

**THREE ESSAYS IN LABOR AND HEALTH ECONOMICS:
INDIVIDUAL DECISIONS ON OCCUPATION, LABOR SUPPLY, AND
DEMAND FOR HEALTH**

A Dissertation

by

JA EUN SHIN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2004

Major Subject: Economics

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ABSTRACT

Three Essays in Labor and Health Economics: Individual Decisions on Occupation,
Labor Supply, and Demand for Health. (May 2004)

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In this dissertation, I examine individual decisions in occupational choice, labor supply, and health care utilization. Occupational choice decisions of female college graduates on whether to teach or not are analyzed to understand the role of fertility and relative wages using a panel estimation method. I also compare the behavioral changes in the labor force participation among teachers and nonteachers conditional on the presence of a new-born baby.

Using the human capital model where a worker decides her hours of work responding to wages, and her human capital is accumulated proportional to her hours of work, I predict that the positive relationship between entry wages and post wages. Empirical evidence suggests that the shock in entry wages may be attributed to post wage differentials.

I examine individuals' choice of health insurance plan and utilization of health care services. Empirical evidence shows that there is favorable self-selection into health maintenance organizations (HMOs) plans and that HMO members use more of office-based and hospital outpatient services. It suggests ineffectiveness of HMO plans in reducing utilization.

To My Lord, Jesus Christ

“How can I repay the Lord for all His goodness to me?

I will lift up the cup of salvation and call on the name of the Lord

I will fulfill my vows to the Lord in the presence of all His people”

(Psalm 116:12-14)

To My Parents, Jum Sook Chang and Ho Il Shin

“May your father and mother be glad and may she who gave you birth rejoice”

(Proverb 23: 25)

To My Husband, Sangho Moon

“My beloved *is* mine, and I *am* his”

(Song of Songs 2:16)

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TABLE OF CONTENTS

	Page
ABSTRACT.....	iii
DEDICATION.....	iv
ACKNOWLEDGMENTS.....	v
TABLE OF CONTENTS.....	vi
LIST OF TABLES.....	viii
LIST OF FIGURES.....	x
 CHAPTER	
I INTRODUCTION.....	1
II FERTILITY, RELATIVE WAGES, AND LABOR MARKET	
DECISIONS: A CASE OF FEMALE TEACHERS.....	4
I. Introduction.....	4
A. Literature Review and Significance.....	4
B. Policy Implications.....	9
II. Estimation Method.....	10
III. Data.....	14
IV. Estimation Results.....	21
A. Wage Equations and Selection Problem.....	21
B. Fertility, College Major and Occupational Choice.....	24
C. Fertility and Participation Decision.....	26
D. Relative Wage Effects on Occupational Choice.....	29
V. Conclusion.....	29
III HUMAN CAPITAL, ENTRY WAGE, AND POST WAGE	
DIFFERENTIALS.....	31
I. Introduction.....	31
II. Theoretical Framework.....	35

CHAPTER	Page
III. Empirical Model.....	42
IV. Data.....	44
V. Estimation Results.....	46
VI. Conclusion.....	50
 IV HMO PLANS, SELF-SELECTION, AND UTILIZATION OF HEALTH CARE SERVICES.....	 53
I. Introduction.....	53
A. Trends and Relevance.....	53
B. Literature Review.....	54
C. New Contribution.....	57
II. Econometric Model.....	58
III. Data.....	61
A. Demographic Characteristics.....	64
B. Health Status and Insurance.....	64
C. Utilization of Health Care Services.....	66
IV. Estimation Results.....	67
A. Insurance Choice.....	67
B. Health Care Services.....	70
C. Office-Based Services.....	72
D. Hospital Outpatient Services.....	73
V. Conclusion.....	74
 V SUMMARY.....	 77
ENDNOTES.....	79
REFERENCES.....	82
APPENDIX.....	87
VITA.....	94

LIST OF TABLES

TABLE	Page
1	Definitions of Variables..... 15
2	Summary Statistics..... 16
3	Average Earnings by Occupation..... 17
4	Family Background by Participation and Occupation Choice..... 18
5	Selection Correction Fixed Effects Estimation of Wages..... 22
6	Selection Correction Fixed Effects Estimation of Wages in the Switching Labor Force Participation Model..... 24
7	Probit Estimation of Occupation Choice Decisions..... 25
8	Probit Estimation of Occupation Choice Decisions in the Switching Labor Force Participation Model..... 25
9	Probit Estimation of Labor Participation Decisions..... 26
10	Probit Estimation of Labor Participation: Teachers..... 27
11	Probit Estimation of Labor Participation: Nonteachers..... 28
12	Entry Wage Effects..... 45
13	Decomposition of Entry Wage Effects: Specification I..... 47
14	Trends in Private Health Insurance: HMO Enrollment 1977-2001..... 54
15	Demographic Characteristics 62
16	Health Status..... 63
17	Utilization of Health Care Services..... 66
18	Probit Estimation of Binary Health Insurance Plan Choice..... 68

TABLE	Page
19 Censored Regression of Utilization: Office-based Services.....	69
20 Censored Regression of Utilization: Hospital Outpatient Services.....	71

LIST OF FIGURES

FIGURE		Page
1	Age-Earning Profiles by Occupation.....	22
2	Changes in Entry Wage Effects (Case 4).....	40
3	Changes in Entry Wage Effects (Case 4, $\rho = \delta$).....	42
4	Estimated Entry Wage Effects.....	48

CHAPTER I

INTRODUCTION

How individuals make decisions over choosing optimal solutions in various economic activities is the fundamental question in microeconomics. In Chapter II, I focus on individual decisions on occupation and labor supply. In particular, I examine the joint decisions of young female college graduates over their occupational choices and labor force participation. A young female would consider childbearing as well as relative wages as important factors in her decision making on whether to be in the labor force and which occupation she would work in. As the presence of a new-born baby possibly demands more hours at home for females, she would choose an occupation which allows her to manage childbearing and working at the same time. I consider the elementary and secondary school teacher as such an occupation and investigate the behaviors of teachers in response to the birth of a new child and the differences in wages, compared to non-teachers.

In Chapter III, the relationships among wages, hours of work, and human capital accumulation are my primary interest. An individual as a worker receives wage offers and decides how many hours she would work given a wage offer to maximize her utility, considering the loss of utility from sacrificing leisure time for work. Provided that firms have only incomplete information on each worker's productivity at the time of making wage offers, there might be some randomness in wages which, if positive, would be an additional incentive to workers to put more effort into working by increasing hours of

This dissertation follows the style and format of *American Economic Review*.

work. Hypothetically, more hours spent at work enhance workers' productivity for the same reason that years of experience receive positive return in wages. I formulate these relationships in a simple human capital model and derive the reduced form wage determination equation for the empirical analysis.

Chapter IV focuses on individual decisions on the choice of private health insurance plan and medical care consumption. Health status and health care services are relatively rarely examined consumption goods in microeconomics. As the standard of living improves and life expectancy is prolonged, demand for health care services to keep healthy and live long and associated medical expenditures become substantial economic problems for both individuals and policy makers.

Demand for health care services emerges conditional on the naturally stochastic occurrence of health problems. Once needs for medical care exist, they are indispensable and expensive. Hence, it is not surprising that people are willing to purchase health insurance given their budget constraints and beliefs regarding the probability of having health problems. Every health insurance offers different arrangement of coverage and cost sharing. Given these differences across plans, an individual makes a decision over health insurance plan choice. Given the plan she has, she would decide how much health care service she would use upon the occurrence of a health problem.

HMO plans are designed to contain the increase in health care expenditures using a tight utilization review and, in return, lowering cost sharing, which acts as a consumer incentive. The utilization review is seen as the device designed to prevent the possible unnecessary use of medical services resulting from the moral hazard behavior of insured

patients. However, it has been suspected that the success of HMO plans in reducing costs is in fact the result of the segmentation of population based on their health condition; expecting little future need for medical care, relatively healthy population are enrolled in HMO plans. As the previous literature provides only ambiguous conclusions and depends on narrow-scoped samples or outdated data, I test this hypothesis using recent data to find evidence expected to be relevant for policy reform. As noted in Ha T. Tu, Peter Kemper, and Holly J. Wong (1999), HMO enrollees have financial incentives for low cost sharing.

Another empirical issue is the non-trivial number of zero observations for the dependent variables. I incorporate possible self-selection into the censored model of utilization and obtain the selection-free estimates of HMO effects.

CHAPTER II

FERTILITY, RELATIVE WAGES, AND LABOR MARKET DECISIONS:

A CASE OF FEMALE TEACHERS

I. Introduction

The primary issue discussed in this paper is the relationship between fertility and relative earnings and labor market decisions by females. In the labor market, females make decisions about whether to participate in the labor force and which occupation they would work at. Occupation subgroups are categorized as teachers and nonteachers. The effects of fertility on labor force participation decision and occupational choice of females are then estimated using a binary dependent variable model of panel data with sample selection corrected. Comparison is made across occupations.

A. Literature Review and Significance

The strong negative correlation between fertility and female labor supply has been well observed and examined since 1960's (Randall J. Olsen, 1994). Many researchers found that with the presence of a new-born child, females are less likely to join in labor force¹ (A. Maureen O'Brien and Clifford B. Hawley, 1986; Raquel Carrasco, 2001). However, much less attention has been paid to the effect of fertility on the occupational choices of female workers. One exception is Geraint Johnes (1999), who estimates the effect of fertility on joint decisions over participation, that is, hours worked (full-time or part-time) and occupation (knowledge work, others). With children under age 16, females prefer staying out of the labor force to working full time. This negative effect is larger if the full time occupation is related with knowledge. This suggests that there exist

systematic differences in labor market status, both labor force participation *and* occupation of a woman depending on her fertility status. Though Johnes (1999) tries to include occupational choices in his analysis of fertility effect, the category of occupation is broadly specified as knowledge (non-manual or skilled manual) work or others.

I focus on the interaction of fertility with a specific occupation, *teaching*. The reason why teaching is of special interest in the analysis of the female labor force can be seen in the distinguishing characteristics of teachers in elementary and secondary schools. First, the dominant portion (68% in 1990; Eric Hanushek and Steven Rivkin, 1997) of total employment in teaching is female. Historically, the teaching profession has been female-dominated.

Fredrick Flyer and Sherwin Rosen (1997) show that teachers do not suffer from reentry wage loss² after they spend time out of the labor force and then reenter. This supports the finding by Solomon W. Polachek (1981) that female-dominated occupations have lower human capital depreciation rates. Nursing is one of the occupations sharing similar characteristics with teaching. However, Flyer and Rosen do not find any significant result for nurses. Their finding provides one explanation why the teaching occupation is held mostly by females. Expecting to get married and have children, females would choose an occupation which imposes little penalty when they return to the job after their temporary leave needed for childbearing or other housekeeping burdens. In this sense, the teaching profession is more favorable to female workers than other occupations might be. However, this implication is not rigorously investigated in any of these studies.

Todd R. Stinebrickner (2002) gives evidence for the direct effect of fertility on attrition behaviors of teachers compared with nonteachers. From the duration analysis, he suggests that the single most important reason for females to leave the labor force is the presence of a new-born child, and this effect is larger if they are teachers. Peter Dolton and Gerald H. Makepeace (1993)³ provide further evidence for the relationship between fertility and teaching occupation in the bivariate binary framework. The number of children has a smaller negative effect on labor force participation among teachers⁴ than among nonteachers. However, it only represents the *indirect* effect of fertility on the choice of occupation through the decision to participate in the labor force. Moreover, results from the switching model estimation, which Dolton and Makepeace (1993) support as more reasonable, are debatable. The reason is that the current occupation is observed only for those who participate in the labor force, so the observations for teachers not in the labor force and nonteachers not in the labor force are not available in the data.

To avoid this identification problem from data limitation, I estimate participation and occupation equations using different samples, thus correcting possible selection bias. The occupation equation of whether or not to teach currently is estimated using the whole sample while the labor force participation decisions are allowed to be heterogeneous across occupational subgroups.⁵ Then, I aim to estimate the *direct* effect of fertility on occupational choice. The following questions are under investigation: 1. When a woman has a new-born child, how likely is she to be in the labor force? 2. Would she be working as a teacher? 3. Between teachers and nonteachers, how different

would the tendency for staying in the labor force be upon a new birth? The previous literature, especially Flyer and Rosen (1997) and Stinebrickner (2002), consistently implies that the teaching profession is favorable for females allowing them to have temporary leave without cost, and in fact teachers behave like that. However, the exact direct effect of fertility on females' occupation decisions remains unexamined.

Contrary to these findings, one distinct characteristic of the teaching occupation makes the opposite predictions on the effect of fertility on labor force participation and occupational choice among females. A great deal of the literature on the issue of decreasing teacher quality finds that wages for teachers are low relative to alternative jobs. Thus, it is argued that to recruit and retain teachers of high quality, relative wages for teachers should be increased at a faster rate. With a new-born child who induces additional child care cost, either pecuniary or time, teachers might be more likely to keep working to compensate the cost than nonteachers, being forced to do this by low relative earnings. Hence, the presence of new-born baby has a positive effect on labor market participation by females and this effect is larger for female teachers than nonteachers. Motivated by the recent policy debate over expansion in educational expenditure in the U.S., whether wages for teachers are relatively low compared to nonteachers and what the role of relative wage for teachers in attracting females into the teaching profession is are studied.

In general, it is believed that the teaching occupation has several advantages for females who have or expect to have children, such as location convenience, or regular holidays and vacation. With a new-born child, teachers can manage to keep working

more easily than it would be the case in other occupations. In addition, the presence of a new-born child is expected to make females more likely to choose the teaching occupation, which is the main focus of this study.

There are several distinguishing features in this paper. First, I employ the panel estimation method. As been noted, panel analysis has advantages in controlling individual unobserved heterogeneous effects correlated with participation, occupation, and wages. Conventional sample selection problems emerge for two reasons: wages are observed only for labor market participants, and wages in nonteaching occupations are not observed for teachers. I manage these problems by applying the method in Jeffrey F. Wooldridge (1995), which is an extension of Heckman's selection correction (James Heckman, 1979) to the panel data. Consequently, the panel estimation of wages does not suffer from any unobserved heterogeneity bias caused by females' individual fixed effects and selection bias resulting from females' labor market decisions. This is one major advantage of the panel approach over any cross-sectional analysis such as Dolton and Makepeace (1993).

Using longitudinal information about occupation, I define teachers in two ways: those who have worked as teachers and those who are currently teaching at a given survey year. Over their lifetime, females can change their occupation for many reasons. There is no obligation or prior belief that once female become teachers, they will stay in the teaching profession thereafter. In the later period in their working life, they might enter the teaching profession after having stayed at home or had other occupations when young. Thus, they may appear as teachers in one year and as nonteachers in another year

over the survey years. With the first definition of teachers, the average characteristic comparison between teachers and nonteachers is documented. Using the second definition for ‘teachers’, fertility is interpreted as having a direct effect on *current* working status as teachers, not on whether teaching is the occupation a female has ever had.

B. *Policy Implications*

To my knowledge, there is little investigation on the relationship between fertility and labor market behavior focusing on teacher-nonteacher comparison using U.S. data. Dolton is one of the major contributors to this literature, but he analyzes the U.K. case only. As in the U.K., there is an enormous amount of discussion and policy implications about teacher labor supply in the U.S. Education policy to reduce classroom size invokes a problem of teacher supply shortage. With job opportunities for women getting broader, the problem of luring high quality female workers away from teaching draws attention.⁶ As a starting point for solutions to these issues, this paper attempts to understand the labor market behaviors of females across occupations, namely, teaching and non-teaching.

This paper provides evidence for the effects of fertility and relative wages on participation and occupational choice by females and differences across occupations. First, there exists a negative selection bias in nonteachers' wages caused by occupational decisions. In terms of wages, nonteachers are worse off than average female college educated workers. Second, the presence of a new-born child aged under 2 has only insignificant and sign-changing marginal effects on working as teachers in a given

survey year. The effect of a new birth on labor participation decisions is negative and significant. This marginal effect substantially differs between teachers and nonteachers. For teachers, it is significantly negative and larger. These findings suggest that the fertility factor does not directly affect occupational decisions, but has significant but different effects on labor force participation decisions across occupations. The fertility condition is found to be an important factor in labor force participation decisions among females, in particular, female teachers.

The relative wage incentive to attract more teachers seems to work. In the pooled sample estimation, teachers' wage relative to nonteachers' shows significant and positive effect on the choice to work as teachers.⁷ Even the larger marginal effect of relative wages on occupational choice is found in the switching participation model.

The rest of this chapter is organized as follows. Section II describes the estimation models and the panel data sample selection correction method. Section III summarizes the data. Section IV discusses the estimation results. Section V concludes the chapter.

II. Estimation Method

The primary model is a binary probit estimation model of two limited dependent variables, which are labor force participation and occupation choice. The model can be written as:

$$(1.1) \quad T^* = W\delta + \alpha F + \beta(\ln Y_t - \ln Y_n) + u,$$

$$(1.2) \quad P^* = Z\gamma + \phi_1 F + \phi_2 L(Y) + \nu,$$

$$(1.3) \quad \ln Y_t = \mu + X_t \phi_t + \varepsilon_t,$$

and

$$(1.4) \quad \ln Y_n = \mu + X_n \varphi_n + \varepsilon_n,$$

where T^* and P^* are latent decision variables of being a teacher and of participating in the labor force, respectively. $T=1$ is observed if $T^*>0$ and $P=1$ is observed when $P^*>0$. $\ln Y_j$ indicates the log hourly wage for an occupation $j=t$ (teaching), n (nonteaching). μ denotes an unobserved heterogeneity assumed to be constant within an individual. Labor force participation decision depends on last year wages, $L(Y)$. W , Z , and X_j , $j=t,n$ denote the explanatory variables including demographic conditions, education, regional labor market conditions, and family factors. The key explanatory variables are the fertility variable, F , and relative log wages across occupations, $\ln Y_t - \ln Y_n$. I measure the fertility factor as the presence of a new-born baby under age 2.

I use a three-step procedure to estimate the model. In the first step (Procedure 1), I derive and estimate the reduced form participation and occupation equations by inserting $\ln Y_t$ and $\ln Y_n$ into T^* . From the estimates of the reduced form equations, the selection correction terms are obtained. The second step (Procedure 2) is to include these additional terms in estimating log wage for each occupation and obtain the predicted values for them. Finally, the structural form equations of T^* and P^* are estimated with the predicted relative log wages derived from the second step (Procedure 3). The first two steps are analogous to Robert J. Willis and Rosen (1979) and Heckman (1979), but both studies are limited to the cross-sectional analysis. Wooldridge (1995) suggests a simple and practical application of the above procedure to the panel data with a selection problem. I employ Wooldridge's method in Procedures 1 and 2 to obtain selection

correction terms for selectivity free wage regressions in panel data. Procedure 3 is implemented using a panel probit estimation.

For correcting the possible self-selection, the procedure by Wooldridge (1995) is implemented in the case of a binary latent selection equation and a main equation in the panel data analysis. The estimation steps are well illustrated in Francis Vella (1998) and Badi Baltagi (2001).

Define a latent dependent variable, h^*_{it} as $h^*_{it} = X_{it}\delta + \varepsilon_{it}$. A dummy variable s_{it} takes a value of 1 if $h^*_{it} > 0$. The main equation is log wage equation given as:

$$\ln Y_{it} = \mu_{it} + X_{it}\varphi + u_{it}.$$

Step 1. For each period $t=1, 2, \dots, T$, estimate the binary selection equation $\Pr(s=1|X)$ as a standard probit model. From it, obtain the selection correction term as an inverse Mill's ratio,

$$\hat{\lambda}_{it} = \frac{\phi(X\hat{\delta})}{\Phi(X\hat{\delta})}, t=1, \dots, T \text{ for } s_{it} = 1.$$

Step 2. Then including this additional term, estimate the following wage equation,

$$\ln Y_{it} = \mu_{it} + X_{it}\varphi + \gamma\hat{\lambda}_{it} + u_{it}$$

by the fixed effects method. This method will eliminate μ_{it} , producing the consistent estimate of φ safe from biases due to both selection and unobserved individual heterogeneity. After Step 1 and Step 2, Procedure 3 as mentioned above is applied to complete the estimation.

I have two selection equations, T^* and P^* , and two wage equations, $\ln Y_t$ and $\ln Y_n$. In the pooled model, I repeat Step 1 for each probit equation and repeat Step 2 for each wage regression to obtain selection bias corrected relative log wages for the structural form probit estimations of T^* and P^* . To allow heterogeneity of labor market participation behavior across occupations, a switching model is tried. The occupational decision equation among labor force participants is given as follows:

$$(1.5) \quad T^* = W\delta + \alpha F + \beta(\ln Y_t - \ln Y_n) + u$$

where $T=1$ if $T^*>0$ and $P_t^*>0$, while $T=0$ if $T^*<0$ and $P_n^*>0$. The labor force participation equations are written separately by occupation groups:

$$(1.6) \quad P_t^* = Z\gamma_t + \phi_1 F + \phi_2 L(Y) + v_t,$$

and

$$(1.7) \quad P_n^* = Z\gamma_n + \phi_1 F + \phi_2 L(Y) + v_n,$$

where $P=1$ if $P_t^*>0$ (for teachers), and $P=1$ if $P_n^*>0$ (for nonteachers), respectively.

Note that the participation decision P_j^* is observed only when occupation j is chosen. It is noted that in the longitudinal analysis, the occupation group is not defined as clearly as in the cross sectional analysis, because females may change their occupations over their lifetime. Thus, it is too restrictive to define ‘teachers’ as those who are teacher once and for all. Instead, I consider the teachers’ group in two ways; one is by occupation history, that is, those who have ever worked in the teaching profession at any point of their lifetime. The demographic comparison is made based on this categorization. The second way is to define ‘teachers’ based on current occupations. In estimating Equations

(1.1) and (1.5), the occupation choice is measured as the current occupational status of labor force participants in a given year. For estimating the switching labor force participation Equations (1.6) and (1.7), a female's status in the labor force is considered within each occupation group.⁸ Specifically, for each occupation group, the participation decisions are regarded as unobservable if the alternative occupation is chosen.⁹ In this way, I compare the response of labor market participation decision and occupation choice to the fertility factor and relative wages between two occupation subgroups.

III. Data

I used the National Longitudinal Survey of Young Women. Several criterions were used to limit the sample for the estimations. To obtain a balanced panel,¹⁰ I only included the sample interviewed in every wave during 1968-1988. There are two reasons why I limited the waves up to 1988. Though survey data is available up to 2001, the key variables regarding fertility, education, occupation and wages were dropped or changed substantially since 1991.¹¹ Since the prime age for childbearing among females is their 20's and 30's, the survey years of 1968-1988 cover most of the information about the respondents during their prime fertility ages from 21 to 44. In 1988, the youngest is aged 31 and the oldest is aged 47. Since the focus of this paper is the effect of fertility conditions on the labor supply behaviors of young women, the limited sample period seems not to cause a serious problem.

The final sample includes only females with at least 16 years of schooling (or equivalently with college or higher education) completed by 1988. Overall, among 5,159 females aged 13-26 interviewed in 1968, 2,712 are interviewed continuously

TABLE 1--DEFINITIONS OF VARIABLES

Time-Varying	
Age	Age of the Respondent in the Survey Year
Education	Highest Grade Completed by the Survey Year
Married	Marital Status Dummy =1 if Married
LFP (Labor Force Participation)	Employment Status Dummy=1 if Participate in the Labor Force
Job	Occupation Dummy =1 if Current/Last Job is Teaching and in the Labor Force
Husband Income	Husband Income (Wage/Salary/Business/Farm/Professional Practice)
Baby Residence	Dummy for the Presence of a New-Born Child Aged under 2 Dummy for Residence in South =1 if in South
Unemployment Rate	Unemployment Rate in the Region of Residence, 0-10 Integer Scale
Time-Invariant	
White	Race Dummy=1 if White
Maxedu	Highest Grade Completed by 1988
Mother's Education	Highest Grade Completed by the Respondent's Mother in 1968
Mother's Occupation Teach	Dummy for Mother's Occupation =1 if Mother Has Ever Been a Teacher Dummy for Teaching Experience =1 if Job=1 at Least Once During Survey Years

until 1988. When the education criterion is applied, 605 remain in my sample.¹² Among them, 306 have teaching experience and 299 do not. The definition of each variable is documented in Table 1.

The summary statistics in Table 2 show the differences in characteristics between teachers and nonteachers.¹³ If a female has teaching experience, she is slightly older and more educated on average, though the difference is much less than a year. A teacher is under slightly stronger pressure from family commitments, such as marriage and fertility, and enjoys higher husband income, compared to a nonteacher counterpart. Then, the lower participation rate for those who have teaching experience is not surprising. Teachers have a stronger correlation with their mothers' occupation being teaching. Mothers of teachers attain less education than mothers of nonteachers.

TABLE 2--SUMMARY STATISTICS

Sample		Have Been Teachers		Have Never Been Teachers	
Variable		Mean	Std. Dev.	Mean	Std. Dev.
Age	Overall	32.53	5.56	32.00	5.38
	Between		3.69		3.72
	Within		4.72		4.50
Education		16.73	.85	16.53	.77
			.87		.83
			0		0
Married		.78	.41	.62	.49
			.38		.42
			.24		.28
White		.86	.35	.85	.35
			.37		.36
			0		0
Presence of a New-Born Baby under Age 2		.13	.34	.12	.32
			.13		.13
			.31		.29
Labor Force Participation		.77	.42	.84	.37
			.28		.27
			.32		.25
Mother's Job=Teaching		.10	.30	.06	.24
			.31		.24
			0		0
Mother's Education in 1968		12.17	2.85	12.65	2.96
			2.84		2.86
			0		0
Husband Income		6.86	4.60	5.52	4.99
			3.84		4.15
			3.05		3.18
Number of Individuals (n)		306		299	

As reported in Appendix (Table A1, Panel A), teachers are relatively more educated even after graduating from college (37.25% of them have 18 years of schooling, implying they have Master's degree). About 57% of females with no teaching experience are college educated only. Panel B in Table A1 reports that teaching experience is highly correlated with a specific college major. Half of teachers receive their Bachelors degree in Education. This tendency does not appear for nonteachers. It indicates that among teachers, college major choice seems to be a predetermining signal

TABLE 3--AVERAGE EARNINGS BY OCCUPATION

Log(Wage)	Have Been Teachers		Have Never Been Teachers	Current Occupation		
	Currently Teaching	Currently Not Teaching	Currently Not Teaching	Teaching	Not Teaching	
Mean	6.28	6.22	6.35	6.43	6.22	6.41
Std. Dev.						
Overall	(.89)	(.88)	(.89)	(.91)	(.88)	(.91)
Between	(.67)	(.83)	(.75)	(.67)	(.83)	(.71)
Within	(.65)	(.55)	(.59)	(.72)	(.55)	(.69)
N	1561	934	625	1559	934	2177
n	292	244	180	273	244	453

^aThe sample includes only females currently participating in the labor force.

^bEarnings are measured as log hourly rate of pay in the current/last job. The annual average Consumer Price Index of All items (seasonally adjusted) released by the Federal Reserve Bank at St. Louis is used to normalize hourly rate of pay (Base year=1982~1984 as 100).

for their future occupation after graduation. As a whole, the simple comparison in characteristics suggests that teachers are different labor force group from nonteachers, especially in terms of their education attainments and college major.

Table 3 compares the average real wage across occupations. The real wage is higher for the nonteaching profession. If a female with teaching experience chooses teaching as her current job, her average earnings are lower than for those who have teaching experience and are not teaching currently. The question is why a female who can make a choice between teaching and nonteaching jobs would choose to be a teacher when she receives a lower wage. This can be explained by the ‘comparative advantage.’ Females who are certified to be teachers are teaching currently because in a nonteaching job, they can not be as competent as those who never teach because of the required skills in a nonteaching job. Though teachers are more educated, most of their schooling is concentrated on the field of education only, hence it does not result in high productivity

TABLE 4--FAMILY BACKGROUND BY PARTICIPATION AND OCCUPATION CHOICE

(PANEL A) THE PRESENCE OF A NEW-BORN BABY UNDER AGE 2

Labor Force		Current/Last Job		Total
		Not Teach	Teach	
Out	Mean	.276	.331	.293
	Std. Dev.	.448	.471	.455
In		.085	.075	.082
		.278	.263	.274
Total		.122	.128	.124
		.327	.334	.329

(PANEL B) THE PRESENCE OF A NEW-BORN BABY UNDER AGE 2

Labor Force		Have Ever Been Teachers		Total
		No	Yes	
Out	Mean	.289	.293	.291
	Std. Dev.	.454	.455	.455
In		.082	.082	.082
		.274	.274	.274
Total		.115	.131	.124
		.320	.338	.330

(PANEL C) MARITAL STATUS (1 IF MARRIED, 0 OTHERWISE)

Labor Force		Current/Last Job		Total
		Not Teach	Teach	
Out	Mean	.946	.985	.985
	Std. Dev.	.226	.121	.200
In		.610	.722	.642
		.488	.448	.479
Total		.676	.777	.705
		.468	.417	.456

(PANEL D) HUSBAND INCOME (AMONG MARRIED FEMALE)

Labor Force		Current/Last Job		Total
		Not Teach	Teach	
Out	Mean	8.96	8.59	8.84
	Std. Dev.	3.36	3.38	3.37
In		8.97	8.58	8.85
		3.03	3.19	3.09
Total		8.97	8.58	8.85
		3.12	3.24	3.17

TABLE 4--CONTINUED
(PANEL E) LABOR MARKET STATUS AMONG THOSE WHO HAVE BEEN TEACHERS

Labor Force	Current/Last Job		Total
	Not Teach	Teach	
Out	71.94	28.06	100.00
	35.42	18.51	28.19
In	51.49	48.51	100.00
	64.58	81.49	71.81
Total	100.00	100.00	100.00
	57.25	42.75	100.00
N	3264	2437	5701

and high wage in a nonteaching job. Once certified as teachers, the teaching profession is where they can achieve their best. Table 4 documents characteristics of teachers in their family commitments and labor market status compared to nonteachers. The detailed statistics are reported on the extent to which females are bound to family commitments in three panels. In Panel A, if a female is currently out of the labor force and her last occupation is teaching, then there is 33.1% chance that she has a new-born baby currently, whereas this probability is only 27.6% if she has worked as a nonteacher. If she is in the labor force as a teacher, she has less chance to have a new birth than when she works as a nonteacher. This observation is also valid in Panel B, when I compare the chance of having a new baby among those with teaching experience and those without. Though there is no difference across occupation groups in the chance of having a new birth while in the labor force, females with teaching experience are more likely to have a new-birth than those without when they stay out of the labor force. In general, when a new-born baby is in the household, teachers are more likely to stay out of labor force than nonteachers. It is consistent with the findings of Stinebrickner (2002). If

females hold a teaching job, their propensity to participate in the labor force is very sensitive to the new birth. Similar results are found for the number of children.

As shown in Table 4 (Panels C, D, and E), if the current/last occupation is teaching in any survey year, then regardless of the labor force participation status, a female in the teachers' group is more likely to be married and her husband will earn less than a nonteacher's husband. This is an interesting observation because as shown in Table 1, when 'teachers' are defined as have teaching experience, husband income is on average higher for teachers than for nonteachers. Combined with Panel D in Table 4, this suggests that females with teaching experience actually work as teachers when husband incomes are lower.

In view of family commitments, a teacher (previously or currently) is more devoted to family ties; if she has a new birth, she stays out of the labor force. As regards supporting the family financially, with low husband income, females choose the teaching profession for secure employment status and maintenance of a baby.

The last panel in Table 4 presents the joint decisions regarding participation and occupation among females with teaching experience. When their (last) occupation is nonteaching, the current participation rate is only 64.6% while it is as high as 81.5% when they have taught (in their last employment). If they are currently out of the labor force, more than 70% of them were not teachers in the previous job. This suggests a strong connection between teaching occupation and labor force participation.

IV. Estimation Results

A. *Wage Equations and Selection Problem*

Table 5 shows the fixed effects estimation of the earnings Equations (1.3) and (1.4). The first (second) column of Table 5 reports the result for those who are working as teachers (nonteachers) in the labor force in the current year. The first thing to notice is the difference in age effect. The linear effect of age is significant for both occupation groups but much larger for nonteachers. The negative effect of the quadratic term of age is significantly negative and much larger in magnitude for nonteachers. Figure 1 illustrates the predicted log wage-age profiles of both groups. The wage profile of teachers is quadratic in age but much flatter compared to that of nonteachers. Nonteachers show the diminishing marginal effect of age on log wage, which is consistent with Flyer and Rosen (1997). Teachers start with higher initial wages but wages rise at a constant rate. Relative to teachers, nonteachers start their career with lower initial wages but benefit from a higher rate of growth during age 25~43. During their 20's and 30's, nonteachers earn more than teachers. Due to the decreasing rate of wage growth among nonteachers after age 43, teachers overtake nonteachers in terms of log wages. This may be related to wage rigidity for teachers resulting from the government regulation, or it may result from the fact that the teaching profession is not as sensitive to how experienced teachers are or how well they catch up with technology advances in the workplace. Other occupations are quick to adapt to new technology, so during the younger age when workers are quick to learn new skills, they benefit from wage gain as they become more experienced. On the contrary, teachers, who are in the

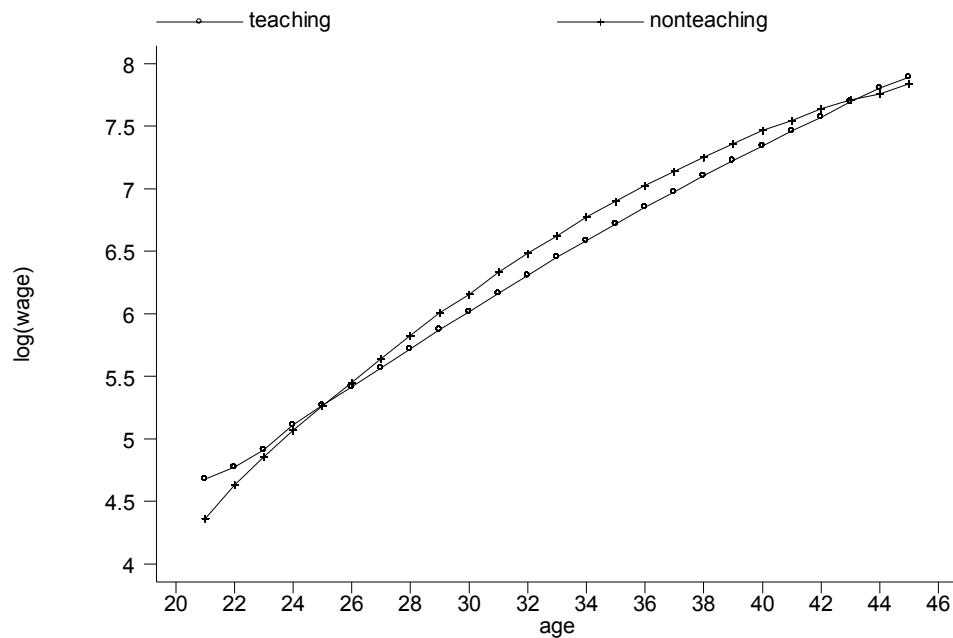


FIGURE 1. AGE-EARNING PROFILES BY OCCUPATION

TABLE 5--SELECTION CORRECTION FIXED EFFECTS ESTIMATION OF WAGES

Variable	Teachers		Nonteachers	
	Equation (1.3)		Equation (1.4)	
Constant	.479	(.337)	-1.752***	(.340)
Age	.215***	(.021)	.358***	(.022)
Age ²	-.0012***	(.0003)	-.0033***	(.0003)
Married	.032	(.037)	-.013	(.034)
Region of Residence	.075	(.048)	-.128**	(.050)
Unemployment Rate	.013	(.009)	.0096	(.010)
Lamda (Participation)	-.113**	(.051)	-.017	(.061)
Lamda (Occupation)	.063	(.053)	-.117**	(.050)
R ² Within	0.914		0.828	
Between	0.689		0.441	
Overall	0.716		0.561	
F	776.61		735.22	
N (n)	731 (211)		1449 (370)	
Fraction of Variance	.865		.799	
Contributed by Fixed Effects				
F (No Fixed Individual Effect)	11.56		9.00	

^a*, **, and *** indicate 10%, 5% and 1% significance, respectively.

^bStandard deviations are in parenthesis.

^cThe dependent variable for teachers (nonteachers) is log hourly wage in any survey year when a female is in the labor force working as an elementary or secondary teacher (working at nonteaching occupations).

first place more adept at doing their job, do not acquire many new skills. Thus, getting more experience does not benefit much when young. However, when old, workers are not as good as they were at learning new skills and tend to stay behind in catching up with technology advances prevalent in the overall economy. Consequently, the fast increasing wage gain from experience is diminished for nonteachers while teachers do not suffer from it because their skill becomes outdated at a relatively slow rate. For this reason, teachers earn more than nonteachers over age 43. In brief, teachers earning profile is much flatter than nonteachers earning profile, implying their heterogeneity in the labor market.

Selection bias from participation is negative for both occupations but significant only for teachers. Selectivity from occupational decisions is positively insignificant for teachers while statistically significant, and negative selection bias is found for nonteachers. This implies that teachers are selected among worse-than-average among all females through their participation choice. Nonteachers are below average among all females in the labor force. When the selection correction is implemented separately for teachers and nonteachers,¹⁴ as shown in Table 6, the negative selection bias in participation among teachers becomes insignificant. On the other hand, the positive selection in occupational choice for teachers is found significant and negative selection in occupational choice for nonteachers is larger than in Table 5. This confirms that nonteachers are negatively selected into nonteaching occupations among all female college graduates in the labor force. Collecting selectivity bias in wages is important in revealing the uncontaminated effect of relative wages on occupational choice.

TABLE 6--SELECTION CORRECTION FIXED EFFECTS ESTIMATION OF WAGES
IN THE SWITCHING LABOR FORCE PARTICIPATION MODEL

Variable	Teachers		Nonteachers	
	Equation (1.3)		Equation (1.4)	
Constant	.246	(.385)	-1.82***	(.348)
Age	.223***	(.024)	.359***	(.021)
Age ²	.0014***	(.0004)	-.0033***	(.0003)
Married	.020	(.055)	-.018	(.034)
Region of Residence	.210***	(.056)	-.130**	(.052)
Unemployment Rate	.022*	(.011)	.009	(.010)
Lamda (Participation)	-.020	(.0.36)	-.048	(.061)
Lamda (Occupation)	.104*	(.059)	-.141***	(.050)
R ² Within	0.926		0.835	
Between	0.656		0.467	
Overall	0.711		0.562	
F	559.92		726.71	
N (n)	502 (183)		1385 (373)	
Fraction of Variance Contributed by Fixed Effect	.883		.745	
F (No Fixed Individual Effect)	12.72		9.51	

^aIn the switching model, at each survey year, participation bias correction in log hourly wages is corrected for the unobserved wages in case of teaching in last job but not in the labor force currently (for teachers' wage), and of not teaching last year but not in the labor force this year (for nonteachers' wages.)

B. *Fertility, College Major and Occupational Choice*

Tables 7 and 8 document the results from the probit estimation of occupation decision Equations (1.1) and (1.5), respectively. Since this is a nonlinear estimation method, the conventional marginal effect interpretation of coefficients is inappropriate. Hence, I report the marginal effect of each explanatory variable on the predicted probability of being teachers in the second column. Among significant variables, age has a negative impact while education has a positive impact. The presence of a new-born baby seems not to have any effect on occupation choice, though it is negative. The largest marginal effect on the probability of being teachers comes from college major. Education major influences to the strongest extent a female to be a teacher. With other college majors such as business, social science, and health/medical science, she is highly

TABLE 7--PROBIT ESTIMATION OF OCCUPATION CHOICE DECISIONS

Variable	Equation (1.1)		Marginal Effect	
Constant	-17.17***	(2.04)		
Age	-.050***	(.014)	-.008***	(.002)
Education	1.03***	(.121)	.156***	(.012)
Married	.257*	(.140)	.037*	(.013)
White	.184	(.201)	.026	(.025)
Baby	-.201	(.192)	-.027	(.013)
Region of Residence	.173	(.218)	.026	(.017)
Mother's Occupation in 1968	-.427*	(.260)	-.051**	(.066)
College Major=Education	1.53***	(.186)	.318***	(.033)
College Major=Business	-1.95***	(.429)	-.103***	(.013)
College Major=Social Science	-1.20***	(.201)	-.114***	(.013)
College Major=Health, Medical Science	-2.36**	(1.03)	-.086***	(.011)
Relative Log Wages	1.74**	(.783)	.265**	(.080)
N (n)	2345 (513)			
Log-Likelihood	-784.00			
Variance of Fixed Effects	2.45	(.112)		
Fraction of Variance Contributed by Fixed Effects (=Rho)	.857	(.014)		
LR Test (H0: Rho=0)	1046.45			

TABLE 8--PROBIT ESTIMATION OF OCCUPATION CHOICE DECISIONS IN THE SWITCHING LABOR FORCE PARTICIPATION MODEL

Variable	Equation (1.5)		Marginal Effect	
Constant	-13.88***	(2.73)		
Age	-.040**	(.019)	-.008**	(.004)
Education	.817***	(.154)	.168***	(.034)
Married	.275	(.307)	.049	(.049)
White	.191	(.408)	.036	(.068)
Baby	.157	(.229)	.035	(.054)
Region of Residence	.061	(.447)	.013	(.092)
Mother's Occupation in 1968	.213	(.297)	.048	(.073)
College Major=Education	1.41***	(.239)	.355***	(.064)
College Major=Business	-1.88***	(.628)	-.139***	(.028)
College Major=Social Science	-1.24***	(.298)	-.161***	(.034)
College Major=Health, Medical Science	-3.22**	(1.63)	-.129***	(.026)
Relative Log Wages	2.71**	(1.13)	.558**	(.242)
N (n)	1413 (467)			
Log-Likelihood	-546.93			
Variance of Fixed Effects	2.43	(.206)		
Fraction of Variance Contributed by Fixed Effects (=Rho)	.855	(.021)		
LR Test (H0: Rho=0)	583.92			

TABLE 9--PROBIT ESTIMATION OF LABOR PARTICIPATION DECISIONS

Variable	Equation (1.2)		Marginal Effect	
Constant	-.141	(1.17)		
Age	-.009	(.010)	-.0008	(.001)
Years of Schooling	.121*	(.072)	.011*	(.006)
Married	-.920***	(.188)	-.067***	(.014)
White	-.737***	(.199)	-.043***	(.009)
Baby	-1.04***	(.099)	-.173***	(.027)
Husband Income	.0087	(.016)	.0008	(.001)
Mother's Education in 1968	-.013	(.021)	-.0011	(.002)
Region of Residence	.023	(.109)	.002	(.010)
Unemployment Rate	-.0022	(.024)	-.0002	(.002)
Last Year Log Hourly Wage	.254***	(.055)	.022	(.006)
N (n)	3135 (557)			
Log-Likelihood	-855.98			
Variance of Fixed Effects	.802	(.082)		
Fraction of Variance Contributed by Fixed Effects (=Rho)	.392	(.032)		
LR Test (H0: Rho=0)	85.69			

likely to be in nonteaching occupations. This suggests that whether to be teachers or not is a decision made during college years, not after graduation. Females in college have expectations of their future occupation and choose a field of study as a preparation for their desired occupation after graduation.

C. Fertility and Participation Decision

In Table 9, the education level shows positive significant effect on participation probability. If a female is married and white, she is less likely to be in the labor force. More education provides better qualifications and more opportunity in the labor market, attracting females to join the labor force. By contrast, marriage plays a discouraging role for females in participating in the labor market. Husband income is not a factor significantly affecting labor force participation decisions among wives. Among all other explanatory factors, the largest negative significant marginal effect on participation is found in the presence of a new-born child, -0.173. This result is precisely

TABLE 10--PROBIT ESTIMATION OF LABOR PARTICIPATION: TEACHERS

Variable	Equation (1.6)		Marginal Effect	
Constant	-1.10	(2.16)		
Age	-.031	(.024)	-.0034	(.002)
Years of Schooling	.158	(.140)	.015	(.017)
Married	-1.28***	(.404)	-.076***	(.025)
White	-.802**	(.346)	-.050***	(.019)
Baby	-1.16***	(.188)	-.212***	(.054)
Husband Income	.023	(.027)	.002	(.002)
Mother's Education In 1968	.004	(.041)	.0003	(.004)
Region of Residence	.130	(.202)	.012	(.019)
Unemployment Rate	.021	(.046)	.002	(.004)
Last Year Log Hourly Wage	.410***	(.135)	.038***	(.014)
N (n)	916 (244)			
Log-Likelihood	-261.59			
Variance of Fixed Effects	.908	(.182)		
Fraction of Variance Contributed by Fixed Effects (=Rho)	.452	(.061)		
LR Test (H0: Rho=0)	23.22			

compatible with the description of Olsen (1994). Like marital status, fertility condition is influential in decisions on labor force participation among females.

Teachers retain many different characteristics from nonteachers in terms of labor market status and family commitment factors. When allowing them to behave heterogeneously in decisions regarding participation as shown in Tables 10 and 11, all significant and negative effects from marital status (married) and racial type (white) are larger for teachers. The significant and negative effect of the presence of a new-born baby is twice as large for teachers relative to nonteachers. For both teachers and nonteachers, family commitments such as marriage and childbearing retract them from the labor force. The finding that teachers are more sensitive in adjusting their labor market status according to their fertility condition is consistent with the discussion in Table 4: teachers have a stronger tendency to be out of the labor force if they have a new birth.

TABLE 11--PROBIT ESTIMATION OF LABOR PARTICIPATION: NONTEACHERS

Variable	Equation (1.7)		Marginal Effect	
Constant	.085	(1.51)		
Age	-.017	(.013)	-.001	(.001)
Years of Schooling	.124	(.093)	.008	(.006)
Married	-.878***	(.251)	-.054***	(.016)
White	-.611**	(.252)	-.029***	(.009)
Baby	-.951***	(.127)	-.125***	(.030)
Husband Income	-.004	(.022)	-.0003	(.001)
Mother's Education in 1968	-.025	(.026)	-.002	(.002)
Region of Residence	.111	(.142)	.008	(.010)
Unemployment Rate	-.0003	(.030)	-.00002	(.002)
Last Year Log Hourly Wage	.271***	(.074)	.018***	(.006)
Log-Likelihood	-546.54			
Variance of Fixed Effects	.870	(.112)		
Fraction of Variance Contributed by Fixed Effects (=Rho)	.431	(.063)		
LR Test (H0: Rho=0)	57.16			

In conclusion, the negative effects of fertility on participation decisions are found to be apparent in my investigation of the female labor supply. This effect varies across occupations and is stronger for teachers. Marital status puts some limitation on females, in particular teachers, to participate in the labor force, but to a lesser extent than the presence of a baby. Upon a new birth, teachers are more likely to be out of the labor force than nonteachers would be. This implies that little wage loss for temporary absence and the slow skill obsolescence hypotheses explain the tendency of teachers to take time off from the job upon the presence of a new-born baby and associated nurturing responsibilities. Without such flexibility in leave-and-reenter options, nonteachers would be less likely to take time off when they expect to have babies (that is, when they are married) and adhere to the job. However, staying out of labor force is a preferred option for nonteachers when they have a child. In this decision making, husband income is unlikely to matter.

D. *Relative Wage Effects on Occupational Choice*

The effect of relative wage on occupational choice is widely discussed and is also one of the most interesting issues in this analysis because of its implication for policy making regarding education expenditures. In Table 6, relative log wages have the second largest¹⁵ positive and significant effect. With a slight increase in wages relative to other occupations, the teaching occupation is apparently attractive to female college graduates. This tendency is even stronger in Table 7.

This suggests that the wage incentive to attract more teachers is effective. The recent dramatic increase in educational expenditure aims mostly to raise teacher salaries and eventually to attract more and better teachers. The cross-sectional results by Johnes (1999) and Dolton and Makepeace (1993) imply similar results. Even after controlling individual fixed effects along with selection correction in wages, there remains a smaller in size but still significantly large (0.558 in the switching model) effect. Females' response to the increase in relative wages is found to be less than what has been usually found in the previous literature. Hence any education policy aimed at improving the teacher supply with better wages needs more careful assessment of its effectiveness. Alternative policy emphasizing how to lead female high school graduating or college student into education majors may be more effective since college major is very important in their after graduation choice of occupation as teachers.¹⁶

V. **Conclusion**

In this paper, using panel data for young females, I investigate the relationship between fertility and relative wages and their participation and occupation decisions.

Several conclusions emerge from the analysis. First, the presence of a new-born baby seems not affect the occupational decisions of whether to work as a teacher or not. The fertility condition strongly affects their labor force participation. This effect varies across occupations, and is larger for teachers. Upon a new birth, teachers are more likely to drop out of the labor force but this does not relate to their decision to work as teachers at a given time period. Once they decide to join the labor force, females' choice of the teaching profession is not correlated with their childbearing.

Second, the direct effect of relative wages on occupational choice has been studied. There is strong evidence that higher relative wages for teachers provide a proper incentive for females to be teaching. This result supports the effectiveness of the recent policy of increasing teacher salary in order to improve teacher quantity. Age-earning profiles are found to be considerably different between teachers (linear) and nonteachers (quadratic). The comparisons across occupations suggest that teachers and nonteachers are heterogeneous in their labor market decisions and earning determinations. The importance of correcting for selection biases properly has also been established.

Other than relative wages, college major is a most important factor in occupational decisions among female college graduates. Therefore, further analysis of the choice of college majors and its relationship with post-graduation occupational choice will be useful to understand what determines supply and quality of teachers and what is the best way to invest educational expenditures to provide more and better teachers for the next generation.

CHAPTER III

HUMAN CAPITAL, ENTRY WAGE, AND POST WAGE DIFFERENTIALS

I. Introduction

One of the most robust findings in labor economics is a positive return on time spent in the labor market investigated in the standard log wage equations. Among various attempts to explain this relationship, the primary model is the general human capital theory, in which the stock of human capital rises with experience in the labor market. There are two main streams to describe how people accumulate their human capital through working. First, Yoram Ben-Porath (1967) and many followers (Jacob Mincer, 1974; Gary Becker, 1975) suggest that people invest in general human capital at the expense of time or direct pecuniary cost, resulting initially in lower wages and subsequently in higher wages in later periods of working life. This so-called ‘On the Job Training’ (OJT) theory of post-schooling human capital investment and wage growth predicts that at the individual level, there will be a negative relationship between the initial wage level and wage growth. At the market level, it also predicts that the present values of the investor’s lifetime wage (with lower initial wage and faster growth) and of the otherwise equivalent noninvestor’s lifetime wage (with higher initial wage but slower growth thereafter) equals one. These two predictions are tested to be valid in the empirical study of David Neumark and Paul Taubman (1995).

The other hypothesis regarding the general human capital accumulation process, namely ‘Learning by Doing’ (LBD) theory, holds that people enhance their productivity by learning skills through work without giving up working hours or wages. In the two-

period model (Ricardo D. Cossa, James Heckman, and Lance Lochner, 1999), workers choose optimal consumption and leisure (in hours) to maximize their present value lifetime utility. This gives different predictions from the OJT and the LBD human capital evolution processes on the relationships among initial wage level, hours worked, and wage growth over time. In the OJT, people reduce hours worked for post-schooling training and receive lower wages initially. Over time, their wages grow faster. Therefore, their wages and hours worked move in opposite directions over time. People who invest on human capital earn lower initial wages and experience higher growth in their future wages. The gap in the initial wages would be compensated by difference in wage growth rates. As age approaches the overtaking point, two wage profiles (one flatter than the other) may converge to each other (Mincer, 1974).

By contrast, in the LBD process, there is no explicit cost for human capital accumulation. Given wage offers, people choose how many hours to work and by working, they enhance their productivity. As wages reflect increases in their stock of human capital, wages increase over time as well, and this increase will be larger for workers who spend more hours at work. Since people adjust their labor supply (measured in hours) responding to wages, the patterns of wage and hours worked would move in parallel with each other; the higher the wages, the more hours they work. Moreover, assuming no costly training and flexible choice in hours worked, a difference in initial wages may cause different choices of hours worked, and so, different amount of accumulated human capital. Eventually, the small gap in initial wages is transmitted to a huge wage differential in the later working years.

Empirical evidence such as Neumark and Taubman (1995) has limitations for verifying that their findings indeed prove the OJT hypothesis because they have not considered the endogenous training participation decisions of workers explicitly. When they find a negative relationship between wage level and wage growth, it is simply argued to be evidence for the OJT. The separate identification and reconciliation between the OJT and LBD models are little examined.

Aiming to provide evidence for the LBD model, my study considers the initial wage effect on post wage differentials. Variation in initial wages is derived from two factors; a worker-specific permanent factor and random transitory components. The fact that people with higher initial wages earn more later than their counterparts with lower initial wages may be attributed to the possibility that people with higher initial wages are smarter (endowed with more human capital). Then, differences in post entry wages are consequences in their difference in innate ability before working. If the growth rate of human capital accumulation does (not) depend on individual endowed or prior-to-working ability, the gap in initial wages will remain as the same extent (increase in the magnitude) in future wages without any slope effect (with positive slope effect). This implies that the permanent components of initial wages are mostly responsible for future wage differentials.

By decomposing entry level wages into their permanent and transitory components (Michael Baker, 1997), the relative accountability of these two components for post wage differentials can be investigated. It is expected that the determination of entry wage is quite different from that of later wages because when a firm decides to hire

someone who enters the market for the first time, the firm usually does not have enough information to accurately judge the productivity of the individual. Therefore, there is more randomness in assigning an initial wage compared with later wages. I define that an individual is *lucky* if he obtains a relatively high wage (relative to others who have similar productivity). Whether this initial luck can motivate the individual to work harder thereafter (say, in order to keep a well-paid job) in his career and this consequently leads to a persistent future high wage is examined in this paper.

In sum, there are two possible ways in which entry level wages may influence future wage: 1. higher initial wages increase hours worked and 2. higher initial wages cause faster wage growth (slope effect). Whether any of these effects is attributed to a permanent factor or to random shock (luck) in the entry level wages is the last question I try to answer.

This paper focuses on the slope effect of entry wages on future wages. It is found that the entry-level wage is indeed an important factor in determining future wages both in the theoretical framework and in the empirical studies. In the LBD framework of human capital accumulation, an individual worker is endowed with innate ability. She adjusts labor supply decisions on hours worked responding to her initial wage. With the LBD, she accumulates her productivity proportional to hours worked. If the level of the starting wage is high, she works for more hours in the next period. This leads her to obtain more human capital during working. Her future wage is likely to be high, directly reflecting her enhanced productivity.

Using a simple regression model, I estimate the effects of entry-level wage and its random component with data from the National Longitudinal Survey of Youth 79. The main finding is that the entry-level wage has a positive effect on future wages and that it persists over time. This effect is found to be attributable to the *random* component of the initial wages, not the component based on observed factors for an individual. This supports the positive relationship between wage level and wage growth predicted by the LBD model.

II. Theoretical Framework

Let a representative worker endowed with innate ability α_0 , which is not fully observed by firms. I assume that once a worker is actually employed, then her ability becomes public information both to her employer and to the firm that she works for. A worker accumulates her human capital through her working experience in the LBD process. The wage paid by the firm to this representative worker is, on the average, equal to the observed output of a worker. The observed output can be decomposed into two parts: worker's productivity, and a random component due to the firm's inability to observe the individual's true ability before hiring her.

Then, wages at time t are determined by the firm's expectation about the marginal product of a worker, α_t^e , plus a random noise ε_t :

$$(2.1) \quad w_t = \alpha_t^e + \varepsilon_t.$$

I let expected the marginal product of a worker at t be the marginal product of the worker at the end of $t-1$:

$$(2.2) \quad \alpha_t^e = \alpha_{t-1}.$$

Following a typical labor supply model, I let a worker adjust her working hours, h_t , responding to her wage as follows:

$$(2.3) \quad h_t = h_0 + \beta(w_t - \alpha_{t-1}) = h_0 + \beta\varepsilon_t.$$

Equation (2.3) says that working hours (or effort input at work) is positively correlated with the difference between the wage and the marginal productivity ($\beta > 0$). If a worker enjoys positive random shock in her productivity at work, she will invest more time on working in response to higher wage than her actual human capital.

Similar to the LBD human capital theory (Cossa, Heckman, and Lochner, 1999), my benchmark model of the accumulation process of a worker's ability depends on working hours as follows:

$$(2.4) \quad \alpha_t = \rho\alpha_{t-1} + \eta h_{t-1}.$$

If $\rho = 1$, then Equation (2.4) implies that the accumulation of human capital is never depreciated. Then through a lifetime, the productivity of a worker keeps increasing. η measures the rate of learning from the last period working.

Simple deduction from Equations (2.3) and (2.4) leads me to:

$$(2.5) \quad \alpha_t = \rho^t \alpha_0 + \frac{1 - \rho^t}{1 - \rho} \eta h_0 + \eta \beta \rho^{t-1} \varepsilon_0 + \eta \beta \sum_{j=1}^{t-1} \rho^{t-1-j} \varepsilon_j.$$

The first term on the right-hand-side (RHS) of (2.5) is the initial human capital of the worker. It is constructed from time-invariant characteristics such as years of schooling, sex, and race. The second term at the RHS of (2.5) is a time-varying component of the obtained productivity from experience in the workplace. It includes

working experience and tenure with a specific employer. The third term, ε_0 , is a random component of the initial wage, which is my main concern.

To predict the sign and trend of the initial wage effect, I consider four cases where different distributional assumptions on the random component of initial wages and variation from the benchmark process of human capital accumulation are considered. In particular,

Case 1. $\rho = 1$, and $\{\varepsilon_t\}$ is *i.i.d.* with mean zero and finite variance σ^2 for $t=1, \dots, T$, ε_0 can have a much larger variation than σ^2 . The human capital accumulation process follows Equation (2.4). Random shock in initial wage reflects the luck of an individual. With $\rho = 1$, Equation (2.5) becomes

$$(2.6) \quad \alpha_t = \alpha_0 + t\eta h_0 + \eta\beta\varepsilon_0 + \eta\beta \sum_{j=1}^{t-1} \varepsilon_j .$$

I find that the initial random shock in wages has a permanent and positive impact on future human capital for all future time periods. This marginal effect is *constant* ($\eta\beta$) for all t .

In this case, I can interpret the error component in the initial wage as the quality of matching between a worker and an employer (or a workplace environment). In general, each worker only has limited access to information about job openings. A worker could afford to search and gather employment opportunity information only when she manages to be employed during the searching process or support herself while unemployed. So her matching with a job would occur at a time when she can not afford the searching process any more and she would choose a job from the offers available to her then. At

any moment, it is not practically possible that a worker searches the best match using the entire information about the job market.

In the other case where a worker does not try to change her employer, her workplace environment with the same employer can still change randomly in the sense that many economy-wide factors that a worker is unable to control may affect her working environment relevant to her productivity. In either case, it is reasonable to assume that the matching quality is random (has a random component) over time.

Case 2. $0 < \rho < 1$, i.e. α_t follows a stationary *AR (1)* process,

$$(2.7) \quad \alpha_t = \rho\alpha_{t-1} + \eta h_0 + \eta\beta\varepsilon_{t-1} \text{ where } 0 < \rho < 1.$$

Equation (2.7) allows the possibility of human capital depreciation over time. It is reasonable that as they get older, workers may forget part of their knowledge accumulated in the past. If they switch jobs and work in different tasks, part of the specific human capital obtained in previous jobs may be lost in their productivity in the next period. In either case, workers' human capital may depreciate for a given time period. Direct deduction from Equation (2.7) leads to:

$$(2.8) \quad \alpha_t = \rho^t \alpha_0 + \frac{1 - \rho^t}{1 - \rho} \eta h_0 + \eta\beta\rho^{t-1} \varepsilon_0 + \eta\beta \sum_{j=1}^{t-1} \rho^{t-1-j} \varepsilon_j.$$

The effect (coefficient) of initial shock, $\eta\beta\rho^{t-1}$, is positive but *monotonically decreasing* over time. Eventually, it dies out to zero. Initial wage differentials caused by uneven random luck among workers will not have a persistent significant effect on future wage differentials.

Case 3. $\rho = 1$, and $\{\varepsilon_t\}$ is a stationary *AR (1)* process, i.e.

$$(2.9) \quad \varepsilon_t = \delta\varepsilon_{t-1} + u_t \text{ where } 0 < \delta < 1 .$$

I assume that the human capital accumulation process is Equation (2.4) with $\rho=1$.

Equation (2.9) indicates that any kind of random luck in the labor market of an individual worker is correlated over time. Once a worker gets lucky, she is more likely to remain lucky in the next period while an unlucky worker is more likely to suffer from her continuous unluckiness in her later working career. I may consider random luck as some unobserved individual heteroskedastic characteristic that helps a worker get a high-paying job or give a good signal to employers. Either directly or indirectly, these factors enable a worker to maintain her luck with employers and keep high wages over time. Since these factors are likely to be related with a worker's personality and attitude towards relationships, work, and risk, they produce a positive correlation with luck over time.

To figure out the effect of temporally correlated random shock on future wages, I combine Equations (2.4) and (2.9) to obtain the following:

$$(2.10) \quad \alpha_t = \alpha_0 + t\eta\beta h_0 + \eta\beta \left(\frac{1 - \delta^t}{1 - \delta} \right) \varepsilon_0 + \eta\beta \sum_{j=1}^{t-1} \sum_{s=1}^j \delta^{j-s} u_s .$$

The initial shock produces a positive effect on future productivity and wage. This effect *monotonically increases* over time with an upper bound of $\eta\beta \left(\frac{1}{1 - \delta} \right)$. Due to the positive and persistent impact of initial luck on future productivity and wages, given that other factors are fixed, the wage differential between lucky workers and unlucky workers in the first period at work does not disappear. This implies that the wage

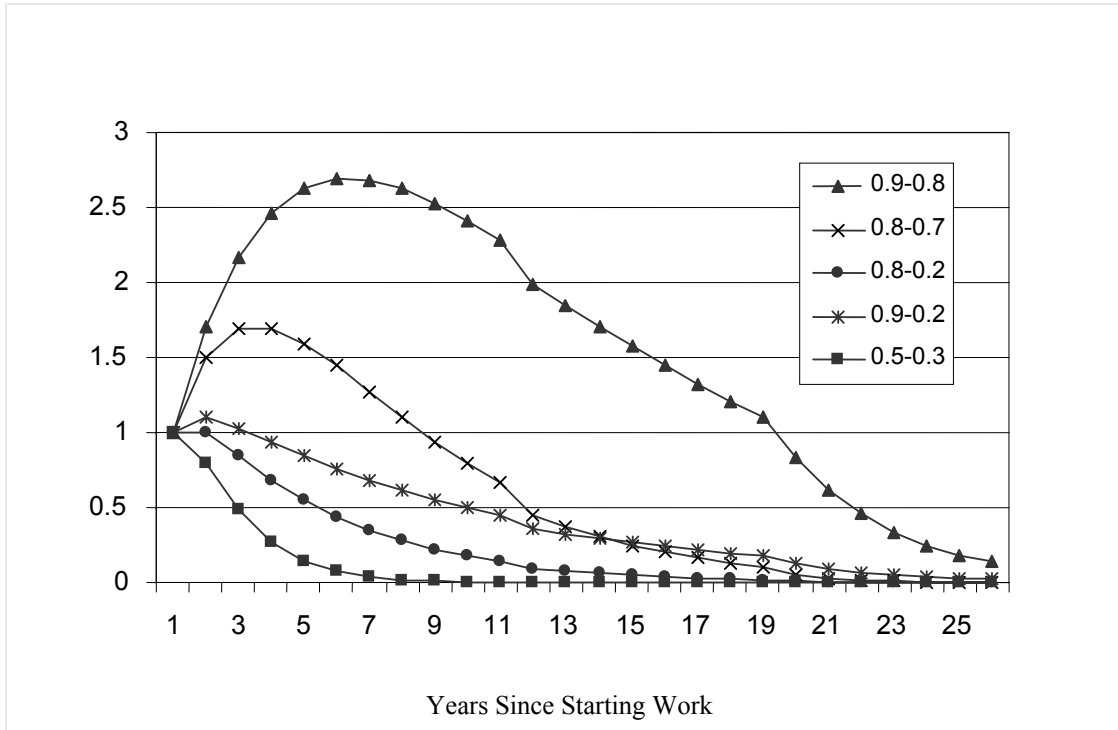


FIGURE 2. CHANGES IN ENTRY WAGE EFFECTS (CASE 4)

differential among experienced workers is a consequence of the variation of initial luck they receive when starting to work.

Case 4. Both $\{\alpha_t\}$ and $\{\varepsilon_t\}$ are stationary *AR (1)* processes. As my most general case, I combine human capital accumulation that allows for partial depreciation and an intertemporal correlation within random luck in wages, i.e., α_t follows Equation (2.7) and ε_t follows Equation (2.9). Then it follows that:

$$(2.11) \quad \alpha_t = \rho^t \alpha_0 + \frac{1 - \rho^t}{1 - \rho} \eta h_0 + \eta \beta \left(\frac{\rho^t - \delta^t}{\rho - \delta} \right) \varepsilon_0 + \eta \beta \rho^{t-1} \sum_{j=1}^{t-1} \sum_{s=1}^j \frac{\delta^{j-s}}{\rho^j} u_s .$$

Now, the marginal effect of initial shock on future wages, $\eta\beta\left(\frac{\rho^t - \delta^t}{\rho - \delta}\right)$ depends on two AR (1) parameters, ρ and δ . Assuming that both ρ and δ are positive numbers between 0 and 1, regardless of the relative magnitude of the two parameters, the effect of initial wage will eventually disappear. However, a converging trend of this effect depends on the specific choices of two parameters. In particular, if $\rho = \delta$, then the effect of initial wage will be $\eta\beta(t\rho^{t-1})$.

Figure 2 illustrates changes in the initial random shock effect over time. Depending on different choices of ρ and δ , the marginal effect follows different patterns in trends. Even in cases of increasing trend, the trend is reversed to decrease at $t > 6$. Intuitively, the reasonable conjecture is that the intertemporal correlation of a worker's productivity is stronger than that of her random shock in wages, say $\rho > \delta$. Figure 3 shows the trend of initial shock when $\rho = \delta$. If ρ is very close to 1, the marginal effect first explodes and then slowly decreases towards zero. As ρ gets smaller toward zero, the exploding trend stabilizes and the initial shock effect converges to zero within a relatively short period of time. Figures 2 and 3 show that changes in the marginal effect of initial shock are not necessarily monotonic. In Case 4, though the marginal effect of initial wages reduces to zero eventually, it does *not monotonically decrease* and the speed of convergence depends on the values of ρ and δ . Hence, during the early period of a working career, workers with positive initial shock might gain larger and larger benefits from it over certain time. Along with longer experience at work, it starts to decrease and eventually leaves no effect.

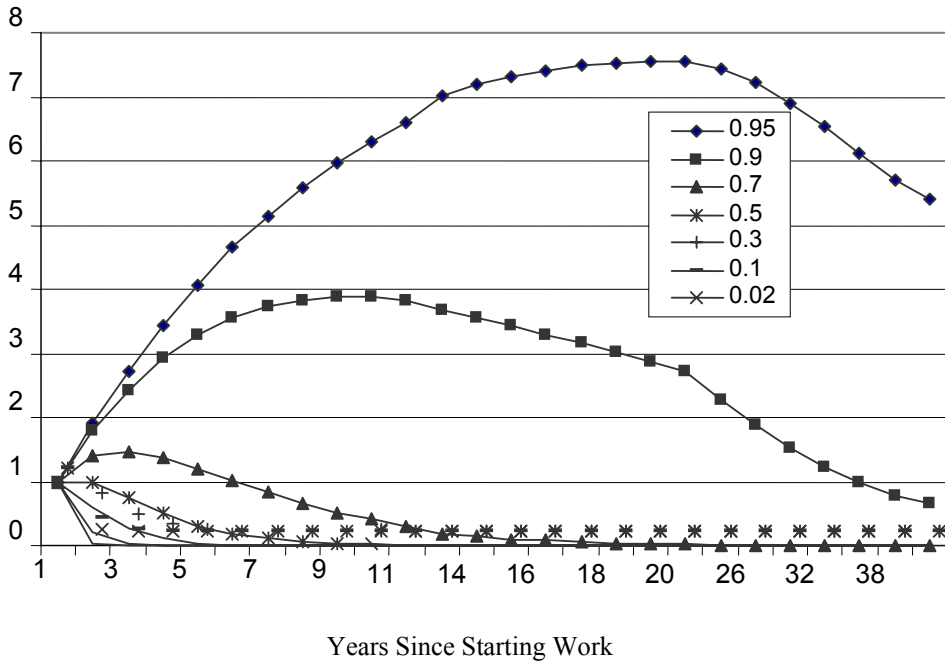


FIGURE 3. CHANGES IN ENTRY WAGE EFFECTS (CASE 4, $\rho = \delta$)

III. Empirical Model

Using Equations (2.2) and (2.6), I can rewrite a wage function of Equation (2.1) according to four possible cases:

$$(2.12) \quad \text{Case 1. } w_t = \alpha_0 + (t-1)\eta h_0 + \eta\beta\varepsilon_0 + v_t \text{ where } v_t = \eta\beta \sum_{j=1}^{t-2} \varepsilon_j + \varepsilon_t,$$

$$(2.13) \quad \text{Case 2. } w_t = \rho^{t-1}\alpha_0 + \frac{1-\rho^{t-1}}{1-\rho}\eta h_0 + \eta\beta\rho^{t-2}\varepsilon_0 + v_t$$

$$\text{where } v_t = \eta\beta \sum_{j=1}^{t-2} \rho^{t-1-j} \varepsilon_j + \varepsilon_t,$$

$$(2.14) \quad \text{Case 3. } w_t = \alpha_0 + (t-1)\eta\beta h_0 + \eta\beta \left(\frac{1-\delta^{t-1}}{1-\delta} \right) \varepsilon_0 + v_t$$

where $v_t = \eta\beta \sum_{j=1}^{t-2} \sum_{s=1}^j \delta^{j-s} u_s + \varepsilon_t$, and

$$(2.15) \quad \text{Case 4. } w_t = \rho^{t-1} \alpha_0 + \frac{1-\rho^{t-1}}{1-\rho} \eta h_0 + \eta\beta \left(\frac{\rho^{t-1} - \delta^{t-1}}{\rho - \delta} \right) \varepsilon_0 + v_t,$$

where $v_t = \eta\beta \rho^{t-2} \sum_{j=1}^{t-2} \sum_{s=1}^j \frac{\delta^{j-s}}{\rho^j} u_s + \varepsilon_t$.

For the empirical analysis, I use two different wage equation specifications to find out which cases more faithfully reflect the data generating process (i.e. the true effect of initial wages). Given a time period t , for each individual i , I consider two log wage regressions.

$$\text{(Regression 1)} \quad w_t = \gamma w_0 + X_t \delta_1 + v_t,$$

and

$$\text{(Regression 2)} \quad w_t = \gamma_0 \alpha_0 + \gamma_1 \varepsilon_0 + X_t \delta_2 + v_t.$$

X includes several demographic and labor force characteristics of a worker, for example, age, years of schooling, sex, race, marital status, years of experience, and AFQT score.

In Regression 2, since both initial ability (α_0) and random shock are unobserved, I need the first-step estimation of the initial wage equation given as:

$$(2.16) \quad w_0 = Z_0 \delta_0 + \varepsilon_0,$$

where Z needs to contain additional variables not contained in X to avoid

multicollinearity in Regression 2. Thus, I approximate α_0 based on observables Z . In

Regression 2, I decompose the initial wage effects into a systematic part and a random shock (luck) part separately. I let Z satisfy the exclusion condition by including some explanatory variables in Z which are excluded in X , such as education squared, an interaction term of education and AFQT score. Also, some family variables such as father's educational attainment, mother's educational attainment, the closest sibling's gender, and educational attainment are used as additional explanatory variables responsible for the determination of initial wage. In particular, I try to control innate ability using these family related variables.

Using obtained initial wages and residuals from Equation (2.16) as

$w_0 = Z_0\hat{\delta} + \hat{\varepsilon}_0 \equiv \hat{w}_0 + \hat{\varepsilon}_0$, Regression 2 is estimated as follows:

$$(2.17) \quad w_t = \gamma_0 \hat{w}_0 + \gamma_1 \hat{\varepsilon}_0 + X_t \delta_2 + \nu_t .$$

In Regression 1, I obtain a preliminary measure of initial effects. Then, whether the source of these effects is systematic or random components of the initial wage is investigated in Regression 2. The questions I pursue are whether there *exists* an effect of initial wage on future wage, how persistent is this effect over time, and what are the effects and trends in its persistence as a random component of the initial wage on future wages.

IV. Data

For the empirical analysis described above, I employ the National Longitudinal Survey of Youth 79. My sample includes only a cross-sectional sample of 6,111 individuals aged 14-21 as of December 31, 1978. Based on the information about employment status over survey years 1979-2000, I track down when they started to work

TABLE 12--ENTRY WAGE EFFECTS

Years Since Initial Work	Coefficient of Entry Wage (t-Ratio)	Std. Dev.	No. Obs.	Adjusted R ²
1	.460 (12.21)	.0377	541	.386
2	.504 (12.88)	.0391	521	.412
3	.393 (7.42)	.0529	506	.244
4	.237 (4.62)	.0512	498	.235
5	.318 (6.38)	.0498	487	.301
6	.418 (7.92)	.0524	498	.317
7	.247 (5.11)	.0485	514	.297
8	.226 (4.12)	.0548	514	.261
9	.332 (4.82)	.0688	501	.191
10	.270 (4.64)	.0581	508	.230
11	.219 (4.55)	.0482	516	.326
12	.308 (5.76)	.0535	500	.344
13	.296 (3.89)	.0760	487	.223
14	.228 (3.28)	.0694	492	.252
15	.210 (3.71)	.0565	501	.268
17	.308 (5.34)	.0578	529	.251
19	.251 (4.33)	.0579	507	.282
21	.245 (3.35)	.0732	447	.200

and years of experience. Then, I limit the time periods for each individual to only *after* all schooling is completed, leaving the number of cross-sectional observations at 752.¹⁷ Then initial wages are defined as the first wage observed *after* years of education completed stop increasing. This allows me to exclude cases where people start work during schooling or return to school after they start working. For each year during 1980-2000, the current wage, my dependent variable, is the wage observed after 1 to 21 years later from the year of starting to work for each worker. For example, if the number of years since starting to work is equal to 3, the current wages are wages in 1982 for people who started to work in 1979, or wages in 1985 for those started to work in 1982, and so on. All wages are converted to the wages for compatibility using the Consumer Price Index. The distributions of years of starting work both overall and within a fixed number of years since the starting year are reported in Table A2.

V. Estimation Results

I implement a simple OLS estimation to find out which theoretical cases described above are indeed consistent with the data. Results are presented in Tables 12 and 13. Table 12 reports the results of Regression 1 where I estimate the effect of initial wages on future wages without decomposing initial wages. It is noteworthy that the effect of initial wage is persistent even after 20 years since workers started to work. On average, one percentage increase in initial wages raises all future wages by 0.28%. In this specification, I am unable to differentiate the effect of explained components of initial wage from that of random shock in initial wages.

Before I interpret this result as a *true* effect of initial wage, I pay attention to the possibility of an endogeneity problem. An endogeneity problem happens if any individual unobserved characteristic makes workers relatively more productive and raises both their initial wage and future wages. Innate ability is the common suspect considered responsible for this endogeneity bias. My data provide a proxy variable for individual innate ability, AFQT scores measure in quantiles. By controlling AFQT scores explicitly, I try to avoid the possibility that the observed persistence of effects of initial wage over time reflects the persistent feature of workers' unobserved ability. Also, some information about family members is included, assuming that these variables may be correlated with an individual's unobserved ability. NLSY79 provides father's and mother's educational attainment reported in 1979, and the closest sibling's gender and years of schooling reported in 1993. Combining these variables in different ways, I decompose initial wages into systemically predicted part and unobserved random (luck)

TABLE 13--DECOMPOSITION OF ENTRY WAGE EFFECTS: SPECIFICATION I

Years Since Initial Work	Coefficient of \hat{w}_0 (t-Ratio)	Std. Dev.	Coefficient of $\hat{\varepsilon}_0$ (t-Ratio)	Std. Dev.	Adjusted R ²
1	1.222 (2.81)***	.4343	.455 (12.04)	.0377	.388
2	.861 (1.99)**	.0392	.501 (12.77)	.0393	.411
3	1.559 (2.73)***	.5701	.386 (7.29)	.0529	.249
4	.502 (0.83)	.6043	.235 (4.57)	.0514	.234
5	.482 (0.81)	.5953	.316 (6.32)	.0501	.300
6	.129 (0.22)	.5966	.417 (7.92)	.0526	.316
7	-.029 (-0.05)	.6295	.249 (5.12)	.0487	.296
8	-.469 (-0.71)	.6562	.233 (4.22)	.0552	.261
9	-.328 (-0.39)	.8342	.339 (4.88)	.0695	.191
10	.086 (0.10)	.8447	.271 (4.64)	.0584	.228
11	.064 (0.11)	.5689	.221 (4.55)	.0485	.325
12	.121 (0.17)	.7266	.309 (5.76)	.0537	.342
13	.452 (0.49)	.9135	.294 (3.84)	.0766	.221
14	-.405 (-0.47)	.8561	.233 (3.34)	.0698	.251
15	.731 (1.02)	.7183	.207 (3.64)	.0567	.267
17	-.543 (-0.77)	.7058	.316 (5.44)	.0581	.252
19	-.862 (-1.32)	.6528	.255 (4.41)	.0578	.285
21	.152 (0.17)	.8738	.246 (3.35)	.0734	.198
Average	.151		.279		

^aThe predicted initial wages and residuals are estimated using age, education, education squared, AFQT score, an interaction term of education and AFQT score, race, sex, and marital status as explanatory variables.

^bDependent variable: logarithm of real current wages for all years of experience, 1 to 18.

^cAll estimated coefficients for $\hat{\varepsilon}_0$ are significant at 1% level. I omit *** for concision.

^dIn the first step regression of initial wage, I include age, gender (dummy), marital status (dummy), race (dummy), education, education squared, AFQT score, an interaction term of education and AFQT score, and dummies for 'year of starting work'.

part. Table 13 presents the results of the initial wage decomposition. The systematic part of initial wage has a large and highly significant effect on future wages during the first 3 years since the year of starting to work. Afterwards, the effect becomes insignificant.

By contrast, the unexplained random component of initial wages (Table 13, Column 3) is consistently positive and highly significant in its impact on future wage up to the most recent data available (year 2000). There is a slight fluctuation in the extent of the effect across time periods. The average effect of one percentage increase in initial wages is a 0.274% increase in future wages up to 21 years after having started work. This result



FIGURE 4. ESTIMATED ENTRY WAGE EFFECTS

provides supporting evidence for my theoretical hypothesis, which held that the positive random shock (luck) in initial wage increases future wages permanently through a worker's human capital accumulation (via working harder). Figure 4 plots the estimates of initial random component effects. Certainly, there are fluctuations in magnitude over time. For the first 3 years, the coefficients are remarkable higher than for the later years. Whatever the causal relationship between initial wages and post wages may be, it is reasonable to assume that initial wages should have a strong relationship with post wages over a short time period. Over a 3-9 year period, the effect of initial random shocks fluctuates across years with a slightly decreasing trend. Over time, the extent of the fluctuation in the initial random shock effect stabilizes. After 10 years, it settles

down to around 0.25, not likely to converge to zero.¹⁸

It is important to integrate my empirical results with one of the theoretical predictions. As shown in Figure 3, the effect of random shock as part of initial wages is decreasing during only a short period time and it does not disappear toward zero even 21 years later. This supports the prediction of Case 1 where I assume the i.i.d. random shocks and no human capital depreciation. Given that my sample only contains relatively young workers (aged 14 to 21 in 1979, and aged 35 to 56 in 2000), no human capital depreciation assumption seems not a restrictive assumption. My empirical results support the proposition that if a worker's luck in job matching and in her performance at work is purely random unrelated with any other direct factors which determine her productivity at a given time, it functions as an incentive for her to spend more time in working and to invest more effort in work. This leads to a permanent increase in her human capital level. Therefore, after over 20 years later, her post wages benefit from the good luck in her initial wage.

An interesting explanation of wage differential within groups is provided. Given the same innate ability, educational attainment and other demographic conditions, workers benefit or suffer from wage inequality, which is caused by differences in their initial luck at work. Once lucky, she is more likely to remain lucky in wages only because she gets lucky in the beginning. Once unlucky, it is difficult to overtake her lucky counterpart. Hence, I observe a persistent wage differential, and this will not be eliminated simply by equalizing systematic determinants of wages across workers.

VI. Conclusion

The standard Mincer wage regression developed by Mincer (1974) and its various successors do not explicitly explain what are unobserved factors in wage determination and what causes wage differentials across individuals. Among all possible unobserved factors, I examine the role of initial wage in understanding the determination of future wages.

I present a human capital accumulation model showing the theoretical predictions of initial wage effects on future wages. I estimate the future wage equation as a function of initial wage which is decomposed as a systemically explained part and an unexplained random part. My finding is consistent with the model assuming that luck is random and independent over time and that there is no human capital depreciation (for relatively young workers). Then a *positive constant* effect from initial luck is predicted and supported by the estimation results.

This suggests that the level of entry wage, specifically its random luck portion rather than the actual productivity portion related to observables, provides an additional incentive for workers to invest more effort at work and maintain their wages high throughout their working life.

Some issues call for further research. One may argue that the random component of initial wage may be related to an individual's ability not observed by economists but (partially) observed by firms who made a hiring. If this is true, then the initial wage effects may reflect unobserved individual heterogeneity rather than luck. To address this concern, one needs some instrumental variables that are (i) correlated with the initial

wage, (ii) not correlated with an individual's future wage, and (iii) not perfectly correlated with the X variables used in Regressions 1 and 2. These three conditions are difficult to satisfy simultaneously. The NLSY data provides only an individual's parents' education, siblings' education and siblings' gender, which can be considered legitimate instruments that satisfy (ii) and (iii). However, these variables have poor explanatory power for individual's initial wage. Regression of entry wages on these variables gives an adjusted R^2 of 0.021. Thus, (i) is violated. In fact the only variables that are (relatively strongly) correlated with initial wages are an individual's own AFQT score, education, and sex, but all these variables are part of the X variable and therefore cannot be used as instruments. Information about family members such as siblings' initial wages and their AFQT score may serve as good candidates for legitimate instruments. However, the NLSY data does not contain this information. I am left with a 'weak' instrumental variable problem. Unless I encounter some 'strong' instruments correlated with innate ability but not part of the X variable (own IQ score and education level), any attempt to rely on instruments fails to properly control unobserved ability in initial wages. Given that it is unlikely that firms can observe all individuals' heterogeneity (ability), it seems fair to say that the random components of initial wage is at least partially attributable to luck. Further research is needed to examine exactly what percentage of the initial wage can be attributable to luck.

Another question is what exactly this *luck* in initial wage means. Obviously, educational attainment, experience, and other well-accepted determinants of wages do not explain it. It can be a matching quality in job searching or at work. It can be an

economic-wide factor such as an unbalanced technology advance favoring some subgroup of workers. It may represent the signaling about how good a worker is, which is perceived by her first employer. In the sense that initial wage is an outcome of both the observed and unobserved productivity of a worker, the random component of initial wage, which I call 'luck,' can be used as an alternative proxy variable for unobserved ability. However, more investigation is necessary to verify which is responsible for the persistent impact of initial luck on post wages.

CHAPTER IV
HMO PLANS, SELF-SELECTION, AND
UTILIZATION OF HEALTH CARE SERVICES

I. Introduction

Since the HMO Act was passed in 1973, HMOs (Health Maintenance Organizations) have become one of the most popular types of managed care plans. Faced with a dramatic increase in health care costs, HMOs implement utilization reviews, a tight authorization process, and a restricted choice of providers as means of managing utilization and quality.

A. Trends and Relevance

During the last two decades, the number of HMO enrollees has proliferated from 9.1 millions (4% of total population) in 1980 to 76.1 millions (26.4% of total population) in 2001 (Source: Health, United States 2003). Between 1977 and 2001, the percentage of the U.S population under age 65 that joined private insurance HMOs increased dramatically from 3.7 to 27.9 percent (Table 14).

Over the same period, national health expenditures per capita increased from \$1,067 to \$5,035, and total national health expenditures as percent of GDP rise from 8.8% to 14.1%. Out of total national health expenditures, the share of private expenditure decreased from 57.3% to 54.6%.

Motivated by relatively slow growth in private health care expenditures and the prevalence of HMOs in the private insurance market, I investigate the effect of HMO enrollment on the utilization of two types of health care services: office-based visits and

TABLE 14--TRENDS IN PRIVATE HEALTH INSURANCE: HMO ENROLLMENT 1977-2001
(UNDER AGE 65)

	1977	1987	1998	2001
Percentage with Private Insurance	79.4	77.7	72.3	71.5
Percentage with Private Health Insurance HMO	3.7	17.1	30.5	27.9

(Source: *Health, United States, 2003*; Amy K. Taylor, Karen M. Beauregard and Jessica P. Vistnes, 1995)

hospital outpatient visits to answer the question of policy effectiveness: Do HMOs succeed in limiting medical service utilizations relative to other insurance arrangements? One complication in this analysis is the endogeneity in health plan choice decisions. The hypothesis regarding self-selection is examined: the utilization reduction effect of HMOs observed in many studies may be a consequence of the selective enrollment of a healthier population in HMO plans, not of the more efficient medical care delivery management of HMOs. To address the issues of non-negativity and high frequency of zero observations for the dependent variables, I employ the censored regression model of utilization.

B. *Literature Review*

Some studies have shown that HMOs are associated with lower hospitalization rates, shorter inpatient hospital days, and the same or more office visits (Sherry Glied, 2000; Robert Miller and Harold Luft, 1994; David M. Cutler and Richard J. Zeckhauser, 2000). However, no conclusive evidence is provided on the hypothesis that HMOs effectively reduce the utilization of health care services. In regard to physician outpatient visits, a comprehensive review is provided in Miller and Luft (1994). They report that among 14 observations from 10 studies, seven show lower physician service use (of which 3 results are statistically significant) while seven find higher use (of which five were statistically

significant). With recent data, 9 of 10 observations document either higher or little difference in HMO plan office visits compared with conventional indemnity (or fee-for-service) plans. There is no evidence that compared to the behavior of indemnity plan members, substantially lower hospital use by HMO enrollees is accompanied by substantially higher use of physician services.

The dramatic changes in form among different managed care plans during the 1990's can be one reason for these seemingly unsettled conclusions. In addition, a statistical reason is discussed by Janet Hunt-McCool, B. F. Kiker, and Ying Chu Ng (1994), who show that the sign and significance of the effects of HMOs on physician office visits and hospital inpatient care are sensitive to a choice of parametric specifications on the functional form of utilization. This sensitivity may be attributed to the ignorance of two data characteristics of observed health care utilization: (1) it is always non-negative, and (2) it contains a high frequency of zero events.

Another statistical aspect that brings ambiguity into the empirical literature is the endogeneity problem of health plan choice decisions jointly determined with utilization decisions (A. Colin Cameron, Pravin K. Trivedi, Frank Milne, and John Piggott, 1988; Donna Gilleskie, 1998). Evidence on self-selection in health plan choice varies across studies depending on data choice, definition of selection, and estimation specification. In most cases, the analysis is focused on the role of demographic, economic, and health related factors in determining health plan choice. Bryan Dowd, Roger Feldman, Steven Cassou, and Michael Finch (1991) find that selectivity bias is small and insignificant. Similarly, Taylor, Beauregard, and Vistens (1995) suggest that HMO enrollees are

younger but not much healthier than those in fee-for-service (FFS) plans, implying that self-selection based on health condition is not a major factor in the cost savings by HMO plans. On the other hand, Marilyn Jackson-Beeck and John H. Kleinman (1983) document that among FFS members, those who are younger and use less health care services switch into HMOs. Joan Buchanan and Shan Cretin (1986) report that younger populations and families with lower income and lower annual medical expenditure prior to switching into HMO plan select HMOs. Evidence presented in Hunt-McCool, Kiker, and Ng (1994) is mixed: positive selection bias on hospital inpatient care, but negative bias on physician office visits. To avoid selection bias from a nonrandom sample, some studies (Willard G. Manning, Joseph P. Newhouse, Naihua Duan, Emmett B. Keeler, and Arleen Leibowitz, 1987; James Ligon, 1993; Ligon 1994) use experimental data of the RAND Health Insurance Experiment. However, the obsolescence of this experiment and the continuously changing health care system leave findings in these studies with little relevance.

Since it is not obvious that health plan choice is independent of the decision on health care utilization, it is important to explicitly address the issue of self-selection in any empirical research on health care service utilization. Tu, Kemper, and Wong (1999) acknowledge the possible selectivity bias. Michelle Mello, Sally Stearns, and Edward Norton (2002) explicitly consider the issue of self-selection and find a substantial selection bias in effects of health insurance choice on utilization. By contrast, Dowd, Feldman, Cassou, and Finch (1991) find contradictory evidence that selectivity bias is neither large nor statistically significant.

Various estimation methods are employed to overcome the limitation of previous studies and to achieve joint estimation of plan choice and utilization, at the same time respecting the unique data characteristics for observed utilizations (Dowd, Feldman, Cassou, and Finch, 1991; Donald S. Kennel and Joseph V. Terza, 2001; Partha Deb and Trivedi, 2002). Due to its computational intensity to practice, each method is used as an exemplary application without any general consent on its implementation.

C. New Contribution

Acknowledging enormous variation in data, estimation methods, and results in the literature about selection and utilization performance of HMOs, I attempt to correctly evaluate the effects of HMO plans on the utilizations of different sites of medical services. First, my study uses recently released, nationally representative data, the Medical Expenditures Panel Survey 2000. Combined, the household component and medical condition component provide comprehensive information about individuals' health-related condition and utilizations across various service sites as well as usual demographic and socioeconomic status. Subjective evaluation on the quality of health care gives me a way to understand the quality management of HMOs. Few of the previous studies use a nationally representative sample. The most recent one used in those studies, the National Medical Expenditure Survey, was collected in 1987. As the structure and enrollment of HMOs changed considerably over last decades, information revealed from recent data may have meaningful policy implications in health care reform debates.

Secondly, I explicitly deal with the problem of a non-trivial number of zero observations using the censored-at-zero MLE model. When ignored, a misspecification problem is a concern since the dependent variable with excessively many zeros may not follow a normal distribution as assumed. To preserve the efficient handling of estimations, I employ a censored MLE model, treating zero values as a consequence of the censoring-at-zero. At the same time, I control the possible bias from endogenous health plan choice decisions using the relatively simple method of correction of Vella (1993).

The remainder of this paper is organized as follows. Section II presents the econometric model where utilization of health care services is determined conditional on the endogenous choice of insurance plan. Details of econometric implementation incorporating self-selection and non-trivial number of zero values for the dependent variables are described. Section III describes the data. The empirical results are presented in Section IV. Section V concludes with comments and suggestions for further research.

II. Econometric Model

I model the non-negativity and non-trivial number of zero observations for the dependent variables within the framework of the censored-at-zero regression. Let Y_i^* denote the value of the latent variable underlying the observed values of utilization, Y_i . The utilization equation is formulated as:

$$(3.1) \quad Y_i^* = X_i\beta + \delta HMO_i + u_i,$$

where X_i indicates exogenous variables, either continuous or discrete. HMO_i is a binary variable that I allow to be endogenous. The censoring takes the form of $Y_i = \max\{0, Y_i^*\}$, that is,

$$(3.2) \quad Y_i = Y_i^* \text{ if } Y_i^* > 0 \text{ or equivalently } u_i > -\{X_i\beta + \delta HMO_i\}$$

and $Y_i = 0$, otherwise.

For the possible endogeneity that the unobservable characteristics in Equation (3.1) are correlated with the determinants of a binary explanatory variable, which is HMO_i in this analysis, Vella (1993) suggests a two-step procedure to obtain consistent estimates. Let the latent variable denoted by H_i^* represent the indirect utility associated with insurance plan that an individual i has chosen (Daniel McFadden, 1980). The value of H_i^* depends on some individual-specific and plan-specific characteristics, Z_i given as $H_i^* = Z_i\gamma + \varepsilon_i$. Then, the observed insurance choice indicator HMO_i is determined based on H_i^* as follows:

$$(3.3) \quad HMO_i = 1 \text{ if } H_i^* > 0 \text{ and } HMO_i = 0 \text{ if } H_i^* \leq 0.$$

In (3.2) and (3.3), errors, u_i and ε_i , are assumed to be jointly normally distributed with zero means, variances σ_u^2 , σ_ε^2 (normalized to 1) and covariance $\sigma_{u\varepsilon}$ expressed as

$$\begin{pmatrix} u \\ \varepsilon \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \sigma_{u\varepsilon} \\ \sigma_{u\varepsilon} & 1 \end{pmatrix} \right]. \text{ In the first step procedure, I estimate the parameters from}$$

Equation (3.3) using the probit model, and obtain $\hat{\gamma}$.

I rewrite Equation (3.2) in terms of its conditional expectation

$$(3.4) \quad E(Y_i|X_i, HMO_i) = X_i\beta + \delta HMO_i + E(u_i|X_i, HMO_i) \text{ if } Y_i^* > 0.$$

Note that $E(u_i|X_i, HMO_i) = E(u_i|HMO_i) \neq 0$ since u_i and ε_i are correlated. Under the bivariate normality assumption, the conditional expectation of u_i conditional on the endogenous binary variable can be expressed as:

$$(3.5) \quad E(u_i|HMO_i = 1) = E(u_i|\varepsilon_i > -Z_i\gamma) = \sigma_{u\varepsilon} \left[\frac{\phi(Z_i\gamma)}{\Phi(Z_i\gamma)} \right]$$

and

$$(3.6) \quad E(u_i|HMO_i = 0) = E(u_i|\varepsilon_i \leq -Z_i\gamma) = \sigma_{u\varepsilon} \left[\frac{-\phi(Z_i\gamma)}{1 - \Phi(Z_i\gamma)} \right],$$

where ϕ and Φ are the probability density function and the cumulative distribution function of the standard normal distribution. Evaluated at the consistent probit estimates $\hat{\gamma}$ of (3.3), the generalized residuals denoted as \hat{v} are given as:

$$(3.7) \quad \hat{v} \equiv \left[\frac{\phi(Z_i\hat{\gamma})}{\Phi(Z_i\hat{\gamma})} \right] \text{ if } HMO_i = 1$$

and

$$(3.8) \quad \hat{v} \equiv \left[\frac{-\phi(Z_i\hat{\gamma})}{1 - \Phi(Z_i\hat{\gamma})} \right] \text{ if } HMO_i = 0.$$

Using Equations (3.5)-(3.8), I rewrite Equation (3.4) as:

$$(3.9) \quad E(Y_i|X_i, HMO_i) = X_i\beta + \delta HMO_i + \sigma_{u\varepsilon} \hat{v} \text{ if } Y_i^* > 0.$$

Then Equation (3.1) can be rewritten as

$$(3.10) \quad Y_i^* = X_i\beta + \delta HMO_i + \sigma_{u\varepsilon} \hat{v} + e_i.$$

where the error, e_i , can be assumed to be uncorrelated with ε_i . The likelihood function for the censored regression model with endogeneity correction of Equation (3.10) can be derived as follows:

$$(3.11) \quad L = \prod_{i=1}^n \Phi\left(-\frac{X_i\beta + \delta HMO_i + \sigma_{u\varepsilon}\hat{v}}{\sigma_u}\right)^{I(Y_i=0)} \cdot \frac{1}{\sigma_u} \phi\left(\frac{Y_i - \{X_i\beta + \delta HMO_i + \sigma_{u\varepsilon}\hat{v}\}}{\sigma_u}\right)^{I(Y_i>0)}$$

The maximum likelihood estimation of Equation (3.11) produces the consistent estimate of δ , indicating the effect of HMO_i on utilization. The coefficient of \hat{v} would give evidence about the role of self-selection in health plan choice.

III. Data

In this analysis, I use data from the 2000 wave of the Medical Expenditure Panel Survey (MEPS). The U.S. Agency for Health Care Policy and Research (AHCPR) and the National Center for Health Statistics (NCHS) collect this nationally representative data to provide information on demographic characteristics, health status, health insurance coverage, employment status and earnings, and various measures of health care utilization and expenditures for the U.S. civilian non-institutionalized population.

I limit my focus on the privately insured non-elderly (aged 18-64) sample. Individuals with Medicare, Medicaid or other types of public insurance are eliminated because this study intends to understand the choice between HMO plans and non-HMO plans among individuals who make decisions in the private market for health insurance. The final sample includes individuals who are covered only by any private health insurance.¹⁹ If individuals are covered by a private health insurance supplementing Medicare coverage, they are excluded from the final sample (N=7,474). The rate of

TABLE 15--DEMOGRAPHIC CHARACTERISTICS
(AGE 18-64, PRIVATELY INSURED)

	Total	HMO	Not HMO
Total	7474	4252	3222
Percentage	100.0	56.9	43.1
Age			
18-24	.100	.108*	.091
25-44	.473	.492*	.449
45-54	.263	.258*	.271
55-64	.163	.143*	.190
Race/Gender/Marital Status			
White	.706	.650*	.780
Black	.115	.131*	.094
Hispanic	.419	.181*	.106
Male	.473	.469	.478
Married	.688	.677*	.704
Employed		.884*	.858
Education			
Less than High School	.149	.156*	.140
High School Graduates	.477	.490*	.459
More than High School	.374	.353*	.401
Poverty Status of Family Income			
Poor	.026	.025	.028
Near Poor	.014	.016*	.011
Low	.083	.088*	.077
Middle	.341	.348*	.331
High	.536	.523*	.554
Family size			
1	.123	.126	.119
2	.282	.258*	.314
3	.205	.203	.207
4+	.390	.413*	.360
Place of residence			
Urban (MSA)	.801	.854*	.730
Northeast	.171	.205*	.127
Midwest	.251	.190*	.332
South	.366	.323*	.391
West	.222	.276*	.150

* indicates that the estimate is statistically different from the corresponding estimate for the non-HMO sample.

HMO enrollment is 56.9% (4,252 in my final sample). According to the MEPS description, the presence of gatekeepers is questioned only if an individual is previously reported as non-HMO members. Hence, it is not possible to identify the role of gatekeepers in the efficiency of utilization management in HMO plans.

TABLE 16--HEALTH STATUS
(AGE 18-64, PRIVATELY INSURED)

	Total	HMO	Not HMO
Perceived Health Status			
Excellent/Very Good/Good	.931	.929	.934
Fair/Poor	.068	.071	.065
Number of Conditions (ICD9codes) (Mean)	3.03	2.92*	3.16
Number of Conditions (ICD9codes) (%)			
0	16.2	16.4	15.9
1-2	36.4	37.1	35.3
3+	47.5	46.5	48.8
Priority List	.315	.304*	.330
Functional Limitation			
IADL	.005	.005	.006
ADL	.003	.004*	.002
Social Limitation	.016	.014*	.020
Cognitive Limitation	.009	.010	.007
Unable to Do Activity	.013	.012	.014
Any Limitation	.138	.132*	.145
Diagnosed Chronic Conditions			
Arthritis	.011	.010	.012
Asthma	.041	.043	.038
Back Problem	.136	.127*	.147
Cancer	.036	.033*	.039
Depression	.133	.139*	.125
Diabetes	.052	.052	.053
Emphysema	.049	.042*	.059
Gallbladder	.010	.010	.009
Hypertension	.151	.151	.151
Ischemic	.027	.025	.030
Health Risks/Attitudes			
Current Smoker	.191	.190	.193
Likely to Take Risks	2.13	2.14	2.12
No Need for Health Insurance [^]	1.44	1.45	1.42
Insurance No Worth Of Cost [^]	2.03	2.01*	2.06
Overcome Illness without Medical Help [^]	2.17	2.14*	2.20
Receiving Routine Medical Care	.705	.706	.703
Overall Quality of Health Care	8.07	7.93*	8.25
Presence of Gatekeeper			.247
Out-of-Pocket Payment			
Amount	415.8	358.6*	491.4
Ratio of Total Payment	.339	.313*	.373

[^] indicates that the measurement is the following; 1 disagree strongly, 2 disagree somewhat, 3 uncertain, 4 agree somewhat, and 5 agree strongly.

Descriptions and summary statistics for the characteristics of HMO enrollees and non-HMO enrollees are presented in Tables 15-17.

A. *Demographic Characteristics*

Table 15 presents the demographic characteristics of HMO and non-HMO enrollees aged 18-64 who are covered by either type of health plan for all of 2000.²⁰ Comparisons show that HMO enrollees are younger; a higher percentage of HMO members are between 18 and 44 years old, while a smaller percentage of them are above age 45. A relatively smaller percentage of HMO members are white: 65% compared to 78% of non-HMO members. More blacks and hispanics are enrolled in HMO plans. HMO members are less educated; only 35.3% are more than high school educated, compared to 40.1% of non-HMO enrollees.

People enrolled in HMO plans are likely to be from families with income ranging from near poor to middle. High income families are more likely to enroll in non-HMO plans. HMO members seem to come from very large families as they are more likely to be blacks and hispanics who tend to have more children than whites and live as extended families across generations.

People enrolled in HMOs are more likely to live in urban areas and in the Northeast or West, while non-HMO members mostly live in the Midwest and the South. This may be due to the different penetration rate of HMOs across regions.

B. *Health Status and Insurance*

Table 16 compares various measures of health status for HMO and non-HMO members in 2000. These data show little evidence that individuals enrolled in HMOs are relatively healthier than those in non-HMO plans. Self-rated health status, various measures of physical limitations, and diagnosed diseases are similar for these two groups.

However, people with certain chronic conditions are slightly less likely to enroll in HMOs than in non-HMOs. HMO members have a smaller number of conditions (ICD9codes²¹) and are less likely to suffer from a disease categorized in the priority list.²² The percentage of enrollees with back problem, cancer, and emphysema is lower among those in HMOs, while HMO members are more likely to have ADL and depression compared with non-HMO members. For those with only HMO coverage all year, 3.3 percent have cancer compared with 3.9 percent of those with non-HMO coverage all year. The rates for emphysema are 4.2 percent compared to 5.9 percent. Although these differences are statistically significant, they are not sizable enough to represent risk segmentation based on health risk. There are no differences in the percentage of HMO or non-HMO enrollees with arthritis, asthma, diabetes, gall bladder, hypertension, and ischemic heart diseases.

Health risks and attitudes, such as being a current smoker and being likely to take risks are examined. There are no statistically significant differences with respect to their risk-taking behaviors. Regarding the attitudes towards health insurance and quality of health care, HMO members are more likely to appreciate their health insurance and medical care; they believe more strongly that health insurance is worth to the cost and that medical help is needed to overcome any illness. However, the evaluation of overall quality of health care is statistically significantly smaller among HMO members than non-HMO members, hinting at quality deterioration in HMO plans.

HMO plans features lower cost sharing, creating financial incentives for enrollees to use more services than for people with non-HMO insurance, all else equal. The last two

TABLE 17--UTILIZATION OF HEALTH CARE SERVICES
(AGE 18-64, PRIVATELY INSURED)

		Utilization					
		Total		HMO		Not HMO	
		Zero (%)	Nonzero	Zero (%)	Nonzero	Zero (%)	Nonzero
Office-Based Visits		26.8	6.34	27.4	6.17*	26.0	6.57
Hospital Outpatient Visits		85.4	2.58	87.1	2.73	83.3	2.41
Cost of Utilization: Out-of-Pocket Expenditure							
Rate of Cost Sharing	Office-Based	.257		.210*		.318	
	Hospital	.123		.083*		.210	
	Outpatient						
Out-of-Pocket Unit Price of Service (In Dollars)	Office-Based	26.8		18.3*		37.7	
	Hospital	54.8		30.5*		79.7	
		Outpatient					

^aThe rate of cost sharing is obtained as total annual out-of-pocket payments for the service divided by total annual medical expenditures. The out-of-pocket unit price of service is defined as total annual amount of out-of-pocket payments for the use of a type of service divided by total number of visits to that service.

rows in Table 17 show that the annual average amount of out-of-pocket payment per person and its ratio to total health care payment are both lower for HMO enrollees. As suggested in Tu, Kemper, and Wong (1999), this implies that HMOs may increase the use of medical care among enrollees. As far as health conditions not being significantly different between HMO and non-HMO members and HMO members being from families with less than high income level, the possible segmentation via insurance choice may occur based on the financial risk each individual is willing to hold.

C. Utilization of Health Care Services

I consider two kinds of health services: office-based visits and hospital outpatient visits. Table 17 documents the pattern of utilization by HMO members and non-HMO members. A higher percentage of HMO members tend to make no use of office-based services and outpatient services. However, the average number of visits is statistically significantly smaller for HMO members only for office-based visits. Importantly, the

frequency of zero observations for both measures of utilization ranges from 26% to 87%, indicating that caution is needed when estimating the utilization function because it is not suitable to assume that this kind of measure of utilization follows a normal distribution with no probability hike at zero.

Evidently, the financial incentive for consumers is well provided in HMOs. The ratio of total out-of-pocket payments to total medical expenditures is substantially higher for non-HMO members. The amount of out-of-pocket payment an individual pays on average per visit would more than double if not covered by HMOs. This implies that for costly services, HMO members may have an incentive to increase utilization (Tu, Kemper, and Wong, 1999).

IV. Estimation Results

A. Insurance Choice

To examine the independent marginal effect of the characteristics presented in Tables 15 and 16 on insurance plan choice, a probit regression is estimated. As shown in Table 18, many of the characteristics that are important in describing enrollment differences in Tables 15 and 16 remain important in the marginal effect analysis. For example, younger individuals prefer HMOs. Blacks and hispanics are more likely to be HMO members compared to whites and other ethnic groups. HMO members are more likely to be employed and less likely to be more than high school educated. Regional and MSA status also remains important in explaining the choice of health plan among non-elderly adults. People in the Northeast and West areas are more likely to enroll in HMOs, supporting the view that HMO enrollment rate is associated with geographical variations

TABLE 18--PROBIT ESTIMATION OF BINARY HEALTH INSURANCE PLAN CHOICE

Variable	Coefficient	Std. Dev.	Marginal Effect
Constant	.530	.211	
Age	-.005	.002	-.0019**
Black	.232	.072	.0893***
Hispanic	.164	.067	.0638**
Male	-.032	.044	-.0127
Married	-.041	.052	-.0161
Employed	.202	.060	.0799***
Less than High School	-.083	.066	-.0328
More than High School	-.140	.044	-.0552***
Family Income	.014	.025	.0069
Family Size	.018	.017	.0053
Urban	.302	.050	.1197***
Northeast	.398	.059	.1509***
Midwest	-.210	.050	-.0829***
West	.454	.057	.1720***
Fair/Poor Health Status	.059	.079	.0231
Number of Conditions (ICD9codes)	-.029	.008	-.0113***
Priority List	-.021	.046	-.0082
Diagnosed Chronic Conditions			
Arthritis	.177	.174	.0695
Asthma	.104	.090	.0409
Cancer	.055	.091	.0218
Depression	.114	.052	.0447**
Diabetes	-.132	.083	-.0520
Emphysema	-.098	.080	-.0387
Gall Bladder	.027	.166	.0108
Hypertension	.137	.057	.0539**
Ischemic	.035	.101	.0136
Health Risks/Attitudes			
Current Smoker	.030	.053	.0119
Likely to Take Risks	.003	.018	.0011
No Need for Health Insurance	.057	.028	.0226**
Insurance No Worth of Cost	-.018	.018	-.0070
Overcome Illness without Medical Help	-.057	.018	-.0226***
Receiving Routine Medical Care	.058	.066	.0229***
Overall Quality of Health Care	-.056	.012	-.0222***
Out-of-Pocket Payment/Total Payment	-.532	.080	-.2093***
Log-Likelihood		-2790.4	

of the penetration rate based on region-specific conditions.²³ Lower cost sharing makes people enroll in HMOs, implying a possible increase in the use of health care service due to this financial incentive for consumers. The negative significant effect of overall rating on health care suggests a negative correlation between HMO enrollment and customer

TABLE 19--CENSORED REGRESSION OF UTILIZATION: OFFICE-BASED SERVICES

Variable	Uncorrected CMLE		Corrected CMLE	
	Coefficient	Std. Dev.	Coefficient	Std. Dev.
HMO Enrollment	-.076	.314	17.2***	2.87
$\hat{\nu}$ (Endogeneity Correction)	-	-	-10.7***	1.77
Constant	-.855	1.58	-10.5***	2.33
Age	-.014	.016	.015	.017
Black	-1.04*	.542	-2.60***	.610
Hispanic	-.683	.496	-1.64***	.535
Male	-.587*	.331	-.320	.333
Married	-.155	.392	-.022	.396
Employed	-.261	.454	-1.60***	.509
Less than High School	.779	.501	-.092	.513
More than High School	.362	.333	1.28***	.367
Family Income	.011	.187	-.120	.189
Family Size	.076	.126	-.010	.128
Urban	.562	.386	-1.51***	.518
Northeast	1.35***	.447	-1.42**	.643
Midwest	.546	.390	1.81***	.444
West	-.013	.434	-2.99***	.660
Fair/Poor Health Status	1.44**	.575	1.04*	.579
Number of Conditions (ICD9codes)	1.42***	.062	1.54***	.067
Priority List	.238	.351	.443	.353
Any Limitation	2.44***	.431	2.57***	.431
Diagnosed Chronic Conditions				
Arthritis	-1.54	1.32	-2.57*	1.33
Asthma	-2.15***	.673	-2.70***	.679
Cancer	.974	.691	.355	.694
Depression	.635*	.387	.052	.401
Diabetes	-.252	.624	.461	.637
Emphysema	-1.17*	.608	-.495	.625
Gall Bladder	-1.26	1.22	-1.37	1.26
Hypertension	-1.20***	.437	-2.17***	.458
Ischemic	-1.15	.773	-1.46*	.770
Health Risks/Attitudes				
Current Smoker	-.209	.601	-.331	.606
Advised to Quit Smoking	-.802	.733	-.961	.737
Likely to Take Risks	.040	.137	.032	.137
No Need for Health Insurance	-.345*	.203	-.561***	.207
Overcome Illness without Medical Help	-.257*	.138	.121	.153
Receiving Routine Medical Care	2.03***	.504	1.45***	.514
Overall Quality of Health Care	.012	.087	.343***	.103
Out-of-Pocket Payment/Total Payment				
Log-Likelihood		-15537.1		-15366.5

satisfaction. Self-perceived health status and risk-taking behaviors remain insignificant.

In contrast to Tables 15 and 16, marital status, family size, and family income as poverty

level lose their significance in affecting health plan choice. In addition, the presence of a condition in the priority list and some chronic problems such as cancer and emphysema are no longer statistically significant.

On the other hand, as people agree more strongly with the statement that they do not need health insurance, they are more likely to enroll HMOs. However, HMO members are likely to feel more need for medical care to overcome illness. These results show that HMO enrollees are less willing to purchase health insurance but potentially more dependent on health care upon the occurrence of any sickness. People with certain chronic conditions such as depression and hypertension are more likely to be HMO members.²⁴

B. *Health Care Services*

Tables 19, 20, and A7 present estimation results of alternative specifications on health care utilization functions. As discussed in Section 3, the potential endogeneity of health plan choice and the non-negativity associated with excess zero events of the dependent variable are of particular concern. For this reason, six sets of results are presented: (1) OLS results of level linear model accounting for neither endogeneity nor non-negativity; (2) OLS results of level linear model associated with Vella's correction accounting only for endogeneity; (3) OLS results of log-linear model accounting only for non-negativity; (4) OLS results of log-linear model with Vella's correction accounting only for endogeneity; (5) Censored MLE results without endogeneity correction; and (6) Censored MLE with endogeneity correction. In Tables 6 (office-based visits) and 7 (hospital outpatient visits), I report results from (5) and (6).

TABLE 20--CENSORED REGRESSION OF UTILIZATION: HOSPITAL OUTPATIENT SERVICES

Variable	Uncorrected CMLE		Corrected CMLE	
	Coefficient	Std. Dev.	Coefficient	Std. Dev.
HMO Enrollment	-.395	.282	29.4***	2.95
\hat{v} (Endogeneity Correction)	-	-	-18.4***	1.82
Constant	-8.70***	1.49	-26.8***	2.41
Age	.065***	.015	.125***	.016
Black	-.455	.525	-3.28***	.602
Hispanic	.396	.461	-1.53***	.502
Male	-.774**	.307	-.486	.309
Married	.562	.367	.818**	.372
Employed	-.585	.389	-2.92***	.455
Less than High School	.121	.452	.933**	.465
More than High School	-.306	.302	1.33***	.343
Family Income	-.173	.171	-.348**	.173
Family Size	-.161	.122	-.340***	.124
Urban	-.719**	.337	-4.24***	.487
Northeast	1.86***	.404	-2.86***	.615
Midwest	1.76***	.348	4.05***	.422
West	-.144	.412	-5.23***	.653
Fair/Poor Health Status	.541	.474	-.013	.478
Number of Conditions (ICD9codes)	.562**	.051	.837***	.059
Priority List	.250	.309	.532*	.311
Any Limitation	.480	.367	.662*	.368
Diagnosed Chronic Conditions				
Arthritis	2.39***	.925	.619	.926
Asthma	-.495	.542	-1.39***	.544
Cancer	2.14***	.527	1.15**	.529
Depression	-.272	.323	-1.40***	.344
Diabetes	-.737	.530	.580	.546
Emphysema	-.889*	.512	.127	.535
Gall Bladder	2.20**	.909	2.00**	.922
Hypertension	-.619*	.373	-2.12***	.403
Ischemic	.701	.599	.257	.593
Health Risks/Attitudes				
Current Smoker	-1.22**	.594	-1.52**	.598
Advised to Quit Smoking	1.38**	.698	1.11	.703
Likely to Take Risks	-.057	.125	-.106	.126
No Need for Health Insurance	-.279	.200	-.698***	.206
Overcome Illness without Medical Help	-.084	.127	.611***	.146
Receiving Routine Medical Care	.552	.497	-.165	.507
Overall Quality of Health Care	-.081	.078	.499***	.097
Out-of-Pocket Payment/Total Payment				
Log-Likelihood		-4161.3		-4061.2

Table A7 presents all other results from (1) to (4) for comparison.²⁵

C. Office-Based Visits

As shown in Table 18, the coefficient of the HMO enrollment dummy variable is positive and highly significant only when correcting for self-selection. HMOs, which are usually seen as having strong restrictions on utilization, in fact encourage the use of office-based health care services. The negative and highly significant coefficient of the endogeneity correction term, \hat{v} , can be interpreted as the fact that the unobserved factors that increase the probability of being enrolled in an HMO lead to lower utilization relative to that of the randomly assigned HMO enrollees. This means that self-selection in health plan choice occurs in a favorable way for HMO plans. Considering the finding that HMO enrollment is not significantly affected by various health conditions, I suggest that the introduction of HMO plans does not succeed in revealing hidden health care needs and sorting populations into different plans accordingly.

If a person is employed, she uses less medical services as her employment status indicates whether her health condition is good enough for her to afford to work. People of more than high school education are likely to use more health care services. This is well documented in the literature showing that the more educated, the more they are concerned with their health because longer working life expectancy is important for them to compensate the opportunity cost they have paid for additional years in education. Racial minorities such as blacks and hispanics tend to depend less on office-based visits. This suggests that cultural differences or health care disparity from the provider side across ethnicity may be an important factor in determining utilization patterns. In regions

where the higher percentage of HMO enrollees dwell (Table 15), utilization is relatively lower; the MSA, the Northeast, and the West show lower utilization. Notably, age and income are not generally significant. My sample consists of individuals with private health insurance coverage. Therefore, out of pocket payments for health care services are relatively small as a fraction of total expenditures and thus utilization is not elastic to income level.

While perceived health condition worse than good, number of conditions, and having any limitation in activity or a medical condition listed as priority lead to more utilization, some chronic diseases have negative effects on utilization; as each type of disease requires different procedures and treatments in a specific way, having one kind of disease does not mean necessarily higher utilization of one specific type of health service. Visits to office-based health providers are affected by attitudes regarding health insurance; if a person believes more strongly that she needs a health insurance, she is likely to use more services. She may believe so since she expects some future occurrence of her health condition, which will require the financial establishment to pay for it. Also not surprisingly, having routine medical check-ups and higher rating on overall quality of health care have significantly positive effects on the level of utilization.

D. Hospital Outpatient Visits

Similar to the case of office-based service, HMO enrollment increases the use of services, and self-selection is positive for HMOs. Interestingly, age, and family income and size become statistically significant, giving intuitively probable signs: older people visit the hospital more often as outpatients. People from larger families and lower-

income families seem to make a smaller number of visits. These findings can be explained by the relatively higher per-visit price of hospital outpatient services relative to office-based care, which should be financed from consumers' own resources; as shown in Table 4, among non-HMO members, the self-financed amount of per-visit to hospital outpatient services is on average \$79.7, which is much higher than the \$37.7 per-visit to office-based services. For HMO members, these amounts are \$30.5 and \$18.3, respectively. As the cost sharing portion of total payments is more burdensome on consumers, family size and family income constrain the use of hospital outpatient services. In the case of relatively cheap office-based services, these family budget constraints may not restrict utilization in a significant way. Similarly, only a person who manages to accumulate some resources over time can afford to make a relatively expensive visit to the hospital.

V. Conclusion

In this study, I use the censored MLE method combined with endogeneity correction to jointly estimate the choice of health insurance plans and health care utilization respecting the possibility of self-selection into insurance plans, and the non-negativity and high frequency of zero events in utilization. I find significant evidence of favorable selection into HMOs; individuals who are more likely to enroll in HMOs are likely to utilize less health care services. HMO enrollees are younger but not particularly healthier than enrollees in non-HMO plans. Often the younger age distribution among HMO members is explained as meaning that HMOs are preferred by people who expect to have children because HMOs have lower out-of-pocket costs for maternity benefits

and pediatric care for children (Taylor, Beauregard, and Vistnes, 1995). Then, the favorable self-selection in health plan choice does not depend on health risk but on financial risk, which is consistent with the finding that HMO enrollment is encouraged by the lower relative burden of cost sharing. Since younger people tend to be more optimistic regarding their health condition and more favorably disposed toward risk-taking when purchasing an insurance plan, they may lean toward an HMO plan regardless of its restrictions on access to services and choice of providers. The arrangement of consumer incentives such as premium, coinsurance rate, and out-of-pocket payments may be more important than the health status of the population in determining their choice of plans.

HMOs encourage the use of office-based and hospital outpatient health services and receive lower evaluation on overall quality of health care. Thus, I conclude that HMOs are not effective in modifying health care use behavior and seem to fail in managing quality and utilization in any significant way.

In sum, this study suggests that demographic and health related factors are less important than generally expected in health insurance choice and utilization of health services. Instead, choice of health plans among individuals appears to depend on financial incentives for consumers. Similarly, the cost effectiveness in terms of utilization performance in a type of health plan may rely on its style of medical care delivery management, such as, provider-side incentive, reimbursement arrangement, and utilization review as well as demand for health care services among consumers. This implies that more investigation of the relationship between health care management

mechanisms and the use of health care services should be conducted to determine which factor is indeed responsible for the success or failure of HMO plans in saving costs. As HMO plans are notorious for their tight utilization control for consumers, the source of cost-saving effects in HMOs may be found in looking at health care provider behaviors. It is possible that providers, not consumers, have an incentive to provide an excessive amount of care or unnecessarily expensive care for their own financial benefit upon a contracted reimbursement mechanism.

An important subject for future empirical work is to implement utilization estimation using a discrete distributional assumption rather than a continuous normal distribution. One modified count model, called the zero-inflated count model (John Mullahy, 1986) is an alternative; by allowing different data generating process for zero observation and nonzero observations, this model explicitly deals with the feature of excess zero events in a count variable assuming a negative binomial distribution. The limitation of this model is concerned with accounting for endogenous regressors. Some econometricians attempt to incorporate the possible self-selection and the zero-inflated count variable, but usually rely on computationally intensive methods and additional specification assumptions to have convergence. Results of any further research on the role of HMO plans in the private insurance market would be relevant to the question of whether the introduction of HMO plans to Medicare and Medicaid is likely to have much of a cost saving impact as supposed and so will pull down the rising trend of government medical expenditures. Much more analysis of these patterns is required before any policy implications can be drawn.

CHAPTER V

SUMMARY

In Chapter II, I conducted a panel analysis to examine the joint decisions of young female college graduates regarding their occupational choices and labor force participation. Due to the advantage of panel estimations, all results are supposed to be robust without any bias from unobserved heterogeneity. I found that contrary to common belief, the presence of a new-born baby does not substantially increase the probability of females being teachers. Rather, college major in education is the most important factor for being teachers, suggesting that the choice of teaching as a career is predetermined during college years, not made after finishing education. However, teachers are more likely to exit the labor force as well as to quit the job when they have a new-born baby, compared to nonteachers. This supports Polachek (1982) in that the teaching profession is relatively favorable for temporary leave; female teachers may return to the job with little wage loss after they leave for maternity.

Relative wages appear to lead females to the teaching profession. This implies that the recent policy to increase wages for teachers may succeed in attracting more teachers, and possibly better teachers.

Chapter III focused on the relationship between entry wages and post wages, which depend on a worker's adjustment in hours of work responding to a random shock in wages. I found empirical evidence that entry wages are positively correlated with post wages until 21 years since the year of starting to work. If a worker is lucky at the beginning (the positive random shock in her entry wage), she will receive higher wages

in the later period of her career. This suggests that the recent increase in wage differentials may be contributed by the persistent effect of the randomness in entry wages.

Results in Chapter IV are more sophisticated in their interpretation due to the problems of adverse selection and moral hazard, which are not explicitly addressed. Both in the descriptive comparison and estimation of marginal effects, health conditions are not particularly important in the choice of health insurance plans, HMOs versus non-HMOs. However, in the utilization analysis, I found strong evidence of favorable self-selection for HMOs, implying that the HMO enrollees are those who potentially use less health care services.

When self-selection is corrected properly, HMO members are likely to use more medical services. This suggests that the tight utilization review in HMOs is not tight enough to reduce the use of health care services. Instead, the consumer incentive of low cost sharing seems to cause the moral hazard problem in the demand for health care services. Cost savings in HMOs may be found on the provider-side incentive in reimbursement arrangements so that providers control the supply of health care services just to meet the necessity. Though people purchase health insurance as a shield against future hazard in health conditions, they choose the plan with more weight on the financial aspect and less weight on health conditions. Therefore, policy reform in health care should be made to assure the affordability of insurance and health care services.

ENDNOTES

¹ Across the literature, different measures for fertility and labor supply are used to find this negative correlation (Martin Browning, 1994). Any measure of ‘fertility’ is found to be negatively correlated with any measure of female labor supply. Common measures of fertility are the presence of a new-born child, the number of children under age 6, number of children under age 16, total number of children in the household, and number of children ever born. Labor supply measures are usually labor force participation or hours worked.

² Nonteachers suffer a 9.5% of wage loss per year out of the labor force.

³ Dolton and Makepeace (1993) use the U.K. college graduates cohort data.

⁴ For teachers, a participation decision is observed only if teaching is chosen.

⁵ The labor force participation equation for teachers uses the sample of females whose current/last occupation is teaching. The nonteachers group include females whose current/last occupation is other than teaching.

⁶ Stinebrickner (2002) shows that contrary to common beliefs, teachers leave their job to stay at home and do not find other occupations. The presence of a new-born baby is suggested as the main reason of this attrition behavior.

⁷ This result is consistent with the findings of Dolton and Makepeace (1993). However, they focus on how responsive the probability for college graduate cohorts of *becoming teachers* is to relative wages.

⁸ For example, the labor force participation information on a female is included in the teacher’s group estimation if she is currently or was most recently teaching in the same year when participation status is reported. In another survey year when she is not teaching, then her labor force participation status is included in the nonteachers’ group estimation.

⁹ Though Dolton and Makepeace (1996) followed the same variable definitions, this approach is problematic. In particular, it is more reasonable to consider that a worker’s labor market status is categorized into three possible cases: non labor force participation, participation as teacher, and participation as nonteachers. Then, rather than a binary choice model, a unordered multiple choice model is preferred. Since the panel estimation of multinomial logit or probit model is computationally intensive, I leave it to further research. A multinomial choice model for investigating teacher-nonteacher comparison in labor market behaviors would be interesting even in a cross-sectional analysis.

¹⁰ NLS-Young Women data heavy attrition rates, which may result in nonrandom sampling problems. When using unbalanced panel sample, the estimation results (not reported here, available upon request) and main conclusions do not change.

¹¹ The wave interval is irregular. The survey years are 68, 69, 70, 71, 72, 73, 75, 77, 78, 80, 82, 83, 85, 87, and 88. The next wave is 1991. Since 1991, the survey has been conducted biannually and has included questions about health condition, history of marriage or labor market activity, and social security and pension.

¹² When restricted to females with at least 16 years of education, the sample becomes small relative to the original sample size: 5,159. This is partly because of the high attrition rate of the NLS-Young Women data, reducing the sample to 2,712 for the balanced panel. The other reason is to make occupational subsamples comparable in their characteristics. Since all teachers in my sample except a few have at least

16 years of education, by removing high school only educated nonteachers, the remaining sample consists of college educated females who are eligible to become teachers and free to choose other jobs. One concern is that many females with no teaching experience are only high school or less educated. This implies that the selection to higher education may be strong among the nonteachers group.

¹³ For this comparison, I define teachers as those who have ever reported their occupation as teaching in elementary or secondary schools. Since occupation can vary over time within an individual, in the switching model estimation, I regard teachers as those who have their current/last job in teaching in any survey year.

¹⁴ Age effects remain consistent with Table 5.

¹⁵ The largest effect is attributed to college major in education in Tables 7 and 8. In the switching model, the effect of relative log wage is indeed the largest among all other explanatory variables including college major in education. All discussions about results in Table 8 are valid for results in the switching model reported in Table 8 as well.

¹⁶ The panel logit estimations both in the fixed effects and in the random effects are implemented. The results are mostly consistent with the findings from the probit estimation reported here, but weak in significance.

¹⁷ Among these 752 individuals, I only consider those who have started to work no later than 1985. Then we are left with 716 individuals. All 36 individuals excluded from my final sample are high school graduates or less than high school educated. Unless some kind of interruption in schooling happens, these individuals are supposed to finish all schooling by age 18. If they have not started to work by 1985 (age 20-27), it implies that they spend 2-9 years without working. By restricting my sample to those who started working by 1985, I allow only limited years of job searching or after school training after finishing all education. In this way, I may exclude a possible discontinuous career effect on estimation results.

¹⁸ The remaining results of the entry wage estimation are in Table A3. Post wage estimations are briefly reported in Table A4. In Table A5, results from different specification of initial wage estimations are presented. In short, the results are consistently similar to Table 13.

¹⁹ I exclude individuals who have multiple coverage as the combination of private and public insurance because their utilization of health care services is reported as a total annual amount so that it is difficult to sort out what portion of the total annual number of visits to specific health services are associated with their coverage and choice of a private insurance plan. For a similar reason, being 'privately insured' is defined as being insured by any private insurance throughout the entire year 2000. Individuals may change their coverage status and insurance plan at any point within year. Hence, based on the monthly insurance status information, I figure the sample with only private insurance for every month in the year 2000.

²⁰ I concentrate on the results for persons enrolled only in HMO and non-HMO plans for the entire calendar year. MEPS 2000 provides the enrollment status at three different points during a year. Based on this information, HMO enrollment in my analysis means that a person is reported to be enrolled in HMO plans throughout a year. Because a person may enroll in both types of plans by switching plans at some point during the year, any conclusions drawn from these statistics would be less meaningful and perhaps misleading.

²¹ The number of condition variables is measured as how many medical problems are held by an individual based on ICD9codes. The list of ICD9codes is the ninth version of the International Classification of Diseases, a standardized list of 3 digits codes to identify a specific medical condition. This list is maintained by the National Center for Health Statistics and the Health Care Financing

Administration. The entire list of ICD9codes is provided as Appendix 2 to the documentation for the Medical Condition component of MEPS 2000.

²² A priority list is constructed based on each condition's prevalence, importance in expense, and relevance to policy. The complete listing of priority conditions is provided by MEPS 2000 (the same documentation as above, Appendix 4). This list is categorized into three groups; long-term life-threatening conditions such as cancer, diabetes, emphysema, hypertension, and ischemic heart disease; chronic manageable conditions including arthritis, asthma, and gall bladder disease; in addition, some mental health issues such as depression are included.

²³ *Health, United States 2003* reports the percent of population enrolled in HMOs by geographical region in year 2000; Northeast 36.5%, Midwest 23.2%, South 22.6%, West 41.7%. However, the number of HMO plans available in a region shows the opposite pattern; Northeast 98, Midwest 161, South 203, West 106. These data shows that the extent of popularity of HMO plans varies across regions reflecting regional variations in adopting new administrative health care systems and in need of managing quality and utilization.

²⁴ To avoid potential bias to include individuals who do not have a choice as to whether to join an HMO, I replicate the regression analysis using a more limited sample, restricting the population to those who have choices in selecting their health care plan. This reduces the sample size from 7,474 to 2,428. The results reported in Table A6 do not change the earlier conclusions. Many variables remain statistically significant except for age, being black, being employed, and having depression as a chronic condition.

²⁵ Estimates of HMO effect in utilization are all insignificant and change signs across specifications and dependent variables. However, when the potential self-selection is controlled, the endogeneity correction term captures the negative correlation between utilization of health care services and the unobserved factors that determine the choice of a plan. Also, HMO enrollment has a positive and highly significant effect on utilization; a result consistent with the CMLE cases. It is also clear that accounting for the non-negativity of the dependent variable and selection bias from the endogenous explanatory variable is important. This is illustrated by changes in the sum of squared residuals (SSR); the non-negativity correction reduces the SSR considerably and the additional endogeneity correction leads to even more reduction in the SSR. Though the main results appear to be similar to results from the CMLE regression, the test for normality on the dependent variable and estimated residual rejects the normal distribution assumption. Hence, I focus on discussing the results obtained from the CMLE model, which account for non-negativity as well as endogeneity without losing observations as it would be the case when taking logs for the dependent variables. The other explanatory variables in four sets of OLS specifications which are not discussed in detail show similar effects in signs and statistical significance to the CMLE results presented in Table 20.

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APPENDIX

TABLE A1--EDUCATIONAL BACKGROUND BY OCCUPATION
(PANEL A) HIGHEST YEARS OF EDUCATION ATTAINMENT

Highest Education Attainment (Years)	Have Been Teachers		Have Never Been Teachers	
	Overall (%)	Between (%)	Overall (%)	Between (%)
16	53.59	38.56	64.51	57.19
17	20.02	24.18	18.02	19.73
18	26.40	37.25	17.47	23.08
Mean	16.73		16.53	
N(n)	2383 (306)		2192 (299)	

(PANEL B) COLLEGE MAJOR

Major	Have Been Teachers	Have Never Been Teachers
Education	50.00	10.37
Business	.98	12.04
Social Science	10.13	18.39
Health, Medical Science	.65	14.72
Other	38.24	44.48
n	306	299

TABLE A2--SAMPLE COMPOSITION BY YEAR OF STARTING WORK

Years Since Initial Work	Year of Starting Work							Sample Size
	79	80	81	82	83	84	85	
1	451	68	19	6	6	9	4	563
2	438	60	18	6	8	9	6	545
3	421	60	19	6	9	9	8	532
4	407	61	20	9	9	10	7	523
5	421	58	17	5	6	10	6	523
6	411	65	19	7	4	9	6	521
7	428	69	23	6	3	9	7	545
8	433	63	20	5	3	11	6	541
9	419	64	21	7	3	11	6	531
10	417	70	24	7	4	9	7	538
11	427	66	22	6	6	10	7	544
12	406	68	25	8	5	12	7	531
13	409	67	25	8	5	13	0	527
14	423	67	25	8	4	0	0	527
15	438	66	27	10	0	0	0	541
17	450	76	29	0	0	0	0	555
19	466	71	0	0	0	0	0	537
21	476	0	0	0	0	0	0	476

^aThe sample size for x year since initial work with x ranging 1 to 21 corresponds to estimation results reported in Table 13. For estimation of x years since initial work, the dependent variables is a post wage at $x +$ year of starting to work. For example, wages in 1982 for workers who have started to work in 1979 and wages in 1983 for workers who have started to work in 1980 and so on are used in the estimation for 3 years since initial work in Table 13.

TABLE A3--ENTRY WAGE REGRESSION

Variable	(1)			(2)		
	Coefficient	t-Ratio	Std. Dev.	Coefficient	t-Ratio	Std. Dev.
Constant	4.293***	17.41	.2465	2.974***	4.57	.6502
Age	.048***	4.02	.0120	.051***	4.22	.0120
Education	.011	.78	.0137	.278**	2.16	.1288
Education ²				-.013**	-2.00	.0067
AFQT	.002***	3.25	.0007	-.005	-.66	.0079
AFQT* Education				-.0007	.98	.0007
White	-.033	-.68	.0482	-.031	-.64	.0481
Male	.256***	8.17	.0313	.249***	7.92	.0314
Married	-.029*	-.79	.0369	-.032	-.87	.0368
Start 79	.705***	5.51	.1278	.688***	5.39	.1278
Start 80	.624***	4.75	.1313	.602***	4.58	.1314
Start 81	.691***	4.88	.1415	.678***	4.80	.1413
Start 82	.305*	1.81	.1684	.277	1.64	.1684
Start 83	.393**	2.23	.1759	.407**	2.31	.1759
Start 84	.365**	2.28	.1594	.345**	2.16	.1595
No. Obs.		697			697	
Adjusted R ²		.240			.244	

^aStart 79-85 dummies for the year of starting to work between 1979 and 1985.

^bResult (1) is associated with Table 12. Result (2) is the first step estimation of initial wage associated with Table 13.

TABLE A4--POST WAGE REGRESSIONS (1980-1994, 1996, 1998, 2000)

	Age	Education	AFQT	White	Male	Married	Exp	Exp ²
1	-.035	.022	-.0005	.015	-.048	.040		
2	-.036	.013	.0008	.028	.050	.032	.216***	
3	-.083***	.004	-.0009	.055	-.138	.068	.681**	-.109*
4	-.036	.026	.0013	-.018	.129	.016	.194	-.001
5	-.031	.055***	.0023	-.066	.188	.038	.132	-.005
6	.005	.036*	.0019	.022	.277*	.080*	-.049	.017
7	.007	.062***	.0034*	-.036	.350**	.021	.024	.004
8	.016	.092***	.0041**	.024	.409**	.013	.168**	-.008
9	.014	.033	.0064**	-.079	.361	.022	.142	-.007
10	-.017	.053**	.0036	-.005	.251	.024	-.054	.007
11	.002	.048***	.0028*	-.006	.277*	.027	.086	-.001
12	.006	.052**	.0022	-.032	.268	.080	.213***	-.008**
13	-.011	.012	.0039	-.031	.123	.121*	.122	-.002
14	.058	-.0008	.0045*	-.037	.407*	.081	.048	.002
15	-.022	.014	.0021	.030	.038	.022	.075*	-.0006
17	.028	.071***	.0034	.019	.428**	-.068	.017	.001
19	.042	.073***	.0058***	-.006	.533***	-.005	-.020	.002
21	-.027	.076***	.0040	.070	.189	-.001	.011	.0009

^aSince the NLSY1979 conducted the survey biannually since 1994, no information about 1995, 1997 and 1999 wages are available.

^bAll of the regressors reported above are included in the regression along with the predicted initial wage, the estimated residual and dummies for each year of starting to work during 1979-1985. Table 2 only presents results of the predicted initial wage and the estimated residual.

^cStandard errors, t-ratios and results for the start-to-work year dummies are provided upon request.

TABLE A5--DECOMPOSITION OF ENTRY WAGE EFFECTS

Years Since Initial Work	Specification II			Specification III		
	\hat{w}_0 (t-Ratio)	$\hat{\varepsilon}_0$ (t-Ratio)	Adj. R ²	\hat{w}_0 (t-Ratio)	$\hat{\varepsilon}_0$ (t-Ratio)	Adj. R ²
1	.561 (1.65)*	.451 (11.36)	.371	.842 (2.34)**	.447 (11.25)	.373
2	.318 (.93)	.495 (12.37)	.415	.487 (1.37)	.493 (12.31)	.415
3	.641 (1.39)	.374 (6.81)	.243	1.105 (2.29)**	.369 (6.72)	.246
4	.560 (1.20)	.213 (4.00)	.230	.497 (.98)	.212 (3.98)	.229
5	.241 (.59)	.314 (6.18)	.295	.015 (.03)	.317 (6.22)	.296
6	-.228 (-.51)	.417 (7.75)	.317	-.270 (-.55)	.419 (7.77)	.317
7	.356 (.77)	.238 (4.85)	.288	.069 (.14)	.241 (4.88)	.288
8	.139 (.27)	.209 (3.73)	.243	-.500 (-.90)	.220 (3.89)	.246
9	.365 (.71)	.254 (4.52)	.264	-.170 (-.30)	.262 (4.61)	.265
10	.102 (.19)	.259 (4.33)	.231	.003 (.01)	.260 (4.34)	.231
11	.153 (.35)	.206 (4.21)	.324	-.130 (-.27)	.210 (4.27)	.324
12	.486 (1.04)	.296 (5.41)	.339	.256 (.46)	.297 (5.42)	.339
13	.652 (1.07)	.310 (3.98)	.226	.351 (.49)	.313 (3.99)	.226
14	.992 (1.52)	.220 (3.06)	.256	-.120 (-.18)	.228 (3.16)	.254
15	.331 (.63)	.203 (3.53)	.275	.309 (.54)	.202 (3.52)	.275
17	.284 (.55)	.292 (4.95)	.256	-.410 (-.75)	.301 (5.08)	.258
19	.369 (.74)	.236 (3.96)	.282	-.520 (-.95)	.246 (4.15)	.285
21	-.164 (-.26)	.227 (3.01)	.198	-.340 (-.49)	.229 (3.04)	.199

^aSpecification II: in the first step regression of initial wage, we include only family variables; father's and mother's educational attainment in 1979, the closest sibling's gender and years of education in 1993.

^bSpecification III: in the first step regression of initial wage, we include age, gender (dummy), marital status (dummy), race (dummy), education, education squared, AFQT score, an interaction term of education and AFQT score and starting-to-work year dummies as well as father's and mother's educational attainment in 1979, the closest sibling's gender and years of education in 1993.

^cAll estimated coefficients for $\hat{\varepsilon}_0$ are significant at 1% level. I omit *** for concision.

^dResults not presented here are provided upon request.

TABLE A6--PROBIT ESTIMATION OF HMO ENROLLMENT DURING THE ENTIRE CALENDAR
YEAR 2000 FOR THOSE HAVING A CHOICE OF PLANS

Variable	Coefficient	Std. Dev.	Marginal Effect
Hispanic	.237	.112	.0849**
More than High School	-.210	.069	-.0784***
Urban	.147	.088	.0559*
Northeast	.667	.101	.2201***
West	.640	.092	.2169***
Number of Conditions (ICD9codes)	-.032	.014	-.0120**
Hypertension	.157	.091	.0586*
No Need for Health Insurance	.097	.043	.0362**
Overall Quality of Health Care	-.082	.020	-.0306***
Out-of-Pocket Payment/Total Payment	-.398	.135	-.1485***
Log-Likelihood		-1077.8	

^aIn the regression, exactly same set of regressors are included. Variables reported in this table are those which have at least 10% level of statistical significance for concision.

TABLE A7--ALTERNATIVE SPECIFICATION OF ESTIMATING UTILIZATION
OF HEALTH CARE SERVICES

Panel 1				
Total office-based visits				
Variable	Linear OLS		Log-Linear OLS	
	Uncorrected	Corrected	Uncorrected	Corrected
HMO Enrollment	-.045 (.292)	12.9 (2.5)***	.007 (.028)	2.14 (.243)***
$\hat{\nu}$ (Endogeneity)	-	-8.03 (1.55)***	-	-1.32 (.150)***
SSR	388615.3	384742.4	2972.0	2902.9
Adjusted R ²	.178	.178	.277	.291
Panel 2				
Total hospital outpatient visits				
Variable	Linear OLS		Log-Linear OLS	
	Uncorrected	Corrected	Uncorrected	Corrected
HMO Enrollment	.015 (.076)	3.39 (.657)***	-.021 (.049)	1.78 (.475)***
$\hat{\nu}$ (Endogeneity)	-	-2.09 (.405)***	-	-1.13 (.295)***
SSR	26501.0	26297.2	451.6	442.9
Adjusted R ²	.056	.062	.095	.110

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