Birth Nativity, Citizenship, and Gender Difference of Immigrant Scientists/Engineers Earnings

Yuying Tong University of North Carolina at Chapel Hill

ABSTRACT In this paper, I employ a random-effect growth curve model on a longitudinal data set of scientists/engineers to model the earning differences by birth nativity, citizenship and gender. Four waves of SESTAT data were arranged into a pooled-cross section time series so that repeated measures of scientists/engineers for each individual in a two-year interval could be used for analysis. The results show that an unobserved random effect explained nearly 30 percent of the variance on the overall earning differences across individuals. We also find that overall foreign-born scientists are not necessarily at a disadvantage for both overall earning and earning growth rate. Citizenship status, however, plays a significant role on foreign-born scientists/engineers' earning disadvantage, but not in the earning growth rate. Women do experience disadvantages in both overall earning and on earning growth rate, but the evidences of foreign-born woman scientists are more disadvantaged than their native counterparts just exist in those foreign-born without citizenships.

Introduction

Due to the large proportion of immigrants and concerns on their adaptation to U.S., a sizable literature has examined the integration of immigrants into the U.S. society. How immigrants perform in the U.S. labor market has been one of the central questions in these studies (Borjas, 1994). Different answers for this question underlie much of current debate on cost and benefit for the host country. Using Census data, the earliest influential work by Chiswick (1978) indicates that relative earnings of immigrants grow fast and eventually overtake the earnings of native workers. Borjas (1985, 1989, 1994), however, suggests that non-random emigration and quality differences across immigrant cohorts would bias this across-section estimates. He finds that the assimilation rate measured in cross-section studies partly due to a decline in the quality of immigrants admitted to United States since 1965, after the Immigration and Naturalization Act eliminated national origins quotas.

It is well known that the relative skills of immigrant cohorts declined substantially when the national origin mix shifted away from the traditional European source countries toward Asian and Latin countries due to the 1965 Immigration Act. Those immigrants are also characterized by being more likely entering to reunite with kin than on the basis of their occupational skills (Duleep and Regets 1996) since one key factor is that an immigrant who becomes a U.S. citizen is allowed to sponsor family members for obtaining visas by this law change. As a consequence, the immigrants in the United States are fairly heterogeneous with respect to ethnicity, social class, and other characteristics correlated with economic stratification. Using census data, previous studies on immigrant earning has taken the immigrant population as a whole or only chosen the sub-sample of men to study the immigrant labor market outcome. Less attention has been paid to group differences across gender, social class etc. For example, Gender gap has been paid much less attention when studying immigrant earnings, and the earning difference between immigrants and their native counterparts for low skilled labor workers might be very different from the high educated groups. There is much work which can be done to study the gender differences of different immigrant groups. This paper will only focus on the high educated group of scientists/engineers to examine the gender difference on average earnings and earning growth using a longitudinal dataset of repeated measures of individuals.

For many decades, highly skilled immigrants have pursued a higher premium on their education and skill by coming to the United States. Only recently well-educated immigrants have been brought to the attention of the general public and policy makers (North 1995), partially because they have high level of productivity in host country and there are less public concerns on the costs of host country (Vernez 1997). The size increased for the well-educated group dramatically in 1990s; 13 percent of all college graduates in the U.S. civilian labor force was foreign-born in 2000, and over one-third arrived in the 1990s. However, the labor market for high educated population became tighter and tighter, and more economic concerns and apprehension arises among natives. How does this group perform in U.S. labor market compared with native born? Are there any group differences in the labor market performance of different race/ethnicity background, gender groups? Answers to these questions will help increase the knowledge about the costs and benefits of having this group in U.S. Previous research has already shed some lights on this subject matter (Bojars 1989; North 1995; Tang 1993; Goyette and Xie 1999; Xie and Shauman 2003). However, most of the studies, except Goyette and Xie (1999), focused on inequalities in labor market outcomes by nativity or generation but overlooked the role of gender.

According to Pedraza (1991), the experience of immigration profoundly impacts the both public and private lives of women. Compared with men, women are more likely to accompany their husbands, or carry along children when they migrate. As Houstoun (1984:919) stressed, women generally migrate to create or reunite a family. Women’s migration is more likely seen as the secondary movements generated by the original migration of economically motivated by males. Hence, different experience of immigration might have different impacts on men and women’s labor market choice and outcome.

As far as immigrant scientists/engineers are concerned, with more autonomy and higher self-esteem, one would expect that the pattern of gender difference among the higher educated immigrant group might be similar to natives. Using 1990 census PUMS data, Goyette and Xie (1999) examined this hypothesis and found that foreign-born female scientists/engineers make about 4.7% less than the combination of other scientists/engineers after considering the impact of immigrant status. However, more input is still needed in this area, especially using longitudinal data. Women's roles in public life and private life change over time, for example, their family responsibilities change over their life course. Using longitudinal data would catch the information of life changes which could impact labor market outcomes in a person's life. Further more, some unobserved factors may correlate with the choice of immigration to U.S., naturalization process, which might affect their performance on the labor market. So a longitudinal data set and more advanced research method need to be used to address earning differences from average earning and earning change overtime for a person.

In this study, I will use repeated measures of the same individuals over different survey years to examine the effect of immigrant status, which includes both birth nativity and citizenship, on the earnings of scientist/engineers by gender. To better solve the problem of unobserved factors, I employ random-effect growth curve models. Random effect growth curve models will give not only the effects from time invariants and time-varying covariates, but also unobserved random effect. Hence, I can determine not only if there is an effect of nativity and citizenship on the scientists/engineers' earning and if there is difference between men and women, but how much the effect and difference is, if they exist.

Literature Review

Prior to the 1965 Amendments to the Immigrants and Nationality Act, immigrants to the United States were regulated by numerical quotas based on the ethnic population of the United State in 1920. This encouraged immigrants from European countries and restricted immigrants from Asia and Latin America. After 1965, the Immigration Act allows more individuals from third world countries to enter the US (including Asians, who have traditionally been hindered from entering America); it also entails a separate quota for refugees. Skill/Professions or the relatives of U.S. Citizens are issued visas to come to U.S and countries of origin are no longer significant barriers for the immigrants. As a result, the new flow of immigrants originates mostly in Asia and Latin America, and they are more mixed on their race/ethnicity. Since one of fundamental shifts of the mechanism to accept immigrants whose skills are what U.S. labor market demands or who have kinships in the United States. As a result, internal heterogeneity might be the most significant characteristic in the current immigrant population in the United States.

Migrant streams often alter the composition of places with respect to ethnicity, social class, and other characteristics correlated with economic stratification (Cobb-Clark, 1993). Ethnicity often defines the boundaries for social and cultural interaction. Previous studies have concluded that it is no longer necessary to provide ad hoc explanation of why the U.S. earnings of immigrants from different countries tend to exhibit so much variation. The economic theory of immigration suggests that this variance can be "explained" in terms of the economic and political conditions that guided the nonrandom sorting of persons across countries at the time of migration (Borjas, 1989). However, compare to this, earning differences among other different immigrant groups are far less clear.

The study on the immigration duration and earnings has led to lots of debate in the literature. The earliest work by Chiswick (1978) used the cross-section of census data and found that the earnings of foreign born persons immediately upon arrival are likely to be lower than the earning of comparable natives. Overtime, however, since immigrants have lower earnings, they also have higher incentives to invest human capital than natives. Immigrants earning can be expected to rise relatively fast as the returns to human capital investments are realized. The “catch-up” earnings profiles reflect the “assimilation” or adaptation of immigrants to the host country’s labor market (Chiswick, 1978, Becker, 1975). This implies that immigrants will be self-selected not only on the basis of wage levels, but also on the basis of wage growth.

However, the conclusion that immigrants have relatively high earnings growth has been challenged on both empirical and theoretical grounds (Duleep and Regets 1997). Borjas (1985) argues that cross-sectional framework used in Chiswick’s study might bias the estimates because nonrandom emigration and immigrant cohort quality changes over time. He argues that if there has been a decline overtime in the earnings ability of immigrants, then the assimilation effect measured in cross-sectional studies could be spuriously inflated by declining immigrant earnings ability. In his other studies, Borjas found that immigrants’ initial wages adjusting for education and age, have decline overtime (Borjas 1992).

Studies using cross-sectional census data can not sufficiently solve the problems of bias due to the cohort quality changes and emigration. In addition, an internal assumption in these studies is that immigrants and natives approximately have similar occupational composition in the United States. However, it is well known that the current immigrants in the U.S. are more likely to be in both lower tail and upper tail of occupational prestige distribution than being in the middle. Since the opportunities sets faced by high educated immigrants are different from other group immigrants, it would be more valuable to compare a particular immigrant group with their native counterparts on the earning patterns than comparing the undifferentiated mass with all natives. An examination from both average earning and earning growth will fully capture the immigrant earning pattern.

As an important part of scientific workforce in the United State, the immigrant scientists/engineers are relatively less heterogeneous with regard to their human capital within group. Although a relatively small proportion in the immigrant population, the number of foreign-born scientists/engineers keeps climbing with each passing year, and a higher percentage of the college-educated foreign born holds post-graduate degrees than the native born, with 43.6 % percent holding a master's, professional, and/or doctoral degrees, compared to 35.2 % of the native-born. Its important impact on U.S. talent labor market has led to heated discussion (Goyette and Xie, 1999), and overall, the research has drawn conclusion on immigrant scientists/engineers to either displacement (North, 1995) or discriminations (Tang, 1993, 2000).

From the perspective of displacement, North (1995) argues that there are two groups of foreign-born scientists/engineers. One group is those who come in one at a time, study at U.S. graduate schools, secure advanced degree and then, in large number, stay in the U.S. The other group is those who enter already holding a degree and participate in U.S. labor market without U.S. education. Because there are so many of them obtain degrees from U.S. graduate school, immigrant scientists occupy positions that might otherwise be taken by women and native-born minorities. In other words, this means that U.S. need not exert itself to expand the efforts to get Americans, particularly women and minorities to enter science and engineering graduate school. According to the displacement perspective, immigrant scientists/engineers take the downward pressure on the payment structure of science and engineer field.

In contrast, the discrimination perspective (Tang, 1993, 2000) posits that immigrant scientist face unfair treatments in the U.S labor market. In studies of Asian scientists in U.S. labor market, Tang argues that there is ample evidence to show that Asians, regardless of gender, continue to have a lower level of income and career status than Caucasians with comparable training and qualifications (Barringer, Takeuchi, and Xenos 1990; Chu 1988; Hirschman and Wong 1984; Nee and Sanders 1985; U.S. Commission on Civil Rights 1988). One reason could be that those minority scientists/engineers are more likely to be confined to employment in the periphery of profession (where opportunities are scarce) and, in turn, suffer from significant income loss and downward occupational mobility (Wu 1980; Sung 1976; Villones 1989). Numerous studies have examined the adverse effect of nativity status on the earnings of Asian immigrants (Hirschman and Kraly 1988; Hirschman and Wong 1981, 1984; Nee and Sanders 1985; Poston and Jia 1989), and less research have paid attention to other underrepresented immigrant groups.

Comparing these two perspectives, both suggest that immigrant scientists/engineers as a whole are in disadvantaged compared with native-born scientists/engineers in the labor market. However, in a further examination, one couldn’t see they are different on what is the ultimate reason of disadvantages: it could be due to either their citizenship status, for example, they are foreign-born but holding U.S citizenships, or simply due to their foreign-born status no matter if they have U.S. citizenship. Foreign-born who are holding U.S. citizenship is naturalized U.S. citizen. In general they have lived in U.S. for at least 5 years, and they have strong claim to rights in U.S. society. In theory they are entitled to the same privileges as native-born citizens (Massey and Bartley 2005). Thus, if it in the latter situation, foreign-born scientists/engineers would still be in the disadvantaged after controlling for citizenship. I have not seen any previous research that look into this point. In this paper, I test this by combining both birth nativity and citizenship status to indicate immigrant status to examine the earning pattern in my model.

In previous studies, one common problem is that the role of gender is often omitted. According to Pedraza (1991), gender plays a central role in the decision to migrate and the composition of the migration flows, with the consequences that composition holds for the subsequent form of immigrant incorporation. There are more men than women among foreign-born, college-educated workers in the scientific workforce. In 2000, fifty-eight percent of foreign-born, college-educated workers are men, and this percentage was even higher among college-educated migrants who have arrived since 1990. In comparison, men constitute 53 percent of the native-born, college-educated workforce. However, women represented only 21.3 percent of the scientists and engineers being admitted with permanent resident status in 1993. Women, as Pedraza (1991) argued, are more likely to be secondary movements of males. So without consideration of gender differences in the study, the picture of immigrants/scientists would be incomplete. As one needs a long term investment and engagement to pursue high degree and work in scientific field, women with special role related to family might make the impact of migration experience on labor market outcome different from the male peers. Thus, inattention to gender difference may result in an inaccurate characterization of the experiences of immigrant scientists and engineers. For example, Goyette and Xie (1999) argue that married women who work in scientific field may be more likely to come to U.S. as secondary immigrants of their husbands. Much more women than men migrate to get unification with their spouses, so their choice on career is greatly limited even if they might have similar education background on the time of migration compared to their male counterparts. Motivated by this, Goyette and Xie, using the 5 percent PUMS data from the 1990 U.S. census, first time systematically studied the effect of immigrant status on labor force participation, earnings and promotion of immigrant scientists/engineers. Their regression result show that foreign born female scientists/engineers earn about 5 percent less than all other group scientists/engineers. They argue that family responsibilities mainly account for women earning disadvantages.

However, the measurement of earning in Goyette and Xie's study is the annual earnings in 1989, and the results from cross-sectional PUMS data are static and as such have no bearing on dynamic process such as the earnings change that could capture the a full picture of gender differences of earning in a person's life course. In addition, cross-sectional data might provide biased estimates on the association of immigration status and mean earnings. The potential bias is due to the well-known problem that a single cross-section regression cannot differentiate the effects between migration experiences and individual characteristics. In this context, immigration status captures the difference in earnings among a typical immigrant scientist/engineer and a native scientist/engineer, while the individual effect captures the productivity (or ability), ambition difference across different individuals. Since individual effects such as ability, ambition, intelligences etc might be correlated with immigration status, using immigrant status as predictor to study earnings outcomes in a cross-section data might bias parameter estimation. That is, in cross section analysis, if immigrant scientists/engineers have no earning disadvantage compare to natives; it may be due to their higher ability or higher career ambition which compensates for the shortfall as immigrants. To deal with the problem, in this paper, I use a repeated individual data set and a random-effect growth curve model to control for unobserved variables such as ability, ambition and intelligent factors. The exact amount of unobserved individual effect is determined by factor of personal characteristics, that is, the personal characteristics that would not change over time.

In sum, this paper will use repeated measures of individual from longitudinal data to examine the effect of birth nativity and citizenship on both mean earnings and earning growth. Gender difference is one of important mission in this paper to fully capture the women immigrant scientists/engineers earning profiles relative to others.

Methodology

Data

I take the longitudinal part of Scientists and Engineers Statistical Data System (SESTAT) integrated data as my analysis dataset. SESTAT is a database of the employment, education, and demographic characteristics of the nation’s scientists and engineers. The SESTAT integrated the survey data from three component surveys, which includes the

National Survey of College Graduates (NSCG), the National Survey of Recent College Graduate (NSRCG) and the Survey of Doctorate Recipients (SDR). All of those surveys have been sponsored every two years since 1993 by the National Science Foundation. In this paper, I use the integrated databases for 1993, 1995, 1997 and 1999. Although the period from 1993-1999 is a relatively short period, the data collected earlier than 1993 is not comparable with data collected in 1990s due to the mechanisms of data collection changes. One also might notice that 1990s is a period for U.S. economic expansion, so I assume the period effect for immigrant scientists/engineers are same for immigrants vs. natives and men vs. women.

The target population of SESTAT includes residents of the United States with at least a bachelor's degree and who, as of the survey period (April 15 for each survey year), was non-institutionalized, 75 years of age or less and either educated in a science or engineering (S&E) field or working in an S&E field. As a result, although some scientists/engineers dropped out from the follow-up surveys and some fresh graduation were recruited; the majority of the respondents still have been measured repeatedly over each survey year, with more than 50,000 individuals surveyed in all fours waves.

The response rates vary across survey components and across survey years, range from 77 percent to 95 percent. Although this data set was integrated from different survey components and years, more than 90 percent measurements are exactly same across different surveys. It is valuable to arrange the longitudinal data into a pooled-cross section time-series in which the unit of analysis is an individual in a particular survey year.

Measures

Dependent variable:

The dependent variable for this study is the natural logarithm of annual salary. This variable was constructed from the salary of principle job the individual holds in the survey reference week (April 15 in the survey year) before deductions. Although it is possible for a scientist/engineer to take secondary job, the total earned income from all jobs was not surveyed in year 1993. Values are top-coded at 150,000 and rounded to the nearest thousand. In addition, non-zero values are bottom-coded, and values greater than zero but less than 5000 are assigned the value "4999". Since salary is a form of recognition for professional contributions and a measure of worth in the scientific community (Long, 2001), it usually accumulates over time. In this study, each person will have at least one and at most four measurement of earning.

Independent variables:

Immigrant status: As argued in the literature part, immigrant scientists/engineers may be in earning disadvantages because of both “displacement theory” which argues immigrants are more likely to accept low paid job and “discrimination theory” which explains immigrants being in labor market disadvantages because of discrimination. Immigrant status is the key predicator of this study, which is measured using both birth nativity and citizenship. Immigrants who own U.S. citizenship have a much broader economy opportunities than immigrants without citizenship (Yang 1994). For example, they enjoy lots of benefits on education and job choices. Previous studies always use birth nativity to indicate immigrant status. However, using foreign-born versus native-born as a dummy variable to indicate immigrant status will lose some important information. To differentiate what is the ultimate reason of disadvantages, for example, foreign-born status (not well assimilated into U.S. society) or citizenship status (policy discrimination toward non-citizen), I will use a categorical variable of three groups as foreign-born without citizenship (FBWOC), foreign-born with citizenship (FBWC) and native-born (NB) to indicate the immigrant status. Since a non-citizen immigrant might be naturalized later on in his work life, so a citizenship will be a time-varying variable in the model.

Demographic variables: Age could be a factor contributed to earning differences between foreign born and native born scientists/engineers. Age could also be a factor contributed to earning differences between males and females since women enter into the science and engineer is relatively new (Long, 2000). The age composition of immigrant scientists/engineers might be different from their native counterparts. Since almost one-third immigrants worked in natural and social science, engineering, and computer-related occupations arrived between 1990 and 2000, immigrant scientists/engineers are generally younger than natives. In the dataset, the earliest cohort was born before 1929 and the latest was born later than 1970. I use the birth cohorts to present the age differences, which makes the age group a time-invariant variable. I grouped them into five categories: 1965 or later, 1955-1964, 1945-1954, 1935-1944 and 1934 or earlier. Gender is measured with a dummy variable of male and female. Race/ethnicity is another variable that might be confounding with the earning differences between foreign-born and natives. Race is recoded into the broad categories including White, Asian and Other. Other includes Hispanic, African Americans, and other under represented minority.

Human capital variables: Although the sample in this study is relatively a homogeneous group with all of them holding high education degrees, the post-graduate education degrees holders are usually significantly different from those holding bachelor degrees. Compare with native-born, foreign-born college graduates are more likely to hold post-graduate degrees. Female college graduates are less likely to hold post-graduate degree compared with males. In this study, I recoded a series of dummy variables to indicate the education, which includes bachelor, master, professional, and other degrees as well as doctoral degrees. It is well known that work experiences is an important explaining variable in individual earning, but a direct measure of work experience in the data set is not available, so I use age as a proxy. At the same time, I use dummy variable (full-time versus. part-time) to indicate employment status, since women are more likely to attend part-time job. All the human capital variables might be changed over the life course, for example, a person might hold a bachelor degree at 1993, but hold a master degree in 1997.

Work field: It is well known that the distributions of men and women within high educated group are extremely uneven (Jacobs 1996). In a cross-national study of high education group, Charles and Bradley (2002) concludes that female underrepresented in engineering, math/computer science (and to a lesser degree, natural science); female overrepresented in education, humanities, and health fields; and approximate gender parity in the social science. They argue that this is consistent with the culture-centered and human-capital accounts, since both of which predict it is characterized by functional or symbolic proximity to traditional female roles (Becker 1991; Reskin 1993). Because of segregation of fields by gender in high educated population, it is necessary control work field to net out this confounding factor. I group the scientists/engineers into five well-established categories for scientists/engineer occupation: computer and mathematical, life and related science, physical and related science, social and related science as well as engineering. Employment sector also is an important factor that impacts earning. Usually industrial offers higher wage than academia or government (Peek, 1995, Goyette and Xie 1999). Employment sector includes four categories: industry, academia, government and other. Work field variable may also be changed for a particular over time.

Family responsibility: Women in contemporary U.S. on average, get better grades in school, take math and science and science classes in the same rate, and earn roughly the same number of bachelor's degree in science and engineering as men. But in the career path, because of childbirth, cultural norms and social expectation, they tend to become scarcer in the highest ranks. Among them, childbirth might be the most significant factor which barrier women's careers. Although there is no evidence that immigrant women scientists/engineers are having more children, the effect of having young children for those women might be bigger than native-born women due to their less social and kinship network support. In this paper, a time-varying variable of number of young children under a certain age will be included for both male and female and to see if it only impacts women's earning.

Statistical Approach

Since individuals were repeatedly surveyed across years, and the motivation of this study is to examine both amount of earnings and slope of earning growth over the survey years, random-effect growth curve model is used. Random effect regression models with a random intercept account for the individual differences in initial earning difference (1993 in this study) when the survey started, and random effect coefficient models account for the individual differences on the slope of earning growth. This paper will analyze the effects of gender, immigration status (including both nativity and citizenship) on earnings over time taking into account the change in employment changes, education changes, and citizenship status changes, changes of the field and employment sector as well as family responsibility.

Most of previous studies on earning which use longitudinal data choose the fixed effect models (England et al, 1988, 1996) to control the unobserved effects. The fixed effects models based on longitudinal data allow us to control for unmeasured effects that are constant across repeated measures over time (Guo and Hipp, 2003). For example, England et al (1996), studied the effect of gender composition on starting wages in an organization, pooled across all job spells for each worker to control for such unmeasured and unchanging personal characteristics as intelligence, preferences resulting from early socialization, life cycle plans, and unmeasured human capital. Compared with fixed effect model, random effect could give an evaluation of variation of outcome based on both individual and measurement levels in a longitudinal data. In addition, random effect growth curve model can give the parameter estimates of time-invariant covariate effects, while in fixed effect model; those variables will be swept out from the model since fixed effect model controls the constant effect in the model. In this study, gender and birth cohorts are seen time invariant variable, and the parameter estimates for them will be important to know to answer the research questions in this paper. In a random effect model, the effects of unobserved variables are estimated side by side with the effects of observed variables.

Random-effect growth curve model can be represented through a two-level hierarchical model. At level 1, each person's earning is represented by an individual growth curve trajectory that depends on a unique set of parameters. These individual growth parameters become the outcome variables in a level-2 model, where they may depend on some person-level characteristics (Raudenbush and Bryk, 2002). In my analysis, each individual is measured at least one time and at most four times, and a random-effect growth curve model may be expressed as follows:

$Y_{ij} = \beta_{0j} + \beta_{1j} time_{ij} + \sum_{k=1}^{p} \beta_{kj} x_{ijk} + e_{ij}$	Level 1	(1)
$\beta_{0j} = \beta_{00} + u_{0j}$	Level 2	(2)
$\beta_{1j} = \beta_{10} + u_{1j}$	Level 2	(3)
$Y_{ij} = \beta_{00} + \beta_{1j} time_{ij} + \sum_{k=1}^{p} \beta_{kj} x_{ijk} + u_{0j} + e_{ij}$	Combined (1) & (2)	(4)
$Y_{ij} = \beta_{00} + \beta_{10} time_{ij} + \sum_{k=1}^{p} \beta_{ij} x_{ijk} + u_{0j} + u_{1j} time_{ij} + e_{ij}$	Combined (1), (2) & (3)	(5)

i =0, 1, 2, 3; j=1, 2, 3, 4, 5, 6…

Equation (4) is a random-intercept only model, and equation (5) includes both random intercept and random coefficient. In this model, y_{ij} is the annualized salary for individual j at time i , β_{00} is the intercept (here it represents the annualized salary at time 0(that is in 1993 survey time). u_j is the individual-specific random effect, and e_{ij} is the measure-specific random effect or the OLS-like error term. The standard assumptions are that u_j and e_{ij} are mutually independent N (0, σ_u^2) and N (0, σ_e^2) random variables, where σ_u^2 and σ_e^2 are between-individual variance and within-individual variances, respectively. P is the number of covariates, and β_{kj} is the coefficient of covariate k. In addition to what is captured by the observed variables (covariates), this model assumes that each measure is subject to two effects. One is unique in each measure (e_{ij}) and the other (u_j) is same for all measures of an individual, but differs by individual. The quantities of σ_u^2 and σ_e^2 are these two effects' variances, respectively. A large-between individual variance indicates large differences in earnings across the individual. The addition of the individual-specific random effect u_j is the only difference between this kind of model and typical OLS model. The assumption is that controlling for the individual-specific random effect u_j , the multiple measures of the individual will be independent.

Result

Table 1 presents the means or percentages of variables by survey year and table 2 displays the means or percentages of variables by gender and by survey year. Gender, race and birth cohorts are time-invariant variables. The immigrant status, employment status, recent degree and field, work sector and number of children are all time-varying variables across years. For example, it is possible for a person who is a Bachelor degree holder in 1993 to become a Master degree holder in 1997. By using time-varying covariates, one can better capture the covariates' effect on the labor market outcome. According to table 1 and table 2, overall the annual salaries for all scientists/engineers are growing over time. There are about 20 percent foreign-born scientists/engineers in the sample. About 12 % scientists/engineers are Asians, which is a largest proportion of minority in the high educated labor market. In the sample, I exclude those people who were out of labor force, and more than 90 % in the rest of respondents are full-time labor force participators. Women are more likely to be part-time workers than men. Women are more likely to have bachelor degree than men, and men are more likely to hold doctorate degrees. The proportion of people in engineer among men is higher than the proportion of people in engineer among women, and reverse is the life and science field. The proportion of having young children under age 12 is higher for male than for female scientists.

Table 3 shows the correlation matrix for the earning across the survey year. Since salary is a form of recognition for professional contributions and a measure of worth in the scientific community (Long, 2001), it usually accumulates over time. In other words, measures close to each other tend to be similar to each other. So there is a possibility of autoregressive structure over time (Guo and Hipp, 2003). This is specially the case for the earnings growth. In addition, due to the attrition and missing, measurements for some individuals in some particular years are not available, so data is not balanced; to solve this problem, a covariance structure that accounts for the first-order autoregressive process (Littell et al, 1996) is used to estimate the parameters.

The model (not shown) indicates that there is about 28% variances are explained by unobserved random effect (individual characteristics) after controlling for the observed covariates. In table 3, time has a positive effect on the earning, which indicates that the overall earning is growing over time. Women scientists/engineers are in disadvantages compared with men since women earn about 16% less than men. As I expected, citizenship plays an important role on immigrant scientists/engineers earnings. The results show that foreign-born without citizenship is really in disadvantages compared with native-born, but those foreign-born with U.S. citizenship are not. This case holds for both male and female. However, female foreign-born without citizenship earn much less comparing with other group females. They earn 13% less than native women, but males just learn 8% less than native men. Those findings suggest that the disadvantages are mainly resulted from the non-citizenship status, that is, the policy discrimination to the foreign-born people without citizenship in the labor market. In addition, women are particularly in disadvantages.

Asian men earn less than their white counterparts, but this pattern does not exist for women. The birth cohorts for 1935-1944 and 1945-1954 are higher than birth cohort of 1934 or earlier, the less earning of older scientists/engineers might be due to their skill differences. This indicates that it is not necessarily the older, the more on earnings for scientists/engineers. It is not surprising that full-time jobs can earn much more than part-time jobs. Also it is expected that all post-graduate degrees can make people earn much more money than bachelor degrees, this holds for both men and women. Comparing with social sciences, all other field can make people make more money. The only exception is the life science for women. As other argued before, people work in academia and government earn less than in industry.

As I mentioned before, random intercept model captures the growth of earning overtime, for example, at time 0 (1993), the intercept represents the logged earning at time 0. For the logged earning at time 1(1995), the earning would be the intercept plus the parameter estimate multiplying by 1, and multiplying by 2 and 3 in time 2 and 3 for a typical person, respectively. Although this can reflect the overall earning differences, the earning growth rate cannot be represented in a random-intercept only model. Fortunately, a random coefficient model can be used to detect the growth rate or slope. Table 5 gives the results for this model. By comparing the parameter estimations for predicting intercept and predicting slope, I found that female have both intercept earning disadvantages and slope disadvantages, which means that women are in the disadvantages not only on the amount of earnings, but also in their earning growth pace. Foreign-born scientists/engineers without citizenships are in disadvantages on the amount of earning (intercept), but they have a faster growing pace relative to their native counterparts for males. Still, foreign-born with citizenship have no differences compared with natives. For the control variables, Asians are in disadvantages regard to intercept, but not in grow pace. Still, birth cohorts are nonlinear on intercept compared with the oldest cohorts, but the earning growth is faster when they are younger. Doctorate degree holders have advantages in both intercept and slope compared with Bachelor for women, but the slope change is negative for men. Although academia and governments jobs have disadvantages regard to the amount of earnings, they have faster growth rate compared with industry jobs.

According to the statistical results described above, women are indeed in earning disadvantage for both intercept and slopes, and foreign-born women without citizenship are particularly in disadvantages. What would be the degree of disadvantages for foreign-born women scientists/engineers relative to foreign-born men? Table 6 presents the results for random growth curve models of immigrant sample only. From the table 6, one can find that foreign-born women make 14.5% less than foreign-born men. And the growth rate is 2 % less than men. Foreign-born scientists/engineers without citizenship earn 11.3% less than those naturalized foreign-born, but they have 1.8% higher growth rate.

Conclusion

Are the immigrant scientists/engineers in the earning disadvantage? What is the difference between males and females? Are female scientists/engineers are particularly in disadvantages? In this article, I use the repeated measures of scientists/engineers to advance the previous study by conducting random-effect growth curve model. This model allows one to control the unobserved random effect such as ability, early socialization, intelligences, and personality for a particular individual. The results show that unobserved random effect explained near 30 percent variance on the earning differences. I found that not all foreign-born scientists/engineers are necessarily in earning disadvantages, but the citizenship status really plays a negative role on the amount of earnings. Foreign-born scientists/engineers without citizenship earn less than both natives and naturalized foreign-born. However, when the models allow the slope to change across the individuals, the earning growth rate of foreign-born scientists/engineers without citizenship became positive, although they are still in earning disadvantages regard to the amount of earnings.

About the gender differences, I found that women scientists/engineers are in disadvantage in both the amount of earning and growth rate. Foreign-born women are in disadvantages comparing with both native women and foreign-born men.

Reference

Becker, G.S. 1975 *Human Capital*, Second Edition. New York: Columbia University Press.

Bojars, George. 1982. The Earnings of Male Hispanic Immigrants in the United States. *Industrial and Labor Relations Review*, 35(3): 343-353. April

Borjas, George. 1989. Economic Theory and International Migration. *International Migration Review*. Vol. 23, No. 3. Pp: 457-484

Borjas, George. 1994. The Economics of Immigration. *Journal of Economics Literature*, Volume 32, and Issue 4 (Dec., 1994), Pp: 1667-1717

Chiswick, B.R. 1978. The Effect of Americanization on the Earnings of Foreign-Born Men. *Journal of Political Economy*, 86(5): 897-921. Oct.

England, Paula, George Farkas, Barbara Kilbourne and Thomas Dou .1988. Explaining Occupational Sex Segregation and Wages: Findings from a Model with Fixed Effects. *American Sociological Review*, Vol. 53, No. 4. (Aug., 1988), pp. 544-558.

England, Paula, Lori L. Reid, and Barbara Kilbourne. 1996. The Effect of the Sex Composition of Jobs on Starting Wages in an Organization: Finding from the NLSY. *Demography* 33: 511-521

Cobb-Clark, Deborah A. 1993. Immigrant Selectivity and Wages: The Evidence for Women. *The American Economic Review*, Vol. 83, No. 4. (Sep., 1993), pp. 986-993.

Goyette, Kimberly and Yu Xie (1999). The Intersection of Immigration and Gender: Labor Force Outcomes of Immigrant Women Scientists” Social Science Quarterly 80: 395-408

Guo, Guang and John Hipp. 2003. “Longitudinal Analysis for Continuous Outcomes: Random Effects Models and Latent Trajectory Models.” Edited by Melissa Hardy & Alan Bryman, Sage Publisher

North, David S. 1995. *Soothing the Establishment: The Impact of Foreign-Born Scientists and Engineers on America*. New York: University Press of America.

Littell, Ramon, George A. Milliken Walter W. Stroup and Russell D. Wolfinger. 1996 *SAS System for Mixed Models* SAS Publications

Long, Scott. 2001. *from Scarcity to Visibility: Gender Differences in the Careers of Doctoral Scientists and Engineers.* National Research Council

Pedraza, Silvia. 1991. “Women and Migration: The Social Consequences of Gender.” *Annual Review of Sociology 17: 303-325*

Raudenbush and Bryk, 2002. *Hierarchical Linear Models*. Second Edition. Sage Publications

Tang, Joyce. 1993. “The Career Attainment of Caucasian and Asian Engineers.” *Sociological Quarterly* 34(3): 467-496

Tang, Joyce. 2000. Doing Engineering: The Career Attainment and Mobility of Caucasian, Black, and Asian-American Engineers. Lanham, Md.: Rowman and Littlefield Publishers.

Vernez, Georges. 1996. How Immigrants Fare in U.S. Education. Rand Report

Xie, Yu, and Kimberlee A. Shauman. 2003. *Women in Science: Career Processes and Outcomes.* Harvard University Press.

Zeng, Zhen and Yu Xie. 2004. “Asian-Americans’ Earnings Disadvantage Reexamined: The Role of Place of Education.” American Journal of Sociology. Vol 109. Pp: 1075-1108

Table1: Mean or Percentage of Variables by Survey Year, SESTAT

Variable	1993	1995	1997	1999
Annual Salary	52636.58	55900.15	62250.95	68358.33
Annual Salary(logged)	10.749	10.661	10.860	10.894
Female	0.262	0.276	0.279	0.277
Asain	0.122	0.121	0.113	0.112
Other under represented minority	0.117	0.112	0.111	0.114
Foreign-born without citizenship	0.072	0.064	0.045	0.042
Foreign-born with citizenship	0.122	0.128	0.133	0.133
Native-born	0.805	0.808	0.821	0.824
Birth Year (1965 or later)	12.230	8.020	8.620	7.150
Birth Year (1955-1964)	32.760	31.740	31.480	31.850
Birth Year (1945-1954)	31.290	33.760	34.750	36.410
Birth Year (1935-1944)	17.390	19.270	19.250	19.650
Birth Year (1934 or earlier)	6.330	7.210	5.900	4.940
Full-time job	0.999	0.924	0.914	0.908
Bachelor	0.409	0.343	0.344	0.317
Master	0.215	0.213	0.222	0.219
Doctorate	0.333	0.393	0.372	0.397
Professional	0.043	0.045	0.049	0.050
Other Degree	0.000	0.007	0.013	0.017
Computer & math Science	0.095	0.089	0.089	0.089
Life & related Science	0.178	0.193	0.188	0.167
Physical & related Science	0.115	0.118	0.117	0.126
Social & related Science	0.181	0.195	0.194	0.211
Engineering	0.272	0.245	0.238	0.229
Non-S&E Degree	0.160	0.160	0.175	0.178
Academia	0.262	0.285	0.273	0.274
Government	0.150	0.131	0.131	0.125
Industry	0.588	0.585	0.597	0.601
Having children under 12	0.338	0.373	0.352	0.338
Number of Individuals	97689	71975	63626	47757

Table2: Mean or Percentage of Variables by Survey Year and Gender, SESTAT

Variable	1993		1995		1997		1999	
	Male	Female	Male	Female	Male	Female	Male	Female
Annual Salary	56008.81	43146.49	60692.62	43338.1	67396.87	48934.36	74062.99	53495.47
Annual Salary(logged)	10.818	10.556	10.787	10.333	10.969	10.577	11.017	10.573
Asain	0.121	0.126	0.122	0.119	0.113	0.114	0.111	0.115
Other under represented minority	0.097	0.172	0.094	0.157	0.095	0.155	0.097	0.160
Foreign-born without citizenship	0.075	0.065	0.068	0.055	0.047	0.041	0.044	0.037
Foreign-born with citizenship	0.122	0.121	0.129	0.124	0.135	0.130	0.134	0.132
Native-born	0.802	0.814	0.803	0.821	0.818	0.829	0.822	0.830
Birth Year (1965 or later)	10.810	16.240	6.760	11.340	7.400	11.770	6.090	9.900
Birth Year (1955-1964)	31.800	35.460	30.370	35.320	30.070	35.140	30.230	36.060
Birth Year (1945-1954)	31.410	30.970	33.550	34.330	34.540	35.310	36.340	36.610
Birth Year (1935-1944)	18.710	13.670	20.960	14.840	21.110	14.420	21.650	14.430
Birth Year (1934 or earlier)	7.280	3.660	8.360	4.170	6.880	3.360	5.680	3.000
Full-time job	0.999	0.997	0.952	0.851	0.943	0.838	0.942	0.821
Bachelor	0.405	0.420	0.336	0.360	0.341	0.352	0.314	0.326
Master	0.205	0.245	0.201	0.246	0.209	0.256	0.206	0.253
Doctorate	0.345	0.299	0.412	0.343	0.391	0.323	0.419	0.342
Professional	0.045	0.035	0.046	0.039	0.049	0.046	0.050	0.050
Other Degree	0.000	0.000	0.005	0.012	0.009	0.023	0.012	0.029
Computer & math Science	0.091	0.108	0.086	0.096	0.086	0.095	0.087	0.094
Life & related Science	0.160	0.227	0.178	0.232	0.174	0.225	0.152	0.205
Physical & related Science	0.128	0.078	0.135	0.074	0.134	0.072	0.145	0.076
Social & related Science	0.136	0.307	0.145	0.327	0.144	0.322	0.163	0.336
Engineering	0.331	0.105	0.305	0.090	0.298	0.083	0.286	0.079
Non-S&E Degree	0.154	0.177	0.151	0.182	0.164	0.203	0.166	0.210
Academia	0.235	0.339	0.256	0.361	0.242	0.353	0.244	0.351
Government	0.149	0.154	0.130	0.131	0.131	0.130	0.124	0.128
Industry	0.616	0.507	0.614	0.508	0.628	0.517	0.631	0.521
Having children under 12	0.621	0.406	0.598	0.491	0.624	0.538	0.582	0.519
Number of Individuals	72077	25612	52099	19876	45892	17734	34511	13246

Table3: Correlation Matrix for Earnings Across Different Survey Years

	Salary93	Salary95	Salary97	Salary99
Salary93	1.000			
Salary95	0.755	1.000		
Salary97	0.713	0.799	1.000	
Salary99	0.654	0.736	0.825	1.000

Table4: Coefficients and Standard Errors of Logged Earnings Measured at a Two-year Intervals by Gender from the SESTAT

	Model1		Model2		Model3	
Variance Structure	Male		Female		All	
	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err
Intercept	9.39 **	0.014	8.993 **	0.027	9.333 **	0.012
t	0.08 **	0.002	0.074 **	0.003	0.079 **	0.002
Female					-0.159 **	0.004
White(omitted)						
Asain	-0.076 **	0.008	0.008	0.015	-0.053 **	0.007
Other under represented minority	-0.097 **	0.007	-0.038 **	0.011	-0.077	0.006
Native-born(omitted)						
Foreign-born without citizenship	-0.084 **	0.009	-0.13 **	0.019	-0.1 **	0.009
Foreign-born with citizenship	0.009	0.007	0.004	0.013	0.005	0.006
Birth Year (1934 or earlier)(omitted)						
Birth Year (1965 or later)	-0.29 **	0.011	-0.087 **	0.025	-0.241 **	0.01
Birth Year (1955-1964)	-0.039 **	0.009	0.114 **	0.023	-0.008	0.008
Birth Year (1945-1954)	0.1054 **	0.009	0.196 **	0.022	0.118 **	0.008
Birth Year (1935-1944)	0.1641 **	0.009	0.198 **	0.024	0.165 **	0.009
Full-time	0.232 **	0.01	1.209 **	0.013	1.229 **	0.008
Bachelor(omitted)						
Master	0.11 **	0.006	0.178 **	0.011	0.127 **	0.005
Doctorate	0.394 **	0.006	0.526 **	0.011	0.429 **	0.005
Professional	0.549 **	0.012	0.585 **	0.023	0.562 **	0.011
Other Degree	0.084 *	0.027	0.181 **	0.034	0.116 **	0.021
Social & related Science(omitted)						
Computer & math Science	0.179 **	0.008	0.245 **	0.015	0.201 **	0.008
Life & related Science	0.033 **	0.007	0.016	0.011	0.032 **	0.006
Physical & related Science	0.085 **	0.008	0.098 **	0.016	0.093 **	0.007
Engineering	0.22 **	0.007	0.332 **	0.016	0.243 **	0.006
Non-S&E Degree	0.128 **	0.008	0.138 **	0.014	0.137 **	0.007
Industry(Omitted)						
Academia	-0.23 **	0.005	-0.218 **	0.009	-0.23 **	0.005
Government	-0.093 **	0.006	-0.013 **	0.012	-0.071 **	0.005
Having 2 more children under age 12						
Having no children under age 12	-0.092 **	0.005	-0.044 **	0.012	-0.081 **	0.005
Having one child under age 12	-0.041 **	0.006	0.005	0.013	0.03 **	0.006
ρAR(1)	0.2405	0.003	0.205	0.005	0.231	0.002
σ2e	0.6361	0.002	0.989	0.005	0.734	0.002
-2LL	480975.3		214395.2		701720	
AIC	480979.3		214399.2		701724	
BIC	480997.8		214399.2		701743	
Number of Subjects	78280		30736		109016	
Number of Observations	204579		76468		281047	

***P<0.001 *P<0.05*

Table5: Coefficients and Standard Errors from Random-Effects Growth Curve Models of logged Earnings Measured at Two-year Intervals from SESTAT

Variance Structure	Male		Female		All	
	Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err
Intercept	9.183 **	0.024	8.946 **	0.035	9.239 **	0.019
t	0.106 **	0.013	0.025	0.021	0.067 **	0.011
Predicting Intercept						
Female					-0.14 **	0.005
White(omitted)						
Asain	-0.074 **	0.009	0.005	0.017	-0.052 **	0.008
Other under represented minority	-0.087 **	0.008	-0.022	0.013	-0.065 **	0.007
Native-born(omitted)						
Foreign-born without citizenship	-0.1 **	0.01	-0.133 **	0.021	-0.113 **	0.009
Foreign-born with citizenship	0.003	0.008	-0.005	0.016	-0.002	0.007
Birth Year (1934 or earlier)(omitted)						
Birth Year (1965 or later)	-0.529 **	0.011	-0.337 **	0.027	-0.484 **	0.011
Birth Year (1955-1964)	0.223 **	0.01	-0.067 *	0.025	-0.194 **	0.009
Birth Year (1945-1954)	-0.04 **	0.01	0.061 **	0.025	-0.024 *	0.009
Birth Year (1935-1944)	0.061 **	0.01	0.105 **	0.027	0.065 **	0.009
Full-time	1.513 **	0.023	1.14 **	0.026	1.462 **	0.016
Bachelor(omitted)						
Master	0.104 **	0.006	0.149 **	0.013	0.115 **	0.006
Doctorate	0.402 **	0.006	0.486 **	0.013	0.424 **	0.006
Professional	0.556 **	0.013	0.551 **	0.028	0.56 **	0.012
Other Degree	0.075	0.061	0.053	0.077	0.058	0.047
Social & related Science(omitted)						
Computer & math Science	0.18 **	0.01	0.221 **	0.016	0.194 **	0.008
Life & related Science	0.028 **	0.008	0.004	0.013	0.024	0.007
Physical & related Science	0.075 **	0.009	0.079 **	0.018	0.081 **	0.008
Engineering	0.218 **	0.007	0.316 **	0.017	0.234 **	0.007
Non-S&E Degree	0.126 **	0.009	0.121 **	0.015	0.129 **	0.008
Industry(Omitted)						
Academia	-0.259 **	0.006	-0.23 **	0.011	-0.254 **	0.005
Government	-0.098 **	0.006	-0.039 *	0.013	-0.083 **	0.006
Having children under 12	0.053 **	0.005	0.033 *	0.011	-0.049 **	0.005
Predciting Slope						
Female					-0.027 **	0.003
White(omitted)						
Asain	-0.005	0.006	0.005	0.011	-0.002	0.005
Other under represented minority	-0.009	0.005	-0.011	0.009	-0.009 *	0.004
Native-born(omitted)						
Foreign-born without citizenship	0.021 *	0.008	0.007	0.016	0.017 *	0.007
Foreign-born with citizenship	0.003	0.005	0.002	0.01	0.002	0.004
Birth Year (1934 or earlier)(omitted)						
Birth Year (1965 or later)	0.27 **	0.009	0.252 **	0.02	0.267 **	0.008
Birth Year (1955-1964)	0.217 **	0.007	0.184 **	0.019	0.209 **	0.007
Birth Year (1945-1954)	0.175 **	0.007	0.147 **	0.018	0.168 **	0.007
Birth Year (1935-1944)	0.13 **	0.007	0.105 **	0.019	0.123 **	0.007
Full-time	-0.22 **	0.011	-0.159 **	0.013	-0.187 **	0.004
Bachelor(Omitted)						
Master	-0.001	0.004	0.022 *	0.009	0.006	0.004
Doctorate	-0.004 *	0.004	0.03 **	0.009	0.006	0.008
Professional	-0.006	0.009	0.018	0.017	-0.001	0.008
Other Degree	0.025	0.026	0.066 *	0.034	0.041 *	0.02
Social & related Science(omitted)						
Computer & math Science	0.001	0.006	0.026 *	0.011	0.009	0.006
Life & related Science	0.008	0.005	0.015	0.009	0.011 *	0.004
Physical & related Science	0.01	0.006	0.022	0.012	0.013	0.005
Engineering	0.006	0.005	0.018	0.012	0.011 *	0.004
Non-S&E Degree	0.001	0.006	0.011	0.01	0.006	0.005
Industry(Omitted)						
Academia	0.029 **	0.004	0.018 *	0.007	0.026 **	0.004
Government	0.016 **	0.005	0.029 *	0.009	0.021 **	0.004
Having children under 12	-0.002	0.004		-0.009	0.005	0.003
-2LL	464526.5		208195.9		678908.2	
AIC	464620.5		208289.9		679006.2	
BIC	465056.1		208681.6		679476.6	
Number of Subjects	78280		30736		109016	
Number of Observations	204579		76468		281047	

***P<0.001 *P<0.05*

Table6: Coefficients and Standard Errors from Random-Effects Growth Curve Models of logged Earnings of Immigrants Scientists/Engineers Measured at Two-year Intervals from SESTAT

Variance Structure	Male	
	Coeff.	Std. Err
Intercept	9.397 **	0.045
t	0.099 **	0.026
Predicting Intercept		
Female	-0.145 **	0.011
White(omitted)		
Asain	-0.096 **	0.01
Other under represented minority	-0.091 **	0.015
Foreign-born with citizenship(omitted)		
Foreign-born without citizenship	-0.113 **	0.01
Birth Year (1934 or earlier)(omitted)		
Birth Year (1965 or later)	-0.48 **	0.026
Birth Year (1955-1964)	-0.208 **	0.021
Birth Year (1945-1954)	-0.061 **	0.021
Birth Year (1935-1944)	-0.002 *	0.021
Full-time	1.371 **	0.039
Bachelor(omitted)		
Master	0.12 **	0.013
Doctorate	0.441 **	0.013
Professional	0.586 **	0.029
Other Degree	0.036	0.111
Social & related Science(omitted)		
Computer & math Science	0.191 **	0.019
Life & related Science	0.043 *	0.018
Physical & related Science	0.053 **	0.019
Engineering	0.164 **	0.016
Non-S&E Degree	0.13 **	0.02
Industry(Omitted)		
Academia	-0.288 **	0.011
Government	-0.118 **	0.015
Having children under 12	-0.032 **	0.01
Predciting Slope		
Female	-0.021 *	0.008
White(omitted)		
Asain	-0.007	0.007
Other under represented minority	-0.001	0.01
Foreign-born with citizenship(omitted)		
Foreign-born without citizenship	0.018 *	0.008
Birth Year (1934 or earlier)(omitted)		
Birth Year (1965 or later)	0.208 **	0.02
Birth Year (1955-1964)	0.159 **	0.016
Birth Year (1945-1954)	0.104 **	0.015
Birth Year (1935-1944)	0.074 **	0.016
Full-time	-0.188 **	0.02
Bachelor(Omitted)		
Master	0.017	0.009
Doctorate	0.018 *	0.009
Professional	0.005	0.021
Other Degree	0.053	0.048
Social & related Science(omitted)		
Computer & math Science	0.008	0.013
Life & related Science	-0.003	0.012
Physical & related Science	0.014	0.013
Engineering	0.008	0.011
Non-S&E Degree	0.01	0.014
Industry(Omitted)		
Academia	0.021 *	0.008
Government	0.022 *	0.01
Having children under 12	0.016 *	0.007
-2LL	125738.4	
AIC	125832.5	
BIC	126206.7	
Number of Subjects	21237	
Number of Observations	52613	

***P<0.001 *P<0.05*