THREE ESSAYS ON EDUCATIONAL DECISIONS AND LABOR MARKET OUTCOMES OF YOUTHS: AN EMPIRICAL ANALYSIS OF SECOND GENERATION IMMIGRANTS AND ETHNIC MINORITIES

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Abstract

Essays on Educational Decisions and Labor Market Outcomes of Youths: An Empirical Analysis of Second Generation Immigrants and Ethnic Minorities

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This thesis investigates human capital accumulation process for second generation immigrants and ethnic minority groups in both Canada and the U.S. A dynamic structural model is developed to respect the dynamic nature of the educational process. The model is then augmented to account for specific characteristics of different surveys used in the three essays.

The first essay focuses on educational attainment of children of immigrants to the U.S. using two cohorts of National Longitudinal Survey of Youth (NLSY79 and NLSY97). It shows that family background characteristics together with cognitive ability are important to children's schooling attendance. It suggests that over the decades, children of immigrants as a group experienced a more significant improvement in educational attainment than children of natives. Preferences and endowments play different roles in explaining the improvements across ethnic groups. This essay also shows additional evidence of positive selection in immigrants similar to the ones discussed in Caponi (2011). Furthermore, educational support programs appear to have larger impacts on educational attainment, especially for Hispanics.

The second essay looks both educational attainment and outcomes in labor mar-

ket. Specifically, it explains differences in education and wages between whites and ethnicity minorities in the U.S. using the recent cohort of National Longitudinal Survey of Youth (NLSY97). This essay reveals significant differences in how labor market rewards education and working experience based on ethnic origins. Furthermore, the decompositions of the observed differentials between whites and minorities show that the differences in educational attainment can largely be explained by differences in endowments, while behavioural differences play a more important role in explaining the ethnic wage gaps.

The third essay focuses on white children of immigrants in both Canada and the U.S. Using 1997 cohort of National Longitudinal Survey of Youth from the U.S. and the 2000 cohort of Youth in Transition Survey from Canada, I find that family background is closely related to educational attainment of white children of immigrants in both countries. Results from counter-factual simulations suggest that incentive-based educational reforms are effective in increasing overall educational attainment for both children of natives and children of immigrants. Furthermore, the desired dollar amount of these educational subsidies are smaller in Canada than in the U.S.

Contribution of Authors

Chapter 1

This paper is co-authored with Dr. Jorgen Hansen and Dr. Miraslav Kucera. The paper uses a model that is similar to the ones developed by Dr. Jorgen Hansen and Dr. Christian Belzil (2002, 2007). I helped Dr. Hansen to augment the model to consider initial educational attainment of individuals at age 16. I collected the raw data from the American National Longitudinal Survey of Youth 1997 cohort. I then created the variables so that they are ready to be estimated. My co-author Dr. Kucera collected the raw data from the American National Longitudinal Survey of Youth 1979 cohort. He also generated the needed variables. I generated descriptive statistics for the two cohorts after receiving the NLSY79 data from Dr. Kucera. With Dr. Hansen's help, I wrote the computer code for estimation. I estimated the model using the code. After estimation, I also designed and wrote the simulation code to perform counter-factual experiments using our model. I drafted the paper and passed it to Dr. Hansen and Dr. Kucera. they editted the paper and made corrections to the paper.

All data cleaning tasks were completed using SAS, while estimation and simulations were performed by using FORTRAN.

Chapter 2

This paper is co-authored with Dr. Jorgen Hansen and Dr. Miraslav Kucera. The model used in this chapter is similar to the one used in chapter 1. The paper also collected information from the same data source as in chapter 1 (NLSY97). I then generated three data sets to represent samples for whites, blacks and Hispanics. For estimation, I modified the estimation code used by chapter 1 so that we can estimate the model seperately for each ethnic group. Then I sent the code to my co-author (Dr. Kucera) to run the estimation. Later we discussed the possible simulations to run and Dr. Kucera designed and ran the actual simulations. Dr. Kucera drafted the paper and sent it to us, we (me and Dr. Hansen) then commented and editted the paper.

SAS and FORTRAN were used to generate all the results reported in the paper.

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I would like to thank professor Casey Warman and professor Christopher Ferral who invited me to present my paper at RDC Conference (2010) titled "Economic Relations Between Children and Parents" at Queen's University. I really appreciate their helpful comments and suggestions to my thesis. I would like to thank all participants to my presentation session at the 44th Annual Conference of the CEA for their comments and advices. I want to thank professor Arthur Sweetman for his helpful suggestions made to my last essay at the 45th Annual Conference of the CEA. I want to also thank professor Susumu Imai at Queen's University as well as professor Petra Todd at University of Pennsylvania for their candid suggestions and comments to my first essay.

I want to use this opportunity to thank my wife who gave up her career in China and joined me in Canada to provide me countless support for my completion of my thesis.

Finally, I would like to thank my parents and my friends who gave me encouragement all the time so that I can keep going this far.

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Introduction

The accumulation of human capital and its return on the labor market has been a popular topic in Labor Economics and has promoted the development of many theories and empirical studies in this field. Similarly, the economic assimilation of immigrants in the host countries has also been a popular research area for several decades, especially in the large immigration countries such as the United States of America and Canada. The current thesis centers around education and labor market outcomes of second generation immigrants and of some minority ethnic groups in the countries.

Educational attainment is such an interesting and popular research area that it has attracted researchers from different disciplines, with sociology and economics among them. I will review the relevant academic literature mainly in economics, acknowledging important contributions from other disciplines.

An extensive survey of sociological and economic literature on educational achievement was provided by Haveman and Wolfe (1995). In their reviewed list of studies, most use linear or non-linear regression methods to reveal how observable personal characteristics are related to educational attainment. According to their survey, parental education and human capital are statistically important determinants of educational attainment. Family environments, such as number of siblings and living with both biological parents are also closely related to educational attainment.

Examples of recent studies in economics that analyze high school drop-out behaviors include Parent, 2006; Rumberger and Lamb, 2003; Tyler et al., 2000; and Eckstein and Wolpin, 1999. For example, Parent (2006) found that working while attending high school had negative impact on the completion of high school and parental educational attainment was considered to be positively related to the probability of completing high school. Using a structural modeling approach, Eckstein and Wolpin (1999) also showed that parental education and cognitive skill measures (GPA in their paper) are closely related to youth's educational attainment. Other studies that focused on higher education in Canada include Belley et al, 2011; Frenette, 2007; Coelli, 2005; Drolet, 2005; Finnie et al., 2005; Frenette, 2005; Corak et al., 2005; Rivard and Raymond, 2004; and Frenette, 2003. These studies also well documented the relationship between family background (including parental education and income) and educational attainment by using regression models.

Many researchers believe that educational decisions are sequential and use transition probability models to investigate the human capital accumulation process. Mare (1980) found that observed parental characteristics (especially parental income) have significant impacts on the grade transition probabilities. Moreover, the effect of parental income becomes less important for higher grade levels. Later on, Cameron and Heckman (1998) proposed an alternative model that controls for unobserved characteristics omitted by Mare (1980), and their results suggest that the effect of family income is negative for those with less than elementary schooling, is largest for those who graduated from high school but attended no further education, and then decline for grade levels above high school completion.

There are also studies that use ordered discrete choice models to analyze educational decisions (see for example, Kucera, 2008; McIntosh and Munk, 2007; Bauer and Riphahn, 2007; Lauer, 2003; Lucas, 2001; and Ermisch and Francesconi, 2001; and Cameron and Heckman, 1998). Among these studies, Bauer and Riphan (2007) looked at intergenerational education transmissions among second-generation immigrants and natives in Switzerland. They found that intergenerational educational attainment mobility is higher among second-generation immigrants than among natives. Furthermore, other family background characteristics such as family size and cost of education do affect the transmission mechanism for both second-generation immigrants and natives. However, the effects of these background variables are limited compared with parental education. Although the method as well as the data source employed in Bauer and Riphan (2007) are quite different than the ones used in this thesis (chapter 1), the current thesis considers parental education to be an important determinant of educational attainment of children of immigrants and natives. It also assumes that the effect of parental education is different for second-generation immigrants and natives. Using Canadian data, Kucera (2008) also analyzes educational decisions of second-generation immigrants in Canada except that he used a static ordered probit model. He found that second-generation immigrants in Canada perform better in terms of educational attainment than native Canadians, and that much of the educational difference is due to unobserved characteristics between second-generation immigrants and natives. The results presented by Kucera (2008) partly motivated chapter 1 and chapter 3 of this thesis which are designed to find if preferences over education in Canada and in the U.S are different for second-generation immigrants and natives, and to find what roles unobserved heterogeneity play in shaping youth's educational decisions.

Another research line in the literature of educational decisions acknowledges the importance of expected future earnings. In order to incorporate expected level of future income into the current decision making process, individuals are assumed to be forward-looking and to care about future benefits when making decisions today. Examples of such research can be found in Belzil and Hansen (2007, 2003, 2002); Eckstein and Wolpin (1999); and in Keane and Wolpin (1997). These studies employ structural dynamic programming methods to analyze educational outcomes in the U.S.

Similar to the methods used in Cameron and Heckman (1998, 2001), Belzil and Hansen (2006) and Sun (2008) use a reduced form dynamic educational decision model to analyze Canadian data. They found that expected future earnings and parental education are positively related to grade progression.

In terms of U.S. and Canada comparisons, Belley et al (2011) use data from the American National Longitudinal Survey of Youth and Canadian Youth in Transition

Survey to examine the role of parental income on post-secondary education (PSE) attendance. They report a much stronger relationship between parental income and PSE attendance in the U.S. relative to Canada, even after controlling for family background and adolescent cognitive achievement. While the current thesis employs the same data, the focus is on the comparison of general educational achievement between natives and second-generation immigrants and between different ethnicity groups (specifically whites, blacks and Hispanics).

Although the above listed papers differ in their methodologies and in their data sources, there are some common key findings shared by most studies.

First, parental human capital (in most cases approximated by parental education) has a large and significant effect on educational attainment of the next generation. Belzil and Hansen (2003) reported that among other family background variables parental education explains more than half of the variations in grade attainment. Moreover, Bauer and Riphahn (2007) argue that parental educational attainment is an important predictor of second generation schooling outcomes even after controlling for other family characteristics.

Second, researchers have different opinions on the effect of credit constraints on educational attainment. For example, Kane (1994) find that college attendance is sensitive to changes in the cost of attending college for American blacks in the 1990s. On the other hand, Carneiro and Heckman (2002) and Cameron and Heckman, (1998, 2001) suggest that long-run family factors (such as family size and structure) are more important than short-term income constraints. Coelli (2005); Drolet (2005) and Finnie et al. (2005) use Canadian data to examine credit constraint issues related to higher education.

Third, scholastic abilities have significant impacts on educational attainment. Heckman et al. (2006) show that both cognitive and noncognitive skills have significant positive effects on education. Frenette and Zeman (2007); and Thiessen

(2007) also show that standardized test scores taken in early teenage years as well as grade-point average in high school are important in determining the probability of completing high school and attending college. No doubt, measures of academic abilities are important to grade transitions.

In addition to the papers above, there is a branch of the literature that has focused on educational attainment of second-generation immigrants (including the previously mentioned Kucera (2008), and Bauer and Riphahn (2007)).

Borjas (1992, 1994) uses the concept of ethnic capital (defined as average skill level of immigrant parents in a certain ethnic group, for example, Hispanics) to explain educational attainment of future generations of immigrants. He also documented sizeable improvements in educational attainment in future generations.

Using the German Socio-Economic Panel, Gang and Zimmermann (2000) compares the educational attainment of second-generation German immigrants to the educational attainment of native Germans in the same cohort (17-38 years old in 1984). They found that ethnic origin matters significantly to educational attainment of children of immigrants after controlling for parental education, social support and assimilation measures. They also found that compared with natives, parental education has no independent effect on educational attainment of immigrants. Using information collected from German Census, Riphahn (2003) found that educational attainment of second-generation immigrants in Germany were significantly lower than that of natives after controlling for their family background, and that the educational gap actually had become larger over time.

Using Dutch data, Van Ours and Veenman (2003) found that parental education plays the most important role in shaping educational decisions of second-generation immigrants, and that second-generation immigrants have lower educational attainment because their parents have lower education. After controlling for parental education, educational differences cannot be explained by ethnicity differences.

Recent study by Dustmann and Theodoropoulos (2010) looks into educational attainment of ethnic minority immigrants and their children.[1] They show that ethnic minority children of immigrants are better educated compared to their native British born white peers. Second-generation immigrants obtain more education than the first generation and third and above generation do. They also show that second-generation ethnic minority immigrants have higher average wages but lower employment rate.

The educational outcomes of immigrants and their descendants also attract studies that use American or Canadian data, as these two countries are popular immigration destinations in the world. In general, studies using U.S. and Canadian data reveal an optimistic future for the success of second-generation immigrants. For example, in the U.S., Card et al. (2000) show that children of immigrants tend to have higher education than children of native born parents. While in Canada, Aydemir et al. (2009) and Aydemir and Sweetman (2008) both show that second-generation immigrants on average acquire more education than children of native born parents, because they have better educated immigrant parents. Other examples that use Canadian and U.S. data include: Chiswick (1977), Carliner (1980), Borjas (1992, 1993, 1994), Trejo (2003), and Smith (2003, 2006) for the U.S., Chiswick and Miller (1988), Sweetman and Dicks (1999), and Worswick (2004) for Canada.

Among the above mentioned studies, Aydemir and Sweetman (2008) is the only study that compares educational attainment of immigrants in Canada to that in U.S. and explains the differences in terms of immigration policies in the two countries. The current thesis also has a chapter that looks into this issue, but with a different methodology and different data sets. Further, Chapter 3 enriches the findings in Aydemir and Sweetman (2008) by confirming the positive effects of parental education on educational attainment of immigrants. However, it also shows that despite different focuses of immigration policies in the two countries, positive self-selections may exist

[1] The authors consider the following ethnic groups to be minority ethnic groups compared with white in Britain: Black Caribbean; Black African; Indian; Pakistani; Bangladeshi and Chinese.

in both countries.[2]

The existing literature on educational attainment of second-generation immigrants confirms that parental education (see Dustmann and Theodoropoulos, 2010) and income (see Bauer and Riphahn, 2007) are important factors in determining educational attainment of children of immigrants. Ethnicity origins of immigrants matter (see Gang and Zimmermann, 2000). Furthermore, cognitive abilities are also documented to be closely related to educational performances of children of immigrants (see Worswick, 2004).

Most of the results in the recent literature are derived from estimation of linear and non-linear regression models. Other studies used reduced form dynamic models, see for example Cameron and Heckman (1998, 2001), and Belzil and Poinas (2008). There are however a few studies that have used structural models to estimate effects of policy changes on educational attainment. Examples of such papers are Keane and Wolpin (1997, 2001), Eckstein and Wolpin (1999), Belzil and Hansen (2002, 2003, and 2007), Attanasio et al (2005), Todd and Wolpin (2006), and Caponi (2011). To my knowledge, Caponi (2011) is the only paper that used structural modeling techniques to analyze educational attainment of second-generation immigrants in the U.S. Specifically, he constructs an intergenerational self-selection model of migration and education which explains the evolution of earnings and education across three generations of Mexican immigrants in the U.S.[3] He found that altruism is important in motivating Mexicans to migrate to the U.S., since they choose to sacrifice (by having a reduction of human capital of their own) upon arrival for the benefits of future generations. He also found that migrants are positively selected from the ability distribution of the home country and their human capital can be substantially transmitted to their children.

[2]Positive self-selection means that countries such as Canada and the U.S. attract individuals with higher labor market abilities to take advantage of better opportunities in the host countries after immigration.

[3]His model features altruistic behavior of the first generation.

Motivated by previous studies that centered around educational attainment of second-generation immigrants (see for example Chiswick (1977), Chiswick and Deb-Burman (2004), Gang and Zimmermann (2000), Trejo (2003), Aydemir and Sweetman (2008), Kucera (2008), and Caponi (2011)) as well as educational attainment of minority ethnicity groups in the host countries (see for example Dustmann and Theodoropoulos (2010), and Cameron and Heckman (2001)), the current thesis is designed to analyze educational decisions of second-generation immigrants (chapter 1 and chapter 3) and of different ethnic groups (chapter 2) incorporating all of the above mentioned important factors (such as family background and cognitive abilities). A structural dynamic programming model is developed and used in all chapters to respect the dynamic nature of the educational decision making process and to recognize the forward looking behavior of rational individuals. The thesis assumes that individuals form their expectations towards future earnings while making their educational decisions. They also know about their scholastic abilities transferred from their parents (measured by standard tests scores and parental education), and their economic resources (captured by parental income, family size and structure).

The methodology in this thesis is based on the ones used in Belzil and Hansen (2002, 2007). In particular, the model assumes that students decide sequentially whether to enter the labor market or to continue to accumulate schooling. Further, students are assumed to be rational and forward-looking individuals who maximize the discounted expected lifetime utility over a finite horizon. Educational decisions are modeled from age 16 and onwards recognizing the possible endogeneity of the highest grade completed at age 16.[4]

This thesis extends the literature of dynamic structural modeling to the field of educational attainment of second-generation immigrants. To my knowledge, this the-

[4]Students may have completed different grade levels by age 16 and this, in turn, may be related to family background, cognitive skills as well as unobserved factors. If this is the case, the highest grade completed at age 16 is endogenous.

sis is one of the first few researches to utilize a fully dynamic structural programming model to analyze educational attainment of second-generation immigrants.[5]

To enrich the literature on education and wage gaps between white and other ethnic groups (Hispanic and black) in the United States, chapter 2 also employs a dynamic structural programming model on recent American data. Specifically, this paper departs from the study by Cameron and Heckman (2001) by using a fully structural dynamic model and presents updated results based on data collected from a more recent cohort of the National Longitudinal Survey of Youth. The older cohort of the same survey was used in Cameron and Heckman (2001).

In particular, the main interests of the thesis are to move beyond the descriptive data analysis that is prevalent in most of the previous work and to examine how family environment and cognitive skills shape youths' educational attainment in a dynamic programming framework. Moreover, the thesis also investigates whether these factors will have different impacts on educational attainment of second-generation immigrant, and of different ethnic groups. In addition, the thesis also tries to explore impacts of counterfactual immigration and/or educational policies on children of immigrants.

This thesis utilizes two comprehensive major micro-level surveys from the U.S. and Canada, the American National Longitudinal Survey of Youth and the Canadian Youth in Transition Survey. These surveys contain detailed information on family background, cognitive ability measures, as well as educational attainment and early labor market outcomes over time, which allows me to analyze individuals' educational decisions in a dynamic environment.

[5]Caponi (2011) who uses American data is another example of structural work on educational attainment of second generation immigrants, however, his approach differs from the one used in this thesis in many aspects. For example, he assumes that first generation immigrants make educational decisions for the second generation and considers three generation's utility maximization when making migration and education plans. In this thesis, individuals (second generation themselves) are assumed to make their own education decisions considering their endowments (parental education, test scores etc.) and environments (family size and structure).

In a more general educational attainment paper, Hansen and Liu (2012) also adopts a similar model on Canadian data to analyze the effects of different education policies in Canada.

The results suggest that parental education, family environment and test scores are all important determinants of educational attainment in both the U.S. and Canada, they confirm with the findings of most studies using American data, see for example, Belley et al., (2011); Urzua, (2008); Belzil and Hansen, (2002, 2003); Cameron and Heckman, (1998, 2001); Keane and Wolpin, (1997, 2001); Tyler et al., (2000), and Kane (1994). They also confirm with the evidences provided by some studies using Canadian data, see for example, Belley et al. (2011); Belzil and Hansen, (2006); Kucera, (2008); Corak et al., (2005); Finnie et al., (2005); Frenette, (2007); Aydemir and Sweetman, (2008); and Aydemir et al., (2008). The thesis also found that unobserved heterogeneity in scholastic and labor market abilities is a factor that should not be ignored when analyzing educational attainment. The current thesis also shows that cognitive skill (as measured by Armed Forces Qualification Test score) is a more important educational attainment predictor than family income. This suggests that long-term factors (ability measures and family environment measures) play a more important role in determining educational attainment.

Given that methods as well as data sources are similar in all three chapters, some findings are also common across chapters. For example, in all chapters, the estimated grade specific cost parameters are all smaller at grade 12 and 16, which suggests that in both the U.S. and Canada, most individuals (regardless of immigration and ethnic groups) have higher utility (or lower cost) by completing either high school (grade 12) or university (grade 16). Another example is that one of the results in chapter 2 indicates that educational gaps between whites and Hispanics are mainly explained by differences in family background and test scores. This result is also found in chapter 1 where the difference in educational attainment between whites and Hispanics is mostly due to differences in parental education, income and test scores.

In chapter 1, the simulation results suggest that father's education and test scores affect second-generation immigrants and children of natives differently in the U.S.

especially for Hispanics from an older American cohort. For example, for the two cohorts of American youths used in this paper, improved cognitive ability as measured by AFQT (Armed Forces Qualification Test) scores have larger positive impacts on educational attainment of second-generation Hispanic immigrants. However, these differences between second-generation immigrants and natives are less obvious for whites especially for the recent cohort of NLSY97.[6] This chapter also shows additional evidence to the ones discussed in Caponi (2011), which suggests that there may exist positive selection with respect to human capital of Hispanic immigrants to the U.S.[7] Finally, counterfactual policy changes show that compared to high school subsidy, educational subsidies designed to reduce the cost of post-secondary education appear to have larger impacts on educational attainment Hispanic children of immigrants.

Chapter 3 further confirms the results from chapter 1. It shows that the main differences in educational attainment between second-generation white immigrants and native whites are due to differences in family background and test scores in the U.S. Simulation results suggest that incentive-based educational reforms, such as to provide educational subsidies to reduce the costs (both monetary and psychic) of completing post-secondary education, are effective in increasing overall educational attainment for both groups. Furthermore, the desired dollar amount of these educational subsidies is smaller in Canada than in the U.S. On the other hand, this chapter suggests that both Canada and the U.S. are able to attract immigrants with higher level of human capital and higher income. In general, the better educated first generation white immigrants in Canada can be partly explained by the successful implementation of the "Point System" immigration policy introduced in 1967. Although the U.S. has a different immigration policy focus that favors family reunification,

[6]Simulation results in Table A1 are obtained by assuming that the impacts from different variables are different for different immigrant/ethnic groups although the estimated parameters representing these differences may not be significant for whites.

[7]Highly motivated Hispanic immigrants may choose to migrate to the U.S. for the benefit of their next generation.

high-skilled immigrants may be attracted to move to the U.S. to take advantage of higher returns in the labor market and of the better educational qualities for their next geneation.[8]

[8]Evidences of positive selection of immigrants are found in this chapter. These evidences are similar to the ones presented in Caponi (2011).

Chapter 1

Educational Attainment of Children of Immigrants: Evidence from Two Cohorts of American Youths[1]

Joint with Professor Jörgen Hansen[2] and Dr. Miroslav Kučera[3]

1.1 Introduction

The economic assimilation of immigrants in the host country's society has been a popular area of research for decades, especially in the U.S. and Canada where the population includes many immigrants as well as descendants of immigrants.

Since more and more immigrants decide to stay and raise their children in the host country, a more complete analysis of costs and benefits associated with immigration should also reflect a longer-term perspective that also considers how children of immigrants succeed relative to children of natives. This is particularly the case in the U.S. given its long history of immigration.

For example, focusing on the assimilation process of immigrants in the U.S., Duncan and Trejo (2008) found that Mexican immigrants generally have lower educational

[1] We thank Susumu Imai and participants at the 44th Canadian Economic Association's meeting in Quebec City and at the conference on Economic Relations Between Children and Parents at Queen's University for comments and discussions. We thank Arthur Sweetman and participants at the 45th Canadian Economic Association's meeting in Ottawa. The usual disclaimer applies.

[2] Concordia University, CIREQ and IZA

[3] Concordia University and Statistics Canada

attainment than American-born individuals. Moreover, most of these immigrants have low levels of schooling (well below high-school). Duncan and Trejo (2008) also reported that at the lower end of the grade distribution, male Hispanic immigrants are more likely to be employed than American-born males. On the other hand, Caponi (2011) finds that positive selection of first generation Mexican immigrants to the U.S. exists. He argues that Mexicans migrate to the U.S. willing to sacrifice by having a reduction of human capital of their own upon arrival for the benefits of future generations. He also found that migrants are positively selected from the ability distribution and their human capital can be substantially transmitted to their children to make them succeed in the host country.

Previous research has shown that children of immigrants generally acquire more schooling than otherwise similar children of native-born parents both in Canada and in the U.S. However, past research has generally been descriptive, and as such, has not been able to explain why such educational differences exist (see Aydemir et al. (2009), Aydemir and Sweetman (2008), and Hansen and Kucera (2004)). For example, an educational gap may arise because of differences in cognitive abilities between children of immigrants and children of natives. Furthermore, these ability differences could occur if abilities are transmitted across generations and if there is a non-random selection of immigrants where only those with high abilities find it worthwhile migrating or are the only ones accepted in the host country.

In order to advance our knowledge in this area, we need to move beyond the descriptive data analysis that is prevalent in previous work. Many of these studies suffer from various data and methodological problems, and generally offer only limited insights into this topic. In this paper, we recognize the need to respect the structure and dynamic nature of the educational process. Consequently, we formulate and estimate an economic model of educational attainment of American youths where young adults optimally choose between school and work based on their own abilities, preferences and opportunities. The behavioral parameters are estimated using data from two cohorts of the National Longitudinal Survey of Youth (NLSY79 and NLSY97), which puts this study among few other papers to compare educational attainments between two cohorts in the context of the labor market outcomes of children of immigrants in U.S.[4]

In this paper, we limit our analysis to two ethnic groups, whites and Hispanics.[5] Descriptive statistics show that family environment is important in shaping young individuals' educational decisions. In each ethnicity group, children of immigrants acquire more schooling, on average, than children of natives. These differences remain, and are even magnified, after controls for family characteristics, test scores and ethnicity are included.

Results from our structural analysis indicate that family background characteristics, in particular parental education and income, have significant positive effects on children's schooling attendance. Moreover, the observed improvement in second-generation immigrants' educational attainment over the decades is closely related to improvements the family environment. The results also indicate that there are some important differences in preferences between second generation immigrants and natives across ethnic groups. This is true for Hispanics from the two cohorts and whites from the older cohort. For instance, father's educational attainment and_Armed Forces Qualification Test scores (AFQT)_are more important to educational decisions for children of immigrants' of Hispanic decent. Children of immigrants seem to value education more than children of natives, especially for Hispanics.[6]

[4]Indeed, it is one of the first studies on this topic that utilizes data from both cohorts. Other recent papers include Belley and Lochner (2007), Altonji et al (2008) and Hansen et al (2011 a and b).

[5]Differences in educational attainment between ethnic groups in the U.S. have been well documented in Kane (1994), Chiswick and Miller (1988), and Cameron and Heckman (2001). We recognize the difference in preference over education by different ethnic groups. We choose whites and Hispanics because these are the two of the three largest ethnic groups in the U.S. blacks are excluded because, we observe very few second-generation black immigrants in our data.

[6]Second-generation Hispanics have higher level of unobserved scholastic ability (or preference of education) than their native peers.

When comparing results from the two cohorts, we find that children of immigrants as a group experienced a more significant improvement in educational attainment than children of natives. In particular, children of white immigrants increased their schooling attainment the most. There are a number of reasons for this increase, including a significantly improved set of family background characteristics and an increase in cognitive skill levels measured by AFQT scores. Children of Hispanic immigrants obtained more schooling than children of native Hispanics in both surveys. They also increased their educational attainment over the twenty-year period when comparing the two cohorts. Furthermore, while family background characteristics improved over this period for children of Hispanic immigrants, this was not as dramatic as that of children of white immigrants.

We used the estimated parameters to perform a number of counterfactual simulations. We considered different policy changes, including a reduction in the cost of attending high school and college. Results from these simulations suggest that, compared to white second-generation immigrants, children of Hispanic immigrants are more responsive to subsidies at the high school and college level. We also considered the effects of an alternative policy where we increase the number of completed years of education for immigrants. This policy is observed to improve educational outcomes of second-generation Hispanics as well. Thus, improved family environments combined with educational support programs appear to have larger impacts on educational attainment of children of immigrants, especially for Hispanics.

Overall, we believe that the results in this paper are interesting given that educational attainment of second-generation immigrant have become a popular research area and raised important questions about the assimilation of immigrants in major immigrant countries (see Aydemir and Sweetman 2008; Aydemir et al. 2009; Colding, Husted and Hummelgaard 2009; Duncan and Trejo 2008; and Riphahn 2003). The rest of the paper is organized as follows. The model is introduced and explained in the next Section. Section 3 is devoted to a description of the data. The main results are presented and discussed in Section 4, we also present model fit and some simulation results, while Section 5 concludes the paper.

1.2 A Structural Model of Schooling and Wages

In this section, we present our structural model. The model extends the ones used in Belzil and Hansen (2002, 2007). Individuals in our model decide sequentially whether to enter the labor market or to continue to accumulate schooling. They are assumed to be rational, forward-looking, and to maximize discounted expected lifetime utility over a finite time horizon, set to the age of 65 (retirement age). There is only one control variable in the model, d_{it}, which equals one if an individual decides to continue accumulate schooling and zero if an individual decides to leave school and enter the labor market. We start modeling educational decisions the year individuals turn 16, $t = 0$[7]. Moreover, at age 16, the amount of schooling accumulated by an individual is denoted by S_{i0}.

1.2.1 Utility of Attending School

Formally, in period t, the utility of attending school is represented by the following equation:

$$U_{it}^{hs} = ln(C_{it}^{hs}) = A^h(X_{it})I(S_{it} = j) + \alpha_0^k S_{i0} + as^k + uh^h + \varepsilon_{it}^{hs} \tag{1.2.1}$$

[7] Age 16 is when most individuals are allowed to work legally in most states in U.S.

$$j = 4, 5, 6, 7...$$

where i stands for individual, k stands for number of unobserved heterogeneity types, while h is an indicator that identifies ethnicity and immigrant status. We distinguish between the following four groups: i) Children of immigrants with Hispanic origin; ii) Children of immigrants with white origin; iii) Children of natives with Hispanic origin; and iv) Children of natives with white origin.

Further, t represents a time period, $\ln C_{it}^{hs}$ is defined as the instantaneous monetary returns of going to school (to make it comparable to the utility of working) for young adults of different immigrant and ethnicity origins. $A^h(.)$ is assumed to be a linear function of X_{it} with different parameters for individuals with different immigration/ethnic backgrounds. X_{it} contains time-invariant individual characteristics in period t, such as household income (averaged over four years), father's education, mother's education, test scores, and finally, immigrant and ethnicity origins. These are initial endowments to each individual that remain fixed over time.

The term $\alpha_0^k S_{i0}$is included to control for the possible endogeneity of initial schooling endowment at age 16 (S_{i0} is the years of schooling completed at age 16). The indicator function, $(S_{it} = j)$, is included to reflect that the utility of attending school may vary with grade levels. In particular, $I(S_{it} = j)$ equals 1 if individual i completes grade level j in period t, and 0 otherwise. Finally, as^k represents unobserved, time invariant heterogeneity while ε_{it}^{hs} represents unobserved, time invariant heterogeneity.[8]

1.2.2 Utility of Working

The instantaneous utility of work is defined by the following equation:

[8] The unobserved heterogeneity could be interpreted as unobserved scholastic ability, motivation, or attitude towards education

$$U_{it}^{hw}(.) = W^h(Z_{it}) + aw^k + uw^h + \varepsilon_{it}^{hs} = \ln(W_{it}^h) \tag{1.2.2}$$

Where $W^h(Z_{it})$ is a linear wage equation which incorporates modified AFQT scores, educational attainment, and working experiences. Unobserved, time invariant heterogeneity is represented by aw^k while immigration/ethnicity status is represented by h.[9] Finally, ε_{it}^{hs} is a pure random wage shock. The instantaneous log wage is further specified as follows:

$$\ln(W_{it}^h) = \beta_0^k * S_{i0} + tstw^h * AFQT_i + retedu^h * S_{it} + retxp^h * Exper_{it} + aw^k + uw^h + \varepsilon_{it}^{hw} \tag{1.2.3}$$

Where $\beta_0^k * S_{i0}$ controls for initial educational attainment at age 16 while $retedu^h$ and $retxp^h$represent the return to schooling and work experience, respectively.

1.2.3 Schooling Interruptions

Arguably, the optimal stopping feature of the model is restrictive. In order to conform more closely to empirical facts, we follow Belzil and Hansen (2002, 2007) to allow schooling interruptions. In particular, we treat a schooling interruption as a state which occurs with an exogenous probability, π_t, and is represented by a binary indicator variableI_{it}. If an interruption occurs in a given time period t, and $I_{it} = 1$, the decision problem is frozen for one period and the stock of schooling remains constant over that period.

[9] Unobserved heterogeneity in the wage equation refers to any unobserved factor that can affect the wage level, including abilities related to labour market, motivation, discrimination etc.

1.2.4 Initial Schooling

It is reasonable to assume that the permanent personal endowments that help explain schooling decisions beyond age 16 are also instrumental in determining how much schooling one has acquired by age 16. A failure to account for this possibility could seriously bias the estimates of the structural parameters. Consequently, we choose to model initial schooling as an ordered-choice, and let initial-schooling grade probabilities depend on a vector of observable individual characteristics as well as on unobserved abilities.

1.2.5 Value Functions

As we have mentioned above, at the beginning of each time period individuals choose between continuing to invest in schooling ($d_{it} = 1$) or terminating schooling investments and entering the labor market ($d_{it} = 0$). The choice of entering the labor market is assumed to be permanent. That is, ($d_{it} = 0$) implies that $d_{ij} = 0$ for all $j = t + 1, ..., T$.

The current discounted value of choosing to remain in schooling at the beginning of period t can be expressed by the following Bellman equation:

$$V_t^{hs}(S_t, \Omega_t) = \alpha_0 S_0 + X' b^h + as^k + uh^h + \varepsilon_t^{hs}$$

$$+\beta\{(1 - P_{t+1})EMAX[V_{t+1}^{hs}(S_{t+1}, \Omega_{t+1}), V_{t+1}^{hw}(S_{t+1}, \Omega_{t+1})] + P_{t+1}E[V_{t+1}^{I}(S_{t+1}, \Omega_{t+1})]\}$$

In particular,

$$V^I_{t+1}(S_{t+1}, \Omega_{t+1}) = \alpha_0 S_0 + X' b^h + as^k + uh^h + \varepsilon^{hs}_{t+1}$$

$$+\beta\{(1 - P_{t+2})EMAX[V^{hs}_{t+2}(S_{t+2}, \Omega_{t+2}), V^{hw}_{t+2}(S_{t+2}, \Omega_{t+2})] + P_{t+2}E[V^I_{t+2}(S_{t+2}, \Omega_{t+2})]\}$$

And β denotes the discount rate, P_{t+2} is the probability that a schooling interruption will occur in period $t + 2$, and $V^I_{t+1}(S_{t+1}, \Omega_{t+1})$ denotes the value an individual receives when he is in the state of interruption in period $t + 1$. The probability of experiencing an interruption in period $t + 1$ is assumed to be exogenous.

The state variable S_t represents educational attainment at the beginning of period t, while Ω_t contains information on the individual's initial educational attainment (S_{i0}), family background and personal characteristics, unobserved heterogeneity represented by the vector $\Theta \in (as^k, uh^k, uw^h, aw^k, \varepsilon^{hs}_t, \varepsilon^{hw}_t)$ and accumulated work experience ($Exper_t$).

The value of terminating schooling and entering the labor market in period t is given by:

$$V^{hw}_t(S_t, \Omega_t) = ln(W^h_t) + \beta E[V^{hw}_{t+1}(S_{t+1}, \Omega_{t+1})|d_t = 0]$$

where the second term on the right-hand side is simply the discounted expected value of working from period $t + 1$ until retirement:

$$\beta E[V^{hw}_{t+1}(S_{t+1}, \Omega_{t+1})|d_t = 0] = \sum_{j=t+1}^{T} \beta^{j-(t+1)}\{Pr(w_{ij} > 0)$$

$$*E[(\beta^k_0 S_{i0} + tstw^h * AFQT_i + retedu^h * S_{ij} + retxp^h * Exper_{ij} + aw^k + uw^h + \varepsilon^{hw}_{ij})|w_{ij} > 0]$$

$$+Pr(w_{ij} > 0) * 0\}$$

Furthermore, the probability of working in period t, $Pr(w_{it} > 0)$, is modeled as follows:

$$Pr(w_{ij} > 0) = Pr(z^*_{ij} > 0) = \Phi(Z^{'}\eta_{it})$$

Where,

$$Z^{'}\eta_{it} = uprw_i^k + upw^h + wsh * S_{i0} + wretedu * S_{it} + wretxp * Exper_{it} + wtstw * AFQT_i$$

Thus, we can write:

$$E[V^{hw}_{t+1}(S_{t+1}, \Omega_{t+1})|d_t = 0]$$

$$= \sum_{j=t+1}^{T} \beta^{j-(t+1)}\{\Phi(Z^{'}\eta_{it}) * (\beta_0^k S_{i0} + tstw^h * AFQT_i + retedu^h S_{ij} + retxp^h * Exper_{ij}$$

$$+aw^k + uw^h) + \lambda * \phi(Z^{'}\eta_{ij})\}$$

Here, λ is a parameter to be estimated along with the other parameters in the model, $\phi(.)$ is the standard normal probability density function while $\Phi(.)$ is the corresponding cumulative distribution function.

Finally, each value function is solved by backward induction and an individual chooses to terminate schooling and enter the labor market permanently in period t if:

$$V_t^{hs}(S_t, \Omega_t) \geq V_t^{hw}(S_t, \Omega_t)$$

1.2.6 Unobserved Heterogeneity

Unobserved heterogeneity includes any unobserved (in the data) individual characteristics, abilities and preferences that determine educational decisions. For example, unobserved heterogeneity includes taste for schooling and working, innate non-cognitive abilities, ambitions etc. Ideally, each individual should be endowed with a unique set of all these factors. However, this is not feasible when we confront our model with survey data. Instead, as is customary in these types of models, we model unobserved heterogeneity as a set of random variables that are discretely distributed. Thus, we assume that individuals can be aggregated into groups that share characteristics, preferences and abilities.

In particular, we assume that there are K groups (or types of individuals), and express the probability of belonging to type k as:

$$p_k = \frac{exp(q_k)}{\sum_{j=1}^{K} q_j}$$

$$q_k = 0,\ k = 1, 2, 3 \ldots K$$

1.2.7 AFQT Scores

The NLSY offers unique opportunities to control for cognitive abilities, measured by the Armed Forces Qualification Test (AFQT) scores. There is ample evidence showing that AFQT scores are closely related to educational achievement.[10] By incorporating test scores in the model we can examine how much of educational differences across ethnic/immigrant groups and time periods are due to changes in cognitive skills.

Both NLSY79 and NLSY97 collect information on a series of standardized achievement tests taken by youths in the first wave of the survey. The AFQT scores were constructed from four subtests of ASVAB.[11] However, the AFQT measures from the two surveys cannot readily be compared at individual levels due to the fact that different methods were utilized to generate the scores in NLSY79 and NLSY97, respectively.[12] Furthermore, the age at which individuals took these tests differs, both within and between surveys. To make the analysis comparable across cohorts, we use AFQT measures generated by Altonji, Bharadwaj and Lange (2009).[13]

1.2.8 The Likelihood Function

The dynamic programming problem is solved using backward recursion and the parameters of the model are estimated using maximum likelihood techniques. The decision rule d_t, $t \in \{0, 1, 2, ..., 13\}$, determines the transition path from school to work. Given the value functions defined above, the transitional probabilities are:

[10] Griliches and Mason (1972), Ashenfelter and Rouse (1999), Belzil and Hansen (2003) and Moretti (2004) are just a few studies that have documented the importance of AFQT scores in educational investments.

[11] Armed Services Vocational Aptitude Battery (ASVAB) contains 10 sub-tests. The four subtests included in AFQT are Word Knowledge; Paragraph Comprehension; Arithmetic Reasoning; and Numerical Operation or Numerical Comprehension.

[12] NLSY79 used Paper and Pencil tests, NLSY97 used Computer Adaptive Tests.

[13] They converted the computer based test scores from NLSY97 into measures that are comparable with the pencil-based test scores from NLSY79.

$$Pr(d_{t+1} = 0|d_t = 1) = Pr[V_t^w(S_t) \geq V_t^s(S_t)]$$

$$Pr(d_{t+1} = 1|d_t = 1) = Pr[V_t^s(S_t) > V_t^w(S_t)]$$

These probabilities can be calculated given distributional assumptions of the time-varying utility shocks. The likelihood function, conditional on unobserved heterogeneity, consists of the following parts:

- The probability of observing a particular sequence of schooling/interruption histories, given by:

$$L_1(k) = Pr\{[d_0(k), I_0(k)], [d_1(k), I_1(k)], ..., [d_\tau(k), I_\tau(k)]\}$$

- The probability of entering the labor market in period $\tau + 1$, at observed wage $w_{i\tau+1}$ which can be expressed as a product of a normal conditional probability and a marginal wage density $f(w_{i\tau+1}(k))$:

$$L_2(k) = Pr(d_{\tau+1}(k) = 0, w_{\tau+1}(k)) =$$

$$Pr(d_{\tau+1}(k) = 0|w_{\tau+1}(k)) * f(w_{\tau+1}(k))$$

- The joint densities of observed wages from $\tau + 2$ until the last observed period T.[14]

[14] Note that T is individual specific.

$$L_3(k) = f[w_{\tau+2}(k), ..., w_T(k)]$$

- The probability of having completed S years of schooling at age 16, given by:[15]

$$L_4(k) = Pr(S_{i0} = s),\ s \in \{7, 8, 9, 10, 11\}$$

- The probability of having an observed wage in period t:

$$L_5(k) = [\Phi(Z^{'}\gamma)^{dw_{\tau+1}} * (1 - \Phi(Z^{'}\gamma))^{1-dw_{\tau+1}}]*$$

$$[\Phi(Z^{'}\gamma)^{dw_{\tau+2}} * (1 - \Phi(Z^{'}\gamma))^{1-dw_{\tau+2}}] * ... * [\Phi(Z^{'}\gamma)^{dw_{\tau+T}} * (1 - \Phi(Z^{'}\gamma))^{1-dw_{\tau+T}}]$$

Hence, the complete conditional likelihood function is:

$$L_i(k) = L_1(k) * L_2(k) * L_3(k) * L_4(k) * L_5(k)$$

Where, $L_i(k)$ is the likelihood contribution of individual i, belonging to type k. Finally, the complete unconditional log-likelihood contribution of individual i is given by:

$$log(L_i) = log \sum_{k=1}^{K} p_k * L_i(k)$$

where p_k is the probability of belonging to group k, defined above.

[15] This probability is obtained using an ordered Probit model.

1.3 Data

In this paper, we utilize data extracted from both the 1979 and 1997 cohorts of the National Longitudinal Survey of Youth, henceforth NLSY79 and NLSY97, respectively. Both surveys provide detailed information on educational achievement, labor market experiences and socio-economic characteristics, including measures of cognitive skills. Moreover, by utilizing both surveys we are able to compare how educational and labor market outcomes of young individuals have changed since 1980s.

Unlike the NLSY79, which had long been a major source of information on the transition from school to work, the use of NLSY97 has until recently been limited by the young age of the respondents. Since the NLSY97 consists of youths aged 12 to 16 in 1996, a meaningful analysis of school to work transitions is only recently becoming feasible for this cohort.[16]

In this study, we focus on how educational and early labour market outcomes of children of immigrants in U.S. compare with children of U.S. born parents. In addition, we limit our attention to males from two ethnic groups, whites and Hispanics. In particular, we define an individual to be an child to immigrant if at least one of the parents was born outside of U.S. Moreover, for the NLSY79 sample, we exclude respondents who were older than 16 when first surveyed (1978). After these sample selections, we end up with 1,571 males from the NLSY79 cohort and 2,225 males from the NLSY97 cohort.

Data on school enrolment status was obtained using grades completed in adjacent survey years.[17] Further, by utilizing information on grades completed in the survey year, the survey month, and the birth month we calculated accumulated grades

[16] By 2007, a majority of the surveyed individuals had completed their schooling (about 85 percent in our sample) and entered the work force.

[17] Thus, an individual observed to have completed a higher grade in the subsequent survey year is defined as being enrolled in school the current year. If instead the individual's highest grade completed is the same in the subsequent year, he is defined as being not enrolled in school the current year.

completed for each year beyond age 16.

Information on hourly wages was collected from 1997 to 2007 in NLSY97 and from 1979 to 2006 in NLSY79. All wage and income measures were adjusted to 1997 dollars. Further, we ignored reported wages that were below the federal minimum wage rate for the year in question.

AFQT scores are utilized to control for measured scholastic ability. Given that test scores are closely correlated with acquired schooling, we use adjusted ability measures in this paper obtained as the residuals from regressions of AFQT scores on years of schooling by the time the tests were taken. Moreover, as discussed in Altonji, Prashant and Lange (2009), the AFQT scores from the two surveys are not directly comparable. To address this issue, we follow their methodology and modify the 1979 scores to make them comparable with the 1997 scores.

Table 1.1 shows that, according to our definition, 10.9 percent of the respondents in the NLSY79 sample were children of immigrants while the corresponding figure for the NLSY97 cohort is 11.6 percent. Further, the proportion of Hispanics increased from 9.2 percent in 1979 to 15.4 percent in 1997. This increase reflects overall changes in the composition of the U.S. population and increases are observed both among children of natives and children of immigrants.

Since this paper tries to analyze educational attainment for two cohorts of children of immigrants, a descriptive analysis of selected socioeconomic characteristics is important. Comparisons are done by immigrant and ethnic groups. Parental education is measured by the highest grade completed. Parental income measures annual gross income, expressed in thousands of 1997 dollars. Information on this income was collected between 1978 and 1985 for the NLSY79 cohort and between 1997 and 2000 for NLSY97 cohort. Finally, accumulated education was taken by the time individual was last surveyed.

Table 1.2 and Table 1.3_show that within each ethnic group, children of immigrants accumulate slightly more education than children of natives, except for whites from the NLSY79. On the other hand, children of immigrants appear to come from families with disadvantageous environment except for second-generation whites from the recent cohort. Their parents have lower incomes and have completed less years of schooling. Moreover, the AFQT scores are, on average, lower for children of immigrants. However, for Hispanics, children of immigrants outperform their native counterparts in terms of educational attainment in both surveys, despite being brought up in less favorable family environments. Similar differences in educational attainment can be observed for whites. However, unlike children of immigrants of Hispanic origin, white children of immigrants have experienced significant improvement across the surveys, both in terms of family background characteristics, educational attainment and test scores.

Other than looking at mean accumulated education, we also take a closer look at distributions of grades completed for children of immigrants from our 1979 sample and 1997 sample. Clearly, from NLSY79 to NLSY97, second-generation educational attainments have been increased significantly, ratio of high school dropouts decreased from 35.67% to 22.09%, more people attended grades beyond 12 than before. The distribution of years of schooling has been shifted to the right for second-generation Hispanics and second-generation whites respectively. This trend is more significant for the whites who have more college graduates and high school graduates than Hispanics in both surveys.

Figures 1.2 through 1.4 show detailed information about grades distributions for different immigration and ethnic groups over the decade. Figure 1.1 and Figure 1.2 plot accumulated grades for children of immigrants from NLSY79 and NLSY97. Figure 1.3 and Figure 1.4 summarize accumulated years of schooling for native children from the two cohorts of NLSY. We can see that, in NLSY79, Hispanics dominated lower end of the education distribution, while whites dominated higher end of the distribution. There is no obvious difference between white children of immigrants and white natives, although white natives do have a slightly right shifted distribution compared to white children of immigrants. Second-generation Hispanics have comparatively less individuals from the lower end than native Hispanics, and they have more individuals at grade 13, 15, 16 and 17. At grade 16, second-generation white immigrants and native whites share the same percentage, second to whites is second-generation Hispanics, then native Hispanics is at the bottom.

In contrast to NLSY79, Hispanics are close to themselves regardless of their immigration status. Second-generation whites dominate two-years College (14 years of schooling) and university (16 years of schooling) shares. Surpassing native whites, second-generation whites in NLSY97 have a much right shifted education distribution. At university level, mostly are second-generation whites, then there are native whites, Hispanics are at the bottom. While other groups have their peak at grade 12 (equivalent to high school diploma), white children of immigrants have their peak at grade 16 (equivalent to university degree).

To make the educational attainment comparison in time dimension, we also plot NLSY79 and NLSY97 in a same figure for each specific group. Among the 4 groups, native whites have minor changes in terms of their education distributions in 20 years. Compared to the older cohort, recent cohort has less 12 grades, more 14 and 17 grades. One can see a right shifting pattern for native Hispanics by comparing the two cohorts. Second-generation Hispanics are also catching up by having more individuals at higher end of the distribution than their predecessors.

Second-generation whites really draw attention by having distinct education distributions over time. In contrast to the older cohort, recent cohort has very few high school dropouts, far more college graduates and university graduates. Not like their early counterparts, Second-generation whites in NLSY97 have largest shares of individuals in university graduates.

1.4 Empirical results

In this section, we present the empirical results from maximizing the likelihood function above. Selected estimates of the structural parameters are presented in Table 1.4 and Table 1.5[18]. Generally, the interpretation of the parameters is not straightforward, although the signs of the estimates provide information about whether the effects on utility of work or school are positive or negative. To quantify the effects on education from changes in observed characteristics we calculate the equivalent of marginal effects by predicting outcomes before and after a change in a particular variable.[19]

1.4.1 Unobserved heterogeneity

The importance of unobserved heterogeneity is illustrated in Table 1.4, which contains estimates of the type-specific intercepts in the utility of attending school equation and log-wage equation as well as estimates of ethnicity/immigrant indicators. The intercept terms of the utility of school range from -2.58 (type 1) to -0.295 (type 2) for the 1979 cohort and from -0.92 (type 2) to 0.23 (type 1) for the 1997 cohort. There is also disparity of the intercept terms in the log-wage equation. They range from -0.47 (type 4) to 1.25 (type 1) for the 1979 cohort and from -0.86 (type 4) to 2.91 (type 1). These estimates suggest the existence of a negative correlation between utility of school and wages in the 1979 cohort while the correlation is positive in the 1997 cohort.

[18] Other parameter estimates are available upon request

[19] The marginal effects are calculated using estimated parameters, although some of these parameters may not be estimated accurately (non-significant)

1.4.2 Return to schooling and work experience

The wage returns to education and experience are found in Table 1.5. We allow the returns to differ across the four groups. For the 1979 cohort the return to education for white children of natives is 0.12 while it is substantially lower for the 1997 cohort, 0.021. Part of this difference is likely due to the differences in labor market exposure across the two cohorts.[20] Regarding differences across the groups, there are no differences between native whites, second-generation whites and second-generation Hispanics in the 1979 cohort. However, for native Hispanics, the return is significantly lower than for the other three groups, 0.023. For the 1997 cohort, the return is significantly higher for second-generation whites (0.075) than for native whites. There are no significant differences in the returns between the other three groups. [21]

The return to work experience for native whites are similar across the cohorts, 0.028 for the 1979 cohort and 0.023 for the 1997 cohort. There are significant differences across the groups in both cohorts. For the older cohort, the return is significantly lower for second-generation Hispanics (0.016) as well as for native Hispanics (-0.002). For the younger cohort, the return for second-generation Hispanics has increased and is significantly higher than that of native whites (0.048). There are no significant differences in the return to work experience for the other groups.

[20] We use data from NLSY79 that covers 1979 through 1996, while NLSY97 covers 1997 through 2007 only. Individuals in the older cohort had chance to enjoy higher returns to education after being in the labor force longer than the ones in recent cohort

[21] The magnitudes of wage returns reported in this paper are similar to the ones presented in Belzil and Hansen (2002, 2003)

1.4.3 Effects of observable characteristics on educational attainment

As mentioned above, because of the non-linear nature of the model, the parameter estimates do not measure marginal impacts of observed variables on outcomes. Instead, to quantify the importance of selected covariates we use the estimated parameters to predict outcomes from the model before and after a change in the variable of interest. These "marginal" effects are presented in Table A1 (in Appendix), by cohort and ethnicity/immigration category. Table A1 is based on estimated parameters of the model, although some parameters used are not significant.

We illustrate the effect of scholastic ability on educational attainment by adding 10 points (about 7% of the mean) to everyone's adjusted AFQT score and recording the subsequent changes in education. The results are shown in the first row of Table A1. For natives and second-generation Hispanics, the effect of this change is larger for the older cohort than for the younger cohort while the opposite is true for white children of immigrants. These counterfactual increases in scholastic ability are predicted to increase schooling attainment by 0.4 to 2.4 percent, depending on group and cohort. The smallest effect is observed for native whites in the 1997 cohort while the largest effect is observed for Hispanic children of immigrants in the 1979 cohort. To summarize, improved scholastic abilities, as captured by the AFQT scores, lead to improved educational outcomes for all groups and for both cohorts. Moreover, among the four groups the increase in AFQT scores has largest effect on Hispanic children of immigrants in both surveys.

The effect of father's education is illustrated by conducting a similar exercise as above. We add one year to father's education and obtain new distributions of education. The results suggest that an increase in father's education has a larger effect on educational attainment of children of native Hispanics (1.1 percent) and children of white immigrants (1.1 percent) in NLSY79 than for the other two groups. Further, the impact is generally much smaller in NLSY97 (ranging from 0 to 0.3 percent).

The third row of Table A1 shows the effect of a simulation where we increased father's education to correspond to the completion of a high school degree if the father had accumulated less than 12 years of schooling. Those with more than 12 years of schooling were unchanged. The effects from this change are relatively large, especially for the 1979 cohort, which may reflect the overall increase in father's education across the cohorts. The increase in education is especially large for native Hispanics in the 1979 cohort (4.2 percent) in NLSY79. For the younger cohort (NLSY97), the impacts are largest for children of immigrants (1.2 – 1.4 percent).

Simulated effects of increases in mother's education are shown in the fourth row of Table A1. For the 1979 cohort, the effects from a one-unit increase in mother's education are smaller than similar effects from increases in father's education. For the 1997 cohort, the effects are similar to those reported for father's education.

The link between household size and educational attainment is illustrated in row five of Table A1 where we present effects on accumulated schooling from reducing number of siblings with one. Like the effects of parental education and AFQT scores, the effects of family size are larger for the 1979 cohort than for the 1997 cohort. However, the effect of a reduction in number of siblings is relatively small across all four groups in the 1979 cohort.

Finally, we explored the effects from increases in parental income. In particular, we increased parental income by $10,000 (about 15% of the mean) for each respondent. This had a slightly larger impact on educational attainment of native Hispanics, whose education on average increased with 0.9 percent for the 1979 cohort and with 0.8 percent for the 1997 cohort. For the other groups, the effects are smaller, ranging from -0.4 to 0.3 percent.

To summarize, the results suggest that scholastic abilities constitute the single most important determinant for educational success. The magnitudes of the estimated impacts of this variable generally exceed the estimated effects of other observable characteristics. Another observation is that in almost all cases, the impacts of changing characteristics are larger for the 1979 cohort than for the 1997 cohort. This pattern is observed for all four groups. A likely reason for this is an increased access to education, in particular higher education, for the younger cohort as a result of directed policies towards making higher education more accessible. Father's education and test scores are more important to educational attainment of second-generation Hispanic immigrants than Hispanic children of natives especially for the older American cohort. However, these differences between second-generation immigrants and natives are less obvious for whites especially for the recent cohort of NLSY97. For whites from the recent cohort, endowment and family background differences explain most of the variations in educational attainment of second-generation immgrants and natives, not preferences. This is also shown in chapter 3 of the thesis.

1.4.4 Model fit

The grade distributions, both observed and predicted by our models, are presented in Table 1.6. A distinctive feature of observed schooling attainments in the 1979 cohort is the bimodality of the distribution across various grade levels. There are two pronounced peaks, one at 12 years of schooling and the other at 16 years, and around 50% of the respondents completed either 12 or 16 years of schooling. Our model is able to predict large frequencies at grade 12 and grade 16, and more generally, when compared to the actual frequencies, the predictions appear quite accurate.

Actual and predicted distributions for the 1997 cohort are shown in the last two columns of Table 1.6. Looking at actual distributions, the proportion that has exactly 12 years of schooling is 8.6 percentage points lower in the 1997 cohort than in the

1979 cohort. Moreover, there is a higher fraction of students completing grades 13 to 16 in the 1997 cohort than in 1979 cohort. When comparing actual and predicted frequencies of schooling attainment, we conclude that our models generate predictions that are generally very similar to the observed frequencies.

Figure 1.5 and Figure 1.6 show observed and predicted log-wages for each cohort. The predicted wage growth is lower than the growth rate of observed wages. The deviations from observed wages are higher at young ages. However, there are relatively few wage observations for these age groups.

1.4.5 Counterfactual simulations

In this section, we illustrate how the distribution of educational attainment would change for Hispanic children of immigrants if their set of observable characteristics would coincide with those of children of natives, both white and Hispanics. We also consider effects of alternative policies, such as subsidies for higher education and educational requirements for first generation immigrants.

Table 1.7 describes average years of education for Hispanic children of immigrants as well as for such children if they had instead been endowed with a different set of background characteristics (those of white or Hispanics children of natives). For the 1979 cohort, educational attainment among Hispanic children of immigrants is predicted to increase with 6 percent if they had the same average endowment as native Hispanics. This observation suggests that second-generation Hispanics "value" education more than their native counterparts do (They have higher level of estimated unobserved ability). Moreover, had they instead been endowed with average characteristics of white natives, their education were predicted to increase by 16.4 percent, corresponding to a 2-year increase in accumulated education. The increase in average grade levels by having endowments of native whites indicates that better family background and higher test scores would have an significant positive impact on second-generation Hispanics. For the 1997 cohort, the increases in educational attainment from the same exercises are lower. For instance, using average characteristics of native whites, education is predicted to increase with 6.9 percent, or 0.9 years. This is less than half the increase predicted for the 1979 cohort. Finally, when we use the characteristics of native Hispanics, there is a slight increase in predicted education, an increase of 0.2 years or 1.8 percent. Compared to the older cohort, differences in preferences over education are less obvious between second-generation and native Hispanics.

Finally, in Table 1.8 we describe effects of providing a subsidy for completing grade 12 and another subsidy provided for grades 13 to 16. Again, we focus on educational attainment of Hispanic children of immigrants. The effect from the first subsidy is a modest increase in average education of 2.1 percent. The subsidy for a college or university education (grades 13 through 16) is predicted to increase accumulated education by 10 percent. Lastly, we consider a policy where we increase the educational attainment of parents to children of Hispanic immigrants if actual education is less than grade 12. The effect of this policy is an increase in average schooling by 0.2 years or by 1.5 percent.

1.5 Conclusions

In this paper, we examine the reasons for differences in educational attainment between children of immigrants and children of natives in the U.S. This issue has recently attracted attention by labor economists as the educational success of immigrants' children imply additional benefits associated with immigration. Most of past research on the economics of immigration has focused on how immigrants perform in the host country's labor market relative to natives while outcomes among their children have been largely ignored.

Moreover, the research that does exist on this topic has not been able to explain why these educational differences between children of natives and children of immigrants exist. It is possible that an educational gap arises because of differences in cognitive abilities. This could arise if the average ability of immigrant parents is higher/lower than the average of natives. Such ability differences could occur if there is a non-random selection of immigrants. Alternatively, educational differences may arise because of differences in preferences and attitudes towards education. It is of great importance to understand what factors contribute to the educational gap and which do not. However, in order to address this, one must go beyond the descriptive methods that have been used in past research and construct a structural model of educational attainment that recognizes the dynamic nature of educational decision-making processes and where estimation of preference parameters is central.

In the paper, we utilize data from two cohorts of the National Longitudinal Survey of Youth, NLSY79 and NLSY97. We find that family background characteristics, in particular parental education and income, family size and structure have significant positive effects on youth's schooling attendance. This is consistent with the existing literature (see for example, Kucera (2008), Belzil and Hansen (2003), Cameron and Heckman (2001), Eckstein and Wolpin (1999), and Keane and Wolpin (1997)). Our results further suggest that scholastic abilities constitute the single most important determinant for educational success. The magnitudes of the estimated impacts of this variable generally exceed the estimated effects of other observable characteristics. This finding is consistent with Heckman et al. (2006) who argues the importance of cognitive abilities in determining educational attainment. Further, the impacts of changing characteristics are generally larger for the 1979 cohort than for the 1997 cohort. This pattern is observed for all four groups. A likely reason for this is an increased access to education, in particular higher education, for the younger cohort as a result of directed policies towards making higher education more accessible. Our findings also indicate that, by having higher unobserved utility of school, Hispanic children of immigrants appear to value education more than children of natives especially for the older cohort. This evidence also supports results discussed in Caponi (2011), which suggests that there exists positive selection with respect to human capital of Hispanic immigrants to the U.S. Because according the immigration theory he proposed, highly motivated Hispanic immigrants may choose to migrate to the U.S. for the benefit of their next generation. Finally, experimental policy changes show that educational support programs appear to have larger impacts on children of immigrants, especially for Hispanics.

Table 1.1: Immigration/Ethnicity Composition of the Sample

Ethnicity and immigrant groups	NLSY79		NLSY97	
Children of immigrants White	6.5%		4.5%	
Children of immigrants Hispanic	4.4%		7.1%	
Children of natives White	84.3%		80.1%	
Children of natives Hispanic	4.8%		8.3%	
	Children of immigrants	Children of natives	Children of immigrants	Children of natives
White	59.6%	94.6%	38.8%	90.6%
Hispanic	40.4%	5.4%	61.2%	9.4%

Table 1.2: Descriptive Statistics for Children of Immigrants

Children of immigrants	Hispanics			Whites		
	NLSY79	NLSY97	% Change	NLSY79	NLSY97	% Change
Father's education	8.1	10.9	22.9%	12.3	14.9	21.1%
Mother's education	7.4	10.3	39.5%	11.7	14.7	25.6%
Parental income	33	33.1	0.1%	45.6	74.8	64%
Number of siblings	4.5	2.7	-40%	2.4	2.3	-8%
Nuclear family	0.6	0.7	6.5%	0.7	0.8	6.8%
AFQT scores	145.1	151	4.1%	167	183.6	9.9%
Accumulated education	11.5	12.5	8.7%	12.7	14.1	10.4%
Number of observations	69	157		102	101	

Table 1.3: Descriptive Statistics for Children of Native Born Parents

Children of natives	Hispanics			Whites		
	NLSY79	NLSY97	% Change	NLSY79	NLSY97	% Change
Father's education	9.9	11.9	20.2%	12.5	13.5	8%
Mother's education	9.5	11.2	17.9%	12.1	13.3	9.9%
Parental income	34.2	42.9	25.5%	49.1	59.5	21.4%
Number of siblings	4.2	2.6	-38.1%	2.8	2.3	-17.9%
Nuclear family	0.6	0.5	-22.6%	0.8	0.6	-25%
AFQT scores	146.7	155.6	6.1%	172.9	172.6	-0.2%
Accumulated education	11.4	12.4	8.4%	13.1	13.3	1.4%
Number of observations	76	184		1324	1783	

Table 1.4: Parameters Associated with the Distribution of Unobserved Heterogeneity (5-Type Model)

Parameter	NLSY79	NLSY97
as^1	-2.583^{***}	0.230
	(0.266)	(0.296)
as^2	-0.295	-0.920^{***}
	(0.280)	(0.294)
as^3	-1.023^{***}	0.047
	(0.188)	(0.419)
as^4	-0.374	-0.882^{***}
	(0.277)	(0.290)
as^5	-1.358^{***}	0.098
	(0.162)	(0.190)
aw^1	1.246^{***}	2.912^{***}
	(0.097)	(0.403)
aw^2	0.630^{***}	1.659^{***}
	(0.104)	(0.048)
aw^3	0.561^{***}	1.835^{***}
	(0.113)	(0.090)
aw^4	-0.473^{***}	-0.857^{***}
	(0.111)	(0.111)
aw^5	1.178^{***}	1.486^{***}
	(0.129)	(0.075)

Note:
$as^1 - as^5$ are type specific unobserved heterogeneities in the utility of school.
Standard errors are in brackets.
*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 1.5: The Wage Returns to Education and to Work Experience

Parameter	NLSY79	NLSY97
$retedu$	0.120^{***}	0.021^{**}
	(0.006)	(0.009)
$retedu_{sh}$	-0.001	-0.008
	(0.011)	(0.009)
$retedu_{sw}$	-0.013	0.054^{***}
	(0.010)	(0.010)
$retedu_{nh}$	-0.097^{***}	-0.014^{**}
	(0.011)	(0.006)
$retexp$	0.028^{***}	0.023^{***}
	(0.002)	(0.006)
$retexp_{sh}$	-0.012^{***}	0.025^{***}
	(0.005)	(0.007)
$retexp_{sw}$	0.001	-0.014
	(0.004)	(0.009)
$retexp_{nh}$	-0.030^{***}	0.001
	(0.005)	(0.007)

Note:
$retedu$ is return to education in the utility of work (reference group native Whites).
$retedu_{sh}$ is return to education for second-generation Hispanics in the utility of work.
$retedu_{sw}$ is return to education for second-generation Whites in the utility of work.
$retedu_{nh}$ is return to education for native Hispanics in the utility of work.
$retexp$ is return to education in the utility of work (reference group native Whites).
$retedxp_{sh}$ is return to education for second-generation Hispanics in the utility of work.
$retexp_{sw}$ is return to education for second-generation Whites in the utility of work.
$retexp_{nh}$ is return to education for native Hispanics in the utility of work.
Standard errors are in brackets.
*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 1.6: Model Fit: Grade Distributions (5-Type Model)

Years of Education	NLSY79		NLSY97	
	Observed in %	Predicted in %	Observed in %	Predicted in %
4	0.06	0	0	0
5	0	0	0	0
6	0.13	0	0.09	0
7	0.70	0.70	0.54	0.49
8	2.04	1.53	2.43	2.56
9	4.46	4.01	4.49	4.76
10	5.22	6.49	6.07	6.16
11	8.78	8.98	6.74	6.34
12	36.09	34.88	27.46	25.71
13	8.85	8.98	9.98	8.22
14	6.81	7.00	10.70	8.27
15	4.52	4.01	5.98	5.17
16	13.69	13.75	15.42	15.51
17	4.33	4.14	6.43	7.82
18	2.42	2.61	2.56	4.67
19	1.65	2.48	0.63	2.79
20	0.25	0.45	0.49	1.26
21	0	0	0	0.22
22	0	0	0	0.04
Mean	12.95	13.04	13.22	13.56

Table 1.7: Counter-factual Simulations of Average Years of Schooling Based on Preferences of Second-generation Hispanics

	Mean years of schooling Using native Hispanic personal characteristics	% Changes in average schooling	Mean years of schooling Using native White personal characteristics	% Changes in average schooling
NLSY79	12.3	6.0	13.5	16.4
NLSY97	12.9	1.8	13.9	6.9

Note:
These simulations are based on estimated model parameters for second-generation Hispanics. Family and personal background characteristics from native Hispanics and native Whites are then imposed on these estimated parameters to generate counter-factual educational outcomes. Based on preferred 5-type model.

Table 1.8: Average Educational Attainment for Second-generation Hispanics Under Alternative Policies, NLSY97

Mean schooling after subidizing grade 12 by 10%	% Changes in average schooling	Mean schooling after subidizing grades 13-16 by 10%	% Changes in average schooling	Mean schooling after increasing parental education to at lesat 12	% Changes in average schooling
13.24	2.1	14.32	10.4	13.17	1.6

Note:
Simulation results are based on 5-type model.
Subsidizing specific grade levels is done by reducing/increasing the psychic and monetary cost/utility of education at these key grade level by 10%.

Figure 1.1: Grade Distributions for White Children of Immigrants, NLSY79 and NLSY97

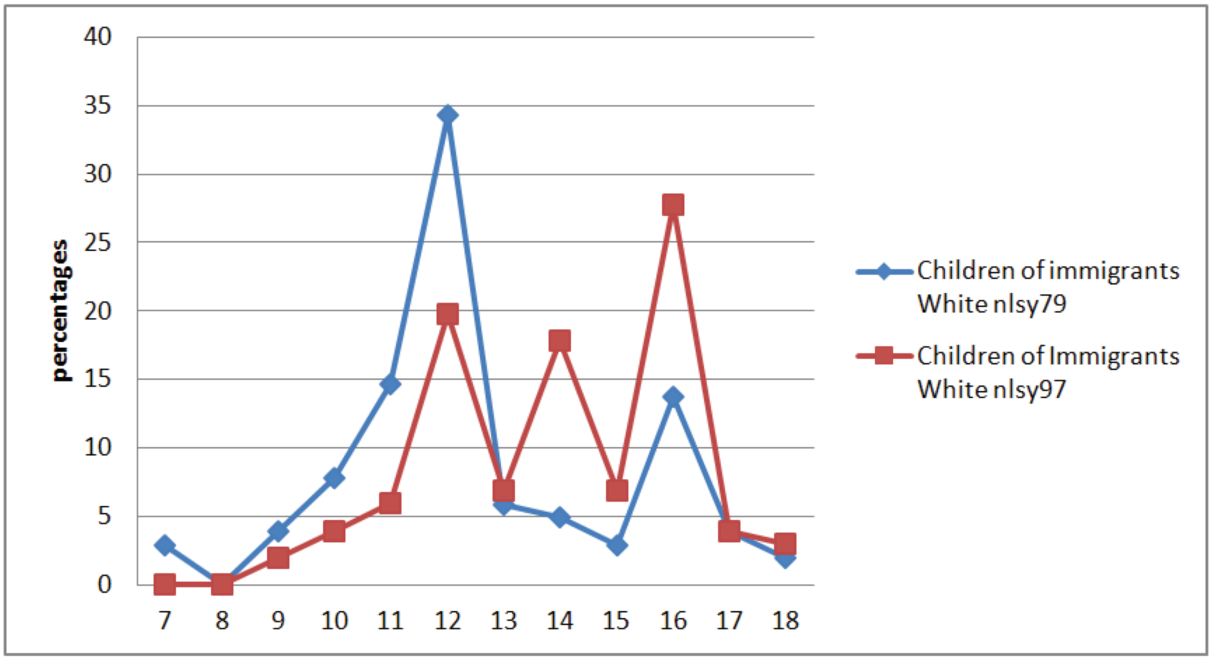


Figure 1.2: Grade Distribution for Hispanic Children of Immigrants, NLSY79 and NLSY97

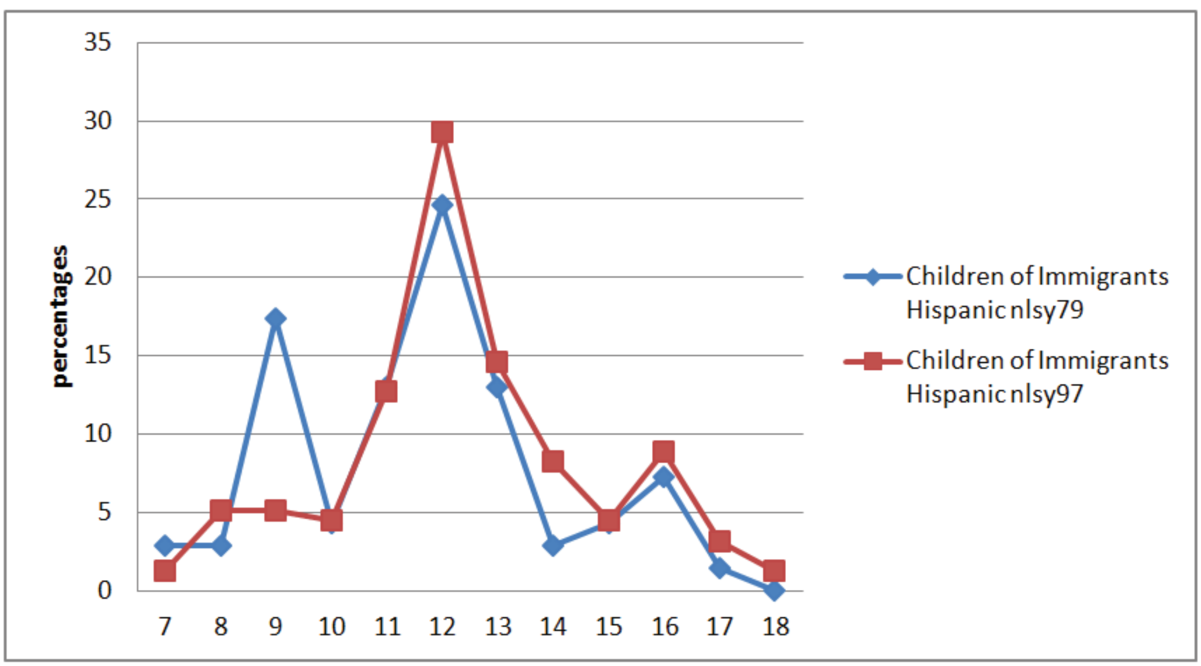


Figure 1.3: Grade Distribution for White Children of Natives, NLSY79 and NLSY97

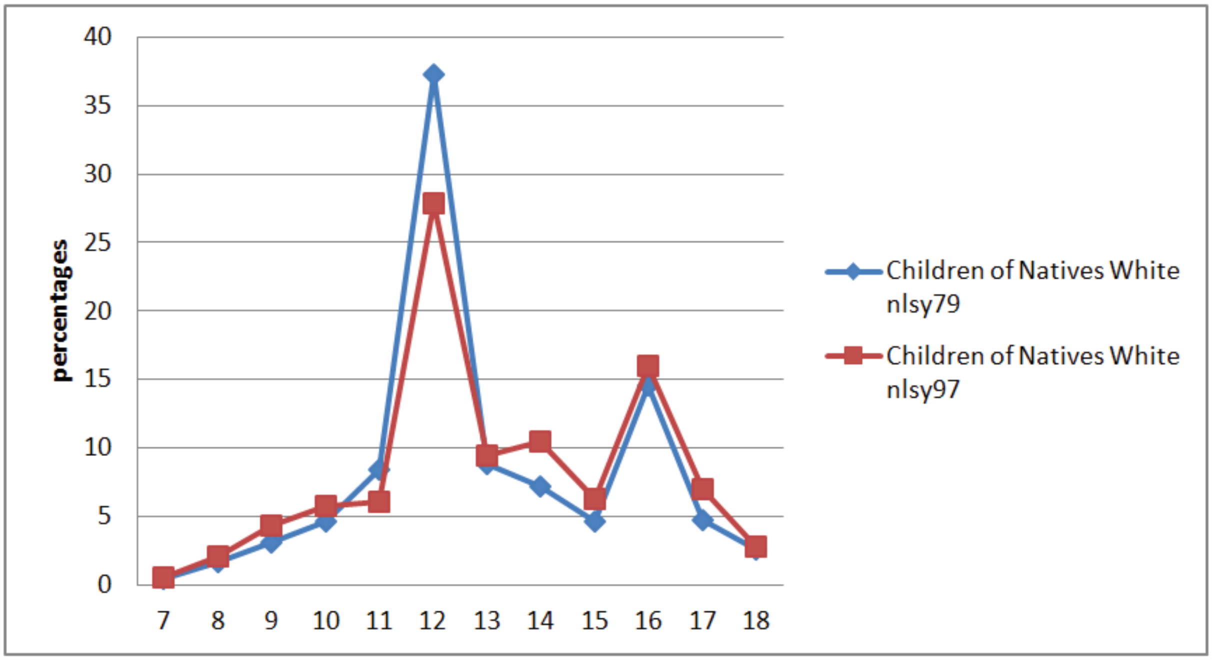


Figure 1.4: Grade Distribution for Hispanic Children of Natives, NLSY79 and NLSY97

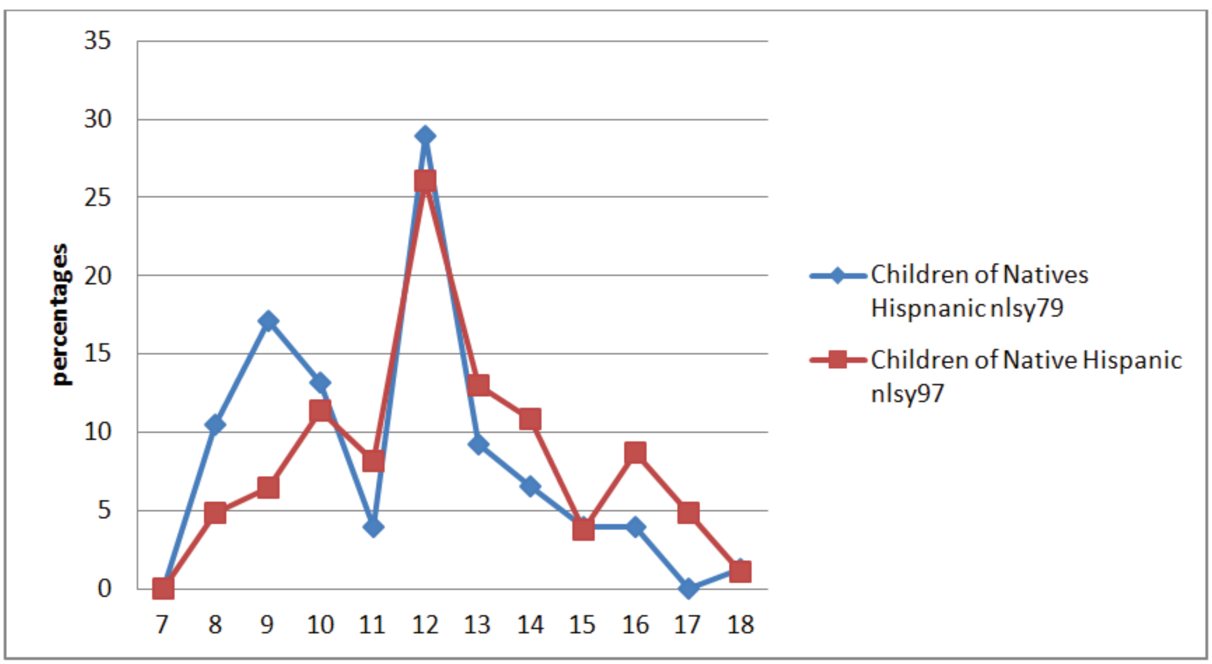


Figure 1.5: Observed and Predicted Average Ln Wages, by Age in NLSY79

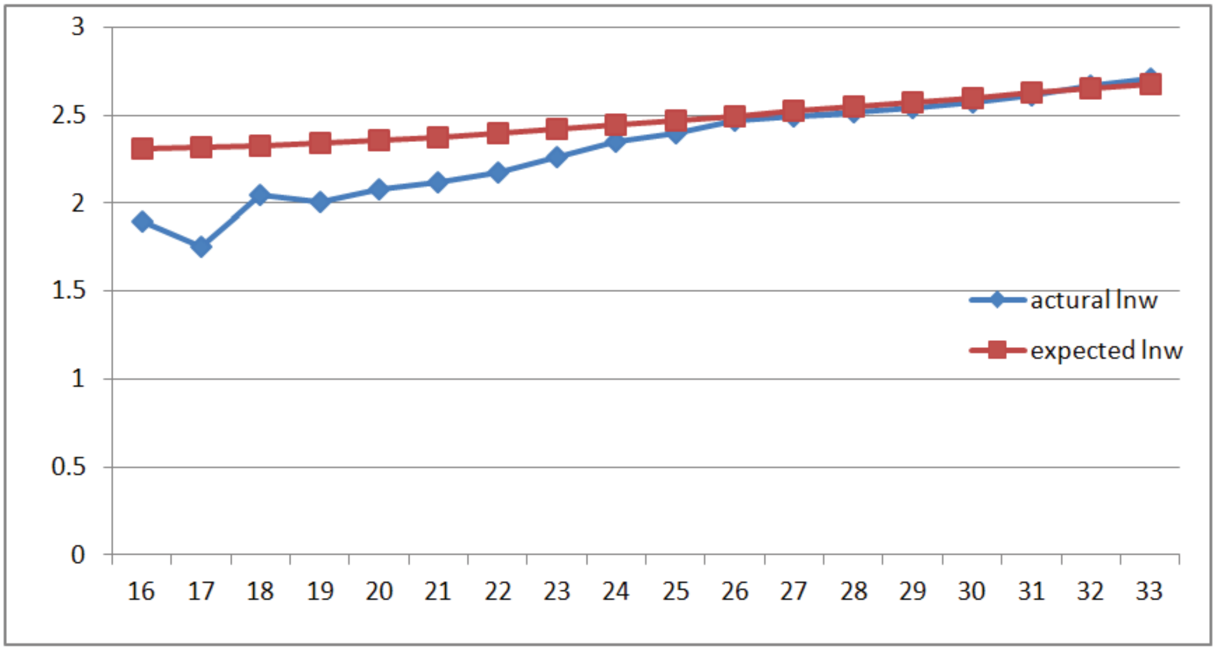
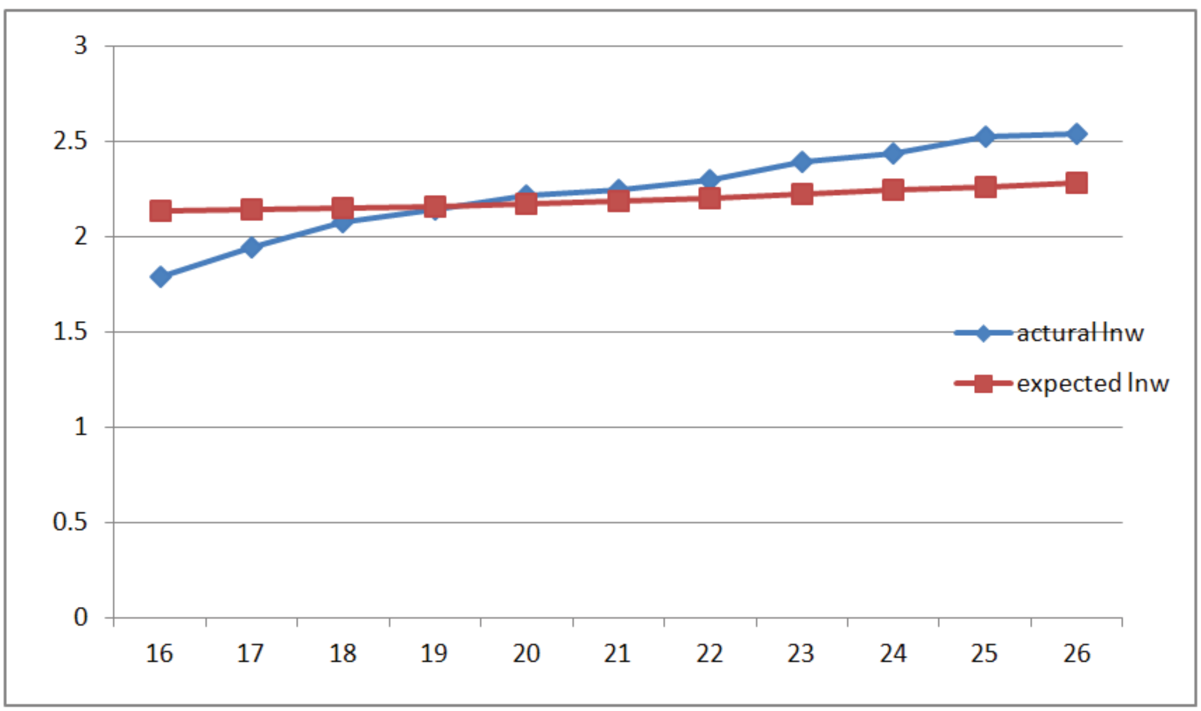


Figure 1.6: Observed and Predicted Average Ln Wages, by Age in NLSY97



Chapter 2

Disparities in Schooling Choices and Wages between Ethnic Minorities and Whites: Evidence from the NLSY97

Joint with Professor Jörgen Hansen and Dr. Miroslav Kučera

2.1 Introduction

Disparities in educational and labour market outcomes between various ethnic groups in the United States have been an active area of research, and the existence of such gaps especially between whites, blacks and Hispanics has been extensively documented.[1] Ethnic minorities have been shown to be, on average, less educated and

[1] According to the Longman Dictionary of Contemporary English, an ethnic is someone who comes from a group of people who are of a different race or religion, or who have a different background from other people in the country. As the term ethnic is more general and clearly encompasses race, we choose to refer to whites, blacks and Hispanics as ethnic rather than racial groups. We choose whites, blacks and Hispanics in this paper because these are the largest ethnic groups in the U.S. and are considered by the National Bureau of Labour Statistics to be major ethnic groups in the U.S.

to earn less than their white counterparts.[2] The literature suggests that differences in schooling between ethnic groups can mainly be explained by parental education, family environment and individual abilities rather than by credit constraints. With regard to wages, the central question has been and remains whether the observed variation across the ethnic groups are due to unequal market prices of skills and experience (wage discrimination), or due to differences in the distributions of education and abilities.

The social sciences literature abounds with studies of ethnic gaps in earnings, education and many other dimensions. Unfortunately, many of them suffer from various data and methodological problems and often offer very limited insight at best. In this paper, we recognize the need to respect the structure and dynamic nature of the process that is in the base of individuals' schooling decisions and their labour market success. Our point of departure in the literature is Cameron and Heckman (2001). In their paper, Cameron and Heckman used a dynamic model of schooling attainment to investigate racial and ethnic disparity in schooling (focusing primarily on college attendance). Contrary to the conventional thinking, they found that parental background and family environment were more important in explaining ethnic differences in schooling then family credit constraints. Besides its importance for policy making, the paper is also an important contribution to empirical economics for its recognition of the dynamics of the schooling attainment process, and attention it paid to important issues such as the effects of unobserved abilities.

Racial differences in schooling and earnings were also subject of a paper by Keane and Wolpin (2000) who estimated a structural dynamic model of school attendance, work and occupational choice, and tested implications of two policy proposals that were expected to have a differential racial impacts: a high-school graduation bonus for students from low-income families, and a wage subsidy to low-wage workers. Although

[2] In the this paper, ethnic minorities are specifically refered to Hispanics and blacks, since these two groups have much less shares than whites in the survey considered.

they recognized the potential effect these schemes may have on the size of the schooling and earnings gaps, they emphasized that equalizing endowments that individuals have when they begin making independent decisions about their future (age 16 in Keane and Wolpin's model) would by itself go a long way toward eliminating ethnic differences in labour market success.

Recent contributions to the literature on ethnic differences, namely Carneiro, Heckman and Masterov (2005), bring into focus the role of cognitive skills and discrimination in explaining ethnic wage gaps. Urzua (2008) extends this focus further by adding non-cognitive skills, and the distinction between measured and unobserved skills, to his study of black-white differences in schooling choices and labour market outcomes. He finds that even after controlling for differences in abilities, significant labour market gaps still exist.

While a great deal of existing research focused on individuals who were completing their schooling and entering the labour market in the late 1970s and early 1980s, much less is known about their successors. Although the younger 1997 cohort of the National Longitudinal Survey of Youth (NLSY97) has been available for some time, its use by researchers has so far been rather sporadic. To our knowledge, only Altonji, Bharadwaj and Lange (2008) have made a more extensive use of the NLSY97 when comparing it to the older 1979 cohort. To our knowledge, no study has yet used the NLSY97 to analyze the existence and sources of ethnic disparities in schooling and earnings.

Our paper addresses this issue by analyzing a sample of men from the 1997 cohort of the NLSY. We propose a structural dynamic model of schooling choice and wages, and use it to estimate various parameters of interest, and to analyze sources of ethnic gaps. We find, among other things, that whites, blacks and Hispanics all face different returns to schooling (lowest for blacks) and work experience (lowest for whites). Furthermore, we find that ethnic differentials in schooling attainments can largely be explained by differences in endowments across the ethnics, and that behavioural differences (differences in parameters) play a prominent role in explaining ethnic differences in wages.

The paper is organized as follows: Section 2 provides description and summary statistics for our sample. Section 3 introduces the structural dynamic model and outlines our estimation strategy. Section 4 presents the key estimation results and decompositions of the ethnic gaps in schooling and wages. Finally, Section 5 concludes the paper.

2.2 Data and Samples

In this paper we utilize data from the 1997 National Longitudinal Survey of Youth (NLSY97). Unlike the 1979 NLSY which has long been a major source of information about the transition of young Americans into the labour market, the use of the 1997 cohort has until recently been limited by the young age of the respondents and insufficient observations of their labour market experiences and outcomes. As the NLSY97 consists of youths who were 12 to 16 years old at the end of 1996, a meaningful analysis of school to work transitions and labour market outcomes is only now becoming feasible. By 2007 – the latest data release available to us – a majority of the surveyed individuals had aged enough to have completed their schooling (about 85% of our sample) and entered the workforce. Nevertheless, it is important to keep in mind that we are still observing only early stages of these individuals' work histories.

In this study, we use data for 3,578 males from 1997 to 2007 cycles of the NLSY97. Whites represent 52.7 percent of our sample, blacks 27.1 and Hispanics 20.2 percent. For each of the three ethnic groups, we have a sufficiently large number of observations to warrant a separate analysis and avoid pooling the three ethnics together. Table 2.1, and Figures 2.1 to 2.6 summarize all the major characteristics of our samples, as well as the differences in schooling attainments and wages across the ethnic groups.

First thing to notice in Table 2.1 are differences in family backgrounds between the white majority and the minorities. Parents of whites are on average more educated than those of blacks, and Hispanic parents have substantially lower education than both white and black parents. Parental income is comparable for blacks and Hispanics, but substantially lower than income of white parents. Furthermore, black and Hispanic families have more children than white families. A very large difference between whites and Hispanics on the one side and blacks on the other is in the family conditions in which they were raised in their formative years. While over 60 percent of whites and 55 percent of Hispanics lived in complete families (with both biological parents) until their mid-teens, a full 73 percent of blacks grew up with only one biological parent.

There are also differences in schooling between whites and the minorities. Although at age 16 (the starting point in our model) all three ethnics have, on average, about 10 years of schooling, the average final educational attainment of whites is more than one year higher than those of blacks and Hispanics. Close to 28 percent of whites complete 16 or more years of schooling, while only 9.5 percent of blacks and 12.3 percent of Hispanics do so (Figure 2.2). In fact, the schooling distribution for whites appears almost bimodal with spikes at grades 12 and 16, while the schooling distributions of blacks and Hispanics are unimodal, peaking at grade 12. Figure 2.3 also confirms that the schooling patterns of the two ethnic minorities are similar to each other but very different from that of the white majority. For example, whites have almost 60 percent probability of completing and continuing past grade 12. In contrast, blacks and Hispanics are only about 40 percent likely to do so.

In order to assess ethnic disparities in abilities, we created a composite index as an average of six specific-ability test scores from the Armed Services Vocational

Aptitude Battery (ASVAB).[3] This set of tests was administered from the summer of 1997 through the spring of 1998 to the NLSY97 respondents who were of varying ages and schooling. To eliminate the effect of these differences on the test results, we use residuals from the regression of our composite ability score on the highest grade completed at the time when the tests were taken. The non-parametric estimates of the distributions of the composite ability score in Figure 2.4 suggest that blacks and Hispanics have similar bell-shaped ability distributions that are centered close to the zero mark. With respect to the minority distributions, the white ability distribution appears to be shifted to the right. Both the mean and the median scores for whites are about one point greater than the corresponding statistics for blacks and Hispanics. The white ability distribution also exhibits slightly larger variability than those of the minorities.

Figure 2.5 and Figure 2.6 show that differences in wages between whites and the minorities are substantial, although more pronounced for blacks than Hispanics. Average hourly wage of blacks starts to diverge from the wages earned by whites rather early, and by their mid-twenties blacks earn on average about 20 percent less than whites. By the same age, Hispanics also earn less than whites, about 15 percent, but their age-wage profile is similar to that of whites for longer than in the case of blacks. In fact, only the last two averages, corresponding to ages 25 and 26, are substantially lower than those of whites. Indeed, given the young age of the NLSY97 respondents at the time of our last observation in 2007, it would be premature to draw any conclusions as to whether the observed divergence of minority wages from the wages of whites will continue, stabilize or diminish.

[3] Similar constructs are used in Heckman, Stixrud and Urzua (2006), and Urzua (2008). The six scores averaged in our ability index are for arithmetic reasoning, mathematics knowledge, paragraph comprehension, word knowledge, coding speed, and numerical operations. Details about the ASVAB tests and their administration can be found on the NLSY97 website (http://www.bls.gov/nls/nlsy97.htm).

2.3 Structural Dynamic Programming Model

The decision horizon begins at the start of the school year at which the individual first reaches age 16. The model terminates after 50 periods when the individual is age 65 and retires. At the beginning of every period, the individual decides whether it is optimal to continue accumulating schooling or to leave school and work for wage. The two alternatives are mutually exclusive, and the choice of entering the labour market is irreversible. Once the individual starts to work, his schooling is complete, and he will continue working until retirement. The individual is assumed to maximize the present discounted value of lifetime utility from age 16 ($t = 1$) to age 65 ($t = T$). The objective function is given by

$$V_t(\Omega_t) = \max_{\{d_j\}_{j=t}^{T}} E\left\{\sum_{j=t}^{T} \delta^{\tau-t}\left[d_j u_j^s + (1-d_j)\, u_j^w\right]\right\},\ t = 1, 2, \ldots, T \tag{2.3.1}$$

where $\delta = 1/(1+r)$ is the subjective discount factor corresponding to the discount rate r, Ω_t is the state space at t, $d_t = 1$ if the individual chooses to continue schooling at t and $d_t = 0$ if he chooses work, and u_t^s and u_t^w are the corresponding per-period utilities. Note that throughout this section, we omit the individual subscript to keep the notation as uncluttered as possible.

2.3.1 Per-period Utility Functions

For each alternative, its per-period utility is logarithmic in the income generated by that alternative which in turn depends on selected observable characteristics, and a random shock. Specifically, the *utility of continuing schooling* is given as

$$u_t^s = \ln(y_t^s) = X^s\beta^s + \sum_{j=s_0+1}^{\overline{S}} \gamma_j^s \, \mathrm{I}(s_t = j) + \epsilon_t^s. \tag{2.3.2}$$

Where the vector X^s contains various characteristics of the family in which the individual grew up, his ability test score, and the schooling grade he completed by age 16 (initial schooling, s_0). The schooling attainment is included via grade indicator such that $\mathrm{I}(s_t = j) = 1$ if the individual is in grade j in period t. This allows for the possibility that the costs of schooling vary over schooling grades. Note that the highest possible grade we allow for is $\overline{S} = 20$.

The *utility of working* is assumed to depend on wage, y_t^w, as follows:

$$u_t^w = \ln(y_t^w) = X^w \beta^w + \gamma^w (s_t - s_0) + \phi^w z_t + \epsilon_t^w, \tag{2.3.3}$$

The vector X^wcontains the individual's ability test score and initial schooling, s_t denotes the years of schooling, and z_t the years of work experience in period t. More complex specifications of the log-wage equation are indeed possible. For example, the return to schooling could vary across individuals and schooling grades. For now, in order to keep the computational costs of estimating the model manageable, we use the simpler specification in (2.3.3). This design is parsimonious, yet sufficiently realistic and fits the data rather well as we show later.

2.3.2 Schooling Interruption

In order to conform more closely to the empirical facts, we also allow for schooling interruptions. For simplicity, we incorporate them as a state which occurs with an exogenous probability, π_t, and is captured by a binary indicator variable, I_t. If an interruption happens in a given period ($I_t = 1$), the decision problem is frozen and the stock of schooling remains constant over that period until the beginning of the next one. Due to the lack of data on parental transfers, we do not distinguish monetary payoff the individual receives when in school from payoff when school is interrupted.[4]

[4]In the absence of information about the reasons for and the activities during schooling interruptions, the interruption state in our model can be thought of as encompassing a variety of events

2.3.3 Initial Schooling Model

It is plausible that the permanent personal endowments that help explain schooling decisions are also instrumental in determining how much schooling one acquires by age 16 when individuals start to decide whether to continue in school or enter the labour market. A failure to account for this possibility could seriously bias the estimates of the structural parameters. Consequently, we choose to model initial schooling as an ordered-choice, is which the individual's initial schooling grade depends on a the value of a latent variable, s_0^*, such that

$$s_0^* = X_0 \beta_0 + \epsilon_0, \tag{2.3.4}$$

where X_0 is a vector of individual's observable characteristic and ϵ_0 is a random disturbance term.

2.3.4 Unobserved Abilities

We assume that the intercepts in the utility of continuing schooling in (2.3.2), the log-wage equation (2.3.3), and the initial-schooling latent regression in 2.3.4 are individual specific. As is customary in this type of models, we model unobserved heterogeneity as a finite mixture. We assume that there are K types of individuals, and that the probability of belonging to type k takes the the form of

$$p_k = \frac{\exp(q_k)}{\sum_{j=1}^{K} \exp(q_j)}, \; k = 1, 2, \ldots, K, \tag{2.3.5}$$

with the restriction that $q_K = 0$. On the basis of the Bayesian Information Criterion, the optimal number of ability types is five.

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such as illness or injury, travel, temporary work or academic failure.

2.3.5 Solution to the Individual's Optimization Problem

The optimization problem in (2.3.1) can be recast in the dynamic programming framework as the maximum over the choice-specific value functions:

$$V_t(\Omega_t) = \max\left[V_t^s(\Omega_t), V_t^w(\Omega_t)\right]. \tag{2.3.6}$$

The present value of the decision to continue schooling can be written as

$$\begin{aligned} V_t^s(\Omega_t) &= u_t^s + \delta\left\{\pi_{t+1}\cdot E\left[V_{t+1}^I(\Omega_{t+1})\right]\right. \\ &\quad \left. + (1-\pi_{t+1})\cdot E\max\left[V_{t+1}^s(\Omega_{t+1}), V_{t+1}^w(\Omega_{t+1})\right]\right\}, \end{aligned} \tag{2.3.7}$$

where $V_t^I(\cdot)$ denotes the net present value of interruption in period t. Due to the lack of information about the income individuals receive when they interrupt their schooling, we do not include schooling interruption as another choice. Instead, we assume that in period t an interruption occurs with exogenous probability, π_t, and that throughout the interruption the individual receives the same income he would have received if he had continued schooling.[5]

The value of working is easier to compute. Given our optimal stopping rule, once an individual completes his schooling and enters the labour market, he will continue working until the termination period T. In that case, no maximization is required and $V_t^w(\cdot)$ is simply the expected discounted value of the stream of log-wages from t up until T:

$$V_t^w(\Omega_t) = u_t^w + \sum_{j=t+1}^{T}\delta^{j-(t+1)}E(u_j^w|u_j^w>0)\cdot\Pr(u_j^w>0). \tag{2.3.8}$$

[5] For details about the procedure for evaluating the $E\max$function and other computational and estimation issues, see Belzil and Hansen (2002).

2.3.6 Estimation

The dynamic programming problem is solved using backward recursion, and the parameters of the model are estimated by maximum likelihood. For the estimation, assumptions about the nature of the random terms in 2.3.2, 2.3.3 and 2.3.4 are required. We assume that all three error terms are iid normal with zero means and constant variances. The likelihood function, conditional on ability type, k, has the following components:

1. The probability of observing a particular sequence of schooling/interruption histories:

$$L_{1k} = \Pr\left\{\left(d_{0k}, I_{0k}\right), \left(d_{1k}, I_{1k}\right), ..., \left(d_{\tau k}, I_{\tau k}\right)\right\},$$

   where τ is the last period in which the individual is in school.

2. The probability of entering the labour market in period $\tau + 1$, at an observed wage $y^w_{\tau+1}$:

$$L_{2k} = \Pr\left(d_{\tau+1,k} = 0 \middle| y^w_{\tau+1,k}\right) \cdot f\left(y^w_{\tau+1,k}\right),$$

   where $f(\cdot)$ denotes the wage density.

3. The joint density of observed wages from $\tau + 2$ up to T:

$$L_{3k} = f\left(y^w_{\tau+2,k}, y^w_{\tau+3,k}, \ldots, y^w_{Tk}\right),$$

   which can also be expressed as a product of marginal densities conditional on the unobserved heterogeneity component.

4. The probability of initial schooling grade, L_{4k}, derived from equation (2.3.4).

The complete likelihood for each individual in the sample is then

$$L = \sum_{k=1}^{K} p_k \cdot L_{1k} \cdot L_{2k} \cdot L_{3k} \cdot L_{4k}, \tag{2.3.9}$$

where the type probability, p_k, is given in equation 2.3.5 above.

2.4 Key Estimation Results

We estimated the structural model separately for whites, blacks and Hispanics. This section summarizes the estimates as presented in Table 2.3 - Table 2.5. In this section, we will point out differences in the parameter estimates across the ethnics, and provide a more detailed investigation into the sources of ethnic disparities in schooling and wages.

2.4.1 Family Background and Individual Abilities in the Utility of Schooling

As can be seen in Table 2.3, leaving aside for the moment the type-specific intercepts and effects of initial schooling, only two covariates appear to be uniformly significant for all three ethnics. One is the effect of observed scholastic ability as measured by the composite ability test score; it is positive and of similar magnitude for whites and blacks (0.034 and 0.029, respectively) while stronger for Hispanics. This is not unexpected and also reported in chapter 1. Presumably, individuals who exhibit higher scholastic ability have lower psychical costs of schooling which would be reflected in higher utility of attending school. The other effect that is significant across all three ethnics is the effect of being raised by both biological parents (variable *nuclear*). It is positive and substantial, especially for Hispanics and whites, and somewhat weaker for blacks. Furthermore, for all three ethnics, growing up in a complete family appears to be the most important of all family-environment characteristics considered in the utility of schooling equation. In comparison, family income is virtually inconsequential. It is insignificant for whites and blacks, and positive but small for Hispanics.

Family size (number of siblings) appears to have a negative effect on blacks, but no significant impact on the schooling utility of whites or Hispanics. With regards to intergenerational transfer of education, we observe a positive and significant correlation between the education of parents and that of their offspring's, although the relationship is not uniformly significant. In our results, mother's education has a positive effect on the schooling utility of whites and blacks, while father's education is positive and significant for whites and Hispanics.

The effects of unobserved abilities are difficult to gauge. They not only work through the type-specific intercepts, but also interact with initial schooling (schooling at age 16). An important fact is that unobserved heterogeneity, represented by the type-specific intercepts in Table 2.3, is significant in determining the schooling utility of whites, but that only selected types are of importance for Hispanics and blacks. We provide a closer look at the impact of unobserved heterogeneity on explaining ethnic differentials in schooling and wages later in this section.

2.4.2 The Effects of Schooling, Work Experience and Abilities on Wages

The wage returns to schooling and work experience are presented in Table 2.4. The return to one year of schooling is the largest for Hispanics (7.9%) followed by the return for Whites (6.1%) and blacks (3.5%). Similarly, labor market experience also has a positive effect on wage, although of smaller magnitude. For whites the return to one year of work experience is about 2.9%, less than half of the return to one year of schooling. It is somewhat bigger for blacks and Hispanics, about 3.5% and 3.9% respectively.

Individual ability as measured by the composite ability test score does increase wage for whites and blacks (insignificant in the case of Hispanics), but the effect is rather small, especially when compared to the magnitudes of the effects of unobserved heterogeneity. The estimates of the type-specific intercepts in the wage equation suggest that type 1 is a dominant high-ability type for blacks, while for Hispanics type 3 is high-ability. In the case of whites, type 3 is low-ability, and there is no clearly dominating high-ability type, as the intercepts for types 1, 2 and 3 have similarly high magnitudes.

Admittedly, our current specification of the wage regression is somewhat limited. It could be improved, for example, by making returns to schooling vary across heterogeneity types, or by relaxing the assumption of local return to schooling being constant across schooling levels. Nevertheless, we believe that our model is an improvement over the standard approaches used in the returns to schooling literature.[6] Despite some variation across the three ethnic groups, our estimates of the wage returns to schooling are lower than those normally found in the traditional ordinary least squares (OLS) literature. The choice of OLS is justified only if realized schooling and unobserved market ability are uncorrelated, a central assumption that is hard to justify. Unlike traditional approaches, we maintain that individuals are heterogeneous with respect to ability in school as well as in the labour market. Our model allows us to estimate the returns to schooling without any need to assume orthogonality between labour market ability and schooling attainment, and without the estimates suffering from the otherwise ubiquitous ability bias.

[6] See, for example, Belzil and Hansen (2007) for a more flexible specification of the wage regression within a similar structural model, and Belzil and Hansen (2002) for a discussion and comparison of structural dynamic models against traditional OLS and instrumental-variable (IV) approaches.

2.4.3 Unobserved Heterogeneity, Schooling Attainment and Wages

In Table 2.6, we present the predicted schooling attainments and wages by the five heterogeneity types along with the estimates of type probabilities (population proportions). We incorporate a rich specification of unobserved heterogeneity which enters all essential parts of our model. Unobserved abilities and tastes determine initial schooling levels, and directly enter the utility of attending school as well as the wage equation. Consequently, the effects of heterogeneity on individual's optimal schooling decisions and wage income are non-trivial. Furthermore, there are differences in how heterogeneity is distributed and how it operates across the three ethnic groups we consider. Majority of whites (39.7%) are of type 4, and so are blacks (38.5%). The predominant type for Hispanics is 3 (39%). Predictions in Table 2.6 show great deal of variation in schooling across ethnics and ability types. For whites, type 3 individuals appear to be those most successful in scholastic terms. Similarly dominating are type 5 individuals in the case of Hispanics. For blacks, type 5 appears to have the highest attainment, but the predicted 12.6 years of schooling is not much higher than the 12 years predicted for types 3 and 4.

2.4.4 In-Sample Predictions and the Fit of the Model

In this section we examine the performance of our model in terms of how well it replicates the actual data that were used to estimate it. Figures 2.7 to 2.9 show that the model predicts the schooling attainment for all three ethnics well. For blacks and Hispanics in particular, the model reproduces the actual schooling fairly closely. The fit is somewhat looser for whites, perhaps because of the more complicated bimodal shape of their schooling distribution, but it is still quite accurate.

Regarding the wage predictions (Figures 2.10 through 2.12), the model also shows a very satisfactory performance. As can be seen in the graphs, the predictions are close to the actual mean wage for ages 18 and over. The predictions for ages 16 and 17 are imprecise, but they are not of much interest as only few individuals would work at such a young age. We can conclude that, overall, the model fits the actual schooling and wage observations well, especially considering the limited amount of data available to estimate it.

2.4.5 Sources of Ethnic Gaps in Schooling and Wages

In the descriptive part of this paper, we pointed out the differences in characteristics and outcomes that exist between the white majority, and the minority groups of blacks and Hispanics. In this section, we investigate these differences more closely using our dynamic structural model. In particular, we focus on the relative importance of differences in endowments, resources and prices in explaining ethnic gaps in educational attainments and wages.

The first step in our assessment was to estimate the model separately for each of the three ethnic groups, thus imposing neither parameter equality nor equality of the distributions of unobserved heterogeneity. In this section, we proceed to summarize the overall importance of behavioural differences and endowments in explaining ethnic differences in the outcomes of interest.[7] That is, our goal is to decompose the mean difference in an outcome, y, between the majority ethnic group, W (whites) and the minority group, M (blacks or Hispanics):

$$\Delta^{WM} = E_W(y|X^W) - E_M(y|X^M), \tag{2.4.1}$$

[7] We follow the same terminology as Cameron and Heckman (2001). Thus, differences due to parameters are 'behavioral differences', and covariates are 'endowments'. Furthermore, in the decompositions, ethnic differences in heterogeneity distributions are contained in the "behavioral difference".

where $E_W(y|x^W)$ denotes the expectation of y conditional on the covariates of group W and evaluated at the parameter vector of group W, and $E_{\theta^M}(y|x^M)$ is interpreted in the same fashion. Depending on the choice of reference group, there are two alternative ways of decomposing the difference in (2.4.1)

$$\Delta^{WM} = [E_W(y|X^W) - E_M(y|X^W)] + [E_M(y|X^W) - E_M(y|X^M)], \tag{2.4.2}$$

and

$$\Delta^{WM} = [E_W(y|X^M) - E_M(y|X^M)] + [E_W(y|X^W) - E_W(y|X^M)]. \tag{2.4.3}$$

In both equations, the first difference on the right-hand side represents the gap due to behavior, and the second one is the gap due to endowments. Note that this type of decomposition can potentially be sensitive to the choice of reference group and, in principle, one can get two very different estimates of the relative importance of endowments and behavior in explaining ethnic differences in education and wages. Therefore, in Tables 2.7 and 2.8 we report both alternatives for a comparison.

In Table 2.7, whites are predicted to attain on average 1.43 more years of schooling than blacks. Regardless which decomposition we employ, only a small portion of the schooling gap can be explained by behavioral differences (21% or 8.4%). That is, the white-black differences in educational attainment appear to be primarily determined by differences in endowments. However, this is not the case with wages. Whites are predicted to earn about 26% more per hour than blacks, and this gap seems to be mostly determined by differences in parameters which explain more than two thirds of the predicted wage gap regardless of the decomposition approach.

Differences between whites and Hispanics (Table 2.8), both in schooling and wages, are not as pronounced as between whites and blacks. On average, whites are predicted to have higher educational attainment, about 0.89 years more, than Hispanics, and earn about 1.16 dollars more per hour. Similarly to blacks, the schooling gap between whites and Hispanics can largely be explained by differences in endowments. Depending on the decomposition approach, the behavioral differences can only explain 6.7% or 3.3% of the educational attainment differential. As for wages, differences in parameters and differences in endowments both seem to explain about half of the white-Hispanic wage gap.

2.5 Summary and Conclusions

In this paper, we propose a structural dynamic programming model of schooling and wages, and estimate it separately for white, black and Hispanic males using the data from the 1997 to 2007 cycles of the NLSY97. The model respects the dynamic nature of schooling decisions made by rational, forward-looking agents, and employs a rich set of observables as well as a model for unobserved heterogeneity to isolate the effects of various individual characteristics on schooling attainment and wages. We find that certain components of family environment have a substantial impact on individual's schooling. Namely, growing up in a complete family (with both biological parents) appears to have a positive and significant effect on educational attainment across all three ethnics. Family income and, somewhat surprisingly, also parental education either have no impact on the utility of attending school, or their effect is not uniform across the three ethnics. The insignificance of family income suggests that policies based on providing monetary incentives to individuals from low-income families to continue schooling may not have the desired outcome.

Our structural estimates of the returns to schooling and work experience reveal some differences in how the market rewards the three ethnics. The return to one year of schooling is the highest for Hispanics at 7.9%, followed by 6.1% for whites and 3.5% for blacks. Whites have the lowest return to work experience (2.9%) of the three ethnic groups (Hispanics 3.9%, blacks 3.5%). Our estimates, especially of the returns to schooling, are smaller than generally found through traditional least-squares analysis.

Having estimated the model parameters, we then simulate schooling and wages for all three ethnics under different assumptions, and decompose the observed differences in outcomes into the part explained by behavioral differences (parameters) and the one explained by differences in endowments (covariates). We find that differences in educational attainments can be to a large extent explained by differences in endowments between whites and the minority groups, which confirms the findings in chapter 1. While behavioral differences explain only a small part of the differences in schooling, they seem to play an important role in explaining differences in wages. This is especially true when comparing whites and blacks as more than two thirds of the black-white wage gap is explained by differences in parameters. This result may imply that there exist discriminations towards ethnic minorities in the labour market. Parameter differences explain about half of the white-Hispanic wage differential.

Table 2.1: Mean Years of Schooling by Ethnic and Heterogeneity Type

Ethnic	Het. Type	% within Ethnic	Mean Schooling
Whites	1	0.189	14.3
	2	0.265	11.5
	3	0.080	19.6
	4	0.397	14.0
	5	0.069	15.1
Blacks	1	0.034	11.1
	2	0.283	10.9
	3	0.071	12.0
	4	0.385	12.0
	5	0.227	12.6
Hispanics	1	0.260	11.6
	2	0.213	11.0
	3	0.390	13.5
	4	0.093	12.7
	5	0.043	19.2

Table 2.2: Sample Means/Proportions of Selected Variables

	Whites		Blacks		Hispanics	
Father's education	13.57	(2.80)	12.10	(2.26)	10.37	(3.90)
Mother's education	13.40	(2.44)	12.32	(2.05)	10.36	(3.56)
Parental income	35.68	(25.78)	23.80	(17.35)	24.45	(17.94)
Num. of siblings	2.28	(1.05)	2.65	(1.43)	2.74	(1.31)
Ability test score	0.48	(1.76)	-0.69	(1.67)	-0.46	(1.62)
Initial education	10.00	(0.76)	9.75	(0.98)	9.88	(0.86)
Final education	13.36	(2.54)	12.04	(2.36)	12.35	(2.30)
Nuclear	0.61		0.27		0.55	
Number of obs.	1,884		971		723	

Standard deviations in parentheses.

Education measured in completed years off schooling.

Parental income in thousands of 1997 dollars.

Nuclear = 1 if the resp. lived with both biological parents until age 14.

Table 2.3: Parameter Estimates: Utility of Schooling

	Whites		Blacks		Hispanics	
Intercept type 1	-0.617	(0.286)	0.435	(0.643)	-1.233	(0.432)
Intercept type 2	-1.089	(0.216)	-0.956	(0.348)	-0.545	(0.457)
Intercept type 3	0.920	(0.001)	2.090	(0.296)	-1.198	(0.451)
Intercept type 4	-0.454	(0.169)	-0.284	(0.169)	-1.075	(0.566)
Intercept type 5	-0.970	(0.282)	-0.184	(0.169)	0.025	(0.002)
Initial ys of educ. type 1	0.107	(0.029)	-0.138	(0.076)	0.139	(0.043)
Initial ys of educ. type 2	0.114	(0.023)	0.102	(0.040)	0.087	(0.034)
Initial ys of educ. type 3	0.167	(0.005)	-0.244	(0.040)	0.155	(0.040)
Initial ys of educ. type 4	0.056	(0.017)	0.002	(0.022)	0.157	(0.048)
Initial ys of educ. type 5	0.148	(0.035)	-0.050	(0.026)	0.353	(0.011)
Father's education	0.030	(0.004)	0.010	(0.006)	0.011	(0.005)
Mother's education	0.020	(0.003)	0.027	(0.007)	0.008	(0.004)
Family income	0.001	(0.001)	0.002	(0.002)	0.004	(0.002)
Number of siblings	-0.006	(0.009)	-0.033	(0.010)	-0.012	(0.013)
Nuclear	0.168	(0.020)	0.066	(0.034)	0.209	(0.036)
Ability score	0.034	(0.007)	0.029	(0.012)	0.055	(0.014)

Standard errors in parentheses. Other Parameter estimates are available upon request.

Table 2.4: Parameter Estimates: Utility of Working

	Whites		Blacks		Hispanics	
Intercept type 1	1.753	(0.148)	2.353	(0.342)	1.314	(0.125)
Intercept type 2	1.735	(0.097)	1.420	(0.102)	0.948	(0.214)
Intercept type 3	0.789	(0.001)	1.222	(0.184)	1.500	(0.090)
Intercept type 4	1.116	(0.117)	1.008	(0.125)	1.127	(0.178)
Intercept type 5	1.751	(0.267)	0.206	(0.304)	-0.007	(0.002)
Initial ys of educ. type 1	0.093	(0.017)	0.096	(0.041)	0.052	(0.016)
Initial ys of educ. type 2	0.024	(0.010)	0.043	(0.012)	0.131	(0.025)
Initial ys of educ. type 3	-0.111	(0.004)	0.130	(0.022)	0.053	(0.020)
Initial ys of educ. type 4	0.093	(0.015)	0.086	(0.019)	0.174	(0.021)
Initial ys of educ. type 5	0.239	(0.030)	0.212	(0.040)	-0.107	(0.004)
Years of schooling	0.061	(0.005)	0.035	(0.008)	0.079	(0.011)
Years of work exper.	0.029	(0.006)	0.035	(0.008)	0.039	(0.014)
Ability score	0.028	(0.005)	0.016	(0.005)	0.011	(0.007)

Standard errors in parentheses. Other Parameter estimates are available upon request.

Table 2.5: Parameter Estimates: Initial Schooling Model

	Whites		Blacks		Hispanics	
Father's education	0.033	(0.007)	0.070	(0.013)	0.033	(0.010)
Mother's education	0.048	(0.007)	0.145	(0.015)	0.047	(0.010)
Family income	0.001	(0.001)	0.002	(0.004)	0.006	(0.003)
Number of siblings	-0.020	(0.022)	-0.069	(0.023)	-0.018	(0.029)
Nuclear	0.136	(0.055)	0.087	(0.077)	0.329	(0.078)
Ability score	0.056	(0.016)	0.017	(0.023)	0.020	(0.030)

Standard errors in parentheses.

Estimates of the cut-off points can be provided on request.

Table 2.6: Mean Years of Schooling by Ethnicity and Heterogeneity Type

	Type	Population proportion	Years of schooling
Whites	1	0.189	14.3
	2	0.265	11.5
	3	0.080	19.6
	4	0.397	14.0
	5	0.069	15.1
Blacks	1	0.034	11.1
	2	0.283	10.9
	3	0.071	12.0
	4	0.385	12.0
	5	0.227	12.6
Hispanics	1	0.260	11.6
	2	0.213	11.0
	3	0.390	13.5
	4	0.093	12.7
	5	0.043	19.2

Table 2.7: Decompositions of White-Black Gaps in Schooling and Wages

	Schooling	Wages
$E_W(y \vert X_W) - E_B(y \vert X_B)$	1.43 (whites 11.8% more)	2.87 (whites 26.0% more)
$E_W(y \vert X_W) - E_B(y \vert X_W)$	0.30 (explains 21% of the gap)	1.95 (explains 67.9% of the gap)
$E_B(y \vert X_W) - E_B(y \vert X_B)$	1.13	0.92
$E_W(y \vert X_B) - E_B(y \vert X_B)$	0.12 (explains 8.4% of the gap)	1.98 (explains 69% of the gap)
$E_W(y \vert X_W) - E_W(y \vert X_B)$	1.31	0.89

Decompositions of the wage differential based on the predicted wage at age 26.

Table 2.8: Decompositions of White-Hispanic Gaps in Schooling and Wages

	Schooling	Wages
$E_W(y \vert X_W) - E_H(y \vert X_H)$	0.89 (whites 7% more)	1.16 (whites 9.1% more)
$E_W(y \vert X_W) - E_H(y \vert X_W)$	0.06 (explains 6.7% of the gap)	0.56 (explains 48.3% of the gap)
$E_H(y \vert X_W) - E_H(y \vert X_H)$	0.83	0.60
$E_W(y \vert X_H) - E_H(y \vert X_H)$	0.03 (explains 3.3% of the gap)	0.59 (explains 50.9% of the gap)
$E_W(y \vert X_W) - E_W(y \vert X_H)$	0.86	0.57

Decompositions of the wage differential based on the predicted wage at age 26.

Figure 2.1: Initial Schooling at Age 16

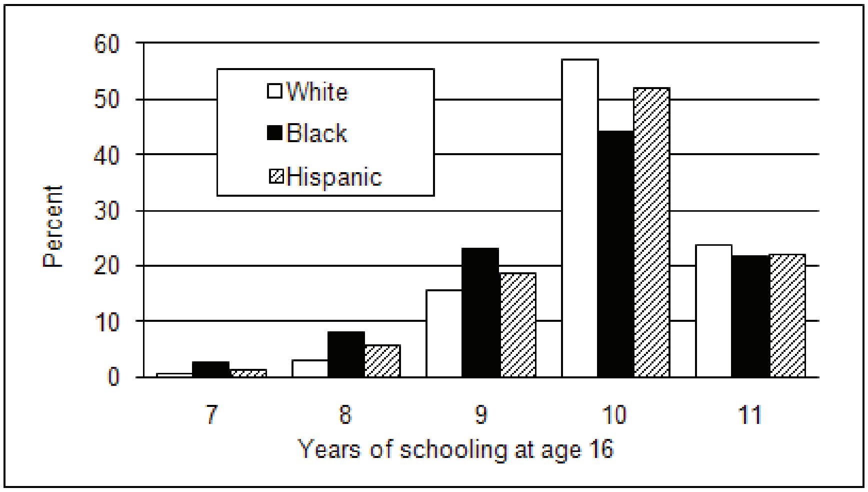


Figure 2.2: Final Schooling Attainment

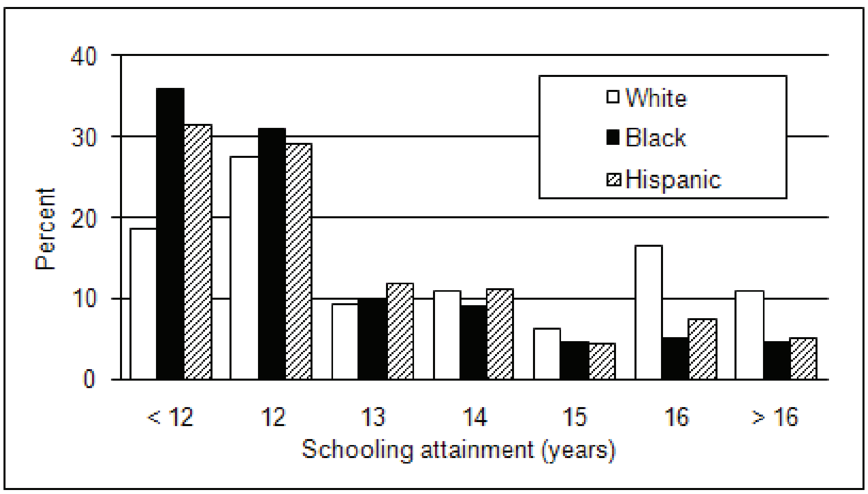


Figure 2.3: Estimated Probabilities of Completing and Continuing Past a Given School Grade

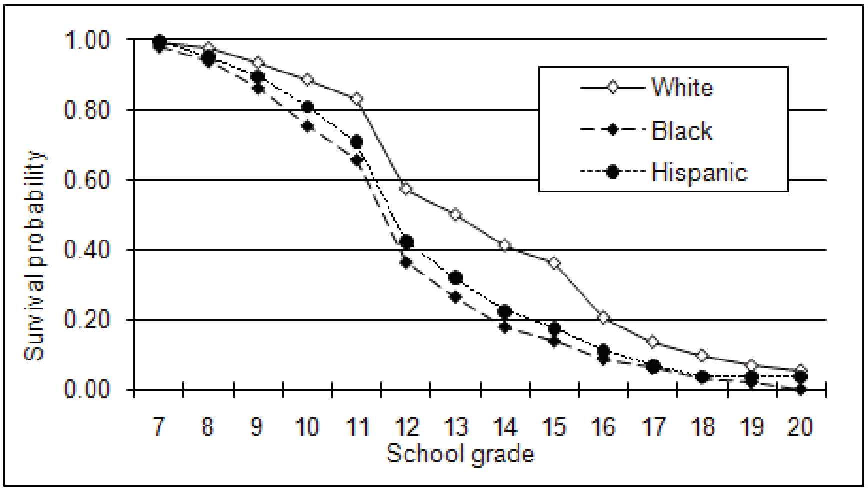


Figure 2.4: Estimated Probability Densities of the Ability Test Scores

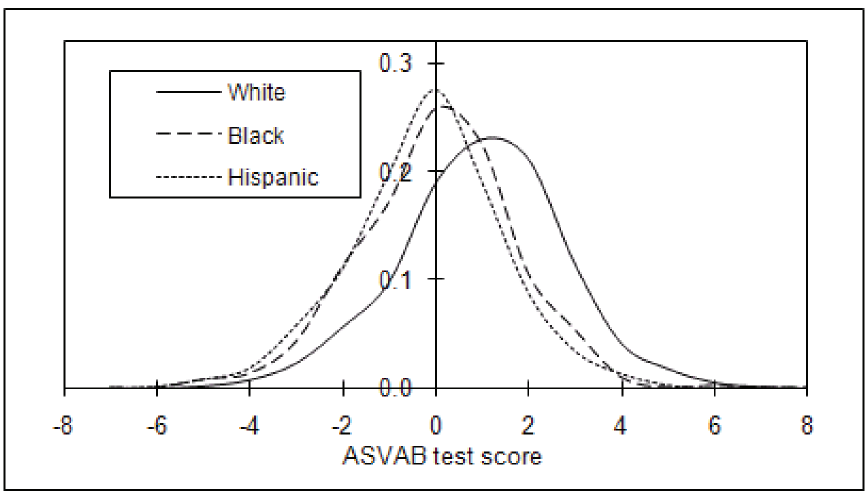


Figure 2.5: Age-Wage Profiles

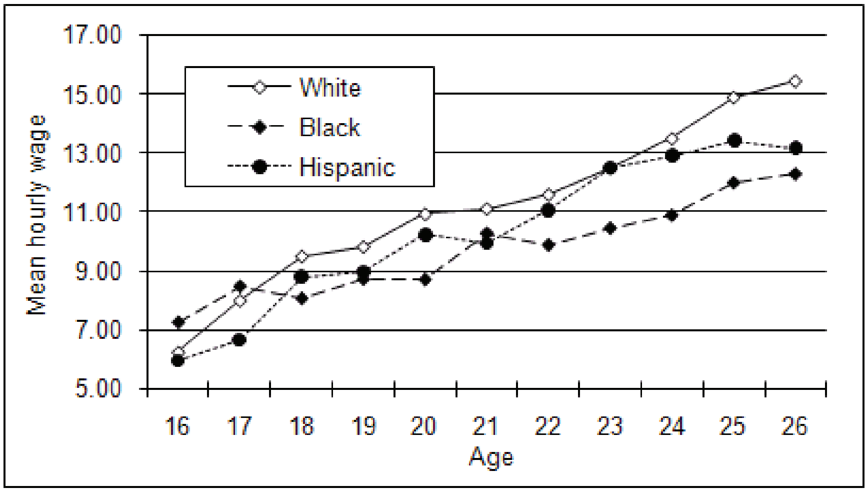


Figure 2.6: Minority Wage As a Percentage of White Wage

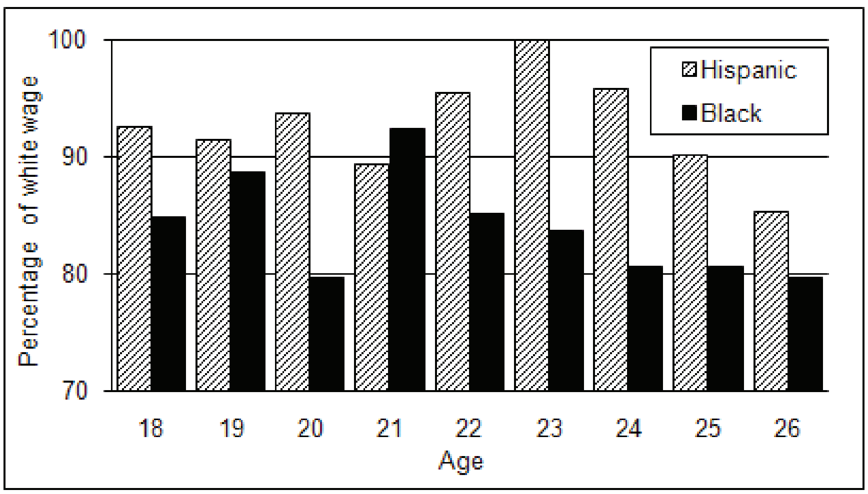


Figure 2.7: Actual and Predicted Schooling: Whites

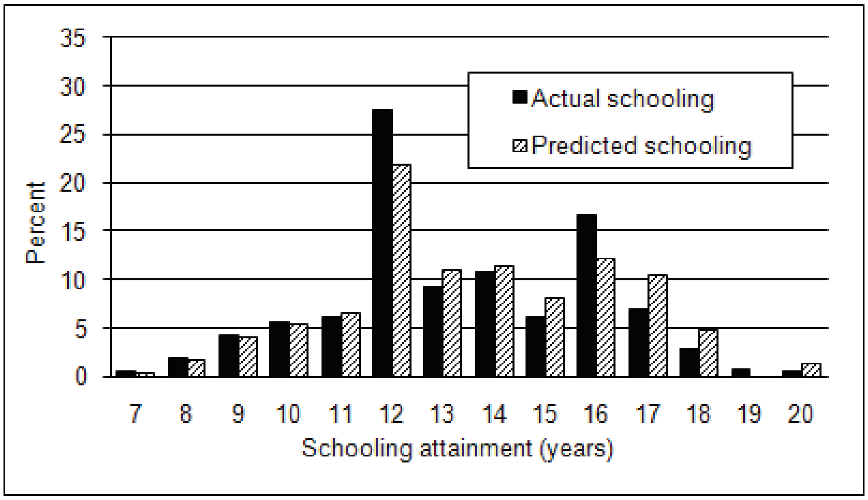


Figure 2.8: Actual and Predicted Schooling: Blacks

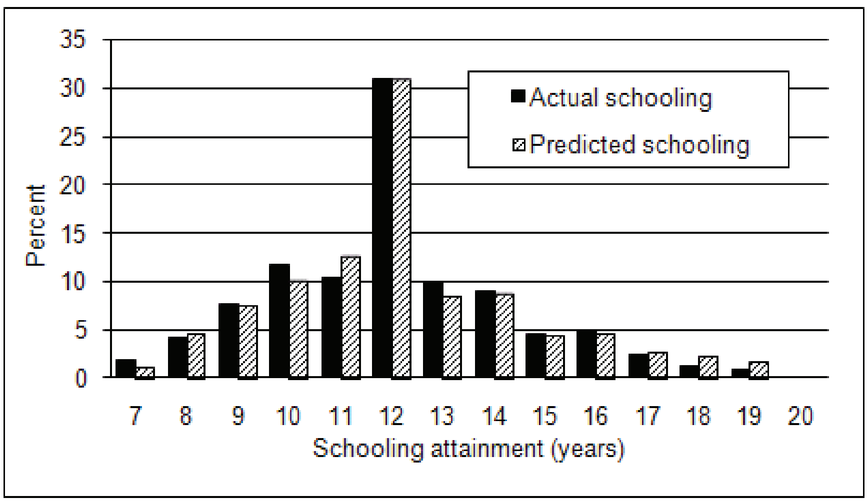


Figure 2.9: Actual and Predicted Schooling: Hispanics

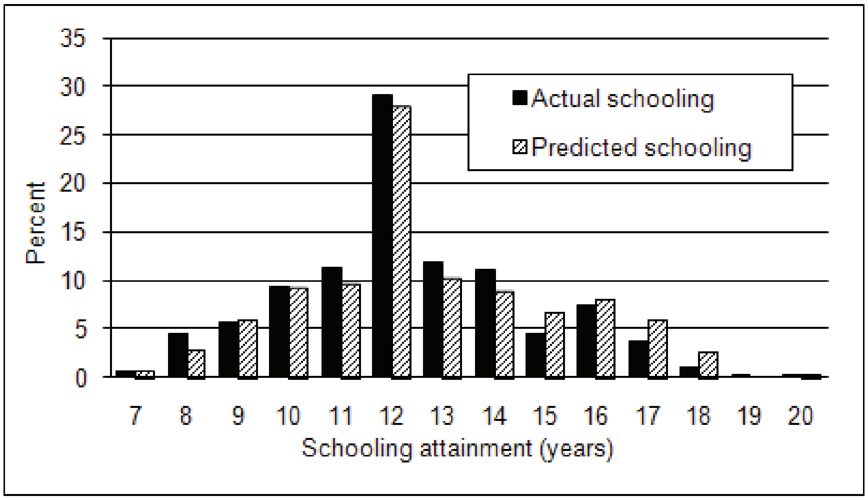


Figure 2.10: Actual and Predicted Wages: Whites

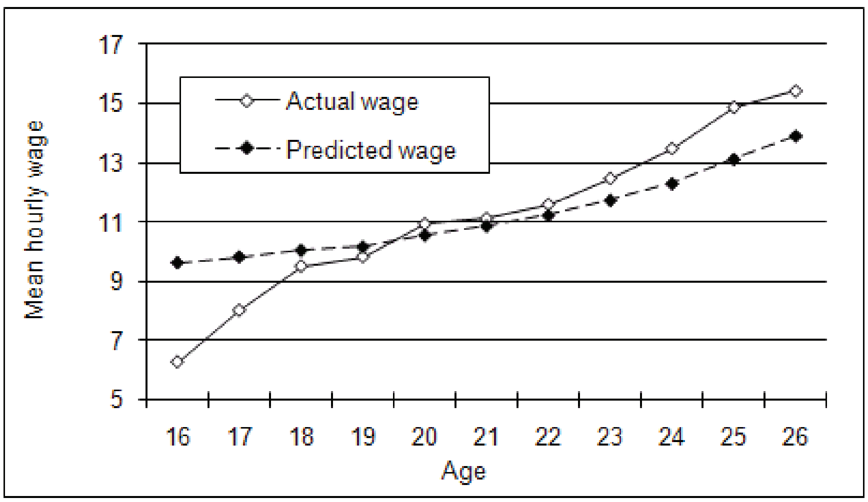


Figure 2.11: Actual and Predicted Wages: Blacks

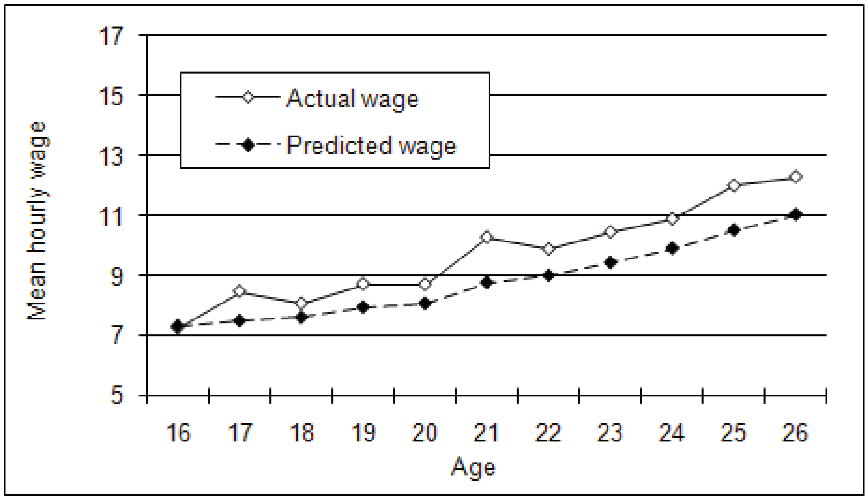
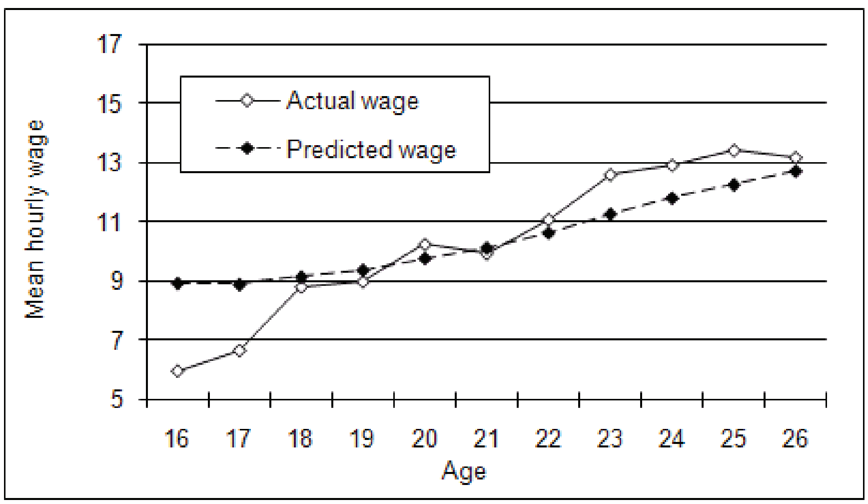


Figure 2.12: Actual and Predicted Wages: Hispanics



Chapter 3

Educational Attainment of Second-Generation Immigrants: A U.S. - Canada Comparison

3.1 Introduction

How immigrants fare in their host or destination countries has generated a huge literature in economics. Most of the work has focused on experiences in countries with relatively long histories of immigration and with highly developed economies, such as the U.S. and Canada (see Abbott and Beach 1993; Baker and Benjamin 1994; Borjas 1994, 2000; Bloom, Grenier and Gunderson 1995 and Camarota 2007). Evidence of wage gaps as well as differences in educational attainment between immigrants and the native population has been well documented in the literature (e.g. Funkhouser and Trejo 1995; Cohen, Zach and Chiswick 1997; Borjas 2000 and Frenette and Morissette 2005).

While a large economic literature exists on how immigrants integrate or assimilate, less attention has been paid to how children of immigrants fare. Since many immigrants decide to stay and raise their children in the host country, a more complete analysis of costs and benefits associated with immigration should reflect a longer-term perspective that also considers how children of immigrants succeed relative to children of natives. This is particularly true for the U.S. and Canada given their long history of receiving immigrants. Existing research (Kucera 2008; Hansen and Kucera 2004; Aydemir and Sweetman 2008; Aydemir, Chen and Corak 2009; Hansen, Liu and Kucera 2011a) have shown that children of immigrants generally acquire more education than otherwise similar children of native-born parents in both Canada and the U.S. However, in Europe, the opposite appear to be true. Studies by Nielsen, Rosholm, Smith and Husted 2001; Van Ours and Veenman 2002, 2003; Riphahn 2003, 2004 and Colding, Husted and Hummelgaard 2009 show that children of immigrants are not as successful as children of natives in terms of educational attainment.

Most of previous work in this area (with the exception of Caponi 2011; and Hansen, Liu, and Kucera 2011a) have been descriptive and therefore not been able to explain why such these educational differences exist. For example, an educational gap may arise because of differences in cognitive abilities between children of immigrants and children of natives. Furthermore, these ability differences could occur if abilities are transmitted across generations and if there is a non-random selection of immigrants where only those with high abilities find it worthwhile migrating or are the only ones accepted in the host country.

In order to advance our knowledge in this area, we need to move beyond the descriptive data analysis that is prevalent in previous studies. Specifically, there is a need to respect the structure and dynamic nature of the educational process when studying these issues. Consequently, in this paper I formulate and estimate an economic model of educational attainment of young adults who optimally choose between school and work based on their own abilities, preferences and opportunities. The behavioural parameters are estimated using data from the 1997 cohort of the National Longitudinal Survey of Youth and from the reading cohort of the Youth in Transition Survey (YITS - cohort A). The two surveys provide an excellent opportunity to conduct a comparable analysis of educational attainment of youths in the U.S. and Canada because of their detailed information on education and family background as well as the similarity of the surveys in terms of sample and questionnaires.

In this paper, the analysis is focused on white males. The NLSY97 identifies three major ethnic groups; whites, blacks and Hispanics. However, the sample sizes in YITS for blacks and Hispanics are not sufficiently large to allow meaningful comparisons between children of immigrants and children of natives in the two countries. Descriptive statistics show that family environment is important in shaping young individuals' educational decisions regardless of their immigration status. This is true in both Canada and the U.S. In Canada. Educational attainment is slightly higher for children of immigrants. Similarly in the U.S., children of immigrants acquire more schooling, on average, than children of native-born parents. Estimation results indicate that family characteristics, in particular parental education and income, have positive effects on children's schooling attendance, yet these effects are small in magnitudes.[1] The positive relations between family background variables and educational attainment are also documented in Keane and Wolpin (1997, 2001); Kucera (2008); and in Belzil and Hansen (2003, 2006). Moreover, in both countries, the observed advantage in second-generation immigrants' educational attainment over children of native-born parents is mostly explained by their stronger family background, not by differences in preference over education.[2] Further, simulation results show that youths in the U.S. are more responsive to reductions in psychic costs than are youths

[1]Simulation results based on improved family environment variables, such as parental education and income, suggest little impact on youths' educational attainment.

[2]This finding is also documented in both chapter 1 and 2

in Canada. In general, the simulation exercises suggest that improved family backgrounds have limited impacts on children's educational attainment in both Canada and the U.S. while incentive-based reforms, which reduce the cost of post-secondary schooling, have bigger impacts.

Overall, I believe that the results in this paper are interesting as they reveal whether and how family background and preferences affect educational decisions in the U.S. and Canada. It also shows that both U.S. and Canada, despite different focuses on immigration policies, attract high "quality" immigrants with higher level of human capital. The higher human capital was then transmitted to their children making them obtain higher educational attainment than their native peers. The rest of the paper is organized as follows. The model is introduced and explained in the next Section. Section 3 presents the data and descriptive statistics. The main results are presented and discussed in Section 4, where I also present how predictions from the model fit observed data. Section 5 provides results from counter-factual simulations based on the estimated model, while Section 6 concludes the paper.

3.2 A Structural Model of School Choices

In this section, I introduce a structural model that I will use to analyze educational choices of young individuals given their immigrant classification. The model is based on the ones used in Belzil and Hansen (2002 and 2007) and Hansen, Liu and Kucera (2011a and 2011b).

I assume that individuals decide sequentially whether to enter the labor market or to continue to accumulate years of schooling. Further, I assume they are rational, forward-looking individuals that maximize discounted expected lifetime utility over a finite time horizon set to the age of 65 (assumed to be the common retirement age). The model has one control variable, d_{it}, which equals one if an individual decides to stay in school and it equals zero if an individual decides to leave school and enter the labor market. Educational decisions are modeled as of age 16. The initial condition (the educational attainment at age 16) is potentially endogenous and denoted by S_{i0}.

3.2.1 Utility of Attending School

Formally, in any period t after age 16, the utility of attending school is represented by the following equation:

$$U_{it}^{hs} = ln(C_{it}^{hs}) = A^h(X_{it})I(S_{it} = J) + \alpha_0^k S_{i0} + as^k + uh^h + \varepsilon_{it}^{hs} \tag{3.2.1}$$

where $J = 4, 5, 6, 7, ...$ and i represents an individual, k represents unobserved heterogeneity support and h is an indicator variable that equals one if an individual is second-generation immigrant.

Further, t represents a time period and $ln(C_{it}^{hs})$ is defined as the instantaneous monetary returns of going to school (to make it comparable to the utility of working) for youth.[3] $A^h(X_{it})$ is assumed to be a linear function of X_{it} with different parameters for individuals with different immigration backgrounds. X_{it} contains time-invariant individual characteristics in period t, such as parent income, father's education, mother's education, test scores, and finally, immigrant status.[4] These are initial endowments of each individual that remain fixed over time.

Empirically, $A^h(X_{it})$ is assumed to take the following form:

$$A^h(X_{it}) = (\beta_1 + \beta_{1s} * secgen_i) * fed1i + (\beta_2 + \beta_{2s} * secgen_i) * fed2_i +$$

[3] One period in the model coincides with one academic year in the data.

[4] In NLSY97, I use the average parental income over four years (1998-2001) while in YITS the only measure of parental income is available for 2000.

$$(\beta_3 + \beta_{3s} * secgen_i) * med1_i + (\beta_4 + \beta_{4s} * secgen_i) * med2_i +$$

$$(\beta_5 + \beta_{5s} * secgen_i) * PI_i + \beta_6 * nsib_i + \beta_7 * nuclear_i +$$

$$(\beta_8 + \beta_{8s} * secgen_i) * test_i$$

Where $secgen_i$ is a binary variable that equals one if an individual has at least one immigrant parent. $fed1_i$ indicates if the father is a high school graduate while $fed2_i$ indicates if the father has completed schooling above high school. Hence, the reference group consists of fathers' with less than high school. $med1_i$ and $med2_i$ represent mothers' education and are similarly defined. PI_i stands for parental income for individual i and $nsib_i$ and $nuclear_i$ represent number of siblings and a nuclear family dummy, respectively. Finally, $test_i$ stands for the test score of individual i.[5]

The term $\alpha_0^k S_{i0}$ is included to control for possible endogeneity of initial schooling endowment at age 16. The indicator function, $I(S_{it} = J)$ is included to reflect that the utility of attending school may vary with grade levels.[6] In particular, $I(S_{it} = J)$ equals one if individual i completes grade level j in period t, and zero otherwise. Finally, as^k represents unobserved, time invariant heterogeneity while ε_{it}^{hs} represents an *iid* normally distributed instant utility shock.

3.2.2 Utility of Working

The instantaneous utility of working is defined by the following equation:

[5] In NLSY97, this variable refers to the residual obtained by regressing ASVAB verbal scores on educational attainment acquired at the time when the test was taken. In YITS it refers to the residual of regressing PISA verbal scores on educational attainment acquired at the time when the test was taken.

[6] Grade specific costs are added to reflect this feature.

$$U_{it}^{w} = ln(w_{it}) = \beta^{w} + retedu^{w} * S_{it} + retxp^{w} * Exper_{it} + retxp^{w2} * Exper_{it}^{2} + \varepsilon_{it}^{w} \quad (3.2.2)$$

Where $retedu^{w}$ and $retxp^{w}$ represent the return to school and return to work experience, respectively. β^{w} is the constant term in the wage equation. All the parameters in the wage equation are assumed to be common for every individual.[7] Thus, the utility of working is assumed to be constant given individual's educational attainment and working experience.

3.2.3 Initial Schooling

It is reasonable to assume that the permanent personal endowments that help explain schooling decisions beyond age 16 are also instrumental in determining how much schooling one has acquired by age 16. A failure to account for this possibility could seriously bias the estimates of the structural parameters. Consequently, we choose to model initial schooling (at age 16) as an ordered-choice and let the grade probabilities depend on both observed and unobserved individual characteristics.

3.2.4 Value Functions

At the beginning of each period, individuals choose between continuing to invest in one more year of schooling ($d_{it} = 1$) or terminating schooling investments and entering the labour market ($d_{it} = 0$) . The decision to enter the labour market is assumed to be permanent. That is, $d_{it} = 0$ implies that $d_{ij} = 0$ for all $j = t+1, ..., T$. The current discounted value of choosing to remain in school at the beginning of

[7] Since many respondents in both NLSY97 and YITS are still enrolled in school at the most recent survey date. I utilize data from the Canadian and the U.S. Censuses to recover the wage parameters. One could also argue that young individuals make their educational decisions by observing the labor market through census.

period t can be expressed by the following Bellman equation:

$$V_t^{hs}(S_t, \Omega_t) = A^h(X_{it})I(S_{it} = J) + \alpha_0^k S_{i0} + as^k + uh^h + \varepsilon_t^{hs} + \tag{3.2.3}$$

$$\beta\{EMAX[V_{t+1}^{hs}(S_{t+1}, \Omega_{t+1}), V_{t+1}^w(S_{t+1})]\}$$

Where β is the discount factor. The state variables S_t represent educational attainment at the beginning of period t, while Ω_t contains information on the individual's initial educational attainment (S_{i0}), personal characteristics, unobserved heterogeneity (represented by the vector $\Theta \in (as^k, uh^h, \varepsilon_t^{hs})$) and accumulated work experience ($Exper_t$) .

The value of terminating schooling and entering the labour market in period t is given by:

$$V_t^w(S_t) = ln(w_t) + \beta E[V_{t+1}^w(S_{t+1})|d_t = 0] \tag{3.2.4}$$

It should be noted that value function associated with working depends only on educational attainment and work experience. Furthermore, every individual share the same labour market outlook regardless of immigration status.

The second term on the right-hand side of $eq.$3.2.4 is simply the discounted expected value of working from period $t+1$ until retirement:

$$E[V_{t+1}^w(S_{t+1})|d_t = 0] = \tag{3.2.5}$$

$$\sum_{j=t+1}^{T} \beta^{j-(t+1)}\{\beta^w + retedu^w * S_{ij} + retxp^w * Exper_{ij} + retxp^{w2} * Exper_{ij}^2\}$$

Finally, each value function is solved using backwards induction and an individual chooses to terminate schooling and enter the labour market permanently in period t if

$$V_t^{hs}(S_t, \Omega_t) \leq V_t^{w}(S_t)$$

3.2.5 Unobserved Heterogeneity

Unobserved heterogeneity includes any unobserved (in the data) individual characteristics, including abilities, motivation, and preferences that determine educational decisions. For example, unobserved heterogeneity includes taste for schooling and working, innate non-cognitive abilities, ambitions etc. Ideally, each individual should be endowed with an unique set of all these factors. However, this is not feasible when we confront our model with survey data. Instead, as is customary in these types of models, I model unobserved heterogeneity as a set of random variables that are discretely distributed. Thus, I assume that individuals can be aggregated into groups that share common characteristics, preferences and abilities.

In particular, I assume that there are K groups (or types of individuals), and express the probability of belonging to type k as

$$p_k = \frac{exp(q_k)}{\sum_{j=1}^{K} exp\,(q_j)}$$

where $q_k = 0,\ k = 1, 2, ..., K$. The number of types or groups (K) is estimated using the Akaike Information Criteria.

3.2.6 The Likelihood Function

The dynamic programming problem is solved using backward recursion and the parameters of the model are estimated using maximum likelihood techniques. The decision rule d_t, $t \in \{0, 1, 2, 3, ..., 11\}$, determines the transition path from school to work. Given the value functions defined above, the transitional probabilities are:

$$Pr(d_{t+1} = 0 | d_t = 1) = Pr(V^w_{t+1}(S_t) \geq V^s_{t+1}(S_t)) \tag{3.2.6}$$

$$Pr(d_{t+1} = 1 | d_t = 1) = Pr(V^w_{t+1}(S_t) < V^s_{t+1}(S_t)) \tag{3.2.7}$$

These probabilities can be calculated given distributional assumptions of the time-varying utility shocks. The likelihood function, conditional on unobserved heterogeneity, consists of the following two parts:

- The probability of observing a particular sequence of schooling histories, given by

$$L_1(k) = Pr\{[d_0(k)], [d_1(k)], ..., [d_\tau(k)]\} \tag{3.2.8}$$

- The probability of having completed S years of schooling at age 16, given by[8]

$$L_2(k) = Pr(S_{i0} = s),\ s \in \{7, 8, 9, 10, 11, ...\} \tag{3.2.9}$$

Hence, the complete conditional likelihood function is given by

$$L_i(k) = L_1(k) L_2(k) \tag{3.2.10}$$

[8] This probability is obtained by using an ordered probit model.

Where $L_i(.)$ is the the likelihood contribution of individual i, belonging to type k. Finally, the complete unconditional log-likelihood contribution of individual i is given by

$$logL_i = log \sum_{k=1}^{K} p_k L_i(k) \tag{3.2.11}$$

Where p_k is the probability of belonging to group k.

3.3 Data

In this paper, I utilize data extracted from the 1997 cohort of the National Longitudinal Survey of Youth for the U.S. and the Youth in Transition Survey (15 years old in 1999) for Canada, henceforth NLSY97 and YITS, respectively.[9] Both surveys provide detailed information on educational achievement and socio-economic characteristics, including measures of cognitive skills. By utilizing both surveys I am able to compare how educational decisions of young individuals, including children of immigrants, were formed over the last decade in both countries. I use information from the beginning of 1997 to the end of 2007 (11 surveys) from NLSY97 and from the beginning of 1999 to the end of 2007 (5 cycles) from YITS.

In the U.S., where the 1979 cohort of the NLSY has long been a major source of information on the transition from school to work, the use of NLSY97 has until recently been limited by the young age of the respondents. Since the NLSY97 consists of youths aged 12 to 16 in 1996, a meaningful analysis of school to work transitions has only now become feasible for this cohort. Similarly, in Canada, the YITS consists of young individuals aged 15 in 1999 and respondents only recently started to make school to work transitions. Both surveys record detailed family environment and educational information on similarly aged youth in both countries. Having access

[9] Individuals were all 15 years old when the Youth in Transition Survey started in 1999

to these surveys gives me a good opportunity to look at how family environment together with cognitive skills shape young adults' educational decisions given their immigration statuses within the two neighboring countries, both with long histories of immigration.

In this study, I focus on how educational and early labour market outcomes of children of immigrants in the U.S. and Canada compare with children of U.S. and Canadian born parents. Furthermore, I want to compare educational attainment of children of immigrants between U.S. and Canada, and find out how these differences relate to their family backgrounds. In particular, an individual is defined to be second-generation immigrant if at least one of his parents was born abroad.

Information on individual's family background is collected from both surveys. Specifically, the following variables are used: immigration status; parental educational attainment; parental income; number of siblings; and whether the child lives with both biological parents at age 14. Test scores measuring individuals' cognitive skills are also utilized. The sample sizes are 1,348 for NLSY97 and 4,731 for YITS.[10]

3.3.1 AFQT and PISA Scores

By incorporating test scores in the model, I examine how much of educational differences across immigrant groups are due to differences in cognitive skills. Fortunately, both the NLSY97 and YITS offer unique opportunities to control for cognitive abilities. In the NLSY97, cognitive skills are measured by the Armed Forces Qualification Test (AFQT) scores. In particular, the AFQT scores were constructed from four subtests of the ASVAB.[11] There is ample evidence showing that AFQT scores are

[10] The NLSY97 data contains white male individuals with complete family background variables and AFQT score information. While In chapter 1 and 2, the data for white males from the same data source (NLSY97) also contain missing information in family background variables or in test scores. This is the reason why sample size for the first two chapters is 1884 for white males, and 1348 in this chapter.

[11] The Armed Services Vocational Aptitude Battery (ASVAB) contains 10 sub-tests. The four subtests included in the AFQT are Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning

closely related to educational achievement. For example, Belley and Lochner (2007) demonstrated that, other than family income, AFQT scores are also important predictors of educational attainment of the youths, especially for higher level education. In Cameron and Heckman (2001), AFQT scores were also used to explain educational gaps between whites and minority groups (blacks and hispanics). Other evidence can also be found in Eckstein and Wolpin (1999) and Keane and Wolpin (1997).

Information on cognitive skills in YITS are obtained from a series of standardized achievement tests taken by youths in the first wave of the survey. The tests were administered by the Programme for International Student Assessment (PISA).[12] However, the AFQT measures from the NLSY97 and the PISA scores from YITS cannot be readily compared at individual levels due to the fact that different methods and aspects were utilized and assessed to generate the scores. Furthermore, the age and grade level at which individuals took these tests differ between the two surveys. In order to make the analysis more comparable across surveys, I use only verbal scores from both surveys.[13]

Moreover, since test scores are utilized to control for measured scholastic abilities and test scores are closely correlated with completed years of schooling by the time when the test is taken, I need to purge the test scores from schooling effect. In order to avoid biased estimates of the preference parameters, I use adjusted ability measures obtained as the residuals from regressions of test scores on years of schooling at the time when individual took the test. The regression results from both surveys can be found in Table 3.14 in the last section.

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and Numerical Operation or Numerical Comprehension.

[12] PISA measures 15 years old students' skills and knowledge levels at the end of their compuslsory education to assess if they are ready to participate as adults in the society. In particular, PISA measures three aspects of individual skills and knowledge: Mathematics, Sciences and Verbal.

[13] Another reason for only considering verbal scores is that many youths in YITS did not complete the math test.

Verbal scores from NLSY97 were constructed by taking average of the Word Knowledge test scores and the Paragraph Comprehension scores.

3.3.2 School Status and Wages

Information on school enrolment status was obtained using monthly full-time school enrolment records from both NLSY97 and YITS.[14] Further, by utilizing information on monthly full-time student status and the date of birth (month), I was able to calculate accumulated grades completed for each academic year beyond age 16.

Information on wage measures was obtained from the 2000 U.S. and Canadian Censuses. Specifically, from each Census, a sample of white males aged between 25 and 65 was collected and used for the log wage regressions. Information on reported annual earnings, hours of work during Census week, weeks worked previous year, age and educational attainment was collected. Hourly wages were derived by dividing annual earnings by annual hours of work. I removed individual observations where the hourly wage was below the federal minimum wage rate in both countries in 1999. A proxy for work experience was obtained by subtracting years of schooling plus 6 from age. Finally, log wage regressions, which take the form of *eq*.3.2.2 above, were estimated and the estimates were used to derive values of work, conditional on educational attainment, for each individual. All wage and income measures were adjusted to 1999 dollars. The OLS log wage regression results can be found in Table 3.3.

3.3.3 Descriptive Statistics

According to my definition of second-generation immigrants, 5.6 percent of the respondents in the NLSY97 sample are children of white immigrants while the corresponding figure for the YITS sample is 10.7 percent. If visible minorities are included, the two figures are instead 12 percent for the U.S. and 15 percent for Canada. In this

[14]Part-time students are treated as workers in this paper.

case, the proportion of Hispanic children of immigrants is much larger in the U.S. than in Canada. This difference reflects the fact that immigration policies in the U.S. focus on "Family Reunion" combined with the fact that there are substantially more Latin American immigrants in the U.S. than in Canada.

3.3.3.1 Family Environment

Table 3.1 and Table 3.2 show descriptive statistics for key variables for both samples. Parental educational is classified into 3 categories: 1) less than high school, 2) high school graduate and 3) above high school. Both samples suggest that children of immigrants tend to have higher educated parents than children of native-born parents. For example, in the NLSY97, father's education is equivalent to or higher than university degree for 45 percent of children of immigrants while this figure is 28 percent for children of natives. A similar pattern is observed for mother's education. In the YITS sample, similar differences are found although the overall educational attainment among parents is lower than in the U.S.

Evidence from the two samples suggests that children of immigrants, compared to native children in both countries, tend to come from larger families and they are more likely to live with both biological parents in their teenage years.

In both the NLSY97 and YITS, parental income is generated by summing up both parents' gross incomes in 2000. This measure is then adjusted to 1999 dollars. In the U.S., average parental income for children of immigrants is around US $76,000 (which using an exchange rate of 1 US$ = CAD $1.45 in 2000 corresponds to about CAD $110,200). This is around 23 percent higher than the average parental income of children of natives (US $61,700). In Canada, similar differences exist between children of immigrants and children of natives although the average income levels are much lower in Canada.

Based on data from the two samples, it appears that children of immigrants in both Canada and the U.S. have stronger family backgrounds than children of native-born parents in the end of the 1990s. Specifically, children of immigrants have higher parental income, better educated parents and are more likely to live with both biological parents when they are young. In Canada, this phenomenon could be partly explained by the implementation of an immigration policy that was introduced in 1967 and focused on bringing highly educated individuals with language and working skills to Canada.

3.3.3.2 Cognitive Abilties

Cognitive abilities were measured in both surveys before the respondents reached the age of 16. I use verbal scores from ASVAB and PISA, respectively, to represent cognitive skill measures. Specifically, ASVAB_Verbal from the NLSY97 is constructed from taking average of the "Word Knowledge" scores and the "Paragraph Comprehension" scores. It is a percentile score that varies between 0 and 100, with a higher score implying higher ability. For YITS, I used reading scores from PISA (2000) as an ability measure. The values of this variable range from 0.84 to 8.87, and higher scores correspond to better performances in the tests.

Children of immigrants in the NLSY97 have on average much higher test scores (at 67%) than children of natives (at 57%). In Canada, the average test scores are slightly higher for children of immigrants (5.09 vs. 5.08)

3.3.3.3 Educational Attainment

Data from the NLSY97 suggests that children of immigrants on average accumulate more years of schooling (13.5) than children of natives (13). Moreover, there are less high school dropouts among children of immigrants (12%) than among children of natives (19.7%). The proportion of students attending college or university is also higher among children of immigrants. In particular, 42 percent of children of immigrants attended college or university while the corresponding figure for children of natives is 33 percent.

A different picture emerges when looking at data from the YITS sample. There are virtually no differences in average years of schooling between the two groups (13.44 vs. 13.41) with second-generation immigrants having slightly higher grades. Moreover, the distribution of years of schooling is similar at each grade level for this sample (see Table 3.4).

It is important to note that there are provincial differences in the organization of education as well as in educational outcomes. For example, in the province of Quebec, students complete their secondary education after completing grade11. If they decide to enrol in post-secondary education, they would normally attend "CEGEP" (College d'enseignement general et professional'). CEGEP is considered a college level education in Quebec and it usually takes two years to complete. After the two years, students can apply to university or complete a third year and obtain a vocational college diploma. Since Quebec is one of the largest provinces in Canada, my sample contains a considerable number of students from this province. The most recent cycle of YITS used in this paper contains personal educational information until the end of 2007 at which time the respondents have reached the age of 23. Given the young age of individuals in the survey, many individuals are still in school when last surveyed (including those who drop out of the survey between cycles). The overall rate of individuals who are observed to have a truncated educational stream is about 9 percent for both children of immigrants and children of natives. For NLSY97, this rate is only 3 percent. This is due to the fact that respondents in this survey were older in 2007 (between 23 and 27 years old).

Based on the information in Table 3.3, 50.2 percent of children of natives in Canada have completed at least 13 years of education (generally beyond high school) while this number is 40.7 percent in the U.S. On the other hand, 51.7 percent of children of immigrants in Canada have finished at least 13 years of schooling while this number is 50.7 percent in the U.S. When higher education (beyond grade 13) is considered, Canadian males are doing better than American males regardless of their parental immigration status. However, native Canadian children are doing much better than their American peers in higher education (beyond grade 13).

3.4 Empirical Results and Model Fit

3.4.1 Estimation Results

The estimated model parameters are presented in Table 3.5- Table 3.9. The parameters were obtained from models designed to control for unobserved heterogeneity.

The results suggest that grade specific utilities or (negative) costs (see Table 3.5) are important in determining educational attainment for both second-generation immigrant and native children. The magnitude for these parameters are large compared to other parameters and they are generally statistically significant. Interestingly, compared with other grade levels, the costs (in Table 3.5) are smaller (implying higher utility) for grade 12 (high school equivalent) and grade 16 (4-year university equivalent) for both the U.S. and Canada. This suggests that in both countries, individuals are trying to get through at least high school before merging into the labour market. The estimated parameters further reveal that higher grades are associated with higher costs, which is expected as post-secondary education is typically financed in part by user fees.

Estimation results based on the NLSY97 sample suggest that family background variables are closely related to educational attainment of the child. Table 3.6 indicates that higher parental educational attainment imply higher utility of attending school for the child and help the child to stay in school longer. The same relationship is observed for family income (Table 3.7). Furthermore, Table 3.7 also suggests that fewer siblings and living with both biological parents both increase the utility of school. As expected, cognitive abilities play a significant role in increasing individuals' utility of school. More importantly, no evidence were found to claim that these family environment variables together with test scores would affect children of immigrants differently ($\beta_{1s} - \beta_{4s}$in Table 3.6, β_{5s} and β_{8s}in Table 3.7). So the higher educational attainment of children of immigrants in the U.S. is mainly explained by their much stronger family background as well as by their better performances in cognitive skill tests.

Results derived from the Canadian sample convey a similar message. From Table 3.6 and Table 3.7, most of the parameters show expected signs (better family background helps to increase the utility of school) and the tie between educational attainment and family environment is strong. For example, improved parental education benefits both children of immigrants and children of natives. However, unlike the U.S. results, number of siblings has no significant effect ($\beta_6$in Table 3.7) on the utility of school. The results show that, in general, young adults' educational decisions in Canada are closely related to their family background. Finally, in Canada, reading test scores do not play a significant role in determining the utility of school.

3.4.2 Model Fit

After recovering the parameters in the empirical model, I generate simulated educational outcomes based on the parameters. Specifically, Table 3.10 shows both observed and simulated grade distributions from both samples. The generated educational outcomes are similar to those observed in the data. It is encouraging to see that the structural dynamic model has the ability to closely fit the data. In the next section, outcomes from several counter-factual simulations of the model are presented in order to illustrate how students are expected to react to alternative changes in characteristics and environment.

3.5 Simulations

Interpreting estimates from structural models is challenging given the usually complex features accompanied with these models. Consequently, it is not straightforward to interpret the magnitude of the estimated parameters from the current model. Instead, simulations are important tools that can be used to understand how outcomes change when parameters or observable characteristics change. For example, the current model can be used to generate counter-factual outcomes when parental educational attainment is modified for some or all respondents. The benefit of estimating a relatively complex dynamic structural model such as the one used in this paper is that it provides us with a unique opportunity to forecast individual behaviour under certain policy changes or reforms.

The credibility of the simulated outcomes depends on whether the model can accurately specify the decision making process of the individuals. A few recent studies have focused on establishing the validity of structural models. Typically, structural models are validated by comparing predicted outcomes from the model with those observed in the data (like Section 3.4.2 in this paper). However, even if the model passes this "internal" model fit criteria, it may not be suitable for predicting outcomes from counter-factual policy environments. Keane and Wolpin (2007) shows that a carefully designed structural model can indeed be used to provide information on individual reactions to policy changes. Other studies that validate structural models include Todd and Wolpin (2006) and Hansen and Liu (2011).

In line with the model assumptions, I assume that the recovered parameters represent individuals' preferences over education.[15] Hence, the reference group is defined as educational outcomes derived from the model described in Section 3.3.2. I will then conduct five alternative simulations using the estimated model and compare the simulated outcomes to those of the reference group.

The first four simulations are carried out by increasing parental education and parental income. Specifically, the idea is to increase parental education for each individual and see how individuals (especially second-generation immigrants) are expected to react. Since parental education and parental income are closely correlated, it is also reasonable to increase parental income together with parental education. To capture the relationship between parental education and income, I regress parental income on parental education and the second-generation immigrant dummy. I then use the OLS estimates to adjust income levels when parental education is increased to a certain level. The OLS results can be found in Table 3.11.

In particular, I first increase educational attainment of fathers (mothers) who have less than high school so that all fathers (mothers) are at least high school graduates. I then in a separate simulation, increase both parents' education in this fashion. In the fourth simulation, I increase educational attainment of both parents who had a high school diploma or less. In Table 3.12, I report changes in average educational attainment for both children of immigrants and children of natives as a result of these counterfactual simulations. In the first three simulations, where parental education is only increased if they have less than a high school diploma, the impacts on children's education are very small. In particular, no effects are found for children of immigrants in the U.S. sample and only simulations 2 and 3 generate (modest) improvements for children of immigrants in Canadian sample. This finding is mainly driven by the fact that very few second-generation immigrants in both samples have parental education

[15] Althogh some of the parameters may not be significantly different from zero.

that is lower than high school. The results for children of natives are similar to those for children of immigrants in both countries. The outcomes of the fourth simulation suggest that if parental education is increased to levels above high school, educational attainment is predicted to increase by one to two percent. Children of immigrants appear to benefit more from improved parental education than children of natives, both in Canada and in the U.S.

The last simulation is designed to evaluate the amount of educational subsidies needed to put an individual through post-secondary education. In particular, the mechanism of the dynamic educational choice model is to compare an individual's lifetime utility of working conditional on his educational level and his utility of school, obtained by staying in school for an additional year. Individuals stay in school because the utility of school exceeds utility of working (high educational attainment possibly entails higher wages in the future). On the contrary, if individuals decide to leave school for work, according to the model, it must imply that utility of earning wages at current educational level exceeds utility of having one more year of education and possibly enjoying higher wages in the future. With the help of the estimated model parameters, I am able to find out the differences between utility of school and utility of work at different grade levels conditional on individual's personal characteristic. These differences can, in turn, be used to infer the range of educational subsidies that would be required to ensure that those who attend post-secondary education also complete their degree.

Specifically, I identify individuals who would potentially, based on the model, obtain high school diploma (grade=12) but have not finished university (grade < 16), I then calculated the subsidy amounts at grades 13, 14, 15 and 16 needed for these individuals to graduate from university (grade 16).

Simulated subsidy levels are reported in Table 3.13. The required subsidies for post-secondary education are generally larger in the U.S. than in Canada. This is true for both children of natives and children of immigrants.[16] Although average annual subsidies are slightly lower for second generation white immigrants than for native whites in both countries, there is no statistical evidence to show that this difference was driven by the immigration status.[17]

Interestingly, regressions of these educational subsidies on individuals' family environment variables suggest that in Canada, only father's education (more than high school) will reduce the subsidy amount for children of immigrants. However, in the U.S., the correlation between family background and university subsidy amounts is higher. It also suggests that father's education, test scores, and living with both parents are factors that can effectively reduce the level of subsidy for children of immigrants in the U.S.[18]

One should be careful when interpreting the dollar amount of subsidies calculated using the model estimates in this environment. The difference between utility of school and utility of work may include many factors. It may contain actual educational cost at different educational levels but it may also contain psychic cost occurred to individuals who would need compensation to stay longer in school. It may also contain any other unobserved cost or disutility of attending school. The estimated annual dollar amounts needed to move individuals beyond certain levels of education (high school or university) will potentially incorporate all possible "costs" faced by decision-making young individuals.

[16] Subsidy amounts were not PPP adjusted, but average exchange rate between U.S. Dollar and Canadian Dollars in 2000 was about 1.45CAD=1USD.

[17] Regression of subsidies on the second-generation immigrant dummy in both countries yield non-significant coefficients and virtually zero R^2.

[18] These regression results are available upon request.

3.6 Conclusion

In this paper, I formulate a dynamic structural model to compare educational attainment of children of immigrants in the U.S. and Canada. Among other things, I analyze to what extent parental education affect educational decisions of children of immigrants in the two countries.

Two samples of young white males were collected from the NLSY97 and YITS, respectively. Descriptive statistics based on the two samples suggest that children of immigrants tend to have stronger family backgrounds than children of natives in both countries. Compared to native children, children of immigrants have better educated parents.

Based on the U.S. sample, children of immigrants have higher educational attainment than children of natives. They are more likely to attend post-secondary education, and less likely to drop out of high school. Compared to native children, they also perform better on standardized tests designed to measure cognitive skills. On the other hand, children of immigrants in Canada have generally the same educational attainment as children of native Canadians and there are no differences in test scores between the two groups.

Extending the literature in understanding educational attainment of second-generation immigrants (see for example, Chiswick and DebBurman (2004), Gang and Zimmermann (2000), Trejo (2003), Aydemir and Sweetman (2008), and Kucera (2008)), I employed a dynamic structural model of school choices in this study to analyze how family environment and test scores affect youths' educational decisions. Estimated parameters of the model suggest that, in the U.S., family background is closely related to educational attainment. Better family environment implies higher educational attainment of the child. Moreover, the results suggest that the educational differences between the two groups in the U.S. are mainly due to differences in family background and test scores rather than differences in preferences towards education. Similar results apply for Canada where the estimated parameters of the model also indicate that family environment is closely related to the educational attainment of the child.

Simulation results suggest that increasing parental educational attainment and parental income have limited positive effects on educational attainment of children of immigrants and natives, both in the U.S. and in Canada. On the other hand, incentive based policy changes such as reducing educational costs can generate relatively large positive effects on educational attainment of youths regardless of their immigration status. Moreover, the required subsidy amounts are larger in the U.S. than in Canada which may imply that costs play a more important role in the U.S. than in Canada. A possible interpretation could be that post-secondary education is more accessible in Canada than in U.S. This is true because Canada has a more generous educational system by having many forms of financial aid policies.

Using recent survey data, this paper suggests that both Canada and America were able to attract "better" immigrants from the world with higher level of human capital. The higher human capital were then transmitted to their children making them obtain higher educational attainment than their native peers. Specifically, the better educated first generation white immigrants in Canada can be partly explained by the successful implementation of the "point system" immigration policy introduced in 1967. However, the U.S. has adopted a different immigration policy focus that favors family reunification after 1960s. It is then reasonable to say that highly-motivated immigrants may have been attracted to the U.S. to take advantage of more opportunities in the labour market and more importantly to take advantage of the better educational qualities for their second generation in the U.S. This offers another evidence to support the argument made by Caponi (2011), which is that migrants are usually positively selected from the ability distribution in the home country, and that they transmit substantial human capital to their children so that their children can benefit more from the host country. It should be noted that the results in this paper are restricted to whites and the analysis ignores outcomes among other ethnicities, such as blacks and Hispanics. It is possible that differences between second-generation immigrants and natives in educational outcomes are larger for those ethnic groups and also that there may exist country differences as well.

Table 3.1: Mean Statistcs of Family Background Variables

	NLSY97		YITS (Reading Cohort)	
Variable	Secgen	Native	Secgen	Native
S_{i0}	9.63	9.41	10.34	10.26
$nsib$	2.35	2.29	1.44	1.40
$nuclear$	0.81	0.68	0.91	0.86
PI	76.45	61.70	77.45	67.30
$PISA-V$	-	-	5.09	5.08
$ASVAB-V$	67.51	57.22	-	-
fed_0	0.11	0.13	0.11	0.20
fed_1	0.21	0.37	0.20	0.24
fed_2	0.68	0.50	0.69	0.56

$Note$**:**

S_{i0}: initial educational attainment upon age 16.
$nsib$: number of siblings in the household at age 16.
$nuclear$: indicator of whether live with both parents before age 16.
PI: parental income in ten thousands dollars.
$PISA-V$: PISA verbal test score.
$ASVAB-V$: ASVAB verbal score.
fed_0: father's education less than highschool.
fed_1: father's education highschool only.
fed_2: father's education higher than highschool.

Table 3.2: Mean Statistcs of Family Background Variables (Continued)

	NLSY97		YITS	
Vriable	Secgen	Native	Secgen	Native
med_0	0.01	0.10	0.08	0.13
med_1	0.25	0.37	0.24	0.30
med_2	0.73	0.53	0.68	0.57
$acedu$	13.53	13.00	13.44	13.41
$secgen$	0.0556		0.1076	

$Note$:

med_0: mother's education less than highschool.
med_1: mother's education highschool only.
med_2: mother's education higher than highschool.
$acedu$: accumulated education in the last observed survey year.
$secgen$: second-generation immigrant dummy.
Secgen: Individuals with at least one immigrant parent
Native: Individuals with both parents non-immigrants

Table 3.3: OLS ln Wage Regression Results from the Censuses

	U.S. Census 2000	Canadian Census 2000
Parameter	Estimates (st.err)	Estimates(st.err)
β^w	1.229***(0.006)	1.711***(0.010)
$retedu^w$	0.085***(0.0003)	0.058***(0.0005)
$retxp^w$	0.028***(0.0003)	0.031***(0.0005)
$retxp^{w2}$	-0.0004***(0.000006)	-0.0004***(0.00001)
Adjusted R^2	0.1775	0.1118

$Note$:

β^w: constant term in the wage regression
$retedu^w$: wage return to years of education
$retxp^w$: wage return to years of working experience
$retxp^{w2}$: coefficient for experience squared

*** significant at 1% level;** significant at 5% level; *: significant at 10% level

Table 3.4: Observed Grade Distributions (Percentage) in the Last Observed Survey Year

	NLSY97		YITS	
Grades	Secgen	Native	Secgen	Native
6	0	0.08	0	0
7	0	0.08	0	0
8	0	1.57	0	0
9	1.33	5.03	0	0.12
10	4.00	5.58	3.73	3.72
11	6.67	7.38	17.09	15.40
12	37.33	39.59	27.50	30.60
13	9.33	8.01	14.15	13.05
14	5.33	4.48	5.11	6.66
15	6.67	4.56	8.25	6.75
16	16.00	13.20	9.82	8.36
17	12.00	6.44	5.70	7.53
18	1.33	2.91	8.45	7.79
19	0	0.86	0.2	0.02
20	0	0.16	0	0
21	0	0.08		

Table 3.5: Estimated Parameters of the 2-Type Model

	NLSY97			YITS		
Parameters	Estimates	Std Error	T-Stat	Estimates	Std Error	T-Stat
Grade Specific Utilities						
$Grd9$	-3.67	3.82	-0.96	-	-	-
$Grd10$	-7.65***	1.88	-4.07	-	-	-
$Grd11$	-1.03	1.13	-0.91	-4.89***	1.39	-3.52
$Grd12$	6.10***	0.92	6.61	0.69	0.49	1.41
$Grd13$	-12.46***	0.81	-15.34	-8.68***	0.40	-21.67
$Grd14$	-6.17***	1.00	-6.15	-6.92***	0.44	-15.66
$Grd15$	-3.28***	1.09	-3.01	-2.96***	0.49	-6.02
$Grd16$	1.17	1.06	1.11	-2.89***	0.50	-5.75
$Grd17$	-10.23***	1.07	-9.52	-5.83***	0.54	-10.80
$Grd18$	-11.68***	1.67	-7.00	-8.89***	0.68	-13.00
$Grd19$	-16.79***	2.55	-6.59	-	-	-

Note:

$Grd9$-$Grd19$: denote grade specific cost/utility (psychic educational cost) parameters in the dynamic programming model

*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 3.6: Estimated Parameters of the 2-Type Model Utility of School

	NLSY97			YITS		
Parameters	Estimates	Std Err	T-Stat	Estimates	Std Err	T-Stat
Utility of School						
α_0^1	1.74	2.47	0.70	0.27	0.23	1.20
α_0^2	0.26	0.20	1.29	1.47	1.90	0.77
as^1	-19.81	27.04	-0.73	2.70	2.52	1.07
as^2	-4.05*	2.10	-1.93	-14.35	19.06	-0.75
uh^h	-0.12	4.13	0.03	-0.61	0.76	-0.80
β_1	0.28	0.37	0.75	0.12	0.18	0.68
β_{1s}	-0.80	1.89	-0.42	-0.12	0.68	-0.18
β_2	1.42***	0.39	3.67	0.31*	0.16	1.89
β_{2s}	-0.66*	1.75	-0.37	-0.05	0.63	-0.07
β_3	1.21***	0.43	2.83	0.24	0.20	1.18
β_{3s}	0.50	4.43	0.11	0.58	0.77	0.75
β_4	1.33***	0.44	3.02	0.42**	0.19	2.14
β_{4s}	0.50	4.43	0.11	1.10	0.75	1.45

Note:

For parameter details, please refer to the model section 2.1

α_0^1 and α_0^2 : capture type specific effects of initial schooling on utility of school.
$\beta_1$and β_{1s} : capture the effect of having father's education at the level of high school for both native children (β_1) and children of immigrants (β_{1s}).
$\beta_2$and β_{2s} : capture the effect of having father's education higher than high school for both native children (β_2) and children of immigrants (β_{2s}).
$\beta_3$and β_{3s} : capture the effect of having mother's education at the level of high school for both native children (β_3) and children of immigrants (β_{3s}).
$\beta_4$and β_{4s} : capture the effect of having mother's education higher than high school for both native children (β_4) and children of immigrants (β_{4s}).

*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 3.7: Estimated Parameters of the 2-Type Model Utility of School (Continued)

	NLSY97			YITS		
Parameters	Estimates	Std Err	T-Stat	Estimates	Std Err	T-Stat
Utility of School						
β_5	0.91***	0.22	4.07	0.04**	0.02	2.41
β_{5s}	0.19	0.72	0.26	-0.04	0.05	-0.83
β_6	-0.22***	0.10	-2.91	-0.02	0.06	-0.36
β_7	0.86***	0.23	3.75	0.33**	0.16	2.06
β_8	0.39***	0.04	9.08	-0.13*	0.07	-1.93
β_{8s}	0.12	0.19	0.64	0.19	0.18	1.08

Note:

$\beta_5$and β_{5s} : capture efftect of parental income on utility of school for both children of natives (β_5) and children of immigrants (β_{5s}).
β_6 : capture the effect of number of siblings on utility of school, which is assumed to be common for both children of natives and children of immigrants.
β_7 : capture the effect of nuclear family on utility of school, which is assumed to be common for both children of natives and children of immigrants.
$\beta_8$and β_{8s} : capture efftect of cognitive skill on utility of school for both children of natives (β_8) and children of immigrants (β_{8s}).

*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 3.8: Estimated Parameters of the 2-Type Model Initial Education-Ordered Probit Estimates

	NLSY97			YITS		
Parameters	Estimates	Std Err	T-Stat	Estimates	Std Err	T-Stat
Ordered Probit						
$st-fed-hs$	3.05***	1.07	2.85	0.038	0.97	0.04
$st-fed-hs-above$	3.22***	1.15	2.81	-0.69	0.89	-0.77
$st-med-hs$	0.76	1.20	0.64	-2.01*	1.17	-1.72
$st-med-hs-above$	0.99	1.25	0.79	-2.09*	1.15	-1.82
$st-PI$	0.73	0.77	0.95	0.09	0.10	0.90
$st-test$	1.00***	0.13	7.75	4.90***	1.01	4.83
$st-nsib$	-0.17	0.32	-0.55	-0.16	0.32	-0.51
$st\_nuclear$	1.76**	0.73	2.41	-1.39	0.96	-1.45
$st-secgen$	4.14***	1.50	2.75	3.01**	1.19	2.53

Note:

$st-fed-hs$: captures the effect of father's education at highschool on individual's eduacation at age 16.
$st-fed-hs-above$: captures the effect of father's education higher than highschool on individual's eduacation at age 16.
$st-med-hs$: captures the effect of mother's education at highschool on individual's eduacation at age 16.
$st-med-hs-above$: captures the effect of mother's education higher than highschool on individual's eduacation at age 16.
$st-PI$: captures the effect of parental income on individual's eduacation at age 16.
$st-test$: captures the effect of cognitive skill on individual's eduacation at age 16.
$st-nsib$: captures the effect of number of siblings on individual's eduacation at age 16.
$st-nuclear$: captures the effect of nuclear family on individual's eduacation at age 16.
$st-secgen$: captures the effect of being a second-generation immigrant on individual's eduacation at age 16.

*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 3.9: Estimated Parameters of the 2-Type Model Initial Education-Ordered Probit Estimates (Continued)

	NLSY97			YITS		
Parameters	Estimates	Std Err	T-Stat	Estimates	Std Err	T-Stat
Ordered Probit						
$stu1-1$	-4.37	26.24	-0.17	-1.37***	0.28	-4.84
$stu1-2$	-2.03***	0.18	-11.37	-2.28***	0.82	-2.79
$stu2-1$	-0.53	1.86	-0.28	-1.56***	0.36	-4.26
$stu2-2$	-1.12***	0.15	-7.20	2.34***	0.68	3.44
$stu3-1$	-4.84	22.52	-0.21	-	-	-
$stu3-2$	0.54***	0.15	3.60	-	-	-
$stu4-1$	-4.09	26.18	-0.16	-	-	-
$stu4-2$	6.34	53.71	0.12	-	-	-
$q1$	-4.79***	0.30	-15.84	-0.41***	0.12	-3.4
$pr1$	1%	-	-	40%		
$pr2$	99%	-	-	60%		

Note:

$stu1-1$ up to $stu4-2$: capture the supports of ordered probit model.
$q1$: help to identify the probability of belonging to a specific type.
$pr1$ and $pr2$: denote the probabilities of belonging to certain type.

*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 3.10: Model Fit Grade Distributions (in percentage) Generated from the Preferred 2-Type Model

	NLSY97		YITS	
Grade Levels	Observed	Model	Observed	Model
6	0.07	0	0	0
7	0.07	0.37	0	0
8	1.48	2.00	0	0
9	4.82	7.05	0.11	0.23
10	5.49	6.53	3.72	3.91
11	7.34	7.86	15.58	14.01
12	39.47	42.95	30.27	32.64
13	8.09	8.46	13.17	13.30
14	4.53	4.08	6.49	5.90
15	4.67	3.56	6.91	6.66
16	13.35	10.68	8.52	8.29
17	6.75	4.15	7.33	7.08
18	2.82	1.04	7.86	2.87
19	0.82	0.30	0.04	3.91
20	0.15	0.22	0	1.20
21	0.07	0.74	0	0
22	0	0	0	0
Mean Accumulated Education	13.03	12.56	13.42	13.45

Table 3.11: OLS Regression Results: Parental Income and Parental Education

	NLSY97			YITS		
Parameters	Estimates	Std Err	T-Stat	Estimates	Std Err	T-Stat
Intercept	27.66***	4.45	6.21	40.46***	1.48	27.40
$fed-hs$	7.31*	4.08	1.79	9.25***	1.48	6.24
$fed-hs-above$	25.98***	4.17	6.23	18.17***	1.33	13.62
$med-hs$	11.06**	4.60	2.40	9.86***	1.63	6.04
$med-hs-above$	26.68***	4.71	5.66	19.98***	1.55	12.70
$secgen$	7.20	5.24	1.37	6.56***	1.51	4.34
adjusted R^2		0.13			0.12	
$F-Stats$		41.04			134.57	
Dependent Mean[19]		62.52			68.39	

Note:

$fed-hs$ father's education at highschool.
$fed-hs-above$ father's education higher than highschool.
$med-hs$ mother's education at highschool.
$med-hs-above$ mother's education higher than highschool.
$secgen$ second-generation immigrant dummy.

*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table 3.12: Simulated Educational Attainment: Means of Years of Schooling

	NLSY97		YITS	
Accumulated Years of Education	Secgen	Native	Secgen	Native
Simulation 1*				
increase those father's education below highschool to highschool graduate, and praental income is increased accordingly.				
Control	12.973	12.532	13.363	13.464
Treatment	12.973	12.553	13.363	13.480
% Changes	0	0.17	0	0.15
Simulation2**				
increase those mother's education below highschool to highschool graduate, and praental income is increased accordingly.				
Control	12.973	12.532	13.363	13.464
Treatment	12.973	12.573	13.413	13.487
% Changes	0	0.33	0.37	0.17
Simulation 3***				
increase those parental education below highschool to higher school graduate and praental income is increased accordingly.				
Control	12.973	12.532	13.363	13.464
Treatment	12.973	12.603	13.41	13.50
% Changes	0	0.57	0.37	0.30
Simulation 4****				
increase those parental education below or equivalent to highschool to above highschool, and parental income is increased accordingly.				
Control	12.973	12.532	13.363	13.464
Treatment	13.253	12.680	13.60	13.64
% Changes	2.16	1.18	1.8	1.5

Table 3.13: Educational Subsidies: High School Graduates but No University

	NLSY97		YITS	
Annual Dollar Amount Subsidies	N	Mean	N	Mean
Children of Immigrants				
University Total	46	9248 US$	310	4250 US$
Grade 13	46	5259 US$	310	1827 US$
Grade 14	46	2245 US$	310	1139 US$
Grade 15	46	995 US$	310	652 US$
Grade 16	46	749 US$	310	631 US$

	NLSY97		YITS	
Annual Dollar Amount Subsidies	N	Mean	N	Mean
Children of Natives				
University Total	750	9037 US$	2457	4479 US$
Grade 13	750	4847 US$	2457	1890 US$
Grade 14	750	1594 US$	2457	1034 US$
Grade 15	750	1135 US$	2457	668 US$
Grade 16	750	1461 US$	2457	886 US$

Note:

The implied policy targeted on individuals with simulated completed grade higher than 12 but lower than 16.
"University Total" means average total subsidy amount
for each individual to complete university. "Grade 13", "Grade 14",
"Grade 15", "Grade 16", denote grade specific average subsidy for a
typical individual to finish a specific grade.
1US$=1.45CA$ in 2000. Not PPP adjusted.

Table 3.14: OLS Regression Results: Test Scores on Initial Education S_{i0}

	NLSY97 ($ASVAB-V$)			YITS ($PISA-V$)		
Parameters	Estimates	Std Err	T-Stat	Estimates	Std Err	T-Stat
$Intercept$	10.99*	5.68	1.94	3.95***	0.28	14.06
$Secgen$	71.52***	25.25	2.83	-3.48***	0.87	-4.01
$Secgen-Grd$	-6.09**	2.47	-2.46	0.35***	0.09	4.03
S_{i0}	4.61***	0.56	8.22	0.11***	0.03	4.03
adjusted R^2	0.0527			0.0069		
F-Stats	25.99			11.99		
Dependent Mean (Test Scores)	57.79			5.08		

$NOTE$:

$Secgen$: second-generation immigrant dummy.
$PISA-V$: PISAverbal test score.
$ASVAB-V$: ASVAB verbal score.
S_{i0}: initial educational attainment upon age 16.
$Secgen-Grd$: Interaction term between $Secgen$ dummy and initial schooling

*** significant at 1% level;** significant at 5% level;* significant at 10% level

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Appendix

Chapter 1

Some of the estimated model parameters of Chapter 1 are reported in the following: A complete parameter estimates are available upon request.

Table A1: Effects on Average Accumulated Years of Education from Changing Background Characteristics

	Mean effects on accumulated years of education in %							
	Native Whites		Native Hispanics		Second-generation Hispanics		Second-generation Whites	
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
1. *AFQT* scores increased by 10	1.38	0.4	0.89	0.73	2.38	1.13	0.31	0.82
2. Father's years of schooling increased by one year	0.19	0.28	1.11	0.26	0.63	0.29	1.09	0
3. Father has highschool diploma	0.74	0.47	4.2	0.79	1.95	1.45	2.27	1.22
4. Mother's years of schooling increased by one year	0.14	0.28	0.33	0.17	-0.63	0.44	0.16	0.48
5. Number of Siblings decreased by one	0.21	0.14	0.33	0.04	0.63	0.15	0.39	0

6. Parental Income increased by $10,000							
0.25	0.33	0.89	0.77	0	0.2	-0.39	0.27

Note:

Based on 5-type model.
persentage changes in mean years of schooling are calculated using our preferred 5-type model. For example, to calculate the impact of increasing parental income by $10,000 (1997 dollar), we calculate mean years of schooling based on our model before and after the parental income changes while holding other background variables constant, then a percentage change between the two means is calculated

Table A1.1: Estimated Parameters Associated with Initial Educational Attainment (5-Type Model)

Parameters	NLSY79	NLSY97	Parameters	NLSY79	NLSY97
$\mu_1(1)$	-1.06^{***}	-1.68^{***}	$\mu_4(1)$	2.50^{***}	2.96^{***}
	(0.07)	(0.14)		(0.14)	(0.16)
$\mu_1(2)$	-1.33^{***}	-1.14^{***}	$\mu_4(2)$	2.11^{***}	2.86^{***}
	(0.08)	(0.07)		(0.08)	(0.10)
$\mu_1(3)$	-1.23^{***}	-0.84^{***}	$\mu_4(3)$	2.66^{***}	2.73^{***}
	(0.07)	(0.10)		(0.14)	(0.10)
$\mu_1(4)$	-1.46^{***}	-1.58^{***}	$\mu_4(4)$	2.45^{***}	3.40^{***}
	(0.14)	(0.06)		(0.15)	(0.09)
$\mu_1(5)$	-1.31^{***}	-1.39^{***}	$\mu_4(5)$	3.46^{***}	3.00^{***}
	(0.10)	(0.11)		(0.14)	(0.09)
$\mu_2(1)$	-0.33^{***}	-0.32^{***}	st^{sh}	-0.12^{*}	0.30^{***}
	(0.08)	(0.05)		(0.07)	(0.02)
$\mu_2(2)$	-0.83^{***}	-0.05	st^{sw}	0.11^{***}	0.08^{***}
	(0.09)	(0.08)		(0.02)	(0.01)
$\mu_2(3)$	-0.52^{***}	-0.003	st^{nh}	-0.10^{*}	0.009
	(0.08)	(0.08)		(0.06)	(0.02)

Note:
This table reports estimated parameters on initial education attainment.
$\mu_j(k)$ denotes type-specific support in the ordered probit model.
$st^{sh}st^{sw}$ st^{nh} denote ethnicity/immigrant dummy in the ordered probit model.
$stfed$ and $stmed$ denote parental education in the ordered probit model.
$sttest$ denote test score; $stpi$ denote parental education; $stnsib$ denote number of siblings
$stnuclear$ denote nuclear family effect on initial schooling.
standard deviations are in bracket,
*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table A1.2: Estimated Parameters Associated with Initial Educational Attainment (5-type model)

Parameters	NLSY79	NLSY97	Parameters	NLSY79	NLSY97
$\mu_2(4)$	-0.48^{***}	-0.02	$stfed$	0.03^{***}	0.02^{***}
	(0.08)	(0.05)		(0.007)	(0.005)
$\mu_2(5)$	-0.37^{***}	-0.08	$stmed$	0.05^{***}	0.04^{***}
	(0.07)	(0.06)		(0.008)	(0.006)
$\mu_3(1)$	1.14^{***}	-1.80^{***}	$sttest$	0.005^{***}	0.008^{***}
	(0.08)	(0.11)		(0.001)	(0.001)
$\mu_3(2)$	0.88^{***}	1.56^{***}	$stpi$	0.0008	0.001^{*}
	(0.08)	(0.07)		(0.001)	(0.0005)
$\mu_3(3)$	1.41^{***}	1.47^{***}	$stnsib$	-0.04^{***}	-0.002
	(0.08)	(0.11)		(0.01)	(0.02)
$\mu_3(4)$	0.95^{***}	2.07^{***}	$stnuclear$	-0.008	0.14^{***}
	(0.08)	(0.05)		(0.07)	(0.02)
$\mu_3(5)$	1.25^{***}	1.70^{***}			
	(0.07)	(0.07)			

Note:
This table reports estimated parameters on initial education attainment.
$\mu_j(k)$ denotes type-specific support in the ordered probit model.
$st^{sh} st^{sw}$ st^{nh} denote ethnicity/immigrant dummy in the ordered probit model.
$stfed$ and $stmed$ denote parental education in the ordered probit model.
$sttest$ denote test score; $stpi$ denote parental education; $stnsib$ denote number of siblings
$stnuclear$ denote nuclear family effect on initial schooling.
standard deviations are in bracket,
*** significant at 1% level;** significant at 5% level;* significant at 10% level

Table A1.3: Estimated Parameters Associated with Probability of Having Observed Wages and Type Probabilities (5-Type Model)

Parameters	NLSY79	NLSY97	Parameters	NLSY79	NLSY97
$uprw^1$	-2.88^{***}	-1.32^{***}	q_1	-0.30^{***}	-2.16^{***}
	(0.19)	(0.36)		(0.08)	(0.13)
$uprw^2$	-2.87^{***}	-0.12	q_2	0.18^{**}	-0.44^{***}
	(0.21)	(0.38)		(0.07)	(0.07)
$uprw^3$	-4.48^{***}	-0.94^{**}	q_3	0.38^{***}	-0.60^{***}
	(0.21)	(0.40)		(0.07)	(0.08)
$uprw^4$	-4.16^{***}	-2.72^{***}	q_4	0.10	-0.22^{*}
	(0.22)	(0.38)		(0.08)	(0.12)
$uprw^5$	-5.99^{***}	-1.51^{***}	p_1	0.13	0.04
	(0.21)	(0.39)			
upw^{sh}	0.29^{***}	0.04	p_2	0.22	0.21
	(0.07)	(0.04)			
upw^{sw}	0.03	-0.31^{***}	p_3	0.27	0.17
	(0.06)	(0.04)			
upw^{nh}	0.22^{***}	0.07^{*}	p_4	0.20	0.26
	(0.07)	(0.04)			
wsh	0.14^{***}	-0.13^{***}	p_5	0.18	0.32
	(0.02)	(0.04)			
$wretedu$	0.52^{***}	0.37^{***}			
	(0.01)	(0.010)			
$wretxp$	0.32^{***}	0.39^{***}			
	(0.004)	(0.006)			
$wtstw$	-0.01^{***}	-0.001^{**}			
	0.001	(0.001)			
λ	-0.14^{***}	-0.11^{***}			
	(0.02)	(0.03)			

Note:
This table reports estimated parameters on probabilities of being observed a wage.
$uprw^k$ denotes type-specific support of being observed a wage.
$upw^{sh}upw^{sw}$ upw^{nh} denote ethnicity/immigrant dummy in the prob of wage equation.
wsh denote initial schooling in the prob of wage equation.
$wretedu$ and $wretxp$ denote education and work experience effect in the prob of wage equation.
λ is the weight parameter in the conditional probabilities of having a observed wage.
q_1-q_5 are threshold parameters determining the probability of individuals belonging to a specific type. p_1-p_5 are caculated type probabilities.
standard deviations are in bracket.
*** significant at 1% level;** significant at 5% level;* significant at 10% level

Chapter 3

Grade distributions based on the model developed in Chapter 3 are reported in the following tables:

Table A3.1: Grade Distributions (in persentage): Control Group

	NLSY97		YITS	
Grade Levels	Secgen	Natives	Secgen	Natives
6	0	0	0	0
7	0	0.39	0	0
8	0	2.12	0	0
9	4.00	7.23	0.20	0.24
10	10.67	6.28	3.34	3.98
11	4.00	8.09	15.32	13.86
12	42.67	42.97	32.61	32.64
13	8.00	8.48	14.54	13.15
14	6.67	3.93	6.09	5.87
15	4.00	3.53	7.66	6.54
16	12.00	10.60	7.66	8.36
17	2.67	4.24	5.30	7.30
18	1.33	1.02	1.77	3.01
19	1.33	0.24	2.55	4.07
20	1.33	0.16	2.95	0.99
21	1.33	0.71	0	0
22	0	0	0	0
Mean Accumulated Education	12.973	12.532	13.363	13.464

Note: The grade distributions are derived from 2-Types Model

Table A3.2: Grade Distributions in %: Simulation 1

	NLSY97		YITS	
Grade Levels	Secgen	Natives	Secgen	Natives
6	0	0	0	0
7	0	0.39	0	0
8	0	2.04	0	0
9	4.00	7.07	0.20	0.24
10	10.67	6.28	3.34	3.93
11	4.00	8.01	15.32	13.78
12	42.67	42.97	32.61	32.52
13	8.00	8.41	14.54	13.10
14	6.67	4.01	6.09	5.83
15	4.00	3.61	7.66	6.61
16	12.00	10.84	7.66	8.41
17	2.67	4.24	5.30	7.39
18	1.33	1.02	1.77	2.98
19	1.33	0.24	2.55	4.17
20	1.33	0.16	2.95	1.04
21	1.33	0.71	0	0
22	0	0	0	0

Note:The grade distributions are derived from 2-Type Model

Table A3.3: Grade Distributions in %: Simulation 2

	NLSY97		YITS	
Grade Levels	Secgen	Natives	Secgen	Natives
6	0	0	0	0
7	0	0.39	0	0
8	0	2.12	0	0
9	4.00	6.68	0.20	0.24
10	10.67	6.28	3.34	3.88
11	4.00	7.86	15.13	13.83
12	42.67	43.28	32.47	32.47
13	8.00	8.33	14.15	13.05
14	6.67	4.01	5.89	5.87
15	4.00	3.61	7.86	6.54
16	12.00	10.92	7.47	8.36
17	2.67	4.40	5.89	7.53
18	1.33	1.02	1.96	3.03
19	1.33	0.24	2.55	4.17
20	1.33	0.16	3.14	1.02
21	1.33	0.71	0	0
22	0		0	0

Note:The grade distributions are derived from 2-Type Model

Table A3.4: Grade Distributions in %: Simulation 3

	NLSY97		YITS	
Grade Levels	Secgen	Natives	Secgen	Natives
6	0	0	0	0
7	0	0.39	0	0
8	0	2.04	0	0
9	4.00	6.44	0.20	0.24
10	10.67	6.21	3.34	3.79
11	4.00	7.62	15.13	13.74
12	42.67	43.36	32.42	32.47
13	8.00	8.48	14.15	12.98
14	6.67	4.01	5.89	5.83
15	4.00	3.77	7.86	6.63
16	12.00	11.15	7.47	8.46
17	2.67	4.40	5.89	7.56
18	1.33	1.02	1.96	3.06
19	1.33	0.24	2.55	4.17
20	1.33	0.16	3.14	1.09
21	1.33	0.71	0	0
22	0	0	0	0

Note:The grade distributions are derived from 2-Type Model

Table A3.5: Grade Distributions in %: Simulation 4

	NLSY97		YITS	
Grade Levels	Secgen	Natives	Secgen	Natives
6	0	0	0	0
7	0	0.39	0	0
8	0	1.81	0	0
9	4.00	5.97	0.20	0.21
10	4.00	5.73	2.55	3.48
11	4.00	7.70	14.15	13.07
12	45.33	42.58	30.65	31.55
13	6.67	9.19	14.73	12.77
14	9.33	3.93	5.89	5.80
15	2.67	4.71	7.47	6.58
16	14.67	11.55	8.45	8.83
17	4.00	4.32	7.47	8.03
18	2.67	1.10	2.16	3.51
19	1.33	0.16	3.14	4.81
20	0	0.16	3.14	1.35
21	1.33	0.71	0	0
22	0	0	0	0

Note:The grade distributions are derived from 2-Type Model