves suffer from certain shortcomings, this approach offers a very interesting alternative perspective of the effects of marriage and children on men's and women's earnings and the earnings gap between them. Marriage and children appear to have very strong negative effects on women's earnings, and little impact on men's, which is a very different story from that implied by the OLS estimators.

In summary, while the fixed effects estimators might themselves suffer from certain biases, this approach offers a very interesting alternative perspective of the effects of marriage and children on men's and women's earnings and the earnings gap between them. In short, marriage and children appear to have very strong negative effects on women's earnings, and little impact on men's, which is a story very different from that implied by the OLS estimators.

IV.15 Conclusion of the Regression Analysis

The regression analysis may be summarized as follows:

- The general possibilities and limits of regression analysis were established, and the work reported here should be thought of as descriptive.

- The nature of analyses of the gender earnings gap of this type were put in the context of always choosing between: i) wanting to add explanatory variables to the regressions which can rightfully account for male-female differences in earnings, and ii) concern that such "controls" might themselves be the *outcomes* of discrimination processes, thus leading to overstatements of the portion of the gap which can be "explained" (and thus underestimating the share which might be due to discrimination). The procedure adopted here was to start with very simple models in order to establish an initial overview of the gender earnings gap, and to then add variables in order to provide a decomposition of these differences.

• In 1984, ENG and MATHSCI men and women had substantially higher earnings than the non-NSE graduates — on the order of 16 and 11 percent respectively — while AGBIOSC graduates earned almost 10 percent *less* than the non-NSE group.

• These early earnings differences by field of study were very similar for men and women, and were partly related to differences in job attachment, as seen by the role of accumulated experience and part-time versus full-time work status in the earnings patterns.

• The overall gender earnings gap was around 14 percent in 1984. A significant portion of this gap was associated with marriage and the presence of children: the initial results indicated that married men and those with children had substantially higher earnings than single and childless men, while for women the effects were much weaker. These effects accounted for about one-half of the gender gap which remained after the different fields of study had been controlled for, and almost all of the gap which could be explained by the variables available in the data.

• A good portion of these marriage and children effects can, in turn, be related to differences in labour market attachment. In particular, marriage and children are associated with more experience and higher rates of full-time work for men. The remaining *direct* effects of the family status variables are small, but significant. Interpretations of causality must be made with caution.

• The job-education match was an important determinant of earnings for all groups in 1984. Women in jobs directly related to their education fared particularly well, and there was actually no gap between the earnings of these women and men in similar situations.

• Occupation and industry play little role in explaining the gender earnings gap, but are — naturally — related to differences by field of study.

• Adding a full set of interaction variables to allow for different relationships between the explanatory variables and earnings for men and women added to the explanatory power of the 1984 earnings model, but did not change the principal results of interest in any way.

• By 1987, the sex-education patterns of earnings had changed substantially: while the ENG and MATHSCI men had lost most of the earnings premiums they enjoyed over non-NSE men less than three years earlier, the advantages of the ENG and MATHSCI women relative to non-NSE women actually *increased* (slightly) over this same period. The earnings of the AGBIOSC graduates lagged behind the non-NSE group about as much as in the earlier period. Once again, these patterns were significantly related to differences in the accumulation of experience and the incidence of part-time work across fields.

• The overall gender earnings gap rose from 14 percent in 1984 to 24 percent in 1987. Thus earnings differences were very substantial for this group of university graduates just five years after the completion of their schooling. The gap was smaller among the ENG and MATHSCI graduates due to the extra advantages of women in these fields, but they lagged behind all the same — just not *as much* as elsewhere.

• About two-fifths of the 1987 gender earnings gap as related to the marriage and children variables, suggesting that a major factor in these male-female earnings differences was the different impacts of family responsibilities on men's and women's earnings. A good portion of these effects were related to differences in job attachment (*i.e.* experience, part-time versus full-time status, *etc.*).

• As in 1984, the job-education match was strongly related to earnings; unlike the earlier year, the gender gap was pretty similar across all categories of match.

• The results were generally very robust across a variety of specifications, including separate regressions by education, sex, and even education-sex group. The only exception was that the marriage and children effects appeared to vary by field of study, although some of the sample sizes were fairly small. There is no clear explanation of why this might be, and future research might pursue these observations further.

• Fixed effects models were implemented to control for certain unobservable individual characteristics which might bias the coefficient estimates — especially the marriage and children effects. The findings suggest that such bias is indeed quite strong in these samples. In particular, while the previous results generally suggested that men who were married and had children had higher earnings than others, while women's earnings were more mixed in this respect, the fixed effects results suggested that men's earnings were largely *unaffected* by marriage and parenthood, while women's earnings were *much lower* as a result.

V. Conclusion

This paper had the goal of providing a descriptive analysis of the sample of recent bachelors-level university graduates provided by the Follow-Up of 1982 Graduates database, with an emphasis on comparisons between NSE and non-NSE graduates, and men versus women. The unique nature of the data and the mix of cross-tabulations and regression analysis covering many different aspects of the education programme and early labour market experiences has provided a perspective on the school-to-work transition which did not previously exist.

The results are not only interesting, but also relevant to policy. In particular, while the analysis is limited in what it can say about actual beneficiaries of the existing Canada Scholarships Program which encourages university students to enter the sciences and engineering, it certainly paints a picture of these fields which is perhaps at odds with the common presumptions which underlie the programme. Most simply, if there is such a demand for NSE graduates, why aren't their earnings higher? This is especially true for the agricultural and biological sciences, where earnings are uniformly lower than not only the other NSE groups, but also relative to the non-NSE graduates. How does current policy square with this? For example, with fifty percent of the scholarships reserved for women, and the majority of NSE women in the AGBIOSC fields, are women being encouraged to enter fields where they are likely to have disappointing careers? And earnings are by no means the sole measure of success used here. Quite the contrary, as these results hold across almost the full array of measures employed, both subjective and objective, regarding evaluations of the education experience, as well as the record of labour market achievement.

The news is by no means all bad. The ENG and MATHSCI men and women — that is, four of the six NSE sex-education groups — have considerably higher earnings than others two years after graduation, and this must be considered as at least somewhat affirming of the Canada Scholarship Program. Further, the ENG and MATHSCI *women's* advantages hold as strongly a full five years after graduation — which would seem to at least partly validate the stated goal of encouraging female NSE students in particular, and the policy instrument of reserving one-half of the scholarships for women. The down side is that the ENG and MATHSCI men are characterised by only average or slightly above average earnings in the later year, while the AGBIOSC men and women have the consistently lower earnings, as mentioned above. Thus four of the six scholarship recipient groups do not do any better than other graduates in the longer term, and two of these have decidedly dismal performances across the board.

It was noted that this does not necessarily mean that the scholarship programme is not effective. In fact, the high-achieving students who obtain the scholarships might do very well in all of these fields — and better than they would have fared elsewhere. This we cannot tell from these data. Nor can we conjecture what the societal returns to the federal government's investment in the Canada Scholarships Program has been, given that the market rates of return may not reflect societal rates of return to investments in these areas of study. Also, the data employed here follow the graduates only five years after graduation and cover only a single cohort, whereas the longer term record or that for another cohort might be very different. What is required is data on the scholarship recipients themselves, and, ideally, being able to follow them over a longer period of time.

Nevertheless, the findings presented here should cause one to pause and think. Then, perhaps some more research, or perhaps a fine-tuning of the Canada Scholarships Program to ensure that the money is used to encourage students to enter into areas where they will be able to make a significant contribution to Canada's economic well-being and at the same time enjoy more successful and personally rewarding careers. It is hoped that this study has made a contribution to this review process. In the meantime, a dissemination of these findings would, by better informing students, allow them to make better education and career choices for themselves.

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Table 1 — Activity Rates (% Distribution) by Sex and Field of Study, 1984[1]

Education Group & Sex	Number of Grads by Sex and Education Group	Employed		Unemployed	Not in the Labour Force	
		Full Time %	Part Time %	%	Enrolled[4] %	Not Enrolled %
AGBIOSC						
Men	325	70	6	9	14	1
Women	327	60	13	14	10	3
ENG						
Men	630	87	2	9	2	0
Women	78	78	4	6	8	4
MATHSCI						
Men	437	83	4	7	5	1
Women	176	81	5	5	6	2
NSE TOTAL						
Men	1,392	82	3	8	6	1
Women	581	69	10	10	8	3
Non-NSE[2]						
Men	2,101	81	7	9	2	1
Women	3,051	74	12	9	2	3
SOCSCI[3]						
Men	510	77	9	10	3	1
Women	647	71	12	10	4	3

[1] The sample consists of individuals who completed their undergraduate degrees in 1982, excluding those who went on to complete a masters or doctorate programme between 1982 and 1987 and those for whom the information given in the table was missing in either of the interview years. These basic sample characteristics hold for all the tables which follow, with some variation according to particular selection criteria (*e.g.* only those with current jobs), and the availability of the information required for each table.

[2] Includes all Non-NSE university graduates, including the social science graduates who are also shown as a separate group in the final row.

[3] Includes economists, who are grouped with commerce and law graduates in the original classifications, but who have been folded into the social science group for this study.

[4] Individuals who were enrolled in school but who were also working or unemployed are included in the relevant labour force category rather than the "Enrolled" category. That is, they are classified as workers rather than students.

Table 2 — Activity Rates (% Distribution) by Sex and Field of Study, 1987[1]

Education Group & Sex	Employed		Unemployed	Not in the Labour Force	
	Full Time %	Part Time %	%	Enrolled[4] %	Not Enrolled %
AGBIOSC					
Men	78	6	4	11	1
Women	65	10	6	10	8
ENG					
Men	91	2	3	3	1
Women	77	1	8	6	8
MATHSCI					
Men	88	2	4	5	0
Women	83	5	4	3	5
NSE TOTAL					
Men	87	3	4	6	1
Women	72	7	6	8	7
Non-NSE[2]					
Men	86	6	4	4	0
Women	75	13	4	4	5
SOCSCI[3]					
Men	83	6	6	4	1
Women	74	11	4	6	6

[1, 2, 3, 4] See the corresponding notes in Table 1 regarding the sample and the structure of the table.

Table 3 — The Number of Graduates and Percentage of Men and Women in Each Field of Study[1]

Field of Study	Number of Graduates	Men %	Women %
Education	1,258	30	70
Fine Arts & Humanities	961	36	64
Commerce & Law	1,042	62	38
Social Sciences	1,157	44	56
Medical & Health Professions	669	30	70
Agriculture & Biological Sciences	652	50	50
Engineering	708	89	11
Mathematics & Physical Sciences	613	71	29

Table 4 — The Distribution of Male and Female Graduates Across Field of Study[1]

Field of Study	Number of Graduates	Men %	Women %
Education	1,258	11	25
Fine Arts & Humanities	961	10	17
Commerce & Law	1,042	19	11
Social Sciences	1,157	15	18
Medical & Health Professions	669	6	13
Agriculture & Biological Sciences	652	9	9
Engineering	708	18	2
Mathematics & Physical Sciences	613	13	5
Total (within rounding)		100	100

[1] See the notes in Table 1 regarding the sample. These are the standard categories of major field specialisation, and together comprise all the graduates in the sample, except for an additional 65 individuals who had no specific field of study (who are included in the non-NSE group elsewhere in the results.)

Table 5 — Reasons for Choosing the Education Programme and Evaluation of the Programme - AGBIOSC Graduates[1,2]

(Statistical tests indicated by *, ♀.[3])

Factor in the Choice & Sex[4]	Number of Grads (100%)	Importance of Each Factor in the Choice of Programme					Success of the Programme by These Criteria				
		1 Not Imp. %	2 %	3 %	4 Very Imp. %	Mean Score	1 Not Succ. %	2 %	3 %	4 Very Succ. %	Mean Score
Specialized Knowledge											
Men	325	5	11	36	49	3.29*	3	30	45	22	2.85*
Women	327	3	9	28	59	3.43*	7	28	46	19	2.77
Help Career											
Men	325	3	9	27	61	3.46*	9	24	41	27	2.86*
Women	327	2	7	23	69	3.59*	7	28	43	23	2.81*
General Skills											
Men	325	6	22	35	37	3.03*	6	27	46	21	2.82*
Women	327	3	19	36	41	3.16*	4	23	48	24	2.93*
Learning Satisfaction											
Men	325	4	11	36	50	3.31♀	3	13	48	36	3.17♀
Women	327	0	7	24	69	3.62*♀	0	8	46	46	3.38*♀

[1] The information is based on a series of questions which asked the respondent to give the importance of the indicated factor in the choice of the educational programme, with 1 representing "not important", 4 representing "very important", and 2 and 3 as intermediate choices; and other questions regarding the successfulness of the programme by these criteria, with 1 representing "not at all successful", 4 representing "very successful", and 2 and 3 as again being intermediate responses. "Mean Score" is the average of these responses as calculated by the author.

[2] See Table 1 regarding the sample.

[3] * in the "Mean Score" column indicates that the distribution of men's or women's responses from 1 to 4 is statistically different from the distribution for non-NSE graduates (as given in Table 9). The pairs of ♀ signs indicate that the distributions are different for men and women. For example, the importance of the various factors in the choice of education programme appears to be statistically different for these AGBIOSC men and women compared to the non-NSE groups in every case but the second from the last; while the only factor where these AGBIOSC men and women differ significantly from one another is job satisfaction — which was a more important decision factor for women than men, and regarding which the programme was judged more successful by the female AGBIOSC graduates their male counterparts (as indicated by the ♀ signs and the mean scores being higher for women than men). See Degroot [19**] regarding the χ^2 test for distributions of discrete values employed here. This discrete distribution test is more appropriate than a standard χ^2 test of the means (which would presume continuous distributions); the "Mean Scores" are, however, useful summary measures and generally good indicators of the direction of the differences in responses across groups. The tests are at a 5% confidence level, meaning that we can be 95% sure that the two distributions are different, with the margin of error due to randomness in the data (as holds with any statistical test). See Table 11 for a summary table for all groups taken together.

[4] Specifically, the factors are i) "To acquire specialized knowledge and skills required in a particular occupation", ii) "To improve career prospects", iii) "To acquire general communication, social, and reasoning skills", iv) "To have the satisfaction of learning and understanding an academic discipline".

Table 6 — Reasons for Choosing the Education Programme and Evaluation of the Programme - ENG Graduates[1,2]

(Statistical tests indicated by *, ♀.[3])

Factor in the Choice & Sex[4]	Number of Grads (100%)	Importance of Each Factor in the Choice of Programme					Success of the Programme by These Criteria				
		1 Not Imp. %	2 %	3 %	4 Very Imp. %	Mean Score	1 Not Succ. %	2 %	3 %	4 Very Succ. %	Mean Score
Specialized Knowledge											
Men	630	3	6	30	61	3.50*	2	17	50	30	3.09*
Women	78	1	6	32	60	3.51	1	14	51	33	3.17*
Help Career											
Men	630	1	4	23	72	3.66*♀	3	14	33	50	3.31*♀
Women	78	1	4	9	86	3.79♀	10	15	29	45	3.09♀
General Skills											
Men	630	6	20	40	33	3.00*♀	4	28	44	24	2.87*
Women	77	4	16	31	49	3.26♀	6	22	49	23	2.88
Learning Satisfaction											
Men	630	3	14	33	50	3.31♀	2	15	47	36	3.17♀
Women	77	1	5	23	70	3.62♀	3	5	41	51	3.41♀

[1, 2, 3, 4] See the corresponding notes in Table 5.

Table 7 — Reasons for Choosing the Education Programme and Evaluation of the Programme - MATHSCI Graduates[1, 2]

(Statistical tests indicated by *, ♀.[2])

Factor in the Choice & Sex[3]	Number of Grads (100%)	Importance of Each Factor in the Choice of Programme					Success of the Programme by These Criteria				
		1 Not Imp. %	2 %	3 %	4 Very Imp. %	Mean Score	1 Not Succ. %	2 %	3 %	4 Very Succ. %	Mean Score
Specialized Knowledge											
Men	437	5	9	30	55	3.35*♀	4	23	42	30	2.98*
Women	176	1	4	28	67	3.61*♀	3	18	48	31	3.07*
Help Career											
Men	437	2	8	19	71	3.60	4	13	33	50	3.28*
Women	176	2	3	22	73	3.66	2	12	40	46	3.30*
General Skills											
Men	437	6	22	43	30	2.96*	7	30	45	18	2.73*
Women	176	4	15	43	38	3.15*	4	28	47	21	2.85*
Learning Satisfaction											
Men	437	2	11	37	50	3.35	3	11	48	38	3.20
Women	176	2	6	31	61	3.51	2	13	39	47	3.30

[1, 2, 3, 4] See the corresponding notes in Table 5.

Table 8 — Reasons for Choosing the Education Programme and Evaluation of the Programme - All NSE Graduates[1,2]

(Statistical tests indicated by *, ♀.[3])

Factor in the Choice & Sex[4]	Number of Grads (100%)	Importance of Each Factor in the Choice of Programme					Success of the Programme by These Criteria				
		1 Not Imp. %	2 %	3 %	4 Very Imp. %	Mean Score	1 Not Succ. %	2 %	3 %	4 Very Succ. %	Mean Score
Specialized Knowledge											
Men	1,392	4	8	31	56	3.40*	3	22	46	28	3.00*
Women	581	2	7	28	62	3.50*	5	23	48	24	2.92*
Help Career											
Men	1,392	2	6	23	69	3.60*	5	16	35	45	3.19*♀
Women	581	2	5	21	72	3.64	6	21	40	33	2.99*♀
General Skills											
Men	1,392	6	21	40	33	3.00*♀	6	28	45	21	2.82*
Women	580	4	17	38	41	3.17*♀	4	24	48	23	2.90*
Learning Satisfaction											
Men	1,392	3	12	35	50	3.32♀	3	13	47	37	3.18♀
Women	580	1	6	26	67	3.59♀	1	9	43	47	3.36♀

[1, 2, 3, 4] See the corresponding notes in Table 5.

Table 9 — Reasons for Choosing the Education Programme and Evaluation of the Programme - Other (Non-NSE) Graduates[1,2]

(Statistical tests indicated by ♀.[3])

Factor in the Choice & Sex[4]	Number of Grads (100%)	Importance of Each Factor in the Choice of Programme					Success of the Programme by These Criteria				
		1 Not Imp. %	2 %	3 %	4 Very Imp. %	Mean Score	1 Not Succ. %	2 %	3 %	4 Very Succ. %	Mean Score
Specialized Knowledge											
Men	2,099	8	13	28	51	3.22♀	9	28	41	22	2.77
Women	3,050	6	8	21	65	3.45♀	7	27	44	22	2.81
Help Career											
Men	2,099	4	8	21	68	3.52♀	8	20	36	37	3.02
Women	3,050	3	5	18	74	3.62♀	8	21	34	37	3.00
General Skills											
Men	2,098	6	15	35	44	3.17♀	4	21	47	28	2.99♀
Women	3,050	5	12	31	52	3.30♀	5	16	47	32	3.06♀
Learning Satisfaction											
Men	2,098	3	12	31	53	3.34♀	3	15	44	38	3.17♀
Women	3,050	2	6	24	68	3.58♀	2	11	42	45	3.30♀

[1, 2, 3, 4] See the corresponding notes in Table 5. Note that the distributions are compared for men versus women only, since these non-NSE graduates comprise the reference group against which the NSE men and women were compared in the tests reported in the preceding tables.

Table 10 — Reasons for Choosing the Education Programme and Evaluation of the Programme - Social Sciences Graduates[1,2]

(Statistical tests indicated by Δ, ♀[3].)

Factor in the Choice & Sex[4]	Number of Grads (100%)	Importance of Each Factor in the Choice of Programme					Success of the Programme by These Criteria				
		1 Not Imp. %	2 %	3 %	4 Very Imp. %	Mean Score	1 Not Succ. %	2 %	3 %	4 Very Succ. %	Mean Score
Specialized Knowledge											
Men	509	13	19	31	37	2.91Δ♀	17	36	34	14	2.44Δ
Women	646	9	16	28	47	3.12Δ♀	15	33	38	13	2.49Δ
Help Career											
Men	509	4	10	24	61	3.42Δ♀	11	24	42	23	2.76Δ
Women	646	3	7	22	68	3.55Δ♀	11	25	39	25	2.79Δ
General Skills											
Men	509	6	13	35	47	3.23Δ♀	3	17	45	35	3.11Δ♀
Women	646	5	10	26	59	3.38Δ♀	4	11	46	38	3.18Δ♀
Learning Satisfaction											
Men	509	4	14	29	53	3.30♀	4	15	42	39	3.16♀
Women	646	3	7	26	64	3.52♀	2	10	40	48	3.34♀

1, 2, 4 See the corresponding notes in Table 5.

3 Δ indicates that the distribution of responses for men or women is different from the distributions of all other male or female graduates (including NSE graduates). This corresponds to the tests of the NSE graduates against all non-NSE graduates represented by * in Tables 5-9 (which are fully described in Table 5). ♀ continues to indicate significant differences in the distributions of responses between male and female graduates.

Table 11 — Summary of Reasons for Choosing the Education Programme and Evaluation of the Programme — All Groups[1]

(Statistical tests indicated by *, ♀, Δ.[2])

Education Group & Sex	Number of Grads (100%)	Importance of Each Factor in the Choice of Programme[3]				Success of the Programme by Each Criterion			
		Spec. Knowl.	Help Career	Gen. Skills	Learn. Satis.	Spec. Knowl.	Help Career	Gen. Skills	Learn. Satis.
AGBIOSC									
Men	325	3.29*	3.46*	3.03*	3.31♀	2.85*	2.86*	2.82*	3.17♀
Women	327	3.43*	3.59*	3.16*	3.62*♀	2.77	2.81*	2.93*	3.38*♀
ENG									
Men	630	3.50*	3.66*♀	3.00*♀	3.31♀	3.09*	3.31*♀	2.87*	3.17♀
Women	78	3.51	3.79♀	3.26♀	3.62♀	3.17*	3.09♀	2.88	3.41♀
MATHSCI									
Men	437	3.35*♀	3.60	2.96*	3.35	2.98*	3.28*	2.73*	3.20
Women	176	3.61*♀	3.66	3.15*	3.51	3.07*	3.30*	2.85*	3.30
NSE TOTAL									
Men	1,392	3.40	3.60*	3.00*♀	3.32♀	3.00*	3.19*♀	2.82*	3.18♀
Women	581	3.50*	3.64	3.17*♀	3.59♀	2.92*	2.99*♀	2.90*	3.36♀
Non-NSE									
Men	2,099	3.22♀	3.52♀	3.17♀	3.34♀	2.77	3.02	2.99♀	3.17♀
Women	3,050	3.45♀	3.62♀	3.30♀	3.58♀	2.81	3.00	3.06♀	3.30♀
SOCSCI									
Men	509	2.91Δ♀	3.42Δ♀	3.23Δ♀	3.30♀	2.44Δ	2.76Δ	3.11Δ♀	3.16♀
Women	646	3.12Δ♀	3.55Δ♀	3.38Δ♀	3.52♀	2.49Δ	2.79Δ	3.18Δ♀	3.34♀

[1] This summarizing table gathers together the "Mean Scores" for each of the four factors from Tables 5-10 to simplify comparisons across education groups. Reminder: a higher number means the factor was more important in the choice of the programme or the programme was judged more successful by the indicated criterion. (See note 1 in Table 5 for a full description of these measures.)

[2] * indicates that the underlying distribution of responses from 0 to 4 for the NSE group of men or women is statistically different from the distribution for the Non-NSE graduates of the same Sex. Δ indicates that the social science group is significantly different from the non-SS graduates. ♀ indicates that the distributions are different for men and women of the same education group. See note 3 in Tables 5 and 10 for a full description of these tests, and Tables 5-10 for the source distributions and tests which are summarized here.

[3] See note 4 in Table 5 for a full description of these factors, which have been referred to in tables 5-10 as: "Specialized Knowledge", "Help Career", "General Skills", and "Learning Satisfaction".

Table 12 — The Relation Between the Current Job and the Education Programme Graduated From, 1984 and 1987[1,2]

(Statistical tests indicated by *, ♀, and Δ.[3])

Education Group & Sex	Number of Grads (100%)	1984: 1 Dir. Rel. %	1984: 2 Part. Rel. %	1984: 3 Not Rel. %	1984: Mean Score	Number of Grads (100%)	1987: 1 Dir. Rel. %	1987: 2 Part. Rel. %	1987: 3 Not Rel. %	1987: Mean Score
AGBIOSC										
Men	142	35	44	20	1.85*	238	50	32	19	1.69*
Women	184	43	42	15	1.71*	217	53	29	18	1.65*
ENG										
Men	460	56	36	8	1.52*	544	75	21	4	1.29*
Women	51	67	25	8	1.41	57	70	26	4	1.33
MATHSCI										
Men	305	58	32	10	1.51*♀	361	68	24	8	1.40
Women	133	59	22	16	1.53*♀	145	69	25	6	1.37
NSE TOTAL										
Men	907	54	36	10	1.57*	1,143	67	24	9	1.41*♀
Women	368	54	32	14	1.61	419	61	27	12	1.51♀
OTHER										
Men	1,354	49	34	17	1.67	1,710	63	26	12	1.49
Women	2,153	53	32	15	1.62	2,385	63	25	12	1.49
SOCSCI										
Men	316	28	45	26	1.98Δ	394	43	40	17	1.73Δ
Women	436	26	44	30	2.03Δ	493	44	37	19	1.74Δ

[1] The information reported in this table is based on two questions: "Was the education programme you completed in 1982 intended to prepare you for this job?" and "Do you use any of the skills acquired through the education programme completed in 1982 [in your job]?" A single "job-education relationship" variable was then created by Statistics Canada: if the individual responded yes to both questions, the variable was coded 1 ("Directly Related"); if the person answered yes to just one of the questions (usually "no" and "yes") the variable was coded 2 ("Partly Related"); if the answer was no to both questions, code 3 ("Unrelated") was assigned. "Mean Score" is the average of these responses as calculated by the author. Note that lower numerical values indicate a stronger relationship.

[2] In addition to the general characteristics of the sample described in note 1 in Table 1 (*i.e.* 1982 BA graduates who did not obtain more advanced degrees from 1982-87), the samples were further restricted to those who were working as of the relevant interview date and for whom earnings were given; were not enrolled as full-time students; and were not missing information on these selection variables or the variable being analysed in the table.

[3] * again indicates that the distribution of responses for the NSE group of men or women is significantly different from the distribution for Non-NSE graduates at the 5% confidence level; Δ indicates that there is a significant difference between the social science group and all other graduates; and ♀ indicates that the distributions are different for the men and women of the given education group. See note 3 in Tables 5 and 11 for further discussion of these tests.

Table 13 — Job Satisfaction (General), 1984 and 1987[1,2]

(Statistical tests indicated by *, ♀, and Δ.)

Education Group & Sex	1984 Number of Grads (100%)	1984: 1 Very Sat. %	1984: 2 Quite Sat. %	1984: 3 Not Very %	1984: 4 Not at All %	1984: Mean Score	1987 Number of Grads (100%)	1987: 1 Very Sat. %	1987: 2 Quite Sat. %	1987: 3 Not Very %	1987: 4 Not at All %	1987: Mean Score
AGBIOSC												
Men	143	42	45	9	4	1.74	238	48	43	9	0	1.62*
Women	184	43	47	9	1	1.68	217	47	46	6	0	1.60
ENG												
Men	460	47	44	7	2	1.64	544	44	49	6	2	1.66*
Women	52	38	52	10	0	1.71	57	42	56	2	0	1.60
MATHSCI												
Men	305	55	37	6	3	1.57	360	50	44	6	0	1.56♀
Women	132	56	35	9	0	1.53	145	59	37	1	3	1.48*♀
NSE TOTAL												
Men	907	49	42	7	3	1.63♀	1,142	47	46	6	1	1.62*
Women	368	47	43	9	1	1.63*♀	419	51	44	4	1	1.56
Non-NSE												
Men	1,360	47	41	8	4	1.69	1,714	53	41	5	1	1.55♀
Women	2,147	49	39	9	3	1.66	2,393	51	40	7	2	1.60♀
SOCSCI												
Men	318	46	37	13	5	1.77Δ	396	48	43	6	2	1.61
Women	434	45	39	11	5	1.77Δ	495	48	41	8	3	1.65

[1] The table is based on the question "Considering all aspects of your job, how satisfied are you with it?". The choice of responses was 1 ("very satisfied"), 2 ("fairly satisfied"), 3 ("not very satisfied"), 4 ("not at all satisfied"), and 5 ("don't know/no opinion"), with those responding the latter not included in the results. Note that a smaller number means the individual was more satisfied with the job.

[2] See the notes to Table 12 regarding the sample, the structure of the table, and the statistical tests.

Table 14 — Job Satisfaction (Salary), 1984 and 1987[1,2]

(Statistical tests indicated by *, ♀, and Δ.)

Education Group & Sex	Number of Grads (100%)	1984					Number of Grads (100%)	1987				
		1 Very Sat. %	2 Quite Sat. %	3 Not Very %	4 Not at All %	Mean Score		1 Very Sat. %	2 Quite Sat. %	3 Not Very %	4 Not at All %	Mean Score
AGBIOSC												
Men	143	15	65	15	5	2.10*	238	20	54	21	6	2.13
Women	183	24	55	19	3	2.01	217	20	53	24	3	2.10
ENG												
Men	460	24	56	16	4	2.00	544	22	60	16	2	1.99
Women	52	27	52	19	2	1.96	56	25	50	23	2	2.02
MATHSCI												
Men	306	29	54	14	3	1.92	361	27	60	11	2	1.89*
Women	133	30	52	14	4	1.92	145	28	59	10	3	1.90
NSE TOTAL												
Men	909	24	57	15	4	1.99	1,143	23	59	15	3	1.99
Women	368	26	53	17	3	1.97	418	23	55	19	3	2.02
Non-NSE												
Men	1,360	24	53	18	5	2.05♀	1,714	22	58	17	3	2.01♀
Women	2,147	30	49	16	6	1.98♀	2,391	24	53	18	5	2.04♀
SOCSCI												
Men	318	24	55	15	6	2.04	396	23	54	19	3	2.03
Women	435	26	47	20	8	2.10Δ	494	22	49	23	5	2.11Δ

[1] The table is based on the question: "Considering the duties and responsibilities of your job, how satisfied are you with the money you make?", with the same choice of responses as described in the preceding table. Note that a smaller number means that the individual was more satisfied with the salary received in the job.

[2] See the notes to Table 12 regarding the sample, the general structure of the table, and the statistical tests.

Table 15 — Overall Evaluation of the Education Programme, 1984[1,2]

(Statistical tests indicated by *, ♀, and Δ.)

Education Group & Sex	Number of Grads (100%)	1 Would Choose the Same Programme %	2 Would Choose a Different Programme %	3 Would Choose No Programme %	Mean Score
AGBIOSC					
Men	325	66	33	0	1.34
Women	327	60	40	0	1.40*
ENG					
Men	630	77	22	1	1.25*
Women	78	74	26	0	1.26
MATHSCI					
Men	436	72	27	1	1.29
Women	176	71	28	1	1.30
NSE TOTAL					
Men	1,391	73	26	1	1.28♀
Women	581	65	34	0	1.35♀
Non-NSE					
Men	2,099	71	28	1	1.31♀
Women	3,051	69	30	1	1.31♀
SOCSCI					
Men	509	59	39	2	1.42Δ♀
Women	647	59	41	0	1.41Δ♀

[1] Based on the question "Given your experience, which educational programme would you have selected?", which was asked in 1984, with the choice of responses indicated in the table. Note that a lower score indicates greater satisfaction with the programme.

[2] See the notes in Table 12 regarding the sample, the general structure of the table, and the statistical tests.

Table 16 — Overall Evaluation of the Education Programme by Labour Force Status, 1984[1,2]

Education Group	Employed		Unemployed	Not in the Labour Force	
	Full Time	Part Time		Enrolled	Not Enrolled
AGBIOSC					
Men	1.34	1.53	1.43	1.20	-
Women	1.36	1.48	1.42	1.47	1.36
ENG					
Men	1.23	1.50	1.41	1.23	-
Women	1.28	-	-	-	-
MATHSCI					
Men	1.27	1.42	1.42	1.38	-
Women	1.24	-	-	1.36	-
NSE TOTAL					
Men	1.26	1.48	1.42	1.26	1.44
Women	1.31	1.48	1.46	1.39	1.33
Non-NSE					
Men	1.28	1.37	1.46	1.28	1.43
Women	1.29	1.31	1.44	1.28	1.37
SOCSCI					
Men	1.40	1.40	1.61	1.47	-
Women	1.39	1.42	1.47	1.46	1.50

[1] Based on the question described in the preceding table. Only the "Mean Score" is reported here. A reminder that a lower score indicates greater satisfaction. See Table 12 regarding the sample and the general structure of the table.

[2] A dash indicates that there were less than 10 observations in the cell.

Table 17 — Distribution of Graduates by Occupation and Mean Earnings by Occupation, 1987[1,2,3,4]

Education Group & Sex	Distribution of Grads by Occupation; Earnings by Occupation; Proportion of Part-Time Workers by Occupation	(1) Bus. Adm.	(2) NSE	(3) Soc. Sci.	(4) Tch. Rel.	(5) Med. Hlth.	(6) Art. Lit. Rec.	(7) Cler.	(8) Sale Serv.	(9) Prim. Occ.	(10) Sec. Occ.
AGBIOSC											
Men	% in Each Occupation	18	17	1	10	17	2	3	12	15	5
	Mean Earnings ($)	30,710	25,080	-	27,540	40,230	-	-	31,970	55,750	21,250
	Proportion Part-Time	[.07]	[.03]		[.13]	[.03]				[.03]	
Women	% in Each Occupation	19	13	3	18	30	2	7	5	1	3
	Mean Earnings ($)	27,530	26,520	-	23,920	27,510	-	14,800	22,640	-	-
	Proportion Part-Time	[.03]			[.13]	[.12]		[.33]	[.18]		
ENG											
Men	% in Each Occupation	15	66	1	2	1	1	2	3	2	7
	Mean Earnings ($)	38,090	36,040	-	28,090	-	-	29,880	44,890	33,550	36,050
	Proportion Part-Time		[.02]		[.09]						[.05]
Women	% in Each Occupation	7	70	0	7	0	2	4	4	2	5
	Mean Earnings ($)	-	32,700	-	-	-	-	-	-	-	-
	Proportion Part-Time										
MATHSCI											
Men	% in Each Occupation	15	61	0	9	1	0	3	8	1	2
	Mean Earnings ($)	40,170	36,350	-	29,060	-	-	38,000	29,640	-	-
	Proportion Part-Time	[.02]			[.09]						
Women	% in Each Occupation	22	52	0	13	2	0	9	1	1	0
	Mean Earnings ($)	32,870	35,040	-	26,500	-	-	20,540	-	-	-
	Proportion Part-Time		[.03]		[.06]						
NSE TOTAL											
Men	% in Each Occupation	15	54	1	6	4	1	2	7	4	5
	Mean Earnings ($)	36,970	35,450	34,000	28,360	38,110	26,400	31,630	34,200	49,290	32,530
	Proportion Part-Time	[.02]	[.01]		[.10]	[.02]				[.02]	[.03]
Women	% in Each Occupation	18	34	1	15	16	1	7	4	1	2
	Mean Earnings ($)	30,110	32,760	-	24,980	27,460	-	17,030	27,200	-	31,440
	Proportion Part-Time	[.01]	[.01]		[.10]	[.12]		[.17]	[.20]		[.11]
Non-NSE											
Men	% in Each Occupation	31	4	7	23	10	5	5	11	1	4
	Mean Earnings ($)	34,500	34,210	38,050	30,750	71,540	28,410	24,990	35,620	29,310	29,320
	Proportion Part-Time	[.01]	[.05]		[.07]	[.02]	[.12]	[.06]	[.08]	[.23]	[.05]
Women	% in Each Occupation	17	2	8	38	15	3	9	5	0	1
	Mean Earnings ($)	28,980	29,400	28,870	28,020	33,840	24,490	19,750	23,160	-	24,750
	Proportion Part-Time	[.05]		[.09]	[.17]	[.18]	[.05]	[.13]	[.10]		

cont..

Education Group & Sex	Distribution of Grads by Occupation; Earnings by Occupation; Proportion of Part-Time Workers by Occupation	(1) Bus. Adm.	(2) NSE	(3) Soc. Sci.	(4) Tch. Rel.	(5) Med. Hlth.	(6) Art. Lit. Rec.	(7) Cler.	(8) Sale Serv.	(9) Prim. Occ.	(10) Sec. Occ.
SOCSCI											
Men	% in Each Occupation	35	7	9	12	2	3	7	20	1	4
	Mean Earnings ($)	34,890	29,620	30,770	30,790	-	29,500	25,630	37,920	-	28,500
	Proportion Part-Time	[.02]	[.08]		[.09]		[.08]	[.04]	[.08]		[.07]
Women	% in Each Occupation	23	4	19	22	4	2	13	12	0	1
	Mean Earnings ($)	26,940	27,000	26,680	29,890	25,650	20,200	18,750	23,520	-	-
	Proportion Part-Time	[.07]		[.09]	[.12]	[.24]		[.17]	[.07]		

1 Based on the standard two digit occupation classification groups, with some grouping together as appropriate. The categories are: 1) managerial, administrative and related; 2) natural sciences, engineering, mathematics; 3) social sciences and related; 4) teaching and related; 5) medicine and health; 6) artistic, literary and related; 7) clerical and related; 8) sales and service; 9) primary resources (farming, fishing, forestry, mining, *etc.*); 10) processing and manufacturing (processing, machining, fabrication, construction, transport, material handling, *etc.*) The distributions for 1984 are available from the author.

2 The numbers in square brackets give the proportion of part-time workers where this is greater than zero.

3 A dash indicates there were less than 10 observations in the cell.

4 See the notes in Table 12 regarding the sample and the general structure of the sample.

Table 18 — Distribution of Graduates by Industry and Mean Earnings by Industry, 1987[1,2]

Education Group & Sex	Distribution of Grads by Industry; Earnings by Industry; Proportion of Part-Time Workers by Occupation	(1) Prim. Ind.	(2) Sec. Ind.	(3) Trade	(4) Fire	(5) Bus. Serv.	(6) Gvt. Serv.	(7) Educ. Serv.	(8) Hlth. Soc. Serv.	(9) Acc. Food
AGBIOSC Men	% in Each Industry	21	16	7	3	5	15	13	14	4
	Mean Earnings ($)	47,690	36,140	31,140	-	22,250	29,600	25,380	34,850	-
	Proportion Part-Time	[.06]	[.03]				[.03]	[.10]	[.06]	
Women	% in Each Industry	10	11	2	5	8	10	21	27	5
	Mean Earnings ($)	22,800	28,500	-	22,800	24,760	29,000	24,330	27,040	16,900
	Proportion Part-Time	[.20]	[.05]		[.10]		[.05]	[.14]	[.09]	[.30]
ENG Men	% in Each Industry	11	48	2	1	22	11	2	1	2
	Mean Earnings ($)	39,770	37,360	37,450	-	34,210	34,670	26,730	-	27,670
	Proportion Part-Time			[.09]		[.03]		[.09]		[.11]
Women	% in Each Industry	13	27	5	0	20	24	7	0	4
	Mean Earnings ($)	29,710	33,870	34,670	-	31,730	34,080	28,500	-	17,500
	Proportion Part-Time	[.14]								
MATHSCI Men	% in Each Industry	10	24	5	9	23	11	13	2	2
	Mean Earnings ($)	38,660	36,410	35,370	37,820	38,710	35,100	29,110	-	-
	Proportion Part-Time	[.03]						[.06]		
Women	% in Each Industry	9	21	4	13	14	14	19	5	1
	Mean Earnings ($)	32,000	33,430	-	32,240	37,680	32,890	26,880	-	-
	Proportion Part-Time	[.08]				[.05]	[.05]	[.04]		
NSE TOTAL Men	% in Each Industry	13	34	4	4	19	12	8	4	2
	Mean Earnings ($)	33,830	33,470	36,830	38,980	37,330	33,460	31,130	61,460	25,680
	Proportion Part-Time	[.03]	[.01]	[.02]		[.02]	[.01]	[.08]	[.05]	[.04]
Women	% in Each Industry	10	17	4	7	12	13	18	16	3
	Mean Earnings ($)	27,400	27,890	26,310	26,100	28,790	28,830	28,290	29,750	20,220
	Proportion Part-Time	[.15]	[.02]		[.04]	[.02]	[.04]	[.10]	[.08]	[.23]
Non-NSE Men	% in Each Industry	2	14	5	8	16	11	25	12	7
	Mean Earnings ($)	42,190	37,030	34,430	38,090	35,230	33,470	27,560	33,500	25,350
	Proportion Part-Time	[.06]	[.03]		[.03]	[.02]	[.04]	[.07]	[.04]	[.10]
Women	% in Each Industry	1	7	2	5	9	9	41	22	5
	Mean Earnings ($)	26,870	31,860	33,360	28,740	31,620	31,640	25,440	27,220	16,920
	Proportion Part-Time	[.07]	[.05]	[.05]	[.04]	[.07]	[.06]	[.15]	[.17]	[.13]

cont.

Education Group & Sex	Distribution of Grads by Industry; Earnings by Industry; Proportion of Part-Time Workers by Occupation	(1) Prim. Ind.	(2) Sec. Ind.	(3) Trade	(4) Fire	(5) Bus. Serv.	(6) Gvt. Serv.	(7) Educ. Serv.	(8) Hlth. Soc. Serv.	(9) Acc. Food
SOCSCI										
Men	% in Each Industry									
	Mean Earnings ($)	2	14	6	12	11	22	13	10	8
	Proportion Part-Time	-	33,740	41,870	42,410	28,710	33,000	31,240	26,620	27,580
			[.06]		[.02]	[.07]	[.04]	[.06]	[.05]	[.06]
Women	% in Each Industry	1	9	2	8	8	13	24	25	9
	Mean Earnings ($)	-	27,390	25,180	24,840	24,080	27,690	30,180	24,050	20,450
	Proportion Part-Time		[.09]		[.03]	[.05]	[.06]	[.10]	[.15]	[.13]

[1] Based on the standard two digit standard industry codes, with some grouping. The categories are: 1) primary industries (farming, fishing, logging, mining, *etc.*); 2) manufacturing, construction, transportation, *etc.*; 3) wholesale and retail trade; 4) finance, insurance, and real estate; 5) business services; 6) government services; 7)education services; 8) health and social services; 9) accommodation and food.

[2, 3, 4] See the corresponding notes in the preceding table.

Table 19 — Mean Earnings By Sex and Field of Study, 1984[1]

(Statistical tests indicated by ♀.[2])

Education Group & Sex	Number of Grads	Mean Earnings All Workers $	Gender Earnings Ratio, All Workers[3]	Mean Earnings Full-Time Workers Only $	Gender Earnings Ratio, Full-Time Only[3]	Percentage of Workers Who Are Full-Time[4] (%)
AGBIOSC						
Men	168	23,480*♀		23,630*		96
Women	190	21,570*♀	.92	22,920*	.97	82
ENG						
Men	474	30,070*♀		30,240*♀		99
Women	53	27,010*♀	.90	27,330*♀	.90	98
MATHSCI						
Men	315	28,870*♀		29,410*♀		97
Women	135	26,900*♀	.93	27,550*♀	.94	96
NSE TOTAL						
Men	957	28,520*♀		28,820*♀		98
Women	378	24,240♀	.85	25,370♀	.88	89
Non-NSE						
Men	1,448	26,570♀		27,260♀		94
Women	2,233	24,260♀	.91	25,430♀	.93	89
SOCSCI						
Men	339	25,630♀		26,450♀		94
Women	447	22,630Δ♀	.88	23,770Δ♀	.90	90

[1] See the notes in Table 12 regarding the sample and the general structure of the table.

[2] * indicates that the mean earnings for the NSE men or women are significantly different from the mean earnings of non-NSE graduates; Δ indicates that earnings are different for the social science graduates versus others; and the pairs of ♀ signs indicate that mean earnings are significantly different for men and women of the given education group. All are based on standard χ^2 tests using a 5% confidence level.

[3] The male-female ratios are calculated as the mean earnings of women divided by the mean earnings of men.

[4] Based on the number of observations entering the mean earnings calculations. (Raw numbers not shown.)

Table 20 — Mean Earnings By Sex and Field of Study, 1987[1]

(Statistical tests indicated by ♀.[2])

Education Group & Sex[3]	Number of Grads	Mean Earnings All Workers $	Gender Earnings Ratio, All Workers[3]	Mean Earnings Full-Time Workers Only $	Gender Earnings Ratio, Full-Time Only[3]	Percentage of Workers Who Are Full-Time[4] (%)
AGBIOSC						
Men	238	33,850♀		34,520*		96
Women	217	25,320*♀	.75	26,720*	.77	89
ENG						
Men	545	36,240♀		36,360*♀		98
Women	57	31,890*♀	.88	32,180*♀	.89	98
MATHSCI						
Men	361	35,570*♀		35,590*♀		99
Women	145	31,790*♀	.89	32,330♀	.91	97
NSE TOTAL						
Men	1,144	35,530♀		35,740*♀		98
Women	419	28,450♀	.80	29,520*♀	.83	93
Non-NSE						
Men	1,714	36,560♀		37,110♀		95
Women	2,393	27,990♀	.77	29,350♀	.79	87
SOCSCI						
Men	396	32,670Δ♀		33,160Δ♀		95
Women	495	25,850Δ♀	.79	26,880Δ♀	.81	90

1, 2, 3, 4 See the corresponding notes in the preceding table.

Table 21 — The Job-Education Relationship and Earnings, 1984[1]

(Statistical tests indicated by * and ♀.[2])

Education Group & Sex	Relationship of Job to Education Programme Graduated From[3]	Distribution of Grads Across Job-to-Education Categories %	Mean Earnings by Category[4] $	Mean Earnings Relative to "Unrelated" Category[6]	Gender Earnings Ratio by Category[7]
AGBIOSC					
Men	Directly Related	35	24,310*	1.28	
	Partly Related	44	25,630*♀	1.35	
	Unrelated	21	19,000		
Women	Directly Related	44	24,780*	1.24	1.02
	Partly Related	46	22,060♀	1.11	0.86
	Unrelated	11	19,950		1.05
ENG					
Men	Directly Related	56	30,520*♀	1.14	
	Partly Related	36	30,600*	1.14	
	Unrelated	7	26,850♀[5]		
Women	Directly Related	66	27,320*[5]♀	-[5]	0.90
	Partly Related	26	29,290*[5]	-[5]	0.96
	Unrelated	8	-		-[5]
MATHSCI					
Men	Directly Related	60	30,740*	1.34	
	Partly Related	32	28,980♀*	1.27	
	Unrelated	9	22,870		
Women	Directly Related	65	29,230*	1.40	0.95
	Partly Related	22	25,600♀	1.22	0.88
	Unrelated	13	20,950		0.92
NSE TOTAL					
Men	Directly Related	54	29,980*♀	1.29	
	Partly Related	36	29,180*♀	1.26	
	Unrelated	10	23,180		
Women	Directly Related	55	27,260*♀	1.33	0.91
	Partly Related	34	23,820*♀	1.16	0.82
	Unrelated	11	20,550		0.89
Non-NSE					
Men	Directly Related	50	28,690*♀	1.26	
	Partly Related	34	27,460*♀	1.21	
	Unrelated	15	22,760♀		
Women	Directly Related	54	27,240*♀	1.34	0.95
	Partly Related	32	24,880*♀	1.23	0.91
	Unrelated	14	20,270♀		0.89

cont.

Education Group & Sex	Relationship of Job to Education Programme Graduated From[3]	Distribution of Grads Across Job-to-Education Categories %	Mean Earnings by Category[4] $	Mean Earnings Relative to "Unrelated" Category[6]	Gender Earnings Ratio by Category[7]
SOCSCI					
Men	Directly Related	29	29,120*♀	1.33	
	Partly Related	46	27,540*♀	1.26	
	Unrelated	25	21,890		
Women	Directly Related	27	25,550*♀	1.23	0.88
	Partly Related	45	24,600*♀	1.18	0.89
	Unrelated	28	20,790		0.95

[1] Full-time workers only. See Table 12 for other notes regarding the sample and the general structure of the table.

[2] * indicates that mean earnings are significantly different for the men or women with directly or partly related jobs relative to those with jobs unrelated to their education; the pairs of ♀ signs indicate that mean earnings are significantly different for men and women with the same job-education relationship. Tests are at the 5% confidence level.

[3] See note 1 in Table 12 for a description of this variable.

[4] A dash indicates a cell with less than 10 observations.

[5] The statistical tests in the third column should be read with caution, since the comparison group ("Women - Unrelated") has relatively few observations (as indicated by the dash — see note above). The ratios in columns 4 and 5 (see the following notes) are not reported for the same reason.

[6] Calculated as the mean earnings of men or women in directly or partly related jobs divided by the mean earnings of those in jobs unrelated to their education. (See also note 2 above.)

[7] Calculated as the mean earnings of women divided by the mean earnings of men of the same education-job match category. (See also note 2 above.)

Table 22 — The Job-Education Relationship and Earnings, 1987[1]

(Statistical tests indicated by * and ♀.[2])

Education Group & Sex	Relationship of Job to Education Programme Graduated From[3]	Distribution of Grads Across Job-to-Education Categories %	Mean Earnings by Category[4] $	Mean Earnings Relative to "Unrelated" Category[6]	Gender Earnings Ratio by Category[7]
AGBIOSC Men	Directly Related	50	39,080*♀	1.64	
	Partly Related	32	33,600*♀	1.41	
	Unrelated	18	23,860		
Women	Directly Related	55	27,480♀	1.13	0.70
	Partly Related	27	26,720♀	1.10	0.80
	Unrelated	18	24,350		1.02
ENG Men	Directly Related	75	36,640♀	1.13	
	Partly Related	20	36,200	1.12	
	Unrelated	4	32,390		
Women	Directly Related	70	32,460*[5]♀	-[5]	0.89
	Partly Related	27	30,400*[5]	-[5]	0.84
	Unrelated	4	-		-[5]
MATHSCI Men	Directly Related	68	36,740♀	1.11	
	Partly Related	24	33,220	1.01	
	Unrelated	8	33,030		
Women	Directly Related	70	33,920*[5]♀	-[5]	0.92
	Partly Related	24	29,590	-[5]	0.89
	Unrelated	6	-		-[5]
NSE TOTAL Men	Directly Related	68	37,040*♀	1.29	
	Partly Related	24	34,540*♀	1.20	
	Unrelated	8	28,780		
Women	Directly Related	62	30,880*♀	1.23	0.83
	Partly Related	26	28,220♀	1.12	0.82
	Unrelated	11	25,090		0.87
Non-NSE Men	Directly Related	64	40,140*♀	1.40	
	Partly Related	25	33,130*♀	1.15	
	Unrelated	11	28,760♀		
Women	Directly Related	64	31,340*♀	1.32	0.78
	Partly Related	25	26,610*♀	1.17	0.80
	Unrelated	11	23,830		0.83

cont.

Education Group & Sex	Relationship of Job to Education Programme Graduated From[3]	Distribution of Grads Across Job-to-Education Categories %	Mean Earnings by Category[4] $	Mean Earnings Relative to "Unrelated" Category[6]	Gender Earnings Ratio by Category[7]
SOCSCI					
Men	Directly Related	44	34,360[9]	1.03	
	Partly Related	40	31,820[9]	0.95	
	Unrelated	16	33,340[9]		
Women	Directly Related	46	28,720[*9]	1.23	0.84
	Partly Related	36	26,280[*9]	1.13	0.83
	Unrelated	18	23,270[9]		0.70

[1, 2, 3, 4, 5, 6] See the corresponding notes in the preceding table regarding the sample, the statistical tests, and the details of the table.

Table 23 — The Presence of Children and Earnings, 1984[1]

(Statistical tests indicated by * and ♀.[2])

Education Group & Sex	Presence of Children	Distribution of Grads by the Presence of Children %	Mean Earnings by the Presence of Children[3] $	Relative Earnings of Those With Children Versus Those Without[5]	Gender Earnings Ratio by the Presence of Children[6]
AGBIOSC					
Men	No	91	23,090		
	Yes	9	28,300	1.23	
Women	No	94	22,830		0.99
	Yes	6	-	-[4]	-[4]
ENG					
Men	No	89	30,020♀		
	Yes	11	31,810	1.06	
Women	No	100	27,330♀		0.91
	Yes	0	-	-[4]	-[4]
MATHSCI					
Men	No	88	29,100♀		
	Yes	12	31,700*	1.09	
Women	No	93	27,100♀		0.93
	Yes	7	-	-[4]	-[4]
NSE TOTAL					
Men	No	89	28,510♀		
	Yes	11	31,260*	1.10	
Women	No	95	25,180♀		0.88
	Yes	5	29,120	1.16	0.93
Non-NSE					
Men	No	76	25,570♀		
	Yes	24	32,730*♀	1.28	
Women	No	81	24,300♀		0.95
	Yes	19	30,310*♀	1.25	0.93
SOCSCI					
Men	No	78	24,640♀		
	Yes	22	32,850*	1.33	
Women	No	83	22,200♀		0.90
	Yes	17	31,510*	1.42	0.96

Notes...

[1] Full-time workers only. See Table 12 for other notes regarding the sample and the general structure of the table.

[2] * indicates that mean earnings are significantly different for men or women with children versus those without children; the pairs of ♀ signs indicate that mean earnings are significantly different for men and women in the same category regarding the presence of children. Tests are at the 5% confidence level.

[3] A dash indicates a cell with less than 10 observations.

[4] The comparison ratios are not reported since the comparison group ("Women — With Children") has relatively few observations (as indicated by the dash).

[5] Calculated as the mean earnings of men or women with children divided by the mean earnings of those without.

[6] Calculated as the mean earnings of women divided by the mean earnings of men for a given category regarding the presence of children.

Table 24 — The Presence of Children and Earnings, 1987[1]

(Statistical tests indicated by * and ♀.[2])

Education Group & Sex	Presence of Children	Distribution of Grads by the Presence of Children %	Mean Earnings by the Presence of Children[3] $	Relative Earnings of Those With Children Versus Those Without[5]	Gender Earnings Ratio by the Presence of Children[6]
AGBIOSC Men	No	77	34,400♀		
	Yes	23	34,940♀	1.02	
Women	No	89	26,960♀		0.78
	Yes	11	24,820♀	0.92	0.71
ENG Men	No	74	35,540♀		
	Yes	26	38,420*	1.08	
Women	No	88	32,220♀		0.91
	Yes	13	-	-[4]	-[4]
MATHSCI Men	No	76	34,970♀		
	Yes	24	37,590♀	1.07	
Women	No	86	32,220♀		0.92
	Yes	14	32,600♀	0.99	0.87
NSE TOTAL Men	No	75	35,120♀		
	Yes	25	37,510*♀	1.07	
Women	No	87	29,570♀		0.84
	Yes	13	29,000♀	0.98	0.77
Non-NSE Men	No	65	35,200♀		
	Yes	35	40,660*♀	1.16	
Women	No	74	28,480♀		0.81
	Yes	26	31,750*♀	1.11	0.78
SOCSCI Men	No	67	32,270♀		
	Yes	33	34,940♀	1.08	
Women	No	77	25,760♀		0.80
	Yes	23	30,820*♀	1.20	0.88

1, 2, 3, 4, 5, 6 See the corresponding notes in the preceding table regarding the sample, the statistical tests, and the details of the table.

Table 25 — Marital Status and Earnings, 1987[1]

(Statistical Tests indicated by *♀.[2])

Education Group & Sex	Marital Status	Distribution of Grads by Marital Status %	Mean Earnings by Marital Status $	Relative Earnings of Marrieds Versus Singles[3]	Gender Earnings Ratio by Marital Status[4]
AGBIOSC					
Men	Single	42	35,490♀		
	Married	55	34,210♀	0.96	
Women	Single	45	27,920♀		0.79
	Married	52	25,780♀	0.92	0.75
ENG					
Men	Single	41	34,410		
	Married	57	37,890*♀	1.10	
Women	Single	45	30,920		0.90
	Married	54	32,900♀	1.06	0.87
MATHSCI					
Men	Single	46	33,840		
	Married	53	37,130*♀	1.10	
Women	Single	38	32,280		0.95
	Married	59	32,280♀	1.00	0.87
NSE TOTAL					
Men	Single	43	34,430♀		
	Married	55	36,920*♀	1.07	
Women	Single	42	29,790♀		0.87
	Married	55	29,300♀	0.98	0.79
Non-NSE					
Men	Single	35	33,980♀		
	Married	62	39,000*♀	1.15	
Women	Single	39	27,770♀		0.82
	Married	56	30,340*♀	1.09	0.78
SOCSCI					
Men	Single	40	31,150♀		
	Married	58	34,720*♀	1.11	
Women	Single	42	25,190♀		0.81
	Married	52	27,770*♀	1.10	0.80

[1] Full-time workers only. See Table 12 for other notes regarding the sample and the general structure of the table. Divorced, separated, and widowed individuals are not considered in this table, largely because there are relatively few of them in the sample (as the percentages indicate)

[2] * indicates that mean earnings are significantly different for men or women who are married versus singles. ♀ indicates that mean earnings are significantly different for men and women of the same marital status. Tests are at the 5% confidence level.

[3] Calculated as the mean earnings of married men or women versus singles.

[4] Calculated as the mean earnings of women divided by the mean earnings of men for a given marital status.

Table 26 — Married Men and Women With Children Versus Singles, 1987[1]

(Statistical Tests indicated by *♀.[2])

Education Group & Sex	Single or Married With Children	Distribution of Grads by Family Status %	Mean Earnings by Family Status $	Relative Earnings of Married Grads With Children Versus Singles[4]	Gender Earnings Ratio by Family Status[5]
AGBIOSC					
Men	Single	42	35,490♀		
	Married with Children	23	35,150♀	0.99	
Women	Single	45	27,920♀		.79
	Married with Children	41	24,950♀	0.89	.71
ENG					
Men	Single	41	34,380		
	Married with Children	26	38,440*	1.12	
Women	Single	43	30,750		0.89
	Married with Children	9	29,200[3]	0.95[3]	0.76[3]
MATHSCI					
Men	Single	46	33,780		
	Married with Children	23	37,520	1.11	
Women	Single	37	32,220		0.95
	Married with Children	12	32,180	1.00	0.86
NSE TOTAL					
Men	Single	43	34,400♀		
	Married with Children	24	37,540*♀	1.09	
Women	Single	41	29,700♀		0.89
	Married with Children	11	28,300♀	0.96	0.93
Non-NSE					
Men	Single	35	34,010♀		
	Married with Children	33	40,930*♀	1.20	
Women	Single	38	27,760♀		0.82
	Married with Children	23	31,940*♀	1.15	0.78
SOCSCI					
Men	Single	40	31,150♀		
	Married with Children	31	35,190*♀	1.13	
Women	Single	41	25,210♀		0.81
	Married with Children	18	30,770*♀	1.22	0.87

[1] Full-time workers only. See Table 12 for other notes regarding the sample and the general structure of the table. Cells have at least 10 observations, except as noted below.

[2] * indicates that mean earnings are significantly different for men or women who are married and have children versus singles. The pairs of ♀ signs indicate that mean earnings are significantly different for men and women of the same family status. Tests are at the 5% confidence level.

[3] Based on only 5 engineering women who are married with children; results should therefore be interpreted very cautiously.

[4] Calculated as the mean earnings of men or women who are married and have children versus the mean earnings of singles.

[5] Calculated as the mean earnings of women divided by the mean earnings of men for a given family status.

Table R1 - 1984 Log-Earnings Regressions Results: Simple Models[1,2]

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	10.15** (1139)	10.12** (953)	10.11** (883)	10.11** (952)	10.11** (890)	10.03** (729)
Female	-.140** (11.3)	-.123** (9.53)	-.104** (7.08)	-.101** (7.80)	-.104** (7.14)	-.058** (3.18)
NSE		.068** (4.64)	.096** (5.28)			
NSE*Female			-.079** (2.61))			
AGBIOSC				-.112** (4.66)	-.116** (3.28)	-.085** (2.45)
AGBIOSC*Female					.007 (0.14)	-.003 (0.06)
ENG				.163** (7.67)	.161** (7.02)	.188** (8.30)
ENG*Female					.004 (0.06)	.003 (0.04)
MATHSCI				.119** (5.43)	.111** (4.15)	.145** (5.46)
MATHSCI*Female					.025 (0.53)	.010 (0.22)
Married						.093** (4.40)
Married*Female						-.071** (2.49)
Unmarried						.137* (1.88)
Unmarried*Female						-.082 (0.97)
Children						.177** (6.56)
Children*Female						-.056 (1.51)
R^2	.025	.030	.031	.047	.047	.080
F	128.1	75.1	52.4	60.7	34.7	32.8
Log-Likelihood	-2886.1	-2875.3	-2871.9	-2830.6	-2830.5	-2744.3

1 There are 4,937 observations in each regression. See the text for further details on the composition of the sample.

2 The number in parentheses is the absolute t-statistic. One asterisk indicates that the coefficient is significantly different from zero by a two-sided t-test at the .05 confidence level. Two asterisks indicates a .01 level of significance. See the text for more details regarding these statistical tests.

Table R2 - 1984 Log-Earnings Regressions Results: Full Models[1]

Variables	(1) Base Model	(2) Adding Women's Marr/Chil Variables[2]	(3) Adding Education-Job Relationship Variables[3]	(4) Adding Occupation and Industry Variables[4]	(5) Adding Women's Exper/Work Variables[5]	(6) Separate Female Effects For All Vars.[6]
Intercept	8.71** (47.5)	8.71** (47.6)	8.65** (48.8)	8.89** (51.5)	8.72** (47.3)	9.05** (31.7)
Female	-.067** (5.37)	-.036** (2.33)	-.111** (4.46)	-.095** (3.90)	-.039 (0.89)	-.609 (1.63)
AGBIOSC	-.068** (2.31)	-.064** (2.15)	-.046 (1.58)	-.091** (3.19)	-.064** (2.16)	-.068** (2.28)
AGBIOSC*Female	.055 (1.35)	.044 (1.10)	.026 (0.66)	.038 (1.00)	.046 (1.12)	.051 (1.25)
ENG	.144** (7.39)	.149** (7.59)	.130** (6.81)	.067** (2.99)	.151** (7.65)	.143** (7.12)
ENG*Female	-.000 (0.01)	-.012 (0.21)	-.019 (0.37)	.037 (0.73)	-.014 (0.26)	-.004 (0.07)
MATHSCI	.119 (5.23)	.125** (5.47)	.105** (4.73)	.052** (2.15)	.126** (5.52)	.121** (5.23)
MATHSCI*Female	.008 (0.21)	-.001 (0.02)	.006 (0.15)	.032 (0.87)	-.004 (0.10)	.008 (0.21)
Married	.019 (1.54)	.043** (2.37)	.040** (2.29)	.034** (2.06)	.044** (2.40)	.050** (2.77)
Married*Female		-.048** (1.97)	-.059** (2.49)	-.056** (2.49)	-.050** (2.03)	-.061** (2.48)
Unmarried	-.067** (2.13)	.029 (0.47)	.018 (0.29)	.033 (0.58)	.029 (0.47)	.056 (0.90)
Unmarried*Female		-.131* (1.84)	-.132* (1.90)	-.124* (1.90)	-.133* (1.86)	-.178** (2.44)
Children	.030* (1.66)	.045* (1.87)	.038* (1.65)	.025 (1.13)	.047* (1.94)	.067** (2.63)
Children*Female		-.035 (1.12)	-.031 (1.02)	-.030 (1.03)	-.037 (1.16)	-.079** (2.20)
Partly Related			.159** (7.69)	.106** (5.28)		
Partly Related * Female			.035 (1.19)	.012 (0.43)		
Directly Related			.186** (9.42)	.123** (6.29)		
Directly Related * Female			.117** (4.31)	.059** (2.22)		

cont.

Variables	(1) Base Model	(2) Adding Women's Marr/Chil Variables[2]	(3) Adding Education-Job Relationship Variables[3]	(4) Adding Occupation and Industry Variables[4]	(5) Adding Women's Exper/Work Variables[5]	(6) Separate Female Effects For All Vars.[6]
R^2	.337	.339	.382	.450	.339	.342
F	104.2	93.3	97.9	79.9	78.7	62.1
Log-Likelihood	-1933.5	-1927.2	-1760.8	-1473.8	-1925.8	-1915.7

[1] The regressions also include the following variables: labour market participation (part-time, full-time) at various specific dates between graduation and the interview date (a proxy for labour market experience, as described in the text), part-time versus full-time status in the current job, (part-time) student status, age, age squared, an indicator of the individual having been in the labour market before being enrolled in the BA programme, "mother" tongue, and region of residence. See also the notes to Table R1.

[2] Includes all the variables in regression 1 plus the interactions of the marital status and children variables with Female (as indicated) to allow these variables to have different effects for men and women.

[3] Includes all the variables in regression 2 plus the education-job relationship variables indicated in the table. "Directly Related" means the individual identified his or her programme as being one intending to prepare students for a particular career *and* the job held at the interview date was indeed related to the education programme, "Partly Related" means just one of these two conditions held, and the omitted reference category is when neither of the conditions held.

[4] Includes all the variables in regression 3 plus two series of dummy variables representing occupation and industry (at the two digit level of classification).

[5] Includes the variables in regression 2 plus interactions of Female with the series of labour market participation variables which proxy for experience and the part-time job indicator. The job relationship and industry/occupation variables are not included.

[6] Includes the variables in regression 5 plus interactions of Female with all the remaining explanatory variables included in the regression, as listed in note 1 above.

Table R3 - 1987 Log-Earnings Regressions Results: Simple Models[1]

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	10.39** (1,205)	10.38** (1,006)	10.38** (935)	10.37** (1,002)	10.38** (940)	10.29** (657)
Female	-.248** (20.3)	-.240** (18.8)	-.241** (16.5)	-.225** (17.5)	-.241** (16.6)	-.150** (7.03)
NSE		.032** (2.22)	.031* (1.74)			
NSE*Female			.003 (0.10)			
AGBIOSC				-.100** (4.40)	-.119** (3.73)	-.101** (3.19)
AGBIOSC*Female					.036 (.079)	-.017 (0.37)
ENG				.099** (4.75)	.083** (3.67)	.097** (4.29)
ENG*Female					.097 (1.49)	.082** (1.27)
MATHSCI				.084** (3.81)	.050* (1.87)	.069** (2.61)
MATHSCI*Female					.102** (2.15)	.080** (1.70)
Married						.097* (4.72)
Married*Female						-.087** (3.04)
Unmarried						.050 (0.82)
Unmarried*Female						.064 (0.86)
Children						.091** (4.19)
Children*Female						-.124 (4.05)
R^2	.068	.069	.069	.078	.079	.094
F	410.2	207.7	138.5	118.8	68.9	44.7
Log-Likelihood	-3556.9	-3554.4	-3554.4	-3526.7	-3523.4	-3478.0

[1] There are 5591 observations in each equation.

Table R4 - 1987 Log-Earnings Regressions Results: Full Models[1]

Variables	(1) Base Model	(2) Adding Women's Marr/Chil Variables[2]	(3) Adding Education-Job Relationship[3]	(4) Adding Occupation and Industry[4]	(5) Adding Women's Exper/Work Variables[5]	(6) Separate Female Effects For All Vars.[6]
Intercept	8.52** (38.0)	8.50** (37.9)	8.47** (38.4)	8.68** (40.5)	8.50** (37.8)	8.54** (25.3)
Female	-.174** (13.5)	-.139** (7.38)	-.137** (4.04)	-.114** (3.44)	-.159** (2.97)	-.347 (0.77)
AGBIOSC	-.035 (1.25)	-.032 (1.14)	-.018 (0.65)	-.062** (2.24)	-.030 (1.07)	-.036 (1.27)
AGBIOSC*Female	-.000 (0.01)	-.006 (0.15)	-.008 (0.21)	-.022 (0.59)	-.008 (0.21)	.004 (0.09)
ENG	.042** (2.11)	.044** (2.21)	.025 (1.26)	.020 (0.86)	.041** (2.03)	.031 (1.54)
ENG*Female	.068 (1.20)	.064 (1.13)	.062 (1.12)	.091* (1.71)	.069 (1.21)	.086 (1.51)
MATHSCI	.015 (0.66)	.018 (0.77)	.009 (0.39)	.011 (0.47)	.019 (0.79)	.009 (0.40)
MATHSCI*Female	.069* (1.68)	.067 (1.62)	.063 (1.56)	.076* (1.96)	.069* (1.67)	.088** (2.09)
Married	.029** (2.32)	.055** (3.05)	.051** (2.88)	.040** (2.36)	0.58** (3.19)	0.60** (3.33)
Married*Female		-.052** (2.06)	-.053** (2.13)	-.052** (2.20)	-.052** (2.07)	-.053** (2.11)
Unmarried	.008 (0.26)	-.037 (0.68)	-.028 (0.54)	-.054 (1.07)	-.038 (0.71)	-.018 (0.33)
Unmarried*Female		.058 (0.89)	.060 (0.94)	.082 (1.35)	.059 (0.91)	.027 (0.42)
Children	.019 (1.32)	.025 (1.29)	.024 (1.24)	.020 (1.11)	.021 (1.06)	.033* (1.65)
Children*Female		-.019 (0.72)	-.029 (1.11)	-.035 (1.37)	-.006 (0.21)	-.032 (1.11)
Partly Related			.165** (6.13)	.134** (5.12)		
Partly Related * Female			-.026 (0.70)	-.039 (1.10)		
Directly Related			.258** (10.4)	.202** (8.21)		
Directly * Female			.005 (0.16)	-.029 (0.89)		

cont.

Variables	(1) Base Model	(2) Adding Women's Marr/Chil Variables[2]	(3) Adding Education-Job Relationship[3]	(4) Adding Occupation and Industry[4]	(5) Adding Women's Exper/Work Variables[5]	(6) Separate Female Effects For All Vars.[6]
R^2	.308	.309	.340	.401	.314	.316
F	88.3	80.2	81.6	68.5	63.5	52.2
Log-Likelihood	-2726.3	-2721.4	-2595.0	-2323.9	-2702.1	-2693.9

[1] The regressions also include the variables listed in the note to Table R2.

[2, 3, 4, 5, 6] See the notes in Table R1 concerning the precise specification of each regression.

Table R5 - Separate Regressions by Sex: Simple Models, 1984 and 1987[1]

Variables	1984		1987	
	(1) Men	(2) Women	(3) Men	(4) Women
Intercept	10.0** (806)	9.97** (768)	10.3** (692)	10.1** (663)
AGBIOSC	-.085** (2.70)	-.088** (2.51)	-.101** (3.36)	-.084** (2.50)
ENG	.188** (9.17)	.191** (2.98)	.096** (4.52)	.178** (2.81)
MATHSCI	.145** (6.04)	.155** (3.76)	.069** (2.73)	.149** (3.65)
Married	.093** (4.86)	.022 (1.05)	.097** (4.97)	.010 (0.48)
Unmarried	.137** (2.08)	.055 (1.21)	.050 (0.87)	.114** (2.55)
Children	.177** (7.25)	.122 (4.49)	.091** (4.41)	-.033 (1.45)
N	2,375	2,562	2,812	2,779
R^2	.100	.025	.045	.013
F	43.8	10.8	22.0	61.8
Log-Likelihood	-1,082.6	-1,623.1	-1,605.0	-1,859.4

[1] The regressions include only the variables indicated in the table.

Table R6 - Separate Regressions by Sex: Full Models, 1984 and 1987[1]

Variables	1984		1987	
	(1) Men	(2) Women	(3) Men	(4) Women
Intercept	9.05** (33.8)	8.44** (33.3)	8.54** (25.5)	8.20** (27.0)
AGBIOSC	-.068** (2.43)	-.017 (0.59)	-.036 (1.28)	-.032 (1.13)
ENG	.143** (7.58)	.139** (2.60)	.031 (1.55)	.117** (2.18)
MATHSCI	.121** (5.57)	.130** (3.75)	.009 (0.40)	.097** (2.79)
Married	.050** (2.95)	-.011 (0.62)	.060** (3.35)	.007 (0.41)
Unmarried	.056 (0.96)	-.121** (3.10)	-.018 (0.32)	.010 (0.26)
Children	.067** (2.79)	-.012 (0.44)	.033* (1.66)	.001 (0.06)
N	2,375	2,562	2,812	2,779
R^2	.306	.338	.210	.313
F	52.0	64.9	30.9	52.3
Log-Likelihood	-773.3	-1,126.5	-1,337.8	-1,355.9

[1] The regressions also include the variables listed in the note to Table R2.

Table R7 - Separate Regressions by Education Group: Simple Models, 1984[1]

Variables	(4) AGBIOSC	(3) ENG	(2) MATHSCI	(1) Non-NSE
Intercept	9.95** (242)	10.3** (568)	10.2** (424)	10.0** (636)
Female	-.018 (0.31)	-.084 (1.54)	-.087* (1.86)	-.039* (1.90)
Married	.113 (1.52)	.038 (1.11)	.027 (0.51)	.129** (4.47)
Married*Female	-.190* (1.88)	.019 (0.19)	.024 (0.28)	-.100** (2.77)
Unmarried	-.083 (0.28)	.043 (0.37)	-.120 (0.75)	.249** (2.52)
Unmarried*Female	-	-	.108 (0.52)	-.177 (1.62)
Children	.114 (0.92)	.006 (0.11)	.127* (1.68)	.206** (6.06)
Children*Female	-.161 (0.89)	-1.005**[2] (2.97)	.090 (0.55)	-.080* (1.85)
N	352	518	445	3,622
R^2	.034	.032	.032	.058
F	2.0	2.8	2.1	32.1
Log-Likelihood	-188.9	-123.5	-167.7	-2,181.2

[1] The regressions include only the variables shown in the table. A dash indicates that there are no individuals of the indicted type in the relevant group.

[2] This result is generated by a single observation: the one woman who has a child has earnings which are about one-third the mean level of other women in this group. One should therefore not generalize from this coefficient.

Table R8 - Separate Regressions by Education Group: Simple Models, 1987[1]

Variables	(1) AGBIOSC	(2) ENG	(3) MATHSCI	(4) Non-NSE
Intercept	10.2** (213)	10.4** (605)	10.4** (389)	10.3** (531)
Female	-.094 (1.37)	-.155** (2.89)	-.035 (0.64)	-.140** (5.52)
Married	.028 (0.37)	.080** (3.07)	.095** (2.27)	.116** (4.01)
Married*Female	-.076 (0.73)	.054 (0.72)	-.144* (1.93)	-.100** (2.68)
Unmarried	-.043 (0.21)	-.018 (0.20)	.080 (0.33)	.077 (1.01)
Unmarried*Female	.056 (0.19)	.512* (1.70)	.046 (0.15)	.036 (0.40)
Children	.102 (1.19)	.042 (1.41)	-.007 (0.15)	.116** (3.98)
Children*Female	-.413** (3.15)	-.143 (1.21)	-.185* (1.94)	-.127** (3.36)
N	448	592	494	4,057
R^2	.077	.068	.060	.074
F	5.2	6.1	4.5	46.2
Log-Likelihood	-306.4	-36.3	-166.8	-2,770.5

[1] The regressions include only the variables shown in the table.

Table R9 - Separate Regressions by Education Group: Full Models, 1984[1]

Variables	AGBIOSC		ENG		MATHSCI		NON-NSE	
	(1) Base Model	(2) Women's Marr/Chil Vars. Added	(3) Base Model	(4) Women's Marr/Chil Vars. Added	(5) Base Model	(6) Women's Marr/Chil Vars. Added	(7) Base Model	(8) Women's Marr/Chil Vars. Added
Intercept	8.37** (10.7)	8.45** (10.7)	9.46** (13.7)	9.46** (13.7)	9.95** (15.0)	9.91** (14.5)	8.52** (39.9)	8.51** (39.9)
Female	-.032 (0.77)	.009 (0.17)	-.071* (1.70)	-.067 (1.31)	-.073** (2.36)	-.059 (1.56)	-.066** (5.04)	-.025 (1.45)
Married	.000 (0.01)	.050 (0.74)	.018 (0.59)	.019 (0.59)	.030 (0.91)	.054 (1.29)	.017 (1.17)	.052** (2.13)
Married*Female		-.094 (1.02)		-.012 (0.13)		-.062 (0.89)		-.059* (1.93)
Unmarried	-.141 (0.52)	-.122 (0.45)	-.038 (0.35)	-.031 (0.28)	.033 (0.39)	.033 (0.25)	-.072** (1.99)	.099 (1.18)
Unmarried*Female		-		-		-.027 (0.16)		-.208** (2.25)
Children	-.063 (0.73)	-.024 (0.21)	.006 (0.12)	.006 (0.12)	.111** (2.03)	.081 (1.29)	.029 (1.40)	.056* (1.87)
Children*Female		-.104 (0.63)		-.066 (0.19)		.105 (0.81)		-.054 (1.45)
N	352	352	518	518	445	445	3,622	3,622
R^2	.247	.252	.214	.214	.423	.425	.333	.336
F	6.1	5.6	7.5	6.8	17.4	14.9	99.9	86.8
Log-Likelihood	-144.8	-143.7	-69.6	-69.6	-52.5	-51.9	-1,556.9	-1,548.5

[1] The regressions also include the variables listed in the note to Table R2. A dash indicates that there are no individuals of this type in the relevant group.

Table R10 - Separate Regressions by Education Group: Full Models, 1987[1]

Variables	AGBIOSC		ENG		MATHSCI		NON-NSE	
	(1) Base Model	(2) Women's Marr/Chil Vars. Added	(3) Base Model	(4) Women's Marr/Chil Vars. Added	(5) Base Model	(6) Women's Marr/Chil Vars. Added	(7) Base Model	(8) Women's Marr/Chil Vars. Added
Intercept	8.96** (1.11)	8.95** (8.10)	8.01** (12.8)	7.97** (12.7)	8.94** (10.9)	8.78** (10.7)	8.29** (31.2)	8.27** (31.1)
Female	-.166** (3.76)	-.079 (1.22)	-.092** (2.79)	-.117** (2.41)	-.106** (3.34)	-.014 (0.29)	-.173** (12.7)	-.136** (6.15)
Married	-.053 (1.10)	-.006 (0.09)	.042* (1.86)	.039 (1.62)	.034 (1.09)	.063* (1.68)	.038** (2.39)	.075** (2.96)
Married*Female		-.092 (0.96)		.033 (0.48)		-.117* (1.76)		-.062* (1.91)
Unmarried	-.074 (0.54)	-.054 (0.27)	-.006 (0.08)	-.065 (0.77)	.150 (1.16)	-.114 (0.53)	.018 (0.49)	-.012 (0.18)
Unmarried*Female		-.053 (0.19)		-.594** (2.10)		.385 (1.44)		.034 (0.43)
Children	.013 (0.21)	.087 (1.09)	.046* (1.72)	.045 (1.63)	-.054 (1.39)	-.030 (0.66)	.025 (1.46)	.025 (0.98)
Children*Female		-.209* (1.69)		-.000 (0.00)		-.150* (1.75)		-.005 (0.16)
N	448	448	592	592	494	494	4,057	4,057
R^2	.250	.261	.282	.289	.303	.320	.309	.310
F	6.5	6.0	10.2	9.2	9.3	8.9	82.0	72.4
Log-Likelihood	-259.8	-256.5	41.0	43.6	-92.9	-87.0	-2176.6	-2173.5

[1] The regressions also include the variables listed in the note to Table R2.

Table R11 - The Earnings Levels (%) of NSE Versus Non-NSE Graduates, 1984 and 1987[1]

Sex-Education Group	Year and Basis of Comparisons					
	1984			1987		
	(1) Simple Models Without Marr/Chil Vars[2]	(2) Adding Marr/Chil Variables to Simple Models[3]	(3) Full Models[4]	(4) Simple Models Without Marr/Chil Vars[5]	(5) Adding Marr/Chil Variables to Simple Models[6]	(6) Full Models[7]
A) Men:						
AGBIOSC	-11.6	-8.5	-6.4	-11.9	-10.1	-3.2
ENG	16.1	18.8	14.9	8.3	9.7	4.4
MATHSCI	11.1	14.9	12.5	5.0	6.9	1.8
B) Women:						
AGBIOSC	-10.9	-8.8	-2.0	-8.3	-11.8	-3.8
ENG	16.5	19.1	13.7	18.0	17.9	10.8
MATHSCI	13.6	15.5	12.4	15.2	14.9	8.5

[1] The Figures correspond to the NSE education group coefficient estimates in the log earnings equations of Tables R1-R4 (see references below), and therefore indicate the average amount, in percentage terms, by which earnings differ for the NSE graduates versus the non-NSE reference group, while holding constant the other factors controlled for in the regressions (which vary as indicated). For each group of NSE men the effect is seen directly in the coefficient on the relevant field of education variable in the regression (AGBIOSC, ENG, MATHSCI); for NSE women, one must add the general field effect plus the woman-specific field effect represented by the field-Female interactions. (For example, the first AGBIOSC effect for men is the -.116 coefficient in equation 5, Table R1 translated into a percentage; for women it is -.116 + .007 = -.109, or -10.9 percent.) While the results reported here come from all-pooled regressions, very similar field effects hold with separate regressions by sex. (See Tables R5 and R6 for the separate regressions by education group corresponding to the results reported in columns 2, 3, 5 and 6, noting that the NSE effects can be seen directly for men and women both in these tables; the separate simple regressions corresponding to columns 1 and 4 are not reported.)

[2] Table R1, equation 5. (These include only the different education effects and the Female intercept shift.)

[3] Table R1, equation 6. (See also Table R5, equations 1 and 2.)

[4] Table R2, equation 2. (See also Table R6, equations 1 and 2.)

[5] Table R3, equation 5. (These include only the different education effects and Female.)

[6] Table R3, equation 6. (See also Table R5, equations 3 and 4.)

[7] Table R4, equation 2. (See also Table R6, equations 3 and 4.)

Table R12 - The Overall Gender Earnings Gap (%) by Education Group, 1984 and 1987[1]

Education Group	Gender Earnings Gap by Education Group (%)		Gap for NSE Graduates Relative to the Gap for Non-NSE Graduates.[2]	
	(1) 1984	(2) 1987	(3) 1984	(4) 1987
Non-NSE	10.4	24.1	-	-
AGBIOSC	9.7	20.5	.93	.85
ENG	10.0	14.4	.96	.60
MATHSCI	7.9	13.9	.75	.58

[1] The figures are based on the simple regressions of equation 5 in Tables R1 (1984) and R3 (1987) which include only the sex and field of education variables; they therefore represent the average level of women's earnings relative to men's, in percentage terms, in each field. These are calculated as the overall gender gap (the coefficient on Female) plus the specific effects in each field as represented by the field*Female interactions. (For example, the gap for the AGBIOSC graduates in 1984 is -.104 + .007 = .097, or 9.7%.) These are referred to as the "overall" gaps to emphasize that no labour supply or productivity factors are controlled for in the regressions upon which these figures are based.

[2] Calculated as the gap for each field divided by the gap for NSE graduates.

Table R13 - The Overall Gender Earnings Gap (%) by Education Group, and After Controlling for Marriage and Children Effects and Other Factors, 1984 and 1987[1]

Education Group	Overall Gender Earnings Gap by Education Group (% - From Table R12)		The Gap After Controlling (Only) for Different Marriage and Children Effects for Men and Women		The Gap After Adding Other Control Variables to the Regressions	
	(1) 1984	(2) 1987	(3) 1984[2]	(4) 1987[3]	(5) 1984[4]	(6) 1987[5]
Non-NSE	10.4	24.1	3.9	14.0	2.5	13.6
AGBIOSC	9.7	20.5	1.8	9.4	.9	7.9
ENG	10.0	14.4	8.4	15.5	6.7	11.7
MATHSCI	7.9	13.9	8.7	3.5	5.9	1.5

[1] The Figures represent the coefficient on "Female" in separate regressions by education group (see references below). The results in the first two columns are based on regressions which include *only* variables representing men's and women's marital status and the presence of children, while the second two columns are based on regressions which include the full set of control variables listed in Table R2.

[2] From Table R7, with each figure corresponding to the appropriate field's regression.

[3] From Table R8.

[4] From Table R9, equations 2, 4, 6, and 8.

[5] From Table R10, equations 2, 4, 6, and 8.

Table R14 - Differences in Earnings (%) by Marital Status and the Presence of Children for Men and Women of All Education Groups Combined, 1984 and 1987[1]

Sex and Marriage and Children Status	Year and Basis of Comparisons			
	1984		1987	
	(1) Simple Regressions[2]	(2) Full Regressions[3]	(3) Simple Regressions[2]	(4) Full Regressions[3]
A) Men:				
Married	9.3	4.3	9.7	5.5
Unmarried	13.7	2.9	5.0	-3.7
Children	17.7	4.5	9.1	2.5
Married + Children[4]	27.0	8.8	18.8	8.0
B) Women:				
Married	2.2	-.5	1.0	.3
Unmarried	5.5	-10.2	11.4	2.1
Children	12.1	1.0	-3.3	.6
Married + Children	14.3	.5	-2.3	.9

[1] The figures correspond to the marriage and children coefficient estimates in the relevant pooled earnings equations of Tables R1-R4 (see references below), and therefore indicate the average amount, in percentage terms, by which earnings differ for i) married and unmarried men and women versus the never-married comparison groups, and ii) those with children versus those without, while holding constant the other factors controlled for in the regressions. For men the effects are seen directly in the regression coefficients for the marriage and children variables; for women, the general marriage/children effects are added to the women-specific marriage/children effects represented by the interactions of these variables with Female. (For example, for the simple regressions of 1984, the men's marriage effect corresponds to the coefficient of .093 in Table R1, equation 6, meaning 9.3%; for women it is .093 - .071 =.022, or 2.2%.) For the simple models of columns 1 and 3, identical results are represented in the separate regressions by sex in Table R5, where the men's and women's effect can both be read directly from the regression coefficients. For the full models, similar but not identical results are seen in the separate regressions by sex of Table R6.

[2] From Tables R1 (1984) and R3 (1987), equation 6, which include only variables for sex, field of education, and marital/fertility status. (Or equivalently, Table R5, equations 1 and 2 for 1984, equations 3 and 4 for 1987.)

[3] From Tables R2 (1984) and R4 (1987), equation 2, which include the full set of control variables listed in Table R2. (Also see the separate equations by sex of Table R6.)

[4] Calculated as the marriage plus children effects added together.

Table R15 - Differences in Women's Earnings (%) Associated With Being Married and Having Children, by Education Group, 1984 and 1987[1]

Year and Education Group	1984		1987	
	(1) Simple Regressions[2]	(2) Full Regressions[3]	(3) Simple Regressions[2]	(4) Full Regressions[3]
A) Married (Vs. Single):				
Non-NSE	2.9	-.7	1.6	1.3
AGBIOSC	-7.7	-4.4	-4.8	-9.8
ENG	5.7	.7	13.4	7.2
MATHSCI	5.1	-.8	-4.9	-5.4
B) Children (Vs. None)				
Non-NSE	12.6	.2	-1.1	2.0
AGBIOSC	-5.5	-12.8	-31.1	-12.2
ENG	-[4]	-6.0	-10.1	4.5
MATHSCI	21.7	18.6	-19.2	-19.5

[1] The figures correspond to the marriage and children coefficient estimates in earnings regressions done separately by field of education (see references below), and therefore indicate the average amount, in percentage terms, by which earnings differ for i) married women versus the reference group of single women, and ii) women with children versus the reference group of those without, while holding constant the other factors controlled for in the different regressions. See Table R14 for an explanation of how the figures shown are derived from the regressions coefficient estimates. While the results reported here come from separate regressions done for men and women of each education group, similar results were found with regressions pooled by sex (with separate marriage/children effects by field permitted), and separate regressions for each education-sex group (results not reported).

[2] From Tables R7 (1984) and R8 (1987), with the figures for each field corresponding to the appropriate regression. These regressions include only variables representing sex and marital/children status.

[3] From Tables R9 (1984) and R10 (1987), regressions 2, 4, 6, and 8. These regressions include the full set of control variables listed in Table R2.

[4] The value implied by the results in Table R7 is not reported here because it is based on a single observation.

Table F1 - Fixed Effects Results: Simple Models[1]

Variables	(1) Female Shift Only	(2) Diff. NSE Effects by Sex	(3) Diff. NSE Effects by Sex, Field	(4) Adding Marr/Chil Variables
Intercept	.239** (28.1)	.249** (22.7)	.249** (22.7)	.239** (19.5)
Female	-.082** (6.86)	-.097** (6.84)	-.097** (6.84)	-.066** (4.10)
NSE		-.026 (1.48)		
NSE*Female		.062** (2.05)		
AGBIOSC			.004 (0.10)	.002 (0.06)
AGBIOSC*Female			.005 (0.10)	.011 (0.23)
ENG			-.038* (1.71)	-.038* (1.74)
ENG*Female			.108* (1.66)	.108* (1.67)
MATHSCI			-.022 (0.87)	-.023 (0.90)
MATHSCI*Female			.077* (1.70)	.079* (1.73)
Newly Married 1984-87				.037* (1.82)
Newly Married * Female				-.070** (2.36)
New Parent 1984-87				.019 (0.82)
New Parent * Female				-.154** (4.30)
R^2	.011	.012	.013	.020
F	47.1	17.1	7.7	7.8
Log-Likelihood	-1947.8	-1945.6	-1944.4	-1928.6

[1] There are 4,160 observations in the sample. The dependent variable is the change in the log of earnings from 1984 to 1987. The regressions include only the variables indicated in the table.

Table F2 - Fixed Effects Results: Fuller Models[1]

Variables	(1) Full Set of Marr/Chil Variables	(2) Adding Labour Force Attachment Variables[2]
Intercept	.270** (16.7)	.158** (4.88)
Female	-.070** (3.15)	-.070** (3.41)
AGBIOSC	-.012 (0.35)	.005 (0.14)
AGBIOSC*Female	.016 (0.33)	-.023 (0.49)
ENG	-.052** (2.34)	-.038* (1.81)
ENG*Female	.110* (1.70)	.093 (1.53)
MATHSCI	-.035 (1.35)	-.025 (1.02)
MATHSCI*Female	.081* (1.79)	.063 (1.47)
Newly Married 1984-87	.016 (0.70)	.007 (0.31)
Newly Married * Female	-.074** (2.20)	-.047 (1.47)
Married Both Years	-.007 (0.29)	-.010 (0.40)
Married Both Years * Female	-.020 (0.57)	-.015 (0.47)
First Child Born 1984-87	-.005 (0.19)	.000 (0.01)
First Child Born * Female	-.142** (3.53)	-.069* (1.81)
Second/Third Child Born 1984-87	-.020 (0.51)	-.017 (0.47)
Second/Third Child Born * Female	-.158** (2.55)	-.103* (1.76)
Same Number of Children 1984-87	-.127** (3.78)	-.111** (3.53)
Same Number of Children * Female	.073 (1.62)	.057 (1.34)

cont.

Variables	(1) Full Set of Marr/Chil Variables	(2) Adding Labour Force Attachment Variables[2]
R^2	.033	.143
F	5.64	23.7
Log-Likelihood	-1901.4	-1651.2

[1] The omitted marriage and children categories are i) never-married in both years, and ii) no children in either year. The regressions also included variables representing those who entered into the unmarried category from 1984 to 1987, those who were unmarried in both years, those who had fewer children in 1987 than 1984, and a residual marital status variable. These results are not reported in the table due to the small numbers and generally small and insignificant coefficient estimates. The sole interesting exception in this regard is that newly unmarried women had earnings which were estimated to be about 14% higher in 1987 than in 1984 (significant at the 10% confidence level) in the first model, and about 7.5% higher at the point estimate (but insignificant) in the second model, where labour force attachment is controlled for (see the following note).

[2] Includes the part-time and full-time participation variables for the specified date in 1986 as a proxy for the accumulation of experience between the two dates, and indicators of changes between part-time and full-time work over the period.

DATE DUE - DATE DE RETOUR

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