REPRESENTATION AND REWARD IN HIGH TECHNOLOGY INDUSTRIES AND OCCUPATIONS: THE INFLUENCE OF RACE AND ETHNICITY

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REPRESENTATION AND REWARD IN HIGH TECHNOLOGY INDUSTRIES AND OCCUPATIONS: THE INFLUENCE OF RACE AND ETHNICITY

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LIST OF ABBREVIATIONS

ADS	Annual Demographic Survey
BLS	Bureau of Labor Statistics
CPS	Current Population Survey
FTFY	Full-time, full year workers
HTSE	High technology, science and engineering
HTNSE	High technology, non-science and engineering
NCES	National Council on Educational Statistics
NHTSE	Non-high technology, science and engineering
NHTNSE	Non-high technology, non-science and engineering
NSF	National Science Foundation
OES	Occupational Employment Survey
R & D	Research and development
SBTC	Skill biased technological change
S & E	Science and engineering
SOC	Standard Occupational Codes
STEM	Science, technology, engineering and mathematics

SUMMARY

Highly educated individuals undertake research and development activities that give rise to innovations, which drive profitability and competitiveness of businesses, regions and countries. Although hiring practices related to jobs in science and engineering should be based on the competitive demand for individuals with the requisite skills, or merit, this may not always be the case. Further, the historical situation in the US is such that some minority groups are at a disadvantage compared to majority whites in more highly rewarded jobs.

Human capital investments, in particular in science and engineering, vary among racial and ethnic groups. These differences may be one source of differences in employment outcomes. This study examined the effects of education, one form of human capital investment, on the distribution of employment and wages among four racial and ethnic groups (non-Hispanic whites, non-Hispanic blacks, Hispanics and Asians) in high technology industries and in science and engineering occupations, for the period 1992 to 2002. The main data used in the analyses came from the March Annual Demographic Survey of the Current Population Survey. Multinomial logit analyses were used to determine the probabilities of employment of the racial and ethnic groups in the industry/ occupational groups, and ordinary least squares, non-parametric regressions and t-tests were used to examine wages. In addition to education, the models controlled for the effects of time, labor market and other individual characteristics. However, the study focused on males because the relatively low representation of females in S & E occupations made analyses using the research design less reliable.

The study found that education played the more important role in determining employment and wages in S & E occupations compared to other occupations and, compared to other factors such as race, demographic and labor market characteristics. The effects of education were greater in S & E jobs in the high technology sector as compared to S & E jobs elsewhere in the economy. However, educational attainment was not the sole factor determining employment; and the effects of education varied with the level of education, race and industry/occupation, in ways that suggest that both employment and wages continue to be influenced by correlates of race.

Specifically, with regard to probability of employment,

- In high technology industries,
    - Asians with graduate education had a higher probability of employment in S & E jobs compared to any other racial group, and to S & E jobs outside of the sector.
    - Blacks and Latinos, regardless of education had significantly lower probabilities of employment in S & E jobs.
    - For non-science and engineering jobs, minorities and whites with graduate education, had no significant difference in the odds of employment.
    - However, blacks and Latinos with bachelors level education or below had significantly lower odds of employment in non-science and engineering jobs compared to whites.
- Outside the high technology sector,
    - There was no significant difference between blacks and whites with graduate degrees in the odds of employment of in S & E jobs.

- o But the odds of similarly educated Latinos being employed in these jobs were significantly lower than those of whites.

With regard to wages,

- Wage gaps between majority whites and minorities were smallest in S & E jobs in the high technology sector, when compared to other jobs in the study.
- Outside the high technology sector, blacks and Latinos with graduate education had significantly lower wages than whites in S & E jobs, with differences being greater for older workers.
- In non-science and engineering jobs in the high technology sector, blacks and Latinos had significantly lower wages than whites regardless of educational level.
- Differences between the wages of whites and Asians did not vary in a systematic manner or were insignificant.

Based on these findings, the study develops a number of policy recommendations related to education, economic development and the labor market. These include programs to attract, recruit, and retain individuals in STEM fields of study at all levels of the education system; for example by coupling STEM education with exposure to the concepts of entrepreneurialism. Economic development policies should simultaneously promote industries that are complementary to high technology industries so that a diverse group of industries are created. Programs should have a component that place special emphasis on under-represented minorities

CHAPTER 1

INTRODUCTION

1.1 Research Motivation and Background

Although the initial enthusiasm towards technology led growth strategies waned somewhat since the decline of technology industries in the late 1990s, many states and regions within the United States continue to use these strategies to stimulate economic growth, create jobs, and increase the tax base of the area. Ultimately, policy makers and economic developers hope to improve the quality of life of citizens and achieve sustainable, long term growth. Even though economic developers are concerned about the quality of jobs created, hence the preoccupation with technology led strategies, they pay little attention to how the benefits from these strategies are distributed.

Labor economic studies show that technology industries and technological changes alter the demand for skilled workers and the returns to skill (1998; Acemoglu, 2002; Aghion & Howitt, 2002; Juhn, Murphy, & Pierce, 1993) and contribute to disparate returns within and across industries. Technology, in its various forms has contributed to the growing inequality observed in the US since the 1970s. Galbraith (1998) argues that high technology industries contribute to increased inequality because workers benefit from the higher wages derived from monopoly profit gains.

Technology growth strategies often result in the growth of high technology industries and jobs in an area. Defining characteristics of high technology industries, include the creation of knowledge through research and development; the employment of a high proportion of highly skilled individuals such as scientists and engineers; and high levels of innovation leading to new products or processes that increase profitability. Thus technology growth strategies give rise to jobs that require high levels of skills and which also have higher than average wages.

This study attempts to determine whether the benefits of high technology industries and jobs are equitably distributed among four racial and ethnic groups, defined in keeping with the approach used by the federal government. The four groups are non-Hispanic whites (persons of European descent); non-Hispanic blacks (individuals of African descent); Hispanics or Latinos (individuals of Latin American or Spanish speaking origin); and Asians (which includes individuals from the Far East, Southeast Asia, the Indian sub-continent, Pacific Island and their descendants). Specifically the study focuses on the distribution of employment and wages in high technology industries and science and engineering occupations in order to determine whether or not disparities exist between the groups. The classification used for race and ethnicity has a number of limitations and these are discussed in a subsequent section.

1.1.1 High Technology Industries and Economic Growth

The economic success of Silicon Valley and Boston Route 128, regions rich in technology firms increased the thrust of localities to encourage the formation and growth of high technology industries. Strategies used include support for research, university – industry partnerships, inter-firm collaborations, and venture capital financing. Successful regions benefit from the high levels of profitability associated with innovative activity, increased employment and higher wages for citizens as well as from higher tax revenues (Markusen, Hall and Glasmeier, 1986; Galbraith, 1998). However, if individuals or groups do not have the requisite education or skills to fill the increased demand, they will not be able to take advantage of the new jobs. As a result, the jobs will be filled by others in the population or in-migrants.

The importance of individual and inter-firm interactions in networks and clusters of firms have been documented for several industries and regions such as Silicon Valley in the US, Third Italy in north-central Italy and Baden Württemberg in Germany. The transmission of business knowledge through individual and inter-organizational interactions increases learning, innovation, economic output and competitiveness (Cooke, 2002; Porter, 1990; Saxenian, 1994). Connections to centers of research as well as interactions with other individuals and firms facilitate knowledge transfer, learning and the exploitation of spillovers. The extent to which minority groups are able to interact with members of the industry and connect to other sources information will not only affect their ability to get jobs in the sector but will also have a bearing on their creativity and successful participation once there. Very few studies consider whether an adequate supply of minorities exists in the high technology sector, and if this is sufficient to establish the networks needed to increase the levels of employment, knowledge flows, and success. Although a high level of integration may make minority networks less necessary, based on the current status quo, there is no reason to believe that such a level of integration exists. The absence of well-developed networks within a particular racial group is likely to limit the opportunities of employment for that group.

High technology economic development strategies are not without their critics. Some argue that the success of Silicon Valley is historically and culturally specific (Saxenian, 1994), and therefore the strategy may be difficult to replicate elsewhere. In addition, high technology regions lack diversity in their industrial mix; have too high wages that are a bane in times of economic downturn (Gittell & Sohl, 2005); and provide benefits that flow disproportionately to highly educated and skilled individuals. Chapple et al. (2004) point to the need for more studies to determine how the benefits from high technology industries flow to different groups. This study attempts to fill that gap.

Evaluations of technology led economic development strategies typically focus on the benefits and disadvantages of high technology industries that accrue to regions or individuals and its effects in the general population (AEA, 2002; Chapple, Markusen, Schrock, Yamamoto, & Yu, 2004; Cozzens & Bobb, 2003; Cozzens et al., 2005) or particular regions (Shapira, 2005). They seldom look at differences across racial or ethnic sub-groups or consider whether these policies exacerbate or reduce racial and ethnic inequalities (Cozzens & Bobb, 2003; Cozzens et al., 2005; Hagey & Malecki, 1986; Markusen, Hall, & Glasmeier, 1986).

In most studies that examine industrial and occupational employment and wage inequalities between different racial and ethnic groups, the focus has not been on a specific examination of the high technology sector (Grodsky & Pager, 2001; Heckman, Lyons, & Todd, 2000; Tang, 1997; Tomaskovic-Devey, 1993; Weeden, 2002). These studies focus on the growing levels of wage inequality in the more traditional industry and occupation groups (management, professional, working class etc.). A number of studies have looked at the factors that influence under-representation in either S&E occupations or high technology industries compared to other industries (NSF, 2004; Tang, 2000). Tang (2000) studied the career mobility and attainment of Asian, white and black engineers in the US using data from 1974 to 1994. Colclough and Tolbert (1990) studied racial and ethnic differences in high technology industries in the southern region of the US and Scott (1992) examined the electronics industry in southern California. However, few recent studies consider racial/ethnic disparities in employment and wages in both high technology industries and occupations in the US as a whole.

Other studies on the effects of technology on wage inequality examine the workforce as a whole and have not looked at racial and ethnic differences (Acemoglu, 2002; Aghion & Howitt, 2002; Bartel & Sicherman, 1999; Mincer, 1991). Previous studies on the effects of technology on inequality use a narrow conceptualization of technology for example, the number of computers, the adoption of information and communications technology, or investments in capital goods (Acemoglu, 1998, 2002; Aghion & Howitt, 2002).

Science and engineering (S&E) skills, which drive the creation of knowledge are important and critical to the success of technology industries. As a result, the demand for and proportion of S&E workers in technology industries is higher than in other industries and this feature is often used as a defining characteristic of technology industries. African Americans, Hispanics and minorities excluding Asians continue to lag behind whites and Asians in the level of educational attainment, in particular in science and engineering studies despite making educational gains since the mid-1970s (NCES, 2003). Although Reich (1991) argues that the growing divide between high and low wage earners is not along racial lines, it is possible that racial/ ethnic differences in human capital investments in high technology industries may result in a representation and reward structure that is divided along racial lines. This may happen even if no deliberate discrimination exists. On the other hand, it is possible that the demand for highly skilled, technical individuals may result in employment opportunities and wage premiums for minorities with the requisite skills that are as high as those enjoyed by whites. However, it is not clear that the demand for skill outweighs long-standing prejudices and discrimination against qualified blacks and Hispanics. Further, since the number of minority-owned companies as well as the social networks that contribute to employment are typically weak or absent in African American communities (Wilson, 1996), the potential for African Americans, Hispanics and other minority groups to participate in and establish successful high technology businesses may not be as strong as whites.

1.2 Research Question

Science and engineering occupations are among the fastest growing in the US, with employment growth rates 3 to 4 times that of other jobs in the 1990s (National Science Board, 2006). As a result, there is a high demand for individuals with skills in S & E. However, investments in human capital, particularly in S & E skills vary between ethnic groups, and this has implications for the representation of different ethnic groups in jobs requiring S & E skills. This study will attempt to determine whether different racial groups benefit in the same way from similar levels of investments in human capital and the demand for highly skilled individuals in high technology industries and science and engineering occupation. It seeks to answer the question of whether the demand for more educated, skilled science and engineering workers outweigh longstanding practices of discrimination in hiring in high technology industries or science engineering jobs during the period 1992 to 2002.

Specifically, the research question asks:

What are the effects of human capital (specifically, education and experience) on employment and wage disparities between four race/ethnicity groups in science and engineering occupations and high technology industries during the period 1992 to 2002? Secondary questions include the following:

1. Are employment returns attributable to human capital similar across race and ethnic groups in high technology or S & E jobs?
2. Are employment and wages in high technology industries or S & E occupations based primarily on merit and market factors?
3. How important are race/ ethnicity compared to education and experience in determining employment and wages?" and
4. Have rising levels of educational attainment changed the level of employment and wage disparities between the racial/ ethnic groups over the period 1992-2002?"

This study compares the effects of human capital accumulation on the distribution of employment and wages between different racial and ethnic groups in high technology industries and science and engineering occupations with its effects on other jobs that fall outside of these two groups. Table 1 shows the descriptors for the four groups of jobs formed by the intersection of high technology and non-high technology industries with science and engineering and non-science and engineering occupations, which are compared in the analyses. The descriptors will be used as shortened forms of the comparison groups in subsequent references to the groups. Reference to high technology jobs includes both S & E and non- S & E jobs.

Table 1. Descriptors of the Comparison Groups of Jobs Formed by the Intersection of Industries and Occupations Used in the Study

Occupation	Industry	
	High Technology	Non-High technology
Science & Engineering	**High technology S & E**	**Other S & E**
Non- Science & engineering	**Other technology-sector**	**Non-technology**

The comparative analyses, with its focus on specific industries and occupations in which employment and returns to skills have long been considered to be based on merit and competition, will contribute to understanding the mechanisms which drive employment and wages among different racial groups in different settings in the US labor market. The research will contribute to a better understanding of the broader issue of the distributional consequences of technology strategies used to promote economic growth, and which become manifest as technology industries and employment.

One of the theories most often used to explain differences between employment and wages of individuals is human capital theory. This is briefly outlined here and will be discussed in greater detail in subsequent sections. According to human capital theory, investments in human capital (education, experience, job training, health, job searches) improve the earnings of individuals, with the returns accruing over the lifetime of the individual (Becker, 1962; Mincer, 1958; Schultz, 1962). Differences in human capital accumulation lead to wage differences between workers and by extension employability and economic well-being.

The central hypotheses are that human capital investments (education and experience) will be the primary determinant of employment and wages with the effects of human capital investment being most pronounced in the more rewarding science and engineering jobs and more so for these jobs in high technology industries. Science and engineering require specialized skills that are largely reflected in the educational attainment and the level of experience of individuals. High levels of competition for the limited number of jobs as well as the competitiveness of industries result in individuals with on average higher levels of human capital (education and experience) getting the jobs.

However, skill is not the only determinant of employment and wages in the labor market and individual returns on investment in human capital depend on many factors. Human capital theory fails to explain of why differences exist and persist across different groups in the society. A number of studies show that blacks and Hispanics are under-represented in S & E fields (NCES, 2003; National Science Board, 2006), while on the other hand, Asians are over-represented compared to their proportions in the population. Several reasons have been advanced to explain the lower representation of blacks and Latinos in S & E fields of study ad occupations. These include early decisions not to pursue S & E studies(Leslie, McClure, & Oaxaca, 1998), with blacks having the perception that past discriminatory practices reduce job opportunities for qualified blacks(Fields, 1998), recognition and financial rewards(Graham & Smith, 2004), among others. Therefore, other hypotheses are that blacks and Hispanics benefit less than whites from similar investments in human capital. As a result, blacks and Hispanics are less likely to be employed in the more rewarding S & E in the high technology sector, despite educational attainment that is comparable to whites.

The persistence of the wage gap between majority whites and minorities have been extensively documented (Altonji & Blank, 1999; Black, Haviland, Sanders, & Taylor, 2006; Heckman et al., 2000; McCall, 2001; Trejo, 1997) and several studies have shown that technology contributes to the growing levels of wage inequality observed in the US (Acemoglu, 2002; Aghion & Howitt, 2002; Galbraith, 1998). Science and engineering jobs require high levels of skills, and society places a high value on these jobs. As a result, on average they are more highly rewarded than other types of jobs. Although it is often believed that the competitive demand and supply of skills play the major role in determining employment and wages for high skill, high reward jobs, Grodsky and Pager (2001) found in their study that black men suffer greater racial penalties in highly rewarded occupations. Thus it is hypothesized that of the four industry/occupation groups, wages will be greatest in high technology, science and engineering jobs and the wage gaps between blacks/ Hispanics will be greatest in these jobs.

Individuals in S & E occupations, who have high levels of educational attainment (masters degrees or above) are expected to have studied specifically in S & E fields and acquired specialized knowledge. As a result, individuals in S & E occupations with high levels of educational attainment are not expected to differ substantially in skills needed for these types of jobs. If there are differences in the probabilities of employment of different racial groups within either group of S & E jobs (those in the high technology sector and those outside) then these differences are not considered to be due solely to what individuals study. It is expected that employment and wages of blacks and Hispanics in both high technology jobs and S & E will improve over time, because of an increase in the level of educational attainment of these groups, and an increase in demand for these skills.

The alternative theories of labor market segmentation, closure and sorting provide additional insights on the distribution and reward structure of science and engineering jobs. Labor market segmentation theorists argue specifically that the labor market is divided into segments, which contain either high or low wage jobs (Taubman & Wachter, 1986). The divisions are not determined by the skills of individuals and individuals in the high wage segment will earn more than those in the low wage segment. Employment and wages depend on a complex interaction of individual characteristics and socio-economic and labor market conditions, which include innate ability, family background, the quality of formal and informal education, access to on-the-job training, and social divisions of occupations and industries. Labor market segmentation provides an explanation of how jobs become differentiated into groups that are not based on differences in skills (for example, S & E jobs in the high technology sector, and those outside) and have differential rewards.

1.2.1 Methods

The study uses data from the Current Population Survey (CPS) for the period 1992 to 2002 augmented with data from other sources and a series of regression analyses. The period of study covers only 11 years from 1992 to 2002, which is convenient for the analyses in some ways, but constrains the findings in other ways. The time period closely overlaps with a period of expansion in the business cycle (NBER, 2001) and represents a period just before the major downturn and slowing of growth in the high technology sector. This makes it attractive to examine if the competitive market demand for high skilled labor favored blacks and Hispanics. The year 2002 also marks the point when the Bureau of Labor Statistics made major changes from the Standard Industrial Classification (SIC) system for coding industries to the North American Industrial Classification System (NAICS) and in the occupational codes used. As a result, the period 1992 to 2002 provides a continuous period over which high technology industries can be identified by 3-digit SIC codes, without the need to resort to bridges between SIC and NAICS industry codes. The SIC-NAICS bridges are often inexact matches at the more detailed industry codes and conversions make analyses based on detailed industry codes more difficult or impossible. A potential disadvantage with the time period selected is that it may be too short to observe major shifts in racial or ethnic differences in employment and wages.

The study uses multinomial logit analyses to estimate the probabilities of employment in the four industry/occupational groups. In the analyses of wages and wage differences, the results from ordinary least squares regression analyses are compared to results from t-tests of group means and graphically to estimates obtained from local linear non-parametric regression. The models developed include the human capital variables (education and experience), race/ethnicity variables together with the interaction effects between education and race. The four racial/ ethnic groups in the study are: non-Hispanic whites, Asians, non-Hispanic blacks and Hispanics (a racially heterogeneous group). The models include variables that define the regions that individuals live, which captures a range of economic, historic and institutional factors; as well as variables which represent other individual and labor market characteristics that influence differences in employment and wages, which are discussed in greater detail in the section on methodology. The magnitude, direction and significance level of the coefficients on the variables in the model will support or refute the hypotheses.

1.3 Scope

This study contrasts the effects of human capital and race on employment and wages of individuals working in jobs formed by the intersection of two tightly defined groups (science and engineering occupations and high technology industries), with employment and wages of individuals who work either in other high technology jobs, other science and engineering jobs or elsewhere. Typically, previous studies examine science and engineering occupations and high technology industries separately, and findings on the number of workers involved vary with the definition adopted. According to the National Science Board, estimates of workers in science and engineering occupations or who use S&E skills, range from about 5 million (3.7%) to 15.7 million (11%) of the non-farm workforce in 2000 (National Science Board, 2006). Based on this definition, the average annual growth rate for the S&E segment of the workforce was 3.6% between the 1990 and 2000 Censuses, or more than triple the average growth rate of other occupations. Thus, science and engineering workers represent an important and growing component of the workforce. Appendix Table 1 (p.197) shows trends in the number of masters and doctoral science and engineering degrees awarded by race for US citzens and permanent residents (National Science Foundation: Division of Science Resource Statistics, 2007).

In the definition of high technology industries used by the Bureau of Labor Statistics in 2002, approximately 15 million workers (11%) were in the high technology sector, with the growth rate of the labor force in some industries in the high technology sector being slower than the growth rate of the labor force nationally and others being faster. The net result being that over the period 1992 to 2002, the proportion of workers in the high technology sector declined relative to the total labor force and the decline was projected to continue through to 2012, see Appendix Table 2 (p. 197) derived from (Hecker, 2005). Not all workers in the high technology sector are S & E workers, as a result, science and engineering workers in the high technology sector are expected to be a relatively small proportion of workforce and thus comprise a select group, which will be compared to other groups of workers. On the other hand, the non-science and engineering workers outside of the high technology sector are a large and heterogeneous group. The end result is that the distribution of workers between the four industry/occupation groups is highly skewed. Despite this, the contrasts set up between the four industry/occupation groups will provide insights on distributional differences that may arise from technology strategies, for example policies that support R & D or high technology industries.

Using occupation related criteria to define science and engineering workforce presents a number of limitations. First, many individuals use science and engineering skills and the information is not reflected in their job title, for example managers, technical service personnel or consultants (National Science Board, 2006). As a result, these individuals may not be included in the correct sub-category of the study. For example, service workers outside of the laboratory and users of technology generate new ideas through the process of "learning-by-doing" and act as important conduits of knowledge from the field to the laboratory. Therefore the pool of workers involved in S & E activities and who require these skills may be much larger than that reflected in occupational titles. Secondly, new occupations may exist that have not been captured in the Standard Occupational Codes (SOC) used, and these are left out of the analysis. If there is a mismatch between what people study, the level of educational attainment and the occupation that they actually work in, it is more difficult to draw conclusions about human capital investments and employment and wage prospects. Further, occupational studies typically consider the primary work activity of individuals and distinguish between individuals in entry level positions and those with greater levels of seniority or those in managerial position. However, this distinction was not made for individuals in the different science and engineering occupations because the information was not captured in the data.

1.3.1 Race and Ethnicity

The four racial/ethnic groups examined in this study (whites, blacks, Asians and Hispanics) are defined in keeping with the approach used by the federal government to categorize race and ethnicity. However, this approach masks important historic, social and cultural differences within each of these groups. All four racial groups represent heterogeneous cultural and social groups with peculiarities that depend on the specific region of origin and when the group arrived in the US. Thus there are differences between average outcomes of blacks whose ancestors were present in the US since the time of slavery and those of more recent Caribbean or African origins(Anonymous, 2003). The outcomes for Hispanics are also different depending on whether they are of

Cuban, Puerto Rican, Mexican or other Latin American origin and if they immigrated to US in the 1950s or 60s or more recently (Fry & Lowell, 2006; Mason, 2004; Trejo, 1997). These arise because of differences in the levels of human capital and other resources associated with a particular wave of migration. Similarly, the group, Asians represents individuals from countries with different levels of economic strength and development for example China, Japan, India as well as less developed countries such as Laos or Cambodia. The study does not distinguish between these groups because of the unavailability of this information for the earlier years in the study and the limitations in the analyses due to small cell sizes, for later years.

In the study, I use the terms blacks or “African Americans”, and Hispanics or Latinos terms interchangeably since they have the same meaning in standard practice. Individuals identified as non-Hispanic American Indians or Aleut Eskimo, are not included in the study because of the small size of the group and the decision to focus only on the four major groups. However, the study includes a small number of individuals who identify themselves as both Hispanic and Native American or Aleut Eskimo. The Hispanic category also includes individuals who self-identify as whites, blacks and Asians.

1.4 Importance of the Study

Political actors, economic developers and other policy makers constantly strive to create policies and programs that increase the number of businesses and their competitiveness, increase employment and increase revenue for the provision of public goods. Policies are not designed intentionally to make one group better off and another worse off, but may do so inadvertently. This study will improve our understanding of the role that technology industries play, if any, in the growing levels of inequality in the US society and in so doing contribute to understanding the impacts of technology-led economic development policies, identify unintended consequences and provide directions for improvement in the design and implementation of policy.

The study represents a systematic exploration of the inter-relationship between three variables (technology, human capital, and race), which are important in the determination of employment and wages, and which have not been explored adequately in the literature. The study captures two notions of technology effects: in the first, individuals create and use technology, and individuals themselves are a part of the process so that the effect is endogenous. Technology effects for science and engineering occupations are considered to be of this type. In the second notion, individuals have less influence on technological changes, but are influenced by the effects of technology. That is, the technology effects are considered exogenous. The two views give rise to different policy implications. It differs from other studies because of its focus on science and engineering occupations in high technology industries separately from those elsewhere in the society and in its efforts to gain insights on the technology sector by contrasting it with what is happening in other industry/occupation groups defined in the study.

It is important that on-going studies take place to assess the progress made towards a more equitable distribution of high reward opportunities. The research also aims to improve our understanding of the mechanisms behind the growing levels of inequality in the society and whether these are adequately explained by economic forces or continue to be driven by more complex societal factors. The study is timely because it will contribute to the debate on the extent to which employment opportunities and wages for minorities have changed in the wake of cutbacks in the enforcement of affirmative action policies during the 1980s. Further, the study examines whether public polices may inadvertently exacerbate undesirable situations. As a result the findings will provide directions for policy interventions to ameliorate imbalances.

Most people agree with the Rawlsian perspective that justice, equity and equality of opportunity are important moral considerations (Nagel, 2003) and that these ought to be taken into account in the policy process. However, the historical development of the American society has created a situation in which the distribution of wealth and other resources remains unequal and the division is observed particularly along racial lines. Given that injustices developed in the past, continued assessment of employment and wage opportunities is needed to ensure that the society moves towards its goals of a just and equitable society. In its efforts to achieve a just society, which provides equal opportunities for all, consideration must also be given to the endowments of individuals and whether they start from a position of advantage or disadvantage (Nagel, 2003; Singer, 1993). Although moral theories do not always provide a clear guide on how to address past dilemmas (for example utilitarian theories focus on benefits to the greatest number and not on minorities), the results of this study will help to determine an appropriate course of action.

African Americans and Hispanics continue to lag behind whites in social and economic outcomes, including education and wages because of the legacy of slavery, institutionalized and informal segregation and on-going discrimination (Massey & Denton, 1993). Growing levels of inequality and marginalization of black males have important social and economic consequences for the entire American society (Goldsmith

& Blakely, 1992). Becker (1975) argues that when individuals perceive that their earnings will be low, they will under invest in education, resulting in the perpetuation of disparities or worse, the drift into a downward spiral. According to (Schultz, 1962), racial or religious discrimination or professional exclusion result in sub-optimum investments in human capital, and thus a lowering of overall economic efficiency. It is therefore important to identify and understand whether disparities exist. Non-participation of particular groups limits the pool from which workers can be drawn and it is important to maintain a growing pool of S & E workers, in order to achieve greater productivity and competitiveness.

The study will increase our understanding of the interplay between human capital investments and industry/occupational outcomes in wages and employment for different ethnic groups. If the workforce is not representative of the population, it is easier to develop racial stereotypes and the process of integration will be slowed. In addition, it will update earlier research and assess whether improvements have occurred in the level of employment and wages for blacks and Hispanics in science and engineering occupations for the specific period of 1992 to 2002 .

1.5 Outline of the Chapters

The discussions and findings from the study are presented in the following sections: First I provide a more detailed review of the literature which includes the theories used to explain differences in employment and wages between individuals or groups; employment and wage inequality between race/ethnicity groups; and the role of technology in wage inequality. Second, I present details of the hypotheses which are driven by human capital theory and the implications from race and ethnicity issues in science and engineering fields of study; third, I provide details on the methodology, which include information on the data and the models used in the analyses; fourth, I discuss the results and findings of the analyses in the three subsequent chapters. In the first of this group, I present the results from the analyses of the effects of human capital and race on the probabilities of employment. In the subsequent chapter, I discuss the effects of other individual characteristics and labor market effects on the probabilities of employment. The third chapter in this group contains the results of the analyses on wage differentials. In the final chapter, I outline the major conclusions from the study, the implications for policy, and directions for future research.

CHAPTER 2

THEORIES AND RELATED WORK ON EMPLOYMENT AND WAGE DIFFERENCES

In neoclassical economics, the aggregate of individual decisions, which are based on preferences for different jobs, wage offers, and levels of skills contribute to the determination of the labor supply in the labor market. Firms on the other hand, demand labor, depending on the consumers desire for their product. Differences between individuals and available jobs, and the balance between the supply and demand of labor help to determine employment and wages in the labor market.

Several theories have been advanced to explain differences in employment and wages of various groups in industries and occupations and how the differential rewards contribute to the growing inequality observed in the US society. However, no single explanation adequately accounts for observed levels of inequality over all periods of time, for all sectors and groups in the society. The following section briefly reviews theories relevant to this research, which can contribute to understanding employment and wage differences between individuals and groups.

The theories reviewed include human capital theory; labor market segmentation, sorting and closure. Measurable differences in education and experience, and other unmeasured skills observed by the employer affect the individuals' overall productivity and contribute to their employment (Carneiro & Heckman, 2002). However employment is also affected by discriminatory practices - closure and sorting mechanisms (Weeden, 2002), which determine the distribution of individuals in differentially rewarded positions.

2.1 Human Capital Theory

In human capital theory, the ability and skills that individuals bring to the labor market determine their earnings. Differences in human capital investments, in particular education, on or off-the-job training and experience give rise to differences in earnings (Becker, 1975; Mincer, 1974). According to human capital theory, individuals act as rational maximizers, who balance investments in education and training according to perceptions of costs and likely benefits, which accrue to the individual over his lifetime (Becker, 1975).

Human capital theory assumes that the returns to education vary uniformly with additional increments in the quantity of education received. However, the returns to education vary at different levels of education. Since the late 1960s, the increased demand for skilled individuals resulted in greater returns to college education compared to high school level education, with the returns to graduate education being greater than the returns to college education with only a bachelors degree. The differences in the returns have been increasing (Lemieux, 2004) and the growing differential is considered to be one of the main drivers of the increasing wage inequality observed in the US since the mid 1970s (Bradbury, 2002; Katz & Murphy, 1992). Highly educated and skilled individuals, whether described as symbolic analysts (R. Reich, 1991) or creative persons (Florida, 2002) earn considerably more than the less educated, or those employed in mundane tasks.

Human capital theory suggests that if blacks and Hispanics perceive that they will benefit less from investments in science and engineering education because of discrimination or lack of awareness of opportunities, they are less likely to pursue science and engineering careers compared to other activities. Individuals choose whether to pursue science or engineering careers, but the choice is constrained by many factors, including financial and institutional constraints, structural conditions and past and current discrimination. Although, Blacks and Hispanics may be under-represented in science and engineering positions because many opt not to pursue these career options, by focusing specifically on individuals in two types of science and engineering occupations, this research attempts to examine differences between minorities and the majority group who claim to have similar skill sets. The study will compare wages of different racial groups in S & E jobs in the high technology sector and outside. In so doing, the study will attempt to determine the relative importance of human capital, race and other factors in determining employment and wages in an environment that has a demand for and places a high premium on skills related to scientific and technical knowledge.

Human capital theory has limitations because it fails to consider many cultural, legal, political, familial and organizational processes that contribute to whether individuals receive a job or not and the rewards (Tomaskovic-Devey, 1993). The theory does not deal adequately with differences in what people study, for example the role of specific skills such as science and engineering, which determine employment in the jobs focused on in this study. Further, it does not take into account differences in the quality of education that individuals receive, and these differences play important roles in determining the jobs that individuals receive in the US labor market. For example, Reich (1991) and Lazonick (2001) question the quality of K-12 public education system, arguing that public education was designed to produce workers for routine jobs in mass production industrial operations. Further disparities in quality also exist within the public school system, with many central city schools, which are more likely to have minority enrollment of more than 75% considered to be of poorer quality (lower test scores, fewer resources due to lower tax base) when compared to suburban schools (NCES, 2005a). In addition, Galbraith (1998) argues that the notion of a competitive labor market, premised in human capital theory is not representative of reality because individuals are limited in their ability to determine wages.

2.1.2 Human Capital and Technology Effects

Technology-skill complementarities and the growth of knowledge economy, which require more highly educated and skilled persons contribute to growing levels of wage and income inequality (Acemoglu, 1998, 2002; Aghion & Howitt, 2002; Mincer, 1991). There is considerable debate on how technology and technological change affect the demand for skilled workers and the returns to skill. Technological change may increase the demand for skilled workers or alternatively it may result in the "deskilling" of previously skilled jobs, slowing the demand for skilled workers. Nelson and Phelps (1966) argue that education or human capital enables individuals to be better innovators and speeds up the process of technological diffusion. With more technological progress, the returns to education are greater and there is more economic growth (Nelson & Phelps, 1966).

Skill-biased technological change (SBTC), which increases the demand for skilled workers leads to a widening of the gap between the wages of skilled and unskilled workers (Goldin & Katz, 1996), which is compounded by the reduction in demand for unskilled workers. Rising educational attainment and demographic changes due to the entry of baby boomers into the labor market increased the supply of more skilled (college educated) workers relative to less skilled (high school education or less) in early 60s to late 70s. The increased supply reduced the wage premium of workers with higher skills and decreased the wage gap between skilled and unskilled workers; this served to offset the effects of technology changes prior to the 1970s. However, in late 1970s, the slow down in the rate of entry of skilled workers and the acceleration in technology changes further increased the demand for skilled workers and the returns to skill, leading to a distinct rise in inequality (Bound & Johnson, 1992; Mincer, 1991). Changes in the returns to skill are believed to contribute to the widening of the black/white wage gap because SBTC favors white workers who have higher average levels of education and are more concentrated in skilled jobs. Blacks and Hispanics on the other hand, are more likely to be in unskilled jobs, thus the employment and wage gap are due in part to differences in the jobs occupied by the racial/ethnic groups. Since predominantly whites and Asians have the science and engineering skills needed by the high technology sector and there is a paucity of blacks and Hispanics in these fields, it is expected that these jobs will be occupied by mainly by whites and Asians. Thus from the perspective of SBTC, differences between racial groups are due to on average differences in types and levels of skills present in the different groups. However, if rewards are due solely to skills, once blacks and Hispanics occupy S & E jobs, there should be little difference in the wages compared to whites.

Acemoglu (2002) argues that the period from1940 to 1990 was characterized by skill-biased technical change that was driven by an increase in the supply of skilled workers. According to Acemoglu, skilled workers produced changes in the workplace, which favored the use of greater skills and gave rise to further changes that increased the demand for skilled workers even further. However, Beaudry and Green (2003) argue that the "skill biased technological change" explanation works well for the period prior to 1987, but is less useful as an explanation for the period from 1988-2000 when skill bias plays a smaller role. They argue that it is the ratio of skilled labor to capital that is more likely to be the main factor driving movements in the US wage structure since the mid-seventies. Thus the mechanisms through which SBTC operates and extent to which these hold over different periods of time are still unclear.

According to Galbraith (1998), the timing of technological change especially as it relates to the adoption of computers does not fit with the timing of increased inequality. Since the increase in inequality predates wide-scale computer adoption, there is little support for the view that SBTC is responsible for growing levels of inequality. In addition, he argues that it is difficult to measure or adequately distinguish technological changes from other economic changes. Technological change is inferred as a cause of inequality simply because of the association of the two. Instead Galbraith suggests that inequality is caused by the types of economic policies pursued by the government, particularly those adopted since the early 1970's which together with business cycle effects culminated in overall poor economic performance. The resulting unemployment levels, slow economic growth rates, high inflation and exchange rates favor technology producing firms, which thrive under the economic conditions created. Monopoly rents and profits are passed on to workers in the form of higher wages. In addition, government policies in the post World War II years up to the 1970's that sought to protect the more vulnerable workers with the pursuit of full employment, price stability and high rates of economic growth, were largely abandoned. The reduction of public services, public investments and other social programs served to exacerbate the levels of inequality in wages, income and wealth. This view suggests that regardless of race, once individuals occupy high reward S & E jobs or other types of jobs in the high technology sector, they should benefit in the same way, all else being equal. However, few recent studies have examined how these effects vary by race.

Technological changes, whether these are associated with changes in the demand for skill or not have been shown to contribute to inequality especially that observed since the late 1970s. However studies differ in their conceptualization of technology and the mechanisms through which technology operates to change the wage structure. Researchers use for example R & D investments, modes of production organization, capital intensity or capital output ratios, and the adoption of computers to represent technology and technological changes (Bartel & Sicherman, 1999; Mincer, 1991). The industry/occupation combinations used in this study captures several important dimensions of technology that are inherent in the concepts of "high technology industry", although these are not explicitly identified in the definition adopted in the study. These include the notions of research and development; rapid change due to new and innovative products and processes; and high proportions of science and engineering occupations with requirements for high levels of skill.

2.2 Labor Market Segmentation, Sorting, and Closure

Segmented labor market approaches were posited as alternatives to neoclassical views such as human capital theory, which emphasize the role of the market and competitive pressures in determining employment and wages (Sakamoto & Chen, 1991; Taubman & Wachter, 1986). The neoclassical views do not explain employment and wage differences adequately. Segmented labor market approaches argue that employment and wage differences are due to divisions or segmentation in the labor market that are not based on skill differences. Institutional constraints or social processes give rise to divisions or submarkets, which have different labor market characteristics and behavioral rules (Piore, 1983; M. Reich, Gordon, & Edwards, 1973). In the dual labor market version of segmented markets, the labor market is comprised of primary and secondary segments, which are differentiated by the degree of stability. The primary segment is characterized as having individuals with greater levels of skills, more stable working habits and higher wages. Further segmentation may develop in the primary segment. Jobs in the secondary segment require fewer skills, discourage stable work habits and pay lower wages (M. Reich et al., 1973). The productivity of workers help to determine wages in the primary sector, however workers wages depend less on productivity in the secondary sector. Thus workers in the secondary sector will have lower wages than workers in the primary sector even when skills are comparable. Boston (1990) found that support for hypotheses from segmented labor market theory varied with race and gender, with the theory being most applicable to the earnings of black males, followed by that of black females then white females. The theory was least applicable to the earnings of white males.

Segmented labor market approaches have the potential to provide insights on the distribution of jobs and wages of different groups in society. However the theory is weak, in that it does not provide adequate guidelines on how labor markets are segmented, so different scholars adopt different approaches to dividing the labor markets. In this study, the two groups of S & E jobs, those within the high technology and those outside, which are expected to require on average similar skills are considered to be part of a segmented labor market..

Previous labor market segmentation studies suggest that the labor market operates differently for whites compared to blacks and other minorities (Boston, 1990). Sorting results in minority groups such as blacks and Hispanics being concentrated in the secondary segment with lower paying jobs even though they may be qualified for more highly skilled positions (Grodsky & Pager, 2001; Huffman & Cohen, 2004). This suggests that blacks and Hispanics are more likely to be employed in S & E jobs outside of the high technology sector and in non-science and engineering positions in high technology industries. High concentrations of minorities in particular jobs may result in lower rewards for these jobs, a devaluation effect (Huffman & Cohen, 2004). The devaluation effect in turn contributes to racial/ ethnic wage inequality. However, it is difficult analytically to separate present and past discrimination effects that are entwined in structural effects. The relative importance of human capital, regional characteristics, and individual characteristics such as race form part of the considerations of this study.

In closure theories, groups, usually those in a dominant position, create social and legal barriers that prevent or restrict access to highly desirable resources and opportunities. Typical closure mechanisms include licensing, credentialing and unionization but in “status based social closure,” exclusion is based on race (Tomaskovic-Devey, 1993). Science and engineering occupations in the wider society represent lucrative, highly paid positions that are held predominantly by white males and Asians (NSF, 2004). It is possible that the dominant group might exclude others from technical positions, for example engineers or architects by limiting access through licensing or educational credentialing requirements or directly by using race to restrict employment in industrial positions. Weeden (2002) argues that occupations that have the greatest skill ratings are those that are subject to more extensive closure strategies and this would contribute to lower representation of blacks and Hispanics.

2.3 Racial Wage Gap

The racial wage gap in the US has been studied extensively with the findings consistently showing that blacks lag behind whites in most sectors and occupations in the economy even when levels of educational attainment are comparable (Anderson & Shapiro, 1996; Card & Lemieux, 1994; Couch & Daly, 2000; Heckman et al., 2000; Hirsch & Schumacher, 1992; Tomaskovic-Devey, 1993). The rate of change in the black-white wage gap has been different for males compared to females. The male wage gap fell steeply in the period immediately following the Civil Rights activities of the 1960s up to 1974. Then from 1974 to 1989, there was relatively little change in the observed male wage gap. However, for the 1990s, there is considerable debate on the extent to which black men made gains relative to whites in the levels of wages (Chandra, 2003; Couch & Daly, 2003; Heckman et al., 2000; Johnson, Kitamura, & Neal, 2000). Carnoy (1996) points to the correspondence between the decline in affirmative action initiatives during the 1980s and the stagnation of the black-white wage gap. In general, the black-white wage gaps are smaller among women, however again there is no consensus on the extent of the gap because of methodological differences between researchers (Neal, 2004).

Employment and wage differences between Latinos and other racial groups have received some attention in the literature (Bradbury, 2002; Mason, 1999, 2004; Mora & Davila, 2006; Queneau, 2005; Roscigno, 2000; Trejo, 1997). However, analyses are complicated because of the heterogeneity of Latinos in terms of nativity, culture, language usage and accents, and phenotypic characteristics such as skin color (Mason, 2004; Tang, 2000). Differences exist depending on whether individuals are of Cuban, Mexican or other Latin American origin. In addition, the large influx of Latinos with low average levels of education in the past three decades confounds assessment of gains that would result from rising educational attainment of native –born Latinos (Carnoy, 1996). In general like blacks, Latinos on average receive lower wages compared to whites with the wage gap widening since the 1980s (Mora & Davila, 2006). Further, darker skinned Mexicans receive greater penalties compared to other lighter skinned groups (Mason, 2004). Factors such as being native-born, English speaking, identification as white, and a non-Hispanic name reduced the penalty (Mason, 2004). However some researchers find that when the level and quality of educational attainment are carefully controlled for, the wage differential between Latino and white males is reduced considerably (Black et al., 2006; Trejo, 1997; Weinberger, 1998).

For Asian males, the Asian –white wage gap is considerably reduced after controlling for education, language, immigration patterns and other cultural factors (Black et al., 2006; McCall, 2001). Based on the results of different types of regression analyses, persistent wage gaps between minorities and majority white males have been attributed to differences in chosen field of study, quality of education received in contrast to the quantity of education, and family background (operationalized as educational attainment of the mother, or family income), which in turn affects educational quality and cultural dispositions ((Black et al., 2006; Roscigno, 2000).

Although a few studies have examined racial wage differences in high technology industries or science and engineering occupations in the past, a systematic exploration of differences has not been done recently. Black-white wage differences in different occupations have been extensively studied, but differences between whites and Latinos or Asians have been less extensively studied. Instead, most studies focus on racial wage differences in the broader economy. The focus on specific subsets of industries and occupations and the comparative approach taken in this study will provide better insights to guide policy.

2.4 Race, Technology and Wages

Several studies have examined the effects of technology and technological changes on wages, and the consensus appears to be that technology in its various forms has contributed to the growing levels of inequality in the US as a whole(Acemoglu, 2002; Aghion & Howitt, 2002; Galbraith, 1998). In studies of high technology industries in the southern region of the United States (Colclough & Tolbert, 1990) and southern California (Scott, 1992), industries with products in the later stages of the product life cycle, which involve routine production processes, generate lower wages. Colclough and Tolbert (1990) use 1980 Census data and Theils information inequality measure, which summarizes the level of inequality in a distribution. On the other hand, Scott (1992) used the results from a survey administered to workers in the southern California area during 1991, which was analyzed using factor analyses and regression. They find that differences in skill and discrimination lead to differential wage premiums for different racial/ ethnic groups, with whites and Asians receiving greater rewards than other ethnic groups. Since these studies are confined to the high technology sector, they do not show if the disparities are more or less than in other sectors. In addition, the studies do not show how racial and ethnic disparities in human capital accumulation affect the distribution of job opportunities in more highly rewarded positions, such as those held by scientists and engineers.

Studies on employment and wage differences between scientists and engineers of different races typically focus on differences across disciplines and in broad sectors such as industry, government and academia, not on intra-industry differences. Tang (1997) finds that employment and wages differences vary depending on the sector (industry, government, education) and the discipline, with Asian males and females having the greatest parity with native-born white males. According to Tang (1997), it is possible that the race-based concept of statistical discrimination could be used to explain the convergence of wages between native born, white males and Asians in science and engineering fields. In the statistical discrimination model, employers with limited information on the productivity of prospective employees base their decisions to hire on the overall perception of the groups' productivity.

2.5 Methodological Issues and the Racial Wage Gap

Although official data indicate that the black-white wage gap has narrowed, there is no consensus in the literature on the extent to which income or wage gaps have closed because of methodological differences in various studies. These include differences in the data source used; the type of inequality measure; sample selection bias; and differences in the interpretation of the results, among others. Couch and Daly (2000) suggest that the black-white wage gap narrowed during the decade of the 1990's. However (Chandra, 2003; Heckman et al., 2000; Johnson et al., 2000), suggest that the observed narrowing of the wage gap has been overstated and that there has been a reversal in the gains made in the decades prior to the 1980's.

According to Heckman et al. (2000), sample choice matters, since different restrictions imposed by the sample selection rules produce different estimates of the size and relative importance of changes. Selective withdrawal from the labor force also matters. If the greater decline in labor force participation rates of blacks compared to whites is taken into account in the assessment of black earnings, progress is considerably less than previously thought. In addition, the interpretation of the decomposition of the sources of progress is altered.

The evaluation of the racial wage gap is further complicated by differences in wages in different labor markets. The effects of slavery, segregation and discrimination, which were more prevalent in southern region, contributed to regional differences in wages (Huffman & Cohen, 2004). Wages in the southern region are consistently lower than northern regions despite economic advances in the southern states. If regional differences are not taken into account in the analyses of the wage gap, then attenuation of racial differences might occur, leading to inaccurate conclusions.

The lack of consensus on the extent of convergence of the racial wage gap and methodological difficulties provide further motivation for the current study. The methodological approach used in this study will overcome some of the difficulties faced by previous studies. The four industry/occupational groups used in this study control for some of the variation in wages due to inter-industry and occupational differences, which influence wage rates and complicate analyses of the wage gap.

CHAPTER 3

HYPOTHESES

Highly educated individuals undertake research and development activities that result in new or modified products and processes, which help to increase the profits of businesses. However, employment and wages are determined by a complex mix of factors including education, labor market, demographic and social factors. The following sections contain details on the hypotheses of the study and these relate to human capital and the context of race and ethnicity issues in science and engineering in the US. In addition, hypotheses are presented on demographic and labor market factors which affect employment and wages.

3.1 Hypotheses Related to Human Capital

Human capital is used to produce goods and ideas; and the absorption and diffusion of technological changes will depend on the levels of human capital investment (Aghion & Howitt, 2002). Higher levels of human capital investment increases productivity because of greater capacity to deal with technical change and to multitask (Aghion & Howitt, 2002). High technology, science and engineering jobs require specialized information for research and innovation. As a result, these jobs have more demanding requirements of skill. Measurable human capital such as education and experience will have a larger effect on the probability of getting into high technology, science and engineering jobs for all race/ethnicity groups. Further the competition for the jobs and the skills demanded result in individuals with the greatest levels of skills getting the jobs and a premium being paid to those who get the jobs. The implications are that individuals or groups of individuals, that have on average lower levels of educational attainment compared to others will have a lower probability of getting jobs in the high technology science and engineering jobs compared to other job categories in the study. In keeping with the approach of (Aghion & Howitt, 2002; Nelson & Phelps, 1966), this study argues that education (skill) will be the most important determinant of employment in high technology, science and engineering jobs.

> **Hypothesis 1:** Education and experience exert greater influence on employment in high technology science and engineering jobs compared to the effects in other industry/occupation groups.

The relative size of effects on the human capital variables (education and experience) on the probability of employment in the industry/occupation groups, which form the dependent variable in the multinomial logit analyses will allow a test of the hypothesis, with the effects on the education variables expected to be greatest in high technology science and engineering jobs, followed by other science and engineering jobs. Table 2 summarizes the tests of the hypotheses from the analyses.

Table 2: Tests of hypotheses from multinomial logit analyses of the probabilities of employment and ordinary least squares analyses of the logarithm of weekly wages

HYPOTHESES	TESTS
H1: Effects of education on the probabilities of employment are greater than effects of any other variable and are greatest in high technology S & E jobs compared to effects in other jobs	α (education) > α (X_{ij} T) α (education) for [HTSE] > α (education) for [NHTSE], [HTNSE];
H2: Increase in potential experience increases the probabilities of employment	α (experience) >0
H3: Blacks and Hispanics have lower probabilities of employment in high technology industries and S & E jobs compared to whites and Asians and probabilities will be least for high technology S & E jobs	α (black, Hispanic) for [HTSE], [NHTSE]<0; α (black, Hispanic) for [HTSE]< α (black, Hispanic) for [NHTSE] [HTNSE]; α (Asian) for [HTSE], [NHTSE]>0
H3A: Asians have higher probabilities of employment in S & E jobs compared to whites	α (Asian) for [HTSE], [NHTSE] >0
H4: Increased levels of education increase the probabilities of employment in high technology industries or S & E occupations less for blacks and Hispanics compared to whites and Asians	α (black x education) for [HTSE], [NHTSE] < 0 α (Hispanic x education) for [HTSE], [NHTSE] <0 α (black, Hispanic) for [HTSE], [NHTSE] <0 α (black, Hispanic) for [HTSE] < α (black, Hispanic) for [NHTSE] ;
H5: The wage gap between blacks or Hispanics and whites will be greatest in high, technology S & E jobs	β (black, Hispanic)<0 β (black x HTSE, black x NHTSE, Hispanic x HTSE, Hispanic x NHTSE) <0
H6: Increase in educational attainment over the period 1992 to 2002 increases the probability of employment of blacks and Hispanics in both types of S & E jobs.	Trend Analysis
H7: Increase in educational attainment over the period 1992 to 2002 reduces the wage gap blacks or Hispanics and whites or Asians.	Trend Analysis

3.1.1 Experience

In human capital theory, experience serves as imperfect proxy for general and specific skills acquired by the individual over a lifetime. For example, individuals acquire firm specific skills, which enable them to be more productive than less experienced individuals. Such skills should enhance the prospects of employment in all industry /occupation groups because of the greater contribution to knowledge creation activities. Experience effects are expected to be more highly valued in high technology science and engineering occupations. However as with other jobs, the effects of experience are expected to increase at decreasing rate up to a maximum.

> **Hypothesis 2:** The probabilities of employment in all industry/occupation groups increase with increase in the level of potential experience, with the effect being greatest for high technology science and engineering jobs.

The coefficients on experience in the multinomial logit models are expected to be significant, positive and largest in high technology science and engineering jobs, compared to the other jobs.

3.2 Hypotheses Related to Human Capital, Race and Ethnicity

3.2.1 Blacks and Hispanics

Several reports of US government agencies, for example the National Science Foundation reports on *Women and Minorities in Science and Engineering* consistently show that blacks and Hispanics are under-represented in science and engineering occupations in broad sectors (government, industry and academe) of the society (National Science Board, 2006; NCES, 2003; NSF, 2004). Blacks and Hispanics lag behind whites and Asians in science and engineering education despite improvements since the start of the surveys in 1982 (NSF, 2002). Asians on the other hand are overrepresented in science and engineering occupations compared to their representation in the population (National Science Board, 2006; Tang, 2000).

Several reasons have been advanced to explain why differences exist in the representation of minorities (blacks, Hispanics and Asians) in science and engineering occupations. According to Leslie et al, (1998), lower representation in science and engineering occupations stem largely from early decisions not to pursue science and engineering subjects, in particular the physical sciences and engineering. Tang (2000) advances that blacks may choose not to pursue careers in science and engineering. This may be because they tend to gravitate towards careers that will provide more benefits to the community or to other disadvantaged individuals such as education and other social sciences rather than careers that provide individual benefits.

Other reasons advanced for the low participation of blacks include lack of role models and mentors who can provide early support and encouragement; unsuccessful recruitment and retention efforts; financial constraints and discriminatory institutional practices (National Science Board, 2006; Tang, 2000). Many black students also perceive that S & E careers will be unrewarding in terms of upward mobility and financial returns because the work of many early black scientists went unheralded for long time in American society. Many black scientists who obtained doctoral degrees from highly recognized institutions found it difficult to obtain jobs within white dominated institutions because of racial discrimination (Fields, 1998 ; Tang, 2000).

Some scholars suggest that differences in the number of students graduating from science and engineering programs are due mainly to differences in the size of the ethnic groups entering the programs (Leslie et al., 1998; Tomaskovic-Devey, 1993). Once minority individuals opt to pursue science and engineering studies, Leslie et al., (1998) suggest that the attrition rates from undergraduate science courses are fairly similar for the different groups. However, others argue that under preparation contributes to greater attrition rates from undergraduate science courses for blacks and Hispanics (NSF, 2002). Under-preparation may stem from several factors that include under-staffed and under-equipped schools; tracking, which groups students in a variety of ways according to perceptions of ability; and poor quality science and mathematics courses and teachers (Clark, 1999). These are in part due to past discriminatory actions within the society. Inadequate exposure and lack of confidence in being able to use science and engineering effectively are viewed as the major deterrents towards pursuing these subjects. Peer effects are also important determinants of participation in science and engineering courses. According to Summers et al (2006), many minority or underrepresented students who are also well prepared leave the college pipeline so other factors besides the level of preparation, aptitude and interest are responsible for minority students discontinuing S & E education. These include academic and cultural isolation, de-motivation and the fear of failure arising from low expectations and the lack of peer support (Summers & Hrabowski, 2006). Thus, past discriminatory activities result in blacks being less certain than their white counterparts about whether they will benefit from science and engineering training in terms of job opportunities, career mobility and earnings (Graham & Smith, 2004). As a result, it is expected that blacks will be under-represented in both science and engineering occupations and in other types of jobs in the high technology sector.

The Hispanic population has grown considerably since the 1990s, and an increasing number of studies have examined the under representation of this group in S & E education and occupations (Santos, 2006; Scott, 1992; Sorge, Newsom, & Hagerty, 2000; Summers & Hrabowski, 2006; Thomas, 1992; Young, 2005). While the cultural and historical background of Hispanics differ from blacks, many similarities exist in the factors that contribute to under representation. These include cultural and language barriers, which lower motivation and lead to disinterest (Escobar, Pickett, Schall, & Coleman, 2006); absence of mentors, role models and peer support(Lundmark, 2004); and systemic factors such as teacher quality and inadequate resources that give rise to the under-preparation of students (Young, 2005).

Given the view that hiring and promotion in S & E occupations are based primarily on the levels of skills possessed and merit, it is possible that blacks and Hispanics may be subject to fewer penalties compared to other sectors in the society. However, since few blacks and Hispanics undertake S & E studies, the implications are that they are collectively less prepared to take up science and engineering positions in high technology or other industries and will be under-represented in science and engineering occupations in both high technology industries and non-high technology industries. Further, they will be concentrated in less rewarding jobs in the high technology sector.

In addition, blacks and Hispanics may be excluded from high technology science engineering jobs because of “skill-based status closure processes”, which arise when more powerful groups use status characteristics such as race or gender to exclude other groups and determine who has access to valuable and more desirable jobs (Huffman &

Cohen, 2004). Further, statistical and taste-based discrimination will contribute to less access to well-paying, high skilled jobs in high technology industries. Residents of central cities, who are predominantly blacks, will also have lower access to high technology industry jobs, which may not be located close to their place of residence. Blacks and Hispanics suffer a greater penalty in relation to employment in high technology science and engineering jobs compared to whites and Asians and compared to other jobs. They are more likely to be concentrated in non-science and engineering occupations because of educational differences, reduced access to the jobs and discrimination effects. Therefore their representation in high technology S & E jobs will not reflect their proportions in the population.

> **Hypothesis 3:** The probabilities of employment in all three industry/occupation groups relative to non-high technology, non-science and engineering jobs will be lower for blacks and Hispanics compared to whites and Asians with the same level of educational attainment and will be lowest for blacks and Hispanics in high technology science and engineering jobs.

In multinomial logit analyses, which include variables for the different racial groups, blacks, Hispanics and Asians with white as the reference group, if the coefficient on the black and Hispanic variables are negative and significant for high technology science engineering jobs, then blacks and Hispanics have a lower probability of employment in these jobs compared whites. Of the three industry/occupation groups relative to the base category, the coefficients on the black and Hispanic variables are expected to be lowest in high technology science and engineering jobs, followed by the effects in other science and engineering jobs.

3.2.2 Asians

Asians have much more positive perceptions of science and engineering professions and view these occupations as a way to avoid discrimination found in other segments of the society (Tang, 2000). Tang argues that Asians are more "opportunity-oriented" and pursue options that are more likely to provide better financial returns and career prospects (Tang, 2000). They consider that hiring and advancement in science and engineering occupations are based more on merit and so gravitate towards these jobs (Tang, 2000). Further, Asians are likely to have developed a more extensive network within the high technology sector, which provides more information and connections to access jobs. Asians are also likely to benefit from statistical discrimination, whereby the group as whole are perceived as being more oriented to quantitative applications such science and engineering and being more diligent and hard-working (Tang, 2000). Thus Asians are expected to be over-represented in science and engineering occupations in the high technology sector and elsewhere compared to their proportion in the population.

> **Hypothesis 3A:** The probability of employment in high technology science and engineering jobs will be higher for Asians compared to whites with the same level of educational attainment.

The coefficient on the Asian variable is expected to positive and significant in high technology science and engineering jobs, indicating that Asians have a higher probability of being employed in these jobs compared to whites.

3.2.4 Human capital and race

According to the premises of human capital theory, although individuals may have the same level of educational attainment from the formal education system, they will also have other skills that are acquired outside of the formal system. Differences in job specific skills or the quality of education are observed by employers and influence whether an individual gets the job or not. Low quality education, the consequence of attending schools with limited resources may result in individuals getting lower average wages. In addition, individuals who do not attend top tier or highly ranked educational institutions, do not benefit from the distinct advantages in employment opportunities and wages for the same level of educational attainment, which these instituions provide in the US.

In addition, various forms of discrimination, the effects of socialization and the perceptions that they will not be adequately rewarded result in blacks and Hispanics seeking other types of occupations for upward mobility and social advancement. That is for blacks and Hispanics, the returns on investment associated with acquiring science education will not be as high as those received by whites and Asians; anticipated future earnings are lower; and their age-earnings profiles will be less steep. Even when blacks and Hispanics obtain higher levels of education, they benefit less from increased levels of educational attainment in science and engineering occupations, when compared to whites and Asians.

Hypothesis 4: Increased levels of educational attainment will increase the probabilities of employment in all industry/occupation groups to a lesser extent for blacks and Hispanics compared to whites and Asians.

In the multinomial logit model with whites as the reference group, the coefficients on the interaction terms between the race and education variables are expected to be negative and significant for blacks and Hispanics. The effects are expected to be most negative for high technology science and engineering occupations. The coefficients on the race and education interaction terms are expected to be positive and significant for Asians, indicating that on average wages of Asians are greater than that of majority whites.

3.3 Hypotheses on Race, Technology and Wages

Galbraith argues that high levels of profit accruing to technology industries provide high wages to individuals working in these industries. In the US, the median wage in high technology industries has been higher than median wages in other industries, however, the wage premiums do not accrue to all jobs and individuals in the industry to the same extent. Returns to individuals will depend on education and skills. More educated and skilled workers benefit from greater returns compared to the less educated (Becker, 1975; Juhn et al., 1993; Mincer, 1974).

Science and engineering jobs in the high technology sector are the most highly rewarded of the industry/occupation combinations used in the study because high levels of innovation lead to greater competitiveness and profitability in the high technology sector. Society places a high value on these jobs (Grodsky & Pager, 2001) and the demand for highly skilled individuals is greater in these jobs, which result in higher wages for individuals with the required skills. It is possible that the under-supply of blacks and Hispanics with science and engineering skills could result in those with S & E skills being better-compensated than similar whites. However, Grodsky and Pager (2001) found in their study on black-white wage gaps, that contrary to the view that high profile occupations are subject to greater rationalization and meritocracy, black men face greater racial disadvantage as they enter into more highly compensated occupations.

Historical, social and cultural factors contribute to lower average levels of educational attainment among blacks and Hispanics (NCES, 2005) and in addition, they are subject to greater discrimination in higher-earning occupations when compared to counterparts in lower paying jobs (Tomaskovic-Devey, 1993). Grodsky and Pager (2001) also argue that blacks are excluded from jobs that require longer training times and other skill demands (higher paying jobs) and which have a high proportion of whites because of discrimination. Differences in unmeasured skills and discrimination contribute to lower average wages for blacks and Hispanics in science and engineering jobs. Conversely, whites and Asians have higher representation and wages in high technology science and engineering jobs compared to other jobs because of they are more likely to study in science and engineering disciplines and statistical discrimination.

Thus, for qualified blacks and Hispanics, it is not clear whether the dynamic and innovative characteristics of high technology industries and the demand for highly skilled individuals give rise to more equitable distributions of employment opportunities and wages compared to what prevails in the rest of the society. The hypothesis is that although blacks and Hispanics benefit from high technology wage premiums, these will be less than the wage premiums received by Asians and whites. As result, blacks and Hispanics continue to have significantly lower wages than similar whites or Asians, and the wage differences are greater in high technology industries and science and engineering occupations and greatest for premium high technology science and engineering jobs.

> **Hypothesis 5:** Of the four industry/ occupation groups, high technology science and engineering jobs will have the highest wages. However, the wage gap between blacks/ Hispanics and whites/ Asians will be greatest in these jobs.

In the regression model for wages, the coefficient on the variable for high technology science and engineering jobs will be positive and larger than the other coefficients related to the industry occupation groups indicating that wages are higher than the reference category (non-high technology non-science and engineering jobs) and for other industry/occupation groups. On the other hand, the coefficients on the interaction terms between race and the industry/ occupational groups will be negative for black and Hispanic variables, indicative indicating that wages will be lower for these groups relative to the reference group (whites).

3.4 The Effect of Time

Educational attainment in the US population including African Americans and Hispanics has increased consistently over the past decades (NCES, 2005b). The increase in demand for highly skilled workers coupled with higher levels of educational attainment enable blacks and Hispanics to take advantage of higher skilled jobs that pay better. As a result, the number of African Americans and Hispanics employed in high technology industries will increase. However, whites and Asians will gain disproportionately more high technology and science and engineering jobs because of unmeasured human capital differences and discrimination. Trend analyses on the probabilities of employment over the period 1992 to 2002 will provide an indication of differences in the rates of employment of blacks and Hispanics.

> **Hypothesis 6:** Increasing levels of educational attainment over the decade 1992 to 2002 increase the probabilities of employment of blacks and Hispanics in the more rewarding science and engineering jobs both inside and outside of the high technology sector; but the rate of increase is lower than that observed for whites and Asians.

According to human capital theory, improvements in the level of educational attainment will increase the returns to individuals and the decrease in the educational gap will decrease the gap in earnings. However because high technology industries continue to be highly profitable due to high levels of returns, and science and engineering jobs remain highly valued in the society, wages for science and engineering jobs in the high technology sector are higher than wages in other jobs. The demand for highly skilled workers remains high, so the wage gap does not narrow to the same extent as that for workers in other industry/occupation groups. Trend analyses on the wage gap over the period 1992 to 2002 will provide an indication of whether there is a decrease.

Thus, the main hypotheses are that employment and wages in all industry/ occupational groups are determined primarily by the level of human capital accumulated, and that human capital exerts an even greater effect in high technology, science and engineering jobs, compared to the other industry/ occupation groups. However, blacks and Hispanics benefit less from higher levels of educational attainment, with the result that blacks and Hispanics are less likely to be employed in high technology science and engineering jobs, when compared to similarly qualified whites and Asians. Even when measured levels of human capital enable blacks and Hispanics to participate in better jobs, they receive lower pay and this is in part due to the cumulative effects of unmeasured human capital, structural conditions and discrimination.

Hypothesis 7: Improvements in educational attainment will decrease the wage gap between the black/Hispanic ethnic groups and whites/Asians over the period 1992 to 2002. However science and engineering jobs in the high technology sector will have the smallest decrease in the wage gap, followed by other jobs in science and engineering, then other high technology jobs.

Trends in the probabilities of employment and wages will be examined over time for the different groups in order to determine if there is support for hypotheses related to time.

3.5 Secondary Hypotheses on Labor Market Effects and Individual Characteristics

At a broad level for all workers, employment, earnings and earnings differentials will depend on the industry, occupation and the type of job activities. These in turn are influenced by government macroeconomic policies and the resulting economic conditions (Galbraith, 1998); institutional factors such as the fall in the real minimum wage and unionization (Fortin & Lemieux, 1997); industry structure and labor market conditions which influence the supply and demand for skilled workers, and trade. The effects are further complicated by the confluence of particular individual and structural conditions. Thus blacks who benefited from relatively high paying manufacturing jobs since the New Deal policies of the 1930s, lost disproportionately as a result of the shift from manufacturing to service jobs (Wilson, 1996). Structural conditions not only influences who gets the job and the wages attached to different jobs, but also impacts human capital accumulation including formal schooling and other training opportunities received by an individual over his or her lifetime.

The analyses takes into consideration differences in economic conditions of eight regions (New England, Mid East, Great Lakes, Plains, South West, Rocky Mountain, Far West and South East) as defined by the Bureau of Economic Analysis. The regions are aggregations of states that were developed based on the homogeneity of the states in terms of economic characteristics, such as industrial composition of the labor force, and demographic, social and cultural characteristics (BEA: Regional Economic Accounts). Regions that have higher concentrations of high technology industries such as the Far West and New England are expected to contribute positive and larger effects on the probabilities of employment and wages in high technology industries and S & E occupations compared to other regions.

Many blacks are concentrated in older, central city areas while the majority of the new jobs have been created in suburban areas where the jobs are less accessible to the inner city residents who need them. The distancing of jobs from individuals in need, or "spatial mismatch hypothesis" contributes to joblessness, lower wages and longer commutes for black workers (Ihlandfeldt & Sjoquist, 1998). It is expected that residents in the central city areas will have lower probabilities of employment and wages in high technology industries and S & E jobs compared to residents in other parts of the urban area. However, these will be greater than those for rural residents.

Other variables that capture labor market conditions include unemployment rates, demographic differences such as proportions of each racial/ethnic group, and the proportion of high technology firms and employees. Areas with higher unemployment rates will have fewer employment opportunities for all workers including high technology workers. Further, both sociological and economic studies find that areas or occupations with high concentrations of blacks have fewer employment opportunities and lower average wages, which contribute to greater black-white inequality (Cohen, 2001; Hirsch & Macpherson, 2004; Hudson, 2007; Huffman & Cohen, 2004). Given that proportions of each racial group in the population are important labor market characteristics, which contribute to the employment opportunities and the wage levels of workers, the study will include these factors in the estimation of wage differences.

Studies show that proximity to a large research university is an important prerequisite to the formation of a high technology sector and as a driver for technology industry growth, not only because they serve as a source of new knowledge and resources but also because they are a source of skilled graduates who remain in the area after completion of their studies (Acs & Armington, 2004; Acs, FitzRoy, & Smith, 2002; Audretsch, Lehmann, & Warning, 2005; Feldman & Florida, 1994). Therefore, it is expected that regions that have a high proportion of science and engineering graduates will be richer in high technology firms and employment opportunities. A positive relationship is expected between the proportion of science and engineering graduates in a state, the number of high technology firms in an area and employment opportunities for high technology workers.

Labor market studies typically consider the employment status of individuals, that is whether workers are employed full time or on a full year basis in wage studies since the characteristics of these individuals are likely to be different from part-time or unemployed workers. The BLS defines full time workers as workers who work at least 35 weeks for the year and full year workers as those who work 50 weeks or more in the year (Bureau of Labor Statistics, 2002). Analyses of samples based on full time, full year workers are generally considered to suffer from sample selection bias, since estimates are based on observations of only those individuals who work (Borjas, 1996). To avoid the issue of sample selection bias, this study includes non-workers (individuals with neither industry nor occupational affiliation or wages) but will control for the employment status of individuals as well as undertake separate analyses for full-time full year workers. Full-time, full year employment is expected to increase the likelihood of being employed compared employment on a part-time basis.

Self-employment status is also considered important in the context of the high technology businesses because it is expected that many small, owner operated establishments will be present in the sector. These firms could include start-ups for research or commercialization of new ideas or service oriented businesses for example in the information technology and communications sector. In addition, self-employed individuals are expected to play an important role in companies used for outsourcing and the formation of spin-off companies. Thus the study will control for the effects of self-employment. Although self-employment is expected to reduce the likelihood of employment in the typical labor market context, it is expected that self-employment will have positive effect on the probabilities of employment in the high technology sector.

The role of unions and their effects on employment and wages have been extensively studied (DiNardo & Lee, 2004; Farber, 1986, 2005; Kaufman, 2002), and despite the declining influence of unions in the US and the closing of the union –non-union wage gap, unionized workers continue to have higher wages than non-union workers (Hirsch, 2004). However, since unions have had difficulty gaining a foothold in high technology firms (Robinson & McIlwee, 1989); and many firms are small or belong to relatively new sectors; unions are expected to have a negative effect on employment in the high technology sector.

Family characteristics such as whether the individual is married, has children and is in the process of owning a home are also expected to influence employment and wages of individuals. These characteristics increase the level of responsibility and confers greater stability as individuals typically try to satisfy financial obligations associated with having a family. Further labor economists argue that due to specialization in the household (married men are able to share household responsibilities with spouses), married men devote more time and effort to the labor market; in the process they acquire more skills and so earn more than single men (Borjas, 1996). From the neoclassical perspective, income and children are positively related, since higher incomes allow individuals to have more children, although this is tempered by the costs associated with raising a child. Labor market studies typically include these variables, which are expected to have a positive effect on employment and wages of men. Usually, marriage and having children will decrease the labor market participation rates of women, especially if they are low wage earners. However, women who earn higher wages will have fewer children and will be less likely to withdraw from the workforce.

CHAPTER 4

METHODOLOGY

In this chapter, I first define the major concepts, “high technology industries”, “science and engineering occupations” and race/ethnicity adopted in this study. This is followed by details of the data, variables and the models used in the analyses. The study uses a pooled cross-section of data from the Current Population Survey for the years 1992 to 2002 as the main data source together with data drawn from several other publicly available datasets to examine employment and wages in the different industry/ occupational groups. I describe this data in Section 4.2. The methodological approaches include the application of multinomial logit to examine the probability of employment in the different industry occupational groups; ordinary least squares regression, t-tests of group means, and local linear non-parametric regressions to examine wages and wage differences; and trend analysis to determine changes taking place over time. I describe the application of these methods in Section 4.3.

4.1 Definitions

The concepts of “high technology industry” and “science and engineering occupation” have numerous definitions in the literature, with no consensus among scholars on the industries or occupations to be included. Further, the concepts change over time (Paytas & Berglund, 2004), reflecting the dynamism of technological change. Researchers adopt different definitions depending on their objectives or those of the policy-maker. The use of a particular definition often depends on the data available to operationalize it.

4.1.1 High Technology Industries

Depending on their needs, different researchers, organizations, and regions use a range of criteria to define or identify “high technology industries”; with the result that lists of high technology industries include different industries and researchers often arrive at conflicting conclusions about the impacts of high technology industries, such as employment levels, growth rates, or contributions to the economy. As a result, the recommendations and outcomes of a study on high technology industries may be influenced by the choice of the definition used. In reviewing recently used definitions of high technology industries, Chapple et al. (2004) note that typically, the definitions result from considerable subjective judgment on the part of the researcher in establishing the bounds of the definition. In addition, the definition may depend on the availability of information needed to establish the definition, with the result that definitions are not static and change over time (Hecker, 2005; Paytas & Berglund, 2004). Criteria used in defining high technology industries include the levels of research and development (R & D) expenditure; employment in R & D or alternatively employment in science and engineering occupations, which include R & D employment as a sub-set; innovativeness (patenting activity) and productivity (Cortright & Mayer, 2004). Policy-makers, administrators and even researchers often use even more general and subjectively defined terms such as “fast growing”, “involve new or leading edge technologies” and “high levels of highly educated workers”.

As a starting point, this study adopts the approach used by Bureau of Labor Statistics (BLS) in 1999 to define high technology industries. These are industries with employment in both research and development (R & D) and technology oriented occupations that are “at least twice the average for all industries in the Occupational

Employment Statistics Survey" (Hecker, 1999, p.19). The definition takes into account the dual criteria of both levels of R & D employment and non- R&D employment in science and engineering. Industries are classified using the Standard Industry Classification (SIC) system, which is used to identify industries in the Current Population Survey during the study period 1992 to 2002. Appendix Table 3 (p. 198) lists the industry descriptions, Standard Industrial Classification (SIC) codes, as well as corresponding industry codes used in the Current Population Survey, identified in the BLS definition, and which are used in this study. For comparison, Appendix Table 3 also lists high technology industries based on alternative definitions: (i) a human capital based definition, which uses the criteria of above average levels of employment in science and engineering occupations (Chapple et al, 2004); and (ii) a state level definition, which emphasizes industries important to the local economy and is a composite of industries identified by other states and organizations (Walcott, 2001).

However in a recent update, the Bureau of Labor Statistics moved to an occupational based definition of high technology industries (Hecker, 2005), similar to that used by Chapple et al 2004 because of the unavailability of R&D information that was used as part of the criteria for the 1999 definition of high technology industries (Hecker, 1999).

4.1.2 Science, Engineering and Other High Technology Occupations

High technology industries are characterized as industries with high levels of innovation and change as a result of above average levels of R & D activities and the employment of science and engineering professionals who accomplish these tasks. Occupations defined as science and engineering require "in-depth knowledge of the theories and principles of science, engineering, and mathematics underlying technology" (Hecker, 2005). Since science and engineering professionals are highly skilled individuals, and human capital accumulation is expected to play a major role in determining employment and wages, this study will examine racial and ethnic differences in employment and wages compared to other industry/ occupation groups for persons with the same level of education and experience. The comparison groups include scientists and engineers in non-high technology industries (other S & E jobs); and individuals in non-science and engineering jobs (e.g. marketing, administration, production, etc.) in high technology industries (other technology-sector jobs) and industries outside of the high technology sector (non-technology jobs).

Appendix Table 4 (p. 199) lists the science and engineering occupations focused on in this study, which include managers with science and engineering backgrounds, certain groups of computer professionals, petroleum and automotive engineers including designers. The list is based on the approach of Chapple et. al (2004), who determine the occupations after careful consideration of the nature of the jobs and consultations with experts in science and engineering, who identify the relevant occupations. The occupations included in a particular definition depend to a considerable extent on the judgment of the researcher, which is similar to how definitions of high technology industries are determined. However, in separate analyses, the study does control for whether individuals are native or foreign-born.

4.2 Data and Data Sources

Data on individual characteristics comes from a pooled cross-section of the March Annual Demographic Survey of the Bureau of Labor Statistics (BLS) for the years 1992 to 2002 downloaded from the BLS website using the DataFerret software[1]. The March ADS samples approximately 60,000 households each year, and is an extension of Current Population Survey, a complex, stratified, multistage sample. The CPS sample is based on civilian, non-institutional population of the US, who live in housing units as well as members of the Armed forces, who live in civilian housing that is not on a military base. The CPS also includes members of the military, if they live with their families on a military base. Military personnel, who live in barracks are not included. The CPS obtains responses from individuals in a group of households that have addresses in close proximity to each other ('hit string'). As a result, the individuals in households from a 'hit string' may have similar demographic and socio-economic characteristics. In addition, the survey includes individuals from same household and this reduces the level of variation even further. The rotation system used in the CPS by the BLS, results in at least half of the households, hence individuals being present in the sample the following year[2]. In order to take the reduction in variability due to these factors into account, the analyses are clustered by the household identification number in the CPS (H_IDNUM).

The data files for each year in study were downloaded separately as ASCII files, then converted to STATA data files using the data dictionary files supplied with the data. The files were appended to form single file containing all the years needed for the analyses. The CPS variable names were recoded to match the variable names used in the study and the conversions checked using cross-tabulations with the original variables to ensure that the variables were coded and labeled correctly. The variables are described in

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[1] US Census Bureau, DataFerret: For the DataWeb http://dataferrett.census.gov/ Accessed October 25, 2007

[2] Annual Demographic Survey, Methodology Overview http://www.bls.census.gov/cps/ads/1995/smethovr.htm Accessed October 25, 2007

greater detail in subsequent sections and include individual characteristics such as age, gender, educational attainment, industry of employment, occupation, marital status and number of children.

The data was examined to identify the extent and patterns of missing data (in CPS coded 0 or as a series of 9s); unusual values for example negative earnings, or experience values; and the skewness and kurtosis of variables using the detailed summaries produced by STATA. The CPS imputes information for missing cases due to non-response using a matching process that is based on the characteristics of similar individuals so no further imputations were done in the analyses. Missing information, for example on race and ethnicity or residence location is dealt with in different ways depending on the variable in question and the implications for the analyses.

Several cases in the sample had missing information on ethnicity (that is, whether the individual is of Hispanic origin or not); location of residence (central city, other parts of a metro area, or a rural area); and on industry, occupation and wages. The missing information was due to "no response", "don't know", "not-identifiable" or in the cases of industry, occupation and wages, the individuals did not work. The CPS did not impute data for these cases as is typically done when there is missing information in the CPS.

If data is missing completely at random or missing at random then, missing data is ignorable, and the decision can be made to eliminate the cases where the information is missing. The remaining data is then assumed to be a random subset of the population and complete case analysis can be performed resulting in unbiased estimates. In order to determine if missing ethnicity information was random, the mean characteristics of four groups, (1) those with missing ethnicity data, (2) Hispanics, (3) non-Hispanics and (4) the sample as a whole were compared and t-tests were done to determine if the differences between the means were significant. The analysis showed that the “missing” group were predominantly white (94%), although Hispanics as a group reported being white with greater frequency (96%) while the proportion of whites among non-Hispanics was (84%). The group “missing” had mean educational attainment, hours worked, and wages that were significantly lower than non-Hispanics but means that were significantly higher than Hispanics as a group. The mean values of educational attainment, hours worked and wages for the missing group were closer to the mean values of same variables for non-Hispanics, than to the mean values for Hispanics. The differences between the mean values of the other variables in the model for Hispanics, non-Hispanics and the missing group were not largely different from each other, so these differences were not tested. The original assumption was that people who are Hispanic may be less likely to report their ethnicity because of the prejudices that exist in the US society, however it was difficult to conclude that this assumption was true from the analysis of the group data. However, it is still possible that more affluent and well-educated Hispanics are less likely to report there ethnicity. Given these findings and the difficulty of assigning individuals to a particular group, Hispanic or non-Hispanic, the decision was made to drop the observations with missing ethnicity data from the analysis because the large sample size available and the relatively small percentage (0.98%) of missing ethnicity data .

Approximately 16% of the sample had information missing on whether individuals lived in the central city; urban area, but not central city; or in a rural area. Attempts to characterize individuals who had missing residential information did not yield any useful patterns. The group with missing residential information differed from the three other groups on numerous characteristics including racial composition, educational level except college, age, marital status, home ownership and income. The group with missing information was combined with those identified as rural to obtain the reference group for the set of variables representing central city, urban but not central city and other area of residence in the analysis.

Negative values of income arise because the CPS codes the earnings of individuals with businesses or farms that incur losses after taking into consideration expenses as negatives. The data was also examined to determine the extent to which the same individuals appeared in the sample in subsequent years by creating groups defined by the individuals household identification number, gender, race, age, occupation, state and whether they lived at the same address in the previous year. Correlations and co-linearity between variables were also examined.

Additional data on regional economic conditions (annual unemployment rate for each state) was downloaded from the BLS Local Area Unemployment Statistics (LAUS)[3]; labor market characteristics (average earnings) is obtained from the Bureau of Economic Analysis [4]; and proportion of high technology firms and employment was calculated from County Business Patterns Data for 1996[5]. Data on the proportion of science and engineering graduates compared to the number of degrees awarded for each race/ethnicity group for the years 1992 to 2002 was obtained from the National Center on Educational Statistics (NCES), Integrated Postsecondary Education Data System

[3] Bureau of Labor Statistics Local Area Unemployment Statistics http://www.bls.gov/lau/home.htm#overview Accessed October 25, 2007
[4] Bureau of Economic Analysis, Regional Economic Profiles – State Personal Income -Table SA30 – State Economic Profiles http://www.bea.gov/bea/regional/spi/ Accessed October 25, 2007
[5] US Census Bureau, County Business Patterns 1995-1996 C1-E96-CBPX-09-US1 CD-ROM

(IPEDS) Completion Survey by Race using WebCASPAR[6] of the National Science Foundation. The data files from the different sources were transformed into STATA data files. Depending on the source of the data, the variables were de-stringed, encoded and recoded to variable names that matched those used in the study with the recoding using cross-tabulations. The CBP data for individual states were appended to a single data file then the proportions of high technology firms and employees were calculated for each state in 1996 based on the "high technology" definition used in this study. The proportions of science and engineering graduates by gender, race, state, and year were calculated for the racial groups defined in the study using the NCES data. The science and engineering fields in the NCES data include engineering, mathematics and computer science, life science, psychology, social science, physical science, science and engineering technology, interdisciplinary science and geosciences. The NCES data did not include information on degrees granted in 1999, so data for 1999 was interpolated using data for 1998 and 2000.

Data on annual unemployment rates for each state from LAUS of the BLS and average earnings by state and year from the BEA is merged to the main dataset matching on year and state; proportion of high technology firms and employees in 1996 from CBP was merged to the main dataset matching on state; and the proportion of science and engineering graduates from the NCES was merged matching on gender, race, state and year. After merging, the main CPS data file with the merged data was collapsed using the merge criteria and compared with the original source data file to check that the data had merged correctly. This check found that the additional variables merged satisfactorily

[6] National Science Foundation, Integrated Science and Engineering Data System (WebCASPAR) http://webcaspar.nsf.gov/index.jsp;jsessionid=97BC60E498E74A2DD9821B7ED887F946?subHeader=WebCASPARHome&showHelp=false Accessed October 25, 2007

into the main CPS file with the exception of the variable for the proportion of science and engineering graduates. There were 61 unmatched cases out of 4488 corresponding to year, state, race, gender cells with no matches in the CPS data. The unmatched cases were all females from the minority groups (blacks, Hispanics, Asians) and were from states which had relatively low populations of these minority groups for example, North or South Dakota.

The complete sample includes full and part time workers, non-workers who have neither industry nor occupational affiliation nor wages; and the self-employed in the 16-65 years age group. Weighted summary statistics (means and standard deviations) for variables in the sample are presented in Table 3 for males and females separately.

4.3 Methods

The multinomial logit model is used to estimate the probabilities of employment in the industry/occupation groups; ordinary least squares regression, t-tests of group means and local linear non-parametric regressions are used to examine wages and wage differences between groups. All analyses are weighted using the probability weight for individuals (MARSUPWT) provided in the CPS data, although there are differences in scholarly opinion on whether survey data from CPS should be weighted.

Some statisticians argue that weights are necessary to address issues relating to the design of the survey, while others view that they are largely irrelevant (Pfeffermann, 1993). The weights attached to individual data in CPS represent the inverse of the individual's probability of being selected into the sample of a complex stratified survey with multiple stages of selection and unequal probabilities of selection[7]. The weights

[7] US Department of Labor, Bureau of Labor Statistics (2002). *Current Population Survey, Design and Methodology. Technical Paper 63RV*

adjust for stratification and potential under-represention of different groups in sampling as well as for non-response. The weighted estimators are expected to produce unbiased population parameters (Korn & Graubard, 1995, 2003; Pfeffermann, 1993; Smith, 1991). However, the weighted estimators will be more variable and the use of weights represents a trade-off between reduced bias from weighting and increased variability (Korn & Graubard, 1995).

According to Smith, a disadvantage of using weighted data is that inferences should be made conditional on the post stratification variables that is, sex, race, and age. Since this is not possible for complex sampling schemes, the reliability of inferences may not be satisfactory (Smith, 1991). Further, if the population data to which the samples are adjusted with the use of weights is out of date, bias may be introduced in analyses. This bias may be worse than that obtained from the use of the un-weighted sample (Smith, 1991). Bias may also be introduced with the use of weights if model parameters are correlated to observations in the population (omitted variables) and with the weights; and if there is model misspecification (Korn & Graubard, 1995, 2003). Pfefferman concludes from review of several studies that although weights can be useful in some circumstances, much more research is needed on the issue (Pfefferman, 1993).

Individuals are grouped by their household identification number (H_IDNUM) using the cluster option in STATA. This is necessary because the CPS samples from groups of households that are in close proximity and collects information from multiple individuals in the same household. Further, the same individuals may appear in the sample in successive years.Thus data on individuals may be similar on multiple characteristics leading to reduced variability and smaller regression standard errors in the analyses. The use of weighted regression analyses and clusters produces robust standard errors, which reduce the effects of heteroskedasticity.

4.3.1 Probability of Employment - Multinomial Logit Model

Multinomial logit regression is used in the analysis because it is anticipated that the effects of the variables on the probability of employment will be different for the different industry/occupation group. The model used is similar to the Mincerian wage function because of the assumption that the determinants of employment will be similar to the determinants of wages. The probability of employment replaces the logarithm of wages as the dependent variable and the main independent variables are the human capital variables, schooling and experience, and the race variables. Experience is included in the linear and quadratic forms, and captures in part, post school investments in training (Mincer, 1974).

The model is specified as:

$$indocc = \alpha_0 + \alpha_1\, hisch + \alpha_2\, coll + \alpha_3\, exp2 + \alpha_4\, exp2^2 + \alpha_5\, black + \alpha_6\, latino + a_7 asian + \alpha_8 blackhi + \alpha_9 blackcoll + \alpha_{10} lathi + \alpha_{11}\, latcoll + \alpha_{12}\, ascoll + \alpha_j X_j + a_k T_{kj} + \varepsilon$$

4.3.2 Variables

In the multinomial logit model, the dependent variable (*indocc*) is the probability of working in one of the four industry/occupation groups (high technology S & E or *htse;* other technology-sector or *htnse;* other S & E or *nhtse;* and non-technology or *nhtnse*), which are viewed as a set of categorical variables.

The main independent variables in the model represent human capital investments (high school and college level education), potential experience and individual level characteristics including race that have an effect on individual employment and wages (Frazier, 1957; Grodsky & Pager, 2001) as well as variables that control for labor market effects. The variables are dummy variables high school education (*hisch)*, coded for 1 for individuals who have completed Grade 12 and graduated from high school or have had some college education but have not received a degree; college-educated (*coll*), coded 1 for individuals who have received at least an associate degree or better. The reference group in the initial model consists of individuals who have not graduated from nor attended high school at all. In alternative specifications of the model, college educated individuals are defined by two separate dummy variables: bachelors education (*bachdeg*), coded 1 for individuals who have received either associate degrees or bachelors degrees; and graduates (*postgrad*), coded 1 for individuals who have attained educational levels beyond bachelors degrees.

The experience variable (*exp2*) is determined by taking the (age of the individual - years of education –6), where six years represents the typical start of the schooling process (Mincer, 1974). Years of education are obtained by transforming the sixteen categories of educational attainment present in the ADS. Negative values obtained from the calculation are recoded to zero. The variable is included in the quadratic form (*exp2sq)* because experience effects are expected to diminish over time, similar to its effect in the wage function (Mincer, 1974).

The race/ethnicity variables are created from the two categories that define race (black, white, Asian etc) and Hispanic origin in the CPS data. The model includes three dummy variables for the race/ethnicity groups defined previously (*black, asian* and *latino*), with whites being the reference group. Interaction terms between the education and race variables, *blackhi, blackcoll, lathi, latcoll* and *ascoll* are introduced to determine if the effects of education are different for each group. The interaction variable (*ashi*) formed from race variable (*asian*) and the high school education variable (*hisch*) could not be included in the models because cell sizes were too small for the standard errors to be computed. In subsequent analyses, the interaction term was adjusted to reflect comparisons were made between Asians with and without college education.

The vector (X_k) represents a set of control variables, which includes individual characteristics such as marital status (*married*), which is coded 1 for individuals who are married or have been previously married and 0 for individuals who have never married; the presence of dependents under 15 years of age (*ownchild),* coded 1 for individuals who have at least one child of their own living in the same household, and 0 otherwise; home-ownership (*house)*, with the variable code 1 for individuals who own or are in the process of owning their homes and 0 other wise. Other control variables include full-time work status(*ftwrk),* coded one for individuals who work at least 35 hours per week, and 0 otherwise; self-employed work status (*selfemp*), coded 1 for individuals who are self-employed and 0 otherwise; and union membership (*union*), coded 1 for individuals who are members of a union or has wages covered by a union contract.

The vector (T_j) represents variables for three of four time periods that the eleven years in the analyses are contracted to. According to Blackburn and Neumark (1993), the time dummies control for variation in wages due to inflation, productivity growth and other cyclical effects. Preliminary analyses showed that 1992 and 1993 differed from subsequent years, so the four time periods used are: the first period (*perio1*) covering 1992 to 1993; the second period (*perio2*) for the years 1994 to 1996; the third period (*perio3*) for 1997 to 1999; and the fourth period (*perio4*) for 2000 to 2001. The reference group for the analyses is the first period, 1992 to 1993. The results based on four time periods are compared to analyses in which dummy variables representing individual years (*time2*=1993, *time3*=1994, *time4*=1995, *time5*=1996, *time6*=1997, *time7*=1998, *time8*=1999, *time9=2000, time10=2001, time11*=2002) are included, with 1992 being the reference year.

In addition, the model includes variables to indicate urban and regional location of individuals home. These are central city (*cencity*) coded 1 for individuals who live in the central city; urban (*urbnocc)*, coded 1 for individuals who live in an urban area but outside of the central city. The reference category for urban status comprises residents of rural areas or undefined residential status. Eight regional variables, defined by the Bureau of Economic Analysis are used to approximate labor market areas with specific employment characteristics. The use of the regions as defined by the BEA represents a compromise between the choice of narrow, well-defined labor market area and suitably sized sample cells with sufficient number of cases to permit analyses. The eight regions are Far West (*fwst),* Great Lakes (*glak),* Mid East (*mest)* New England (*neng*), Plains (*plns*), Rocky Mountain (*rkmt*), South West (*swst*) with the South East region being the reference group. The Appendix Table 5 (p. 200) shows the six regions and corresponding states, for a total of 51 states that include Hawaii and Alaska. The aggregations were developed based on information from the mid-1950s, and differences with the current industrial structure and demographic characteristics of the regions are likely. The trend in economic analyses of the labor market has been to use smaller areas such as metropolitan statistical areas or county level data. However smaller aggregations are not feasible in this study because of cell size constraints. To further characterize the labor market area, the following variables determined at the state level are included: annual unemployment rate of the state (*unemp*); proportion of high technology firms in the state in 1996 (*phtf96*), proportion of high technology workers in 1996 (*phtemp96*), and proportion of college graduates with science and engineering degrees (*pscideg2)* by gender, race/ethnicity group and the years 1992 to 2002. The use of characteristics at the state level represents a compromise between the use of more detailed labor market information for example, county level data and the availability of county information in the CPS to do the matching. The CPS did not provide information on the county of residence of individuals until 1996. The variable representing the proportion of S&E college graduates was introduced as a proxy for information on what individuals actually study.

Although defining the labor market as BEA regions reduced the incidence of small or empty cells compared to when MSAs are used, cross tabulations of data by industry/ occupational category and race undertaken by sex, year, region and college education indicated that many cells still had a small number of cases, in particular those regions that lacked racial diversity such as New England and/or high technology industries (Mid East and Rocky Mountains).

4.3.3 Analyses

Estimations of the probabilities of employment are obtained using MLOGIT command of STATA. Groups of variables are introduced sequentially into the model with the human capital variables (high school and college level education) introduced first; this is followed by the introduction of the race variables (black, Asian and Latino), then the interaction variables between the human capital and race variables are introduced.

Finally, the control variables, which include the other individual characteristics, time dummies, region dummies, and labor market characteristics, are introduced. The probabilities of employment in each industry occupation group, for each racial and ethnic group are estimated for high school and college educated individuals for each year of analysis and all other characteristics held at mean values of the groups.

Additional analyses were done in which the reference category for the group of education variables is changed from the initial specification of not being a high school graduate (variables *hisch* and *coll* included in the model) to high school graduates (*nohisch* and *coll* included in the model) as the reference category. The model specification is changed subsequently so that college educated individuals (*nohisch, hisch* in model) form the reference category. The specifications of the models were also varied to separate college education into two groups representing individuals that had at least an associate degree (*bachdeg)* and individuals that had at least masters level degrees (*postgrad*) forming the reference categories.

Many labor market studies exclude part-time workers, workers with no income as well as individuals outside of the profile of the CPS sample such as the institutionalized population, in particular the incarcerated. The characteristics of individuals who do not work are different from those who work, thus a sample based only on workers with wages, will not be truly representative of the population. However, if the analyses include only individuals with employment information, the results will have selection bias (Chandra, 2003; Heckman et al., 2000). In order to minimize the effects of selection bias, the analyses are done using the sample with individuals who do not have information about employment (non-workers) as well as part-time and full-time workers. It was considered important to include part-time workers, with reduced hours due to outsourcing or sub-contracting arrangements since these practices are commonplace in high technology industries. Comparative analyses are done with a sample based on full-time, full-year workers (individuals who work at least 35 hours per week and 50 weeks for the year) and the sample with full, part-time and non-workers in order to determine if the samples lead to similar conclusions about the hypotheses and research question.

Previous studies suggest that foreign born scientists and engineers play an important role in the US scientific enterprise with more than 25% of doctorate level scientists and engineers being born outside of the US (National Science Board, 2006; Tang, 2000). Additional analyses to investigate whether native-born or foreign-born status of individuals had an effect on the probability of employment in high technology industries or science and engineering jobs were done for the years 1994-2002. The effects are determined by including a variable foreign (*foreign)* coded 1 for individuals born outside of the United States or its territories, and 0 otherwise. The analyses are restricted to the years 1994 to 2002 because the information is available starting in 1994.

Since many of the concerns raised in regard to foreign-born scientists and engineers relate to individuals of Asian descent, the effects of being foreign born are examined for Asians in particular. The effects of foreign born status for Latinos are also considered because of the recent surge of Latino immigrants into the population. Preliminary analyses showed that the effects of variables related to the Asian sub-population (*asian* and associated interaction terms) were very unstable with the direction and significance of the effects being very sensitive to the specification of the model. This was possibly due to small cell sizes. As a result, changes were made to the specification of the model for evaluating the effects of being foreign born. Only two educational groups were used in the analysis; the educational levels represent individuals with at least an associate degree (*coll*), as defined previously compared to individuals who had no college education, as the reference group. Time effects or changes relative to the base year 1994 were insignificant over the period, so the time dummies were excluded in order to simplify the analysis. The coefficients on the variables did not change greatly with the exclusion of the time dummies from the model.

In order to determine whether the effect of being foreign born was different for Asians and Latinos, interaction terms between the variables for foreign and Asian (*forasian*); and the variables for foreign and Latino (*forlat*) were introduced into the model. The model also included a three-way interaction term between the variables for foreign, Asian and college level education (*forascoll)* as well as the interaction variable between foreign and college education (*forcoll*) to complete the set of interaction variables.

The analyses are run separately for male and female workers because the effects of the covariates on wages are different for male and females and the separation of the two groups will facilitate disentangling the effects of the different variables. Reasons for the differences include among other factors differences in decision-making in relation to labor supply (number of children, husbands income), labor force participation rates and changes in the labor force participation rates over time (Borjas, 1996). Occupational sorting and segregation also produce differences in the characteristics of male and female wages.

4.3.4 Wages and the Wage Gap – Regression Analyses

The study uses ordinary least squares regression analyses, Heckman variation of OLS, t-tests of group means and local linear non-parametric regression analyses to examine wages an wage differences. Initial plans to use hierarchical linear modeling, which provides a parsimonious approach to modeling wages while simultaneously controlling for individual level characteristics and differences attributable to regional effects were abandoned. Preliminary investigations showed that the approach was not appropriate for the proposed analyses because the intra-class correlation coefficient (ICC) was too low. The ICC, which indicates the proportion of variance in the dependent variable which is due the second-level unit of analysis, in this case the BEA regions, was only about 1% for the null model. It is possible that the characteristics of the BEA regions, which are comprised of diverse groups of states, had the effects averaged out for the larger area.

This study used the Mincerian wage function, a human capital based model, in which education and experience are incorporated as the main explanatory variables. Mincer developed the model in 1974 and it is commonly used in wage analyses(Heckman, Lochner, & Todd, 2005; Mincer, 1974). The dependent variable is the natural logarithm of weekly wages, which adjusts for the skewness in the distribution of individual wages. Weekly wages are obtained by dividing annual wages reported in the CPS data (wages for the prior year) by the number of weeks worked in that year. Top coded wages reported in the years 1992 to 1995 are multiplied by 1.5 ((Katz & Autor, 1999). The CPS changed the way it reported top codes after 1995 and instead of reporting a single top code, the CPS computed several top codes, which is the mean value of top coded wages for groups matched on characteristics such as gender, race, and ethnicity.

Although, the top coded values were identified through histograms of the wage data, the values were not changed for the years after 1995, because the top codes were the mean values of the wages of high earners. The wages are adjusted by the chain weighted Personal Consumption Expenditure deflator to 2000 dollars from the National Income and Product Accounts (Katz & Autor, 1999) [8]. Other explanatory variables of interest such as race and geography are incorporated into the model to provide information on earnings differentials based on these characteristics. Since the approach is well established, straight-forward to apply and provides estimates of the differentials needed, it is preferred to approaches starting from an aggregate production function.

Since analyses on the probability of employment in the industry/occupation groups showed differences in the effects of education at the bachelors and graduate level, separate variables were used to represent college education. The human capital variables were high school education (*hisch*), bachelor's degree (*bachdeg*), and graduate education (*postgrad*). The reference group for education in the initial set of models consists of individuals without high school education. Centered values of the experience variable and its quadratic were used in an effort to reduce multicollinearity (Tabachnick and Fidell, 2007); however values of the variance inflation factor remained above ten[9], even with the centered variables.

The models were weighted with the CPS probability weight MARSUPWT and clustered using the household identification number (H_IDNUM), which takes into the

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[8] Bureau of Economic Analysis, National Income and Product Accounts. Table 2.5.4 Price Indexes for Personal Consumption Expenditures by Type of Expenditure http://www.bea.gov/national/nipaweb/SelectTable.asp?Selected=N Accessed October 25, 2007

[9] UCLA Academic Technology Services, Regression Diagnostics, Chapter 2 in Regression with STATA Web Book http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter2/statareg2.htm Retrieved June 18, 2007

account the reduction in variability in the analyses because individuals living in the same household may be similar. The use of weights and the cluster option produces robust standard errors that reduce problems due to heteroskedasticity. Individuals with negative earnings (self-employed individuals who reported losses from their businesses) were not included in the analyses. In addition, individuals who reported very low wages, that is weekly wages of less than \$98 in 2000 dollars, which is approximately one-half of the weekly pay based on a 40 hour work week and the1997 real federal minimum wage of \$5.15 per hour were excluded from the sample (Katz & Autor, 1999).

The model is specified as:

$$lnwkinc = \beta_{0j} + \beta_1\, hisch + \beta_2 bachdeg + \beta_3\, postgrad + \beta_4 exp2 + \beta_5\, exp2^2 + \beta_6 black + \beta_7\, asian + \beta_8 latino + \beta_9 blackhi + \beta_{10} blackbach + + \beta_{11} blackpost + \beta_{12} lathi + \beta_{13} latbach + \beta_{14} latpost + \beta_{15}\, asbach + \beta_{16} aspost + \beta_{17} htse + \beta_{18} htnse + \beta_{19}\, nhtse + \beta_{20} blackhtse + \beta_{21}\, asianhtse + \beta_{22} lathtse + \beta_{ij} X_{ij} + \beta_k T_k + r$$

The variables are introduced sequentially into the model, starting with the human capital variables. This is followed by the race variables, the race and education interaction terms, then the control variables which are the same as those described previously for the multinomial logit model. The coefficients on the variables for each racial group are the expected wage differences between the racial group and whites with the same background characteristics for industries and occupations other than high technology S & E. Variables for the industry/occupational groups (*htse, htnse, and nhtse*) and the series of interaction terms between and race and industry/occupational groups (*blackhtse, asianhtse* and *lathtse etc.*) are included to control for the job of the individual and whether the effects are different by race. If the coefficient on *htse* is significant and positive, this will indicate whether the expected wages of whites working in science and engineering occupations in high technology industries is more than the expected wages of similar individuals working in non-S &E occupations in high technology industries. The coefficients on the race by industry interaction terms are the differences between the expected wage premiums received by whites compared to the expected wage premiums received by the other racial groups. If the coefficient is significant and positive, it will be an indication that the expected wage premium for the racial group is greater than that for whites, holding other factors constant.

The Heckman variation of OLS, t-tests of group means and local linear non-parametric regressions are used to provide comparisons with the OLS estimates. Models based on OLS suffer from a number of limitations that lead to biased estimates and threaten the validity of findings. These include selection effects mentioned previously, omitted variables and non-independence of the error term and possible mis-specification of the model. The Heckman variation of OLS provides some correction for selection effects when the wage analyses are run using a sample that includes non-workers, instead of full-time, full-year workers only. However this provides only limited correction for selection effects because the sample still excludes the incarcerated, a subpopulation of primarily black males with less than average levels of educational attainment. The variables used in the first stage (selection) equation include marital status (*married),* children in household under 18 (*ownchild*), home ownership (*house*), and the human capital variables for high school (*hisch*), bachelor's degree (*bachdeg*), and graduate (*postgrad*) education. The variables were the same as defined previously. The second stage model was identical to OLS wage model with the logarithm of weekly wages as the dependent variable, and with the variables *married, ownchild* and *house* excluded. The variables were excluded because of constraints in the specification of the Heckman model, which requires that some of the variables used in the selection stage of model to be different from those in the second stage.

The t-tests of group means and local linear non-parametric estimations provided an indication of the bias due to omitted variables and model mis-specification respectively. The t-tests were done on differences between the weekly incomes of white males and each of the other race/ethnicity groups sorted by education (graduate or bachelors), experience level (defined as three categories: <10 years; 11-20 years; and >20 years of experience), and industry /occupational group.

Local linear non-parametric regressions provides estimates of the dependent variable (log weekly wages) at a focal value of the predictor variable (Fox, 2000). The estimates were weighted to give more weight to values that were close to the focal value. The analyses were done with the dependent variable (log weekly wages) against the experience variable (*exp2)* for white males compared to the values for each of the other race/ethnicity groups sorted by education (graduate, or bachelors) and industry/occupational groups. The results were compared graphically with the estimates from OLS.

4.4 Limitations

The study suffers from a number of limitations, and threats to the validity which were not resolved fully in the analyses. These relate to data, methodological, and conceptual issues, which are discussed below. According to (Heckman et al., 2000), estimates of earnings and earnings differentials are influenced by the choice of data, labor-force selection issues, and model specification. In the analyses, the sample is restricted by characteristics related to age and employment and the cut-off points chosen affect the estimated results, such as the returns to schooling, and the racial wage gap. In addition, the analyses cover a limited time period, 1992 to 2002, and it is possible that the findings may not extend to other time periods since the combination of observable and unobservable factors such as government policies, or business cycle effects that change over time and affect wages may have different effects at a different period in time.

4.4.1 Data Source and Data

Several national surveys, for example the Panel Survey of Income Dynamics (PSID) and the National Longitudinal Survey provide data on employment and wages of individuals. These surveys potentially can provide richer sources of information on wage and individual characteristics, which can be used to overcome endogeneity issues. However, since the focus of this study was on high technology industries and occupations, many of which are relatively new, the March Annual Demographic Survey of the CPS was chosen as the data source because it uses more recent industry and occupational classification codes compared to the other surveys. Despite this, many high technology industries and occupations may not be adequately classified or even included, so are not captured in the correct group for the study. Although data from the Annual Demographic Survey are widely used in the analysis of wages and wage inequality, other limitations in the data have been recognized (Heckman et al., 2000). These include survey sampling errors and reporting errors; in particular earnings may be misrepresented or suffer from problems of recall as these are self-reported values for the previous year of the survey. The errors constitute a form of measurement error that is potentially a major problem in large public surveys(Black et al., 2006).

4.4.2 Endogeneity Issues

The results of the analyses may also be biased because wages are observed only for individuals who work and since the characteristics of individuals who work, for example educational attainment and race, are different from those who do not work, there is a selection effect(Heckman et al., 2000). Since black males are disproportionately more likely to withdraw from the workforce, either through unemployment or incarceration, the effects of education may be overstated and the wage gaps between whites and minorities understated.

Data from the CPS suffer from a number of drawbacks; in particular it does not contain information on numerous factors that are important in the determination of employment and wages. These include information on the ability of individuals, what they study and family background characteristics (Altonji & Blank, 1999). In addition there is inadequate information on past labor market experience, specific information on tenure in the present job and on training received outside of the formal educational system. Many of these variables are correlated with other variables in the model, for example education and experience and their omission leads to endogeneity and biased estimates, which severely limits the conclusions drawn about racial differences in labor market experience.

Differences in ability levels affect the level of formal schooling, the acquisition of post-school skills and the wages received (Heckman, Lochner, & Taber, 1998). Higher levels of ability, which are not accounted for in the model result in a positive bias on the education variables, that is, the effects of education appear to be greater than they really are in the model. The effects of the un-observables are found in the residual, which is often used as an alternative measure of wage inequality that varies over time.

Instrumental variables are often used to overcome effects of endogeneity due to omitted variables. However, it is difficult to find suitable instruments that fit the assumptions needed: (i) instrument relevance that is the instrument has an effect on the instrumented variable; (ii) the instrument is uncorrelated with the error term; and (iii) the instrument has no effect on the dependent variable outside of its effect on the instrumented variable. Estimates of the returns to education based on weak instruments are as problematic as those based on ordinary least squares analyses in which endogeneity exist (Card, 2001). The analyses produce widely varying estimates of the returns to schooling depending on the conditions of the analyses and the type of instrument used. Given the absence of suitable instruments in the CPS and the potential problems with weak instruments, instrumental variables approach was not pursued in this study.

The study used several approaches to assess the extent of the bias. The first approach was to estimate bounds on the probabilities of employment using data from the IPEDS Survey on the proportion of science and engineering degrees obtained in each year of the study by each racial and ethnic group (*pscideg2)* following (Manski, 1995). Manski (1995) gives worst case bounds as follows:

$$P(y \mid x) = P(y \mid x, z=1)P(z=1 \mid x) + P(y \mid x, z=0)\, P(z=0 \mid x)$$

Where $P(y)$ is the probability of employment in one of the industry/occupation groups; x is race/ethnicity and $P(z=1|x)$ is the probability of receiving a science and engineering degree for a particular racial and ethnic group and $P(z=0 \mid x)$ is the probability of not receiving a science and engineering degree. However the bounds derived using this approach, were too wide to be useful. Despite efforts, it was not possible to come with suitable assumptions to restrict the bounds or identify the parameters. As a compromise, the variable for proportion of science and engineering graduates (*pscideg2*) was introduced in the model as a proxy variable to control for whether an individual has studied science and engineering or not. In addition, wages were estimated using local linear non-parametric methods and compared graphically with OLS estimations.

Biased coefficients, in particular on the race variables make it difficult to conclude that discrimination is taking place. The coefficients on the race variables reflect not just discrimination effects but also the effects of unobservable variables that are related to race such as differences in unmeasured skills, or weak ties that help in securing jobs (Granovetter, 1983). Continued efforts are needed to resolve issues due to omitted variables.

4.4.3 Model mis-specification

Heckman et al (2005) point out that the specification of the wage model, put forward by Mincer which is linear in education and quadratic in experience, does not capture many of the features evident in earnings function in recent decades. For example, it is possible that there is an interaction between education and experience, and that experience should be represented as a higher order polynomial. Further, returns to education in the form wages, vary at different levels of schooling and these differences have increased since the

1980s. Thus the returns to education for graduate education relative to bachelor's degrees have increased to a greater extent than the returns to bachelor's education relative to high school; and high school relative to not having high school education. Mis-specification of the model leads to biased estimates of the coefficients, which is similar to that obtained with omitted variables. However, alternative specifications to the wage model were not used in the study, this is an area that can be considered in future research. Instead estimates from the Mincer model were compared to non-parametric estimations. Ulrick, (2005) found that estimates of the black/white wage gap based on non-parametric estimations were very similar to parametric estimates obtained using the Mincer model, thus the Mincer model was appropriate under certain circumstances.

4.4.4 Wage Imputations and Top Coding

The CPS imputes wages for individuals who respond to parts of the survey, but provide no response on wages, or have wages that are inadvertently missing, matching on several observed variables. However, wage data cannot be treated as missing at random since one cannot assume that characteristics of non-respondents are the same as that of respondents but instead depends on the question that is asked (Manski, 1995). As a result, the CPS wage imputations are considered problematic since the imputed wages may not be valid.

Wage data in ADS/CPS are top-coded, so the upper bounds do not truly reflect the wage differentials that exist. Prior to 1996, the CPS used a single value of 99,999 as the top code, which led to a truncation of the wage data. In 1996, the CPS switched to using the mean value of top-coded wages for specific sub-populations, with the result that there was no longer a single top code in the sample. The issue of truncation was unresolved in the analyses.

CHAPTER 5

HUMAN CAPITAL AND RACE EFFECTS ON EMPLOYMENT

This chapter provides the results of the analyses on the effects of human capital and race on the probabilities of employment in high technology S & E, other technology-sector and other S & E jobs. These results provide evidence to support or refute Hypotheses 1 through 4 of the study and thus help answer the research question. First, I discuss the characteristics of the sample, which includes full, part-time workers and non-workers, then present the findings from the multinomial logit analyses on the probabilities of employment in the industry/occupation groups. The effects of the human capital variables, represented as different levels of education are discussed first for white males. This is followed by the results for the effects of human capital variables on the probabilities of employment of blacks, Hispanics and Asians. Finally, I present the results of multinomial logit analyses for a sample based on full-time, full year workers only and discuss the implications of using the two different samples.

5.1 Sample Characteristics

Table 3 summarizes the main characteristics of the male and female sub-samples and shows that the pooled sample consists of approximately 48% males and 52% females, which is similar to the figures obtained in Census 2000, with 49% and 51% for males and females respectively. The racial distribution in the combined sample of males and females is 73% non-Hispanic whites, 12% non-Hispanic blacks, 3.5% Asians and 11% Hispanics, which again is comparable to national averages from Census 2000.

Table 3: Comparison of means and standard deviations of characteristics of male and female full, part-time and non-workers

	Female		Male	
Variable	**Mean**	**S.D.**	**Mean**	**S.D.**
Race/Ethnicity				
White	0.725	0.447	0.737	0.440
Black	0.131	0.338	0.114	0.318
Asian	0.038	0.191	0.037	0.188
Latino	0.106	0.307	0.113	0.316
Education				
Without High School	0.180	0.384	0.198	0.399
High School	0.528	0.499	0.502	0.500
College	0.292	0.454	0.299	0.458
Industry/Occupation				
High Technology Employment	0.044	0.206	0.097	0.296
Science & Engineering Occupations	0.012	0.108	0.043	0.202
High Technology / S & E	0.005	0.072	0.024	0.152
Non-High Technology / S & E	0.007	0.081	0.019	0.137
High Technology / Non-S & E	0.039	0.193	0.073	0.261
Non-High Technology / Non-S & E	0.949	0.220	0.884	0.320
Other Characteristics				
Age	38.356	13.319	37.913	13.247
Marital Status	0.733	0.442	0.664	0.472
Children Present	0.474	0.499	0.413	0.492
Home Ownership	0.677	0.468	0.685	0.465
Foreign Born	0.130	0.337	0.137	0.344
Self Employed	0.052	0.223	0.103	0.303
Full Time Worker	0.374	0.484	0.533	0.499
Union Member or Coverage	0.021	0.142	0.030	0.170
Average Income $	14591	20486	28069	36351
Region/Locality				
New England	0.051	0.220	0.052	0.221
Mid East	0.172	0.377	0.167	0.373
Great Lakes	0.164	0.371	0.164	0.370
Plains	0.068	0.252	0.069	0.254
South East	0.244	0.429	0.239	0.426
South West	0.105	0.307	0.106	0.307
Rocky Mountains	0.031	0.172	0.032	0.177
Far West	0.165	0.371	0.172	0.377
Central City	0.249	0.433	0.245	0.430
Other Urban Area	0.414	0.493	0.418	0.493
Rural	0.190	0.392	0.191	0.393
Annual Unemployment Rate	5.432	1.487	5.433	1.496
Proportion High Technology Firms (1996)	0.050	0.012	0.051	0.012
Proportion High Technology Employment (1996)	0.059	0.023	0.059	0.024
N	521917		488707	

Approximately 53% of females have high school education, while 50% of the males in the sample have high school education. However the proportion having college education is comparable for both genders at approximately 29%. Figures 1 and 2 show plots of the proportions of male college and high school graduates as a proportion of their racial and ethnic group. The proportion of college graduates increase very gradually for all groups over the period of the study with Asians having the highest proportion of college graduates at about 45%. Just over 30% of whites are college graduates while the proportion of black and Latino college graduates range from 14 to 19% and 11 to 13% respectively over the period.

Approximately 63% of males are full-time, full-year workers (workers who work more than 35 hours per week and at least 50 weeks in the year) while only 41% of females are full-time, full year workers. Approximately 14% of males are non-workers, who report no income, industry or occupation of employment, with the corresponding percentage for females being 27%.

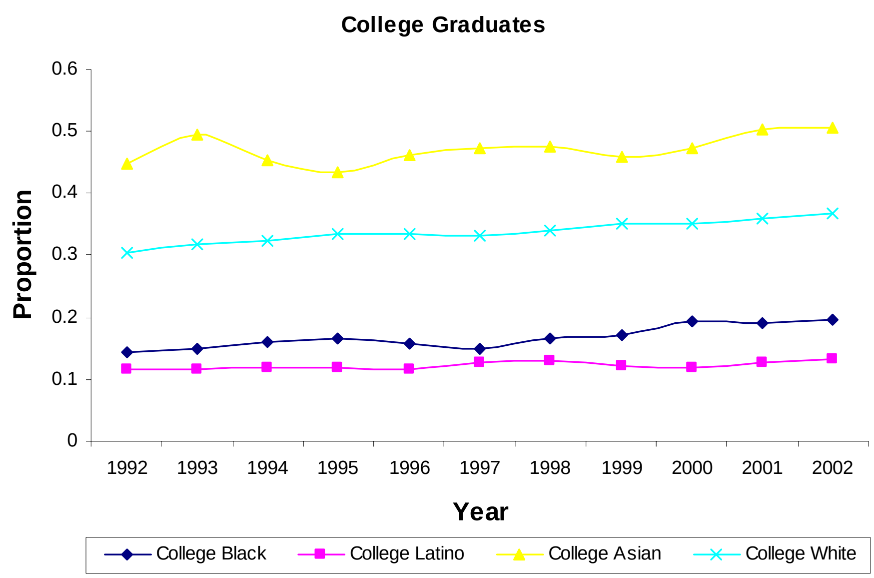


Figure 1: Proportion of Male College Graduates in each Racial Group in Sample

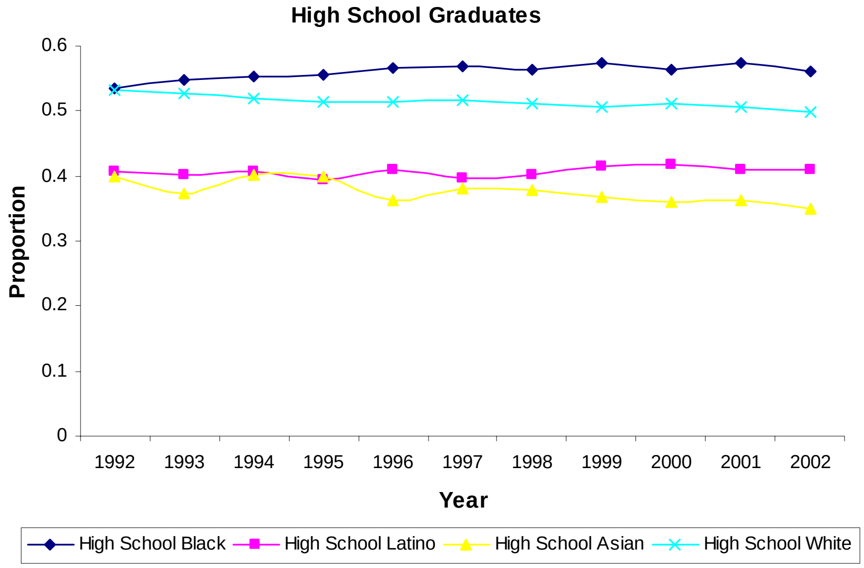


Figure 2: Proportion of Male High School Graduates in each Racial Group in Sample

The remainder of the sample is comprised of individuals who work part-time.

Based on the definition of science and engineering jobs used in the study, only 4.3% of males occupy these jobs, with approximately 2.4% being in the high technology S & E jobs and 1.9% in other S & E jobs. Approximately 9.6% of males are in high technology industry jobs. Thus, the majority of individuals (just over 88%) are in non-technology jobs resulting in the distribution of employment in the industry/ occupation categories being highly skewed. For females, the proportion of individuals in science and engineering jobs is just over 1.2%, with 0.5% being in the high technology S & E and 0.7% in other S & E jobs. This observation is consistent with the findings of previous studies, which show that women are under-represented in science and engineering occupations when compared to men (National Science Board, 2006; Tang, 2000). The low representation of females in high technology or science and engineering jobs will make the proposed analyses less reliable. Not surprisingly, given the paucity of science and engineering jobs relative to other types of jobs, the probability of employment in science and engineering jobs relative to other jobs is low.

5.2 Regression Analyses and Model Fit

Table 4 shows the effects of the variables on the odds ratios of employment in each of the three industry/occupation groups (high technology S & E, other technology-sector, and other S & E jobs) for males. The odds ratio is interpreted as the factor by which the odds of employment in high technology S & E, other technology-sector and other S & E jobs change for a unit change in the independent variable relative to the base outcome, non-technology jobs. The effects of the variables on the odds of employment in the restricted models are not discussed; however, details of the effects in the full model are presented and discussed in subsequent sections.

Model 1 includes the human capital variables for high school education (*hisch),* college education (*coll*), and the experience variable, in linear and quadratic forms (*exp2, exp2sq*). The likelihood ratio values increase significantly (LR chi2, $p< 0.000$); and AIC and BIC statistics decrease indicating a marginal improvement in model fit when the race/ethnicity variables were introduced (Model 2). As expected, the effects due to human capital variables are reduced and all variables are statistically significant in these highly restricted models. Model 3 includes the interaction terms between the education and race variables (*blackhi, blackcoll, lathi, latcoll,* and *ascoll)*. The log likelihood values increase significantly and tests of the goodness of fit of the models provide strong support for the model with the interaction terms. The magnitude of the effects of the variables changes to reflect differences in the interpretation of the coefficients.

Table 4: Odds ratios of employment from multinomial logit analyses of human capital and race variables for male full, part-time and non-workers

	Model 1			Model 2			Model 3		
	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-High Technology/ Science & Engineering	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-High Technology/ Science & Engineering	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-High Technology/ Science & Engineering
High school	14.6400***	2.2417***	10.3151***	13.1234***	2.1061***	9.3385***	10.3551***	2.0615***	7.7616***
	(2.935)	(0.062)	(1.691)	(2.639)	(0.059)	(1.540)	(2.178)	(0.071)	(1.431)
College	144.3205***	3.1218***	68.4488***	118.2257***	2.8361***	57.9200***	84.8968***	2.7749***	44.0059***
	(28.714)	(0.090)	(11.131)	(23.637)	(0.085)	(9.511)	(17.764)	(0.100)	(8.053)
Experience	1.0175***	1.0842***	1.0321***	1.0204***	1.0852***	1.0342***	1.0207***	1.0850***	1.0347***
	(0.004)	(0.002)	(0.005)	(0.004)	(0.002)	(0.005)	(0.004)	(0.002)	(0.005)
Experience (Squared)	0.9991***	0.9984***	0.9990***	0.9990***	0.9983***	0.9990***	0.9990***	0.9984***	0.9989***
	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)
Black				0.4634***	0.7185***	0.6208***	0.0980**	0.5778***	0.2749*
				(0.033)	(0.023)	(0.041)	(0.079)	(0.057)	(0.140)
Latino				0.5423***	0.7666***	0.5793***	0.0646***	0.7870***	0.1823***
				(0.033)	(0.019)	(0.035)	(0.048)	(0.043)	(0.078)
Asian				2.0877***	1.1444**	1.7947***	0.941	1.064	1.016
				(0.101)	(0.051)	(0.099)	(0.193)	(0.072)	(0.183)
Black x High school							3.484	1.3171**	1.464
							(2.849)	(0.137)	(0.766)
Black x College							5.2861*	1.180	2.7585*
							(4.263)	(0.136)	(1.418)
Latino x High school							5.5700*	0.945	2.6434*
							(4.222)	(0.060)	(1.166)
Latino x College							9.8451**	0.990	3.6230**
							(7.402)	(0.074)	(1.573)
Asian x College							2.4403***	1.148	1.9633***
							(0.512)	(0.098)	(0.373)
Psuedo R-square	0.077			0.081			0.081		
chi2	1.20E+04			1.30E+04			1.30E+04		
p	0.000			0.000			0.000		

Note: (1) Numbers in parentheses are standard errors; (2) * Significant at p<0.05; ** Siginificant at p<0.01; *** Significant at p<0.000
(3) Reference group comprises white males who are not high school graduates

Thus in the model with the race variables and interaction terms, the effects of the education variables (*hisch, coll*) are the differences in the odds of employment for white males with high school or college education respectively compared to those who have not graduated high school. The effects of the race variables (*black, latino, asian*) are differences between white males who have not graduated from high school and similar members of each racial group, respectively.

Table 5 shows the odds ratios for models with the addition of control variables for individual and labor market characteristics and compares the odds ratios for the models with college education as a single variable (Model 4), and then as two separate variables, one for bachelor's level education (*bachdeg*) and the other for graduate education (*postgrad*), (Model 5). In both models, white males without high school education form the reference groups. The coefficients on the education variables decrease in all three industry/ occupation groups with the addition of the control variables; however, the directions of change on the race variables are different in each of the industry/occupation groups.

The goodness of fit of the models improve with the addition of the control variables on individual and labor market characteristics. However the change in log likelihood accounted for by the variables in the model is quite small (approximately 12%) and the McFaddens R^2 value is only 0.118 which is somewhat less than the 0.2 to 0.4 range, typically considered as acceptable for the effect size of the model (Tabachnick & Fidell, 2007). Wald tests provide no support for combining any of the industry /occupation categories.

Table 5: Comparison of odds ratios from multinomial logit models with all variables and college education included as (1) a single variable and (2) as bachelors and graduate degrees for male full, part-time and non-workers

	Model 4			Model 5		
Variables	**High Technology/ Science & Engineering**	**High Technology/ Non-Science & Engineering**	**Non-high Technology/ Science & Engineering**	**High Technology/ Science & Engineering**	**High Technology/ Non-Science & Engineering**	**Non-high Technology/ Science & Engineering**
High school	7.8355***	1.6880***	6.2629***	7.8767***	1.6855***	6.2676***
	(1.6516)	(0.0594)	(1.1543)	(1.6604)	(0.0593)	(1.1553)
College	55.5015***	2.1436***	33.3930***			
	(11.6691)	(0.0788)	(6.1203)			
Bachelors Degree				54.0375***	2.2203***	33.4999***
				(11.3695)	(0.0832)	(6.1456)
Graduate Degree				61.3064***	1.9252***	33.3291***
				(13.0127)	(0.0836)	(6.2151)
Experience	0.9884*	1.0467***	1.0110*	0.9893*	1.0469***	1.0118*
	(0.0048)	(0.0027)	(0.0051)	(0.0048)	(0.0027)	(0.0051)
Experience (squared)	0.9997*	0.9990***	0.9995***	0.9997*	0.9990***	0.9995***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Black	0.1252**	0.7297**	0.3145*	0.1245**	0.7302**	0.3134*
	(0.1009)	(0.0723)	(0.1599)	(0.1004)	(0.0723)	(0.1593)
Latino	0.0460***	0.7150***	0.1520***	0.0459***	0.7151***	0.1514***
	(0.0344)	(0.0398)	(0.0650)	(0.0344)	(0.0398)	(0.0647)
Asian	0.5806**	0.9792	0.8043	0.5917*	0.9770	0.8124
	(0.1223)	(0.0703)	(0.1500)	(0.1245)	(0.0702)	(0.1514)
Black x High school	3.2983	1.2604*	1.4095	3.3000	1.2604*	1.4105
	(2.6972)	(0.1312)	(0.7368)	(2.6986)	(0.1312)	(0.7373)
Black x College	4.7179	1.0373	2.4901			
	(3.8049)	(0.1197)	(1.2801)			
Black x Bachelors				4.6610	1.0261	2.3917
				(3.7596)	(0.1209)	(1.2337)
Black x Graduate				5.2154*	1.0261	2.9430*
				(4.3066)	(0.1903)	(1.5737)
Latino x High School	6.6924*	1.0482	3.0143*	6.6825*	1.0487	3.0178*
	(5.0736)	(0.0666)	(1.3288)	(5.0660)	(0.0666)	(1.3304)
Latino x College	13.0549***	1.1354	4.2624***			
	(9.8211)	(0.0852)	(1.8503)			
Latino x Bachelors				13.1685***	1.0952	4.3064***
				(9.9158)	(0.0870)	(1.8746)
Latino x Graduate				13.1622***	1.2569	4.1033**
				(10.0806)	(0.1552)	(1.9012)
Asian x College	2.3288***	1.0681	1.8186**			
	(0.4871)	(0.0913)	(0.3460)			
Asian x Bachelors				1.7269*	1.0739	1.3250
				(0.3700)	(0.0987)	(0.2622)
Asian x Graduate				3.4904***	1.0761	2.9471***
				(0.7551)	(0.1311)	(0.5923)
Married	1.3489***	1.3566***	1.2139***	1.3052***	1.3638***	1.1946***
	(0.0544)	(0.0328)	(0.0527)	(0.0528)	(0.0330)	(0.0519)
Cont'd						

Table 5 *cont'd*

Variables	Model 4: High Technology/ Science & Engineering	Model 4: High Technology/ Non-Science & Engineering	Model 4: Non-high Technology/ Science & Engineering	Model 5: High Technology/ Science & Engineering	Model 5: High Technology/ Non-Science & Engineering	Model 5: Non-high Technology/ Science & Engineering
Own child in household	0.9042***	0.9050***	0.9287*	0.9063**	0.9038***	0.9296*
	(0.0272)	(0.0159)	(0.0312)	(0.0273)	(0.0159)	(0.0313)
Buying/Own House	1.1796***	1.2706***	1.2246***	1.1782***	1.2739***	1.2282***
	(0.0387)	(0.0238)	(0.0420)	(0.0388)	(0.0239)	(0.0423)
Full-time Worker	2.8769***	2.6537***	2.8091***	2.8711***	2.6513***	2.8069***
	(0.0956)	(0.0487)	(0.0972)	(0.0953)	(0.0487)	(0.0971)
Self- Employed	0.4732***	0.4334***	0.1085***	0.4655***	0.4355***	0.1078***
	(0.0228)	(0.0131)	(0.0103)	(0.0226)	(0.0132)	(0.0102)
Union Member/Covered	0.1789***	0.8136***	0.5187***	0.1793***	0.8131***	0.5190***
	(0.0241)	(0.0329)	(0.0482)	(0.0241)	(0.0328)	(0.0482)
Year 1994-1996	0.5283***	0.5730***	0.5038***	0.5282***	0.5731***	0.5029***
	(0.0252)	(0.0147)	(0.0245)	(0.0252)	(0.0147)	(0.0245)
Year 1997-1999	0.6407***	0.6565***	0.5593***	0.6380***	0.6565***	0.5562***
	(0.0358)	(0.0208)	(0.0327)	(0.0358)	(0.0208)	(0.0326)
Year 2000-2002	0.6438***	0.6005***	0.5289***	0.6406***	0.6008***	0.5260***
	(0.0345)	(0.0179)	(0.0300)	(0.0344)	(0.0179)	(0.0299)
Live in Central City	1.5787***	1.1663***	1.2176***	1.5643***	1.1707***	1.2183***
	(0.0684)	(0.0277)	(0.0527)	(0.0679)	(0.0279)	(0.0526)
Live in other urban area	2.0467***	1.3675***	1.3251***	2.0330***	1.3703***	1.3232***
	(0.0726)	(0.0261)	(0.0479)	(0.0721)	(0.0262)	(0.0478)
New England	1.6782***	1.5418***	0.9709	1.6629***	1.5468***	0.9677
	(0.0907)	(0.0518)	(0.0586)	(0.0901)	(0.0520)	(0.0583)
Mid-Eastern Region	1.0233	1.0095	1.0458	1.0182	1.0115	1.0435
	(0.0493)	(0.0282)	(0.0513)	(0.0492)	(0.0283)	(0.0512)
Great Lakes	1.2025***	1.7055***	0.9638	1.2041***	1.7052***	0.9631
	(0.0573)	(0.0452)	(0.0485)	(0.0576)	(0.0451)	(0.0485)
Plains	0.9142	1.1851***	1.0218	0.9133	1.1843***	1.0173
	(0.0626)	(0.0456)	(0.0651)	(0.0626)	(0.0455)	(0.0648)
South West	1.4091***	1.2876***	1.1867**	1.4158***	1.2864***	1.1888**
	(0.0782)	(0.0407)	(0.0697)	(0.0785)	(0.0406)	(0.0698)
Rocky Mountains	1.3254***	1.0490	1.1144	1.3420***	1.0480	1.1209
	(0.0895)	(0.0442)	(0.0754)	(0.0907)	(0.0442)	(0.0759)
Far West	1.4490***	1.1754***	1.0206	1.4721***	1.1743***	1.0363
	(0.0761)	(0.0369)	(0.0577)	(0.0773)	(0.0369)	(0.0584)
Unemployment Rate	0.9872	1.0267***	0.9700*	0.9858	1.0269***	0.9688*
	(0.0135)	(0.0081)	(0.0147)	(0.0135)	(0.0081)	(0.0147)
Proportion S&E degrees	15.0904***	3.4573***	8.7378***	12.7306***	3.5152***	7.8579***
	(4.6878)	(0.6235)	(2.7931)	(3.9762)	(0.6347)	(2.5182)
Pseudo R-Square	0.1172			0.1179		
chi2	21000			22000		
p	0.0000			0.0000		

Note: (1) Numbers in parentheses are standard errors; (2) * Significant at p<0.05; ** Significant at p<0.01; *** Significant at p<0.000; (3) Reference groups for dummy variables: Education & race- white male who has not graduated high school; marital status- never married; child in household - no children; work status -not a full-time, full-year worker; self-employment status - not employed by own business; union status - not a member or covered by a union; Year - 1992-1993; metro status - rural resident; region of residence - South East

Based on the Hausman tests, the hypotheses that the differences between the coefficients are systematic can be rejected. In general, the effects of the variables are most similar for the two groups of science and engineering jobs, however, differences exist between two groups of jobs, which provide insights on the relative importance of human capital, race and structural effects.

5.3 The Effects of Human Capital for White Males

The interpretations of the effects of the variables in the following discussions are based on Model 5, in which all the variables including the controls are present. The discussions below focus primarily on the sign or direction and the relative size of the effect compared to other variables. Positive or negative changes in the log odds lead to an increase or decrease in the expected probability respectively, although the relationship will not be linear and the actual probabilities will depend on the value of the other variables. However, because many factors such as labor market and firm characteristics, individual ability and skills that may or may not be observed by the employer and which are related to the independent variables such as education and race are omitted from the model, the estimated coefficients are considered to be biased and interpretations on the size of the effect has to be done with caution.

5.3.1 Effects of High School and College Education for White Males

Table 6 summarizes the effects of different levels of educational attainment on the odds ratios of employment in the three industry/occupational groups relative to non-technology jobs for white males. Holding all else constant, having either high school or college education compared to not being a high school graduate significantly increases the odds of employment in high technology S & E, other technology-sector and other S &

E jobs relative to non-technology jobs for white males. Based on the results of Wald and likelihood ratio tests, the effects of high school education on the odds of employment in the two groups of S & E jobs are not significantly different from each other for white males (Appendix Table 6 on p. 201).

The magnitude of effects college education on the odds of employment in the three industry/occupation groups are different, with the effects being greatest in high technology S & E jobs, followed by the effects in other S & E jobs, then other technology-sector jobs. As expected, having college education (bachelors or graduate degrees) significantly increases the odds and probability of employment to a greater extent than high school level education. Having a graduate degree significantly increases the odds of employment in high technology S & E jobs, when compared to all other levels of education including a bachelor's degree. However, there is no significant difference between the effects of bachelors and graduate degrees on the odds of employment in other S & E jobs (Appendix Table 6).

Table 6: Summary of the Effects of Education on the Odds Ratios of Employment in Different Industry/Occupation Groups for White Males

	High Technology/ Science & Engineering	High Technology/ Non-science & Engineering	Non-High Technology/ Science & Engineering
High School	7.8767	1.6855	6.2676
Bachelors	54.0375	2.2203	33.4999
Graduate	61.3064	1.9252	33.3291
(Reference group: Not a high school graduate)			
No High School	0.1207	0.5933	0.1596
Bachelors	6.8604	1.3173	5.3450
Graduate	7.7832	1.1422	5.3177
(Reference group: High school graduate)			
No High School	0.0185	0.4504	0.0299
High School	0.1458	0.7591	0.1871
Graduate	1.1345	0.8671	0.9949 NS
(Reference Group: Bachelors degree)			

Note: NS = Not siginificant; All other values are significant at p<0.000

In contrast, having a bachelor's degree significantly increases the odds of employment in other technology-sector jobs, when compared to a graduate degree (Table 5 and Appendix Table 6).

Employers of individuals in high technology S & E jobs appear to be more discerning in employment practices, and demand greater skills, which suggest that individuals are more likely to be formally trained when compared to individuals in other S & E jobs. A graduate degree is worth more in high technology S & E jobs compared to other S & E jobs. Thus individuals in high technology S & E jobs have on average more years of formal education compared to individuals in other S & E jobs. Individuals with the best qualifications get high technology S & E jobs because of the small number of jobs and the resulting competition that exists for these jobs. Individuals who consider themselves to be scientists and engineers without having college level training or degrees in science and engineering (National Science Board, 2006), are employed in S & E jobs outside of the high technology sector. These findings are not surprising given that industries with the largest concentrations of S & E jobs outside of the high technology sector are construction, and telephone utility companies. The group also includes universities and colleges, which are expected to behave somewhat differently in the demands for skill compared to the other two. On the other hand, industries with the largest numbers of high technology S & E jobs are computer related industries, engineering and architectural services, and research and development.

Shorter product life cycles and rapid obsolescence result in greater competitive pressures for industries in the high technology sector compared to industries outside of this sector, which employ scientists and engineers. The highly competitive environment faced by the high technology sector with a strong demand for new and innovative products drives the need for greater competencies and abilities to perform knowledge creating activities such as research and development. Increased competitiveness is reflected in greater profitability within the industry and this translates to higher wages for that sector. When successful, high technology industries are able to exert greater monopoly powers compared to other industries, further enhancing the level of profitability (Galbraith, 1998).

This analysis suffers from the limitation that the education variables only tell whether the person has high school or college level education, and we do not know the discipline or field that the individual studied. However this study assumes that individuals employed as scientists and engineers are more likely to have studied in these disciplines and that only a small proportion of individuals in the sample working in science and engineering occupations would have studied other disciplines. This assumption is expected to hold more so for college-educated individuals.

In addition, the analyses do not take into consideration whether individuals are being employed in entry-level positions, or in managerial and professional positions that require greater levels of skills. This distinction is usually made in studies on the employment of individuals in different occupations.

5.4 Human Capital Effects for Other Racial/ Ethnic Groups

This section compares the effects of different levels of education on the probabilities of employment in high technology S & E, other technology-sector and other S & E jobs for the minority groups and whites. The results are discussed successively for blacks, Hispanics, and Asians; first for individuals without high school education then for individuals with high school and college education in each industry/occupation group.

Table 7 summarizes the odds ratios of employment between minorities and whites in high technology S & E, other S & E and other technology-sector jobs for different levels of education. Figures 3, 4, and 5 show estimates of the probabilities of employment in high technology S & E, other S & E and other technology-sector jobs respectively at college and high school levels of education for males in each racial group[10]. Tests on specific hypotheses on differences between racial groups at different levels of education and the effects of education are given in Appendix Tables 6-9 (pp. 201, 212, 222, 229).

Table 7: Comparison of the Odds Ratios Employment between Minority and White Males at Different Levels of Education

Race/Ethnicity	**Education**			
	Graduate	**Bachelors**	**High School**	**No High School**
High technology/ Science and engineering				
Blacks	0.6494*	0.5804 ***	0.4109 ***	0.1245**
Latinos	0.6035 **	0.6038 ***	0.3064 ***	0.0459 ***
Asians	2.0653 ***	1.0218 NS	0.5917 *	
High technology/ Non-science and engineering				
Blacks	0.7492 NS	0.7480 ***	0.9203*	0.7302**
Latinos	0.8988 NS	0.7818 ***	0.7499 ***	0.7151 ***
Asians	1.0514 NS	1.0492 NS	0.9770 NS	
Non-high technology/ Science and engineering				
Blacks	0.9222 NS	0.7510**	0.4420 ***	0.3134*
Latinos	0.6212 **	0.6535 ***	0.4569 ***	0.1514 ***
Asians	2.3943 ***	1.0765 NS	0.8124 NS	

Note: (1) Odds ratios are the differences between minorities and whites when the refence group in the model is set to the educational level shown
(2) Both high school and non-high school graduates are included for Asians under high school
(3) NS - Not significant; * - Significant at p<0.05; ** - Significant at p<0.01; *** Significant at p<0.000.

[10] The totals of probabilities are across jobs for each racial group.

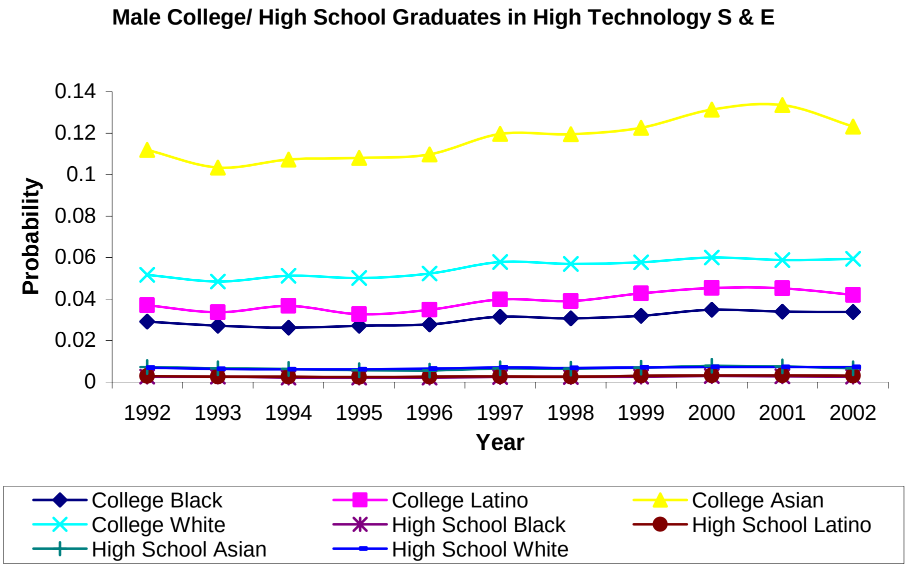


Figure 3: Probabilities of Employment in High Technology, S & E Jobs for Male College and High School Graduates for 1992 to 2002

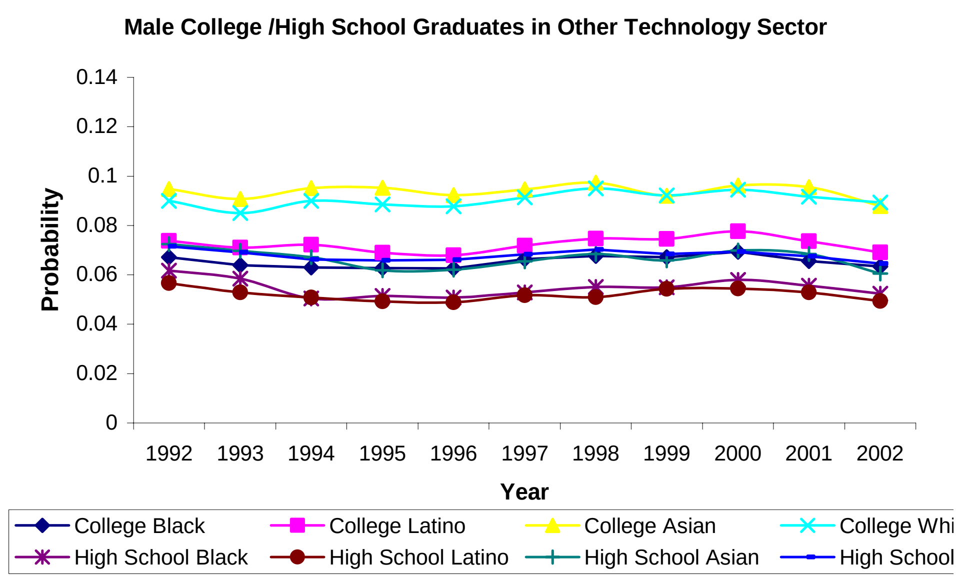


Figure 4: Probabilities of Employment in Other Technology Jobs for Male College and High School Graduates for 1992 to 2002

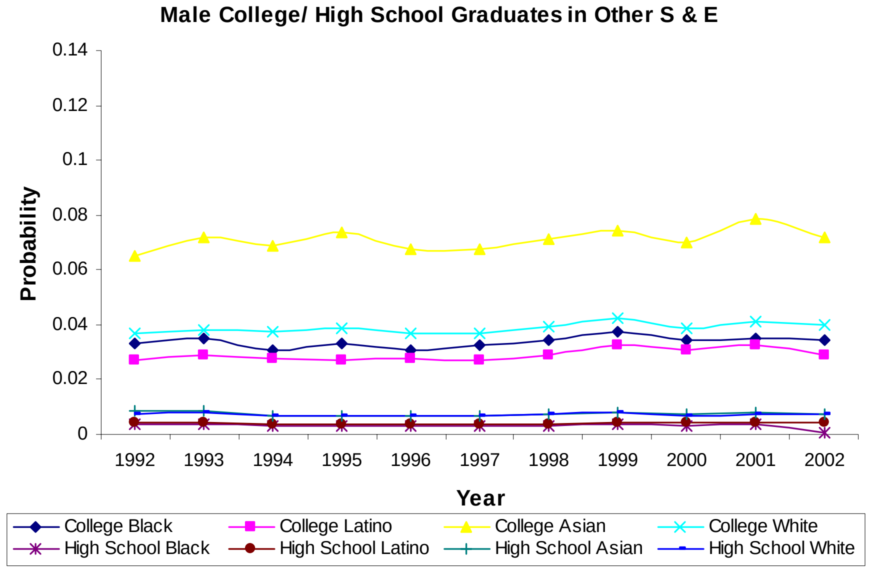


Figure 5: Probability of Employment in Other Science and Engineering Jobs for Male College and High School Graduates for 1992 to 2002

As expected, the probabilities of working in the smaller number of S & E jobs are lower than the probabilities of working in other technology-sector and non-technology jobs for all race/ ethnicity groups, regardless of education.

5.4.1 Minority/ White Differences With Less Than High School Level Education

Blacks and Latinos without high school education have significantly lower odds (and probabilities) of employment in both high technology industries and S & E jobs relative to non-technology jobs compared to whites (Table 5). For blacks and Latinos without high school education, the odds of employment in high technology industry jobs are not significantly different from each other (Appendix Table 6). Asians without college education have significantly lower odds of employment in high technology S & E jobs relative to non-technology compared to whites[11]; but have significantly higher odds compared to blacks and Latinos (Table 5). However, there is no significant difference

[11] No standard errors were computed when the *ashi* variable was included in the model, so comparisons had to be made between Asians with and without college education.

between the odds of Asians and whites without high school education working in other S & E or other technology-sector jobs relative to non-technology jobs. Thus with the exception of high technology S & E jobs, Asians without college education have greater parity with similar whites. On the other hand, blacks and Latinos are at a disadvantage.

5.4.2 Black /White Differences With High School and College Level Education

5.4.2.1 High Technology S & E Jobs

The incremental gains from high school and college (bachelors and graduate levels combined) education are not significantly different for blacks compared to whites (Table 5, Model 4). For high school educated individuals, blacks have significantly lower odds of employment in high technology S & E jobs relative to non-technology jobs and other technology-sector jobs. However the differences between the odds of employment for blacks and whites with high school education are not significant relative to other S & E jobs (Appendix Table 7 on p. 212).

When bachelors and graduate education levels are considered separately, the incremental gains in going from either without or with high school education to having graduate level education are only marginally higher than for bachelors degree; tests no show no significant difference between the effects of the two levels of education for blacks when compared to whites (Table 5, Model 5; Appendix Tables 6 and 7). Blacks with bachelors degrees have significantly lower odds of employment in high technology S & E jobs relative to each of the three other job groups when compared to whites (Appendix Table 8 on p. 229). Further, graduate education does not improve the odds of employment of blacks in high technology S & E jobs significantly compared to having only a bachelors degree. The odds of employment of blacks with graduate degrees remain significantly lower than whites in high technology S & E jobs relative to non-technology jobs (Table 7; Appendix Table 9 on p. 229). The differences are not significant relative to other technology-sector jobs or other S & E jobs. In Figures 3 and 6, the probabilities of college educated blacks (and Latinos) working in high technology S & E jobs are 2 and 3 percentage points lower than whites in 1992 and 2002 respectively. However the differences were 5 and 6 percentage points lower than Asians in 1992 and 2002 for blacks with bachelors degrees and 15 percentage points lower than Asians at the graduate level (Figure 6). Blacks and Latinos with either bachelors or graduate levels of education have no significant difference between the odds of employment in both types of S & E jobs.

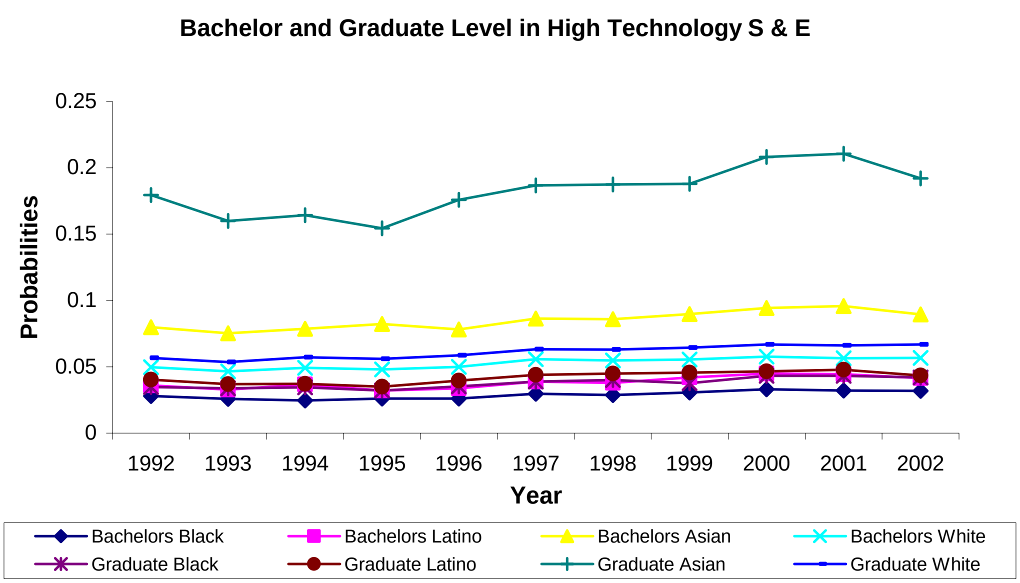


Figure 6: Probabilities of Employment in High Technology, S & E Jobs for Males with Bachelors and Graduate Education for 1992 to 2002

Thus the net effects of the coefficients on the race variable and the race/ education interaction terms are that blacks, regardless of educational level have significantly lower odds and probabilities of employment in high technology S & E jobs relative to non-technology jobs compared to whites and Asians (Tables 5 and 7, and Figures 3 and 6). Even with graduate education, blacks are less likely than whites to be employed in high technology S & E jobs.

5.4.2.2 Other Technology Sector Jobs

High school education improves the odds of being employed in other technology-sector jobs relative to non-technology and other S & E jobs to a greater extent for blacks compared to whites (Table 5). However, the odds of employment of high school educated blacks in other technology-sector jobs relative to the three other job groups remain significantly lower than whites but not significantly different from similar Asians (Table 7 and Appendix Table 7). In other technology-sector jobs, differences between the probabilities of employment of the different racial groups with high school level education only, are less than a percentage point (Figure 4).

Holding all else constant, blacks with bachelor's level education have significantly lower odds of employment in other technology-sector jobs relative to non-technology compared to whites (Table 7). There is no significant difference between the odds of employment of blacks and whites with bachelor's degrees in other technology-sector jobs relative to other S & E jobs (Table 7; Appendix Table 8). Blacks with graduate education have no significant difference in odds of employment in other technology-sector jobs, relative to each of the three other job groups, compared to whites

(Table 7, Appendix Table 9). Thus, blacks and whites have greater parity in the odds of employment in other technology-sector jobs as educational levels increase.

5.4.2.3 Other S & E Jobs

Holding all else constant, blacks with high school education have significantly lower odds of employment in other S & E jobs relative to non-technology or other technology-sector jobs compared to whites (Table 7; Appendix Table 7). However, the differences are not significant for other S & E relative to high technology S & E jobs.

Relative to non-technology jobs, blacks with bachelor's degrees have significantly lower odds of employment in other S & E jobs compared to similar whites (Table 7). However relative to high technology S & E jobs, blacks with bachelors education have significantly higher odds of employment in other S & E jobs compared to similar whites (Appendix Table 8). There is no significant difference between the odds of employment for blacks and whites with graduate level education in other S & E jobs relative to each of the three other job groups (Appendix Table 9).

Differences between the odds of employment of blacks and whites are more pronounced for S & E jobs relative to non-S & E jobs, with smaller differences being observed between two groups of S & E jobs. As the levels of education increase, the differences between odds of employment of blacks and whites in S & E jobs are reduced. However even with graduate education, blacks have significantly lower odds of employment in high technology S & E jobs relative to non-technology jobs compared to whites, but the differences are not significant relative to other technology-sector or other S & E jobs. There are no significant differences between odds of employment of blacks and whites with graduate education in other S & E jobs relative to the other three job groups.

The differences between blacks and whites/Asians at low levels of education can be attributed in part to differences in what individuals study. At lower levels of education, fewer blacks may specialize in S & E fields, so this could be responsible for driving the observed differences. However at higher levels of education, greater levels of specialization are expected and the match between occupation/job and the field of study is expected to be better. The differences between probabilities of employment of blacks and whites or Asians with graduate education in the two groups of S & E jobs suggest that the factors determining employment in the two groups of jobs are different. Education and what individuals study are not the only factors under consideration. Differences attributed to the race of the individual are important. The implications for policy will be discussed further.

5.4.3 Hispanics

The incremental gains of Latinos from high school and college (both bachelors and graduate) are significantly greater than comparable whites in both types of S & E jobs (Table 5, Model 5). However, Latinos with high school level education have significantly lower odds of employment in high technology S & E, other technology-sector, and other S & E relative to any of the other job groups compared to whites (Appendix Table 7). The odds of employment of Latinos with both bachelors and graduate degrees are significantly lower than similar whites for high technology S & E jobs relative to other technology-sector and non-technology jobs, but these differences are not significant relative to other S & E jobs (Appendix Tables 8 and 9). Latinos with bachelor's education have significantly lower odds of being employed in other technology-sector or other S & E jobs relative non-technology jobs compared to whites, but there is no significant difference between odds of employment in these two jobs relative to each other (Appendix Table 8).

There is no significant difference between the odds of employment of Latinos and whites with graduate level education in other technology-sector jobs relative to non-technology jobs. However, the difference between odds of employment of Latinos and whites in other S & E jobs relative to non-technology jobs remains significant even with graduate education (Table 7). From Figure 3, the differences between probabilities of employment in high technology S & E jobs for Latinos and whites with college education are 1 and 2 percentage points for 1992 and 2002 respectively; the differences for Latinos and Asians were 7 and 8 percentage points in 1992 and 2002 respectively.

Holding all else constant, the odds of employment of blacks and Latinos without high school education in the high technology sector are not significantly different from each other (Appendix Table 6). Although statistical tests show that the odds of high school educated Latinos working in the other technology sector are significantly lower than similar blacks, the differences are not discernibly large (Appendix Table 7). There is no significant difference between the odds of employment of black and Latino college graduates (either bachelors or graduate degrees) in high technology S & E, other S & E or other technology-sector jobs.

Both high school and college education (bachelors and graduate degrees) increase the odds of employment in both types of S & E jobs relative to non-technology jobs to a greater extent for Latinos compared to whites. However, given the wide disparities between Latinos without high school education and other ethnic groups, the gains from education are not enough to increase the probabilities of employment in high technology S & E, other technology-sector and other S & E jobs above those of whites or Asians. These observations provide further support for the view that both what individuals study and race are important in determining employment.

5.4.4 Asian/White Differences With College Level Education

There are no significant differences between odds of employment of whites and Asians with bachelors degrees in either high technology S & E, other technology-sector, and other S & E jobs relative to any of the other jobs (Table 7, Appendix Table 8). Asians with graduate level education have significantly greater the odds of employment in both types of S & E jobs relative to non-technology and other technology-sector jobs compared to similar whites (Table 7; Appendix Table 9). However, there is no significant difference between odds of employment of Asians and whites with graduate degrees in high technology S & E jobs relative to other S & E jobs, and for other technology-sector jobs relative to non-technology jobs. Asians with college education (both bachelors and graduate levels) have significantly higher odds of employment in both types S & E jobs compared to blacks and Hispanics (Appendix Tables 8 and 9).

Figures 3 and 5 show that the probabilities of working in S & E jobs are greatest for college educated Asian males with probabilities ranging from 0.10 to 0.13 and 0.06 to 0.08 for high technology S & E and other S & E jobs respectively, depending on the year. Large differences exist between the probabilities of employment of Asian males with graduate degrees and other racial groups with either graduate or bachelors education in both types of S & E jobs (Figures 6 to 8).

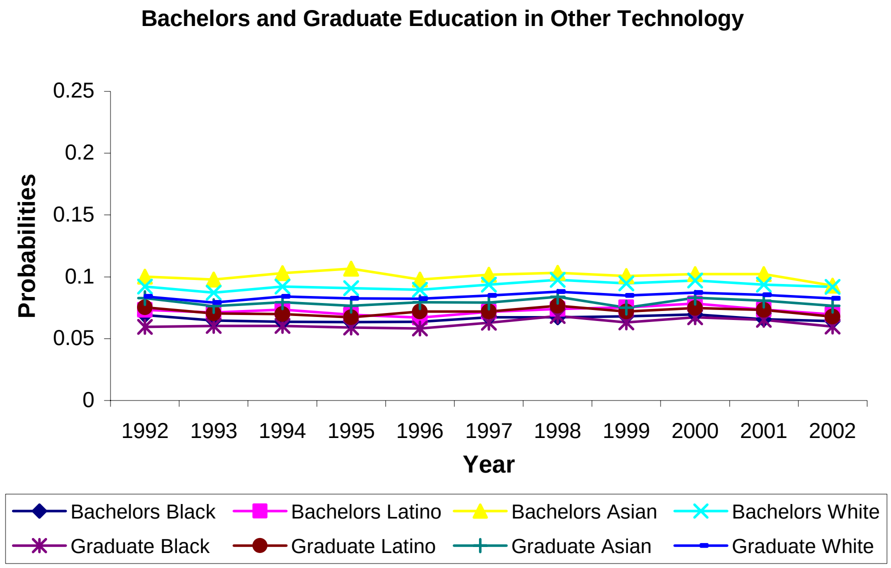


Figure 7: Probabilities of Employment in High Technology, Non-S & E Jobs for Males with Bachelors and Graduate Education for 1992 to 2002

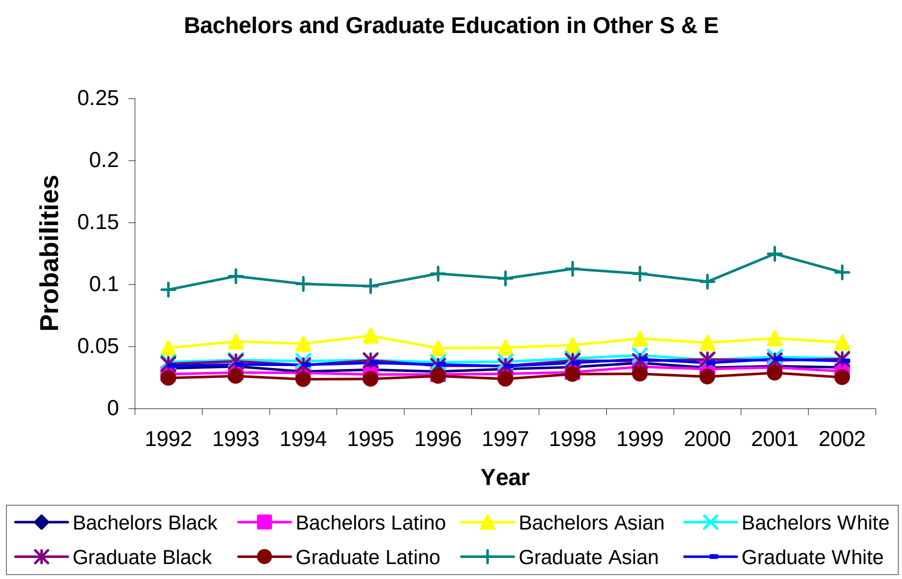


Figure 8: Probabilities of Employment in Non-High Technology, S & E Jobs for Males with Bachelors and Graduate Education for 1992 to 2002

The probabilities of Asian males with graduate education working in high technology S & E jobs are between 10 and 12 percentage points greater than those of similar white males. Asian males with graduate education are almost twice as likely to work in the high technology S & E jobs compared to other S & E jobs.

Both college and non-college educated Asian males have marginally higher probabilities (1-3 percentage points difference) of working in other technology-sector jobs compared to the other racial groups, with the gap being somewhat larger in 1992 and 1998 compared to other years (Figure 5). However, the percentage point differences between the probabilities of employment of Asians and other racial groups are not as great as the differences in S & E jobs.

The declining employment opportunities in high technology industries affected Asians to a greater extent compared to other ethnic groups, with Asians showing greater fluctuations in the probabilities of employment over the period. Higher probabilities of employment of Asians with graduate degrees in S & E jobs compared to other racial groups may be a reflection of the view that Asians are more likely to study in S & E fields compared to other groups (Tang, 2000). This coupled with the demand for higher levels of specialized skills (graduate level training) in high technology S & E jobs compared to other S & E jobs result in individuals who have these skills getting the jobs Alternatively, Asians with graduate degrees may have greater preference for S & E jobs in the high technology sector compared to those outside (Tang, 2000); or that they have better networks in high technology S & E jobs that enable them to get these jobs. On the other hand, the observation may be the result of statistical discrimination, in which employers perceive that skills of Asians are superior to other racial groups and so employ them in preference to other workers.

The magnitude, direction and statistical significance of the *asian* variable are very sensitive to the specification of the model and the inclusion of different labor market variables. For example, the direction and significance level of the *asian* variable changed when the variable for the proportion of S & E graduates (*pscideg2)* by gender, race, state, and year was introduced into the model. The sensitivity may be due to the small number of Asians in the sample; hence, the findings related to the *asian* variable may not be reliable.

5.4.5 Education, Race and Employment

As expected, the differences between the odds of employment of minorities and whites are greatest when comparisons are made relative to non-technology jobs; the gap narrows when comparisons are made between the high technology S & E, other technology-sector and other S & E jobs, with the difference being least for comparisons between the two groups of S & E jobs. The differences indicate that the patterns of employment of the different racial groups in S & E jobs are different from other technology-sector or non-technology jobs; and are more similar to each other. However, the magnitude and statistical significance of the differences vary with the comparison pair, the race/ethnicity group and the level of education. The odds difference relative to non-technology jobs may be driven in part by differences in what individuals study.

College education more so graduate levels of education exerts the largest effects on the probabilities of employment in high technology S & E jobs compared to the effects in other jobs in particular the non-science and engineering jobs. Thus, the results support the first hypothesis in the study, that is the effects of education are greatest in high technology S & E jobs compared to all other jobs; the study shows that this holds regardless of race. It is possible that the competitive environment of the high technology sector drives the demand for higher levels of skills; thus the sector attracts more highly educated and skilled individuals compared to the non-high technology sector.

Blacks and Hispanics regardless of educational levels are less likely to be employed in the high technology S & E jobs relative to non-technology jobs compared to whites and Asians. Further Latinos have significantly lower odds of employment in other technology-sector and other S & E jobs compared to whites with the exception of Latinos with graduate level education in other technology-sector jobs. These observations provide some support for the third hypothesis, that is the probabilities of employment in the high technology S & E jobs are lower for blacks and Hispanics compared to whites with the same level of educational attainment. The observation that Asians with graduate degrees have higher odds of employment in S & E jobs also provides partial support for the third hypotheses.

Incremental gains due to higher levels of educational attainment vary with the minority group, the industry/occupational group, and the level of education under consideration. There is no significant difference between the gains that blacks and whites receive in going from high school to college education; however the benefits to Hispanics are significantly greater than whites. The odds of employment in high technology industries and S & E jobs increase with increasing levels of education for blacks/ Hispanics compared to whites. In consequence, there are no significant differences between the odds of employment of blacks and whites with graduate degrees in other technology-sector or other S & E jobs. However, blacks and Hispanics continue to have lower probabilities of employment in high technology S & E jobs compared to whites. Thus, there is only partial support for the fourth hypothesis in the study, which states that improvements in educational attainment would increase the probabilities of employment in the high technology industries or science and engineering jobs less for blacks and Hispanics compared to whites and Asians.

The observed racial differences reflect a complex mix of social, cultural and other factors that give rise to social phenomena.. Although it was hoped to have a clearer pattern or picture from the results of the analyses, it is not possible to sort out unequivocally that a single mechanism contributes to the different observations. These difficulties stem partly from the differences in employment prospects which arise when we consider each industry/occupation group, racial group and the level of educational attainment. These factors not only influence what individuals study, the career choices that are made and the prospects of obtaining technology jobs. Thus differences in the coefficients on the minority variables reflect not only current labor market discrimination but also pre-market factors which affect career preferences and choices (Altonji & Blank, 1999).

The under-representation of blacks and Hispanics in the high technology sector and science and engineering occupations is in keeping with several studies, which consistently show that blacks and Hispanics are under-represented in science and engineering occupations relative to their proportion in the population (Leslie et al., 1998; National Science Board, 2006) and compared to whites and Asians. It is possible to argue that the lower employment prospects in these jobs are because fewer blacks and

Hispanics study S & E and despite the educational qualifications attained, lack job specific skills needed by employers. Leslie et al (1998) suggest a number of reasons that include parental background, perception of self and belief in one's ability, which contribute to the under-representation of minorities in science and engineering studies. These influences are built up and persist over the lifetime of individuals and translate to differences in matriculation rates.

Within the K-12 educational system, blacks are steered away from science and mathematics or attend schools and classes with inadequate resources for science education (Clark, 1999; Tang, 2000). Even when under-represented minority students of African American and Hispanic descent express an interest in science careers and are well prepared in sciences and mathematics, a disproportionately larger number discontinue science studies in college compared to whites (Summers & Hrabowski, 2006). The higher attrition rate is attributed in part to academic and cultural isolation and to the view that there may be discrimination in employment practices. Thus African Americans and Hispanics are not convinced that they will be adequately rewarded in science and technology fields. The results of this study show that blacks and Hispanics have lower odds of employment of in high technology jobs relative to other jobs in the economy, regardless of educational level, which suggests that these fears are justified. Summers and Hrabowski point to the need for programs that generate interest in studying science and mathematics, as well programs that help in the retention of under-represented minorities.

Since, the effects of having studied science and engineering are more likely to be apparent after college level education and to a lesser extent after high school, the observation that Asians with high school education or less have a higher probability of being employed in high technology S & E jobs compared to blacks and Hispanics suggest that statistical discrimination is working in favor of Asians. That is the perception that Asians as group are strong in the sciences and engineering has affected their employment status in the high technology sector favorably. Statistical discrimination maybe less apparent in real science and engineering jobs because emphasis maybe placed on credentials and fields of study of the individual.

Since there is no significant difference between the odds of employment of blacks and whites with graduate degrees in other S & E jobs relative to non-technology jobs, closure effects due to race appear to be greatest in the premium high technology S & E jobs. This is keeping with the view that more lucrative jobs are likely to be subject to more extensive closure strategies (Weeden, 2002). The observation is also in keeping with the view that affirmative action has had greater success in the academic environment since S & E jobs in universities and colleges make up a large portion of the S & E jobs outside of the high technology sector.

It could be argued that other S & E jobs for example in construction and utilities, which make up a large portion of these jobs, are less demanding in the skills compared to the demands for skills in high technology S & E. As a result, individuals with on average lower skills get other S & E jobs. Differences in employment patterns could be attributed to differences in job specific skills not reflected in the level of educational attainment such as the area of specialization and the quality of education received. The differences in skills are not apparent from the level of educational attainment, but are observed by employers and are reflected in hiring practices.

Blacks and Hispanics may also be hampered in getting high technology S & E jobs because of lack of awareness about these jobs. Many employers use existing employees to help identify and recruit suitable employees. Granovetter (1983) argues that acquaintances or contacts, described as weak ties are more important in getting information about jobs than the strong ties such as that which exist between family members and close friends. The low representation of Blacks and Hispanics in high technology S & E jobs results in fewer colleagues who can provide information about jobs and help to establish contacts with potential employees, hence blacks and Hispanics have less opportunity to get these jobs.

It is difficult to distinguish between the effects of human capital and race, both statistically and in the real world, because the level of human capital acquired is determined by race. Employers can also conceal racial differences in hiring practices under the guise of differences in more subjectively determined skills. A limitation of this study is that it is not possible to separate and identify these different causes from CPS dataset. Surveys or interviews specifically designed to elicit this information would help in this regard.

The results suggests that increasing the number of blacks and Hispanics who study S & E will not by itself overcome low levels of representation in high technology S & E jobs for example. In addition to policies that increase the representation of blacks and Hispanics in S & E fields of study, there is the continued need for legislation and the sensitization of individuals responsible for hiring, which will improve employment prospects of under-represented minorities. If disparities are allowed to persist and grow, there may be greater stereotyping and divisions within the society. Society will have the sorting of individuals into particular jobs, which is observed for example with the increasing proportions of African Americans who gravitate towards jobs in the sports and entertainment fields. Whether argued from the viewpoint of economic efficiency or social equity, systems should be in place that will enable the best minds to access to science and engineering education and opportunities to pursue careers in these fields.

5.4.5 Effect of Potential Experience

The effects of potential experience are different for jobs in the high technology sector and other S & E jobs relative to non-technology jobs. Potential experience is a proxy for real work experience of individuals, which is not available in the data. It does not take into account differences in the entry or exit of individuals from the labor market because of reasons other than education. The odds of working in high technology S & E relative to non-technology decrease at decreasing rate with experience up to 21 years of experience (Table 5, Model 5). However for other technology-sector jobs, the effect of experience increases at a decreasing rate up to 24 years of experience. Holding all else constant, for other S & E jobs, the effects of the experience variable increase at a decreasing rate up to 12 years of experience. However, the odds ratios for potential experience are very close to one, indicating that each additional year of potential experience results in relatively small changes in the odds of employment in the three industry/occupational groups.

Potential experience is negatively correlated with the probability of working in high technology S & E jobs relative to non-technology jobs. This observation is in keeping with anecdotal accounts of high technology industries as fast changing, dynamic industries that favor youth. It is possible that younger workers are better able to produce the rapid levels of change needed for high technology industries to thrive. The effect of youth is not as marked in other S & E jobs, with the effect of experience increasing at a decreasing rate up to 10 years of experience relative to non-technology jobs. Other technology-sector jobs show the expected pattern in the relationship between experience and the probability of employment (Mincer, 1974) with the effect of experience increasing at a decreasing rate up to 24 years of experience. With the exception of high technology S & E jobs, these results provide partial support for the second hypothesis. That is, the probabilities of employment increase with increasing levels of experience.

5.5 Human Capital and Race Effects for Full-time, Full-year Male Workers

The results of the comparative analyses between the sample with non-workers, part-time and full-time workers and the sample based only on full-time, full year workers are discussed in this section. The discussion is focused on effects of human capital and race in order to determine if results continue to support or refute the hypotheses in the study. Table 8 compares the characteristics of the two samples for males. The racial composition of the sample based on full-time, full year workers is different from the sample with non-workers, with the proportion of whites and blacks being 76% and 9% respectively, in the sample of full-time, full-year workers; the sample with non-workers consists of 62% whites and 20% blacks. Thus blacks form a disproportionately larger share of the part-time or non-worker groups. As expected, the educational make-up of the groups are also quite different; 11% of the group of full-time, full year workers do not have high school education; 51% have high school education; and 38% have college education. In contrast, 47% of individuals in the group with non-workers do not have high school education; 41% have high school education; and 13% have college education. Surprisingly, the mean ages of the two groups are similar at 39 years.

The results of the multinomial logit analyses for the sample of males that included full-time, full year as well as part-time and non-workers are compared with the results from the sample with only full-time, full year workers in Table 9. The results show that holding all else constant for white males, the effects of education (high school and college) although similar in direction and relative magnitude to effects in the sample with non-workers, are lower in all three industry/occupation groups relative to non-technology jobs (the base category). This is not surprising because the average levels of educational attainment are higher in sample of full-time, full year workers and so the estimated changes or effects of education will not be as large.

Compared to similar white males, black and Hispanic males without high school education have significantly lower odds of employment in all three industry/ occupation groups relative to non-technology jobs, with the effects being even lower in high technology S & E jobs. However for full-time full-year workers, Asians and whites without high school education do not have significantly different odds of employment in the high technology sector. Although college education significantly increases the odds of employment in high technology S & E jobs to a greater extent for blacks compared to whites, the odds of employment of college-educated blacks are significantly lower than the odds of employment of whites.

Table 8: Comparison of means and standard deviations of characteristics of male full, part-time and non-workers with full-time, full year workers

	Full, Part-time & Non-Workers		Full-time Full-Year	
Variable	**Mean**	**S.D.**	**Mean**	**S. D.**
Race/ Ethnicity				
White	0.7369	0.4403	0.7534	0.4310
Black	0.1139	0.3177	0.0714	0.2576
Asian	0.0366	0.1879	0.0347	0.1830
Latino	0.1125	0.3160	0.1405	0.3475
Education				
Without High School	0.1985	0.3989	0.1176	0.3222
High School	0.5021	0.5000	0.5107	0.4999
College	0.2994	0.4580	0.3716	0.4832
Industry/ Occupation				
High Technology Employment	0.0971	0.2961	0.1247	0.3304
Science & Engineering Occupation	0.0428	0.2025	0.0577	0.2331
High Technology / S & E	0.0238	0.1524	0.0308	0.1728
Non-High Technology / S & E	0.0190	0.1366	0.0268	0.1616
High Technology / Non-S & E	0.0733	0.2606	0.0939	0.2917
Non-High Technology / Non-S & E	0.8839	0.3204	0.8484	0.3586
Other Characteristics				
Age	37.9129	13.2469	40.0154	10.8948
Marital Status	0.6641	0.4723	0.8076	0.3942
Children Present	0.4127	0.4923	0.4688	0.4990
Home Ownership	0.6849	0.4646	0.7156	0.4511
Foreign Born	0.1373	0.3442	0.1521	0.3591
Self Employed	0.1026	0.3034	0.1314	0.3378
Full Time Worker	0.5329	0.4989	0.7339	0.4419
Union Member or Coverage	0.0297	0.1697	0.0406	0.1973
Average Income $	28069	36351	39859	38479
Region/Locality				
New England	0.0515	0.2211	0.0800	0.2713
Mid East	0.1673	0.3732	0.1665	0.3726
Great Lakes	0.1637	0.3700	0.1437	0.3508
Plains	0.0690	0.2535	0.0958	0.2943
South East	0.2387	0.4263	0.1979	0.3985
South West	0.1056	0.3073	0.0975	0.2967
Rocky Mountains	0.0323	0.1768	0.0667	0.2496
Far West	0.1719	0.3773	0.1517	0.3588
Central City	0.2447	0.4299	0.2252	0.4177
Other Urban Area	0.4178	0.4932	0.3926	0.4883
Rural	0.1909	0.3930	0.2165	0.4119
Annual Unemployment Rate	5.4333	1.4956	5.433	1.496
Proportion High Technology Firms (1996)	0.0506	0.0117	0.051	0.012
Proportion High Technology Employmen	0.0592	0.0236	0.059	0.024
N	488707		306003	

Table 9: Comparison of odds ratios from multinomial logit models for male, full, part-time and non-workers with male full-time, full year workers

	Full, Part-time and Non-Worker			Full-time, Full year		
	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-high Technology/ Science & Engineering	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-high Technology/ Science & Engineering
High school	7.8355***	1.6880***	6.2629***	5.7767***	1.3839***	5.0578***
	(1.6516)	(0.0594)	(1.1543)	(1.6581)	(0.0577)	(1.1914)
College	55.5015***	2.1436***	33.3930***	39.2060***	1.7096***	26.6187***
	(11.6691)	(0.0788)	(6.1203)	(11.2096)	(0.0734)	(6.2455)
Experience	0.9884*	1.0467***	1.0110*	0.9715***	1.0244***	0.9971
	(0.0048)	(0.0027)	(0.0051)	(0.0054)	(0.0032)	(0.0058)
Experience (squared)	0.9997*	0.9990***	0.9995***	1.0002	0.9996***	1.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Black	0.1252**	0.7297**	0.3145*	0.0643**	0.8929	0.5626
	(0.1009)	(0.0723)	(0.1599)	(0.0669)	(0.1091)	(0.2980)
Latino	0.0460***	0.7150***	0.1520***	0.0204***	0.5960***	0.0862***
	(0.0344)	(0.0398)	(0.0650)	(0.0212)	(0.0380)	(0.0416)
Asian	0.5806**	0.9792	0.8043	0.7433	0.9708	0.6071*
	(0.1223)	(0.0703)	(0.1500)	(0.1660)	(0.0767)	(0.1389)
Black x High school	3.2983	1.2604*	1.4095	7.4279	1.0281	0.8840
	(2.6972)	(0.1312)	(0.7368)	(7.8105)	(0.1317)	(0.4815)
Black x College	4.7179	1.0373	2.4901	8.9402*	0.8587	1.4115
	(3.8049)	(0.1197)	(1.2801)	(9.3398)	(0.1182)	(0.7567)
Latino x High School	6.6924*	1.0482	3.0143*	14.4048*	1.2245**	5.3202***
	(5.0736)	(0.0666)	(1.3288)	(15.1045)	(0.0879)	(2.6477)
Latino x College	13.0549***	1.1354	4.2624***	30.6623**	1.2899**	7.4305***
	(9.8211)	(0.0852)	(1.8503)	(31.9849)	(0.1081)	(3.6399)
Asian x College	2.3288***	1.0681	1.8186**	1.9301**	1.1183	2.4487***
	(0.4871)	(0.0913)	(0.3460)	(0.4285)	(0.1052)	(0.5678)
Married	1.3489***	1.3566***	1.2139***	1.2503***	1.2177***	1.0912
	(0.0544)	(0.0328)	(0.0527)	(0.0551)	(0.0328)	(0.0521)
Own child in household	0.9042***	0.9050***	0.9287*	0.9156**	0.9359***	0.9464
	(0.0272)	(0.0159)	(0.0312)	(0.0297)	(0.0182)	(0.0340)
Buying/Own House	1.1796***	1.2706***	1.2246***	1.2632***	1.3212***	1.2911***
	(0.0387)	(0.0238)	(0.0420)	(0.0459)	(0.0279)	(0.0489)
Cont'd						

Table 9 ***cont'd***

	Full, Part-time and Non-Worker			Full-time, Full year		
	High Technology/ Science & Engineering	**Technology/ Non-Science & Engineering**	**Non-high Technology/ Science & Engineering**	**High Technology/ Science & Engineering**	**Technology/ Non-Science & Engineering**	**Non-high Technology/ Science & Engineering**
Full-time Worker	2.8769***	2.6537***	2.8091***			
	(0.0956)	(0.0487)	(0.0972)			
Self- Employed	0.4732***	0.4334***	0.1085***	0.3396***	0.3350***	0.0810***
	(0.0228)	(0.0131)	(0.0103)	(0.0186)	(0.0113)	(0.0084)
Member/Covered by union	0.1789***	0.8136***	0.5187***	0.1954***	0.8989**	0.6082***
	(0.0241)	(0.0329)	(0.0482)	(0.0277)	(0.0371)	(0.0574)
Year 1994-1996	0.5283***	0.5730***	0.5038***	1.0004	1.0084	0.9517
	(0.0252)	(0.0147)	(0.0245)	(0.0474)	(0.0270)	(0.0476)
Year 1997-1999	0.6407***	0.6565***	0.5593***	1.1117	1.0986**	0.9638
	(0.0358)	(0.0208)	(0.0327)	(0.0632)	(0.0367)	(0.0583)
Year 2000-2002	0.6438***	0.6005***	0.5289***	1.1852**	1.0443	0.9517
	(0.0345)	(0.0179)	(0.0300)	(0.0642)	(0.0324)	(0.0551)
Live in Central City	1.5787***	1.1663***	1.2176***	1.5600***	1.1693***	1.2130***
	(0.0684)	(0.0277)	(0.0527)	(0.0730)	(0.0306)	(0.0564)
Live in other urban area	2.0467***	1.3675***	1.3251***	2.0650***	1.3861***	1.3355***
	(0.0726)	(0.0261)	(0.0479)	(0.0784)	(0.0288)	(0.0511)
New England	1.6782***	1.5418***	0.9709	1.7202***	1.5741***	0.9512
	(0.0907)	(0.0518)	(0.0586)	(0.0984)	(0.0569)	(0.0612)
Mid-Eastern Region	1.0233	1.0095	1.0458	1.0446	1.0265	1.0450
	(0.0493)	(0.0282)	(0.0513)	(0.0535)	(0.0312)	(0.0538)
Great Lakes	1.2025***	1.7055***	0.9638	1.2243***	1.7323***	0.9507
	(0.0573)	(0.0452)	(0.0485)	(0.0617)	(0.0497)	(0.0508)
Plains	0.9142	1.1851***	1.0218	0.9154	1.2008***	0.9834
	(0.0626)	(0.0456)	(0.0651)	(0.0674)	(0.0494)	(0.0667)
South West	1.4091***	1.2876***	1.1867**	1.4059***	1.3367***	1.1409*
	(0.0782)	(0.0407)	(0.0697)	(0.0834)	(0.0458)	(0.0709)
Rocky Mountains	1.3254***	1.0490	1.1144	1.3469***	1.0513	1.0983
	(0.0895)	(0.0442)	(0.0754)	(0.0963)	(0.0490)	(0.0791)
Far West	1.4490***	1.1754***	1.0206	1.4829***	1.2062***	1.0231
	(0.0761)	(0.0369)	(0.0577)	(0.0842)	(0.0412)	(0.0610)
Unemployment Rate	0.9872	1.0267***	0.9700*	0.9945	1.0322***	0.9766
	(0.0135)	(0.0081)	(0.0147)	(0.0145)	(0.0089)	(0.0157)
Proportion science degrees	15.0904***	3.4573***	8.7378***	14.2694***	3.6499***	8.1530***
	(4.6878)	(0.6235)	(2.7931)	(4.7587)	(0.7184)	(2.7819)
Pseudo R-Square	0.1172			0.0830		
chi2	21000			12000		
p	0.0000			0.0000		
N	488707			305996		

Note: (1) Numbers in parentheses are standard errors; (2) * Significant at p<0.05; ** Significant at p<0.01; *** Significant at p<0.000; (3) Reference groups for dummy variables: Education & race- white male who has not graduated high school; marital status- never married; child in household - no children; work status - not a full-time, full-year worker; self-employment status - not employed by own business; union status - not a member or covered by a union; Year - 1992-1993; metro status - rural resident; region of residence - South East

The probabilities of employment of black males are between 2 and 3 percentage points lower than whites in high technology S & E jobs, and between 9 and 11 percentage points lower than Asians, depending on the year (Appendix Table 10 on p. 235). Latinos gain significantly more from college education compared to whites, but still have significantly lower odds of employment in S & E jobs compared to whites and Asians. Differences between the probabilities of employment in high technology S & E jobs for Latinos and whites, and Latinos and Asians are 1 and between 8 and 10 percentage points respectively, depending on the year. Thus Asians have highest probabilities of employment in high technology S & E jobs and this is even greater than the probabilities of employment in other science and engineering jobs.

Compared to whites and Asians, college educated blacks and Latinos have significantly lower odds and probability of employment in other technology-sector jobs relative to non-technology jobs. However the odds and probabilities of blacks and Hispanics being employed in other technology-sector jobs are greater than those of being employed in S & E jobs.

The effects of the experience variable are similar to the results obtained from the analyses of the sample that included non-workers. The effects are negative in high technology S & E jobs relative to non-technology jobs, indicating that less experienced or younger workers have higher odds of employment in high technology S & E jobs. However the experience variable is not significant for other S & E jobs. For other technology-sector jobs, relative to the base category, the effect of experience increases at a decreasing rate up to 31 years of experience and is significant. Experience serves as an indicator of non-specific or general skills, which individuals possess; therefore having more experience increases ones prospects of employment in other technology-sector relative to non-technology jobs.

The results of the analyses based on the sample of full-time, full-year workers are similar to the results obtained for analyses based on the sample with part-time and non-workers. The probabilities are shifted upwards, because non-workers are excluded and attenuation of the effects of the variables does not take place. Asians are more likely to be employed in the high technology sector or in S & E jobs compared to any other group. Even with college education and controlling for a range of factors, blacks and Latinos have significantly lower odds of employment in both types of high technology jobs compared to whites and Asians.

The results of the analyses with full-time full year workers complement the findings of the analyses done with the sample that included non-workers and support the first, second, and third hypotheses of the study. That is, high technology S & E jobs have more demanding educational requirements compared to the other jobs examined in the study. Blacks and Hispanics have lower probabilities of employment in high technology S & E jobs compared to similarly educated whites and Asians with the disadvantage being greater in high technology S & E jobs compared to all other jobs. Although the analyses show that having high school or college education increased the odds being employed in S & E jobs to the same extent as whites, black and Hispanic high school and college graduates still have lower probabilities of employment high technology S & E jobs, for reasons other than education, thus there is partial support for the fourth hypothesis. Conclusions from the analyses based on a sample that included full, part-time and non-workers are the same as those from analyses based on a sample based on full-time, full year workers, which is typically used in labor economic studies. Although the magnitude of the effects of the variables is different, there is no disadvantage in using either sample to draw conclusions about the hypotheses and the research question.

5.6 Summary

The variables for educational attainment have the greatest effects on probabilities of employment in high technology S & E jobs for white males, with the effects of education being somewhat smaller in other S & E jobs and even less in other technology-sector jobs. These findings support the first hypothesis in the study which anticipated that education would have the greatest effects on determining the probabilities of employment.

The odds of employment in high technology S & E jobs decrease at a decreasing rate with additional years of experience but increase at a decreasing rate for other types of jobs. However the odds of employment in other technology-sector and other S & E jobs increase at a decreasing rate with each additional year of experience. Thus, the effects of potential experience on the odds of employment in high technology S & E jobs are different from the second hypothesis and with the typical pattern observed for other types of jobs in the economy. However the effects in other technology-sector and other S & E jobs are as expected.

Black males with graduate level of education have significantly lower odds of employment in high technology S & E jobs but do not have significantly different odds of employment in other S & E jobs or other technology-sector jobs compared to whites. Regardless of educational level, Hispanics have significantly lower odds or probabilities of employment in both types of S & E jobs compared to whites. The odds of employment in S & E jobs are significantly higher for Asians with graduate education compared to similar whites and other individuals with lower levels of education. Asians with graduate degrees are twice as likely to be employed in high technology S & E jobs compared to other S & E jobs. Thus, the results partially support the third hypothesis of the study, which posited that blacks and Hispanics would have lower probabilities of employment in S & E jobs.

Minorities and whites differ in the gains received from high school and college level education and the differences vary with the industry/occupation group and with the minority group. High school and college education increase the odds of employment in S & E jobs to the same extent for both blacks and whites. However, for Hispanics, the gains from attaining college and high school education are significant and positive compared to whites. But again these are insufficient to overcome the large initial gap between whites and Hispanics without high school education, so a gap remains in actual probability of employment. However the data do indicate that, education makes a large contribution towards reducing the disparities between Hispanics and whites. These findings provide only partial support for the fourth hypothesis in the study, which posited that the effects of high school and college education on the probability of employment in the three industry/occupational groups would be lower for blacks and Hispanics, compared to whites and Asians. However the hypothesis is supported for the case of high technology S & E jobs.

This study shows that the patterns of employment in high technology industries and S & E occupations are different for the racial/ethnic groups. Neoclassical economists would argue that Asians chose to be in high technology S & E jobs more than in other types of jobs, while the other groups choose different jobs. However individual choice is not the only reason why fewer blacks and Latinos are employed in the high technology sector or in S & E jobs. A distinct preference for high technology S & E jobs does not necessarily translate to individuals getting the jobs. Networks which provide information on available jobs, contacts with employers and statistical discrimination contribute towards Asians getting the jobs. The absence of a critical mass of blacks and Latinos in high technology industries limits networking opportunities. In addition closure may restrict opportunities of employment in lucrative high technology S & E jobs.

Among whites and Asians, individuals with higher than average levels of educational attainment, that is graduate education, get high technology S & E jobs, therefore competition appears to be an important factor in determining who gets the job. The large effects of education variables in high technology S & E provide some support for the view that merit or educational attainment play important roles in the allocation of science and engineering jobs, which require high levels of skills. Blacks and Hispanics are excluded from the more highly rewarded high technology, S & E jobs to a greater extent, suggesting that race and ethnicity continue to be important factors in determining employment. Further, differences in the incremental effects of additional education by race and job type, as defined in this study and discussed in Section 5.4 support this conclusion.

CHAPTER 6

EFFECTS OF TIME, INDIVIDUAL AND LABOR MARKET CHARACTERISTICS ON EMPLOYMENT

In addition to human capital and race, several other factors influence the employment of individuals in science and engineering jobs as well as other jobs. These include changes due to time; regional or labor market factors; and whether the individual owns a home or not, is married, or has full or part-time work status. In the subsequent sections, I discuss the effects of these factors as well as the effects of whether an individual is foreign or native-born on the probability of employment in the industry/ occupation groups. Finally, I briefly discuss the differences in how these factors affect the employment of males and females.

6.1 Effect of Time

Although the analyses show that the odds of employment in both high technology industries and S & E occupations decrease over the period of the study in comparison to 1992 and 1993, the changes in probabilities of employment for each racial group over the period are small. The effects of the variables, standard errors and probabilities are similar when either time dummies for individual years or the contraction to four time periods were used. The probabilities of employment in high technology industries follow a similar trend over the period 1992 to 2002, for all racial/ethnic groups (Figures 3 and 4). Holding all else constant, the probabilities of employment in all three industry/occupation groups (high technology S & E, other technology-sector and other S & E) decrease relative to non-technology jobs and compared to 1992. For both college and high school educated individuals, the decline is greatest between 1992 and 1993, followed by relatively little change in the remaining years. Individuals with high school only education have lower probabilities of working in high technology S & E jobs compared to college educated individuals with differences being marginally larger in 2002 compared to 1992 (3 percentage points for blacks and Latinos, 4 percentage points for whites and 10 percentage points for Asians in 1992, with corresponding differences of 3, 5 and 11 percentage points in 2002). The employment patterns of the different racial groups (relationships between probabilities of employment) remain fairly constant over the time period of analysis. However Asians have greater fluctuations in the probabilities of employment in high technology S & E jobs compared to other racial groups. The decline of both high technology and S & E jobs in 1992 foreshadowed the more obvious fall-out in the technology sector, which peaked in the late 1990s. The findings do not support Hypothesis 6 which anticipated that the probabilities of employment of blacks and Hispanics in high technology industries and S & E jobs would increase over time. It is possible that the time frame used in this study is too short to see changes in phenomena that stem from deeply rooted social, economic and cultural effects.

6.2 Regional and Other Labor Market Effects

Compared to the South East region, individuals in all regions except the Plains and Mid West, have greater odds of working in high technology S & E jobs relative to non-technology jobs (Table 5). The odds differences are greatest for New England, followed by the Far West, South West, Rocky Mountains, and then the Great Lakes. The odds of individuals working in high technology S & E jobs in the Mid West regions are not significantly different from the South East. It is not unexpected that the New England region has significantly greater probability of employment in high technology S & E jobs compared to the South East. However, the odds of employment in high technology S & E jobs in the Far West which contains the states of California and Washington, dominant high technology centers in the US, was expected to be greater than that observed when compared to the South East. The results highlight the limitations of using broadly defined regions as the labor market areas since the broad areas mask differences taking place in more narrowly defined labor market areas

The odds of working in other S & E jobs are not significantly different from the South East region for all regions except the South West, where the odds of working in other S & E jobs are greater than in the South East. The odds of working in other technology-sector jobs relative to non-technology jobs surprisingly do not follow the same pattern as high technology S & E jobs, with the odds of working in other technology-sector jobs being significantly greater for Great Lakes, New England, South West, Plains and the Far West compared to the South East. The odds of employment in the Rocky Mountain and Mid East regions are not significantly different from the South East. It is possible that regional differences between odds of employment in high technology industry jobs reflect differences in the types of high technology industries in each region and the differences in demand for S & E workers compared to other types of workers. The positive and significant coefficients on variables for New England, Far West and South West regions in high technology S & E jobs indicate that these regions contain high technology industries that demand more S & E workers compared to industries in the South East. Relative to the South East, high technology industries in the Great Lakes regions demand more workers who are not scientists and engineers.

Compared to rural areas, living in a metro area including the central city increases the odds of working in high technology S & E, other technology-sector and other S & E relative to non-technology jobs with the effects being greatest for high technology S & E jobs. Therefore, not surprisingly rural residents have lower access to and odds of employment in high technology industries or S & E jobs compared to residents in the central city. However, the odds of employment in these jobs are greater in the urban areas outside of the central city, compared to the central city.

The unemployment rate in the area is not significantly related to the odds of employment in both types of S & E jobs relative to non-technology jobs. This observation may be due to the relatively small proportion of S & E jobs in the labor market. Thus there is a stronger relationship between the unemployment rate and the demand for other jobs that reflect the strength of the areas' economy. Although the unemployment rate has significant positive relation to the odds of employment in other technology-sector jobs, the odds ratio is close to one, indicating that change in odds for a unit change in the unemployment rate was small.

The proportion of science and engineering graduates in an area (*pscideg2)* significantly increases the odds of employment in all three industry/occupational groups relative to non-technology jobs. The effects are greater for S & E jobs compared to other technology-sector jobs; however, there is no significant difference between the effects in the two groups of S & E jobs. The effects of *pscideg2* reflect not only the demand for individuals skilled in science and engineering but also the importance of the close proximity of universities involved in scientific research or application of technology to industries that produce or require new knowledge and so have a high demand for workers involved in the creation of knowledge.

Although goodness of fit tests for models containing the variables representing the proportion of high technology firms in an area in 1996 (*phtf96*) and the proportion of high technology employment in high technology firms in 1996 (*phtemp96*) provide strong support for the models with these variables, they were omitted from the final models because the exponentiated coefficients and standard errors were very high (e.g. coefficient of 9.2e+3 and standard error of 2.1e+4 for *phtf96*). However, correlation and collinearity tests did not indicate high levels of collinearity with other variables in the model. The addition or subtraction of variables for the proportion of high technology firms and employees from the models had the greatest effects on the direction and significance of the coefficients on the region variables and very little effect on the human capital and race variables. Therefore, it is assumed that the effects of these variables were captured in the region variables and conclusions from the human capital variables would not be affected by their omission.

6.3 Effect of Other Individual Characteristics

Owning a home, being married, full time work status all increase the probability of working in high technology S & E, other technology-sector and other S & E jobs relative to non-technology jobs (Table 5). However, having a child, being self employed or a member of a union decrease the probability of working in the high technology sector and in S & E occupations. With the exception of the variable for self-employed status, the direction of the effects are in keeping with hypotheses made earlier. Being self-employed, was expected to increase the probability of employment in high technology S & E jobs.

6.4 Effect of Foreign Born Status

The effects of the human capital, race, foreign born status and interaction terms on the odds of employment in high technology industries and science and engineering occupations (high technology S & E, other technology-sector and other S & E) for the period 1994 to 2002 are shown in Table 10. Model 1 does not include the *foreign* variable; Model 2 includes the variable, *foreign*; and Model 3 includes the interaction terms between variables for race, education and foreign-born status: *forlat,* forasian*,* *forcoll*, and *forascoll*. Appendix Table 11 (p. 236) shows tests of specific hypotheses on the relationships between race, education, foreign born status and the interaction terms.

The direction and significance of the effects of most variables are stable to the change in the time period of analysis and to the inclusion of the variable for foreign-born, with the exception of the *asian* variable and to a lesser extent the *latino* variable, which are sensitive to changes in the specification of the model. However, the magnitudes of effects are different for the 1994 to 2002 period compared to the 1992 to 2002 period of analysis. The differences are attributed to changes that occur over time, as well as to changes in the specification of the model.

In Models 1 to 3, the education variable (*coll*), represents the ratio of the odds of employment for white males with and without college education, that is, the reference group is comprised of white males without college education. Being foreign born significantly increases the odds of employment in both types of S & E jobs, relative to non-technology jobs during the period 1994 to 2002, if the effects of race and the level of educational attainment are not taken into consideration (Table 10, Model 2).

Table 10: Human capital, race and the effects of being foreign born on the odds ratios of employment (1994-2002)

	Model 1			Model 2			Model 3		
	High Technology/ S & E	**High Technology/ Non-S & E**	**Non-high Technology/ S & E**	**High Technology/ S & E**	**High Technology/ Non-S & E**	**Non-high Technology/ S & E**	**High Technology/ S & E**	**High Technology/ Non-S & E**	**Non-high Technology/ S & E**
College	8.1341***	1.3352***	5.8224***	8.0655***	1.3355***	5.8062***	7.9046***	1.3136***	5.6240***
	(0.3394)	(0.0264)	(0.2409)	(0.3367)	(0.0264)	(0.2400)	(0.3325)	(0.0264)	(0.2363)
Experience	0.9904	1.0431***	1.0141*	0.9900	1.0431***	1.0140*	0.9907	1.0433***	1.0148**
	(0.0052)	(0.0030)	(0.0056)	(0.0052)	(0.0030)	(0.0056)	(0.0052)	(0.0030)	(0.0056)
Experience (squared)	0.9997**	0.9991***	0.9994***	0.9997**	0.9991***	0.9994***	0.9996**	0.9991***	0.9994***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Black	0.3758***	0.8799**	0.4484***	0.3707***	0.8802**	0.4464***	0.3737***	0.8825**	0.4541***
	(0.0593)	(0.0371)	(0.0582)	(0.0586)	(0.0371)	(0.0579)	(0.0594)	(0.0372)	(0.0590)
Latino	0.1777***	0.6241***	0.2965***	0.1352***	0.6313***	0.2662***	0.2314***	0.7442***	0.4258***
	(0.0224)	(0.0209)	(0.0328)	(0.0179)	(0.0240)	(0.0313)	(0.0369)	(0.0311)	(0.0558)
Asian	0.5910*	0.9946	0.6899	0.4235***	1.0095	0.6003*	0.9806	0.5598***	1.2384
	(0.1371)	(0.0779)	(0.1410)	(0.1015)	(0.0805)	(0.1273)	(0.4017)	(0.0926)	(0.3907)
Black x College	1.4950*	0.8317*	1.7974***	1.4472*	0.8325*	1.7765***	1.4082	0.8128**	1.6955***
	(0.2693)	(0.0650)	(0.2747)	(0.2605)	(0.0651)	(0.2715)	(0.2551)	(0.0638)	(0.2599)
Latino x College	3.3300***	1.3149***	2.1564***	3.6373***	1.3095***	2.2348***	2.8567***	1.1065	1.5880**
	(0.4805)	(0.0838)	(0.2920)	(0.5281)	(0.0839)	(0.3046)	(0.4721)	(0.0776)	(0.2357)
Asian x College	2.6156***	1.1348	2.1185***	2.5820***	1.1364	2.1097***	0.9408	1.9347**	1.0958
	(0.6028)	(0.1053)	(0.4419)	(0.5955)	(0.1055)	(0.4402)	(0.4039)	(0.4063)	(0.3764)
Foreign-born				1.6184***	0.9789	1.2167**	1.4053*	0.8769*	0.8251
				(0.0849)	(0.0318)	(0.0735)	(0.2285)	(0.0509)	(0.1202)
Foreign x Latino							0.4683***	0.8311**	0.6026***
							(0.0676)	(0.0582)	(0.0881)
Foreign x Asian							0.3597*	2.2992***	0.5099
							(0.1823)	(0.4330)	(0.2168)
Foreign x College							1.3328	1.4000***	1.9138***
							(0.2236)	(0.0980)	(0.2927)
College							2.9798*	0.3841***	1.4110
							(1.5754)	(0.0913)	(0.6382)
Pseudo R-Square	0.1183			0.1188			0.1194		
chi2	19000			19000			19000		
p	0.0000			0.0000			0.0000		

Note: (1) Numbers in parentheses are standard errors; (2) * Significant at p<0.05; ** Significant at p<0.01; *** Significant at p<0.000; (3) Reference groups for dummy variables: Education & race- white male who has not graduated high school; Foreign-born- individuals born in the US

However, the effects of being foreign-born on the odds of employment in other technology-sector jobs for non-college graduates are not significant.

In Model 3, which includes the interaction terms, the odds of employment in high technology S & E jobs relative to non-technology jobs are significantly higher for foreign-born, black or white males without college education compared to native-born males, holding all else constant. Since the proportion of whites in the group is likely to be higher than that of blacks, the observed effects of the foreign-born variable are likely driven by the characteristics of white individuals. Analyses that are more detailed are needed to disentangle the effects; however, these are outside the scope of the present study. Compared to similar native born males, foreign-born white and black males without college education have significantly lower odds of employment in other technology-sector jobs, but the difference is not significant for S & E jobs outside of the high technology sector.

The odds of employment of foreign-born, college educated whites and blacks in high technology S & E are not significantly different from native-born individuals. However they have significantly higher odds of employment in other technology-sector and other S & E jobs compared to similar native-born individuals.

Regardless of educational level, foreign born Latinos have significantly lower odds of employment in both types of science and engineering jobs and other technology-sector jobs relative to non-technology jobs compared to similar whites (Table 8, Model 3). The differences between native and foreign- born college- educated Latinos vary in magnitude and significance depending on the industry/occupation group, but were not as great as those for non-college graduates. These are due to differences in the contribution of foreign college education and the findings are in keeping with other studies, which suggest that the average levels of human capital accumulation in the recent surge of Latino immigrants is relatively low. Thus the wage gap between native born Latinos, who have been able to take advantage of educational opportunities in the US and whites is less than the gap with foreign-born individuals (Trejo, 1997).

The odds of employment of native born Asians, with or without college education are not significantly different from whites in both types S & E jobs relative to non-technology jobs, holding all else constant (Table 8, Model 3). Foreign-born Asians without college education have significantly lower odds of employment in both types of S & E jobs compared to similar whites and to native-born Asians. However foreign-born college educated Asians have significantly higher odds of employment in high technology S & E jobs compared to native-born Asians, although the ratio is close to unity for other S & E jobs. The odds ratio of employment in both types of S & E jobs and other technology-sector jobs for foreign-born college-educated Asians and similar whites are close to unity. The results from the analyses of foreign-born individuals are partly in keeping with results of the earlier part of the study, which found that Asians with graduate level education had significantly higher odds of working in S & E jobs in the high technology sector compared to whites. However, in the earlier set of analyses, the odds of employment for Asians with bachelor's degrees or less were not significantly different from similar whites. Thus the effects of being foreign born, may in part be driven by a large proportion of individuals with graduate degrees among the cohort of foreign individuals. It could also be argued that the large difference between high technology S & E and other S & E may be driven by a high proportion of foreign-born

Asians with graduate degrees in the former jobs. However, the analyses of the effects of college education were not separated into graduate and bachelors level education for foreign-born individuals, because of limitations due to small cell sizes when the data are separated across these multiple dimensions. The disentanglement of the causal direction of these effects is beyond the scope of this present study.

The odds of employment of native born Asians without college education in other technology-sector jobs are significantly lower than similar whites. However, foreign born-Asians without college education have higher odds of employment in these jobs compared to native-born Asians, or whites. The higher odds of employment of foreign-born Asians without college education in other technology-sector jobs may be due to the formation of more extensive networks between recent immigrants, which contributes towards getting jobs.

In general, the coefficients and standard errors associated with the effect of being foreign born are unstable and give conflicting results in different models for college educated Asians, as a result the conclusions from the analyses are considered tentative. The results suggest that foreign-born college educated Asians and whites have significantly higher odds of being employed in S & E occupations compared to native born Asians and whites. This may be driven by a higher proportion of individuals with graduate degrees, which drive employment in S & E jobs. The ratio of the odds of employment of foreign-born Asian and white college graduates are close to unity in both types of S & E jobs as well as other technology-sector jobs indicating little difference exists between the odds of employment of foreign born Asians and whites. Similarly there is no significant difference between the odds of employment of native-born Asian and white college educated individuals in both types of S & E jobs.

6.5 Male and Female Differences

In keeping with the findings of other studies, S & E jobs are dominated by males, with the male dominance being even more pronounced in high technology S & E jobs compared to other industries. Table 3 shows that in the sample, just over 1% of females are in the combined set of S & E jobs. The relatively small number of female S & E workers and the resulting skewed distribution of observations severely limited the reliability of the analyses. In addition, it was not possible to run analyses for full-time, full year female workers or to separate the effects of college education into bachelors or graduate levels because standard errors were either not computed or were excessively high. Reasonable standard errors were obtained for samples that included part-time workers, indicating that part-time workers were an important component of the female S & E workforce.

6.5.1 Human Capital Effects

Table 11 shows that for white females, college and high school education effects are among the largest predictors of employment in high technology industries and S & E jobs. Similar to males, the effects of human capital are greater for S & E jobs compared to the non-S & E jobs. The effects of high school and college education on the odds of employment are somewhat higher for males, with the exception of the effect of high school education in other S & E jobs.

Table 11: Comparison of odds ratios from multinomial logit models for female, full, part-time and non-workers with female full-time, full-year workers

	Full, Part-time and Non-Workers			Full-time Full year Workers		
	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-high Technology/ Science & Engineering	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-high Technology/ Science & Engineering
High school	6.6189***	1.2863***	6.9203***	2.7646*	0.8725*	6.5630***
	(3.0888)	(0.0590)	(2.0393)	(1.3635)	(0.0497)	(2.5059)
College	34.0770***	1.2301***	25.6855***	12.7274***	0.7578***	21.6784***
	(15.6486)	(0.0595)	(7.5337)	(6.1441)	(0.0449)	(8.2474)
Experience	1.0432***	1.0481***	1.0714***	1.0235*	1.0140***	1.0610***
	(0.0105)	(0.0034)	(0.0092)	(0.0120)	(0.0040)	(0.0105)
Experience (squared)	0.9977***	0.9988***	0.9977***	0.9983***	0.9996***	0.9981***
	(0.0003)	(0.0001)	(0.0002)	(0.0003)	(0.0001)	(0.0003)
Black	0.3565	0.7018***	0.3000	0.3480	0.6449***	0.0000***
	(0.3920)	(0.0739)	(0.3125)	(0.3867)	(0.0857)	0.0000
Latino	0.7881	0.9992	0.2881	0.6815	0.8758	0.1301
	(0.5898)	(0.0661)	(0.1886)	(0.5209)	(0.0734)	(0.1393)
Asian	0.5540	1.4703***	0.4468**	0.6971	1.5467***	0.5479
	(0.1960)	(0.1024)	(0.1310)	(0.2666)	(0.1274)	(0.1731)
Black x High school	1.6522	1.3981**	2.4375	1.6974	1.4624**	3.5000E+07
	(1.8528)	(0.1569)	(2.5640)	(1.9303)	(0.2059)	.
Black x College	2.1117	1.2818*	2.6917	2.0435	1.3657*	3.8e+07***
	(2.3331)	(0.1564)	(2.8169)	(2.2842)	(0.2046)	-7.4000E+06
Latino x High School	0.4696	0.9424	1.6846	0.6118	1.0064	3.8801
	(0.3695)	(0.0710)	(1.1401)	(0.4950)	(0.0950)	(4.2184)
Latino x College	0.8940	0.8075*	2.0826	1.0074	0.8985	3.8269
	(0.6797)	(0.0768)	(1.3868)	(0.7849)	(0.1034)	(4.1405)
Asian x College	2.9454**	0.8626	3.2919***	2.2722*	0.8697	2.8747***
	(1.0286)	(0.0792)	(0.9559)	(0.8599)	(0.0941)	(0.8964)
Married	1.1130	1.1226***	1.0674	1.0405	1.0885*	1.0713
	(0.0786)	(0.0329)	(0.0703)	(0.0794)	(0.0361)	(0.0768)
Own child in household	0.6019***	0.7582***	0.7525***	0.6864***	0.8339***	0.8763*
	(0.0357)	(0.0170)	(0.0404)	(0.0459)	(0.0219)	(0.0512)
Buying/Own House	1.1927**	1.1608***	1.4232***	1.1777*	1.1887***	1.4353***
	(0.0721)	(0.0271)	(0.0798)	(0.0806)	(0.0325)	(0.0902)
Full-time/Full Year Worker	3.6906***	3.8177***	3.4509***			
	(0.2105)	(0.0798)	(0.1678)			
Self- Employed	1.0396	0.9844	0.1758***	0.5031***	0.5353***	0.0750***
	(0.1102)	(0.0416)	(0.0363)	(0.0770)	(0.0314)	(0.0233)
Member/Covered by union	0.1416***	0.5659***	0.5098***	0.1721***	0.6295***	0.5922**
	(0.0427)	(0.0406)	(0.0816)	(0.0531)	(0.0482)	(0.1025)

Cont'd

Table 11 *cont'd*

	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-high Technology/ Science & Engineering	High Technology/ Science & Engineering	High Technology/ Non-Science & Engineering	Non-high Technology/ Science & Engineering
Year 1994-1996	0.4003***	0.5174***	0.4539***	0.8228*	0.9760	0.8422*
	(0.0367)	(0.0163)	(0.0353)	(0.0811)	(0.0354)	(0.0708)
Year 1997-1999	0.5097***	0.6245***	0.5297***	0.9246	1.0455	0.8818
	(0.0551)	(0.0240)	(0.0496)	(0.1080)	(0.0457)	(0.0895)
Year 2000-2002	0.5894***	0.5418***	0.5066***	1.1925	0.9896	0.9400
	(0.0599)	(0.0198)	(0.0441)	(0.1314)	(0.0409)	(0.0887)
Live in Central City	1.5240***	1.2070***	1.7873***	1.5669***	1.1502***	1.7645***
	(0.1282)	(0.0365)	(0.1260)	(0.1478)	(0.0404)	(0.1385)
Live in other urban area	2.1001***	1.3691***	1.8000***	2.2019***	1.3448***	1.8676***
	(0.1482)	(0.0338)	(0.1097)	(0.1740)	(0.0384)	(0.1273)
New England	1.8476***	1.6743***	1.1217	1.6186***	1.6603***	1.1160
	(0.1954)	(0.0691)	(0.1078)	(0.1918)	(0.0791)	(0.1220)
Mid-Eastern Region	1.4446***	1.1317***	1.1039	1.3178**	1.1662***	1.1849
	(0.1356)	(0.0385)	(0.0867)	(0.1373)	(0.0457)	(0.1033)
Great Lakes	1.4852***	1.5904***	1.1087	1.4282***	1.6326***	1.1428
	(0.1392)	(0.0518)	(0.0846)	(0.1475)	(0.0610)	(0.0965)
Plains	1.0959	1.1744***	1.1793	0.9930	1.1493*	1.1918
	(0.1509)	(0.0557)	(0.1204)	(0.1552)	(0.0630)	(0.1341)
South West	1.6871***	1.0491	0.9173	1.6098***	1.0923	0.9455
	(0.1903)	(0.0451)	(0.0954)	(0.2007)	(0.0544)	(0.1075)
Rocky Mountains	1.8413***	1.2982***	1.1742	1.9042***	1.2989***	1.1659
	(0.2329)	(0.0678)	(0.1313)	(0.2707)	(0.0808)	(0.1464)
Far West	1.8424***	1.2750***	1.0782	1.7190***	1.3031***	1.1018
	(0.1966)	(0.0489)	(0.1027)	(0.2052)	(0.0586)	(0.1184)
Unemployment Rate	0.9352*	1.0009	0.9267**	0.9562	1.0129	0.9258**
	(0.0253)	(0.0099)	(0.0225)	(0.0287)	(0.0117)	(0.0250)
Proportion science degrees	106.3564***	2.9398***	14.9313***	138.3186***	2.9672***	12.0193***
	(66.8919)	(0.7000)	(8.3253)	(96.9260)	(0.8302)	(7.4495)
Pseudo R-Square	0.0925			0.0434		
chi2	13000			.		
p	0.0000			.		

Note: (1) Numbers in parentheses are standard errors; (2) * Significant at p<0.05; ** Significant at p<0.01; *** Significant at p<0.000; (3) Reference groups for dummy variables: Education & race- white male who has not graduated high school; marital status- never married; child in household - no children; work status - not a full-time, full-year worker; self-employment status - not employed by own business; union status - not a member or covered by a union; Year - 1992-1993; metro status - rural resident; region of residence - South East

Holding all else constant, the odds of employment in high technology S & E jobs relative to non-technology jobs increase 8 times and 56 times respectively for males (Table 5, Model 4) and by 6 times and 34 times for white females (Table 11 for full, part-time and non-workers). For other S & E jobs, the odds increase by 6 times and 33 times with high school and college education respectively, for males; and increase by 6 times and 26 times with high school and college education respectively, for females. Similar to the effects for males, the effects of education (college and high school) are significantly greater for females for S & E jobs compared to other jobs, but are not significantly different when the two groups of S & E jobs are compared. Holding all else constant, for white females the effects of college education are significantly greater for other technology-sector jobs compared to non-technology jobs. The differences in the effects of education may be due to the heterogeneity of non-S & E jobs compared to the more well-defined, homogenous S & E category.

Unlike males, for whom the odds of employment in high technology S & E jobs relative to non-technology jobs decrease with experience, holding all else constant, each additional year of experience increases the odds of employment at a decreasing rate in all three industry/occupation groups. The increase continues up to 9 years of experience for high technology S & E jobs, 15 years for other S & E jobs and 20 years for other technology-sector jobs. This corresponds with predictions from human capital wage models and patterns that are observed for most jobs; that is, as individuals spend a longer time in the work world, they develop job specific and other skills such as interpersonal skills, which improve the prospects for employment and wages.

6.5.2 Human Capital and Race

Holding all else constant, the odds of employment of black and Latina females without high school education in S & E jobs are not significantly different from white females. However the odds of employment of black females without high school education in other technology-sector jobs are significantly lower than similar white females while there is no significant difference between the odds of employment of Latina and similar white females. The odds of employment of Asian females without high school education in high technology S & E are not significantly different from comparable whites. However, Asian females without high school education have significantly lower odds of employment in other S & E jobs, but higher odds of employment in other technology-sector jobs.

Figures 9, 10 and 11 show the estimated probabilities of employment in the three industry/ occupation groups for high school and college educated females by race. Similar to males, the effects of education for different racial/ethnic groups vary with high school and college education and with the industry/occupation group. College education plays the dominant role in determining employment in S & E jobs. There is no significant difference between the gains of white and black or Latina females from either high school or college education in S & E jobs. College educated black and Latina females have significantly lower odds (and probabilities) of employment in S & E jobs compared to similar whites. Asian females gain significantly more from college education compared to similar whites with the result that the odds (and probabilities) of college educated Asian females working in science and engineering jobs are higher than those for white, black or Latina females. The odds of college educated black females working in other technology-sector jobs are not significantly different from white females. However the odds for Latina females are significantly lower than whites.

It is possible that Asian females have higher probabilities of employment in high technology industries and S & E jobs because they study in science and engineering disciplines to greater extent, in particular at the college level compared to the other groups (Tang, 2000).

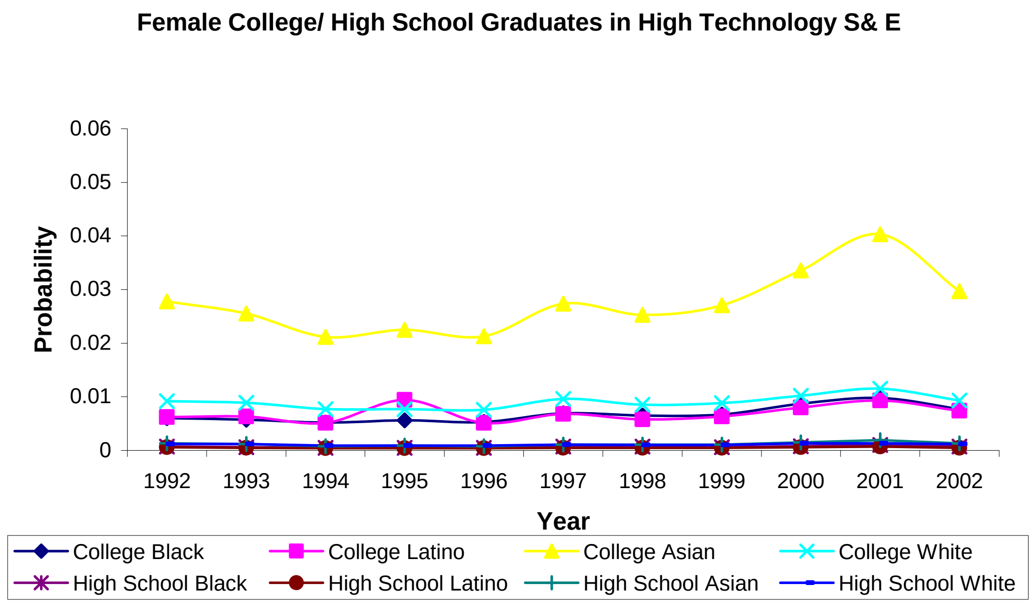


Figure 9. Probabilities of Employment in High Technology S & E Jobs for Female College and High School Graduates for 1992 to 2002

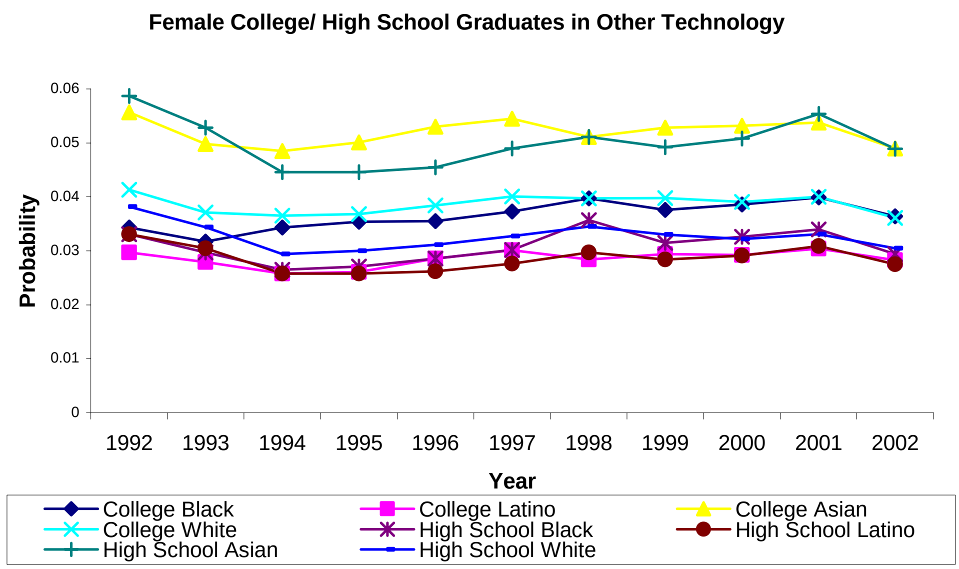


Figure 10. Probabilities of Employment in Other Technology Jobs for Female College and High School Graduates for 1992 to 2002

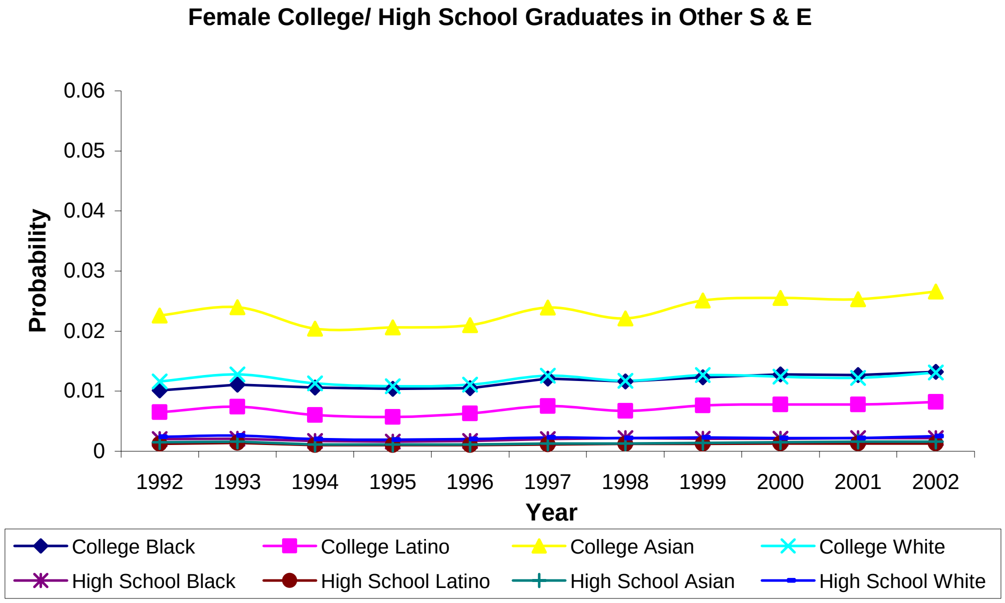


Figure 11. Probabilities of Employment Other S & E Jobs for Female College and High School Graduates for 1992 to 2002

Higher probabilities of employment may also result from more extensive contacts, who provide them with information on jobs as well as recommendations. Further, statistical discrimination may work in favor of Asians, as employers have the perception that Asians as a group have familiarity and competency in dealing with technological issues.

The differences between patterns of employment of the four racial/ ethnic groups in high technology industries and S & E occupations show that education is not the only factor under consideration in the determination of where individuals are employed. The observation that Asian women without high school education have higher odds of employment in other technology-sector jobs suggests that statistical discrimination is working in their favor compared to women in the other racial and ethnic groups.

The low representation of females in high technology industries or S & E occupations suggests that more needs to be done to encourage and support science, technology and engineering studies among females. The support will need to start early in the education system with programs at K-12 as well as in college in order to minimize and overcome the effects of attrition. Even greater efforts are needed to attract and train black and Latina females in science and engineering.

6.6 Summary

The direction of the effects of the control variables are as expected in most cases, with the magnitude of the effects being much smaller than the effects due to the human capital and race variables. Owning a home, and being married significantly increase the odds of employment in all three industry/occupation groups relative to non-technology jobs for both males and females, in keeping with hypotheses. On the other hand, the presence of children, and union membership or coverage decrease the odds of employment.

The negative effects of having a child in the household and being self-employed are surprising, especially for high technology jobs. For males, given the negative relationship between experience and the probability of employment, the negative effect of having a child in the household on the probability of employment in high technology S & E jobs may be tied to the observation that these jobs favor younger workers. Alternatively, high technology jobs may require long working hours, which adversely affects the tendency to have children. It was anticipated that the prevalence of small technology start-ups, out-sourcing and other sub-contracting arrangements would have resulted in self-employment status having a positive effect for high technology jobs relative to non-technology jobs. Therefore the negative effect of this variable was unexpected, although the findings are typical of labor market studies.

The findings of a significant decline in the probabilities of employment for 1994 to 2002 relative to 1992 and 1993 are not surprising given the findings of other studies (Hecker, 1999, 2005), which show that the growth of jobs in the high technology sector for this period, depended on the specific industries under consideration. Although jobs in the high technology service sector grew rapidly, manufacturing jobs were declining similar to other types of manufacturing jobs in the economy. Further examination of the data is needed to determine which group of jobs contributed to the decline; however, this is beyond the scope of the present study. The overall absence of growth in high technology jobs may have contributed to the lack of support for Hypothesis 6 in the study, which anticipated that the employment of blacks and Hispanics in high technology science and engineering jobs would have increased over the decade.

The effects of the variables controlling for labor market characteristics are as anticipated. The large positive effect of the variable representing the proportion of science graduates in the area (*pscideg2*) reflect the importance of the presence of universities that provide trained graduates as well as research output that contribute to the success of high technology industries. Successful industries will have a better capacity to provide jobs to individuals.

The results suggest that foreign-born college educated Asians and whites have significantly higher odds of being employed in S & E occupations compared to native born Asians and whites. This may be driven by a higher proportion of individuals with graduate degrees among the college educated, since skills appear to be the most important determinant of employment in S & E jobs. The odds of employment for foreign-born Asian and white college graduates are very similar in both types of S & E jobs as well as other technology-sector jobs; likewise, there is no significant difference between the odds of employment of native-born Asian and white college educated individuals. However foreign-born individuals without college education are at a disadvantage compared to similar whites in most jobs, except for foreign-born Asians in other technology-sector jobs. This may be due to the formation of more extensive networks between recent immigrants. Regardless of educational level, foreign born Latinos have significantly lower odds of employment in both types of science and engineering jobs and other technology-sector jobs relative to non-technology jobs compared to similar whites.

CHAPTER 7

EFFECTS OF HUMAN CAPITAL AND RACE ON WAGES

The preceding chapters discussed the effects of human capital, race and other factors on the probabilities of employment in the different industry/occupation groups. This chapter provides further insights on the racial and ethnic distribution of benefits from high technology jobs with the examination of the effects of human capital and race on wages for the sample of male, full-time, full-year workers (those who work more than 35 hours per week and 50 weeks in the year). First, I present an assessment of the data and the regression models with the sequential introduction of the variables. In subsequent sections, I discuss the effects of human capital on wages in non-technology jobs, followed by the effects in high technology S & E jobs, then other technology-sector jobs, and finally in other S & E jobs for different racial groups. Trends over time are discussed and an overview of the findings is provided.

7.1 Evaluation of the Data and Regression Model

The results and implications of the examination of residuals for normality, linearity and the presence of outliers with high leverage in the data for the logarithm of weekly wages are presented in this section. The qnorm plot (plot of quantiles of the variable (log weekly wages) against the quantiles of a normal distribution) from STATA indicated no deviation from normality for the mid range of the data; however, there were deviations from normality at the tails with the deviations being greatest at the upper end. Inter-quartile range (iqr) tests, which identify outliers that are 3 interquartile ranges above and below the first and third quartile respectively, indicated that the outliers were severe enough to affect the normality of the distribution. The deviations from normality are due to the effects of top-coding of wages as well as the presence of a small number of outlier cases, which had unusual combinations of multivariate characteristics and high residual values compared to the rest of the sample. The outlier cases were identified from an examination of the highest and lowest values of the residuals. Upper tail outliers were due to five Hispanic males with very high wages (>$400,000 per annum), who had not been top-coded and who did not have high school education. Although some of these values may be due to data entry errors, elimination of the outlier cases from the sample did not change the regression coefficients or standard errors substantially, so it was decided to keep these in the model. In keeping with findings from other studies, the wage data from the CPS survey did not conform to assumptions needed for unbiased and efficient estimations based on ordinary least squares analyses.

The results of the analyses with the variables introduced sequentially into the model are presented in Table 12 starting with Model 1 which includes the human capital variables (education and experience). Model 2 includes the race variables (blacks, Latinos and Asians), with white males without high school education being the reference group. Model 3 shows the results of the analyses with the race and education interaction terms; and finally Model 4 has the control variables included. Reversing the order of introduction of the human capital and race variables did not affect the size of these effects.

The goodness of fit of the models improved with the successive addition of each group of variables. The percentage of variation explained increased from 26% with the human capital variables to 38% based on adjusted R^2 values for the model with the control variables and interaction terms included.

Table 12: Coefficients and standard errors for OLS regression analyses of the logarithm of weekly wages with sequential introduction of variables for male full-time, full year workers (Models 1-4)

	Dependent Variable Logarithm of Weekly Wages				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
High School	0.355	0.300	0.279	0.230	0.230
	(82.09)**	(67.65)**	(47.27)**	(41.38)**	(41.42)**
Bachelors degree	0.745	0.673	0.656	0.532	0.535
	(148.01)**	(130.28)**	(100.48)**	(86.40)**	(86.59)**
Graduate degree	1.115	1.037	1.013	0.865	0.868
	(162.11)**	(148.33)**	(123.19)**	(111.54)**	(111.70)**
Experience (centered)	0.046	0.046	0.046	0.031	0.031
	(99.58)**	(99.73)**	(100.16)**	(66.66)**	(66.77)**
Experience (squared, centered)	-0.001	-0.001	-0.001	0.000	0.000
	(69.52)**	(70.96)**	(71.40)**	(49.00)**	(49.07)**
Black		-0.191	-0.166	-0.119	-0.122
		(36.82)**	(12.19)**	(9.62)**	(9.79)**
Latino		-0.187	-0.239	-0.290	-0.289
		(44.40)**	(31.15)**	(38.76)**	(38.37)**
Asian		-0.068	-0.129	-0.188	-0.185
		(7.89)**	(11.61)**	(16.35)**	(15.60)**
Black x High school			-0.017	-0.039	-0.041
			-1.150	(2.85)**	(3.03)**
Black x Bachelors			-0.051	-0.062	-0.077
			(2.89)**	(3.91)**	(4.76)**
Black x Graduate			-0.108	-0.142	-0.158
			(3.80)**	(5.37)**	(5.88)**
Latino x High school			0.080	0.090	0.090
			(8.61)**	(10.46)**	(10.39)**
Latino x Bachelors			0.055	0.092	0.077
			(4.17)**	(7.61)**	(6.25)**
Latino x Graduate			0.074	0.121	0.107
			(2.76)**	(4.83)**	(4.24)**
Asian x Bachelors			0.065	0.052	0.039
			(3.61)**	(3.09)**	(2.24)*
Asian x Graduate			0.175	0.124	0.097
			(8.01)**	(6.01)**	(4.19)**

Cont'd

Table 12 ***cont'd***

	Dependent Variable Logarithm of Weekly Wages				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
High technology/ S & E				0.260	0.236
				(43.07)**	(37.11)**
High technology/ non-S & E				0.161	0.163
				(39.66)**	(35.76)**
Non-high technology/ S & E				0.201	0.186
				(31.86)**	(26.93)**
Black x High technology/ S & E					0.150
					(4.68)**
Black x High technology/ non-S & E					0.031
					(2.12)*
Black x Non-high technology/ S & E					0.144
					(5.25)**
Latino x High technology/ S & E					0.165
					(5.95)**
Latino x High technology/ non-S & E					-0.042
					(3.20)**
Latino x Non-high technology/ S & E					0.145
					(5.62)**
Asian x High technology/ S & E					0.129
					(5.14)**
Asian x High technology/ non-S & E					-0.046
					-1.950
Asian x Non-high technology/ S & E					0.027
					-1.070
X_{ijj}				+	+
Observations	298802	298802	298802	298802	298802
R-squared	0.260	0.270	0.280	0.380	0.380

Note: (1) Robust t-statistics in parentheses; (2) * Significant at p<0.05; ** Significant at p<0.01; (3) Reference groups for dummy variables: Education & race- white male who has not graduated high school; (4) X_{ij} is a matrix of control variables with reference groups as follows: marital status- never married; child in household - no children; work status -not a full-time, full-year worker; self-employment status - not employed by own business; union status - not a member or covered by a union; Year - 1992-1993; metro status - rural resident; region of residence - South East; Industry/ Occupation group – non-technology industry workers.

There was strong support for the models with the larger number variables and the interaction terms. As expected the effects of education decreased with the addition of the race variables and with the introduction of the control variables. The F tests on the significance of the groups of variables based on differences in the R^2 values were not very meaningful because of the large sample size.

7.2 Effects in Non-High Technology, Non-Science and Engineering Jobs

In Table 13, the results of Model 5, which contains race and industry interaction terms, are compared to the results of analyses using the Heckman two stage selection method (Model 6). Holding all else constant, high school education increases the expected value of weekly wages for white male full-time, full year workers in non-high technology non-science and engineering jobs by 23% compared to that of individuals without high school education; having a bachelor's degree increases wages by 53% and graduate level education increases wages by 87%. The corresponding gains are significantly lower for similar blacks being (0.23-0.04) or 19%, (0.53-0.08) or 45%, and (0.87-0.16) or 71% respectively; for Latinos the changes are significantly higher than similar whites at (0.23+0.09) or 32%, (0.53+0.08) or 62% and (0.87+0. 1) or 97% respectively; for Asians the changes are (0.53+0.04) or 57% and (0.87+0.1) or 97% respectively.

The Heckman analysis produces similar patterns, although the sizes of the effects are different (Table 13, Model 6). The Heckman selection model suggests that the educational gains are overstated, if the analysis does not take into consideration those who work part-time or are non-workers. From the Heckman model, the changes due high school education, bachelors degrees and graduate education relative to not having high school education are 17%, 49% and 83% for whites; 4%, 31% and 63% for blacks; and 11%, and 38%, for Latinos with high school and bachelors education. There was no significant difference between the gains of whites and Latinos from graduate education. Whites and Asians do not have significant difference in the gains from a bachelor's education. However the gains from graduate education are significantly higher for Asians.

Table 13: Comparison of the effects of selected variables from OLS regression analyses on the logarithm of weekly wages with effects from Heckman selection analyses for males (models are run with all variables included)

	OLS	Heckman Selection	
High School	0.230	0.167	0.524
	(41.42)**	(22.70)**	(81.63)**
Bachelors degree	0.535	0.486	0.782
	(86.59)**	(60.48)**	(91.93)**
Graduate degree	0.868	0.831	0.925
	(111.70)**	(84.14)**	(72.06)**
Experience (centered)	0.031	0.07	
	(66.77)**	(140.22)**	
Experience (squared, centered)	0.000	-0.001	
	(49.07)**	(101.31)**	
Black	-0.122	-0.074	
	(9.79)**	(5.10)**	
Latino	-0.289	-0.115	
	(38.37)**	(13.39)**	
Asian	-0.185	-0.15	
	(15.60)**	(10.27)**	
Black x High school	-0.041	-0.129	
	(3.03)**	(8.09)**	
Black x Bachelors	-0.077	-0.179	
	(4.76)**	(8.86)**	
Black x Graduate Degree	-0.158	-0.201	
	(5.88)**	(5.75)**	
Latino x High school	0.090	-0.037	
	(10.39)**	(3.66)**	
Latino x Bachelors	0.077	-0.108	
	(6.25)**	(6.77)**	
Latino x Graduate Degree	0.107	-0.039	
	(4.24)**	-1.3	
Asian x Bachelors	0.039	0.033	
	(2.24)*	-1.48	
Asian x Graduate Degree	0.097	0.115	
	(4.19)**	(4.14)**	
High technology/ science & engineering	0.236	0.314	
	(37.11)**	(36.65)**	
High technology/ non-science & engineering	0.163	0.238	
	(35.76)**	(44.81)**	
Non-high technology/ science & engineering	0.186	0.251	
	(26.93)**	(29.11)**	
Xij	+	+	
Observations	298802	488707	488707
R-squared	0.380		

Note: (1) * Significant at $p<0.05$; ** Significant at $p<0.01$; (2) Reference groups for dummy variables: Education & race- white male who has not graduated high school; X_{ij} includes matrix of control variables with reference groups for the dummy variables: marital status- never married; child in household - no children; work status -not a full-time, full-year worker; self-employment status - not employed by own business; union status - not a member or covered by a union; Year - 1992-1993; metro status - rural resident; region of residence - South East

Despite differences in gains, all minorities have significantly lower expected wages in non-high technology, non-science and engineering jobs compared to whites regardless of educational level. For blacks, the gap increases with educational level: (-0.12-0.04) or 16% lower than whites for high school education; (-0.12-0.08) or 20% lower for bachelors and (-0.12-0.16) or 28% for graduate education. The coefficients on the education, race and race and education interaction terms are jointly significant. The Latino-white gap is about the same for individuals with high school and bachelors education at about (-0.29+0.08) or 20% lower, then goes to (-0.29+0.11) or 18% for individuals with graduate education. For Asians, the differences decrease with educational attainment and are (-0.18+0.04) or 14% and (-0.18+0.1) or 8% for bachelors and graduate degrees respectively.

The coefficients for each race, educational attainment level and their interaction are jointly significant and the size of the effects correspond with those obtained when the regressions are run separately for each industry /occupational group or race and when the reference groups for education are changed to different levels. In the OLS analyses, the effects of potential experience were not separated by industry/ occupational groups and the expected value of potential experience increased at a decreasing rate up to 31 years of experience.

The findings in this study are similar in some aspects with the results of other studies, that is wage gains or the "returns to education" for different racial groups vary at different levels of educational attainment (Bradbury, 2002; Heckman et al., 2005). This study finds that holding all else constant; blacks receive lower returns to high school and college education compared to whites. However, Heckman et al 2005, using 1990 census data, and non-parametric estimation methods found that blacks received higher returns to high school and college education relative to whites, when the set of all jobs in the economy are examined. The differences in the findings may be due to differences in the time period of analysis or maybe due to differences in the estimation methods. In other studies, Black (2006) found that blacks and Hispanics had lower wages than whites based on wage data in 1993 National Longitudinal Survey. However black-white wage differences become insignificant if controls are included for individuals from the south and the educational background of parents. Other studies suggest that Latino- white wage differences disappear in studies where differences in education and skill are carefully controlled for (Weinberger, 1998) or if English language is the language spoken at home(Black et al., 2006).

7.3 Effects in High Technology, S & E Jobs

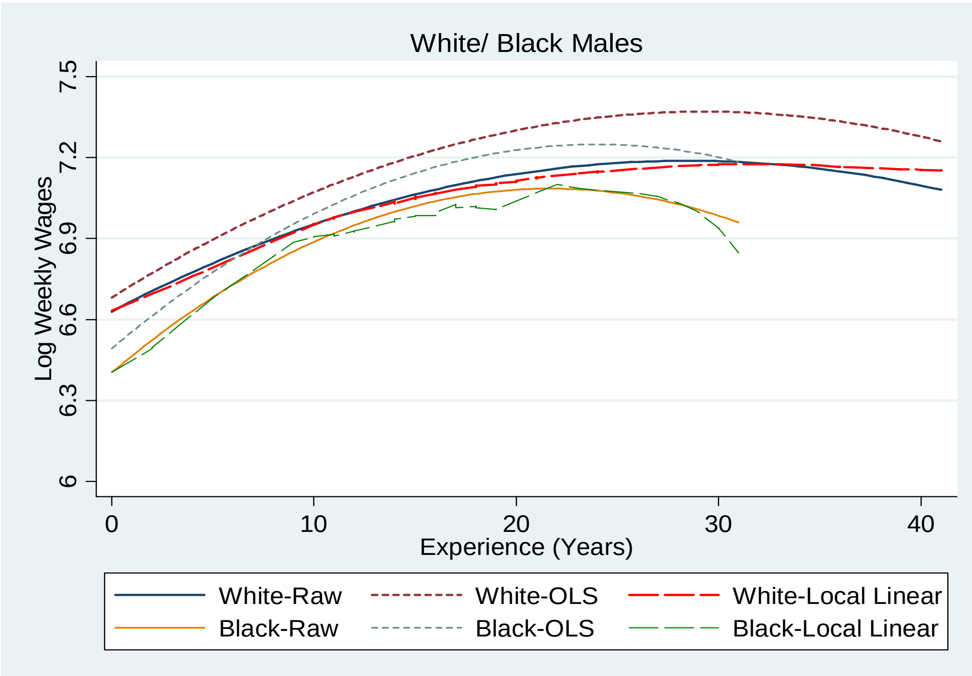
In high technology industries and science and engineering occupations, the magnitude of the effects of college education (bachelors and graduate levels) was larger than the effects for high school level education or below, therefore the variables for college education are more important. The following sections focus on wage differences between minorities and whites with graduate and bachelors level education in high technology industries and science and engineering jobs. The information obtained will provide sufficient insights on the wage differences between whites and minorities to answer the research question.

7.3.1 Blacks

Based on the results of OLS regression analyses (Table 13, Model 5), regardless of educational levels, blacks earn significantly less than whites (negative values on the race coefficient and increasingly negative values on education interaction terms, which are not offset by the coefficient relating to the variable for high technology S & E). The wage gaps are smaller in high technology industries and science and engineering jobs, compared to non-technology jobs and are smallest for S & E jobs compared to the non-S & E jobs. Based on OLS estimations, expected weekly wages of blacks with graduate education are 13% less than whites and this difference is significant. The difference is also significant in the model run separately for each industry/occupational group

Figure 12a shows smoothed plots of the predicted values of the logarithm of weekly wages from OLS regression; the raw data using a quadratic fit function in STATA; and local linear non-parametric regression fit against years of potential experience for black and white males with graduate education in high technology S & E jobs. The three pairs of plots show similar patterns in the wage gaps between black and white individuals, with the OLS predicted values of wages being somewhat higher than the values based on the raw data and non-parametric regression estimation. The OLS estimates have an upward bias because omitted variables such as ability that are positively correlated with education and income produce a positive bias on education, which in turn increase estimates of income. The wage-experience plots show greater divergence between the wages of younger black and white workers (those below 10 years of experience); some convergence towards the mid-range of the plots for workers between 10 and 25 years of experience; then divergence for older workers (experience greater than 20 years). This pattern can also be seen in the first panel of Table 14, which shows the values of mean wage differences between blacks and whites with graduate, bachelors and high school level education.

(a)



(b)

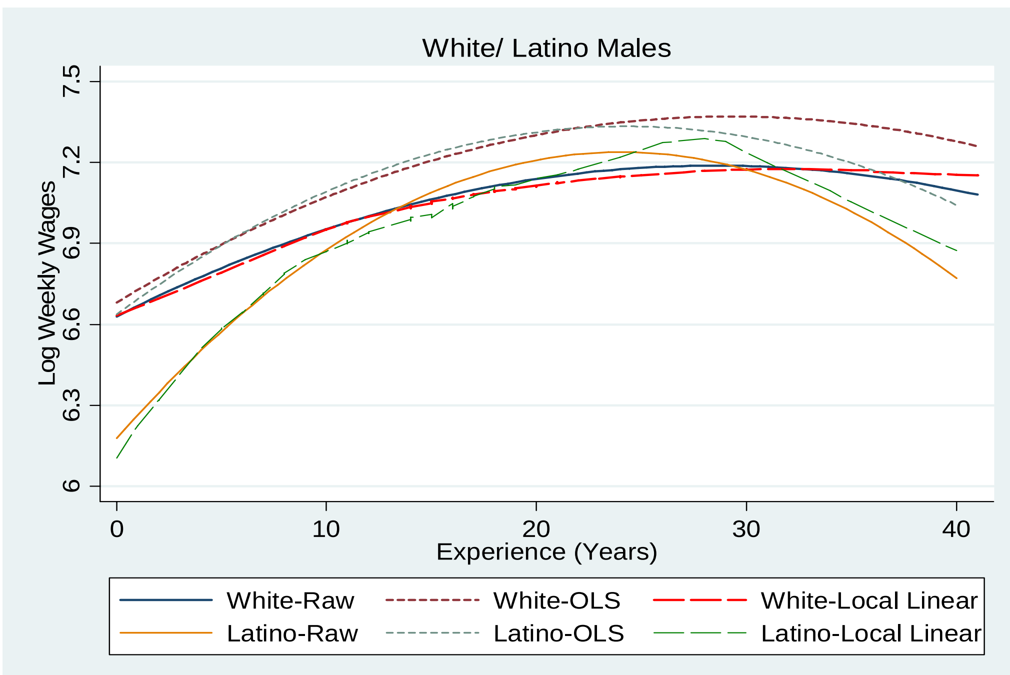


Figure 12: Comparison between logarithm of weekly wages in high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with graduate degrees

(c)

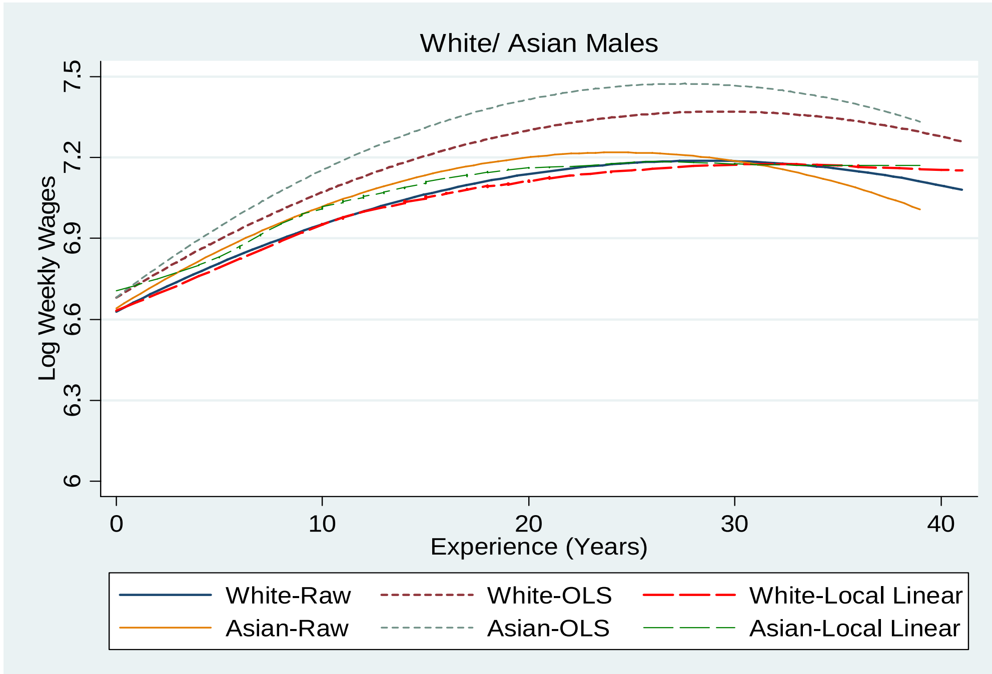


Figure 12. Cont'd, comparison between logarithm of weekly wages in high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with graduate degrees

The first panel shows the data for high technology S & E jobs, in which the black-white wage differences at the graduate level are not significant based on t-tests of differences in mean wages. However, the absence of statistical significance may be due to the small sample sizes of the groups used in the t-tests. On the other hand, the larger sample size used in the OLS regression makes it easier to get statistical significance even for relatively small effects, so statistical significance is less meaningful.

Figure 13a shows that the pattern is somewhat different for blacks and whites with bachelors level education, with the log of weekly wages for the younger cohort of blacks (less than 10 years experience) being higher than the log weekly wages for whites; however for older workers, the mean wages of whites are higher. The first panel of Table 14 shows a similar pattern in the differences between the mean wages of black and white workers with bachelor's education in high technology S & E jobs; however, the differences are not statistically significant in the small sample t-test. The differences are also not significant in the regression models run separately by the industry-occupational group. Based on OLS estimates, expected weekly wages of blacks with bachelors education are 5% lower than whites.

The estimation methods provide mixed results on the statistical significance of the wage differences between blacks and whites with graduate education in high technology S & E jobs; however, the differences are systematic and could be economically meaningful. The importance of the dollar value of the difference (approximately $100 per week or $5000 per annum) will be relative to the overall earnings of the individual and will be less important for high earners but tangible for workers with modest incomes. Based on sample data, blacks with graduate education in high technology S & E jobs, earn an average of approximately $50,000 per annum, while whites with the same level of educational attainment earn $55,000.

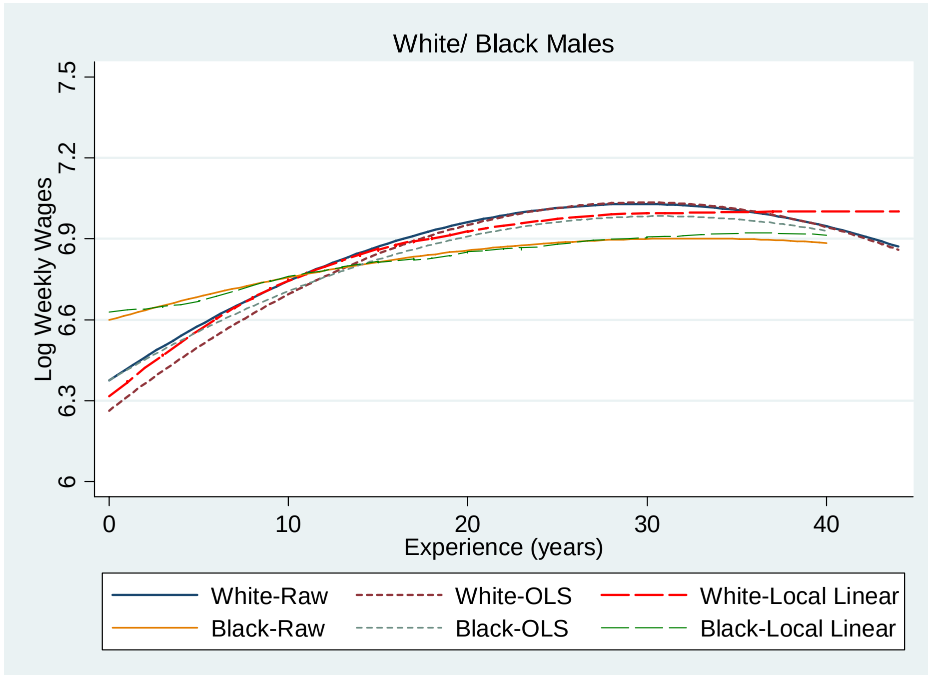
Changes in the response to Civil Rights legislation over the period of study could serve as a possible explanation for the patterns of divergence and convergence in wage gap between black and white workers. Since, the sample represents data on individual wages for the period 1992 to 2002, individuals with 10 to 20 years experience would have entered the labor market just after the passage of civil rights legislation and possibly may have benefited from both legislative actions as well as from heightened awareness of the undesirability of overt acts of "taste-based" discrimination.

Table 14: T-tests of differences between the mean weekly wages of minorities and whites at different levels of education and experience

	Education		
	Post Graduate	**Bachelors**	**High School**
High Technology Science and Engineering			
<10 Years Experience			
Black	-106	26	-45
Latino	-150 *	18	-41
Asian	55	197 ***	50
11-20 Years Experience			
Black	81	-18	-31
Latino	-53	-21	-57
Asian	138 *	81	-89
>20 Years Experience			
Black	-231 *	-102	55
Latino	-1	-33	115
Asian	-60	18	139
High Technology Non-Science and Engineering			
<10 Years Experience			
Black	-361 **	-27	-6
Latino	-286 **	-101 **	-27
Asian	74	-61	-45 *
11-20 Years Experience			
Black	-232	-262 ***	-84 ***
Latino	-403 **	-282 ***	-88 ***
Asian	-129	2	-100 ***
>20 Years Experience			
Black	-416 *	-307 ***	-97 ***
Latino	-339 *	-251 **	-119 ***
Asian	-104	-222 ***	-190 ***
Non-High Technology Science and Engineering			
<10 Years Experience			
Black	51	-9	99
Latino	-154 *	21	-20
Asian	28	89 *	214
11-20 Years Experience			
Black	-93 ***	-38	13
Latino	-240 **	18	-34
Asian	52	42	126
>20 Years Experience			
Black	-199 **	-99 *	-52
Latino	-271 *	24	-120 **
Asian	-167 *	-21	32

Note: * - Significant at $p<0.05$; ** - Significant at $p<0.01$; *** - Significant at $p<0.000$

(a)



(b)

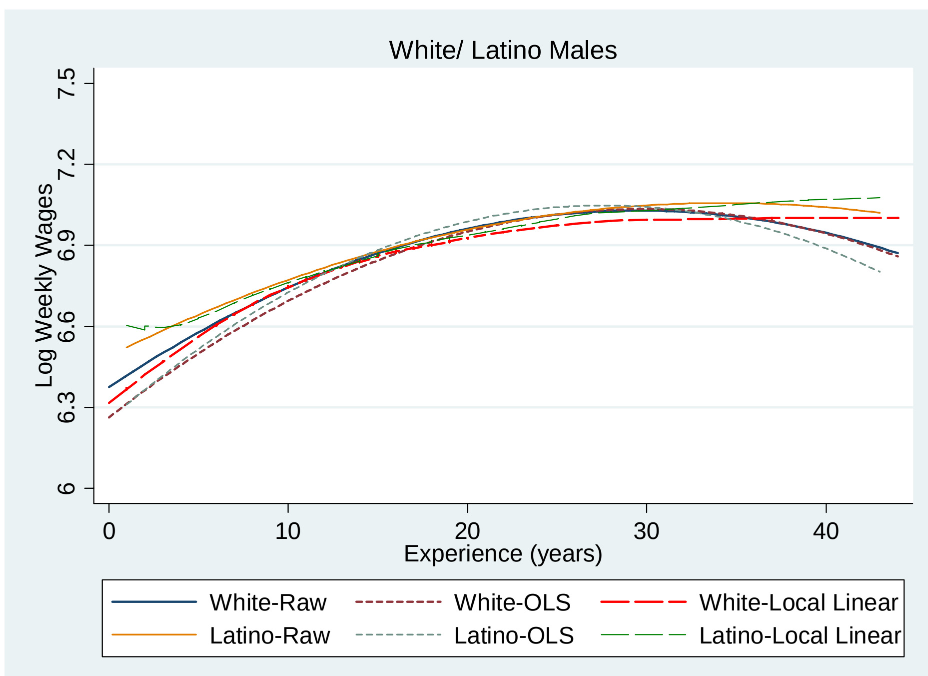


Figure 13. Comparison between logarithm of weekly wages in high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with bachelors degrees

(c)

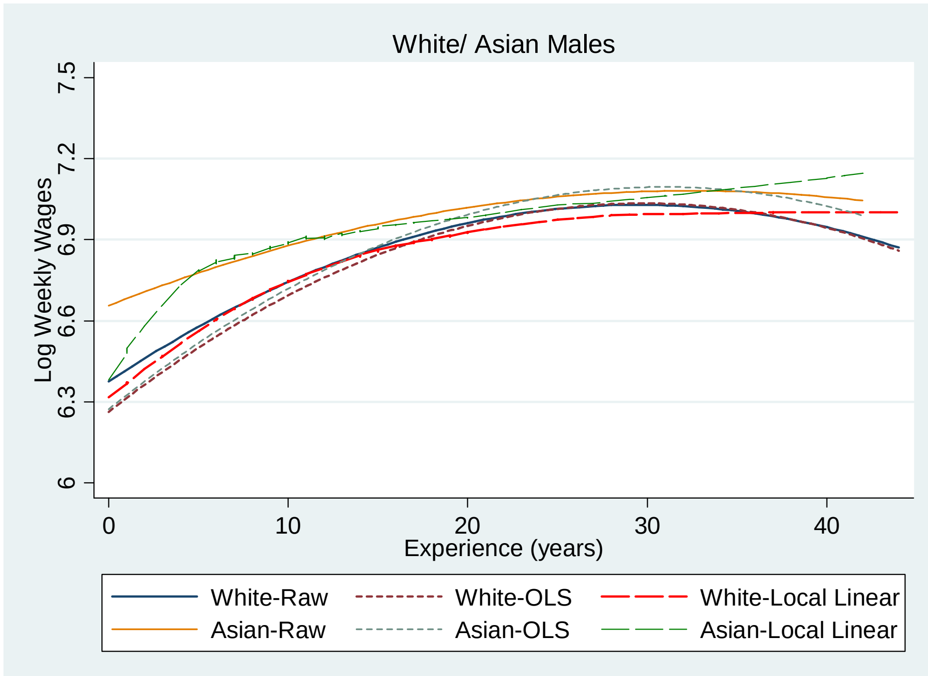


Figure 13. Cont'd comparison between logarithm of weekly wages in high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with bachelors degrees

The widening gap for the younger cohort of blacks suggest that gains made by blacks are reversing and this may be due to weakening of the enforcement of affirmative action legislation (Altonji & Blank, 1999). It may also be indicative of statistical discrimination, in which employers feel that even though the blacks have graduate education, they have less of "something", whether drive or motivation that is presumed greater in whites or Asians.

7.3.2 Latinos

Based on the results of OLS regression analyses, Latinos earn significantly less than whites in high technology S & E jobs, however the differences do not vary systematically with changing education or experience levels. The OLS estimates suggest expected weekly wages of Latinos with graduate education are only 2% less than whites.

Figure 12b shows plots of predicted values of the logarithm of weekly wages, the logarithm of wages from the raw data and local linear non-parametric estimates against experience for Latinos and whites with graduate level education in high technology science and engineering jobs. The log weekly wage plots of Latino and white workers with graduate education cross several times at different experience levels for all three estimation methods (Figure 12b). The small sample t-tests in Table 14 show that Latinos with graduate education and 10 years of experience or less, earn significantly less than whites, however the difference is not significant at the other levels of experience.

The wage differences between Latinos and whites with bachelor's education are less than those of individuals with graduate education; OLS estimates suggest that Latinos with bachelor's education earn 5% less than similar whites in high technology S & E jobs and this is statistically significant. Figure 13b, which shows plots of the logarithm of weekly wages for Latinos and whites with bachelor's education suggests that wages are very similar except for individuals at the extremes of the range of the experience data. Based on the results of small sample t-tests shown in Table 14, there is no significant difference between the wages of whites and Latinos with bachelor's education in high technology S & E jobs.

The heterogeneity of Latinos and differences in racial identification give rise to less systematic wage differences with whites. More highly educated Latinos, many of whom may racially identify as white possibly face less discrimination than the less educated. Lower average wages of Latinos in the economy as a whole and the wage gap between Latinos and whites have been attributed lower average levels of human capital (Trejo, 1997) .

7.3.4 Asians

The results of OLS analyses indicate that expected weekly wages of Asians with graduate education are 5% higher than similar whites in high technology S & E. Plots of log weekly wages based on the three estimation methods shown in Figure 12c support these findings. The plots based on the raw data and local linear non-parametric estimations suggest that wages of older Asian workers (more than 30 years of experience) are less than similar whites. The results in Table 14 indicate a similar trend; however, the results are not statistically significant.

The OLS estimates suggests that Asians with bachelor's degrees earn on average 1% less expected weekly wages compared to similar whites. However Figure 13c, which shows differences based on the three, suggests that Asian-white wage differences vary with the level of experience of individuals. The plots show that the log of weekly wages are very similar to whites. Table 14 shows mean weekly wages of Asians with bachelor's degrees are higher than that of similar whites, but these differences are not significant, with the exception of a single case. The highly significant positive value of the wage difference shown in Table 14 could be due to a small set of unusually high values, which are influential due to the small sample sizes used by the t-tests.

7.4 Effects in High Technology, Non-Science and Engineering Jobs

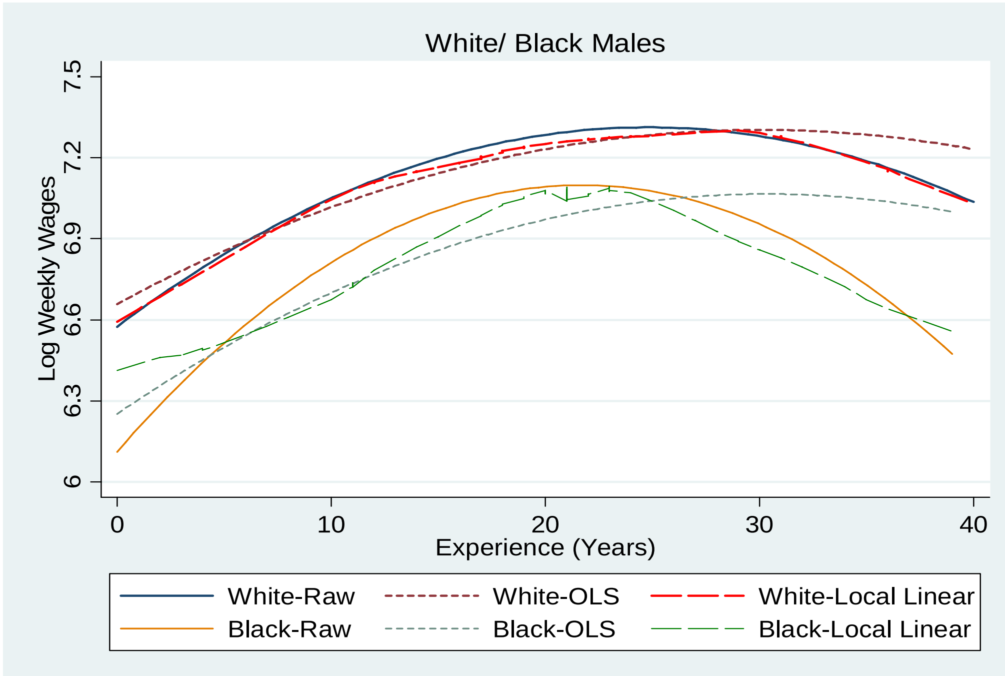
7.4.1 Blacks

The OLS estimates of differences between the weekly wages of blacks and whites in other technology-sector jobs are similar to those in non-technology sector. Blacks on average earn significantly less than whites at all levels of education. Individuals with graduate education earn 25% less than whites do and those with bachelor's education earn 17% less. These findings are supported by Figure 14a which shows plots of the log of weekly wages based on OLS estimates, the raw data, and local linear non-parametric estimations against years of potential experience for black and white males with graduate education in other technology-sector jobs. The plots show that the gap is least for workers with 11-20 years of experience, which is similar to workers in high technology S & E jobs. The results in the second panel of Table 14 show that blacks with graduate education and less than 10 years or greater than 20 years of experience have significantly lower wages than whites. Figure 15a shows a similar plot for individuals with bachelor's degrees. For individuals with bachelor's degrees, the gap is smallest for individuals with less than 10 years of experience and is significantly larger for individuals with greater than 10 years of experience (Table 14). The weekly wage differences translate to $17-20,000 annually for individuals with graduate education and $12-15,000 for individuals with bachelor's education.

7.4.2 Latinos

Latinos regardless of educational level have significantly lower wages than whites in other technology-sector jobs. The OLS estimates are 22% and 25% lower for individuals with graduate level education and those with bachelors respectively. Figures 14b and 15b show plots of estimates of log weekly wages for Latinos and whites with graduate and bachelors degrees respectively. The second panel of Table 14 shows mean weekly wage differences.

(a)



(b)

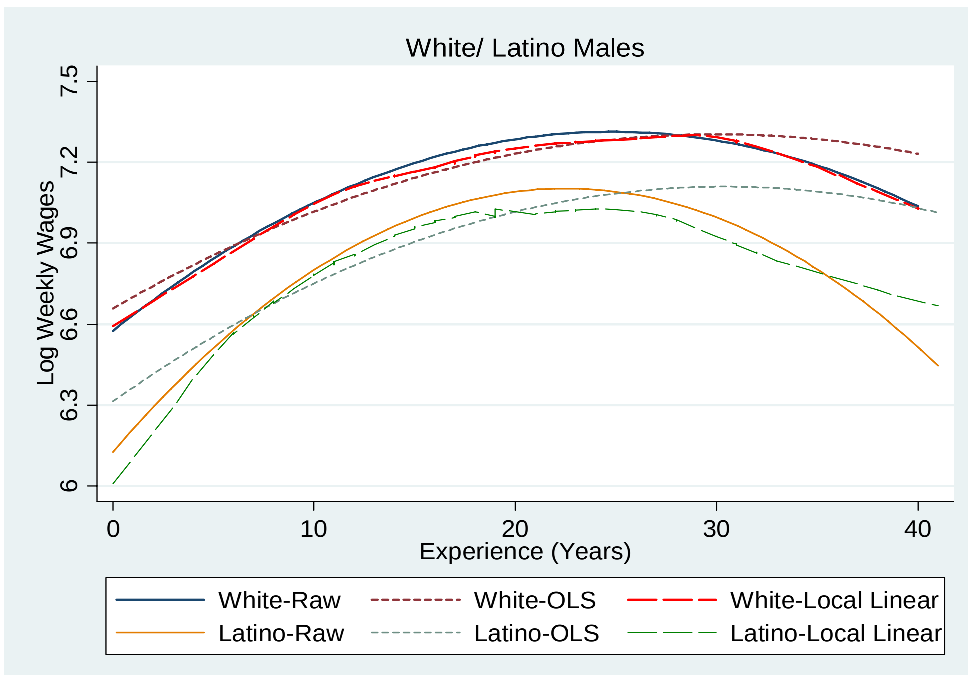


Figure 14: Comparison between logarithm of weekly wages in high technology non-science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with graduate degrees

(c)

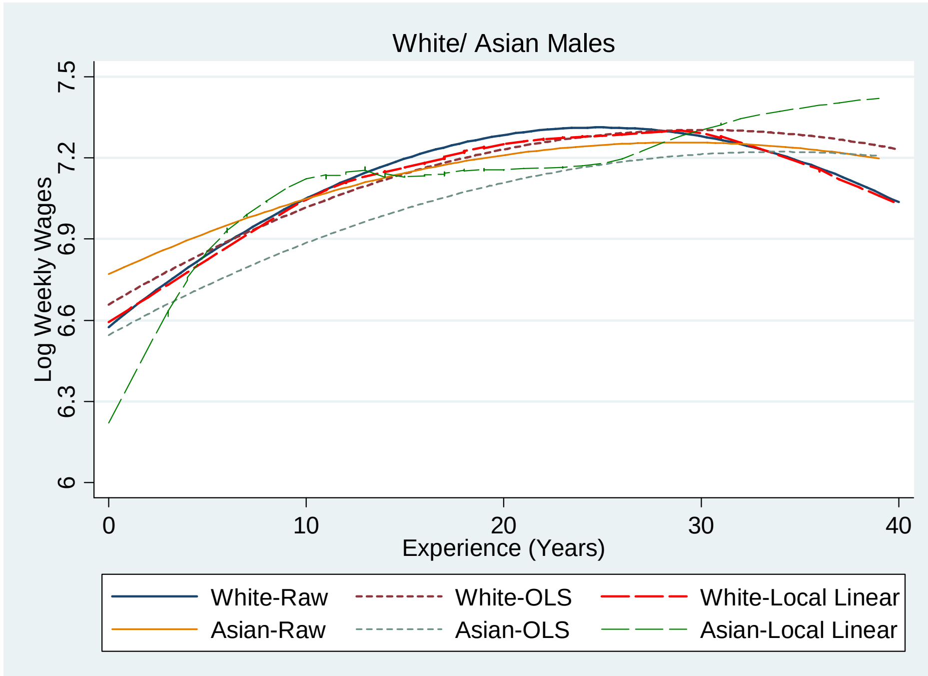


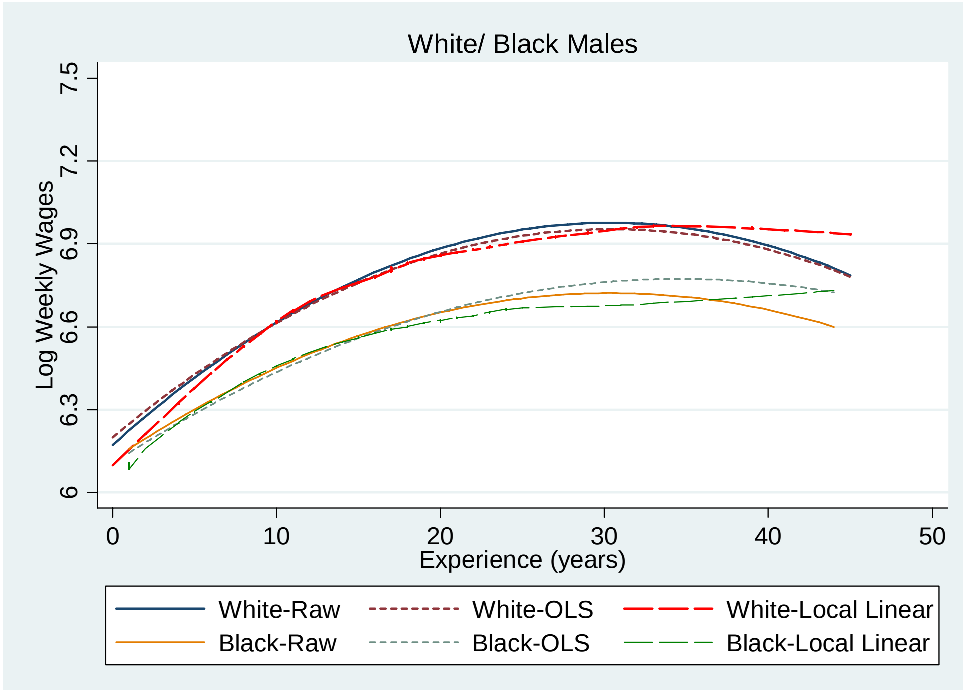
Figure 14 cont'd comparison between logarithm of weekly wages in high technology non-science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with graduate degrees

The differences in Table 14 are all significant, with only a single exception. Similar to blacks, even highly educated Latinos appear to suffer from discrimination since it is not easy to rationalize why it should be believed that Latinos and blacks lack skills possessed by whites or Asians that are observed by the employer and are not reflected in educational qualifications.

7.4.3 Asians

Based on the results of OLS analyses, Asians have significantly lower expected weekly wages than similar whites do do with the wage difference being 13% for individuals with graduate education and 19% for individuals with bachelor's education.

(a)



(b)

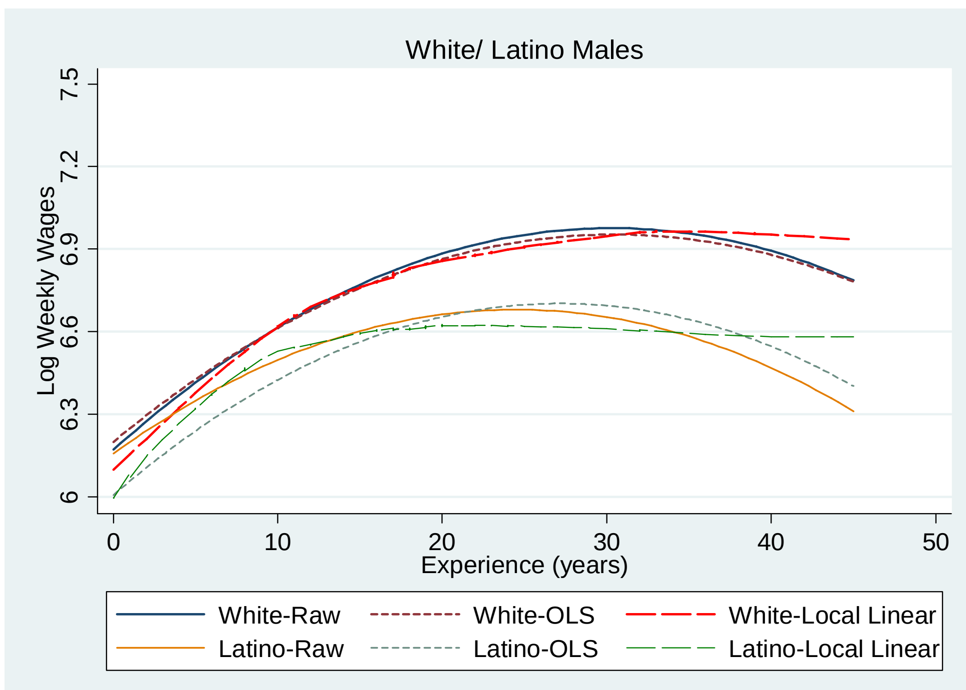


Figure 15. Comparison between logarithm of weekly wages in high technology non-science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with bachelors degrees

(c)

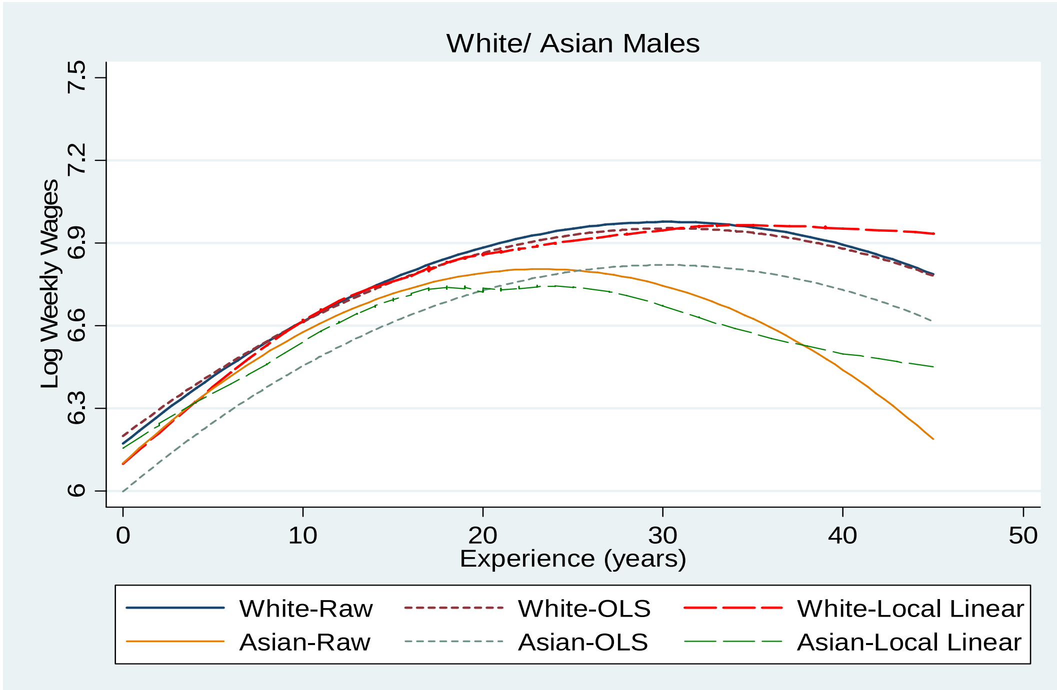


Figure 15 cont'd comparison between logarithm of weekly wages in high technology non-science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with bachelors degrees

Figure 14c shows fairly similar plots of log weekly wages of Asians with graduate education compared to whites for all three estimation methods. However, there is greater divergence in log weekly wages between individuals with bachelor's education (Figure 15c). From Table 14, relative to whites, younger Asian workers and those with higher levels of education have less significant wage differences compared to older or less educated workers.

7.5 Effects in Non-High Technology Science and Engineering

7.5.1 Blacks

The OLS estimations indicate that blacks with graduate education on average earn 14% less in weekly wages than whites in other S & E jobs. Figure 16a and Table 14 show that the differences are less pronounced for younger workers and are larger and statistically significant for workers with more than 10 years of experience. Blacks with bachelor’s degrees earn on average 6% less in weekly wages compared to similar whites. Large sample OLS analysis suggests that these results are significant; however the results of t-tests (Table 14) indicates that the differences are significantly less only for workers with more than 20 years of work experience. The differences are not significant when regression models are run separately by industry-occupational group.

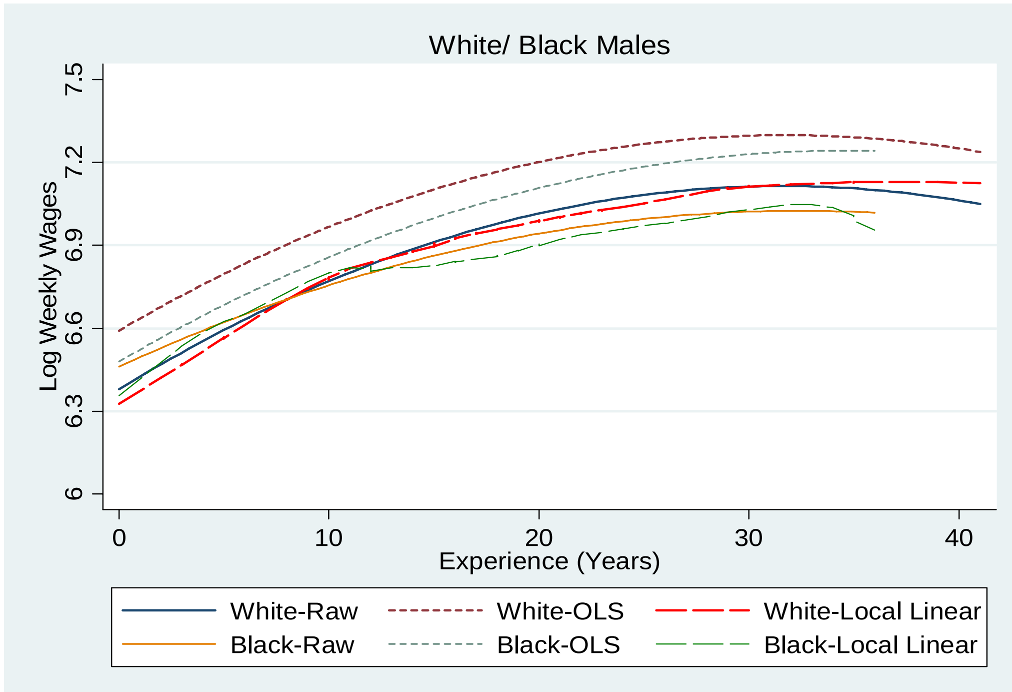
7.5.2 Latinos

Similar to blacks, Latinos with graduate education earn significantly lower wages than similar whites in other S & E jobs. Based on OLS estimations, the difference is only 4%; however from Table 14 mean wage differences are considerably larger, with the differences being greater for older workers. The differences translate to approximately 20% lower for Latinos with the dollar values of weekly wages averaging about $900 per week for Latinos and $1100 per week for whites. Figure 16b shows the divergence in the log weekly wages for individuals with graduate education and more than 25 years of experience. In general, the wage differences between Latino and white workers with bachelor’s degrees are numerically smaller and are not significant.

7.5.3 Asians

In other S & E jobs, wage differences between Asians and whites, with either graduate or bachelors education did not change in a systematic way with changes in educational levels or experience. This may be due to small sample sizes for Asians in other S & E jobs, which result in the analyses being influenced by a small number of extreme values. The study found that Asians in science and engineering occupations were predominantly employed in the high technology sector.

(a)



(b)

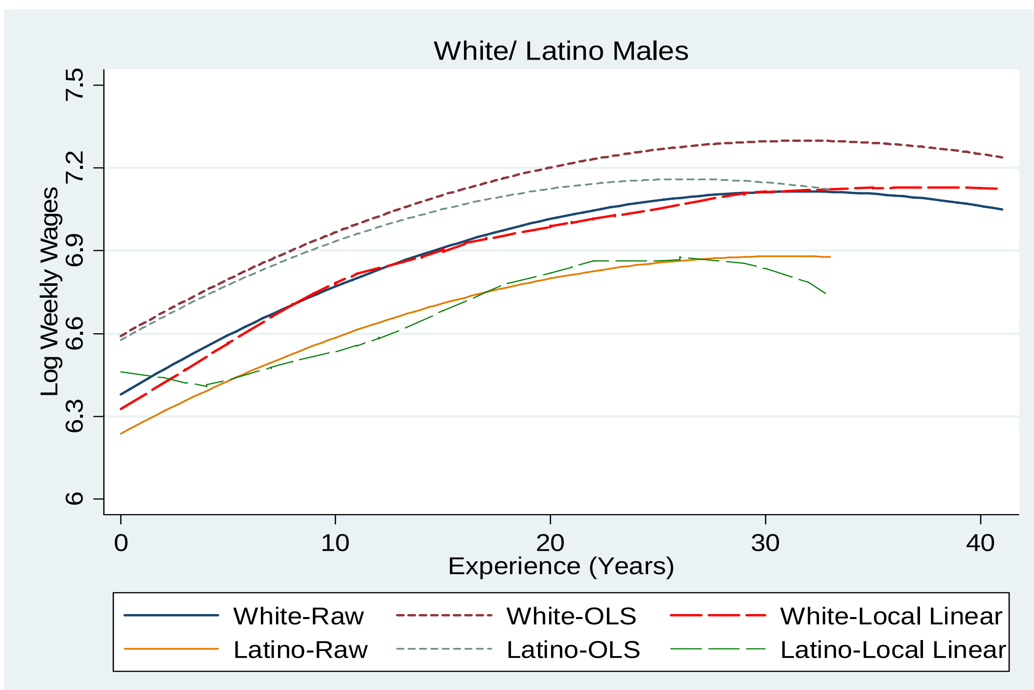


Figure 16: Comparison between logarithm of weekly wages in non-high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with graduate degrees

(c)

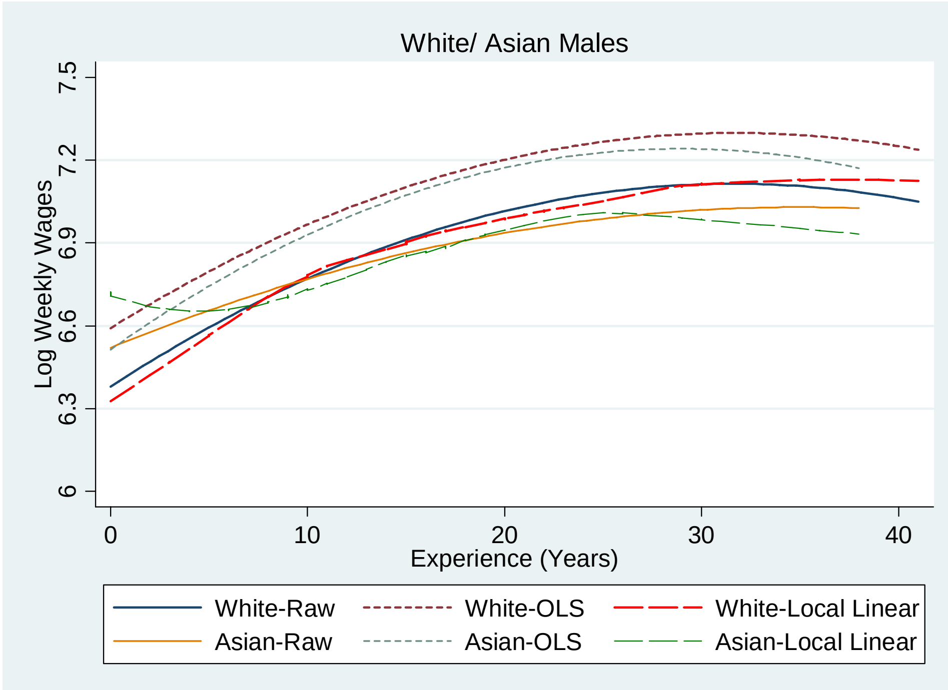
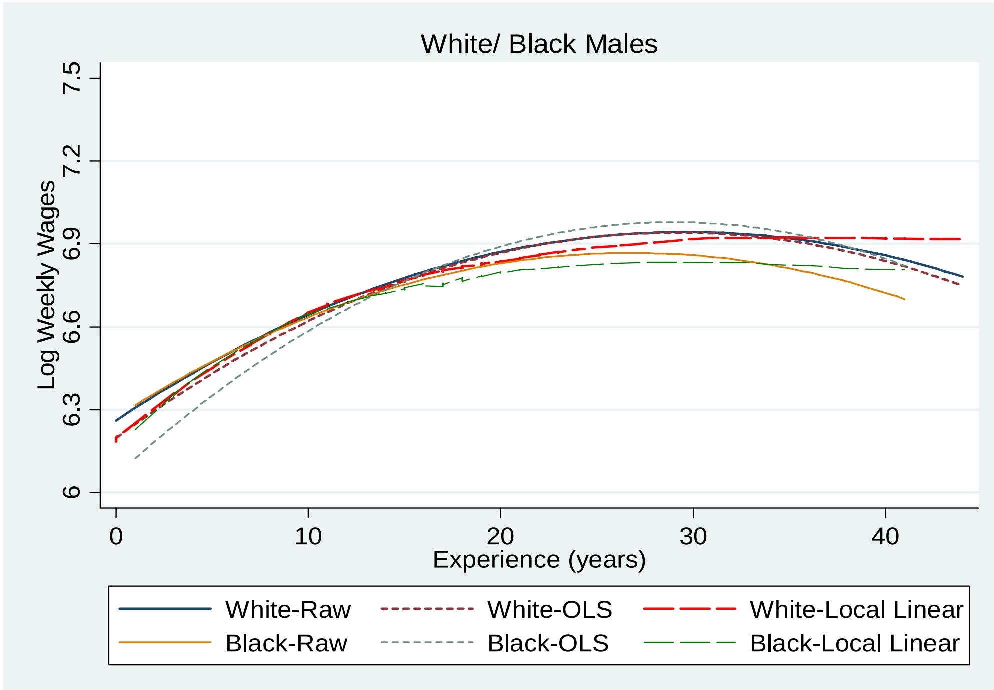


Figure 16 cont'd comparison between logarithm of weekly wages in non-high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with graduate degrees

7.6 Effects of Human Capital and Race on Wages

This study compares the effects of human capital and race on employment and wages in high technology industries and in science and engineering jobs with the effects elsewhere in the economy. The focus on a narrowly defined set of industries, then on a narrowly defined set of occupations within those industries and on specific levels of educational attainment within these occupations are expected to capture most of the major skill needs for the jobs. Other unmeasured skills such dedication, motivation, determination etc are not expected to be on average very different within this narrowly defined group.

(a)



(b)

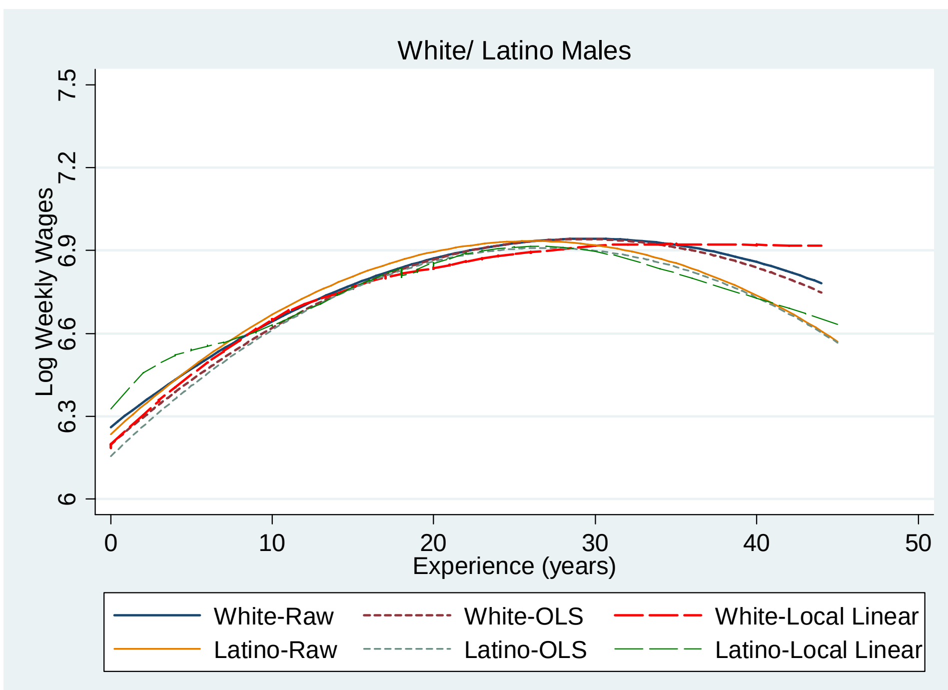


Figure 17: Comparison between logarithm of weekly wages in non-high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with bachelors degrees

(c)

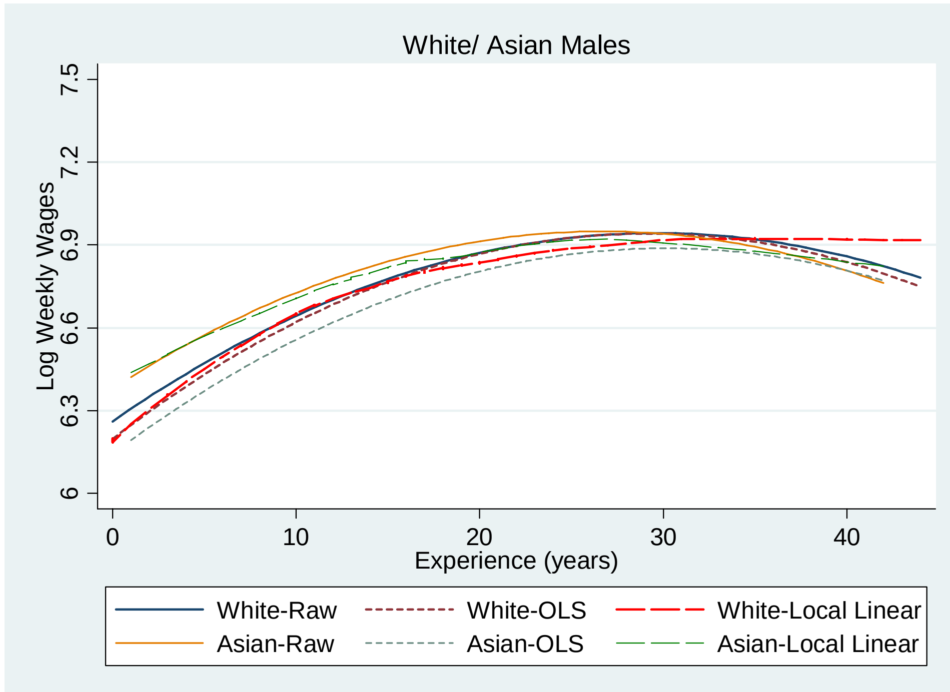


Figure 17 cont'd Comparison between logarithm of weekly wages in non-high technology science and engineering jobs based on raw data, OLS predicted values, and local linear non-parametric estimates for whites and (a) blacks; (b) Latinos; (c) Asians with bachelors degrees

As a result any significant differences in race effects in high technology science and engineering jobs are attributed directly to differences in treatment by race and not to unobserved skill or educational quality differences. Although the estimates of the regression coefficient will still be biased, the patterns of the relationships between the variables and the statistical significance of the effects are sufficient to support or refute the hypotheses.

The results show a complicated set of relationships between the wages of minorities and whites that depend on the race or ethnicity of the individual, educational qualifications, the industry or occupation of employment and the time period when the individual entered the labor market. Despite the variations, it is clear that minority- white wage gap is not as significant statistically nor numerically as large in high technology S & E jobs compared to other jobs for individuals with college education. Although blacks and Latinos with college education have greater difficulty entering these jobs (based on the results of the first part of this study on the probability of employment), weekly wages are not significantly different from whites once they are employed. It is still possible that there may be significant differences in non-wage compensation such as benefits and bonuses as these are more likely to be subject to discretionary allocation. However such an analysis was beyond the scope of this study.

The findings are contrary to Hypothesis 5, which predicted lower wages for Blacks and Latinos compared to whites. It was anticipated that differences observed by the employer, such as the quality of college attended would result in blacks and Latinos having lower wages that whites and Asians. Further it is also easier to hide discriminatory practices under the guise of real or perceived differences in skills that are unrelated to formal educational attainment. Thus Blacks and Latinos would be subject to a penalty because of discriminatory practice. Based on the findings, merit in particular educational qualification appears to play an important role in determining wages in high technology S & E jobs. However, given the low supply of black and Latino individuals in science and engineering occupations, and the need to give some semblance of attention to affirmative action goals should drive up the demand for the few highly qualified individuals, and increase the wages of these individuals beyond that of whites. Thus it appears that the competition for black and Latino scientists and engineers in the labor market is not that strong. On the other hand, this may be a major contributing factor in the small difference in the wages between blacks or Latinos and whites in high technology science and engineering jobs.

The picture is somewhat different in other S & E jobs. Although the odds of black and Latino scientists and engineers with graduate qualifications getting jobs is not significantly different from white counterparts, they are paid significantly less than whites. Other S & E jobs are primarily in the utilities, academia, and government, so this finding is somewhat surprising. It is possible that blacks and Latinos may feel that they are in a weaker negotiating position because fewer opportunities are available to them, so they start off with lower pay when compared to similar whites. It is also contrary to expectations since it was hypothesized that the wage gaps would be greater in the more rewarding high technology S & E jobs and smaller in other S & E jobs. It is difficult to draw conclusions about the wage gap between whites and Asians because of problems with the sample size.

For other technology-sector jobs, regardless of educational qualification, blacks and Latinos earn significantly lower wages than whites. Other technology-sector jobs, like the non-technology jobs comprise a more diverse set of jobs with different educational and skill requirements compared to S & E jobs. These differences could be due to differences in average characteristics of the groups, which vary by race e.g. in the quality of education. It is also possible that minorities with college level education have been forced into jobs that require fewer skills and pay lower wages, when compared with whites with similar levels of education. Therefore job segregation can result in lower average wages for minorities, despite having levels of educational attainment comparable to whites. Labor market segmentation theory provides a more reasonable explanation for differences in wages in these types of jobs. The pattern is no different from what happens in non-science and engineering jobs outside of the high technology sector.

7.7 Effect of Time

Figures 18 and 19 show plots of predicted values of log weekly wages from OLS against year when the wage data was collected for individuals with graduate and bachelors education respectively. The plots provide support for the findings in the previous section that is, white-minority wage differences are least in science and engineering occupations. For individuals with graduate degrees, there is little indication of convergence in wages over time. The wages of blacks in high technology S & E jobs appear to be increasing at the same rate as whites while those for Asians and Latinos are diverging. In other S & E jobs, the wages of minorities appear to be diverging relative to whites and for individuals with bachelors education, wage differences are less pronounced. The wage gaps between minorities and whites in non-science and engineering jobs, at both educational levels did not change greatly over the study period.

The results of the study provide little support for Hypothesis 7, which suggests that increasing levels of educational attainment would lead to a narrowing of the wage gap over the period. The tendency is to towards divergence for individuals with higher levels of education; however, it is possible that the 11-year period used for the study is much too short to see major shifts in the wages between groups.

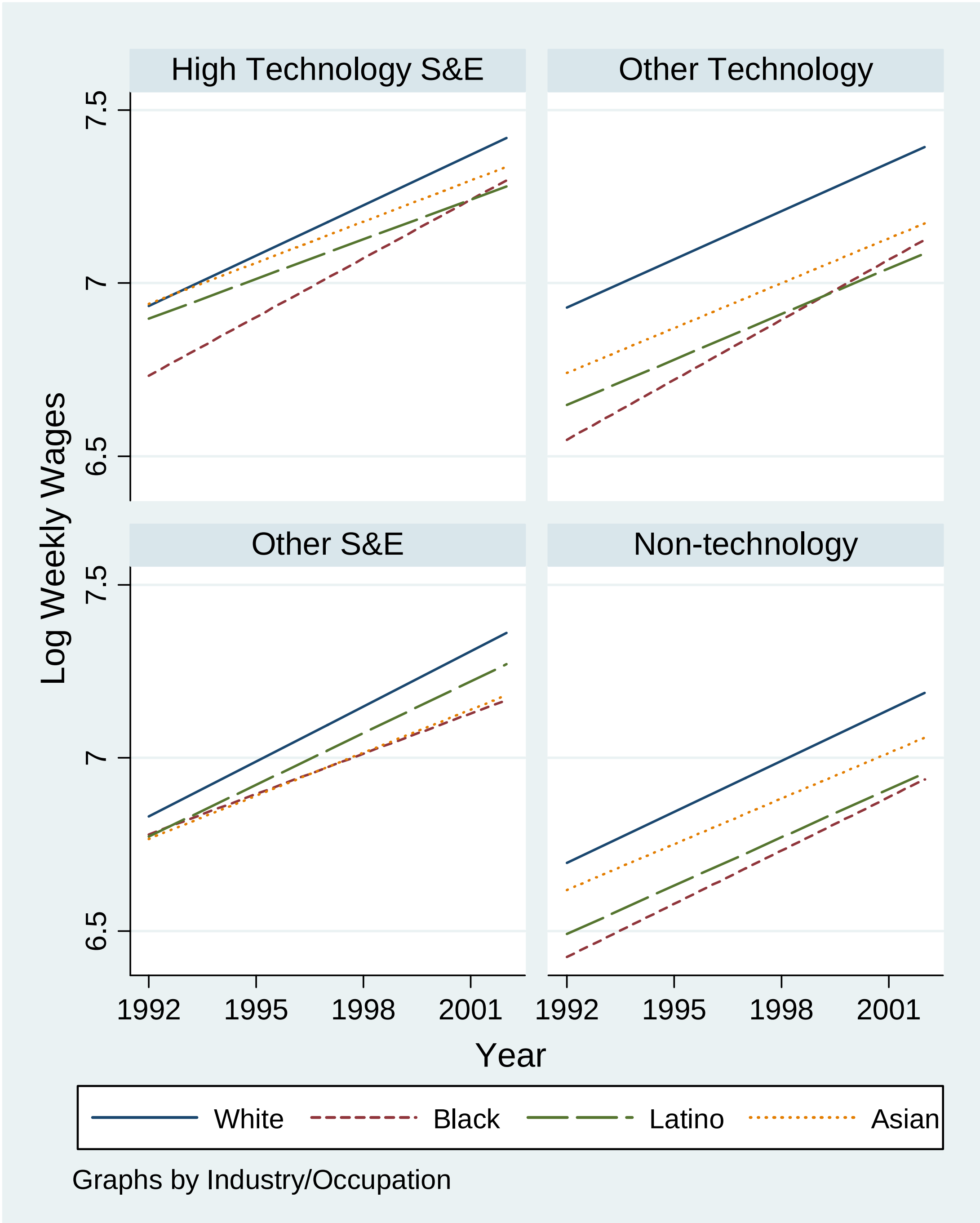


Figure 18: Logarithm of weekly wages (OLS predicted values) in each industry/occupation group, and for each racial group with graduate degrees

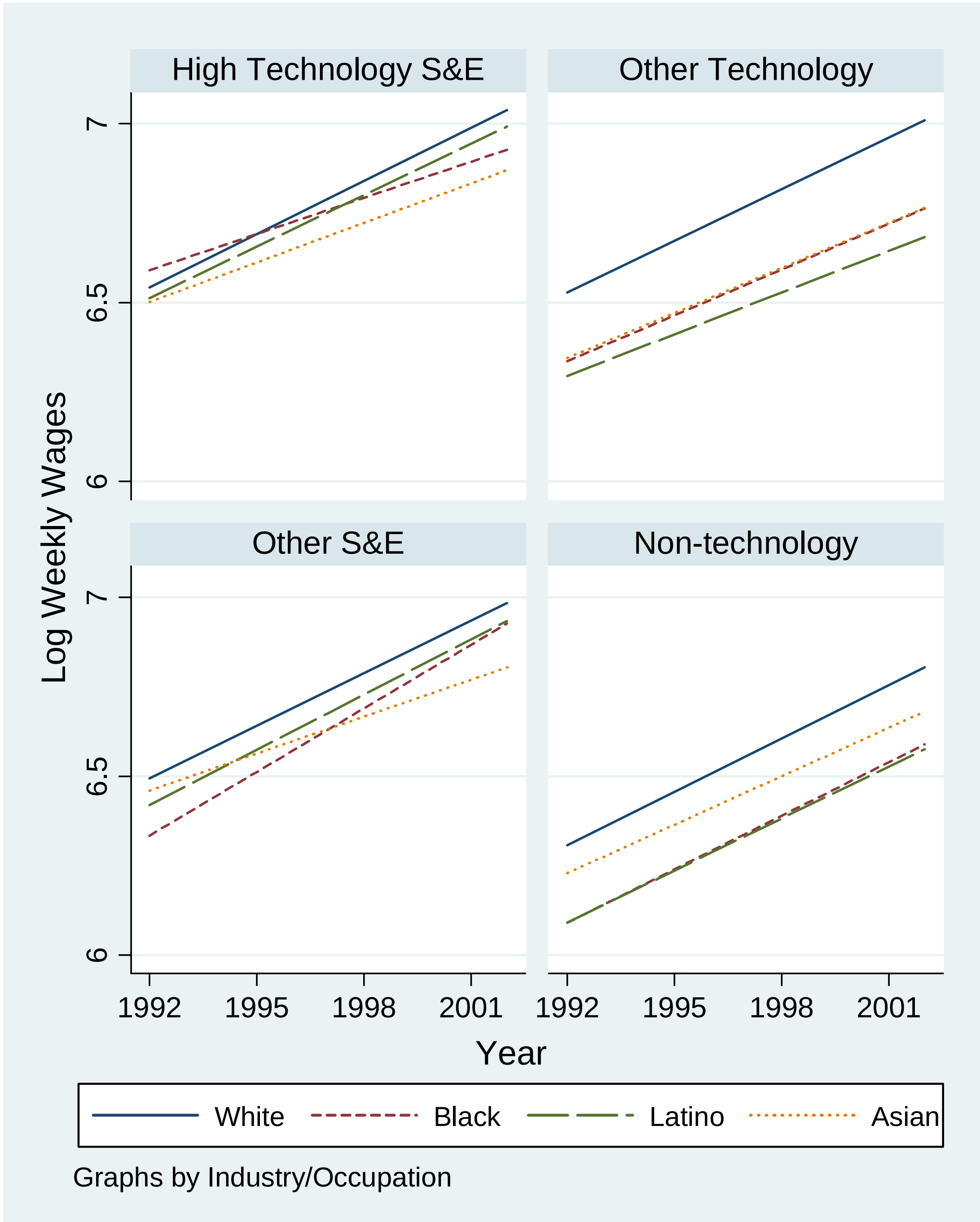


Figure 19: Logarithm of weekly wages (OLS predicted values) in each industry/occupation group, and for each racial group with bachelors degrees

7.8 Summary

The study finds that the effects of human capital (education and experience) in the determination of wages in high technology industries and science and engineering occupations vary for the different racial and ethnic groups. The analyses show that college education in particular graduate level education is more important in the determination of wages in high technology S & E jobs with the effects of race being less pronounced for these jobs compared to other jobs (white –minority gaps are smallest in these jobs). Wages increase at a decreasing rate with potential experience; however, the wage-experience profiles vary by race and education, with the profiles of Latino and white college graduates being most similar. However the black-white and the Asian-white wage gaps vary at different levels of experience. Since wages, wage-experience profiles and the wage gaps between whites and minorities vary with race/ethnicity, it is clear that wages are not determined solely by human capital considerations (merit) and market factors. Race plays an important role in determining wages, and the extent to which race is important varies with both time and the racial group being considered. The levels of wage disparities appear not have changed over the decade for blacks and Latinos. However, younger Asian workers and those with college education have greater parity with whites.

For non-science and engineering jobs whether in the high technology sector or outside, blacks and Latinos earn significantly lower wages than whites. Younger Asian males and those with graduate level education have greater parity with whites in the high technology sector. In non-science and engineering jobs, the influence of race is greater than that in science and engineering jobs with the roles of merit and market factors taking on lesser roles compared to science and engineering jobs.

CHAPTER 8

CONCLUSIONS

8.1 Introduction

This study is a systematic exploration of how human capital and race interact to affect employment and wage inequality in the knowledge economy. Although several studies have examined how human capital and technological changes affect inequality, few studies have addressed whether racial and ethnic disparities are exacerbated or ameliorated by these effects.

Previous studies have examined factors that influence under-representation in S&E fields of study or high technology industries separately, or looked at the growing levels of wage inequality in the more traditional divisions of industries or occupations (for example, manufacturing, services; or management, professional, and working class etc.). Other studies that examine the effects of technological change operationalize technology as the extent to which information and communications technologies are adopted (Bartel & Sicherman, 1999), or investments in capital goods (Acemoglu, 2002; Aghion & Howitt, 2002) with no attention paid to racial and ethnic differences of the impact. There is no consensus in the literature on the relative importance of the different factors, which contribute to under-representation and wage inequality. This study provides information on the relative importance of human capital and race in determining employment and wages in high technology industries and science and engineering occupations and shows how they influence racial and ethnic inequalities in these jobs. The multidisciplinary perspective results in information that can be used to improve the design and implementation of policies in education, economic development and labor market.

The study also updates earlier studies to show changes in the employment and wages of blacks and Hispanics in science and engineering occupations during the 1990s. Scientists and engineers are highly skilled individuals who drive the creation and use of knowledge to produce innovations that are important for productivity, competitiveness and growth. Thus, the study provides insights on how to maintain and grow the pool of S & E workers so that the exclusion of particular segments of the society, which limits the pool from which workers can be drawn, is minimized.

The study finds that human capital plays the more important role in determining employment and wages in S & E occupations when compared to race, and other demographic and labor market characteristics. This is even more so for S & E jobs in the high technology sector. Educational attainment increases the odds of employment in high technology S & E jobs to a greater extent compared to S & E jobs outside of the high technology sector. Therefore employment in S & E jobs in the high technology sector is highly competitive especially for white males.

Minorities and whites differ in the gains received from additional education and the differences vary with the industry/occupation group and with the minority group. Although blacks and Latinos have significantly larger gains compared to whites in several instances, these are often not sufficient to overcome the large initial gaps that exist between whites and minorities without high school level education. Regardless of educational attainment, blacks and Hispanic males have significantly lower odds of employment in high technology S & E jobs. However, racial wage gaps are smallest in high technology S & E jobs.

Blacks with graduate degrees do not have significantly different odds of working in S & E jobs outside of the high technology sector, or in other technology-sector jobs, compared to whites. However, older blacks have significantly lower wages than white counterparts in both S & E jobs outside of the high technology sector and in other technology-sector jobs. Younger black workers and those with bachelor's level education do not have significantly different wages in S & E jobs outside of the high technology sector, when compared to whites. The patterns suggest that blacks even with high levels of education have greater difficulties getting premium high technology S & E jobs compared to S & E jobs in academia or the utilities. Closure mechanisms (Tomaskovic-Devey, 1993) or the absence of networks or ties (Granovetter, 1983) may contribute to this.

Latinos, regardless of educational attainment have significantly lower odds of employment in both high technology industries and in S & E jobs compared to whites. In general, wage differences between whites and Latinos are not significant in high technology S & E jobs. However Latinos with graduate level education have significantly lower wages than whites in S & E jobs outside of the high technology sector. The wages of Latinos are significantly lower than whites in non-science and engineering jobs, which comprise a diverse set of jobs requiring different levels of skills and with different wage levels. The Latino-white wage gap is greatest in these jobs.

Asian males with graduate education are more likely to be employed high technology S & E jobs when compared to whites and other minorities and to other S & E jobs. Although competition and merit may play an important role in determining employment, the significantly higher odds and probabilities of employment of Asians in S & E suggest that networks and statistical discrimination may also be important. There are no significant differences between the odds of employment of Asians and whites with bachelor's level education or less in S & E jobs. Asian males have greater parity in wages with white males in S & E jobs compared to blacks and Hispanics. However for other technology sector jobs, only Asians with graduate education have wages that are not significantly different from whites, while those with lower levels of education have significantly lower wages.

8.2 Contributions to Knowledge

Many labor economic studies focus on evaluating the returns to education and wage inequalities at the broad, national level rather than on specific policy contexts. Although the major objective of this study was not to estimate a value for the returns to education, the goal of many labor market studies, this study contributes to efforts to improve the estimates of the returns to schooling. The study provides support for the view that point estimates of the returns may not necessarily be useful ((Manski, 1995), especially from the perspective of policy. The returns to schooling depend on many factors, and different values of the returns exist, depending on the demographic composition of the sample by race, age or other factors; industries or occupations; the level of education; region or time period under consideration. As a result, there is a wide variation in the estimates of returns to schooling, even when instrumental variables are used to overcome omitted variables bias.

The study does suggest the need to focus on specific contexts or sub-groups to determine the returns to education or the levels of wage inequality, rather than on broad groups or areas. Differences in outcomes may be masked when averages are looked at across large groups. The findings as well as the theory or explanations developed in one context or for one group may not hold for all groups (Boston, 1990). For example, in keeping with the findings of (Boston, 1990), the demands for skill and competition play major roles in determining employment for whites in high technology science and engineering jobs, but these are less so for blacks and Hispanics. The examination of specific contexts will increase our understanding of issues facing different groups in the society and improve policy-making.

Although the Current Population Survey is often used to study wage inequality in different groups, it is not often used to examine employment and wages of different racial and ethnic groups in S & E occupations. The dataset most commonly used to examine employment of scientists and engineers is the Scientists and Engineers Statistical Data System (SESTAT) of the NSF. This study shows that the CPS can be used as an alternative source of information on individual characteristics and wages for scientists and engineers. This study along with those that use different datasets can provide feedback to the entities that design surveys and collect data, with the result that national surveys such as the CPS can be revised and improved.

The comparative design as well as the non-parametric methodology used in the study provide support for alternative methodologies that are being explored to solve methodological problems, which plague many labor economic studies. This follows recent approaches such as kernel density estimates in non- or semi- parametric estimations (Black et al., 2006; Ulrick, 2005) that were used to obtain better estimates of the wage inequalities, and the returns to education.

8.3 Policy Implications

Public policy analyses often require contributions of knowledge from multiple disciplines in order to arrive at policies that work best in the long run and solve pressing problems. Thus policy makers and their advisors have to look at issues from different perspectives and consider the needs of constituents who may not necessarily be part of the majority group. This study uses an interdisciplinary perspective to investigate employment and wage differences and draws heavily on insights from labor economics and to a lesser extent on sociology. The analyses serve to increase our understanding of the distribution of employment and wages among different racial and ethnic groups and as the basis for recommendations to improve the design and implementation of policies.

The findings from this study indicate that an important policy goal would be to reduce the level of under-representation of blacks and Hispanics in S & E occupations, in particular within the high technology sector. The policies adopted should not only increase the supply of under-represented groups but also influence and increase market demand for black and Hispanic scientists and engineers, since the study shows that institutional barriers and not just education affect employment of non-Asian minoritites. The policies needed to address the policy problem and achieve these objectives cut across several policy areas and include policies in education and training, economic development, the labor market, and affirmative action. Specific policy recommendations as well as suggestions for future research are discussed in detail in the subsequent sections.

8.3.1 Education and Training

The findings show that education is the most important factor determining employment in high technology science and engineering jobs. Therefore Federal, state and local governments need to continue efforts to encourage non-Asian minorities and other groups to pursue education to both bachelors and graduate levels of college educaton. As other studies have recommended, in order to increase the opportunities for education and training, schools and colleges should be provided with greater resources (funding for recruitment and training of teachers, materials, equipment etc.) to expand the number of science and mathematics courses available so that enrollment levels can increase in the fields of study needed by the sector. Additional resources should be provided at all levels of the educational system (K-college) so that adequate numbers of students can be in the pipeline. In addition, more programs that provide grants, fellowships and other financial aid, which reduce investment costs in S & E education could be made available to minority students.

The results of this study show that white and Asian males benefit disproportionately from the jobs created in the high technology sector, when compared to blacks and Hispanics. One reason for this is that Asians are more likely to pursue graduate education compared to other groups (Black et al., 2006) and to study in science and engineering disciplines (National Science Foundation: Division of Science Resource Statistics, 2007; Tang, 2000). Although economists argue that individuals make choices on the careers to pursue, these choices are often constrained by historical, cultural and other institutional factors. Since these factors affect how benefits from high technology industry growth strategies are distributed, and to whom these are distributed, policy makers need to take these differences in educational choices into account. In addition, adjustments need to be made to address imbalances in cases where policies benefit one group disproportionately more than others, even though most policies will not result in an even distribution of benefits.

In order to increase the supply of non-Asian minority scientists and engineers, policies are needed to attract minority groups to science and engineering fields of study and to increase opportunities available for workers to be trained. As other studies have shown, special emphasis should be placed on the active recruitment of under-represented groups into mathematics and science courses in high schools and colleges, in addition to the recruitment efforts that target individuals, in general. Policies should include greater support for existing programs as well as the implementation of new programs that raise the profile and popularize science and mathematics at all levels of the school system.

Further, in order to increase the level of attraction to and retain students in science and engineering fields of study, STEM education could be coupled with exposure to the principles of entrepreneurship so that both the products of research and research itself are viewed as potential business opportunities at an early stage. Such an approach could be used to attract individuals who are more interested in business or entrepreneurial activities and might not normally be interested in science(Kauffman Foundation, 2007). In addition, students with an interest in S & E would be exposed to additional avenues to use S & E skills besides being in the academic environment. These programs can be used to attract not only under-represented minorities to S & E programs, but other groups as well since the need to increase interest in S&E goes beyond under-represented minorities. Policy makers and implementors need to be cognizant of the potential for disparities to develop in the formulation and implementation phases, so special attention needs to be placed on the inclusion of under-represented groups.

These findings provide support for previous studies, which indicate that non-Asian minorities are under-represented in S & E fields of study. Education and training to meet the demands of high technology industries have implications for education policies not only for disadvantaged minorities, but also for the wider society (Galbraith, 1998; Lazonick, 2001). These earlier studies argue that adequate levels of graduates in science and engineering fields are needed to maintain innovativeness and competitiveness in the global economy. Therefore this study supports earlier initiatives of public, private and non-profit groups, including Congress to increase the number of participants in science and engineering fields, not just the under-repesented minorities.

A recent review of Federal government programs identified 207 separate programs to improve science, technology, engineering and mathematics (STEM) education in the US in 2004 (Kuenzi, Matthews, & Mangan, 2006). The report identifies several new and existing initiatives that specifically aim to increase the number and skills of new and existing STEM teachers, increase the number of students studying science at the K-12, undergraduate and graduate levels and provide support for graduate and early career research (Kuenzi et al., 2006).

Education researchers, think tanks, industry and other interest groups on STEM education need to continue their efforts to maintain the level of interest and attention of policy-makers on this issue. This will ensure that adequate funds are appropriated to different programs and new programs are bought on stream. In addition, as Kuenzi et al

(2006) point out in their report, policy makers and implementers could aim for better co-ordination and synergy between different programs.

8.3.2 Economic Development

In keeping with policy recommendations made in the previous section to raise the level of educational attainment, in particular for minorities in science and engineering, economic developers should consider becoming facilitators of collaborative relationships between the education and private sectors to increase support for both science and technology education programs and for individuals in the K-20 system, as the literature on STEM education recommends. This support could include provision of funds to enhance teacher training in the delivery of science education to under-prepared students; resources for teaching aids and scholarships; and participation in mentoring and internship programs.

The study finds that whites and Asians have higher odds and probabilities of being employed in high technology industries and science and engineering jobs compared to similarly educated blacks and Hispanics. Therefore, economic developers and other policy makers need to consider policies that will increase the diversity of racial and ethnic groups in high technology industries and science and engineering occupations. Recruitment and attraction strategies should address the issue of diversity, and encourage individuals of different origins to come to the area, rather than ignore the issue. In addition, recruitment strategies should target businesses that focus on needs of different racial/ ethnic groups.

On the other hand, in order to overcome disparities due to exclusion and the absence of opportunity, states and regions can facilitate increased ownership and success of black-owned high technology businesses, since research has shown that black businesses are more likely to employ other blacks (Boston, 1995). This can be done through initiatives such as the Minority Business Enterprise programs, which address issues of capital and markets and which can be extended to include the building of inter-industry or university-industry partnerships. Special efforts can also be made to facilitate networking of blacks and other minorities.

Since the findings of this study support the general view that, high technology industries provide relatively few jobs compared to jobs available in other sectors, benefits are likely to come mainly from multiplier effects. Therefore a technology based strategy should include recruitment and support for businesses that complement those in the targeted technology sector. This recommendation is congruent with approaches that emanate from theories on agglomeration economies or cluster strategies. This approach will produce jobs that require a broader range of different skills. Further in keeping with previous studies, the strategies should pay special attention to the skills available in the population of the area and as well as attract new skills. Again this particular strategy is not targeted solely to minorities, so caveats have to be included that raise awareness on the potential for disparate outcomes among racial and ethnic groups.

8.3.3 Labor Market

The findings of this study suggest that business development and recruitment efforts aimed at high technology industries and firms are likely to benefit white and Asians males to a greater extent than black and Hispanic males. Since blacks and Hispanics tend not to pursue science and engineering, they are less likely to take advantage of the opportunities created and will have continued under-representation in these technology based jobs. Depending on the composition of the population if qualified workers are not present in the area, the jobs that are created may be filled by in-migrants. In-migration could lead to a shift in the demographics, for example, if there are relatively few Asians in the area, and many of the new workers are of Asian descent. Policy makers then have to be concerned that racial tensions do not develop, if locals feel that changes are taking place too rapidly, even if these perceptions are not true. Policy makers should openly address the issue of diversity and foster multiculturalism and diversity through leadership and specific programs. This approach is in keeping with that suggested by (Florida, 2002).

8.3.4 Affirmative Action Policies

The study shows that minority groups differ from whites and with each other in the gains from additional schooling or education and these gains vary in the different industry/occupation groups. Minority/white employment disparities in science and engineering occupations are different at each level of education, being greatest at the lowest level of education. Further, the study shows that differences in employment opportunities and wages persist in high technology industries and science and engineering occupations even when the levels of educational attainment are comparable. This finding supports the position that increasing the numbers of minority students who undertake and complete S & E studies is necessary but not sufficient to overcome existing disparities.

Institutional differences in racial and ethnic employment and wage outcomes indicate that affirmative action policies need to be continued. Policies that encourage employers to provide equal employment opportunities should be kept in place. In addition, policies that encourage diversity in the workplace, and which penalize discriminatory actions should be retained. Since many people have stereotypic images of different racial groups, increasing the diversity of different racial and ethnic group will contribute to breaking down stereotypes. However, other practices and policies would need to be put in place.

It is important to know that these disparities exist and the extent to which they exist, therefore policies that mandate the collection of longitudinal data related to the distribution of employment and wages among different racial and ethnic groups should be continued. Information collected can be used to raise awareness on the level of disparities so that individuals, businesses and other organizations can take steps to reduce these.

In addition, government agencies should continue to support research to identify and increase understanding of racial and ethnic disparities. Institutions can examine factors that result in different outcomes for individuals when both education and skills are held constant. If racial and ethnic disparities are found, steps can be taken at the institutional level to address factors that lead to differences.

Previous studies which show that affirmative action policies influence the behavior of firms and therefore affect labor market outcomes (Altonji & Blank, 1999) support these policy recommendation. Also, there is strong evidence that civil rights policies helped blacks and women in the 1970s (Altonji & Blank, 1999), although non-Hispanic white women benefitted to a greater extent than other groups.

8.4. Future Research

The study finds that the dynamics of employment in the two groups of S & E jobs differ depending on racial/ethnic group. There is need for greater understanding of the differences in choices, opportunities and other factors that influence decision making of different groups. Although there are a number of studies, for example (Tang, 2000; Xie & Goyette, 2003) on the career choices of different racial groups, further studies are needed to better understand the career choices of different minority groups specifically within the context of working in the high technology sector. The findings of econometric studies should be complemented with additional studies based on surveys or interviews, which will provide information on the sector, firms and individuals, which is not available in the CPS data. The studies would ty to get a better understanding of the aspirations, expectations and opportunities available to individuals. This includes for example, the effect of school quality on the skills developed in S & E; its influence on labor market outcomes; the influence of "soft skills" in hiring and promotion; and the role of social networks. In addition, the research agenda on S & E employment and wages could include the examination of firm specific factors related to hiring and promotion practices; and the effect of regional variables such as technology policies and the linkages if any, to patterns of employment and wages.

Further research should also be carried out to determine if the findings of this study hold up using alternative specifications of the research parameters. For example, research could cover the years after 2002; alternative definitions of high technology industries or science and engineering occupations; and the use of the North American Industrial Classification System (NAICS). Government agencies began switching to the NAICS towards the end of the decade of the 1990s, which provides more detailed and representative classification of industries in the economy compared to the previously used SIC system. This study used the older SIC system in the definition of high technology industries and many high technology industries may not have been correctly identified and classified under this system. Research based on the NAICS system should provide better representation of the patterns of employment in high technology industries.

The study used a narrow definition of science and engineering occupations and includes only individuals with occupations considered to be a scientist or engineer. It excludes many individuals involved in technology related activities or who use scientific and engineering knowledge extensively in the performance of job functions that are not reflected in the job title. This includes individuals in government administration, management, sales or legal activities. Further work needs to be done to redefine the concept of science and engineering occupations and identify the individuals involved to better reflect the importance and use of science and engineering skills. The information will provide a better indicator of the size ad scope of the problem and the level of urgency needed for policy intervention. Future work should also examine the issue of whether outcomes and the patterns of disparity are different for scientists compared to engineers.

This study focuses only on benefits relating to employment and wages. Further studies should be done to examine the distribution of benefits that relate to the acquisition of assets and the creation of wealth in high technology sector. These include studies on the participants of patent ownership, license or royalty payments, share ownership, equity investments and profit distribution through bonuses. In addition, the role of minority groups in venture capital investment should be examined.

In order to facilitate the expansion and ownership of minority owned high technology businesses, further studies are needed to understand the profile of owners and operators of these businesses as well as the characteristics of these businesses. For example are they university spin-offs; do they benefit from technology transfer and commercialization programs of universities; what are the levels of collaborations with university researchers, or other industries; are these the same as similar majority-owned high technology firm operators or do they face the same barriers as traditional minority firms? Previous studies identify that the observed employment and wage disparities are due in part to deficiencies in the education system, with the result that under-represented minorities are least likely to have the skills needed for S & E activities (assumed to be a large proportion of the residual in the wage model).

8.5 Concluding Comments

The study uses a multidisciplinary approach to examine employment and wage differences between different racial and ethnic groups and provides empirical information to improve the design and implementation of policy. It draws on theory and methodological approaches of labor economics to provide insights on the outcomes of economic development strategies. Its focus is on outcomes for individuals within the context of specific industries, rather than on firms or the outcomes for a regional economy. The study complements and provides empirical support for observations from previous studies as well as identifies potential avenues for future research in order to gain a better understanding of a complex social problem.

APPENDIX

VARIABLES, DEFINITIONS AND REGRESSION OUTPUT

Appendix Table 1. Trends in masters and doctoral degrees awarded in science and engineering fields by race/ ethnicity

	White		Black		Hispanic		Asian		Total
	Masters	Doctorate	Masters	Doctorate	Masters	Doctorate	Masters	Doctorate	
1997	53,769	13,828	4,870	615	3,220	658	6,180	2,529	85,669
1998	52,328	14,004	4,894	644	3,462	754	6,554	2,135	84,775
2000	49,850	13,443	5,492	710	3,746	729	6,990	1,706	82,666
2001	48,792	12,760	6,117	703	4,077	674	7,045	1,617	81,785
2002	48,410	11,913	6,133	685	4,089	724	6,814	1,616	80,384
2003	49,582	12,024	6,783	664	4,371	741	7,566	1,511	83,242
2004	54,045	12,018	7,433	746	5,062	715	8,559	1,491	90,069

Note: US citizens and permanent residents
Source: National Science Foundation, Division of Science Resource Statistics. (2007) Women, Minorities and Persons with Disabilities in Science and Engineering , 2007 Tables E-3 and F-11 (NSF 07-315)

Appendix Table 2. Comparison of high technology employment with total employment, 1992, 2002 and projected 2012

	Employment (000)			Employment Change	
	1992	2002	2012	Percent change 1992-2002	Percent change 2002-2012
Total non-farm wage and salary workers	109,526	131,063	152,690	19.7	16.5
High technology industry workers	13,415	14,422	16,067	7.5	11.4
Percentage high technology worke	12.2	11.0	10.5		

Source: Hecker (2005)

Appendix Table 3. Comparison of SIC Codes for Three Classifications High Technology Industries and Corresponding CPS Codes Used in the Study

BLS High/ Medium[12] (Hecker, 1999)	Human Capital (Chapple et al, 2004)	Georgia High/ Medium[13] (Walcott, 2001)	CPS Industry Codes	Industry Description
		018		Undercover food crops
	131	131	42	Crude petroleum & natural gas
	148		50	Non-metallic minerals services, except fuels
	211		130	Cigarettes
281*	281	281	192	Industrial inorganic chemicals
282	282	282	180	Plastics materials & synthetic resins
	283	283*	181	Drugs
284		284		Soaps, cleaners & toilet goods
285		285		Paint & allied products
286*	286	286	192	Industrial organic chemicals
287		287		Agricultural chemicals
289		289		Miscellaneous chemical products
291		291		Petroleum refining
		335		Nonferrous rolling. Drawing
348	348	348	292	Ordnance & accessories
351	351	351	310	Engines & turbines
353		353		Construction and related machinery
		354		Metal working machinery
355	355	355	331	Special industry machinery, except metalworking
356		356		General industrial machinery
357*	357	357 *	322, 321	Computer & office equipment
361		361*		Electric distribution equipment
362		362		Electrical industrial apparatus
		364		Electric lighting, wiring equipment
		365*		Audio-video equipment, pre-recorded records, tapes
366*	366	366*	341	Communications equipment
367*	367	367*	350	Electronic components & accessories
371		371		Motor vehicles and equipment
372*	372	372*	352	Aircraft parts
376*	376	376*	362	Guided missiles, space vehicles & parts
381*	381	381*	371	Search, detection, navigation, guidance equipment
382*	382	382*	371, 372	Laboratory apparatus & analytical, optical instruments
384	384	384*	372	Surgical, medical dental instruments
386	386	386*	380	Photographic equipment & supplies
		481*		Radio-telephone, telephone communications
	482	482*	442	Telegraph & message communication
		484*		Cable, other pay TV services
	489	489*	442	Communications services not elsewhere classified
	493		452	Combination electric & gas & other utility
	601		700, 701	Central reserve depository institutions
	631		711	Life insurance
	671		710	Holding offices
737*	737	737*	732	Computer programming & data processing services
		781		Motion picture, video production and allied services
		806		Hospitals, specialty and dialysis
		807		Medical laboratories
871	871	871*	882	Engineering , architectural , & surveying services
873*	873	873*	891	Research, development & testing services
874	874	874	892	Management & public relations services
	899	899	893	Other business services

[12] Industries with * designated high technology intensive industries

[13] Four-digit SIC codes adjusted to three-digit codes in keeping with data availability in March Current Population Survey. In a few cases, CPS data are available only at the two-digit level

Appendix Table 4. Science and Technology (S&T) Occupations based on OES[14] Code and CPS Code

OES Code	CPS Code	Occupational Title
13017		Engineering, math, natural sciences managers
22102	44	Aeronautical & astronautical engineers
22105	45	Metallurgists/metallurgical, ceramic &materials engineers
22108	46	Mining engineers
22111	47	Petroleum engineers
22114	48	Chemical engineers
22117	49	Nuclear engineers
22121	53	Civil engineers
22123	54	Agricultural engineers
22126	55	Electrical & electronic engineers
22127		Computer engineers
22128	56	Industrial engineers except safety
22132		Safety engineers, except mining
22135	57	Mechanical engineers
22138	58	Marine engineers
22199	59	All other engineers
24102	69	Physicists & astronomers
24105	73	Chemists except biochemists
24108	74	Atmospheric & space scientists
24111	75	Geologists, geophysicists & oceanographers
24199	76	All other physical scientists
24302	79	Foresters & conservation scientists
24305	77	Agricultural and food scientists
24308	78	Biological scientists
24311	83	Medical scientists
24399		All other life scientists
24999		All other natural scientists & related workers
25102	64	Systems analysts
25103		Database administrators
25105	229	Computer programmers
25111	233	Programmers, numerical tools & processors
25302	65	Operations/systems researchers & analysts except computer
25310	66	Mathematical scientists
25312	67	Statisticians
25319	68	All other mathematical scientists
25399		All other systems researchers
25999		All other computer scientists

Adapted from: Chapple et al 2004

[14] OES – Occupational Employment Statistics Code

Appendix Table 5. States in the Economic Regions Defined by the Bureau of Economic Analysis

New England	Mid East
Connecticut	Delaware
Maine	District of Columbia
Massachusetts	Maryland
New Hampshire	New Jersey
Rhode Island	New York
Vermont	Pennsylvania
Great Lakes	**Plains**
Illinois	Iowa
Indiana	Kansas
Michigan	Minnesota
Ohio	Missouri
Wisconsin	Nebraska
	North Dakota
	South Dakota
South East	**South West**
Alabama	Arizona
Arkansas	New México
Florida	Oklahoma
Georgia	Texas
Kentucky	
Louisiana	
Mississippi	
North Carolina	
South Carolina	
Tennessee	
Virginia	
West Virginia	
Rocky Mountain	**Far West**
Colorado	Alaska
Idaho	California
Montana	Hawaii
Utah	Nevada
Wyoming	Oregon
	Washington

Appendix Table 6. Regression Model and Tests for the Effects of Race and Education (High School, Bachelors and Post Graduate Education, Reference Group - Without High School Education; Model 5).

```
mlogit indocc hisch bachdeg postgrad exp2 exp2sq black latino asian blackhi blackbach /*
> */blackpost lathi latbach latpost asbach aspost married ownchild  house ftwork selfemp
union  /*
> */perio2 perio3 perio4 /*
> */cencity urbnocc neng mest glak plns swst rkmt fwst/*
> */ unemp  pscideg2[pweight=MARSUPWT] /*
> */if male==1 & A_REORGN~=9 & A_REORGN~=10, cluster(H_IDNUM)

(sum of wgt is   9.2293e+08)
Iteration 0:   log pseudolikelihood = -227235.66
Iteration 1:   log pseudolikelihood = -215887.41
Iteration 2:   log pseudolikelihood = -209666.84
Iteration 3:   log pseudolikelihood = -207259.33
Iteration 4:   log pseudolikelihood = -206267.06
Iteration 5:   log pseudolikelihood = -203682.35
Iteration 6:   log pseudolikelihood = -201708.23
Iteration 7:   log pseudolikelihood = -200576.07
Iteration 8:   log pseudolikelihood =    -200446
Iteration 9:   log pseudolikelihood = -200440.01
Iteration 10:  log pseudolikelihood = -200439.55
Iteration 11:  log pseudolikelihood = -200439.53
Iteration 12:  log pseudolikelihood = -200439.53

Multinomial logistic regression                   Number of obs   =     488707
                                                  Wald chi2(108)  =   21579.54
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -200439.53                 Pseudo R2       =     0.1179

                           (Std. Err. adjusted for 137784 clusters in H_IDNUM)
------------------------------------------------------------------------------
             |               Robust
      indocc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
htse         |
       hisch |   2.063913   .2107991     9.79   0.000     1.650755    2.477072
     bachdeg |   3.989677   .2104001    18.96   0.000     3.577301    4.402054
    postgrad |   4.115884    .212257    19.39   0.000     3.699868      4.5319
        exp2 |   -.010778   .0048968    -2.20   0.028    -.0203754   -.0011805
      exp2sq |  -.0002576   .0001211    -2.13   0.033     -.000495   -.0000202
       black |  -2.083266   .8059605    -2.58   0.010     -3.66292   -.5036124
      latino |  -3.082361   .7492863    -4.11   0.000    -4.550935   -1.613786
       asian |  -.5247515   .2104577    -2.49   0.013    -.9372411   -.1122619
     blackhi |   1.193935   .8177506     1.46   0.144    -.4088267    2.796697
   blackbach |   1.539235   .8065963     1.91   0.056    -.0416643    3.120135
   blackpost |   1.651618   .8257459     2.00   0.045     .0331859     3.27005
       lathi |   1.899494   .7580921     2.51   0.012     .4136613    3.385328
     latbach |   2.577824   .7529946     3.42   0.001     1.101982    4.053666
     latpost |   2.577351   .7658724     3.37   0.001     1.076269    4.078433
      asbach |   .5463403     .21425     2.55   0.011     .1264179    .9662626
      aspost |   1.250012   .2163348     5.78   0.000     .8260039    1.674021
     married |   .2663259   .0404542     6.58   0.000      .187037    .3456147
    ownchild |  -.0983649   .0301213    -3.27   0.001    -.1574015   -.0393283
       house |   .1639923   .0329574     4.98   0.000     .0993969    .2285877
      ftwork |   1.054697   .0331945    31.77   0.000     .9896369    1.119757
     selfemp |  -.7646903   .0486145   -15.73   0.000     -.859973   -.6694077
       union |  -1.718488   .1345951   -12.77   0.000     -1.98229   -1.454687
      perio2 |  -.6382939   .0477315   -13.37   0.000    -.7318459   -.5447419
      perio3 |  -.4493672   .0560427    -8.02   0.000    -.5592089   -.3395256
      perio4 |  -.4452739   .0536716    -8.30   0.000    -.5504684   -.3400795
     cencity |   .4474164   .0434061    10.31   0.000     .3623421    .5324907
     urbnocc |   .7095276   .0354626    20.01   0.000     .6400222    .7790329
        neng |   .5085394   .0541842     9.39   0.000     .4023402    .6147385
        mest |   .0180304   .0483271     0.37   0.709    -.0766891    .1127498
        glak |   .1857726   .0478127     3.89   0.000     .0920615    .2794837
        plns |  -.0906425   .0684875    -1.32   0.186    -.2248756    .0435906
        swst |   .3476679    .055479     6.27   0.000     .2389311    .4564046
        rkmt |   .2941854   .0675669     4.35   0.000     .1617567    .4266141
```

fwst	.3867218	.05251	7.36	0.000	.283804	.4896396
unemp	-.0142635	.0136721	-1.04	0.297	-.0410603	.0125334
pscideg2	2.544009	.3123317	8.15	0.000	1.93185	3.156168
_cons	-8.27844	.2606604	-31.76	0.000	-8.789325	-7.767555
htnse						
hisch	.5220769	.0351788	14.84	0.000	.4531277	.591026
bachdeg	.7976565	.0374534	21.30	0.000	.7242492	.8710638
postgrad	.6550435	.0434425	15.08	0.000	.5698978	.7401892
exp2	.0458118	.0026045	17.59	0.000	.0407071	.0509165
exp2sq	-.0009632	.0000553	-17.40	0.000	-.0010717	-.0008547
black	-.3144973	.0990863	-3.17	0.002	-.5087028	-.1202918
latino	-.3354003	.0557075	-6.02	0.000	-.4445849	-.2262156
asian	-.0232842	.0718315	-0.32	0.746	-.1640714	.1175031
blackhi	.2314208	.1041285	2.22	0.026	.0273328	.4355089
blackbach	.0257514	.1178379	0.22	0.827	-.2052066	.2567094
blackpost	.0257774	.1855044	0.14	0.889	-.3378046	.3893593
lathi	.0475974	.0635132	0.75	0.454	-.0768863	.172081
latbach	.0909315	.0794469	1.14	0.252	-.0647815	.2466444
latpost	.2286519	.1234621	1.85	0.064	-.0133293	.4706331
asbach	.0713332	.0919469	0.78	0.438	-.1088794	.2515459
aspost	.0733615	.121836	0.60	0.547	-.1654326	.3121556
married	.3103091	.0242236	12.81	0.000	.2628318	.3577865
ownchild	-.1010945	.0175992	-5.74	0.000	-.1355882	-.0666007
house	.2421152	.0187359	12.92	0.000	.2053934	.2788369
ftwork	.9750637	.0183776	53.06	0.000	.9390441	1.011083
selfemp	-.831211	.0302008	-27.52	0.000	-.8904035	-.7720186
union	-.2068715	.0403966	-5.12	0.000	-.2860473	-.1276957
perio2	-.5567075	.0257176	-21.65	0.000	-.607113	-.5063019
perio3	-.4208319	.0316292	-13.31	0.000	-.482824	-.3588398
perio4	-.5095096	.0297829	-17.11	0.000	-.567883	-.4511362
cencity	.1576119	.0238031	6.62	0.000	.1109586	.2042651
urbnocc	.3150513	.0191014	16.49	0.000	.2776132	.3524895
neng	.4361665	.0336084	12.98	0.000	.3702952	.5020378
mest	.0114598	.0279305	0.41	0.682	-.043283	.0662027
glak	.5336581	.0264747	20.16	0.000	.4817686	.5855476
plns	.1691115	.0384558	4.40	0.000	.0937395	.2444835
swst	.2518217	.0316003	7.97	0.000	.1898864	.3137571
rkmt	.0469114	.0421875	1.11	0.266	-.0357746	.1295973
fwst	.1606727	.0314059	5.12	0.000	.0991183	.2222271
unemp	.0265657	.0078658	3.38	0.001	.011149	.0419823
pscideg2	1.257096	.1805723	6.96	0.000	.903181	1.611011
_cons	-4.854336	.1020168	-47.58	0.000	-5.054285	-4.654387
nhtse						
hisch	1.835388	.184325	9.96	0.000	1.474118	2.196659
bachdeg	3.511542	.1834528	19.14	0.000	3.151982	3.871103
postgrad	3.506431	.1864771	18.80	0.000	3.140942	3.871919
exp2	.0117463	.0050658	2.32	0.020	.0018174	.0216752
exp2sq	-.0004999	.0001204	-4.15	0.000	-.0007358	-.0002639
black	-1.160375	.5084196	-2.28	0.022	-2.156859	-.1638912
latino	-1.887844	.4276714	-4.41	0.000	-2.726065	-1.049624
asian	-.2077594	.1863388	-1.11	0.265	-.5729767	.1574579
blackhi	.3439452	.5227232	0.66	0.511	-.6805736	1.368464
blackbach	.8720234	.515826	1.69	0.091	-.1389769	1.883024
blackpost	1.079427	.5347135	2.02	0.044	.0314075	2.127446
lathi	1.104529	.4408522	2.51	0.012	.2404745	1.968583
latbach	1.460105	.4352968	3.35	0.001	.6069385	2.313271
latpost	1.411795	.4633394	3.05	0.002	.5036662	2.319923
asbach	.2814358	.1978774	1.42	0.155	-.1063967	.6692682
aspost	1.080838	.2009829	5.38	0.000	.6869189	1.474757
married	.1777938	.0434623	4.09	0.000	.0926093	.2629783
ownchild	-.0730411	.0336763	-2.17	0.030	-.1390455	-.0070368
house	.2055825	.0344179	5.97	0.000	.1381247	.2730403
ftwork	1.032082	.0345856	29.84	0.000	.9642951	1.099868
selfemp	-2.22726	.0948596	-23.48	0.000	-2.413181	-2.041339
union	-.6558058	.0929235	-7.06	0.000	-.8379326	-.473679
perio2	-.6874136	.0486497	-14.13	0.000	-.7827653	-.5920619
perio3	-.586716	.0585572	-10.02	0.000	-.7014859	-.471946
perio4	-.6423882	.0567788	-11.31	0.000	-.7536725	-.5311038
cencity	.1974164	.0432057	4.57	0.000	.1127347	.2820981
urbnocc	.2800544	.0361466	7.75	0.000	.2092083	.3509004
neng	-.0328689	.0602676	-0.55	0.585	-.1509912	.0852535

```
        mest |   .0426079   .0490724     0.87   0.385    -.0535723    .1387881
        glak |  -.0375815   .0503939    -0.75   0.456    -.1363516    .0611887
        plns |   .0171216   .0636982     0.27   0.788    -.1077247    .1419678
        swst |   .1729303   .0587276     2.94   0.003     .0578263    .2880342
        rkmt |   .1141712   .0676888     1.69   0.092    -.0184965    .2468389
        fwst |   .0356354   .0563994     0.63   0.527    -.0749053    .1461761
       unemp |  -.0316967   .0151785    -2.09   0.037     -.061446   -.0019474
    pscideg2 |   2.061522    .320461     6.43   0.000      1.43343    2.689614
       _cons |   -7.42371    .256605   -28.93   0.000    -7.926646   -6.920773
------------------------------------------------------------------------------
(indocc==nhtnse is the base outcome)


. listcoef hisch bachdeg postgrad black latino asian blackhi blackbach blackpost/*
> */ lathi latbach latpost asbach aspost
(pweights not compatible with summarize; weights will be treated as aweights)

mlogit (N=488707): Factor Change in the Odds of indocc

Variable: hisch (sd=.49999619)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   1.54184    7.238   0.000   4.6732   2.1617
htse    -nhtse    |   0.22852    0.826   0.409   1.2567   1.1210
htse    -nhtnse   |   2.06391    9.791   0.000   7.8767   2.8065
htnse   -htse     |  -1.54184   -7.238   0.000   0.2140   0.4626
htnse   -nhtse    |  -1.31331   -7.019   0.000   0.2689   0.5186
htnse   -nhtnse   |   0.52208   14.841   0.000   1.6855   1.2983
nhtse   -htse     |  -0.22852   -0.826   0.409   0.7957   0.8920
nhtse   -htnse    |   1.31331    7.019   0.000   3.7185   1.9283
nhtse   -nhtnse   |   1.83539    9.957   0.000   6.2676   2.5035
nhtnse  -htse     |  -2.06391   -9.791   0.000   0.1270   0.3563
nhtnse  -htnse    |  -0.52208  -14.841   0.000   0.5933   0.7703
nhtnse  -nhtse    |  -1.83539   -9.957   0.000   0.1596   0.3994
----------------------------------------------------------------

Variable: bachdeg (sd=.41387698)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   3.19202   14.983   0.000  24.3376   3.7476
htse    -nhtse    |   0.47813    1.736   0.083   1.6131   1.2188
htse    -nhtnse   |   3.98968   18.962   0.000  54.0375   5.2134
htnse   -htse     |  -3.19202  -14.983   0.000   0.0411   0.2668
htnse   -nhtse    |  -2.71389  -14.556   0.000   0.0663   0.3252
htnse   -nhtnse   |   0.79766   21.297   0.000   2.2203   1.3912
nhtse   -htse     |  -0.47813   -1.736   0.083   0.6199   0.8205
nhtse   -htnse    |   2.71389   14.556   0.000  15.0878   3.0747
nhtse   -nhtnse   |   3.51154   19.141   0.000  33.4999   4.2774
nhtnse  -htse     |  -3.98968  -18.962   0.000   0.0185   0.1918
nhtnse  -htnse    |  -0.79766  -21.297   0.000   0.4504   0.7188
nhtnse  -nhtse    |  -3.51154  -19.141   0.000   0.0299   0.2338
----------------------------------------------------------------

Variable: postgrad (sd=.27124764)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   3.46084   16.069   0.000  31.8437   2.5568
htse    -nhtse    |   0.60945    2.189   0.029   1.8394   1.1798
htse    -nhtnse   |   4.11588   19.391   0.000  61.3064   3.0539
htnse   -htse     |  -3.46084  -16.069   0.000   0.0314   0.3911
htnse   -nhtse    |  -2.85139  -14.983   0.000   0.0578   0.4614
htnse   -nhtnse   |   0.65504   15.078   0.000   1.9252   1.1944
nhtse   -htse     |  -0.60945   -2.189   0.029   0.5436   0.8476
nhtse   -htnse    |   2.85139   14.983   0.000  17.3118   2.1672
```

```
nhtse   -nhtnse   |   3.50643   18.804   0.000  33.3291   2.5886
nhtnse  -htse     |  -4.11588  -19.391   0.000   0.0163   0.3274
nhtnse  -htnse    |  -0.65504  -15.078   0.000   0.5194   0.8372
nhtnse  -nhtse    |  -3.50643  -18.804   0.000   0.0300   0.3863
-----------------------------------------------------------------

Variable: black (sd=.31767825)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
htse    -htnse    |  -1.76877   -2.180   0.029   0.1705   0.5701
htse    -nhtse    |  -0.92289   -0.970   0.332   0.3974   0.7459
htse    -nhtnse   |  -2.08327   -2.585   0.010   0.1245   0.5159
htnse   -htse     |   1.76877    2.180   0.029   5.8636   1.7540
htnse   -nhtse    |   0.84588    1.633   0.102   2.3300   1.3083
htnse   -nhtnse   |  -0.31450   -3.174   0.002   0.7302   0.9049
nhtse   -htse     |   0.92289    0.970   0.332   2.5166   1.3407
nhtse   -htnse    |  -0.84588   -1.633   0.102   0.4292   0.7644
nhtse   -nhtnse   |  -1.16038   -2.282   0.022   0.3134   0.6917
nhtnse  -htse     |   2.08327    2.585   0.010   8.0307   1.9383
nhtnse  -htnse    |   0.31450    3.174   0.002   1.3696   1.1051
nhtnse  -nhtse    |   1.16038    2.282   0.022   3.1911   1.4457
-----------------------------------------------------------------

Variable: latino (sd=.31602115)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
htse    -htnse    |  -2.74696   -3.658   0.000   0.0641   0.4197
htse    -nhtse    |  -1.19452   -1.387   0.166   0.3029   0.6856
htse    -nhtnse   |  -3.08236   -4.114   0.000   0.0459   0.3775
htnse   -htse     |   2.74696    3.658   0.000  15.5952   2.3824
htnse   -nhtse    |   1.55244    3.602   0.000   4.7230   1.6333
htnse   -nhtnse   |  -0.33540   -6.021   0.000   0.7151   0.8994
nhtse   -htse     |   1.19452    1.387   0.166   3.3020   1.4586
nhtse   -htnse    |  -1.55244   -3.602   0.000   0.2117   0.6123
nhtse   -nhtnse   |  -1.88784   -4.414   0.000   0.1514   0.5507
nhtnse  -htse     |   3.08236    4.114   0.000  21.8098   2.6488
nhtnse  -htnse    |   0.33540    6.021   0.000   1.3985   1.1118
nhtnse  -nhtse    |   1.88784    4.414   0.000   6.6051   1.8159
-----------------------------------------------------------------

Variable: asian (sd=.1878823)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
htse    -htnse    |  -0.50147   -2.315   0.021   0.6056   0.9101
htse    -nhtse    |  -0.31699   -1.153   0.249   0.7283   0.9422
htse    -nhtnse   |  -0.52475   -2.493   0.013   0.5917   0.9061
htnse   -htse     |   0.50147    2.315   0.021   1.6511   1.0988
htnse   -nhtse    |   0.18448    0.930   0.352   1.2026   1.0353
htnse   -nhtnse   |  -0.02328   -0.324   0.746   0.9770   0.9956
nhtse   -htse     |   0.31699    1.153   0.249   1.3730   1.0614
nhtse   -htnse    |  -0.18448   -0.930   0.352   0.8315   0.9659
nhtse   -nhtnse   |  -0.20776   -1.115   0.265   0.8124   0.9617
nhtnse  -htse     |   0.52475    2.493   0.013   1.6900   1.1036
nhtnse  -htnse    |   0.02328    0.324   0.746   1.0236   1.0044
nhtnse  -nhtse    |   0.20776    1.115   0.265   1.2309   1.0398
-----------------------------------------------------------------

Variable: blackhi (sd=.24441205)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
htse    -htnse    |   0.96251    1.169   0.243   2.6183   1.2652
```

```
htse    -nhtse    |   0.84999    0.878   0.380   2.3396   1.2309
htse    -nhtnse   |   1.19394    1.460   0.144   3.3000   1.3389
htnse   -htse     |  -0.96251   -1.169   0.243   0.3819   0.7904
htnse   -nhtse    |  -0.11252   -0.211   0.833   0.8936   0.9729
htnse   -nhtnse   |   0.23142    2.222   0.026   1.2604   1.0582
nhtse   -htse     |  -0.84999   -0.878   0.380   0.4274   0.8124
nhtse   -htnse    |   0.11252    0.211   0.833   1.1191   1.0279
nhtse   -nhtnse   |   0.34395    0.658   0.511   1.4105   1.0877
nhtnse  -htse     |  -1.19394   -1.460   0.144   0.3030   0.7469
nhtnse  -htnse    |  -0.23142   -2.222   0.026   0.7934   0.9450
nhtnse  -nhtse    |  -0.34395   -0.658   0.511   0.7090   0.9194
----------------------------------------------------------------

Variable: blackbach (sd=.12394379)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   1.51348    1.859   0.063   4.5425   1.2063
htse    -nhtse    |   0.66721    0.698   0.485   1.9488   1.0862
htse    -nhtnse   |   1.53924    1.908   0.056   4.6610   1.2102
htnse   -htse     |  -1.51348   -1.859   0.063   0.2201   0.8290
htnse   -nhtse    |  -0.84627   -1.602   0.109   0.4290   0.9004
htnse   -nhtnse   |   0.02575    0.219   0.827   1.0261   1.0032
nhtse   -htse     |  -0.66721   -0.698   0.485   0.5131   0.9206
nhtse   -htnse    |   0.84627    1.602   0.109   2.3309   1.1106
nhtse   -nhtnse   |   0.87202    1.691   0.091   2.3917   1.1141
nhtnse  -htse     |  -1.53924   -1.908   0.056   0.2145   0.8263
nhtnse  -htnse    |  -0.02575   -0.219   0.827   0.9746   0.9968
nhtnse  -nhtse    |  -0.87202   -1.691   0.091   0.4181   0.8976
----------------------------------------------------------------

Variable: blackpost (sd=.0593159)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   1.62584    1.926   0.054   5.0827   1.1012
htse    -nhtse    |   0.57219    0.584   0.559   1.7721   1.0345
htse    -nhtnse   |   1.65162    2.000   0.045   5.2154   1.1029
htnse   -htse     |  -1.62584   -1.926   0.054   0.1967   0.9081
htnse   -nhtse    |  -1.05365   -1.875   0.061   0.3487   0.9394
htnse   -nhtnse   |   0.02578    0.139   0.889   1.0261   1.0015
nhtse   -htse     |  -0.57219   -0.584   0.559   0.5643   0.9666
nhtse   -htnse    |   1.05365    1.875   0.061   2.8681   1.0645
nhtse   -nhtnse   |   1.07943    2.019   0.044   2.9430   1.0661
nhtnse  -htse     |  -1.65162   -2.000   0.045   0.1917   0.9067
nhtnse  -htnse    |  -0.02578   -0.139   0.889   0.9746   0.9985
nhtnse  -nhtse    |  -1.07943   -2.019   0.044   0.3398   0.9380
----------------------------------------------------------------

Variable: lathi (sd=.20897501)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   1.85190    2.435   0.015   6.3719   1.4726
htse    -nhtse    |   0.79497    0.908   0.364   2.2144   1.1807
htse    -nhtnse   |   1.89949    2.506   0.012   6.6825   1.4873
htnse   -htse     |  -1.85190   -2.435   0.015   0.1569   0.6791
htnse   -nhtse    |  -1.05693   -2.375   0.018   0.3475   0.8018
htnse   -nhtnse   |   0.04760    0.749   0.454   1.0487   1.0100
nhtse   -htse     |  -0.79497   -0.908   0.364   0.4516   0.8469
nhtse   -htnse    |   1.05693    2.375   0.018   2.8775   1.2472
nhtse   -nhtnse   |   1.10453    2.505   0.012   3.0178   1.2596
nhtnse  -htse     |  -1.89949   -2.506   0.012   0.1496   0.6724
nhtnse  -htnse    |  -0.04760   -0.749   0.454   0.9535   0.9901
nhtnse  -nhtse    |  -1.10453   -2.505   0.012   0.3314   0.7939
----------------------------------------------------------------
```

Variable: latbach (sd=.1047087)

Odds comparing Alternative 1 to Alternative 2		b	z	P>|z|	e^b	e^bStdX
htse	-htnse	2.48689	3.289	0.001	12.0239	1.2974
htse	-nhtse	1.11772	1.288	0.198	3.0579	1.1242
htse	-nhtnse	2.57782	3.423	0.001	13.1685	1.3099
htnse	-htse	-2.48689	-3.289	0.001	0.0832	0.7707
htnse	-nhtse	-1.36917	-3.102	0.002	0.2543	0.8664
htnse	-nhtnse	0.09093	1.145	0.252	1.0952	1.0096
nhtse	-htse	-1.11772	-1.288	0.198	0.3270	0.8896
nhtse	-htnse	1.36917	3.102	0.002	3.9321	1.1542
nhtse	-nhtnse	1.46010	3.354	0.001	4.3064	1.1652
nhtnse	-htse	-2.57782	-3.423	0.001	0.0759	0.7634
nhtnse	-htnse	-0.09093	-1.145	0.252	0.9131	0.9905
nhtnse	-nhtse	-1.46010	-3.354	0.001	0.2322	0.8582

Variable: latpost (sd=.05277521)

Odds comparing Alternative 1 to Alternative 2		b	z	P>|z|	e^b	e^bStdX
htse	-htnse	2.34870	3.046	0.002	10.4719	1.1320
htse	-nhtse	1.16556	1.309	0.191	3.2077	1.0634
htse	-nhtnse	2.57735	3.365	0.001	13.1622	1.1457
htnse	-htse	-2.34870	-3.046	0.002	0.0955	0.8834
htnse	-nhtse	-1.18314	-2.486	0.013	0.3063	0.9395
htnse	-nhtnse	0.22865	1.852	0.064	1.2569	1.0121
nhtse	-htse	-1.16556	-1.309	0.191	0.3117	0.9403
nhtse	-htnse	1.18314	2.486	0.013	3.2646	1.0644
nhtse	-nhtnse	1.41179	3.047	0.002	4.1033	1.0774
nhtnse	-htse	-2.57735	-3.365	0.001	0.0760	0.8728
nhtnse	-htnse	-0.22865	-1.852	0.064	0.7956	0.9880
nhtnse	-nhtse	-1.41179	-3.047	0.002	0.2437	0.9282

Variable: asbach (sd=.10588233)

Odds comparing Alternative 1 to Alternative 2		b	z	P>|z|	e^b	e^bStdX
htse	-htnse	0.47501	2.102	0.036	1.6080	1.0516
htse	-nhtse	0.26490	0.933	0.351	1.3033	1.0284
htse	-nhtnse	0.54634	2.550	0.011	1.7269	1.0596
htnse	-htse	-0.47501	-2.102	0.036	0.6219	0.9509
htnse	-nhtse	-0.21010	-0.973	0.330	0.8105	0.9780
htnse	-nhtnse	0.07133	0.776	0.438	1.0739	1.0076
nhtse	-htse	-0.26490	-0.933	0.351	0.7673	0.9723
nhtse	-htnse	0.21010	0.973	0.330	1.2338	1.0225
nhtse	-nhtnse	0.28144	1.422	0.155	1.3250	1.0302
nhtnse	-htse	-0.54634	-2.550	0.011	0.5791	0.9438
nhtnse	-htnse	-0.07133	-0.776	0.438	0.9312	0.9925
nhtnse	-nhtse	-0.28144	-1.422	0.155	0.7547	0.9706

Variable: aspost (sd=.07728383)

Odds comparing Alternative 1 to Alternative 2		b	z	P>|z|	e^b	e^bStdX
htse	-htnse	1.17665	4.989	0.000	3.2435	1.0952
htse	-nhtse	0.16917	0.593	0.553	1.1843	1.0132
htse	-nhtnse	1.25001	5.778	0.000	3.4904	1.1014
htnse	-htse	-1.17665	-4.989	0.000	0.3083	0.9131
htnse	-nhtse	-1.00748	-4.419	0.000	0.3651	0.9251
htnse	-nhtnse	0.07336	0.602	0.547	1.0761	1.0057
nhtse	-htse	-0.16917	-0.593	0.553	0.8444	0.9870

```
nhtse   -htnse    |   1.00748    4.419   0.000   2.7387   1.0810
nhtse   -nhtnse   |   1.08084    5.378   0.000   2.9471   1.0871
nhtnse  -htse     |  -1.25001   -5.778   0.000   0.2865   0.9079
nhtnse  -htnse    |  -0.07336   -0.602   0.547   0.9293   0.9943
nhtnse  -nhtse    |  -1.08084   -5.378   0.000   0.3393   0.9199
----------------------------------------------------------------


. test [htse]black=[htse]latino

 ( 1)  [htse]black - [htse]latino = 0

           chi2(  1) =    0.89
         Prob > chi2 =    0.3456

. test [htse]black=[htse]asian

 ( 1)  [htse]black - [htse]asian = 0

           chi2(  1) =    3.55
         Prob > chi2 =    0.0594

. test [htse]asian=[htse]latino

 ( 1) - [htse]latino + [htse]asian = 0

           chi2(  1) =   10.99
         Prob > chi2 =    0.0009

.
. test [htnse]black=[htnse]latino

 ( 1)  [htnse]black - [htnse]latino = 0

           chi2(  1) =    0.04
         Prob > chi2 =    0.8402

. test [htnse]black=[htnse]asian

 ( 1)  [htnse]black - [htnse]asian = 0

           chi2(  1) =    5.79
         Prob > chi2 =    0.0161

. test [htnse]asian=[htnse]latino

 ( 1) - [htnse]latino + [htnse]asian = 0

           chi2(  1) =   12.33
         Prob > chi2 =    0.0004

.
. test [nhtse]black=[nhtse]latino

 ( 1)  [nhtse]black - [nhtse]latino = 0

           chi2(  1) =    1.41
         Prob > chi2 =    0.2352

. test [nhtse]black=[nhtse]asian

 ( 1)  [nhtse]black - [nhtse]asian = 0

           chi2(  1) =    3.11
         Prob > chi2 =    0.0776

. test [nhtse]asian=[nhtse]latino

 ( 1) - [nhtse]latino + [nhtse]asian = 0

           chi2(  1) =   13.04
         Prob > chi2 =    0.0003
```

```
. test [htse]black [htse]blackbach

 ( 1)  [htse]black = 0
 ( 2)  [htse]blackbach = 0

           chi2(  2) =   36.83
         Prob > chi2 =    0.0000

. test [htnse]black [htnse]blackbach

 ( 1)  [htnse]black = 0
 ( 2)  [htnse]blackbach = 0

           chi2(  2) =   28.85
         Prob > chi2 =    0.0000

. test [nhtse]black [nhtse]blackbach

 ( 1)  [nhtse]black = 0
 ( 2)  [nhtse]blackbach = 0

           chi2(  2) =   15.30
         Prob > chi2 =    0.0005

.
. test [htse]latino [htse]latbach

 ( 1)  [htse]latino = 0
 ( 2)  [htse]latbach = 0

           chi2(  2) =   57.39
         Prob > chi2 =    0.0000

. test [htnse]latino [htnse]latbach

 ( 1)  [htnse]latino = 0
 ( 2)  [htnse]latbach = 0

           chi2(  2) =   53.12
         Prob > chi2 =    0.0000

. test [nhtse]latino [nhtse]latbach

 ( 1)  [nhtse]latino = 0
 ( 2)  [nhtse]latbach = 0

           chi2(  2) =   46.80
         Prob > chi2 =    0.0000

.
. test [htse]asian [htse]asbach

 ( 1)  [htse]asian = 0
 ( 2)  [htse]asbach = 0

           chi2(  2) =    6.63
         Prob > chi2 =    0.0364

. test [htnse]asian [htnse]asbach

 ( 1)  [htnse]asian = 0
 ( 2)  [htnse]asbach = 0

           chi2(  2) =    0.61
         Prob > chi2 =    0.7357

. test [nhtse]asian [nhtse]asbach

 ( 1)  [nhtse]asian = 0
 ( 2)  [nhtse]asbach = 0

           chi2(  2) =    2.10
         Prob > chi2 =    0.3505
```

```
.
. test [htse]black [htse]blackpost

 ( 1)  [htse]black = 0
 ( 2)  [htse]blackpost = 0

           chi2(  2) =   12.47
         Prob > chi2 =    0.0020

. test [htnse]black [htnse]blackpost

 ( 1)  [htnse]black = 0
 ( 2)  [htnse]blackpost = 0

           chi2(  2) =   13.31
         Prob > chi2 =    0.0013

. test [nhtse]black [nhtse]blackpost

 ( 1)  [nhtse]black = 0
 ( 2)  [nhtse]blackpost = 0

           chi2(  2) =    5.43
         Prob > chi2 =    0.0662

.
. test [htse]latino [htse]latpost

 ( 1)  [htse]latino = 0
 ( 2)  [htse]latpost = 0

           chi2(  2) =   26.95
         Prob > chi2 =    0.0000

. test [htnse]latino [htnse]latpost

 ( 1)  [htnse]latino = 0
 ( 2)  [htnse]latpost = 0

           chi2(  2) =   37.71
         Prob > chi2 =    0.0000

. test [nhtse]latino [nhtse]latpost

 ( 1)  [nhtse]latino = 0
 ( 2)  [nhtse]latpost = 0

           chi2(  2) =   26.66
         Prob > chi2 =    0.0000

.
. test [htse]asian [htse]aspost

 ( 1)  [htse]asian = 0
 ( 2)  [htse]aspost = 0

           chi2(  2) =   70.38
         Prob > chi2 =    0.0000

. test [htnse]asian [htnse]aspost

 ( 1)  [htnse]asian = 0
 ( 2)  [htnse]aspost = 0

           chi2(  2) =    0.34
         Prob > chi2 =    0.8420

. test [nhtse]asian [nhtse]aspost

 ( 1)  [nhtse]asian = 0
 ( 2)  [nhtse]aspost = 0
```

```
          chi2(  2) =   74.84
        Prob > chi2 =    0.0000

.
. test [htse]blackbach=[htse]blackpost

 ( 1)  [htse]blackbach - [htse]blackpost = 0

          chi2(  1) =    0.29
        Prob > chi2 =    0.5885

. test [htnse]blackbach=[htnse]blackpost

 ( 1)  [htnse]blackbach - [htnse]blackpost = 0

          chi2(  1) =    0.00
        Prob > chi2 =    0.9853

. test [nhtse]blackbach=[nhtse]blackpost

 ( 1)  [nhtse]blackbach - [nhtse]blackpost = 0

          chi2(  1) =    1.19
        Prob > chi2 =    0.2747

.
. test [htse]latbach=[htse]latpost

 ( 1)  [htse]latbach - [htse]latpost = 0

          chi2(  1) =    0.00
        Prob > chi2 =    0.9839

. test [htnse]latbach=[htnse]latpost

 ( 1)  [htnse]latbach - [htnse]latpost = 0

          chi2(  1) =    1.16
        Prob > chi2 =    0.2820

. test [nhtse]latbach=[nhtse]latpost

 ( 1)  [nhtse]latbach - [nhtse]latpost = 0

          chi2(  1) =    0.06
        Prob > chi2 =    0.8000

.
. test [htse]asbach=[htse]aspost

 ( 1)  [htse]asbach - [htse]aspost = 0

          chi2(  1) =   50.02
        Prob > chi2 =    0.0000

. test [htnse]asbach=[htnse]aspost

 ( 1)  [htnse]asbach - [htnse]aspost = 0

          chi2(  1) =    0.00
        Prob > chi2 =    0.9937

. test [nhtse]asbach=[nhtse]aspost

 ( 1)  [nhtse]asbach - [nhtse]aspost = 0

          chi2(  1) =   48.33
        Prob > chi2 =    0.0000

.
. test [htse]bachdeg=[htse]postgrad

 ( 1)  [htse]bachdeg - [htse]postgrad = 0
```

```
          chi2(  1) =   12.42
        Prob > chi2 =    0.0004

. test [htnse]bachdeg=[htnse]postgrad

 ( 1)  [htnse]bachdeg - [htnse]postgrad = 0

          chi2(  1) =   21.59
        Prob > chi2 =    0.0000

. test [nhtse]bachdeg=[nhtse]postgrad

 ( 1)  [nhtse]bachdeg - [nhtse]postgrad = 0

          chi2(  1) =    0.01
        Prob > chi2 =    0.9171
```

Appendix Table 7. Regression Model and Tests for the Effects of Race and Education (No High School, Bachelors and Post Graduate Education, Reference Group - High School Education; Model 5A).

```
. mlogit indocc nohisch bachdeg postgrad exp2 exp2sq black latino asian blacknohi/*
> */ blackbach blackpost latnohi latbach latpost asbach aspost married ownchild  house
ftwork selfemp  union  /*
> */perio2 perio3 perio4 /*
> */cencity urbnocc neng mest glak plns swst rkmt fwst/*
> */ unemp  pscideg2[pweight=MARSUPWT] /*
> */if male==1 & A_REORGN~=9 & A_REORGN~=10, cluster(H_IDNUM)

(sum of wgt is   9.2293e+08)
Iteration 0:   log pseudolikelihood = -227235.66
Iteration 1:   log pseudolikelihood = -215887.41
Iteration 2:   log pseudolikelihood = -209666.84
Iteration 3:   log pseudolikelihood = -207259.33
Iteration 4:   log pseudolikelihood = -206267.06
Iteration 5:   log pseudolikelihood = -203682.35
Iteration 6:   log pseudolikelihood = -201708.23
Iteration 7:   log pseudolikelihood = -200576.07
Iteration 8:   log pseudolikelihood =    -200446
Iteration 9:   log pseudolikelihood = -200440.01
Iteration 10:  log pseudolikelihood = -200439.55
Iteration 11:  log pseudolikelihood = -200439.53
Iteration 12:  log pseudolikelihood = -200439.53

Multinomial logistic regression                   Number of obs   =     488707
                                                  Wald chi2(108)  =   21579.54
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -200439.53                 Pseudo R2       =     0.1179

                           (Std. Err. adjusted for 137784 clusters in H_IDNUM)
------------------------------------------------------------------------------
             |               Robust
      indocc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
htse         |
     nohisch |  -2.063913   .2107991    -9.79   0.000    -2.477072   -1.650755
     bachdeg |   1.925764   .0389829    49.40   0.000     1.849359    2.002169
    postgrad |    2.05197   .0461394    44.47   0.000     1.961539    2.142402
        exp2 |   -.010778   .0048968    -2.20   0.028    -.0203754   -.0011805
      exp2sq |  -.0002576   .0001211    -2.13   0.033     -.000495   -.0000202
       black |  -.8893309    .141912    -6.27   0.000    -1.167473   -.6111884
      latino |  -1.182866   .1213765    -9.75   0.000     -1.42076   -.9449724
       asian |  -.5247515   .2104577    -2.49   0.013    -.9372411   -.1122619
   blacknohi |  -1.193935   .8177506    -1.46   0.144    -2.796697    .4088267
   blackbach |   .3453001   .1693985     2.04   0.042     .0132852    .6773151
   blackpost |    .457683   .2286328     2.00   0.045     .0095709    .9057951
     latnohi |  -1.899494   .7580921    -2.51   0.012    -3.385328   -.4136613
     latbach |   .6783296   .1417394     4.79   0.000     .4005256    .9561336
     latpost |   .6778564    .199807     3.39   0.001     .2862419    1.069471
      asbach |   .5463403     .21425     2.55   0.011     .1264179    .9662626
      aspost |   1.250012   .2163348     5.78   0.000     .8260039    1.674021
     married |   .2663259   .0404542     6.58   0.000      .187037    .3456147
    ownchild |  -.0983649   .0301213    -3.27   0.001    -.1574015   -.0393283
       house |   .1639923   .0329574     4.98   0.000     .0993969    .2285877
      ftwork |   1.054697   .0331945    31.77   0.000     .9896369    1.119757
     selfemp |  -.7646903   .0486145   -15.73   0.000     -.859973   -.6694077
       union |  -1.718488   .1345951   -12.77   0.000     -1.98229   -1.454687
      perio2 |  -.6382939   .0477315   -13.37   0.000    -.7318459   -.5447419
      perio3 |  -.4493672   .0560427    -8.02   0.000    -.5592089   -.3395256
      perio4 |  -.4452739   .0536716    -8.30   0.000    -.5504684   -.3400795
     cencity |   .4474164   .0434061    10.31   0.000     .3623421    .5324907
     urbnocc |   .7095276   .0354626    20.01   0.000     .6400222    .7790329
        neng |   .5085394   .0541842     9.39   0.000     .4023402    .6147385
        mest |   .0180304   .0483271     0.37   0.709    -.0766891    .1127498
        glak |   .1857726   .0478127     3.89   0.000     .0920615    .2794837
        plns |  -.0906425   .0684875    -1.32   0.186    -.2248756    .0435906
        swst |   .3476679    .055479     6.27   0.000     .2389311    .4564046
        rkmt |   .2941854   .0675669     4.35   0.000     .1617567    .4266141
        fwst |   .3867218     .05251     7.36   0.000      .283804    .4896396
```

unemp	-.0142635	.0136721	-1.04	0.297	-.0410603	.0125334
pscideg2	2.544009	.3123317	8.15	0.000	1.93185	3.156168
_cons	-6.214527	.1712503	-36.29	0.000	-6.550171	-5.878882
htnse						
nohisch	-.5220769	.0351788	-14.84	0.000	-.591026	-.4531277
bachdeg	.2755796	.0196112	14.05	0.000	.2371424	.3140168
postgrad	.1329666	.0292514	4.55	0.000	.0756349	.1902983
exp2	.0458118	.0026045	17.59	0.000	.0407071	.0509165
exp2sq	-.0009632	.0000553	-17.40	0.000	-.0010717	-.0008547
black	-.0830765	.0398668	-2.08	0.037	-.161214	-.004939
latino	-.2878029	.0354751	-8.11	0.000	-.3573328	-.218273
asian	-.0232842	.0718315	-0.32	0.746	-.1640714	.1175031
blacknohi	-.2314208	.1041285	-2.22	0.026	-.4355089	-.0273328
blackbach	-.2056694	.0750193	-2.74	0.006	-.3527046	-.0586343
blackpost	-.2056435	.1624367	-1.27	0.206	-.5240135	.1127266
latnohi	-.0475974	.0635132	-0.75	0.454	-.172081	.0768863
latbach	.0433341	.0667044	0.65	0.516	-.0874041	.1740723
latpost	.1810546	.1158147	1.56	0.118	-.0459381	.4080472
asbach	.0713332	.0919469	0.78	0.438	-.1088794	.2515459
aspost	.0733615	.121836	0.60	0.547	-.1654326	.3121556
married	.3103091	.0242236	12.81	0.000	.2628318	.3577865
ownchild	-.1010945	.0175992	-5.74	0.000	-.1355882	-.0666007
house	.2421152	.0187359	12.92	0.000	.2053934	.2788369
ftwork	.9750637	.0183776	53.06	0.000	.9390441	1.011083
selfemp	-.831211	.0302008	-27.52	0.000	-.8904035	-.7720186
union	-.2068715	.0403966	-5.12	0.000	-.2860473	-.1276957
perio2	-.5567075	.0257176	-21.65	0.000	-.607113	-.5063019
perio3	-.4208319	.0316292	-13.31	0.000	-.482824	-.3588398
perio4	-.5095096	.0297829	-17.11	0.000	-.567883	-.4511362
cencity	.1576119	.0238031	6.62	0.000	.1109586	.2042651
urbnocc	.3150513	.0191014	16.49	0.000	.2776132	.3524895
neng	.4361665	.0336084	12.98	0.000	.3702952	.5020378
mest	.0114598	.0279305	0.41	0.682	-.043283	.0662027
glak	.5336581	.0264747	20.16	0.000	.4817686	.5855476
plns	.1691115	.0384558	4.40	0.000	.0937395	.2444835
swst	.2518217	.0316003	7.97	0.000	.1898864	.3137571
rkmt	.0469114	.0421875	1.11	0.266	-.0357746	.1295973
fwst	.1606727	.0314059	5.12	0.000	.0991183	.2222271
unemp	.0265657	.0078658	3.38	0.001	.011149	.0419823
pscideg2	1.257096	.1805723	6.96	0.000	.903181	1.611011
_cons	-4.332259	.098657	-43.91	0.000	-4.525623	-4.138895
nhtse						
nohisch	-1.835388	.184325	-9.96	0.000	-2.196659	-1.474118
bachdeg	1.676154	.0390155	42.96	0.000	1.599685	1.752623
postgrad	1.671042	.0493438	33.87	0.000	1.57433	1.767754
exp2	.0117463	.0050658	2.32	0.020	.0018174	.0216752
exp2sq	-.0004999	.0001204	-4.15	0.000	-.0007358	-.0002639
black	-.8164302	.1239937	-6.58	0.000	-1.059453	-.5734069
latino	-.7833154	.1080384	-7.25	0.000	-.9950667	-.5715641
asian	-.2077594	.1863388	-1.11	0.265	-.5729767	.1574579
blacknohi	-.3439452	.5227232	-0.66	0.511	-1.368464	.6805736
blackbach	.5280782	.1506959	3.50	0.000	.2327196	.8234369
blackpost	.7354816	.207277	3.55	0.000	.3292261	1.141737
latnohi	-1.104529	.4408522	-2.51	0.012	-1.968583	-.2404745
latbach	.3555757	.133526	2.66	0.008	.0938696	.6172817
latpost	.3072658	.2073126	1.48	0.138	-.0990594	.7135909
asbach	.2814358	.1978774	1.42	0.155	-.1063967	.6692682
aspost	1.080838	.2009829	5.38	0.000	.6869189	1.474757
married	.1777938	.0434623	4.09	0.000	.0926093	.2629783
ownchild	-.0730411	.0336763	-2.17	0.030	-.1390455	-.0070368
house	.2055825	.0344179	5.97	0.000	.1381247	.2730403
ftwork	1.032082	.0345856	29.84	0.000	.9642951	1.099868
selfemp	-2.22726	.0948596	-23.48	0.000	-2.413181	-2.041339
union	-.6558058	.0929235	-7.06	0.000	-.8379326	-.473679
perio2	-.6874136	.0486497	-14.13	0.000	-.7827653	-.5920619
perio3	-.586716	.0585572	-10.02	0.000	-.7014859	-.471946
perio4	-.6423882	.0567788	-11.31	0.000	-.7536725	-.5311038
cencity	.1974164	.0432057	4.57	0.000	.1127347	.2820981
urbnocc	.2800544	.0361466	7.75	0.000	.2092083	.3509004
neng	-.0328689	.0602676	-0.55	0.585	-.1509912	.0852535
mest	.0426079	.0490724	0.87	0.385	-.0535723	.1387881

```
        glak |  -.0375815   .0503939    -0.75   0.456    -.1363516    .0611887
        plns |   .0171216   .0636982     0.27   0.788    -.1077247    .1419678
        swst |   .1729303   .0587276     2.94   0.003     .0578263    .2880342
        rkmt |   .1141712   .0676888     1.69   0.092    -.0184965    .2468389
        fwst |   .0356354   .0563994     0.63   0.527    -.0749053    .1461761
       unemp |  -.0316967   .0151785    -2.09   0.037     -.061446   -.0019474
    pscideg2 |   2.061522    .320461     6.43   0.000      1.43343    2.689614
       _cons |  -5.588321   .1806024   -30.94   0.000    -5.942296   -5.234347
------------------------------------------------------------------------------
(indocc==nhtnse is the base outcome)

.
. listcoef black latino asian blacknohi blackbach blackpost/*
> */ latnohi latbach latpost asbach aspost
(pweights not compatible with summarize; weights will be treated as aweights)

mlogit (N=488707): Factor Change in the Odds of indocc


Variable: black (sd=.31767825)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.80625   -5.509   0.000   0.4465   0.7740
htse    -nhtse    |  -0.07290   -0.400   0.689   0.9297   0.9771
htse    -nhtnse   |  -0.88933   -6.267   0.000   0.4109   0.7539
htnse   -htse     |   0.80625    5.509   0.000   2.2395   1.2919
htnse   -nhtse    |   0.73335    5.652   0.000   2.0821   1.2623
htnse   -nhtnse   |  -0.08308   -2.084   0.037   0.9203   0.9740
nhtse   -htse     |   0.07290    0.400   0.689   1.0756   1.0234
nhtse   -htnse    |  -0.73335   -5.652   0.000   0.4803   0.7922
nhtse   -nhtnse   |  -0.81643   -6.584   0.000   0.4420   0.7715
nhtnse  -htse     |   0.88933    6.267   0.000   2.4335   1.3265
nhtnse  -htnse    |   0.08308    2.084   0.037   1.0866   1.0267
nhtnse  -nhtse    |   0.81643    6.584   0.000   2.2624   1.2961
----------------------------------------------------------------

Variable: latino (sd=.31602115)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.89506   -7.172   0.000   0.4086   0.7536
htse    -nhtse    |  -0.39955   -2.508   0.012   0.6706   0.8814
htse    -nhtnse   |  -1.18287   -9.745   0.000   0.3064   0.6881
htnse   -htse     |   0.89506    7.172   0.000   2.4475   1.3269
htnse   -nhtse    |   0.49551    4.387   0.000   1.6413   1.1695
htnse   -nhtnse   |  -0.28780   -8.113   0.000   0.7499   0.9131
nhtse   -htse     |   0.39955    2.508   0.012   1.4912   1.1346
nhtse   -htnse    |  -0.49551   -4.387   0.000   0.6093   0.8551
nhtse   -nhtnse   |  -0.78332   -7.250   0.000   0.4569   0.7807
nhtnse  -htse     |   1.18287    9.745   0.000   3.2637   1.4533
nhtnse  -htnse    |   0.28780    8.113   0.000   1.3335   1.0952
nhtnse  -nhtse    |   0.78332    7.250   0.000   2.1887   1.2809
----------------------------------------------------------------

Variable: asian (sd=.1878823)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.50147   -2.315   0.021   0.6056   0.9101
htse    -nhtse    |  -0.31699   -1.153   0.249   0.7283   0.9422
htse    -nhtnse   |  -0.52475   -2.493   0.013   0.5917   0.9061
htnse   -htse     |   0.50147    2.315   0.021   1.6511   1.0988
htnse   -nhtse    |   0.18448    0.930   0.352   1.2026   1.0353
htnse   -nhtnse   |  -0.02328   -0.324   0.746   0.9770   0.9956
nhtse   -htse     |   0.31699    1.153   0.249   1.3730   1.0614
nhtse   -htnse    |  -0.18448   -0.930   0.352   0.8315   0.9659
```

```
nhtse   -nhtnse   |  -0.20776   -1.115   0.265   0.8124   0.9617
nhtnse  -htse     |   0.52475    2.493   0.013   1.6900   1.1036
nhtnse  -htnse    |   0.02328    0.324   0.746   1.0236   1.0044
nhtnse  -nhtse    |   0.20776    1.115   0.265   1.2309   1.0398
----------------------------------------------------------------

Variable: blacknohi (sd=.17316938)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.96251   -1.169   0.243   0.3819   0.8465
htse    -nhtse    |  -0.84999   -0.878   0.380   0.4274   0.8631
htse    -nhtnse   |  -1.19394   -1.460   0.144   0.3030   0.8132
htnse   -htse     |   0.96251    1.169   0.243   2.6183   1.1814
htnse   -nhtse    |   0.11252    0.211   0.833   1.1191   1.0197
htnse   -nhtnse   |  -0.23142   -2.222   0.026   0.7934   0.9607
nhtse   -htse     |   0.84999    0.878   0.380   2.3396   1.1586
nhtse   -htnse    |  -0.11252   -0.211   0.833   0.8936   0.9807
nhtse   -nhtnse   |  -0.34395   -0.658   0.511   0.7090   0.9422
nhtnse  -htse     |   1.19394    1.460   0.144   3.3000   1.2297
nhtnse  -htnse    |   0.23142    2.222   0.026   1.2604   1.0409
nhtnse  -nhtse    |   0.34395    0.658   0.511   1.4105   1.0614
----------------------------------------------------------------

Variable: blackbach (sd=.12394379)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.55097    3.015   0.003   1.7349   1.0707
htse    -nhtse    |  -0.18278   -0.839   0.401   0.8330   0.9776
htse    -nhtnse   |   0.34530    2.038   0.042   1.4124   1.0437
htnse   -htse     |  -0.55097   -3.015   0.003   0.5764   0.9340
htnse   -nhtse    |  -0.73375   -4.439   0.000   0.4801   0.9131
htnse   -nhtnse   |  -0.20567   -2.742   0.006   0.8141   0.9748
nhtse   -htse     |   0.18278    0.839   0.401   1.2005   1.0229
nhtse   -htnse    |   0.73375    4.439   0.000   2.0829   1.0952
nhtse   -nhtnse   |   0.52808    3.504   0.000   1.6957   1.0676
nhtnse  -htse     |  -0.34530   -2.038   0.042   0.7080   0.9581
nhtnse  -htnse    |   0.20567    2.742   0.006   1.2283   1.0258
nhtnse  -nhtse    |  -0.52808   -3.504   0.000   0.5897   0.9366
----------------------------------------------------------------

Variable: blackpost (sd=.0593159)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.66333    2.425   0.015   1.9412   1.0401
htse    -nhtse    |  -0.27780   -0.945   0.345   0.7574   0.9837
htse    -nhtnse   |   0.45768    2.002   0.045   1.5804   1.0275
htnse   -htse     |  -0.66333   -2.425   0.015   0.5151   0.9614
htnse   -nhtse    |  -0.94113   -3.706   0.000   0.3902   0.9457
htnse   -nhtnse   |  -0.20564   -1.266   0.206   0.8141   0.9879
nhtse   -htse     |   0.27780    0.945   0.345   1.3202   1.0166
nhtse   -htnse    |   0.94113    3.706   0.000   2.5629   1.0574
nhtse   -nhtnse   |   0.73548    3.548   0.000   2.0865   1.0446
nhtnse  -htse     |  -0.45768   -2.002   0.045   0.6327   0.9732
nhtnse  -htnse    |   0.20564    1.266   0.206   1.2283   1.0123
nhtnse  -nhtse    |  -0.73548   -3.548   0.000   0.4793   0.9573
----------------------------------------------------------------

Variable: latnohi (sd=.22381026)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -1.85190   -2.435   0.015   0.1569   0.6607
```

```
htse    -nhtse    |  -0.79497   -0.908   0.364   0.4516   0.8370
htse    -nhtnse   |  -1.89949   -2.506   0.012   0.1496   0.6537
htnse   -htse     |   1.85190    2.435   0.015   6.3719   1.5136
htnse   -nhtse    |   1.05693    2.375   0.018   2.8775   1.2669
htnse   -nhtnse   |  -0.04760   -0.749   0.454   0.9535   0.9894
nhtse   -htse     |   0.79497    0.908   0.364   2.2144   1.1947
nhtse   -htnse    |  -1.05693   -2.375   0.018   0.3475   0.7893
nhtse   -nhtnse   |  -1.10453   -2.505   0.012   0.3314   0.7810
nhtnse  -htse     |   1.89949    2.506   0.012   6.6825   1.5298
nhtnse  -htnse    |   0.04760    0.749   0.454   1.0487   1.0107
nhtnse  -nhtse    |   1.10453    2.505   0.012   3.0178   1.2804
----------------------------------------------------------------

Variable: latbach (sd=.1047087)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.63500    4.163   0.000   1.8870   1.0687
htse    -nhtse    |   0.32275    1.695   0.090   1.3809   1.0344
htse    -nhtnse   |   0.67833    4.786   0.000   1.9706   1.0736
htnse   -htse     |  -0.63500   -4.163   0.000   0.5299   0.9357
htnse   -nhtse    |  -0.31224   -2.132   0.033   0.7318   0.9678
htnse   -nhtnse   |   0.04333    0.650   0.516   1.0443   1.0045
nhtse   -htse     |  -0.32275   -1.695   0.090   0.7242   0.9668
nhtse   -htnse    |   0.31224    2.132   0.033   1.3665   1.0332
nhtse   -nhtnse   |   0.35558    2.663   0.008   1.4270   1.0379
nhtnse  -htse     |  -0.67833   -4.786   0.000   0.5075   0.9314
nhtnse  -htnse    |  -0.04333   -0.650   0.516   0.9576   0.9955
nhtnse  -nhtse    |  -0.35558   -2.663   0.008   0.7008   0.9635
----------------------------------------------------------------

Variable: latpost (sd=.05277521)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.49680    2.322   0.020   1.6435   1.0266
htse    -nhtse    |   0.37059    1.346   0.178   1.4486   1.0198
htse    -nhtnse   |   0.67786    3.393   0.001   1.9697   1.0364
htnse   -htse     |  -0.49680   -2.322   0.020   0.6085   0.9741
htnse   -nhtse    |  -0.12621   -0.548   0.584   0.8814   0.9934
htnse   -nhtnse   |   0.18105    1.563   0.118   1.1985   1.0096
nhtse   -htse     |  -0.37059   -1.346   0.178   0.6903   0.9806
nhtse   -htnse    |   0.12621    0.548   0.584   1.1345   1.0067
nhtse   -nhtnse   |   0.30727    1.482   0.138   1.3597   1.0163
nhtnse  -htse     |  -0.67786   -3.393   0.001   0.5077   0.9649
nhtnse  -htnse    |  -0.18105   -1.563   0.118   0.8344   0.9905
nhtnse  -nhtse    |  -0.30727   -1.482   0.138   0.7355   0.9839
----------------------------------------------------------------

Variable: asbach (sd=.10588233)

Odds comparing    |
Alternative 1     |
to Alternative 2  |       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.47501    2.102   0.036   1.6080   1.0516
htse    -nhtse    |   0.26490    0.933   0.351   1.3033   1.0284
htse    -nhtnse   |   0.54634    2.550   0.011   1.7269   1.0596
htnse   -htse     |  -0.47501   -2.102   0.036   0.6219   0.9509
htnse   -nhtse    |  -0.21010   -0.973   0.330   0.8105   0.9780
htnse   -nhtnse   |   0.07133    0.776   0.438   1.0739   1.0076
nhtse   -htse     |  -0.26490   -0.933   0.351   0.7673   0.9723
nhtse   -htnse    |   0.21010    0.973   0.330   1.2338   1.0225
nhtse   -nhtnse   |   0.28144    1.422   0.155   1.3250   1.0302
nhtnse  -htse     |  -0.54634   -2.550   0.011   0.5791   0.9438
nhtnse  -htnse    |  -0.07133   -0.776   0.438   0.9312   0.9925
nhtnse  -nhtse    |  -0.28144   -1.422   0.155   0.7547   0.9706
----------------------------------------------------------------
```

```
Variable: aspost (sd=.07728383)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   1.17665    4.989   0.000   3.2435   1.0952
htse    -nhtse    |   0.16917    0.593   0.553   1.1843   1.0132
htse    -nhtnse   |   1.25001    5.778   0.000   3.4904   1.1014
htnse   -htse     |  -1.17665   -4.989   0.000   0.3083   0.9131
htnse   -nhtse    |  -1.00748   -4.419   0.000   0.3651   0.9251
htnse   -nhtnse   |   0.07336    0.602   0.547   1.0761   1.0057
nhtse   -htse     |  -0.16917   -0.593   0.553   0.8444   0.9870
nhtse   -htnse    |   1.00748    4.419   0.000   2.7387   1.0810
nhtse   -nhtnse   |   1.08084    5.378   0.000   2.9471   1.0871
nhtnse  -htse     |  -1.25001   -5.778   0.000   0.2865   0.9079
nhtnse  -htnse    |  -0.07336   -0.602   0.547   0.9293   0.9943
nhtnse  -nhtse    |  -1.08084   -5.378   0.000   0.3393   0.9199
----------------------------------------------------------------

.
.
. test [htse]black=[htse]latino

 ( 1)  [htse]black - [htse]latino = 0

           chi2(  1) =    2.65
         Prob > chi2 =    0.1035

. test [htse]black=[htse]asian

 ( 1)  [htse]black - [htse]asian = 0

           chi2(  1) =    2.11
         Prob > chi2 =    0.1468

. test [htse]asian=[htse]latino

 ( 1) - [htse]latino + [htse]asian = 0

           chi2(  1) =    7.73
         Prob > chi2 =    0.0054

.
. test [htnse]black=[htnse]latino

 ( 1)  [htnse]black - [htnse]latino = 0

           chi2(  1) =   17.08
         Prob > chi2 =    0.0000

. test [htnse]black=[htnse]asian

 ( 1)  [htnse]black - [htnse]asian = 0

           chi2(  1) =    0.55
         Prob > chi2 =    0.4563

. test [htnse]asian=[htnse]latino

 ( 1) - [htnse]latino + [htnse]asian = 0

           chi2(  1) =   11.65
         Prob > chi2 =    0.0006

.
. test [nhtse]black=[nhtse]latino

 ( 1)  [nhtse]black - [nhtse]latino = 0

           chi2(  1) =    0.04
         Prob > chi2 =    0.8344
```

```
. test [nhtse]black=[nhtse]asian

 ( 1)  [nhtse]black - [nhtse]asian = 0

           chi2(  1) =    7.61
         Prob > chi2 =    0.0058

. test [nhtse]asian=[nhtse]latino

 ( 1) - [nhtse]latino + [nhtse]asian = 0

           chi2(  1) =    7.73
         Prob > chi2 =    0.0054

.
. test [htse]black [htse]blackbach

 ( 1)  [htse]black = 0
 ( 2)  [htse]blackbach = 0

           chi2(  2) =   69.00
         Prob > chi2 =    0.0000

. test [htnse]black [htnse]blackbach

 ( 1)  [htnse]black = 0
 ( 2)  [htnse]blackbach = 0

           chi2(  2) =   22.93
         Prob > chi2 =    0.0000

. test [nhtse]black [nhtse]blackbach

 ( 1)  [nhtse]black = 0
 ( 2)  [nhtse]blackbach = 0

           chi2(  2) =   52.05
         Prob > chi2 =    0.0000

.
. test [htse]latino [htse]latbach

 ( 1)  [htse]latino = 0
 ( 2)  [htse]latbach = 0

           chi2(  2) =  130.47
         Prob > chi2 =    0.0000

. test [htnse]latino [htnse]latbach

 ( 1)  [htnse]latino = 0
 ( 2)  [htnse]latbach = 0

           chi2(  2) =   80.27
         Prob > chi2 =    0.0000

. test [nhtse]latino [nhtse]latbach

 ( 1)  [nhtse]latino = 0
 ( 2)  [nhtse]latbach = 0

           chi2(  2) =   77.67
         Prob > chi2 =    0.0000

.
. test [htse]asian [htse]asbach

 ( 1)  [htse]asian = 0
 ( 2)  [htse]asbach = 0

           chi2(  2) =    6.65
         Prob > chi2 =    0.0359
```

```
. test [htnse]asian [htnse]asbach

 ( 1)  [htnse]asian = 0
 ( 2)  [htnse]asbach = 0

           chi2(  2) =    0.64
         Prob > chi2 =    0.7244

. test [nhtse]asian [nhtse]asbach

 ( 1)  [nhtse]asian = 0
 ( 2)  [nhtse]asbach = 0

           chi2(  2) =    2.08
         Prob > chi2 =    0.3530

.
. test [htse]black [htse]blackpost

 ( 1)  [htse]black = 0
 ( 2)  [htse]blackpost = 0

           chi2(  2) =   44.90
         Prob > chi2 =    0.0000

. test [htnse]black [htnse]blackpost

 ( 1)  [htnse]black = 0
 ( 2)  [htnse]blackpost = 0

           chi2(  2) =    7.64
         Prob > chi2 =    0.0220

. test [nhtse]black [nhtse]blackpost

 ( 1)  [nhtse]black = 0
 ( 2)  [nhtse]blackpost = 0

           chi2(  2) =   43.54
         Prob > chi2 =    0.0000

.
. test [htse]latino [htse]latpost

 ( 1)  [htse]latino = 0
 ( 2)  [htse]latpost = 0

           chi2(  2) =  104.22
         Prob > chi2 =    0.0000

. test [htnse]latino [htnse]latpost

 ( 1)  [htnse]latino = 0
 ( 2)  [htnse]latpost = 0

           chi2(  2) =   66.46
         Prob > chi2 =    0.0000

. test [nhtse]latino [nhtse]latpost

 ( 1)  [nhtse]latino = 0
 ( 2)  [nhtse]latpost = 0

           chi2(  2) =   59.17
         Prob > chi2 =    0.0000

.
. test [htse]asian [htse]aspost

 ( 1)  [htse]asian = 0
 ( 2)  [htse]aspost = 0

           chi2(  2) =   70.75
```

```
        Prob > chi2 =    0.0000

. test [htnse]asian [htnse]aspost

 ( 1)  [htnse]asian = 0
 ( 2)  [htnse]aspost = 0

          chi2(  2) =    0.36
        Prob > chi2 =    0.8336

. test [nhtse]asian [nhtse]aspost

 ( 1)  [nhtse]asian = 0
 ( 2)  [nhtse]aspost = 0

          chi2(  2) =   74.94
        Prob > chi2 =    0.0000

.
. test [htse]blackbach=[htse]blackpost

 ( 1)  [htse]blackbach - [htse]blackpost = 0

          chi2(  1) =    0.30
        Prob > chi2 =    0.5810

. test [htnse]blackbach=[htnse]blackpost

 ( 1)  [htnse]blackbach - [htnse]blackpost = 0

          chi2(  1) =    0.00
        Prob > chi2 =    0.9999

. test [nhtse]blackbach=[nhtse]blackpost

 ( 1)  [nhtse]blackbach - [nhtse]blackpost = 0

          chi2(  1) =    1.20
        Prob > chi2 =    0.2733

.
. test [htse]latbach=[htse]latpost

 ( 1)  [htse]latbach - [htse]latpost = 0

          chi2(  1) =    0.00
        Prob > chi2 =    0.9979

. test [htnse]latbach=[htnse]latpost

 ( 1)  [htnse]latbach - [htnse]latpost = 0

          chi2(  1) =    1.23
        Prob > chi2 =    0.2675

. test [nhtse]latbach=[nhtse]latpost

 ( 1)  [nhtse]latbach - [nhtse]latpost = 0

          chi2(  1) =    0.06
        Prob > chi2 =    0.8040

.
. test [htse]asbach=[htse]aspost

 ( 1)  [htse]asbach - [htse]aspost = 0

          chi2(  1) =   50.04
        Prob > chi2 =    0.0000

. test [htnse]asbach=[htnse]aspost

 ( 1)  [htnse]asbach - [htnse]aspost = 0
```

```
          chi2(  1) =    0.00
        Prob > chi2 =    0.9866

. test [nhtse]asbach=[nhtse]aspost

 ( 1)  [nhtse]asbach - [nhtse]aspost = 0

          chi2(  1) =   48.34
        Prob > chi2 =    0.0000

.
. test [htse]bachdeg=[htse]postgrad

 ( 1)  [htse]bachdeg - [htse]postgrad = 0

          chi2(  1) =   12.34
        Prob > chi2 =    0.0004

. test [htnse]bachdeg=[htnse]postgrad

 ( 1)  [htnse]bachdeg - [htnse]postgrad = 0

          chi2(  1) =   21.87
        Prob > chi2 =    0.0000

. test [nhtse]bachdeg=[nhtse]postgrad

 ( 1)  [nhtse]bachdeg - [nhtse]postgrad = 0

          chi2(  1) =    0.01
        Prob > chi2 =    0.9039

.
```

Appendix Table 8. Regression Model and Tests for the Effects of Race and Education (No High School, High School Post Graduate Education, Reference Group – Bachelors Education; Model 5B).

```
mlogit indocc nohisch hisch postgrad exp2 exp2sq black latino asian blacknohi blackhi/*
> */ blackpost latnohi lathi latpost asnocoll aspost married ownchild  house ftwork
selfemp union  /*
> */perio2 perio3 perio4 /*
> */cencity urbnocc neng mest glak plns swst rkmt fwst/*
> */ unemp  pscideg2[pweight=MARSUPWT] /*
> */if male==1 & A_REORGN~=9 & A_REORGN~=10, cluster(H_IDNUM)

(sum of wgt is   9.2293e+08)
Iteration 0:   log pseudolikelihood = -227235.66
Iteration 1:   log pseudolikelihood = -215887.41
Iteration 2:   log pseudolikelihood = -209666.84
Iteration 3:   log pseudolikelihood = -207259.33
Iteration 4:   log pseudolikelihood = -206267.06
Iteration 5:   log pseudolikelihood = -203682.35
Iteration 6:   log pseudolikelihood = -201708.23
Iteration 7:   log pseudolikelihood = -200576.07
Iteration 8:   log pseudolikelihood =    -200446
Iteration 9:   log pseudolikelihood = -200440.01
Iteration 10:  log pseudolikelihood = -200439.55
Iteration 11:  log pseudolikelihood = -200439.53
Iteration 12:  log pseudolikelihood = -200439.53

Multinomial logistic regression                   Number of obs   =     488707
                                                  Wald chi2(108)  =   21579.54
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -200439.53                 Pseudo R2       =     0.1179

                           (Std. Err. adjusted for 137784 clusters in H_IDNUM)
------------------------------------------------------------------------------
             |               Robust
      indocc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
htse         |
     nohisch |  -3.989677   .2104001   -18.96   0.000    -4.402054   -3.577301
       hisch |  -1.925764   .0389829   -49.40   0.000    -2.002169   -1.849359
    postgrad |   .1262065   .0359301     3.51   0.000     .0557848    .1966282
        exp2 |   -.010778   .0048968    -2.20   0.028    -.0203754   -.0011805
      exp2sq |  -.0002576   .0001211    -2.13   0.033     -.000495   -.0000202
       black |  -.5440307   .0966436    -5.63   0.000    -.7334487   -.3546128
      latino |  -.5045365   .0789116    -6.39   0.000    -.6592004   -.3498725
       asian |   .0215888   .0865735     0.25   0.803    -.1480923    .1912698
   blacknohi |  -1.539235   .8065963    -1.91   0.056    -3.120135    .0416643
     blackhi |  -.3453001   .1693985    -2.04   0.042    -.6773151   -.0132852
   blackpost |   .1123828   .2036194     0.55   0.581    -.2867039    .5114696
     latnohi |  -2.577824   .7529946    -3.42   0.001    -4.053666   -1.101982
       lathi |  -.6783296   .1417394    -4.79   0.000    -.9561336   -.4005256
     latpost |  -.0004732   .1770527    -0.00   0.998    -.3474901    .3465437
    asnocoll |  -.5463403     .21425    -2.55   0.011    -.9662626   -.1264179
      aspost |   .7036721   .0994779     7.07   0.000      .508699    .8986453
     married |   .2663259   .0404542     6.58   0.000      .187037    .3456147
    ownchild |  -.0983649   .0301213    -3.27   0.001    -.1574015   -.0393283
       house |   .1639923   .0329574     4.98   0.000     .0993969    .2285877
      ftwork |   1.054697   .0331945    31.77   0.000     .9896369    1.119757
     selfemp |  -.7646903   .0486145   -15.73   0.000     -.859973   -.6694077
       union |  -1.718488   .1345951   -12.77   0.000     -1.98229   -1.454687
      perio2 |  -.6382939   .0477315   -13.37   0.000    -.7318459   -.5447419
      perio3 |  -.4493672   .0560427    -8.02   0.000    -.5592089   -.3395256
      perio4 |  -.4452739   .0536716    -8.30   0.000    -.5504684   -.3400795
     cencity |   .4474164   .0434061    10.31   0.000     .3623421    .5324907
     urbnocc |   .7095276   .0354626    20.01   0.000     .6400222    .7790329
        neng |   .5085394   .0541842     9.39   0.000     .4023402    .6147385
        mest |   .0180304   .0483271     0.37   0.709    -.0766891    .1127498
        glak |   .1857726   .0478127     3.89   0.000     .0920615    .2794837
        plns |  -.0906425   .0684875    -1.32   0.186    -.2248756    .0435906
        swst |   .3476679    .055479     6.27   0.000     .2389311    .4564046
        rkmt |   .2941854   .0675669     4.35   0.000     .1617567    .4266141
```

fwst	.3867218	.05251	7.36	0.000	.283804	.4896396
unemp	-.0142635	.0136721	-1.04	0.297	-.0410603	.0125334
pscideg2	2.544009	.3123317	8.15	0.000	1.93185	3.156168
_cons	-4.288763	.1712845	-25.04	0.000	-4.624474	-3.953051
htnse						
nohisch	-.7976565	.0374534	-21.30	0.000	-.8710638	-.7242492
hisch	-.2755796	.0196112	-14.05	0.000	-.3140168	-.2371424
postgrad	-.142613	.030494	-4.68	0.000	-.2023802	-.0828458
exp2	.0458118	.0026045	17.59	0.000	.0407071	.0509165
exp2sq	-.0009632	.0000553	-17.40	0.000	-.0010717	-.0008547
black	-.2887459	.0655089	-4.41	0.000	-.417141	-.1603508
latino	-.2444688	.0582616	-4.20	0.000	-.3586595	-.1302781
asian	.0480491	.0730807	0.66	0.511	-.0951864	.1912846
blacknohi	-.0257514	.1178379	-0.22	0.827	-.2567094	.2052066
blackhi	.2056694	.0750193	2.74	0.006	.0586343	.3527046
blackpost	.000026	.1697986	0.00	1.000	-.3327732	.3328252
latnohi	-.0909315	.0794469	-1.14	0.252	-.2466444	.0647815
lathi	-.0433341	.0667044	-0.65	0.516	-.1740723	.0874041
latpost	.1377205	.1241898	1.11	0.267	-.1056871	.381128
asnocoll	-.0713332	.0919469	-0.78	0.438	-.2515459	.1088794
aspost	.0020283	.1208699	0.02	0.987	-.2348723	.2389289
married	.3103091	.0242236	12.81	0.000	.2628318	.3577865
ownchild	-.1010945	.0175992	-5.74	0.000	-.1355882	-.0666007
house	.2421152	.0187359	12.92	0.000	.2053934	.2788369
ftwork	.9750637	.0183776	53.06	0.000	.9390441	1.011083
selfemp	-.831211	.0302008	-27.52	0.000	-.8904035	-.7720186
union	-.2068715	.0403966	-5.12	0.000	-.2860473	-.1276957
perio2	-.5567075	.0257176	-21.65	0.000	-.607113	-.5063019
perio3	-.4208319	.0316292	-13.31	0.000	-.482824	-.3588398
perio4	-.5095096	.0297829	-17.11	0.000	-.567883	-.4511362
cencity	.1576119	.0238031	6.62	0.000	.1109586	.2042651
urbnocc	.3150513	.0191014	16.49	0.000	.2776132	.3524895
neng	.4361665	.0336084	12.98	0.000	.3702952	.5020378
mest	.0114598	.0279305	0.41	0.682	-.043283	.0662027
glak	.5336581	.0264747	20.16	0.000	.4817686	.5855476
plns	.1691115	.0384558	4.40	0.000	.0937395	.2444835
swst	.2518217	.0316003	7.97	0.000	.1898864	.3137571
rkmt	.0469114	.0421875	1.11	0.266	-.0357746	.1295973
fwst	.1606727	.0314059	5.12	0.000	.0991183	.2222271
unemp	.0265657	.0078658	3.38	0.001	.011149	.0419823
pscideg2	1.257096	.1805723	6.96	0.000	.903181	1.611011
_cons	-4.05668	.0997899	-40.65	0.000	-4.252264	-3.861095
nhtse						
nohisch	-3.511542	.1834528	-19.14	0.000	-3.871103	-3.151982
hisch	-1.676154	.0390155	-42.96	0.000	-1.752623	-1.599685
postgrad	-.0051118	.0423582	-0.12	0.904	-.0881323	.0779087
exp2	.0117463	.0050658	2.32	0.020	.0018174	.0216752
exp2sq	-.0004999	.0001204	-4.15	0.000	-.0007358	-.0002639
black	-.2883519	.0903616	-3.19	0.001	-.4654573	-.1112465
latino	-.4277397	.0818125	-5.23	0.000	-.5880893	-.2673901
asian	.0736764	.0989852	0.74	0.457	-.1203312	.2676839
blacknohi	-.8720234	.515826	-1.69	0.091	-1.883024	.1389769
blackhi	-.5280782	.1506959	-3.50	0.000	-.8234369	-.2327196
blackpost	.2074034	.1893235	1.10	0.273	-.1636639	.5784707
latnohi	-1.460105	.4352968	-3.35	0.001	-2.313271	-.6069385
lathi	-.3555757	.133526	-2.66	0.008	-.6172817	-.0938696
latpost	-.0483099	.1946823	-0.25	0.804	-.4298802	.3332603
asnocoll	-.2814358	.1978774	-1.42	0.155	-.6692682	.1063967
aspost	.7994023	.1149766	6.95	0.000	.5740523	1.024752
married	.1777938	.0434623	4.09	0.000	.0926093	.2629783
ownchild	-.0730411	.0336763	-2.17	0.030	-.1390455	-.0070368
house	.2055825	.0344179	5.97	0.000	.1381247	.2730403
ftwork	1.032082	.0345856	29.84	0.000	.9642951	1.099868
selfemp	-2.22726	.0948596	-23.48	0.000	-2.413181	-2.041339
union	-.6558058	.0929235	-7.06	0.000	-.8379326	-.473679
perio2	-.6874136	.0486497	-14.13	0.000	-.7827653	-.5920619
perio3	-.586716	.0585572	-10.02	0.000	-.7014859	-.471946
perio4	-.6423882	.0567788	-11.31	0.000	-.7536725	-.5311038
cencity	.1974164	.0432057	4.57	0.000	.1127347	.2820981
urbnocc	.2800544	.0361466	7.75	0.000	.2092083	.3509004
neng	-.0328689	.0602676	-0.55	0.585	-.1509912	.0852535

```
        mest |   .0426079   .0490724     0.87   0.385    -.0535723    .1387881
        glak |  -.0375815   .0503939    -0.75   0.456    -.1363516    .0611887
        plns |   .0171216   .0636982     0.27   0.788    -.1077247    .1419678
        swst |   .1729303   .0587276     2.94   0.003     .0578263    .2880342
        rkmt |   .1141712   .0676888     1.69   0.092    -.0184965    .2468389
        fwst |   .0356354   .0563994     0.63   0.527    -.0749053    .1461761
       unemp |  -.0316967   .0151785    -2.09   0.037     -.061446   -.0019474
    psicdeg2 |   2.061522    .320461     6.43   0.000      1.43343    2.689614
       _cons |  -3.912167   .1804883   -21.68   0.000    -4.265918   -3.558417
------------------------------------------------------------------------------
(indocc==nhtnse is the base outcome)

.
listcoef black latino asian blacknohi blackhi blackpost/*
> */ latnohi lathi latpost asnocoll aspost
(pweights not compatible with summarize; weights will be treated as aweights)

mlogit (N=488707): Factor Change in the Odds of indocc


Variable: black (sd=.31767825)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.25528   -2.266   0.023   0.7747   0.9221
htse    -nhtse    |  -0.25568   -2.052   0.040   0.7744   0.9220
htse    -nhtnse   |  -0.54403   -5.629   0.000   0.5804   0.8413
htnse   -htse     |   0.25528    2.266   0.023   1.2908   1.0845
htnse   -nhtse    |  -0.00039   -0.004   0.997   0.9996   0.9999
htnse   -nhtnse   |  -0.28875   -4.408   0.000   0.7492   0.9124
nhtse   -htse     |   0.25568    2.052   0.040   1.2913   1.0846
nhtse   -htnse    |   0.00039    0.004   0.997   1.0004   1.0001
nhtse   -nhtnse   |  -0.28835   -3.191   0.001   0.7495   0.9125
nhtnse  -htse     |   0.54403    5.629   0.000   1.7229   1.1887
nhtnse  -htnse    |   0.28875    4.408   0.000   1.3348   1.0961
nhtnse  -nhtse    |   0.28835    3.191   0.001   1.3342   1.0959
----------------------------------------------------------------

Variable: latino (sd=.31602115)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.26007   -2.819   0.005   0.7710   0.9211
htse    -nhtse    |  -0.07680   -0.715   0.475   0.9261   0.9760
htse    -nhtnse   |  -0.50454   -6.394   0.000   0.6038   0.8526
htnse   -htse     |   0.26007    2.819   0.005   1.2970   1.0857
htnse   -nhtse    |   0.18327    1.894   0.058   1.2011   1.0596
htnse   -nhtnse   |  -0.24447   -4.196   0.000   0.7831   0.9257
nhtse   -htse     |   0.07680    0.715   0.475   1.0798   1.0246
nhtse   -htnse    |  -0.18327   -1.894   0.058   0.8325   0.9437
nhtse   -nhtnse   |  -0.42774   -5.228   0.000   0.6520   0.8736
nhtnse  -htse     |   0.50454    6.394   0.000   1.6562   1.1729
nhtnse  -htnse    |   0.24447    4.196   0.000   1.2769   1.0803
nhtnse  -nhtse    |   0.42774    5.228   0.000   1.5338   1.1447
----------------------------------------------------------------

Variable: asian (sd=.1878823)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.02646   -0.255   0.799   0.9739   0.9950
htse    -nhtse    |  -0.05209   -0.423   0.672   0.9492   0.9903
htse    -nhtnse   |   0.02159    0.249   0.803   1.0218   1.0041
htnse   -htse     |   0.02646    0.255   0.799   1.0268   1.0050
htnse   -nhtse    |  -0.02563   -0.217   0.828   0.9747   0.9952
htnse   -nhtnse   |   0.04805    0.657   0.511   1.0492   1.0091
nhtse   -htse     |   0.05209    0.423   0.672   1.0535   1.0098
```

```
nhtse   -htnse    |   0.02563    0.217   0.828   1.0260   1.0048
nhtse   -nhtnse   |   0.07368    0.744   0.457   1.0765   1.0139
nhtnse  -htse     |  -0.02159   -0.249   0.803   0.9786   0.9960
nhtnse  -htnse    |  -0.04805   -0.657   0.511   0.9531   0.9910
nhtnse  -nhtse    |  -0.07368   -0.744   0.457   0.9290   0.9863
----------------------------------------------------------------

Variable: blacknohi (sd=.17316938)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -1.51348   -1.859   0.063   0.2201   0.7694
htse    -nhtse    |  -0.66721   -0.698   0.485   0.5131   0.8909
htse    -nhtnse   |  -1.53924   -1.908   0.056   0.2145   0.7660
htnse   -htse     |   1.51348    1.859   0.063   4.5425   1.2996
htnse   -nhtse    |   0.84627    1.602   0.109   2.3309   1.1578
htnse   -nhtnse   |  -0.02575   -0.219   0.827   0.9746   0.9956
nhtse   -htse     |   0.66721    0.698   0.485   1.9488   1.1225
nhtse   -htnse    |  -0.84627   -1.602   0.109   0.4290   0.8637
nhtse   -nhtnse   |  -0.87202   -1.691   0.091   0.4181   0.8598
nhtnse  -htse     |   1.53924    1.908   0.056   4.6610   1.3055
nhtnse  -htnse    |   0.02575    0.219   0.827   1.0261   1.0045
nhtnse  -nhtse    |   0.87202    1.691   0.091   2.3917   1.1630
----------------------------------------------------------------

Variable: blackhi (sd=.24441205)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.55097   -3.015   0.003   0.5764   0.8740
htse    -nhtse    |   0.18278    0.839   0.401   1.2005   1.0457
htse    -nhtnse   |  -0.34530   -2.038   0.042   0.7080   0.9191
htnse   -htse     |   0.55097    3.015   0.003   1.7349   1.1442
htnse   -nhtse    |   0.73375    4.439   0.000   2.0829   1.1964
htnse   -nhtnse   |   0.20567    2.742   0.006   1.2283   1.0516
nhtse   -htse     |  -0.18278   -0.839   0.401   0.8330   0.9563
nhtse   -htnse    |  -0.73375   -4.439   0.000   0.4801   0.8358
nhtse   -nhtnse   |  -0.52808   -3.504   0.000   0.5897   0.8789
nhtnse  -htse     |   0.34530    2.038   0.042   1.4124   1.0881
nhtnse  -htnse    |  -0.20567   -2.742   0.006   0.8141   0.9510
nhtnse  -nhtse    |   0.52808    3.504   0.000   1.6957   1.1378
----------------------------------------------------------------

Variable: blackpost (sd=.0593159)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.11236    0.437   0.662   1.1189   1.0067
htse    -nhtse    |  -0.09502   -0.359   0.720   0.9094   0.9944
htse    -nhtnse   |   0.11238    0.552   0.581   1.1189   1.0067
htnse   -htse     |  -0.11236   -0.437   0.662   0.8937   0.9934
htnse   -nhtse    |  -0.20738   -0.851   0.395   0.8127   0.9878
htnse   -nhtnse   |   0.00003    0.000   1.000   1.0000   1.0000
nhtse   -htse     |   0.09502    0.359   0.720   1.0997   1.0057
nhtse   -htnse    |   0.20738    0.851   0.395   1.2304   1.0124
nhtse   -nhtnse   |   0.20740    1.095   0.273   1.2305   1.0124
nhtnse  -htse     |  -0.11238   -0.552   0.581   0.8937   0.9934
nhtnse  -htnse    |  -0.00003   -0.000   1.000   1.0000   1.0000
nhtnse  -nhtse    |  -0.20740   -1.095   0.273   0.8127   0.9878
----------------------------------------------------------------

Variable: latnohi (sd=.22381026)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
```

```
htse    -htnse    |  -2.48689   -3.289   0.001   0.0832   0.5732
htse    -nhtse    |  -1.11772   -1.288   0.198   0.3270   0.7787
htse    -nhtnse   |  -2.57782   -3.423   0.001   0.0759   0.5616
htnse   -htse     |   2.48689    3.289   0.001  12.0239   1.7447
htnse   -nhtse    |   1.36917    3.102   0.002   3.9321   1.3586
htnse   -nhtnse   |  -0.09093   -1.145   0.252   0.9131   0.9799
nhtse   -htse     |   1.11772    1.288   0.198   3.0579   1.2842
nhtse   -htnse    |  -1.36917   -3.102   0.002   0.2543   0.7361
nhtse   -nhtnse   |  -1.46010   -3.354   0.001   0.2322   0.7212
nhtnse  -htse     |   2.57782    3.423   0.001  13.1685   1.7806
nhtnse  -htnse    |   0.09093    1.145   0.252   1.0952   1.0206
nhtnse  -nhtse    |   1.46010    3.354   0.001   4.3064   1.3865
----------------------------------------------------------------

Variable: lathi (sd=.20897501)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.63500   -4.163   0.000   0.5299   0.8757
htse    -nhtse    |  -0.32275   -1.695   0.090   0.7242   0.9348
htse    -nhtnse   |  -0.67833   -4.786   0.000   0.5075   0.8678
htnse   -htse     |   0.63500    4.163   0.000   1.8870   1.1419
htnse   -nhtse    |   0.31224    2.132   0.033   1.3665   1.0674
htnse   -nhtnse   |  -0.04333   -0.650   0.516   0.9576   0.9910
nhtse   -htse     |   0.32275    1.695   0.090   1.3809   1.0698
nhtse   -htnse    |  -0.31224   -2.132   0.033   0.7318   0.9368
nhtse   -nhtnse   |  -0.35558   -2.663   0.008   0.7008   0.9284
nhtnse  -htse     |   0.67833    4.786   0.000   1.9706   1.1523
nhtnse  -htnse    |   0.04333    0.650   0.516   1.0443   1.0091
nhtnse  -nhtse    |   0.35558    2.663   0.008   1.4270   1.0771
----------------------------------------------------------------

Variable: latpost (sd=.05277521)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.13819   -0.702   0.482   0.8709   0.9927
htse    -nhtse    |   0.04784    0.192   0.848   1.0490   1.0025
htse    -nhtnse   |  -0.00047   -0.003   0.998   0.9995   1.0000
htnse   -htse     |   0.13819    0.702   0.482   1.1482   1.0073
htnse   -nhtse    |   0.18603    0.834   0.404   1.2045   1.0099
htnse   -nhtnse   |   0.13772    1.109   0.267   1.1477   1.0073
nhtse   -htse     |  -0.04784   -0.192   0.848   0.9533   0.9975
nhtse   -htnse    |  -0.18603   -0.834   0.404   0.8302   0.9902
nhtse   -nhtnse   |  -0.04831   -0.248   0.804   0.9528   0.9975
nhtnse  -htse     |   0.00047    0.003   0.998   1.0005   1.0000
nhtnse  -htnse    |  -0.13772   -1.109   0.267   0.8713   0.9928
nhtnse  -nhtse    |   0.04831    0.248   0.804   1.0495   1.0026
----------------------------------------------------------------

Variable: asnocoll (sd=.13755588)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.47501   -2.102   0.036   0.6219   0.9367
htse    -nhtse    |  -0.26490   -0.933   0.351   0.7673   0.9642
htse    -nhtnse   |  -0.54634   -2.550   0.011   0.5791   0.9276
htnse   -htse     |   0.47501    2.102   0.036   1.6080   1.0675
htnse   -nhtse    |   0.21010    0.973   0.330   1.2338   1.0293
htnse   -nhtnse   |  -0.07133   -0.776   0.438   0.9312   0.9902
nhtse   -htse     |   0.26490    0.933   0.351   1.3033   1.0371
nhtse   -htnse    |  -0.21010   -0.973   0.330   0.8105   0.9715
nhtse   -nhtnse   |  -0.28144   -1.422   0.155   0.7547   0.9620
nhtnse  -htse     |   0.54634    2.550   0.011   1.7269   1.0780
nhtnse  -htnse    |   0.07133    0.776   0.438   1.0739   1.0099
nhtnse  -nhtse    |   0.28144    1.422   0.155   1.3250   1.0395
----------------------------------------------------------------
```

```
Variable: aspost (sd=.07728383)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.70164    5.029   0.000   2.0171   1.0557
htse    -nhtse    |  -0.09573   -0.700   0.484   0.9087   0.9926
htse    -nhtnse   |   0.70367    7.074   0.000   2.0212   1.0559
htnse   -htse     |  -0.70164   -5.029   0.000   0.4958   0.9472
htnse   -nhtse    |  -0.79737   -5.105   0.000   0.4505   0.9402
htnse   -nhtnse   |   0.00203    0.017   0.987   1.0020   1.0002
nhtse   -htse     |   0.09573    0.700   0.484   1.1005   1.0074
nhtse   -htnse    |   0.79737    5.105   0.000   2.2197   1.0636
nhtse   -nhtnse   |   0.79940    6.953   0.000   2.2242   1.0637
nhtnse  -htse     |  -0.70367   -7.074   0.000   0.4948   0.9471
nhtnse  -htnse    |  -0.00203   -0.017   0.987   0.9980   0.9998
nhtnse  -nhtse    |  -0.79940   -6.953   0.000   0.4496   0.9401
----------------------------------------------------------------


.
. test [htse]black=[htse]latino

 ( 1)  [htse]black - [htse]latino = 0

           chi2(  1) =    0.11
         Prob > chi2 =    0.7427

. test [htse]black=[htse]asian

 ( 1)  [htse]black - [htse]asian = 0

           chi2(  1) =   19.46
         Prob > chi2 =    0.0000

. test [htse]asian=[htse]latino

 ( 1) - [htse]latino + [htse]asian = 0

           chi2(  1) =   21.59
         Prob > chi2 =    0.0000

.
. test [htnse]black=[htnse]latino

 ( 1)  [htnse]black - [htnse]latino = 0

           chi2(  1) =    0.28
         Prob > chi2 =    0.5996

. test [htnse]black=[htnse]asian

 ( 1)  [htnse]black - [htnse]asian = 0

           chi2(  1) =   12.41
         Prob > chi2 =    0.0004

. test [htnse]asian=[htnse]latino

 ( 1) - [htnse]latino + [htnse]asian = 0

           chi2(  1) =   10.48
         Prob > chi2 =    0.0012

.
. test [nhtse]black=[nhtse]latino

 ( 1)  [nhtse]black - [nhtse]latino = 0

           chi2(  1) =    1.43
         Prob > chi2 =    0.2325
```

```
. test [nhtse]black=[nhtse]asian

 ( 1)  [nhtse]black - [nhtse]asian = 0

          chi2(  1) =    7.63
        Prob > chi2 =    0.0058

. test [nhtse]asian=[nhtse]latino

 ( 1) - [nhtse]latino + [nhtse]asian = 0

          chi2(  1) =   16.65
        Prob > chi2 =    0.0000

.
```

Appendix Table 9. Regression Model and Tests for the Effects of Race and Education (No High School, High School and Bachelors Education, Reference Group – Post Graduate Education; Model 5C).

```
mlogit indocc nohisch hisch bachdeg exp2 exp2sq black latino asian blacknohi blackhi/*
> */ blackbach latnohi lathi latbach asnocoll asbach married ownchild house ftwork
selfemp union /*
> */perio2 perio3 perio4 /*
> */cencity urbnocc neng mest glak plns swst rkmt fwst/*
> */ unemp  pscideg2[pweight=MARSUPWT] /*
> */if male==1 & A_REORGN~=9 & A_REORGN~=10, cluster(H_IDNUM)

(sum of wgt is   9.2293e+08)
Iteration 0:   log pseudolikelihood = -227235.66
Iteration 1:   log pseudolikelihood = -215887.41
Iteration 2:   log pseudolikelihood = -209666.84
Iteration 3:   log pseudolikelihood = -207259.33
Iteration 4:   log pseudolikelihood = -206267.06
Iteration 5:   log pseudolikelihood = -203682.35
Iteration 6:   log pseudolikelihood = -201708.23
Iteration 7:   log pseudolikelihood = -200576.07
Iteration 8:   log pseudolikelihood =    -200446
Iteration 9:   log pseudolikelihood = -200440.01
Iteration 10:  log pseudolikelihood = -200439.55
Iteration 11:  log pseudolikelihood = -200439.53
Iteration 12:  log pseudolikelihood = -200439.53

Multinomial logistic regression                   Number of obs   =     488707
                                                  Wald chi2(108)  =   21579.54
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -200439.53                 Pseudo R2       =     0.1179

                           (Std. Err. adjusted for 137784 clusters in H_IDNUM)
------------------------------------------------------------------------------
             |               Robust
      indocc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
htse         |
     nohisch |  -4.115884    .212257   -19.39   0.000      -4.5319   -3.699868
       hisch |   -2.05197   .0461394   -44.47   0.000    -2.142402   -1.961539
     bachdeg |  -.1262065   .0359301    -3.51   0.000    -.1966282   -.0557848
        exp2 |   -.010778   .0048968    -2.20   0.028    -.0203754   -.0011805
      exp2sq |  -.0002576   .0001211    -2.13   0.033     -.000495   -.0000202
       black |  -.4316479    .179876    -2.40   0.016    -.7841983   -.0790975
      latino |  -.5050097   .1601355    -3.15   0.002    -.8188694   -.1911499
       asian |   .7252609   .0967017     7.50   0.000     .5357291    .9147927
   blacknohi |  -1.651618   .8257459    -2.00   0.045     -3.27005   -.0331859
     blackhi |   -.457683   .2286328    -2.00   0.045    -.9057951   -.0095709
   blackbach |  -.1123828   .2036194    -0.55   0.581    -.5114696    .2867039
     latnohi |  -2.577351   .7658724    -3.37   0.001    -4.078433   -1.076269
       lathi |  -.6778564    .199807    -3.39   0.001    -1.069471   -.2862419
     latbach |   .0004732   .1770527     0.00   0.998    -.3465437    .3474901
    asnocoll |  -1.250012   .2163348    -5.78   0.000    -1.674021   -.8260039
      asbach |  -.7036721   .0994779    -7.07   0.000    -.8986453    -.508699
     married |   .2663259   .0404542     6.58   0.000      .187037    .3456147
    ownchild |  -.0983649   .0301213    -3.27   0.001    -.1574015   -.0393283
       house |   .1639923   .0329574     4.98   0.000     .0993969    .2285877
      ftwork |   1.054697   .0331945    31.77   0.000     .9896369    1.119757
     selfemp |  -.7646903   .0486145   -15.73   0.000     -.859973   -.6694077
       union |  -1.718488   .1345951   -12.77   0.000     -1.98229   -1.454687
      perio2 |  -.6382939   .0477315   -13.37   0.000    -.7318459   -.5447419
      perio3 |  -.4493672   .0560427    -8.02   0.000    -.5592089   -.3395256
      perio4 |  -.4452739   .0536716    -8.30   0.000    -.5504684   -.3400795
     cencity |   .4474164   .0434061    10.31   0.000     .3623421    .5324907
     urbnocc |   .7095276   .0354626    20.01   0.000     .6400222    .7790329
        neng |   .5085394   .0541842     9.39   0.000     .4023402    .6147385
        mest |   .0180304   .0483271     0.37   0.709    -.0766891    .1127498
        glak |   .1857726   .0478127     3.89   0.000     .0920615    .2794837
        plns |  -.0906425   .0684875    -1.32   0.186    -.2248756    .0435906
        swst |   .3476679    .055479     6.27   0.000     .2389311    .4564046
```

rkmt	.2941854	.0675669	4.35	0.000	.1617567	.4266141
fwst	.3867218	.05251	7.36	0.000	.283804	.4896396
unemp	-.0142635	.0136721	-1.04	0.297	-.0410603	.0125334
pscideg2	2.544009	.3123317	8.15	0.000	1.93185	3.156168
_cons	-4.162556	.1738896	-23.94	0.000	-4.503373	-3.821739
htnse						
nohisch	-.6550435	.0434425	-15.08	0.000	-.7401892	-.5698978
hisch	-.1329666	.0292514	-4.55	0.000	-.1902983	-.0756349
bachdeg	.142613	.030494	4.68	0.000	.0828458	.2023802
exp2	.0458118	.0026045	17.59	0.000	.0407071	.0509165
exp2sq	-.0009632	.0000553	-17.40	0.000	-.0010717	-.0008547
black	-.2887199	.1577568	-1.83	0.067	-.5979176	.0204777
latino	-.1067483	.110947	-0.96	0.336	-.3242005	.1107038
asian	.0500773	.1075354	0.47	0.641	-.1606882	.2608429
blacknohi	-.0257774	.1855044	-0.14	0.889	-.3893593	.3378046
blackhi	.2056435	.1624367	1.27	0.206	-.1127266	.5240135
blackbach	-.000026	.1697986	-0.00	1.000	-.3328252	.3327732
latnohi	-.2286519	.1234621	-1.85	0.064	-.4706331	.0133293
lathi	-.1810546	.1158147	-1.56	0.118	-.4080472	.0459381
latbach	-.1377205	.1241898	-1.11	0.267	-.381128	.1056871
asnocoll	-.0733615	.121836	-0.60	0.547	-.3121556	.1654326
asbach	-.0020283	.1208699	-0.02	0.987	-.2389289	.2348723
married	.3103091	.0242236	12.81	0.000	.2628318	.3577865
ownchild	-.1010945	.0175992	-5.74	0.000	-.1355882	-.0666007
house	.2421152	.0187359	12.92	0.000	.2053934	.2788369
ftwork	.9750637	.0183776	53.06	0.000	.9390441	1.011083
selfemp	-.831211	.0302008	-27.52	0.000	-.8904035	-.7720186
union	-.2068715	.0403966	-5.12	0.000	-.2860473	-.1276957
perio2	-.5567075	.0257176	-21.65	0.000	-.607113	-.5063019
perio3	-.4208319	.0316292	-13.31	0.000	-.482824	-.3588398
perio4	-.5095096	.0297829	-17.11	0.000	-.567883	-.4511362
cencity	.1576119	.0238031	6.62	0.000	.1109586	.2042651
urbnocc	.3150513	.0191014	16.49	0.000	.2776132	.3524895
neng	.4361665	.0336084	12.98	0.000	.3702952	.5020378
mest	.0114598	.0279305	0.41	0.682	-.043283	.0662027
glak	.5336581	.0264747	20.16	0.000	.4817686	.5855476
plns	.1691115	.0384558	4.40	0.000	.0937395	.2444835
swst	.2518217	.0316003	7.97	0.000	.1898864	.3137571
rkmt	.0469114	.0421875	1.11	0.266	-.0357746	.1295973
fwst	.1606727	.0314059	5.12	0.000	.0991183	.2222271
unemp	.0265657	.0078658	3.38	0.001	.011149	.0419823
pscideg2	1.257096	.1805723	6.96	0.000	.903181	1.611011
_cons	-4.199293	.1021963	-41.09	0.000	-4.399594	-3.998992
nhtse						
nohisch	-3.506431	.1864771	-18.80	0.000	-3.871919	-3.140942
hisch	-1.671042	.0493438	-33.87	0.000	-1.767754	-1.57433
bachdeg	.0051118	.0423582	0.12	0.904	-.0779087	.0881323
exp2	.0117463	.0050658	2.32	0.020	.0018174	.0216752
exp2sq	-.0004999	.0001204	-4.15	0.000	-.0007358	-.0002639
black	-.0809485	.1671672	-0.48	0.628	-.4085901	.2466931
latino	-.4760497	.1784206	-2.67	0.008	-.8257477	-.1263516
asian	.8730787	.1044849	8.36	0.000	.668292	1.077865
blacknohi	-1.079427	.5347135	-2.02	0.044	-2.127446	-.0314075
blackhi	-.7354816	.207277	-3.55	0.000	-1.141737	-.3292261
blackbach	-.2074034	.1893235	-1.10	0.273	-.5784707	.1636639
latnohi	-1.411795	.4633394	-3.05	0.002	-2.319923	-.5036662
lathi	-.3072658	.2073126	-1.48	0.138	-.7135909	.0990594
latbach	.0483099	.1946823	0.25	0.804	-.3332603	.4298802
asnocoll	-1.080838	.2009829	-5.38	0.000	-1.474757	-.6869189
asbach	-.7994023	.1149766	-6.95	0.000	-1.024752	-.5740523
married	.1777938	.0434623	4.09	0.000	.0926093	.2629783
ownchild	-.0730411	.0336763	-2.17	0.030	-.1390455	-.0070368
house	.2055825	.0344179	5.97	0.000	.1381247	.2730403
ftwork	1.032082	.0345856	29.84	0.000	.9642951	1.099868
selfemp	-2.22726	.0948596	-23.48	0.000	-2.413181	-2.041339
union	-.6558058	.0929235	-7.06	0.000	-.8379326	-.473679
perio2	-.6874136	.0486497	-14.13	0.000	-.7827653	-.5920619
perio3	-.586716	.0585572	-10.02	0.000	-.7014859	-.471946
perio4	-.6423882	.0567788	-11.31	0.000	-.7536725	-.5311038
cencity	.1974164	.0432057	4.57	0.000	.1127347	.2820981
urbnocc	.2800544	.0361466	7.75	0.000	.2092083	.3509004

```
        neng |  -.0328689   .0602676    -0.55   0.585    -.1509912    .0852535
        mest |   .0426079   .0490724     0.87   0.385    -.0535723    .1387881
        glak |  -.0375815   .0503939    -0.75   0.456    -.1363516    .0611887
        plns |   .0171216   .0636982     0.27   0.788    -.1077247    .1419678
        swst |   .1729303   .0587276     2.94   0.003     .0578263    .2880342
        rkmt |   .1141712   .0676888     1.69   0.092    -.0184965    .2468389
        fwst |   .0356354   .0563994     0.63   0.527    -.0749053    .1461761
       unemp |  -.0316967   .0151785    -2.09   0.037     -.061446   -.0019474
    pscideg2 |   2.061522    .320461     6.43   0.000      1.43343    2.689614
       _cons |  -3.917279   .1853301   -21.14   0.000     -4.28052   -3.554039
------------------------------------------------------------------------------
(indocc==nhtnse is the base outcome)

.
listcoef black latino asian blacknohi blackhi blackbach/*
> */ latnohi lathi latbach asnocoll asbach
(pweights not compatible with summarize; weights will be treated as aweights)

mlogit (N=488707): Factor Change in the Odds of indocc

Variable: black (sd=.31767825)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.14293   -0.615   0.538   0.8668   0.9556
htse    -nhtse    |  -0.35070   -1.509   0.131   0.7042   0.8946
htse    -nhtnse   |  -0.43165   -2.400   0.016   0.6494   0.8719
htnse   -htse     |   0.14293    0.615   0.538   1.1536   1.0465
htnse   -nhtse    |  -0.20777   -0.947   0.344   0.8124   0.9361
htnse   -nhtnse   |  -0.28872   -1.830   0.067   0.7492   0.9124
nhtse   -htse     |   0.35070    1.509   0.131   1.4201   1.1179
nhtse   -htnse    |   0.20777    0.947   0.344   1.2309   1.0682
nhtse   -nhtnse   |  -0.08095   -0.484   0.628   0.9222   0.9746
nhtnse  -htse     |   0.43165    2.400   0.016   1.5398   1.1470
nhtnse  -htnse    |   0.28872    1.830   0.067   1.3347   1.0961
nhtnse  -nhtse    |   0.08095    0.484   0.628   1.0843   1.0260
----------------------------------------------------------------

Variable: latino (sd=.31602115)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.39826   -2.267   0.023   0.6715   0.8817
htse    -nhtse    |  -0.02896   -0.128   0.898   0.9715   0.9909
htse    -nhtnse   |  -0.50501   -3.154   0.002   0.6035   0.8525
htnse   -htse     |   0.39826    2.267   0.023   1.4892   1.1341
htnse   -nhtse    |   0.36930    1.823   0.068   1.4467   1.1238
htnse   -nhtnse   |  -0.10675   -0.962   0.336   0.8988   0.9668
nhtse   -htse     |   0.02896    0.128   0.898   1.0294   1.0092
nhtse   -htnse    |  -0.36930   -1.823   0.068   0.6912   0.8898
nhtse   -nhtnse   |  -0.47605   -2.668   0.008   0.6212   0.8603
nhtnse  -htse     |   0.50501    3.154   0.002   1.6570   1.1730
nhtnse  -htnse    |   0.10675    0.962   0.336   1.1127   1.0343
nhtnse  -nhtse    |   0.47605    2.668   0.008   1.6097   1.1623
----------------------------------------------------------------

Variable: asian (sd=.1878823)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.67518    5.222   0.000   1.9644   1.1353
htse    -nhtse    |  -0.14782   -1.138   0.255   0.8626   0.9726
htse    -nhtnse   |   0.72526    7.500   0.000   2.0653   1.1460
htnse   -htse     |  -0.67518   -5.222   0.000   0.5091   0.8809
htnse   -nhtse    |  -0.82300   -5.878   0.000   0.4391   0.8567
htnse   -nhtnse   |   0.05008    0.466   0.641   1.0514   1.0095
nhtse   -htse     |   0.14782    1.138   0.255   1.1593   1.0282
```

```
nhtse   -htnse    |   0.82300    5.878   0.000   2.2773   1.1672
nhtse   -nhtnse   |   0.87308    8.356   0.000   2.3943   1.1783
nhtnse  -htse     |  -0.72526   -7.500   0.000   0.4842   0.8726
nhtnse  -htnse    |  -0.05008   -0.466   0.641   0.9512   0.9906
nhtnse  -nhtse    |  -0.87308   -8.356   0.000   0.4177   0.8487
-----------------------------------------------------------------

Variable: blacknohi (sd=.17316938)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
htse    -htnse    |  -1.62584   -1.926   0.054   0.1967   0.7546
htse    -nhtse    |  -0.57219   -0.584   0.559   0.5643   0.9057
htse    -nhtnse   |  -1.65162   -2.000   0.045   0.1917   0.7513
htnse   -htse     |   1.62584    1.926   0.054   5.0827   1.3252
htnse   -nhtse    |   1.05365    1.875   0.061   2.8681   1.2002
htnse   -nhtnse   |  -0.02578   -0.139   0.889   0.9746   0.9955
nhtse   -htse     |   0.57219    0.584   0.559   1.7721   1.1042
nhtse   -htnse    |  -1.05365   -1.875   0.061   0.3487   0.8332
nhtse   -nhtnse   |  -1.07943   -2.019   0.044   0.3398   0.8295
nhtnse  -htse     |   1.65162    2.000   0.045   5.2154   1.3311
nhtnse  -htnse    |   0.02578    0.139   0.889   1.0261   1.0045
nhtnse  -nhtse    |   1.07943    2.019   0.044   2.9430   1.2055
-----------------------------------------------------------------

Variable: blackhi (sd=.24441205)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
htse    -htnse    |  -0.66333   -2.425   0.015   0.5151   0.8503
htse    -nhtse    |   0.27780    0.945   0.345   1.3202   1.0703
htse    -nhtnse   |  -0.45768   -2.002   0.045   0.6327   0.8942
htnse   -htse     |   0.66333    2.425   0.015   1.9412   1.1760
htnse   -nhtse    |   0.94113    3.706   0.000   2.5629   1.2586
htnse   -nhtnse   |   0.20564    1.266   0.206   1.2283   1.0515
nhtse   -htse     |  -0.27780   -0.945   0.345   0.7574   0.9344
nhtse   -htnse    |  -0.94113   -3.706   0.000   0.3902   0.7945
nhtse   -nhtnse   |  -0.73548   -3.548   0.000   0.4793   0.8355
nhtnse  -htse     |   0.45768    2.002   0.045   1.5804   1.1184
nhtnse  -htnse    |  -0.20564   -1.266   0.206   0.8141   0.9510
nhtnse  -nhtse    |   0.73548    3.548   0.000   2.0865   1.1969
-----------------------------------------------------------------

Variable: blackbach (sd=.12394379)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
htse    -htnse    |  -0.11236   -0.437   0.662   0.8937   0.9862
htse    -nhtse    |   0.09502    0.359   0.720   1.0997   1.0118
htse    -nhtnse   |  -0.11238   -0.552   0.581   0.8937   0.9862
htnse   -htse     |   0.11236    0.437   0.662   1.1189   1.0140
htnse   -nhtse    |   0.20738    0.851   0.395   1.2304   1.0260
htnse   -nhtnse   |  -0.00003   -0.000   1.000   1.0000   1.0000
nhtse   -htse     |  -0.09502   -0.359   0.720   0.9094   0.9883
nhtse   -htnse    |  -0.20738   -0.851   0.395   0.8127   0.9746
nhtse   -nhtnse   |  -0.20740   -1.095   0.273   0.8127   0.9746
nhtnse  -htse     |   0.11238    0.552   0.581   1.1189   1.0140
nhtnse  -htnse    |   0.00003    0.000   1.000   1.0000   1.0000
nhtnse  -nhtse    |   0.20740    1.095   0.273   1.2305   1.0260
-----------------------------------------------------------------

Variable: latnohi (sd=.22381026)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+----------------------------------------------
```

```
htse    -htnse    |  -2.34870   -3.046   0.002   0.0955   0.5912
htse    -nhtse    |  -1.16556   -1.309   0.191   0.3117   0.7704
htse    -nhtnse   |  -2.57735   -3.365   0.001   0.0760   0.5617
htnse   -htse     |   2.34870    3.046   0.002  10.4719   1.6916
htnse   -nhtse    |   1.18314    2.486   0.013   3.2646   1.3032
htnse   -nhtnse   |  -0.22865   -1.852   0.064   0.7956   0.9501
nhtse   -htse     |   1.16556    1.309   0.191   3.2077   1.2981
nhtse   -htnse    |  -1.18314   -2.486   0.013   0.3063   0.7674
nhtse   -nhtnse   |  -1.41179   -3.047   0.002   0.2437   0.7291
nhtnse  -htse     |   2.57735    3.365   0.001  13.1622   1.7804
nhtnse  -htnse    |   0.22865    1.852   0.064   1.2569   1.0525
nhtnse  -nhtse    |   1.41179    3.047   0.002   4.1033   1.3716
----------------------------------------------------------------

Variable: lathi (sd=.20897501)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.49680   -2.322   0.020   0.6085   0.9014
htse    -nhtse    |  -0.37059   -1.346   0.178   0.6903   0.9255
htse    -nhtnse   |  -0.67786   -3.393   0.001   0.5077   0.8679
htnse   -htse     |   0.49680    2.322   0.020   1.6435   1.1094
htnse   -nhtse    |   0.12621    0.548   0.584   1.1345   1.0267
htnse   -nhtnse   |  -0.18105   -1.563   0.118   0.8344   0.9629
nhtse   -htse     |   0.37059    1.346   0.178   1.4486   1.0805
nhtse   -htnse    |  -0.12621   -0.548   0.584   0.8814   0.9740
nhtse   -nhtnse   |  -0.30727   -1.482   0.138   0.7355   0.9378
nhtnse  -htse     |   0.67786    3.393   0.001   1.9697   1.1522
nhtnse  -htnse    |   0.18105    1.563   0.118   1.1985   1.0386
nhtnse  -nhtse    |   0.30727    1.482   0.138   1.3597   1.0663
----------------------------------------------------------------

Variable: latbach (sd=.1047087)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |   0.13819    0.702   0.482   1.1482   1.0146
htse    -nhtse    |  -0.04784   -0.192   0.848   0.9533   0.9950
htse    -nhtnse   |   0.00047    0.003   0.998   1.0005   1.0000
htnse   -htse     |  -0.13819   -0.702   0.482   0.8709   0.9856
htnse   -nhtse    |  -0.18603   -0.834   0.404   0.8302   0.9807
htnse   -nhtnse   |  -0.13772   -1.109   0.267   0.8713   0.9857
nhtse   -htse     |   0.04784    0.192   0.848   1.0490   1.0050
nhtse   -htnse    |   0.18603    0.834   0.404   1.2045   1.0197
nhtse   -nhtnse   |   0.04831    0.248   0.804   1.0495   1.0051
nhtnse  -htse     |  -0.00047   -0.003   0.998   0.9995   1.0000
nhtnse  -htnse    |   0.13772    1.109   0.267   1.1477   1.0145
nhtnse  -nhtse    |  -0.04831   -0.248   0.804   0.9528   0.9950
----------------------------------------------------------------

Variable: asnocoll (sd=.13755588)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -1.17665   -4.989   0.000   0.3083   0.8506
htse    -nhtse    |  -0.16917   -0.593   0.553   0.8444   0.9770
htse    -nhtnse   |  -1.25001   -5.778   0.000   0.2865   0.8420
htnse   -htse     |   1.17665    4.989   0.000   3.2435   1.1757
htnse   -nhtse    |   1.00748    4.419   0.000   2.7387   1.1486
htnse   -nhtnse   |  -0.07336   -0.602   0.547   0.9293   0.9900
nhtse   -htse     |   0.16917    0.593   0.553   1.1843   1.0235
nhtse   -htnse    |  -1.00748   -4.419   0.000   0.3651   0.8706
nhtse   -nhtnse   |  -1.08084   -5.378   0.000   0.3393   0.8618
nhtnse  -htse     |   1.25001    5.778   0.000   3.4904   1.1876
nhtnse  -htnse    |   0.07336    0.602   0.547   1.0761   1.0101
nhtnse  -nhtse    |   1.08084    5.378   0.000   2.9471   1.1603
----------------------------------------------------------------
```

```
Variable: asbach (sd=.10588233)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
htse    -htnse    |  -0.70164   -5.029   0.000   0.4958   0.9284
htse    -nhtse    |   0.09573    0.700   0.484   1.1005   1.0102
htse    -nhtnse   |  -0.70367   -7.074   0.000   0.4948   0.9282
htnse   -htse     |   0.70164    5.029   0.000   2.0171   1.0771
htnse   -nhtse    |   0.79737    5.105   0.000   2.2197   1.0881
htnse   -nhtnse   |  -0.00203   -0.017   0.987   0.9980   0.9998
nhtse   -htse     |  -0.09573   -0.700   0.484   0.9087   0.9899
nhtse   -htnse    |  -0.79737   -5.105   0.000   0.4505   0.9190
nhtse   -nhtnse   |  -0.79940   -6.953   0.000   0.4496   0.9188
nhtnse  -htse     |   0.70367    7.074   0.000   2.0212   1.0774
nhtnse  -htnse    |   0.00203    0.017   0.987   1.0020   1.0002
nhtnse  -nhtse    |   0.79940    6.953   0.000   2.2242   1.0883
----------------------------------------------------------------

. test [htse]black=[htse]latino

 ( 1)  [htse]black - [htse]latino = 0

           chi2(  1) =    0.10
         Prob > chi2 =    0.7567

. test [htse]black=[htse]asian

 ( 1)  [htse]black - [htse]asian = 0

           chi2(  1) =   33.11
         Prob > chi2 =    0.0000

. test [htse]asian=[htse]latino

 ( 1) - [htse]latino + [htse]asian = 0

           chi2(  1) =   45.08
         Prob > chi2 =    0.0000

.
. test [htnse]black=[htnse]latino

 ( 1)  [htnse]black - [htnse]latino = 0

           chi2(  1) =    0.93
         Prob > chi2 =    0.3342

. test [htnse]black=[htnse]asian

 ( 1)  [htnse]black - [htnse]asian = 0

           chi2(  1) =    3.24
         Prob > chi2 =    0.0717

. test [htnse]asian=[htnse]latino

 ( 1) - [htnse]latino + [htnse]asian = 0

           chi2(  1) =    1.09
         Prob > chi2 =    0.2964

.
. test [nhtse]black=[nhtse]latino

 ( 1)  [nhtse]black - [nhtse]latino = 0

           chi2(  1) =    2.75
         Prob > chi2 =    0.0974

. test [nhtse]black=[nhtse]asian
```

```
( 1)  [nhtse]black - [nhtse]asian = 0

          chi2(  1) =   25.23
        Prob > chi2 =    0.0000

. test [nhtse]asian=[nhtse]latino

 ( 1) - [nhtse]latino + [nhtse]asian = 0

          chi2(  1) =   46.07
        Prob > chi2 =    0.0000

.
```

Appendix Table 10. Comparison of Probabilities of Employment of Male, College-educated Full-time, Full Year Workers with Full, part-time and Non-workers in High Technology S & E Jobs for 1992 to 2002

Year	Full-time Full Year				Full, Part-time & Non-workers			
	Blacks	Latinos	Asians	Whites	Black	Latino	Asian	White
1992	0.0344	0.0443	0.1284	0.0597	0.0291	0.037	0.1119	0.0517
1993	0.0318	0.0393	0.1212	0.0564	0.0272	0.0336	0.1034	0.0485
1994	0.0333	0.0458	0.1259	0.0593	0.0263	0.0367	0.1073	0.0513
1995	0.0336	0.0414	0.1255	0.057	0.0272	0.0328	0.108	0.0501
1996	0.0342	0.047	0.1284	0.0595	0.0278	0.0349	0.1097	0.0523
1997	0.0375	0.0501	0.1409	0.0642	0.0315	0.0398	0.1197	0.0579
1998	0.0361	0.0479	0.1394	0.0616	0.0307	0.0391	0.1194	0.0569
1999	0.0373	0.0512	0.1343	0.0632	0.0319	0.0427	0.1225	0.0578
2000	0.0393	0.0526	0.1491	0.0658	0.0349	0.0454	0.1314	0.06
2001	0.0397	0.0526	0.1515	0.0654	0.034	0.0452	0.1335	0.0588
2002	0.0398	0.0505	0.1406	0.0643	0.0338	0.042	0.1231	0.0594

Note: Probabilities sum across industry/ occupation groups for each race and are calculated with other characteristics set at group mean value.

Appendix Table 11. Regression and Tests for Analyses on the Effects of Being Foreign-born for Model with Three-way Interaction between Foreign, Asian and College Education

```
mlogit indocc coll exp2 exp2sq black latino asian blackcoll/*
> */ latcoll ascoll foreign forlat forasian forcoll forascoll /*
> */married ownchild house ftwork selfemp union /*
> */cencity urbnocc neng mest glak plns swst rkmt fwst/*
> */ unemp   pscideg2/*
> */[pweight=MARSUPWT] /*
> */if male==1 & A_REORGN~=9 & A_REORGN~=10 & year~=1992 & year~=1993, cluster(H_IDNUM)

(sum of wgt is   7.6479e+08)
Iteration 0:   log pseudolikelihood = -184422.38
Iteration 1:   log pseudolikelihood = -175365.55
Iteration 2:   log pseudolikelihood = -164509.88
Iteration 3:   log pseudolikelihood = -162934.04
Iteration 4:   log pseudolikelihood = -162448.65
Iteration 5:   log pseudolikelihood = -162399.78
Iteration 6:   log pseudolikelihood =  -162399.4
Iteration 7:   log pseudolikelihood =  -162399.4

Multinomial logistic regression                   Number of obs   =     394737
                                                  Wald chi2(93)   =   19295.98
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood =  -162399.4                 Pseudo R2       =     0.1194

                           (Std. Err. adjusted for 117000 clusters in H_IDNUM)
------------------------------------------------------------------------------
             |               Robust
      indocc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
htse         |
        coll |    2.06745   .0420577    49.16   0.000     1.985018    2.149881
        exp2 |  -.0093494   .0052925    -1.77   0.077    -.0197225    .0010236
      exp2sq |  -.0003571   .0001305    -2.74   0.006    -.0006128   -.0001014
       black |  -.9843193   .1588629    -6.20   0.000    -1.295685   -.6729536
      latino |  -1.463633   .1592748    -9.19   0.000    -1.775806    -1.15146
       asian |  -.0196338   .4096427    -0.05   0.962    -.8225188    .7832512
   blackcoll |   .3423394   .1811185     1.89   0.059    -.0126464    .6973252
     latcoll |   1.049652   .1652693     6.35   0.000       .72573    1.373574
      ascoll |  -.0610354   .4293674    -0.14   0.887    -.9025801    .7805093
     foreign |    .340224   .1626127     2.09   0.036      .021509    .6589389
      forlat |  -.7586006   .1444128    -5.25   0.000    -1.041645   -.4755567
    forasian |  -1.022457   .5068668    -2.02   0.044    -2.015897   -.0290162
     forcoll |   .2872734   .1677732     1.71   0.087    -.0415561    .6161028
   forascoll |   1.091861   .5287071     2.07   0.039     .0556138    2.128108
     married |   .2944059   .0436273     6.75   0.000     .2088981    .3799138
    ownchild |  -.1535807   .0321529    -4.78   0.000    -.2165993   -.0905622
       house |    .174249   .0356443     4.89   0.000     .1043874    .2441105
      ftwork |   1.271739   .0428361    29.69   0.000     1.187782    1.355696
     selfemp |  -.7620579   .0525485   -14.50   0.000    -.8650512   -.6590647
       union |  -1.579302   .1481949   -10.66   0.000    -1.869759   -1.288845
     cencity |   .4431671   .0477125     9.29   0.000     .3496522    .5366819
     urbnocc |   .6990079   .0391827    17.84   0.000     .6222112    .7758046
        neng |   .4763678   .0596515     7.99   0.000      .359453    .5932826
        mest |   .0682988   .0524412     1.30   0.193    -.0344841    .1710816
        glak |   .1947049   .0520107     3.74   0.000     .0927659     .296644
        plns |  -.0900928   .0728084    -1.24   0.216    -.2327945     .052609
        swst |   .4028456   .0604665     6.66   0.000     .2843335    .5213577
        rkmt |   .2663477    .073583     3.62   0.000     .1221276    .4105678
        fwst |   .4779571   .0570982     8.37   0.000     .3660467    .5898675
       unemp |  -.0746294    .014529    -5.14   0.000    -.1031056   -.0461532
    pscideg2 |   2.164181   .3379237     6.40   0.000     1.501863    2.826499
       _cons |  -6.636052   .1622191   -40.91   0.000    -6.953996   -6.318109
-------------+----------------------------------------------------------------
htnse        |
        coll |   .2727666    .020104    13.57   0.000     .2333635    .3121698
        exp2 |   .0423644   .0028393    14.92   0.000     .0367994    .0479294
      exp2sq |  -.0009233   .0000604   -15.28   0.000    -.0010417   -.0008049
       black |  -.1249527   .0422012    -2.96   0.003    -.2076655   -.0422398
```

```
      latino |  -.2954618   .0417564    -7.08   0.000    -.3773029   -.2136207
       asian |  -.5802149   .1653554    -3.51   0.000    -.9043055   -.2561243
   blackcoll |  -.2072726   .0785129    -2.64   0.008    -.3611551   -.0533902
     latcoll |   .1012385   .0700904     1.44   0.149    -.0361362    .2386131
      ascoll |   .6599627   .2100176     3.14   0.002     .2483359     1.07159
     foreign |  -.1313379   .0580318    -2.26   0.024    -.2450782   -.0175976
      forlat |  -.1849666   .0700309    -2.64   0.008    -.3222246   -.0477087
    forasian |   .8325623   .1883141     4.42   0.000     .4634736    1.201651
     forcoll |   .3364946   .0699881     4.81   0.000     .1993204    .4736688
   forascoll |  -.9569585   .2377744    -4.02   0.000    -1.422988   -.4909293
     married |    .281191    .026519    10.60   0.000     .2292147    .3331672
    ownchild |  -.1347675   .0192141    -7.01   0.000    -.1724264   -.0971085
       house |   .2325834    .020771    11.20   0.000     .1918729    .2732938
      ftwork |   1.199635    .023233    51.63   0.000     1.154099     1.24517
     selfemp |  -.8215054   .0332901   -24.68   0.000    -.8867527    -.756258
       union |  -.0746084   .0447986    -1.67   0.096    -.1624121    .0131953
     cencity |   .1581727   .0267249     5.92   0.000     .1057929    .2105525
     urbnocc |   .3205415   .0213066    15.04   0.000     .2787814    .3623015
        neng |   .3911656   .0376416    10.39   0.000     .3173893    .4649418
        mest |   .0062692   .0308427     0.20   0.839    -.0541814    .0667197
        glak |    .516015   .0291767    17.69   0.000     .4588297    .5732003
        plns |   .0970744   .0422327     2.30   0.022     .0142999    .1798489
        swst |   .2701125   .0345598     7.82   0.000     .2023766    .3378484
        rkmt |   .0373519   .0457591     0.82   0.414    -.0523343     .127038
        fwst |   .2316529   .0346176     6.69   0.000     .1638036    .2995021
       unemp |  -.0189891   .0086134    -2.20   0.027     -.035871   -.0021071
    pscideg2 |   .9732281   .2000122     4.87   0.000     .5812113    1.365245
       _cons |  -4.651343   .0942339   -49.36   0.000    -4.836038   -4.466648
-------------+----------------------------------------------------------------
nhtse        |
        coll |    1.72704   .0420082    41.11   0.000     1.644705    1.809374
        exp2 |   .0146935   .0055266     2.66   0.008     .0038615    .0255256
      exp2sq |  -.0006321   .0001314    -4.81   0.000    -.0008896   -.0003746
       black |  -.7893455   .1298924    -6.08   0.000     -1.04393   -.5347611
      latino |  -.8537569   .1310421    -6.52   0.000    -1.110595   -.5969191
       asian |   .2137891   .3155316     0.68   0.498    -.4046415    .8322196
   blackcoll |   .5279986   .1532689     3.44   0.001      .227597    .8284003
     latcoll |   .4624575   .1484424     3.12   0.002     .1715157    .7533994
      ascoll |   .0914773     .34353     0.27   0.790    -.5818292    .7647838
     foreign |   -.192249   .1456993    -1.32   0.187    -.4778144    .0933164
      forlat |  -.5064227   .1461545    -3.46   0.001    -.7928803   -.2199651
    forasian |  -.6734835   .4252246    -1.58   0.113    -1.506908    .1599414
     forcoll |   .6490926   .1529268     4.24   0.000     .3493616    .9488235
   forascoll |   .3442972   .4522816     0.76   0.447    -.5421584    1.230753
     married |   .1868796   .0477397     3.91   0.000     .0933115    .2804477
    ownchild |   -.122081   .0361626    -3.38   0.001    -.1929583   -.0512037
       house |   .2309582   .0378432     6.10   0.000     .1567869    .3051294
      ftwork |   1.328318   .0471912    28.15   0.000     1.235825    1.420811
     selfemp |  -2.205999   .1048374   -21.04   0.000    -2.411476   -2.000521
       union |  -.5841193   .1066618    -5.48   0.000    -.7931725    -.375066
     cencity |   .1929302    .048195     4.00   0.000     .0984697    .2873906
     urbnocc |   .2936444   .0402074     7.30   0.000     .2148393    .3724494
        neng |  -.0105171   .0665903    -0.16   0.875    -.1410318    .1199975
        mest |   .0705483   .0538236     1.31   0.190     -.034944    .1760406
        glak |  -.0606395   .0552039    -1.10   0.272    -.1688371    .0475581
        plns |   .0192963   .0680514     0.28   0.777    -.1140819    .1526745
        swst |   .1498588   .0651301     2.30   0.021     .0222062    .2775113
        rkmt |   .1158677   .0735072     1.58   0.115    -.0282037    .2599392
        fwst |   .0934029   .0617042     1.51   0.130    -.0275351     .214341
       unemp |  -.0543768   .0163304    -3.33   0.001    -.0863838   -.0223698
    pscideg2 |   2.125096   .3558707     5.97   0.000     1.427603     2.82259
       _cons |  -6.511913   .1754368   -37.12   0.000    -6.855762   -6.168063
------------------------------------------------------------------------------
(indocc==nhtnse is the base outcome)

.
. test [htse]foreign [htse]forasian

 ( 1)  [htse]foreign = 0
 ( 2)  [htse]forasian = 0

           chi2(  2) =    6.39
         Prob > chi2 =    0.0409
```

```
. test [htse]foreign [htse]forasian [htse]forcoll [htse]forascoll

 ( 1)  [htse]foreign = 0
 ( 2)  [htse]forasian = 0
 ( 3)  [htse]forcoll = 0
 ( 4)  [htse]forascoll = 0

           chi2(  4) =  129.81
         Prob > chi2 =    0.0000

.
. test [htse]asian [htse]ascoll [htse]forasian [htse]forascoll

 ( 1)  [htse]asian = 0
 ( 2)  [htse]ascoll = 0
 ( 3)  [htse]forasian = 0
 ( 4)  [htse]forascoll = 0

           chi2(  4) =   12.00
         Prob > chi2 =    0.0173

.
. test [htse]asian [htse]ascoll

 ( 1)  [htse]asian = 0
 ( 2)  [htse]ascoll = 0

           chi2(  2) =    0.33
         Prob > chi2 =    0.8462

. test [htse]asian

 ( 1)  [htse]asian = 0

           chi2(  1) =    0.00
         Prob > chi2 =    0.9618

.
. test [htnse]foreign [htnse]forasian

 ( 1)  [htnse]foreign = 0
 ( 2)  [htnse]forasian = 0

           chi2(  2) =   20.55
         Prob > chi2 =    0.0000

. test [htnse]foreign [htnse]forasian [htnse]forcoll [htse]forascoll

 ( 1)  [htnse]foreign = 0
 ( 2)  [htnse]forasian = 0
 ( 3)  [htnse]forcoll = 0
 ( 4)  [htse]forascoll = 0

           chi2(  4) =   45.48
         Prob > chi2 =    0.0000

.
. test [htnse]asian [htnse]ascoll [htnse]forasian [htnse]forascoll

 ( 1)  [htnse]asian = 0
 ( 2)  [htnse]ascoll = 0
 ( 3)  [htnse]forasian = 0
 ( 4)  [htnse]forascoll = 0

           chi2(  4) =   21.17
         Prob > chi2 =    0.0003

.
. test [htnse]asian [htnse]ascoll

 ( 1)  [htnse]asian = 0
 ( 2)  [htnse]ascoll = 0
```

```
           chi2(  2) =   12.78
         Prob > chi2 =    0.0017

. test [htnse]asian

 ( 1)  [htnse]asian = 0

           chi2(  1) =   12.31
         Prob > chi2 =    0.0004

.
. test [nhtse]foreign [nhtse]forasian

 ( 1)  [nhtse]foreign = 0
 ( 2)  [nhtse]forasian = 0

           chi2(  2) =    6.36
         Prob > chi2 =    0.0416

. test [nhtse]foreign [nhtse]forasian [nhtse]forcoll [nhtse]forascoll

 ( 1)  [nhtse]foreign = 0
 ( 2)  [nhtse]forasian = 0
 ( 3)  [nhtse]forcoll = 0
 ( 4)  [nhtse]forascoll = 0

           chi2(  4) =   51.73
         Prob > chi2 =    0.0000

.
. test [nhtse]asian [nhtse]ascoll [nhtse]forasian [nhtse]forascoll

 ( 1)  [nhtse]asian = 0
 ( 2)  [nhtse]ascoll = 0
 ( 3)  [nhtse]forasian = 0
 ( 4)  [nhtse]forascoll = 0

           chi2(  4) =    7.55
         Prob > chi2 =    0.1095

.
. test [nhtse]asian [nhtse]ascoll

 ( 1)  [nhtse]asian = 0
 ( 2)  [nhtse]ascoll = 0

           chi2(  2) =    4.46
         Prob > chi2 =    0.1075

. test [nhtse]asian

 ( 1)  [nhtse]asian = 0

           chi2(  1) =    0.46
         Prob > chi2 =    0.4981

.
. test [htse]foreign [htse]forlat

 ( 1)  [htse]foreign = 0
 ( 2)  [htse]forlat = 0

           chi2(  2) =   27.86
         Prob > chi2 =    0.0000

. test [htse]foreign [htse]forlat [htse]forcoll

 ( 1)  [htse]foreign = 0
 ( 2)  [htse]forlat = 0
 ( 3)  [htse]forcoll = 0

           chi2(  3) =  110.07
```

```
        Prob > chi2 =    0.0000

.
. test [htse]latino [htse]latcoll [htse]forlat

 ( 1)  [htse]latino = 0
 ( 2)  [htse]latcoll = 0
 ( 3)  [htse]forlat = 0

          chi2(  3) =  230.99
        Prob > chi2 =    0.0000

.
. test [htse]latino [htse]latcoll

 ( 1)  [htse]latino = 0
 ( 2)  [htse]latcoll = 0

          chi2(  2) =   91.06
        Prob > chi2 =    0.0000

. test [htse]latino

 ( 1)  [htse]latino = 0

          chi2(  1) =   84.44
        Prob > chi2 =    0.0000

.
. test [htnse]foreign [htnse]forlat

 ( 1)  [htnse]foreign = 0
 ( 2)  [htnse]forlat = 0

          chi2(  2) =   37.79
        Prob > chi2 =    0.0000

. test [htnse]foreign [htnse]forlat [htnse]forcoll

 ( 1)  [htnse]foreign = 0
 ( 2)  [htnse]forlat = 0
 ( 3)  [htnse]forcoll = 0

          chi2(  3) =   48.70
        Prob > chi2 =    0.0000

.
. test [htnse]latino [htnse]latcoll [htnse]forlat

 ( 1)  [htnse]latino = 0
 ( 2)  [htnse]latcoll = 0
 ( 3)  [htnse]forlat = 0

          chi2(  3) =  100.37
        Prob > chi2 =    0.0000

.
. test [htnse]latino [htnse]latcoll

 ( 1)  [htnse]latino = 0
 ( 2)  [htnse]latcoll = 0

          chi2(  2) =   52.96
        Prob > chi2 =    0.0000

.
. test [htnse]latino

 ( 1)  [htnse]latino = 0

          chi2(  1) =   50.07
        Prob > chi2 =    0.0000
```

```
.
. test [nhtse]foreign [nhtse]forlat

 ( 1)  [nhtse]foreign = 0
 ( 2)  [nhtse]forlat = 0

           chi2(  2) =   20.89
         Prob > chi2 =    0.0000

. test [nhtse]foreign [htse]forlat [nhtse]forcoll

 ( 1)  [nhtse]foreign = 0
 ( 2)  [htse]forlat = 0
 ( 3)  [nhtse]forcoll = 0

           chi2(  3) =   72.50
         Prob > chi2 =    0.0000

.
. test [nhtse]latino [nhtse]latcoll [nhtse]forlat

 ( 1)  [nhtse]latino = 0
 ( 2)  [nhtse]latcoll = 0
 ( 3)  [nhtse]forlat = 0

           chi2(  3) =  121.10
         Prob > chi2 =    0.0000

.
. test [nhtse]latino [nhtse]latcoll

 ( 1)  [nhtse]latino = 0
 ( 2)  [nhtse]latcoll = 0

           chi2(  2) =   49.58
         Prob > chi2 =    0.0000

. test [nhtse]latino

 ( 1)  [nhtse]latino = 0

           chi2(  1) =   42.45
         Prob > chi2 =    0.0000

.
.
```

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