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ABSTRACT

The occupational transferability of skills learned in school and on the job has been studied very little. This paper reports some estimates of the monetary trade-off between specialization and occupational flexibility in the Ph.D's choice of major at undergraduate and graduate school. These estimates are based for the most part on multiple regression analysis of educational background and career data for a sample of 30,000 Ph.D.'s in the sciences. These data indicate that Ph.D.'s whose education is more occupationally specific, because they took the same field as an undergraduate major as that in which they earned their Ph.D., have career mobility that is 10% lower than those Ph.D.'s whose education was less specialized. In addition, when a specialist moves out of her Ph.D. occupation she receives a salary increment for the occupational switch that is about $800 less than the non-specialist's. On the other hand, specialists who remain employed in their Ph.D. field earn a return of about $80 per year on the extra skill they acquired in their Ph.D. specialty by taking the same field as an undergraduate major. (Author)

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SEATTLE, WASHINGTON 98195

July 27, 1973

The research reported herein was performed pursuant to a grant with the National Institute of Education, U.S. Department of Health, Education, and Welfare. Contractors undertaking such projects under Government sponsorship are encouraged to express freely their professional judgment in the conduct of the project. Points of view or opinions stated do not, therefore, necessarily represent official National Institute of Education position or policy.

U.S. DEPARTMENT OF

HEALTH, EDUCATION, AND WELFARE

NATIONAL INSTITUTE OF EDUCATION

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Abstract

The occupational transferability of skills learned in school and on the job has been studied very little. This paper reports some estimates of the monetary trade-off between specialization and occupational flexibility in the Ph.D.'s choice of major at undergraduate and graduate school. These estimates are based for the most part on multiple regression analysis of educational background and career data for a sample of 30,000 Ph.D.'s in the sciences. These data indicate that Ph.D.'s whose education is more occupationally specific, because they took the same field as an undergraduate major as that in which they earned their Ph.D., have career mobility that is 10% lower than those Ph.D.'s whose education was less specialized. In addition, when a specialist moves out of her Ph.D. occupation, she receives a salary increment for the occupational switch that is about $800 less than the non-specialist's. On the other hand, specialists who remain employed in their Ph.D. field earn a return of about $80 per year on the extra skill they acquired in their Ph.D. specialty by taking the same field as an undergraduate major.

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Preliminary stages of this research were supported by the Ford Foundation Program for Research in University Administration, University of California--Berkeley. (The results of this earlier research are reported in Morris [16, 17].) I am particularly indebted to Stephen Hoenack who was instrumental in securing the data upon which this research is based, and to Dr. Milton Levine of the National Science Foundation for supplying these data from the National Register of Scientific and Technical Personnel.

The Institute for Economic Research at the University of Washington supplied some additional funds which were necessary to complete the calculations reported herein. David Baylon spent many hours figuring out how these funds could be spent; I am grateful to him and Wes Erck for computer programming assistance.

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Two commonly held beliefs about the Ph.D. degree and those few people who own one are (1) that the degree certifies the completion of very specific training for research, and sometimes teaching, in some specialized scientific discipline; and (2) that the economic rewards for having a Ph.D. degree are so small, and the behaviour of Ph.D.'s in general seemingly so eccentric, that Ph.D. holders must somehow be less subject than the average person to the kinds of economic motives that are believed to guide the behavior of most participants in the labor market -- e.g., attempting to maximize income while doing as little work as possible without being fired.

It is true that the average before-tax rate of return to graduate education has been estimated to be at most 7% for white males[1], and perhaps as low as less than 1%[2]. However, such rate of return studies do not take into account changes in the labor-leisure choice which are coincident with the attainment of a graduate degree; they also ignore the consumption component of the expenditure on graduate education.[3] Such adjustments would probably raise estimated returns to a level consistent with the hypothesis that Ph.D.'s follow economic incentives in making the decision to obtain a Ph.D.

In fact, the proposition that Ph.D.'s are not much influenced by economic motives is rather surprising on its face, because Ph.D.'s would seem to be less subject than other members of the labor force to the kinds of institutional constraints that would force their behavior to deviate from the economic model. The conventional theories should better explain and predict their choices than they do the choices of some other group, such as women or blacks, whose economic options are quite circumscribed by institutional barriers.

As this reasoning would suggest, there has been some recent work that shows economic incentives are very important in explaining the behavior of Ph.D.'s. For example, Freeman [10] examined the significance of such incentives in explaining occupational mobility of Ph.D. holders. He concluded, "Post-degree mobility patterns.... can be explained in terms of economic motivation. The average income in fields feeding workers to a specialty is below the income of fields receiving workers from the specialty. The level of mobility appears to be influenced by the relative income among fields and by the 'technological similarity' among fields."[4] Freeman also found that relative demand conditions influenced the choice of field of study by students enrolling in Ph.D. degree programs.[5]

1 Hanoch [11], page 322.

2 Bailey and Schotta [3], page 29.

3 See Morris [18] for a theoretical discussion and critique of rate of return analysis.

4 Freeman [10], chapter 4, page 77.

5 In an unpublished thesis, Breneman [6] provided some theoretical analysis and empirical evidence that indicated Ph.D. holders respond to market conditions in the various scientific fields by using their influence as faculty to make it more or less difficult for others to attain the Ph.D., depending on whether there is an excess or shortage of Ph.D.'s as compared to available jobs.

Evidence has also begun to accumulate that contradicts the first belief listed above about the Ph.D. degree -- the assertion that a Ph.D.'s choice of occupation is unique and irreversible. Studies by Brown [8] and the National Research Council [20], plus the study just mentioned by Freeman, all found that there was substantial occupational switching by people with Ph.D. degrees. For example, the NRC study showed that, for a cohort of persons who obtained their Ph.D. by 1955, about 25% had swtiched by 1962 into a job that made use of a specialty field different than their Ph.D. discipline.[6]

Based on the same sample of 30,168 Ph.D.'s from the National Register of Scientific and Technical Personnel which is used in the present study, I found in some preliminary work that the average retention rate in 1966 for these Ph.D.'s, all of whom had attained their degree by 1960, was 61%, ranging from 35% in engineering to 79% in psychology.[7] These data suggest strongly that as the years pass after receipt of their degree, many Ph.D.'s find desirable the idea of working in some new discipline, and a substantial number are given the opportunity to do just that.

Yet evidence such as that provided in these four studies is not conclusive enough to shake the belief that if a person wants to be, say, an economist, she had better get a Ph.D. in economics, rather than mathematics or physics. Looking at evidence similar to that used in these studies Weiss concluded, "...the working life pattern of the typical scientiest is characterized by an early investment in education and occupational stability."[8]

It is the purpose of this paper to outline a theory of Ph.D. occupational mobility that emphasizes the trade-off in educational choices between specialization and occupational flexibility. This trade-off has been essentially ignored in previously published theoretical and empirical work on education and human capital. Much empirical evidence is offered as a test of the theory of occupational mobility and educational choice. Some estimates are given of the costs of specialization to those Ph.D.'s who later decide to change occupations, as well as some estimates of the returns to specialization for those who don't change fields.

1. A Simple Theory of Ph.D. Occupational Mobility

The conventional theory of human capital has been solely concerned with analyzing the choice of number of years of education to acquire, an occasional footnote or brief aside being devoted to the choice of quality for each of those educational years.[9] Yet if educational investments are productive of more than one kind of skill (human capital), then choosing the mix of those skills to acquire

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[6]See National Research Council [20], Appendix 15 for detailed tables of retention rates by scientific discipline.

[7]Morris [16], pages 37-38, or [17], pages 166-167.

[8]Weiss [22], page 838.

[9]See, for example, Becker [4] or Blaug [5].

is at least as critical a decision as deciding whether to go to school another year. Investment productivity measures such as the rate of return are of no help in making this choice of mix, unless the average combinations of skills are specified in the income streams being compared.

As an example of this type problem, consider a person who has just graduated from high school and knows she wants to become a scientist in some field, say physics. Should her undergraduate training be in physics, as well as her Ph.D. work? Or should she study statistics or chemistry as an undergraduate? If she later in her career decides that she wants to change occupations from physicist to statistician, will her choice of undergraduate field have made any difference?

The confidence she has at age eighteen that she wants to be a physicist until age sixty-five will of course have a lot to do with the answer to these questions. But if she is not almost certain, then she would probably like to know something about the trade-off between specialization and occupational flexibility, in terms of the costs associated with specializing in physics both in undergraduate and graduate school and later deciding to become a statistician. Or in terms of the returns to be gained by specializing in physics if she spends her career doing physics.

The extent to which her educational training provides a mix of skills that is useful in more than one occupation would thus partially define her opportunity to change occupations. The occupational generality or specificity of on-the-job training after graduation would also affect her occupational mobility.

Becker has provided an extensive analysis of general and specific on-the-job training as related to employer mobility.[10] The essential idea developed was that general training would be useful to any employer, so that the employee would bear the full costs of such training as a deduction from current wages. That is, tuition would be deducted from the employee's pay to cover the costs of her training -- time and effort devoted to learning instead of working, teaching provided by others, equipment and materials used.

Completely specific on-the-job training, on the other hand, would only raise the worker's productivity as long as she remained with the employer from whom she received the training. If she quit or was fired after the training period, then the returns from that training would be lost. The employee and employer would share this loss in proportion to their share in the cost of training. These shares, in turn, would depend on such factors as the rate of labor turnover, the extent to which such turnover was employee or employer induced, and the attitudes of each party toward risk.

These concepts are readily applied to the consideration here of Ph.D. occupational mobility, as long as the distinction between job (employer) mobility and occupational mobility is kept in mind. Inasmuch as there are a number of employers for each scientific speciality, most occupational training -- e.g., reading journals, attending seminars, and discussing new concepts with colleagues -- is employer general for Ph.D.'s. That portion which is also occupationally

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[10] See Becker [4], pages 8-29.

general would have tuition costs that would be paid in full by the scientist as a deduction from her current salary.

However, even that part which is occupationally specific would be paid for by the scientist as a salary deduction. An academic institution, for example, would be reluctant to pay the costs of training, say, a star physicist who would later in her career be likely to move to some more prestigious university. The employed scientist must thus bear the risk of undertaking occupationally-specific training whose value would be lost if she later decided to change fields. The major exception to this principle would occur when some particular occupation was severely short of scientists; in which case all employers might find it in their interests to pay the costs of training scientists in other fields to learn the scientific skills of the speciality in short supply, or the costs of making those few in the field much more productive.

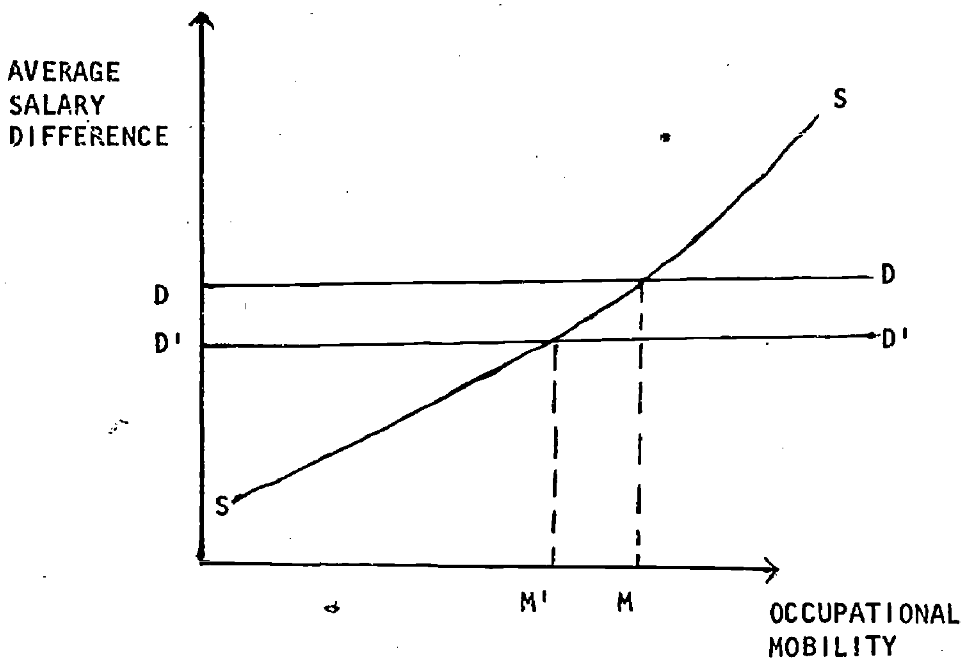
On the other hand, some occupationally-general training is employer specific, and the costs are borne by the employer. For example, certain administrative tasks at an academic institution require that the scientists who must do them be somewhat trained before they undertake these tasks. Scientists appear to regard such tasks as distasteful; but they do them precisely because training costs are paid by the university, and because some of the returns from that training are handed over to keep the scientist with administrative skills on the payroll.

In general, for both occupationally-general and-specific training that is also employer specific, the costs would tend to be shared on the basis of the same kinds of considerations that determine shares in the special case of many employers who hire for one occupation. The complication added when employees can do more than one occupation is that the risk of losing the return on training costs is greater for both employer and employee when the on-the-job learning is occupationally specific, as well as employer specific. For this reason, the portion of total on-the-job training that is specific to both employer and occupation would be small relative to training that is general in at least one of the two dimensions, regardless of how the costs of such training are shared.

The difficulty in testing these hypotheses about on-the-job training for Ph.D.'s is that no one has developed a classification schema that identifies the occupational and employer specificity of the various training activities in which scientists engage. On the other hand, there is a simple way to classify the specificity of educational training, if the natural identification is made between academic disciplines and occupational specialties. That is, suppose a Ph.D. in, say, chemistry is taken to be the usual educational training required to be a chemist. Then the person who also took her undergraduate degree in chemistry would have more specific training than someone who took an undergraduate degree in physics. Other factors being equal, the former Ph.D. would be more specialized in chemistry and her educational training would have given her less occupational flexibility.

Graph 1 can be used to illustrate the effect on the Ph.D.'s career mobility of the decision to be specialized in chemistry. The curve labeled SS represents the propensity for a Ph.D. to change

GRAPH 1



occupations during her career as a function of the difference between the average salary she would be paid in occupations that she chose to move into, and the average salary in the occupations from which she moved. The SS, or mobility supply, curve slopes upward because the Ph.D.'s desire to change occupations would be an increasing function of the opportunity cost of remaining in a given occupation from some point unil the end of her career.

Given the Ph.D.'s abilities, experiences, and educational training (in short, her cognitive and affective characteristics); given any ascriptive characteristics (for example, sex, race, or ethnic origin); and given her current salary, there is some maximum salary increase that an employer would be willing to pay to bid the Ph.D. out of her current occupation into some other one. For her whole career, the average of these salary increases offered to induce occupation switching would be given on Graph 1 by the intersection of the perfectly elastic mobility demand curve DD with the vertical axis. Observed occupational mobility -- the number of different occupations in which the Ph.D. worked during her career -- would depend on both the supply of, and demand for, mobility, as is illustrated by the intersection point M on Graph 1.

The Ph.D. who chose to specialize in chemistry would find that the demand of employers for her occupational mobility would be lower than demand for mobility of someone less specialized, as indicated by D'D' on Graph 1. Because she would be less productive in another occupation, say, physics, than the chemistry Ph.D. who had an undergraduate degree in physics, her career mobility (M') would be lower. On the other hand, specialization would have payoffs if she remained in chemistry; so that occupational mobility would be given up in return for greater productivity (and correspondingly higher salary) in her field of specialization.[11]

These two hypotheses -- that specialization reduces career mobility because it shifts the mobility demand curve down, and that specialization pays off for the Ph.D. who remains employed in her speciality -- can be empirically tested. The formal model to be estimated includes the mobility demand and supply curves, and an equation for the salary of the Ph.D. in her Ph.D. field just prior to her first occupation change. The latter is included in the structural model to determine whether Ph.D.'s who change occupations are being pushed out of their field by a low salary, or drawn out by a relatively high offer in another occupation, as compared to the average salary being paid in the Ph.D.'s speciality. It will also be used to estimate whether any tuition costs are being paid for on-the-job training of Ph.D.'s who change occupations.

The basic salary (S) of the Ph.D. just prior to an occupation change thus is:

$$(1) \quad S = \alpha_0^{(1)} + \sum_i \alpha_i^{(1)} Z_i + \beta_1^{(1)} \text{ SEX} + \beta_2^{(1)} \text{ NONCIT} + \sum_i \gamma_i^{(1)} Z'_i + U^{(1)},$$

where Z is a vector of dummy variables that describes the Ph.D.'s educational background by the following characteristics:

1. Specialization in the same field for undergraduate and graduate work.
2. Ph.D. field (agricultural science, astronomy, biological science, biomedical science, chemistry, earth science, engineering, mathematics, physics, psychology, statistics, interdisciplinary).
3. Undergraduate field (the Ph.D. fields plus economics, linguistics and sociology).
4. School type (top-rated graduate, second level graduate, liberal arts undergraduate, all others).

SEX is a dummy variable that takes on the value one if the Ph.D. is a woman; NONCIT equals one if the Ph.D. is not a U.S. citizen. Z' is a vector of dummy variables that describes the Ph.D.'s career profile by age, professional experience, years since the Ph.D. degree was awarded, time between B.S. (or B.A.) and Ph.D., employer type (academic, business, government), academic rank (dean, tenured professor, non-tenured professor, all others), and geographical area of employment.

The variable $U^{(1)}$ is an error term that includes the effect of variables, such as ability, which are not included in the data on which the equation is estimated. The superscripts on the error term and the coefficients refer to the structural equation in which each belongs.

Dummy variables measuring the Ph.D.'s career timing are included in the basic salary equation to measure the embodiment of knowledge in the Ph.D. at various points in her career, and the deterioration of that knowledge throughout the remainder of her career. Consider

[11] See Morris [19] for a more detailed theoretical analysis of the economic implications of knowledge transferability among occupations.

the following coefficients for these effects:

	Born in t_0	B.S. in t_1	Ph.D. in t_2
Embodied Knowledge	b_0	b_1	b_2
Deterioration	d_0	d_1	d_2

In a continuous time income model in which embodiment and deterioration are exponential, the effect of time on income y(t) would be given by:

$$y(t) = \exp\,[b_0t_0 + b_1t_1 + b_2t_2 - d_0(t-t_0) - d_1(t-t_1) - d_2(t-t_2)].$$

In addition, if on-the-job training takes place continuously after completion of the Ph.D., then income would be raised with the passage of time by another exponential factor $a(t-t_2)$, where a is the net rate of accumulation which is here assumed constant over the Ph.D.'s career.

Some manipulation of these exponential coefficients yields the following:

$$y(t) = \exp\,[(b_0 + b_1 + b_2)t_0 - (d_0 - b_1 - b_2)(t - t_0) -$$
$$(d_1 + b_1 + d_2 + b_2)(t - t_2) - (d_1 + b_1)(t_2 - t_1) +$$
$$a(t - t_2)],$$

where $t - t_0$ equals age, $t - t_2$ equals years since the Ph.D. degree, $t_2 - t_1$ equals time from B.S. to Ph.D., and $t - t_2$ equals professional experience. For example, the longer the time between undergraduate and graduate degrees, the greater the cost in foregone income of not using the knowledge embodied in undergraduate school while in graduate school to earn a Ph.D. Rather than assuming that embodiment and deterioration of knowledge effects were exponential, five-year-interval dummy variables were included in the salary equation for each of these career timing factors.

One interesting implication of this continuous time, exponential effects model is that if supply and demand are in equilibrium, the rate of a Ph.D.'s salary growth is completely dependent on the net rate of on-the-job training which is undertaken, as it is given by:

$$y'(t)/y(t) = a-d_0-d_1-d_2.$$

A person can thus select her salary level by deciding when and how long to attend school, but income growth depends on whether the net rate of on-the-job training exceeds the combined rates of deterioration of knowledge embodied at birth and in school. If the net training rate is not constant over time, but is, say, single-peaked, then the Ph.D.'s salary could grow early in her career and then fall off at the end. This would explain the single-peaked age-income profiles which are often observed.[12]

The passage of time is not the only reason why a Ph.D.'s salary would grow. As indicated above, a person could always change occupations if the salary increase for doing so is attractive. Over her career, the average salary increase ΔS_0 offered would be given by the mobility demand curve:

$$(2) \quad \Delta S_0 = \alpha_0^{(2)} + \sum_j \alpha_j^{(2)} Z_j^T + \gamma_1^{(2)} S + U^{(2)},$$

where Z^T is the vector of dummy variables for educational background, truncated to include only Ph.D. field and specialization variables. Since Ph.D. field and employment field are identical at the time the Ph.D. begins to change occupations, the coefficients on the Ph.D. field variables measure, in part, the relative transferability of knowledge in the twelve scientific fields included in the present study. The coefficient on the specialization variable should be negative, if the hypothesis that specialization reduces mobility demand is true.

Salary level in the Ph.D.'s home field before she first changes her occupation is included in the structural equation for mobility demand to hold constant the effects of relative salary levels prior to occupational switching. The coefficient $\gamma_1^{(2)}$ should be negative because the higher the salary base before the Ph.D. changes occupations, the lower the average salary increase she would get, other factors being equal.

The final structural equation is for mobility supply, and is given by:

$$(3) \quad M = \alpha_0^{(3)} + \alpha_1^{(3)} Z_1 + \delta^{(3)} \Delta S_0 + U^{(3)},$$

where M is the number of different occupations in which a Ph.D. works during her career and Z_1 is the specialization dummy variable. Z_1 is included in the mobility supply equation to estimate whether specialists are expressing an occupational preference by studying the same scientific specialty in undergraduate and graduate school. If they are, then $\alpha_1^{(3)}$ would be negative. $U^{(3)}$ includes the effects of any variations in occupational preference not measured by the specialization variable.

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[12] On the other hand, adjusting income for age but not date of birth -- as is typically done in cross-section estimation, and as was done here because of an oversight when the data were being readied for regression analysis -- could give a humped earnings profile even if the net training rate always exceeded the combined effects of deterioration. This could happen because the birth-date effect $b_0 + b_1 + b_2$ for older Ph.D.'s would be much lower than for younger ones, and it might outweigh the positive income growth rate for people above a certain age. Thus aging would appear to slow salary growth, when it is actually age that lowers a Ph.D.'s relative salary level in a cross-section of Ph.D.'s.

2. The National Register Sample

Before reporting the estimated coefficients of the structural model, a brief description of the data used in this study would seem appropriate since sample size and the amount of information included for each person are both far greater than is typical. These data are from the National Register of Scientific and Technical Personnel which is compiled biennially by the National Science Foundation. The sample contains biographical information, data on educational training, plus quite detailed career data for the years 1960, 1962, 1964 and 1966, on 30,168 individuals who received a Ph.D. in some scientific discipline prior to 1960. Because the NSF did not collect much data on Ph.D.'s in the humanities and social sciences, other than psychology, until quite recently, there were only 6 persons in the sample with a Ph.D. in these fields, all in economics. Ph.D.'s in psychology accounted for 14% of the sample; the other 86% were in agricultural science (2%), astronomy (1%), biological science (17%), biomedical science (1%), chemistry (23%), earth science (6%), engineering (3%), mathematics (5%), physics (13%), statistics (1%), interdisciplinary (10% in biochemistry, geochemistry, physical chemistry, biophysics and social psychology), with 4% being unclassifiable because of blank, miscoded or inconsistent data.

These data were first screened to eliminate all individuals whose records contained incomplete or inaccurate information on any of the variables used in this study. Any Ph.D. not employed full time during the 1960-1966 interval was also excluded. The usable sample was thus reduced to 18,408 Ph.D.'s in twelve scientific specialties (all the economics Ph.D.'s were eliminated by these adjustments).

This sample was then split into two parts -- one containing 1841 records (10%), and the other containing the remaining 16,567 -- by selecting each tenth record for the smaller subsample. Each of these subsamples is independent of the other and is a random sample of the population of full-time employed Ph.D.'s in the sciences, at least to the same extent that the National Register is, since I have no reason to believe that the blank data exclusions are systematically related to any of the variables used in the analysis here.

The purpose for subsampling was so that the one-in-ten sample could be used to correct computer programming errors that would have been costly if they occurred while manipulations were being performed on the sample of 18,408 Ph.D.'s. More importantly, I wanted to use the small sample to examine the variability of the data in the National Register; to decide what variables should be used as dummy variable referent groups; and to form some opinions about relationships between mobility, salary, career status, and educational background which are not completely specified in the simple theory of occupational mobility outlined in the first section. For example, this analysis convinced me that sex and citizenship were important in explaining salary levels, but not the salary changes associated with occupational mobility.

More simply said, any subtle or not so subtle modifications in statistical tests or structural equations which I might have been tempted to do to make the empirical results agree more closely with my theory of occupational mobility, were done on the small subsample. This gave me a detailed set of structural relationships which were then tested on the large subsample, in the sense that this paper reports the results of all regressions calculated on that sample in which the dependent variable was any one of the endogenous variables of the structural system set out above.

3. An Estimate of the Lifetime Reduced Form for Mobility

As a first test of the effect of specialization on career mobility, the reduced form for the number of occupations in which a Ph.D. worked during her career was estimated. Inasmuch as the career profile variables (Z') would have only weak effects on a Ph.D.'s career mobility -- they would affect mobility only through their effect on the Ph.D.'s salary level in her home specialty just prior to her first change in occupation, these variables were excluded from the lifetime reduced form for mobility.

Career mobility M was measured as the number of different occupations in which the Ph.D. reported herself employed during her career through 1966, assuming that she began her career employed in the scientific specialty in which she obtained her Ph.D. Occupation was identified with the scientific field which the Ph.D. reported to be most closely related to her current job in 1964 and 1966, and with the scientist's self-reported professional identification in 1960 and 1962.[13]

The results of regressing M on the educational background and ascriptive variables are given in Table 1. The first thing to note about these estimated coefficients is that specialization has the effect of reducing career mobility by 10%, as was predicted by the theory outlined in Section 1. However, whether this is a demand side effect, or just the expression of a preference for their home field by Ph.D.'s who studied the same science in undergraduate and graduate school, cannot be determined from the estimated coefficients in the reduced form.

The undergraduate and graduate specialty field effects are listed in order of their magnitude for Ph.D. major. Most of the undergraduate majors had little effect on career mobility, except that majoring in agricultural science, earth science or linguistics was associated with career mobility that was about 15% less than average. This could reflect a number of factors -- the low productivity of the knowledge in a field such as linguistics for people who become scientists in the fields included in the National Register sample, the additional specialization effect on career mobility in a field such as earth science in which the simple coefficient of correlation between choosing to major in it as an undergraduate and choosing it as a graduate field is 0.82,[14] or the additional specialization effect of

[13] The National Science Foundation (see their American Science Manpower [21]) uses the practice of identifying a scientist's field with her report of area of greatest scientific competence on the basis of her total educational and work experience. In his work, Weiss [22] chose to identify occupation with area of greatest scientific competence, rather than with specialty most used in current job.

[14] The simple coefficient of correlation between majors in biological science, physics and psychology was also about 0.80; it was about 0.64 for chemistry and mathematics; 0.55 for astronomy and engineering; 0.35 for agricultural and biological sciences; and 0.15 for statistics and the interdisciplinary specialties.

Table 1

REGRESSION COEFFICIENTS (AND STANDARD ERRORS) FOR THE LIFETIME MOBILITY REDUCED FORM

Major Field	Ph.D.	UG
Agricultural Science	1.19 (0.03)	-0.23 (0.04)
Interdisciplinary	0.65 (0.03)	0.03 (0.06)
Biomedical Science	0.62 (0.05)	0.01 (0.05)
Engineering	0.43 (0.04)	0.02 (0.03)
Chemistry	0.10 (0.03)	0.04 (0.03)
Statistics	0.07 (0.07)	0.13 (0.22)
Earth Science	0.03 (0.04)	-0.23 (0.05)
Biological Science	0*	-0.14 (0.04)
Astronomy	-0.12 (0.09)	-0.10 (0.10)
Mathematics	-0.15 (0.04)	-0.01 (0.03)
Physics	-0.20 (0.03)	0
Psychology	-0.31 (0.04)	0.07 (0.04)
Economics	-	-0.01 (0.05)
Linguistics	-	-0.22 (0.06)
Sociology	-	-0.02 (0.08)

	Grad	UG
Top 15 Grad.	0.02 (0.05)	0.002 (0.03)
Next 91 Grad.	-0.01 (0.04)	0.03 (0.02)
Liberal Arts	-	-0.02 (0.04)
All Others	0	0

Specialization Effect

-0.16 (0.06)

Specialization - School Type Interaction

	Grad	UG
Top 15 Grad.	0.01 (0.06)	0.02 (0.03)
Next 91 Grad.	-0.04 (0.06)	-0.05 (0.02)
Liberal Arts	-	0.02 (0.05)
All Others	0	0

Ascriptive Variables

SEX	-0.002	(0.03)
NONCIT	0.12	(0.05)

Constant = 1.65
Regression Standard Error = 0.62
N = 16,567
$\bar{M}$ = 1.61
$\hat{\sigma}_M$ = 0.75

*Referent groups have coefficients constrained to be zero, so that effects of other groups within each characteristics variable are measured relative to the referent group.

choosing a specialty that is in low demand such as agricultural science was during the early sixties.

The Ph.D. field effects are quite large in many cases. Thus Ph.D.'s in agricultural science changed occupations about 75% more than average. As Brown [7] and Freeman [10] report, agricultural scientists were in quite low demand during the early sixties, so it is not surprising to find that Ph.D.'s in that field moved into other occupations at a much greater rate than Ph.D.'s in any other field.

Ph.D.'s in the interdisciplinary fields ranked second in career mobility, as would be expected for these fields which have high knowledge transferability to other specialties -- for example, biochemists can readily become chemists or biologists inasmuch as they are a little of both to begin with. Because only about 4% of the Ph.D.'s in the interdisciplinary fields also had an undergraduate major in one of those areas, and because demand for the interdisciplinary specialties varied from low to high, the extra 40% career mobility for these Ph.D.'s is almost totally due to the relatively high knowledge transferability in these disciplines.

Similarly, engineering and the biomedical sciences must rank high in knowledge transferability, because both were in high demand. This demand effect would tend to lower career mobility for Ph.D.'s in these two fields, so that it would be more difficult for an employer to hire them in some other occupation. Despite the lower salary increases that employers could offer them, the amount of re-training needed in the occupations to which these scientists moved must have been low enough that re-training tuition deductions were relatively low so that the salary increases offered for changing occupations were raised more by this effect, than they were reduced by the demand effect. Scientists in engineering and the biomedical sciences thus ranked among the top four in career mobility.

In mathematics, physics and psychology the demand effect dominated any knowledge transferability effect, as all three fields were in moderate to high demand during the sixties. Statistics was also in high demand, so its mobility ranking would indicate that field has greater knowledge transferability than other high demand fields, as would be expected.

To determine if the type and quality of school attended had any effect on career mobility and salary levels, the graduate and undergraduate institutions were grouped into four categories. Graduate schools were categorized by taking the 106 institutions selected by Cartter [9] for his 1964 survey of quality of graduate instruction in twenty-nine disciplines in all schools which awarded at least ten Ph.D. degrees per year. These 106 schools were divided into two groups. The top fifteen contained the thirteen universities which Cartter rated as leading in one of five general areas of study -- biological sciences, engineering, humanities, physical sciences and social sciences;[15] plus two additional schools -- Cornell which was rated as one of the top ten graduate schools in a 1925 survey by Hughes [12] and as one of the top ten in a 1957 rating by Keniston [13], and Johns Hopkins which was one of the top ten in Hughes' ranking.

[15] See Cartter [9], page 107.

These fifteen schools thus include all the top-rated institutions of graduate study during the period in which Ph.D.'s in the National Register sample were attending graduate school. The remaining 91 schools covered in the Cartter report were classified as second-level institutions of graduate study.

Undergraduate schools were classified into four categories. The first two included the same schools as the two groupings of the Cartter report schools. To determine if undergraduate instruction at a small, liberal-arts type school was different than instruction at the large universities which devote much of their resources to graduate study, thirty-one of the high quality liberal arts schools were classified into a third control group for undergraduate study.[16] An institution was selected for this category if it was mainly an undergraduate school offering a liberal arts type of training; and if the school was given a prestige rating of A or B on a scale of A through F by Brown [7] in his study of the labor market for academic personnel, or the school was rated as being highly productive of scientists in studies by Knapp and Goodrich [14] and Knapp and Greenbaum [15] of the social and collegiate origins of American scientists.

As indicated by the estimated coefficients listed in Table 1, the type of institution attended had little effect on career mobility.[17] Similarly, women tended to be just as mobile as men. But non-citizens were somewhat more mobile than U.S. citizens.

One problem with the regression estimates listed in Table 1 is that occupational switching is only measured between the Ph.D. degree and 1960 occupation, and then at two-year intervals after 1960 until 1966. The number of occupations in which a Ph.D. could work is thus from one to five. On the other hand, estimated coefficients for the educational background and ascriptive variables are supposed to measure the effect these characteristics have on career mobility. That is, ideally I want to relate career mobility M' to these characteristics, but I only had a measure of mobility M during a portion of each Ph.D.'s career. Since $M' = M + \varepsilon$, the error term in structural equation (3) is actually $U^{(3)} - \varepsilon$. If the unobserved portion (ε) of career mobility is highly correlated with any of the educational background or ascriptive variables, then the estimates reported in Table 1 would be biased.

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[16] See Morris [16], page 28, for a listing of these schools.

[17] The specialization-school type interaction effects can be read as non-specialization-school type interactions by simply changing signs on the regression coefficients listed in Table 1. This follows from the fact that if D is a dummy variable in the regression $M = \alpha_0 + \alpha_1 D + U_1$, and 1-D is the corresponding dummy for the opposite characteristic in the regression $M = \beta_0 + \beta_1(1-D) + U_1$, then $\hat{\alpha}_0 = \hat{\beta}_0 + \hat{\beta}_1$ and $\hat{\alpha}_1 = -\hat{\beta}_1$, where $\hat{\alpha}_0$, $\hat{\alpha}_1$, $\hat{\beta}_0$, and $\hat{\beta}_1$ are ordinary least squares estimators.

Now the size of the unobserved part of career mobility depends in part on the portion of a Ph.D.'s career over which mobility M is measured. For example, occupational switching would tend to occur rather early in a career so that the returns from learning a new occupation could be fully captured. One way to check whether unobserved mobility is correlated with any of the independent variables in the reduced form is, thus, to add the career profile variables Z' for 1960 to the regression of M on educational background and ascriptive characteristics. When this was done, the estimates reported in Table 1 changed very little. In fact, only three out of the 38 varied by as much as 25% of one standard error, and the largest change was only 66%. One of these three -- the effect of attending one of the second-level graduate schools -- was also the only estimate to change signs, inasmuch as its estimated effect was quite close to zero to begin with.

So adding career profile variables to the lifetime reduced form did not change any of the estimated coefficients by a statistically significant amount. However, the standard error of the regression was reduced to 0.61, which is a numerically small but statistically significant reduction.[18] One can conclude that unobserved career mobility is not significantly correlated with educational background or ascriptive variables, but career profile variables are important in explaining the difference between mobility over a Ph.D.'s career and mobility over a portion of her career.

One final note before turning to estimation of the structural equations is that those Ph.D.'s who stayed in the same geographic area during 1960-1966, or worked for the same employer type throughout that period, changed occupations less often than average by 2% and 5%, respectively. As one would expect, there is positive correlation between employer, geographic, and occupational mobility.

4. Some of the Determinants of 1960 Salary Level

The structural equation for salary just prior to a possible change in occupation was estimated by regressing the natural logarithm of 1960 salary on the variables listed on the right-hand side of equation (1). The sample for this regression was restricted to those Ph.D.'s who were still working in their Ph.D. field as of 1960.[19] This constraint reduced the sample size about 7%, from 16,567 to 15,353.

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[18] All testsare at the 0.01 confidence level unless otherwise stated. For this test the F statistic had a value of 5.97 with 40 and 16,488 degrees of freedom.

[19] A Ph.D. could have switched out of her home specialty prior to 1960 and then back in by 1960. For the entire sample of 30,168 Ph.D.'s, 61% were employed in their Ph.D. field as of 1966; at most 22% of these people had switched out after receiving their Ph.D. and then back in by 1966. So as of 1966 at most 13% of the Ph.D.'s had switched out and back. The proportion who would have done the same by 1960 is probably much lower, given that 29% received their Ph.D. between 1956 and 1960, and 61% received their degree after 1950.

Table 2 reports the estimated effects of the various 1960 salary determinants. These effects were calculated from the log salary regression by comparing the salary of the average Ph.D. in a particular category of the characteristic in question -- for example, the salary for the average Ph.D. in physics -- with the salary of the average Ph.D. in the referent group for that characteristic -- in the case of Ph.D. field this is the salary of the average Ph.D. in biological science. Thus for the Ph.D. of average age, sex, professional experience, undergraduate major, etc., having a Ph.D. in physics was worth $1589 more in 1960 than having a degree in biological science. The standard error of this estimate was $150, which was calculated to be in the same numerical ratio to $1589 as the log salary regression coefficient was to its standard error.[20]

The Ph.D. field effects are ranked by size. Inasmuch as these Ph.D.'s are employed in the occupation which corresponds to their Ph.D. specialty, this ranking gives an index of relative demand in 1960. Not surprisingly the ranking agrees almost exactly with the rankings Brown [7] and Freeman [10] developed for relative demand in their empirical work based on salary data for the early sixties. In those two studies, statistics, physics, engineering, biomedical science, and mathematics were classified as high demand fields. Chemistry,

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[20]That is, the t-statistics for the estimates reported in Table 2 are the same as for the actual log salary regression coefficients. An interesting aside at this point is that an examination of Table 2 reveals two obvious examples of why the t-test is often an inappropriate way to determine whether a variable "belongs" in a regression equation.

First, for the career timing variables, standard errors are monotonic increasing with respect to each of the three characteristics. This simply reflects the fact that the distribution of the effect of one of these variables on income has greater absolute variation about its average effect for larger values of the variable in question, due to the cumulative influence of such non-controllable factors as luck throughout a Ph.D.'s career. A simple-minded t-test on, say, the effect of being in the 55-59 age category would reject the hypothesis that this variable belongs in the regression. What is actually the case is that this age variable has an effect on income that varies widely about a relatively small average (or mean effect).

Second, for the undergraduate field variables, standard errors vary between $131 and $334, except for the standard errors for the estimated effect of having an undergraduate degree in statistics or astronomy. These two fields just happen to be the same two which only 7 and 26 people, respectively, chose as a major, as compared to the minimum of 67 who chose other undergraduate fields. So in this case the large standard errors reflect the fact that estimates of the mean based on small samples are imprecise, and do not imply that these two variables should be excluded from the regression equation.

TABLE 2

COMPUTED EFFECTS (AND STANDARD ERRORS) OF 1960 SALARY DETERMINANTS

Major Field

	Ph.D.	UG
Statistics	$2639 (323)	$232 (1017)
Physics	1589 (150)	0
Engineering	1197 (178)	91 (149)
Biomedical Science	1067 (222)	-188 (222)
Mathematics	711 (160)	-311 (133)
Psychology	684 (148)	-365 (178)
Astronomy	476 (345)	304 (605)
Agricultural Science	329 (164)	-363 (187)
Interdisciplinary	325 (110)	-95 (247)
Earth Science	151 (147)	-179 (199)
Chemistry	139 (97)	-239 (131)
Biological Science	0	-402 (152)
Economics	-	435 (284)
Linquistics	-	-215 (264)
Sociology	-	-557 (334)

School Type

	Grad	UG
Top 15 Grad.	$249 (226)	$191 (98)
Next 91 Grad.	-101 (147)	49 (82)
Liberal Arts	-	74 (183)
All Others	0	0

Specialization Effect

$54 (451)

Specialization - School Type Interaction

	Grad	UG
Top 15 Grad.	$-195 (272)	$-61 (144)
Next 91 Grad.	-158 (259)	9[illegible] (104)
Liberal Arts	-	-131 (222)
All Others	0	0

Employer Type (1960)

Academic	$ -1779	(133)
Business	0	
Gov.	-2549	(58)

Time from B.S. to Ph.D.

0-4	$599	(81)
5-9	222	(62)
10 +	0	

Ascriptive Variables

SEX	$ -1741	(113)
NONCIT	255	(216)

Academic Rank (1960)

Dean	$2764	(494)
Ten. Prof.	649	(133)
Non-Ten.Prof.	155	(137)
All Others	0	

Table 2

(Continued)

Career Timing (1960)

Age		
1-29	0	
30-34	$ 762	(89)
35-39	1138	(106)
40-44	1096	(126)
45-49	836	(151)
50-54	374	(178)
55-59	-143	(219)
60-64	-654	(292)
65 +	-2047	(496)

Ph.D. Degree	Years Since Ph.D. Degree		Professional Experience	
0-4	0		0	
5-9	$ 938	(63)	$ 550	(71)
10-14	1735	(92)	1403	(95)
15-19	2349	(134)	2086	(121)
20-24	2565	(161)	2796	(146)
25-29	3140	(208)	2963	(182)
30-34	4139	(283)	3480	(219)
35+	4681	(515)	3645	(309)

Geographi Area (1960)

Northeast	$509	(132)
Middle Atlantic	507	(109)
South Atlantic	170	(115)
East North Central	434	(111)
East South Central	276	(129)
West North Central	505	(128)
West South Central	356	(126)
Mountain	456	(132)
Pacific	941	(122)
Outside 48 Contiguous States	0	

Constant = $8350
Regression Standard Error = $2993
$\underline{N}$ = 15,353
$\bar{S}$ = $11,940
$\hat{\sigma}_S$ = $4168

psychology, and astronomy were moderate demand fields. While agricultural science, earth science and biological science were listed as being in relatively low demand.

In comparison to Ph.D. field, the undergraduate major choice has relatively little influence on 1960 salary, ranging from a low of -$577 for a degree in sociology to a high of $435 for an undergraduate major in economics. Interestingly enough, economics, astronomy, statistics, engineering and physics are the fields that provide knowledge that is useful on average no matter what scientific area one's Ph.D. is in. This is some empirical support for the advice often given to undergraduates who intend to pursue graduate studies. That advice being to study a discipline that will develop skills in abstract reasoning and quantitative methodology.

The school type effects are small, and at least for the effect of the undergraduate institutions, about as expected. Undergraduate and graduate instruction at one of the top 15 schools of graduate study both rank first in terms of payoff in 1960 salary. However, undergraduate study at one of the small, liberal arts colleges is better than attending one of the second level graduate schools.

The return to specialization is small, but positive, as one would expect for extra course work at the undergraduate level in the field in which a Ph.D. is employed in 1960. The interaction between specialization and choice of school, however, in the case of training at a liberal arts college, entirely offsets the positive returns from specializing and doing undergraduate work at one of these small schools. Similarly, specialists who attended one of the top 15 graduate institutions at either the undergraduate or graduate level incur a cost that offsets the return to specializing. The optimal choice for specialists turns out to have been going to undergraduate school at one of the second level graduate institutions, and then taking a Ph.D. from a school not even included in Cartter's survey.

Interpreting these estimates for the specialization-school type interaction is quite problematic. The general conclusion is that for specialists, the more prestigious the school the greater the future salary costs of studying there. Now there has been some work that suggests quality of an institution is not positively related to student achievement.[21] But no one has suggested that there is an inverse relationship. One possible explanation is that since size and prestige tend to be positively correlated among the institutions that offer both undergraduate and graduate degrees, the inverse relationship may reflect the fact that specialists get a quantity of instructional resources devoted to their training at the smaller schools, that more than offsets any lower quality of those resources. Inasmuch as the liberal arts colleges are not likely to be in general oriented toward the kind of instruction needed by people who devote themselves to the rather exclusive study of one scientific specialty, specialists who went to one of these colleges for a B.S. suffered similar quantity disadvantage relative to someone who attended one of the smaller universities oriented toward graduate instruction.

[21] See, for example, Astin [2].

Employer type and academic rank have salary effects that correspond to casual observation. What is more interesting is that women are on average paid $1,750 less than men with the same educational backgrounds and career profiles.[22]

The career timing effects are about what would be predicted by the model of embodied knowledge and deterioration given in Section 1. The longer one takes to get a Ph.D. after having a B.S., the lower one's salary is. The net rate of on-the-job training is positive for all ages; that is, the estimated effect of professional experience is monotonic increasing with respect to age. However, the estimated effect of number of years since the Ph.D. was awarded is also monotonic increasing, instead of decreasing as the model of Section 1 predicted. Apparently, the high correlation between professional experience and years since the Ph.D. degree prevented identification of the separate effects on salary of job training and the deterioration of knowledge embodied in undergraduate and graduate study.[23]

The age-income profile estimated for Ph.D.'s is single-peaked, with income rising with age until the Ph.D. reaches 40 and falling after that point. At about age 55, the typical Ph.D.'s income falls below the salary she made when she first was employed as a scientist. However, as indicated in footnote 12 above, this humped profile with a negative tail may be the result of misspecification, instead of the result of aging.

Finally, Table 2 gives the estimated salary differentials by geographic area. Employers in the contiguous U.S. pay higher salaries than those outside, no matter what part of the country the Ph.D. works in. The Pacific region pays the highest salaries, while the South Atlantic pays the lowest, for employers inside the contiguous states.

As Table 2 shows the estimated specialization effect is quite small. One possible explanation is that specialists who moved out of their specialty occupation after 1960 might have spent time on the job prior to 1960 learning about some other occupation. The $54 would then be low because specialists who were planning to change occupations would be paying a tuition for this training that would be deducted from their 1960 salaries.

To test for such an effect, a dummy variable was added to the log salary regression that took the value one for specialists who remained in their Ph.D. occupation through 1966. Adding this variable did not change the estimated coefficients for any of the previously included variables by as much as one standard error, but it did increase the estimated specialization effect to $194. On the other hand, the dummy variable had an estimated coefficient that showed immobile specialists

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[22] It is quite unlikely that the differential is due to any ability difference between men and women. In a sample of highly educated people, Ashenfelter and Mooney [1] concluded, "The misspecifications, caused by the absence of an ability variable, seem to be quite small indeed." (Page 86) That is, the estimated coefficients for control variables in their study were about the same, whether they included an ability control variable or not.

[23] The five-year interval dummy variables have estimated simple correlation coefficients that range from 0.35 to 0.50. The continuous variables would be much more highly correlated.

were paid \$308 (standard error = \$52) less in 1960 than the specialists who changed occupations after 1960. This is just the opposite of what would be expected if the mobile specialists were paying tuition for occupational training prior to 1960 that was specific to an occupation in which they were not employed. If the mobile specialists were in essence pushed out of their Ph.D. occupation because they were not competitive with those who remained employed in the given occupation after 1960, the estimated effect would also have been opposite of the result that occurred.

To determine if those Ph.D.'s who changed occupations after 1960 were being paid differentially for characteristics other than specialization, the log salary form of (1) was reestimated on two subsamples--one containing the 8,802 Ph.D.'s who remained in their Ph.D. specialty through 1966, and the other containing the 6,551 Ph.D.'s who left home after 1960. Table 3 contains some of the results of those two regressions.

The first thing to note is that the mobile Ph.D.'s were earning an average salary in 1960 of \$12,320, versus \$11,660 for the immobile Ph.D.'s. But after adjusting for educational background, career profile, and ascriptive variables, both groups were being paid the same--on average about \$8,500 for uncontrolled characteristics such as luck and ability. The main reason for the higher average salary of the mobile Ph.D.'s is that this group is slightly older, more experienced, and has a greater portion of its jobs with business-type employers, than does the group of Ph.D.'s who were encouraged, or chose, to remain in their home specialty through 1966.

So uncontrolled effects, such as ability, are distributed equally in the two subsamples, or are distributed so that the different effects of these unobserved characteristics offset their differential importance. Since the latter event is quite unlikely, one can conclude that the mobile Ph.D.'s are not being forced out of their Ph.D. occupation because they are less able than the immobile Ph.D.'s in each field.

Second, the formal hypothesis that the regression coefficients are identical could be rejected at the 5% confidence level, but not at the 1% level.[24] However, some of the individual coefficient estimates differ for at least one of the two subsamples by at least two standard errors from their estimates over the whole sample.[25] All the

[24]The F-statistic is 1.30 with 77 and 15,199 degrees of freedom.

[25]This is a case in which individual coefficients in two regressions are significantly different, but the regressions as a whole are not. In Section 3 there was an example of the case in which adding variables to a regression reduces its standard error significantly, without altering the estimated coefficients for any of the already included variables. However, two subsample regressions could not explain significantly more variance than the whole sample regression, unless as least one coefficient was significantly different for the two subsamples.

Table 3

COMPUTED 1960 SALARY EFFECTS (AND STANDARD ERRORS) FOR IMMOBILE AND MOBILE SPECIALISTS

	Major Field			
	Ph.D.		UG	
	Im	Mob	Im	Mob
Statistics	$2292 (496)	$2835 (461)	$-192 (1200)	$772 (1674)
Physics	1487 (204)	1993 (252)	0	0
Engineering	393 (298)	1681 (256)	389 (193)	-462 (232)
Biomedical Science	30 (3575)	1162 (271)	222 (363)	-704 (335)
Mathematics	676 (220)	905 (292)	-143 (156)	-802 (258)
Psychology	765 (200)	951 (284)	-347 (217)	-932 (345)
Astronomy	986 (479)	-39 (567)	-292 (644)	1575 (1324)
Agricultural Science	955 (735)	250 (219)	-167 (272)	-742 (296)
Interdisciplinary	131 (606)	260 (169)	-263 (425)	-326 (374)
Earth Science	296 (260)	32 (281)	-205 (248)	-479 (371)
Chemistry	-114 (142)	339 (170)	-22 (157)	-700 (221)
Biological Science	0	0	-279 (201)	-863 (257)
Economics	-	-	391 (325)	706 (570)
Linguistics	-	-	75 (322)	-1098 (631)
Sociology	-	-	-625 (395)	-564 (637)

Table 3 (Continued)

	School Type				School Type - Specialization Interaction			
	Grad		UG		Grad		UG	
	Im	Mob	Im	Mob	Im	Mob	Im	Mob
Top 15 Grad.	$ 67 (320)	$332 (294)	$373 (192)	$132 (172)	$-202 (407)	$ 66 (395)	$-203 (212)	$100 (209)
Next 91 Grad.	-286 (188)	-2 (78)	1 (138)	65 (127)	-10 (389)	-123 (377)	168 (153)	71 (150)
Liberal Arts	-	-	-383 (319)	368 (263)	-	-	307 (333)	-330 (327)
All Others	0	0	0	0	0	0	0	0

Specialization Effect

Im	$80	(426)
Mob	-211	(397)

Employer Type

	Im	Mob
Academic	$-2210 (175)	$-1311 (203)
Business	0	0
Government	-2686 (80)	-2423 (88)

Academic Rank

	Im	Mob
Dean	$3430 (682)	$1945 (718)
Ten. Prof.	984 (173)	291 (206)
Non-Ten. Prof.	312 (167)	-67 (206)
All Others	0	0

	Im	Mob
Constant	$8519	$8433
Regression Std. Error	2873	3133
$\bar{S}$	11,660	12,320
$\hat{\sigma}_S$	3996	4361
N	8802	6551

characteristics within which such differences occurred are reported in Table 3.[26]

The data in Table 3 show that there is a small payoff of $80 to specialization among the immobile Ph.D.'s, but that extra educational training at the undergraduate level was associated with a cost of $211 among the mobile Ph.D.'s. This could be the result of mobile specialists paying tuition for job training that they are doing to become competitive with non-specialists when both groups begin looking for jobs in other occupations. If that is true, then tuition costs are about $300, because the $211 would be the sum of the $80 return to educational specialization while still employed in the specialty field and a $291 cost for extra on-the-job training that is probably specific to some other occupation.

While on the topic of on-the-job training, I should mention that the mobile Ph.D.'s as a group have payoffs for each five-year increment in years since the Ph.D. degree that are from $150 to $700 higher than the corresponding effects for the immobile Ph.D.'s. Similarly, professional experience pays off in an amount from $50 to $642 greater, except in the 5-9 years category where immobile Ph.D.'s are paid $580 more than the 0-4 years reference group, while mobile Ph.D.'s are paid $568 for the additional 5 years experience. These results suggest that mobile Ph.D.'s do more on-the-job training during their careers. Since the smaller extra payments for experience to mobile Ph.D.'s occur during the early years of their careers, the mobile Ph.D.'s are probably paying the costs of some of this training, but are clearly not incurring full tuition costs. Perhaps employers pick up some of the costs of occupationally general training in the expectation that doing so will enable them to induce the mobile Ph.D. to change occupations without changing employers.[27]

Some of the estimates in Table 2 that differ by subsample, other than the specialization effect, are also worth mentioning. First, for both immobile and mobile Ph.D.'s, statistics and physics were still the two top paying fields. However, engineers ranked seventh among immobile Ph.D.'s, but were third in pay for the mobile subsample. This could reflect the fact that 71% of the engineers in the whole sample changed occupations after 1960, so that the statement that engineers are in high demand is as much a statement about the ease with which engineers can find jobs in other high-paying scientific specialties, as it is a statement about the demand for people to work as engineers. Consequently, it is the more able engineering Ph.D.'s who at some point in their career find that the extra pay they get as an engineer is not as great as the amount they could get by switching into some other

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[26] Only two variables that are not reported in Table 3 had estimated effects in the two subsamples that differed from each other (as opposed to one of them differing from the estimated effect in the whole sample) by more than two standard errors. These were the Mountain geographic area and the 20-24 years since Ph.D. dummy variables.

[27] For example, academic astrology being what it is, a star Ph.D. in economics is the same to a college dean or university president, whether she has an office in the economics department or the statistics department.

occupation. The same analysis could hold for Ph.D.'s in the bio-medical sciences, 94% of whom switched occupations after 1960.[28]

On the other hand, immobile Ph.D.'s in astronomy and agricultural science are much higher on the relative pay scale than their mobile counterparts. These fields were in moderate to low demand during the early sixties, so that only the most able would find it profitable to remain in the occupation during a period of low demand, especially in two fields which would seem to have a knowledge core that is less transferable than the skills learned in engineering or medicine. That is, for fields in low demand with low skill transferability, the less able Ph.D.'s are pushed into other occupations. For high demand, high knowledge transferability fields, the more able Ph.D.'s are bid into other occupations by promises of higher pay.

In terms of the returns to undergraduate major, astronomy, economics, physics and statistics are top-ranked for the mobile Ph.D.'s, but only economics and physics hold their top rank among immobile Ph.D.'s. The school type effects for immobile Ph.D.'s rank as they did for the whole sample, except that a liberal arts undergraduate training has a cost to the non-specialist instead of a return. In general, these data continue to suggest that specialists who intend to stay in their specialty should be more concerned with the quantity than quality of instructional resources devoted to their training.

The school type effects for the mobile non-specialists are ranked similarly to those for the immobile Ph.D.'s who studied different fields in undergraduate and graduate school. Except that a liberal arts training pays off for these mobile Ph.D.'s by giving them more general, and less specific, training in their undergraduate major. Mobile specialists, on the other hand, are the exception to the rule that quantity is more important than quality for specialists. High quality educational training in one discipline apparently offers more occupationally general knowledge than does a larger quantity of lower quality instruction. Perhaps this is just another way of saying that genius teaches about general principles, while hard and extensive work teaches the detail.[29]

5. Estimation of Mobility Supply and Demand

Of the 11,100 specialists (72% of 15,353) who were employed in their Ph.D. field in 1960, 64% remained in the same occupation through 1966. On the other hand, of the 4,253 non-specialists (28% of 15,353), only 39% remained in their home occupation through 1966. Of the 1,551 Ph.D.'s in the interdisciplinary specialties, only 25 (1.6%) remained in one of these specialties through 1966. Furthermore, the specialists and

[28]It is well to remember that some of the effects reported in Table 3 are quite poorly estimated. In fact, all variables which have standard errors over $500 are imprecisely estimated because Ph.D.'s with a particular one of those characteristics make up less than 0.5% of the subsample.

[29]There are people who design and create theories; and people who put on the finishing touches, make repairs and keep the theories in order. The skills of the former are more occupationally general.

non-specialists who changed occupations were paid an average salary increase of $1,828 to do so, while those Ph.D.'s who remained at home had only an average salary increase of $1,785 in the three two-year intervals from 1960 through 1966.

These averages are consistent with the hypothesis that the more occupationally specific a Ph.D.'s educational training is, the lower her career mobility. They are also consistent with the hypothesis that mobility supply is an increasing function of the average salary increase paid for an occupation change. However, to sort out demand and supply effects, the structural parameters in equations (2) and (3) must be estimated.

There is one critical difficulty with the salary data in the National Register sample in terms of using it to measure the salary change associated with an occupation change. That is that the four observations on basic salary level are separated in time by two years, yet when a Ph.D. changed occupations there was an instantaneous salary increase paid to induce the Ph.D. to leave her current field. It is the career average of this instantaneous salary effect that is given by ΔS_0 in the structural supply and demand equations.

The total average salary increment over the three two-year time spans would be the sum of the average increase obtained by changing occupations (ΔS_0), any average increase due to a change in employer (ΔS_J), the effects of aging (dS/dt), and random effects (ε) caused by such unobservable factors as luck. Formally, then, the total average salary increment is given by the following equation:

$$(4) \qquad \Delta S_T = \Delta S_0 + \Delta S_J + \frac{dS}{dt} + \varepsilon.$$

Using ΔS_T as a measure of the average instantaneous salary increment ΔS_0 would thus give an errors-in-variables downward bias to the estimated slope coefficient $\delta^{(3)}$ in the structural supply equation (3). The standard solution to an errors-in-variables problem is to use exogenous information in the sample to estimate an instrumental variable to replace the poorly measured one in regression calculations. Unfortunately that procedure assumes that the exogenous information in the sample gives an estimate of ΔS_0 that is not biased by leaving out an unobserved variable which is important in explaining the salary increments actually paid to induce mobility.

In the National Register sample, what might be labeled as ability is just such an unobserved variable. The educational background, ascriptive, and career profile variables provide an estimate of ΔS_0 that is negatively correlated with career mobility (simple correlation coefficient = -0.20 in the whole sample of 15,353 Ph.D.'s; it is -0.03 in the subsample of mobile Ph.D.'s). On the other hand, averaging only salary change in intervals during which an occupation change took place, gives an estimate of ΔS_0 which has a larger proportion of its variance explained by occupation change, than does the average ΔS_T of all three salary increments during 1960-1966. This estimate has a simple coefficient of correlation that is 0.01 for the mobile subsample.[30]

Inasmuch as there was no good solution to the problem of measuring ΔS_0 in the National Register sample, the estimates obtained for the mobility supply slope coefficient are probably quite biased toward zero. Table 4 reports the estimated structural supply equations obtained by regressing the number of occupations in which a Ph.D. worked during 1960-1966 on the specialization dummy variable and the estimate of ΔS_0 just discussed, as well as on the total average salary increment ΔS_T.

As expected, the estimates obtained for the slope coefficient are positive, but so small as to be inconsequential, when the estimate of ΔS_0 is used as a measure of the salary increment associated with an occupation change. On the other hand, specialists have a substantially greater preference than do non-specialists for the occupation for which graduate study prepared them. However, those specialized Ph.D.'s who have been induced to change occupations at least once are just about as likely to change occupations more than once, as are mobile non-specialists.

For the whole sample, total average salary change was inversely related to career mobility. Average salary change was positively associated with mobility among the mobile Ph.D.'s.

Given the problem of finding a good measure for ΔS_0, it is not surprising that obtaining an estimate of the structural demand equation (2) was the most difficult problem I encountered. This was especially the case with the estimated specialization effect, because specialists preference for their home occupation meant that those who did leave home were paid some additional amount to do so.[31] Yet my hypothesis was that they would have been paid even more to switch occupations if their educational training had been more general, less occupationally specific.

So I needed some control variable that isolated that portion of the salary increase paid to specialists that induced them to change occupations, from that negative portion that represented the cost of

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[30] For those Ph.D.'s who never changed occupations there did not seem to be any very accurate measure available of salary offers they received, or could have received on inquiry; because these offers were never observed since this group never changed occupations. It was decided that the average ΔS_T of the three salary increments would be a better estimate of ΔS_0 for this group, than the estimate that assumed $\Delta S_0 \equiv 0$. Combining this estimate with the average increment during occupation change intervals for the mobile Ph.D.'s gave a measure of ΔS_0 that also had a simple correlation coefficient of 0.01 in the whole sample of the 15,353 Ph.D.'s in their home fields as of 1960.

[31] In the one-in-ten sample used for preliminary analysis, the mobile specialists had a \$233 higher ΔS_0 than did the immobile specialists, after adjusting for educational background, geographic area, employer type and 1960 salary.

Table 4

.D MOBILITY SUPPLY CURVES

	Regression Standard Error	$\hat{\sigma}_M$	$\bar{M}$	N
$M = 1.75 - \underset{(0.01)}{0.34Z_1} + \underset{(0.0027)}{0.0062} (\Delta S_0/1000)$	0.64	0.66	1.52	15353
$M = 2.24 - \underset{(0.01)}{0.06Z_1} + \underset{(0.0021)}{0.0014} (\Delta S_0/1000)$	0.44	0.44	2.21	6551
$M = {}^{\prime}.77 - \underset{(0.01)}{0.34Z_1} - \underset{(0.00045)}{0.00032} (\Delta S_T/1000)$	0.64	0.66	1.52	15353
$M = 2.23 - \underset{(0.01)}{0.06Z_1} + \underset{(0.0005)}{0.0011} (\Delta S_T/1000)$	0.44	0.44	2.21	6551

the increment in occupationally specific training that specialists obtained by studying the same discipline in undergraduate, as well as graduate, school. Of course it was just such a control for ability (or agressiveness, or originality) that I did not have, as was indicated above.

What was done was to substitute the demand relationship (2) into the supply equation (3), and estimate this semi-reduced form. The demand equation was then estimated by calculating its coefficients from the coefficients in this regression, and the estimated mobility supply equation coefficients. Now this is straigtforward enough, but recall that there is an important left out variable in the demand relationship specified in equation (2), which was labeled "ability" above. This variable is positively correlated with the specialization measure, so that the specialization effect $(\alpha_1^{(3)} + \alpha_1^{(2)}\delta^{(3)})$ will be biased toward zero (from below) in the semi-reduced form. Using an unbiased estimate of the salary increment effect $\delta^{(3)}$ in the mobility supply equation, to calculate the demand side specialization effect, would thus give an estimate of $\alpha_1^{(2)}$ that was baised upward and might even have the wrong sign. Just as would happen when a direct estimate of the structural demand equation was attempted.[32]

One possible solution is to use an estimate of the supply equation slope that is also biased in the same way. Consider the semi-reduced form:

$$(5) \quad M = \alpha_0^{(3)} + \alpha_1^{(3)} Z_1 + \delta^{(3)}[\alpha_0^{(2)} + \sum_j \alpha_j^{(2)} Z_j^T + \gamma_1^{(2)} S] + (\delta^{(3)}U^{(2)} + U^{(3)}).$$

The expression in brackets is essentially the variation in ΔS_0 that is explained by exogenous information in the National Register sample; that is, it varies just as the instrumental variables estimator for ΔS_0 does.[33] So the estimated coefficient $\delta^{(3)}$ that is implicit in the coefficient estimates in the semi-reduced form (5) would be the same as the estimate of the slope coefficient in the mobility supply equation (3), when ΔS_0 is replaced by its instrumental variables estimator.

Table 5 reports the estimated mobility demand equation coefficients calculated from the semi-reduced form (5), and the mobility supply curve estimated using instrumental variables.[34] As the theory outlined in

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[32] See Appendix Table 1 for these direct estimates on the two sub-samples. The additional right-hand variables for employer type and geographic area were included in those regressions to hold constant any effect of price level changes, or any salary growth differences in the three employer-type channels.

[33] The only difference would be that the bracketed expression also contains the error $U^{(1)}$; but as long as this error is not correlated with any of the sample's exogenous variables, or with either of the other structural equation error terms, then it has no effect on the estimated relationship between mobility and the instrumental variables estimator for ΔS_0.

[34] The instrumental variables estimator was estimated on the mobile subsample, and then applied to the immobile Ph.D.'s to give an estimate of unobserved salary offers ΔS_0 to this latter group. The estimated supply equations using this instrumental variable for ΔS_0 were $M = 2.18 - .30Z_1 - .00023\ \Delta S_0$ for the whole sample of 15,353 Ph.D.'s, and $M = 2.27 - .06Z_1 - .000013\Delta S_0$ for the subsample of 6,551 mobile Ph.D.'s.

Table 5

ESTIMATED MOBILITY DEMAND CURVES

	Ph.D. Field	
	Whole Sample	Mobile Ph.D.'s
Statistics	$-1012	-5817
Physics	350	501
Engineering	-2232	-6723
Biomedical Science	-3070	557
Mathematics	240	-3189
Psychology	519	-1019
Astronomy	119	5674
Agricultural Science	-3436	-2996
Interdisciplinary	-3663	-10429
Earth Science	119	-3568
Chemistry	-1029	-6647
Biological Science	0	0

Specialization Effect		1960 Salary Effect	
Whole	$-837	Whole	-.048
Mobile	-2203	Mobile	-.407

	Whole	Mobile
Constant	$3807	$13,535
$\overline{\Delta S_0}$	1804	1,828
$\hat{\sigma}_{\Delta S}$	1912	2,518

Section 1 would predict, specialists were penalized for their more occupationally specific educational training by about \$800, in terms of the salary increments they were paid to change occupations. Among just the mobile Ph.D.'s, the estimated costs of specialization were even greater--about \$2,200. However, the estimated slope coefficient $\delta^{(3)}$ is biased downward when the mobility supply equation is estimated on just the mobile subsample, because that subsample was selected to exclude Ph.D.'s who did not change occupations. Thus the estimated equation for mobility demand among the mobile Ph.D.'s has coefficients that are all quite biased upward in absolute value.

The 1960 salary effect is negative, representing the fact that Ph.D.'s who were highly paid in 1960 were less likely to find a job in another occupation that would increase their salaries as much on average as those who were in the lower paying occupations in 1960. The Ph.D. field effects do not isolate the influence of relative knowledge transferability as I had hoped, because the effects of demand and ability on salary interacted strongly in the sample with skill transferability.

6. Conclusion

The occupational transferability of skills learned in school is an important determinant of a Ph.D.'s career mobility. The costs of specialization to a Ph.D. who later in her career changes occupations are estimated to be \$800, even though that Ph.D. would probably undertake additional on-the-job training to prepare for such a switch. These costs, plus the greater preference specialists have for work in their specialty field, reduce the career mobility of specialized Ph.D.'s about 10%. On the other hand, specialists who remain employed in their Ph.D. field earn a return of \$80 per year on the extra skill they acquired in their Ph.D. specialty by taking the same field as an undergraduate major.

Appendix Table 1

ESTIMATED COEFFICIENTS FOR SALARY GROWTH DETERMINANTS

	Ph.D. Field				1960 Geographica Area		
	Im	Mob.			Im	Mob.	
		ΔS_0	ΔS_T			ΔS_0	ΔS_T
Statistics	$809	$995	$321	N.E.	$ -3	$335	$129
	(216)	(358)	(185)		(91)	(230)	(119)
Physics	597	549	386	M.AT.	23	241	141
	(43)	(142)	(73)		(75)	(189)	(98)
Engineering	424	448	246	S.AT.	-207	235	-1
	(103)	(161)	(83)		(89)	(227)	(117)
Biomedical Science	305	-266	129	E.N.C.	31	274	167
	(463)	(225)	(116)		(78)	(195)	(101)
Mathematics	855	582	397	E.S.C.	-98	-185	-182
	(57)	(195)	(100)		(96)	(233)	(120)
Psychology	415	488	257	W.N.C.	-250	98	14
	(44)	(159)	(82)		(89)	(222)	(115)
Astronomy	722	356	-114	W.S.C.	-159	11	-91
	(183)	(518)	(267)		(89)	(224)	(116)
Agricultural Science	-270	-838	-494	MTN.	-244	101	-73
	(354)	(172)	(89)		(91)	(235)	(121)
Interdisciplinary	139	-184	-7	PAC.	-30	179	134
	(258)	(124)	(64)		(80)	(202)	(104)
Earth Science	153	216	-39	OUT.	0	0	0
	(56)	(180)	(93)				
Chemistry	127	66	-29	Moved	25	341	268
	(45)	(111)	(57)	(1960-1966)	(30)	(71)	(36)
Biological Science	0	0	0				

Appendix Table 1 (Continued)

Specialization Effect

Im	Mob ΔS_0	Mob ΔS_T
$38	$78	$64
(35)	(86)	(44)

1960 Salary Effect

Im	Mob ΔS_0	Mob ΔS_T
-.081	-.041	-.015
(.003)	(.008)	(.004)

1960 Employer Type

	Im	Mob ΔS_0	Mob ΔS_T
Acad.	$-212	$-212	$-277
	(36)	(76)	(39)
Bus.	0	0	0
Govt.	-84	111	218
	(42)	(88)	(45)
Changed Type (1960-1966)	-77	-154	-175
	(37)	(83)	(43)

	Im	Mob ΔS_0	Mob ΔS_T
Constant	$2515	$2186	$1836
Reg. Std. Error	1220	2486	1281
$\overline{\Delta S}$	1785	1828	1734
$\hat{\sigma}_{\Delta S}$	1286	2518	1317
N	8802	6551	6551

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