TWO ESSAYS IN LABOR ECONOMICS

A Dissertation

by

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

DOCTOR OF PHILOSOPHY

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December 2012

Major Subject: Economics

ABSTRACT

The first essay studies the long term trend of internal migration in the United States. Over the last forty years, there has only been a modest change in the overall interstate migration rate in the United States. However, different demographic groups have seen very different patterns of changes. The migration rate for families with two college graduate spouses dropped from 5.66% in 1965-1970 to 2.82% in 2000-2005. As for the families with college-graduate husband, it dropped from 4.05% to 2.15% during the same time frame. Interstate migration rates for other types of families or singles have seen little change. This paper extends Mincer's family migration model into a search framework and directly estimates the effects of female labor force participation, spousal earning ratio, correlation of earnings from job offers, and home ownership on the migration propensity by using the Current Population Survey (CPS) data in the period of 1982-2005. Endogeniety issues of these variables are appropriately addressed. According to the Blinder-Oaxaca decomposition analysis, we find that the increasing female labor force participation rate and earning ratio of wife to husband are the primary determinants for the decline in the interstate migration rate of families with two college-graduate spouses and families with a college-graduate husband in the 1980s-1990s. The rising home ownership accounts for a large portion of the decrease in the migration rate of highly educated families, in the 1990s-2000s.

The second essay studies the impact of changing youth cohort size on the unemployment rate. Although an increase in youth cohort size is often found to exert an upward pressure on the aggregate unemployment rate, it has been provided some empirical evidences and a theoretical model to the contrary. We find that the estimated elasticity of unemployment rate is quite sensitive in a fixed effect model, with the inclusion of year dummies, when there is a strong temporal correlation between the youth cohort size and the unemployment rate. Both the sign and magnitude of the estimates vary significantly when using data from different time periods. We propose an alternative way to control for the fixed effects and obtain consistent estimates across the time periods in the United States. Our results support the conventional wisdom of positive correlation between youth cohort size and aggregate unemployment rate. This positive effect of the youth cohort size is strongest for the youngest workers and gradually diminishes for older workers, which implies that the young and the prime age workers are not perfect substitutes to the employers.

To Evan

ACKNOWLEDGEMENTS

First of all, I am grateful to Texas A&M University for having me in the Economic PhD program, from which I have gained so much knowledge and research experience in the study of Economics.

I wish to express my sincere thanks to my advisor, Dr. Li Gan, for his caring, patience, and excellent guidance toward the completeness of my thesis. I also thank all my committee members-Dr. Steven Puller, Dr. Jonathan Meer, and Dr. Joanna Lahey- who provide me valuable guidance and suggestions.

I thank my parents for their unceasing encouragement and unconditional love forever. I would never have been able to finish my dissertation without the support and help from my husband Shuai Yang. He is always there cheering me up and stand by me through the good times and bad.

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1. INTRODUCTION

1.1 The Slowdown of Family Migration in the United States

The U.S. population is known for its high geographic mobility.[1] However, compared with earlier generations, Americans are now less mobile. Over the last forty years, before the current recession, the interstate migration rate in the United States has been modestly slowing down from 3.76% in 1965-1970 to 2.76% in 2000-2005.[2] The decrease in the migration rate, however, is far from homogeneous across different demographic groups. Power couples, defined as the couples with two college graduates, have seen the greatest drop in their migration propensity from 5.66% in 1965-1970 to 2.82% in 2000-2005. Couples with college-graduate husband also witness a great decrease in their interstate migration rate from 4.05% to 2.15% during the same time frame. In contrast, singles, couples with a college-graduate wife, and couples with two high school graduates have seen little change in their migration

[1] Throughout section 2, we only focus on the interstate migration, because we are focused on job-related geographic migration. Since 1999, the CPS shows that over one-half of the migrations within counties are due to housing-related reasons, such as purchasing or upgrading a house. Less than 10% migrants report they migrate for jobs. In contrast, for interstate migrants, the percentage of housing-related reasons drops to about one-fifth while the percentage of job-related reasons rises to one-third (Frey 2009). Therefore, the intercounty migration is of less interest since these movers are more likely to move cross the relevant political boundaries but remain in the same labor market (Greenwood 1997). Metropolitan area could be regarded as a good approximation of a local labor market. However there are several drawbacks to define migrations based on metropolitan areas. First, many datasets provide the location information to the county or state level. One may try to aggregate the county level variable to a metropolitan area level. However, the boundaries of the metropolitan areas are not fixed in a long period since the subdivisions of metropolitan areas are revised every few years in order to reflect the varying local social and economic factors. Measuring migrations consistently in a relatively long time period is impossible. Second, metropolitan areas do not cover the entire country. According to the definition by the Office of Management and Budget, a metropolitan area contains a core urban area of 50,000 or more population, and a micropolitan area contains an urban core of population between 10,000 and 50,000. If the origin and destination of the migration are defined base on metropolitan area, migration from less urban areas to metro areas, then the population flows between less urban areas will not be counted.

[2] These rates are directly calculated from the CPS. They are averaged for a 5 years interval. The data used for this statistics include working age people with age between 16 and 64.

propensities. Meanwhile, the share of couples with at least one college graduate in the population has been increasing steadily over the years. Since the migration rates of the college-graduate couples are much higher than the rates of other couples, the dramatic decrease in the migration propensity of the highly educated couples only translates to a modest decrease in the overall migration rate.

In Section 2, two basic explanations are explored for the declining migration propensities of married couples with college backgrounds. The first explanation links the falling migration propensity to a set of factors related to the labor market. These factors include the female labor force participation, earning ratio of wife to husband, and the correlation of gains from migration between spouses. The second explanation is related to the changes in home ownership rates. We extend Mincer's [1978] family migration model into a search framework. The extension allows us to formally model and estimate the joint effects of these determinants on the family migration propensities. We also propose a method to directly measure the correlation of the gains from the migration of the two spouses.

In the past four decades, both the female labor force participation rate and their earnings increase significantly. Therefore, the earning ratio of wife to husband increases over time as well. In general, the family migration decision is initiated by the husband's job changes, opportunity cost in the couples of dual workers will increase when the wife's earnings account for a larger portion in the family income. The correlation of the earnings from job offers between spouses may also be important in determining migration propensity. A lower correlation reduces the probability of receiving job offers that are beneficial for the whole family.

In the second explanation, we consider the effect of changing home ownership on migration. The average home ownership rate in the Unites States increases from 62% in 1960 to 68% in 2000 according to the U.S. Census data. The home ownership rate also displays different trends among different types of families. Home ownership is endogenously related to the migration decision, because it is difficult to determine whether owners are unlikely to move, or movers do not like to own since they anticipate they are going to move. The estimated influences of the home ownership on the migration propensity will be biased if we directly use the home ownership observed in the data. To overcome this endogeneity, we predict the home ownership status by employing the state averages of home value, per-capita income, property tax rates, mortgage rates and their interactions with some of the observed personal characteristics.

By drawing data from the CPS over the 1982-2005 period, we first test the deterrent effects of the labor market variables and home ownership on the migration propensity in a logit model. Then a variation of the Blinder-Oaxaca technique, developed by Fairlie was adopted to investigate the contributions of these changing factors in explaining the decreasing family migration, particularly for the families with two college graduates and a college-graduate husband. The decomposition analysis reveals that over the decades from 1980s to 1990s, increasing female labor force participation and the earning ratio between wife and husband accounts for about 60% of the decline in the migration rate for families with two college graduates. The correlation of earnings from new job offers only explains a small part of the slowdown in the migration in this period. Increasing home ownership is primarily responsible for the decline of migration rate for these families during the period of 1990s-2000s. Similar results are obtained for families with a college-graduate husband. In addition to these determinants, the changing age structure of the population also contributes to the declining migration rate over the three decades in our sample period. The average age of the family head is increasing steadily due to the aging of baby boom generation.

In section 2, we first provide the related literature. Section 2.2 introduces the data set. Section 2.3 presents the trends of aggregate interstate migration rate and family migration rate in the United States. Section 2.4 develops our theoretical framework which serves as a guidance in the empirical analysis. Section 2.5 discusses the empirical strategies and outlines the results. Section 2.6 presents the accounting study for the changes in the family migration rate. A conclusion is given in Section 4.1.

1.2 "Cohort Crowding Effect" of Youth Share on Unemployment Rate

The unemployment rate of young workers, defined as those aged between 16 and 24, is higher than that of the prime age workers aged between 25 and 64. Therefore, as the share of youth in the population increases, the overall unemployment rate may also increase, a so-called "cohort crowding" effect. Korenman and Neumark [2000] confirm the cohort crowding effect by using a panel of 15 OECD countries in the period of 1970–1994, supporting the literature based on the time series analysis. To the contrary, by using U.S. state data from 1978-1996, Shimer [2001] provides some empirical evidences and a theoretical model that prove otherwise. He finds that the effect of youth cohort size on the unemployment rate is significantly negative.

This study contributes to the literature by proposing an explanation to this contradictory empirical evidence. First, we find even more contradictory evidences if using data from different time periods. The estimates obtained by using the US state panel from 1997 to 2008 are negative, contradictory to the results using the panel from 1978-1996. The estimates from the OECD 1995-2009 panel are mostly positive but insignificant, different from the results using the 1970-1994 panel. We argue that the reason for these inconsistencies is the strong temporal correlation of youth cohort size due to the baby boom and the historical trend of unemployment rates.

The baby boom after World War II is one of the most important demographic phonomena over the last half century. During the period of 1970s to mid 1990s, the youth cohort size has seen a sharp decline for both the US and the OECD countries. In the meantime, the overall unemployment rate in the US has a decreasing trend in the US but increasing trend in the OECD countries, creating a strong and dominating temporal relationship between the youth cohort size and the unemployment rate. After mid 1990s, the trend in the youth cohort size disappears, and the temporal correlation no longer plays an important role.

Essentially, the temporal correlations in the unemployment rate and youth share in either the U.S. or the OECD countries are due to the baby boom. Without the baby boom, temporal variation of the youth cohort size would be small and there is no long-run trend of the youth cohort size across so many years. However, the baby boom is a not a historical normality. The estimates obtained from the conditional model in a certain time period, by controlling for the year effects, does not provide much predicting power in other periods.

We next turn to the unconditional model, which investigates the cross-sectional dimension of the panel data, to explore consistent estimates. We identify an outlier effect in the U.S. After controlling for the outlier effect, we find that the total effect of the youth cohort size on the aggregate unemployment rate, revealed by the cross sectional analysis, is consistently positive across two time periods in the U.S. In addition, evidence from the indirect effects of youth cohort size also support the conventional 'cohort crowding' literature. Specifically, youth cohort size has the strongest positive effect on the youth unemployment rate. The marginal effect on the age-group specific unemployment rate gets smaller as we move toward the older age groups. These findings are in accordance with the hypothesis that young workers and prime age workers are not perfectly substitutable for the employers.

The cross-sectional evidence by itself could not build a causality between the youth cohort size and the unemployment rate, since it is subject to the bias coming from the state fixed effects. We propose an innovative method to control for both the state fixed effects and the non-random sampling problem. This is our second contribution to the literature. We first construct a randomized data set in the U.S. by shuffling observations across the years for each state. Then we break them up into two data groups. State fixed effects are removed by taking the difference between the averages in two data groups. To obtain the statistical significance of this procedure, we repeat the whole process thousands of times. The estimates from this pseudo-panel indicate that the evidence from the cross-sectional analysis is a causality instead of a correlation.

In section 3, we first provide the related literature. Section 3.2 discusses the temporal correlation between unemployment rate and youth cohort size, and discusses the reasons of the inconsistent estimates in the literature. Section 3.3 introduces the data sets. Section 3.4 provides empirical strategies on how to solve for the inconsistency, and reports the empirical results. We conclude in section 4.2.

2. THE SLOW DOWN OF FAMILY MIGRATION IN THE UNITED STATES

2.1 Related Literature

2.1.1 The Trend of Migration Rate in the United States

The decline of the overall interstate migration rate in the United States has drawn the attention of economists recently. It has been well documented that during the latest recession, the overall migration rate in the U.S. has sharply gone down, from in 2007 to in 2010.

Kaplan and Wohl [2010], however, point out that the decrease in the migration rate since the latest recession is not as dramatic as seen in the published estimates. When correcting the changes in the imputation procedures, the interstate migration rate in recent years simply follows a long-term declining trend over the past several decades. For this reason, this paper focused on the long term declining migration trend, while ignoring the recent sharp decline because of potential measurement problem associated with the most recent data. Molloy, Smith, and Wozniak [2011] have also documented the declining migration trend since the 1980s in the United States. They argue that it is of more merit to investigate the migration rate over a longer time period, instead of focusing on the short-run cyclical phenomenon, if the recent drop in the migration rate is no more than a continuation of a long-term falling trend. However, even though they find that there is a widespread decrease in the interstate migration rate across different subgroups of the population, the underlying reasons are still unknown and puzzling. They do not identify the decreasing family migration rate in their study.

Pingle [2007] studies the trend in aggregate interstate migration rate in the United States from the 1950s to the early 2000s. However, when the military personnel and their related families are extracted from the overall population, the declining migration propensity is not as significant as originally assessed in the data. Therefore, he concludes that the decline in military personnel is the primary determinant for the decreasing interstate migration rate. For most U.S. civilians, they are as mobile as before in changing locations.

Among earlier studies (Rogerson [1987], Long [1988] and Greenwood [1984], Greenwood [1997]) finds that there is a significant decrease in the annual migration propensity of young people ages 20-24 from 8.9 percent in the 1970s to 5.8 percent in the 1980s. The possible explanations include the lower marriage rate, higher unemployment rate, and cohort crowding effect for the baby boom generation. But these are still untested hypotheses due to a limited amount of data available for a thorough analysis.

Another recent study on the long run trend of the migration rate in the United States is by Partridge, Rickman, Olfert, and Ali [2010]. The sample period they focus on is the 2000s. They hypothesize that the migration rate in the United States in the past decade is low because the economy is approaching a spatial equilibrium. All of the differences in amenities across regions have already been internalized into the prices and wages. People no longer feel the need to move to another state, due to this spatial equilibrium. However, their empirical findings provide no support for such a conjecture.

2.1.2 Migration, Education, Home Ownership and Family Ties

Since the 1960s, economists have considered migration as an investment in human activity (Sjaastad [1962]). People are rational actors and compare moving costs with benefits in making migration decisions. If the return from the migration outweighs the cost, then it would be better off to change locations, in terms of higher utility.

The most recent study which follows this approach is by Kennan and Walker [2011]. Their work directly verifies that the individual's migration decisions are affected by the prospects of future income in a structural dynamic model. It also adds additional evidence to the findings in Topel [1986] and Blanchard and Katz [1992], which indicate that labor flows are responsive to differential local labor market conditions.

Mincer [1978] provides a theoretical analysis in distinguishing between the individual and family migration choices. To maximize the total utility of the family, one of the spouses may sacrifice the personal gains which could be obtained by making the decision individually, and follow that decision which is optimal for the family. For example, the family would choose to relocate if one spouse's net gain in moving to a new place exceeds the losses of the other. The family would move, and the spouse who is taking a loss is called the tied mover. The spouse who forgoes his/her own gain from migration becomes a tied stayer. If the relocation decision involves multiple location options, both husband and wife may become tied movers or tied stayers at the same time since the final destination may not be the best for each of the spouses, but is optimal for the entire family. The difference and correlation of the gains from migration between husband and wife play important roles in the family migration decision. Otherwise, if the gains from migration for the wife and husband are perfectly correlated - meaning, when each receives a positive gain, and vice versa - then marital status does not affect the migration decision at all. If the correlation between the two individual gains is weak, the migration probability would be reduced. Gemici [2011] employs a dynamic model of household migration decisions by using the Panel Study of Income Dynamics (PSID) and finds that in accordance with the implications in Mincer [1978], if the spouse in the family were single, the migration rate should be about 5-7 percent higher than the migration rate observed when they are married.

Another set of related literature is about the relationship between education and migration propensity. Especially for long-distance moves, college-educated people have been found to be much more likely to move than those with less education. The labor market for the college graduates is larger in scope. College graduates are more aware of opportunities in other locations far away from their current locations. Therefore, they are more willing to take the benefit of different economic opportunities resulting from moving. Based on the CPS data from 1980 to 2000, after controlling for age, state of origin, and year fixed effects, Basker [2003] finds that the probability of migration increases with education. In a recent study, Wozniak [2010] shows that workers with higher educational attainment are more likely than high school graduates to live in a state that has high labor demand. She also concludes that higher-educated workers are more sensitive to the local labor market conditions in choosing a state of residence. If college graduates are the main force in migration, and the migration propensity for them declines, then the aggregate migration rate would be significantly affected. It is crucial to understand the underlying reasons behind such a decline.

By investigating the Census data from 1970s to 1990s, Costa and Kahn [2000] find that the power couples are increasingly concentrated in large metropolitan areas. They argue that it is due to the co-location problem faced by this type of couples, and not because of the increasing urbanization of the college-educated. However, by using the PSID, Compton and Pollak [2007] find no evidence showing that power couples are more likely to migrate to large metropolitan areas than other family types, such as part-power or lower power couples. Within a family, the migration decision is relevant to the husband's education, not the wife's. Their findings suggest that this higher proportion of power couples is the result of a higher rate of power couple formation in the metropolitan area. It is not because power couples form a family elsewhere and then migrate to large labor markets for better opportunities or amenities. Our findings in this paper may enrich the story by indicating that once power couples are formed in the metropolitan areas, they are less likely to migrate nowadays since they are trapped by the increasing home ownership and the exacerbating co-location problem.

Another important determinant of migration is home ownership (Henley [1998], Dietz and Haurin [2003]). Most earlier studies find that homeowners are less likely to migrate than renters are. The most direct reason is that homeowners incur more substantial transaction cost than that of renters. Since housing is a financial investment, the homeowners may also compare the capital gains with their initial housing investment and consider the down payment constraints on purchasing a new home in the potential destination. Most recently, Winkler [2010] develops a dynamic structural model and examines the effect of home ownership on mobility and labor income. He provides evidence that owning a home makes workers less likely to move in response to labor market shocks. He also finds that home owners who suffer from a decrease in home equity are 40% less mobile. However, none of these studies explicitly controls for the endogeneity of the home ownership.

Many macroeconomic factors would also influence the population flow. For example, spatial differences such as local labor demand and living amenities would cause a worker to relocate. However, these possible explanations are not the focus in this paper. Firstly, family migration and individual migration show quite different patterns. If the spatial equilibrium is the crux, then it should not discriminate singles against couples. Second, Molly, Smith and Wozniak [2011] also show that the net population flow across the regions have not changed substantially over the past 25 years, which in turn does not support the spatial equilibrium theory.

2.2 Data

The primary data source used in this paper is the Current Population Survey (CPS), the March Supplement from the Integrated Public Use Microsamples (IPUMS), which provides nationwide representative data on migration across a long time period. We could identify the interstate migration through the variable "MIGRATE1" in the IPUMS-CPS, which informs whether the respondent has moved across different states, across counties within a state, within the county, or has stayed in the same house in the previous year. It has been available for most years since 1963, except for 1972-1975, 1978-1980, 1985, and 1995. The CPS also provides detailed demographic and socioeconomic characteristics including home tenure, occupation, industry, employment status, and earnings. Information about the home ownership status in the respondent's current location has been available in the CPS since 1976. Yearly earnings have been available since the 1960s, however, the actual number of working weeks and weekly working hours used to calculate hourly wages can only be obtained after 1977. Therefore if we employ hourly wage or working hours in our analysis, the data set would begin from 1977. All annual earnings or hourly wages are deflated to the 2010 U.S. dollar value by the Consumer Price Indexes (CPI)-All Urban Consumers, released by the U.S. Bureau of Labor Statistics (BLS). The IPUMS-CPS has been providing consistent long-term classification codes of occupations since 1968. There are about 400 occupation categories according to the 1990 occupation scheme. For the purpose of our analysis, we classify them into seven broadly defined categories.[1]

The sample used in this study only consists of working-age individuals whose ages

[1] They are managerial occupations, professional specialty occupations, technical, sales and administrative support occupations, service occupations, farming, forestry, and fishing occupations, precision production, craft, and repair occupations, operators, fabricators, and laborers occupations.

are between 25 and 64. Respondents that are less than 25 years old are excluded, since many of them still affiliate with their parents and are not independent enough to make their own major decisions, such as migration. People serving in the military and those who were in school when they were surveyed are excluded as well. These two groups of people are not the targeted people whose migration decisions respond to common economic incentives as concerned in this paper. The sample unit used in our econometric analysis is at a family level, not by the individual or household, since our ultimate goal is to explain changes in the family's migration decisions. For households with multiple families, we only focus on the primary family with the household head.

We also exclude any data recorded in the CPS after 2005. The migration rate has fallen sharply since 2006, a time around the most recent economic recession. Kaplan and Wohl [2010] point out that this dramatic change in the migration rates results from the change in the imputation procedure of CPS missing data. In the analysis of the CPS before 2006, interstate migration rate is overestimated. Therefore, after the bias is corrected by the CPS prior to 2006, a gap is generated. Kaplan and Wohl [2010] show that the migration rate in the last few years simply follows a continuation of the long run downward trend after unifying the data analysis. In our analysis, to make the estimates comparable across these years, we mainly focus on the data before 2006 and circumvent any inconsistency created by the imputation method of the CPS.

In addition to CPS data, we also collect several housing market related variables at the state level to predict home ownership prior to migration. These variables include median housing price, morgage rate, property tax rate and median income. The souces for each are listed below:

Housing price - Lincoln Institute of Land Policy (Land and Property Values in the U.S.).

Mortgage Rate - Federal Housing Finance Agency.

Property Tax - The Tax Foundation Property Taxes on Owner (2004-2009). Census Bureau - American Housing Survey (1980-2000).

Income - U.S. Department of Commerce: Bureau of Economic Analysis.

2.3 Trends in the Interstate Migration Rate in the United States

Panel A in Figure 2.1 shows the rate of the population that migrated across states by using the CPS data from 1964 to 2005. It indicates the number of interstate movers out of 100 people. The overall interstate migration rate is observed as almost stable in the past fifty years.[2]

As the first step to understand the aggregate trend of cross-state migration rate, it is critical to know if this trend is widespread among all kinds of demographic groups, or if it is a less representative phenomenon for specific subgroups in the population. We calculate the group specific migration rates conditionally on several major demographic characteristics, including age, gender, race, marriage status, and educational attainment. Specifically, we have two age groups. People between the ages of 25-40 and 41-64 are regarded as the young and the old in the prime age population, respectively.[3] For marital status, people who are divorced, widowed, or separated at the time of the survey are allocated to the singles group. We have three

[2] The data used in this subsection only include people who are older than 25. The figures reported about the migration rate in the two periods of 1965-1970 and 2000-2005 are based upon the working age population. When the youngest group are excluded, there is almost no declining trend of the overall migration rate.

[3] We could make the categories even finer instead of just breaking down people into the young and the old. For example, each age between 25 and 64 could be considered as an individual age group. However, since we are going to figure out the aggregate migration rate by year, observations in each age cell with smaller amount of observations would reduce the statistical significance of the estimates. We also examined the results by doing this way. The variance of the trend is greater, but the overall pattern is quite similar.

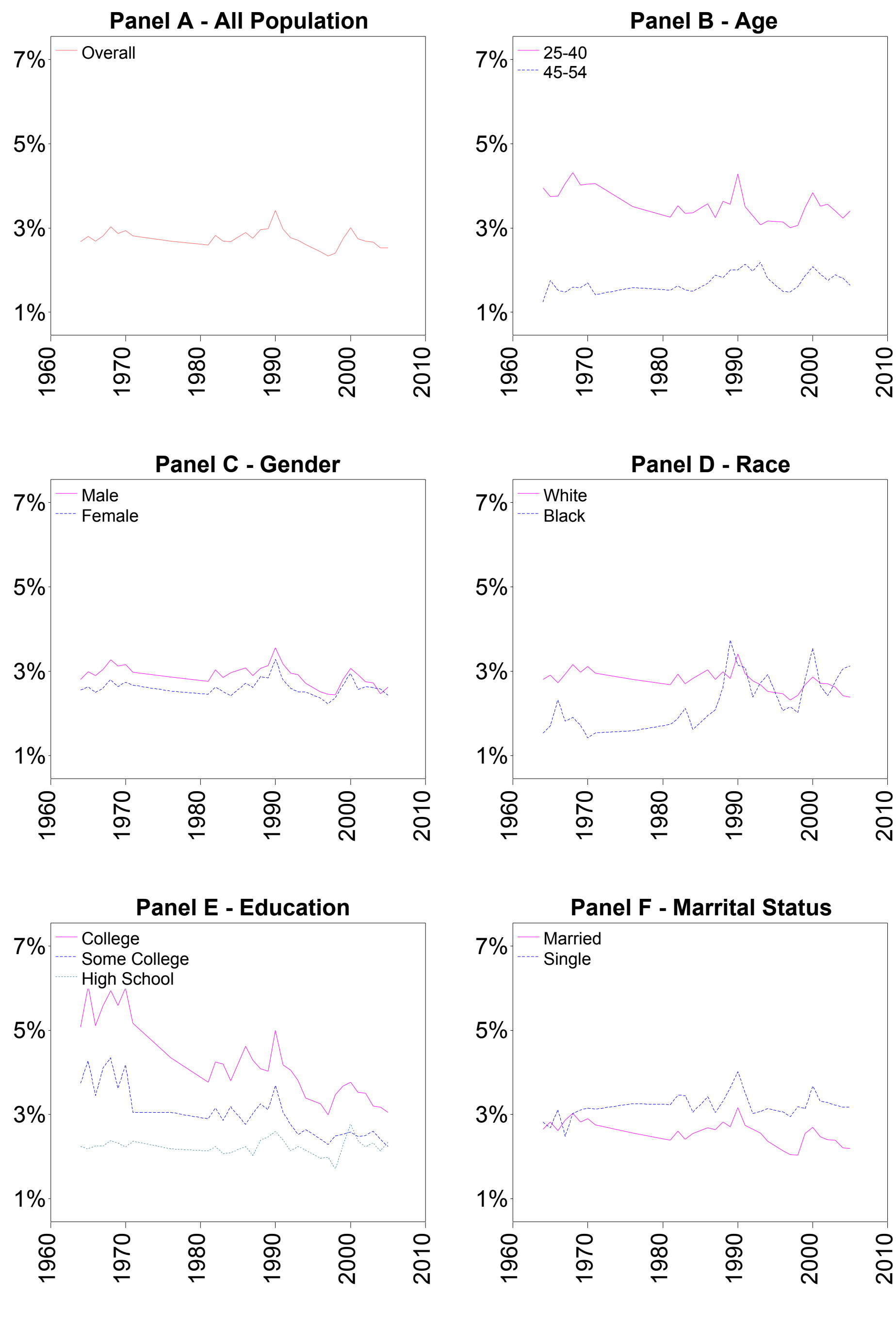

Figure 2.1: Interstate Migration by Demographic Groups (1964-2005).

groups by educational attainment at this stage: the high school, some college, and the college graduate. The high school graduate includes those who have no more than 12 years of schooling. The graduate with some college includes those who have some college background but do not obtain a bachelor degree. The college educated are defined as those who have completed at least 4 years of college.

Two series of migration rates by age groups are plotted in Panel B of Figure 2.1. The group specific migration rates by the young and the old do not show a significant difference in the pattern of the overall trend, even though there is modest decline in the migration propensity of the young.

In Figure 2.1 - Panel C, it is shown that the migration rate for females is lower than that for males before 2000. This gap is generated by the difference of the migration propensities in the singles group, since married couples usually migrate as a family unit, which shows less discrepancy by gender. Single females are less likely to migrate than their male counterparts. Mincer [1978] points out that single women, especially the young single women, are more attached to their families or relatives. There is no discernable difference in the migration pattern over the years between male and female and the migration rates of these groups are closely tracing the aggregate migration rate.

The migration propensities by different races plotted in Figure 2.1-Panel D indicate that blacks are more likely to be affected by the economic environment. As whites account for the majority of the population in the United States, it is not surprising that the evolution of migration rate for this group almost replicates the one we have seen from the aggregate rate for the whole nation.

The most interesting findings come from the groups segmented by educational attainment and marital status. As shown in Figure 2.1 - Panel E, the decreasing trend is most substantial for college graduates: a decrease of 15 percent from 1960s to 1980s and another 10 percent from 1980s to 2000s. The trend is more modest for the group with some college. In contrast, the propensity of migration for high school graduates barely changes during the sample period. The migration rate of college graduates is all-around higher than that for those with some college or high school degree, since jobs requiring college degrees are more specialized, and college graduates would benefit the most from a broader geographic scope to reduce the search frictions. As the migration rates mainly drop among the college and some college graduates, the migration propensity of these three groups with different education background tend to converge in the 2000s.

Figure 2.1 - Panel F shows different patterns of the migration trend for singles and the married. The migration propensity of the married started from almost the same level as the singles in 1960s. Since then, migration rate for the married has been falling stage by stage while the migration rate of singles has been increasing modestly in the past 50 years.

Based upon the findings above, as the second stage analysis, we decompose the demographic groups even further by interacting educational attainment with marital status. Since the graduates with some college and college graduates have similar migration trends as shown in Figure 2.1- Panel E, we group together people who have completed at least 2 years of college with college graduates to simplify our analysis.

We therefore have four types of married couples and two types of singles. The four types of married people are power couples with two college graduates, couples with a college-graduate husband, couples with a college-graduate wife, and couples with two high school graduates. A power couple is defined as a couple in which both the husband and wife are college graduates. In Costa and Kahn [2000], they do not distinguish between couples with a college-graduate husband and the couples with a college-graduate wife. However, given the specific problem we are discussing here, a couple with a college-graduate husband or a college-graduate wife might display quite different migration behavior. When both husband and wife have less than 13 years of schooling, the couple is regarded as a couple with two high school graduates. Similarly, according to the educational attainment, there are college singles and high school singles. Figure 2.2 shows the trends of the migration rate for four types of couples and two types of singles separately.

When comparing the migration propensities for couples, we find that power couples and couples with a college-graduate husband show a sharp decrease in the trends of migration rate, while couples with a college-graduate wife and couples with two high school graduates have stable migration propensities. For singles, the migration rate of college graduates follows a more modest declining trend only after the 1990s, whereas the migration rate of high school singles is almost constant over time.

These findings suggest that the group-specific migration propensity evolves differently among these six types of couples. The contribution of each group's migration propensity trend to the pattern of the overall migration rate is not clear yet. These groups have different shares in the total population and their shares vary greatly in the sample period as well. The educational attainment of these individuals in the United States has been increasing steadily. This trend could be reflected by the share of people who have completed secondary education. Since 1964, the proportion of people with at least one year of college has almost tripled, from around 20 percent to almost 60 percent. Given that college graduates generally have higher migration rates, if the migration propensity of college graduates is fixed over the years, as that in the 1960s, then the overall interstate migration rate should increase rather than show a modest decline or stagnant trend. Therefore, within the group of college graduates, the interstate migration propensity of the married couples drops so sig-

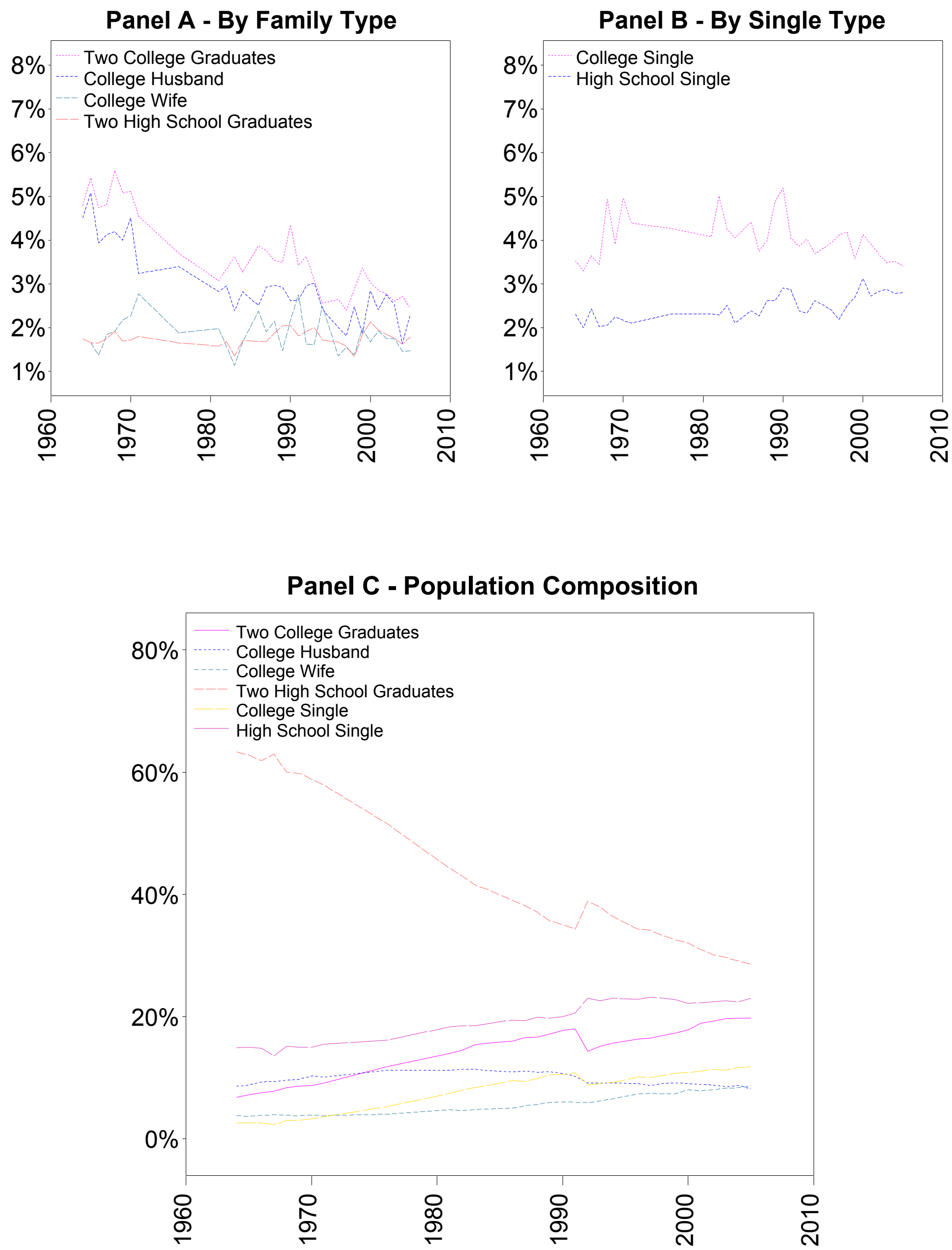

Figure 2.2: Interstate Migration by Family Types (1964-2005).

nificantly that the potential increase in the migration rate that would have resulted from an increasing proportion of these people is canceled.

The bottom panel in Figure 2.2 also presents the proportion of these groups over the years. As expected, the share of couples with two high school graduates in the population drops sharply from 60 percent in the 1960s to 25 percent in the 2000s. The share of high school singles varies in the range of 14-18 percent over the years. Overall, it increases very slightly. In contrast, the greatest increase in the share is coming from the group of power couples. The percentage of people that are coming from a power couple family is only 10% in the 1960s. Since then, this rate has been continually increasing and it reached 30 percent in 2005. The share of couples with one college-graduate wife also increases, but the change is small compared with power couples. The share of college singles are increasing along with the rising number of college graduates.

The increasing rate of college singles, together with the quite stable time series of high school singles, suggests that the marriage rate of Americans has been declining over the past years. It is indeed true that in the mid-1960s the marriage rate was about 80 percent of all U.S. men and women aged 18-64, but since then, the marriage rate had begun to decline as more women gained higher education and joined the workforce. More women become career-oriented and therefore delay their marriage age and first-child delivery. Divorce rate of Americans also increases, probably because women are getting more economically independent. Married couples are less likely to migrate, compared with their single counterparts, because they are tied together in the migration decision. The decreasing share of married couples tends to offset the influence of their decreasing migration propensity on the overall interstate migration pattern.

We next conduct several counterfactual analysis to explicitly show how changes in the migration propensities across groups and the changing population composition affects the overall migration rate.

First, we set the population shares of all six types of people to be constant as the 1960s averages and use the observed group-specific migration rate to predict a counterfactual series.

$$\hat{M_i}^t = \sum_{i=1}^{6} \bar{S}_i^{1960} M_i^t \,, \tag{2.1}$$

where i denotes the six types of people, $\bar{S}_i$ is the averaged population share in the 1960s, and M_i is the group-specific migration rate. Unsurprisingly, as shown in Figure 2.3 - Panel A, if the composition has remained constant at the level of the averages in the 1960s, the overall migration rate should have fallen more than what we have seen. It indicates that the increasing share of the college educated tends to pull up the overall migration rate.

Second, if the migration propensities for all groups are held constant at the 1960s levels, the predicted counterfactual series would be

$$\hat{M_i}^t = \sum_{i=1}^{6} S_i^t \bar{M}_i^{1960} \,. \tag{2.2}$$

Here S_j is the actual population share and $\bar{M}_i$ denotes the average migration rate in the 1960s for group i. The predicted series of overall migration rate have been steadily increasing over the past 50 years because the share of the more mobile people-the college-educated-is increasing, see Figure 2.3 Panel B. These results suggest that it is the declining migration propensities of these subgroups that drives down the overall migration rate.

To quantify the significance of the migration propensity of each group in determining the the overall migration rate separately, we hold the migration propensity

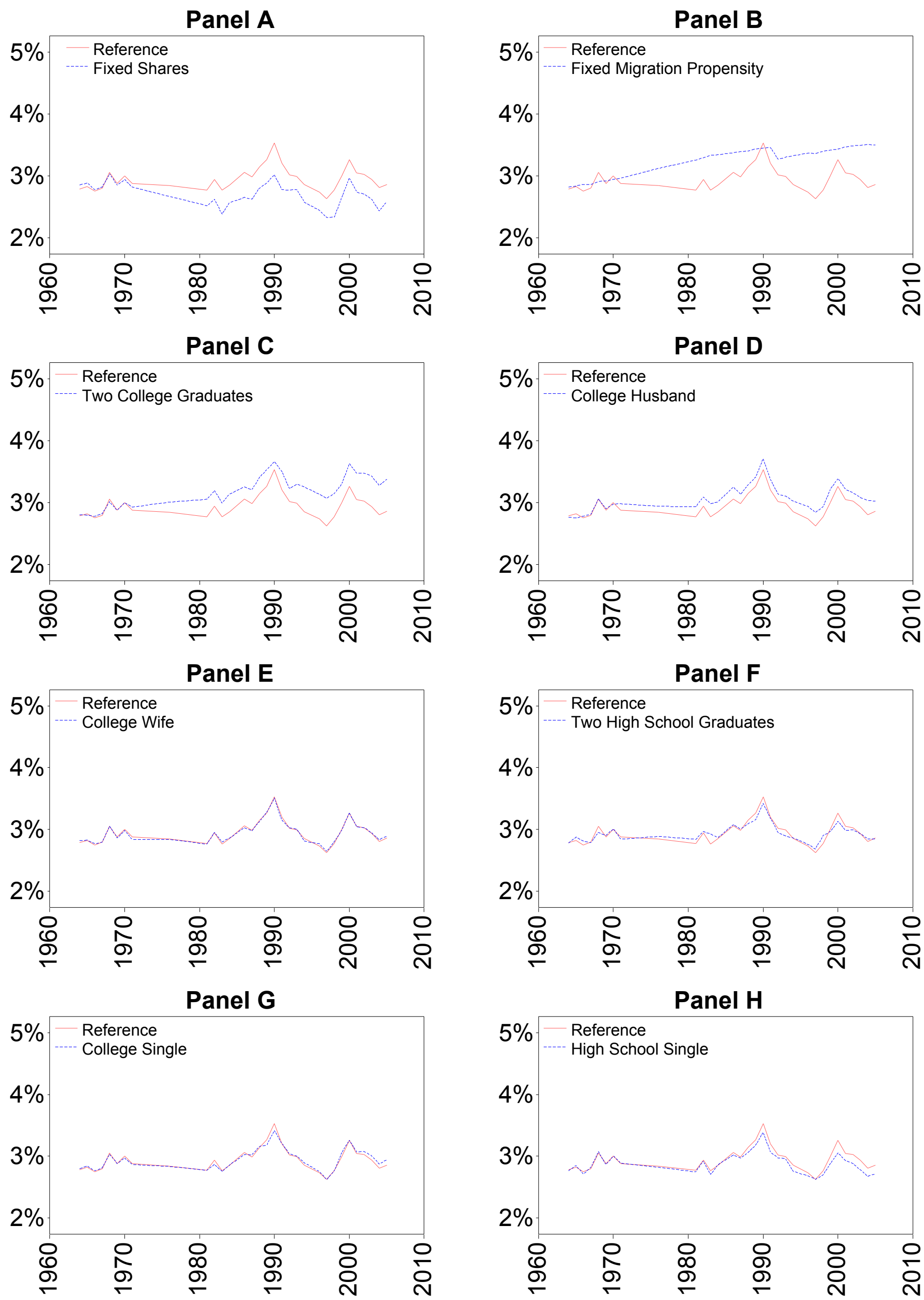

Figure 2.3: Accounting Analysis of the Change in Migration Rate (1964-2005).

for one type of people fixed at the average level in 1960s in turn, and compare these predicted series of aggregate migration rates with the actual aggregate migration rate. Note that the predicted migration propensity becomes

$$\hat{M}_i^{\,t} = S_i^t \bar{M}_i^{1960} + \sum_{j \neq i} S_j^t M_j^t \,. \tag{2.3}$$

The effect on the overall migration rate due to the change in the migration propensity of each group is isolated by examining the gap between reference series and predicted series. When comparing the remaining panels plotted in Figure 2.3, the greatest gap between the predicted and the reference series is obtained by controlling the migration propensity for the power couple. If everything else changes in the manner as it actually does, except for the migration propensity of power couples, we should not have seen a decline in the overall migration rate at all. The migration propensity of couples with a college-graduate husband shows effects similar to that of the power couples, but with a much smaller magnitude. For other groups, the predicted series closely track the reference series over the years, indicating little effect of the changing migration propensities of these groups. The evidence revealed by this counterfactual analysis basically corresponds to the findings presented in Panel E and Panel F of Figure 2.1, but it directly shows us how large the effect of the declining migration propensity from power couples and couples with a college-graduate husband could be on the overall pattern of the migration rate.

The main task is to provide explanations for the findings described in this subsection. Note that these factors should mainly affect the couples rather than the singles, since we find that it is the migration propensity of couples that drop, not the singles'. In addition, these determinants would have larger effects on power couples and couples with a college-educated husband.

When comparing the decision-making of migration by singles and couples, we find that the family migration decision is made by the family members jointly rather than individually. Spouses are tied to each other in the migration decision. Migration does not necessarily mutually benefit both husband and wife, especially when the husband and wife are strongly attached to their jobs. The conflicts between a working husband and a working wife in the migration decisions is usually inevitable, if the earning difference between husband and wife is insignificant, or the chance of a mutual gain from migration is small. Another important difference between singles and couples is that couples are more likely to reside in their own houses, while singles tend to live in their parent's house, or they will rent. The transaction cost associated with selling and purchasing new houses when people move has an impeding effect on migration. We expect that the housing-related considerations for migration decisions should be more prevalent among the the couples.

2.4 Conceptual Framework

Mincer [1978] develops a theoretical analysis in distinguishing between the individual and family migration decisions. The framework is based on the assumption that married couples maximize the total utility of the family, not the utility of anyone of the spouses. In this setup, one of the spouses may sacrifice the personal gains that could be obtained by making the migration decision individually, when that spouse follows the migration decision which is optimal for the whole family. For example, one family would choose to stay if one of the spouse's net gain from moving to another location is less than the losses of the other spouse. The conflict in the gains from migration between the spouses will deter migration. In this example, the individual gains from the migration of the two spouses have opposite signs, and one spouse's gain dominates that of the other, which implies that the difference and correlation of the gains from migration between husband and wife both play important roles in the family migration decisions.

In the spirit of Mincer [1978], we develop a simple theoretical model for family migration in a search framework, where we discuss the penitential roles played by the female labor force participation, earning ratio of wife to husband, correlation of the gains received between the spouses from migration, and home ownership status in determining the family migration. Our framework extends Mincer's theory model in three aspects. First, the husband and wife, and the whole family's gain from migration is explicitly derived from earning draws. In Mincer's model, the gains from migration is not materialized into measurable components. Therefore the hypothesis of the model cannot be directly tested. Our set-up in this paper facilitates later empirical analysis as the gain from the migration is not readily observable in the data, but the earnings for husband and wife are available as long as they work. It also enables us to propose a method to estimate the correlation of earnings from job offers between husband and wife. Second, we fit the female labor force participation into the model. It allows us to examine to what extent female's willingness to work at an extensive margin affects the migration probability. Third, we specify the migration cost as a transaction cost associated with home ownership. Therefore, the effect of home ownership on the migration is incorporated. The model allows us to assess the joint effects of the factors targeted in this paper in a unified framework.

We suppose that the current earnings of the husband and wife are e_h^0 and e_w^0, respectively. A dummy δ is introduced to indicate the wife's choice of labor force participation. The husband and wife are receiving new job offers from other states in each period. The new offered earnings are denoted as e_h and e_w for the husband and wife, respectively. And they are assumed to fulfill a bivariate normal distribution, i.e., $(e_h, e_w) \sim N(\gamma_h e_h^0, \gamma_w e_w^0, \sigma_h^2, \sigma_w^2, \rho)$. Here γ_i $(i = h, w)$ is a discount factor of the average earning from the job offers relative to the current earning, and ρ denotes the correlation between the husband's and wife's earnings from new job offers. For the sake of simplicity, we would further assume that the moving cost is solely caused by owing a home and neglect all the other possible moving costs. Therefore, the moving cost discussed here could be regarded as the transaction cost of selling and buying a home. Transaction cost is assumed to be proportional to the family earnings, since housing is a normal good. A family with higher earnings are more likely to own a more valuable house, and the transaction cost varies with the value of the house. Δ signifies home ownership. It is greater than zero and changes along with the home value for home owners, while it is zero for renters.

Then the net gain of the family from migration $G_f = e_h + \delta w_w - (e_h^0 + \delta e_w^0)(1+\Delta)$ satisfies the normal distribution $N(\mu_{G_f}, \sigma_{G_f}^2)$, with

$$\mu_{G_f} = \gamma_h e_h^0 + \delta \gamma_w e_w^0 - (e_h^0 + \delta e_w^0)(1 + \Delta) \tag{2.4a}$$

$$\sigma_{G_f}^2 = \sigma_h^2 + \delta^2 \sigma_w^2 + 2\rho\delta\sigma_h\sigma_w \, , \tag{2.4b}$$

as the mean and variance, respectively. Because $\gamma_h, \gamma_w < 1$, μ_{G_f} is negative and the center of the distribution of the net gain is to the left of $G_f = 0$. This agrees with the common sense that only a small portion of the population moves within a short time period.

The family decides to migrate if they can receive benefits from moving, i.e., the net gain is positive. Thus, the probability of family migration is $\text{Prob}(G_f > 0)$, which equals the area of the distribution of the gain to the right of $G_f = 0$, can be represented as

$$\text{Prob}(G_f > 0) \;\; = \;\; 1 - \Phi\left(-\frac{\mu_{G_f}}{\sigma_{G_f}}\right) = \Phi\left(\frac{\mu_{G_f}}{\sigma_{G_f}}\right) . \tag{2.5}$$

where

$$\frac{\mu_{G_f}}{\sigma_{G_f}} = \frac{[\gamma - (1+\Delta)]e_h^0}{\sigma_h} \frac{1+\delta r_w}{\sqrt{1+\delta^2 r_\sigma^2 + 2\rho\delta r_\sigma}} \,. \tag{2.6}$$

Here r_w denotes the earning ratio of wife to husband e_w^0/e_h^0, and $r_\sigma = \sigma_w/\sigma_h$, the ratio of the standard deviation of earnings from job offers between the spouses. Note that we have make the assumption that $\gamma_h = \gamma_w \equiv \gamma$.[4] We also assume that the standard deviation of an individual's earnings monotonically vary with the value of it. The higher the current earnings is, the greater the variation of earnings from new job offers. Specifically, $\sigma_i/e_i^0 = \alpha_i$, which is a constant. Under this condition, we have $r_\sigma = \sigma_w/\sigma_h = \alpha_w/\alpha_h r_w \equiv \alpha r_w$.

Taking the partial derivative of r_w on equation (2.5), we have the marginal effect of the earning ratio of wife to husband as,

$$\begin{aligned} &\frac{\partial \mathrm{Prob}(G_f > 0)}{\partial r_w} \qquad (2.7)\\ &= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\mu_{G_f}^2}{2\sigma_{G_f}^2}\right) \frac{[\gamma - (1+\Delta)]e_h^0}{\sigma_h} \cdot \frac{\delta(1+\alpha\rho\delta r_w - \alpha^2\delta r_w - \alpha\rho)}{(1+2\alpha\rho\delta r_w + \delta^2\alpha^2 r_w^2)^{3/2}} \,. \end{aligned}$$

If $\delta \neq 0$, the sign of the above equation depends on the sign of $1+\alpha\rho\delta r_w - \alpha^2\delta r_w - \alpha\rho$, which is positive when the following conditions are satisfied,

$$\alpha > \frac{-\rho(1-\delta r_w) - \sqrt{\rho^2(1-\delta r_w)^2 + 4\delta r_w}}{2\delta r_w} \,, \tag{2.8a}$$

$$\alpha < \frac{-\rho(1-\delta r_w) + \sqrt{\rho^2(1-\delta r_w)^2 + 4\delta r_w}}{2\delta r_w} \,. \tag{2.8b}$$

Since $\alpha > 0$, while the right side of inequality (2.8a) is negative, so inequality (2.8a)

[4] Relaxing this assumption would not alter the model predictions, but only make the equations for marginal effects more redundant.

holds automatically. If we further assume that, compared with men, women normally do not have their mean job offers more disperse across geographic locations. Therefore, $\alpha = \alpha_w/\alpha_h \leq 1$. The right side of inequality (2.8b)

$$\frac{-\rho(1-\delta r_w) + \sqrt{\rho^2(1-\delta r_w)^2 + 4\delta r_w}}{2\delta r_w} \geq 1\,. \tag{2.9}$$

"=" holds only if $\rho = 1$. So inequality (2.8b) holds unless both $\alpha = 1$ and $\rho = 1$. Therefore, the marginal effect of the earning ratio is generally negative. Only if $\alpha = 1$ and $\rho = 1$, the earning ratio has no effect on the family migration rate. Note that here the deterrent effect still exists due to the confliction between individual gains of the two spouses even if $\rho = 1$ when $\alpha < 1$. It seems to conflict with Mincer's theory, in which the earning ratio/differnce between spouses is irrelevant to the migration decision once the gains of migration are perfectly correlated between the two spouses. This is because the definitions of ρ are different in Mincer [1978] and our paper. In Mincer's model, the correlation ρ is the correlation of gains from migration. Therefore, when $\rho = 1$, if the husband's gain is greater (less) than 0, the wife's gain is also greater (less) than 0. The family migration decision based on the husband's own gain is the same as the migration decision based on the wife's own gain. There is no confliction between their individual gains when making the family migration decision. In our model, ρ is the correlation between the earnings of the two spouses' job offers from earning draws. $\rho = 1$ means that if the husband's earning from his new job offer e_h is greater (less) than his average γe_h^0, the wife's earning from her new job offer e_w is also greater (less) than her average γe_w^0. However, as $\gamma < 1$, it is still possible that e_h is greater than the current earning e_h^0, while e_w is less than the current earning e_w^0, or vice versa. In such cases, the gain of family migration might be negative. Only when $\alpha = 1$ and $\rho = 1$, the probabilities of becoming a tied mover in the family migration are equalized between the husband and wife. Hence the earning ratio of wife to husband has no influence on the family migration decision. From equation (2.7), we also find that when $\delta = 0$, the wife does not have any contribution to the gains from family migration. In this case, the family decides migrate or not just in the same way as the husband makes the choice on his own.

Similarly, when the inequality equation defined in inequalities (2.8a) and (2.8b) holds, we find

$$\begin{aligned} &\frac{\partial \mathrm{Prob}(G_f > 0)}{\partial \delta} \\ &= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\mu_{G_f}^2}{2\sigma_{G_f}^2}\right) \frac{[\gamma - (1+\Delta)]e_h^0}{\sigma_h} \cdot \frac{r_w(1 + \alpha\rho\delta r_w - \alpha^2\delta r_w - \alpha\rho)}{(1 + 2\alpha\rho\delta r_w + \delta^2\alpha^2 r_w^2)^{3/2}} < 0\,. \end{aligned} \tag{2.10}$$

The labor force participation of the wife deters migration. When wife's labor force attachment is strong, i.e., $\delta = 1$, then wife's individual gain from migration contributes to the total family gain, which lowers the family migration propensity when everything else is controlled for. Wife's willingness to work raises the chance that one of the spouses gains but the other loses in the migration . When $\delta = 0$, the family's gain from migration is totally determined by the husband's personal gain. The wife has no contribution to the family income, nor any confliction with her husband's individual migration decision.

For the correlation of the earnings from new job offers, we have

$$\begin{aligned} &\frac{\partial \mathrm{Prob}(G_f > 0)}{\partial \rho} \\ &= -\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\mu_{G_f}^2}{2\sigma_{G_f}^2}\right) \frac{[\gamma - (1+\Delta)]e_h^0}{\sigma_h} \frac{\alpha\delta r_w(1 + \delta r_w)}{(1 + 2\alpha\rho\delta r_w + \alpha^2\delta^2 r_w^2)^{3/2}} \geq 0\,. \end{aligned} \tag{2.11}$$

The marginal effect of the correlation in earnings is positive unless $\delta r_w = 0$. As the correlation in earnings becomes small or even negative, it is very likely that one of the spouses gains but the other loses in the family migration. Therefore, the probability of a joint gain from the migration decreases. When $\delta r_w = 0$, the earnings of the wife are negligible. In this situation, the family's gain from migration is the same as the husband's personal gain, the correlation becomes irrelevant in determining the family migration probability.

Finally, for the moving cost, we have

$$\begin{aligned}&\frac{\partial \mathrm{Prob}(G_f > 0)}{\partial \Delta} \\ &= -\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\mu_G^2}{2\sigma_G^2}\right) \frac{e_h^0}{\sigma_h} \frac{1 + \delta r_w}{\sqrt{1 + \alpha^2 \delta^2 r_w^2 + 2\alpha\rho\delta r_w}} < 0\,.\end{aligned} \tag{2.12}$$

As expected, the moving cost deters migration for all values of δ and ρ. In order for the family which owns a house to move, the family income has to increase more to offset the moving cost in the migration.

In sum, the above theory model predicts that the family migration probability decreases with the earning ratio of wife to husband, wife's labor force participation and home ownership, while it increases with the correlation of earnings from new job offers between spouses. Compared with singles, possible conflicts between the individual gains from migration of the two spouses is an important determinant for the lower migration propensity of families. In addition, as married couples are generally much more likely to own a house, differences in the migration probabilities between singles and families could be partially attributed to the home ownership.

Before ending this subsection, we would point out some limitations of this model. First, when discussing the gain from migration, we assume equal bargaining power between the husband and wife on the family migration decision. (We simply add the gain of the husband and wife to obtain the family gain from migration). But in reality, there exists unobserved factors that affect the bargaining power. For example, one spouse of the family, usually the wife, may not be as much career-oriented as the other spouse, which produces an unbalanced bargaining power regardless what job offers they receive. In addition, it is very likely that the bargaining power of spouses depends on their education background, which reflects their potential earning ability. That is because individuals with higher education usually invest more in their education and thus are more eagerly searching for better jobs. Therefore, families with dual college graduates are more likely to have equal bargaining powers than families with a college husband or wife. In this sense this model works best for power-couples.

2.5 Empirical Strategy

2.5.1 Home Ownership Prior to Migration

One challenge in our econometric analysis is that, in the CPS, it only reports the respondent's current home ownership status, not the pre-migration home ownership status in the previous year of the interview.

Two alternative methods could be employed to solve the problem. First, we may relate the pre-migration home ownership status to the post-migration home ownership. We need a different panel data set such as PSID to estimate such relationship and use the coefficient estimates to predict the pre-migration home ownership in the CPS data. The usable PSID data starts in 1964 and ends in 1992, but the CPS data employed in this paper covers the period of 1982-2005. We have to implicitly assume that the preference of home ownership of households pre- or post-migration does not vary over time when their basic characteristics are controlled for, and the samples in two data sources are comparable. In addition to these assumptions we need to make, the measure constructed for the pre-migration home ownership in this way is endogenous to the decision of migration. Therefore, the estimate for the effect of home ownership on migration is biased.

To address the endogeneity of home ownership, we propose a alternative measure for the pre-migration home ownership. Instead of using the observed home ownership status after migration, we employ the state averages of housing value, per-capita income, property tax and mortgage rate to predict the house purchasing decisions. For a household, these factors are exogenously determined. We proceeds in two steps. Firstly, the home ownership of a family in the current state is estimated by a set of controls together with these variables.

$$\begin{aligned} \mathrm{I}[Home = 1] &= \alpha + \beta^{'} X + \gamma^{'} Z + +\delta^{'} D + \theta^{'} D \times Z + \lambda_h^{'} Z \times CLG_h + \lambda_w^{'} Z \times CLG_w \\ &\quad + \psi_h^{'} D \times Z \times CLG_h + \psi_w^{'} D \times Z \times CLG_w + \varepsilon \,, \end{aligned} \tag{2.13}$$

where X represents a vector of demographic variables, including age, wife's and husband's education, head's race, marriage status, number of kids under 18. Z = [Income, Propterty Tax, Mortgage, Home Value], which characterizes the housing market in a state. D are the year dummies. CLG_h and CLG_w indicate whether the husband and wife are college graduates or not. The sample period starts in 1982, since it is the earliest year in which the location of a household preceding the survey year is available in the CPS. After the parameters in the regression are estimated, for each family, we replace the housing value, per-capita income, property tax, and mortgage rate by the values associated with the state in the previous year. The pre-migration home ownership is identified by the family's characteristics and the exogenous economic determinants, which affect the overall home ownership in a state. To create more variations at the individual level, we interact these economic variables with the husband's and wife's educational attainment, as well as the year dummies.

2.5.2 Correlation in the Earnings Between Wife and Husband

Before moving to the econometric analysis, another variable to be constructed is the correlation in the earnings of new job offers from all of the possible locations between husband and wife. As shown in the theoretical model, it is a proxy of the correlation in the gains from migration after the transaction cost is extracted. For a particular individual, his job offers should be primarily determined by his personal characteristics such as age, education attainment, working experience, etc. If we assume the payoffs for these characteristics are the same across different labor markets, and one doesn't change occupations when changing jobs, then the job offers he receives are only affected by the heterogenous rewards specific to the occupation in each labor market. An software engineer may expect higher net earnings if he works on the same position in the Silicon Valley in the northern California than he could earn elsewhere. The higher payment for a soft engineer in Silicon Valley is more likely due to the agglomeration economy and economic externality over that area, not because those companies value more of the college degree possessed by the software engineer. In this sense, the correlation in the earnings of new job offers between husband and wife is potentially determined by their initial occupation choices, once other personal characteristics are controlled for.

Suppose the labor market is segmented into K sub-markets, with each of these sub-markets considered as a state in our context. Within a family, each spouse could receive job offers from all of the states. We use $w_h(k, m)$ ($w_w(k, m)$) to denote the m-th job offer from state k for the husband(wife) within a period. In addition to personal characteristics, the expected earnings of a worker are assumed to be related with a state-specific premium for his/her occupation. Specifically,

$$w_{i,j}(k,m) = \alpha_{k,j} + \beta_1 g_i + \beta_2 r_i + \beta_3 s_i + \beta_4 x_i + \beta_5 x_i^2 + \epsilon_m, \quad i = h, w. \tag{2.14}$$

where $\alpha_{k,j}$ is the state average payoff for the worker's occupation j. g_i, r_i, s_i, and x_i denote the gender, race, education, and age, respectively. ϵ_m is a random error term and its mean is zero. Therefore, an individual's average wage from all potential job offers is given by,

$$\begin{aligned}
\overline{w}_{i,j} &= \frac{1}{KM}\sum_k \sum_m \left(\alpha_{k,j} + \beta_1 g_i + \beta_2 r_i + \beta_3 s_i + \beta_4 x_i + \beta_5 x_i^2 + \epsilon_m\right) \\
&= \frac{1}{K}\sum_k \left(\alpha_{k,j} + \beta_1 g_i + \beta_2 r_i + \beta_3 s_i + \beta_4 x_i + \beta_5 x_i^2\right) \\
&= \frac{1}{K}\sum_k \alpha_{k,j} + \beta_1 g_i + \beta_2 r_i + \beta_3 s_i + \beta_4 x_i + \beta_5 x_i^2, \quad i = h, w.
\end{aligned} \tag{2.15}$$

We further assume that there is no additional correlation in the error terms for any workers after we control the personal characteristics and his occupation. Under this assumption, the correlation of earnings between the husband with occupation j_h and wife with occupation j_w becomes,

$$\begin{aligned}
& \mathrm{Corr}(w_{h,j_h}(k,m), w_{w,j_w}(k,n)) \\
=\; & \frac{1}{KM^2}\sum_k \sum_{m,n} \left(\alpha_{k,j_h} + \beta_1 g_h + \beta_2 r_h + \beta_3 s_h + \beta_4 x_h + \beta_5 x_h^2 + \epsilon_m - \overline{w}_{h,j_h}\right) \\
& \times \left(\alpha_{k,j_w} + \beta_1 g_w + \beta_2 r_w + \beta_3 s_w + \beta_4 x_w + \beta_5 x_w^2 + \epsilon_n - \overline{w}_{w,j_w}\right) \\
=\; & \frac{1}{K}\sum_k \left(\alpha_{k,j_h} - \frac{1}{K}\sum_l \alpha_{l,j_h}\right)\left(\alpha_{k,j_w} - \frac{1}{K}\sum_l \alpha_{l,j_w}\right).
\end{aligned} \tag{2.16}$$

The above equation indicates that the correlation of earnings within a family is mainly from the differences in payoffs for the occupations of the husband and wife across states. If the occupations of the husband and wife are the same, changes in the earnings between husband and wife by moving to the same location are perfectly correlated. If their occupations are different, the correlation is less than 1. In other words, when the signs of the two terms in the parenthesis differ, then the correlation is negative.

The above equations direct us to construct the measure of this correlation between the husband and wife as follows. For a particular occupation, we first regress the earnings on the workers characteristics including sex, race, age, education, and state fixed effects. For each occupation in one period, we obtain a set of estimates for the state dummies. Upon substituting the estimates of the state dummies of j_h and j_w into equation (2.16), we could have the value of ρ, the correlation of earnings from job offers in a family with occupation pair of (j_h, j_w).

Table 2.1: Employment Status and Migration.

	Wife		Husband	
	Migrants	Non-Migrants	Migrants	Non-Migrants
Employed at $t-1$	7810	329723	10437	416542
Non-Employed at $t-1$	2996	105797	459	18978
Employed Ratio	72.3%	75.7%	95.8%	95.75%

One problem to be addressed is that there are samples with missing values on the occupation code. According to the CPS data description, it records the respondent's primary occupation. If the respondent was working when they are surveyed, he reports his job for the week prior to the survey.[5] If the respondent was not working,

[5]If a respondent was working when he was interviewed, he is guaranteed to have a occupation recorded in the CPS.

Table 2.2: Occupation Record and Employment Status in the CPS (1982-2006).

Occupation and Employment Status for Wife			
No. of Families = 446326	Worked at $t-1$	Not worked at $t-1$	Total
Employment = 0 at t, Occupation = 0	23155 (20%)	94996 (80%)	118151
Employment = 0 at t, Occupation $\neq$ 0	14550 (67%)	7025 (33%)	21575
Total of Employment = 0 at t			139726(31%)
Total of Employment = 1 at t			306600(69%)

Occupation and Employment Status for Husband			
No. of Families = 446326	Worked at $t-1$	Not worked at $t-1$	Total
Employment = 0 at t, Occupation = 0	5645 (28%)	14802 (72%)	20447
Employment = 0 at t, Occupation $\neq$ 0	17214 (86%)	2871 (14%)	20085
Total of Employment = 0 at t			40532(9%)
Total of Employment = 1 at t			405794(91%)

then he was asked for his most resent job. We could not observe the occupation for some of the respondents if they never work, thus none occupation can be identified. In all of our regression analysis, we exclude the families where husband has no occupation record. It does not affect our final results since these families only accounts for a small portion of the whole sample. Men's labor force participation rate is much higher than women and their labor force participation choice is less likely subject to the influence from migration. According to the final sample that we construct, the employment ratios of the husbands from migrant families in the pre- and post-survey years are nearly the same as those of the husbands from non-migrant families. The comparison are shown in Table 2.1. In contrast, we cannot simply omit the families where wives report no occupation. According to Table 2.2, about 80% of the wives who were not working when being interviewed and have no occupation recorded did not work anytime in the previous year either. We believe a majority of them were non-labor force participants. However, the remaining 20% of those wives reported that they worked sometime in the previous year. The migration rate among these families is high, since it is common that a wife who migrates along with her husband could not immediately find a job in the new location. If we eliminate these families from the analysis, we would miss a group of typical migrant couples. Therefore, instead of deleting the families where there are no occupation codes for the wives, we assign them the values of earnings correlation in the following way. For a family where the husband has an occupation j_h but wife's occupation is missing, we calculate a weighed average of the correlation measure by using the values of the families with occupation pair of $(j_h, j_w), j_w = 1, 2, ..., 7$. The number of the families in which the husband has occupation j_h and the wife has occupation j_w is taken as the weight. Compared with averaging across all families, we take into account the distribution of the husband's and wife's job choices combination. For example, if men with occupation 1 are more likely to marry with women with occupation 2, the correlation in the earnings between a husband and wife with occupation 1 and occupation 2 should be given more weight, once we predict the earnings correlation for the families where husband has occupation 1 but wife's occupation code is missing.

2.5.3 Wife's Labor Force Participation and Wife-Husband Earning Ratio

The theoretical model predicts that the wife's employment status and the earning ratio between wife and husband negatively affect the family migration decisions. As Long [1974] and Mincer [1978] noted, the proper employment status which should be used to measure the deterrent effects are the ones that occur before migration.[6] In CPS, it reports the employment and labor force status during the survey week in March, as well as the total weeks and usual hours worked per week prior to the survey year. However, we couldn't directly employ the reported values of the employment status and earnings in the preceding year even though the information is available in the data set. It may confound the causal relationship between labor force outcome variables and migration choices. If nonworking wives foresee the potential of a family migration in the near future, they might not be actively searching for employment in the current local labor market. The negative relationship between the observed wife's labor force status and the migration decision would be downward biased in presence of this possibility. This above concern also applies to the effect of pre-migration wife-husband earning ratios on migration. Wives may work fewer weeks and earn less in expectation to migration.

To avoid any endogeniety issue, we construct exogenous measures for the work related variables. Specifically, we predict wife's labor force participation through a

[6] Wives who work in the origin states may not immediately find a new job after the family moves to a new state when they are surveyed. They report nonworking doesn't mean they are not willing to work. The labor force variables we want to employ here should reflect the real working propensity of wives.

standard static labor supply model. First, hourly wages are calibrated if both annual earnings and total working hours are known. Second, a wage equation is estimated to predict and impute wages for workers and non-workers, respectively.

The wage equation is specified as:

$$\begin{aligned} \ln w_{i,t,k} = \alpha_{i,t,k} &+ \beta_1 \text{Age}_{i,t,k} + \beta_2 \text{Age}^2_{i,t,k} + \beta_3 \text{White}_{i,t,k} + \beta_4 \text{Black}_{i,t,k} \\ &+ \beta_5 \text{Educ}_{i,t,k} + \beta_6 D^j_{i,t,k} + \varepsilon_{i,t,k} \qquad (2.17) \\ i = f, m \quad & j = 2, 3, ...51 \quad t = 1980, 1990, 2000 \quad k = \text{full-time, part-time} \end{aligned}$$

where the data is divided into groups based on gender i and work type k for each year group t. The respondents who reported working at least 26 weeks in the past year are labeled as full time workers, in contrast to workers who only worked less than 26 years. Only observations with valid hourly wage within the range of \$2.5 to \$250 are used in the regression.[7] In estimating the labor force participation function we also need to impute the hourly wage for nonworkers since their wages are unobserved. Following Juhn [1992], Juhn and Murphy [1997], Blau and Kahn [2007], we assign the nonworkers with predicted hourly wages imputed from regressions for the part-time workers.

The labor supply model is given by,

$$\text{E} = \alpha_0 + \beta_1 \ln \text{w}_{own} + \beta_2 \ln \text{w}_{spouse} + A'\text{Z} + \varepsilon \qquad (2.18)$$

where E is employment status, w_{own} and w_{spouse} is one's own and spouse's hourly predicted or imputed wage offer, Z is a vector of other control variables including family non-wage income, one's one and spouse's age, race, education attainment, and

[7] All the earning related variables are adjusted to the 2011 dollar values.

number of kids.

In addition to the choice of labor force participation, we also need to construct a measure for the earning ratio of wife to husband. Actual reported values of salary income could not be directly employed. Firstly, if wife's labor force participation is delayed by the prospective migration decision, the earnings of wife in these families would be lower. Therefore the effect of earning ratio on the migration is biased as well. Secondly, measurement errors on earnings or zero earnings of wife or husband tend to enlarge the variance of the earning ratio.

An earnings equation is estimated separately for each year and gender group. Apparently, earnings are positively affected by the working hours. But the focus in this paper is not on the source of the changes in earnings. In other words, we don't specify the increase (decrease) in earnings is resulting from the more (less) working hours or higher (lower) hourly wages. To predict a person's earnings conditional on employment, we implicitly assume that the respondent will work for an average amount of time given the the average wage received by workers with similar characteristics. The variables used in the earning equation are similar to the wage function, but they also include number of kids and family non-wage income. Earning ratio is defined as the log difference in earnings between husband and wife.

2.5.4 Empirical Specifications

There are two main purposes of the empirical analysis in this paper. Firstly, the literature review and the theoretical model revealed above suggest a group of variables that would have substantial effects in the family migration. We want to test the effects of these variables in a reduced form regression. All the endogenous variables are appropriately treated as described in the above subsection. Secondly, we want to examine how the changing distribution of these variables over time could explain the declining trend of family migration, particularly in the families with two college graduates and a college-graduate husband.

The sample period starts from 1982 and ends in 2005. If the regression is estimated by year, the small sample of migrants in each year would make the migration rate volatile and the estimates become unstable across years. To increase the sample size and minimize the measurement error, we group the observations, compare and explain the difference in migration rates across these year groups. Since we look at a long term trend in migration rate across over thirty years, we could still make a valid investigation without loss of generality. Three year groups are defined for the periods of 1982-1990, 1991-1999, and 2000-2005. The samples used in the empirical analysis are restricted to families where head ages 25-54 and two spouses are both present at the survey time. The husband in a family should work in two sequent years and occupation code is available.

Several logit regressions are estimated in this subsection for each type of family and period. They represent reduced forms of the migration decision functions. The regression is of the form:

$$\begin{aligned} \mathrm{I}[M_{it}=1] \quad = \quad & \alpha + \beta_1 \mathrm{Age}_{it} + \beta_2 \mathrm{Sex}_{it} + \beta_3 \mathrm{NumKids}_{it} + \beta_4 \mathrm{White}_{it} + \beta_5 \mathrm{Black}_{it} \\ & + \gamma_1 \mathrm{Wife}_{it}^{\mathrm{Employment}} + \gamma_2 \mathrm{Earning\ Ratio}_{it} + \gamma_3 \mathrm{Correlation}_{it} + \gamma_5 Home_{it} \\ & + D_{1990} + D_{2000} + s_j + \varepsilon_{it}\,, \end{aligned} \tag{2.19}$$

where M_{it} is a binary variable indicating whether the family has moved across states in the past year. Each observation represents a family record in period t. All the demographic characteristic variables for the family are assigned according to the head's record.[8] $\mathrm{Wife}_{it-1}^{\mathrm{Employment}}$ is the predicted wife's labor force status prior to mi-

[8]The head could be the wife. Ideally, we would like to only use the male head. However, the

gration. Earning Ratio_{it} represents the predicted earning ratio of wife to husband. Correlation_{it} is the computed correlation of potential earnings from job offers between husband and wife. In the CPS data, about 20 percent of the married people reported no occupation. There is no missing occupation code for the respondents who were employed when they were surveyed. Among the individuals with no occupation reported, about 80 percent did not work in the pre-survey year either. As a result, the majority of the individuals without occupation recorded are those who didn't work in two adjacent years. For these samples with unobservable occupations, we assign them a weighted average of the correlation values. D_{1980}, D_{1990} and D_{2000} are year group dummies when the model is estimated by using the pooled data over 1981-2005.

2.5.5 Empirical Results

Estimation results for different family types are displayed in Table 2.3. Comparing the findings across the four types of families, we find that families with older head have lower migration propensity, as expected. The negative effect is significant at the 5% level for all groups except the families with a highly educated husband. The migration probability is negatively affected by the number of school age children, indicating that the school choice for kids is another major concern that might discourage migration. For families with two college graduates and a college-graduate husband, we find strong evidence that pre-migration home ownership impedes migration. The probability of owning a house has the most striking effect in determining who is likely to migrate across states borders in these families. Take families with two

female head accounts for 20% of the data. If we exclude it, then we will lose a larger number of observations. Even though the U.S. is one of the countries with the highest mobility, the migration rate is still low. For the sake of accuracy in the estimates, we need to make sure the data is large enough to be statistically meaningful. However, when the sample is restricted to families with a male head, the main results in this paper still hold.

Table 2.3: Logit Regression for Probability of Migrating Across States (1982-2006).

	All Families		Power		Part-Power Husband		Part-Power Wife		Low-Power	
	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.
Age	-0.0470	0.0032	-0.0417	0.0060	{-0.0212}	0.0125	-0.0417	0.0158	-0.0456	0.0094
Sex	-0.0644	0.0278	{-0.0564}	0.0376	{-0.1306}	0.0871	{0.0033}	0.0870	-0.1351	0.0595
White head	-0.1569	0.0550	{0.0337}	0.0889	{0.1108}	0.1843	{-0.1412}	0.2434	-0.3016	0.1294
Black head	-0.2652	0.0655	-0.2104	0.0925	{0.0203}	0.1854	{-0.1041}	0.2251	-0.5525	0.1283
No. of children	-0.2304	0.0154	-0.2511	0.0237	-0.2603	0.0418	-0.1482	0.0592	-0.1526	0.0304
Home ownership	-1.0195	0.2265	-2.2691	0.5171	-2.3077	0.8758	{-0.0032}	1.0924	{-0.7343}	0.5716
Wife Employment	-1.0740	0.0645	-1.3035	0.1040	-1.0663	0.1418	-1.4016	0.3206	-0.8891	0.1118
Log earning ratio	-0.4318	0.0595	-0.5284	0.0873	-0.8181	0.1487	{0.1139}	0.2281	{-0.1932}	0.1158
Correlation	0.6350	0.0701	0.7576	0.1072	0.6430	0.1981	0.6304	0.1961	0.4689	0.1283
Dummy 1980-1990	0.0949	0.0333	0.1323	0.0525	{-0.0718}	0.0979	0.2409	0.1100	{-0.0710}	0.0635
Dummy 1990-2000	0.0869	0.0290	0.0904	0.0453	{0.0648}	0.0837	{0.1531}	0.1071	{-0.0761}	0.0589
Intercept	-1.2299	0.1433	0.3880	0.2805	-1.1359	0.4003	-1.8360	0.6136	-1.0948	0.2678
No. of Observations	425133		173984		58556		46498		145329	

[1] Dependent Variable: Migration = 1 if the family reports a different state from where they were one year ago; 0 otherwise.

[2] Note: {} indicates insignificance at the 10% level.

[3] State dummies are included in all specifications.

college graduates as an example, according to the estimates from the model, a 10% percentage increase in home ownership from 80% to 88% decreases the migration probability by about 16% from 2.75% to 2.3%. For families with a college educated wife and two high school graduates, the effect of home ownership on the migration decision is barely significant, even though the estimate is still negative. If we look at the marginal effect of home ownership on migration probability in equation (2.12), the magnitude of it varies with husband's earnings. Note that these families usually have lower asset value of their properties, which is associates with the lower earnings. Therefore, the negative effect of home ownership on migration could be smaller for these families. Wife's predicted employment probability enters the regression with a significant negative coefficient for all four types of families. The effect is much stronger for the two college graduates and college-wife families. Conditional on other covariances including the earnings, wife's labor force attachment plays a significant role in determining migration. Families with a career oriented wife are less likely to migrate due to the potential penalty to career break caused by migration, especially when the wife is a tied-mover within the family. The negative coefficient of earning ratio of wife to husband provides evidence that if wife's earnings accounts for a greater portion of the total family income, the family migration probability is lower. The estimates of the constructed measure for correlation among gains from migration of spouses also verify the prediction of the theory model. Even though the measure for the correlation in wage offers between husband and wife constructed in this paper only serves as a crude proxy, it still gives us insight into the effects of family ties on the family migration. There is no strong evidence showing that the gender of a family's head or race significantly affects the family migration. Families with white head have higher probability to migrate when both spouses are college educated or only the husband has a college degree. But the estimates are not statistically significant.

Table 2.4: Logit Regression for Probability of Migrating Across States-Two College Graduates.

	1982-2006		1982-1990		1991-1999		2000-2006	
	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.
Age	-0.0417	0.0060	-0.0362	0.0132	-0.0444	0.0126	-0.0423	0.0090
Sex	{-0.0564}	0.0376	{-0.1876}	0.1069	{-0.0840}	0.0714	{-0.0354}	0.0502
White head	{0.0337}	0.0889	{0.0782}	0.1966	{-0.0963}	0.1803	{0.1185}	0.1334
Black head	-0.2104	0.0925	-0.5120	0.1851	{-0.2844}	0.1750	{0.1165}	0.1384
No. of children	-0.2511	0.0237	-0.1952	0.0446	-0.2841	0.0489	-0.3086	0.0398
Home ownership	-2.2691	0.5171	-2.7563	1.0832	-1.8593	1.0201	-2.5507	0.8698
Wife Employment	-1.3035	0.1040	-1.1130	0.1550	-1.4786	0.1894	-1.4688	0.2209
Log earning ratio	-0.5284	0.0873	-0.2997	0.1360	-0.6929	0.1907	-0.8626	0.1744
Correlation	0.7576	0.1072	1.1146	0.2496	0.5980	0.1787	0.6832	0.1596
Intercept	0.3880	0.2805	{0.7426}	0.5023	{0.4503}	0.4725	{0.4692}	0.4993
No. of Observations	173984		43097		52433		52433	

[1] Dependent Variable: Migration = 1 if the family reports a different state from where they were one year ago; 0 otherwise.

[2] Note: {} indicates insignificance at the 10% level.

[3] State dummies are included in all specifications.

Table 2.5: Logit Regression for Probability of Migrating Across States-College Husband.

	1982-2006		1982-1990		1991-1999		2000-2006	
	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.	Coeff.	Std.err.
Age	{-0.0212}	0.0125	-0.0324	0.0186	{-0.0442}	0.0288	0.0433	0.0262
Sex	{-0.1306}	0.0871	{0.0114}	0.1879	{-0.0519}	0.1594	-0.3244	0.1274
White head	{0.1108}	0.1843	{-0.1538}	0.2918	{-0.2557}	0.3700	1.0901	0.3696
Black head	{0.0203}	0.1854	{-0.2235}	0.2973	{0.0111}	0.3347	{0.3993}	0.3510
No. of children	-0.2603	0.0418	-0.3248	0.0630	-0.3006	0.0867	-0.1434	0.0842
Home ownership	-2.3077	0.8758	{-2.1548}	1.3054	{-0.1888}	1.9592	-6.9143	1.9555
Wife Employment	-1.0663	0.1418	-1.0314	0.1723	-1.0217	0.2981	-1.6313	0.5084
Log earning ratio	-0.8181	0.1487	-0.8974	0.2013	-0.8940	0.3283	-0.8441	0.3627
Correlation	0.6430	0.1981	1.0030	0.3866	0.6238	0.3297	{0.3780}	0.3241
Intercept	-1.1359	0.4003	-1.3833	0.6450	-1.4142	0.7035	{-0.0062}	0.8389
No. of Observations	58556		21720		17411		18005	

[1] Dependent Variable: Migration = 1 if the family reports a different state from where they were one year ago; 0 otherwise.

[2] Note: {} indicates insignificance at the 10% level.

[3] State dummies are included in all specifications.

The above estimates also reveal that families of different types display different decision-making process on migration, as many variables have differential estimates among those specifications. [9]When we investigate how the economic factors explain the downward trend for each family type, we prefer to use the specific regressions that truly reflects the migration decision process for that group.

As a robust check of the stability of parameters, we also run the regression by employing samples of different windows for families where husband has a college degree. The results are displayed in Table 2.4 and Table 2.5. It shows the estimates are not sensitive to the samples selected for these two types of families.

2.6 Accounting for Changes in the Family Migration Rate

In this subsection, we consider the extent to which changes in the distribution of socio-economic factors such as earning ratio of wife to husband and home ownership contributed to the slowing down of family migration in the past 30 years. To accomplish this goal, we apply the estimates in the benchmark regression to decompose the change in the migration rate for each family group. Before we move to that step, we should recognize that the secular trend in the migration rate could result from three sources of changes. The first part is due to the changes in the distributions of individual characteristics over time, as we just mentioned. The second part is due to the changes in the parameters of the benchmark regression, which indicates that individual's preferences have shifted. It is difficult to explain the changes in individual's behavior by economic theories. Unobserved or unmeasurable variables which are not included in the benchmark model could also contribute to the changes in the trend of migration. In this paper, we only focus on the first source of change.

[9]In this paper, we primarily focus on the downward trend in migration of different family types, particularly of the power couples, rather than the gaps of migration rate between these groups from a cross-section perspective.

For separating the contribution of measurable characteristics on the outcome variable, the Blinder-Oaxaca decomposition technique(Blinder [1973],Oaxaca[1973]) has become an standard methodology in the past decades. However, the Blinder-Oaxaca technique, which originally developed from linear regressions, cannot be directly applied to non-linear regressions with a binary dependent variable (Fairlie [2005, 2007]). Since the outcome variable we investigate here is a binary choice variable on migration, we would adopt the non-linear decomposition technique developed by Fairlie.[10]

I perform a decomposition of the gap in migration rate over the period of 1980s to 2000s for all of the four family types by using the parameter estimates obtained from the pulled regression of each group. The results for the decomposition are displayed in Table 2.6. First, we illustrate the results for families with two college graduates. When the samples are aggregated into three periods, there is an 1% drop in the average migration rate from 1980s to 1990s, and a 0.57% drop from 1990s to 2000s. The included variables explain 88.6% of the total gap between 1980s and 1990s,and 82.1% of the gap between 1990s and 2000s. But when we look at the contribution of a specific variable, we find that it may have different amounts of contribution in different periods. The probability of owning a house only explains 2.2% of the decrease in the migration rate in the 1990s. However, it becomes the most important factor that causes the decrease in the migration rate in the 2000s. The contribution is 71.8%, which is quite material. This finding is in line with the phenomenon that home ownership for this group of family has been increasing significantly since the mid 1990s. In Figure 2.4, it shows that the home ownership of families with two college graduates increases from about 83% in the 1990s to 88% in the 2000s.

[10]The difference between the standard Blinder-Oaxaca technique and the method extended by Fairlie is extensively explored and discussed in Fairlie[2005].

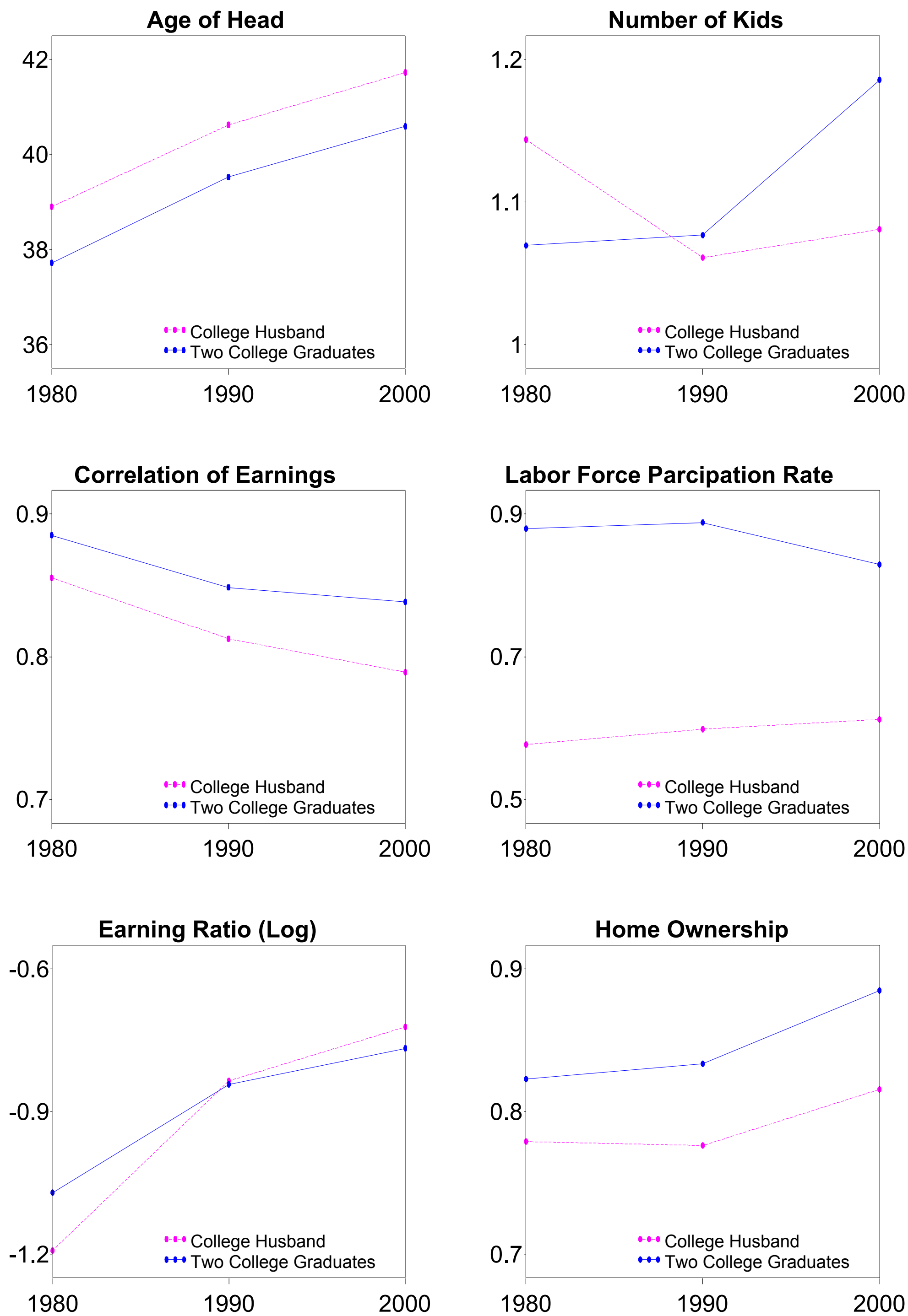

Figure 2.4: The Mean Values of the Explanatory Variables over the Decades of 1980, 1990, and 2000.

Table 2.6: Predicted Changes in Migration Rate-by Family Type.

	Predicted Changes in Migration Rate							
	Power				Part-Power Husband			
	1980-1990		1990-2000		1980-1990		1990-2000	
	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.
Age	-0.0019	19.5%	-0.0013	22.8%	-0.0007	10.4%	-0.0005	11.5%
Sex,Race	-0.0004	3.8%	-0.0006	9.9%	0.0008	-12.1%	-0.0006	13.2%
No. of children	0.0009	-8.8%	-0.0008	14.5%	0.0015	-22.1%	0.0002	-4.8%
Wife Employment	-0.0015	15.2%	0.0022	-38.7%	-0.0018	26.3%	-0.0004	9.5%
Log earning ratio	-0.0045	44.8%	-0.0011	19.3%	-0.0081	121.3%	-0.0016	37.0%
Home ownership	-0.0002	2.2%	-0.0041	71.8%	0.0008	-11.6%	-0.0022	50.3%
Correlation	-0.0008	7.5%	0.0000	0.5%	-0.0003	5.0%	-0.0001	2.7%
State Dummies	-0.0005	5.1%	0.0010	-18.0%	-0.0013	20.0%	0.0016	-26.0%
Delta Migration Rate	-0.0100		-0.0057		-0.0067		-0.0044	
Total Explained Change	-0.0089	88.6%	-0.0047	82.1%	-0.0091	135.8%	-0.0036	81.8%
Total Unexplained Change	-0.0011	11.4%	-0.0010	17.9%	0.0024	-35.8%	-0.0008	18.2%
	Predicted Changes in Migration Rate							
	Part-Power Wife				Low Power			
	1980-1990		1990-2000		1980-1990		1990-2000	
	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.
Age	-0.0008	23.2%	-0.0010	32.2%	-0.0020	71.7%	-0.0007	-239.7%
Sex,Race	0.0001	-1.6%	0.0001	-3.6%	0.0001	-3.8%	-0.0004	-138.8%
No. of children	-0.0002	5.6%	-0.0004	11.4%	0.0016	-57.8%	0.0000	6.5%
Wife Employment	-0.0005	16.2%	0.0014	-44.9%	-0.0007	26.7%	-0.0001	-38.9%
Log earning ratio	0.0002	-6.4%	0.0001	-4.5%	-0.0009	32.0%	-0.0004	-131.5%
Home ownership	0.0000	1.4%	0.0003	-8.7%	0.0004	-12.7%	-0.0003	-99.7%
Correlation	-0.0008	25.4%	-0.0002	7.4%	-0.0004	14.3%	-0.0002	-64.7%
State Dummies	-0.0002	4.7%	0.0000	1.3%	-0.0010	36.2%	0.0006	206.2%
Delta Migration Rate	-0.0033		-0.0030		-0.0028		0.0003	
Total Explained Change	-0.0022	66.7%	0.0003	-10.0%	-0.0029	106.6%	-0.0015	-500.7%
Total Unexplained Change	-0.0011	33.3%	-0.0033	110.0%	0.0002	-6.6%	0.0018	600.7%

[1] Dependent Variable: Migration = 1 if the family reports a different state from where they were one year ago; 0 otherwise.

Wife's labor force attachment, measured by the predicted wife's employment status, contributes to the decline of migration rate in distinct ways in different periods. The change of wife's labor force participation decisions accounts for roughly 15% of the total decrease in the migration rate from 1980s to 1990s. In contrast, the estimate of its contribution from 1990s to 2000s is -38.7%, which indicates that this factor should actually increase the family migration between the 1990s and 2000s. The migration rate still falls between these two decades, as we observed, since the negative effect of this factor is partially offset by other environment changes, such as the home ownership increase, which contributes to the decrease of migration rate in a quite opposite direction. Not surprisingly, when we look at the secular changes in predicted probability of wife's employment, there is a break-up of the long term upward trend in the 1990s. The slowdown in the growth of female labor supply between the 1990s and 2000s is also documented in Blau and Kahn [2007]. The Earning ratio of wife to husband has greater contributions in the 1990s than in the 2000s. The contribution of this variable is 19.3% in the 2000s, whereas the magnitude of the contrition in the 1990s is as twice larger as that number. It reflects the fact that the increase in the earning ratio of wife to husband is more substantial between 1980s and 1990s. The change of age structure in the population consistently explains about 20% of the decrease in the migration rate of two college graduates couples across the three decades. Due to the ageing of the baby boom generation, the average age of the family head continually increases in the past 30 years, which leads to a lower migration rate. In comparison with the variables discussed above, the contribution of the correlation in the gains from migration between wife and husband is small, which is only 7.5% from 1980s to 1990s, then almost disappears in the period of 1990s-2000s. Even though the magnitude of the contribution is immaterial, the changing pattern is consistent with the findings that there is only a significant drop of the correlation measure in the 1990s. Of the other explanatory variables, the head's gender and race only account for a small portion of the total change in the migration rate over the three periods. The number of kids under 18 years old firstly increases the migration rate in the 1980s to 1990s, and then decreases the migration rate over the 1990s to 2000s with a slightly larger effects.

Overall, for the variables that we are primarily interested in, the decomposition estimates for the families with a college-graduate husband are similar to those of the two college graduates. There is also a dramatic change of the contribution from the home ownership probabilities across time(-11.6% in the 1980s-1990s and 50.3% in the 1990s-2000s). Both Wife's employment propensity and earning ratio between wife and husband show stronger effects in explaining the slowdown of migration rate in the 1980s-1990s and in the 1990s-2000s. Another interesting results are revealed by the estimates for state dummies. For both families with two college graduates and a college-graduate husband, differences across the last two decades in changes in the state effects expedite the migration rather than slow it down. Again, the negative effects are compensated by the positive effects from other explanatory variables. A possible explanation for this result is that the development of high technology industry and the geographic concentration of industry during the 1990s and 2000s promote the migration of labor into the states where they possess the skills demanded in those highly concentrated industries.

The results reported in Table 2.6 also shows that the explanatory variables have weak powers in explaining the migration patterns over time for the families with a college wife or two high school graduates. However, as we have seen, the migration rates for these two types of families are much lower than the families of two college graduates and a college husband. The family economic status, partially determined by educational background, indicates that they may have lower sensitivity to migrate in response to economic incentives. In the families with a college wife, even though the wife has higher education, but because women are usually less career oriented and less mobile than man, and the college wife may have higher bargaining power over their high-school graduated husband, this type of family could have quite different decision making process regarding to migration. Over the three decades that are included in the empirical analysis, the long term trend of migration rate for these two types of family barely changes. If we look at the coefficient estimates in the baseline regressions for these families, it is not hard to figure out that many of them are not statistically significant, which would also impair the decomposition analysis.

As a robust check of the decomposition results obtained from the pooled sample across three decades, we also calculate the decompositions using coefficients of each decade for both families with two college graduates and a college graduate husband. The results are reported in Table 2.7 and Table 2.8, respectively. The decompositions for families with two college graduates by using different sets of coefficients are stable. In comparison, the decomposition estimates for families with a college graduate husband are more sensitive to the coefficients used. But most of the variations are due to the imprecision of many of the coefficient estimates in the logit regressions which are based on shorter sample periods. The sample size of families with power husband is less than one third of the sample size of families with power couples. Also, the number of migrants are small because of the lower migration rate.

Table 2.7: Predicted Changes in Migration Rate-Families with Two College Graduates.

	Predicted Changes in Migration							
	1980-2000 Equation				1980 Equation			
	1980-1990		1990-2000		1980-1990		1990-2000	
	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.
Age	-0.0019	19.5%	-0.0013	22.8%	-0.0024	24.1%	-0.0016	28.1%
Sex,Race	-0.0004	3.8%	-0.0006	9.9%	-0.0006	6.2%	-0.0012	21.8%
No. of children	0.0009	-8.8%	-0.0008	14.5%	0.0001	-1.4%	-0.0011	20.0%
Wife Employment	-0.0015	15.2%	0.0022	-38.7%	-0.0008	8.0%	0.0022	-39.1%
Log earning ratio	-0.0045	44.8%	-0.0011	19.3%	-0.0026	25.7%	-0.0005	8.9%
Home ownership	-0.0002	2.2%	-0.0041	71.8%	-0.0007	6.7%	-0.0045	79.3%
Correlation	-0.0008	7.5%	0.0000	0.5%	-0.0010	10.4%	-0.0002	4.2%
State Dummies	-0.0005	5.1%	0.0010	-18.0%	0.0033	3.2%	0.0022	-39.0%
Delta Migration Rate	-0.0100		-0.0057		-0.0100		-0.0057	
Total Explained Change	-0.0089	88.6%	-0.0047	82.1%	-0.0047	47.0%	-0.0048	84.1%
Total Unexplained Change	-0.0011	11.4%	-0.0010	17.9%	-0.0053	53.0%	-0.0009	15.9%

	Predicted Changes in Migration							
	1990Equation				2000 Equation			
	1980-1990		1990-2000		1980-1990		1990-2000	
	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.
Age	-0.0023	23.3%	-0.0012	22.0%	-0.0020	20.0%	-0.0012	20.8%
Sex,Race	-0.0003	3.5%	-0.0005	9.0%	-0.0003	2.6%	-0.0004	7.2%
No. of children	0.0000	-0.4%	-0.0007	11.9%	0.0004	-3.9%	-0.0008	14.6%
Wife Employment	-0.0013	13.3%	0.0023	-40.5%	-0.0014	13.6%	0.0023	-40.0%
Log earning ratio	-0.0051	50.7%	-0.0017	29.2%	-0.0057	57.5%	-0.0012	21.9%
Home ownership	-0.0008	7.9%	-0.0027	48.1%	-0.0006	6.2%	-0.0043	75.6%
Correlation	-0.0007	6.6%	-0.0001	1.8%	-0.0007	6.5%	-0.0001	1.7%
State Dummies	0.0005	-4.6%	0.0016	-27.9%	-0.0001	0.9%	0.0000	0.7%
Delta Migration Rate	-0.0100		-0.0057		-0.0100		-0.0057	
Total Explained Change	-0.0100	100.2%	-0.0030	53.7%	-0.0104	103.5%	-0.0058	102.5%
Total Unexplained Change	0.0000	-0.2%	-0.0026	46.3%	0.0004	-3.5%	0.0001	-2.5%

[1] Dependent Variable: Migration = 1 if the family reports a different state from where they were one year ago; 0 otherwise.

Table 2.8: Predicted Changes in Migration Rate-Families with College Husband.

	Predicted Changes in Migration Rate							
	1980-2000 Equation				1980 Equation			
	1980-1990		1990-2000		1980-1990		1990-2000	
	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.
Age	-0.0007	10.4%	-0.0005	11.5%	-0.0023	35.1%	-0.0007	15.9%
Sex,Race	0.0008	-12.1%	-0.0006	13.2%	0.0012	-19.7%	0.0001	-1.3%
No. of children	0.0015	-22.1%	0.0002	-4.8%	0.0037	-55.2%	0.0000	0.2%
Wife Employment	-0.0018	26.3%	-0.0004	9.5%	-0.0009	14.2%	-0.0005	12.1%
Log earning ratio	-0.0081	121.3%	-0.0016	37.0%	-0.0088	131.8%	-0.0015	34.2%
Home ownership	0.0008	-11.6%	-0.0022	50.3%	-0.0002	3.5%	-0.0015	33.5%
Correlation	-0.0003	5.0%	-0.0001	2.7%	-0.0004	6.4%	-0.0002	4.0%
State Dummies	-0.0013	20.0%	0.0016	-26.0%	-0.0023	33.9%	0.0010	-23.3%
Total Change	-0.0067		-0.0044		-0.0067		-0.0044	
Total Explained Change	-0.0091	135.8%	-0.0036	81.8%	-0.0100	149.3%	-0.0033	75.0%
Total Unexplained Change	0.0024	-35.8%	-0.0008	18.2%	0.0033	-49.3%	-0.0011	33.3%
	Predicted Changes in Migration Rate							
	1990 Equation				2000 Equation			
	1980-1990		1990-2000		1980-1990		1990-2000	
	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.	Cont.	Pct.
Age	-0.0021	31.2%	-0.0009	19.2%	0.0040	-60.5%	0.0016	-36.1%
Sex,Race	0.0014	-21.1%	-0.0001	1.4%	-0.0012	18.8%	-0.0027	58.7%
No. of children	0.0024	-36.6%	-0.0005	10.2%	0.0011	-16.9%	0.0001	-1.3%
Wife Employment	-0.0014	20.6%	-0.0003	7.6%	-0.0037	55.7%	-0.0012	27.8%
Log earning ratio	-0.0108	162.4%	-0.0017	38.6%	-0.0110	164.2%	-0.0025	57.2%
Home ownership	0.0008	-11.9%	-0.0002	4.1%	0.0042	-63.2%	-0.0050	110.8%
Correlation	0.0001	-1.4%	-0.0002	4.8%	0.0009	-13.6%	-0.0001	2.9%
State Dummies	-0.0026	39.4%	0.0018	-41.4%	-0.0030	44.7%	-0.0011	24.0%
Total Change	-0.0067		-0.0044		-0.0067		-0.0044	
Total Explained Change	-0.0122	182.1%	-0.0021	47.7%	-0.0087	129.9%	-0.0109	247.7%
Total Unexplained Change	0.0055	-82.1%	-0.0023	52.3%	0.0020	-29.9%	0.0065	-147.7%

[1] Dependent Variable: Migration = 1 if the family reports a different state from where they were one year ago; 0 otherwise.

3. YOUTH COHORT SIZE AND UNEMPLOYMENT RATE

3.1 Related Literature

Young workers, as a demographic group, are lacking in working experience in the early stage of their careers. They are more likely to experiment with different types of jobs or employers to find a good match. Therefore, compared with prime age workers, young workers have a higher probability to be separated from a job. Moreover, the youth are less confined to family obligations before they get married. They are more mobile across jobs and locations. Instability is another important factor that contributes to the higher unemployment rate of young workers. As the age structure of the population shifts toward or away from the youth, the potential effect of changing population composition on the aggregate unemployment rates is still an open question.

The baby boom after World War II provides a natural experiment to investigate the effects of the change in demographic composition on labor market outcomes. When the baby boomers enter the labor market, the proportion of young workers in the labor force significantly increases. Focusing on the total effect of youth cohort size, many authors predicate and confirm that the baby boom and the subsequent baby bust would push up the aggregate unemployment rate in the 1970s first, then pull it down in the 1980s and the 1990s. (Perry [1970], Flaim [1979], Gordon [1982], Flaim [1990], and Shimer [1998].) The similar time pattern in the trends of youth share and aggregate unemployment rate leads many economists to conjecture that there is a causality rather than just a coincidence between the two variables. However, studies with a time series analysis fail to control for other possible macro shocks which may also affect the decrease in the aggregate unemployment rate, such as oil price or government policies. Therefore, these analysis can hardly establish a causal relationship between the aggregate unemployment rate and youth cohort size.

Korenman and Neumark [2000] construct a panel data set collected from 15 OECD countries in the period of 1970-1994. The panel feature of the data allows them to control for country fixed effects and year effects in the regression. Their findings are consistent with the previous 'cohort crowding' literature and the studies which employ time series analysis. The estimated elasticity is about 0.3 and is statistically significant.

Shimer [2001] also applies the panel data method to investigate the the relationship between the annual state unemployment rates and state youth share in the United States from 1978 to 1996. The more disaggregate unemployment rates of different age groups make it possible to examine the impact of young cohort size on both the aggregate and age-group specific unemployment rates.[1] The indirect marginal effects of youth cohort size on the unemployment rates of different groups are estimated separately in this study. Surprisingly, Shimer [2001] shows that an increase in the youth share in the working age population in a state will decrease the aggregate unemployment rate with an elasticity of -2 in that state. Moreover,

[1]There are two aspects of the effects of youth cohort size on the unemployment rate. First, the aggregate unemployment rate for a region is calculated as a weighted average of unemployment rates of various age cohorts. The size of each age cohort is considered as the weight. A change in the weights would lead to a change in the aggregate unemployment rate. This is recognized as the direct composition effect of cohort size. Second, workers in different age cohorts might be imperfectly substitutable. The increase in the number of workers in certain age cohort could have differential impacts on the job opportunities of workers in different age cohorts. This is the indirect effect of cohort size on the unemployment rate. Suppose u_i is the aggregate unemployment rate and w_i^j refers to the ratio of the labor force in age cohort j to the overall labor force summed over all age cohorts, then u_i is given by

$$u_i = \sum_{j=1}^{J} w_i^j u_i^j, \tag{3.1}$$

where J is the number of age cohorts or groups in region i. For ease of illustration, we can simply assume that there are two broad age cohorts in the labor force, the young and the old. Then the aggregate unemployment rate in region i becomes he finds that the increase of youth population not only reduces the unemployment rate of the youth, but also more substantially reduces the unemployment rates of the prime age workers. Foote [2007] updates Shimer [2001]'s data to 2005. He finds that the negative correlation between youth cohort size and unemployment rate does not hold true for the U.S. data set, which covers a much longer time period. He attributes it to the presence of spacial correlation in the state-level data. Even though the estimates, obtained by correcting the error terms through various specifications, become positive, none of them are significant. Foote [2007] concludes the paper by doubting the reliability of the regional panel data in macro-analysis. Unlike Foote [2007], we split all the available data from 1978 to 2008 into two sub-periods. In this way, we could identify the breaking point in the estimates. Foote [2007] points out the instability of the estimates, but he does not provide further discussion on the relationship between the youth cohort size and unemployment rate.

$$u_i = w_i^y u_i^y + w_i^o u_i^o = w_i^y (u_i^y - u_i^o) + u_i^o. \tag{3.2}$$

For the simplest case, if age-specific unemployment rates u_y and u_o are unaffected by the change in the cohort sizes, measured by w_y and w_o, then the marginal effect of youth cohort size on the aggregate unemployment rate is

$$\frac{\partial u_i}{\partial w_i^y} = u_i^y - u_i^o > 0, \tag{3.3}$$
$$since \;\; u_i^y > u_o^o.$$

With only the direct effect considered, the aggregate unemployment rate u_i would increase along with the youth cohort size w_y. Once the indirect effect is accounted for, equations (**??**) and (**??**) are transformed into the following forms,

$$u_i = w_i^y u_i^y(w_i^y) + w_i^o u_i^o(w_i^y) = w_i^y (u_i^y(w_i^y) - u_i^o(w_i^y)) + u_i^o(w_i^y) \tag{3.4}$$

$$\frac{\partial u_i}{\partial w_y} = [u_i^y - u_i^o] + w_i^y [\frac{\partial u_i^y(w_i^y)}{\partial w_i^y} - \frac{\partial u_i^o(w_i^y)}{\partial w_i^y}] + \frac{\partial u_i^o(w_i^y)}{\partial w_i^y} \tag{3.5}$$

In equation (3.5), the marginal effect of youth cohort size on the total unemployment rate consists of two parts. The term $u_i^y - u_i^o$ is the direct effect specified in equation (3.5). The remaining terms represent the indirect effect. As a priori, the signs of both $\frac{\partial u_i^y(w_i^y)}{\partial w_i^y}$ and $\frac{\partial u_i^o(w_i^y)}{\partial w_i^y}$ are uncertain, as is the difference between the two terms. If $\frac{\partial u_i^y(w_i^y)}{\partial w_i^y} > \frac{\partial u_i^o(w_i^y)}{\partial w_i^y} > 0$, then the total effect outweighs the direct effect.

The most recently relevant work that investigates the effects of cohort size on labor market outcomes is given by Jaimovich and Siu [2009]. Instead of studying the cohort effects on the unemployment rate, they focus on the consequences of demographic change on business cycle volatility. They calculate several measures for the business cycle volatility and use the panel method which is very similar to that of Shimer [2001] on G7 countries from the mid-1960s to 1999. They find that an increase in the share of volatile-age labor force[2] significantly increases the business cycle volatility.

3.2 Temporal Correlation between Unemployment Rate and Youth Cohort Size

3.2.1 The Impact of Youth Cohort Size on Unemployment Rate in the U.S. and OECD: A Revision

The baseline regression is the same as Shimer [2001]:

$$\log unemp_{it} = \alpha + \beta \log youthshare_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{3.6}$$

where $unemp_{it}$ and $youthshare_{it}$ are the unemployment rate and the youth share for state i in year t, respectively. The $youthshare_{it}$ is defined as the ratio of the population with the ages of 16-24 and ages of 16-64. It measures the youth cohort size in the population. The youth share is calculated by using the population instead of the labor force to circumvent the potential endogeniety caused by the choices of labor force participation.[3] β measures the elasticity of the unemployment rate to changes in the youth share. δ_i is the state fixed effect and γ_t is the year effect that

[2]The volatile-age labor force in this paper is defined as the population share of group with age 16-29 and 60-64.

[3]But the results presented here are robust when the youth share is defined as the youth cohort size in the labor force.

absorbs nationwide macroeconomic shocks. Table 3.1 illustrates the estimates of the coefficient for youth share by using data sets from two different sample periods by age group.[4] The first subsample is the same as in Shimer [2001], from 1978 to 1996. The second subsample is from later years, from 1997-2008. The second and fourth column in Table 3.1 correspond to IV estimates with lagged birth rates as the instrumental variable for youth share. Before 1996, the estimates of β are consistent with those in Shimer [2001], which are significantly negative. The estimates for prime age workers are larger than those for young workers aged 16-19 and 20-24. By contrast, β becomes positive and statistically significant for the youngest age group after 1997. The IV estimates have the same signs as OLS estimates, but differ in their magnitudes.

Shimer [2001] develops a theory model to explain his empirical findings in 1978-1996. The model is a modification of the standard search-and-match model in the labor literature. The model incorporates the concept of "trade externality" proposed by Diamond [1982], which predicts that the hiring cost of firms is lower in regions where there is a larger portion of young workers in the labor force. Because young workers are more likely to be unmatched or mismatched to the employers, they have greater incentive to relocate. Firms are attracted by these more active markets and therefore generate more job vacancies. Both of the young and old workers could benefit from the job creation of new firms. Once the negative indirect effect dominates the positive direct effect, the aggregate unemployment rate may even decrease. The discrepancy in the estimates across different time periods in the U.S. raises questions to the explanation based on search and match theories. If capital continually flows to areas with a high share of young workers and creates more job opportunities there, then the negative relationship between the youth share and unemployment

[4] Table 3.2 shows the results obtained by using OECD data.

rates found in the 1980s and 1990s should have continued through the 2000s, contradictory to the empirical evidence. Instead, proposes another explanation that may help us to understand the contradiction. We show that the non-random sampling of the youth cohort size in the data plays an important role in the inconsistency of the estimated elasticities in both the United States and OECD countries.

Table 3.1: The Impact of Youth Cohort Size on Unemployment Rate in the U.S., 1978-2008.

	1978-1996		1997-2008	
	OLS	IV	OLS	IV
16-64	-1.722**	-1.646***	0.458	1.253***
	(0.236)	(0.268)	(0.371)	(0.400)
16-19	-1.359***	-1.008***	0.510*	1.213***
	(0.222)	(0.248)	(0.307)	(0.367)
20-24	-1.914***	-2.049***	0.362	0.880*
	(0.254)	(0.279)	(0.365)	(0.452)
25-34	-1.903***	-2.001***	0.324	1.224**
	(0.279)	(0.351)	(0.483)	(0.489)
35-44	-2.274***	-1.988***	-0.063	0.625
	(0.320)	(0.380)	(0.423)	(0.496)
45-54	-2.686***	-2.734***	1.310**	1.849**
	(0.350)	(0.439)	(0.303)	(0.482)
55-64	-2.603***	-3.272***	-0.403	0.597
	(0.444)	(0.491)	(0.589)	(0.679)

[1] New-West Standard errors are reported in the parenthesis.

[2] Instrumental variables for youth share include lagged birthrate, year and state dummies.

[3] *** significant at 1 percent level. ** significant at 5 percent level. * significant at 10 percent level.

Table 3.2: The Impact of Youth Cohort Size on Unemployment Rate in OECD Countries, 1971-2009.

	1978-1996		1997-2008	
	OLS	IV	OLS	IV
15-64	-1.219**	-1.620***	-0.178	-0.074
	(0.437)	(0.446)	(0.401)	(0.425)
15-24	-1.394***	-1.820***	0.009	0.152
	(0.446)	(0.457)	(0.392)	(0.392)
25-34	-2.074***	-2.308**	-0.304	-0.183
	(0.540)	(0.554)	(0.463)	(0.484)
35-44	-1.315***	-1.541***	-0.722	-0.703
	(0.531)	(0.531)	(0.425)	(0.461)
45-54	-0.785	-0.857*	-0.463**	-0.454
	(0.529)	(0.522)	(0.394)	(0.437)
55-64	-0.898	-0.640	-0.882**	-0.722*
	(0.581)	(0.585)	(0.396)	(0.433)

[1] New-West Standard errors are reported in the parenthesis.

[2] Instrumental variables for youth share include lagged birthrate, year and state dummies.

[3] *** significant at 1 percent level. ** significant at 5 percent level. * significant at 10 percent level.

We next compare the coefficient estimates of the youth share in different model specifications. Table 3.3 presents the estimates from four model specifications in two time periods in the United States. Specification (1) and (2) are unconditional models without controlling for year effects, while specification (3) and (4) are conditional models with year dummies included in the regression. Specification (1) is the pooled OLS regression. In specification (2) and (4), we control for the state fixed effect. Column 1 to 4 report the estimates for the period of 1978-1996. There is a notable difference in the estimates between the conditional and unconditional model. It shows that benchmark negative estimates reported in Shimer [2001] are driven by

Table 3.3: The Impact of Youth Cohort Size in Different Model Specifications in the U.S., 1978-2008.

	1978-1996				1997-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
16-64	0.404***	0.507***	-0.508***	-1.723***	-0.226**	0.620***	-0.258***	0.458**
	(0.076)	(0.064)	(0.132)	(0.157)	(0.110)	(0.210)	(0.098)	(0.159)
R^2	0.0295	0.4605	0.323	0.7669	0.0071	0.5269	0.2348	0.7511
16-19	0.079	0.114***	-0.416***	-1.360***	-0.108**	0.456***	-0.410***	0.510**
	(0.077)	(0.059)	(0.148)	(0.180)	(0.131)	(0.223)	(0.126)	(0.203)
R^2	0.0011	0.5365	0.1453	0.6928	0.0163	0.5942	0.1159	0.6943
20-24	0.312***	0.384***	-0.518***	-1.914***	-0.408**	0.481**	-0.435**	0.362
	(0.086)	(0.071)	(0.159)	(0.202)	(0.127)	(0.242)	(0.119)	(0.216)
R^2	0.0141	0.4670	0.2165	0.6891	0.0173	0.4934	0.1617	0.6368
25-34	0.188**	0.258***	-0.598***	-1.903***	-0.202**	0.504***	-0.236**	0.325
	(0.087)	(0.075)	(0.152)	(0.192)	(0.132)	(0.266)	(0.117)	(0.216)
R^2	0.0050	0.4144	0.2969	0.7229	0.0040	0.4222	0.2414	0.6559
35-44	-0.089	-0.023	-0.887***	-0.274**	-0.358**	0.199	-0.402***	-0.063
	(0.093)	(0.086)	(0.162)	(0.235)	(0.136)	(0.275)	(0.121)	(0.225)
R^2	0.0010	0.3284	0.2903	0.6349	0.0117	0.4248	0.2431	0.6527
45-54	-0.037	0.110	-1.236***	-2.69***	-0.514***	1.485***	-0.562***	1.309***
	(0.095)	(0.092)	(0.165)	(0.260)	(0.149)	(0.311)	(0.132)	(0.259)
R^2	0.0002	0.2759	0.3057	0.5898	0.0198	0.3974	0.2554	0.6224
55-64	-0.242**	0.053	-1.885***	-2.603***	-0.922***	-0.059	-1.006***	-0.403
	(0.120)	(0.117)	(0.217)	(0.366)	(0.167)	(0.383)	(0.157)	(0.352)
R^2	0.0071	0.2600	0.2515	0.4799	0.0493	0.3233	0.2027	0.4785
No. of Obs.	931	931	931	931	588	588	588	588

[1] All of these specifications report the OLS standard errors.

[2] Specification (1) is pooled OLS. Specification (2) is with-in estimator excluding year dummies.

[3] *** significant at 1 percent level. ** significant at 5 percent level. * significant at 10 percent level.

Table 3.4: The Impact of Youth Cohort Size in Different Model Specifications in OECD Counties, 1971-2009.

	1971-1995				1996-2009			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
15-64	0.793***	-1.902***	3.035***	1.219***	0.049	0.539**	-0.218	-0.178
	(0.292)	(0.281)	(0.251)	(0.276)	(0.261)	(0.240)	(0.265)	(0.226)
R^2	0.0194	0.5341	0.5350	0.8260	0.0002	0.7115	0.1112	0.8127
15-24	0.757***	0.1677***	2.80***	1.394***	-0.103	0.333	-0.242	0.010
	(0.324)	(0.298)	(0.291)	(0.306)	(0.266)	(0.210)	(0.277)	(0.208)
R^2	0.0156	0.5532	0.4916	0.8285	0.0007	0.7850	0.0675	0.8460
25-34	0.609*	-2.137***	3.147***	2.074***	-0.187	0.426	-0.470	-0.304
	(0.346)	(0.347)	(0.263)	(0.330)	(0.287)	(0.266)	(0.291)	(0.253)
R^2	0.0094	0.4883	0.6269	0.8220	0.0020	0.7054	0.1149	0.8061
35-44	0.519	-2.717***	3.372***	1.315***	-0.024	0.096	-0.291	-0.722**
	(0.354)	(0.313)	(0.281)	(0.324)	(0.272)	(0.265)	(0.277)	(0.252)
R^2	0.0062	0.5826	0.6002	0.8372	0.0000	0.6741	0.1066	0.7852
45-54	0.154	-2.858***	2.800***	0.785**	0.319	0.230	0.109	-0.463
	(0.366)	(0.309)	(0.319)	(0.329)	(0.296)	(0.255)	(0.308)	(0.248)
R^2	0.0005	0.6165	0.5134	0.8422	0.0055	0.7471	0.0764	0.8252
55-64	-0.498	-2.200***	1.256***	0.898***	-0.358	0.207	-0.748**	-0.882***
	(0.367)	(0.305)	(0.379)	(0.362)	(0.352)	(0.288)	(0.363)	(0.273)
R^2	0.0055	0.6261	0.3136	0.8058	0.0049	0.7713	0.0909	0.8504
No. of Obs.	337	337	337	337	210	210	210	210

[1] New-West Standard errors are reported in the parenthesis.
[2] Instrumental variables for youth share include lagged birthrate, year and state dummies.
[3] *** significant at 1 percent level. ** significant at 5 percent level. * significant at 10 percent level.

the inclusion of year dummies in the regression. In the second period of 1997-2008, which is updated in this paper, the variation in the estimated coefficients of youth share across these different specifications are reduced. Estimates from unconditional and conditional models are quite similar. Table 3.4 reports the estimates for equation (3.6) by applying OECD country panels from 1971 to 2009. To make it comparable with the estimates from the United States, we also divide the whole OECD sample into two sub-samples with time frames of 1971-1995 and 1996-2009. As shown in the table, in the period of 1978-1996, the positive effect of youth cohort size reported in earlier panel studies and in Table 3.2 of this paper is also driven by the year effects.

3.2.2 Conditional and Unconditional Marginal Effect of Youth Cohort Size

There are two ways to identify the marginal effect of youth cohort size on the unemployment rate when using the panel data: conditional or unconditional on year effects. The findings described in the previous subsection indicate that estimates from the two models differ significantly both in sign and magnitude across different panels. To provide a more formal theoretical explanation on the difference between unconditional and conditional model, consider the regression specified in equation (3.6). For simplicity, we use y, X_1, X_2 to denote the unemployment rate, youth share, and the set of year dummies, respectively. Given the assumption[5] that

$$E[\varepsilon|X_1, X_2] = 0, \tag{3.7}$$

the mean of y conditional on the youth share and year effects is given by,

$$E[y|X_1, X_2] = X_1\beta_1 + X_2\beta_2. \tag{3.8}$$

[5] Apparently, the error terms in this setting are autocorrelated and heterogeneous, but it would not affect the basic results developed here by relaxing this assumption.

To obtain the unconditional marginal effect of youth cohort size on unemployment rate, we should integrate out the year effects represented by X_2 in the above equation,

$$\begin{aligned} E[y|X_1] &= \int E[y|X_1, X_2]g(X_2|X_1)dX_2 \\ &= \int (X_1\beta_1 + X_2\beta_2)g(X_2|X_1)dX_2 \\ &= \int X_1\beta_1 g(X_2|X_1)dX_2 + \int X_2\beta_2 g(X_2|X_1)dX_2 \\ &= X_1\beta_1 + E[X_2|X_1]\beta_2. \end{aligned} \tag{3.9}$$

The difference between the conditional and unconditional mean of y is given by the term of $E[X_2|X_1]\beta_2$. Notice that $E[X_2|X_1]$ is a function of X_1. To have consistent estimates of the marginal effect of X_1 on y obtained from equations (3.8) and (3.9), $E[X_2|X_1]$ should be constant. That is, X_1 is uncorrelated with X_2. If $E[X_2|X_1]$ is not a constant, but depending upon X_1, then the estimates will vary across the conditional and unconditional model. Whether the estimates from the conditional model are reliable depends on the robustness of the correlation between X_1 and X_2. If it is robust, then the estimate from the unconditional model without controlling X_2 is biased. The estimate is biased downward or upward depending upon how X_1 and X_2 is correlated. In such cases, adding X_2 in the regression is justifiable. However, if the relationship between these two variables varies over time, any inference made from the estimates obtained by including X_2 could be misleading if applying to different periods. In the specific problem we are discussing in this study, the positive temporal correlation between youth share and unemployment rate might be just a coincidence in the period of 1978-1996 in the U.S and 1971-1995 in the OECD countries. However, the stability of estimates from the conditional model requires a random sampling of the data.

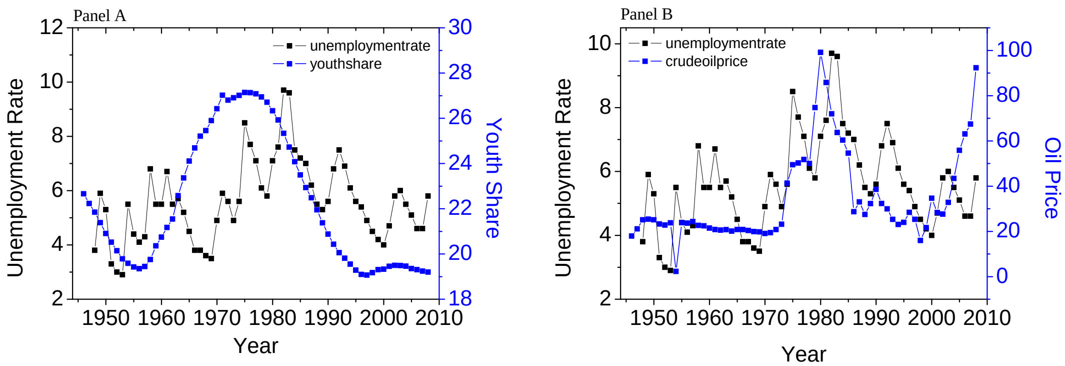

Figure 3.1: The Trend of Unemployment Rate, Youth Share and Oil Price in the U.S.

In the age composition of population in the U.S., there is a dramatic change due to the baby boom generation who were born in the years from 1946 to 1964.[6] Panel A in Figure 3.1 plots the national trend of youth share and unemployment rate in the U.S. in the postwar period. Youth share starts to rise in 1955 and peaks in 1978, from a national average of about 19% to 27%. From the end of the 1970s to the mid 1990s, there is a steady decline of youth share due to the baby bust. Youth share has remained at a plateau around a level of 19%-20% since 1996. The graph also shows that within the period of 1978-1996, the aggregate unemployment rate experiences a notable fall as well. There are two business cycles within this period. The average unemployment rate in the first cycle is much higher than that in the second one. It is unclear whether the positively temporal correlation in the youth share and unemployment rate in the period of 1978-1996 is a causality or a coincidence, which is the difficulty encountered in studies with time series analysis. If it is just a coincidence, the non-sampling problem would arise. Unfortunately, the baby boom is a non-replicable historical event. We are not able to test this spurious

[6]According to U.S. Census Bureau (January 3, 2001). "Oldest Baby Boomers Turn 60!"

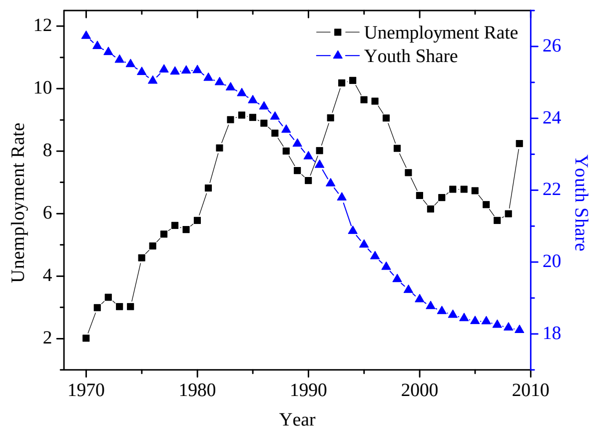

Figure 3.2: The Trend of Unemployment Rate and Youth Share in the OECD Countries.

correlation in another similar baby boom period. There is some evidence showing that the decreasing unemployment rate might be caused by other macroeconomic factors. For instance, it is observed that oil shocks are also historically correlated with economic recessions in the U.S. (Mork [1989], Ferderer [1996], Hamilton [1996] and Hooker [1996]) Panel B of Figure 3.1 shows the time series for the oil price and unemployment rate of the U.S. from 1946 to 2008. After 1970s, it reveals a closer correlation between oil price and unemployment rate. The trend of oil price graphically fits the trend of unemployment rate much better than the youth share, but with a one year lag.

Figure 3.2 presents a similar set of time series of aggregate unemployment rate and youth share for 15 OECD countries. The baby boom is not a unique demographic phenomenon in the United States. Actually, WWII brought most western countries a baby boom in the 1950s and 1960s. There is more variation in the youth cohort size across countries. The proportion of youth cohort in the population starts to fall in the early 1970s in countries like the United States, Canada, Australia, Ireland, Netherlands, and Finland. The baby boom in these countries begins immediately after the war. In other OECD countries, such as Germany, Italy and U.K., which are damaged greatly by the war, birth rates only increase when the economy starts to recover several years after the war. Therefore there is a lag in the falling trend of youth cohort size in these countries. Overall, in 1970-1994, the annual average of youth share in OECD countries decreases, while the annual average of unemployment rate increases. The two business cycles that occurred around the early 1980s and 1990s match those observed in the United States. But in OECD countries, the overall unemployment rate was much higher in the second cycle in the period of 1970-1995. If the declining youth share should decrease the unemployment rate according to the 'cohort crowding effect', then the graph demonstrates that there must be other factors that substantially affect the unemployment rate.

In sum, in Shimer [2001] and Korenman and Neumark [2000], the consequences of demographic change in the age structure for the unemployment rate are investigated in a period when the youth cohort size falls significantly. The decline of youth share caused by exogenous historical reasons is spuriously correlated with the temporal variation of unemployment rate. Regardless of whether the correlation is positive or negative, the exercise of including year dummies in the fixed effect model is subject to a non-random sampling problem. The analysis does not imply that the inclusion of year dummies in the fixed effect model is inappropriate; it simply illustrates under what circumstances should we be careful about the consistency of the estimates across different specifications, as well as the implicit random sampling assumption.

3.3 Data

Part I - United States

1. Unemployment Rate: Unemployment rate data by state by age group are from the LAUS program in the Bureau of Labor Statistics. The data cover from 1976 to 2009. 1976 is the first year that comparable unemployment rate data across states are available.

2. Demographic Data: Population by age from 1970 to 2009 are from Census Bureau Population Estimates.

3. Birth Rate and Death Rate are collected from historical Statistical Abstract of United States. The lagged birth rates from 1954 to 1992 are used as the Instrumental Variable for Youth Share in 1978-2008. Birth rate, death rate, together with the population by age are used to restore the migration data for every state in each year.

Part II - OECD Countries

1. Unemployment Rates by age groups and Demographic distribution are obtained from OECD. Stat Extracts. *http://stats.oecd.org/Index.aspx*

2. Birthrate are collected from various issues of International Historical Statistics: 1970-2005.

Part III - Ipums Census (1980,1990 and 2000).

3.4 Empirical Analysis

3.4.1 Empirical Strategies

Because the estimates obtained from conditional model, which controls for year effects by including year dummies, are not robust in different cross sections and sample periods, there is no prediction power of the conditional model. We next turn to the unconditional model for more reliable and consistent estimates. In this subsection, we explore the unconditional marginal effect of youth cohort size on unemployment rate. For the strategies proposed in this subsection, we primarily

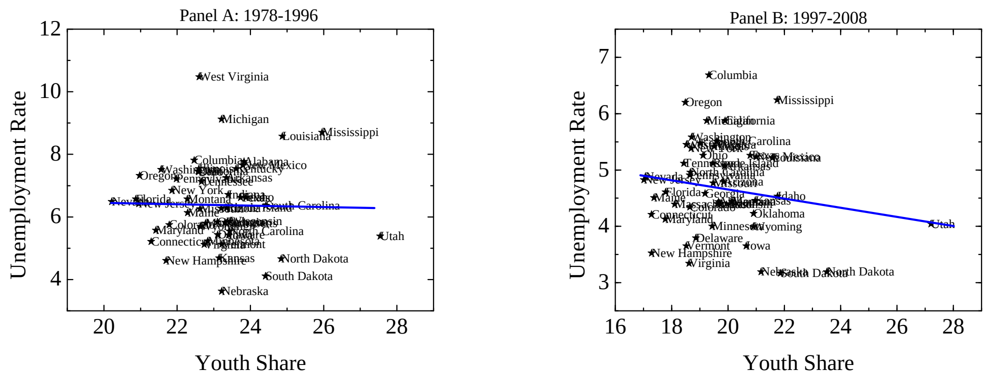

Figure 3.3: Correlation between State Average of Unemployment Rate and Youth Share in the U.S.

focus on the U.S. data. The sample size of the OECD countries data is too small to be statistically significant at any level in the cross-sectional analysis.

As a first attempt, we average the youth share and unemployment rate over different sample periods for each state. Figure 3.3 presents the scatters and fitted lines of the averages for the aggregate unemployment rate and youth share across 49 states. Panel A and B are for the periods of 1978-1996 and 1996-2008, respectively. The fitted line indicates the direction of the correlation between the two variables in each period. Comparing the two panels, we find that the fitted line in Panel B is downward sloping. However, it is driven by four states which are located in the right corner of the graphs, North Dakota, South Dakota, Nebraska and Utah. The former three states are contiguous farm states in the mid-west, with large agriculture sectors and low population density. Specifically, there are more than 50 percent of the population living in the rural area and working on farms in these three states. On the one hand, the unemployment rates there are persistently lower than most other states. The development of healthy agricultural industry and enriched natural resources make these states less vulnerable to macroeconomic shocks and economic recessions. On the other hand, birth rates are higher in these states all year-round. When youth share in most of the other states drops to around 20 percent, it remains high in these same states. High demand for labor on farms might be one of the reasons for the high birth rates. Another state with the highest birth rate is Utah, which is recognized by its highly religious homogeneity of Mormonism. Also, the unemployment rate in Utah is much lower compared with the national average. The attractiveness of youth to the firms, according to the basic thought conveyed in the the theory developed in Shimer [2001], might be one of the possible reasons. Nevertheless, as shown in the figure, Utah is an outlier far apart from the bulk of the other states. Utah's mode is hardly replicable for other states. We are more interested in the more general cases of other states for the sake of providing an explanation applied to the more general situations.

We propose two strategies to deal with the possible outlier effects. Firstly, we drop the states which are likely to be outliers in the analysis and revise the cross sectional evidence on the relationship between averages of unemployment rate and youth share for the remaining states. Secondly, we conduct a population weighted regression analysis. Any outlier effects would be reduced by the population weights.

The cross-sectional analysis above is still hard to build a causal relationship for the unemployment rate and youth cohort size. Even though the year effects are controlled for by taking averages, state specific characteristics are not eliminated, such as state taxes or benefit policies, industrial mix, demographic composition in ethnicity or average education attainment, etc. Consider a state with a higher average unemployment rate in a certain time period: it is possible that the state has a higher share of employment in sectors with higher unemployment rates, due to the negative national demand shocks. At the same time, the youth share is relatively high in that state because of the higher lagged birthrate. The question is whether the industrial mix or the high youth share is the main source of the high unemployment rate, or whether the two effects coexist. This is the main drawback of the cross sectional analysis.

In order to remove the state fixed effect in determining the relationship between youth cohort size and unemployment rate, we propose the following statistical procedures to construct a pseudo panel for the United States. In this pseudo panel, the chronology of the original data set is disrupted. We turn our attention away from the conditional model because we have concern that the estimates could be driven by the spurious temporal correlation between youth cohort size and unemployment rate. In our alternative unconditional model, we intend to eliminate this possibility.

1. In each sample period, we shuffle the sets of observations across years and divide these randomized data into two year groups for each individual state. Therefore, the combination of years in each year group will be different across states. By randomizing the order of the data for each state, we could avoid the effects of the temporal trends of youth cohort size and unemployment rate.

2. Calculate the average unemployment rate and youth share for each state in each year group within a sample period.

3. For each state, take the difference of the averages in unemployment rate and youth share between two year groups.

4. Each practice from Step 1 to Step 3 is considered as an attempt. Run the OLS estimation by using the values obtained from Step 3 for each attempt. Record the estimated coefficient and the standard errors.

5. Repeat Step 1 to Step 4 for 10,000 times[7].

6. Plot the distribution of the estimated coefficients obtained from these 10,000

[7]The results show that it makes little difference to have more attempts.

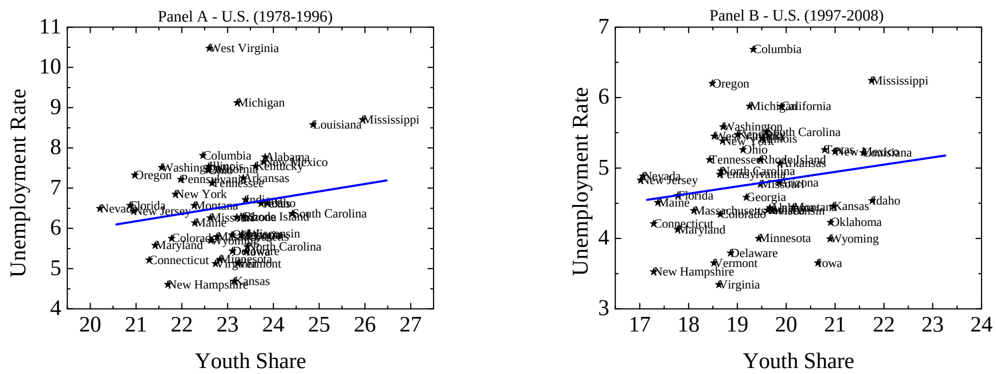

Figure 3.4: Correlation between State Average of Unemployment Rate and Youth Share in the U.S.-Exclude outliers.

attempts.

3.4.2 Cross Sectional Evidence for the U.S.

In Figure 3.4, Panel A and B present the the scatters and fitted lines for the state average of aggregate unemployment rate and youth share after we drop those four states mentioned above. As the figure illustrates, there is a positive correlation between unemployment rate and youth share in both periods. In order to show the indirect effects of youth share on the age group specific unemployment rates, Panel A to Panel F in Figure 3.5 and Figure 3.6 also graphically link the age group specific unemployment rate with the youth share in two periods of 1978-1996 and 1997-2008. Panel A and B present the results for the two youngest groups. Panel C to F are for four population groups aged from 25 to 64. The fitted line for the unemployment rate and youth share rotates rightward when we go through from the panels for younger age groups to older age groups in both periods. The positive relationship between state averages of unemployment rate and youth share diminishes and becomes negative for the eldest cohort.

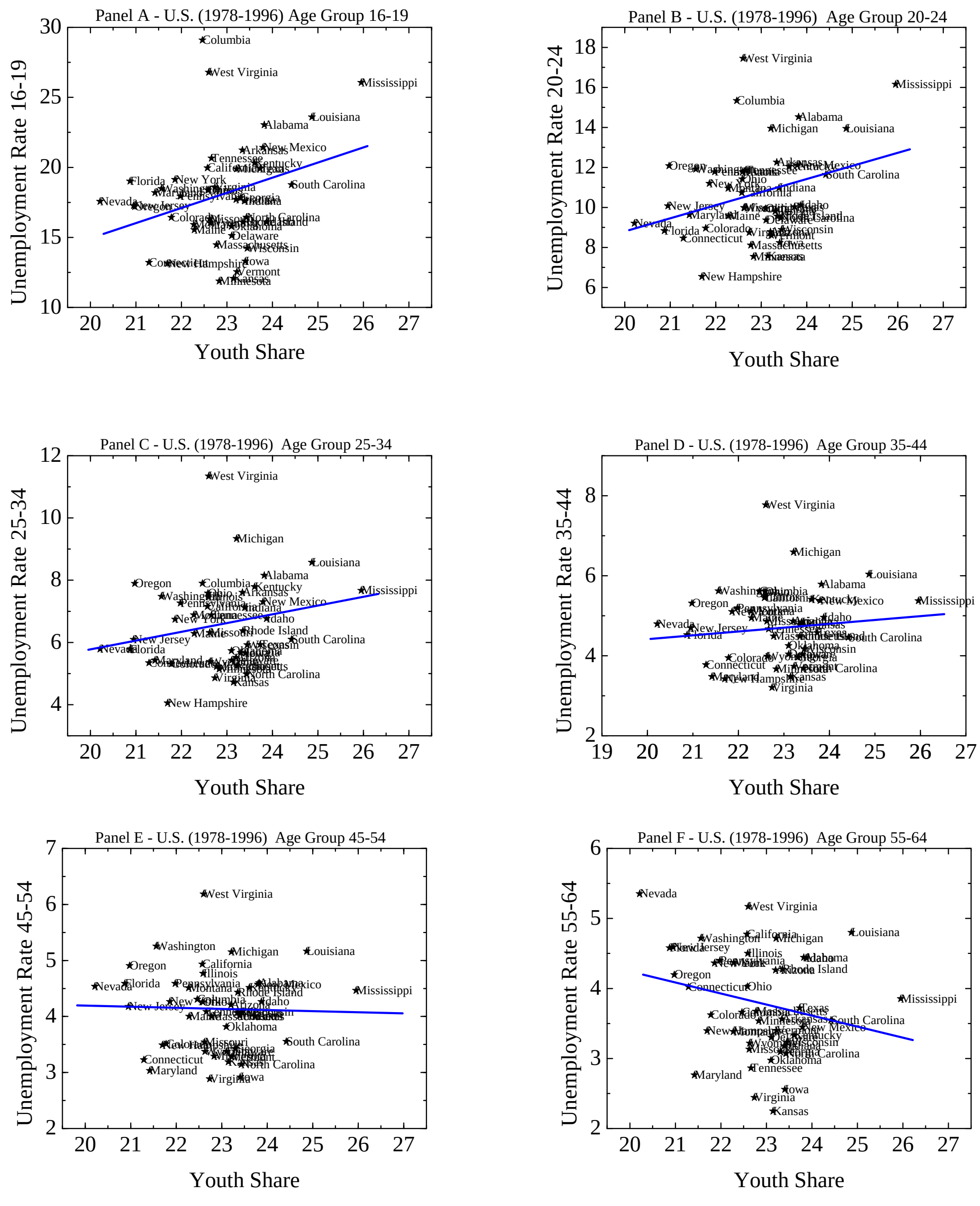

Figure 3.5: State Average of Unemployment rate and Youth Share by Age Group in the U.S. in 1978-1996 - Excluding Outliers.

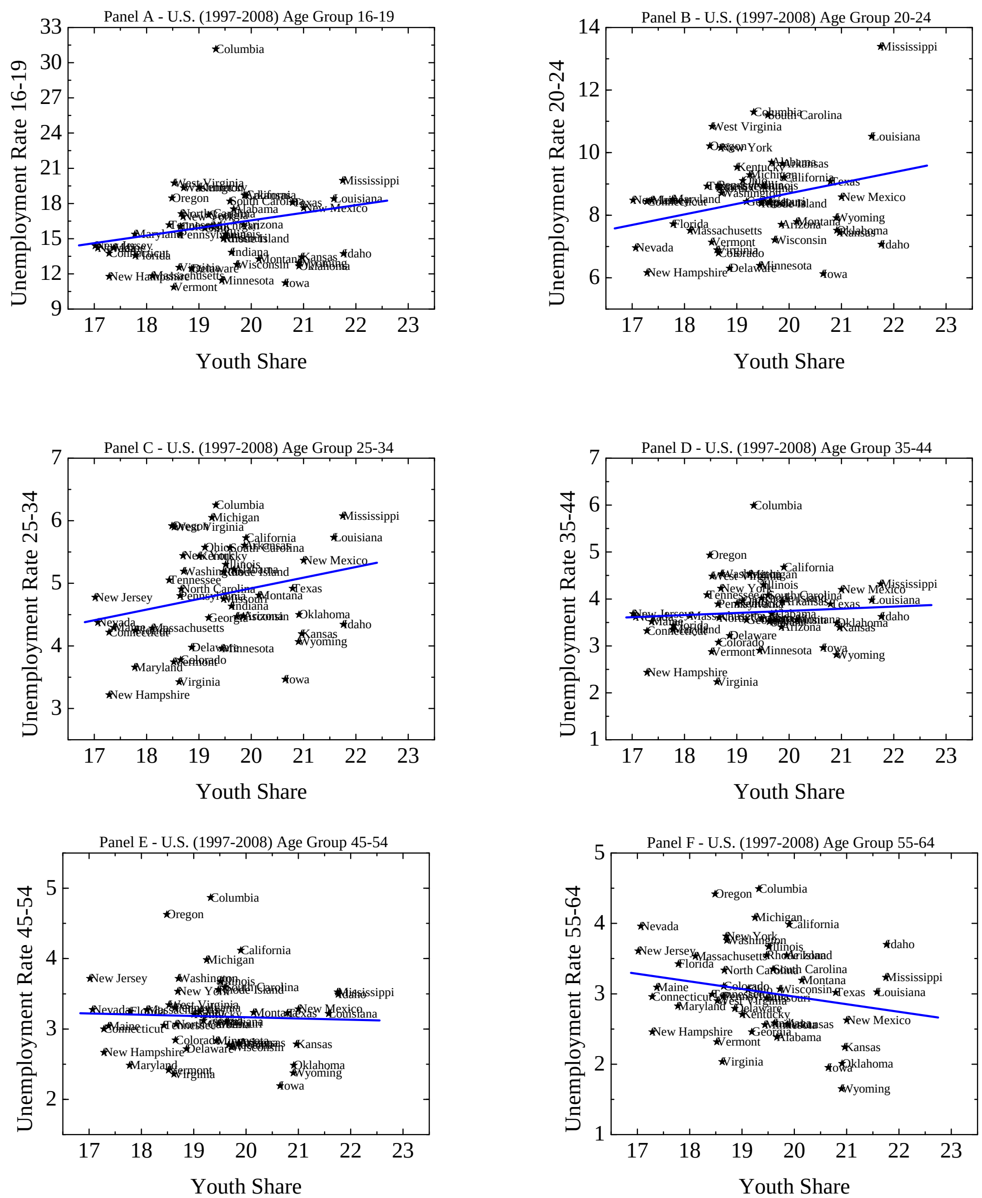

Figure 3.6: State Average of Unemployment Rate and Youth Share by Age Group in the U.S. in 1997-2008 - Excluding Outliers.

Table 3.5: Cross-Sectional Analysis for U.S. in 1978-1996.

	(1)		(2)		(3)		(4)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
16-64	-0.006	0.116	0.075	0.227	0.082	0.088	0.137	0.135
	(0.148)	(0.141)	(0.174)	(0.161)	(0.151)	(0.138)	(0.162)	(0.146)
16-19	0.018	0.706*	0.356	1.225**	0.358	0.680*	0.564	0.891**
	(0.045)	(0.421)	(0.525)	(0.464)	(0.387)	(0.342)	(0.401)	(0.354)
20-24	0.081	0.223	0.383	0.537*	0.304	0.195	0.465*	0.315
	(0.028)	(0.264)	(0.316)	(0.292	(0.261)	(0.240)	(0.275)	(0.252)
25-34	-0.033	0.021	0.069	0.129	0.076	0.014	0.141	0.061
	(0.165)	(0.158)	(0.192)	(0.181)	(0.172)	(0.157)	(0.184)	(0.167)
35-44	-0.072	0.019	-0.014	0.101	0.004	-0.020	0.041	0.011
	(0.11)	(0.106)	(0.129)	(0.121)	(0.119)	(0.108)	(0.128)	(0.115)
45-54	-0.107	-0.052	-0.086	0.031	-0.088	-0.056	-0.071	-0.038
	(0.087)	(0.089)	(0.102)	(0.097)	(0.095)	(0.087)	(0.103)	(0.093)
55-64	-0.227**	0.082	-0.253**	-0.019	-0.239**	-0.138	-0.245	-0.130
	(0.087)	(0.151)	(0.102)	(0.103)	(0.098)	(0.093)	(0.107)	(0.100)

[1] New-West Standard errors are reported in the parenthesis.
[2] Instrumental variables for youth share include lagged birthrate, year and state dummies.
[3] *** significant at 1 percent level. ** significant at 5 percent level. * significant at 10 percent level.

Table 3.6: Cross-Sectional Analysis for U.S. in 1997-2008.

	(1)		(2)		(3)		(4)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
16-64	-0.077	-0.035	-0.072	0.013	0.052	0.120	0.122	0.191**
	(0.066)	(0.082)	(0.086)	(0.109)	(0.077)	(0.077)	(0.190)	(0.085)
16-19	-0.336	-0.105	-0.281	0.181	0.289	0.667**	0.061*	1.008**
	(0.297)	(0.367)	(0.381)	(0.484)	(0.276)	(0.268)	(0.319)	(0.286)
20-24	-0.177	-0.202	-0.076	-0.060	0.015	0.006	0.173	0.129
	(0.132)	(0.162)	(0.169)	(0.213)	(0.137)	(0.140)	(0.158)	(0.155)
25-34	-0.065	-0.074	-0.007	0.007	0.059	0.069	0.158*	0.148*
	(0.069	(0.085)	(0.008)	(0.111)	(0.082)	(0.083)	(0.094)	(0.092)
35-44	-0.077	-0.069	-0.062	-0.035	0.025	0.064	0.086	0.122
	(0.057)	(0.071)	(0.074)	(0.094)	(0.067)	(0.068)	(0.078)	(0.075)
45-54	-0.109**	-0.074	-0.125**	-0.057	-0.043	0.027	-0.017	0.070
	(0.048)	(0.061)	(0.062)	(0.081)	(0.059)	(0.061)	(0.070)	(0.068)
55-64	-0.155**	-0.101	-0.190**	-0.090	-0.109*	-0.014	-0.102	0.024
	(0.052)	(0.068)	(0.066)	(0.090)	(0.067)	(0.070)	(0.080)	(0.079)

[1] New-West Standard errors are reported in the parenthesis.

[2] Instrumental variables for youth share include lagged birthrate, year and state dummies.

[3] *** significant at 1 percent level. ** significant at 5 percent level. * significant at 10 percent level.

In Table 3.5, we present the estimated effects of average youth cohort size on average unemployment rates obtained from regressions for the period of 1978-1996. Column 1 and 2 report the results when all of the 49 states are included. Column 3 and 4 give the estimates when Utah is dropped out. In Column 2 and 4, we replace the average youth share by the ones predicted by the lagged birthrates in order to control for the potential endogeneity. Of particular interest, we also investigate the relationship between youth share and age group specific unemployment rates in these regressions. Even though the estimates are largely insignificant due to the small sample size and high variations in unemployment rate and youth share among the 49 states, the changes in the coefficients reveal a similar pattern as we move along these columns from younger to older groups. The estimated effects of youth share on unemployment rates are getting smaller and smaller. It indicates that the youth cohort size has differential effects on the unemployment rates for different age groups, consistent with the hypothesis that workers of different ages are imperfect substitutes. When we compare OLS estimates with IV estimates, obtained by using the lagged birthrate as the instrumental variable, we find that the OLS estimates are much smaller in magnitude than the IV estimates. It indicates that the endogeneity problem is indeed present. In addition, across the years, Table 3.6 shows that the endogeneity problem becomes much stronger in the latter period of 1997-2008. After we drop Utah from the analysis, both the OLS and IV estimates become more positive. The change in the estimates confirms the previous conjecture that Utah is a state that drives down the possible crowding effects of youth share. The IV estimates for the youngest age group of 16-19 are statistically significant at a 5% level with or without Utah included, as shown in Column 2 and Column 4. The magnitude of these estimates is also of economic significance. For the majority of states in the U.S., it implies that a state with 5 percent higher youth share in the population, projected by the higher birthrate back to 16-24 years ago, is associated with a 0.3-0.5 percent higher unemployment rate for the youngest workers aged 16-19 in the labor force.

Groups (3) and (4) in Panel A and B of Table 3.5 reports the results of population weighted regressions. In group (4), the state of Utah is also excluded in the regression. Except for the oldest groups with age 45-54 and 55-64, the estimates turn positive, which further demonstrates the presence of outlier effects.

As a robust check for the above results, we also apply these specifications on samples across an approximate 5 or 10 year interval. For example, for samples with a 10 years interval, the time span for each sub-period is from 1978-1989, 1990-1999, and 2000-2008. Results are largely similar even though they are not reported in this paper.

3.4.3 Results after Controlling for State Fixed Effects

Figure 3.7 presents the distributions of the estimates for the impact of youth share on the aggregate unemployment rate, in two separate sample periods from our alternative procedures. The mean of the estimates are about 0.15 in both periods. But the variance is larger in the second period. Figure 3.8 shows the distributions of estimates by age groups in 1978-1996. The mean values of these estimates for the group of 16-19 and 20-24 is the largest among six age groups, which are 0.15 and 0.22. The means are shifting to the right as we move toward the older age group. The changing pattern of the estimated effects of youth cohort size on differen age groups is preserved. In 1997-2008, the variance of these estimates enlarges for most age groups. But the positive effects of youth cohort size on unemployment rate still exists among younger age groups, as shown in Figure 3.9. There is one exception though: the effect of youth cohort size on the unemployment rate of the age group of

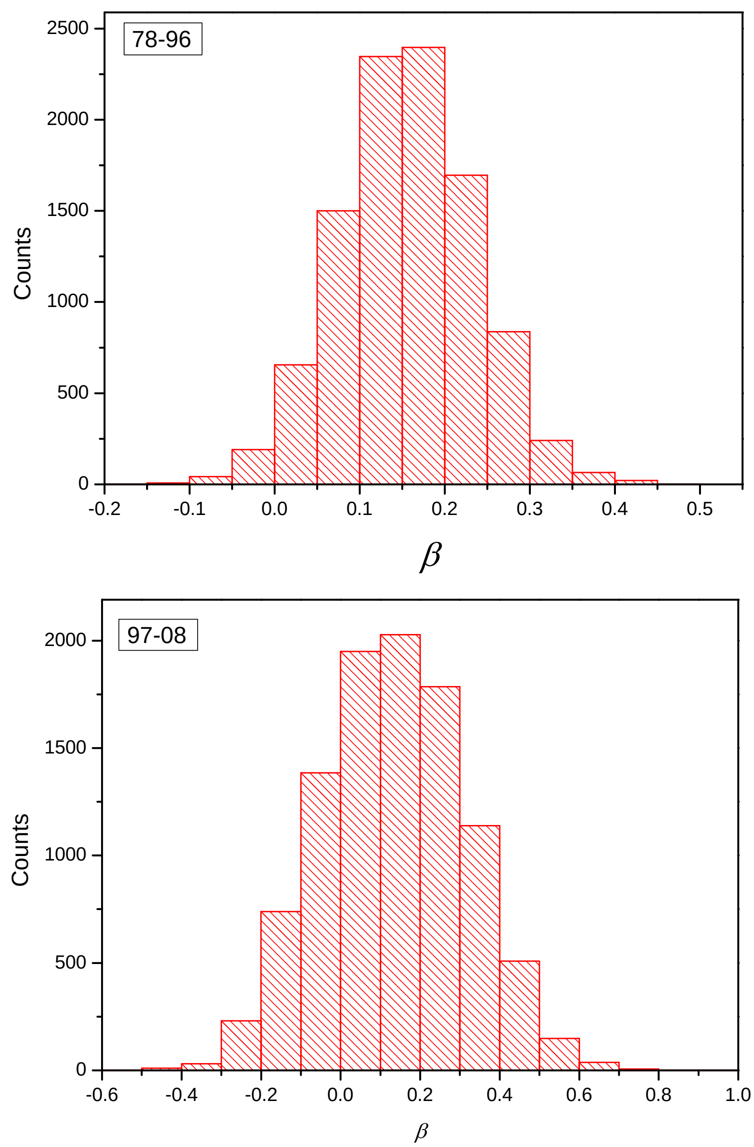

Figure 3.7: Distributions of the OLS Estimates for the Impact of Youth Share on the Aggregate Unemployment Rate in the U.S.

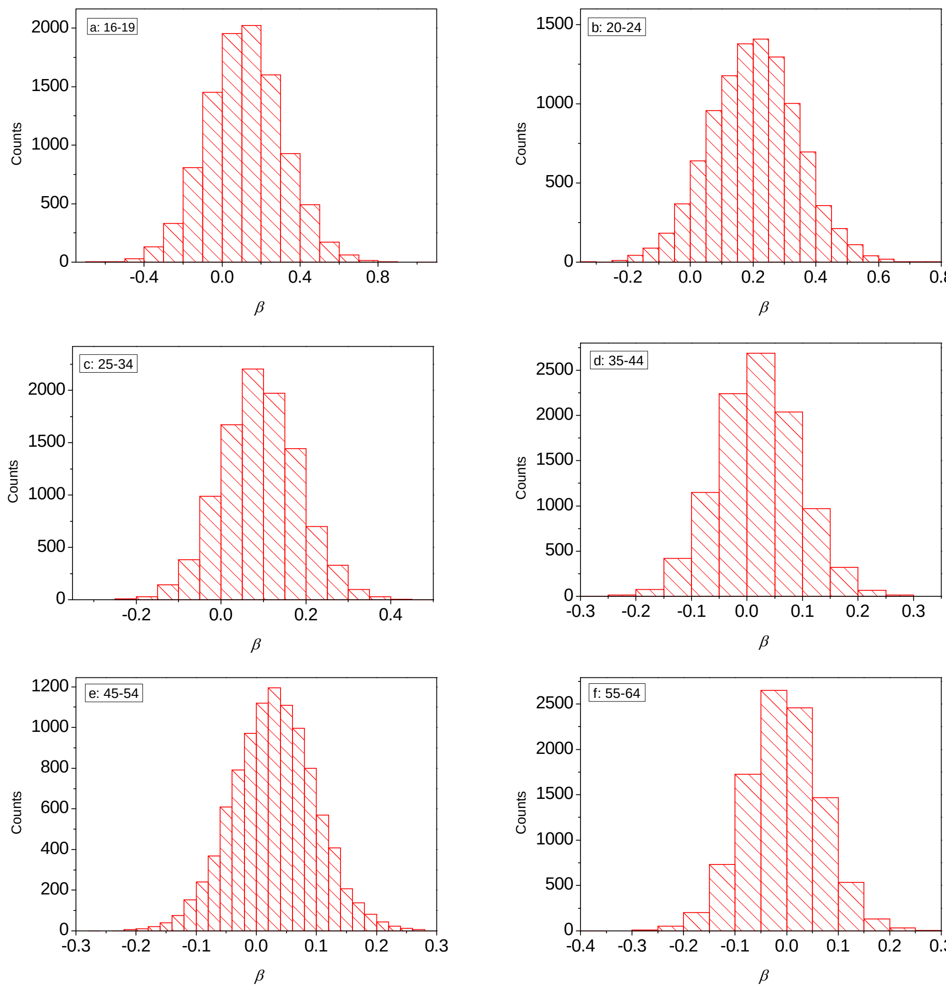

Figure 3.8: Distributions of the OLS Estimates for the Impact of Youth Share on the Age-Group Specific Unemployment Rate in the U.S. in 1978-1996.

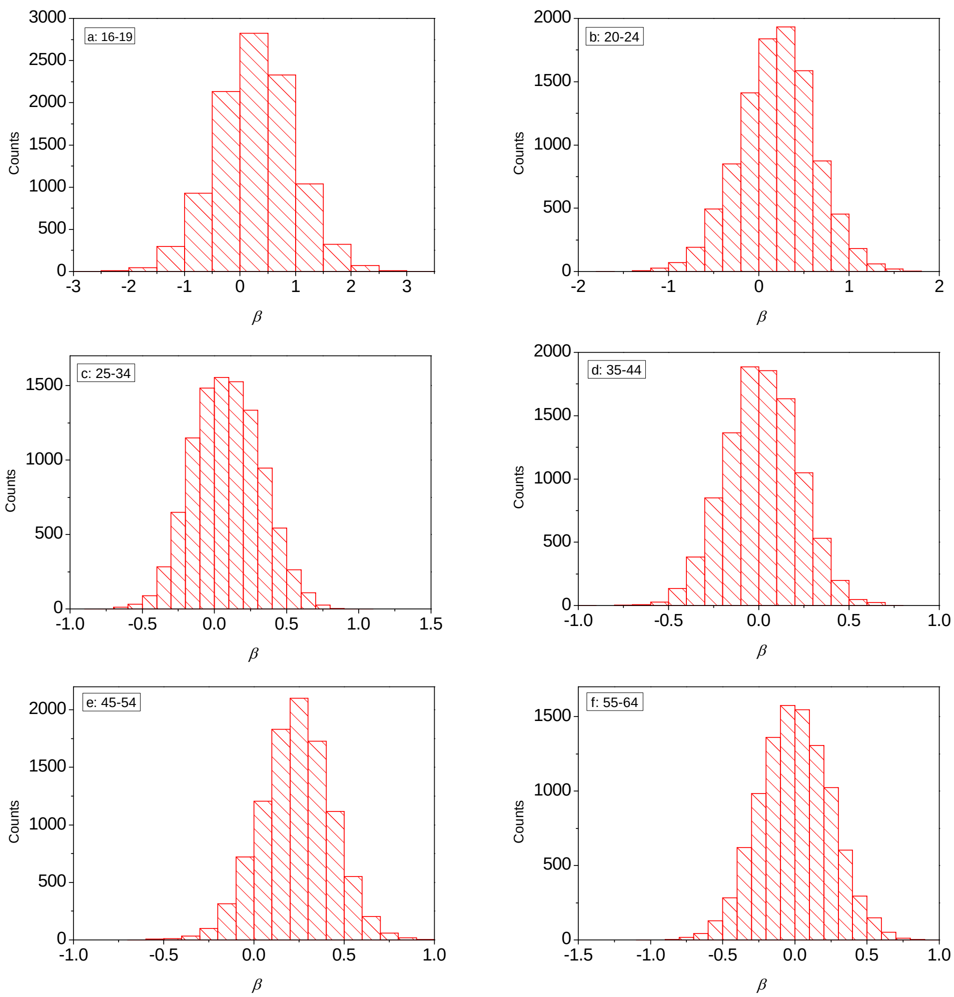

Figure 3.9: Distributions of the OLS Estimates for the Impact of Youth Share on the Age-Group Specific Unemployment Rate in the U.S. in 1997-2008

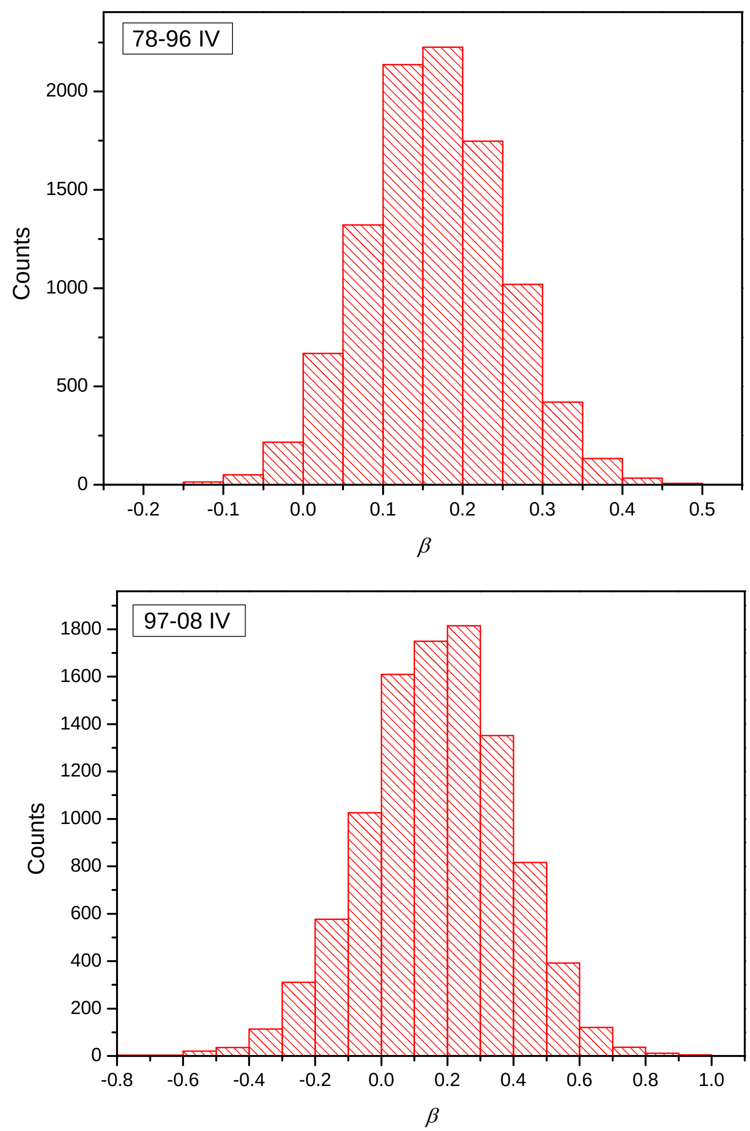

Figure 3.10: Distributions of the IV Estimates for the Impact of Youth Share on the Aggregate Unemployment Rate in the U.S.

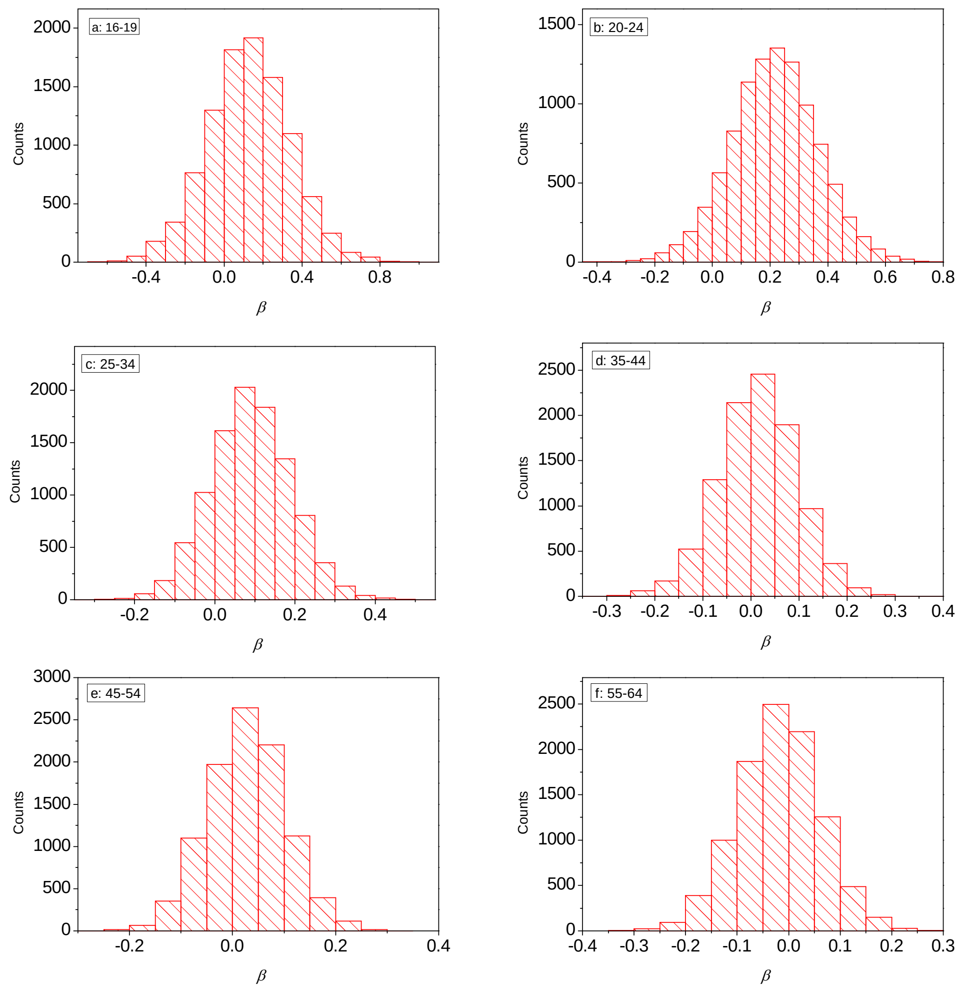

Figure 3.11: Distributions of the IV estimates for the Impact of Youth Share on the Age-Group Specific Unemployment Rate in the U.S. in 1978-1996.

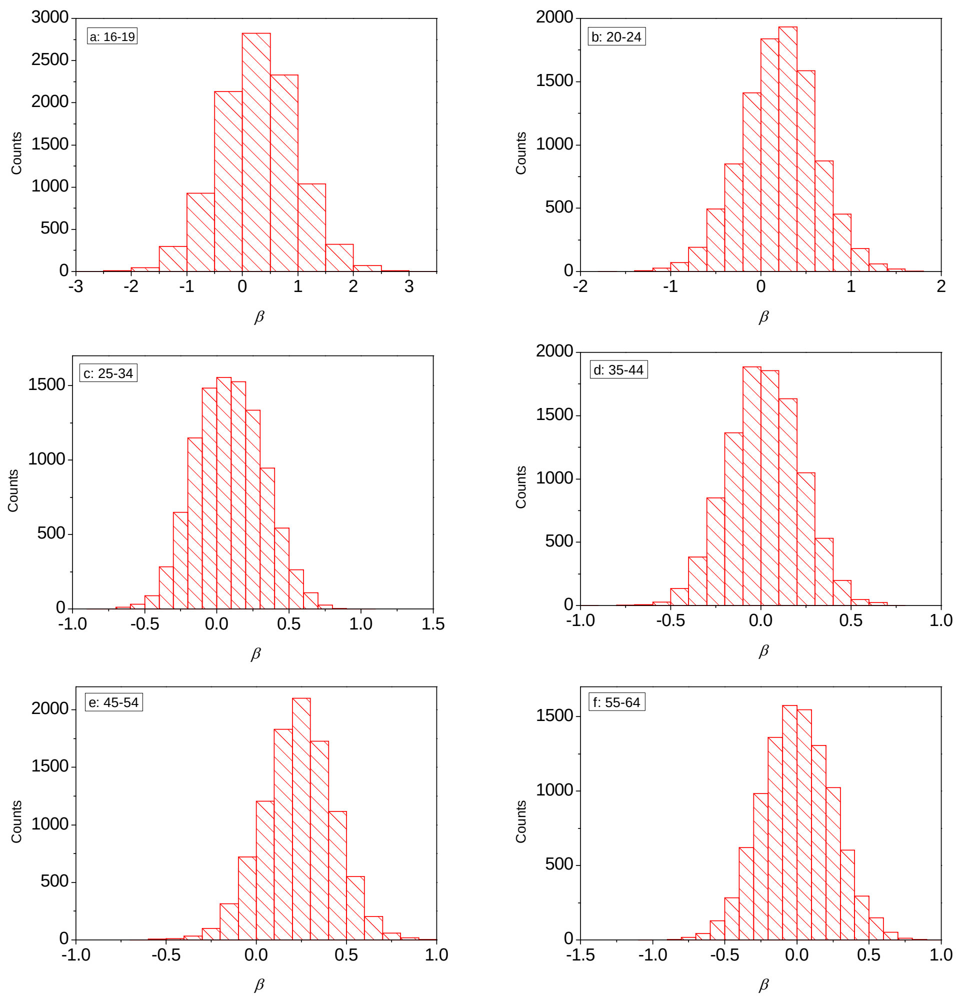

Figure 3.12: Distributions of the IV Estimates for the Impact of Youth Share on the Age-Group Specific Unemployment Rate in the U.S. in 1997-2008.

45-54 is positive. The IV estimates described in Figure 3.10, Figure 3.11 and Figure 3.12 are quite similar to the OLS estimates, which indicates the temporal migration does not really impair the estimated effects of youth cohort size.

Table 3.7 reports the composition of the estimates according to the sign and statistical significance. We have classified the estimates of coefficient into four categories: significantly positive, insignificantly positive, significantly negative and insignificantly negative. The numbers in each column corresponds to the counts out of 10,000 for each category and age group. For younger age groups, the proportion of positive estimates strongly dominates the negative estimates. For instance, in 10,000 attempts for the age group of 16-19 in the period of 1978-1996, 7246 estimates are positive while only 2574 estimates are negative. As we move from the youngest to the oldest age group, we find that the total counts of positive estimates are monotonically decreasing. In contrast, the total counts of negative estimates are increasing along with the age. For the oldest group of 54-64, negative estimates become the majority from the 1000 attempts. In either case, the nonsignificant estimates outweigh the significant ones in total numbers for each age group. Again, IV estimates presented in the bottom panel in Table 3.7 are quite close to the OLS estimates.

The above results show that after controlling for state fixed effects by taking difference between two average values obtained from a randomized data set, the decaying pattern of the estimated marginal effect of youth share on the unemployment rate still exist. It is relatively strongest and positive for the youngest age group. However, due to large variance of the randomized data for only 49 states, the overall effects of youth share on the unemployment rate is weak.

Table 3.7: The Distribution of the Estimates from the Pseudo Panel in the U.S., 1978-2008.

OLS							
1978-1996	16-19	20-24	25-34	35-44	45-54	55-64	Overall
$\beta > 0, t > 1.96$	979	3211	1618	487	629	208	4930
$\beta > 0, t < 1.96$	6267	6093	6832	5612	6083	4425	4829
$\beta < 0, t > 1.96$	58	1	8	101	97	323	0
$\beta < 0, t < 1.96$	2696	695	1542	3800	3191	5044	241
1997-2008	16-19	20-24	25-34	35-44	45-54	55-64	Overall
$\beta > 0, t > 1.96$	1044	1243	818	453	3446	503	1493
$\beta > 0, t < 1.96$	5548	5704	5485	4890	5368	4486	6110
$\beta < 0, t > 1.96$	259	197	184	451	23	666	44
$\beta < 0, t < 1.96$	3149	2856	3513	4206	1163	4345	2353
IV							
1978-1996	16-19	20-24	25-34	35-44	45-54	55-64	Overall
$\beta > 0, t > 1.96$	932	2971	1360	389	547	152	4582
$\beta > 0, t < 1.96$	6421	6278	6814	5413	5945	3971	5134
$\beta < 0, t > 1.96$	59	7	18	165	89	418	0
$\beta < 0, t < 1.96$	2588	744	1808	4033	3419	5459	284
1997-2008	16-19	20-24	25-34	35-44	45-54	55-64	Overall
$\beta > 0, t > 1.96$	1072	807	724	367	1663	394	1459
$\beta > 0, t < 1.96$	6401	5584	6142	5286	6628	5107	6449
$\beta < 0, t > 1.96$	46	175	67	190	28	253	52
$\beta < 0, t < 1.96$	2481	3434	3067	4157	1681	4246	2040

3.4.4 Inference from OECD Countries

We investigate the cross-sectional analysis by employing the OECD countries data, which is another source of data used in the previous literature about the relationship between youth cohort size and unemployment rate. In 1971-1995, we also find some evidence for a clockwise rotating pattern of the correlation between youth cohort size and country averages of unemployment rate by age group in 15 OECD countries. The younger the age group, the greater the positive relationship between unemployment rate and youth share. This pattern could be explained by the imperfect substitutability between workers in different age groups. The youth cohort size has strongest effects on the youngest group since young workers are perfect substitutes for young workers themselves. The substitutability between the youngest workers and other age group workers declines as the the age of other workers increases. However, even though we find a similar pattern in OECD countries, the correlation is still positive for the oldest groups with age of 45-64. In contrast, in the cross states data collected from the U.S., the sign of the correlation is negative for the oldest group. The rotation of the fitted lines among different age groups are more dramatic in the U.S. There are two possible explanations for the discrepancy. Firstly, young workers in more aggregated sections, such as countries, are still more likely to be substitutes to the old workers. However, across states within a country, migration cost is substantially lowered and young workers could migrate away from the high youth unemployment rate state. Therefore, prime age workers in states with high youth unemployment rates face less competition from the younger group. Secondly, it is more likely that the high unemployment rates in some OECD countries such as Ireland, United States, Canada, and Netherland are not related to their higher youth cohort sizes during the period of 1971-1995. It is the unobservable country-specific characteristics that lead a recession of the economy. At the country level, this probability is much higher. The macro policies would be more heterogenous across countries than within countries. Also, these country-specific policies may change over time. Neither state or year fixed effects could fully control this kind of variation. Therefore, even though the substitutability of the young workers for other age group of workers decreases, the gap in the unemployment rates between higher and lower youth cohort size countries doesn't diminish. In the second period of 1995-2009, the relative size of youth cohort barely changes, but there is no notable correlation between the unemployment rate and youth cohort size in the OECD countries based upon the cross-sectional analysis. All in all, the cross-sectional evidence is not stable in the OECD countries across the time.

3.4.5 Robust Checks by Using Micro Data in the U.S.

All the analysis in the previous subsections is based on the aggregate data. The evidence from unconditional model by using data in the U.S. suggests that increase in youth share has a positive effect on the unemployment rate. In this subsection, we investigate whether the results also hold true if we employ micro level data. For this end, we construct data from the IPUMS for the 1970, 1980, 1990 and 2000 Census. We estimate

$$P(Unemployment_{ij} = 1) = \phi(X\beta + \gamma_1 Y_j + \gamma_2 U_j + \varepsilon_{ij}) \tag{3.10}$$

where $Unemployment_{ij}$ is an indicator variable showing the individual is unemployed or not. X is a vector of standard control variables for individual characteristics, including age, gender, marriage status, race, educational attainment and home ownership. Y_j and U_j are two aggregate variables indicating the youth cohort size and overall unemployment rate in the state j which the individual resides in. We are interested at the estimates of γ_1 since it is the marginal effect of the youth cohort size on individual's unemployment probability. The model is firstly estimated conditional on individuals who are in the labor force. Since the youth cohort size and unemployment rate may also affect the labor force participation decisions of workers, if the cohort crowding effect exists, then some of the workers, who find it hard to get a job when there are two many competing peers, may simply drop out of the labor force. To capture this effect, we conduct the probit model separately for the labor force participation decisions.

$$P(Laborforce_{ij} = 1) = \phi(X\beta + \gamma_1 Y_j + \gamma_2 U_j + \varepsilon_{ij}) \tag{3.11}$$

We first estimate the above two equations for all states. For the comparison of the indirect effects of youth cohort size on the unemployment rate, we also disaggregate the whole sample into several age groups. Moreover, we compare the estimates obtained by including or excluding Utah in the analysis to test the outlier effect,if any at all.

The results are reported in Table 3.8. Under each decennial census, the first and second column present the estimates by using the data from all states and from the states excluding Utah, respectively. The effects of youth share on the labor force participation probability of individuals are listed in Panel A. Estimates in Panel B show us how the youth cohort size affects the unemployment probability conditional on the choice of labor force participation. The "Cohort Crowding" literature also predicts that higher youth cohort size would dampen the enthusiasm of labor force participation, since many young people would withdraw from the labor market if they are pessimistic about finding work due to fierce competition among peers. For the age group of 16-24 in Penal A, the significant estimates are all in negative values across

Table 3.8: Effects of Youth Cohort Size on the Labor Force Participation and Unemployment Probability -U.S. Census 1970-2000.

	1970		1980		1990		2000	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A								
16-64	0.034	0.019	0.296***	0.386***	-0.012	-0.191***	-0.079***	-0.155***
	(0.024)	(0.025)	(0.018)	(0.020)	(0.013)	(0.022)	(0.010)	(0.013)
16-24	-0.181***	-0.225***	-0.112**	-0.002	-0.043	0.054	0.011	-0.215***
	(0.051)	(0.053)	(0.046)	(0.049)	(0.041)	(0.051)	(0.031)	(0.043)
25-34	0.101	0.133**	0.064*	0.255**	-0.023	-0.151***	-0.089***	-0.074**
	(0.056)	(0.058)	(0.038)	(0.041)	(0.028)	(0.040)	(0.023)	(0.029)
35-44	0.059	0.057	-0.022	0.034*	-0.098***	-0.262***	-0.029	-0.047*
	(0.058)	(0.060)	(0.045)	(0.048)	(0.029)	(0.044)	(0.021)	(0.026)
45-54	-0.148**	-0.192***	0.287**	0.261**	-0.043	-0.305***	-0.123***	-0.260***
	(0.056)	(0.058)	(0.044)	(0.046)	(0.032)	(0.055)	(0.022)	(0.027)
55-64	0.146**	0.077	0.710**	0.706**	0.044	-0.463***	0.0006	-0.157**
	(0.057)	(0.059)	(0.041)	(0.042)	(0.030)	(0.075)	(0.024)	(0.030)
Panel B								
16-64	0.064	0.070	0.024	0.084**	0.031*	-0.148***	-0.014	0.090***
	(0.050)	(0.052)	(0.032)	(0.033)	(0.015)	(0.243)	(0.019)	(0.033)
16-24	0.297***	0.330***	0.192**	0.242***	0.019	0.190***	-0.032	0.188***
	(0.093)	(0.097)	(0.060)	(0.064)	(0.046)	(0.057)	(0.042)	(0.057)
25-34	0.383**	0.40**	0.275**	0.384***	0.052	-0.082*	0.055	0.188***
	(0.109)	(0.113)	(0.058)	(0.062)	(0.031)	(0.044)	(0.038)	(0.048)
35-44	-0.222**	-0.235*	0.1000	0.203**	-0.036	-0.223***	-0.026	0.032
	(0.117)	(0.120)	(0.076)	(0.080)	(0.132)	(0.049)	(0.037)	(0.046)
45-54	-0.147*	-0.143	-0.277**	-0.219**	-0.091**	-0.285***	-0.034	0.088
	(0.118)	(0.122)	(0.084)	(0.088)	(0.035)	(0.061)	(0.042)	(0.051)
55-64	-0.332**	-0.346***	-0.695**	-0.729***	0.014	-0.434***	-0.293***	-0.265***
	(0.142)	(0.146)	(0.098)	(0.102)	(0.032)	(0.077)	(0.060)	(0.072)

[1] Panel A reports the effect of youth share on the labor force participation probability.
[2] Panel B reports the effect of youth share on the unemployment probability.
[3] All of regression include a set of control variables on personal characteristics.
[4] Region dummies are included.
[5] *** significant at 1 percent level. ** significant at 5 percent level. * significant at 10 percent level.

the census years. For other age groups, the results are mixed. As shown in Panel B, for the youngest groups with age of 16-24 and 25-34, higher youth share in the state where the an individual lives significantly increase his probability of unemployment. This positive effect is quite stable over the four census years which represent four decades. Also consistent with the findings in our cross-sectional analysis by using the aggregate data, for the oldest group between the age of 55-64, it shows that the higher the youth cohort size, the lower the unemployment rate probability.

We also find the evidence of outlier effects by comparing the estimates from Columns (1) and (2) for each census year. For example, when we exclude the state of Utah from our analysis, the effect of youth share on the unemployment probability will be much stronger.

4. CONCLUSION

4.1 The Slowdown of Family Migration in the United States

This paper documents a notable long-term declining trend of the family interstate migration rate. It contributes to the migration literature in several aspects. Firstly, we have developed a much deeper understanding about the migration trend in the United States. Previous studies have not reached an agreement on how the migration propensity has evolved over the past decades. Most of them focus on the overall migration rate without appropriate disaggregation for the whole population. We find that the aggregate interstate migration rate in the U.S. only declines modestly over the past 40 years. There is no clear-cut trend of the overall migration rate because of the heterogeneity in the changes of migration propensities across different demographic groups. At the same time, the composition of the population also varies, which further confounds the trend in the overall migration rate. Specifically, the migration propensity of highly educated couples, especially that of the power couples, drops so sharply that it offsets the expected increasing migration rate resulting from the rising shares of college graduates in the population. Only based upon these much more detailed findings could we possibly find out the fundamental reasons that explain the change in the migration propensities for the whole economy.

Secondly, in order to explain this dramatic decline of the migration rate for the highly educated couples, we extend Mincer's [1978] family migration model into a search framework. Thus we can formally model and estimate the effects of family ties on the changing family migration propensities. To our knowledge, we make the first attempt in the literature to measure the correlation of the gains from migration between spouses. We explicitly explore the possible sources of the gains from migration. We approximate it by using the correlation of the earnings between the husband and wife from their potential job offers. Under the assumption of uncorrelated error terms in the wage functions, we show that the correlation and its changes are identified by the differentiated payoffs for different occupations across the states.

Home ownership is exogenously determined in the extended theory model. It affects the migration probability jointly with the earnings ratio and earnings correlation. Empirically, previous studies, which examine the effects of home ownership on migration, neglect the endogeneity issue that is involved. The observed home ownership status is endogenously determined with the migration decisions. It is unclear whether the owners are unlikely to move or the movers are unlikely to own. The effects of home ownership will be overestimated if the endogeneity issue is not addressed, even though it is correct that owning a house deters migration. In this paper, we predict the home ownership by using state averages of housing prices, per-capita income, mortgage rates, and property taxes, which are exogenous to the individual family's migration decision.

The earnings of the wife or husband are affected by their labor force participation decisions. The observed earnings in the CPS are the earnings for the previous calendar year in which the migration occurs. It is possible that the movers quit their jobs or stop searching for new jobs when they expect that they are going to move in the near future. This possibility would also reduce the precision of our estimates. Therefore, we calculated the predicted earnings for husband and wife under the assumption that they will work for an average amount of time once they choose to work. We treat the endogeniety of wife's labor force participation in a similar fashion.

Finally, after we test the hypothesis developed in the theory model in a baseline logit regression, we perform a decomposition analysis for the decrease in the migration rate. For families with two college graduates, the increasing female labor force participation rate and earning ratio of wife to husband explain about 60% of the decline in the interstate migration rate in the 1980s-1990s. For families with a college graduate, these two factors are more than sufficient to fully account for the decrease in the migration rate. However, during the period of 1990s-2000s (prior to 2006), the rising home ownership is the primary determinant that drives down the migration rate for both types of families. In addition to the economic factors, we also find that the ageing population due to the end of baby boom also contributes to the reduction in the family migration rate, since younger people have more incentive to migrate for job opportunities and human capital enhancement.

4.2 "Cohort Crowding Effect" of Youth Share on Unemployment Rate

When we revise the literature about the impact of youth cohort size on the unemployment rate, we find that, regardless of using a panel data across states or countries, we couldn't obtain consistent estimates in a fixed effect model with the inclusion of year dummies in different time periods. The negative relationship between youth cohort size and unemployment rate found in the U.S. data in 1978-1996 does not show up in the post-1996 period. We also find that in the OECD data, the inclusion of year effects reverses the positive estimates in 1971-1995 to negative ones in 1996-2009. We attribute the inconsistency of the estimates to changes in the correlation between the temporal variations of the unemployment rate and youth share .

Due to the limitation of a fixed effect model with year dummies in studying this particular problem, we focus more on the unconditional model, which could circumvent the issues caused by year effects. In a standard fixed effect model, variation across sections is deleted by the inclusion of state or country dummies. Since it is usually difficult to verify the causality of the relationship revealed by the cross-sectional evidence, this part of variation, which could encompass substantial information regarding the effects of youth cohort size, is largely neglected. In this paper, we explicitly investigate the evidence provided by this dimension of the panel data. Through the cross-sectional analysis, we find consistent effects of the youth cohort size on the unemployment rate in the United States. In addition, we propose an alternative method to obtain a random sample across the years. The correlation between the temporal variation of youth share and unemployment rate is greatly reduced in these constructed pseudo panels. The estimates from these pseudo panels, which allows us to control for state fixed effects, support our cross-sectional evidence. We demonstrate that higher youth share in the population in a state will tend to push up the aggregate unemployment rate. This total effect encompasses both direct and indirect effects. Our estimates for the indirect effects of youth cohort size on age-group specific unemployment rate, based upon the unconditional models, are contrary to those empirical findings in Shimer [2001], but consistent with the "cohort crowding" literature.

The strategies proposed in this paper can hardly apply to the OECD data. Firstly, there are only 15 countries and the sample size is too small to make any reliable inference from an unconditional model. Secondly, there is more variation of the unemployment rates across countries. Confounding factors, such as macroeconomic policies, are unobservable and likely to change over time. The effects of these factors could be mixed with that of the youth cohort size and cannot be easily captured by the country fixed effects.

In a more comprehensive study, we would like to test the "Cohort Crowding" effect by employing more disaggregated data across metropolitan areas or cities. Unfortunately, to our knowledge, both the aggregate and age-group specific unemployment rate data are not available at the metropolitan area level in the United States. But our strategy primarily relies on the identification of the indirect effects through these age-group specific unemployment rates. Moreover, even though these data could be available in the future, there are still two challenges faced by the economists. First, the jurisdiction of metropolitan areas varies over time, which makes the data less comparable across time, especially in a period of several decades. Secondly, migration across metropolitan areas is more prevalent than the migration across states or countries, which intensifies the endogeneity problem. To instrument the endogenous variable of youth cohort size, we also need lagged birthrates for metropolitan areas.

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